
**Automatic Recognition of Pakistan Sign Language using
Computer Vision Techniques**



Ph.D. Thesis

By

Syed Muhammad Saqlain

88-FBAS/PHDCS/F12

Supervisor

Dr. Jamal Abdul Nasir

Assistant Professor DCS&SE, FBAS, IIU

Department of Computer Science & Software Engineering

Faculty of Basic & Applied Science

International Islamic University, Islamabad

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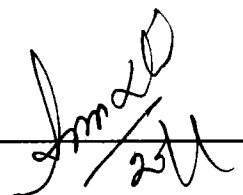
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It is certified that we have read this thesis, titled "*Automatic Recognition of Pakistan Sign Language using Computer Vision Techniques*" submitted by **Mr. Syed Muhammad Saqlain**, Reg. No. 88-FBAS/PhD(CS)/F12, and it is our judgment that this thesis is of sufficient standard to warrant its acceptance by the International Islamic University Islamabad for the Doctor of Philosophy in Computer Science.

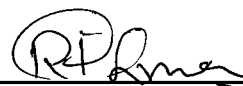
Committee:

External Examiners

Dr. Muazzam A Khan Khattak, Associate Professor
Department of Computer Science
Quid-e-Azam University Islamabad

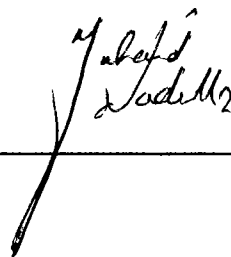


Dr. Arif ur Rehman, Associate Professor
Department of Computer Science
Bahria University, Islamabad



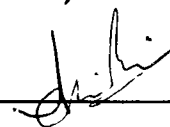
Internal Examiner

Dr. Muahmmad Nadeem, Assistant Professor
Department of Computer Science & Software Engineering
International Islamic University Islamabad



Supervisor

Dr. Jamal Abdul Nasir, Assistant Professor
Department of Computer Science & Software Engineering
International Islamic University Islamabad



Declaration

I hereby declare that this thesis, neither as a whole nor as a part thereof has been copied out from any source. It is further declared that no portion of the work presented in this report has been submitted in support of any application for any other degree or qualification of this or any other university or institute of learning.

Syed Muhammad Saqlain

Dedication

This thesis is dedicated to My family, especially to my father, mother, wife, brother, sisters, beloved daughter(Syeda Hoorain Zahra) and son(Syed Muhammad Irtaza Haider).

Syed Muhammad Saqlain

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Abstract

Languages are key source of communication for human beings which vary from region to region and nation to nation. In absence to the knowledge of a particular language, the oldest method of conveying a message is through use of hand, body and facial expressions. Almost 436 million people in the world are suffering from hard hearing which is about 5% of the total population. Use of human body gestures for communication by the deaf form base for the sign languages. Pakistan sign language(PSL) is influenced by Urdu i.e., national language of Pakistan. There are 38 alphabet signs for PSL and out of them 36 are represented by static hand gestures while 2 are continuous i.e., represented by hand motion.

Automatic sign language recognition helps in communication between normal and deaf people. Little efforts are made for Pakistan sign language recognition. One of the main challenge for presenting some computational technique is absence of dataset with rotation and scale variances generated through multiple signers and categorization of PSL signs that should be based on their physical appearance. Rest of the open issues are accurate detection of hands under complex backgrounds, extraction of signer independent scale and rotation invariant lower dimensional feature sets. As well as, different kernel functions show their strength under different environments and there is a need to present a classification methodology that should use ensemble of all those kernel functions.

Paistan sign language(PSL) dataset is presented that is created by taking services of the seven native signers and supervised by expert of the sign languages. The signs from each of the signer are taken at three different distances. The rotational variance in each of the class is upto 45 degree. A combinatory approach of you only look once(YOLO) based convolutional neural network(CNN) and morphological operations is presented for detecting, localizing and extracting the hand from the input images. YOLO-CNN is used for the detection and localization of hands followed by suppressing the background through the use of skin detector in HSV color space. The extraction of hand is accomplished through the use of morphological operations. Salient features from an image are key to the classification task. We have presented symmetric mean based binary patterns(sMBP) feature vector that extends the uniform binary pattern through maintaining rotation invariance. The task is accomplished through exploiting

the symmetric properties of circular neighboring points. Error-correcting output codes(ECOC) provide a general-purpose method for improving the performance of inductive learning programs on multiclass problems. ECOC based support vector machines are used for classification purpose that use linear, polynomial and radial basis function based kernels with one-vs-one and one-vs-all modalities. As well as, we have presented scale invariant sMBP using ensemble of kernels from ECOC based support vector machines(SI-sMBP). The selection of particular bin calculated from images at four different scale resolutions(Gaussian pyramid) is accomplished by proposing a new metric i.e., impact of a bin at particular level of pyramid. The proposed SI-sMBP is not only invariant to the size of the sign images but ensemble takes advantage of all the three kernels. The results of SVM kernels are ensembled by presenting ensemble of kernels algorithm(EoKA). To introduce the scale invariance, SI-sMBP was presented that wasn't only insensitive to noise but scale and rotation invariant as well. It resulted a feature vector of increased dimension. We have applied principle component analysis(PCA) based feature extraction methodology for features dimension reduction. The resultant feature set is subject to classification using ensemble of kernels based support vector machines. The recognition of continuous PSL alphabets is an important task that leads towards the recognition of words and sentences. We have used features of the local optical flow features to accomplish the said task. The proper nouns and the words absent from the dictionary or the unknown words to the signers are represented through fingerspelling. A framework for the recognition of PSL words is presented that uses previously presented PSL static alphabet recognition methodology as its baseline. Use of hamming distance and auxiliary PSL word dictionary is adopted to complete the recognition task. Automatic recognition of PSL alphabets into the predefined categories is presented as well. The seven categories are defined using visibility, shape and orientations of fingers and hand. The histograms of the uniform local binary patterns(ulbp) for the neighboring distance of one, two and three are computed and concatenated to form a single feature vector. At a later step, six statistical features of the combined histogram are computed used for class. The proposed techniques are evaluated through accuracy, precision and recall.

List of Publications

- **Research Publications from Thesis**

1. Human Behavior Classification using Geometrical Features of Skeleton and Support Vector Machines, *Computers, Materials & Continua* 61(2), 2019.
2. Shape Based Pakistan Sign Language Categorization Using Statistical Features and Support Vector Machines, *IEEE Access* 6(1), 2018.
3. A comparative study on mixture of Gaussians for object segmentation, *International Journal of Advanced and Applied Sciences* 4(6), 2017.
4. Symmetric Mean Binary Pattern based Pakistan Sign Language Recognition using Multiclass Support Vector Machines, *Neural Computing & Applications*, Under Review.
5. Scale and Rotation Invariant Mean Binary Patterns for Pakistan Sign Language Recognition using MultiClass Support Vector Machines, *Multimedia Systems*, Under Review.
6. Sign Language Recognition Using Multiple Kernel Learning: A Case Study of Pakistan Sign Language, *IEEE Access*, Under Review.
7. Activity Analysis of Objects in Motion using Combined Histogram of Local Optical Flow Features and Support Vector Machines, *Computers, Materials & Continua*, Under Review.
8. A Hierarchical Model for Hand Detection & Localization using Deep Learning, Super Pixels and Morphological Operations, *IEEE Access*, Under Review.
9. FingerSpelling Recognition for Pakistan Sign Languages using Ensemble Classifiers over Reduced Dimension Feature set, To be Submitted.

- **Others**

1. Context based Adoption of Ranking and Indexing Measures for Cricket Team Ranks, *Computers, Materials & Continua*, 2020.
2. An efficient cryptographic technique using modified Diffie–Hellman in wireless sensor networks, *International Journal of Distributed Sensor Networks* 16(6), 2020.
3. Support Vector Machines-based Heart Disease Diagnosis using Feature Subset, Wrapping Selection and Extraction Methods, *Computers and Electrical Engineering* 84, 2020.
4. Image Analysis using Human Body Geometry and Size Proportion Science for Action Classification, *Applied Sciences*, 2020.

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 17. Clinical Document Construction by using HL7 with Medical Drop Box for Exchange of Electronic Health Records under Country Medical Law, International Journal of Computer Science and Information Security 14 (10), 2016.
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 19. Conversion of Legal Text to a Logical Rules Set from Medical Law Using the Medical Relational Model and the World Rule Model for a Medical Decision

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- Support System, informatics 3 (1), 2016.
20. A Novel Approach for Ranking Authors in an Academic Network, International Journal of Computer Science and Information Security 14 (7), 2016.
 21. Medical Drop Box (MDB); A National Health Information Exchange And Management System For Medical Industry, The Professional Medical Journal 23 (4), 2016.
 22. Ontology based semantic search in Holy Quran, International Journal of Future Computer and Communication 2 (6), 2013.
 23. A robust and enhanced approach for human detection in crowd, 15th International Multitopic Conference (INMIC), 2012, Paistan.
 24. Proposed architectural model for optimal transformation of decision table and decision tree into knowledge base, Indian Journal of Science & Technolog, 2010.
 25. Wavelet based multi-focus image fusion using adaptive sized blocks, 2009, Pakistan.
 26. Block level multi-focus image fusion using wavelet transform, 2009, Malaysia.

List of Acronyms

ANN	Artificial Neural Networks
Cat	Category
CNN	Convolutional Neural Network
ECOC	Error Correcting Output Codes
EOH	Edge Oriented Histogram
FV	Feature Vector
HOG	Histogram of Oriented Gradients
KNN	K-Nearest Neighborhood
LBP	Local Binary Pattern
MBP	Mean Binary Pattern
MLP	Multi-Layer Perceptron
NN	Nearest Neighborhood
OvA	One vs All
OvO	One vs One
PCA	Principle Component Analysis
PSL	Pakistan Sign Language
QDA	Quadratic Discriminant Analysis
RBF	Radial Basis Function
SI-LBP	Scale Invariant Local Binary Pattern
SI-sMBP	Scale Invariant Mean Binary Pattern
SI-uLBP	Scale Invariant Local Binary Pattern
SLR	Sign Language Recognition
sMBP	Symmetric Mean Binary Pattern
SVM	Support Vector Machine
uLBP	Uniform Local Binary Pattern
uMBP	Uniform Mean Binary Pattern
YOLO	You Only Look Once
SOF	Sum of Optical Flow
HSOFF	Histogram of Sum of Optical Flow Features
SLOFH	Sum of Local Optical Flow Histogram

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Chapter 1

Introduction

Language has always been a key source of communication among human beings. There are a variety of languages that vary from region to region and nation to nation. Whenever you move from one region to another or communicate with someone from other nation either you need to learn the language of that region or nation or you need an interpreter for communication. In the absence of knowing someone's language and interpreter, gestures can be a source for basic level communication. Gestures can originate from the motion of any part of the body but commonly originate from the movement of the hand or facial expressions. Gesture recognition is an area of computer vision that deals in interpreting gestures by using different algorithms. Across the world, millions of people live with a disability of hearing loss. Out of those, a vast majority belongs to the countries having low or lower-middle economies. The said countries are mostly inherited with more serious financial issues and providing appropriate ear and hearing care services to the deaf community is quite critical. The world health organization WHO) has pointed out that approximately a total of 436 million people are suffering from hearing impairment, this figure is about 5% of the total world population [1]. Unlike normal humans, the deaf can't use acoustic languages for their communication. Sign Language is a language that conveys the message by using body language instead of using acoustic words. It may involve a combination of hand shapes their orientation and movement along with arms or facial expressions to express the thoughts. They share many similarities with spoken languages (sometimes called oral languages, which depend primarily on sound), which is why linguists consider both to be natural languages, but there are also some significant differences between signed and spoken languages.

1.1 History of Sign Languages

Visual gestures have been widely used by humans, long before the evolution of the first formal sign language. It were native Americans who used hand signs for communicating with other

tribes and to communicate with Europeans for trade purposes[2]. Martha's Vineyard, an island off the Massachusetts coast, was settled by the people carrying genes for deafness. Since this island was separated from the mainland, the trait quickly spread among the inhabitants and a large deaf population was established. It resulted in the development of a regional sign language used by the deaf not only for communicating among themselves but the hearing ones as well.

During the eleventh century, basic gestures were developed by the monks which were used as a special tool for essential communication during a vow of silence. Later on, in the 15th century a Spanish Benedictine monk, Pedro Ponce de Leon, used those gestures for educating his deaf students in Spain[3]. Prior to him, the deaf were mistreated and persecuted by viewing them as being unable to learn or to participate in society. His services not only registered him as the first teacher of the deaf community but paved the way for the creation and instruction of formal sign languages. Juan Pablo Bonet, a Spanish priest and linguist, followed the services of Pedro Ponce and extended his work. In 1620, he published the first manual alphabet system with the intent that it be taught to deaf people throughout Spain.



Figure 1.1: Juan Pablo Bonet and a sample of his manual alphabet

1.1.1 First Formal Sign Language

Although, much effort was put in Spain for developing the first official sign language but it was actually produced in France. It was the result of efforts made by Charles Michel de l'Eppe, a French priest, who had been an ardent advocate for the deaf rights. He established a public school for the deaf kids i.e., "Institution Nationale des Sourds-Muets a Paris", and is remembered as the 'Father of the Deaf' [4]. In his institute, children across the whole country got admitted and came with a variety of communication signs used by them at homes. Using those gestures along with manual signs, l'Eppe produced a sign language dictionary. This standardized sign language is now referred to as Old French Sign Language and quickly spread across Europe and to the United States.

1.2 Worldwide Sign Language

A common misconception is that all sign languages are the same worldwide or that sign language is international. There are many types of sign language, major types are static signs,



Figure 1.2: Charles Michel de l'Eppe, Father of the Deaf

dynamic signs, continuous signs, manual signs, signer dependent, signer independent, 2D and 3D signs. The continuous sign language recognition systems aim to recognize/interpret the complete sentences as hello, bye, and okay. Some other types like manual signs in which four components are used to form a sign, namely handshape, movement, palm orientation, and location. A dynamic sign/gesture includes motion or continuous movement of the finger/body parts whereas a static sign is a fixed pose that does not include any continuous movement. Aside from the pidgin International Sign, each country generally has its own, native sign language, and some have more than one, though sign languages may share similarities, whether in the same country or another one. No one knows how many sign languages there are; the 2013 edition of Ethnologue lists 137[5]. Some of the well-known sign languages are American sign language, Australian sign language, British sign language, German sign language, Arabic sign language, Chinese sign language and Pakistan sign language, etc.

1.3 Pakistan Sign Language

Urdu language is also used for communication by large people in the world estimated at 250 million. In Pakistan, every 1.6 of 1000 people are deaf[6], more than five million deaf in the area where Urdu is a basic language for communication. Other regional languages (Sindhi, Pushto, Punjabi, Baluchi) also form blends with PSL. Most of the hearing individuals, learning manual communication tend to adopt this combination of Urdu word order with PSL for expressive purposes. In an educational setting, this would help in gaining mastery over the Urdu Language structure.

Pakistan Sign Language is a visual-gestural language having its own vocabulary and syntax and like any other language, is subject to change, improvements, and growth. It is important to

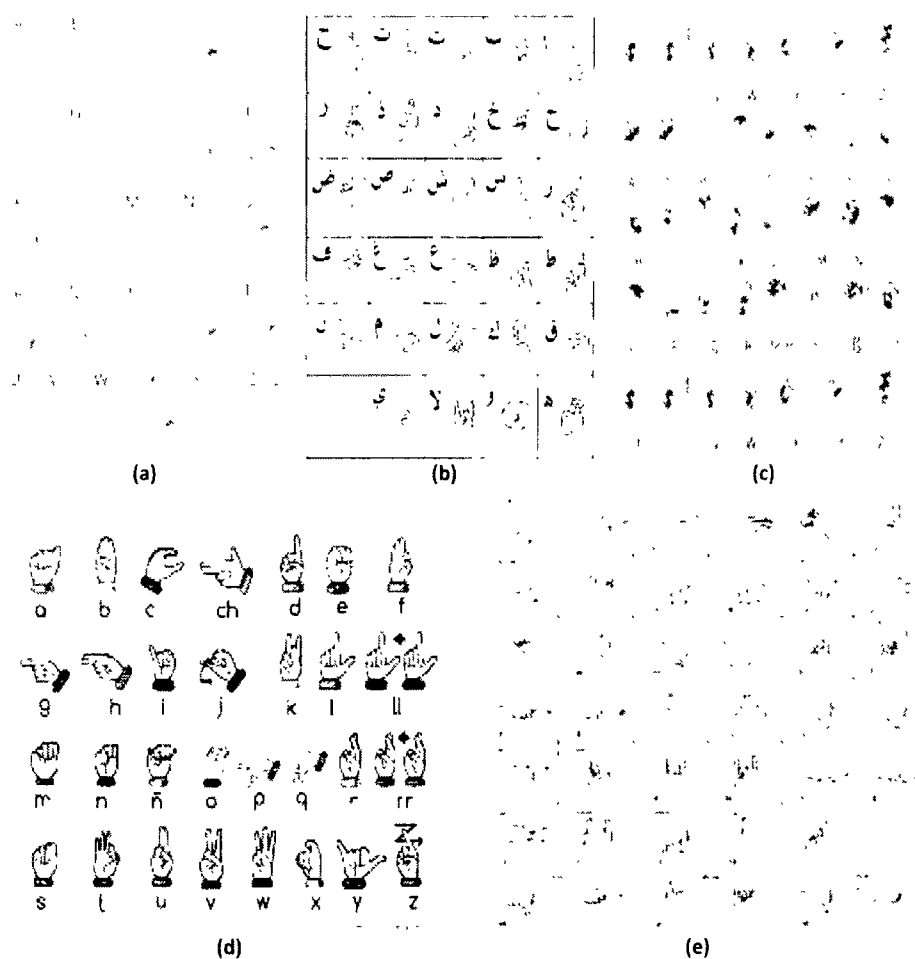


Figure 1.3: Sign Language Alphabets detail (a)American Sign Language (b)Arabic Sign Language (c)German Sign Language (d)Spanish Sign Language (e)Korean Sign Language

note that sign language is influenced by spoken languages. When they interact with each other, a variety of blends or combinations of two languages occur. The British Sign Language (BSL) with English forms Sign English. In American, Sign Exact English (SEE) is the outcome of American Sign Language (ASL) & English. Similarly, Sign Urdu emerged as a result of the interaction of PSL with Urdu [3]. The Urdu language has 38 Urdu alphabets. There are 38 handshapes to represent the same number of Urdu alphabets. Out of them, thirty-six signs have static representation concerning hand and fingers positions.

1.4 Parameters for Representation of PSL Alphabets

There are two basic parameters for the static PSL alphabets: shape and orientation of the hand.

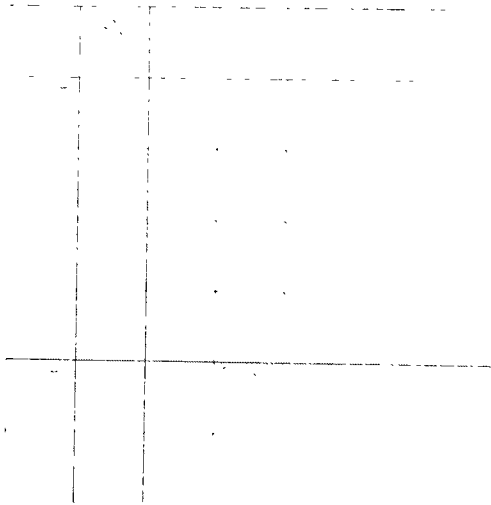


Figure 1.4: Pakistan Sign Language Static Alphabets

1.4.1 Hand shape

As implied, each sign takes on a certain shape in the hand, called a hand shape. The handshapes of signs are a very key parameter. The Bureau of American Ethnology published a glossary of PSL signs that illustrate the hand shapes involved. Fist, thumb in front of fingers (A or B)

- Fist, thumb at the side of fingers (C).
- Fingers clenched, thumb touching the middle of the index finger (D).
- Fingers hooked, thumb touching back tip of the index finger (E)
- Fingers hooked, thumb at the side of fingers (F)
- Fingers hooked, thumb touching tips of fingers (G)
- Fingers slightly bent, thumb at side tip of the index finger (H)
- Fist, except index finger forming hook with the thumb holding tip of the index finger (I)
- Fist, except index finger, fully extended (J, K, or M)
- Fist, except index finger and thumb, extended, thumb bends at last joint to form 90 degree angle with the index finger (L)
- Fist except for index and middle fingers fully extended (N)
- Thumb, index, and middle finger pointing upward and separated, ring finger and pinky curved horizontally (O)
- All fingers and thumb pointing upward and separated, palm cupped (P and Q)

- All fingers and thumb fully extended and separated (R)
- All fingers and thumb fully extended and held together (S and T)
- Fingers gathered to a point, palm cupped, with thumb in the middle (U)
- Fingers slightly bent, thumb at the side of the index finger (V)
- All fingers and thumb extended, relaxed (Y)

1.4.2 Orientation

This refers to the orientation of the palm and is represented by the following mutations.

- Up
- Down
- Non-dominant side
- Dominant side
- Toward signer
- Away from signer

1.5 Interpretation of Sign Languages

In order to develop a communication mechanism between the deaf and hearing, there is a need of interpretation for sign languages into natural languages. The task of interpretation may be accomplished by either knowing the specific sign language or services of an expert would be required. Unfortunately, not a large number of people are equipped with the knowledge of sign languages and hiring some expert for the purpose is not cost effective as well[7]. In Pakistan, there are 92 sign language experts[8] and they are only available in its big cities i.e., Islamabad, Karachi, Lahore etc. Many Computer Vision-based algorithms have been designed to recognize world-famous sign languages i.e., algorithms for German Sign Language(GSL), American sign language(ASL), Irish sign language(ISL), etc.

1.6 Research Motivations

In Pakistan, 1.6 of every 1000 people are deaf and there is a need for communication between them and hearings. There is a lack of sign language experts who could participate as an interpreter between them. In the absence of experts, intelligent computational model based

machines can serve the job. The computational models need to be trained over PSL dataset represented by scale and rotation invariant low dimensional feature set. It must have the ability to differentiate the sign classes from each other. It forms the motivation for pursuing our research thesis.

1.7 Challenges

Sign language recognition has been a key area of research for the last decades but little work has been done for Pakistan sign language. There exist challenges for classifying the alphabets of sign languages i.e.,

- In order to validate the intelligent computational techniques proposed for the classification task, there is always a need of a dataset having a reasonable size. There is no dataset for Pakistan sign language available for research purposes. The existing research was validated over the PSL datasets with very few instances having no intraclass variations.
- Hand detection and localization is the first and the key step for recognizing the signs generated by those hands. Most of the work has accomplished the task through threshold based skin detectors or segmentation based techniques. Under the varying illumination and complex background, the said techniques significantly fail to detect the hands properly and leading towards false classification for hand signs.
- There is always a need to represent the hand signs with the feature set that should be scale and rotation invariant and must be resilient to the noise in the image. The feature set should not only be salient but its dimension should be comparatively low.
- The selection of the classifier is challenging and even the different parameter tuning of the same classifier may result differently. There is a need to present a classification scheme that should use the strengths of all the tuned parameters(through ensembles of classifiers).
- Continuous signs are generated through the motion of the hand and fingers. Their recognition leads to provide the base for the recognition of words and sentences of the sign language. The task of analysing continuous signs is different from the static signs as the former involves temporal variations in them.
- Mostly, the proper nouns and modern terms are not part of the sign language vocabulary. They may be represented through fingerspelling. Automatic recognition and interpretation of signs need to be presented.
- Within the same sign language, multiple signs have resemblance in their representation. The categorization of the signs based on their appearance is an interesting task and needs to be solved.

1.8 Problem Statement

There is no standard Pakistan sign language(PSL) dataset available that having intra-class variations. Hand detection and localization is an important problem in recognition of the sign languages. There is a need to present the feature set for recognizing PSL alphabets that is noise, scale and rotation invariant but not compromising its dimension. Support vector machines(SVMs) may be equipped with different kernels having their own individual strengths and weaknesses, there is a gap to ensemble the powers of different kernels at once for solving PSL recognition problems. Interpretation of continuous PSL alphabets that may lead to the recognition of PSL words needs to be resolved. The proper nouns and the words that are not present in a sign language are shown through fingerspelling. A framework for transforming PSL fingerspelling to natural language is missing in the literature. To categorize the PSL alphabets based on their appearance forms an interesting problem as well.

1.9 Research Contributions

This dissertation covers the challenges towards computer vision based recognition of Pakistan sign language. The proposed methodologies are implemented and tested over through a PSL dataset developed under the supervision of a PSL expert. The detailed contribution of this study is as follow:

- Hand detection and localization is one of the important tasks for HCI based applications and sign language recognition. It is a challenging task in the scenes having complex background. As well as, the hand is a non rigid object and under varying illumination conditions the problem becomes more interesting. In this thesis, hand detection, localization and extraction methodology is proposed that utilizes YOLO based CNNs followed by the conventional skin detector and morphological operations are used as post-processing.
- The efficiency of a computer vision system mainly depends on the selection of the feature set that should be invariant to noise, scale and rotation. In this thesis, we have proposed binary pattern based feature vector that is not only resilient to the noise but invariant to rotation and scaling as well. The dimension of the feature vector is reduced as well that not only resulted in lower computational cost but more accurate as well
- The selection of the classifier is challenging and even the different parameter tuning of the same classifier may result differently. In this thesis use of an ensemble of SVM kernels is exploited through presenting the proposed algorithm whose results give a clear reflection that the performance of kernel ensemble is better than the individual kernels.

- A methodology for the recognition of PSL Continuous signs from the videos is proposed that extracts feature vector through local optical flow features. The presented methodology can be used to interpret PSL words and sentences as well.
- Recognition of the proper nouns(names of the persons, countries, brands etc) and the words absent from the dictionary of the sign language may be represented by the fingerspelling. A framework for the translation of the fingerspelling through vision based approach is presented that takes advantage of the proposed alphabet recognition techniques and introducing the concept of the external dictionary for serving the said purpose.
- Many PSL alphabets have similarities with the other ones on the base of their shapes and orientation. Categorization of PSL alphabets on the base of their shapes and other features is proposed as well.
- We have contributed to the PSL by creating its dataset. Seven signers took part in generating PSL alphabet images that have a variety of variations in terms of scale, orientation and illumination.

1.10 Thesis Organization

The rest of the thesis is organized as: chapter 2 presents details of baseline computational techniques adopted for proposing the research models; In chapter 3, literature review of the existing techniques along their limitation is presented; Chapter 4 explains all the details of the presented PSL dataset and performance evaluation metrics; Chapter 5 presents the proposed methodology for hand detection and localization; In chapter 6, semi-symmetric mean binary patterns for Pakistan sign language recognition are presented; Chapter 7 presents scale invariant semi-symmetric mean binary patterns used for Pakistan sign language recognition through proposed ensemble of ECOC-based SVMs; Chapter 8 presents the reduced dimensional feature vector obtained through principle component analysis; In chapter 9, recognition of PSL continuous alphabets through videos is proposed while a framework for the translation of the PSL words generated through fingerspelling is presented in chapter 10; Chapter 11 proposes shape based categorization of the Pakistan sign language alphabets using statistical features of uniform local binary pattern histograms; In chapter 12, comparative results of proposed and comparatives techniques are presented; while chapter 13 concludes the presented thesis.

Summary

This chapter presents introduction of the sign languages in general but more specifically Pakistan sign language. It provides motivation of the research presented in the thesis, objectives, problem

statement, research contributions and organization of the thesis.

Chapter 2

Sign Language Recognition

This chapter provides an overview of the basic communication source among human beings along with the methodologies for automating the communication with deaf i.e., sign languages. Section 1 provides a basic idea about the sign languages, section 2.2.1.3 describes and provides details about convolutional neural network(CNN) and deep learning, in section 2.2.2.4 detailed overview of the local binary patterns(LBP) and their variants are discussed, while section 2.2.3.1 explains one of the feature dimension reduction technique i.e., principal component analysis(PCA). The last section of the chapter, section 2.2.5, discusses support vector machines(SVMs) in the context of solving multiclass problems.

2.1 Machine based Sign Language Interpretation

Hearing people have lack of knowledge about sign languages and the expert of those languages are not so common as well. The problem of understanding the hand gestures generated by the deaf may be resolved through the use of technological advances. The hand gestures for the sign languages may be captured through different manners i.e., shown in figure 2.1. It may be observed that bare hand images through RGB camera are simplest of all to generate, while the rest of all either needs some specialized environment or devices.

2.2 Computer Vision based Sign Language Recognition

Sign languages represented through images taken from RGB-camera are interpreted by vision based intelligent computational techniques. They involve image processing based methodologies for detecting and localizing sign hands followed by extraction of salient features(with minimal dimension) and at the last use of some classifier for categorizing the input signs into predefined classes. A generic methodology for a vision based sign language recognition system

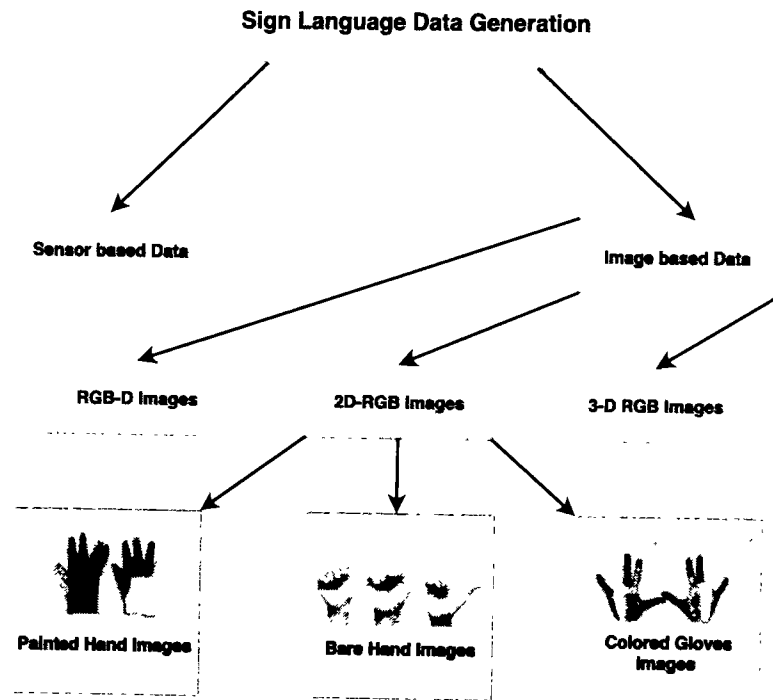


Figure 2.1: Sign Language Generation

is shown in figure 2.2.

2.2.1 Hand Detection & Localization

Hand detection is the foremost step that is utilized for achieving hand related applications such as hand gesture recognition for human-machine interface, virtual gaming, hand-controllable screens and interfaces, for security purposes to keep eye on the suspicious activities, in sports, in pose estimation, for robotic applications (human-robot interaction) and many more. Thus, this means that effective hand detection is necessary as the accuracy of the further tasks to be applied directly depends on the precise detection of hands. So, the results are directly dependent upon the efficient detection of hands.

2.2.1.1 Skin color based Hand Detection

One of the most well-known color space used in the digital images is RGB that encodes an additive combination of three primary colors i.e., red, blue and green represented by R, G and B respectively. This color space may be visualized by a 3D cube where each of the dimensions corresponds to all the three components, normal to each other. The color space is quite simple but isn't perceptually uniform i.e., the distances in the RGB color space are not corresponding (linearly) to the human perception. Luminance and chrominance are not separable in RGB model and luminance for a point in RGB model may be computed through linear combinations of all the three components. Therefore, changing the luminance of a given skin

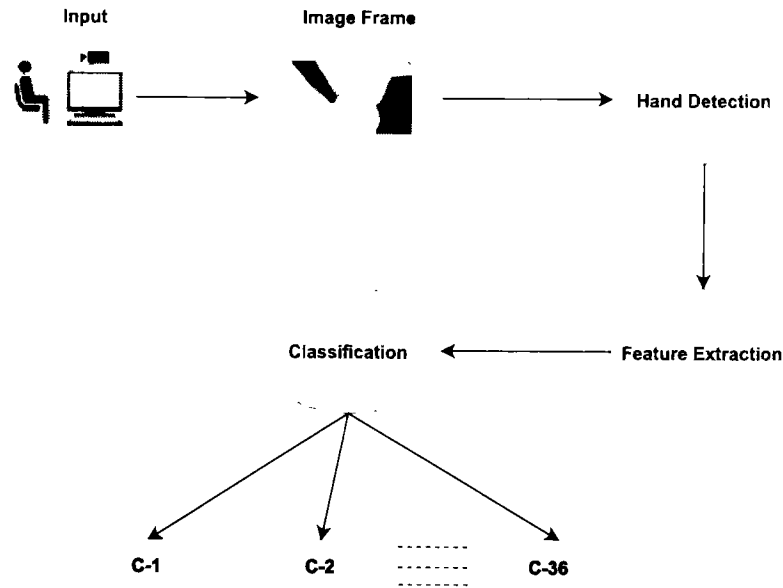


Figure 2.2: Computer Vision based Sign Language Recognition

patch affects all the R, G, and B components. Threshold based techniques applied over all the three components may provide an outcome as detected skin.

In TV transmissions orthogonal color spaces are used that include YCbCr, YUV and YIQ. YCbCr is used in image and video compressions i.e., JPEG and MPEG respectively, while YIQ is used for TV transmission using NTSC standard. They are called orthogonal color spaces as well. The conversion from RGB to the orthogonal space is not so complex but can be done through a linear transformation. In all of these color spaces illumination channel(Y) is separable from the other two. Illumination change doesn't effect the chrominance channels and they are exploited to detect the skin.

Same as, skin detection is achieved by the perceptual color spaces as well i.e., HSL(HLS), HSI and HSV/HSB. The color models have separate three components i.e., hue, saturation and brightness(L,I or V). There is a transformation from RGB space to the HSV space but that is not linear one. The key advantage of using these color spaces for skin detection lies in thresholding hue and saturation components only while the third component is responsible for illumination and it changes for brightness effects, thus leaving it out.

An effort has been presented to use all the three color spaces in a combination[9] for skin detection. The formulas are given as:

$$\begin{aligned}
 &0.0 \leq H \leq 50.0 \text{ and } 0.23 \leq S \leq 0.68 \text{ and } R > 95 \\
 &\text{and } G > 40 \text{ and } B > 20 \text{ and } R > G \text{ and } R > B \\
 &\text{and } \|R - G\| > 15 \text{ and } A > 15
 \end{aligned} \tag{2.1}$$

and

$$\begin{aligned}
 &R > 95 \text{ and } G > 40 \text{ and } B > 20 \text{ and } R > G \text{ and } R > B \text{ and} \\
 &\|R - G\| > 15 \text{ and } A > 15 \text{ and } Cr > 135 \text{ and} \\
 &Cb > 85 \text{ and } Y > 80 \text{ and } Cr \leq (1.5862 * Cb) + 20 \text{ and} \\
 &Cr \geq (0.3448 * Cb) + 76.2069 \text{ and} \\
 &Cr \geq (-4.5652 * Cb) + 234.5652 \text{ and} \\
 &Cr \leq (-1.15 * Cb) + 301.75 \text{ and} \\
 &Cr \leq (-2.2857 * Cb) + 432.85
 \end{aligned} \tag{2.2}$$

2.2.1.2 Features based Hand Detection

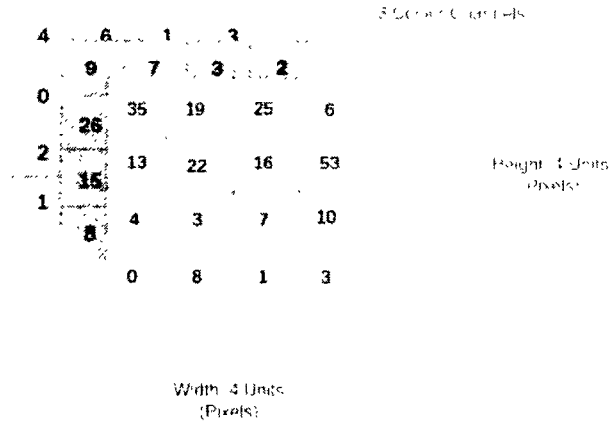
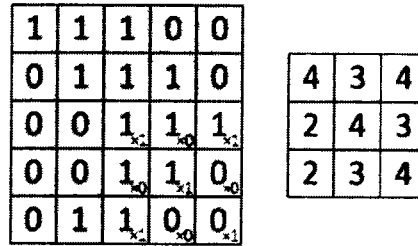
A hand may be detected from images through object detection based approaches. One of the important step is to find discriminative features representing the hand images. Those features are subject to the classification using different models like artificial neural network, support vector machines, Bayesian classifiers etc. The features may be of the geometrical, statistical, or hybrid type. To be robust and of discriminative nature, the feature set should be scale and rotation invariant covering different illumination conditions. Some of the core methodologies used for detecting a hand from images may involve contour analysis, histogram of oriented gradients, interest points based detector, Haar like features and scale invariant feature transforms. Literature provides many other techniques as well that are either the extension of these feature computation techniques or novel in their nature.

2.2.1.3 Deep Learning for Hand Detection

The task of detecting hands from the input images can be accomplished through deep learning based techniques as well. In the area of deep learning studies, convolutional neural network(CNN) belongs to a class of deep neural networks. We can input an image to CNN and it assigns priorities to the objects present in the image for distinguishing one from the other. A convolution neural network needs low pre-processing as compared to the other techniques that require more computation. ConvNet is similar to the patterns of human brain where each neuron response to stimuli of a restricted field. The collection of these types of fields (Receptive fields) makes overlapping and covers the whole area. Convolutional neural networks can capture the spatial dependencies as well as temporal dependencies in the image by applying the selected filters.

In figure 2.3, an RGB image three channels are given. It will be computationally very costly if the dimension of the image is very high for example 8K (7680×4320). CNN reduces the image into a easy to process form without losing the features of the image as image features for important to good prediction.

Let suppose the dimension of the *image* = $5 \times 5 \times 1$. In figure 2.4 the green channel bear a

Figure 2.3: $4 \times 4 \times 3$ RGB ImageFigure 2.4: Convolution of $5 \times 5 \times 1$ image with a $3 \times 3 \times 1$ filter to obtain $3 \times 3 \times 1$ convolved feature

resemblance to the image i.e. $5 \times 5 \times 1$ image. The element carry forward the convolutional kernel or filter K which is represented in yellow area. K is selected as $3 \times 3 \times 1$ image matrix, given in figure 2.

$$\text{Kernel/Filter, } K = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \quad (2.3)$$

The kernel or filter moves nine times and on every movement it performs matrix multiplication for kernel K and the portion P of image, given in figure 2.5. The filter moves for right to the left side until the whole image is processed. For a $M \times N \times 3$ image the convolution process is shown in figure 2.6. Convolution is used for high-level features extraction. The network is not limited to one layer. the first layer extracts the low-level features i.e. color of the channels, edges and gradient orientation, etc. Other layers contain a high-level understanding of the image and contain the whole shape of the image. The result of the convolution is either a convoluted feature having the reduced dimensionality by valid padding or it remains the same dimensionality or is increased by the same padding.

Next comes the pooling layer that reduces the convoluted features. It is an important factor for reducing the computational requirements for processing data by reducing the dimensionality of

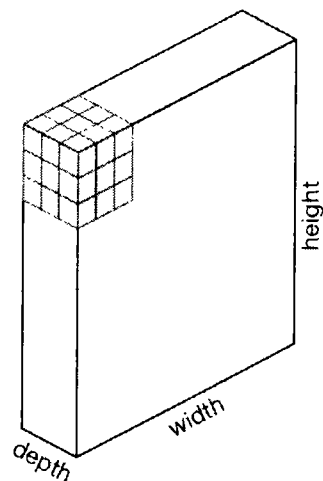


Figure 2.5: Kernel's movement

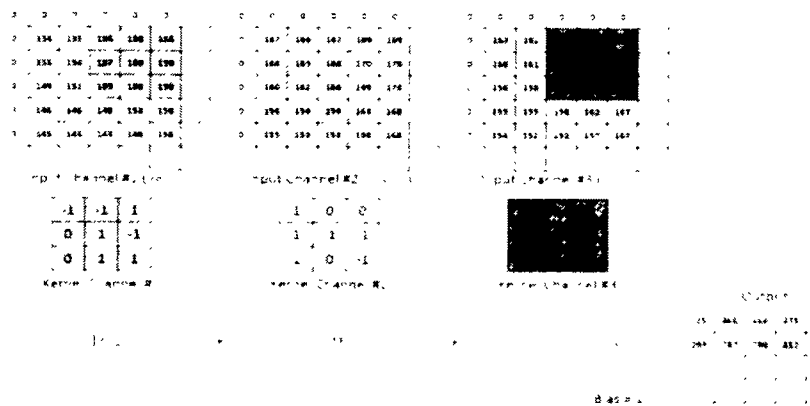


Figure 2.6: A $M \times N \times 3$ convolution with $3 \times 3 \times 3$ kernel

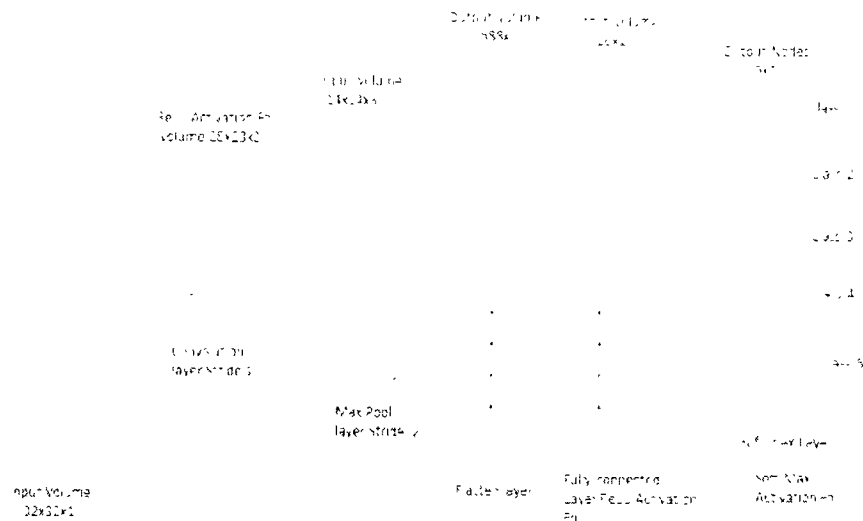


Figure 2.7: Fully connected CNN



Figure 2.8: Object recognition through CNN[14]

the features. It is also important for the extraction of the dominant features as these features are rotation and position invariants. Pooling can be done either using Max pooling or average pooling. The result of the Max pooling is the maximum value that is obtained from the portion of the image while the result of the average pooling is the average value. The convolutional and pooling layer forms the i -th layer of CNN. The number of layers can be increased while computing the low-level features. The model can now fully understand the features. The next process is the classification of the data.

At last, learning the non-linear combinations of the features produced by the convolutional layer, a fully connected layer is used. The image is converted to a suitable form of MLP. The output may be fed to the feed-forward NN and on every iteration, the backpropagation is applied. The model is able now to classify certain data. Figure 2.7 shows a fully connected CNN.

The most common use of CNN is its application in visual imagery. CNN is a derived and regularized version of MLP. CNN is considered more robust for assembling of complex data and use hierarchical pattern. The applications of CNN are image recognition, video analysis, natural language processing, drug discovery, Health risk assessment, Checkers game, fine tuning etc. Figure 2.8 shows the example of CNN used for object recognition.

A mathematical operation operated by two functions , let say function $f(x)$ and function

$g(x)$ and these two operation produces another function. [10]. The new function shows the overlapped amount of the one function that is shifted over the other function. The convolution of $f(x)$ and $g(x)$ is following.

$$f(x) * g(x) = \int_{-\infty}^{+\infty} f(\Gamma) \times g(x - \Gamma) d\Gamma \quad (2.4)$$

Where $f(x)$ and $g(x)$ are two functions and T represents a continuous step of time, the $*$ operator is convolution operator, $\times$ is multiplication operator.

Due to the high performance and advantages of CNN, researchers used CNN and other deep learning approaches for many problems of image processing area. Ronan Collobert et al. [11] applied Deep Neural Networks with multitasking learning for natural language processing. H. A. Haenssle et al. [12] recognized the dermoscopic melanoma through deep learning convolutional neural network. For sentiment analysis of short text, Dos Santos and Gatti [13] used Deep Convolutional Neural Networks. In [14] spiking deep convolutional neural networks were used for object recognition.

Besides the other research areas, CNN and deep learning techniques are used in the field of sign language recognition. Tao et al. [15] recognized American sign language through CNN, while Jalal et al. [10] applied Deep Neural Networks for recognition of American sign language. Rao et al. [16] used deep convolutional neural network for sign language recognition for a large dictionary size of the dataset. Suri and Gupta [17] recognized sign language through CNN with the use of wearable IMUs. Bengali sign language recognition was accomplished by Hossen et al. [18] using deep convolutional neural networks.

2.2.2 Feature Computation

Feature computation is the key to vision based classification problems and a good feature set computed over an image should represent the diverse nature of objects in a discriminant manner, as they are provided as input to the classifiers. There are many feature extractors from an image and some of the important ones are discussed as follows:

2.2.2.1 Histogram of Oriented Gradients

This method extracts features from all locations in an image so we can refer to it as 'dense features extraction' algorithm. It is commonly used for object detection, human face, human body detection, and vehicle detection. The flow of the algorithm is given in figure 2.9.

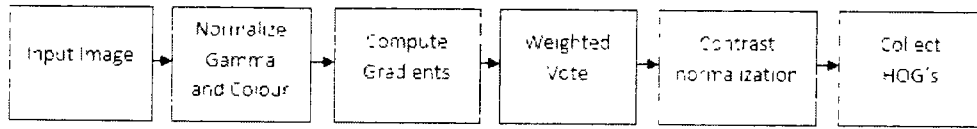


Figure 2.9: Histogram of Oriented Gradients

Figure 2.9 is showing all the steps involved in computing HOG features. The image can be divided into a block size of 2x2, 8x8, 16x16 or 64x64. The block size is further divided into cell size. Usually, cell size is kept up to 4x4, 8x8 or 16x16. Vertical and horizontal gradients are calculated for each pixel in a cell using Sobel or canny operators i.e.,

$$G_x(x, y) = I(x + 1, y) - I(x, y) \quad (2.5)$$

$$G_y(x, y) = I(x, y + 1) - I(x, y) \quad (2.6)$$

Where $G_x(x, y)$ and $G_y(x, y)$ are the horizontal and vertical gradient respectively. The magnitude and phase of both gradients are calculated in the following way.

$$G(x, y) = \sqrt{G_x^2 + G_y^2} \quad (2.7)$$

$$\theta(x, y) = \arctan\left(\frac{G_y(x, y)}{G_x(x, y)}\right) \quad (2.8)$$

The next step is to create the HOG for all cells. Bins are selected for an angle in order to calculate the histogram.

2.2.2.2 Edge Oriented Histogram

The edge orientation histogram features can be considered very informative image features. It recognizes the edges (borders or contour) and builds a histogram with the direction of the gradients. The edges may be computed using the canny edge detection algorithm that recognizes them in five directions i.e. horizontal, vertical, two diagonals and one non-directional. Once the orientations are computed, their histogram is computed. The number of histograms bins are kept as k i.e., $k=0$ to $n-1$. ($n = 16$ or 32 or 64 or 128 .) i.e., range of gray level intensity falling in each bin = $256/\text{number of histogram bins}$. For 64 bins, the gray intensity range per each bin is given by [0-3] [4-7] [8-11] [12-15]..... [252-255]. The histogram is the feature set to the corresponding image.

2.2.2.3 Bag of Word Features

Bag-of-words(BoW) is defined as "histogram representation based on independent features". BoW based features are used for solving the image classification problems where features are

treated as words. While classifying documents, the bag of words represents the frequency of the words i.e., a sparse histogram over the vocabulary. When applying over an image, the vector represents the occurrence frequency of a vocabulary of features in an image. BoW model treats an input image as a document and applies following operations over it i.e., (i) feature description, (ii) feature description and (iii) generation of codebook for these features.

Once features are detected, an image is abstracted by several local patches. It is followed by the representation of the features as numerical vectors called as feature descriptors. The representation of the features into description vectors should be able to handle different variations available in the images i.e., scale, illumination and rotation. One of the widely used representations is the Scale invariant feature transform that transforms each feature patch into 128-dimensional vector. The last step is to convert the representation of detected features into codewords or codebook and it gives different patches but having intra similarities the same code. One of the adopted way to those similarities is K-means clustering applied over all the vectors thus centers of the clusters define those codewords. Thus, each patch in an image is mapped to a certain codeword through the clustering process and the image can be represented by the histogram of the codewords. Since the BoW model is an analogy to the BoW model in NLP, generative models developed in text domains can also be adapted in computer vision.

2.2.2.4 LBP and It's Variants

Local binary pattern is an effective and important features descriptor in image processing. It is mostly used in detection/recognition problems like facial expression recognition, sign language recognition, finger pattern recognition, etc. the algorithm of LBP takes a 3×3 pixels window of the image and process it. The central pixel value of the 3×3 window image is compared with the surrounding 8 pixels. If the value of the surrounding pixel is less than the central value, it will assign 0 to the surrounded value otherwise it assigns 1 to the surrounding neighbor pixel if the value is greater or equal to the central pixel. All 8 pixels are compared and a binary 3×3 image is formed which consist 0 or 1 value. This process goes until the last pixel of the original image. The mathematical expression of LBP is given in equation below.

$$LBP_{P,R} = \sum_{P=0}^{P-1} s(g_P - g_c) 2^P \quad (2.9)$$

$$s(x) = f(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases} \quad (2.10)$$

The working of the LBP operator is given in figure 2.10.

To improve local binary pattern, a lot of variations are added in the original LBP descriptor. Bello-Cerezo et al. [19] applied a modified LBP for color textures classification. Two extensions

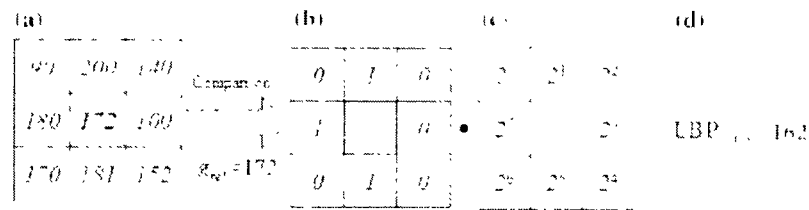


Figure 2.10: working of the LBP operator[19]

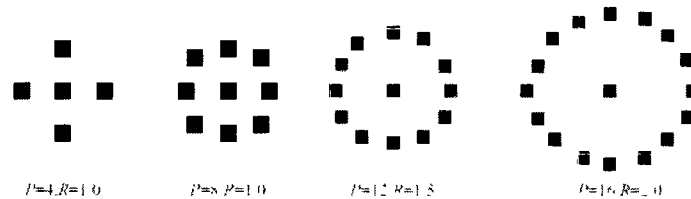


Figure 2.11: Improved Local binary patterns with different radius and Pixels[19]

of LBP are used i.e. ILBP (Improved binary patterns) and ELBP (Extended Local binary patterns). Zhao et al. [20] applied an extension LBP called IRELBP for scene classification. the IRELBP uses angular difference and radial difference. Facial expression recognition is done in [21] using an extended version of LBP called Improved Local binary patterns (ILBP). The radius size and number of pixels are kept different, given in figure 2.11.

Xiao et al. [22] proposed a 2-D LBP approach for texture image classification. Edge LBP is proposed in [23]. LBP is extended to surfaces using rings and ring is defined on the basis of sphere mesh in the intersection. Figure 2.12 shows an example of rings and mesh vertices.

2.2.3 Feature Dimension Reduction

Once the image features are computed they are subject to use by classifiers for predicting the true class. The computed feature set may contain the features that are either redundant or dimension of the feature set is huge that takes higher computation or their presence may result in compromise to the classification accuracy. The issue may be resolved by applying either feature selection or feature extraction techniques for obtaining feature subsets of lower

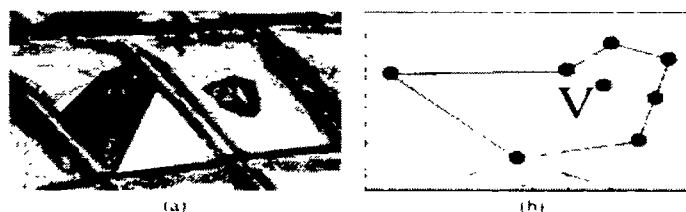


Figure 2.12: a. On the basis of triangles two rings are defined b. The mesh vertices shown as red dots[22]

dimensions. This would not only reduce computation cost for classification but suppression of redundant features would enhance the classification accuracy as well. Some of the techniques for feature dimension reduction are presented in the coming subsections.

2.2.3.1 Principal component analysis (PCA)

Principal component analysis is a dimensionality reduction technique mostly used for the dimension reduction of large datasets. PCA transforms the large set variables into a form that consists small set of variables and contains most of the information which is presented in the large set. The effect of the dimensionality reduction is a small decrease in the accuracy, but for simplicity and understanding of data set PCA is very important and it trades with a little accuracy for simplicity [24]. Visualization and exploration of small datasets are easier and also faster for machine learning algorithms in terms of time consumption. Thus, PCA reduces the dimensionality of the large data set and preserves more information as much as possible. The following steps are taken for dimensionality reduction through PCA.

Initialization is the step where the range of the variables is standardized to ensure that each of the variable equally contributed for analysis. Standardization is necessary in the case where there are large differences and those large ranges variables can dominate the small ranges variables which leads to biased results. Transformation of the data to the comparable scales resolves this hazard. Standardization of the data is shown through the following equation. Standardization transforms all the variables to the same scale.

$$Z = \frac{value - mean}{standardddeviation} \quad (2.11)$$

The next step is covariance matrix computation that ensures and finds the relationship between variables. In some situations, variables are formed in a way that they contain information that is redundant which leads to biased results. For the identification of such relationships between the variables, the covariance matrix is used. In the following equation, P represents the number of dimensions. The $p \times p$ is a symmetric covariance matrix.

$$\begin{bmatrix} cov(x, x) & cov(x, y) & cov(x, z) \\ cov(y, x) & cov(y, y) & cov(y, z) \\ cov(z, x) & cov(z, y) & cov(z, z) \end{bmatrix} \quad (2.12)$$

Where x, y, z represents the 3-dimensional dataset variables.

To determine the principal components, eigenvector are computed over the covariance matrix. The principle components are variables formed as a result of linear combination of the variables. The new formed principle components are not related.

Once the eigenvectors are calculated, they form in the descending order by their eigenvalues. The components or values which have less significance are dropped and only those components which are of high significance are kept in a vector, called the features vector. The final dataset can be formed in the following way.

$$\text{Final DataSet} = (\text{Feature Vector})^T * (\text{Standardized Original DataSet})^T \quad (2.13)$$

Many researchers applied principal component analysis for dimensionality reduction because of the accuracy and efficiency. García-Gil et al. [25] proposed a model for the discretization of big data and the features dimensionality reduction is done using the PCA. Kramer [26] proposed a multivariate data analysis NLPCA for both linear and non-linear data dimensionality reduction. A modified model for PCA called SPCA is presented in [27] which is better for multivariate data as well as for gene expression arrays.

2.2.3.2 Feature Selection Techniques

Feature selection is the process that is heavily used in machine learning and statistics. It is also known as variable subset selection, variable selection or attribute selection. It selects a subset of relevant features that is then used for the construction of the prediction model. Feature selection may be taken as the set of search algorithms along with some evaluation metrics that finds minimal size feature subset providing least classification error. The choice of evaluation metric heavily influences the algorithm, and it is these evaluation metrics which distinguish between the three main categories of feature selection algorithms: wrappers, filters and embedded methods.

Wrapper methods are used for feature subset selection that uses a prediction model for ranking the feature subset. For every subset, the model is trained over the training data and tested on hold-out set. The feature subset giving the least prediction error over the hold-out data is the selected one. The main issue with the wrapper methods lies in the higher computational cost but usually, they produce a subset that performs better for that particular type of model or typical problem.

In filter methods, some statistical scores for each of the attributes are calculated and they are ranked in descending order. The features with the highest scores are selected and a predictive model is generated. Some of the well-known statistical scores are Pearson correlation, mutual information, Kendall correlation, Chi Squared, Fisher score and information gain. Normally filter based methods have lower computational costs than the wrapper-based methods, but they produce a feature set that is not tuned to a specific type of predictive model. The low tuned feature subset means it is more general and produces lower prediction performance.

Embedded methods are the ones in which feature selection is an essential and integrated part of the learning algorithm itself. One of the well known embedded methods is the decision

tree that recursively selects the features in building the tree and divides the sample set into smaller subsets. The more child nodes in a subset are in the same class, the more informative the features are. The process of decision tree generation is also the process of feature selection.

2.2.4 Classification Algorithms

Numerous algorithms are used to solve classification problems but to prove the authority of one over the other is not possible. Their strength and weakness depend on the nature of the problem and dataset. For example, if the classes are linearly separable, the linear classifiers like Logistic regression, Fisher's linear discriminant can outperform sophisticated models and vice versa.

2.2.4.1 Decision Tree

The decision tree is mainly used for building the regression and classification models in a way of tree structure. The representation of the decision tree is the adoption of if-then rules that are mutually exclusive and exhaustive for serving the classification purpose. The rules are learned in a sequence through the use of items from training data one by one. Once a rule is learned, the records covered by the rules get removed. The whole process keeps on going over the training data till some termination condition is reached.

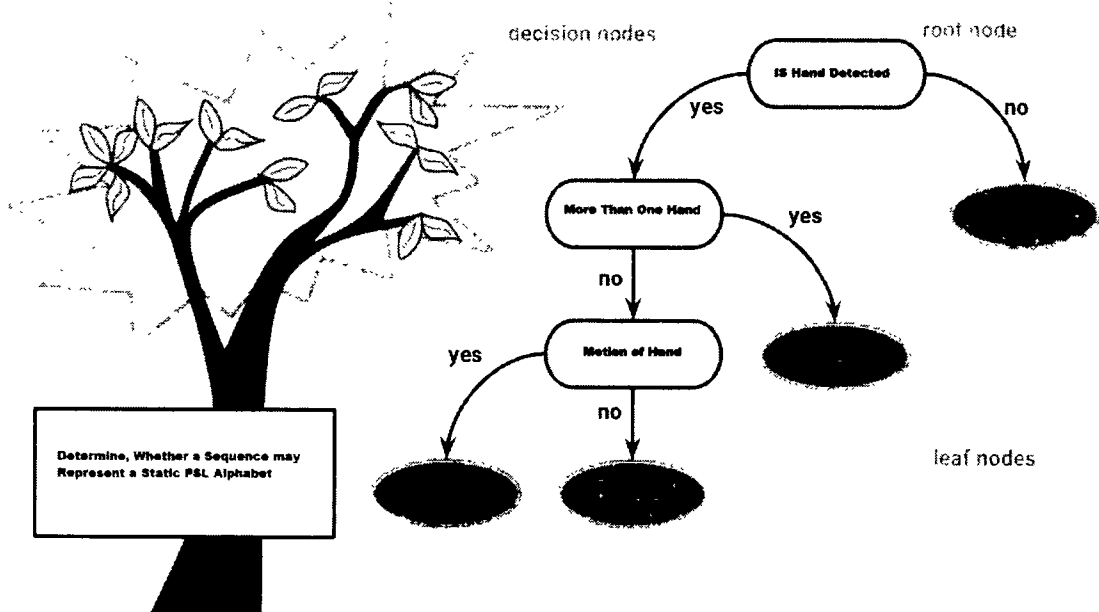


Figure 2.13: Decision Tree Classifier

The divide and conquer based top-down approach is used for constructing the decision tree. The attributes used to construct should be categorical or in advance they should be discretized. The attributes at the top of the tree are more discriminative and have higher classification impact and it is calculated using information gain score. There is always a chance for a decision tree to

get over-fitted which leads to the generation of too many branches. As well as, the presence of outliers or noisy data may create anomalies. Once a tree gets over-fitted, its performance over the training data is high while poor for the new data. This can be avoided by pre-pruning which halts tree construction early or post-pruning which removes branches from the fully grown tree.

2.2.4.2 Naive Bayes

A probabilistic classifier, Naive Bayes, the inspiration of the Bayes theorem is used for the problems where attributes are assumed to be conditionally independent.

$$p(X|C_i) = \prod_{k=1}^n p(x_k|C_i) \times p(x_1|C_i) \times \cdots p(x_n|C_i) \quad (2.14)$$

The classification is achieved through computing the maximal posterior, $p(C_i|X)$, by applying the Bayes theorem. Even if the features are not conditionally independent, the performance of the Naive bayes is not discouraging. Even though its simplicity, the theorem is easily scalable to large scale datasets and computational cost is linear. It may be effected by the zero probability problem where it fails to give a correct prediction. The issue is resolved through laplacian estimation.

2.2.4.3 Artificial Neural Networks

Artificial Neural Networks(ANN) are the inspiration of human necrology where signals are transmitted through neurons. ANN is a hierarchical representation of different connected layers known to be input, hidden and output layers. While each layer can have multiple neurons. The data is provided to the network through its input layer while the output layer is responsible for providing the predicted class. During the training phase network adjusts its weights through the learning process while the trained model classifies the test data. There are different architectures of ANN that can be useful on different nature of the problems i.e., for most of the cases feed-forward ANNs result in reasonable accuracies while CNNs are specialized for applications.

There can be shallow or deep neural networks. Shallow neural networks are the ones that have a single hidden layer while the term deep means more hidden layers. As the number of layers increases, the learning complexity increase as well but producing more accurate results. Usually, Artificial Neural Networks perform better with continuous-valued inputs and outputs.

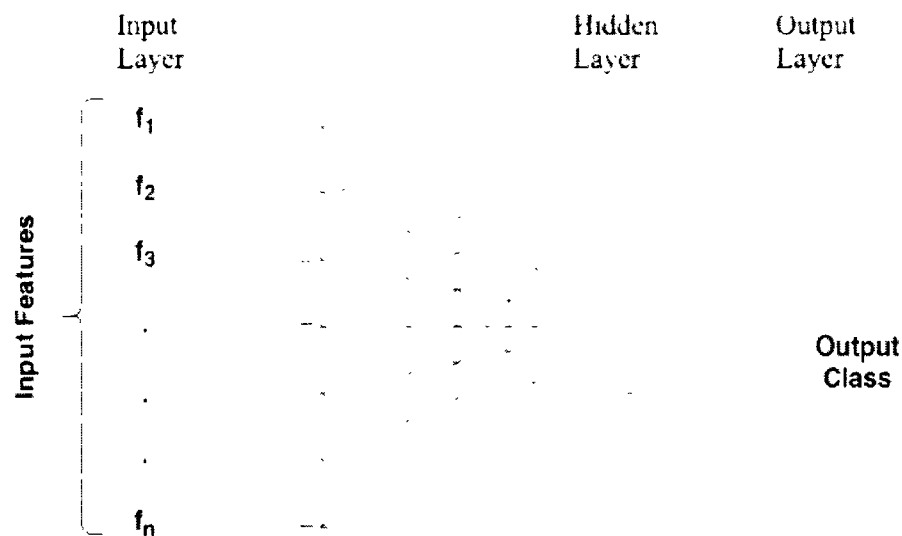


Figure 2.14: Artificial Neural Network

2.2.4.4 K-Nearest Neighborhood(KNN)

k-Nearest Neighbor is a lazy learning classifier that uses all of the training data by storing it into an n-dimensional space. In order to classify test data, it finds K nearest neighbors by computing the distances between the training and test data. The class from which most of the neighbors from those computed ones belong, is the predicted class. For the real-valued data it returns the mean of k nearest neighbors. While using weighted KNN, where distances are given weights(lower for higher distances), the query is shown in figure 2.15.

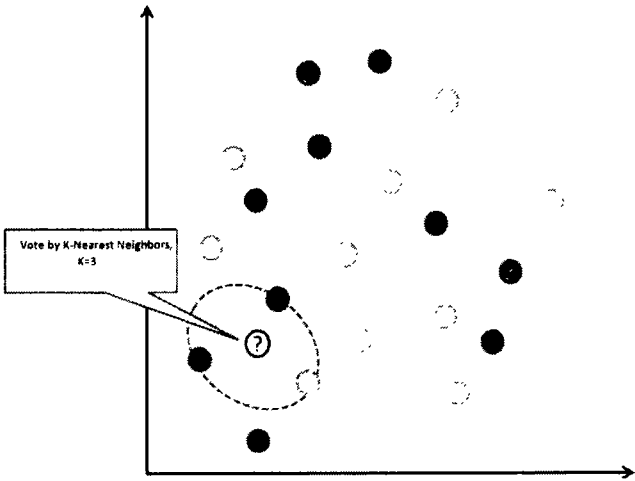


Figure 2.15: K-Nearest Neighborhood Classifier

Usually KNN is robust to noisy data since it is averaging the k-nearest neighbors.

Figure 2.16: SVM Hyperplane[30]

2.2.5 Support vector machines(SVM)

Support vector machine is a supervised machine learning classification algorithm widely used in many classification problems. The aim of the support vector machine is to find an optimal decision boundary called hyperplane. This hyperplane is in N-dimensions where N is the number of features and this hyperplane divides the features into N features Classes. SVM is also called maximum margin classifier and besides classification, it is also used for regression and novelty detection purposes. Many researchers [28, 29] used SVM for classification while in [30] SVM is used for image retrieval.

SVM is a binary classifier and it divides the data given to it into two classes. SVM has the concept of hyperplane which is drawn between the classes and it is the line which best separates (linearly) the two classes. The nearest points to the hyperplane are called support vectors. Although SVM is a binary classifier it has many extensions which enables SVM to classify data of multiple classes.

A hard margin SVM is the simplest case of support vector machine. Hard margin SVM requires at least one hyperplane for separation of data into two classes. A linear classifier is the example of the hard margin SVM. In figure 2.16 SVM divides the two classes data with the hyperplane. The hyperplane is drawn in such a way that it keeps the maximum margin between the two classes. The best considered hyperplane is that where there is a high margin between two classes.

In a linear SVM the if the output of the SVM is greater than 1, it is identified with one class and -1 is identified with other class. The range of the values [1, -1] acts like margin. The main task is the maximization of the margin of SVM between the hyperplane and the data points belongs to the classes. The loss function helps in maximizing the margin as given below.

$$c(x, y, f(x)) = \begin{cases} 0 & \text{if } y * f(x) \geq 1 \\ 1 - y * f(x) & \text{else} \end{cases} \quad (2.15)$$

In case where the predicted label of the SVM and actual label is same, the cost function of the SVM is 0. In case these labels are not same then the loss value is calculated. A regularization is

Table 2.1: Error correcting output code for 10 classes classification

Classes	Code Word														
	f_0	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}
0	1	1	0	0	0	0	1	0	1	0	0	1	1	0	1
1	0	0	1	1	1	1	0	1	0	1	1	0	0	1	0
2	1	0	0	1	0	0	0	1	1	1	1	0	1	0	1
3	0	0	1	1	0	1	1	1	0	0	0	0	1	0	1
4	1	1	1	0	1	0	1	1	0	0	1	0	0	0	1
5	0	1	0	0	1	1	0	1	1	1	0	0	0	0	1
6	1	0	1	1	1	0	0	0	0	1	0	1	0	0	1
7	0	0	0	1	1	1	1	0	1	0	1	1	0	0	1
8	1	1	0	1	0	1	1	0	0	1	0	0	0	1	1
9	0	1	1	1	0	0	0	0	1	0	1	0	0	1	1

added to the cost function for balancing the margin maximization and loss. The cost function is given below.

$$\min_w \lambda \|w\|^2 + \sum_{i=1}^n (1 - y_i \langle x_i, w \rangle) \quad (2.16)$$

SVM is a binary classifier it takes two input classes to classify either the class belongs to 1 or -1. There are multiple extensions of SVM which enables SVM to classify a more than two classes.

2.2.5.1 Error Correcting output Codes based SVMs

A model called error correcting output coding is able to use SVM as well as KNN and Naive Bayes etc for solving multi-class classification problems. ECOC is a matrix of binary values as given in table 1.

The number of columns in the code is called the length of code while rows shows the number of classes to be classified. Error correction output code for N-classes should satisfy the following conditions. A row in the code is called a codeword.

- 1. Row separation:** A codeword is separated by hamming distance from other codewords.
- 2. Column separation:** The distance between the columns i.e. column i and other columns should be large and also the hamming distance between i and the complement of each of the other columns should also be large. Once this condition is satisfied then each of the bit position function f_i will be uncorrelated to the functions $f_j, j \neq i$ which are to be learned for bit positions.

It is a robust model for classification of multiple classes and many of the researchers used

ECOC [31–33] for classification of multi-class problems.

Summary

Brief detail about sign language recognition (SLR) is presented in the chapter. It covers hand detection, feature extraction, feature dimension reduction to classification issues. The presented material provides details of the techniques used in achieving the proposed research.

TH. 27.2.73

Chapter 3

Literature Review

In this chapter, the techniques which are previously presented for sign language recognition are reviewed. This study aims to discover the involvement of the researchers in the area of sign language recognition and to recognize the limitation and difficulties faced by previous approaches. Several hand detection approaches, feature dimensionality reduction techniques, and classification methods are observed.

3.1 Sing language recognition approaches

In the recent past, researchers have presented methodologies to recognize different sign languages. Paulraj M Petal focused on the Malaysian sign language and obtained a success rate of about 91% [34]. Lee and Tsai [35] proposed a sign language system for Taiwan that takes 3D hand gesture data and recognizes 20 static signs. Invariant features for occlusion, rotation, scaling, and hand translation were used to train and test the neural network classifier, and a 96.58% accuracy was received. Similarly, Munib et al. [36] proposed a technique for the interpretation of sign gestures of American sign language alphabets from static images using Hough transform as a feature space and neural networks for classification purposes. They used 15 images for a single sign and achieved a success rate of 92.3%. Oz and Leu [37] suggested a 50-word ASL recognizer using a neural network. San-Segundo et al. [38] presented generator of the Spanish language from signs through avatar representing the signs. Karami et al. [39] presented recognizer for static Persian signs using wavelets as features and neural network for classification by producing an accuracy of 94.06% over 32 Persian alphabets. Jiang et al. [40] presented Chinese Sign language recognition over continuous signs. They used self-organizing maps for classification and obtained 82.9% accuracy for 513 signs.

Kausar et al. [41] presented a fuzzy-based classifier for Pakistani Sign Language recognition, considering only static signs. They used fingertip and finger position forming feature vector for

sign recognition. Eun-Jung holden et al. [42] worked on Australian Sign Language (Auslan) by developing a recognition system with three components. The first one was the tracking module that identified face and hands. The second part was about feature extraction while the third and last was the recognition module that used Hidden Markov Model for Auslan words and sentences. Tauseef et al. [43] worked on Urdu sign language using static images of hands and color intensity as a feature. Ahmad et al. [44] worked on Urdu OCR and developed a system to recognize Urdu written script. Their main purpose was to test an algorithm developed for feature extraction and segmentation. Their system worked on the fixed font (Ariel, Size 36). Sheikh [45] worked on Urdu and Arabic script and developed a system that detects the mouse movement and recognizes it as an Urdu or Arabic alphabet. Piater et al. [46] presented a technique for recognition of continuous natural signing. The authors achieved their goal by implementing three phases i.e., active appearance models for detailed face tracking to quantify facial expressions such as the mouth and eye aperture and eyebrow raise, hand tracking using color and Appearance, and tracking upper-body articulated pose, linking the face to the hands for increased overall robustness. Similarly, Bilal et al. [47] conducted a study designed to recognize sign language recognition through hand gestures. They primarily studied the techniques focused on 3D hand modeling, appearance-based methods and hand shape analysis. They primarily studied techniques focused on 3D hand modeling, approaches based on appearance, and analysis of the hand shape. Kausar and Javed [48] presented a survey on trends in recognition of sign language. The author has explored numerous methods for defining areas of issue and challenges faced by researchers. Tariq et al. [49] suggested a cost-effective, non-intrusive webcam-based solution whereby an individual from any part of the world may train the sign language learning system. They claimed that it understood signs and translated them into words. Hand recognition is done by using thresholding based on skin color, contour detection and convexity defect for hand detection and identification of important points on the hand respectively. Neural Network is used for the classification of numeric and alphabets with 65% and 57% precision. Cooper et al. [50] dealt with the understanding of sign language using linguistic sub-units. They considered three sub-units that were obtained from the appearance data and inferred from 2D or 3D tracking data. Results achieved with 76% success rate by Herath et al. [51] from their work on Sinhala sign language for static signs. They found the centroid of each part of the hand and the ratio of the width of the sign to each part is used as a feature parameter and distance matching is used to match the sign. Eigenvalue Weighted Euclidean Distance-Based classification technique is used to recognize Indian sign language by Singha and Das [52]. Two hand based signs have been used as sample data. Abid et al. [53] presented a system for recognition of dynamic sign language and voice recognition for smart home interactive applications. They used the Bag-of-Features and a local part model approach for bare hand dynamic gesture recognition from video. The K-means++ method was applied to cluster the visual words. Dynamic hand gesture classification was conducted by using a Bag-of-features (BOF) and non-linear support vector machine (SVM) methods. They tested

on 6 gestures in 16 scenarios with an average 97% success. Agarwal and Thakur [54] presented a technique using Microsoft Kinect device to capture the images. Multiclass SVM is used for classification whereas the technique is used to recognize numerical gestures 0 – 9. They achieved 81% accuracy using linear kernel and 87% accuracy using the RBF kernel. Similarly, authors in de Souza and Pizzolato [55] used SVM and Hidden Conditional Random Fields to recognize Brazilian sign language in the context of Finger-spelling and Natural articulated words. They used feature vector as extracted from depth information and based on linguistic investigations. Goyal et al. [56] presented a system for deaf and dumb people using Indian sign language recognition using stationary images as input while SIFT is used as key feature. They tested their technique for static 9 signs and achieved 95% accurate results. Forster et al. [57] proposed a technique for improving continuous sign language recognition using MLP and HMM using real-life data to test their technique using different scenarios with different signers, sign vocabulary, and sentences achieving 22.1% and 38.6% WER.

Abella et al. [58] presented Multimodal descriptors for Multi-class hand pose recognition in the context of HCI based applications. They compared two techniques based on feature descriptors as Multi-modal Hand Shape (MHS) and Fourier-based Hand Shape (FHS), which compute local and global 2D-3D hand shape statistics to robustly describe hand poses. They showed that by fusing MHS and FHS better results may be obtained in contrast to individual feature descriptors. Karthick et al. [59] transformed Indian Sign language into text using Leap Motion Controller. Dynamic Time Warping and Intelligence Sense algorithms were used for converting the hand gestures into an appropriate text Leap Motion controller having an inbuilt camera and two IR sensors to capture hand signals. Chaudhary and Ryait [60] presented techniques to recognize American Sign Language using an Artificial Neural network. They only worked on static gestures. Then height, area, centroid, and distance of the centroid from the origin (top-left corner) of the image are used as features. They achieved 85% success. Curiel and Collet [61] presented the implementation of an automatic sign language (SL) sign annotation framework based on formal logic, the Propositional Dynamic Logic (PDL). They focused to show how a generic annotation system can be constructed upon these underlying theoretical principles, regardless of the tracking technologies available or the input format of corpora. In Ayshee et al. [62] presented Fuzzy rule-based Bengali Sign Language recognition. They tested the technique on only two Bengali letters. Thorat et al. [63] presented the Indian Sign Language Recognition System using SIFT features on static gestures. P.F.F.A. Mashagba proposed an Automatic Isolated-Word Arabic Sign Language Recognition System Based on Time Delay neural networks. The research uses the multivariate Gaussian Mixture Model (GMM) based on the characteristic of the well-known Hue Saturation Lightness Model (HIS) in determining the colors within the video frames. In this research, the mean and covariance of the three-colored region within the frames are determined and used to help us in segmenting each frame (picture) into two colored regions and outlier regions. The proposed system obtained a word recognition rate of 70.0% in the testing set. Riad et al. [64] presented work describing

an isolated SLR system that extracts geometric features from a camera for the hand gesture and builds a geometric model for the hand gesture. The rule-based classifier was then used for the recognition process based on the determined geometric features of a specific gesture. The proposed model was tested on seven Arce words. The overall recognition rate was about 95.3%. In Trigueiros et al. [65] described a technique which at real-time can interpret the Portuguese Sign Language Experiments showed that the system was able to reliably recognize the vowels in real-time, with an accuracy of 99.4% with one dataset of features and accuracy of 99.6% with a second dataset of features. They implemented a system to recognize only vowels. W.W. Kong and Surendra Ranganath presented a segment-based probabilistic approach to robustly recognize continuous sign language sentences. The recognition strategy is based on a two-layer conditional random field (CRF) model. The continuously signed sentences are first segmented, and the sub-segments are labeled SIGN or ME (movement epenthesis) by a Bayesian network (BN) which fuses the outputs of independent CRF and support vector machine (SVM) classifiers. They obtained a recall rate of 95.7% and a precision of 96.6% for unseen samples from seen signers, and a recall rate of 86.6% and a precision of 89.9% for unseen signers.

Kumar et al. [66] used a multimodal framework for sign language recognition from facial expressions and signer gestures. Two types of gadgetry i.e. leap motion and Kinect are used for recording sign gestures and facial expressions respectively. They have extracted a features vector of six points i.e. fingertips and center of the palm for hand gesture while using Kinect, a feature vector of seventy-one different points is obtained. The hidden Markov model (HMM) is used for gesture recognition while later on, feature combination is done, and different classification approaches are used. They reported an accuracy rate of 96.05% and 94.27% for single and double hand gestures, respectively. The approach in [67] is based on bare hand images for Farsi sign language recognition. a hand detection algorithm detects the hand region of the signer which is further processed for obtaining the hand boundary. Features of Fourier coefficients amplitude are extracted from the hand boundary image and further classified by three different classification techniques i.e. Bayesian, KNN and MLP. An image-based recognition is presented in [68] for English language alphabets recognition. images are obtained from sign language videos that are processed to extract the hand and facial features using a convex hull. A neuro-fuzzy classification approach is used to recognize the signs. The recognized signs are further framed into Natural language processing (NLP) for the formation of sentences. Csóka et al. [69] used a simple and efficient method for recognition of American sign language from bare hand images. Initially, images are taken at different rotations and angles and the LoG filter is applied. Next, fast features are extracted from the input images and classified through CNN. They reported an accuracy rate of 91.34%. Pu et al. [70] presented a technique for the interpretation of continuous sign language. Their technique consisted of two steps, i.e. the 3D convolutionary residual network (3D-ResNet) used for extraction of features and the sign video represented as a 3-d sequence of CNN features. Panchal and Patel [71]

proposed a model for Indian sign language recognition and converted a sign gesture into text, voice and vice versa. By transforming an RGB frame into an HSV frame, they used skin color filtering, followed by a Gaussian low pass filter. Afterward, statistical features were computed i.e., mean, covariance and eigenvalues. The features were subject to the Euclidean distance metric for classification purposes. Alzohairi et al. [72] presented an approach for the static alphabets of the Arabic sign language. The features extraction phase included computation of HOG, EHD, LBP, DTW and GLCM descriptors. The classification was carried out using the one-vs-all SVMs. Experimental results revealed that the HOG descriptor was proved more accurate than the rest of the descriptors. Hassan et al. [73] presented the Hausa sign language classification strategy using static, manual and non-manual sign images. Fourier descriptors were extracted and particle swarm optimization was used for their enhancement. The classification was carried out using the Artificial Neural Network (ANN), which reported a 93.0% accuracy. Recognition of static and continuous hand gestures representing American sign language was accomplished, where gestures were captured through leap motion controller [74]. The device was used to extract the basic hand features including sphere radius of hand palm, positions of the hand and fingertips, and standard deviation of the palm position. The extracted features were subject to the classification task through deep neural network (DNN) and SVM classifiers. Bantupalli and Xie [75] presented a computer vision-based approach for American sign language (ASL) recognition over the video sequences where temporal and spatial features were extracted. Afterward, convolutional neural network (CNN) was applied for the recognition using spatial features while recurrent neural network (RNN) was used for recognition through temporal features. Mahmud et al. [76] proposed an approach for ASL recognition. As an initial step, they suppressed the image noise and extracted the histogram of the oriented gradients (HOG) features. The extracted features were subject to KNN classifier and accuracy of 94.23% was reported. Same like, bag of features (BoF) were extracted and classified using SVM which achieved lesser recognition accuracy i.e. 86%.

3.2 Pakistan sign language (PSL) Recognition

Alvi et al. [77] presented a technique for recognition of Pakistan sign language (PSL) alphabets. PSL gestures were classified using the statistical template matching technique. Mean and standard deviation were used as statistical features from images of glove hands. Kausar et al. [41] presented a fuzzy classifier to recognize the PSL alphabets. Colored gloves were used to identify fingertips and finger joints. The angle between the fingertip and corresponding finger joint was computed to identify the position of each finger. Tauseef et al. [43] presented a recognition system for translating hand gestures into the Urdu alphabets. They painted the fingers using three basic colors i.e. red(R), green(G) and blue(B). Boundaries and orientation over R, G and B regions and proportion percentages regarding R, G and B regions were computed. Rule based classification was performed producing 97% accuracy over static sign

images. Ali [78] presented Haar algorithm to recognize Urdu signs. The author used a sliding window and the window sub-image is matched using the classifier. Instead of using some feature vector, the technique is fully dependent on the classifier. Saqib and Kazmi [79] proposed a co-relation-based approach for the recognition PSL static alphabets. They have used normalized co-relation for finding the closest fit of the alphabets in the dataset. A thin, 370-sample dictionary was used. The solution was able to recognize 34 out of 37 PSL signs and achieved an accuracy rate of 89.2%, but was unable to accommodate changes in size, rotation and illumination of hand signs. SVM based classification for the identification of PSL static signs [80] has been introduced. Hand area segmentation was accomplished as a preprocessing step and region of interest (ROI) was extracted. During the next step, two types of features were extracted, i.e. region-based (HU moments) and boundary-based (Fourier descriptors). Experimental results attained 83% accuracy on 60 samples. Shape descriptors (HU moments) and central moments (image property analysis) were extracted and used Fourier descriptors to obtain a 1-dimensional signature for representing PSL signs [81]. Ranking based mechanism was used for classification and accuracy of 83.3% and 92.3% was achieved for two datasets. A two phase approach for the recognition of PSL alphabets was presented [82] where signs were recorded as a first step while the translation was performed at the later stage. The signs were recorded through the Kinect device which extracted various information about different segments of the human body, i.e. right and left shoulders, head, left and right wrist, spine and hip bone. Such features were processed for matching with the dictionary using the DTW algorithm and the recognition rate of 91% was reported. The approach for PSL recognition was presented by Khan et al. [83] using discrete wavelet transform (DWT) as feature set. The extracted features are fed into artificial neural networks (ANN) and achieved an accuracy of 86.4% for a dataset of 500 samples. The dataset contained the images having no variation with respect to rotation, illumination and scaling, rendering the method very constrained. Malik et al. [84] used thresholding for identification of the hand skin followed by transforming the threshold image into PCA space and then performing the classification task with KNN. Finger positions were used to form feature vector for classifying PSL alphabets [85]. This was accomplished by locating the thumb through template matching and finding the fingers with reference to the thumb position. The technique was validated over 420 samples and an accuracy 84.2% was reported.

3.3 Hand Detection Approaches

Yu et al. [86] presented an approach for hand detection that initially computes the wrist cutting edge and the palm area. The approach used a ToF depth camera to find the number of fingers. The palm area of the hand is captured using morphological operations. Yeo et al. [87] tracked and recognized the hand for gesture recognition. They used low-cost hardware. The hand detection module was given a binary image as input and shape analysis was performed using

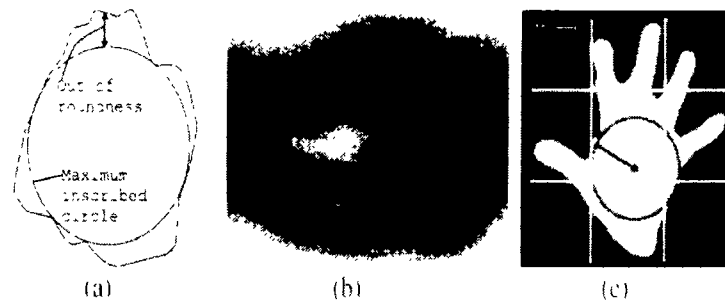


Figure 3.1: (a) Maximum inscribed circle, (b) Inside hand, (c) Limiting region of interest[87]

the polygon approximation. Next, the palm detection was implemented by setting the Region of Interest(ROI) that identified the palm as a circle shape as shown in figure 3.1. Finger locations were tracked by analyzing the contour characteristics.

Simon et al. [88] proposed a Multiview bootstrapping technique for hand keypoint detection. A Kinect based hand detection technique was presented by Lee et al. [89]. It was implemented by finding the number of fingers and the hand area. Raheja et al. [90] used depth images taken through Kinect device for detecting the hand region. Fingers were detected through using OpenNI. To separate the background of the image, the depth value of the image was used, resulting in hand region as output. Afterward, distance transforms were applied that helped to detect the center of the hand. Fingers were localized by removing the palm area of the hand. In Dhawan and Honrao [91] discussed HCI applications where the use of hands can be promising. Bambach et al. [92] studied the social interactions on the Egohands dataset having several videos for 48 persons contacting and interacting in a real-world environment. The dataset provided a pixel level information for above 15000 hand samples. They used appearance models in CNN and introduced a method called candidate region generation for detecting and localizing the hands. Huang et al. [93] presented a hand detection approach from egocentric videos. The hand-related motion and egocentric cues are taken into account for region detection. Initially, the regions that probably belong to the hand were determined by using their motion patterns across each frame. Using this information, the hand region was detected by taking the scores of the adjacent pixels. The score was calculated from the egocentric cues i.e. location, position, appearance continuity, and consistency

3.4 Feature Representation for Sign Languages

So far, a variety of features are used by sign language recognition techniques. In this section, a review of features being used to represent hand signs(2-D and 3-D images) and feature selection techniques is presented.

3.4.1 Features from 2-Dimensional Images

Jitcharoenport et al. [94] used hand orientation along with bend and stretch of each finger to form a feature set for Thai sign language. While, Bauer and Hienz [95] extracted the hand shape, its orientation and location for German sign language. American sign language was recognized using the depth contrast features [96]. The authors used 11 colored gloves for feature extraction. Ahmed et al. [80] recognized ten static alphabets of Pakistan sign language using region-based HU-moments and Fourier descriptors features. Ibrahim et al. [97] recognized Arabic sign language by finding coordinates for the center of gravity of hand, velocity, movement and orientation of the hand. The approach presented by Nagarajan and Subashini [98] was based on edge orientation histogram features and Sombandith et al. [99] used histogram of oriented gradients (HOG) features. Two-dimensional wavelet transforms are used for PSL recognition by Karami et al. [100] while, Albelwi and Alginahi [101] used shift and rotation invariant Fourier descriptors features for the same purpose. Pansare et al. [102] used centroid and area of hand edge region which was put to matching with the training images using euclidean distance. The approach presented by Lim et al. [103] used a block-based histogram of optical flow for sign language recognition. Fayyaz and Ayaz [104] used speeded up robust features (SURF) for recognition of static signs of English alphabets. Solís-V et al. [105] used normalized moments as these features are invariant to scale and translation. Wang et al. [106] introduced a hand gesture recognition system that extracted the hand in YUV color space by means of skin detection followed by connected component analysis. Authors extracted LBP features and transformed them into the principal component analysis (PCA Domain for Dimension Reduction). SVM-based classifier was used over a dataset of 630 images and achieved 94.22% accuracy. Jasim and Hasanuzzaman [107] used LBP based features to recognize Bangladesh and Chinese sign languages from the still images. The classification task was accomplished by SVMs. Santa et al. [108] used LBP based features for recognition and translation of Bangla alphabets from still images. The classification task was accomplished by SVMs. Hruz et al. [109] used multiple feature extraction techniques for the recognition of sign language recognition including local binary patterns. Experiments on the base of individual and combined feature sets were gathered and the local binary pattern was most accurate in signer dependent mode with an accuracy of 94.36%, while using signer independent mode it reported an accuracy rate of 58.18%. Zare and Zahiri [67] computed Fourier coefficient amplitude from the hand boundary and used for the recognition of Farsi sign language. Convex hull was used for feature extraction by computing the convex points from the hand and head region [68]. Alzohairi et al. [72] used HOG, EHD, LBP, DTW and GLCM descriptors for Arabic sign language recognition. Mean, covariance and eigenvalue were used to form a feature vector for Indian sing language [71]. S. T. Hassan in [73] extracted the Fourier descriptors for Hausa sign language recognition. In [75] temporal and spatial features are extracted for American sign language recognition. Mahmud et al. [76] extracted histogram of oriented gradients (HOG), and Bag of features (BoF) for American sign language recognition.

3.4.2 Features from 3-Dimensional Images

Yang [110] used 3-D model for the recognition of sign languages where signs were captured through the Kinect sensor. Once hand and face regions were detected, 10 feature points were computed from the skeleton. Kumar et al. [111] proposed a twin motion algorithm for recognition of 3D signs. To project the motion features on a graph, a wide RRJRD and narrow RRJRD based characterization were computed and each sign was differentiated by a set of spatiotemporal projections. Elons et al. [112] used PCNN models to generate the 2D features by generating the image signature followed by constructing optimized quality 3D features. The technique presented by Kumar et al. [113], used Microsoft Kinect and leap motion sensors for capturing fingers and palm area. A set of 11 features was obtained for a single hand sign while for a two-hand sign, the dimension of the feature set was 22. Zhang et al. [114] used accelerometer and EMG Sensors for gesture recognition. Accelerometer identified the rate of change of velocity along three-axis i.e., (x,y,z) , while EMG sensor obtained a 4-dimensional feature vector. As well as, Li et al. [115] presented an accelerometer and sEMG based approach to get three basic components i.e. hand shape, orientation and movement. Chai et al. [116] used Kinect for sign language recognition. The presented approach used a 3D motion trajectory for representing a sign. The sign representation was compared with the sign language dictionary producing its true class. Pigou et al. [117] presented a CNN based approach. The feature set was obtained from CNN and a pooling scheme was used to get interesting information. An electromyogram(EMG) was used [118] that provided a feature set for the classification of static alphabets. Chong and Lee [74] extracted the hand palm sphere radius, position of the palm and fingertips, and standard deviation of the palm position using a leap motion controller.

3.4.3 Features selection techniques

Feature selection techniques are used to find an optimal feature subset that not only suppresses redundant features but the resultant subset may improve the classification accuracy as well.

Fleuret [119] presented feature selection technique that worked on the basis of conditional mutual information. Forman [120] the author considered the twelve-feature selection matrices for the problem of text classification [120–122]. Other literature related to ranking methods [123–125] uses class densities of binary data. Relief algorithm [126, 127] is a filtered based approach for feature selection in which feature relevance criteria are used. The branch and bound method [128, 129] used the tree structure to find the different subsets from input feature set. Particle swarm optimization (PSO) [130] and genetic algorithm [131] produced computationally feasible results for features selection. The approach of sequential features selection (SFS) [132, 133] reduces the dimensionality of the features set by starting an empty set and add one by one features in the set. The subset with the best performance was required subset. Another approach called sequential floating forward selection (SFFS) [132, 134] is found to be more robust than the SFS. A modified genetic algorithm (CHCGA) [133, 135] is

used for features selection. Using the weights of a classifier [120, 136, 137] based on feature ranking. In [138–140] principle component analysis (PCA) was used for features dimension reduction.

3.5 Classification Approaches

Many classification approaches are used for sign language recognition depending on the type of data. Choice of the classifier that suits a situation is very important to correctly classify the input data with a reasonable accuracy rate.

Albelwi and Alginahi [101] used K-nearest neighbor (KNN) for classification and reported an accuracy rate of 90.55% for Arabic sign language recognition. Solís-V et al. [105] recognized Mexican sign language using artificial neural networks (ANN) by remaining 93% accurate. Euclidean distance was used for classification [97] of Arabic sign language. Ali Karami [100] used multi-layered perceptron (MLP) for recognition of Persian sign language and scored 94.06% accuracy. M. Hruz [109] used hidden Markov model (HMM) for the recognition of signer dependent and independent hand gestures. Sombandith et al. [99] recognized Lao sign language using a template matching technique. SVM model was used for classification of static signs [80, 98]. Kausar et al. [41] applied a fuzzy classifier for the classification of PSL alphabets. Jadooki et al. [141] presented fusion feature mining techniques for American sign language(ASL) recognition while Dong [96] used a random forest classifier. Zare and Zahiri [67] used three classification methods i.e. Bayes, KNN and Neural network for Farsi sign language and the accuracy results were compared. Kumar et al. [142] used an extended HMM called coupled HMM for classification. Abreu et al. [118] through a one-vs-all SVM for Brazilian sign language. Hemina Bhavsar [68] classified the English alphabets by Neuro-Fuzzy classification approach. Multiclass SVMs using one-vs-all modality were used for Arabic sign language classification [72]. ANN was used for Hausa Sign language recognition [73]. Chong and Lee [74] used deep neural network (DNN) and SVM for ASL recognition while convolution neural network (CNN) and recurrent neural network (RNN) were used as well [75]. Gonen et al. [143] proposed a multiclass posterior probabilistic support vector machine (PPSVM) for classification. Conventional SVM classifies the input data into two classes, called binary SVM. They proposed a neighbor-based density estimator and extended it to the multiclass classifier. The presented model decreased the favoritism effect and thus the error rate was reduced. They have tested the model for 20 datasets and observed that the model performs better than the conventional SVM approach. For the classification of text, Berger [31] proposed an error-correcting output coding approach. The presented methodology decomposed the multi-classification problem into sub-parts and then collected the results of each part to form the original problem's result. ali Bagheri et al. [32] proposed the Error-Correcting Output Codes based classification that used multiple binary classifiers and combined them to solve

multiclass problems. They dealt with problems of image vision i.e. logo recognition and shape classification by using the decision trees and AdaBoost. Compared to other multiclass classification approaches ECOC was proved more accurate and efficient. Dietterich and Bakiri [33] presented the comparison of classification algorithms i.e. decision-tree algorithms C4.5 and CART, the one-per-class (OPC) approach, meaningful distributed output, and ECOC. Their comparison revealed that ECOC performed well than the other classification approaches.

3.6 Existing Techniques Analysis Regarding PSL

We have provided a comparative analysis based on existing techniques in the presented literature. The analysis is for the techniques with regard to Pakistan sign language(PSL) and shown in table 3.1 i.e.,

Table 3.1: Comparative Analysis for PSL Techniques

Technique	Hand Detection	Feature Extraction	Input	Resistant to Noise	Scale Invariant	Rotation Invariant	Classification Technique	Dataset Size
Alvi et al [77]	No	Mean & Variance	Digital Glove	No	No	No	Least mean Square	2500
Kausar et al [41]	Thresholding	Geometrical Features	Colored Gloves	No	No	Yes	Fuzzy	Not Given
Tauseef et al [43]	Thresholding	Geometrical	Painted Hand	No	Fixed Scales	Yes	Rule Based Technique	Not Given
Ali [78]	No	Haar Features	Barred Hand	No	No	Yes	Template Matching	Not Given
Saqib and Kazmi [79]	No	No	Barred hand	No	No	No	Correlation based Matching	370
Ahmed et al [80]	Thresholding	Hue moments	Barred Hands	No	Yes	Yes(Full)	SVM	600
Kausar et al [81]	K-means segmentation	Hue moments	Barred Hands	Yes	Yes	Yes(Full)	Euclidean Distance	597
Races et al [85]	No(Manual Cropping)	Geometrical Features	Barred Hands	No	No	No	Hard coded Rule Based	420
Khan et al. [83]	Thresholding	DWT	Barred Hands	No	Yes	No	ANN	500
Malik et al [84]	Thresholding	PCA Transformed	Barred Hands	No	No	No	KNN	1140

3.7 Research Questions

In the light of the presented analysis, the following research questions are identified i.e.,

- Hand detection and localization under complex environment is a serious issue. The false or poor extraction of hand regions from frames leads to failure in its relevant applications.
- None of the Existing techniques for PSL recognition is insensitive to noise.
- YOLO(you only look once), is proved to be faster than RCNN in performing the same task of RCNN. Would it be more accurate for detecting and localizing hand regions in the complex background?
- Standard LBP and its variations are sensitive to noise. A major limitation of LBP is its sensitivity to affine transformations.
- An ensemble classifier performs better than individual classifiers. Would an ensemble classifier combining different kernel types perform better than ensembles from a single kernel type alone?

- Optical flow provides a clue of presented motion in videos. Would the features of local optical flow help to recognize the activity of an object?
- LBP Histograms are used as feature space for classification tasks. Can statistical features having much lesser dimension than LBP histogram be used for solving the same problem?

Summary

This chapter presents the study of the existing research regarding the automatic recognition of sign languages. In particular, the focus is made on different approaches necessary to accomplish the required task. A comparative analysis of PSL recognition techniques is presented as well covering their pros and cons that enabled us to find research gaps.

Chapter 4

Dataset and Performance Evaluation Metrics

Introduction

In this chapter, we are going to present the detail of the Pakistan sign language(PSL) dataset, the information about the dataset generated through the known signers and the split of it into train and test sets. The statistics of the dataset taken through unknown signers are presented as well. To evaluate the proposed research, a detail of evaluation metrics is discussed here.

4.1 Dataset for Static Alphabets of PSL

Pakistan sign language has a total of 38 alphabet signs and out of those two are represented by the motion of the fingers and hand while the rest of them are static ones. There is a lack of public datasets representing PSL signs and it motivated us to generate our own static hand dataset. The proposed solutions take the PSL sign recognition problem as a classification problem. The alphabets are defined into thirty six classes represented by $C - 1, C - 2, C - 3, \dots, C - 36$. The complete details of the thirty six classes are shown in figure 4.1.

4.1.1 PSL Dataset Generation

The PSL signs are captured by the seven signers under the controlled environment. The images are captured at a resolution of 1920×1080 . The signs from each of the signers are taken from three different distances and examples of the signs are represented in figure 4.2. D1, D2 and D3 are the 2.5, 3.5 and 4.5 feet distance of the center of the camera from the hand under the room illumination environment. To adopt rotation invariance, each class contains the variation in its signs having rotation upto 45 degrees.

Class	Desc.	Sign	Class	Desc.	Sign	Class	Desc.	Sign
C-1	AIN		C-13	HAY		C-25	SEEN	
C-2	ALIF		C-14	HHAY		C-26	SHEEN	
C-3	BAY		C-15	KAF		C-27	SAAY	
C-4	BYAY		C-16	KHAY		C-28	SWAD	
C-5	CHAY		C-17	LAM		C-29	TAY	
C-6	DAL		C-18	MEEM		C-30	TOUY	
C-7	DDAL		C-19	NOON		C-31	TTAY	
C-8	DWAD		C-20	NOONGHUNA		C-32	WOW	
C-9	FAY		C-21	PAY		C-33	YAY	
C-10	GHAF		C-22	QAF		C-34	ZAL	
C-11	GHAIN		C-23	RAY		C-35	ZAY	
C-12	HAMZA		C-24	SAY		C-36	ZOUY	

Figure 4.1: PSL Alphabets Description

4.1.2 Division PSL Dataset into Known & Unknown Subsets

Overall, seven signers contributed in the generation of the whole dataset. The dataset is initially bifurcated into categories i.e., the dataset of known signers and dataset of unknown signers. The signs from five of the signers are kept in the subset dataset from the known signers while the other two signers are kept in a subset dataset from the unknown signers.

4.1.2.1 Details of Dataset from Known Signers

As we are well aware of the training and test phenomena, a dataset is normally divided into two subsets i.e., training and test data. If signs from the same signer are both in train and test data, the whole of the dataset is treated as taken from known signers as the same signer is participating in both of the phases. Table 4.1 is showing class wise split of the dataset from the known signers into train and test subsets along with mean number of signs in each of the classes. Originally, there were total of 5756 signs in the dataset of the known signers and it was for all 36 classes. The split is on the base of 70% and 30% for train and test data respectively that resulted 4052 images in train and 1704 in test sets. On average each of the class has 159.89 images in the dataset from the known signers, 112.56 in training and 47.33 images in the test dataset.

Figure 4.3 is showing a graphical relationship between the number of signs in each class from

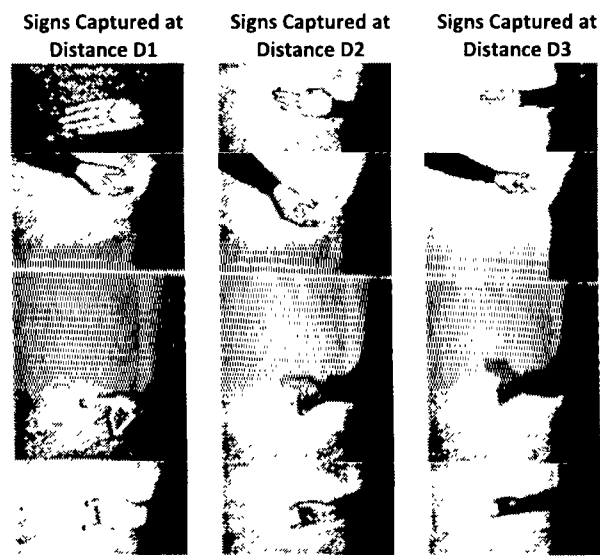


Figure 4.2: PSL Alphabets taken at three Distance: An Example

the known signers’ dataset to the mean signs of the same set. The highest class to mean ratio is for the class C-33 that has a total of 232 signs and the ratio is 1.45, while the class C-32 has the least number of sign images i.e., 86, and the ratio is 0.53. The rest of the classes have their class to mean ratios between 0.53 to 1.45. Figure 4.4 is showing the graphical relationship between

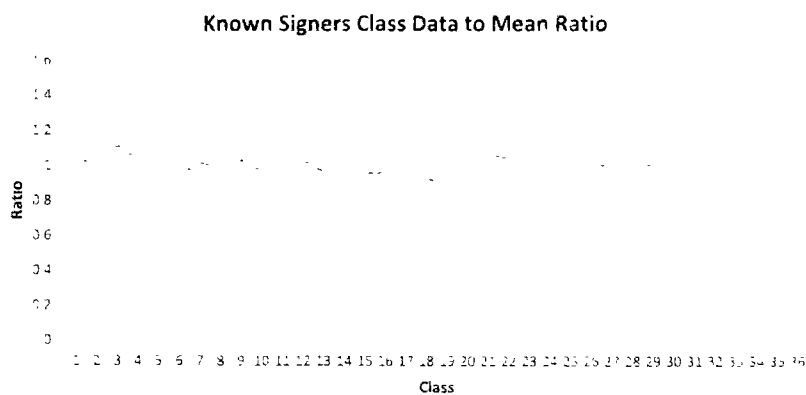


Figure 4.3: Ratio between Class Population to Average Population for Known Signers

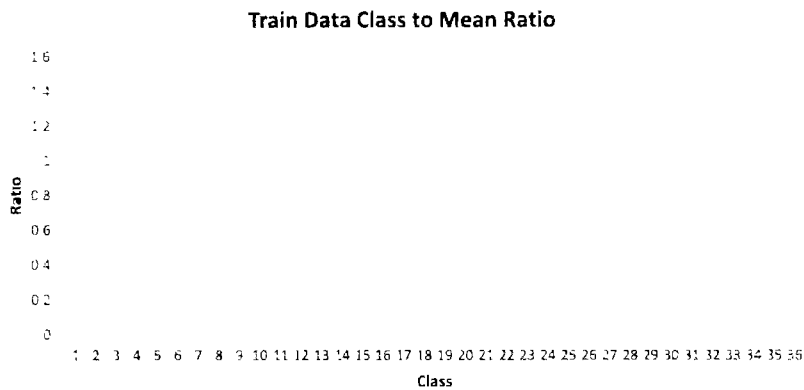
the number of signs in each class to the mean number of signs in training data while figure reffig3:5 is for the test data. Same as the graph for the whole dataset, the highest ratios for both the train and test dataset are representing C-33 and the lowest is corresponding to C-32. The number of samples for C-33 are 169 and 69 in training and test subsets respectively, while it is 61 and 25 for C-32 in training and test sets respectively.

4.1.2.2 Details of Dataset from Unknown Signers

As already explained that, seven signers contributed for creating PSL dataset and five of them were kept in a subset with title Known signers dataset. The rest of the two signers have contributed in creating dataset of unknown signers. The term unknown is used as the signs

Table 4.1: Dataset Statistics for Known Signers

Class	Training Samples	Test Samples	Class Total	Class	Training Samples	Test Samples	Class Total
C-1	117	50	167	C-19	104	43	147
C-2	112	47	159	C-20	111	47	158
C-3	125	53	178	C-21	120	50	170
C-4	116	49	165	C-22	118	49	167
C-5	117	49	166	C-23	105	44	149
C-6	106	45	151	C-24	103	44	147
C-7	115	48	163	C-25	121	51	172
C-8	111	46	157	C-26	114	48	162
C-9	116	49	165	C-27	112	47	159
C-10	109	46	155	C-28	111	47	158
C-11	118	49	167	C-29	113	48	161
C-12	116	49	165	C-30	110	46	156
C-13	108	46	154	C-31	108	45	153
C-14	119	50	169	C-32	61	25	86
C-15	108	45	153	C-33	163	69	232
C-16	108	46	154	C-34	110	46	156
C-17	119	50	169	C-35	104	44	148
C-18	104	43	147	C-36	120	51	171
Training		Test		Accumulative			
Sum	4052		1704			5756	
Average	112.55		47.33			159.89	

**Figure 4.4:** Ratio between Class Population to Average Population for Train Dataset

generated by the two signers have not contributed in the training process of the classifier i.e., signs are unknown to the classification model. In this dataset, overall 1416 images are there and their class wise distribution is 36, 40, 41, 34, 36, 44, 48, 36, 42, 40, 43, 39, 37, 33, 39, 44, 42, 45, 41, 37, 35, 40, 36, 39, 42, 41, 40, 39, 41, 39, 37, 47, 37, 36, 33 and 37 for classes C-1 through C-36 respectively. The average number of signs in each of the class are 39.33.

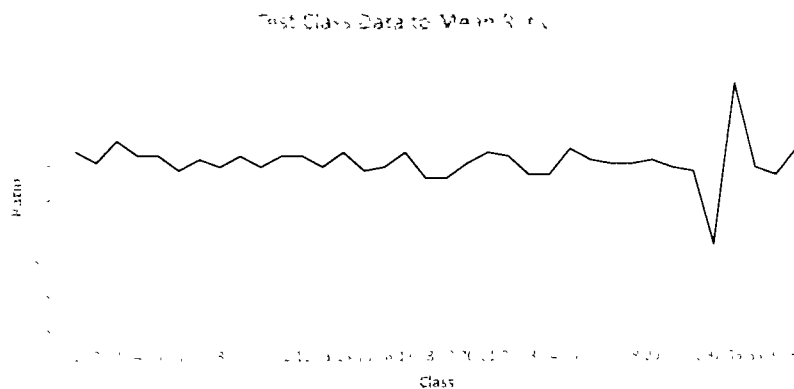


Figure 4.5: Ratio between Class Population to Average Population for Test Dataset

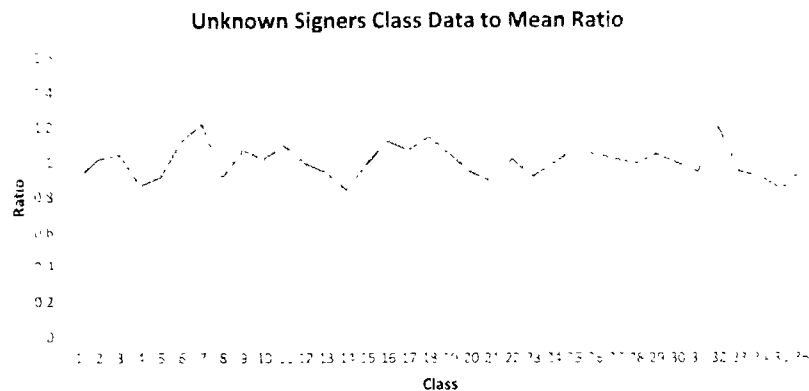


Figure 4.6: Ratio between Class Population to Average Population for Unknown Signers

Figure 4.6 is showing a relationship between the number of images in each class of the dataset from unknown signers to the average number of signs in each class. It may be observed that the highest ratio between class population to mean population is 1.22 for the class C-7 having 48 images in it while class C-35 have the least of the ratio value i.e., 0.84 representing 33 signs. The rest of the classes have in between higher and lower figures.

4.1.3 Dataset for Evaluating Proposed Technique for Recognition of Continuous PSL Alphabets

The proposed model is validated over Weizmann and PSL datasets. A total of 160 video sequences were used to represent three actions of the Weizmann dataset while 66 videos for the same number of Pakistan sign language(PSL) alphabets were generated. The split for both the dataset was 70% (training) and 30% (test).

4.1.4 Dataset for Hand Detection & Localization

Following Datasets are used to evaluate the proposed model for hand detection & localization i.e.,

- EgoHands[144] contains 48 different videos of egocentric interactions with pixel-level ground-truth annotations for 4,800 frames and more than 15,000 hands.
- In Oxford hands dataset[145], hand instances larger than a fixed area of the bounding box (1500 sq. pixels) are considered 'big' enough for detections and are used for evaluation. This gives around 4170 high quality hand instances.
- PSL dataset for static alphabets.

4.2 Experimental Setup

In this section, the detail of machine configurations and the tools used for implementing the proposed methodologies is presented.

4.2.1 Machine Configurations

Google Colab is used for testing hand detection and localization using CNN. Following machine configurations are used:

- GPU: 1xTesla K80 , compute 3.7, having 2496 CUDA cores , 12GB GDDR5 VRAM
- CPU: 1xsingle core hyper threaded Xeon Processors @2.3Ghz i.e(1 core, 2 threads)
- RAM: 12.6 GB
- Disk: 33 GB

4.2.2 Tools used for Implementation

following tools are used for implementing the proposed techniques i.e.,

- Python for hand detection and localization.
- Matlab R2015(a) for implementing all other research.

4.3 Performance Evaluation Metrics

In order to evaluate the proposed technique, we have used four metrics i.e., precision, recall and accuracy. These measures are defined as:

4.3.1 Precision

The precision is generally defined as, "It provides measurement about proportion of predicted positive labels which are actually positive." i.e.,

$$\text{Precision} = \frac{(\Sigma \text{True Positive})}{(\Sigma \text{True Positive} + \Sigma \text{False Positive})} \quad (4.1)$$

4.3.2 Recall

Recall measures what proportion of actual positive label is correctly predicted as positive i.e.,

$$\text{Recall} = \frac{(\Sigma \text{True Positive})}{(\Sigma \text{True Positive} + \Sigma \text{False Negative})} \quad (4.2)$$

4.3.3 Accuracy

The degree to which the result of a measurement, calculation, or specification conforms to the correct value or a standard i.e.,

$$\text{Accuracy (ACC)} = \frac{(\Sigma \text{TP} + \Sigma \text{TN})}{(\Sigma \text{TP} + \Sigma \text{FP} + \Sigma \text{TN} + \Sigma \text{FN})} \quad (4.3)$$

where TP= true positive, FP=false positive, TN=true negative and FN=false negative.

Summary

In this chapter, detail of the PSL dataset captured through the participation of the seven native signers is presented. The alphabet images are taken at three different distances and partitioned into two subgroups i.e., data from known and unknown signers. Different statistics regarding the number of data instances for each of the classes in training and test subset along with performance evaluation metrics are presented as well.

Chapter 5

Hand Detection & Localization from Images and Videos

Introduction

In order to recognize the sign languages, the first and most important step is to detect a human hand from an image that is responsible for generating signs. The task of detecting and localizing the hands had been achieved by the use of hierarchical processes i.e., one responsible for segmenting the objects in an image and the other for recognizing and localizing those objects. There are a variety of techniques used for segmenting and finding the blobs in an image ranging from supervised techniques involving threshold based to the unsupervised ones i.e., C-mean, K-mean, etc. The classification purpose may be achieved through statistical, syntactical and Neural based classifiers. Backpropagation NN, support vector machines, CNN, etc are widely used for the classification purpose and except CNN all the other are subject to a set of feature set. CNNs can extract the feature through their own architecture, solely by the operations of convolutions but they are unable to localize the same objects in a single go. The issue is resolved by the extension of CNN i.e., RCNN, which recognizes and localizes the object in a single go. YOLO(you only look once), is proved to be faster than RCNN in performing the same task of RCNN. Once the object is being localized through an enclosing rectangle, still there remains some region of the background. HSV color space separates the luma from the color information that could be efficiently used in modeling threshold for separating foreground from the background inside the rectangle enclosing the object. We have proposed a hand detecting, localizing and extracting technique that uses YOLO-CNN for hand detection and localization followed by suppressing the background through the use of a skin detector in HSV color space and then extracting that hand through the use of morphological operations.

5.1 Proposed Solution

The flow of the proposed hand detector is shown in figure 5.1. It involves hand detection and localization through drawing a bounding box around it using YOLO based CNN. Afterward, hand segmentation is performed by presenting SDA that uses HSV color model for skin detection. Once the hand is segmented, post processing is applied over the resultant of SDA. The post processing is applied through hand detection algorithm(HDA) and fill hole inside objects(FHO) algorithm. The post processing step would enable the refined bounding box around the hand i.e., the background would be removed and enhancement would be the objective. The proposed methodology is tested over egohands[144] and oxfords[145] dataset having images with complex background and complex egocentric interaction [146]. As well as, the proposed methodology is tested on the PSL dataset that has images with simple but varying illumination background.

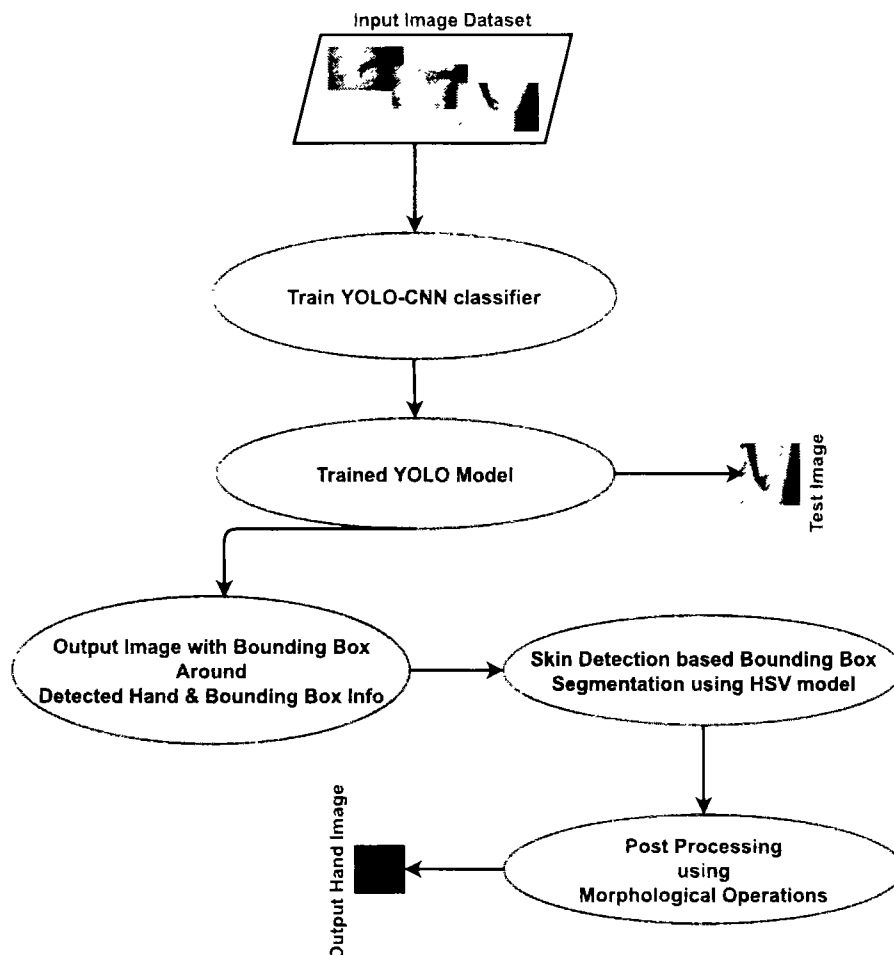


Figure 5.1: Flow diagram of the Proposed Research

5.1.1.2 Rectified Linear Unit

In ReLU, we apply a threshold on the activations for reducing the computational cost. It is computed as:

$$f(x) = \max(1, x) \quad (5.1)$$

This function set all the pixels values to zero which are below 1. Figure 5.5 shows an example of ReLU.

1.5	5	6	0.2	8
8	5	5	1	0
5	6	1	8	9
88	20	0.5	22	21
95	74	281	0.6	74
121	0.9	32	55	96

(a)

0	5	6	0	8
8	5	5	1	0
5	6	0	8	9
88	20	0	22	21
95	74	281	0	74
121	0	32	55	96

(b)

Figure 5.4: Example of computations at Relu Layer

5.1.1.3 Pooling

Pooling is a form of downsampling through non-linear operation. The object of the pooling layer is to reduce the spatial size of the representation. It reduces the number of parameters and resultantly the computation. Many functions are available to accomplish the task of pooling but max-pooling is frequently used and that was our choice as well.

With max pooling, we applied a 2×2 size filter over an image with a stride of 2 at every depth slice. A pooling layer 2×2 and with stride 2 shrinks the input image to $\frac{1}{2}$ of its original size. Figure 5.5 shows an image and the output of the max pooling. The image we input to the max pooling is of size 4×4 and the output size from max pooling 2×2 .

1	0	2	3
4	6	6	8
3	1	1	0
1	2	2	4

(a)

6	8
3	4

(b)

Figure 5.5: Pooling Layer Computation using Max Function(MaxPool):Example

5.1.1.4 Fully Connected Neural Network

The last two layers of the YOLO network are fully connected. The first of them takes the input features from the convolutional layers and the second one computes the output. The final layer uses linear activation function i.e.,

$$f(x) = Cx \quad (5.2)$$

A straight line function where activation is proportional to the input (which is the weighted sum from neurons). The derivative with respect to x is c . That means the gradient has no relationship with x . It is a constant gradient and the descent is going to be on the constant gradient. If there is a prediction error, the changes made by backpropagation are constant and not depending on the change in input $\delta(x)$.

5.1.1.5 Output of the YOLO-CNN

Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor. Here $B=2$, $S=7$ and $C=2$, so the output tensor would be of dimension $7 \times 7 \times 12$.

5.1.2 Hand Segmentation using HSV based Skin Detector

Prior to the feature extraction from PSL alphabet images, skin detection is applied for segmenting the hand from the background. To process skin detection, we have used color properties in the HSV domain presented in skin detection algorithm(HLA).

Algorithm 1 Skin Detection Algorithm(SDA)

Input: Hand Bounding Box(HBB)

Output: Segmented Hand Image(SHI)

1: Convert RGB into HSV space i.e., HSVI.

2: Separate H, S and V channels from HSVI.

3: Blur H and S channels.

* Construct Binary MaskBM for specific S and H values*

4: **repeat**

5: **if** $S(i,j) \in [0.23, 0.68]$ and $H(i,j) \in [0.0, 50.0]$ **then**

6: $BM(i, j) = 1$

7: **else**

8: $BM(i, j) = 0$

9: **end if**

10: **until** $\forall 1 \leq i \leq HLI, 1 \leq j \leq HLI$

11: Apply AND operation over BM and HBB to get the segmented hand image i.e.,
 $SHI = (HBB)AND(BM)$

Hand localization algorithm takes the image inside the bounding box as input and then transforms this portion of the image from RGB to HSV color model. The hue and the saturation components were blurred using a 3×3 average mask that smooths the image by making the colors continuous and suppressing the quantization effects. The V component is not put to the blurring so that the original image may not look like the blurred one. The HLA computes the binary mask for the S and H values i.e. if the Hue value at a specific position, (x,y) , is in

between 0.23 to 0.68 and saturation values lie in between 0.0 to 50.0 that mask represents 1 otherwise 0. The binary mask is applied over the HBB for segmenting the hand and suppressing the other objects in the box.

5.1.3 Post Processing using Morphological Image Processing

Once the hand bounding box has been segmented through SDA, it is subject to the post processing using morphological image processing techniques. The post processing step is accomplished by presenting two algorithms i.e., hand localization algorithm(HLA) and fill holes inside object(FHO) algorithm.

Algorithm 2 : Hand Localization Algorithm(HLA)

Input: Segmented Hand Image(SHI)

Output: Localized Hand Image(LHI)

- 1: Convert SHI into binary image i.e., HBI.
 - 2: Find the number of components(K) and their areas in the image using connected component analysis i.e., $C = \{C_1, C_2, C_3, \dots, C_K\}$.
 - 3: Fill the holes inside object using FHO algorithm.
 - 4: Find largest of the C_i , $1 \leq i \leq K$, and its enclosing rectangle say C_L
 - 5: Extract C_L from the processed binary image and its corresponding part from the SHI i.e., $SHA(C_L)$.
 - 6: Apply AND operation over C_L and $SHA(C_L)$ to get the localized hand image i.e., $LHI = SHA(C_L) \text{ AND } (C_L)$
-

HLA takes a segmented bounding box containing hand image, SHI, and firstly converts this sub-image into its binary version and computes the number of components in the binarized image using connected component analysis. Areas of all the components are calculated and if there was any hole inside those blobs, they are filled through FHO algorithm. Lastly, the component with the largest area is retained and after the computation corresponding part of the hand from the segmented image is extracted i.e., LHI.

The FHO algorithm takes the binarized image as an input having multiple blobs and then FHO computes boundary points of all the blobs. From the boundary points of all the blobs, maximum and minimum position along x and y-axis is computed. If a blob exists inside another blob i.e., its boundary points are inside the boundary of the outer object then the inner object is treated as a hole and is filled.

Algorithm 3 Fill Holes inside Objects (FHO)**Input:** Segmented and Processed Image having Blobs**Output:** Image with filled holes within Blobs

```

1: Find the boundaries of the objects present in the image.
2: Build boundary set  $BOS_1, BOS_2, \dots, BOS_p$  for each object  $OB_1, OB_2, \dots, OB_p$ .
3: Find minimum and maximum along horizontal and vertical for each set.i.e,  $BOS_j x_{min}, BOS_j x_{max}, BOS_j y_{min}, BOS_j y_{max}. 1 \leq j \leq p$ 
4: for  $1 \leq t \leq p$  do
5:   for all  $OB_s$  such as  $OB_s \subset OB_t$  do
6:     if  $(BOS_s x_{min} > BOS_t x_{min}) AND (BOS_s x_{max} < BOS_t x_{max}) AND (BOS_s y_{min} > BOS_t y_{min}) AND (BOS_s y_{max} < BOS_t y_{max})$  then
7:        $OB_s$  is a hole within  $OB_t$ 
8:     end if
9:     for (each point  $pm \in OB_s$ ) do
10:      if  $pm$  is background then
11:        Mark  $pm$  as foreground.
12:      end if
13:    end for
14:  end for
15: end for

```

5.1.4 Output of the YOLO-CNN

The final layer of the architecture produces output in the form of probability of the class and coordinates of the bounding box enclosing the hand. In order to normalize the width and height of the bounding box, we have divided them with image width and height respectively and the results are between 0 and 1. We parametrized the bounding box and y coordinates to be offsets of a particular grid cell location so they are also bounded between 0 and 1.

The system splits the given image into $S \times S$ grids. If the center of an object falls into a grid cell, that grid cell is responsible for detecting that object. Each grid cell predicts B bounding boxes and confidence scores for those boxes. These confidence scores reflect how confident the model is that the box contains an object and also how accurate it thinks the box is that it predicts. Formally we define confidence as $Pr(Object) * IOU_{pred}^{truth}$ where $Pr(Object)$ is the probability of an object in a bounding box, IOU_{pred}^{truth} is the intersection over the union between ground truth and predicted hand. If no object exists in that cell, the confidence scores should be zero. Otherwise, we want the confidence score to equal the intersection over union (IOU) between the predicted box and the ground truth.

$$Pr(Class_i|Object) * Pr(Object) * IOU_{pred}^{truth} = IOU_{pred}^{truth} \quad (5.3)$$

which gives us class-specific confidence scores for each box. These scores encode both the probability of that class appearing in the box and how well the predicted box fits the object. The IOU is calculated as:

$$IOU = \frac{AreaofOverlap}{AreaofUnion} \quad (5.4)$$

In order to apply Intersection over Union for evaluating an object detector, we need: (a) The ground-truth bounding boxes. (b) The predicted bounding boxes from our model. The example of IOU is shown in figure 5.6. The green box is the predicted one while the red represents the ground truth.

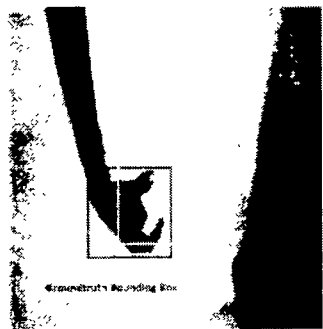


Figure 5.6: Intersection over Union (IOU) Example

In all reality, it's extremely unlikely that the (x, y)-coordinates of our predicted bounding box are going to exactly match the (x, y)-coordinates of the ground-truth bounding box. The grading of predicted bounding boxes is elaborated in figure 5.7.

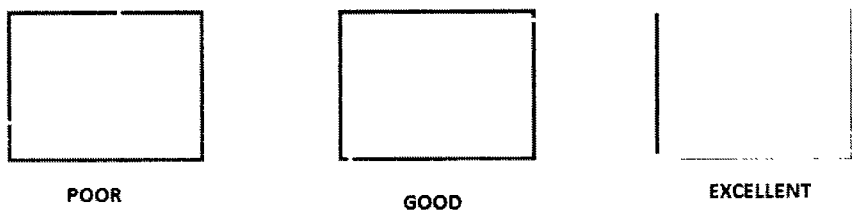


Figure 5.7: IOU Grading Example

5.2 Results & Discussion

In this section, the results achieved through the proposed hand extraction methodology and discussion over those results is presented. YOLO-CNN is trained over the three different learning rates and test results over all the three trained models are presented as well. The varying learning rates are 0.0001, 0.00001 and 0.000001 with bath size 16 and step 192. The number of epochs during training was not kept as constant but we would keep on till the loss

doesn't decrease in three consecutive epochs. Google cloud machine is used for implementing YOLO-CNN i.e., Google Colab which is freely available for the researchers.

Figure 5.8 is graphically showing the training process of the YOLO-CNN while using the learning rate 0.0001. The graph is representing training loss against each of the epoch. In the first of the epoch, the training loss was 0.27 that reduced upto 0.09 for 5th epoch. The training loss decreased to 0.056 for the 13th epoch and 0.047 loss for 16th. It couldn't get lesser during the epochs 17 and 18, so the training process was taken as completed. It took 2 hrs and 30 minutes to complete the whole training process.

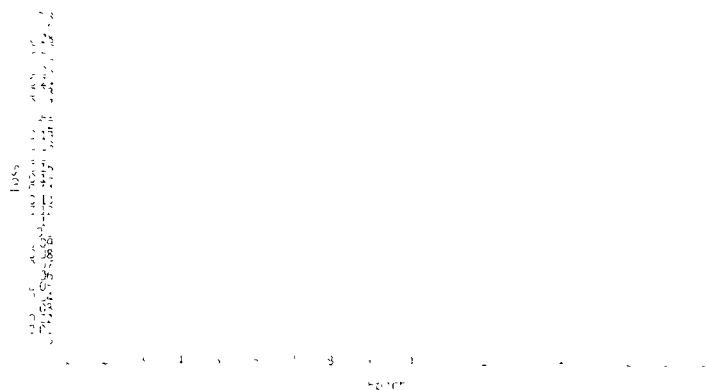


Figure 5.8: Training Loss at 0.0001 Learning Rate

The training loss occurred during each of the epoch while keeping the learning rate 0.00001 is graphically shown in figure 5.9. It may be observed that the initial loss was 0.29 i.e., for the first epoch. As training kept proceeding the loss gradually started to decrease till it was 0.027 for the 30th epoch. The loss for the 31 epoch was 0.026 and it remain the same for the next two epochs as well that concluded the training process. The total training time was 4 hrs and 35 minutes.

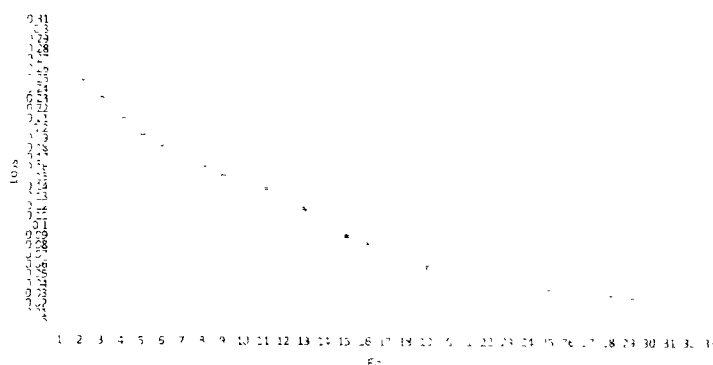


Figure 5.9: Training Loss at 0.00001 Learning Rate

While training the YOLO network by keeping the learning rate 0.000001, the loss in each of the epoch is shown in figure 5.10. It took 48 epochs to train the network which took an approximate time of 6 hrs and 13 minutes. The loss that occurred during the first epoch was 0.28 that gradually kept on decreasing with the increasing number of epochs. The loss for the epoch 44 and 45 was 0.014 but it decreased to 0.013 for the 46th epoch and couldn't be reduced for the next two epochs as well and the training procedure was terminated.

Figure 5.10: Training Loss at 0.000001 Learning Rate

Figure 5.11 is showing the pictorial results of each of the steps involved in the proposed architecture. In fact, prior to the input layer, each of the input is resized to 448×448 dimension followed by its logical split into a grid of sized 7. During the training phase, input images along a vector having five attributes is supplied to the network i.e., x,y,w,h,C. The coordinated point (x,y) represents the center of the grid responsible for enclosing the object, w is the width of the bounding box while h shows its height. C is the confidence for the class and it was kept 1 for the hand images. During the training phase, the network assigns different weights to the grids of the input image by considering the confidence score for the specific class. Each bounding box consists of 5 predictions: x, y, w, h, and confidence. The (x, y) coordinates represent the center of the box relative to the bounds of the grid cell. The width and height are predicted relative to the whole image. Finally, the confidence prediction represents the IOU between the predicted box and any ground truth box. Each grid cell also predicts C conditional class probabilities, $Pr(Class_i|Object)$. These probabilities are conditioned on the grid cell containing an object. We only predict one set of class probabilities per grid cell, regardless of the number of boxes B. At test time we multiply the conditional class probabilities and the individual box confidence predictions.

Figure 5.11(b) is showing the hand detected by YOLO-CNN in the form of the green bounding box. The next of the image, figure 5.11(b), is the one corresponding to the predicted bounding box. When proposed SDA is applied over the extracted bounding box sub image, the result achieved is shown in figure 5.11(c) that not only segmented the hand area but due to the reflection and illumination conditions part of the wrist area was segmented as well. The segmented output bounding box is provided as input to the proposed HLA that initially fills the holes inside the objects using the proposed FHO followed by finding the largest of the

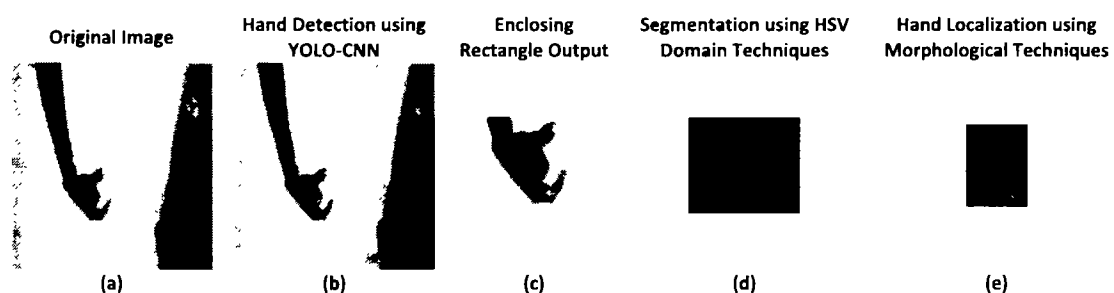


Figure 5.11: Results of the Proposed Technique

object in the extracted bounding box. The largest of the object is extracted and shown in figure 5.11(d). The need of HLA and FHO can be reflected from the figure 5.12(a,b,c) explaining output for an example sign, (a) is showing the output of the SDA, (b) is showing the results of post processing using HLA prior to the use of FHO and (c) is showing the output of the HLA after using FHO algorithm.

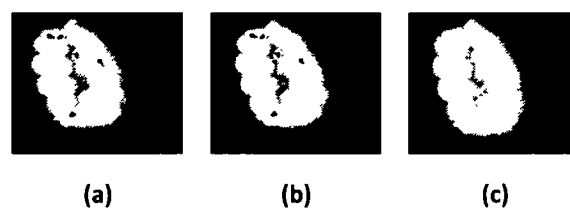


Figure 5.12: Output of Each Post-processing Step

The comparative results of the proposed methodology for the learning rates 0.0001, 0.00001 and 0.000001, when applied over the dataset of the known signers, is presented in figure 5.13. The comparative analysis is based on the two performance metrics i.e., precision and recall. Overall, 1704 images having hand content were tested over the trained model of YOL-CNN that correctly predicted and localized 1641 hands and 53 hand images couldn't be detected. At the same time, the model wrongly predicts 25 non-hand areas as the correct hands. The same dataset when tested over the model trained with the learning rate 0.00001, 1667 true hands were detected while remaining could not be predicted. As well as, it falsely detected 27 non hand regions as hands. In the same manner testing with 0.000001 learning based model predicted 1685 hands correctly while 9 non hands were misclassified to the hand class. The remaining 19 hands couldn't get correctly detected. Figure 5.13(a,b) clearly reflects that the precision achieved through the model trained over the learning rate 0.000001 was highest i.e., 99.5%, while it remained lowest with the score 98.41% for the learning rate 0.00001. The comparative results for the mentioned learning parameters through the recall metric are graphically presented in figure 5.13. It may be observed that the performance of the model trained over the learning rate 0.000001 received the highest precision among its other fellows with a score 98.9%.

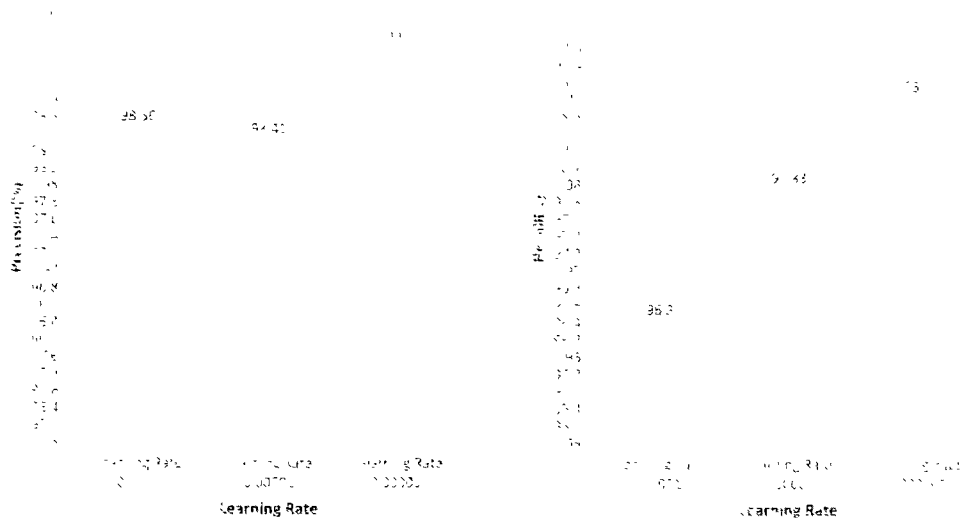


Figure 5.13: Comparative Analysis for Different Learning Rates using Known Signers PSL Dataset

Same as figure 5.13, figure 5.14 is showing the comparative results but for the image dataset generated through the unknown signers i.e., figure 5.14(a) for comparative precision and figure 5.14(b) representing recall. The set having sign images through the unknown signers contains a total of 1416 and when tested over the model trained through 0.0001 learning rate, correctly identified 1379 hands and 37 couldn't get predicted. At the same time, 31 non-hand patches were wrongly classified as hand, resulting in precision and recall 97.8% and 97.39% respectively. When a learning rate of 0.00001 is used for training YOLO-CNN and tested over the signs through the unknown signers, a total of 1391 hands were correctly identified and 25 others couldn't get the correct prediction. The number of misclassification for the non-hand sub-images as hand were 25.

The calculated precision value for the said results was 98.16% while 98.23% was recall score for the same results. Same as others, the results for 0.000001 learning rates were as follows: 1403 hand images correctly predicted while for the 13 other hand signs network was unable to predict while 14 non hands were wrongly classified as hands. It resulted the precision score as 99.01% and recall 99.08%.

Table 5.1 is showing the comparative results of the comparative techniques with the YOLO-CNN based architecture when applied over the two standard datasets i.e., Oxford and EgoHands dataset. It may be observed that the adopted YOLO-CNN has shown better results in terms of average precision. It was 98.5% and 81.4% for EgoHands and Oxford datasets respectively. Faster R-CNN and Skin based technique[149] attained 96% precision(second highest) for the EgoHands dataset while it was better precision among the other fellows for the Oxford hand dataset by Adam Ahmed et al. [154] with the average precision value 72.1%.



Figure 5.14: Comparative Analysis for Different Learning Rates using UnKnown Signers PSL Dataset

Table 5.1: Average Precision(%) based Comparative Results

	Oxford hand dataset [145]	EgoHands dataset [144]
R-CNN [149, 150]	31.23	57.27
R-CNN and skin [149]	49.51	92.96
Faster R-CNN [149, 151]	14.22	50
Faster R-CNN and Skin [149]	31.12	96
Bambach et al. [152]	N/A	84.2
Multiple proposals [145]	48.2	N/A
Deng et al. [153]	58.1	77.1
Adam Ahmed[154]	72.1	93.1
YOLO-CNN	81.4	98.5

Summary

In this chapter, we have proposed a methodology for the detection, localization and extraction of the hand under different illumination and complex background conditions. The hand detection and localization is achieved through YOLO based CNN followed by skin detection using the HSV color model. Afterward, morphological operations are performed for extracting the segmented hand region.

Chapter 6

Symmetric Mean Binary Pattern based PSL Recognition

Introduction

Salient features from an image are key to the classification task. We have presented symmetric mean based binary patterns(sMBP) feature vector that extends the uniform binary pattern through maintaining the rotation invariance. The task is accomplished through exploiting the symmetric properties of circular neighboring points. Error-correcting output codes(ECOC) provide a general-purpose method for improving the performance of inductive learning programs on multiclass problems. ECOC based support vector machines are used for classification purposes that use linear, polynomial and radial basis function based kernels with one-vs-one and one-vs-all modalities.

6.1 Proposed Approach

The proposed approach presents enhanced binary pattern based features which are not only resistant to the noise but invariant to the rotation as well. The work flow of the proposed methodology is shown in figure 6.1.

6.1.1 Symmetric Median Binary Pattern Histogram

We have proposed a technique for extraction of the feature vector that is tolerant to the noise and rotation in a hand sign. The proposed symmetric median binary pattern Histogram is calculated as follows:

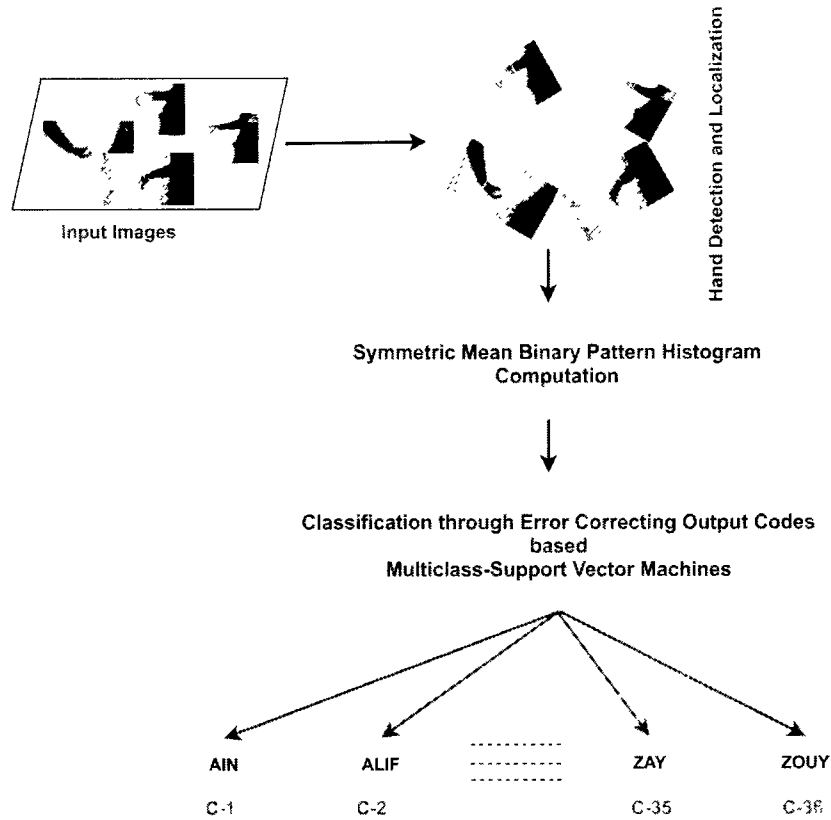


Figure 6.1: Work Flow of the Proposed Approach

6.1.1.1 Mean value for Binary Pattern

Local binary patterns (LBP) are sensitive to the noise as they are calculated over a local patch. The impact of a noisy pixel would make the binary pattern a member of the wrong bin in the histogram. The standard LBP is computed as:

$$LBP_{NP,R} = \sum_{n=1}^{NP} d(g_n - g_c) 2^n \quad (6.1)$$

where

$$d(i) = \begin{cases} 1, & \text{if } i \geq 0 \\ 0, & \text{Otherwise} \end{cases} \quad (6.2)$$

The noise impacts g_c , resulting miscalculation of the binary patterns. To counter the effect of the noise, the value of g_c would be replaced by g_m in equation 6.1 i.e.,

$$g_m = \frac{1}{NP} \sum_{n=1}^{NP} g_n \quad (6.3)$$

where g_m represents mean of the pixel values in a window of dimension $k \times k$ and $NP = 2^k$.

6.1.2 Proposed Symmetric Mean Binary Pattern

In order to classify the Pakistan sign language(PSL), we have presented the extension of the LBP that not only takes its advantage but its inherent issues are countered as well. While considering the sign languages, different signers represent the signs with varying angles of the fingers. None of the two human signers can produce identical representation and even the same signer can't produce the exact copy of his sign. At the same time, this variance must not be upto such an extent that may lead to result the specific sign similar to some other sign. We have exploited these facts about the generated signs and proposed local features in the form of a binary pattern that not only is resistant to the noise but the rotation variations in the signs as well. The proposed technique uses mean calculated over the local window of size 3×3 and computes its difference from all the pixels except center pixel and generates the binary pattern using equation 6.2 and 6.3. While the binary patterns have been generated, those patterns for the standard LBP are simply converted to the decimal values leaving 256 levels i.e., the feature vector for the LBP histogram has a dimension of 1×256 .

While the uniform LBP patterns are represented in figure 11.1 that generates a feature histogram of dimension 1×59 .

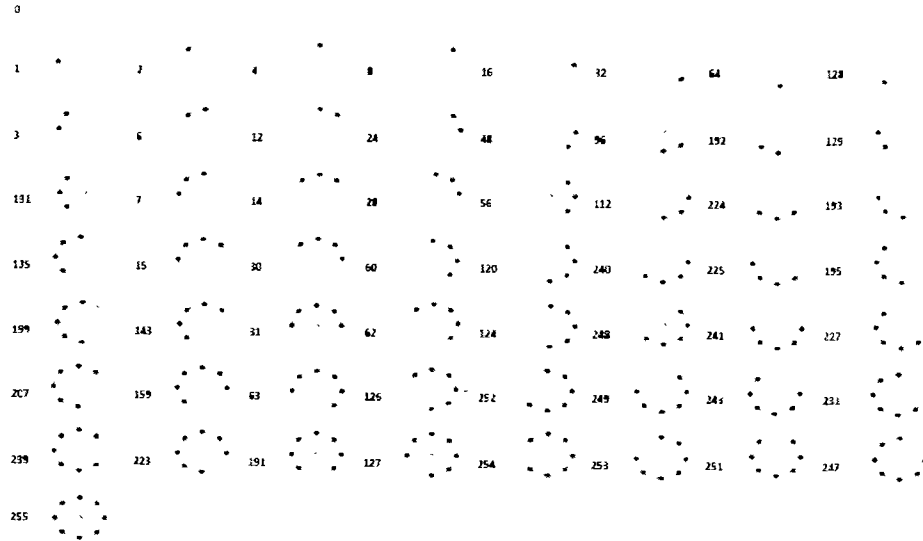


Figure 6.2: Local Binary Pattern Configurations

$$LBP_{NP,R}^{riu2} = \begin{cases} \sum_{n=1}^{NP} d(g_n - g_m), & \text{if } U(LBP_{NP,R}) \leq 2 \\ NP + 1, & \text{if } U(LBP_{NP,R}) > 2 \end{cases} \quad (6.4)$$

where

$$U(LBP_{NP,R}) = |d(g_{NP} - g_m) - d(g_0 - g_m)| + \sum_{n=1}^{NP} |d(g_n - g_m) - d(g_{n-1} - g_m)| \quad (6.5)$$

In an LBP pattern, a transition from 1 to 0 and back from 0 to 1 or vice versa represents the edge(change). If the resultant pattern have more transition it means its redundant one. While pattern with no change is the flat region.

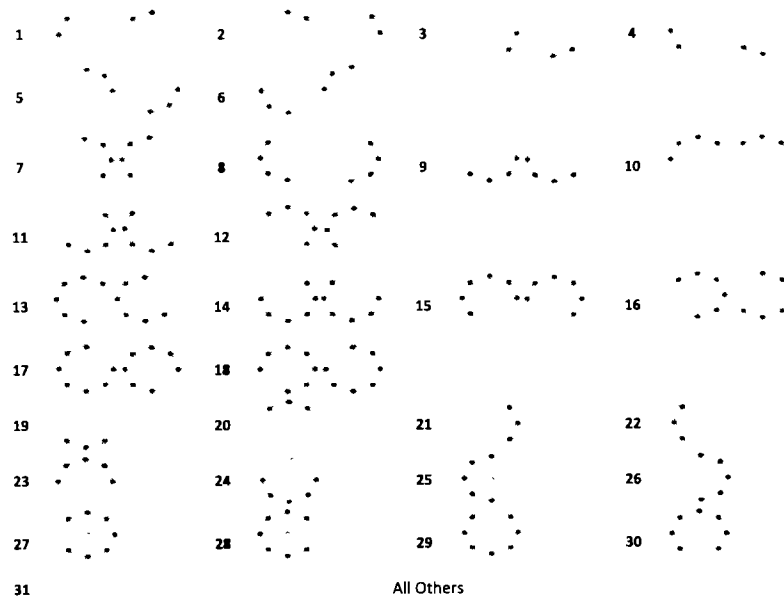


Figure 6.3: Proposed Symmetric MBP Configurations

Once the uniform MBP are generated the proposed symmetric MBP are designed using configurations shown in figure 6.3. The proposed coding design takes the liberty symmetric property of circle in all of its quadrants. The symmetric property is used with reference to center points of each quadrants i.e.,

$$code_g = LEFT - Sym(Q_h) || RIGHT - Sym(Q_h) \quad (6.6)$$

where $code_g$ is the value binary pattern "g", LEFT-Sym and Right-Sym represent left and right symmetry while $0 \leq h \leq 3$ and $1 \leq g \leq 30$.

6.1.3 Classification

In the proposed technique, multi-class Support Vector Machines(SVMs) are used for sign classification. The decision functions for the binary-class linear SVMs are represented by $(u \cdot s_j + c) \leq -1$ if $t_j = -1$ and $(u \cdot s_j + c) \geq 1$ if $t_j = 1$. The two relations can be combined to cover both the cases i.e., $t_j(u \cdot s_j + c) \geq 1$, where t represents the class, s is the input feature vector, u represents weight and c is the margin. The classification of PSL signs for 36 classes represented by the feature vectors of dimension 1×31 each may not be a linear problem. Decision function for the non-linear classification is represented as $f(s) = u \cdot \Phi(s) + c$. This is presented as the features that are linearly non-separable, are transformed to a higher dimensional space using kernel functions. In a kernel-based SVM, u may be represented

as $u = \sum_{j=1}^m \beta_j \Phi(s_j)$. Decision function for a non-linear classification problem having multidimensional feature set can be transformed over a higher dimension and is represented as:

$$f(s) = \sum_{j=1}^m \beta_j \Phi(s_j) \cdot \Phi(s) + c \quad (6.7)$$

where $\Phi(s_j) \cdot \Phi(s)$ is defined as the kernel function and denoted as $KF(s, s_j)$. By replacing $\Phi(s_j) \cdot \Phi(s)$ by $KF(s, s_j)$ the decision function is given as:

$$f(s) = \sum_{j=1}^m \beta_j \cdot KF(s, s_j) + c \quad (6.8)$$

6.1.4 Support Vector Machines Kernels

There are mathematical functions used in support vector machines(SVM) whose major responsibility is to transform input data into the required form. We have used three kernels for SVMs i.e., linear, polynomial and radial basis function (RBF).

6.1.4.1 Linear Kernel

The Linear kernel is the simplest kernel function. It is given by the inner product $\langle x, y \rangle$ plus an optional constant c . Kernel algorithms using a linear kernel are often equivalent to their non-kernel counterparts. Mathematically it may be represented as:

$$KF(s, s_j) = s' \cdot s_j \quad (6.9)$$

6.1.4.2 Radial Basis Function(RBF) or Gaussian Kernel

The Gaussian kernel is an example of radial basis function kernel and is represented as:

$$KF(s, s_j) = e^{\frac{(-|s-s_j|^2)}{2\sigma^2}} \quad (6.10)$$

where σ is the adjustable parameter and plays a major role in the performance of the kernel.

6.1.4.3 Polynomial Kernel

The Polynomial kernel is a non-stationary kernel. Polynomial kernels are well suited for problems where all the training data is normalized. The polynomial kernel may be represented as:

$$KF(s, s_j) = (\alpha s' s_j + c1)^d \quad (6.11)$$

where α is tuning and $c1$ is the constant parameter while d is the degree of the polynomial.

6.1.5 OvO Multiclass Modality

In order to adopt the binary class SVM for the multi-class problem of N categories and using the one-vs-one(OvO) approach, we need to build $\frac{N(N-1)}{2}$ binary SVM classifiers[155]. In the presented research $N=36$, so $C = \frac{36(36-1)}{2}$ binary SVM classifiers are modeled i.e. $C=630$. The classifiers may be termed as C-1 vs C-2, C-1 vs C-3,....., C-35 vs C-36. The final classification of the input feature set, s , through the one-vs-one multi-class classifiers is achieved as:

$$f(s) = \arg \max_p \left(\sum_q f_{p,q}(s) \right) \quad (6.12)$$

where $p, q \in \{C-1, C-2, C-3, \dots, C-36\}$ and $f_{p,q} \in \{C-1 \text{ vs } C-2, C-1 \text{ vs } C-3, \dots, C-35 \text{ vs } C-36\}$. The class with the maximum votes will be represented as an output. While for representing the error correcting output code(ECOC) pattern at a later stage, the output in the ECOC matrix will be one for the cell position (p,q) and minus one at the position (q,p) where p was the output class. This will be done for all the binary classifiers involved in the process.

6.1.6 OvA Multiclass Modality

In order to implement the one-vs-all(OVA) modality for the multiclass problem, N many binary classifiers are used where N represents the number of classes. In the current problem the set, S , is representing a set of alphabet classes i.e., $S=\{C-1, C-2, C-3, \dots, C-36\}$. The set of classifiers may be represented as $SC=\{C-1 \text{ vs } \{\text{All minus } C-1\}, C-2 \text{ vs } \{\text{All minus } C-2\}, C-3 \text{ vs } \{\text{All minus } C-3\}, \dots, C-36 \text{ vs } \{\text{All minus } C-36\}\}$. The distance from the decision boundaries for each of the class, $C_i \in SC$, is computed using $y = u \cdot \Phi(s) + c$.

6.1.7 Error Correcting output Codes

Error-correcting output coding is a recipe for solving multi-way classification problems. It works in two stages: first, independently construct many subordinate classifiers, each responsible for removing some uncertainty about the correct class of the input; second, apply a voting scheme to decide upon the correct class, given the output of each weak learner. ECOC trains L binary classifiers and transforms the results of the multiple classifications into a matrix, which is called ECOC codebook [156]. A decoder is applied to interpret the codebook and to predict the labels of the samples. There are multiple methods to encode or decode a codebook. Codebooks can also be encoded as dense or sparse. For dense codebooks, only +1 and -1 are generated as labels for each sample in each binary classifier. In sparse codebooks, +1, -1 and 0 are allowed, where 0 labels the samples that are not classified. This efficiency is more important in problems with a relatively large number of classes[155].

Once the multiclass classifier is tested using the trained model, an output codeword corresponding to the combination of the classifiers is generated. In order to compute the output class, the

hamming distance between the output codeword and the codeword of each class is computed. The class whose codeword has minimum hamming distance from the output codeword is the class of the test feature set. The hamming distance between the two codewords is computed as:

$$HD = cw_1 \oplus cw_2 \quad (6.13)$$

6.1.7.1 Error Correcting Output Codes for OvA Multiclass Modality

For dense codebooks, only +1 and -1 are generated as labels for each sample in each binary classifier.

	C-1 vs {All minus C-1}	C-1 vs {All minus C-1}	C-1 vs {All minus C-1}	C-1 vs {All minus C-1}	C-1 vs {All minus C-1}
CW C-1	+1	-1	-1	-1	-1
CW C-2	-1	+1	-1	-1	-1
CW C-3	-1	-1	+1	-1	-1
CW C-4	-1	-1	-1	+1	-1
CW C-5	-1	-1	-1	-1	+1

6.1.7.2 Error Correcting Output Codes for OvO Multiclass Modality

Before generation of the whole matrix, it checks the validity of the ECOC Matrix by checking two criteria:

- 1st criterion: each column had to have at least one +1 and one -1 value.
- 2nd criterion: each column and its negative should not be the same as its previous columns.

	C-1 vs C-2	C-1 vs C-3	C-1 vs C-4	C1-C5	C-2 vs C-3	C-2 vs C-4	C-2 vs C-5	C-3 vs C-4	C-3 vs C-5	C-4 vs C-5
CW C-1	+1	+1	+1	+1	0	0	0	0	0	0
CW C-2	-1	0	0	0	+1	+1	+1	0	0	0
CW C-3	0	-1	0	0	-1	0	0	+1	+1	0
CW C-4	0	0	-1	0	0	-1	0	-1	0	+1
CW C-5	0	0	0	-1	0	0	-1	0	-1	-1

6.2 Results & Discussion

In this section, we present the results achieved through the proposed methodology and the discussion over the results will be presented as well.

Figure 6.4 is showing the different variations of the PSL alphabets taken through the different signers or by the same signer but captured on different occasions. It is worth noting that even the same signer would not be able to produce the same sign as produced on another occasion. Same as it is quite obvious that there would be quite variations among the signs generated by the different signers. Some of the example signs are represented, one sign per row, i.e., C-3, C-22, C-14, and C-28. The different variants of the C-3 can be seen in the first row, where

the fist faces the camera and all four fingers are pointed towards the right direction while the thumb is in the closed position. Among all five samples, there is a change in the skew angle of the fingers. The second row shows the variations among sign representation of class C-22. Here, the signs are showing the combination of thumb and index finger forming a semi-circle and pointing to the left. Again there is a visible angular change among the example signs with respect to the direction of the arc. In the same manner, the third row is representing signs for C-14. The signs for C-14 class are shaped by a thumb and combination of all the fingers showing a parabolic shape in the downward direction. Again the rotational changes among all the signs of the samples are quite evident. The last row shows variants of the signs from C-28 and formed by fist facing camera with all the four closed fingers and thumb in an upward direction. This sign belongs to a group of categories where variations are with respect to angle shifts in the upward direction.

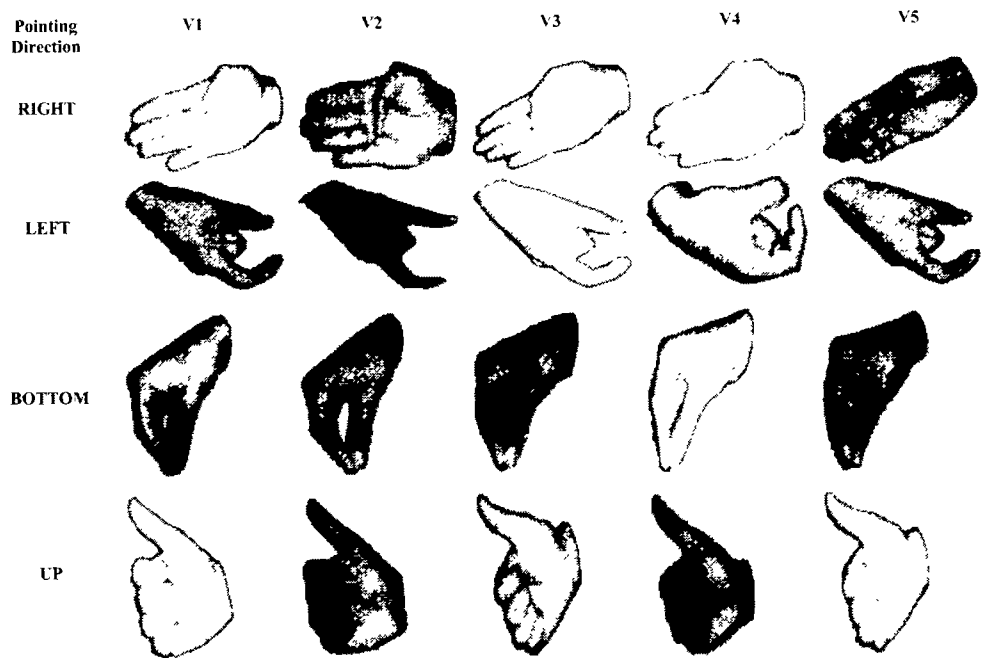


Figure 6.4: Variations in PSL Signs by Signers

From the example signs shown in figure 6.4 there is a strong clue that the rotational variance among the intra-class signs may be visualized within the two quadrants(maximum) of a circle. The circle in its four quadrants may be shown in figure 6.5.

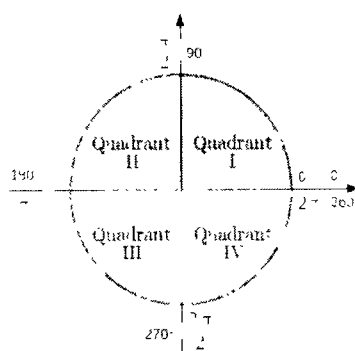


Figure 6.5: Representation of the Circle in four Quadrants

As the design of the local binary pattern (LBP) has already been discussed, the binary pattern with reference to any of the pixels is calculated by computing from eight circular neighbors of the reference pixel. While computing the features of the hand representing the PSL signs, LBP computes texture features of the hand but they are not invariant to the rotation produced by the different signers for the same sign. From the sample signs shown in 6.4, there is a need for a feature extractor that should be invariant to the mild rotation. The neighbors of the reference pixel used for LBP and shown in four quadrants are represented in figure 6.6.

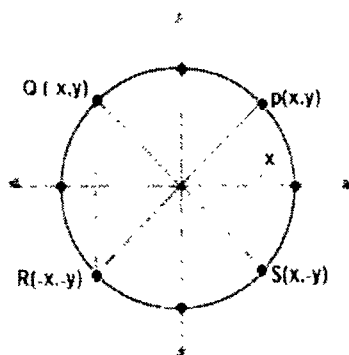


Figure 6.6: Representation of the Circle in four Quadrants

In order to be invariant to the problem of mild rotation i.e., rotation is within a single quadrant or two consecutive (maximum), the proposed semi-symmetric binary patterns serve the job. While in a binary pattern only two consecutive 1's are there, the symmetry is proposed within the same quadrant and for the three 1's, symmetry in consecutive quadrants is retained. In general, the symmetry in the same or neighboring quadrants is tackled through the proposed symmetric MBP.

75	60	65	75	60	65	75	65	65	75	65	65
60	0	71	60	90	71	97	71	71	97	71	71
70	65	75	70	65	75	70	98	75	70	98	75
Pepper Noise at Reference Pixel			Mean value for Binary Pattern			Salt Noise at Reference Pixel			Mean value for Binary Pattern		
1	1	1	1	0	1	0	0	0	0	0	0
1		1	0		1	0		0	1		0
1	1	1	1	1	1	0	0	0	0	1	0
LBP			MBP			LBP			MBP		
(a)			(b)			(c)			(d)		

Figure 6.7: Comparative response of MBP and LBP over Noisy Data

The standard local binary pattern is not resistant to the noise present in the image, leading towards incorrect patterns. In figure 6.7 two of the example patches of an image are presented that are separately affected by the salt and pepper noises. Figure 6.7(a) is an example where pixel under interest is corrupted by the pepper noise along with the response in the form of local binary pattern. All the bit positions contain 0's resulting in the pattern as 11111111, resulting the decimal as 255. The proposed technique computes the mean of all the pixels in the window and replaces the pixel under the interest with the calculated mean and this is shown in 6.7(b). Along with the mean value replacement, the calculated binary pattern is shown as well i.e., 01011111. The resultant binary pattern when converted to the decimal number is 250. The idea behind calculating the mean values lies in the concept that none of the pixels can be isolated in their nature rather they should be the same or like their neighboring ones. Figure 6.7(c) is showing the image patch where the pixel under the interest is corrupted by the salt noise along with the calculated local binary pattern i.e., 00000000, resulting in 0 value in decimal. The resulting binary pattern is wrong due to the impact of the salt noise and this is dealt with through the mean filter by replacing the pixel under interest by 96.7, the mean value. The resultant mean binary pattern is 10000010 giving a decimal value of 65. So the MBP is robust against the presence of noise in an image.



Figure 6.8: Example PSL Alphabet for extracting Binary Pattern Histogram Features

Once the binary pattern for the pixel under the interest is calculated, its decimal value corresponds to some bin of the histogram. The histogram of the standard LBP has 256 bins resulting feature vector of dimension 1×256 . As an eight length binary pattern can produce 256 patterns means there is a correspondence of one to one between the number of bins and the

generated binary patterns. Figure 6.8 is taken as an example sign image whose feature features are calculated and showed in proceeding graphs.

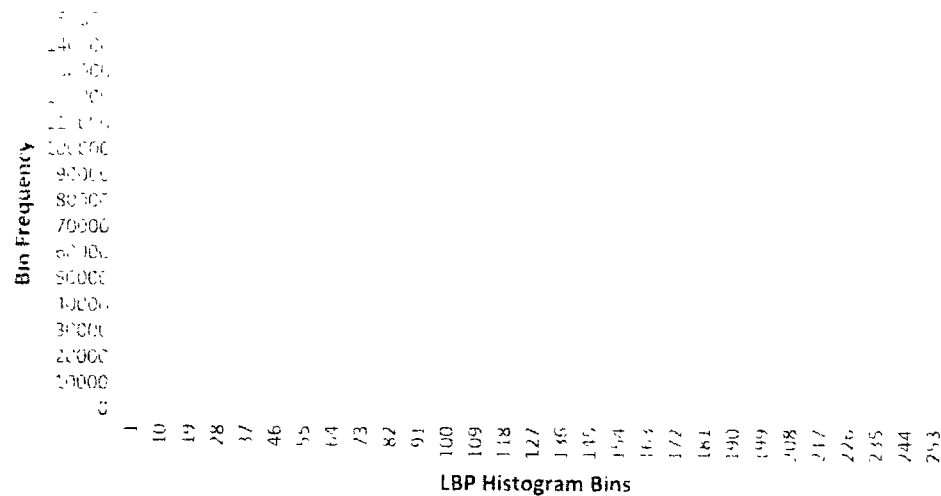


Figure 6.9: LBP Histogram of Example PSL Alphabet

Figure 6.9 is the graphical representation of the LBP histogram calculated for the reference image shown in figure 6.8. Clearly it has 256 bins reflecting the binary pattern values 0-255. LBP histogram retains all the combinations of 8-bit binary patterns which not only

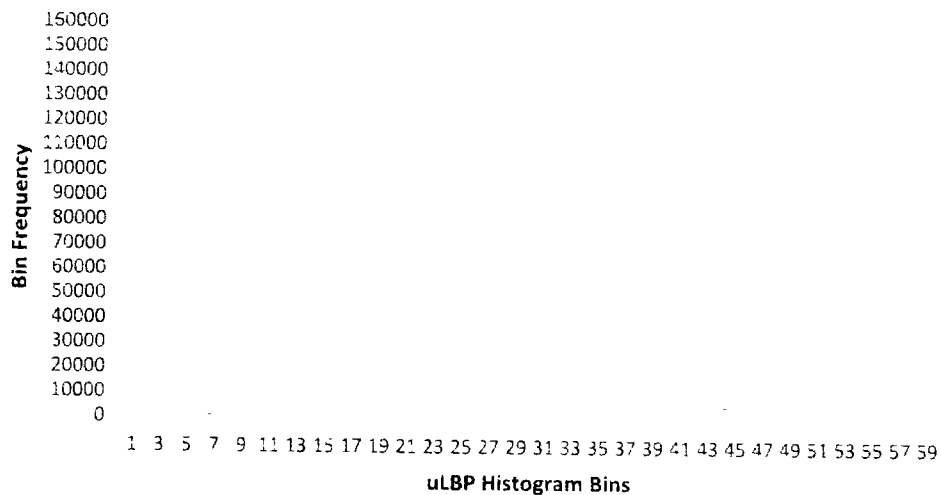


Figure 6.10: Uniform LBP Histogram of Example PSL Alphabet

has a high dimensional feature vector but the redundant features are part of it. It not only increases the computational complexity but the when used for the classification purpose results in compromise of it. In order to counter the effects of the LBP histogram, uniform local binary patterns are used as shown in figure 6.2. Uniform LBP only retains those patterns which have

at the most one transition from 0 to 1 and vice versa and keeps all the other patterns into one bin. The redundant patterns are suppressed while giving high weight to the patterns fulfilling the criteria. The uLBP histogram has 59 bins resulting feature vector of dimension 1×59 . The uLBP histogram for the example image (figure 6.8) is shown in figure 6.11. As already

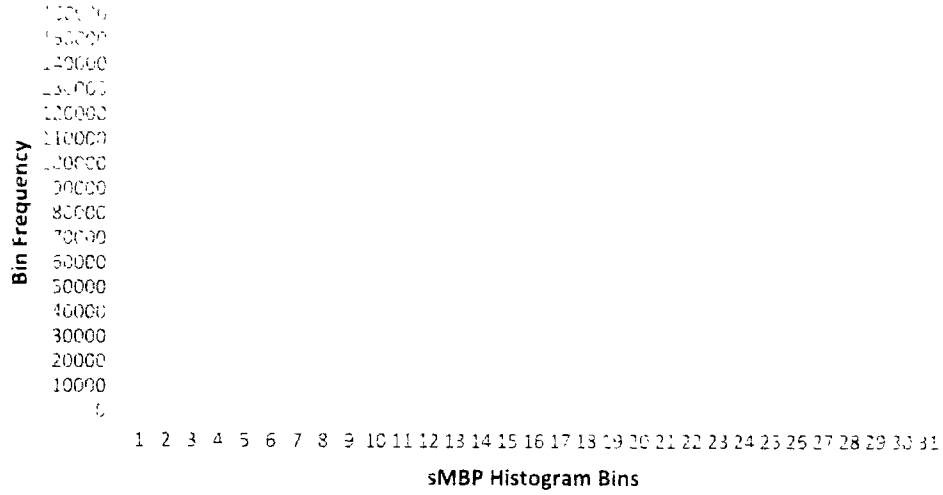


fig6-

11.png

Figure 6.11: Symmetric MBP Histogram of Example PSL Alphabet

discussed, there is rotation in the signs generated by the different signers for the same alphabet. Neither LBP nor uLBP takes care of the patterns computed over the rotated signs. The angular displacement is of such kind that it is visible in a single or two neighboring quadrants. The proposed semi symmetric MBP serves the job by computing a histogram of 31 bins giving a feature vector of dimension 1×31 . The symmetric patterns are assigned the same bin resulting rotation invariance feature vector. The visualization of Semi sMBP is shown in figure 6.11 which is computed over sign represented in figure 6.8. Error correcting output code based support vector machines are used for PSL classification. These codes can correct the errors of classification upto $\frac{N}{2}$, where N is the length of the codeword. Suppose the output codeword from the classifier was OPCW=1110 for the image belonging to Class C1. The actual codeword for the three classes C1, C2 and C3 were 1100, 0101 and 0011 respectively. Although the output codeword doesn't match with the codeword of any of the three classes while computing the Hamming distance we get:

$$HD(OPCW, CWC1) = 1110 \oplus 1100 = 1 \quad (6.14)$$

$$HD(OPCW, CWC1) = 1110 \oplus 0101 = 3 \quad (6.15)$$

$$HD(OPCW, CWC1) = 1110 \oplus 0011 = 3 \quad (6.16)$$

So the nearest distant codeword from the output codeword belongs to the C1, so the sign is

1

1

assigned to the correct class. Although there was an error while computing the actual class but the nature of ECOC enabled to counter that error and produce correct output. Codeword detail for OvA multiclass modality and for all the 6 classes is represented in figure 6.12. We were not able to provide the codeword detail for OvO approach as the dimension of the table was 36×630 , which can't be printed on the page.

6.2.1 Comparative Results for the Proposed Technique

In this subsection comparative results achieved through the proposed technique by using OvO and OvA multiclass modality through Gaussian, linear and polynomial kernel are presented. The results are based on the two evaluation metrics i.e., precision and recall. The comparative results for the known and unknown signers are represented separately.

6.2.1.1 Comparative Results for Known Signers

Graphical representation of kernel based comparative results of classification recall for the known signers is shown in figure 6.13(a). The presented results are achieved through proposed semi sMBP using ECOC based SVMs using Gaussian, linear and polynomial kernels. All three kernels are tested with both of the multiclass modalities i.e., OvO and OvA. It may be observed that for the classes C-7, C-11 and C-20 linear kernel based OvO modality over sMBP achieved the highest precision among all the six approaches by securing a score of 90.48%, 90.70% and 55.56% respectively. RBF kernel with OvO modality obtained the highest precision for the four of the classes i.e., C-11, C-13, C-21 and C-22 with the scores 95%, 88%, 100% and 97.83% respectively. The same setting with the polynomial kernel had leading scores among all the other experiments for the classes C-1, C-2, C-4, C-6, C-12, C-20, C-21, C-23, C-24, C-25, C-27, C-28, C-31, C-32 and C-33 with 93.02%, 88.89%, 97.96%, 93.18%, 100%, 97.73%, 100%, 97.56%, 97.62%, 95.83%, 93.33%, 94.00, 88.37, 91.30 and 86.54 respectively. Using linear kernel for the OvA modality over the proposed technique couldn't perform that well and achieved the highest precision score for only C-16 by securing 68.42% value. With the same multiclass modality i.e., OvA, and Gaussian kernel proposed technique remained highest in terms of precision for the following classes i.e., C-8(95.74), C-9(91.11), C-14(93.48%), C-15(89.13%), C-17(98.04%), C-19(95.12%), C-29(97.87%), C-34(91.30%) and C-35(86.96%). For the classes, C-3, C-5, C-18, C-26 and C-36 the proposed sMBP with the OvA multiclass modality using polynomial kernel achieved the highest precision values with the scores 93.48%, 93.55%, 95.35%, 91.67%, and 88% respectively. In terms of precision, among all the six experiments with the discussed settings, linear kernel based proposed sMBP with OvA modality showed the lowest of the scores i.e., for 29 classes.

Same as above but the comparative visualization on the basis of recall is presented in figure 6.13(b). The proposed technique with the linear kernel through OvO remained quite moderate while comparing with other kernels and multiclass modality. It achieved highest recall score for



Figure 6.13: Kernel Based Comparative Analysis of Classification Metrics for Known Signers

the classes C-16, C-22 and C-30 by attaining score of 91.30%, 92% and 32.61% but performed lowest for C-10, C-12, C-13, C-24, C-31 and C-36 by securing 58.70%, 91.84%, 67.39%, 90.91%, 71.11%, and 78.43% recall values respectively. While for the rest of the classes its performance was satisfactory. The results for the same evaluation metric but obtained through the proposed technique using Gaussian kernel with OvO multiclass modality were best among other fellows for the C-4, C-5, C-10, C-11, C-13 and C-21 with recall scores 97.96%, 93.88%, 82.61%, 98%, 95.65% and 96.08% respectively. The discussed experimental setup couldn't perform better for C-9, C-12, C-16 and C-24 and could only achieve 77.55%, 91.84%, 82.61%, and 90.91% respectively. The same multiclass modality for the proposed technique but using polynomial kernel obtained good recall scores by leading for the classes C-3, C-4, C-6, C-8, C-9, C-15, C-22, C-23, C-24, C-28, C-29, C-31 and C-32 with values 94.34%, 97.96%, 91.11%, 97.87%, 93.88%, 95.56%, 92%, 90.91%, 93.18%, 100%, 97.92%, 84.44% and 91.30% respectively. The setup didn't receive the lowest score for any of the thirty six classes.

While discussing the proposed technique using OvA multiclass modality, the linear kernel couldn't perform better and remained behind all the fellow settings for the twenty five classes i.e., C-2, C-3, C-4, C-6, C-7, C-8, C-11, C-14, C-15, C-17 through C-21, C-23, C-25 to C-30 and C-32 through C-35 with the recall scores of 65.96%, 73.58%, 93.88%, 73.33%, 71.43%, 78.72%, 42%, 78%, 68.89%, 88%, 4.55%, 75%, 55.32%, 82.35%, 77.27%, 76.47%, 68.75%, 63.83%, 93.62%, 87.50%, 15.22%, 65.22%, 70.83%, 41.30% and 45.45% respectively. It showed best of the result for 24 where it achieved 93.18, the highest shared score with the experimental settings of Proposed sMBP(polynomial kernel) using OvO & OvA modalities. The performance of the proposed technique over the Gaussian kernel are quite moderate, highest among all the fellows for the classes C-1, C-12, C-17, C-18, C-20, C-21, C-26, C-27, C-34 and C-35 with recall values of 90%, 97.96%, 100%, 97.73%, 97.87%, 96.08%, 89.58%, 95.74%, 91.30% and 90.91% respectively. The scores 90.91 and 78.43 for the classes C-24 and C-36 are lowest ones for the said classes among all the six experiments. At last, the proposed sMBP using polynomial based SVMs with OvA modality achieved highest recall among its fellows for the classess C-2, C-4, C-7, C-12, C-14, C-17, C-19, C-24, C-25, C-29, C-30, C-33, C-34 and C-36 with 80.85%, 97.96%, 91.84%, 97.96%, 92%, 100%, 97.73%, 93.18%, 94.12%, 97.92%, 32.61%, 95.83%, 91.30%, 86.27% values respectively, while it remain at bottom for classes C-1, C-5, C-22 and C-26 with the scores of 62%, 59.18%, 66% and 68.75%.

6.2.2 Comparative Results for Unknown Signers

Same as the previous subsection, here the comparative results achieved from the proposed sMBP with variations in kernel settings and multiclass modalities are presented graphically but for the unknown signers. Here, again to of the evaluation metrics are taken into the consideration i.e., precision and recall.

Figure 6.14(b) is showing comparative precisions of the proposed sMBP for all the three

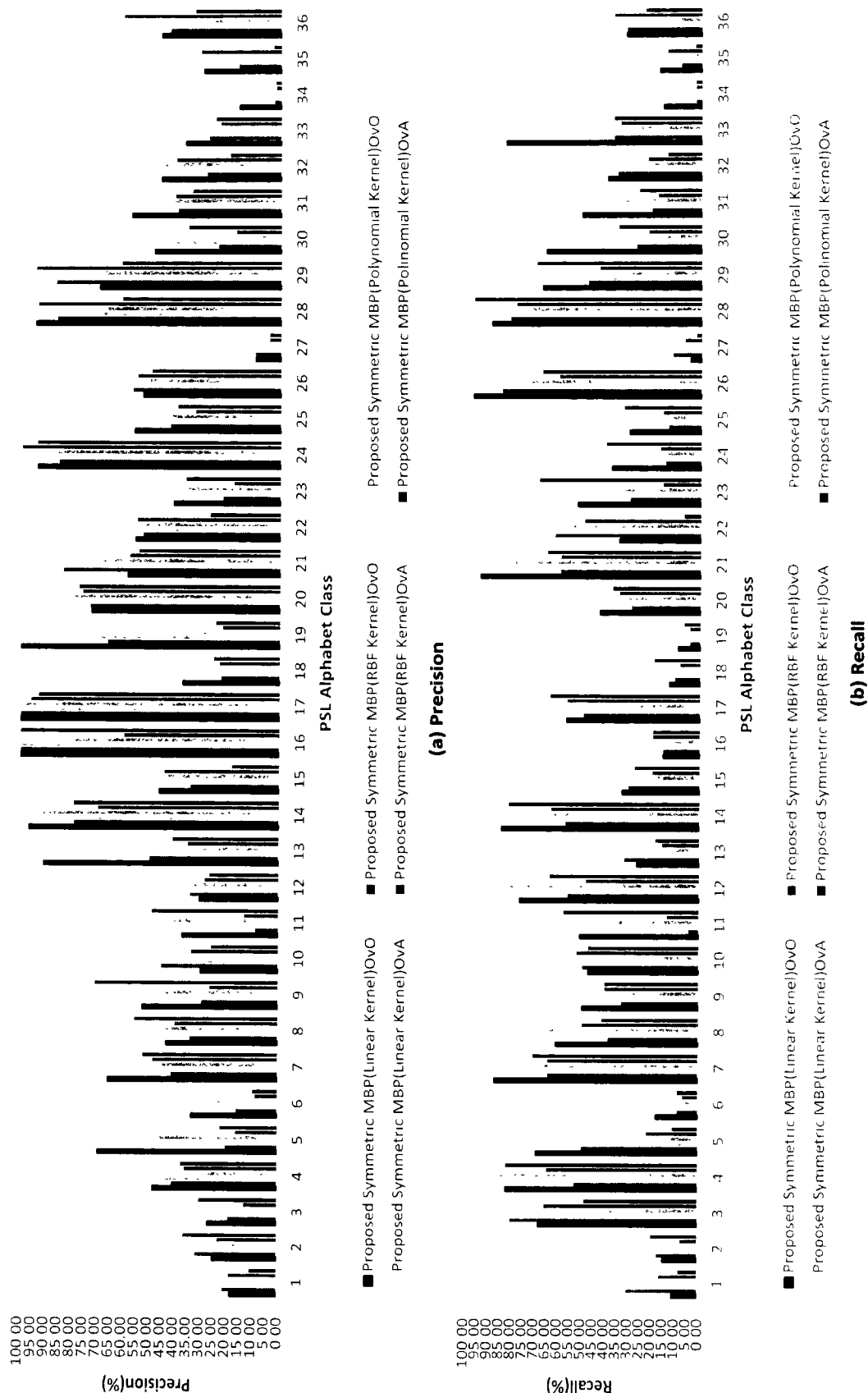


Figure 6.14: Kernel Based Comparative Analysis of Classification Metrics for UnKnown Signers

described kernels and all the two multiclass modalities but testing over the dataset from the unknown signers. The results from the use of OvO modality and linear kernel, best of the results among all the six experiments are achieved. It achieved the highest precision for the twelve of the classes (in comparison to all others), while remained lowest for one class only and comparative results for the remaining ones. The best of the results were for the classes i.e., C-5, C-7, C-13, C-14, C-16 through C-19, C-25, C-28, C-30 and C-34 with the values 69.44%, 65.63%, 90.91%, 96.55%, 100%, 100%, 37.50%, 100%, 56.52%, 94.59%, 49.06% and 16.22% respectively and the lowest score was for the class C-24 (85.71% Precision). The weakest of the setup was proved to be sMBP using multiclass SVMs with the OvA modality along with RBF kernel. The results showed that the mentioned technique got lowest of the results among all the fellows for the twelve classes i.e., C-3, C-5, C-6, C-9, C-14, C-16, C-19, C-23, C-25, C-30, C-33 and C-34 with the precision values 12.98%, 16.33%, 8.82%, 26.56%, 70%, 60%, 22.22%, 18.18%, 33.33%, 17.65%, 23.64% and 2.27% respectively while it could show better (highest) results for the classes C-24, C-29 and C-36 having precision values 100%, 94.74%, and 60.87%. The performance of the rest of the techniques are as follows: RBF kernel with OvO got highest for four classes each, polynomial with OvO achieved best results for nine classes but poor for the three classes, linear kernel with OvA modality had the highest precision for the eleven classes but least for the six classes and at last polynomial kernel with OvA modality remained second from the bottom as it could perform better for the three classes but was worst of the all for the eleven classes. Same as figure 6.14(a), figure 6.14(b) shows the comparative results through unknown signers but for the evaluation metric recall. Among all the six techniques, sMBP with the linear kernel and OvO multiclass settings performed better than all the other fellows by showing the highest recall for the eleven classes while remained at the bottom for only two classes. The classes where its performance was high are C-6, C-9, C-14, C-21, C-26 and C-30 through C-35 with scores 18.18%, 50%, 84.85%, 94.29%, 97.56%, 66.67%, 51.35%, 40.43%, 83.78%, 16.67% and 18.18% respectively while the classes with poor performance were C-10 (47.50%) and C-16 (15.91%). The proposed sMBP with the Gaussian kernel and OvA modality couldn't perform better and was at the bottom with respect to its other fellows. The recall for the twelve of the classes was at the bottom while for only two classes the results were at the top. The classes whose recall was poor are C-2, C-6, C-7, C-12, C-15, C-19, C-21, C-23, C-26, C-31, C-33 and C-34 with the corresponding scores as 7.50%, 6.82%, 64.58%, 48.72%, 20.51%, 4.88%, 60%, 16.67%, 60.98%, 18.92%, 35.14% and 2.78%. The better results were for the C-10 and C-36 with values 52.50 and 37.84 respectively. While for the other techniques the statistics are as follows: Gaussian kernel using OvO modality had better results for four classes but poor results for the twelve classes, six classes showed highest values for the six classes while least score for the three classes using OvO modality and polynomial kernel, OvA multiclass scheme with the linear kernel got highest results for the twelve classes but at the same time it was with poor recall performance for the eleven classes and when the proposed techniques were tested on the signs generated by the unknown signers

with OvA based polynomial kernel it could perform better for the six classes while couldn't perform for the seven classes. All the other classes where neither a technique had highest nor the lowest scores, they performed average.

6.2.3 Classification Matrices for the Proposed Techniques

In this subsection, we have presented the classification matrices representing the outcome of the proposed technique using linear, Gaussian, polynomial kernel for multiclass SVMs with OvO and OvA modalities. Two set of classification matrices are there i.e.,

- (i) Test results obtained by applying the proposed techniques over the signs taken through known signers.
- (ii) Results achieved of the proposed techniques when applied over the dataset of the unknown signers.

These classification matrices are self explanatory by presenting precision, recall, omission and commission errors for the individual classes along with the overall accuracy of the proposed techniques. The overall accuracy for the proposed sMBP used for classification through the linear kernel based multiclass SVMs using the OvO model achieved an overall accuracy of 79.78%(figure A.1) for the known signers while it was 43.56%(figure A.7) for the unknown ones. The proposed technique with the same SVM modality but with the Gaussian kernel was 86.62%(figure A.2) accurate over the test feature set of the known signers, it was 32.91%(figure A.8) accuracy for the unknown signers. While the accuracy over the known signers for the polynomial kernel was 87.78%(figure A.3) and 44.77%(figure A.9) for the unknown signers.

While performing the experiments using feature set calculated through proposed sMBP and classifying by multiclass SVMs with OvA modality following results were achieved:

- (a) Linear kernel produced an overall accuracy of 70.94%(figure A.3) for the known signer's data set while it was 43.57%(figure A.10) classification accuracy for the dataset of the unknown signers.
- (b) RBF kernel based produced technique using OvA modality achieved an overall accuracy of 87.61%(figure A.4) for the signs generated by the known signers while 32.91%(figure A.11) accuracy was obtained over the dataset generated by the unknown signers.
- (c) Polynomial kernel based proposed technique achieved accuracies of 84.61%(figure A.5) and 38.28%(figure A.12) for the signs taken through known and unknown signers respectively.

Summary

Symmetric mean binary pattern-based Pakistan sign language recognition is presented here. Noise is suppressed by introducing the mean value of the local image patch of size 3×3 and

replacing the pixel under interest with it. Rotation invariance is achieved through proposing symmetric mean binary patterns that exploit symmetric properties of circular points in adjacent quadrants. The task of classification is accomplished by error correcting output codes based support vector machines using three kernels i.e., linear, polynomial and radial basis function. The proposed technique achieved the best overall accuracy value 87.61% for the dataset of known signers while the same response for the dataset of unknown signers was 48.1% accurate.

Chapter 7

Scale Invariant Semi-Symmetric Mean Binary Pattern based PSL Recognition using Ensemble of ECOC-SVM Kernels

Introduction

In chapter 6, we have presented symmetric mean binary pattern which was insensitive to the noise and rotation of the hand in sign image but not equipped with the scale invariance. Secondly, we used three kernels for the ECOC based multiclass SVMs leaving overall six results but realistically three for each of the modality i.e., OvO and OvA. The results were not able to conclude the authority of the proposed technique for any of the specific kernels i.e., for the signs from known signer polynomial kernel received the highest accuracy while for the unknown ones linear kernel was better. So there is a need for a solution that must combine and utilize the strengths of all the three kernel functions resulting in higher precision, accuracy and recall.

7.1 Proposed Approach

In order to resolve the limitations of the proposed sMBP, we have presented scale invariant sMBP using ensemble of kernels from ECOC based support vector machines(SI-sMBP). The proposed SI-sMBP is not only invariant to the size of the sign images but the ensemble takes advantage of all three kernels. The proposed approach is graphically presented in figure 7.1 that clearly describes process flow i.e., (i)the input is the hand imaged detected and localized by

YOLO-CNN followed by morphological operations. (ii) Scale invariants sMBP are extracted by sampling the hand image into a 4 level pyramid through Gaussian operations. (iii) ECOC multiclass SVMs are trained, tested over three kernels and returning class prediction and class posterior probability as output. (iv) The output posterior probabilities are used to ensemble the output of all the three kernels and producing single output(class prediction).

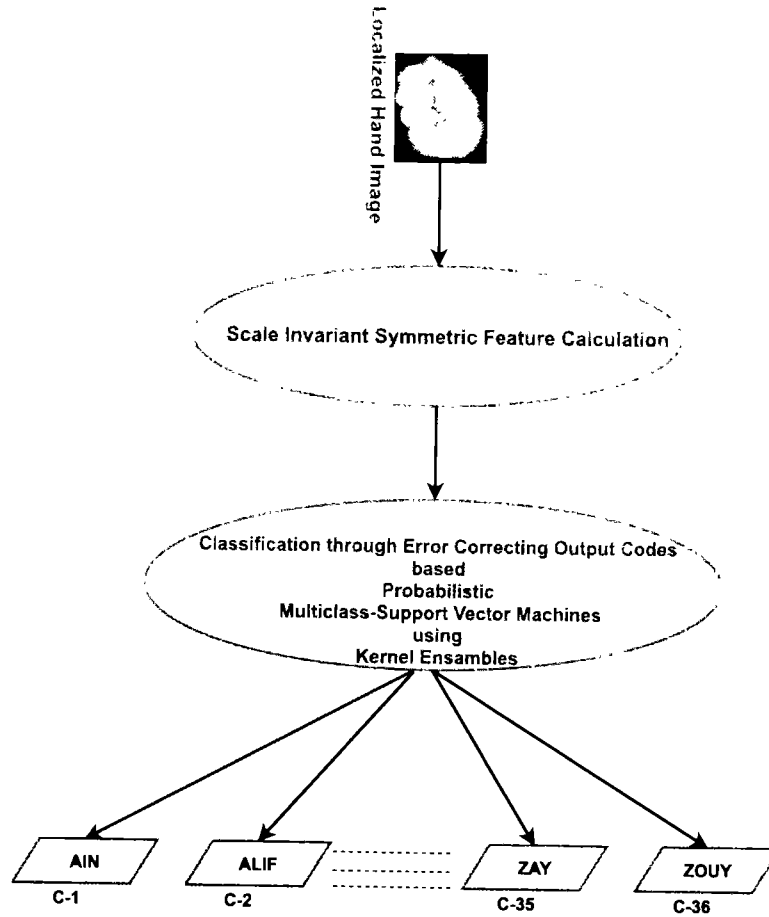


Figure 7.1: Work Flow of the Proposed Approach

7.1.1 Feature Extraction

In order to extract the features from the hand sign image, following steps are performed as explained in figure 7.2:

7.1.1.1 Gaussian Image Pyramid

Image pyramids, the hierarchical representation of the image at different levels and each level represents half-sized image from the previous one. The extraction of features from an image at different scales makes them scale invariant[157]. Gaussian image pyramid is the hierarchical representation where an image is put to blurring at each level through Gaussian filter and

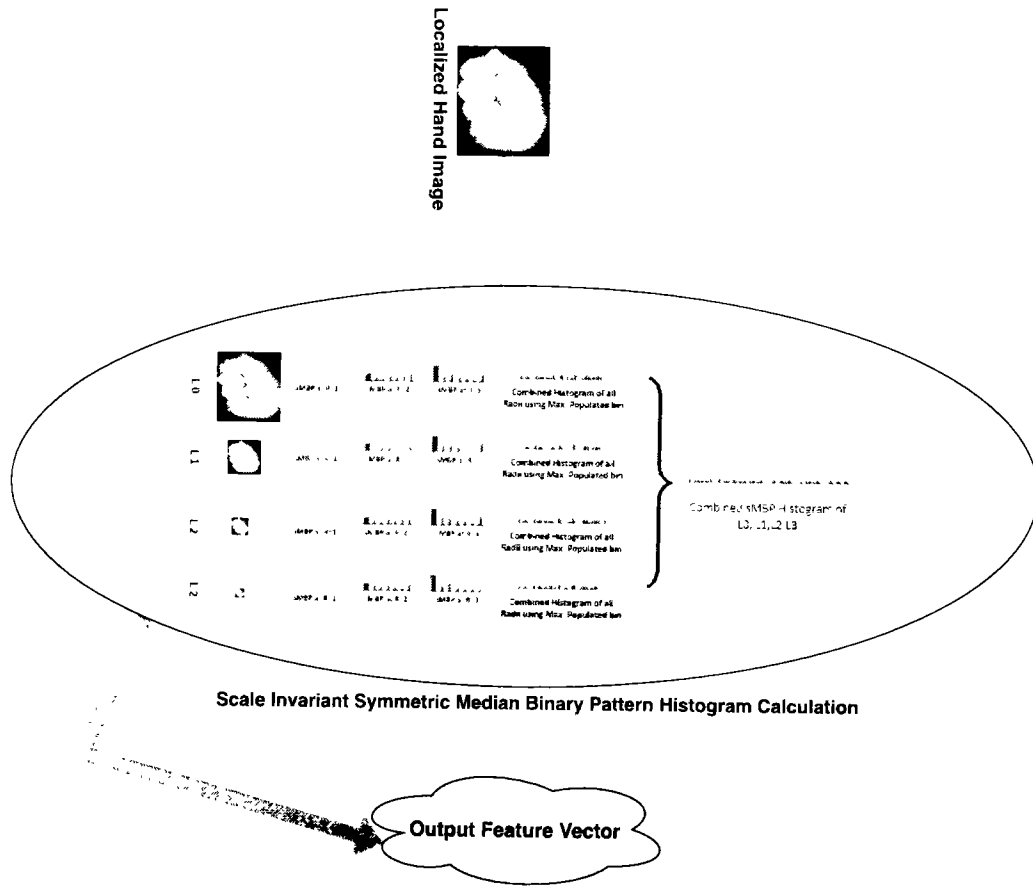


Figure 7.2: Feature Set

afterward sub-sampling is applied to get the next level image.

$$I_B = G_\sigma \cdot I \quad (7.1)$$

Where G is the Gaussian filter and is represented as:

$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (7.2)$$

The absence of blurring prior to the sampling step may create an aliasing effect in the sampled image.

7.1.1.2 Proposed Scale Invariant Symmetric MBP

The configuration of the symmetric MBP has already been explained in the last chapter and here we will adopt the same in the context of scale invariance. Images generated at four different scales in the Gaussian pyramid would be exploited to create a baseline for the scale invariance plus the symmetric MBP would be calculated at three different radii. As explained previously

that the first step to compute sMBP is the calculation of uniform binary patterns i.e.,

$$MBP_{NP,R}^{ru2} = \begin{cases} \sum_{n=1}^{NP} d(g_n - M_c), & \text{if } U(MBP_{NP,R}) \leq 2 \\ NP + 1, & \text{if } U(MBP_{NP,R}) > 2 \end{cases} \quad (7.3)$$

here NP is kept as 8, the values of R=1,2,3. Subsequently, sMBP based patterns are extracted that gives an output feature vector, $FV_{R_i}^{L_k}$ of dimension 1×31 . The operations are performed at each level of the image available in the pyramid i.e., $\{I_0, I_1, I_2, I_3\}$, that results three output feature vectors at each level e.g., at L=0 the output feature vectors would be $FV_{R_1}^{L_0}$, $FV_{R_1}^{L_1}$ and $FV_{R_3}^{L_0}$. All the three radii and their corresponding eight points are shown in figure 7.3. The

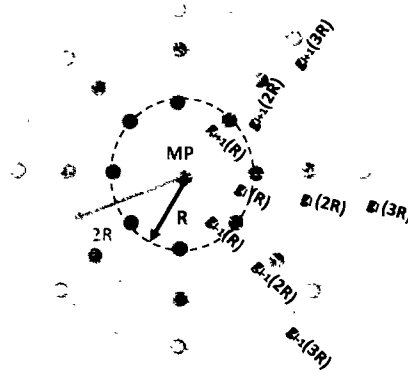


Figure 7.3: MultiScale MBP

neighboring pixels are determined through neighbor pixels determination algorithm(NPDA) as defined in chapter 5. Once the feature vector, $FV_{R_i}^{L_k}$, at each level is computed and is subject to the determination of the dominant feature at each level. The importance of a bin at a level, k, was determined by its population [157]. The major limitation in finding the salient binary pattern feature bin through [157] lies in the half size of an image in the subsequent level of the pyramid. This would always favor the bin computed at lower resolution image while suppressing the impact of bins computed at higher resolution images(probable of having more noisy points). The proposed technique introduces a new factor, the impact of a bin, at a certain level. The impact of a bin is calculated as:

$$Impact_{(B_m)} = \frac{freq(B_m)}{M \times N} \quad (7.4)$$

where $freq(B_m)$ is the population of m^{th} bin, M and N represent width and height of the image respectively. In context of uMBP the $1 \leq m \leq 31$. Once the impact of each bin at an image of each level(0-3) is computed, the competency process for the selection of a particular bin from the four levels is accomplished. A bin, m, is selected from the four sets(corresponding to L0 to L3 images) each having 31 bins i.e.,

$$BestImpact_m = \max\{Impact_{(B_m)}^{L_k} : 0 \leq k \leq 3\} \quad (7.5)$$

The feature vector, FV_{R_i} , at each of the radius, $R_i : 1 \leq i \leq 3$, is computed as:

$$FV_{R_i} = \bigcup \{Bin(BestImpact_m) : 1 \leq m \leq 31\} \quad (7.6)$$

The final feature vector, FV, would be the concatenation of the feature vectors computed at all the three radii i.e.,

$$FV = FV_{R_1} \cup FV_{R_2} \cup FV_{R_3} \quad (7.7)$$

This results the final feature vector of dimension 1×93 .

7.1.2 Ensemble of Kernels using Multi-Class ECOC SVMs

The distance from the decision boundaries for each of the class, $C_i \in SC$, is computed using $y = u \cdot \Phi(s) + c$. The probability estimates are computed from the computed decision boundaries using the sigmoid function [158, 159] i.e.,

$$P(C_i|FV) = \frac{1}{(1 + e^{(-y_i)})} \quad (7.8)$$

where $P(C_i)$ represents the probability of i^{th} class using decision boundaries from the classifier. The process of ensembling the outcomes of all the three kernels is presented through ensemble of kernels algorithm(EoKA).

The EoKA works by taking input class probabilities through ECOC-SVM classifier using the three kernels i.e., L_{cpu} , R_{cpu} and P_{cpu} representing linear RBF and polynomial kernels respectively. At first, it finds the indexes corresponding to the maximum class probabilities giving class numbers i.e., I_{pHv} for each of the three kernels. Afterward, each class frequency through using predicted class output from all the three kernels. The EoKA returns the class number as output if it is predicted unanimously through all the kernels or having at least two frequency values. If there exists a tie i.e., all the three classifiers produced a unique output class, the corresponding output probabilities through all the three classifiers and for all the thirty six classes are added to form a single vector with the sum of probabilities for all the classes i.e., SV. The index of the maximum value in SV, 1×36 , corresponds to the predicted class. However, if there were again some tie, EoKA moves to the initial input and for each class finds maximum probability outcome among all the three input vectors. It again produces a vector with dimension 1×36 i.e., m. The index corresponding maximum value in m is the predicted class.

Algorithm 4 : Ensemble of Kernels Algorithm(EoKA)**INPUT:** Linear Kernel Class Probability Vector(L_{cpv}), RBF Kernel Class Probability Vector(R_{cpv}), Polynomial Kernel Class Probability Vector(P_{cpv})**OUTPUT:** Predicted output Class (C)

- 1: Find maximum probability and its index in each class probability vector i.e.,
 $(p_{Hv}, I_{pHv}) = \max(P(v)) : v \in \{L_{cpv}, R_{cpv}, P_{cpv}\}$
 - 2: Find frequency, f_i of each number reflected in I_{pHv} , $i \in \{I_{pHL_{cpv}}, I_{pHR_{cpv}}, I_{pHP_{cpv}}\}$
 - 3: Find maximum frequency i.e., $m = \max(f_i)$.
 - 4: Find numbers $\{n_p : \text{freq}(n_p) == m\}$.
 - 5: **if** n_p is unique **then**
 - 6: $C = n_p$.
 - 7: **else**
 - 8: Calculate Sum vector(SV) i.e., $SV = L_{cpv} + R_{cpv} + P_{cpv}$
 - 9: Find maximum score from sum vector i.e., $m_{SV} = \max(SV)$
 - 10: Find vector of Indexes having m_{SV} i.e., $[I] = \text{find}(SV, m_{SV})$
 - 11: **if** I has only one value **then**
 - 12: $C = I$
 - 13: **else**
 - 14: Find class probabilities corresponding to each index in vector I from
 L_{cpv}, R_{cpv} and P_{cpv} .
 - 15: Construct a vector of probabilities for each of the index extract in last step
i.e., $V_{index} = \{p_{index}(L_{cpv}), p_{index}(R_{cpv}), p_{index}(P_{cpv})\} : index \in I$
 - 16: find maximum of each vector i.e., $m_{index} = \max(V_{index})$
 - 17: find maximum amongst maximum of vectors i.e., $r = \max(m_r) : \forall r \in I$
 - 18: $C = R$
 - 19: **end if**
 - 20: **end if**
-

7.2 Results & Discussion

Initially, the input image is rescaled to 256×256 and termed as an image at level 0. The resized image is subject to the Gaussian blur followed by sampling of scale, s , equals 2. The process continues till we have reached level L3. At each of the steps, the Gaussian with $\sigma=1$ and window of size 5×5 is used. The output of the whole process is represented in figure 7.4 i.e., Gaussian Image pyramid. The sMBP is applied on each level of the image in the pyramid using radius 1 to 3. For each of the radius, $\{R_i : 1 \leq i \leq 3\}$, four feature vectors were calculated with dimension 1×31 each. All the four feature vectors at each of the radius are combined to form a single vector of the same dimension as its originators. The process of structuring a single feature vector from the four individuals is accomplished through the mechanism of best survival. This process takes the impact of each bin, B_m , from the four levels

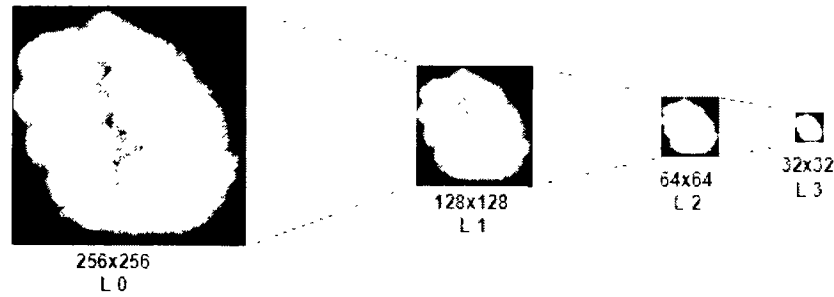


Figure 7.4: Gaussian Image Pyramid

i.e., $B_m^k : 0 \leq k \leq 3$. Suppose for the 10^{th} bin computed at radius 1 and level $L=0$ the impact is 0.08 while 0.1 for $L=1$, 0.11 for $L=2$ and 0.099 impact computed from histogram of sMBP at level $L=3$. It may be observed that the impact of the said bin is highest when computed at $L=2$, so the ultimate choice at 10^{th} bin of FV_{R_1} would be the frequency from the level two image. If a specific bin from two or more of the histograms has the same impact, then the one computed at higher resolution would be retained as it is near to original image size.

Figure 7.5 through figure 7.7 are showing the example histograms computed through SI-LBP, SI-uLBP and SI-sMBP respectively. The histogram computed through SI-LBP has a dimension of 1×768 which is a huge one. There, LBP histograms at three different radii were calculated, each having the dimension 1×256 , and afterward, all the three histograms were concatenated to form a single histogram.

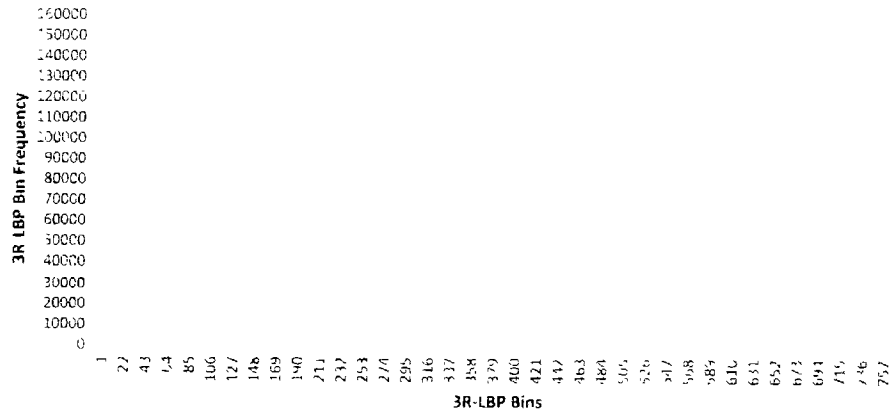


Figure 7.5: Scale Invariant LBP Histogram

Figure 7.6 is the graphical representation calculated from scale invariant uniform local binary pattern (SI-LBP) methodology. As already explained in the previous chapter, uLBP suppresses redundant features while retains salient ones. The dimension of the feature vector computed at a single radius is 1×59 and when computed at all the three radii and then merged to form a single histogram has the final dimension as 1×177 .

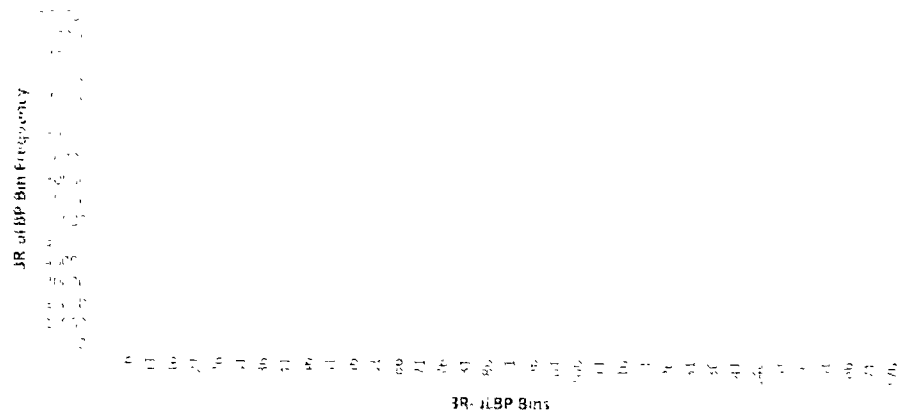


Figure 7.6: Scale Invariant Uniform LBP Histogram

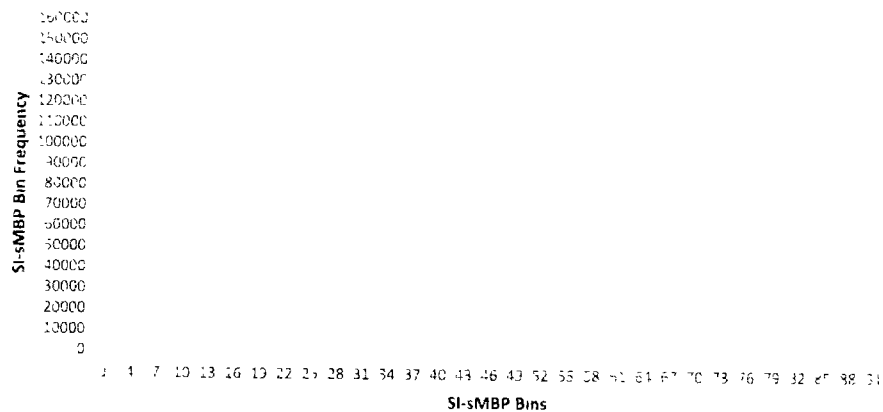


Figure 7.7: Scale Invariant Symmetric MBP Histogram

At last, figure 7.7 is showing the histogram of the proposed methodology that is not only invariant to the rotation but scale as well. It may be observed that the dimension of the feature histogram is 1×93 . This reflects that accommodating saliency along with the reduction in dimension of the feature space is the prospect of the proposed methodology. The extracted feature set, FV , is provided to all the three trained SVM models using linear, polynomial and RBF kernels. Once the models predict the output class, they provide class membership probability as well. Suppose there were three classes encoded by 1, 2 and 3. The trained classification models produced the output for feature vector, FV_c , are 1, 1 and 2 for linear, polynomial and RBF kernel respectively. The ensemble mechanism counts the frequency of the output classes i.e., Class 1 has two votes while class 2 has 1 vote and class 3 has 0 votes. From the voting results, the ensemble would predict the true class as 1. If there is any tie in voting like the scenario of the output is 1,2 and 3 then all of the classes have one vote each and a decision can't be taken. As all the three trained models output the probability vectors

as well i.e., 1×3 for the current example. Let the output probability vectors for the scenario where voting resulted in a tie are $[0.45, 0.3, 0.2]$, $[0.23, 0.61, 0.16]$ and $[0.19, 0.29, 0.52]$ for the linear, polynomial and RBF kernel based classifiers respectively. In this scenario, the proposed technique sums all the three probability vectors resulting $[0.87, 1.20, 0.88]$. Now the highest of the value in resulting vector is 1.20 that is corresponding to class 2, so the predicted class would be 2. If still there occurs a tie then the class corresponding to the highest probability in all of the three vectors would be the predicted class.

7.2.1 Comparative Results

In this subsection, we are going to present the comparative results achieved through the proposed technique while using linear, polynomial and RBF kernels through OvO and OvA modality. The techniques are validated over the dataset generated through known and unknown signers. The presented comparison is based on two evaluation metrics i.e., precision and recall.

7.2.2 Comparative Results using Dataset of Known Signers

Figure 7.8(a) is a graphical representation of the comparative precision based results when the proposed technique with different configurations is validated over the dataset of the known signers. It may be observed that SI-sMBP using linear kernel based multiclass SVM through OvO modality received the highest of the results for the classes C-16, C-17, C-19 and C-22 with precision scores 100%, 100%, 100% and 97.87% respectively. The proposed technique with OvO modality using RBF kernel achieved better results for C-2(93.75%), C-7(100%), C-11(95.83%), C-12(100%), C-15(100%), C-16(100%), C-20(95.65%) and C-21(100%). The technique with the same configuration but using polynomial kernel remain on the top for the classes C-4, C-15, C-16, C-17, C-18, C-27, C-29, C-30 and C-35 with precision scores 100%, 100%, 100%, 100%, 97.67%, 97.72%, 100%, 100% and 90.70% respectively. While testing the proposed technique using linear kernel through OvA modality, it couldn't lead in the precision score for any of the classes but it remained at the bottom among its fellows by securing the lowest scores for 26 classes i.e., C-1, C-2, C-4, C-5, C-6, C-8, C-9, C-10, C-11, C-13, C-14, C-16, C-17, C-18, C-19, C-20, C-21, C-24, C-25, C-27, C-28, C-29, C-31, C-32, C-34 and C-35. While using OvA modality with RBF kernel, the proposed technique remained on top for the classes C-8, C-12, C-15, C-16, C-17, C-22 and C-33 with precision values 100%, 100%, 100%, 100%, 100%, 97.87%, and 91.42% respectively. Using the same modality but with the polynomial kernel, the proposed technique achieved the highest precision scores for the seven classes among all the eight fellow configurations i.e., C-1, C-3, C-5, C-12, C-16, C-24 and C-32 with values 97.30%, 100%, 95.74%, 100%, 100%, 97.78% and 94.74% respectively. The proposed ensemble of kernels for SI-sMBP features, OvO modality performed best among all the fellows by observing the highest precision score for the 17 classes. The best of the scores achieved by the technique were 93.75%, 100%, 100%, 100%, 100%, 95.74%, 95.35%, 97.96%,

100%, 100%, 100%, 100%, 97.87%, 89.58%, 100% and 90.70% for the classes C-2, C-4, C-6 through C-10, C-14 through C-17, C-19, C-22, C-25, C-26, C-30, and C-35 respectively. The technique remained on the lower side for none of the classes. At last, the discussion about the proposed ensemble of kernels using OvA modality concludes that it performed on a higher side for the classes C-3, C-8, C-12, C-13, C-15 through C-17, C-23, C-28, C-31, C-34 and C-36 with precision values 100%, 100%, 100%, 97.50%, 100%, 100%, 100%, 97.67%, 92.16%, 100%, 100% and 100% respectively.

Same as figure 7.8(a), figure 7.8(b) is showing the comparative results over the known signer's dataset but it is based on the recall metric. The proposed SI-sMBP based features when used in ECOC SVM with linear kernel in OvO modality showed good results for the seven classes and remained at the top for them by securing recall values 100%, 100%, 100%, 100%, 93.88%, 100% and 100% for C-16, C-17, C-18, C-21, C-22, C-24 and C-28 respectively. It couldn't perform better for the classes C-4, C-14, C-25 and C-30. When the RBF kernel is used with the modalities, the proposed technique could attain higher results for the classes C-1, C-2, C-13, C-25, C-28, C-29 and C-32 by achieving 95%, 94.74%, 89.13%, 98.04%, 100%, 93.75% and 76% respectively. The experiment under discussion was not able to achieve competitive results for the CLASS c-4 and stayed at the bottom. For the polynomial kernel used in OvO multiclass SVM settings, the proposed technique was able to achieve highest results for the classes C-9, C-12, C-13, C-16, C-17, C-22, C-23, C-28, C-29 and C-31 with recall scores 97.96%, 100%, 89.13%, 100%, 100%, 93.88%, 100%, 100%, 93.75% and 88.89% respectively. However, it remains at the bottom for the classes C-4 and C-8. It is important to note that when the linear kernel is used in OvA configuration the proposed approach couldn't perform better as was with the precision metric. It remain at the bottom among all the fellows and couldn't perform better for 32 classes with the least classification recall. It could only show moderate scores for the classes C-8, C-12, C-22, and C-25. As well as, the experiment couldn't achieve the best of results even for a single class. When the RBF kernel was used with the OvA scheme, it got higher scores for the four classes i.e., C-15, C-22, C-27 and C-28 with recall values 100%, 93.88%, 93.62% and 100% respectively. However, its results for class C-8 were at the shared bottom. When the proposed SI-sMBP features based SVM classifier with OvA modality was tested over known signer's dataset it was best among the fellows for the 13 classes i.e., C-4, C-6, C-10, C-12, C-13, C-14, C-16, C-17, C-18, C-22, C-24, C-26, C-28 and C-33 with 100%, 95.56%, 95.65%, 100%, 89.13%, 98.0%, 100%, 100%, 100%, 100%, 95.83%, 100% and 100% recall values respectively. In comparison to the others, it stayed at the bottom for class C-3. Same as precision, the proposed ensemble of kernels with OvO multiclass modality showed equal best of the performance for the recall metric as well by securing the highest scores for 18 classes and not at the bottom for any of the class. It attained highest recall for the classes C-2 through C-5, C-7, C-13, C-16 through C-18, C-22, C-24, C-25, C-27 through C-30, C-32 and C-34 with scores 95.74%, 98.11%, 100%, 95.92%, 100%, 89.13%, 100%, 100%, 100%, 93.88%, 100%, 98.04%, 93.62%, 100%, 93.75%, 100%, 76% and 95.65% respectively.

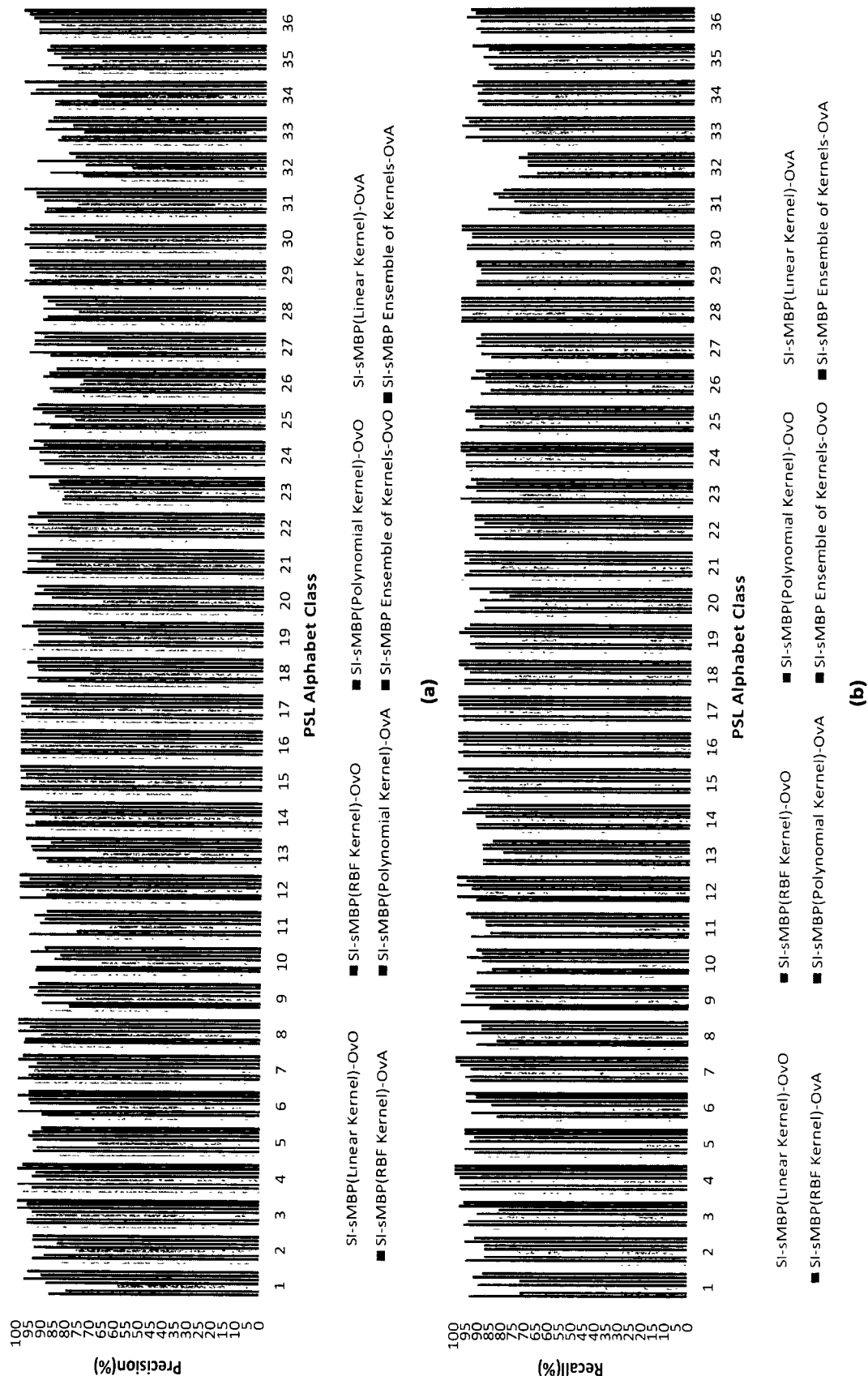


Figure 7.8: Kernel Based Comparative Analysis of Classification Metrics for Known Signers

Lastly, the proposed ensemble of all the three kernels using OvA tuning the results were equally best with the ensemble of kernels through OvO modality by attaining highest recall for 18 classes. The classes where proposed ensemble(OvA) attained good results are C-4 through C-8, C-11, C-12, C-15 through C-18, C-22, C-24, C-28, C-30, C-35 and C-36 having scores 100%, 95.92%, 95.56%, 100%, 97.83%, 95.92%, 100%, 100%, 100%, 100%, 100%, 93.88%, 100%, 100%, 93.75%, 100%, 95.45% and 96.08% respectively. Same as the case of precision proposed ensemble didn't have to face bottom for any of the 36 classes.

7.2.3 Comparative Results using Dataset of UnKnown Signers

The results achieved through the proposed methodology when SI-sMBP features are fed into ECOC SVM using all the three kernels and two different multiclass mechanisms are discussed here. The discussion is with reference to the two evaluation metrics i.e., precision and recall, received over signs generated through unknown signers.

Figure 7.9(a) is presenting comparative results on the basis of precision and it may be observed from the graphs that the performance of the proposed technique over the linear kernel through OvO modality are higher than all other settings for the classes C-13, C-14, C-16, C-17, C-18, C-25, C-27 and C-33 having precision 100%, 100%, 100%, 100%, 48.28%, 71.43%, 33.33% and 33.33% respectively. While it couldn't perform better for the classes i.e., C-19, C-20, C-21, C-26 and C-32. The proposed technique using OvO modality with RBF kernel could show better results for one class only i.e., C-28(97.06%). However, it was behind other fellows for the classes C-6 through C-9, C-15, C-19, C-24, C-31, C-32, C-34 and C-36. While using the multiclass phenomena but using polynomial kernel, the results were higher among the others for the classes C-3, C-6, C-10, C-13, C-16, C-17, C-22, C-25, C-26 and C-35 with respective precision values 29.47%, 46.34%, 84.21%, 100%, 100%, 100%, 79.41%, 71.43%, 73.08%, and 53.57%. The technique couldn't perform better for the following categories i.e., C-12, C-14, C-19 and C-32. Using OvA multiclass modality through linear kernel, the proposed methodology achieved higher results with precision scores 61.29%, 66.67%, 100%, 44.83%, 100%, 100%, 59.38%, 100%, 70.59% and 100% for the classes C-2, C-8, C-14 through C-17, C-23, C-24, C-31 and C-36 respectively. The results for the classes C-10, C-13, C-19, C-22, C-32 and C-35 respectively. The same multiclass tuning as the previous case but using RBF kernel produced higher precision for only two classes i.e., C-24(100%) and C-30(5.69%). It remained behind other techniques for the classes C-3, C-5, C-11, C-18, C-19, C-23, C-25, C-27 and C-32. The last kernel selection i.e., polynomial, using OvA mutation produced good results for the classes C-7(74.28%), C-9(47.37%), C-11(47.5%) and C-12(51.06%). Unlike the results for the known signers' dataset, the proposed kernel ensemble with OvO modality showed better results for only four classes i.e., C-4(69.77%), C-5(46.78%), C-16(100%) and C-17(100%), while remained at the bottom for five of the classes i.e., C-1, C-2, C-19, C-29 and C-32. The proposed ensemble through OvA modality was better than its fellow one by

achieving higher results for the classes C-1, C-14, C-16, C-20, C-21, C-24, C-29 and C-34 with precision values 31.25%, 100%, 100%, 90.48%, 82.93%, 100%, 100% and 100% respectively. However, it remained at the shared bottom with all fellows for the classes C-19 and C-32. It is an important observation that the proposed techniques were not able to classify any of the signs for the classes C-19 and C-32.

Same like the last discussion, figure 7.9(b) is showing comparative results of the proposed technique with different variations but for the recall evaluation metric and the unknown signers' dataset. When proposed SI-sMBP based features are provided to the ECOC based multiclass SVM through the use of OvO modality and linear kernel, it achieved higher results for the classes C-7, C-13, C-21, C-26, C-31 and C-33 with recall values of 87.5%, 32.43%, 100%, 100%, 51.35% and 100% respectively. It remained at the bottom for class C-10. With the same multiclass modality as discussed earlier but through RBF kernel, the proposed technique achieved better results among other fellows for the classes C-1, C-9, C-22 and C-36 with respective recalls 47.22%, 61.90%, 67.5% and 54.05%. As well as, the technique was at the bottom for the following classes i.e., C-6, C-7, C-11, C-13, C-15, C-16, C-21, C-26 and C-34. The technique with OvO multiclass setting and polynomial kernel showed higher results for the eight classes i.e., C-6(43.18%), C-19(17.07%), C-22(67.5%), C-27(20%), C-29(70.73%), C-30(89.74%), C-32(19.15%) and C-35(45.45%), while remained at the bottom for the two classes(C-17 and C-20). Changing multiclass modality to OvA and using the linear kernel, the proposed technique got top scores with reference to the fellows for classes C-2, C-4, C-8, C-11, C-18, C-20 and C-25 having 47.5%, 97.06%, 66.67%, 60.47%, 66.67% and 70.27% respectively. On the other side, it couldn't get even moderate results in comparison to others for the classes C-3, C-14, C-15, C-19, C-27, C-28, C-29 and C-36. The same modality as for the linear kernel, the proposed methodology with the RBF kernel showed the highest scores for the two classes only i.e., C-10(52.5%) and C-22(67.5%). It remained on lower side for the 13 classes i.e.,(C-4, C-6, C-12, C-13, C-18, C-21, C-23, C-24, C-25, C-30, C-32, C-33 and C-35). The proposed technique with OvA modality using polynomial kernel was able to show better results for the four of the classes i.e., C-15, C-16, C-23 and C-24 with 56.41%, 52.27%, 58.33% and 51.28% respectively. While it was not able to perform better for the C-1, C-5, C-8, C-9, C-13, C-14, C-19, C-22, C-31, C-32 and C-34 categories. The proposed ensemble of kernels was able to show promising results for the classes C-13(32.43%), C-34(11.11%) and C-36(54.05%), while it was poor for the class C-2. Lastly, the proposed kernel ensemble using OvA mechanism showed best of the results for the following classes i.e., C-3, C-12, C-14, C-17 and C-28 by securing 85.37%, 74.36%, 84.85%, 76.19% and 94.87% respectively. It is important to note that the proposed ensemble was the only one that didn't remain at the bottom for any of the classes.

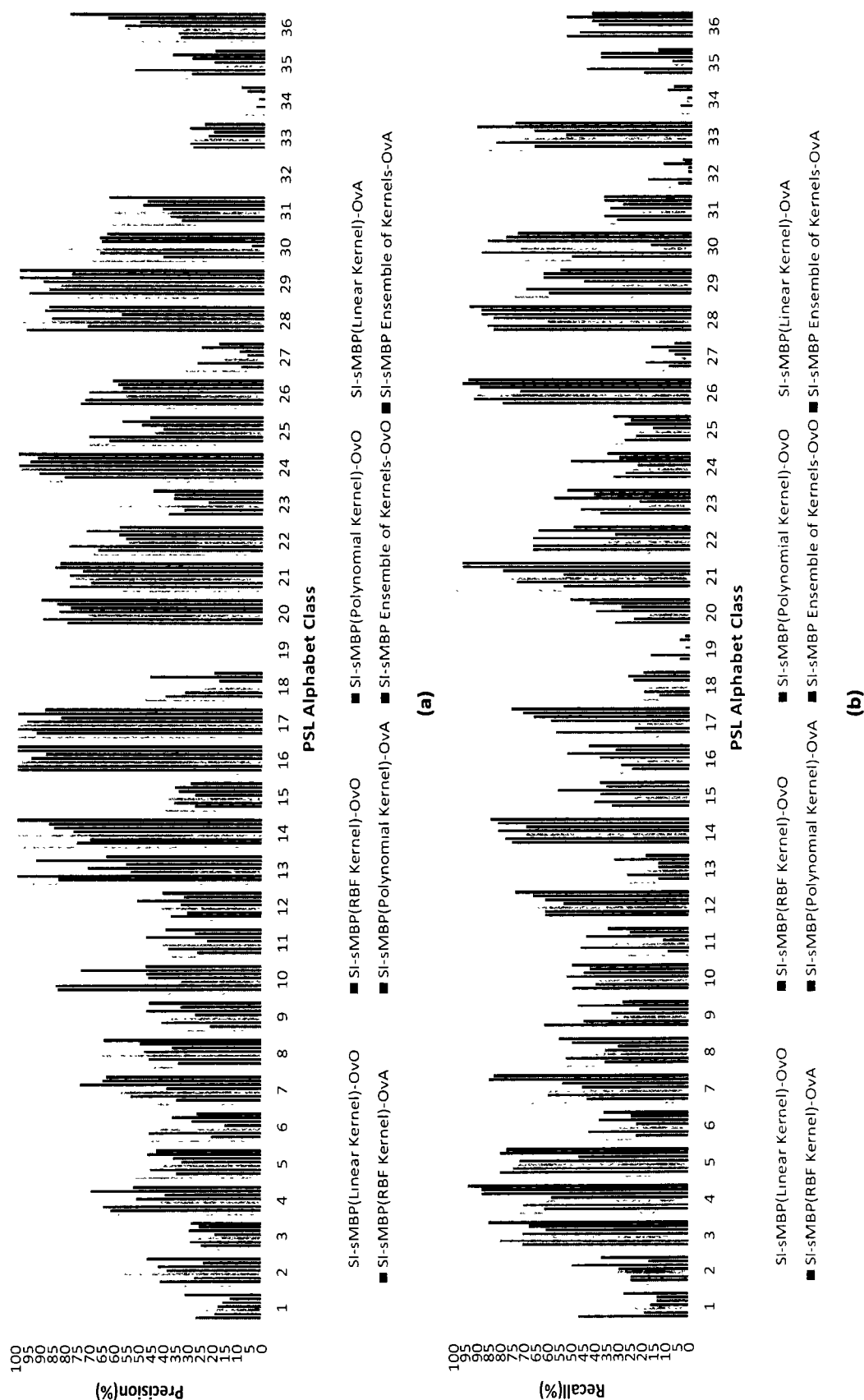


Figure 7.9: Kernel Based Comparative Analysis of Classification Metrics for UnKnown Signers

7.2.4 Classification Matrices for the Proposed Techniques

In this subsection, we have presented the classification matrices representing the outcome of the proposed technique using linear, Gaussian, polynomial kernel and ensemble of kernels for multiclass SVMs using OvO and OvA modalities. Two set of classification matrices are there i.e.,

- Test results obtained by applying the proposed techniques over the signs taken through known signers.
- Results achieved of the proposed techniques when applied over the dataset of the unknown signers.

These classification matrices are self explanatory by presenting precision, recall, omission and commission errors for the individual classes along with the overall accuracy of the proposed techniques. The overall accuracy for the proposed sMBP used for classification through the linear kernel based multiclass SVMs using the OvO model achieved an overall accuracy of 87.27%(figure B.1) for the known signers while it was 50.44%(figure B.9) for the unknown ones. The proposed technique with the same SVM modality but with the RBF kernel was 92.72%(figure B.2) accurate over the test feature set of the known signers, it was 41.60%(figure B.10) accurate for the unknown signers. While the accuracy over the known signers for the polynomial kernel was 92.84%(figure B.3) and 47.39%(figure B.11) for the unknown signers. When all the kernels were ensembled for OvO mutation, it received an accuracy of 94.72%(figure B.4) for the known signers while it got the same metric valued 49.29%(figure B.12) for the signs generated by unknown signers.

While performing the experiments using feature set calculated through proposed sMBP and classifying by multiclass SVMs with OvA modality following results were achieved:

1. Linear kernel produced an overall accuracy of 79.46%(figure B.5) for the known signer's data set while it was 48.66%(figure B.13) classification accuracy for the dataset of the unknown signers.
2. RBF kernel based produced technique using OvA modality achieved an overall accuracy of 92.49%(figure B.6) for the signs generated by the known signers while 36.65%(figure B.14) accuracy was obtained over the dataset generated by the unknown signers.
3. Polynomial kernel based proposed technique achieved accuracies of 92.96%(figure B.7) and 36.65%(figure B.15) for the signs taken through known and unknown signers respectively.
4. The ensemble of all the three kernels received accuracy value 95.19%(figure B.8) for the known signers and 49.58%(figure B.16) for the unknown signers.

Summary

This chapter enhances the sMBP feature extraction by employing scale invariance in it. Scale invariance is achieved through presenting the concept of strength of a histogram bin computed at different radii and combining the sMBP histograms at different resolutions of Gaussian image pyramid. The Ensemble of kernels phenomena has been adopted as well, improving the efficiency of the proposed technique.

Chapter 8

Reduced Dimensional Scale Invariant sMBP for PSL Classification Using PCA & ECOC based Ensemble of Multiclass SVMs

Introduction

We have already presented two of the methodologies for solving the problem of Pakistan sign language recognition i.e., sMBP and SI-sMBP. The proposed sMBP was rotation invariant with lesser feature dimensional vector, 1×31 , and insensitive to noise but was not scale invariant. To introduce the scale invariance, SI-sMBP was presented that wasn't only insensitive to noise but scale and rotation invariant as well. It resulted in a feature vector of increased dimension i.e., 1. There is a need to reduce the dimension of the feature that should not only achieve a feature vector with lesser dimension but redundant ones should be suppressed as well.

8.1 Proposed Approach

Here we are presenting the PCA based SI-sMBP that would reduce the dimension of the feature vector and an ensemble of the kernels would be applied to achieve better results.

The Proposed approach takes the scale invariant feature subset as an input which is computed as defined in the last chapter. The dimension feature vector computed through Scale invariant symmetric median binary pattern $f_{v_{SIS-MBP}}$ is 1×93 , higher than the dimension of feature vector, $f_{v_{S-MBP}}$, through the symmetric median binary pattern. It is quite evident that the

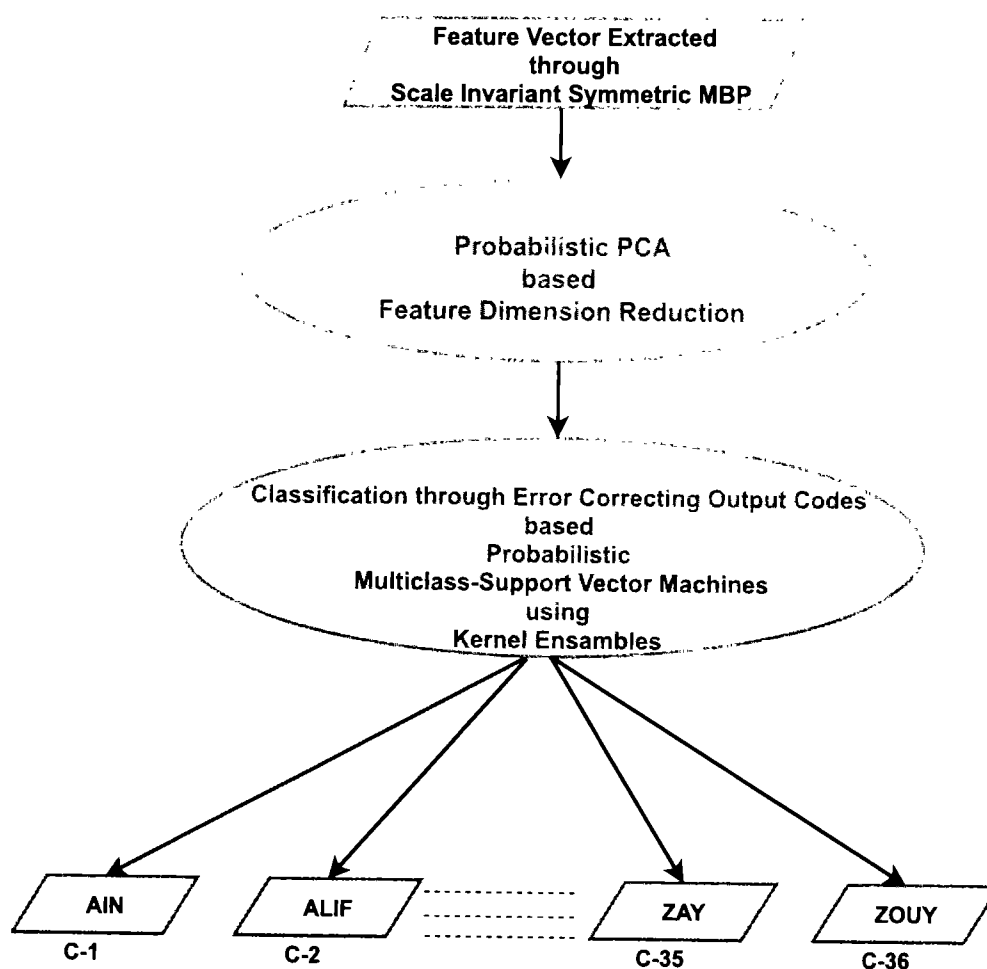


Figure 8.1: Work Flow of the Proposed Approach

dimension of the $f_{v_{SIS-MBP}}$ is three times of $f_{v_{S-MBP}}$ resulting in higher computation. The higher dimension is not only a question of higher computation but the redundant features may degrade the computational efficiency as well. In the proposed approach, we have applied principle component analysis (PCA) based feature extraction methodology for suppressing the dimension of $f_{v_{SIS-MBP}}$. The detail of the proposed technique is defined in PCA-SIS-MBPA and given as:

Algorithm 5 : PCA based Scale Invariant Symmetric Median Binary Pattern Calculation Algorithm(PCA-SIS-MBP)**INPUT:** Feature Vector $f_{v_{SIS-MBP}}$ **OUTPUT:** Classification Matrix Vector($cmv_{PCA-SIS-MBP}$)

- 1: Initialize classification matrix vector, ($cmv_{PCA-SIS-MBP} = \{ \Phi \}$)
- 2: Initialize kernel vector, $kv = \{ \text{Linear, RBF, Polynomial} \}$
- 3: Initialize multi class modality vector, $mcmv = \{ \text{OvO, OvA} \}$
- 4: Initialize feature dimension vector, ($fdv = \{ 0 \}$)
- 5: Initialize method sequence variable, $msv = 0$
- 6: Repeat through step 10 $\forall i \in mcmv$
- 7: Repeat through step 10 $\forall j \in kv$
- 8: Increment msv by 1.
- 9: Use Feature Reduction Algorithm(AFRA) to apply feature dimension reduction i.e., ($cm(msv), \text{class-model}(msv) = \text{AFRA}(f_{v_{SIS-MBP}}, kv(j), mcmv(i))$)
- 10: Apply Covariance Matrix, $cm(msv)$, over test data to get reduced dimensional test data i.e., rd_{td}
- 11: Perform testing over test data using class model obtained through AFRA i.e., ($cmv_{PCA-SIS-MBP}(msv), \text{class_prob_mat}(msv) = \text{ECCSVMTest}(\text{class-model}(msv), rd_{td})$)
- 12: Compute output class using Ensemble of Kernels Algorithm(EoKA).
- 13: compute classification matrix i.e., cm_En_OvO
- 14: Compute output class for OvA through Ensemble of Kernels Algorithm(EoKA).
- 15: compute classification matrix i.e., cm_En_OvA
- 16: $cmv_{PCA-SIS-MBP}(7) = cm_En_OvO$
- 17: $cmv_{PCA-SIS-MBP}(8) = cm_En_OvA$
- 18: Return $cmv_{PCA-SIS-MBP}$

8.1.1 Reduced Dimensional Feature Subset

PCA is used for feature extraction. We calculated feature means ($\bar{f}_i$), feature standard deviations (σ_{f_i}) and covariances (σ_{f_i, f_j}) for input data. All the features have different value ranges like some of them have binary values while others have numeric or fractional values. Features with higher range values participate heavily in the covariance Matrix other than the features with a lower value range. To avoid the influence of any feature we standardized the features before calculating the eigenvalues.

$$\bar{f}_i = \sum_{k=1}^n \frac{f_{i_k}}{n} \quad (8.1)$$

The standard deviation, (σ_{f_i}), of each histogram bin f_i is calculated as:

$$\sigma_{f_i} = \sqrt{\frac{\sum_{k=1}^n (f_{i_k} - \bar{f}_i)^2}{n - 1}} \quad (8.2)$$

and variance is squared standard deviation i.e.,

$$\sigma_{f_i}^2 = \frac{\sum_{k=1}^n (f_{i_k} - \bar{f}_i)^2}{n-1} \quad (8.3)$$

The covariance between f_i and f_j is represented by:

$$\text{cov}(f_i, f_j) = \sigma_{f_i f_j} \quad (8.4)$$

and is computed as:

$$\sigma_{f_i f_j} = \frac{\sum_{k=1}^n (f_{i_k} - \bar{f}_i)^2 (f_{j_k} - \bar{f}_j)^2}{n-1} \quad (8.5)$$

The covariance matrix using standardized covariances is represented as

$$C = \begin{pmatrix} \sigma_{f_1 f_1} & \sigma_{f_1 f_2} & \cdot & \cdot & \sigma_{f_1 f_p} \\ \sigma_{f_2 f_1} & \sigma_{f_2 f_2} & \cdot & \cdot & \sigma_{f_2 f_p} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \sigma_{f_p f_1} & \sigma_{f_p f_2} & \cdot & \cdot & \sigma_{f_p f_p} \end{pmatrix} \quad (8.6)$$

For covariance matrix C , we are now looking for a unit vector v that maximizes $v C v^T$. Then we took the eigenvectors and eigenvalues of C , and denote them by $ev_1, ev_2, \dots, ev_p$ and $\lambda_1, \lambda_2, \dots, \lambda_p$ respectively, such that $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \dots \geq \lambda_p$. For an eigenvector ev_i we calculated $v^T C v$ by using

$$ev_i^T C ev_i \Rightarrow ev_i^T \cdot (\lambda_i ev_i) \Rightarrow \lambda_i (||ev_i||_2)^2 \Rightarrow \lambda_i \quad (8.7)$$

from eq(7) we can see that $\lambda_1 = 1$ for ev_1 . For some arbitrary vector v , since eigenvectors form orthogonal basis so we have $v = \sum_{i=1}^p \alpha_i ev_i < v, ev_i >$. Based on orthogonal basis we defined $v^T \cdot C \cdot v$ as

$$\left(\sum_{i=1}^p \alpha_i ev_i \right)^T \cdot C \cdot \left(\sum_{i=1}^p \alpha_i ev_i \right) \Rightarrow \left(\sum_{i=1}^p \alpha_i ev_i \right) \cdot \left(\sum_{i=1}^p \lambda_i \alpha_i ev_i \right) \Rightarrow \sum_{i=1}^p \lambda_i (\alpha_i)^2 (||ev_i||_2)^2 \Rightarrow \sum_{i=1}^p \lambda_i \alpha_i^2 \quad (8.8)$$

where $\alpha_i = < v, ev_i >$ and α_i^2 are all positive and with sum 1. we choose K eigenvectors based on at least 92% cumulative percent of variance, $r_k = \frac{\sum_{j=1}^K \lambda_j}{\sum_{j=1}^p \lambda_j} * 100$. K vectors used for projection, $v_1, v_2, \dots, v_k$, are assumed to be pairwise orthogonal and total variance of the projection on these vectors are represented by

$$\sum_{i=1}^k \sum_{j=1}^P \lambda_i \alpha_{ij}^2 \Rightarrow \sum_{i=1}^P \lambda_i \beta_i \quad (8.9)$$

where $\beta_i = \sum_{j=1}^K$. By applying projection matrix on $M \times P$ data we obtained $M \times K$ reduced dimensional data.

Algorithm 6 : Feature Reduction Algorithm(FRA)

INPUT: Feature Vector ($f_{v_{SIS-MBP}}$), Chosen Kernel Value (kv), Multiclass Modality (mcm)

OUTPUT: PCA Matrix(PCA-Mat), Classification Model(class-model)

- 1: Calculate Covariance Matrix, cm, using training data from $f_{v_{SIS-MBP}}$
 - 2: Compute Eigenvalues of cm
 - 3: Repeat through step 10 foreach eigenvalue starting from lower to higher
 - 4: Compute Principle Components Matrix(PCM) corresponding to the Eigenvalues
 - 5: Apply computed PCM over training data from $f_{v_{SIS-MBP}}$ to get reduced dimension feature vector $f_{v_{SIS-MBP_{RD_{Train}}}}$
 - 6: Train Error Correcting SVM using Kernel Vector kv with Multiclass Modality (mcm) getting classification model(C-Model) over $f_{v_{SIS-MBP_{RD_{Train}}}}$
 - 7: Apply computed PCM over validation data from $f_{v_{SIS-MBP}}$ to get reduced dimension feature vector $f_{v_{SIS-MBP_{RD_{Valid}}}}$
 - 8: Compute classification accuracy(C-Acc) by testing Error Correcting SVM with C-Model over $f_{v_{SIS-MBP_{RD_{Valid}}}}$
 - 9: Find maximum classification accuracy involving minimum principle components, assign corresponding PCM to PCA-Mat and C-Model to class-model
-

8.2 Classification

The task of classification through ECOC multiclass SVM has already been explained in 6 and 7, so here we don't need to replicate the whole process.

8.3 Results and Discussion

In this section, We will present the results of the proposed technique applied over the PSL dataset. The presented results constitute graphs representing the process of selecting principle components through PCA for feature dimension reduction, comparative results in the form of precision and recall for known and unknown signers through using both the multiclass modalities for classification i.e., One-V-One and One-V-All.

8.3.1 Principle Components Selection

Here the procedure for the selection of principal components of PCA for the feature reduction dimension is presented graphically. The selection of the components is achieved through training the classifiers on the reduced dimension data and then validating the trained model on

reduced dimensional validation data. The original dimension of the feature vector, $f_{USIS-MBP}$, was 93. The dimension of the input feature vector is selected from two through ninety three step by step and accuracy for each dimension of the feature vector is computed. The number of principal components is selected through which corresponding feature vectors attained maximum accuracy while retaining the minimum number of components.

8.3.1.1 Multiclass SVMs with One-vs-One Modality

Figure 11.2 is showing the validation accuracies obtained, when the different number of components are selected for linear kernel based multiclass support vector machines using the One-v-One modality. When the number of components is kept as one, the classifier was unable to converge while for the two components the validation accuracy was 6.60%. The validation accuracy kept on improving till 33 components were selected. The validation accuracy for the reduced dimensional feature set of 33 was 85.27%. The number of principal components 34 through 45 lengths, either remained equal or below 85.27%, so till the point, 33 principal components were the best choice. The validation accuracies kept on improving from 46-48 where the maximum of the accuracy was for the 48 components i.e., 86.35%. From 49 components till 93 the validation accuracies remained lower than 86.35%. It was accuracy of 82.97% for all the 93 components. The best optimal choice remained with the principle components of length 48 resulting same for the reduced dimensional feature set.

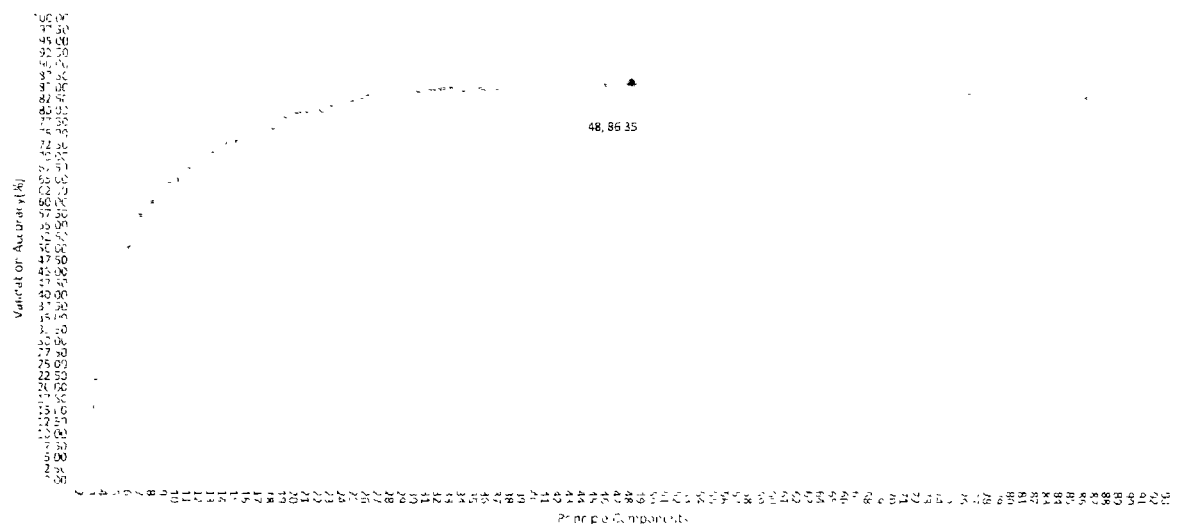


Figure 8.2: Validation Accuracies for PCA Components: Linear Kernel(OvO)

The graphical representation for the process of feature dimension selection using RBF kernel is shown in figure 8.3. The minimum number of principal components was two producing the validation accuracy as 23.33%. The validation accuracies kept on improving when the selection of principal components was systematically increased to 12. The accuracy for twelve lengthed

extracted feature vector was 88.24%. The validation accuracies for the components with the length in between 13 and 23 weren't on a single pattern i.e., at some feature vector size the accuracy improved while for the other it got decreased. When the principal components were selected as 24 the validation accuracy was achieved as 89.46%. The process carried on till the selected principal components reached 93. It's worth noting that no improvement was noticed beyond 89.46% for all the feature vectors of length in between 25 and 93. So, the selected number of principal components for the RBF kernel resulting the best of the validation accuracy is twenty four.

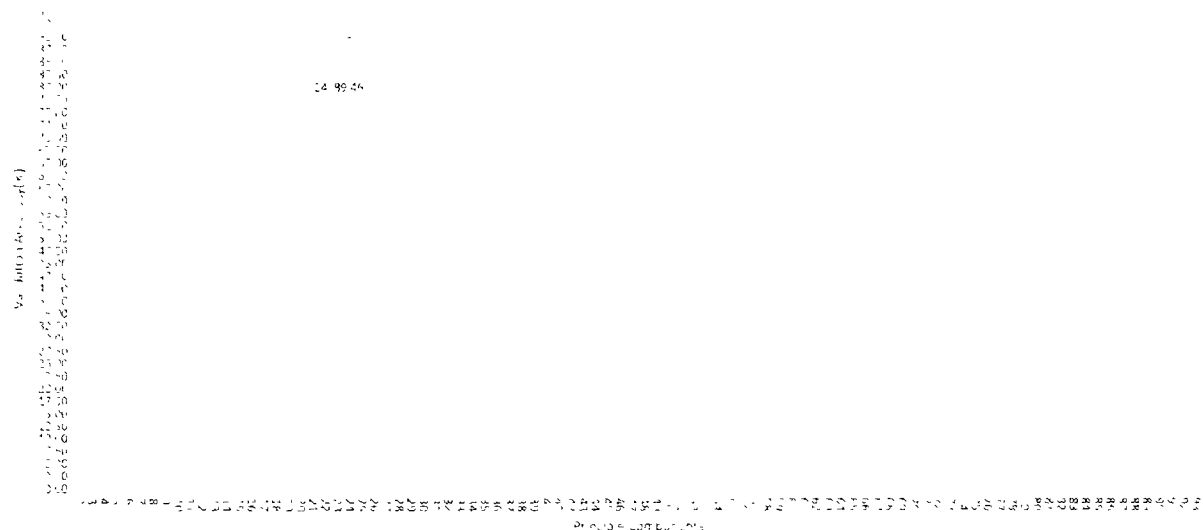


Figure 8.3: Validation Accuracies for PCA Components: RBF Kernel(OvO)

Same as for the other two kernels, linear and RBF, figure 8.4 shows the process of principal components selection along with their validation accuracies through polynomial kernel based SVMs. While selecting only two components corresponding to the top two eigenvalues, the score of 11.02% validation accuracy was achieved. The upward trend of the validation accuracies kept on till the fifteen principal components were selected. It was 91.89% for the first 15 components. The validation accuracy got lower when another component was added. Again, the validation accuracies started to get increasing till the selected number of components reached 22 where the attained validation accuracy was 93.78%. This proved to be the highest of all i.e., none of the other combinations achieved accuracies higher than 93.78%. It was 85.27%, when all the 93 components were retained.

8.3.1.2 Multiclass SVMs with One-vs-All Modality

Same as the previous discussion for OvO modality of SVMs, here the procedure for feature dimension reduction is presented and it is through OvA modality based multiclass SVMs.



Figure 8.4: Validation Accuracies for PCA Components: Polynomial Kernel(OvO)

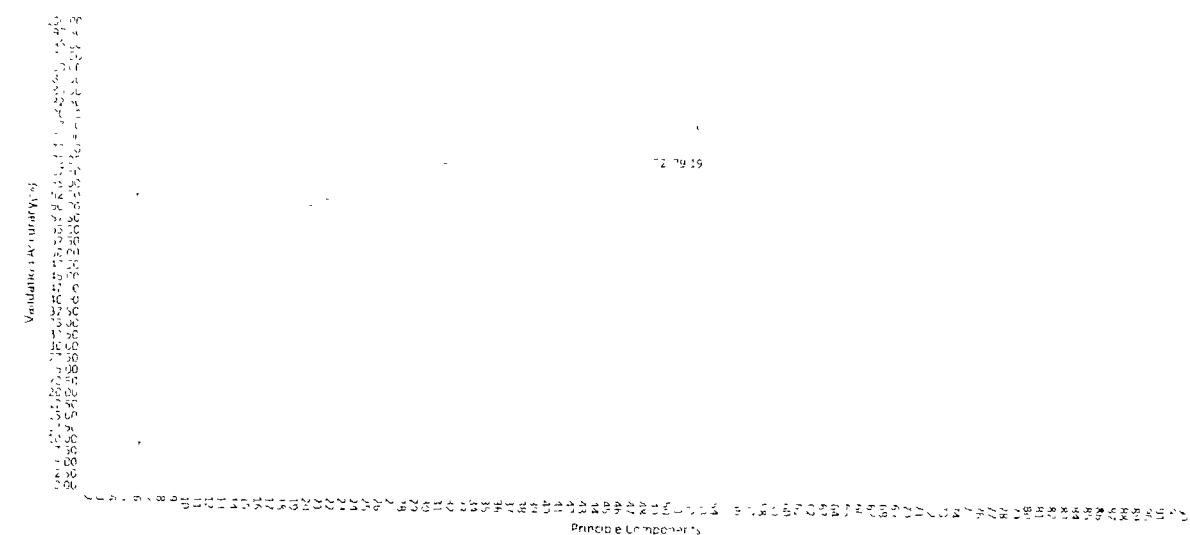


Figure 8.5: Validation Accuracies for PCA Components: Linear Kernel(OvA)

Figure 11.5 is showing the process of PCA components selection for transforming the feature vector onto a lower dimensional space. The selection is achieved through using the OvA modality of multiclass SVMs for the linear kernel. It may be observed for the first two principal components, the classifier was unable to get optimized(showing the accuracy as zero). In comparison to the O-v-O modality the validation accuracy for the combination of top ten components, validation accuracy was no more than 30% while it was about 65% for the same number of components. By adding more components, the validation accuracy kept on increasing with 86.35% with 48 selected components. All the 93 components were added one by one to the list but none of the combinations achieved higher validation accuracy than the top 48 ones. It was accuracy of 77.56% for all the 93 components i.e., the feature vector length remained the

same as in the original space.



Figure 8.6: Validation Accuracies for PCA Components: RBF Kernel(OvA)

As far as figure 11.6 is concerned, it depicts the principal components selected for feature dimension reduction by using radial functions based multiclass SVMs using the OvA approach. When two of the principal components(corresponding to the highest eigen score) are selected for projecting the original feature dimension onto a space of two dimensional feature space, the accuracy through the validation process was 24.30%. The validation accuracy kept on increasing as the number of principal components gets on the same till fourteen components corresponding to fourteen highest eigen score got selected(90.81%). The accuracy dropped for the fifteen components but again it got improving from 16 till 24. From there onward the validation accuracy didn't have the uniform pattern but at some number of components it was improved and on others it was low. The process kept on progressing till the number of selected components was 37 for which the validation accuracy was 94.18%. The same accuracy was obtained for the features space transformed onto 38,39,40,44,51 and 52 dimensional PCA space(number of selected principal components). No other selected components lead to a higher validation accuracy than 94.18%. When the number of selected components was 93, the validation accuracy was 86.22%. The final outcome of the process was in the form of selecting 37 components that resulted in the highest validation accuracy while retaining the minimal number of principal components.

Same as for the other two cases, figure 11.7 explains the process for the polynomial kernel. When the two principal components corresponding to the highest eigenvalues are selected resulting in transforming the feature vector to the two dimension PCA spaced feature vector, the validation accuracy was very low i.e., 0.51%. The validation accuracy was gradually increased from the selection of three to fourteen when it reached at 88.24% while for the inclusion of



Figure 8.7: Validation Accuracies for PCA Components: Polynomial Kernel(OvA)

fifteenth and sixteenth components the accuracy was decreased. The validation accuracy for sixteen to forty components remained in between 87.70% and 93.65%. When the PCA based forty components were selected corresponding to top forty one eigenvalues, the validation accuracy was achieved with the score of 94.05%. For the rest of the principal components, till all the 93 components were used, the validation accuracy higher than 94.05% could not be achieved. So the PCA transformed feature dimension for the polynomial based multiclass SVMs using OvA modality is 41.

8.3.2 Comparative Results of the Proposed Technique for Known Signers

The comparative results of the proposed technique PCA-SI-sMBP using linear, RBF and polynomial kernels for multiclass SVMs and PCA-SI-sMBP Ensemble through OvO and OvA are presented in figure 8.8(a). The figure shows the results for representing precision metric for the test data of known signers i.e., training data has signs from the same signers as well. While using polynomial kernel for multiclass SVMs with OvO modality(PCA-SI-sMBP), it has highest of the precision for the ten classes i.e., C-1,C-2,C-5,C-6,C-11,C-13, C-18, C-26, C-31, C-34 and C-36. The linear kernel remained best precision among all the three kernels for C-23, C-30 and C-33. The performance of the PCA-SI-sMBP with RBF kernel is better than its other fellows for the seven classes i.e., C-3, C-9, C-10, C-12, C-17, C-20 and C-27. While for the rest of the classes either two of the kernels or all the three kernels have equal precision value. When OvA modality was used for PCA-SI-sMBP, for the linear kernel the results for C-14 and C-2 remained highest among other kernels having 100% precision(others have lessor). For the RBF

kernel the results were highest for the following classes i.e., C-5, C-8, C-9, C-10, C-13, C-15, C-18, C-19, C-22, C-25, C-28, C-33, C-34 and C-35. Using polynomial kernel, the results for the classes C-2, C-3, C-4, C-6, C-12, C-16, C-21, C-24 and C-31 were highest than through the other two kernels. The highest results for the remaining classes (other than discussed for all the three kernels using OvA) were either shared by any of the two kernels or are shared by all the three kernels. While using PCA SIS MBP Ensemble through OvO, the precision for C-1, C-3, C-4, C-7, C-8, C-11, C-14, C-15, C-16, C-19, C-20, C-21, C-28, C-29, C-32, C-35 and C-36 remained 100%. The precision was increased for the classes C-9, C-18, C-26 and C-34 in comparison to all the three kernels when the proposed ensemble is implemented. The precision for the rest of the classes either remained the same as the highest of the values among all the kernels or decreased due to lower scores from other kernels.

The precision of classes C-6 and C-33 remained highest through the proposed SI-sMBP Ensemble for OvA multiclass modality i.e., 100% and 87.50% respectively. While the precision score for the classes C-1, C-2, C-7, C-8, C-14, C-16, C-17, C-19, C-21, C-28, C-29 and C-32 remained 100% but not the only one classifier having 100% precision for the mentioned classes i.e., the same score is shared by any of the other schemes as well.

Same as above, figure 8.8(b) is showing the comparative results for recall of the proposed techniques using different kernels and multiclass modalities. While using OvO modality, PCA-SI-sMBP with linear kernel did not achieve highest recall among its fellows (all the others) for any of the class but shared the highest with the others for C-4, C-12, C-16, C-17, C-21, C-28 and C-29 with 100% score. The scenario remained the same for PCA-SI-sMBP with RBF kernel (OvO). The shared highest recall for the mentioned technique was achieved for the C-4, C-10, C-12, C-15, C-16, C-17, C-18, C-20, C-22, C-24, C-26, C-27, C-28, C-29, C-30, C-13, C-32, C-33 and C-35 classes by achieving scores of 100% each (4-30), 88%, 87.5%, 96.77% and 92.31% respectively. With the same technique and the same modality but using polynomial kernel, the results for the classes C-2, C-5, C-6 and C-19 remained highest among all the other fellows by scoring 100%, 100%, 92.3% and 100% respectively but sharing the highest scores for the C-1, C-4, C-7, C-8, C-11, C-12, C-15, C-16, C-17, C-18, C-21, C-22, C-24, C-27, C-28, C-29, C-30, C-31, C-34, C-35 and C-36 represented as 100%, 100%, 94.74%, 96.30%, 94.74%, 100%, 100%, 100%, 100%, 100%, 100%, 100%, 100%, 100%, 100%, 94.44%, 100%, 93.33%, 95.24%, 93.30% and 100% respectively. While the proposed ensemble achieved highest recall for C-3 with 100% score and shared the top score with other techniques for the classes C-1, C-2, C-4, C-5, C-7, C-8, C-11 to C-18, C-21 to 24, C-32 to C-34 and C-36.

While discussing recall based results for the proposed PCA-SI-sMBP using all the three kernels and the ensemble based technique but using OVA multiclass modality, the score remained lowest for the C-1 to C-9, C-11 to C-13, C-17, C-18, C-20, C-23, C-24, C-26, C-27, C-29, C-31, C-32 and C-34 to C-36 for the PCA-SI-sMBP (linear kernel). The results with the same technique but with RBF kernel clearly reflect that the highest scores are shared with the other



Figure 8.8: Kernel Based Comparative Analysis of Classification Metrics for Known Signers

techniques by achieving 100%, 95.65%, 100%, 100%, 100%, 100%, 100%, 100%, 100%, 100%, 100% and 92.31% for the classes C-4,C-5,C-10,C-12,C-15,C-16,C-17,C-21,C-22,C-30 and C-35 respectively. With the same multiclass modality, PCA-SI-sMBP using polynomial kernel achieved the highest score among its fellows for the C-9 class with 96.55% value. The shared highest recall values are for the classes C-4, C-7, C-10, C-11, C-12, C-16, C-17, C-20, C-21, C-23, C-25, C-26, C-28 and C-30. The recall scores for the proposed ensemble through OvA modality are 96.30%, 95.24%, 96.30%, 100%, 95.65%, 88.46%, 89.47%, 96.30%, 93.10%, 100%, 94.74%, 100%, 80%, 85.71%, 100%, 100%, 100%, 100%, 84.21%, 95.65%, 100%, 100%, 100%, 100%, 100%, 100%, 94.44%, 100%, 94.44%, 100%, 93.33%, 75%, 90.32%, 90.48%, 92.31% and 91.67% for the all the classes(C-1 through C-36) respectively.

8.3.3 Comparative Results of the Proposed Technique for UnKnown Signers

In this subsection the comparative results of the proposed techniques are presented but they are for the unknown signers. The representation of the results are for the same evaluation metrics as presented for the known signers i.e., precision and recall.

Figure 8.9(a) shows the comparative precision scores through the proposed techniques i.e., PCA-SI-sMBP(Linear Kernel)-OvO, PCA-SI-sMBP(RBF Kernel)-OvO, PCA-SI-sMBP(Polynomial Kernel)-OvO, PCA-SI-sMBP(Linear Kernel)-OvA, PCA-SI-sMBP(RBF Kernel)-OvA, PPCA-SI-sMBP(Polynomial Kernel)-OvA, SI-sMBP Ensemble of Kernels-OvO and SI-sMBP Ensemble of Kernels-OvA. The highest score for the C-1 is 35.29% for SI-sMBP Ensemble of Kernels-OvA while the lowest is 13.33% PCA SIS MBP(Polynomial Kernel)-OvO. The highest scores for the rest of the classes(C2 through C-36) are 44.68%, 40.68%, 77.78%, 65.85%, 35.56%, 50.72%, 100%, 65.22%, 51.35%, 63.16%, 52.08%, 100%, 100%, 36%, 100%, 100%, 53.57%, 0%, 86.36%, 73.68%, 76.19%, 68.42%, 92.86%, 66.67%, 92.50%, 37.04%, 100%, 81.25%, 66.67%, 82.35%, 0%, 35.90%, 23.53%, 33.33% and 93.33% for the PCA-SI-sMBP (Linear Kernel)-OvO, PCA-SI-sMBP (Linear Kernel)-OvO, SI-sMBP Ensemble of Kernels-OvA, PCA-SI-sMBP (Linear Kernel)-OvO, PCA-SI-sMBP (Polynomial Kernel)-OvO, SI-sMBP Ensemble of Kernels-OvA, SI-sMBP Ensemble of Kernels-OvA, SI-sMBP Ensemble of Kernels-OvO, PCA-SI-sMBP (Polynomial Kernel)-OvO, PCA-SI-sMBP (RBF Kernel)-OvO, PCA-SI-sMBP (RBF Kernel)-OvA, PCA-SI-sMBP (Polynomial Kernel)-OvA, PCA-SI-sMBP (Linear Kernel)-OvA, SI-sMBP Ensemble of Kernels-OvA, for all the techniques except PCA-SI-sMBP (Polynomial Kernel)-OvA, for all the techniques, PCA-SI-sMBP (RBF Kernel)-OvA, for all the techniques, SI-sMBP Ensemble of Kernels-OvO, SI-sMBP Ensemble of Kernels-OvO, PCA-SI-sMBP (RBF Kernel)-OvA, SI-sMBP Ensemble of Kernels-OvA, PCA-SI-sMBP (RBF Kernel)-OvO, PCA-SI-sMBP (RBF Kernel)-OvA, PCA-SI-sMBP (RBF Kernel)-OvO, SI-sMBP Ensemble of Kernels-OvO, for the three of techniques (PCA-SI-sMBP (Linear Kernel)-OvO, PCA-SI-sMBP (Linear Kernel)-OvA, PCA-SI-sMBP (RBF

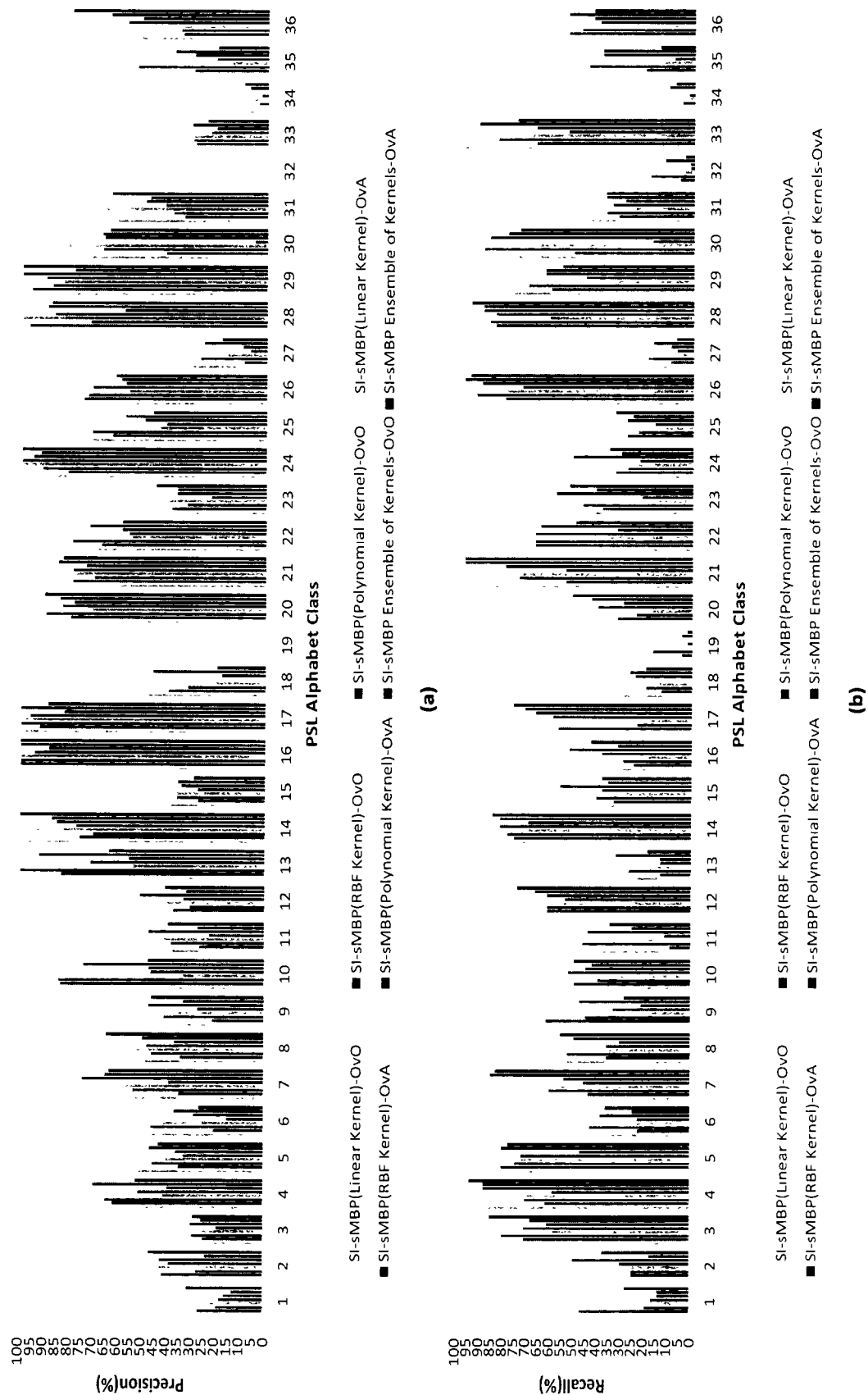


Figure 8.9: Kernel Based Comparative Analysis of Classification Metrics for UnKnown Signers

Kernel)-OvA), PCA-SI-sMBP (RBF Kernel)-OvO, PCA-SI-sMBP(Linear Kernel)-OvO, for the two of techniques(PCA-SI-sMBP (RBF Kernel)-OvO, SI-sMBP Ensemble of Kernels-OvO), for all the techniques, SI-sMBP Ensemble of Kernels-OvO, SI-MBP Ensemble of Kernels-OvO, PCA-SI-sMBP (RBF Kernel)-OvA and PCA-SI-sMBP (Linear Kernel)-OvA respectively. It is worth noting that none of the techniques was able to achieve the precision value of more than 0% for the C-19 and C-32. The performance of the four of the techniques best i.e., PCA-SI-sMBP (Linear Kernel)-OvO, PCA-SI-sMBP (RBF Kernel)-OvA, SI-sMBP Ensemble of Kernels-OvO and SI-sMBP Ensemble of Kernels-OvA by sharing best performance for the ten classes each. The least of the performance was by PCA-SI-sMBP (Polynomial Kernel)-OvA with having lowest precision scores for the eight classes.

Figure 8.9(b) is showing the comparative recall graphs for all the thirty six classes and these are using all the proposed methodologies but for the PSL alphabets taken from the unknown signers. The best of the recall scores are through the proposed SI-sMBP Ensemble of Kernels-OvA that achieved leading ones for the twelve classes i.e., C-5, C-7, C-9, C-10, C-12, C-15, C-17, C-19, C-20, C-21, C-26 and C-28 with the values 88.89%, 72.92%, 40.48%, 50%, 94.87%, 46.15%, 52.38%, 12.20%, 64.86%, 88.57%, 100% and 84.62% respectively. While the lowest of the performance was through proposed PCA-SI-sMBP(RBF Kernel)-OvO that remained lowest among its fellows for the thirteen classes i.e., C-2, C-5, C-6, C-7, C-12, C-19, C-21, C-22, C-24, C-26, C-27, C-30 and C-35 with the values of 30%, 55.56%, 13.64%, 39.58%, 61.54%, 0%, 57.14%, 15%, 33.33%, 90.24%, 2.5%, 61.54% and 15.15% respectively.

8.3.4 Classification Matrices of the Proposed Technique for Known Signers:

The self explanatory classification matrices for the known signers using linear, RBF and polynomial kernels through OvO, OvA based classifications modalities are presented in this subsection. Each of the classification matrices represents the precision, recall, omission error and commission errors of the individual classes. The overall accuracy is shown in each of the matrices as well.

8.3.5 Classification Matrices of the Proposed Technique for Unknown Signers:

The self explanatory classification matrices for the unknown signers using linear, RBF and polynomial kernels and OvO, OvA based classifications are presented in Appendix C.

Summary

In the last two chapters, feature vectors resilient to the noise, rotation and scaling conditions were proposed that emerged to increase the size of the feature vector. Here, we have used principal component analysis to reduce the dimension of the feature vector. Dataset is partitioned into three subsets i.e., train, test and validation subsets. The feature vector with the least dimension but with the highest validation accuracy is selected as the final vector.

Chapter 9

PSL Continuous Alphabets Classification using Combined Histogram of Local Optical Flow Features and Support Vector Machines

Introduction

Continuous signs are generated through the motion of the hand and fingers. Their recognition leads to provide a base for the recognition of words and sentences of the sign language. The task of analyzing continuous signs is different from the static signs as the former involves temporal variations in them. A methodology for the recognition of PSL Continuous signs from the videos is proposed that extracts a feature vector through local optical flow features. The presented methodology can be used to interpret PSL words and sentences as well.

9.1 Proposed Methodology

The flow diagram of the proposed technique is presented in Fig. 9.1 where input is taken in the form of a video having moving object whose activity is to be analyzed. The proposed model detects and tracks the object using deep learning based YOLO-CNN followed by computing local optical flow features(LOFF) of the detected object. Sum of LOFF from all the frames is computed i.e., (SLOFF). A concatenation of histograms of SLOFF(CSLOFF) for all the features is performed that forms the required feature vector. The task of object activity classification is

performed using ECOC based multiclass SVMs.

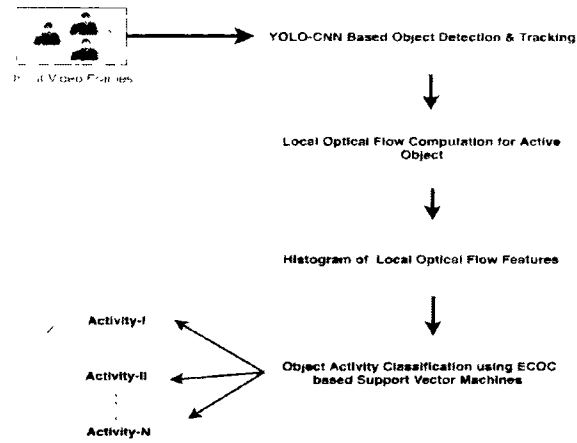


Figure 9.1: Flow Diagram of Proposed Technique

9.1.1 Deep Learning Based Hand Detection & Tracking

The first task for the recognition of continuous PSL alphabets is hand detection and tracking. We have presented detection based hand tracking using Yolo-CNN explained in chapter 5. The tracking purpose is achieved through providing each frame of video to YOLO-CNN that detects hand and provides coordinates of the hand enclosing window. In the preceding steps, the content of these hand enclosing windows is used to extract the key features.

9.1.2 Local Optical Flow Computation

Optical flow is used to represent the motion of the objects in a video. In the case of a continuous alphabet, it is represented by the motion of fingers and hand itself. Optical flow may provide an important clue in representing a continuous alphabet. Instead of computing the motion information in the whole of the video frame, we have adopted it to the hand region only termed as local optical flow. To serve the required purpose, we have used Horn and Schunk(HS)[160] methodology that uses a gradient constraint (brightness constancy) with a global smoothness to obtain an estimated velocity field. The HS algorithm accomplishes it by implementing two main processes i.e., (i) An estimation of partial derivatives (ii) Minimization of the sum of the errors by an iterative process to present the final motion vector.

9.1.2.1 Estimation of the Partial Derivatives

This section presents the estimation process of the classical derivatives of image intensity or brightness from the image sequence. The brightness of each pixel is constant along its motion trajectory in the image sequence. The relationship in continuous images sequence will be taken into account to estimate the original intensity for a gradient constraint. Let $Win(x,y,t)$ denote

the gradient intensity (brightness) of point (x,y) in the images at time t. In each image sequence, Win_x , Win_y , and Win_t are computed for each pixel.

$$Win_x = \frac{1}{4} \{Win(x, y+1, t) - Win(x, y, t) + Win(x+1, y+1, t) - Win(x+1, y, t) + Win(x, y+1, t+1) - Win(x, y, t+1) + Win(x+1, y+1, t+1) - Win(x+1, y, t+1)\} \quad (9.1)$$

$$Win_y = \frac{1}{4} \{Win(x+1, y, t) - Win(x, y, t) + Win(x+1, y+1, t) - Win(x, y+1, t) + Win(x+1, y, t+1) - Win(x, y, t+1) + Win(x+1, y+1, t+1) - Win(x, y+1, t+1)\} \quad (9.2)$$

$$Win_t = \frac{1}{4} \{Win(x, y, t+1) - Win(x, y, t) + Win(x+1, y, t+1) - Win(x+1, y, t) + Win(x, y+1, t+1) - Win(x, y+1, t) + Win(x+1, y+1, t+1) - Win(x+1, y+1, t)\} \quad (9.3)$$

9.1.2.2 Minimization of Sum of Errors

In practice, the image intensity or brightness measurement may be corrupted by quantization or noise. According to the equation for the rate of change of image brightness:

$$Win(x, y, t) = Win(x+u, y+v, t+1) \quad (9.4)$$

$$\epsilon = uWin_x + vWin_y + Win_t = 0 \quad (9.5)$$

where u and v are the horizontal and vertical motion vectors of optical flow, respectively, one cannot expect ϵ to be zero. The problem is to minimize the sum of errors in the equation for the rate of change of image brightness as near as 0. So, the smoothness weight (α) is iteratively presented as:

$$u^{k+1} = \bar{u}^k - Win_x[Win_x\bar{u}^k + Win_y\bar{v}^k + Win_t]/[\alpha^2 + Win_x^2 + win_y^2] \quad (9.6)$$

$$v^{k+1} = \bar{v}^k - Win_y[Win_x\bar{u}^k + Win_y\bar{v}^k + Win_t]/[\alpha^2 + Win_x^2 + win_y^2] \quad (9.7)$$

where $\bar{u}$ and $\bar{v}$ denote horizontal and vertical neighborhood averages (and), which initially are set to zero and then the weighted average of the value at neighboring points based on the

kernel is applied for further iterations using Eq. (9.6, 9.7). The smoothness weight (α) plays an important role where the brightness gradient is small, for which the suitable value should be determined.

9.1.3 Local Optical Flow Features Computation

Once local optical flow for each frame of the video is computed, there is a need to extract discriminant features from the computed motion vectors. Here, we have used two key features for representing PSL continuous alphabets i.e., horizontal velocity, vertical velocity magnitude and orientation. Horizontal and vertical velocities are already been computed, while the magnitude of both the velocity vectors is computed as:

$$Magnitude = \sqrt{u^2 + v^2} \quad (9.8)$$

While the orientation corresponding to the computed velocities are represented as:

$$Orientation = \tan^{-1}\left(\frac{v}{u}\right) \quad (9.9)$$

9.1.4 Histograms of SOF Features

Local optical flow over an object window in the consecutive frames represents the motion information of the object. A continuous alphabet is represented by actions of hand and fingers in a sequence of frames that can be represented by the cumulative optical flow information among all the frames. We have computed sum of optical flow features(SOFF) for all the frames representing an activity i.e.,

$$SOFF_i = \sum_{j=1}^n OFF_i : i \in \{\text{Horizontal Velocity, Vertical Velocity, Magnitude, Orientation}\} \quad (9.10)$$

Where n is the number of frames representing activity and OFF is the optical flow feature. The use of $SOFF_i$ as a feature space would not only require higher computation but due to their redundant nature, may not result in better classification. We have computed a histogram of each of the three computed vectors i.e.,

$$P = \sum_{r=1}^k HSOFF_i(r) \quad (9.11)$$

Where $P = m \times n$: m, n represents the height and width of the local window enclosing an object and k as the total number of bins of the histogram. All the histograms are combined to

form a single feature vector for the whole activity i.e.,

$$FV = \bigcup HSOFF_i : i \in \{\text{Horizontal Velocity, Vertical Velocity, Magnitude, Orientation}\} \quad (9.12)$$

9.1.5 Continuous PSL Alphabets Classification

The proposed approach uses multi-class Support Vector Machines(SVMs) for sign classification. Given a feature vector, FV, with dimension $1 \times K$ where K is kept for 64, 32 and 16 for the three distinct experiments. The use of four feature histograms to represent FV of an activity, the classification of the activity among three classes makes it a non linear problem. The decision function for the non-linear classification is represented as:

$$f(FV) = u \cdot \phi(FV) + c \quad (9.13)$$

where u and c represent weights and class margin respectively while ϕ is the kernel function that transforms the feature vector, FV, from lower to the higher dimensional space. In a kernel-based SVM, u may be represented as:

$$u = \sum_{j=1}^m \beta_j \phi(FV_j) \quad (9.14)$$

Placing the value of u in relation 9.13, the decision function would become

$$f(FV) = \sum_{j=1}^m \beta_j \phi(FV_j) \times \phi(FV) + c \quad (9.15)$$

Where $\phi(FV)\phi(FV_j)$ is defined as the kernel function and denoted as $KF(FV, FV_j)$. By replacing $\phi(FV)\phi(FV_j)$ with $KF(FV, FV_j)$, the decision function is given as:

$$f(FV) = \sum_{j=1}^m \beta_j KF(FV, FV_j) + c \quad (9.16)$$

We have adopted three kernels for solving the presented problem i.e. linear, radial basis function(RBF) and polynomial kernels. Error-correcting output code is a technique for solving problems of multiclass nature. It operates in two stages i.e., first, constructing several subordinate classifiers separately, each responsible for eliminating some ambiguity about the correct input class; second, applying a voting scheme to decide on the correct class, given the output of each weak learner. ECOC trains L binary classifiers and converts the multiple classification outcomes into a matrix called ECOC codebook. To interpret the codebook and predict the sample labels, a decoder is applied. There are several methods to encode or decode a codebook. Codebooks may also be densely or sparsely encoded. For dense codebooks, in each binary classifier, only +1 and -1 are generated as labels for each sample. In sparse

codebooks +1, -1 and 0 are specified where 0 labels non-classified samples. Its efficiency is more significant in problems having a higher number of classes. Once the multiclass classifier is tested using the trained model, an output codeword is generated which corresponds to the classifier combination. The hamming distance between the output codeword and the codeword for each class is calculated to determine the output class. The class whose codeword has a minimum Hamming distance from the output codeword is the class of test feature set. The hamming distance between the two codewords is computed as:

$$HD = cw_1 \oplus cw_2 \quad (9.17)$$

9.1.6 Results and Discussions

In this section, the results achieved through the proposed methodology when applied over the datasets, discussed in the previous section, and discussion over them is presented.

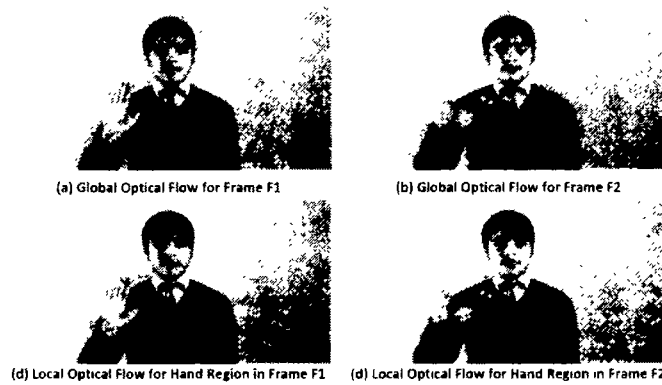


Figure 9.2: Hand Detection and Optical Flow Vectors Representation for Example Frames of PSL Alphabets

Figure 9.2 is showing the sample frames of the PSL videos where the signer is producing continuous alphabets. Figure 9.2(a),(b) are the pictorial representations where global optical flow over the whole frames are computed and plotted. It may be easily observed that motion vectors for all the objects are computed i.e., head and body movements other than the hand. This leads to the extraction of a feature vector resulting in compromise to the task of activity analysis of the required object. The proposed methodology in its first hand detects and localizes the required object in the frame through YOLO based CNNs. The detected objects are subject to the computation of optical flow in the localized regions i.e., the hand region for PSL continuous alphabet recognition and shown in figure 9.2(c) and figure 9.2(d). It is evident that the plotted optical flow is only for the localized region of the hand and outliers motions vectors would not be able to affect the accuracy.

As the computed local optical flow is the representation of the motion of the object in the consecutive frames and we need to analyze the whole video for anticipating the activity of the

object. Therefore, we have computed the sum of local optical flow(SLOF) presented in all frames of the video. i.e. $LOF_1 + LOF_2 + \dots + LOF_n$, where n is the total number of frames.

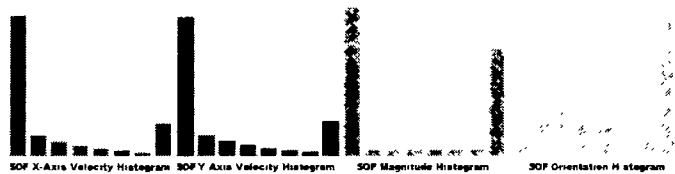


Figure 9.3: Combined Histogram using Sum of Optical Flow Histograms for Individual Feature

Four of the features from SLOF are extracted that represent velocities along with horizontal and vertical directions, velocity magnitude and orientations. The extracted features are the sum of the corresponding features in all the frames. The size of all of the four feature vectors corresponds to the size of the object in the image frames that may not be a good choice for classification purposes. For each of the individual features, the histogram of size k is computed. Instead of using four histograms, all the four histograms are concatenated to form combined SLOFH (CSLOFH) with size $4 \times k$ and shown in figure 9.3. We have tested the proposed approach by keeping $k = 16, 8, 4$ resultantly the size of CSLOFH was 64, 32 and 16.

Figure 9.4, through figure 9.6 are showing the confusion matrix obtained through applying ECOC SVM using feature vector, CSLOFH, of size 64, 32 and 16 respectively. For the class C-I, the precision score for both the multiclass configurations, two of the kernels(linear and RBF) and all the sizes of CSLOFH remained 100%. As well as, it remained 100% for the polynomial kernel with OvO modality but with the 90% for OvA multiclass SVMs. The best of recall for C-I i.e., 100%, was achieved when CSLOFH feature set of size 32 was used. The highest precision for C-II was through the use of RBF kernel i.e., 100% and it was for all the CSLOFH sizes and both the multiclass modalities. The best of the recall scores were for RBF kernel for CSLOFH of size 64, 16 and OvA and OvO modality respectively.

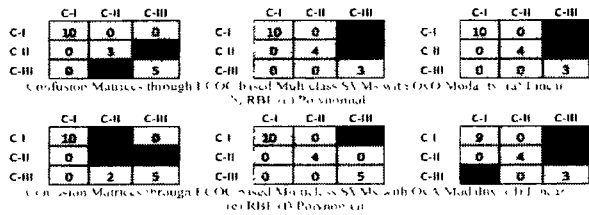


Figure 9.4: Results for PSL dataset using CSLOFH of Length 64

The highest precision for class C-III of PSL dataset was achieved through RBF kernel with all the CSLOFH sizes(except 64 sized) and both the multiclass modalities i.e., 83.33%. The same scenario happened for the recall with a score of 100%.

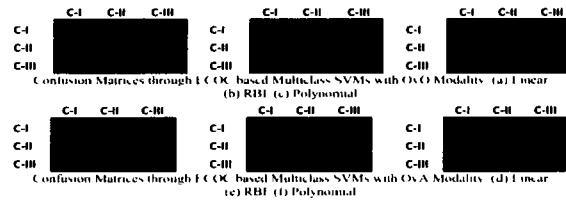


Figure 9.5: Results for PSL dataset using CSLOFH of Length 32

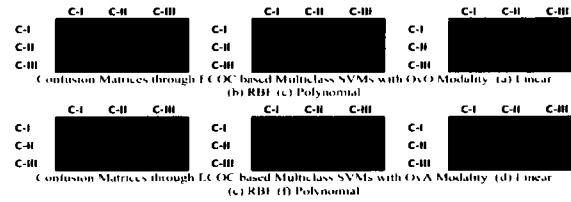


Figure 9.6: Results for PSL dataset using CSLOFH of Length 16

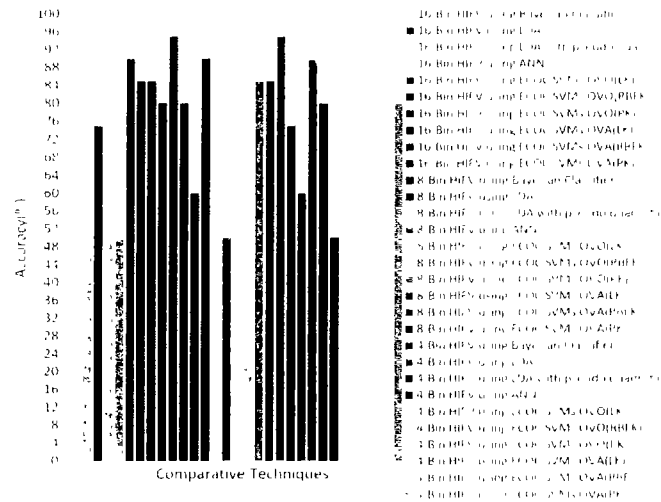


Figure 9.7: Comparative Results of the Proposed Technique with Existing Research over PSL Dataset

Figure 9.7 is an accuracy based comparative analysis of the proposed CSLOFH feature vector but for the PSL dataset with different feature dimensions, kernels and multiclass modalities. In the comparative analysis other than the ECOC-SVMs settings Bayesian, LDA variants and ANN classifier based results are presented as well. From the comparative statistics, it may be observed that while keeping the size of the histogram of individual feature vector(HIFV) as 1×16 the highest of the accuracy was 95% while ECOC-SVM classifier with RBF kernel(RBFK) and OvA multiclass modality was used. ANN classifier attained the least of accuracy with a score of 50%. When the size of HIFV was kept 1×8 , the best of the accuracy was achieved through RBF kernel based SVMs i.e., 95% for both OvO and OvA modalities. Among the rest of the

classifiers, 90% accuracy was achieved through LDA. While ANN couldn't perform better for the feature vector of size 1×32 and remain at the bottom with 50% accuracy. In case of HIFV with size 1×4 , all the classifiers except psedu quadratic LDA and multiclass SVMs with RBF kernel using OvA modality attained the same results as HIFV with size 1×8 . The results of both the mentioned classifiers are improved i.e., 80% accuracy for psedu quadratic LDA as compared to 60% and 80% accuracy for SVMs with RBF kernel using OvA modality (with HIFV size 1×4) compared to 75% accuracy (with HIFV size 1×8). It may be concluded that the results with the feature vector of size 1×16 and 1×32 are almost the same. It may also be deduced that as the feature vector size gets increased, classification accuracy is compromised for most of the classifiers.

Summary

This chapter presents the recognition of the continuous PSL alphabets from videos. Histogram features from local optical flow are computed that contribute to form a combined histogram. Classification task is completed using multiclass support vector machines. Results from different configurations involving size of feature vectors, selection of SVM kernels and multiclass modalities are presented as well.

Chapter 10

Pakistan Sign Language Word Recognition from Videos and Images using Fingerspelling

Introduction

Fingerspelling (or dactylology) is used to represent the alphabets and words of a natural language or number system through the hand signs. The alphabets are shown through the isolated hand signs while the words are spelled through a series of hand signs each representing a single alphabet. These finger or hand alphabets are adopted in deaf education as well. Fingerspelling has been introduced into certain sign languages by educators, and as such has some structural properties that are unlike the visually motivated and multi-layered signs that are typical in deaf sign languages. In many ways, fingerspelling serves as a bridge between the sign language and the oral language that surrounds it. In different sign languages, fingerspelling is used for different purposes. When there is no exact sign available for an oral word in a sign language, to represent some proper noun or to put emphasis or clarification, these fingerspelling may be used. The use of fingerspelling in sign languages is diminishing over time like 8.7% casual signing of ASL are generated through fingerspelling[161] while 10% for the same have participated through fingerspelling for Auslan[162] which is lower than the historic use of fingerspelling. Fingerspelling does not seem to be used much in the sign languages of Eastern Europe, except in schools[163] and Italian Sign Language is also said to use very little fingerspelling, and mainly for foreign words. Sign languages that make no use of fingerspelling at all include Kata Kolok and Ban Khor Sign Language. Many of the words in Pakistan Sign Language utilize the two-handed, or manual, alphabet. The one-handed alphabet employed by American Sign Language has become the international standard and is recognizable nation-wide.

Although, Urdu finger spelling is not in common use yet it may be used in the same scenarios as used by other sign languages. Here we have presented a framework for automatic recognition of the PSL words that are generated through fingerspelling.

10.1 Proposed Framework for PSL Fingerspelling Recognition

The work flow of the proposed framework is presented in figure 10.1 that may process two kinds of the input i.e. (i) PSL video (ii) PSL images. When input is provided in the form of video frames, the proposed framework extracts the isolated PSL alphabets that matches the case of PSL fingerspelling images. The next of the task is hand detection, localization and tracking followed by the feature extraction. The classification task leads to provide class code of the PSL individual alphabets those in combination provide translated Urdu word. The proposed framework has used the concept of classification error during translation phase using external dictionary.

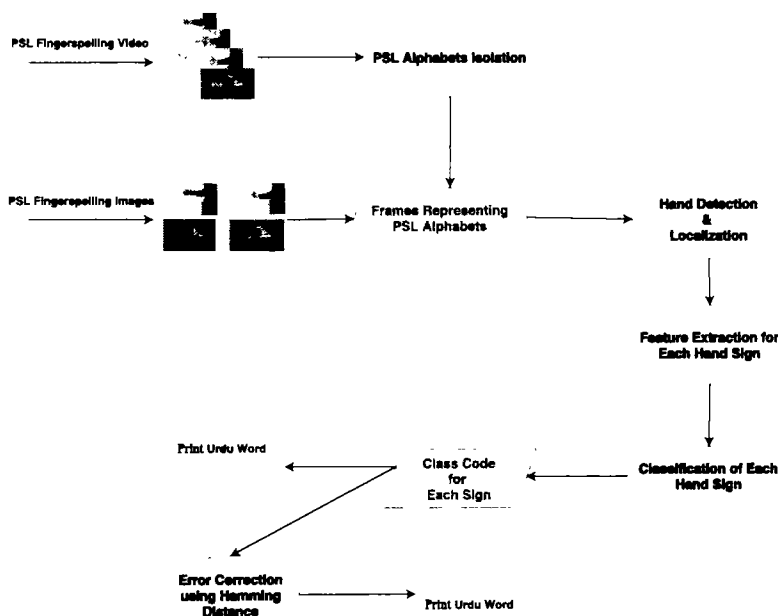


Figure 10.1: Work Flow of the Proposed Framework

10.1.1 PSL Alphabets Isolation

While PSL alphabet images are provided as input, there is no need to process in this step as they are already isolated. In case videos are input, individual alphabet hands are extracted through PSL alphabets isolation & extraction algorithm(PAIEA).

Algorithm 7 : PSL Alphabets Isolation & Extraction Algorithm(PAIEA)

INPUT: Input Video iV **OUTPUT:** Set of PSL Isolated Alphabets($sPIA$)

- 1: Detect & Localize hand region using YOLO-CNN as explained in 5. Detection in each frame serves the purpose of hand tracking.
- 2: Detect motion in hand regions through hand regions in consecutive Frames i.e.,

$$Win_t = ||win(x, y, t) - win(x, y, t + 1)|| \quad (10.1)$$

- 3: Compute centroid of the hand enclosing rectangle using following formula i.e.,

$$(x_c, y_c) = ((x_0 + x_n)/2, (y_0 + y_n)/2) \quad (10.2)$$

- 4: If motion vectors have low values and the centroid of the rectangle remains constant for t seconds, extract the hand i.e., $sPIA = sPIA \cup \{\text{Extracted Hand}\}$
 - 5: Otherwise, Repeat step 1 through 3
 - 6: Wait for t_1 seconds, if the hand gets out of the frame, continue steps 1 through 5 and store each extracted hand separately.
-

PAIEA takes input video and as its first step, detects and localizes the hand in each of the frame using YOLO based CNNs(the process is already explained in chapter 5). The next of the phase is subject to the detection of the hand. The motion vectors within the hand enclosed window is computed through finding differences between hand windows detected in consecutive frames. In case of no sufficient motion in the hand window for a specific period of time, the hand is extracted representing an individual alphabet. The process is repeated till all the individual alphabets are not extracted.

10.1.2 Feature Extraction & Classification

The feature computation process over the extracted hands (in a sequence) is accomplished using PCA SI-sMBP as presented in chapter 8 while classification purpose is served through multiclass SVMs using ensemble of kernels i.e. defined in chapter 7. The sequential output of the classifier would result Urdu alphabets that would represent a word(combination of the output alphabets)

10.1.3 PSL Alphabets Encoding

We have presented PSL alphabets encoding in table 10.1 that would help us to verify the output word.

Table 10.1: PSL Alphabets Coding

Class	Desc.	Code	Class	Desc.	Code	Class	Desc.	Code
C-1	AIN	0	C-13	HAY	c	C-25	SEEN	o
C-2	ALIF	1	C-14	HHAY	d	C-26	SHEEN	p
C-3	BAY	2	C-15	KAF	e	C-27	SAAY	q
C-4	BYAY	3	C-16	KHAY	f	C-28	SWAD	r
C-5	CHAY	4	C-17	LAM	g	C-29	TAY	s
C-6	DAL	5	C-18	MEEM	h	C-30	TOUY	t
C-7	DDAL	6	C-19	NOON	i	C-31	TTAY	u
C-8	DWAD	7	C-20	NOONGHUNA	j	C-32	WOW	v
C-9	FAY	8	C-21	PAY	k	C-33	YAY	w
C-10	GHAFA	9	C-22	QAF	l	C-34	ZAL	x
C-11	GHAIN	a	C-23	RAY	m	C-35	ZAY	y
C-12	HAMZA	b	C-24	SAY	n	C-36	ZOUY	z

10.1.4 Computing PSL Fingerspelling Accuracy

The overall accuracy for the recognition of PSL words is dependent on the accuracy of the individual words. Let, the whole fingerspelling is a system and each of the alphabet in it is a component. Like the Pythagorean theorem, the system accuracy is equal to the square root of the sum of the squares of each component's absolute accuracy i.e.,

$$\text{Fingerspelling Acc.} = \sqrt{(\text{Alphabet}_1 \text{ Acc.})^2 + (\text{Alphabet}_2 \text{ Acc.})^2 + \dots + (\text{Alphabet}_n \text{ Acc.})^2} \quad (10.3)$$

10.1.5 Error Corrections using Hamming Distance

We have employed the concept of the error correction to the classification accuracy of the system. The concept is materialized through the use of the Urdu language words coding dictionary. Figure 10.2 is showing examples from such a dictionary (the whole of the dictionary needs to be generated) where Urdu word along its code and length is given.

Figure 10.3 shows the systematic output of the proposed methodology and the translated Urdu word. The fingerspelling was representing the four length Urdu Word whose individual components are classified as C-1, C-13, C-28 and C-6. The output code representing the fingerspelling video is 1cr5.

Word	Word Code	Word Length
احمد	1ch5	4
نیکال	lwklg	5
پانستون	Kieosl1	7
کینو	lwiv	4
تیر	pwm	3
نید	5iw1	4
یس	2o	2
ٹرک	sme	3
کتاب	es12	4

Figure 10.2: Coding Detail for Example Words of PSL

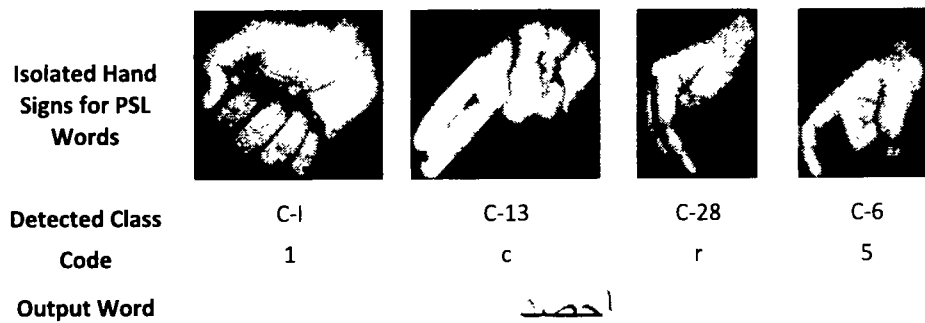


Figure 10.3: PSL Word Translation using Proposed Model

The introduction of the Urdu word encoding scheme helps to validate the correctness of the fingerspelling translation and minimizing the accuracy error through correcting them. The input fingerspelling is an example where one of the alphabet represented by class C-18 is misclassified as class C-28. The fingerspelling was representing a four-length word 'Ahmed' but classified as 'Ahsed'. To validate the translated word hamming distance between the output code of the fingerspelling and the code of the vocabulary words of the matching lengths is computed. If the output code has zero hamming distance with some of the stored code, the output is correct and printed as output word i.e.,

$$HD = \text{output code} \oplus \text{vocabulary code with match length with output code} \quad (10.4)$$

$$HD = 1cr5 \oplus 1ch5 = 1 \quad (10.5)$$

$$HD = 1cr5 \oplus lwiv = 4 \quad (10.6)$$

Summary

This chapter is about presenting the recognition of the PSL words generated through the fingerspelling. We have employed the sI-sMBP feature vector computed in the previous chapters and external urdu words coding dictionary with the combination of hamming distance is used to complete the translation task.

Chapter 11

Shape based Pakistan Sign Language Categorization using Statistical Features of Uniform Local Binary Patterns

Introduction

Automatic recognition of PSL alphabets into the predefined categories is presented here. The seven categories are defined using the visibility, shape and orientations of both the fingers and the hand. The histograms of the uniform local binary (lbp) for the neighboring distance of one, two and three are computed and concatenated to form a single vector. At a later step, six statistical features of the combined histogram are computed i.e., standard deviation, variance, skewness, kurtosis, entropy and energy. The classification is achieved using support vector machines (SVM). The modality of one-vs-one is used for the adoption of binary SVM into the multi-class SVM. The proposed technique is validated over the dataset of 3414 PSL signs, taken through the help of seven native signers. The performance of the proposed technique is evaluated by precision, recall, accuracy and f-measure while it is elaborated through the classification matrix, tabular and graph representations.

11.1 Proposed Solution

The Proposed technique is elaborated in figure 11.1 where the input image is subject to the preprocessing in prior to the calculation of uniform LBP features over the 16×16 blocks with half overlapping. The uniform histograms of all the blocks are concatenated to form a

single 1-D vector. In a second step, the statistical features of concatenated uniform LBP are calculated. The statistical features are then fed to the multiclass SVM, resulting in one of the seven predefined categories.

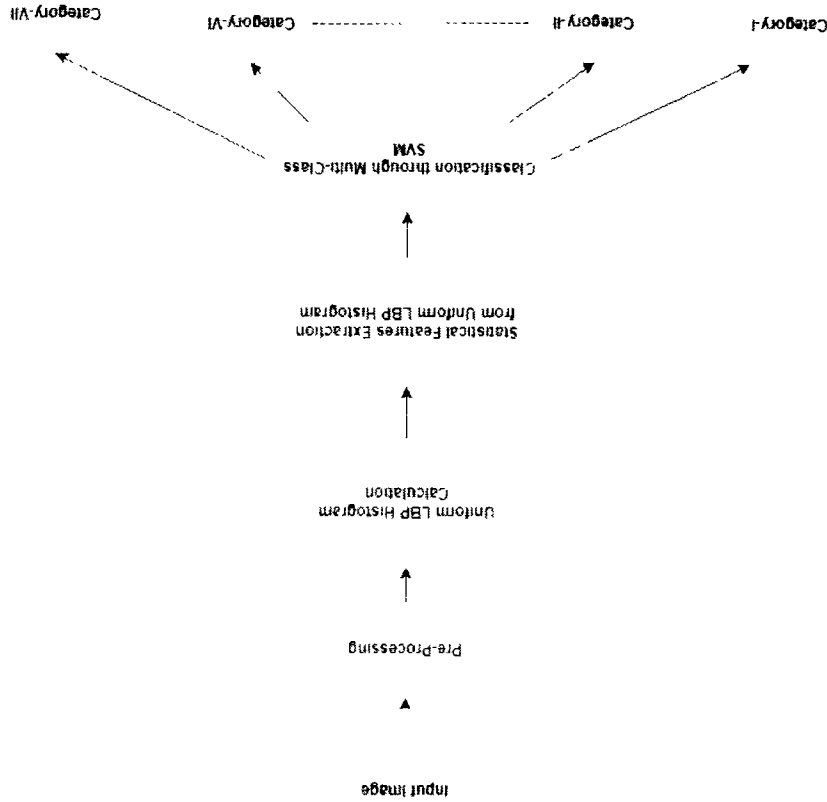


Figure 11.1: Flow diagram of the Proposed Research

11.1.1 Uniform LBP

The standard lbp is calculated as:

$$LBP_{NP,R} = \sum_{n=1}^n d(g_n - g_c) 2^{NP} \quad (11.1)$$

where

$$d(i) = \begin{cases} 1, & \text{if } (i \geq 0) \\ 0, & \text{Otherwise} \end{cases} \quad (11.2)$$

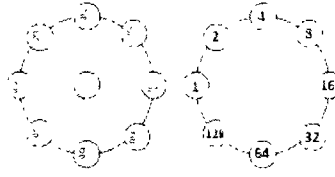


Figure 11.2: Standard LBP Configuration

The bit pattern representation of the lbp is shown in figure 11.2. While, the uniform lbp is obtained through the given expression i.e.,

$$LBP_{NP,R}^{riu2} = \begin{cases} \sum_{n=1}^{NP} d(g_n - g_c), & \text{if } U(LBP_{NP,R}) \leq 2 \\ NP + 1, & \text{if } U(LBP_{NP,R}) > 2 \end{cases} \quad (11.3)$$

where

$$U(LBP_{NP,R}) = |d(g_{NP} - g_c) - d(g_0 - g_c)| + \sum_{n=1}^{NP} |d(g_n - g_c) - d(g_{n-1} - g_c)| \quad (11.4)$$

In an LBP pattern, a transition from 1 to 0 and back from 0 to 1 or vice versa represents the edge(change). If the resultant pattern has more transitions, it is a redundant one. On the other hand, a pattern with no change represents a flat region. The features of the interest are flat regions and regions with one or two transitions and their patterns are called uniform LBP. The uniform LBP patterns have 59 different combinations. These are shown along with their corresponding patterns in figure 11.3.

Algorithm 8 Neighbor Pixels Determination Algorithm(NPDA)

Input: Number of Neighboring Pixels(NNP), Distance(d)

Output: Neighbor Pixel Positions $(x_k, y_k) : 1 \leq k \leq NNP$

- 1: $step = \pi / NNP$;
 - 2: **repeat**
 - 3: $y_i = -d * \sin((i - 1) * step)$
 - 4: $x_i = -d * \cos((i - 1) * step)$
 - 5: **if** (x_i, y_i) is not the valid pixel position **then**
 - 6: interpolation is used to find valid location for i^{th} neighbor
 - 7: **end if**
 - 8: **until** $\forall 1 \leq i \leq NNP$
-

The neighboring pixels(NP) are determined by neighbor pixels determination algorithm(NPDA). The NPDA works by taking the required number of neighboring pixels at a distance, d, from the pixel under consideration and returns the exact position of the required neighbor pixels.

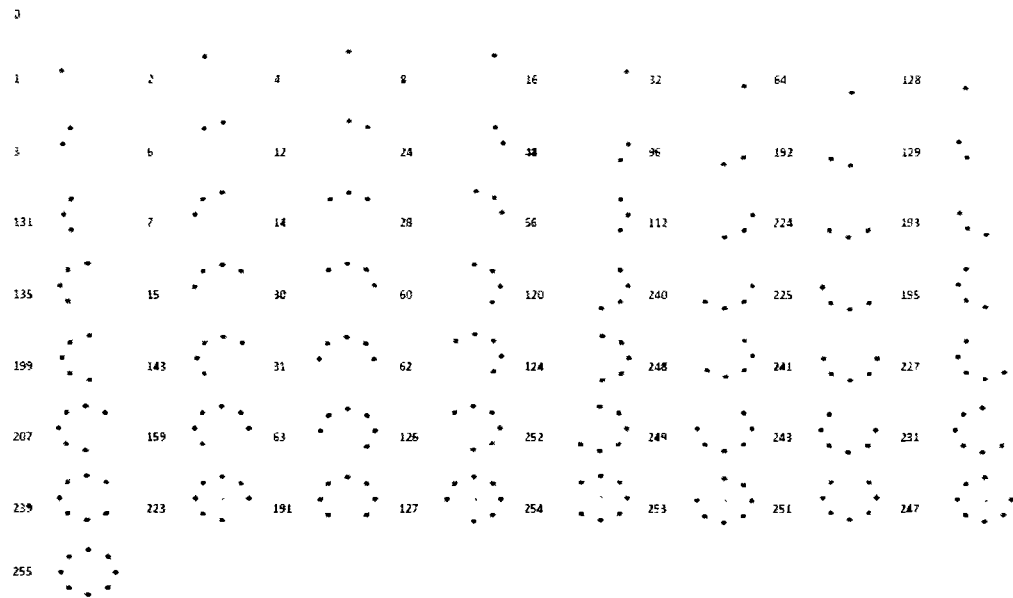


Figure 11.3: Uniform LBP Configuration

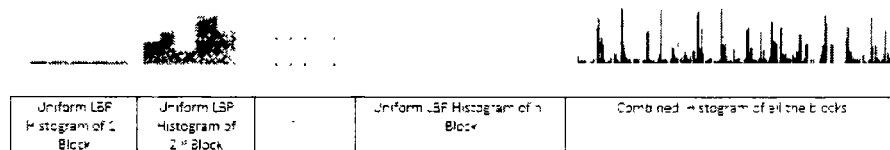


Figure 11.4: Concatenated uniform-LBP Histogram of the 16x16 Blocks

The histogram of uniform lbp calculated for each of 16×16 block is then concatenated to form a 1-D histogram as shown in figure 11.4.

11.1.2 LBP Histogram based Features

In the proposed approach, we have used six statistical features of lbp histogram i.e., standard deviation, variance, skewness, kurtosis, entropy and energy. The first four of the features are termed as first, second, third and fourth order moments along the mean respectively. The details of all the six features are presented here.

11.1.2.1 Standard Deviation

Definition 11.1.1. Given an lbp Histogram $LBPH$ with its number of bins(N) and mean i.e., μ_{LBPH} , the standard deviation σ gives information about all the $LBPH$ member scores deviation from the μ_{LBPH} .

The standard deviation of the lbp histogram is calculated through the following relation:

$$\sigma = \frac{\sqrt{\sum_{n=1}^N (LBPH_n - \mu)^2}}{N} \quad (11.5)$$

and

$$\mu_{LBPH} = \frac{\sum_{n=1}^N LBPH_n}{N} \quad (11.6)$$

11.1.2.2 Variance

Variance of the lbp histogram is defined as:

Definition 11.1.2. *Given an lbp Histogram LBPH with N number of bins, the variance of the LBPH is its squared deviation from the mean.*

while the statistic is computed through the given relation i.e.,

$$\sigma^2 = \frac{(\sqrt{\sum_{n=1}^N (LBPH_n - \mu)^2})^2}{N} \quad (11.7)$$

11.1.2.3 Skewness

The skewness is called the third moment along the mean and with reference to the lbp histogram, it may be defined as:

Definition 11.1.3. *The Skewness, γ_1 , of a lbp histogram, LBPH, represents the relationship between the distribution of LBPH and the normal one.*

The skewness is computed as following:

$$\gamma_1 = \frac{\frac{1}{N} \sum_{n=1}^N (LBPH_n - \mu)^3}{\sqrt{\frac{1}{N} \sum_{n=1}^N (LBPH_n - \mu)^2}^3} \quad (11.8)$$

11.1.2.4 Kurtosis

Kurtosis is the fourth moment about the mean and its definition in context of lbp histogram is given as:

Definition 11.1.4. *The Kurtosis(K) of an lbp histogram LBPH along the mean, μ , represents peakness of the histogram distribution with reference to the mean position. Higher the kurtosis means more outliers and vice versa.*

For the given histogram of N bins, it is calculated as:

$$K = \frac{\frac{1}{N} \sum_{n=1}^N (HV_n - \mu)^4}{(\frac{1}{N} \sum_{n=1}^N (HV_n - \mu)^2)^2} \quad (11.9)$$

11.1.2.5 Entropy

The entropy is said to be the disorderness of a system, while in the given context it is defined as:

Definition 11.1.5. *Given the uniform lbp histogram(LBPH), the entropy represents the variation of probability distribution function(pdf) of the LBPH. lower the entropy means flat histogram and vice versa.*

The entropy of a uniform lbp histogram(LBPH) is computed by:

$$E_n = \log(step) - \sum_{i=1}^N (pLBPH_i * \log(pLBPH_i)) \quad (11.10)$$

where

$$pLBPH_i = \frac{pLBPH_n}{\sum_{j=1}^N pLBPH_j}$$

the $pLBPH_i$ represents the pdf of the i^{th} member of the LBPH, while the step is calculated as: and

$$step = H(2) - H(1)$$

step represents the difference between two consecutive member positions of the LBPH. We have used step=1.

11.1.2.6 Energy

The energy, E_r of a lbp histogram is defined as:

Definition 11.1.6. *Given the probability distribution function($pLBPH$) of the LBPH, the energy(E_r) gives information about the distribution of the LBP values.*

It is computed through equation (10) i.e.,

$$E_r = \sum_{n=1}^N (pLBPH_n * pLBPH_n) \quad (11.11)$$

The LBP histograms for each of the PSL alphabets are calculated for three distances i.e., $d=1$, $d=2$ and $d=3$. At each distance, all the block histograms are concatenated to form the concatenated uniform LBP histograms. All six features are separately calculated for each of the concatenated uniform histograms. The feature sets for all the three concatenated uniform LBP histograms are merged to form the final feature set, s , as shown in figure 11.5.

μ	σ	γ_k	k	E_n	E_r	μ	σ	γ_k	k	E_n	E_r	μ	σ	γ_k	k	E_n	E_r
Statistical Features of Combined LBP of all Blocks at d=1						Statistical Features of Combined LBP of all Blocks at d=2						Statistical Features of Combined LBP of all Blocks at d=3					

Figure 11.5: Concatenation of Statistical features at $d=1,2,3$

11.1.3 Classification

In the proposed technique, multi-class Support Vector Machine(SVM) is used for PSL alphabet classification (i.e., PSL alphabets categorization). The input dataset $m \times p$ is divided into two subsets: 1) Train-Data and 2) Test-Data. As dimension of the input feature set is eighteen(18), the train-Data becomes of order $t_r \times 18$ while test-Data is $t \times 18$. The solution to the problem of multi-class is achieved through the combination of multiple binary class SVMs.

The decision functions for the binary-class linear SVMs are represented by $(u.s_j + c) \leq -1$ if $t_j = -1$ and $(u.s_j + c) \geq 1$ if $t_j = 1$. The two relations can be combined to cover both the cases i.e., $t_j(u.s_j + c) \geq 1$ where t represents the class, s is the input feature vector, u represents weight and c is the margin. The categorization of PSL signs into seven categories(each category contain multiple alphabets), each of the sign represented through a 18-dimensional feature set, is non-linear problem. Decision function for the non-linear classification is represented as $f(s) = u.\Phi(s) + c$. This is presented as we are dealing with the research problem having input feature subset instead of a single dimensional problem. For a higher dimensional data convergence, SVM kernel functions are widely used. In a kernel-based SVM, u may be represented as $u = \sum_{j=1}^m \beta_j \Phi(s_j)$. Decision function for a Non-linear classification problem having multidimensional feature set can be represented as:

$$f(s) = \sum_{j=1}^m \beta_j \Phi(s_j) \cdot \Phi(s) + c \quad (11.12)$$

where $\Phi(s_j) \cdot \Phi(s)$ is defined as the kernel function and denoted as $KF(s, s_j)$. By replacing $\Phi(s_j) \cdot \Phi(s)$ by $KF(s, s_j)$ the decision function is given as:

$$f(s) = \sum_{j=1}^m \beta_j \cdot KF(s, s_j) + c \quad (11.13)$$

In order to solve the non-linear separable problems(with high dimension feature set), the radial basis function based kernel is identified as the most suitable. This is due to the RBF kernel being known to be used in solving infinite dimension problems. The RBF kernel can be represented as

$$KF(s, s_j) = e^{(-\gamma \|s - s_j\|^2)} \quad (11.14)$$

By substituting (13) into (12), the required decision function becomes:

$$f(s) = \sum_{j=1}^m \beta_j \cdot e^{(-\gamma \|s - s_j\|^2)} + c \quad (11.15)$$

In order to adopt the binary class SVM for the multi-class problem of N categories and using the one-vs-one approach, we need to build $\frac{N(N-1)}{2}$ binary SVM classifiers[?]. In the presented research N=6, so $C = \frac{7(7-1)}{2}$ binary SVM classifiers are modeled i.e C=21. The classifiers may be termed as CatI-vs-CatII, CatI-vs-CatIII,....., CatVI-vs-CatVII. The final classification

of the input feature set, s , through the one-vs-one multi-class classifiers is achieved as:

$$f(s) = \arg \max_p \left(\sum_q f_{p,q}(s) \right) \quad (11.16)$$

where $p, q \in \{CatI, CatII, CatIII, \dots, CatVII\}$ and $f_{p,q} \in \{CatI - vs - CatII, CatI - vs - CatIII, \dots, CatVI - vs - CatVII\}$.

11.2 Dataset and Evaluation Metrics

In this section details of dataset and the metrics used to evaluate the proposed technique are presented.

11.2.1 Dataset

Here, the complete detail of the dataset is presented. It may be observed from figure 11.6 that the PSL alphabets are partitioned into predefined seven groups. The alphabets are split into these categories on the basis of the shape and orientations of both the hand and fingers. The description of each of the categories is given in Table 12.1.

Table 11.1: PSL Alphabet Category Description

Categories	Description
Cat-I	Fist Facing Camera with Most Fingers Closed
Cat-II	Fingers Making Camera Facing Arc
Cat-III	Fingers Making Elliptical Shape sidewise
Cat-IV	One to Three fingers opened/tilted right while rest closed
Cat-V	Upward fingers facing camera
Cat-VI	Two fingers making Victory like symbol upward or downward
Cat-VII	Fingers facing down

It is obvious from figure 11.6 that category-I is having seven signs read as 'Alif', 'Tay', 'Seen', 'Wao', 'Choti Yay', 'Bari Yay' and 'sauud'. Category-II again has seven alphabet signs i.e., 'Saay', 'Dal', 'Zaal', 'Ain', 'Ghain', 'Noon Ghuna' and 'Kaaf'. Category-III have five alphabets i.e., 'Daal', 'Sheen', 'Tauy', 'Zauy' and 'hay' while category-IV has seven signs as well i.e., 'Chay', 'Hae', 'Zaay', 'Gaaf', 'Hamza', 'Taey' and 'Khaey'. Category-V is defined over five signs including 'Bay', 'Fay', 'Ra'ay', 'Alif Paish', 'Laam' and 'Zavad'. Category-VI is composed of three alphabets having 'Ray', 'Kaaf', 'Paay' while category-VII has 'Meem' and 'Noon' in it.

The dataset is created through the help of seven signers. Overall 3414 sign images are created. The details of dataset used in multi-class SVM for classification through one-versus-one modality is shown in table 11.2. Out of total 3414 signs, 2384 are used for training while 1030 signs served for testing purpose.

Figure 11.7 gives information about the ratios of training and test data, for all the seven classes.

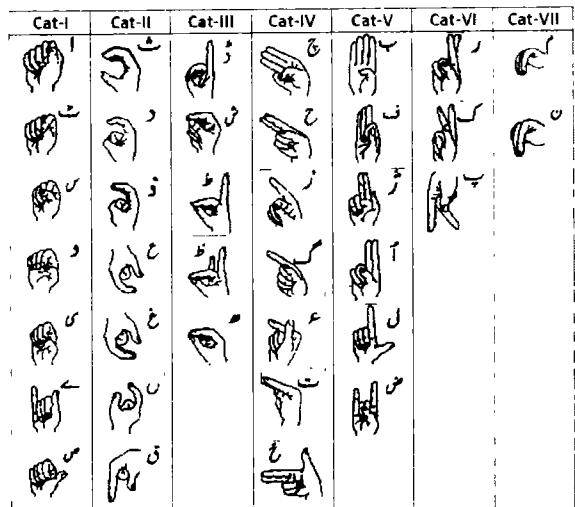


Figure 11.6: PSL Alphabet Categories

Table 11.2: PSL Dataset Description

	Cat-I	Cat-II	Cat-III	Cat-IV	Cat-V	Cat-VI	Cat-VII	Total Images
Training	444	451	315	406	419	209	140	2384
Test	186	191	135	188	180	90	60	1030

For all the categories, the mean number of signs of training sets is 341 while for the test data it is 147.14.

The graph shows the ratios between the signs in training, test set and their respective means. In the case of the training data, category-I has the highest ratio(1.32) to the mean of all the categories while the category-VII has least ratio(0.41). In the case of test data, the same categories hold high and low ratios with the numbers 1.30 and 0.41 respectively.

11.3 Results and Discussion

In this section, we present the results achieved through the proposed technique along detail discussion over them.

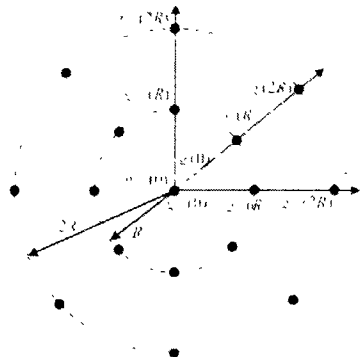


Figure 11.8: Example results of 8-neighbors determination through NPDA at $d=1$ and $d=-2$

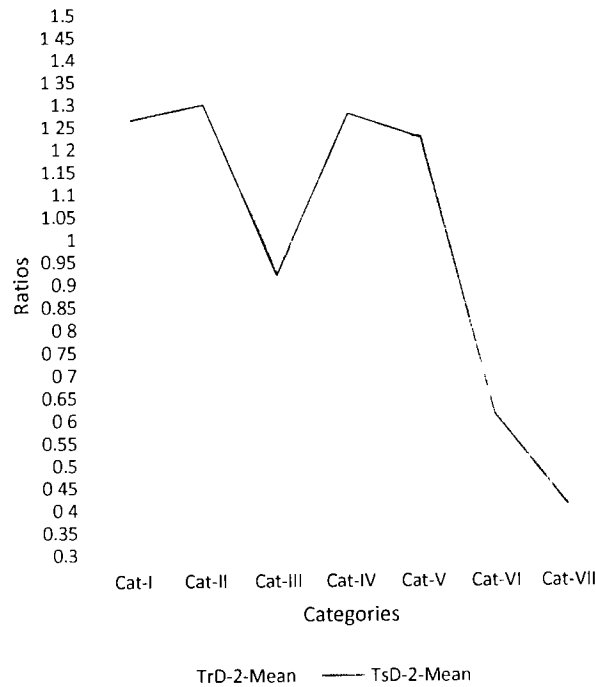


Figure 11.7: Training to Test data ratios for PSL Alphabet Categories

In this research, we have calculated the LBP patterns at three different distances i.e., $d=1,2,3$ and for all three distances, the number of neighboring points is taken as eight. The different radii are kept to make the LBP pattern scale invariants. While the required neighboring points along with the distance is provided to the NPDA, it returns the exact position of all the eight neighboring pixels i.e., $(x_k, y_k) : 1 \leq k \leq 8$. The example pixels positions at two different distances may be visualized in figure 11.8

Table 11.3 through Table 11.5 show the details of all the six features extracted through the proposed technique. The features are explained here in the form of their mean, minimum and maximum values. These feature statistics are calculated for the training data only. Table 11.3 is showing the uniform LBP histogram feature statistics when the distance is kept as one. It may

Table 11.3: Max, Min and Mean values of Statistical Features for PSL Categories calculated at $d=1$

	Standard Deviation			Variance			Skewness			Kurtosis			Entropy			Energy		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Cat-I	2692.49	1523.3	7141.7	8596280.18	2320600	51003000	5.44	2.58	7.47	36.85	10.59	56.92	2.99	0.93	3.44	3.12	1.13	16.62
Cat-II	3548.90	2417.6	5428.6	12896867.41	5844600	29469000	6.93	6.19	7.39	51.45	43.942	56.08	2.71	1.87	3.20	4.49	2.25	9.77
Cat-III	4008.71	1693.6	5349.5	16993368.25	2868400	28617000	6.93	3.42	7.38	51.48	17.535	55.93	2.49	1.89	3.35	5.80	1.30	9.49
Cat-IV	4205.86	3224.7	5438.6	17935650.25	10398000	29579000	7.11	6.62	7.37	53.19	48.193	55.83	2.40	1.82	2.82	6.10	3.70	9.80
Cat-V	3454.30	2270.3	5577.9	12473531.26	5154300	31113000	6.69	5.44	7.41	48.10	36.266	56.26	2.71	1.76	3.20	4.36	2.03	10.29
Cat-VI	3321.21	2779.2	4658.3	11202056.46	7723800	21700000	6.67	6.09	7.19	48.71	42.785	54.07	2.76	2.18	2.10	3.95	2.85	7.29
Cat-VII	3677.53	2825.8	4152.3	13563634.29	7985100	17242000	6.99	6.4546	7.19	52.02	46.724	54.05	2.65	2.44	2.98	4.70	2.93	5.87

be observed that the highest 'average' standard deviation is for the cat-IV while the least is for the cat-I, the same pattern exists for all the other features as well. The 'min' statistics for all the

six features give reflection that cat-I has least of all the categories. The same doesn't happen for the 'max' calculation e.g., cat-I has lesser average standard deviation but the highest 'max' standard deviation among other categories. The same reflection is there for all the other five features as well when 'max' values are studied. It may be concluded that the cat-I has wide range of values for all the six features while cat-VII has reverse of it.

Table 11.4 is showing the same statistics of the features as by the table 11.3 but for the features

Table 11.4: Max, Min and Mean values of Statistical Features for PSL Categories calculated at d=2

	Standard Deviation			Variance			Skewness			Kurtosis			Entropy			Energy		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Cat-I	2492.39	1328.0	6948.8	7542137.61	1763500	48286000	5.47	2.73	7.48	36.91	11.27	56.93	3.13	1.01	3.57	2.78	0.94	15.74
Cat-II	3351.83	2291.9	5212.8	11519244.79	5253000	27173000	6.88	6.13	7.38	50.82	42.91	55.96	2.82	1.96	3.29	4.04	2.05	9.02
Cat-III	3807.17	1538.8	5122.8	15389991.43	2367800	26243000	6.94	3.63	7.37	51.46	18.97	55.86	2.60	1.98	3.48	5.27	1.17	8.73
Cat-IV	4005.14	3033.3	5247.4	16284705.42	9200700	27535000	7.12	6.68	7.37	53.31	48.73	55.91	2.51	1.91	2.94	5.56	3.30	9.14
Cat-V	3255.47	2124.7	5408.1	11126994.75	4514300	29248000	6.77	5.68	7.42	49.82	38.60	56.36	2.84	1.86	3.31	3.92	1.81	9.68
Cat-VI	3111.33	2552.4	4409.9	9850793.78	6514800	19447000	6.72	6.17	7.19	49.21	43.69	54.08	2.89	2.30	3.13	3.51	2.45	6.56
Cat-VII	3481.36	2611.2	3899.0	12155533.57	6818100	15202000	6.93	6.47	7.14	51.28	46.83	53.55	2.75	2.55	3.11	4.24	2.54	5.21

extracted from uniform lbp histogram calculated at a distance of two. The least average and minimum standard deviation is for the category-I while the highest of the maximum standard deviations is for the same as well. The same pattern follows for the case of variance as the variance is squared of the standard deviation. Category-I signs have the highest range of standard deviation values while the category-VII has the least range, the same is for variance, skewness, kurtosis and Energy as well. The category-I has same response for the entropy but the least of the value range is for the category-II.

Same as above for the table 11.3 and table 11.4, table 11.5 is showing feature statistics in the form of mean, minimum and maximum. The statistics are for the features extracted from the uniform LBP histogram calculated at a distance of three. Same as the previous two cases, category-I has wider and category-VII has a narrow range of values for all the six features extracted from the histogram of distance three.

Originally, the SVM classifiers has nature of solving the binary class problems. In order to solve the multi-class problem, we have used one-vs-one SVM classifier adoption. In order to classify the PSL alphabets into seven categories, we have used fifteen(15) binary SVM classifiers. Each of the classifier was trained for the two specific categories while it was tested for the whole test dataset e.g., SVM classifier for CatI-VS-CatII is trained over the training data for category-I

Table 11.5: Max, Min and Mean values of Statistical Features for PSL Categories calculated at d=3

	Standard Deviation			Variance			Skewness			Kurtosis			Entropy			Energy		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Cat-I	2365.53	1313.1	6758.2	6817425.68	1724200	45673000	5.27	2.93	7.47	34.036	12.17	56.91	3.18	1.06	3.61	2.53	0.91	14.90
Cat-II	3173.76	2219.9	4988.9	10328021.06	4927900	24889000	6.69	5.65	7.34	48.57	36.31	55.57	2.89	2.03	3.31	3.65	1.93	8.28
Cat-III	3625.12	1541.1	4895.4	13969731.75	2375000	23965000	6.82	3.71	7.35	50.08	17.87	55.63	2.65	2.04	3.50	4.81	1.12	7.99
Cat-IV	3819.69	2895.3	5057.4	14823849.01	8382600	25578000	7.06	6.57	7.36	52.60	47.45	55.78	2.57	1.97	2.99	5.08	3.03	8.50
Cat-V	3089.19	2043.3	5243	10033909.79	4175000	27489000	6.67	5.43	7.40	48.58	35.29	56.19	2.91	1.89	3.34	3.56	1.70	9.11
Cat-VI	2933.31	2372.6	4169.5	8764429.19	5629100	17385000	6.59	5.95	7.16	47.75	41.20	53.68	2.96	2.39	3.18	3.15	2.15	5.90
Cat-VII	3292.79	2448.9	3682.3	10875540.71	5996900	13559000	6.75	6.27	7.072	49.29	44.54	52.81	2.80	2.61	3.17	3.82	2.27	4.68

and category-II only i.e., 444 and 451 alphabet signs for category one and two respectively, while all 1030 signs of test data are used for testing. The same process is repeated for all the other 14 binary classifiers as well. The predicted label to the sign other than the training data is dependent on outcome of all the fifteen trained models. Out of the twenty one results, the class label which is repeated maximum time is assigned the category label. An example PSL alphabet sign, which is originally from category-I is need to be tested, it is tested over all the fifteen trained models. The output of the models is in following order: five(05) models labeled the sign as category-I, three(03) models each labeled the alphabet sign from category five and seven while four(04) models predicted it from category three. The maximum predicted labels are five(05) for the category-I, so the sign is labeled to it.

It is to note from the classification matrix(table 11.6) of the proposed technique, 133 signs

Table 11.6: Classification Matrix of the Proposed Technique

	<i>Cat-I</i>	<i>Cat-II</i>	<i>Cat-III</i>	<i>Cat-IV</i>	<i>Cat-V</i>	<i>Cat-VI</i>	<i>Cat-VII</i>	<i>Recall</i>	<i>Class Accuracy</i>
<i>Cat-I</i>	133	11	19	5	18	0	0	0.72	0.95
<i>Cat-II</i>	0	151	10	13	11	4	2	0.79	0.93
<i>Cat-III</i>	0	3	111	17	12	1	1	0.81	0.92
<i>Cat-IV</i>	0	12	15	145	11	5	0	0.77	0.89
<i>Cat-V</i>	1	7	11	15	140	5	1	0.78	0.90
<i>Cat-VI</i>	0	3	2	7	8	70	0	0.78	0.97
<i>Cat-VII</i>	0	4	3	7	0	1	45	0.75	0.98
<i>Positive Detected</i>	134	183	172	217	201	86	49	77.18% (Overall Accuracy)	
<i>Precision</i>	0.99	0.83	0.65	0.67	0.70	0.81	0.92		
<i>F-Measure</i>	0.83	0.81	0.98	0.72	0.74	0.79	0.83		

of the category-I are correctly classified while 53 alphabet signs are misclassified as category II, III, IV and V. As well as, out of 844 signs from other categories only one sign is wrongly classified to the category-I making the count of false positive as 1. The true negative for the category-I are counted as 843 while the false negative figure are 53. The statistics for all the other six categories can be interpreted in the same way. The overall accuracy of the proposed approach is 77.18%. As well as, the detailed statistics for all the evaluation metrics against the remaining categories are shown in the matrix.

Figure 11.9 shows the comparative results of the proposed technique in the form of four evaluation metrics i.e., precision, recall, accuracy and f-measure. It is obvious from the graphs, the highest of the precision(0.99) is for category-I while the least is for category-IV(0.72). In the same manner, the proposed technique achieved the highest recall for the category-III(0.92) and it was 0.72(least) for the category-I signs. The highest accuracy was achieved for the category-VII(98%), while the accuracy for the category-IV remained at the bottom(89%). At last, the f-measure scores for category III and IV are 98% and 72% respectively.

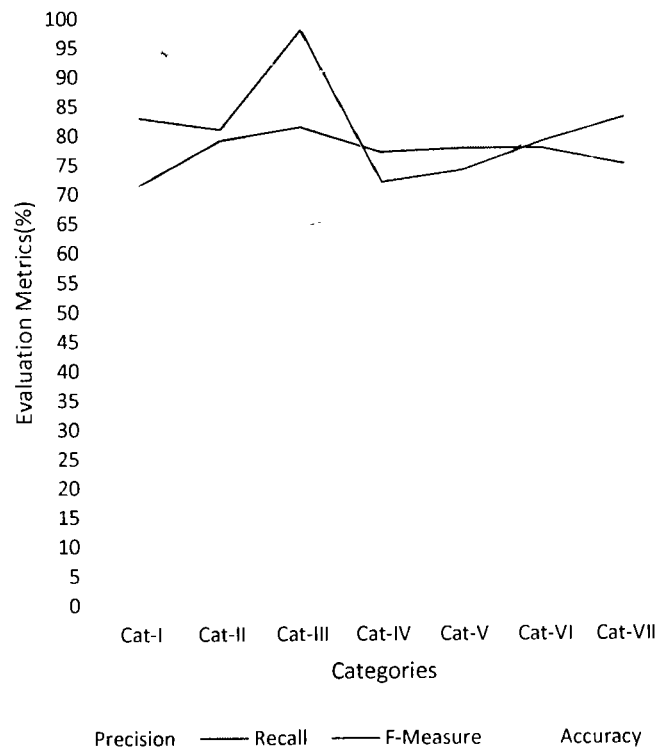


Figure 11.9: Categorization Results of the Proposed technique

Summary

A problem of categorizing the Pakistan sign language(PSL) alphabets on the basis of shape, visibility and orientation of hand and fingers is solved in the presented research. The six statistical features of the LBP histogram are calculated i.e., standard deviation, variance, skewness, kurtosis, entropy and energy. The extracted features represent the sign in a more discriminative way and are fed to the multi-class support vector machines(SVMs) for classification. The proposed technique has achieved considerably good categorization results.

Chapter 12

Comparative Results

Introduction

In this chapter, we have presented the comparative results of the proposed techniques with the existing standard models and research techniques. The proposed techniques whose results are to be emphasized are sMBP, SI-sMBP, SI-sMBP using Ensemble kernels, PCA SI-sMBP and PCA SI-sMBP using Ensemble kernels. The results of the proposed techniques are presented using linear, RBF and polynomial kernels for One-v-One(OvO) and One-v-All(OvA) multiclass modalities. The techniques are evaluated using three metrics i.e., accuracy, precision and recall over the data set taken through known and unknown signers separately. In order to present the authenticity of the proposed techniques, the results from the baseline are presented as well i.e., mean binary pattern(MBP), uniform MBP(uMBP), local binary pattern(LBP), uniform LBP(uLBP), scale invariant MBP(SI-MBP), scale invariant LBP(SI-LBP), scale invariant uLBP(SI-uLBP) and scale invariant uMBP(SI-uMBP). All the results presented here are extracted through implementing and testing over self created PSL dataset. The other comparative techniques are bag of features (BOF) based technique[164], uLBP-KNN and LBP-KNN [165], edge orientation histogram(EOH) with nearest neighbor(NN) [166], uLBP-NN [107], PCA based LBP using SVM-RBF [106], LBP based SVM-RBF [108] and HOG-SVM [167]. As well as, the classifier based comparative results over the proposed sMBP are presented i.e., Shallow Neural Network, Deep Neural Network with one and two hidden layers, linear discriminant analysis(LDA), quadratic discriminant analysis(QDA) and Bayesian classifier

At the end comparative results in the form of precision and recall for the known and unknown signers dataset are presented where comparison among all the techniques are shown for each of class signs i.e., C-1 to C-36.

12.1 Comparative Analysis based on Accuracy

Comparative analysis based the accuracy obtained through the proposed and comparative techniques is presented in table 12.1 and it is for the signs generated by the known signers. The presentation is self-explanatory and it may be deduced that in comparison to different variants of binary patterns calculated at radius one, the proposed sMBP showed better results among all of its fellows for all the three kernels while OvO multiclass modality was used. While it was higher for the RBF and linear but couldn't lead for the polynomial kernel. In the same manner, the proposed SI-sMBP showed the highest accuracy for all the three kernels using OvO modality but remained second to the SI-umLBP for OvA modality. Different results were achieved from the three kernels and to get the uniformity of the results where the strength of all the three kernels may be utilized, the ensemble of kernels based technique was proposed. The proposed kernel ensemble from the results of SI-sMBP achieved 94.7183% accuracy for OvO modality while it was 95.1878% through OvA multiclass modality.

Table 12.1: Accuracy Score(%) of Comparative Techniques for Known Signers

S. No	Technique	One-v-One			One-v-All		
		Polynomial	RBF	Linear	Polynomial	RBF	Linear
1	MBP	72.5307	63.9977	67.0953	76.6507	73.4094	67.9472
2	uMBP	86.1485	82.2911	76.3296	86.5000	87.3950	69.5500
3	LBP	63.0869	55.2817	59.4484	67.4883	64.8474	59.3897
4	uLBP	87.1274	82.5117	77.5822	86.9695	84.8592	70.8920
5	EOH	88.5563	84.2723	77.3474	87.0258	86.7934	74.2934
6	HOG	90.0230	84.1500	84.5000	93.1925	89.1400	85.3873
7	BOF, Dardas and Georganas [164]	80.1508	66.4322	60.4523	80.0503	75.8794	73.3330
8	Proposed sMBP	87.7849	86.6160	79.7779	84.6289	87.6096	70.9496
9	SI-LBP	78.4624	70.3052	74.7653	84.9178	80.4577	75.2934
10	SI-uLBP	91.8427	86.3850	82.1009	92.1362	90.1408	81.4554
11	SI-MBP	86.2089	78.5798	81.5141	91.6080	84.7418	83.2160
12	SI-uMBP	92.1948	88.3803	86.1502	94.8944	93.2512	83.9202
13	Prop. SI-sMBP	92.8404	92.7230	87.2653	92.9577	92.4883	79.4601
14	Prop. SI-sMBP using Ensemble Kernels		94.7183			95.1878	
15	Prop. PCA SI-sMBP	94.4744(22)	94.7439 (24)	88.0054(48)	92.7224 (41)	92.8571 (37)	79.1671 (51)
16	Prop. PCA SI-sMBP using Ensemble Kernels		96.2264			94.6092	
Classifiers based Results over Proposed sMBP							
17	Shallow Neural Network			53.0684			
18	Deep Neural Network(1-Hidden Layer)			54.9			
19	Deep Neural Network(2-Hidden Layer)			55.6984			
20	Linear Discriminant Analysis(LDA)			63.5301			
21	Quadratic Discriminant Analysis(QDA)			86.8954			
22	Bayesian Classifier			12.858			
Other Comparative Techniques							
23	LBP R=2, KNN(K=5 best), Kindiroglu et al. [165]			68.8380			
24	uLBP R=2, KNN(K=5), Kindiroglu et al. [165]			80.4577			
25	Eoh, KNN(K=1), Pansare and Ingle [166]			89.3779			
26	uLBP R=2, NN, (M. Jasim)			86.9718			
27	uLBP R=1, PCA(50) SVM-RBF, Wang et al. [106]			49.0610			
28	LBP R=1, SVM-RBF, Santa et al [108]			55.1643			
29	HOG, SVM, Alzohairi et al. [167]			91.25			

To introduce the feature of scale invariance in the proposed sMBP, it leads to the higher feature space i.e., 1×93 vector. To reduce the dimension of the feature space from the proposed SI-sMBP, PCA was used that not only targeted to reduce feature dimension but at the same time, less important features were suppressed by transforming original feature space to the higher covariance space. Through the use of the OvO multiclass modality, it produced 94.47%(1×22

feature vector), 94.74%(1 × 24 feature vector) and 88.0%(1 × 24 feature vector) accuracies for the polynomial, RBF and linear kernels respectively. For the same kernels but using the OvA modality, the proposed PCA SI-sMBP got the accuracies of 92.72%(1 × 41 feature vector), 92.86%(1 × 37 feature vector) and 79.17%(1 × 51 feature vector) respectively. When an ensemble of kernels is used for OvO and OvA the accuracies are 96.23% and 94.61% respectively. It is important to know that the proposed techniques performed better than all its comparative techniques whether they were baseline to the proposed techniques or the existing research. The best of the results from the existing research was from HOG-SVM [167] by obtaining 91.25% accuracy. While testing the proposed sMBP feature vector over comparative classifiers, Quadratic Discriminant Analysis(QDA) remained on top but second to ECOC-SVMs with an accuracy score 86.89%.

While testing all the comparative techniques over the dataset of the unknown signers, results are shown in table 12.2. It may be observed that neither EOH based techniques i.e., EOH-ECOC SVM, EOH-KNN[166], nor use of HOG features in HOG-ECOC SVM, HOG-SVM [167] could not produce even average level results. Same as others, BOF features [164] were among failures. Binary pattern based techniques were however quite better in the context of the current scenario. The best of the accuracies achieved among all the binary patterns based techniques using ECOC-SVM through OvA, OvO and over all the three kernels(polynomial, RBF and linear) are as follows i.e., 42.02%(MBP over the linear kernel,OvA modality), 46.05%(uMBP over linear kernel,OvA modality), 37.71%(LBP over the linear kernel, OvA modality), 48.87%(uLBP over linear kernel,OvA modality), 43.57% for SI-LBP over linear kernel with OvA modality, 46.75% through SI-uLBP over linear kernel with OvA modality, 50.57%(SI-MBP over the linear kernel,OvA modality) and 45.20%(SI-uMBP over linear kernel,OvA modality). The other comparative techniques based on binary patterns got the following results i.e., LBP,uLBP at R=2 with KNN(K=5)[165] obtained 21.54%, 26.20% accuracy, uLBP at R=2 with NN [107] achieved 30.58% accuracy, LBP at R=1 with SVM-RBF [108] produced 18.14% accuracy and uLBP at R=1 with the reduced dimension feature set, 1 × 50, through PCA and tested through SVM-RBF[106].

Table 12.2: Accuracy Score(%) of Comparative Techniques for UnKnown Signers

S. No	Technique	One-v-One			One-v-All		
		Kernel					
		Polynomial	RBF	Linear	Polynomial	RBF	Linear
1	MBP	36.2994	25.2119	37.9237	40.8898	32.9802	42.0198
2	uMBP	41.8079	30.1554	43.6441	43.3616	36.7938	46.0452
3	LBP	29.4492	25.0706	33.8277	34.8870	28.1780	37.7119
4	uLBP	43.0085	29.8023	47.6695	41.5960	33.1921	48.8701
5	EOH	0.9018	1.1299	0.2825	0.6356	0.7062	0.9887
6	HOG	0.9181	1.2712	1.0593	0.5650	0.5650	0.7768
7	BOF, Dardas and Georganas [164]	5.5085	4.4492	4.0254	5.2260	4.3785	4.1667
8	Proposed sMBP	44.7740	36.0169	48.0932	38.2768	32.9096	43.5734
9	SI-LBP	38.0650	28.0367	40.6073	44.9859	34.3927	46.7514
10	SI-uLBP	46.8220	31.9209	50.4237	46.3983	36.7232	50.5650
11	SI-MBP	39.3362	30.5791	44.2090	49.2938	37.1469	45.1977
12	SI-uMBP	45.2684	33.9689	47.9520	51.9068	41.3842	51.6949
13	Prop. SI-sMBP	47.3870	41.5960	50.4412	45.1977	36.6525	48.6582
14	Prop. SI-sMBP using Ensemble Kernels		49.2938			49.5763	
15	Prop. PCA SI-sMBP	43.0791	40.1130	49.2938	43.9266	41.0311	48.7288
16	Prop. PCA SI-sMBP using Ensemble Kernels		49.3232			50.9887	
Classifiers based Results over Proposed sMBP							
17	Shallow Neural Network			40.7486			
18	Deep Neural Network(1-Hidden Layer)			40.25			
19	Deep Neural Network(2-Hidden Layer)			42.2316			
20	Linear Discriminant Analysis(LDA)			45.8333			
21	Quadratic Discriminant Analysis(QDA)			40.8192			
22	Bayesian Classifier			10.3107			
Other Comparative Techniques							
23	LBP R=2, KNN(K=5 best), Kindiroglu et al. [165]			21.5395			
24	uLBP R=2, KNN(K=5), Kindiroglu et al. [165]			26.2006			
25	Eoh, KNN(K=1), Pansare and Ingle [166]			1.2712			
26	uLBP R=2, NN, (M. Jasim)			30.5791			
27	uLBP R=1, PCA(50) SVM-RBF, Wang et al. [106]			16.0311			
28	LBP R=1, SVM-RBF, Santa et al. [108]			18.1497			
29	HOG, SVM, Alzohairi et al. [167]			1.4831			

The accuracy results for the proposed techniques were 48.09%(sMBP with linear kernel and OvO modality), 50.44%(SI-sMBP with linear kernel and OvO modality) and 48.73%(PCA SI-sMBP linear kernel and OvA modality). All the results have clearly provided the justifications of the ensemble kernels i.e., SI-sMBP produced best of its accuracies with the polynomial kernel used in OvA modality, when tested over a dataset generated by the known signers. The same technique showed its best for the unknown signers through linear kernel and OvO modality. So, none of the single experimental settings could lead to better performance for both known and unknown signers and we needed to produce a technique that should use the strengths of all the settings. The proposed Ensemble kernels based technique over SI-sMBP produced 94.72% and 95.19% accuracies through OvO and OvA modality respectively while the ensemble of kernels over PCA SI-sMBP achieved accuracies of 96.23% and 94.61% through OvO and OvA modalities respectively. While, proposed sMBP feature vector is used for the classification purpose but with the classifiers other than SVMs i.e., Shallow Neural Network, Deep Neural Network with one and to hidden layers, LDA, QDA and Bayesian classifier, LDA stood at the top with being 45.83% accurate.

12.2 Comparative Analysis based on Precision

As discussed in the previous section for accuracy metric, precision based comparative statistics over the dataset of known signers are presented in table 12.3. The proposed sMBP received 87.8%, 86.6% and 79.7% scores for polynomial, RBF and linear kernels respectively while OvO multiclass modality was adopted.

Table 12.3: Precision Score(%) of Comparative Techniques for Known Signers

S. No	Technique	One-v-One			One-v-All		
		Kernel			Polynomial	RBF	Linear
1	MBP	73.4	65.7	68.3	75.6	72.6	66.7
2	UMBP	86.7	83.1	77.0	87.8	87.7	75.9
3	LBP	64.7	57.2	60.6	67.4	65.3	58.0
4	ULBP	88.0	84.3	78.8	88.0	85.3	73.1
5	EOH	89.0	85.5	78.4	89.7	88.8	75.5
6	HOG	90.4	87.0	85.3	93.6	90.2	86.1
7	BOF, Dardas and Georganas [164]	80.3	67.6	62.5	80.8	77.3	75.0
8	Proposed S-MBP	87.8	86.6	79.7	85.5	88.2	72.2
9	SI-LBP	79.9	72.7	74.8	84.8	81.0	75.0
10	SI-ULBP	91.9	87.7	83.0	92.2	90.4	81.3
11	SI-MLBP	86.8	80.3	82.4	91.7	85.2	83.3
12	SI-UMLBP	92.2	89.6	86.7	95.0	92.8	84.3
13	Prop. SIS-MBP	93.1	92.7	87.1	93.4	92.4	79.2
14	Prop. SIS-MBP using Ensemble Kernels	94.7			95.2		
15	Prop. PCA SIS-MBP	94.9	95.1	88.6	93.3	93.2	89.3
16	Prop. PCA SIS-MBP using Ensemble Kernels	96.5			95.0		
Classifiers based Results over Proposed sMBP							
17	Shallow Neural Network				52.4		
18	Deep Neural Network(1-Hidden Layer)				59.5		
19	Deep Neural Network(2-Hidden Layer)				55.4		
20	Linear Discriminant Analysis(LDA)				61.5		
21	Quadratic Discriminant Analysis(QDA)				81.7		
22	Bayesian Classifier				23.6		
Other Comparative Techniques							
23	LBP R=2,KNN(K=5 best),Kindiroglu et al. [165]				69.9		
24	uLBP R=2, KNN(K=5), Kindiroglu et al. [165]				81.0		
25	Eoh, KNN(K=1), Pansare and Ingle [166]				89.8		
26	uLBP R=2, NN, Jasim and Hasanuzzaman [107]				87.3		
27	uLBP R=1, PCA(50) SVM-RBF, Wang et al. [106]				83.9		
28	LBP R=1, SVM-RBF, Santa et al. [108]				64.4		
29	HOG, SVM, Alzohairi et al. [167]				92.5		

While the OvA modality was used, the proposed sMBP had a precision score of 85.5%, 88.2% and 72.2% were achieved for polynomial, RBF and linear kernels respectively. When scale invariance was incorporated in the proposed SI-sMBP, the scores were improved and the precisions were 93.1%(polynomial), 92.7%(RBF), 87.1%(linear) through OvO multiclass mechanism and 93.4%(polynomial), 92.4%(RBF), 79.2%(linear) scores by OvA tuning. Although SI-sMBP was quite better than sMBP as it incorporated scale invariance in it yet there was room for improvement if redundant features could be suppressed. The proposed PCA transformed SI-sMBP not only reduced the dimension of the feature set extracted through SI-sMBP but improved the results as well i.e., 94.9%, 95.1%, 88.6% through polynomial, RBF and linear kernels by using OvO mechanism and 93.3%, 93.2%, 89.3% precision scores through all

the three kernels in sequence but using OvA modality. The results of the ensemble techniques are better than all of the other fellows (proposed and existing research) i.e., 94.7%(OvO), 95.2%(OvA) by ensemble of kernels used in SI-sMBP and 94.7%(OvO), 95.2%(OvA) through kernel ensembles for PCA transformed SI-sMBP. The results for the other baseline techniques and the existing research are presented in table 12.3 as well. From the classifiers based results over the proposed sMBP, it may be observed that QDA remained at top with 81.7% precision score while the Bayesian classifier couldn't perform well and achieved a precision score 23.6%.

Table 12.4: Precision Score(%) of Comparative Techniques for Unknown Signers

S. No	Technique	One-v-One			One-v-All		
		Kernel					
		Polynomial	RBF	Linear	Polynomial	RBF	Linear
1	MBP	45.8	36.4	45.8	46.4	46.8	39.6
2	uMBP	46.5	41.4	48.7	48.5	45.5	51.8
3	LBP	35.7	34.5	40.2	37.9	31.3	41.4
4	uLBP	50.9	42.0	51.1	44.5	40.0	53.2
5	EOH	0.5	0.5	0.6	0.5	0.6	0.5
6	HOG	0.5	0.6	0.7	0.4	0.7	0.7
7	BOF, Dardas and Georganas [164]	6.2	5.0	3.4	1.6	2.2	4.7
8	Proposed sMBP	50.3	44.0	53.9	40.8	40.9	46.3
9	SI-LBP	38.8	28.6	41.2	45.4	35.0	47.4
10	SI-uLBP	47.2	32.4	50.7	46.6	37.1	50.9
11	SI-MBP	47.4	42.6	49.6	53.2	43.4	50.4
12	SI-uMBP	50.7	46.1	52.2	54.0	48.2	50.7
13	Prop. SI-sMBP	52.6	48.0	53.0	47.2	43.1	53.9
14	Prop. SI-sMBP using Ensemble Kernels	52.8			52.5		
15	Prop. PCA SI-sMBP	47.2	49.5	52.2	48.1	48.9	52.3
16	Prop. PCA SI-sMBP using Ensemble Kernels	52.5			52.7		
Classifiers based Results over Proposed sMBP							
17	Shallow Neural Network				45.3		
18	Deep Neural Network(1-Hidden Layer)				47.6		
19	Deep Neural Network(2-Hidden Layer)				43.8		
20	Linear Discriminant Analysis(LDA)				48.5		
21	Quadratic Discriminant Analysis(QDA)				44.9		
22	Bayesian Classifier				10.0		
Other Comparative Techniques							
23	LBP R=2,KNN(K=5 best),Kindiroglu et al. [165]				25.4		
24	uLBP R=2, KNN(K=5), Kindiroglu et al. [165]				32.9		
25	Eoh, KNN(K=1), Pansare and Ingle [166]				1.2		
26	uLBP R=2, NN, Jasim and Hasanuzzaman [107]				36.2		
27	uLBP R=1, PCA(50) SVM-RBF, Wang et al. [106]				40.9		
28	LBP R=1, SVM-RBF, Santa et al. [108]				26.6		
29	HOG, SVM, Alzohairi et al. [167]				1.7		

Same like table 12.3, table 12.4 is presenting the comparative precision results but for the unknown signers. Just like accuracy results the precision results for the EOH, BOF and HOG based results are on quite a lower side. The comparative techniques that are using binary patterns based features have acquired better results and as the proposed techniques are using binary patterns at their baseline, they showed promising results. The best of the precision by the proposed sMBP is through use of RBF kernel with OvA modality by acquiring 46.8% scores while the SI-sMBP received 53.9% precision (higher than other experiment settings for SI-sMBP) by linear kernel through OvA modality. As far as the proposed PCA based SI-sMBP

is concerned it achieved 52.3% precision for the linear kernel by using OvA multiclass settings and that is higher among other kernels configuration. The proposed ensemble of kernels while using SI-sMBP features attained 52.8% and 52.5% precision scores for the Ov-O and OvA modalities respectively while PCA based ensembles got 52.5% and 52.7% scores. From the existing research, [106] achieved better than fellows with 40.9% precision and [166] got the lowest one i.e., 1.2%. Among the seven classifiers over the proposed sMBP, LDA showed better results by achieving 48.5% precision value.

12.3 Comparative Analysis based on Recall

The comparative analysis for the third of the evaluation metric, recall, when the techniques are validated over the dataset of the known signers is shown in table 12.5. It may be observed that the highest of the recall scores are achieved by the proposed PCA transformed SI-sMBP and it is for all the three kernel based comparisons and for both of the two multiclass modalities. It achieved following recall scores i.e., 94.6%, 94.9%, 88.2%, 93.0%, 93.0% and 89.4% for polynomial(OvO), RBF(OvO), linear(OvO), polynomial(OvA), RBF(OvA) and linear(OvA) respectively. The recall score for the ensemble of kernels from SI-sMBP are 94.4% and 94.8% for the OvO and OvA multiclass schemes while the proposed PCA transformed SI-sMBP ensemble attained 96.2% and 94.8% recall through OvO and OvA respectively. The lease of the recall was through uLBP calculated R=1 and PCA transformed by retaining 50 components [106] and its value was 48.4%. It is evident from the presented statistics that while testing the proposed sMBP over different classifiers (other than SVMs), same like accuracy and precision, QFA remained on top by attaining 86.8% recall values.

The same metric as explained in table 12.5 but for the unknown signers is presented in table 12.6. It may be deduced from the presented statistics that like the other two metrics, the techniques using feature set other than the binary patterns couldn't show promising results. The highest of the recall score among the techniques using other than binary patterns as feature set was 5.9% only and it was through [164] using BOF with polynomial kernel and OvA multiclass tuning. It was 52.2% recall, the highest one achieved by SI-uMBP and it was through linear kernel with OvA modality. The proposed techniques achieved good recall scores and the top one was 51.6% through ensemble of kernels using feature set from PCA transformed SI-sMBP. Same like the accuracy and precision statistics of the seven classifiers over the proposed sMBP(for the dataset of unknown signers), LDA showed the highest results with 48.3% recall.

Table 12.5: Recall Score(%) of Comparative Techniques for Known Signers

S. No	Technique	One-v-One			One-v-All		
		Kernel			Polynomial	RBF	Linear
1	MBP	72.4	63.7	67.1	75.5	72.6	67.1
2	uMBP	86.3	82.1	76.0	87.7	87.7	73.4
3	LBP	62.7	54.8	59.1	67.0	64.1	58.1
4	uLBP	87.7	82.2	77.2	87.9	84.8	70.0
5	EOH	88.5	84.2	77.0	89.3	88.0	75.4
6	HOG	90.1	84.2	84.6	93.2	89.3	85.6
7	BOF, Dardas and Georganas [164]	80.6	66.7	60.8	80.8	76.7	74.4
8	Proposed sMBP	87.7	86.5	79.6	85.1	88.1	71.5
9	SI-LBP	78.0	69.6	73.9	84.8	80.2	74.4
10	SI-uLBP	91.6	85.9	81.5	92.0	89.9	80.8
11	SI-MBP	86.0	78.2	81.2	91.4	84.5	82.7
12	SI-uMBP	91.8	88.0	85.8	94.6	92.3	83.5
13	Prop. SI-sMBP	92.5	92.5	87.0	92.6	91.9	79.1
14	Prop. SI-sMBP using Ensemble Kernels	94.4			94.8		
15	Prop. PCA SI-sMBP	94.6	94.9	88.2	93.0	93.0	89.4
16	Prop. PCA SI-sMBP using Ensemble Kernels	96.2			94.8		
Classifiers based Results over Proposed sMBP							
17	Shallow Neural Network				52.6		
18	Deep Neural Network(1-Hidden Layer)				54.1		
19	Deep Neural Network(2-Hidden Layer)				55.1		
20	Linear Discriminant Analysis(LDA)				63.5		
21	Quadratic Discriminant Analysis(QDA)				86.8		
22	Bayesian Classifier				12.6		
Other Comparative Techniques							
23	LBP R=2,KNN(K=5 best),Kindiroglu et al. [165]				68.3		
24	uLBP R=2, KNN(K=5), Kindiroglu et al. [165]				80.1		
25	Eoh, KNN(K=1), Pansare and Ingle [166]				89.4		
26	uLBP R=2, NN, Jasim and Hasanuzzaman [107]				86.7		
27	uLBP R=1, PCA(50) SVM-RBF, Wang et al. [106]				48.4		
28	LBP R=1, SVM-RBF, Santa et al. [108](Umme Santa)				54.6		
29	HOG, SVM, Alzohairi et al. [167]				92.3		

12.4 Class-wise Comparative Classification Results

In this section, comparative analysis of the results for each of the classes is presented graphically and it is for precision and recall. The results are separately shown for each of the metrics and both the datasets i.e., known and unknown signers. As all of the baseline techniques are implemented using each of three kernels i.e., polynomial, RBF and linear, for both OvO and OvA modalities but in the current analysis, the one having the best precision among the six is presented.

Table 12.6: Recall Score(%) of Comparative Techniques for UnKnown Signers

S. No	Technique	One-v-One			One-v-All		
		Polynomial	RBF	Linear	Polynomial	RBF	Linear
1	MBP	36.8	25.5	38.4	41.2	33.2	42.3
2	uMBP	42.1	30.2	44.4	43.6	36.9	46.4
3	LBP	30.0	25.4	34.5	35.2	28.5	38.3
4	uLBP	43.6	30.3	48.3	42.0	33.5	49.3
5	EOH	1.2	1.1	1.2	0.7	0.8	0.7
6	HOG	1.0	1.3	1.1	0.6	0.6	0.8
7	BOF, Dardas and Georganas [164]	5.3	2.8	4.5	5.9	5.0	2.6
8	Proposed sMBP	45.1	36.1	48.5	38.4	33.1	43.7
9	SI-LBP	47.1	38.5	50.5	48.5	38.6	50.5
10	SI-uLBP	55.4	46.3	57.2	47.7	42.0	53.0
11	SI-MBP	40.2	31.1	45.0	49.6	37.5	45.7
12	SI-uMBP	45.8	33.9	48.7	52.1	41.7	52.2
13	Prop. SI-sMBP	47.9	42.2	50.6	45.6	37.1	48.8
14	Prop. SI-sMBP using Ensemble Kernels	49.9			50.1		
15	Prop. PCA SI-sMBP	43.2	40.6	50.0	44.6	41.4	49.4
16	Prop. PCA SI-sMBP using Ensemble Kernels	49.5			51.6		
Classifiers based Results over Proposed sMBP							
17	Shallow Neural Network				40.8		
18	Deep Neural Network(1-Hidden Layer)				40.2		
19	Deep Neural Network(2-Hidden Layer)				42.2		
20	Linear Discriminant Analysis(LDA)				43.8		
21	Quadratic Discriminant Analysis(QDA)				41.0		
22	Bayesian Classifier				10.0		
Other Comparative Techniques							
23	LBP R=2,KNN(K=5 best),Kindiroglu et al. [165]				21.9		
24	uLBP R=2, KNN(K=5), Kindiroglu et al. [165]				26.4		
25	Eoh, KNN(K=1), Pansare and Ingle [166]				1.2		
26	uLBP R=2, NN, Jasim and Hasanuzzaman [107]				31.0		
27	uLBP R=1, PCA(50) SVM-RBF, Wang et al. [106]				16.0		
28	LBP R=1, SVM-RBF, Santa et al. [108]				18.3		
29	HOG, SVM, Alzohairi et al. [167]				1.4		

12.4.1 Precision based Class-wise Comparative Analysis

Figure 12.1 is showing the precision based comparative results of the existing research, baseline techniques and the proposed methodologies. It may be observed that for the class C-1 PCA SI-sMBP (polynomial kernel in Ova) remains at the top with 100% precision and for the other 35 classes the top score holders are as follows: SI-uMBP (poly OA) scored 95.6%, (kernel ensembles PCA SI-sMBP (OA), uLBP (poly OO)) with score 100%, (SI-uLBP (poly OA), SI-uMBP (poly OA), PCA SI-sMBP (RBF OO), PCA SI-sMBP (Poly OA), ensemble PCA SI-sMBP (OO), ensemble PCA SI-sMBP (OA)) scoring 100%, HOG-SVM [167] with 100%, (SI-sMBP (Poly OO), ensemble PCA SI-sMBP (OO)) scoring 100%, (PCA SI-sMBP (RBF OO), PCA SI-sMBP (Poly OA), ensemble PCA SI-sMBP (OO)) scored 100%, (PCA SI-sMBP (RBF OO), ensemble PCA SI-sMBP (OO)) having 100%, [106] with score 100%, PCA SI-sMBP (RBF OO) scored 100%, PCA SI-sMBP (Poly OA) with score 100%, (SI-uLBP (Poly OA), SI-sMBP (Poly OA), PCA SI-sMBP (RBF OO), PCA SI-sMBP (Poly OA)) having 100%, SI-uMBP (Poly OA) scored 100%, (SI-uLBP (Poly OA), SI-uMBP (Poly OA), SI-sMBP (Poly OA), SI-sMBP (Poly OO)) with 100%, (SI-sMBP (Poly OA), SI-sMBP (Poly OO), PCA SI-sMBP (RBF

OO), PCA SI-sMBP(Poly OA), Ensemble PCA SI-sMBP(OO), Ensemble PCA SI-sMBP(OA)) scoring 100%, (uMBP(Poly OA), SI-uMBP (Poly OA), SI-sMBP(Poly OA), SI-sMBP(Poly OO), PCA SI-sMBP(RBF OO), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) having 100%, SI-uLBP(Poly OA) with 100%, (PCA SI-sMBP(RBF OO), ensemble PCA SI-sMBP(OO)) scoring 100%, PCA SI-sMBP(RBF OO) with 95.8%, (SI-MBP(Poly OA), SI-uMBP (Poly OA), PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA), LBP [165], [107]) scored 100%, PCA SI-sMBP(RBF OO) with 100%, [167] having 100%, PCA SI-sMBP(Poly OA) with 100%, sMBP(RBF OA) having 91.8%, [107] scoring 97.5%, uMBP(Poly OA) with 97.8%, SI-uMBP (Poly OA) attaining 100%, (SI-MBP(Poly OA), [106]) having 100%, SI-sMBP(Poly OO) with 100%, PCA SI-sMBP(Poly OA) scoring 100%, (PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA), [106]) with 100%, SI-MBP(Poly OA) having 100%, ensemble PCA SI-sMBP(OA) scoring 100%, SI-MBP(Poly OA) with 91.1% and (PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OA)) with 100% recall for classes C-3 to C-36 respectively.

Figure 12.2 is representing the same comparative analysis as shown in figure 12.1 but here it is about the results for the dataset of the unknown signers. It may be observed that following techniques showed promising precision scores for the classes 1 through 36 i.e., SI-uMBP (Linear OA) achieved 45.8%, SI-sMBP(Linear OA) got 61.3%, SI-uLBP(Linear OA) received 56.1%, 88.2% score from SI-LBP(Linear OA), sMBP(Linear OO) attained 69.4%, uLBP(Linear OA) with 58.3%, SI-uLBP(Linear OA) having 100%, uLBP(Linear OA) with 73.7%, SI-uMBP(Linear OA) acquired 66.7%, ULBP(Linear OA) had 50%, uMBP(Linear OA) with 75%, SI-LBP(Linear OA) scored 92.3%, SI-sMBP(Linear OO) achieving 100%, (SI-sMBP(Linear OA), SI-sMBP(Linear OO)) with 100%, MBP (Linear OA) getting 57.1%, (MBP (Linear OA), uMBP(Linear OA), LBP(Linear OA), sMBP(Linear OO), SI-MBP(Poly OA), SI-uMBP (Linear OA), SI-sMBP(Linear OA), SI-sMBP(Linear OO), PCA SI-sMBP(Linear OO), PCA SI-sMBP(Linear OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(O A), [106]) scoring 100%, (MBP (Linear OA), uMBP(Linear OA), SI-MBP(Poly OA), SI-uMBP (Linear OA), SI-sMBP(Linear OA), SI-sMBP(Linear OO), PCA SI-sMBP(Linear OO), PCA SI-sMBP(Linear OA), Ensemble PCA SI-sMBP(OO), Ensemble PCA SI-sMBP(O A), [106]) with 100%, SI-sMBP(Linear OO) receiving 48.3%, [107] scoring 26.3%, ([107], [106]) with 100%, SI-uLBP(Linear OA) scoring 100%, SI-MBP(Poly OA) with 77.1%, Ensemble PCA SI-sMBP(O A) scoring 68.4%, (uMBP(Linear OA), LBP(Linear OA), uLBP(Linear OA), SI-MBP(Poly OA), SI-uMBP (Linear OA), SI-sMBP(Linear OA)) having 100%, SI-sMBP(Linear OO) with 71.4%, SI-uLBP(Linear OA) scoring 90.2%, SI-uMBP (Linear OA) with 64.7%, (SI-sMBP(Linear OA), PCA SI-sMBP(Linear OO), PCA SI-MBP(Linear OA)) with 100%, (uLBP(Linear OA), uLBP[165]) with 100%, uLBP(Linear OA) having 72.7%, Ensemble PCA SI-sMBP(OO) getting 82.4%, uLBP[165] having 75%, SI-LBP(Linear OA) having 64.9%, [164] with 36.1%, [164] with 84.8% and SI-sMBP(Linear OA) achieved 100% recall score respectively. It may be noted that for the individual classes precision results(over unknown signers), linear kernel performed better and it was leading when OvA modality was used.

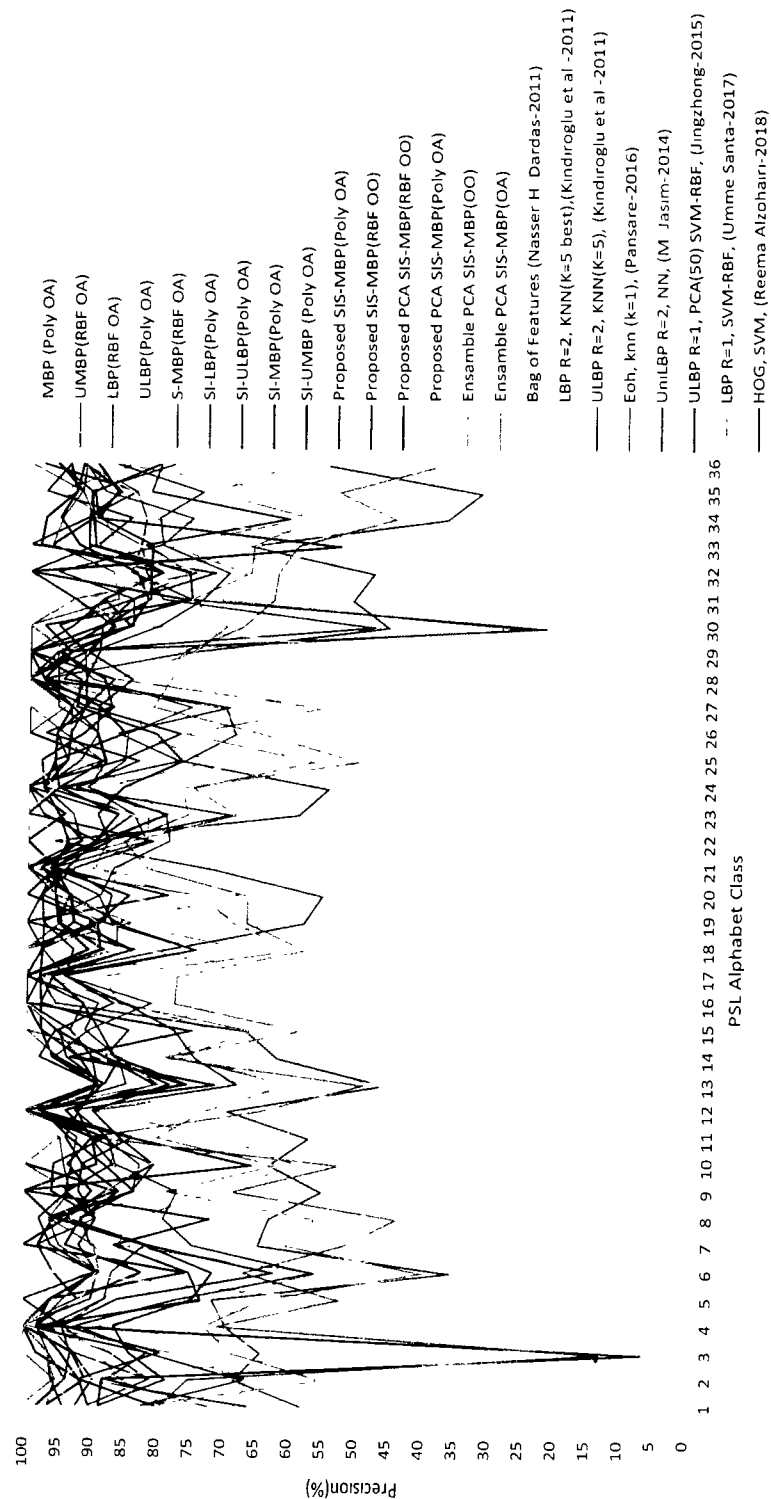


Figure 12.1: Precision based Comparative Analysis of the Proposed and Other Techniques for Known Signers

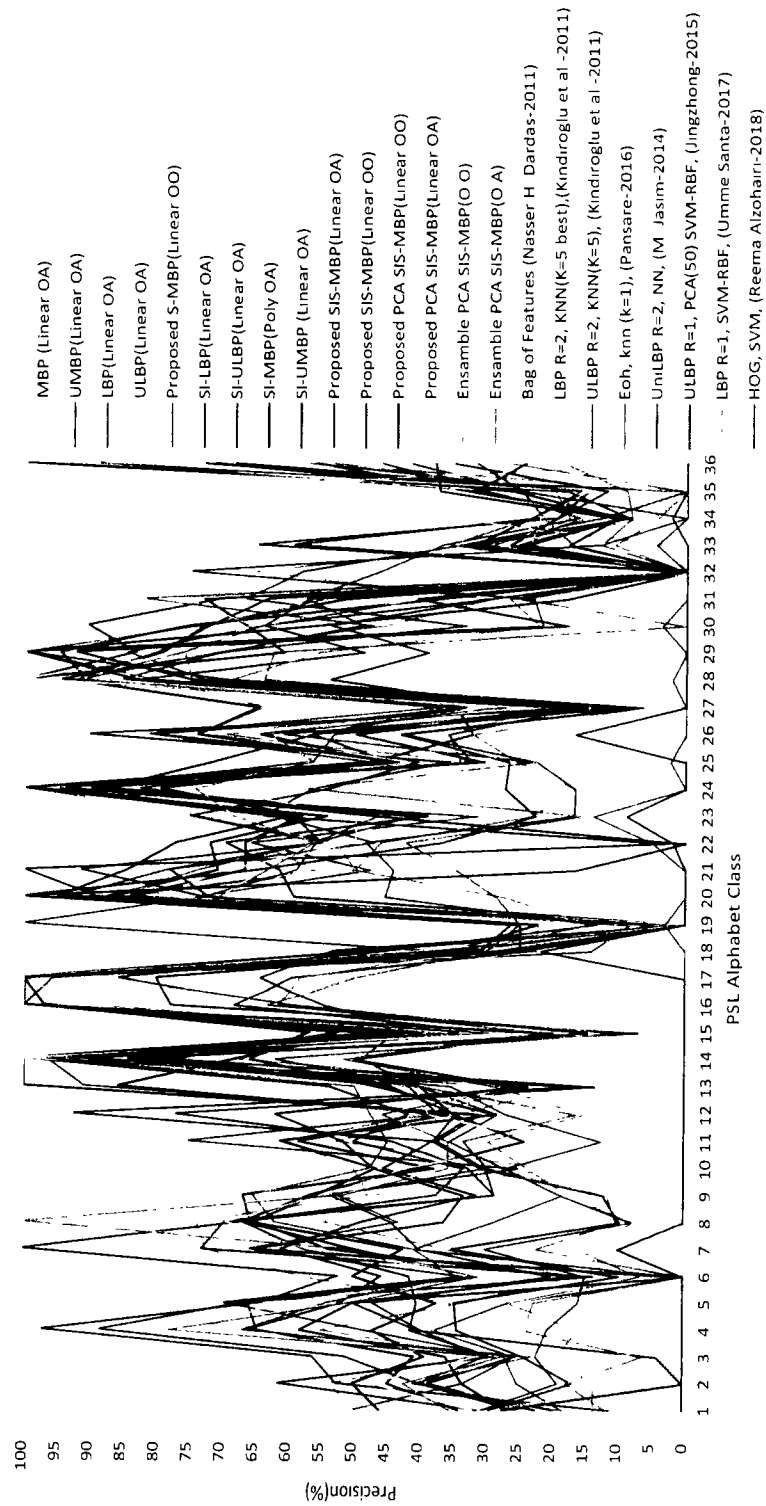


Figure 12.2: Precision based Comparative Analysis of the Proposed and Other Techniques for Unknown Signers

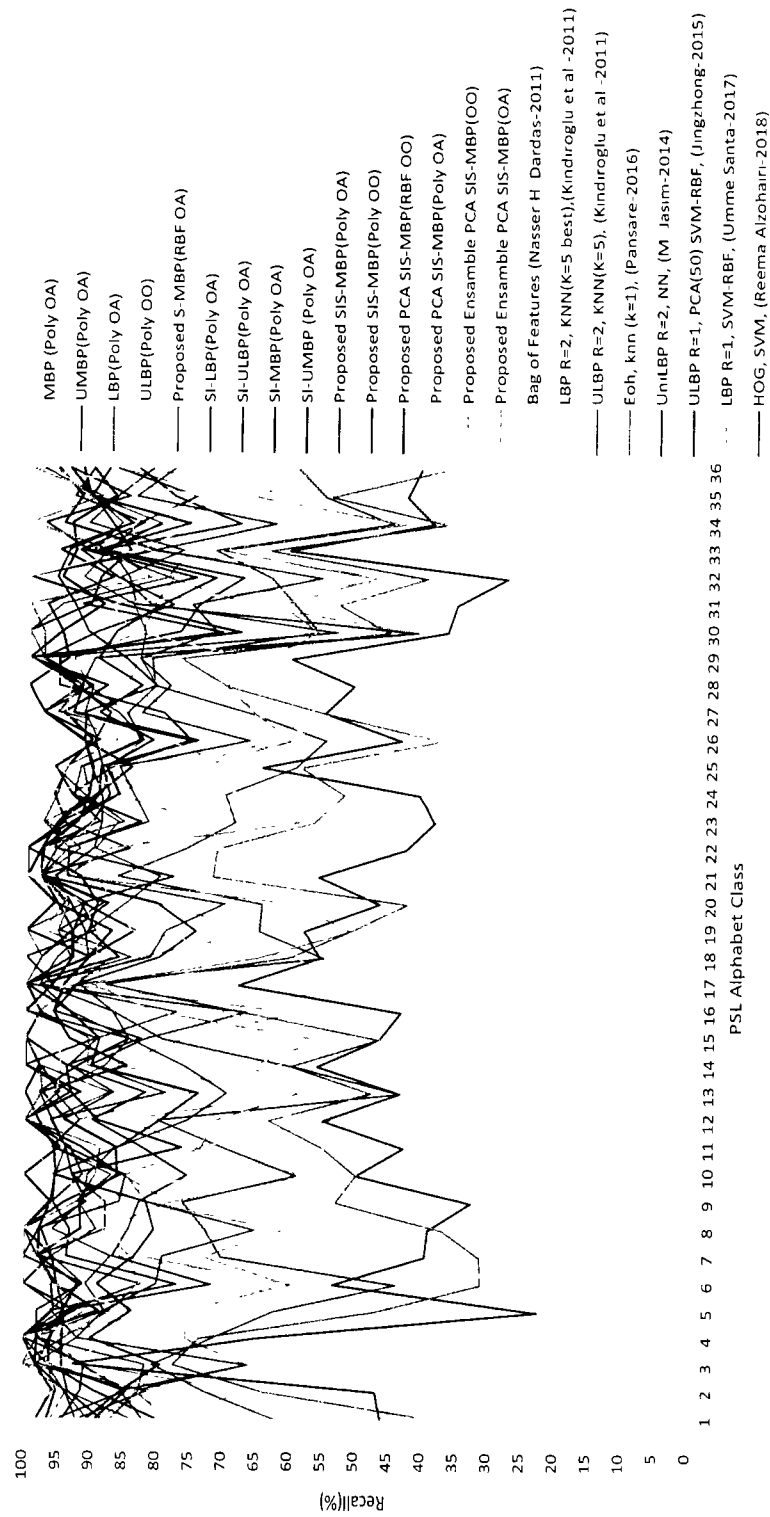


Figure 12.3: Recall based Comparative Analysis of the Proposed and Other Techniques for Known Signers

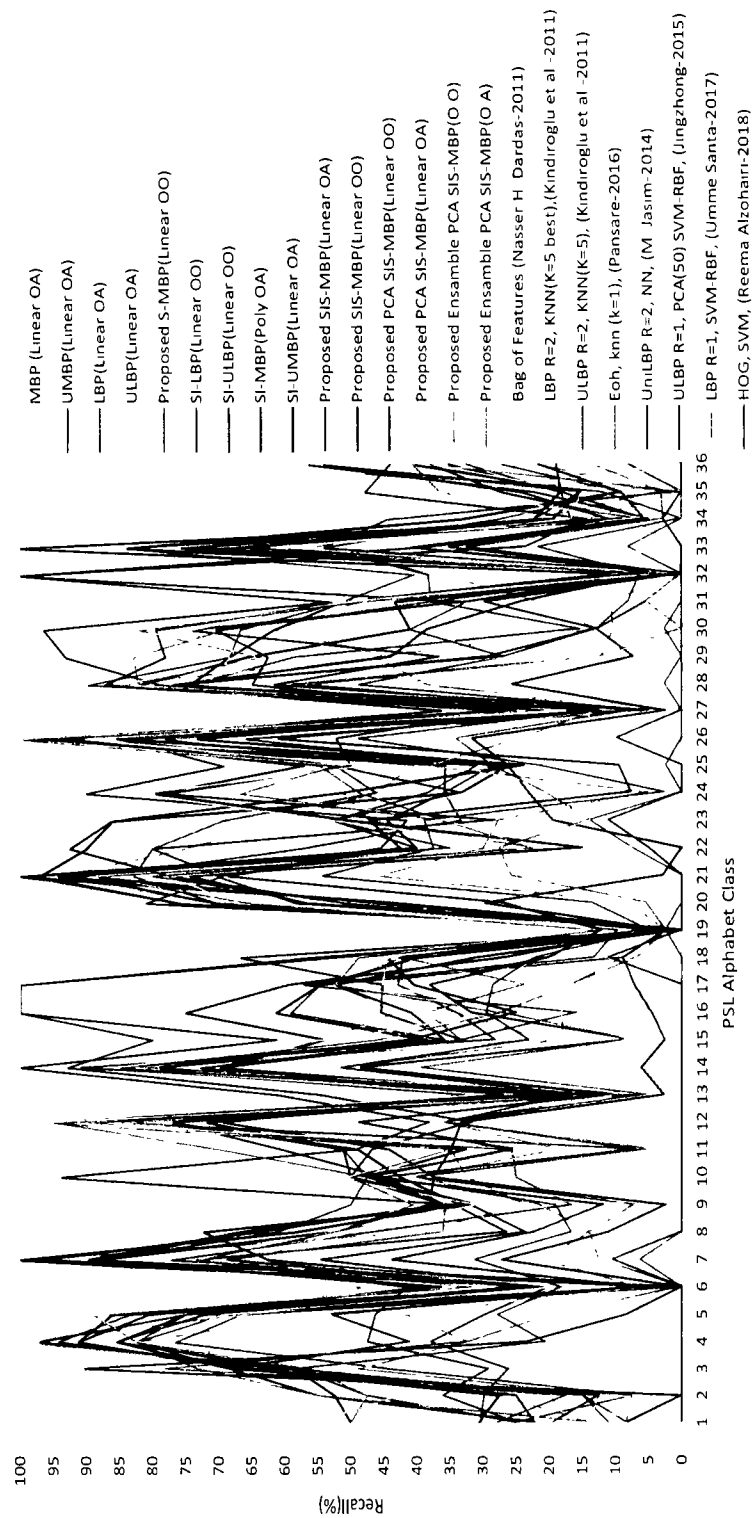


Figure 12.4: Recall based Comparative Analysis of the Proposed and Other Techniques for Unknown Signers

12.4.2 Recall based Class-wise Comparative Analysis

Here we are presenting comparative recall based class-wise results achieved through the proposed and other techniques. The comparative analysis takes best performance of baseline and existing techniques (from all of the three kernels in OvO and OvA configurations) and all the recall performances from the proposed techniques. The highest of the recall among all the fellows for individual classes is explained as i.e., ensemble PCA SI-sMBP(OO) achieved 100% recall for the class C1 while SI-sMBP(RBF OO) is the best performer for class C2 with 95.7% recall. The other performances for the classes C3 through C6 are presented as: ensemble PCA SI-sMBP(OO) with 100%, (SI-uLBP(Poly OA), SI-uMBP (Poly OA), SI-sMBP(Poly OA), PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) achieving 100%, [166] got 100%, [164] with 96.2%, (SI-MBP(Poly OA), [167]) with 100%, [167] getting 97.8%, SI-uMBP (Poly OA) receiving 100%, (PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA)) with 100%, [166] with 95.9%, (SI-uMBP (Poly OA), SI-sMBP(Poly OA), PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) achieved 100%, [166] scored 95.7%, SI-sMBP(Poly OA) with 98.0%, (PCA SI-sMBP(RBF OO), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) securing 100%, (uLBP(Poly OA), SI-uLBP(Poly OA), SI-MBP(Poly OA), SI-uMBP (Poly OA), SI-sMBP(Poly OA), PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) with 100%, (uLBP(Poly OA), S-MBP(RBF OA), SI-MBP(Poly OA), SI-uMBP (Poly OA), SI-sMBP(Poly OA), PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) having 100%, (PCA SI-sMBP(RBF OO), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) scored 100%, SI-sMBP(Poly OA) with 100%, PCA SI-sMBP(RBF OO) got 100%, (PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) sharing 100%, (PCA SI-sMBP(RBF OO), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA), [107]) getting 100%, (PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) with 100%, (SI-LBP(Poly OA), PCA SI-sMBP(RBF OO), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) shared 100%, (PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OA)) with 100%, (PCA SI-sMBP(RBF OO), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) scored 100%, (PCA SI-sMBP(RBF OO), ensemble PCA SI-sMBP(OO)) achieved 100%, (SI-sMBP(Poly OA), SI-sMBP(RBF OO), PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) shared 100%, (SI-uLBP(Poly OA), PCA SI-sMBP(RBF OO)) with 100%, (PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) sharing 100%, [164] with 96.2%, [164] with 100%, SI-sMBP(Poly OA) scoring 100%, SI-uMBP (Poly OA) with 97.8%, SI-uLBP(Poly OA) scored 97.7% and ensemble PCA SI-sMBP(OO) with 100% recall respectively. It is important observance that the proposed techniques majorly dominated the presented statistics and showed their impact to solve the PSL recognition problem.

Same as figure 12.3, figure 12.4 is presenting the recall based comparison but for the dataset of unknown signers. It may be deduced from the graph that the following classes got better recall for the individual classes(1 through 36) i.e., PCA SI-sMBP(Poly OA) (100%), SI-MBP(Poly OA)(55%), [106](90.2%), uLBP(Poly OA)(100%), SI-uMBP (Poly OA)(86.1%), SI-sMBP(Poly OA)(38.6%), SI-uMBP (Poly OA)(100%), SI-MBP(Poly OA)(66.7%), ensemble PCA SI-sMBP(OA)(40.5%), SI-uLBP(Poly OA)(93.8%), ensemble PCA SI-sMBP(OO)(69.8%), (PCA SI-sMBP(RBF OO), PCA SI-sMBP(Poly OA), ensemble PCA SI-sMBP(OO), ensemble PCA SI-sMBP(OA)) (94.9%), SI-uLBP(Poly OA)(61.1%), SI-LBP(Poly OA)(92.9%), SI-LBP(Poly OA)(80%), (SI-LBP(Poly OA), SI-uLBP(Poly OA))(100%), (SI-LBP(Poly OA) SI-uLBP(Poly OA))(100%), SI-sMBP(Poly OA)(66.7%), (ensemble PCA SI-sMBP(OA), [107])(12.2%), (uLBP(Poly OA), SI-uMBP (Poly OA))(75.7%), (uLBP(Poly OA), SI-sMBP(RBF OO))(100%), SI-uMBP (Poly OA)(90%), (SI-MBP(Poly OA), SI-uMBP (Poly OA))(86.1%), (90.0%), SI-uLBP(Poly OA)(69.2%), SI-sMBP(RBF OO)(100%), SI-uLBP(Poly OA)(36.4%), S-MBP(RBF OA)(89.7%), SI-uLBP(Poly OA)(93.1%), SI-uLBP(Poly OA)(96.4%), SI-sMBP(RBF OO)(51.5%), (SI-LBP(Poly OA), SI-uLBP(Poly OA))(100%), SI-sMBP(RBF OO)(100%), uMBP(RBF OA)(44.4%), SI-LBP(Poly OA)(47.8%) and SI-uLBP(Poly OA)(56.3%) respectively.

Summary

This chapter presents comparative results of the proposed techniques with baselines and existing research. The results are analyzed on the basis of three evaluation metrics i.e., accuracy, precision and recall. The discussion over the results, achieved through applying the proposed techniques on the dataset of known and unknown signers is presented as well.

Chapter 13

Conclusions and Future Directions

Automatic sign language recognition helps in communication between normal and deaf people. Throughout the last decade, it has been an important area of interest for computer science researchers. Many efforts have been presented for interpreting the worldwide sign languages but very little effort is done for Pakistan sign language. One of the main challenges for presenting some computational techniques is the absence of a dataset with rotation and scale variances generated through multiple signers and the categorization of PSL signs that should be based on their physical appearance. The rest of the open issues are accurate detection of hands under complex backgrounds, extraction of signer independent scale and rotation invariant lower dimensional feature sets. As well as, different kernel functions show their strength under different environments and there is a need to present a classification methodology that should use an ensemble of all those kernel functions.

In this thesis, we have presented the following contributions: (1) classification of Pakistan sign language(PSL) alphabets by proposing semi-symmetric mean binary pattern-based features and applying error correcting output codes based support vector machines(ECOC-SVMs), (2) By extending the proposed technique features are adopted to cover scale invariance and using an ensemble of SVM kernels, (3) The feature space covering scale and rotation invariance is subject to the feature dimension reduction using principal component analysis, (4) Prior to the phase of feature extraction, hands are detected and localized through YOLO(you only look once) based convolutional neural networks(CNN) with subject to post-processing using morphological operations, (5) Shape based signs categorization is presented as well, (6) It was all possible to validate the proposed techniques over the PSL dataset generated by seven native signers.

A combinatory approach of you only look once(YOLO) based convolutional neural network(CNN) and morphological operations is presented for detecting, localizing and extracting the hand from the input images. YOLO-CNN is used for the detection and localization of hands

followed by suppressing the background through the use of skin detector in HSV color space. The extraction of hands is accomplished through the use of morphological operations.

Salient features from an image are key to the classification task. We have presented symmetric mean based binary patterns(sMBP) feature vector that extends the uniform binary pattern through maintaining rotation invariance. The task is accomplished by exploiting the symmetric properties of circular neighboring points. Error-correcting output codes(ECOC) provide a general-purpose method for improving the performance of inductive learning programs on multiclass problems. ECOC based support vector machines are used for classification purposes that use linear, polynomial and radial basis function based kernels with one-vs-one and one-vs-all modalities.

Symmetric mean binary pattern which was insensitive to the noise and rotation of the hand in sign image but not equipped with the scale invariance. Secondly, we used three kernels for the ECOC based multiclass SVMs leaving overall six results but realistically three for each of the modality i.e., OvO and OvA. The results were not able to conclude the authority of the proposed technique for any of the specific kernels. To resolve the limitations of the proposed sMBP, we have presented scale invariant sMBP using an ensemble of kernels from ECOC based support vector machines(SI-sMBP). The selection of a particular bin calculated from images at four different scale resolutions(Gaussian pyramid) is accomplished by proposing a new metric i.e., the impact of a bin at a particular level of the pyramid. The proposed SI-sMBP is not only invariant to the size of the sign images but the ensemble takes advantage of all three kernels. The results of SVM kernels are ensembled by presenting ensemble of kernels algorithm(EoKA).

The proposed sMBP was rotation invariant with lesser feature dimensional vector, 1×31 , and insensitive to noise but was not scale invariant. To introduce the scale invariance, SI-sMBP was presented that wasn't only insensitive to noise but scale and rotation invariant as well. It resulted in a feature vector of increased dimension i.e., 1. There is a need to reduce the dimension of the feature that should not only achieve a feature vector with lesser dimension but redundant ones should be suppressed as well. In the proposed approach, we have applied principle component analysis(PCA) based feature extraction methodology for features dimension reduction. The resultant feature set is subject classification using ensemble of kernels based support vector machines i.e., linear, RBF and polynomial.

The PSL signs are captured by the seven signers under the controlled environment. The images are captured at a resolution of 1920×1080 . The signs from each of the signers are taken from three different distances and examples of the signs are represented in figure 4.2. D1, D2 and D3 are the 2.5, 3.5 and 4.5 feet distance from the center of the camera to the hand but under the room illumination environment. In order to adopt rotation invariance, each class contains the variation in its signs having rotation upto 45 degrees. Originally, there was a total of 5756

signs in the dataset of the known signers and it was for all 36 classes. The split is on the base of 70% and 30% for train and test data respectively that resulted in 4052 images in train and 1704 in test sets. On average each of the class have 159.89 images in the dataset from the known signers, 112.56 in training and 47.33 images in the test dataset.

The proposed YOLO-CNN based hand detector tested over the dataset of the known signers produced a precision value of 99.5%(highest) through the model trained over the learning rate 0.000001 while it remained lowest with the score 98.41% for the learning rate 0.00001. The highest recall was 98.9% and it was for 0.000001 learning rate. When tested over the dataset of unknown signers, the learning rate of 0.000001 produced the highest results i.e., precision score as 99.01% and recall 99.08%.

While testing the proposed sMBP over a dataset of the known signers, the highest of the results were achieved through the use of polynomial kernel for ECOC-based multiclass SVM using OvO modality(87.78% accuracy, 87.8% precision, 87.7% recall) while it was highest through RBF kernel using OvA modality(accuracy 87.6%, 88.2% precision, 88.1% recall). When the proposed technique is validated over the dataset of unknown signers, the best of the results is through the use of linear kernel for both of the modalities i.e., OvO(48.09% accuracy, 53.9% precision, recall 48.5%) and OvA(43.57% accuracy, precision 46.3%, 43.7% recall).

The proposed scale invariant sMBP using ensemble of kernels when applied over the dataset of the known signers achieved the following results through OvO and OvA multiclass approaches i.e., OvO(accuracy 94.72%, precision 94.7%, recall 94.4%) and OvA(accuracy 95.19%, precision 95.2%, recall 94.8%). The same approach but applied over the dataset of unknown signers have the results OvO(49.29% accuracy, 52.8% precision, 49.9% recall) and OvA(49.58% accuracy, 52.5% precision, 50.1% recall). With the reduced dimensional feature set transformed over PCA, suppressed the role redundant features and the proposed SI-sMBP produced highest results in comparison to all of the proposed techniques i.e., OVO(known signers(accuracy 96.23%, precision 96.5%, recall 96.2%), unknown signers(accuracy 49.32%, precision 52.5%, recall 49.5%)) and OVO(known signers(accuracy 94.61%,precision 95.0%, recall 94.8%), unknown signers(accuracy 50.99%, precision 52.7%, recall 51.6%)).

Recognition of the continuous PSL alphabets from videos was accomplished through the use of histogram features from a local optical flow that contributes in forming a combined histogram. The classification task was completed using multiclass support vector machines. While keeping the size of the histogram of individual feature vector(HIFV) as 1×16 , it produced the highest of the accuracy i.e. 95%, using ECOC-SVM classifier with RBF kernel(RBFFK) and OvA multiclass modality.

PSL Words recognition generated through fingerspelling was presented as well where PCA based sI-sMBP was used as a feature vector and an external Urdu words coding dictionary with the combination of hamming distance was used to complete the translation task.

A problem of categorizing the Pakistan sign language(PSL) alphabets on the basis of shape, visibility and orientation of hand and fingers are solved by using six statistical features of the calculated lbp histogram i.e., standard deviation, variance, skewness, kurtosis, entropy and energy. The extracted features represent the sign in a more discriminative way and are fed to the multi-class support vector machines(SVMs) for classification. The performance of the proposed technique is presented in the form of a classification matrix and line graph showing the statistics of accuracy, precision, recall and f-measure. The proposed technique has achieved considerably good categorization results.

13.1 Future Directions

In future, the research for the recognition of PSL sentences may be employed. Furthermore, new feature vectors may be explored. As well as, deep learning based convolutional neural networks can be utilized for the recognition of PSL.

Appendix A

Classification Matrices for Semi-Symmetric Mean Binary Pattern based PSL Recognition

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	41	0	0	0	0	0	0	1	0	0	4	0	0	0	0	0	0	0	0	0	1	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	82.00	18.0
C-2	0	37	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	5	1	0	0	0	0	78.72	21.3
C-3	0	0	49	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	92.45	7.5	
C-4	0	0	0	47	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.92	4.1	
C-5	0	0	0	0	41	0	0	0	0	3	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	83.67	16.3	
C-6	0	0	0	0	0	34	0	0	0	0	0	2	0	1	0	0	0	0	0	0	2	0	0	0	1	0	1	0	2	0	0	0	0	2	0	0	75.56	24.4
C-7	0	0	0	0	0	0	38	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	77.55	22.4	
C-8	0	0	0	0	0	0	0	41	0	0	0	0	0	0	1	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	79.59	20.4
C-9	0	2	1	0	0	0	0	0	39	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	79.59	20.4
C-10	0	0	0	0	0	0	0	0	0	27	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	79.59	20.4
C-11	9	1	0	0	0	0	0	0	0	0	39	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	3	0	0	1	0	0	0	79.59	20.4	
C-12	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	78.00	22.0
C-13	0	0	0	0	4	0	0	0	0	1	0	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91.84	8.2
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	67.39	32.6	
C-15	0	0	2	0	0	0	0	3	0	0	0	0	0	0	39	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	80.00	20.0
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	86.67	13.3
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91.30	8.7
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	96.00	4.0
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70.45	29.5
C-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.18	6.8
C-21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	68.09	31.9
C-22	4	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90.20	9.8
C-23	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	92.00	8.0
C-24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86.36	13.6
C-25	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90.91	9.1
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	78.43	21.6
C-27	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	75.00	25.0
C-28	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	72.34	27.7
C-29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			

Figure A.1: Classification Matrix of Proposed Technique using Linear Kernel for Known Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	43	0	0	0	0	0	0	2	0	0	4	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	86.00	14.00		
C-2	0	39	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	1	0	0	82.98	17.02	
C-3	0	0	47	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	88.68	11.32		
C-4	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	97.96	2.04		
C-5	0	0	0	0	46	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	93.88	6.12		
C-6	0	0	0	1	0	38	0	0	0	0	1	3	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	84.44	15.56		
C-7	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89.80	10.20			
C-8	0	0	1	1	0	0	1	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.62	6.38		
C-9	0	1	2	0	0	0	0	0	38	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	3	0	0	1	1	0	0	77.55	22.45		
C-10	0	0	0	0	2	0	0	0	0	38	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.61	17.39		
C-11	1	0	0	0	0	0	0	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	3	0	86.61	13.33		
C-12	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	98.00	2.00		
C-13	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	91.84	8.16		
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.65	4.35		
C-15	0	0	0	0	0	0	0	1	0	0	0	0	0	0	39	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	1	0	0	1	0	82.00	18.00		
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86.67	13.33		
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.61	17.39		
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	98.00	2.00		
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	93.18	6.82		
C-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.74	4.26		
C-21	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	96.08	3.92		
C-22	4	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90.00	10.00		
C-23	0	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	37	0	0	0	0	2	0	0	1	0	0	0	0	84.09	15.91		
C-24	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	1	1	0	0	0	90.91	9.09		
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	3	1	0	0	86.27	13.73		
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	85.42	14.58		
C-27	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91.49	8.51			
C-28	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.74	4.26			
C-29	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.83	4.17			
C-30	0	0	0	0	0	0	4	0	0	0	0	0	0	0	5	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	13	0	0	28.26	71.74			
C-31	0	5	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	77.78	22.22			
C-32	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	3	0	0	82.61	17.39		
C-33	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	42	1	0	87.50	12.50	
C-34	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	2	2	1	0	0	0	0	0	0	0	0	0	0	0	3	0	0	1	29	0	63.04	36.96
C-35	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	88.64	11.36		
C-36	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	42	82.35	17.65		
Positive Classified	48	50	52	51	52	41	51	48	43	40	59	48	50	45	44	57	50	50	41	48	49	46	42	41	49	55	50	48	50	38	45	46	51	35	47	51	Overall Accuracy	86.62	
Precision(%)	89.58	78.00	90.38	94.12	88.46	92.68	86.27	91.67	88.37	95.00	83.05	93.75	88.00	91.11	88.64	66.67	98.00	82.00	90.24	93.75	100.00	97.83	88.10	97.56	89.80	74.55	86.00	93.75	92.00	34.21	77.78	82.61	82.35	82.86	82.98	82.35			
Omission Error(%)	10.42	22.00	9.62	5.88	11.54	7.32	13.73	8.33	11.63	5.00	16.95	6.25	12.00	8.89	11.36	33.33	2.00	18.00	9.76	6.25	0.00	2.17	11.90	2.44	10.20	25.45	14.00	6.25	8.00	65.79	22.22	17.39	17.65	17.14	17.02	17.65			

Figure A.2: Classification Matrix of Proposed Technique using RBF Kernel for Known Signers:OvO

[illegible]

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	28	0	0	0	1	0	0	0	1	0	8	0	0	0	0	0	0	0	0	0	4	6	0	0	0	0	0	2	0	0	0	0	0	0	0	0	56.00	44.00	
C-2	0	31	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2	1	0	0	0	6	2	0	0	0	65.96	34.04	
C-3	0	0	39	0	1	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	4	0	0	0	0	2	0	0	0	73.58	26.42		
C-4	0	1	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	93.88	6.12		
C-5	0	0	0	0	32	0	0	0	0	6	0	0	6	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	1	0	0	0	1	0	0	65.31	34.69	
C-6	0	0	0	0	0	33	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	1	0	2	0	0	3	0	0	0	1	2	0	73.33	26.67		
C-7	3	0	0	1	0	0	35	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	7	71.43	28.57		
C-8	0	0	2	0	0	0	1	37	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	4	78.72	21.28		
C-9	2	1	1	1	0	0	0	1	41	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	83.67	16.33	
C-10	0	0	0	0	5	0	0	0	0	29	0	0	9	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	63.04	36.96	
C-11	11	7	0	6	0	0	0	0	0	0	21	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42.00	58.00		
C-12	0	0	0	0	0	0	0	0	0	1	0	47	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.92	4.08		
C-13	0	0	0	0	4	0	0	0	0	10	0	0	28	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	60.87	39.13	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	78.00	22.00		
C-15	0	0	1	1	0	0	1	2	0	0	0	0	0	0	31	0	3	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	3	68.89	31.11		
C-16	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	39	0	0	0	2	0	0	0	0	0	0	0	0	0	3	1	0	0	0	0	84.78	15.22		
C-17	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	44	0	0	2	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	88.00	12.00		
C-18	1	0	0	0	4	0	0	0	0	0	1	1	0	0	0	0	0	2	23	0	0	0	0	0	0	0	1	5	0	0	0	0	0	3	3	0	4.55	95.45	
C-19	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	2	0	3	0	0	0	0	2	0	0	3	0	75.00	25.00	
C-20	0	0	0	0	0	7	0	0	0	0	0	0	0	0	2	0	1	0	0	26	4	0	0	2	0	1	0	0	0	0	0	0	0	0	0	1	55.32	44.68	
C-21	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	1	0	0	0	42	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	82.35	17.65	
C-22	9	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	0	1	0	0	0	0	0	0	0	78.00	22.00		
C-23	0	0	0	0	0	0	1	4	0	3	0	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	1	0	0	0	0	1	0	0	0	77.27	22.73	
C-24	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	1	93.18	6.82		
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	0	1	9	2	0	0	76.47	23.53	
C-26	0	0	0	0	1	0	0	0	0	0	0	0	0	11	0	0	0	1	0	1	0	0	0	0	0	33	0	0	0	0	0	1	0	0	0	68.75	31.25		
C-27	0	2	1	1	0	1	0	0	7	0	0	0	0	0	1	0	0	1	0	1	0	0	2	0	0	0	0	30	0	0	0	0	0	0	0	63.83	36.17		
C-28	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	93.62	6.38			
C-29	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	42	0	0	0	0	0	0	87.50	12.50		
C-30	0	0	0	0	0	0	3	1	0	0	0	1	0	0	4	16	0	0	0	3	0	0	0	0	0	0	0	1	0	7	0	0	0	1	8	15.22	84.78		
C-31	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	1	3	0	0	33	1	1	0	0	73.33	26.67		
C-32	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	6	0	1	1	0	0	0	30	1	3	0	0	65.22	34.78	
C-33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	6	1	0	0	0	0	3	1	34	1	0	0	70.83	29.17	
C-34	0	0	0	0	2	6	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	1	4	1	6	1	0	0	0	0	0	0	19	3	0	41.30	58.70	
C-35	0	0	0	0	2	0	0	0	0	10	0	0	5	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	5	0	0	0	0	20	1	45.45	54.55	
C-36	0	0	0	1	0	0	2	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	42	82.35	17.65		
Positive Classified	55	49	44	58	47	53	43	47	56	61	33	53	49	50	41	57	51	6	62	40	51	51	48	49	49	59	55	50	59	58	13	45	46	41	32	32	67	70.94	
Precision(%)	50.91	63.27	88.64	79.31	68.09	62.26	81.40	78.72	73.21	47.54	63.64	88.68	57.14	78.00	75.61	88.42	86.27	33.33	53.73	65.00	82.35	76.47	70.83	83.67	66.10	60.00	60.00	74.58	72.41	53.85	73.33	65.22	82.93	59.38	62.50	62.69			
Omission Error(%)	49.09	36.73	11.36	20.69	31.91	37.74	18.60	21.28	26.79	52.46	36.36	11.32	42.86	22.00	24.39	31.58	13.73	66.67	46.77	35.00	17.65	23.53	29.17	16.33	33.90	40.00	40.00	25.42	27.59	46.15	26.67	34.78	40.63	37.50	37.31				

Figure A.4: Classification Matrix of Proposed Technique using Linear Kernel for Known Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	45	0	0	0	0	1	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	90.00	10.00	
C-2	0	38	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	3	1	0	0	0	80.85	19.15	
C-3	0	0	49	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	92.45	7.55	
C-4	0	0	1	47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	95.92	4.08	
C-5	0	0	2	0	43	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	87.76	12.24	
C-6	0	0	0	0	0	39	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86.67	13.33	
C-7	0	0	0	0	0	1	40	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	81.63	18.37	
C-8	0	0	0	0	0	0	1	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.74	4.26	
C-9	0	1	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	83.67	16.33	
C-10	0	0	0	0	0	1	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	82.61	17.39	
C-11	2	0	1	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	88.00	12.00	
C-12	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.96	2.04	
C-13	0	0	0	0	3	0	0	0	0	2	0	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	84.78	15.22	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	1	0	6	0	0	0	0	0	0	0	0	0	86.00	14.00	
C-15	0	0	1	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	91.11	8.89	
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89.13	10.87	
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.73	2.27	
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88.64	11.36	
C-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.87	2.13	
C-21	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	96.08	3.92
C-22	5	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.00	18.00
C-23	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	1	0	0	0	0	0	0	0	0	84.09	15.91
C-24	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	90.91	9.09
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	88.24	11.76
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	89.58	10.42
C-27	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.74	4.26	
C-28	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.83	4.17	
C-29	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	28.26	71.74
C-30	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	5	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.00	20.00	
C-31	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.61	17.39	
C-32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	83.33	16.67	
C-33	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91.30	8.70	
C-34	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90.91	9.09	
C-35	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	78.43	21.57	
C-36	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Overall Accuracy	87.61	
Positive Classified	52	46	60	48	49	43	46	47	45	42	51	51	45	46	46	62	51	51	41	52	50	42	40	44	44	49	52	48	47	32	44	44	52	46	46	49	Overall Accuracy	87.61
Prediction(%)	86.54	82.61	81.67	97.92	87.76	90.70	86.96	95.74	91.11	90.48	86.27	94.12	86.67	93.48	89.13	66.13	98.04	84.31	95.12	88.46	98.00	97.62	92.50	90.91	91.84	82.69	86.54	93.75	97.87	40.63	81.82	86.36	76.92	91.30	86.96	81.63		
On-tation Error(%)	13.46	17.39	18.33	2.08	12.24	9.30	13.04	4.26	8.89	9.52	13.73	5.88	13.33	6.52	10.87	33.87	1.96	15.69	4.88	11.54	2.00	2.38	7.50	9.09	8.16	17.31	13.46	6.25	2.13	59.38	18.18	13.64	23.08	8.70	13.04	18.37		

Figure A.5: Classification Matrix of Proposed Technique using RBF Kernel for Known Signers:OVA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	31	0	0	0	0	1	0	0	0	1	6	0	0	0	0	0	0	0	1	0	1	3	0	0	0	0	0	0	0	1	0	0	1	2	0	1	0	62.00	38.00
C-2	0	38	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	6	0	0	0	0	80.85	19.15		
C-3	0	0	43	0	0	0	0	2	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	3	1	0	0	81.13	18.87		
C-4	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	97.96	2.04		
C-5	0	1	0	0	29	0	0	0	0	5	0	0	4	2	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	6	0	59.18	40.82		
C-6	0	0	0	0	0	39	0	0	0	0	0	3	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	86.67	13.33		
C-7	1	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	91.84	8.16		
C-8	0	0	1	1	0	0	0	40	0	0	0	0	0	0	0	2	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	85.11	14.89		
C-9	0	0	1	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	2	0	1	0	0	85.71	14.29		
C-10	0	0	0	0	0	0	0	1	0	31	0	0	4	0	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	7	0	67.39	32.61		
C-11	0	0	0	1	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	92.00	8.00		
C-12	0	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.96	2.04		
C-13	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	92.00	8.00		
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	91.11	8.89		
C-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	1	84.78	15.22	
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00		
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	93.18	6.82		
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.73	2.27		
C-19	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	89.36	10.64	
C-20	2	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	45	2	0	0	0	0	0	0	0	0	0	0	0	0	0	88.24	11.76		
C-21	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	33	0	0	0	0	0	0	2	0	0	1	0	1	2	0	1	66.00	34.00
C-22	4	0	0	1	0	0	0	1	0	0	1	0	0	2	0	0	0	0	0	0	1	0	0	37	1	0	0	0	0	0	0	0	0	1	1	0	84.09	15.91	
C-23	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	93.18	6.82	
C-24	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	2	0	1	0	0	94.12	5.88	
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	33	0	0	0	0	0	1	0	1	68.75	31.25		
C-26	0	0	1	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	1	1	0	0	74.47	25.53		
C-27	1	1	0	0	1	0	0	5	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	45	0	0	1	0	0	0	95.74	4.26		
C-28	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	1	0	0	97.92	2.08		
C-29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	3	32.61	67.39		
C-30	0	0	0	0	0	0	2	0	0	0	0	0	0	0	5	20	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.22	17.78		
C-31	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	40	1	0	0	86.96	13.04		
C-32	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	95.83	4.17		
C-33	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	1	0	0	91.30	8.70	
C-34	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	38	0	86.36	13.64
C-35	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	86.27	13.73	
C-36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	2	0	0	0	44	86.27	13.73		
Positive Classified	40	45	46	51	31	42	50	43	50	37	54	54	52	62	50	62	52	43	47	46	46	38	46	46	46	57	36	41	51	51	29	57	44	58	48	56	50	Overall Accuracy (%)	84.61
Precision(%)	77.5	84.4	93.5	94.1	93.5	92.9	90.0	93.0	84.0	83.8	85.2	88.9	76.9	74.2	82.0	62.9	96.2	95.3	91.5	91.3	97.8	86.8	80.4	89.1	84.2	91.7	85.4	88.2	92.2	51.7	64.9	90.9	79.3	87.5	67.9	88.0			
Omission Error(%)	22.50	15.56	6.52	5.88	6.45	7.14	10.00	6.98	16.00	16.22	14.81	11.11	23.08	25.81	18.00	37.10	3.85	4.65	8.51	8.70	2.17	13.16	19.57	10.87	15.79	8.33	14.63	11.76	7.84	48.28	35.09	9.09	20.69	12.50	32.14	12.00			

Figure A.6: Classification Matrix of Proposed Technique using Polynomial Kernel for Known Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	4	0	0	2	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	2	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11.11	88.9
C-2	0	6	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	14	5	1	0	0	15.00	85.0
C-3	0	0	28	2	2	0	0	0	3	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	3	0	0	0	0	0	0	0	0	68.29	31.7
C-4	0	0	2	28	0	0	0	1	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.35	17.6
C-5	0	0	0	0	25	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	1	0	69.44	30.6
C-6	0	0	1	0	0	8	1	1	0	0	0	0	0	0	0	0	0	2	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	24	0	1	18.18	81.8
C-7	0	0	0	0	0	0	42	3	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	87.50	12.5	
C-8	0	0	11	0	0	0	0	22	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	61.11	38.9	
C-9	0	0	9	2	0	0	0	2	21	0	0	2	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	4	0	0	0	0	0	0	0	50.00	50.0	
C-10	0	0	0	0	2	4	0	0	0	19	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47.50	52.5	
C-11	17	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	51.16	48.8	
C-12	0	0	6	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	76.92	23.1	
C-13	0	0	0	0	2	0	0	0	0	22	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27.03	73.0	
C-14	0	0	0	0	1	0	0	5	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	84.85	15.2	
C-15	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	33.33	66.7	
C-16	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15.91	84.1	
C-17	0	0	0	0	0	0	2	4	0	0	0	0	0	0	0	0	24	0	0	0	1	6	0	0	0	0	0	0	0	0	0	0	0	0	0	57.14	42.9	
C-18	0	0	0	0	0	3	0	1	0	0	0	21	0	0	0	0	0	6	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	13.33	86.7	
C-19	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	8	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9.76	90.2	
C-20	0	0	10	1	0	0	0	0	1	0	0	1	0	0	2	0	0	0	0	16	2	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	43.24	56.8
C-21	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94.29	5.7
C-22	1	0	0	2	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	10	14	0	0	0	0	0	0	0	0	0	0	0	0	0	35.00	65.0
C-23	0	0	7	2	0	0	0	3	0	0	0	0	0	0	3	0	0	0	0	0	0	0	19	0	0	0	2	0	0	0	0	0	0	0	0	0	52.78	47.2
C-24	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38.46	61.5	
C-25	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	30.95	69.0	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	97.56	2.4
C-27	0	0	16	8	0	0	0	0	12	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	5.00	95.0
C-28	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89.74	10.3	
C-29	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	68.29	31.7	
C-30	0	0	0	0	0	0	4	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	66.67	33.3
C-31	0	8	1	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51.35	48.6	
C-32	0	1	1	6	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40.43	59.6	
C-33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	83.78	16.2	
C-34	0	0	0	3	0	1	6	4	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16.67	83.3	
C-35	0	0	0	0	4	0	0	0	0	0	18	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18.18	81.8	
C-36	0	0	0	0	0	0	9	5	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32.43	67.6	
Positive Classified	22	24	104	58	36	24	64	51	40	63	59	98	11	29	28	7	24	16	4	22	56	25	46	16	23	75	20	37	40	53	33	41	84	37	20	26	Overall Accuracy (%)	48.09
Precision(%)	18.18	25.00	26.92	48.28	69.44	33.33	65.63	43.14	57.50	30.16	37.29	30.61	90.91	96.55	46.43	100.00	100.00	37.50	100.00	72.73	58.93	56.00	41.30	93.75	56.52	53.33	10.00	94.59	70.00	49.06	57.58	46.34	36.90	16.22	30.00	46.15		
Omission Error(%)	81.82	75.00	73.08	51.72	30.56	66.67	34.38	56.86	42.50	69.84	62.71	69.39	9.09	3.45	53.57	0.00	0.00	62.50	0.00	27.27	41.07	44.00	58.70	6.25	43.48	46.67	90.00	5.41	30.00	50.94	42.42	53.66	63.10	83.78	70.00	53.85		

Figure A.7: Classification Matrix of Proposed Technique using Linear Kernel for UnKnown Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	11	0	0	6	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	2	1	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30.56	69.44	
C-2	0	7	8	0	0	0	0	3	0	0	2	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	2	0	0	0	5	9	2	0	0	0	17.50	82.50
C-3	0	0	33	0	0	0	0	1	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	80.49	19.51	
C-4	0	0	12	18	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	52.94	47.06	
C-5	0	0	0	0	18	0	0	0	0	8	0	0	2	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	50.00	50.00	
C-6	0	0	2	0	0	4	3	0	0	0	0	1	0	0	0	0	0	9	0	0	0	0	3	0	0	0	4	0	0	0	4	0	1	0	12	0	1	9.09	90.91
C-7	0	0	0	4	0	0	31	1	0	0	0	1	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	3	64.58	35.42		
C-8	0	0	7	1	0	0	5	14	1	0	0	0	0	0	1	0	0	0	0	0	0	5	0	0	0	0	0	2	0	0	0	0	0	0	0	0	38.89	61.11	
C-9	0	0	17	0	0	0	0	0	1	14	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	33.33	66.67		
C-10	0	0	0	0	6	3	0	0	0	20	0	0	1	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	1	6	0	50.00	50.00	
C-11	26	0	0	0	0	0	0	0	5	0	2	0	0	0	0	0	0	0	0	2	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	4.65	95.35		
C-12	0	0	7	0	0	0	1	2	4	0	0	22	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	56.41	43.59		
C-13	0	0	0	0	11	0	0	0	0	10	0	0	12	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	3	32.43	67.57		
C-14	0	0	0	0	4	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	57.58	42.42		
C-15	0	1	21	2	0	0	0	2	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	30.77	69.23		
C-16	0	0	0	0	13	3	1	0	0	0	0	0	0	0	1	0	7	0	1	0	0	0	1	1	0	3	1	0	0	3	7	0	0	1	0	1	15.91	84.09	
C-17	4	0	0	0	0	3	1	0	0	0	5	0	0	0	3	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50.00	50.00		
C-18	0	0	0	0	3	3	1	0	0	0	0	17	0	0	0	0	0	5	0	0	0	0	7	0	0	1	0	0	0	0	0	0	7	1	0	0	11.11	88.89	
C-19	0	0	0	0	1	2	3	0	1	0	0	14	0	0	0	0	0	6	2	0	0	0	0	0	0	3	1	0	0	0	1	3	3	0	1	0	4.88	95.12	
C-20	0	0	5	3	0	0	0	2	0	0	0	0	0	0	3	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	1	0	0	2	0	29.73	70.27		
C-21	7	0	5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	1	0	0	0	0	0	0	0	0	0	0	0	0	0	60.00	40.00		
C-22	2	0	0	1	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	3	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62.50	37.50	
C-23	0	0	10	2	1	0	0	5	0	0	0	1	0	0	3	0	0	0	0	0	0	0	11	0	0	0	0	2	0	0	1	0	0	0	0	0	30.56	69.44	
C-24	0	0	0	0	7	4	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	2	6	0	3	0	0	0	0	1	0	0	4	13	14	0	15.38	84.62
C-25	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	14.29	85.71		
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	1	0	85.37	14.63		
C-27	0	0	20	0	0	0	0	3	5	0	3	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	1	0	0	0	0	12.50	87.50		
C-28	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	82.05	17.95		
C-29	0	0	3	0	3	1	0	0	1	1	0	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	20	1	0	0	0	0	48.78	51.22		
C-30	0	0	3	0	0	2	11	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	10	28.21	71.79		
C-31	0	6	5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	2	0	0	0	8	2	2	0	0	21.62	78.38		
C-32	0	0	6	5	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	17	9	0	0	36.17	63.83		
C-33	0	1	9	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	1	0	0	0	0	0	8	14	0	0	37.84	62.16		
C-34	0	0	0	0	3	3	7	1	1	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	5	0	0	1	0	1	2.78	97.22	
C-35	0	0	0	0	19	0	0	0	0	5	0	1	1	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	1	0	3	0	9.09	90.91	
C-36	0	0	0	0	0	0	0	10	4	1	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	4	0	0	4	0	12	32.43	67.57	
Positive Classified	52	22	173	44	89	25	75	41	47	44	22	64	24	24	35	7	21	22	3	15	25	47	49	7	14	61	49	37	23	45	20	59	50	35	18	28	Overall Accuracy (%)	36.02	
Precision(%)	21.15	31.82	19.08	40.91	20.22	16.00	41.33	34.15	29.79	45.45	9.09	34.38	50.00	79.17	34.29	100.00	100.00	22.73	66.67	73.33	84.00	53.19	22.45	85.71	42.86	57.38	10.20	86.49	86.96	74.44	40.00	28.81	28.00	2.86	16.67	42.86			
Omission Error(%)	78.85	68.18	80.92	59.09	79.78	84.00	58.67	65.85	70.21	54.55	90.91	65.63	50.00	20.83	65.71	0.00	0.00	77.27	33.33	26.67	16.00	46.81	77.55	14.29	57.14	42.62	89.80	13.51	13.04	75.56	60.00	71.19	72.00	97.14	83.33	57.14			

Figure A.8: Classification Matrix of Proposed Technique using RBF Kernel for UnKnown Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	6	0	0	5	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16.67	83.33
C-2	0	4	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	3	0	0	0	13	5	6	0	0	0	10.00	90.00
C-3	0	0	30	2	1	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	1	0	0	0	0	0	73.17	26.83
C-4	0	0	4	28	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	87.35	17.65
C-5	0	0	0	0	29	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	1	0	80.56	19.44
C-6	0	0	2	0	0	6	2	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	7	0	0	1	1	0	0	0	0	0	1	12	0	1	13.64	86.36
C-7	0	0	0	0	0	0	31	3	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	64.58	35.42	
C-8	0	0	13	0	0	0	0	21	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	58.33	41.67	
C-9	0	0	14	2	0	0	0	0	18	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	42.86	57.14	
C-10	0	0	0	0	2	2	0	0	0	19	0	0	4	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0	4	0	0	0	0	1	5	0	47.50	52.50
C-11	11	0	0	0	0	0	0	0	3	0	24	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	2	1	0	0	0	0	0	0	0	55.81	44.19	
C-12	0	0	7	0	0	0	0	3	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	64.10	35.90	
C-13	0	0	0	0	8	0	0	0	0	20	0	0	5	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	0	13.51	86.49
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	63.64	36.36	
C-15	0	0	11	1	0	0	4	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	1	0	0	35.90	64.10	
C-16	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	8	0	0	1	0	0	0	0	0	2	0	0	0	8	13	0	0	0	0	0	18.18	81.82	
C-17	0	0	0	0	0	0	4	7	0	0	0	0	0	0	0	16	0	0	0	0	7	0	0	0	0	0	0	0	4	0	0	0	0	0	3	38.10	61.90	
C-18	0	0	0	0	0	2	3	0	0	0	0	17	0	0	0	0	0	9	0	0	0	8	0	0	0	0	0	0	0	0	0	0	5	0	1	20.00	80.00	
C-19	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	8	6	0	0	0	0	0	0	2	0	0	0	0	0	0	4	0	0	14.63	85.37	
C-20	0	0	4	1	0	0	0	0	1	0	0	2	0	0	6	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	1	0	0	0	4	24.32	75.68	
C-21	0	0	0	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	29	0	0	0	0	0	0	0	3	0	0	0	0	0	0	82.86	17.14	
C-22	1	0	0	2	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	3	24	0	0	0	0	0	0	6	0	0	0	0	0	0	60.00	40.00	
C-23	0	0	11	0	0	0	0	2	0	0	0	0	0	0	3	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	55.56	44.44	
C-24	0	0	0	0	1	7	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	12	0	6	0	0	1	1	0	0	5	7	13	0	30.77	69.23	
C-25	0	4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	1	0	28.57	71.43	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	97.56	2.44	
C-27	0	0	11	4	0	0	0	2	13	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	15.00	85.00	
C-28	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	34	0	0	0	0	0	0	87.18	12.82		
C-29	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	30	0	0	0	0	1	0	73.17	26.83	
C-30	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	10	43.59	56.41		
C-31	0	11	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	14	3	4	0	0	37.84	62.16	
C-32	0	8	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	17	18	0	0	36.17	63.83	
C-33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	4	29	0	0	78.38	21.62	
C-34	0	0	0	3	0	0	5	3	0	0	0	4	0	0	0	0	0	3	0	0	0	2	0	0	0	0	2	0	0	2	0	0	0	5	0	7	13.89	86.11
C-35	0	0	0	0	16	0	0	0	0	1	0	0	7	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	1	0	15.15	84.85	
C-36	0	0	0	0	0	0	9	6	1	0	0	1	0	0	2	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	3	0	0	2	0	11	29.73	70.27
Positive Classified	18	29	108	53	57	19	70	51	43	41	49	74	16	22	49	8	16	34	7	10	39	33	61	14	22	61	34	48	44	36	37	36	82	42	14	39	Overall Accuracy (%)	44.77
Precision(%)	33.33	13.79	27.78	52.83	50.88	31.58	44.29	41.18	41.86	46.34	48.98	33.78	31.25	55.45	28.57	100.00	100.00	26.47	85.71	90.00	74.36	72.73	32.79	85.71	54.55	65.57	17.65	70.83	58.18	47.22	37.84	47.22	35.37	11.90	35.71	28.21		
Omission Error(%)	66.67	86.21	72.22	47.17	49.12	68.42	55.71	58.82	58.14	53.66	51.02	66.22	68.75	4.55	71.43	0.00	0.00	73.53	14.29	10.00	25.64	27.27	67.21	14.29	45.45	34.43	29.17	31.82	52.78	62.16	52.78	64.63	88.10	64.29	71.79			

Figure A.9: Classification Matrix of Proposed Technique using Polynomial Kernel for Unknown Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	0	0	0	12	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	1	0	0	1	0	0	0	0.00	100.0	
C-2	0	7	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	1	1	0	0	0	1	0	9	0	6	4	0	2	5	1	0	0	0	17.50	82.5	
C-3	0	17	6	0	0	0	2	5	3	0	3	0	3	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	41.46	58.5	
C-4	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	97.06	2.9	
C-5	0	0	1	0	16	0	0	0	15	0	0	1	0	0	0	0	0	0	0	0	0	2	0	0	1	0	1	0	0	0	0	0	0	0	0	44.44	55.6	
C-6	0	0	2	1	0	5	5	1	1	0	0	0	1	0	0	0	3	0	0	0	0	0	0	0	0	10	4	0	0	1	0	0	9	1	0	11.36	88.6	
C-7	0	0	0	0	0	0	46	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.83	4.2		
C-8	0	0	4	1	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	75.00	25.0	
C-9	0	0	8	6	1	0	0	1	19	1	0	0	0	1	0	0	2	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	45.24	54.8	
C-10	0	0	0	0	3	0	0	0	20	0	0	3	0	0	0	0	0	0	0	0	4	7	0	0	0	0	0	0	0	1	0	0	0	10	0	50.00	50.0	
C-11	0	0	0	0	0	0	0	0	0	25	0	0	3	0	0	0	0	0	0	0	4	7	0	0	0	0	0	0	6	0	0	0	0	0	0	58.14	41.9	
C-12	0	0	2	3	0	0	1	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	84.62	15.4	
C-13	0	0	0	0	6	0	0	0	24	0	0	4	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	84.62	15.4	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0	0	0	10.81	89.2	
C-15	0	2	12	0	0	1	8	0	0	2	0	0	0	12	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	84.85	15.2	
C-16	0	0	0	0	1	0	0	0	0	0	0	1	0	0	18	0	2	0	4	0	0	0	1	0	0	0	0	0	0	13	0	0	4	0	0	40.91	59.1	
C-17	0	0	0	0	0	7	3	1	0	0	3	0	0	0	0	14	3	0	0	0	3	0	3	0	0	0	2	0	0	2	0	0	0	1	0	33.33	66.7	
C-18	0	0	0	0	0	1	6	1	0	0	18	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	4	0	12	0.00	100.0	
C-19	0	0	0	0	2	2	1	0	0	0	15	0	0	0	0	0	3	3	0	0	27	2	0	0	0	0	9	0	0	0	0	0	1	0	5	0	7.32	92.7
C-20	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	0	2	0	0	0	0	1	0	0	72.97	27.1	
C-21	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.86	17.1		
C-22	3	0	0	6	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	1	0	0	0	0	0	0	55.00	45.0	
C-23	0	0	3	1	0	0	0	4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	26	0	0	1	0	0	0	0	0	0	0	0	0	72.22	27.8	
C-24	0	1	0	0	3	1	0	0	1	0	0	0	0	0	3	0	3	0	0	0	0	0	0	12	0	3	0	0	2	3	0	0	0	1	6	0	30.77	69.2
C-25	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	2	0	23	0	2	1	0	0	5	2	2	1	0	0	54.76	45.2	
C-26	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	0	0	0	0	95.12	4.9	
C-27	0	7	5	0	1	0	0	15	0	0	0	0	0	2	0	0	0	0	0	1	0	0	2	0	0	0	7	0	0	0	0	0	0	0	0	17.50	82.5	
C-28	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	2	0	0	0	0	0	0	0	29	0	1	0	0	1	0	74.36	25.6		
C-29	0	0	0	0	0	0	0	0	0	2	0	12	0	0	1	0	0	0	0	0	0	0	0	0	0	13	0	0	0	6	0	0	0	0	0	31.71	68.3	
C-30	0	0	0	1	0	1	11	4	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	15.38	84.6		
C-31	0	3	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	3	1	0	14	0	0	1	0	0	37.84	62.2	
C-32	0	3	8	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	15	0	0	40.43	59.6		
C-33	0	2	1	3	3	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	0	4	0	0	1	0	18	0	0	0	48.65	51.4	
C-34	0	0	1	5	0	0	8	0	0	4	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	3	0	0	3	0	0	1	4	0	2.78	97.2	
C-35	0	0	0	0	0	0	0	0	24	0	0	4	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0	0	1	1	0	3.03	97.0	
C-36	0	0	0	1	0	1	12	6	0	0	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	3	0	4	10.81	89.2	
Positive Classified	4	14	56	118	34	14	99	58	41	92	49	97	13	30	21	22	14	28	9	32	40	40	52	13	51	72	34	43	19	36	22	28	43	30	34	14	Overall Accuracy (%)	43.57
Precision(%)	0.00	50.00	30.36	27.97	47.06	35.71	46.46	46.55	46.34	21.74	51.02	34.02	30.77	93.33	57.14	81.82	100.00	0.00	33.33	84.38	72.50	55.00	92.31	45.10	54.17	20.59	67.44	58.42	16.67	63.64	67.86	41.86	3.33	2.94	28.57			
Mission Error(%)	100.00	50.00	69.64	72.03	53.94	64.29	53.54	53.66	78.26	48.98	65.98	69.23	5.67	42.86	18.18	0.00	100.00	66.67	15.63	27.50	45.00	50.00	7.69	54.90	45.83	79.41	32.56	31.58	83.33	36.36	32.14	58.14	96.67	97.06	71.43			

Figure A.10: Classification Matrix of Proposed Technique using Linear Kernel for UnKnown Signers: OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	6	0	0	5	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	2	3	10	0	0	0	0	0	1	0	0	0	0	0	0	0	0	16.67	83.33
C-2	0	3	15	0	0	0	0	7	0	0	5	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	6	0	1	0	0	7.50	92.50
C-3	0	0	27	1	0	0	0	1	8	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	65.85	34.15
C-4	0	0	6	22	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	64.71	35.29	
C-5	0	0	4	0	8	0	0	1	0	11	0	0	4	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	1	0	0	0	0	0	22.22	77.78
C-6	0	0	2	2	0	3	3	0	1	0	0	1	0	0	0	0	6	0	0	0	0	0	3	0	0	0	4	1	0	0	3	0	0	14	0	1	6.82	93.18
C-7	0	0	0	2	0	0	31	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	64.58	35.42	
C-8	0	0	7	3	0	0	3	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	2	0	0	0	0	0	0	0	0	50.00	50.00	
C-9	0	0	17	0	0	0	0	0	17	0	0	0	0	0	3	0	0	0	0	0	2	0	0	0	0	0	0	3	0	0	0	0	0	0	0	40.48	59.52	
C-10	0	0	0	0	4	5	0	0	0	21	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	52.50	47.50	
C-11	22	0	0	0	0	0	0	1	5	0	6	0	0	0	0	0	0	0	0	0	1	4	0	0	0	0	0	3	1	0	0	0	0	0	0	13.95	86.05	
C-12	0	0	11	0	0	0	2	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	4	0	0	0	0	48.72	51.28	
C-13	0	0	0	0	12	0	0	0	0	16	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16.22	83.78	
C-14	0	0	3	0	1	0	0	0	0	0	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	63.64	36.36	
C-15	0	0	24	2	0	0	0	3	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20.51	79.49	
C-16	0	0	10	0	0	4	0	0	0	2	0	0	0	2	0	9	0	0	0	0	0	0	0	0	0	0	0	5	0	0	8	0	0	4	0	0	20.45	79.55
C-17	0	0	3	0	0	0	0	0	0	0	7	0	0	0	5	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	57.14	42.86	
C-18	0	0	0	0	2	5	1	0	1	0	0	18	0	0	0	0	0	4	1	0	0	0	4	0	0	0	0	0	0	0	0	0	1	5	0	0	8.89	91.11
C-19	0	0	2	0	0	3	3	0	0	0	2	12	0	0	0	0	0	0	5	2	0	0	1	0	0	0	7	0	0	0	0	0	0	0	0	4.88	95.12	
C-20	0	0	4	3	0	0	0	1	2	0	0	0	0	0	1	0	1	0	0	13	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	35.14	64.86	
C-21	1	0	8	3	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	60.00	40.00	
C-22	1	0	0	2	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	8	20	0	0	0	0	0	0	1	0	0	0	0	0	0	50.00	50.00	
C-23	0	0	15	3	0	3	0	6	1	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	2	0	0	0	0	0	0	0	16.67	83.33	
C-24	0	0	3	0	3	5	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17.95	82.05	
C-25	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	4	8	16	1	0	0	16.67	83.33
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	5	0	0	0	0	0	0	0	25	0	0	1	1	0	0	0	0	60.98	39.02	
C-27	0	0	21	2	0	0	0	4	6	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	7.50	92.50	
C-28	2	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	79.49	20.51	
C-29	0	0	4	0	1	0	0	0	1	2	0	5	0	0	2	0	2	0	0	0	0	0	0	0	0	0	1	18	2	0	0	0	0	0	0	43.90	56.10	
C-30	0	0	2	0	0	4	10	4	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	23.08	76.92	
C-31	0	6	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	9	0	0	0	7	1	0	0	18.92	81.08	
C-32	0	0	6	6	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	13	0	0	23.40	76.60	
C-33	0	1	11	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	4	13	0	0	35.14	64.86	
C-34	0	0	0	3	3	1	4	0	3	0	0	6	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	2	2.78	97.22
C-35	0	0	1	0	15	0	0	0	0	10	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	15.15	84.85
C-36	0	0	0	0	0	1	7	5	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	4	0	14	37.84	62.16
Positive Classified	32	13	208	61	49	34	64	45	64	62	45	66	17	30	18	15	25	17	9	17	36	36	33	7	21	45	62	33	19	51	17	27	55	44	16	23	Overall Accuracy (%)	32.91
Precision(%)	18.75	23.08	12.98	36.07	16.33	8.82	48.44	40.00	26.56	33.87	13.33	28.79	35.29	70.00	44.44	60.00	96.00	23.53	22.22	76.47	58.33	55.56	18.18	100.00	33.33	55.56	4.84	93.94	94.74	17.65	41.18	40.74	23.64	2.27	31.25	60.87		
Omission Error(%)	81.25	76.92	87.02	63.93	83.67	91.18	51.56	60.00	73.44	66.13	86.67	71.21	64.71	30.00	55.56	40.00	4.00	76.47	77.78	23.53	41.67	44.44	81.82	0.00	66.67	44.44	95.16	6.06	5.26	82.35	58.82	76.36	97.73	68.75	39.13			

Figure A.11: Classification Matrix of Proposed Technique using RBF Kernel for UnKnown Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	3	0	0	4	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	1	6	0	0	0	0	0	5	0	0	0	0	0	0	0	8.33	91.67	
C-2	0	8	1	0	0	4	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	1	0	4	1	0	1	0	0	8	1	0	0	0	0	20.00	80.00	
C-3	0	0	20	4	0	0	0	2	0	0	0	1	0	1	2	0	0	0	0	0	0	1	0	2	0	0	5	1	0	1	0	0	0	1	0	0	48.78	51.22	
C-4	0	0	0	28	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	82.35	17.65		
C-5	0	0	0	0	4	4	0	1	0	16	0	3	0	0	4	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	11.11	88.89		
C-6	3	0	2	1	1	4	1	0	0	0	2	0	0	0	7	0	0	2	0	0	0	0	1	0	0	0	6	3	2	0	0	0	2	8	0	2	70.83	29.17	
C-7	0	0	0	0	0	0	34	2	0	0	0	0	0	0	7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	41.67	58.33		
C-8	0	0	8	2	0	0	0	15	0	0	0	0	0	0	5	0	0	0	0	0	0	1	0	2	0	0	1	5	0	0	0	0	0	0	0	40.48	59.52		
C-9	0	0	10	3	0	0	0	0	17	0	0	0	0	0	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	12	47.50	52.50		
C-10	0	0	0	0	0	5	1	0	0	19	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	58.14	41.86		
C-11	7	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	2	2	0	0	6	0	0	0	0	0	0	0	0	1	0	64.10	35.90	
C-12	2	0	0	0	0	0	0	1	0	2	0	25	0	1	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	64.10	35.90		
C-13	0	0	0	0	1	0	1	0	0	16	0	1	7	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	1	7	0	18.92	81.08	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	1	0	81.82	18.18		
C-15	0	0	10	2	0	0	3	0	0	0	0	4	0	0	11	0	2	0	0	0	0	0	0	3	0	1	1	0	0	0	0	0	0	1	0	28.21	71.79		
C-16	0	0	0	0	3	0	0	0	2	0	0	0	0	0	0	9	0	1	0	0	0	0	0	2	1	0	0	0	0	7	10	3	0	0	0	20.45	79.55		
C-17	0	0	0	0	0	0	0	1	0	0	0	1	0	0	3	0	27	1	0	0	6	0	0	0	0	0	0	0	0	2	0	0	0	0	0	64.29	35.71		
C-18	0	0	0	0	0	3	0	0	0	0	0	19	0	0	0	0	0	0	9	3	0	0	0	3	0	0	0	1	0	0	0	0	0	4	0	20.00	80.00		
C-19	1	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	3	3	0	0	0	2	0	0	5	2	0	0	0	1	1	0	1	4	0	7.32	92.68	
C-20	0	0	0	0	0	0	0	0	0	1	0	6	0	0	7	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	2	1	0	0	37.84	62.16		
C-21	3	0	0	4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	23	0	0	0	0	0	0	0	0	0	0	0	0	0	65.71	34.29		
C-22	2	0	0	7	0	0	0	3	0	0	1	0	0	0	0	0	0	0	4	0	8	3	0	0	0	0	0	0	0	12	0	0	0	0	0	7.50	92.50		
C-23	0	0	2	0	0	0	0	0	0	1	0	0	0	0	4	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	4	0	69.44	30.56		
C-24	2	0	1	0	5	4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	1	0	0	0	0	5	1	0	1	6	0	41.03	58.97
C-25	0	4	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	14	1	0	0	0	0	2	1	0	33.33	66.67		
C-26	0	0	0	0	0	0	0	0	2	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	2	0	0	0	2	1	0	68.29	31.71	
C-27	4	0	6	7	0	1	0	0	5	0	0	0	0	1	5	0	0	0	0	3	0	0	0	5	0	0	0	1	1	0	0	0	0	1	0	2.50	97.50		
C-28	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0	97.44	2.56			
C-29	0	0	0	0	0	1	0	0	0	0	0	6	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	1	0	29	1	0	0	0	0	70.73	29.27		
C-30	0	0	0	0	0	1	16	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	35.90	64.10			
C-31	0	7	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	2	0	0	0	10	7	0	0	27.03	72.97		
C-32	0	2	1	5	0	0	0	0	0	2	6	0	0	0	0	0	0	0	3	0	0	0	0	2	0	3	2	0	0	0	0	0	7	17	2	0	14.89	85.11	
C-33	0	0	3	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	14	0	0	37.84	62.16	
C-34	1	0	2	2	0	9	6	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	3	1	0	1	0	0	1	0	6	2.78	97.22	
C-35	0	0	0	0	3	0	0	0	0	10	0	3	9	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	1	0	0	0	1	0	1	0	3.03	96.97
C-36	0	0	0	0	0	3	3	2	0	0	0	1	0	0	2	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	10	0	0	2	0	9	24.32	75.68	
Positive Classified	28	22	66	75	18	41	65	27	24	73	51	93	17	34	60	9	29	35	12	18	42	11	68	17	35	56	22	62	47	39	29	35	55	43	31	27	Overall Accuracy (%)	38.28	
Precision(%)	10.71	36.36	30.30	37.33	22.22	9.76	52.31	55.56	70.83	26.03	49.02	26.08	41.18	79.41	18.33	100.00	93.10	25.71	25.00	77.78	54.76	27.27	36.76	94.12	40.00	50.00	4.55	61.29	61.70	35.90	34.48	20.00	25.45	2.33	3.23	33.33			
Omission Error(%)	89.29	63.64	69.70	62.67	77.78	90.24	47.69	44.44	29.17	73.97	50.98	73.12	58.82	20.59	81.67	0.00	6.90	74.29	75.00	22.22	45.24	72.73	63.24	5.88	60.00	50.00	95.45	38.71	38.30	64.10	65.52	80.00	74.55	97.67	96.77	66.67			

Figure A.12: Classification Matrix of Proposed Technique using Polynomial Kernel for UnKnown Signers: OvA

Appendix B

Classification Matrices for Scale Invariant PSL Recognition

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)		
C-1	41	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.00	18.0		
C-2	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	3	1	0	0	0	87.23	12.8		
C-3	0	0	50	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	94.34	5.7		
C-4	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.96	2.0		
C-5	0	0	0	0	44	0	0	0	0	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	89.80	10.2		
C-6	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1	4	0	0	0	0	0	0	0	0	0	0	0	84.44	15.6		
C-7	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	95.83	4.2			
C-8	0	0	1	1	0	0	0	39	0	0	0	3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	84.78	15.2		
C-9	0	0	0	2	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	4	1	0	0	0	1	0	0	0	81.63	18.4		
C-10	0	0	0	0	5	0	0	0	0	34	0	0	2	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	1	0	73.91	26.1		
C-11	9	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	79.59	20.4		
C-12	0	0	1	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.92	4.1		
C-13	0	0	0	0	3	0	0	0	0	2	0	0	36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	78.26	21.7		
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	84.00	16.0		
C-15	0	0	0	0	0	0	0	1	0	0	0	0	0	0	42	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.33	6.7	
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0		
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0		
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0		
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	79.07	20.9	
C-20	0	0	0	0	0	6	0	0	0	0	0	0	0	0	1	0	0	0	0	0	32	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	68.09	31.9
C-21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0	
C-22	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.88	6.1	
C-23	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90.91	9.1
C-24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0
C-25	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	80.39	19.6
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	2	0	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	79.17	20.8	
C-27	0	0	0	0	0	0	0	0	5	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	87.23	12.8	
C-28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0		
C-29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91.67	8.3	
C-30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89.13	10.9		
C-31	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.00	20.0		
C-32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	68.00	32.0		
C-33	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86.96	13.0		
C-34	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	76.09	23.9	
C-35	0	0	0	0	0	0	0	0	0	5	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	72.73	27.3	
C-36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	84.31	15.7		
Positive Classified	52	50	54	49	53	48	47	40	45	42	46	50	43	48	46	50	46	50	53	34	44	55	47	48	50	49	50	47	52	48	45	41	27	71	42	41	51	Overall Accuracy (%)	87.27	
Precision(%)	78.85	82.00	92.59	97.96	83.02	79.17	97.87	97.50	88.89	80.95	84.78	94.00	83.72	87.50	91.30	100.00	100.00	81.13	100.00	72.73	90.91	97.87	83.33	88.00	83.67	76.00	87.23	90.38	91.67	91.11	87.80	62.96	84.51	83.33	78.05	84.31				
Omission Error(%)	21.15	18.00	7.41	2.04	16.98	20.83	2.13	2.50	11.11	19.05	15.22	6.00	16.28	12.50	8.70	0.00	0.00	18.87	0.00	27.27	9.09	2.13	16.67	12.00	16.33	24.00	12.77	9.62	8.33	8.89	12.20	37.04	15.49	16.67	21.95	15.69				

Figure B.1: Classification Matrix of Proposed Technique using Linear Kernel for Known Signers:OvO

[illegible]

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	36	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	72.00	28.00
C-2	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	2	0	0	0	87.23	12.77
C-3	0	0	50	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	94.34	5.66
C-4	0	0	0	48	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.96	2.04
C-5	0	0	0	0	47	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	95.92	4.08
C-6	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	93.33	6.67
C-7	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	95.83	4.17	
C-8	0	0	0	0	0	0	0	38	1	0	0	3	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	1	0	0	0	0	0	0	0	0	82.61	17.39
C-9	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.96	2.04
C-10	6	0	0	0	2	0	0	0	0	39	0	0	1	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	1	0	84.78	15.22
C-11	0	0	0	0	0	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	85.71	14.29	
C-12	0	0	0	0	0	0	0	0	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-13	0	0	0	0	2	0	0	0	0	1	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	89.13	10.87
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	92.00	8.00	
C-15	0	0	1	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	95.56	4.44	
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.67	2.33	
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.35	4.65	
C-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89.36	10.64	
C-21	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	1	0	0	0	0	0	0	0	0	0	0	0	0	0	96.00	4.00	
C-22	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.88	6.12
C-23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.73	2.27	
C-25	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	92.16	7.84
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0	0	0	0	87.50	12.50
C-27	0	0	1	0	0	0	0	0	2	0	0	0	0	3	0	0	0	0	0	1	0	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	91.49	8.51
C-28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	100.00	0.00	
C-29	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	93.75	6.25	
C-30	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.83	2.17	
C-31	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	1	0	0	0	88.89	11.11	
C-32	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	98.55	1.45	
C-33	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.48	6.52	
C-34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88.64	11.36	
C-35	0	0	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94.12	5.88
C-36	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	48	Overall Accuracy (%)	92.84	
Positive Classified	45	46	52	48	51	42	48	39	53	42	55	55	44	49	43	46	50	43	44	44	49	53	46	49	47	44	52	45	45	44	19	80	49	43	51			
Precision(%)	80.00	89.13	96.15	100.00	92.16	100.00	95.83	97.44	90.57	92.86	76.36	89.09	93.18	93.88	100.00	100.00	100.00	97.67	93.18	95.45	97.96	93.88	83.02	93.48	95.92	89.36	97.73	90.38	100.00	100.00	90.91	89.47	85.00	87.76	90.70	94.12		
Omission Error(%)	20.00	10.87	3.85	0.00	7.84	0.00	4.17	2.56	9.43	7.14	23.64	10.91	6.82	6.12	0.00	0.00	0.00	2.33	6.82	4.55	2.04	6.12	16.98	6.52	4.08	10.64	2.27	9.62	0.00	0.00	9.09	10.53	15.00	12.24	9.30	5.88		

Figure B.3: Classification Matrix of Proposed Technique using Polynomial Kernel for Known Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)		
C-1	46	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	92.00	8.00			
C-2	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	95.74	4.26			
C-3	0	0	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	98.11	1.89			
C-4	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00			
C-5	0	0	0	0	47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.92	4.08			
C-6	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	91.11	8.89		
C-7	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00			
C-8	0	0	0	1	0	0	0	0	41	0	0	0	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	89.13	10.87		
C-9	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	0	0	0	0	0	91.84	8.16			
C-10	0	0	0	0	2	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	89.13	10.87		
C-11	2	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.88	6.12		
C-12	0	0	1	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.92	4.08		
C-13	0	0	0	0	1	0	0	0	0	0	2	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89.13	10.87		
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	96.00	4.00		
C-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	97.78	2.22		
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00		
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00		
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00		
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.67	2.33		
C-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	87.23	12.77		
C-21	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	98.00	2.00	
C-22	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.88	6.12	
C-23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.18	6.82	
C-24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	98.04	1.96	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	89.58	10.42	
C-27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	93.62	6.38	
C-28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	93.75	6.25	
C-30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-31	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86.67	13.33	
C-33	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	76.00	24.00	
C-34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.10	2.90	
C-35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.65	4.35	
C-36	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88.64	11.36	
Positive Classified	51	48	54	49	50	41	48	41	47	43	49	49	47	49	44	46	50	44	42	45	50	47	48	48	52	48	48	52	46	46	41	24	74	51	43	49	Overall Accuracy (%)	94.72		
Precision(%)	90.20	93.75	96.30	100.00	94.00	100.00	100.00	100.00	95.74	95.35	93.88	95.92	87.23	97.96	100.00	100.00	97.73	100.00	91.11	98.00	97.87	85.42	91.67	96.15	89.58	91.67	90.38	97.83	100.00	95.12	79.17	90.54	86.27	90.70	97.96					
Onsation Error(%)	9.80	6.25	3.70	0.00	6.00	0.00	0.00	0.00	4.26	4.65	6.12	4.08	12.77	2.04	0.00	0.00	2.27	0.00	8.89	2.00	2.13	14.58	8.33	3.85	10.42	8.33	9.62	2.17	0.00	4.88	20.83	9.46	13.73	9.30	2.04					

Figure B.4: Classification Matrix of Proposed Technique using Ensemble of Kernel for Known Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	30	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	1	4	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	60.00	40.0	
C-2	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	3	0	0	4	2	0	0	0	74.47	25.5		
C-3	0	1	43	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	82.69	17.3		
C-4	0	0	0	48	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	96.00	4.0		
C-5	0	0	0	0	33	0	0	0	0	3	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	3	0	67.35	32.7		
C-6	0	0	0	0	0	30	0	0	0	0	0	1	0	0	0	0	0	2	0	4	0	0	0	5	0	0	0	0	0	0	0	0	0	3	0	66.67	33.3		
C-7	1	0	0	0	0	0	44	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	91.67	8.3		
C-8	0	0	1	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	2	0	0	0	0	0	0	0	0	88.89	11.1		
C-9	0	1	0	0	1	0	0	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	79.59	20.4		
C-10	0	0	0	0	5	0	0	0	0	33	0	1	4	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	71.74	28.3	
C-11	17	3	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	4	0	48.98	51.0			
C-12	0	0	0	0	0	0	1	0	0	0	0	46	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.88	6.1		
C-13	0	0	0	0	2	0	0	0	0	5	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	76.09	23.9		
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	42	0	0	0	1	0	0	0	0	0	0	0	0	6	0	0	0	0	0	1	0	84.00	16.0			
C-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	89.13	10.9		
C-16	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.83	2.2		
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	96.00	4.0		
C-18	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	33	5	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	76.74	23.3		
C-19	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	9	32	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	74.42	25.6		
C-20	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	2	0	0	30	2	0	0	0	0	1	0	1	0	0	0	0	2	0	0	66.67	33.3		
C-21	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	1	46	1	0	0	0	0	0	0	0	0	0	0	0	0	0	92.00	8.0		
C-22	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	2	0	0	0	0	0	0	0	91.84	8.2		
C-23	0	0	0	0	2	0	0	3	0	2	0	0	1	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	0	2	0	1	0	75.00	25.0	
C-24	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	95.45	4.5	
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	0	0	0	0	0	2	5	0	0	0	82.35	17.6		
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	1	0	0	0	0	0	40	2	0	0	0	0	0	1	0	83.33	16.7			
C-27	0	1	1	3	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	1	0	1	0	0	65.96	34.0		
C-28	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	1	0	95.74	4.3			
C-29	1	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	5	1	0	0	0	0	0	3	0	0	35	0	0	0	0	0	72.92	27.1			
C-30	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	1	0	78.85	21.2		
C-31	0	4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	32	3	0	0	71.11	28.9			
C-32	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	14	7	0	0	56.00	44.0		
C-33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	6	0	0	0	0	0	0	4	56	0	0	81.16	18.8		
C-34	0	0	0	0	0	5	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	2	1	2	0	0	0	0	0	0	0	33	1	0	71.74	28.3		
C-35	0	0	0	0	2	0	0	0	0	3	0	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	5	0	0	0	1	28	0	63.64	36.4	
C-36	0	0	0	1	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	40	78.43	21.6		
Positive Classified	51	46	45	54	49	44	47	44	51	49	38	49	53	48	44	47	51	46	44	44	45	53	46	37	49	53	52	47	58	40	49	41	25	74	47	41	51	Overall Accuracy (%)	79.46
Precision(%)	58.82	76.09	95.56	88.89	67.35	68.18	93.62	90.91	76.47	67.35	63.16	93.88	66.04	87.50	93.18	95.74	94.12	71.74	72.73	66.67	86.79	97.83	89.19	85.71	79.25	76.92	65.96	77.59	87.50	83.67	78.05	56.00	75.68	70.21	68.29	78.43			
Omission Error(%)	41.18	23.91	4.44	11.11	32.65	31.82	6.38	9.09	23.53	32.65	36.84	6.12	33.96	12.50	6.82	4.26	5.88	28.26	27.27	33.33	13.21	2.17	10.81	14.29	20.75	23.08	34.04	22.41	12.50	16.33	21.95	44.00	24.32	29.79	31.71	21.57			

Figure B.5: Classification Matrix of Proposed Technique using Linear Kernel for Known Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)		
C-1	45	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	90.00	10.00		
C-2	0	41	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	2	0	1	0	0	87.23	12.77		
C-3	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	0	0	0	0	0	90.57	9.43		
C-4	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.96	2.04		
C-5	0	0	0	0	46	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	93.88	6.12		
C-6	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	5	0	0	0	0	0	84.44	15.56		
C-7	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	93.75	6.25		
C-8	0	0	1	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.65	4.35		
C-9	0	0	1	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	91.84	8.16	
C-10	0	0	0	0	1	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	0	0	89.13	10.87	
C-11	5	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	87.76	12.24		
C-12	0	0	1	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.88	6.12		
C-13	0	0	0	0	0	0	0	0	0	5	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.43	19.57	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	88.00	12.00		
C-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.83	2.17	
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	49	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	98.00	2.00	
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.35	4.65	
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.35	4.65	
C-20	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	91.49	8.51	
C-21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	98.00	2.00	
C-22	1	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.88	6.12	
C-23	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.18	6.82
C-24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.73	2.27
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	1	0	0	0	0	0	0	0	0	0	0	0	94.12	5.88
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	89.58	10.42	
C-27	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	93.62	6.38	
C-28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	2	0	0	0	0	0	0	91.67	8.33		
C-30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	1	2	0	0	0	2	95.65	4.35
C-31	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	77.78	22.22	
C-32	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	72.00	28.00	
C-33	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	92.75	7.25	
C-34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.48	6.52	
C-35	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90.91	9.09	
C-36	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	92.16	7.84	
Positive Classified	51	44	51	51	49	40	47	44	48	48	47	46	39	45	45	45	49	44	44	49	50	47	46	46	46	55	57	46	51	45	62	38	24	70	44	47	50	Overall Accuracy	92.49	
Precision(%)	88.24	93.18	94.12	94.12	93.88	95.00	95.74	100.00	93.75	95.42	91.49	100.00	94.87	97.78	100.00	100.00	100.00	93.18	93.18	87.76	98.00	97.87	89.13	93.48	87.27	75.44	95.65	92.16	97.78	70.97	92.11	75.00	91.43	97.73	85.11	92.16				
Omission Error(%)	11.76	6.82	5.88	5.88	6.12	5.00	4.26	0.00	6.25	14.58	8.51	0.00	5.13	2.22	0.00	0.00	0.00	6.82	6.82	12.24	2.00	2.13	10.87	6.52	12.73	24.56	4.35	7.84	2.22	29.03	7.89	25.00	8.57	2.27	14.89	7.84				

Figure B.6: Classification Matrix of Proposed Technique using RBF Kernel for Known Signers:OvA

Figure B.7: Classification Matrix of Proposed Technique using Polynomial Kernel for Known Signers: OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	46	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	88.00	12.00
C-2	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	91.49	8.51	
C-3	0	0	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	96.23	3.77	
C-4	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-5	0	0	0	0	47	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.92	4.08	
C-6	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.56	4.44	
C-7	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-8	0	0	0	1	0	0	0	41	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.83	2.17	
C-9	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.88	6.12	
C-10	0	0	0	0	0	2	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	91.30	8.70	
C-11	2	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.92	4.08	
C-12	0	0	1	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-13	0	0	0	0	0	1	0	0	0	0	2	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	84.78	15.22	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	92.00	8.00	
C-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.35	4.65	
C-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.74	4.26
C-21	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	98.00	2.00
C-22	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.88	6.12
C-23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.45	4.55
C-24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	96.08	3.92
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	93.75	6.25
C-27	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	91.49	8.51
C-28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	93.75	6.25	
C-30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-31	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.22	17.78	
C-32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	72.00	28.00	
C-33	0	1	0	0	0	0	0	0	0	0	0	0	0																										

Figure B.8: Classification Matrix of Proposed Technique using Ensemble of Kernel for Known Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)		
C-1	8	0	0	1	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	3	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22.22	77.8	
C-2	0	10	0	0	0	0	0	0	3	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	6	1	0	0	0	0	0	2	2	14	0	0	0	25.00	75.0	
C-3	0	0	27	0	2	0	0	0	9	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	65.85	34.1	
C-4	0	0	0	31	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91.18	8.8	
C-5	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	1	0	80.56	19.4		
C-6	0	0	0	0	0	16	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	22	0	0	36.36	63.6			
C-7	0	0	0	0	0	0	42	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	87.50	12.5			
C-8	0	0	12	0	0	0	0	19	2	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	52.78	47.2		
C-9	0	0	17	2	0	0	0	0	16	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	4	0	0	0	0	0	0	0	0	38.10	61.9		
C-10	0	0	0	0	8	1	0	0	0	15	0	0	0	0	0	0	0	2	0	0	0	0	3	0	0	0	0	0	0	2	0	0	0	0	9	0	37.50	62.5		
C-11	23	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44.19	55.8		
C-12	0	0	7	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	69.23	30.8		
C-13	0	0	0	0	9	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	7	0	32.43	67.6		
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	84.85	15.2			
C-15	0	0	11	1	0	0	0	2	2	0	2	0	0	14	0	0	0	0	0	0	0	0	3	0	0	1	0	0	0	0	0	0	0	0	0	3	35.90	64.1		
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	8	0	0	0	2	0	0	11	0	0	0	1	0	0	3	0	1	40.91	59.1		
C-17	0	0	0	1	0	0	2	4	0	0	0	0	0	0	0	0	22	0	0	2	4	0	0	0	0	0	0	0	0	3	0	0	0	0	0	1	52.38	47.6		
C-18	0	0	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	14	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	1	0	31.11	68.9			
C-19	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	100.00	0.0		
C-20	0	0	9	0	0	0	0	2	3	0	0	0	0	0	0	2	0	0	0	16	2	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	43.24	56.8		
C-21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0		
C-22	5	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	12	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40.00	60.0		
C-23	0	0	10	2	1	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	16	0	0	0	0	3	0	0	0	0	0	0	0	0	44.44	55.6		
C-24	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	2	0	0	0	6	2	0	0	1	1	35.90	64.1			
C-25	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	15	0	0	35.71	64.3				
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	100.00	0.0			
C-27	0	0	14	3	0	0	0	2	13	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	15.00	85.0			
C-28	0	3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	34	0	0	0	0	0	87.18	12.8				
C-29	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	32	0	0	0	0	0	78.05	22.0			
C-30	0	0	0	0	0	0	3	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	3	79.49	20.5			
C-31	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	6	8	1	0	51.35	48.6			
C-32	0	0	0	2	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	5	35	0	0	10.64	89.4			
C-33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0				
C-34	0	0	0	4	0	5	12	5	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	3	0	2	8.33	91.7			
C-35	0	0	0	0	7	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	9	0	27.27	72.7			
C-36	0	0	0	0	0	0	10	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	6	0	0	0	14	37.84	62.2			
Positive Classified	36	26	107	47	56	35	69	39	51	33	50	86	12	28	35	18	22	29	0	27	57	23	41	16	21	73	18	37	40	43	30	13	111	35	27	25	Overall Accuracy (%)	50.44		
Precision(%)	22.22	38.46	25.23	65.96	51.79	45.71	60.87	48.72	31.37	45.45	38.00	31.40	100.00	100.00	40.00	100.00	100.00	48.28	0.00	59.26	61.40	69.57	39.02	87.50	71.43	56.16	33.33	91.89	80.00	72.09	63.33	0.00	33.33	8.57	33.33	56.00				
Omission Error(%)	77.78	61.54	74.77	34.04	48.21	54.29	39.13	51.28	68.63	54.55	62.00	68.60	0.00	60.00	60.00	0.00	0.00	51.72	100.00	40.74	38.60	30.43	60.98	12.50	28.57	43.84	66.67	9.11	20.00	27.91	36.67	100.00	66.67	91.43	44.00					

Figure B.9: Classification Matrix of Proposed Technique using Linear Kernel for Unknown Signers:OvO

Class	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C30	C31	C32	C33	C34	C35	C36	Recall (%)	Commission Error(%)	
C-1	17	0	0	6	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47.22	52.78
C-2	0	10	0	0	0	0	0	0	12	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	3	0	0	0	0	7	0	3	0	0	0	25.00	75.00
C-3	0	0	29	0	0	0	0	1	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70.73	29.27
C-4	0	0	6	21	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	61.76	38.24
C-5	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.56	19.44
C-6	0	0	0	0	0	10	2	2	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	3	0	0	0	4	0	0	16	0	1	22.73	77.27	
C-7	0	0	0	0	0	0	21	1	1	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	7	43.75	56.25
C-8	0	0	11	0	0	0	5	13	1	0	0	0	0	0	3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	36.11	63.89
C-9	0	0	9	0	0	0	0	1	26	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	61.90	38.10
C-10	0	0	0	0	5	1	1	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	1	9	0	50.00	50.00
C-11	30	0	0	0	0	0	0	0	5	4	0	0	0	0	0	0	1	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.00	90.70
C-12	0	0	6	0	0	1	0	1	5	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	61.54	38.46	
C-13	0	0	0	0	24	0	0	0	4	0	0	5	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25.00	75.00
C-14	0	0	0	0	0	1	2	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	1	0	4	0	0	0	0	0	0	0	0	0	0	75.76	24.24
C-15	0	0	7	2	0	0	4	13	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33.33	66.67	
C-16	0	0	0	0	2	4	1	0	8	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33.33	66.67	
C-17	6	0	0	0	0	0	2	4	1	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	1	0	0	4	0	0	9	0	0	3	0	1	25.00	75.00	
C-18	0	0	1	0	0	6	1	0	0	0	22	0	0	0	2	0	0	6	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	57.14	42.86
C-19	0	0	1	0	0	1	5	0	0	0	0	16	0	0	0	0	0	2	2	0	0	0	3	0	0	0	1	0	0	0	0	0	0	1	1	0	13.33	86.67	
C-20	0	0	5	0	0	1	0	1	0	0	0	0	0	0	7	0	1	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	12	0	1	0	4.88	95.12	
C-21	8	0	3	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32.43	67.57	
C-22	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	19	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	54.29	45.71
C-23	0	0	11	2	0	0	0	3	0	0	0	0	0	0	4	0	0	0	0	0	5	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	67.50	32.50
C-24	0	0	0	0	1	8	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	38.89	61.11
C-25	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	4	0	0	0	33.33	66.67	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28.57	71.43	
C-27	0	0	12	0	0	0	3	2	14	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	0	80.49	19.51
C-28	2	2	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	4	0	0	0	0	0	0	0	0	10.00	90.00	
C-29	0	0	2	0	0	5	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	33	0	0	0	0	0	0	84.62	15.38
C-30	0	0	0	0	0	0	6	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	60.98	39.02	
C-31	0	4	5	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	20	0	0	0	0	11	51.28	48.72	
C-32	0	3	0	2	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	12	0	0	0	0	0	0	32.43	67.57
C-33	0	1	8	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	5	0	0	0	0	0	3	0	0	0	6.38	93.62
C-34	0	0	1	1	0	7	7	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	67.57	32.43
C-35	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0.00	100.00	
C-36	0	0	0	0	0	3	3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	1	0	0	0	0	0	0	0	7	0	0	21.21	78.79
Positive Classified	63	24	117	34	83	48	60	38	122	24	15	64	6	33	47	11	26	15	3	15	24	40	36	16	19	44	41	34	26	48	35	3	84	38	23	57	Overall Accuracy (%)	41.60	
Precision(%)	26.98	41.67	24.79	61.76	34.94	20.83	35.00	34.21	21.31	83.33	26.67	37.50	83.33	75.76	27.66	100.00	92.31	40.00	0.00	80.00	79.17	67.50	38.89	81.25	63.16	75.00	9.76	97.06	96.15	41.67	34.29	0.00	29.76	0.00	30.43	35.09			
Omission Error(%)	73.02	58.33	75.21	38.24	65.06	79.17	65.00	65.79	78.69	16.67	73.33	62.50	16.67	24.24	72.34	0.00	7.69	60.00	100.00	20.00	20.83	32.50	61.11	18.75	36.84	25.00	90.24	2.94	3.85	58.33	65.71	100.00	70.24	100.00	69.57	64.91			

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	7	1	0	3	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	19.44	80.56	
C-2	0	10	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	4	0	2	0	0	0	0	0	8	2	9	0	0	25.00	75.00	
C-3	0	0	33	1	1	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	80.49	19.51		
C-4	0	0	6	24	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	70.59	29.41		
C-5	0	0	0	0	27	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	75.00	25.00		
C-6	0	0	0	0	0	19	1	2	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	17	0	1	43.18	56.82		
C-7	0	0	0	0	0	0	29	2	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	60.42	39.58			
C-8	0	0	0	13	0	0	0	19	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	52.78	47.22		
C-9	0	0	16	1	0	0	0	0	19	0	0	0	0	2	0	0	0	0	0	1	0	0	1	0	0	0	2	0	0	0	0	0	0	0	0	45.24	54.76		
C-10	0	0	0	0	7	0	0	0	0	16	0	0	0	0	0	0	0	4	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	5	0	40.00	60.00		
C-11	18	0	0	1	0	0	0	0	2	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	46.51	53.49			
C-12	0	9	0	0	0	0	0	0	0	0	0	24	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	61.54	38.46			
C-13	0	0	0	0	15	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	7	0	27.03	72.97	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	1	0	0	0	0	78.79	21.21			
C-15	0	0	11	0	1	0	3	3	0	0	0	0	0	0	16	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	41.03	58.97		
C-16	0	0	0	0	0	2	0	0	0	0	0	0	0	9	0	13	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	11	0	0	0	29.55	70.45		
C-17	1	0	0	0	0	0	3	0	0	0	0	1	0	0	2	0	10	0	0	0	7	5	0	0	0	0	0	0	0	10	0	2	0	0	1	23.81	76.19		
C-18	0	0	0	0	0	0	1	0	0	0	0	26	0	0	0	0	0	0	9	2	0	0	4	0	0	0	0	0	0	0	0	0	0	1	2	0	20.00	80.00	
C-19	0	0	0	0	0	2	0	0	0	0	0	15	0	0	0	0	0	6	7	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	3	4	0	17.07	82.93
C-20	0	0	4	0	0	0	0	1	3	0	0	0	0	0	6	0	0	0	0	9	0	0	0	0	0	0	0	0	10	0	0	0	0	1	0	3	24.32	75.68	
C-21	7	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	74.29	25.71		
C-22	3	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	4	27	0	0	0	0	0	0	0	1	0	0	0	0	0	67.50	32.50		
C-23	0	1	8	1	1	0	0	4	0	0	0	0	0	4	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	47.22	52.78		
C-24	0	0	0	0	0	13	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	6	0	0	0	0	0	0	0	2	1	4	28.21	71.79	
C-25	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	10	2	13	0	0	23.81	76.19	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1	0	0	38	0	0	0	0	0	0	0	0	0	0	92.68	7.32	
C-27	0	0	12	1	0	0	0	4	12	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	8	0	0	0	0	0	0	0	0	20.00	80.00	
C-28	0	4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0	87.18	12.82		
C-29	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	70.73	29.27		
C-30	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	1	89.74	10.26		
C-31	0	8	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	1	12	0	0	37.84	62.16	
C-32	0	4	0	0	0	0	0	0	1	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	30	0	0	0	19.15	80.85	
C-33	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	31	1	0	0	83.78	16.22	
C-34	0	0	0	2	0	3	6	3	0	0	0	2	0	0	0	0	0	4	0	0	0	0	1	0	0	0	0	3	0	0	0	0	0	2	0	10	5.56	94.44	
C-35	0	0	0	0	7	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	1	0	0	1	0	15	0	45.45	54.55	
C-36	0	0	0	0	0	2	7	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	4	0	0	2	0	18	48.65	51.35	
Positive Classified	36	36	112	37	59	41	54	41	46	19	52	78	10	37	44	13	10	28	11	10	37	34	52	12	14	52	29	47	33	52	36	17	100	49	28	50	Overall Accuracy (%)	47.39	
Precision(%)	19.44	27.78	29.46	64.86	45.76	46.34	53.70	46.34	41.30	44.21	38.46	30.77	100.00	70.27	36.36	100.00	100.00	32.14	0.00	90.00	70.27	79.41	32.69	91.67	71.43	73.08	27.59	72.34	87.88	67.31	38.89	0.00	31.00	4.08	53.57	36.00			
Omission Error(%)	80.56	72.22	70.54	35.14	54.24	53.66	46.30	53.66	58.70	15.79	61.54	69.23	0.00	29.73	63.64	0.00	0.00	67.86	100.00	10.00	29.73	20.59	67.31	8.33	28.57	26.92	72.41	27.66	12.12	32.69	61.11	100.00	95.92	46.43	64.00				

Figure B.11: Classification Matrix of Proposed Technique using Polynomial Kernel for Unknown Signers: OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)		
C-1	5	0	0	5	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13.89	86.11	
C-2	0	7	0	0	0	0	0	0	6	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	1	2	0	0	0	3	2	12	0	0	0	0	17.50	82.50
C-3	0	0	28	0	0	0	0	1	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	68.29	31.71	
C-4	0	0	1	30	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88.24	11.76	
C-5	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	80.56	19.44	
C-6	0	0	0	0	0	11	0	2	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	23	0	0	25.00	75.00		
C-7	0	0	0	0	0	0	41	1	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	85.42	14.58	
C-8	0	0	12	0	0	0	0	18	2	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50.00	50.00	
C-9	0	0	16	1	0	0	0	0	20	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	47.62	52.38	
C-10	0	0	0	0	7	1	0	0	0	17	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	1	11	0	42.50	57.50	
C-11	30	0	0	0	0	0	0	0	1	0	11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25.58	74.42	
C-12	0	0	8	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	3	0	0	0	66.67	33.33	
C-13	0	0	0	0	13	0	0	0	0	3	0	0	12	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	8	0	32.43	67.57	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	81.82	18.18	
C-15	0	0	11	1	1	0	1	2	2	0	0	0	0	0	14	0	0	0	0	0	0	0	4	0	0	0	1	0	0	0	0	0	0	0	0	2	35.90	64.10		
C-16	0	0	0	0	0	3	0	0	0	0	0	0	0	3	0	14	0	0	0	0	3	0	0	0	1	0	7	0	0	0	0	0	6	0	0	0	31.82	68.18		
C-17	0	0	0	0	0	0	2	1	0	0	0	0	0	0	2	0	30	0	0	0	1	0	0	0	0	0	0	0	3	0	2	0	0	0	1	71.43	28.57			
C-18	0	0	0	0	0	0	2	0	0	0	0	23	0	0	0	0	0	12	1	0	0	0	4	0	0	0	1	0	0	0	0	0	2	0	0	0	26.67	73.33		
C-19	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	8	2	0	0	0	0	0	0	2	0	0	0	0	0	10	0	0	0	4.88	95.12			
C-20	0	0	6	0	0	0	0	1	1	0	0	0	0	0	4	0	0	0	0	16	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	43.24	56.76		
C-21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.14	2.86		
C-22	3	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	4	0	0	15	0	0	0	0	2	0	0	0	0	6	1	0	0	65.00	35.00		
C-23	0	0	10	3	1	0	0	1	0	0	0	0	0	0	4	0	0	0	0	0	0	26	0	0	0	11	0	0	0	0	0	2	1	18	0	0	0	41.67	58.33	
C-24	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30.77	69.23		
C-25	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	18	0	0	0	26.19	73.81		
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	97.56	2.44		
C-27	0	0	13	0	0	0	0	3	15	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	7	0	0	0	0	0	0	0	0	0	17.50	82.50	
C-28	0	3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	89.74	10.26		
C-29	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	26	0	0	0	0	1	2	0	63.41	36.59	
C-30	0	0	0	0	0	0	3	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	3	79.49	20.51	
C-31	0	7	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	2	10	2	0	0	37.84	62.16	
C-32	0	2	0	0	0	0	0	0	1	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	6	33	0	0	0	12.77	87.23	
C-33	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	0	0	0	91.89	8.11		
C-34	0	0	0	3	0	4	10	3	0	0	0	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	4	0	5	11.11	88.89		
C-35	0	0	0	0	11	0	0	0	0	3	0	0	1	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	13	0	39.39	60.61		
C-36	0	0	0	0	0	0	6	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	2	0	0	0	5	0	0	0	0	20	54.05	45.95		
Positive Classified	38	29	109	43	62	30	63	36	60	23	40	81	13	31	39	14	30	26	3	19	40	36	41	13	19	67	27	39	33	46	29	11	109	52	34	31	Overall Accuracy (%)	49.29		
Precision(%)	13.16	24.14	25.69	69.77	46.77	36.67	65.08	50.00	33.33	73.91	27.50	32.10	92.31	87.10	35.90	100.00	100.00	46.15	0.00	84.21	85.00	72.22	36.59	92.31	57.89	59.70	25.93	89.74	78.79	67.39	48.28	0.00	31.19	7.69	38.24	64.52				
Omission Error(%)	86.84	75.86	74.31	30.23	53.23	63.33	34.92	50.00	66.67	26.09	72.50	67.90	7.69	12.90	64.10	0.00	0.00	53.85	100.00	15.79	15.00	27.78	63.41	7.69	42.11	40.30	74.07	10.26	21.21	32.61	51.72	100.00	68.81	92.31	61.76	35.48				

Figure B.12: Classification Matrix of Proposed Technique using Ensembles of Kernels for Unknown Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)		
C-1	9	0	0	4	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25.00	75.0	
C-2	0	19	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	9	0	0	0	0	0	0	0	1	1	7	0	0	47.50	52.5
C-3	0	0	24	2	2	0	0	0	7	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	58.54	41.5		
C-4	0	0	0	33	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97.06	2.9		
C-5	0	0	1	0	27	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	1	0	1	75.00	25.0		
C-6	0	0	0	1	0	17	1	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	8	2	0	0	0	0	0	5	0	38.64	61.4			
C-7	0	0	0	0	0	0	42	0	0	24	1	0	0	0	1	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	87.50	12.5		
C-8	0	0	7	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	66.67	33.3			
C-9	0	0	0	17	1	4	0	0	0	15	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	1	0	35.71	64.3		
C-10	0	0	0	0	0	4	1	0	0	0	0	2	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	45.00	55.0			
C-11	7	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	3	0	0	0	3	4	0	0	0	0	0	0	0	0	0	0	0	0	60.47	39.5			
C-12	0	0	2	4	0	0	0	0	1	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	76.92	23.1			
C-13	0	0	0	0	11	0	0	0	0	15	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	60.47	39.5			
C-14	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	3	0	18.92	81.1			
C-15	0	8	7	2	0	0	0	5	0	0	1	2	0	0	13	0	0	1	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	1	0	69.70	30.3			
C-16	1	0	0	0	0	0	0	0	0	2	0	0	2	0	0	20	0	0	8	0	8	0	0	0	0	0	0	2	0	0	0	0	0	0	0	33.33	66.7			
C-17	0	0	0	0	0	0	7	3	1	0	0	3	0	0	0	0	19	7	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	4	1	0	45.45	54.5		
C-18	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	30	1	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	45.45	54.5			
C-19	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	27	0	0	0	1	0	0	0	0	6	0	0	0	0	0	0	2	0	0	100.0			
C-20	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1	0	26	2	0	0	0	0	0	1	0	0	0	0	0	0	0	3	0	70.27	29.7		
C-21	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	0	0	0	0	0	0	0	0	0	0	0	0	0	91.43	8.6			
C-22	9	0	0	3	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	4	16	0	0	0	0	0	0	0	0	0	0	0	0	0	40.00	60.0			
C-23	0	1	8	0	3	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	1	0	0	52.78	47.2		
C-24	0	1	2	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	3	0	0	0	0	8	0	33.33	66.7			
C-25	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	0	0	0	1	0	0	0	0	22	0	0	0	0	0	4	0	0	52.38	47.6			
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	39	0	0	0	0	0	0	1	0	95.12	4.9			
C-27	0	0	12	3	2	0	0	0	14	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.00	95.0			
C-28	3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	24	0	0	0	1	0	61.54	38.5				
C-29	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	15	0	0	0	0	0	36.59	63.4			
C-30	0	0	0	0	0	1	6	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	74.36	25.6			
C-31	0	6	0	8	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32.43	67.6			
C-32	0	0	5	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	12	1	0	0	4.26	95.7			
C-33	0	0	1	2	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	2	39	0	0	72.97	27.0		
C-34	0	0	0	1	0	9	5	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	5.56	94.4				
C-35	0	0	0	0	10	0	0	0	0	14	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	18.18	81.8			
C-36	0	0	0	1	0	1	12	3	0	0	0	0	0	0	2	0	0	4	0	0	0	0	0	0	0	0	1	1	0	0	2	0	0	3	0	7	18.92	81.1		
Positive Classified	29	31	84	80	67	41	73	36	40	54	52	72	13	23	29	20	19	121	1	36	41	29	32	13	49	69	12	24	18	32	17	9	87	23	33	7	Overall Accuracy	48.66		
Precision(%)	31.03	61.29	28.57	41.25	40.30	41.46	57.53	66.67	37.50	33.33	50.00	41.67	53.85	100.00	44.83	100.00	100.00	24.79	0.00	72.22	78.05	55.17	59.38	100.00	44.90	56.52	16.67	100.00	83.33	90.63	70.59	0.00	31.03	8.70	18.18	100.00				
Omission Error(%)	68.97	38.71	71.43	58.75	59.70	58.54	42.47	33.33	62.50	66.67	50.00	58.33	46.15	0.00	55.17	0.00	0.00	75.21	100.00	27.78	21.95	44.83	40.63	0.00	55.10	43.48	83.33	0.00	16.67	9.38	29.41	100.00	68.97	91.30	81.82	0.00				

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)		
C-1	6	0	0	6	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	2	0	14	0	0	0	0	0	0	1	0	0	0	0	0	0	0	16.67	83.33		
C-2	0	12	5	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1	0	0	9	7	0	0	0	0	30.00	70.00		
C-3	0	0	29	0	0	0	0	0	6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	2	0	0	0	0	0	70.73	29.27		
C-4	0	0	9	20	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	58.82	41.18		
C-5	0	0	0	0	26	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	1	0	0	0	0	0	72.22	27.78		
C-6	0	0	4	0	0	10	1	0	5	0	0	0	0	0	0	0	4	0	0	0	0	0	1	0	0	0	0	0	0	0	4	0	0	15	0	0	22.73	77.27		
C-7	0	0	0	0	0	0	22	0	0	0	0	2	0	0	10	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	12	0	0	0	0	0	45.83	54.17		
C-8	0	0	13	1	0	0	4	13	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	36.11	63.89		
C-9	0	0	15	0	0	0	1	1	14	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	7	0	0	0	0	0	33.33	66.67		
C-10	0	0	0	0	5	5	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	7	0	52.50	47.50		
C-11	23	1	0	0	0	0	0	0	1	0	5	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	3	3	0	0	0	0	0	0	11.63	88.37		
C-12	0	0	7	0	0	1	0	2	1	0	0	21	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	5	0	0	0	0	0	53.85	46.15		
C-13	0	0	0	0	16	0	0	0	0	12	0	0	5	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	3	0	13.51	86.49		
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1	3	0	0	0	0	0	81.82	18.18		
C-15	0	1	6	2	0	0	0	1	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	38.46	61.54		
C-16	0	0	1	0	2	4	0	0	0	2	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	3	0	0	12	0	0	0	3	0	0	38.64	61.36	
C-17	0	0	0	0	0	0	0	0	0	0	2	0	0	0	4	0	25	0	0	0	1	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	59.52	40.48		
C-18	0	0	0	0	2	6	0	0	2	0	0	20	0	0	0	0	0	0	0	0	0	4	0	0	0	0	1	0	0	0	0	0	0	10	0	0	100.00	0.00		
C-19	0	0	3	0	3	6	1	0	0	0	0	11	0	0	0	0	0	2	1	0	0	0	2	0	2	0	5	0	0	0	0	6	0	0	1	0	0	2.44	97.56	
C-20	0	0	6	0	0	0	0	0	2	0	0	0	0	0	5	0	1	0	0	15	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	40.54	59.46		
C-21	4	0	4	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	54.29	45.71		
C-22	0	0	0	1	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	4	27	0	0	0	0	0	0	1	0	0	0	0	0	0	0	67.50	32.50		
C-23	0	0	10	2	1	4	0	2	0	0	0	0	0	0	7	0	0	0	0	0	0	8	0	0	0	0	0	2	0	0	0	0	0	0	0	0	22.22	77.78		
C-24	0	0	0	0	4	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	1	0	0	0	0	5	0	0	11	1	1	23.08	76.92		
C-25	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	5	0	0	0	0	16.67	83.33		
C-26	0	0	0	0	1	0	0	0	0	0	0	0	0	7	0	0	0	0	1	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	73.17	26.83			
C-27	0	0	11	0	0	0	2	3	6	0	0	0	0	0	3	0	0	0	0	0	0	1	0	0	0	0	0	3	0	0	11	0	0	0	0	0	7.50	92.50		
C-28	0	2	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	0	2	0	0	0	0	0	84.62	15.38		
C-29	0	0	5	0	1	0	0	0	0	0	0	7	1	1	0	1	0	1	0	0	0	0	0	0	0	0	4	0	0	19	2	0	0	0	0	0	46.34	53.66		
C-30	0	0	3	0	0	7	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	7	0	0	0	0	0	17.95	82.05		
C-31	0	5	5	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	35.14	64.86		
C-32	0	2	2	4	0	4	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	1	17	0	0	2.13	97.87	
C-33	0	2	12	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	20	0	0	54.05	45.95		
C-34	0	0	0	0	3	6	8	1	3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	8	0	0	0	0	0	1	0	4	2.78	97.22		
C-35	0	0	0	0	15	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	2	0	0	0	1	0	0	0	1	0	3	0	9.09	90.91
C-36	0	0	0	1	0	3	3	4	0	0	0	1	0	0	2	0	0	0	0	0	0	0	4	0	0	0	1	0	0	0	3	0	0	0	0	15	40.54	59.46		
Positive Classified	33	31	150	39	79	65	56	27	51	45	22	63	7	35	54	18	26	7	2	18	24	48	35	9	17	42	42	38	21	123	31	1	85	32	14	26	Overall Accuracy (%)	36.65		
Precision(%)	18.18	38.71	19.33	51.28	32.91	15.38	39.29	48.15	27.45	46.67	22.73	33.33	71.43	77.14	27.78	94.44	96.15	100.00	0.00	83.33	79.17	56.25	22.86	100.00	41.18	71.43	7.14	86.84	90.48	5.69	41.94	0.00	23.53	3.13	21.43	57.69				
Omission Error(%)	81.82	61.29	80.67	48.72	67.09	84.62	60.71	51.85	72.55	53.33	77.27	66.67	28.57	22.86	72.22	5.56	3.85	100.00	100.00	16.67	20.83	43.75	77.14	0.00	58.82	28.57	92.86	13.16	9.52	94.31	58.06	100.00	76.47	96.88	78.57	42.31				

Figure B.14: Classification Matrix of Proposed Technique using RBF Kernel for Unknown Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)		
C-1	5	0	0	3	0	0	0	0	0	0	8	0	0	0	0	0	0	1	0	0	0	5	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	13.89	86.11	
C-2	0	20	1	0	0	0	0	0	0	0	3	0	0	1	0	0	0	0	0	0	0	0	0	0	4	4	0	0	0	0	0	3	0	4	0	0	0	50.00	50.00	
C-3	0	0	25	4	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	7	1	0	0	60.98	39.02	
C-4	2	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	88.24	11.76		
C-5	0	0	0	0	17	0	0	4	0	5	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	4	0	0	0	47.22	52.78	
C-6	2	0	3	1	0	17	0	0	0	0	0	0	0	0	0	0	8	1	0	0	0	0	0	0	0	6	1	0	0	0	0	0	3	2	0	0	38.64	61.36		
C-7	0	0	0	0	0	0	26	1	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	4	54.17	45.83			
C-8	0	0	10	3	0	0	0	11	0	0	0	0	0	3	0	0	0	0	0	0	0	8	0	0	0	0	0	1	0	0	0	0	0	0	0	0	30.56	69.44		
C-9	0	0	13	9	3	0	0	0	9	0	2	0	0	3	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	21.43	78.57		
C-10	0	0	0	0	0	0	0	0	0	18	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	45.00	55.00		
C-11	8	1	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	1	0	0	2	3	0	0	0	0	0	5	4	0	0	0	0	0	0	0	44.19	55.81		
C-12	4	0	1	0	1	0	0	1	0	0	24	0	0	4	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	61.54	38.46		
C-13	0	0	0	5	0	0	7	1	10	0	0	5	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	4	0	13.51	86.49		
C-14	0	0	0	0	0	4	0	0	0	0	0	0	23	0	0	0	5	0	0	0	0	0	0	0	0	0	4	0	1	0	0	0	0	0	1	0	69.70	30.30		
C-15	0	0	8	4	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	56.41	43.59			
C-16	0	0	0	0	6	0	0	2	0	0	0	0	0	0	23	1	2	0	1	0	0	2	1	0	0	0	0	1	0	0	5	0	0	0	0	0	52.27	47.73		
C-17	0	0	0	1	0	0	0	1	0	0	0	1	0	0	4	0	28	1	0	0	3	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	66.67	33.33		
C-18	0	0	0	0	0	5	0	0	0	0	0	14	0	0	0	0	0	11	0	0	0	0	6	0	0	0	0	0	0	0	0	0	9	0	0	0	24.44	75.56		
C-19	2	0	0	0	0	2	0	0	0	0	2	2	0	0	0	0	0	22	0	0	0	0	0	0	4	0	0	0	0	0	0	0	6	0	0	1	0.00	100.00		
C-20	0	0	2	0	0	0	0	0	0	0	0	3	0	0	10	0	0	0	0	11	0	0	0	0	0	0	4	6	0	0	0	0	0	0	0	1	29.73	70.27		
C-21	1	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.00	20.00		
C-22	3	0	0	4	0	0	0	0	0	0	3	0	0	0	0	0	7	0	0	5	13	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	32.50	67.50		
C-23	0	0	3	0	0	0	0	2	0	0	0	0	0	0	6	0	0	0	0	0	0	21	0	0	0	0	4	0	0	0	0	0	0	0	0	0	58.33	41.67		
C-24	1	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	2	0	2	0	0	0	0	0	0	1	6	1	51.28	48.72		
C-25	0	5	0	0	0	4	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	12	1	0	0	0	0	0	18	0	0	28.57	71.43			
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	37	0	0	0	0	0	3	0	0	90.24	9.76			
C-27	2	2	12	6	2	0	0	0	7	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	1	1	0	0	10.00	90.00		
C-28	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	35	0	0	0	0	0	0	0	0	89.74	10.26			
C-29	0	0	1	0	2	0	0	0	0	0	0	3	0	0	0	0	2	0	0	2	0	0	0	0	0	0	1	0	0	0	26	4	0	0	0	0	63.41	36.59		
C-30	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	1	87.18	12.82			
C-31	0	8	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2	1	0	0	0	11	1	7	0	0	29.73	70.27		
C-32	0	2	0	0	2	0	0	0	1	0	3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	34	0	0	2.13	97.87		
C-33	0	5	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	67.57	32.43		
C-34	0	4	0	0	0	17	3	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0.00	100.00			
C-35	0	0	0	0	8	0	0	0	0	5	0	0	3	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	0	0	39.39	60.61		
C-36	0	0	0	1	1	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	4	3	0	0	2	0	0	0	0	16	43.24	56.76		
Positive Classified	31	47	84	76	47	59	35	30	19	38	40	47	9	27	64	26	34	61	1	14	38	22	57	21	24	64	39	60	26	51	22	3	118	8	43	31	Overall Accuracy (%)	45.20		
Precision(%)	16.13	42.55	29.76	39.47	36.17	28.81	74.29	36.67	47.37	47.37	47.50	51.06	55.56	85.19	34.38	88.46	82.35	18.03	0.00	78.57	73.68	59.09	36.84	95.24	50.00	57.81	10.26	58.33	100.00	66.67	50.00	0.00	21.19	0.00	30.73	51.61				
Omission Error(%)	83.87	57.45	70.24	60.53	63.83	71.19	25.71	63.33	52.63	52.63	52.50	48.94	44.44	14.81	65.63	11.54	17.65	81.97	100.00	21.43	26.32	40.91	63.16	4.76	50.00	42.19	89.74	41.67	0.00	33.33	50.00	100.00	78.81	100.00	69.77	48.39				

Figure B.15: Classification Matrix of Proposed Technique using Polynomial Kernel for Unknown Signers: OVA

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Figure B.16: Classification Matrix of Proposed Technique using Ensemble of Kernel for Unknown Signers:OvA

Appendix C

Classification Matrices for Reduced Dimensional Scale Invariant sMBP based PSL Classification

[illegible]

[illegible]

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-2	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-3	0	0	21	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	77.78	22.22
C-4	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-5	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-6	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	92.31	7.69	
C-7	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	94.74	5.26	
C-8	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	96.30	3.70	
C-9	0	0	1	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	1	0	0	82.76	17.24
C-10	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	70.59	29.41
C-11	1	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94.74	5.26	
C-12	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-13	0	0	0	0	1	0	0	0	0	2	0	0	21	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	84.00	16.00
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.24	4.76	
C-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.65	4.35
C-21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	94.44	5.56
C-24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	83.33	16.67
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	94.74	5.26
C-27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	100.00	0.00
C-28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	100.00	0.00	
C-29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	94.44	5.56
C-30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.33	6.67
C-32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	81.25	18.75	
C-33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.55	6.45	
C-34	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	95.24	4.76
C-35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	92.31	7.69
C-36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
Positive Classified	28	21	22	22	24	25	18	26	26	14	18	19	21	20	20	19	16	19	19	23	24	17	23	26	17	19	26	15	17	15	13	35	21	13	24	24	Overall Accuracy (%)	94.47
Precision(%)	96.43	100.00	95.45	100.00	95.83	96.00	100.00	100.00	92.31	85.71	100.00	94.74	100.00	100.00	100.00	94.74	93.75	100.00	95.65	100.00	100.00	73.91	96.15	88.24	94.74	69.23	100.00	100.00	88.24	93.33	100.00	82.86	95.24	92.31	100.00			
Omission Error(%)	3.57	0.00	4.55	0.00	4.17	4.00	0.00	0.00	7.69	14.29	0.00	5.26	0.00	0.00	0.00	5.26	6.25	0.00	4.35	0.00	0.00	26.09	3.85	11.76	5.26	30.77	0.00	0.00	11.76	6.67	0.00	17.14	4.76	7.69	0.00			

Figure C.3: Classification Matrix of Proposed Technique using Polynomial Kernel for Known Signers:OvO

Figure C.4: Classification Matrix using Ensemble of Kernel for Known Signers:OvO

[illegible]

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-1	21	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	77.78	22.2																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-2	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	5	0	5	0	0	0	0	66.67	33.3																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-3	0	1	20	0	0	0	0	0	3	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	74.07	25.9																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																								
C-4	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	95.45	4.5																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																								
C-5	0	0	0	0	17	0	0	0	0	3	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	73.91	26.1																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-6	0	0	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	1	0	0	80.77	19.2																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-7	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	89.47	10.5																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-8	0	0	0	0	0	0	0	24	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88.89	11.1																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-9	0	0	0	0	1	0	0	0	23	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	79.31	20.7																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-10	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	82.35	17.6																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-11	5	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	2	0	0	42.11	57.9																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-12	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94.44	5.6																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-13	0	0	0	0	1	0	0	1	0	1	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	2	0	72.00	28.0																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-14	0	0	0	1	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	3	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	85.71	14.3																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-15	0	3	1	0	0	0	0	0	1	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	70.00	30.0																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	12	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	80.00	20.0																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-18	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	14	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	73.68	26.3																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	14	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	73.68	26.3																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-20	0	0	0	1	0	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	15	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	65.22	34.8																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.0																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-22	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94.12	5.9																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																								
C-23	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	2	0	0	77.78	22.2																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-24	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88.00	12.0																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																								
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	88.89	11.1																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-26	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	1	0	0	89.47	10.5																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-27	0	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	2	0	0	1	0	0	66.67	33.3																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
C-28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	93.33	6.7																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																								
C-29	0	0	0	0	0	3	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	66.67	33.3																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																								
C-30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	100.00	0.0																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																									
C-31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

[illegible]

Figure C.7: Classification Matrix of Proposed Technique using Polynomial Kernel for Known Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	96.30	3.70
C-2	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	95.24	4.76	
C-3	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	96.30	3.70	
C-4	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-5	0	0	0	0	22	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.65	4.35	
C-6	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	88.46	11.54	
C-7	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	89.47	10.53	
C-8	0	0	0	0	0	0	0	26	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	96.30	3.70	
C-9	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	93.10	6.90	
C-10	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-11	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	94.74	5.26	
C-12	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-13	0	0	0	0	2	0	0	0	0	1	0	0	20	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80.00	20.00	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	85.71	14.29	
C-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	84.21	15.79	
C-20	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.65	4.35	
C-21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	100.00	0.00
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	100.00	0.00
C-27	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	94.44	5.56	
C-28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	100.00	0.00	
C-29	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	94.44	5.56	
C-30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	100.00	0.00	
C-31	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	93.33	6.67	
C-32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	3	0	0	75.00	25.00
C-33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	90.32	9.68	
C-34	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	90.48	9.52	
C-35	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	92.31	7.69	
C-36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91.67	8.33	
Positive Classified	26	21	26	23	25	23	17	26	29	18	18	19	22	18	21	18	15	22	16	23	24	18	19	28	22	24	18	15	15	12	32	20	13	23	Overall Accuracy (%)	94.61		
Precision (%)	100.00	95.24	100.00	95.65	100.00	100.00	100.00	100.00	93.10	94.44	100.00	94.74	90.91	100.00	95.24	100.00	86.36	100.00	100.00	95.65	100.00	94.44	94.74	89.29	91.92	79.17	94.44	100.00	100.00	100.00	87.50	93.33	95.00	92.31	95.65			
Omission Error(%)	0.00	4.76	0.00	4.35	0.00	0.00	0.00	0.00	6.90	5.56	0.00	5.26	9.09	0.00	4.76	0.00	13.64	0.00	4.35	0.00	5.56	5.26	10.71	18.18	20.83	5.56	5.56	0.00	0.00	0.00	6.25	6.67	12.50	5.00	7.69	4.35		

Figure C.8: Classification Matrix of Proposed Technique using Ensemble of Kernel for Known Signers: OVA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	18	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50.00	50.0	
C-2	0	21	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	11	1	0	0	0	0	0	1	2	1	0	0	0	52.50	47.5
C-3	0	0	24	1	0	0	0	0	5	0	1	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	58.54	41.5	
C-4	0	0	0	29	0	1	0	2	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	85.29	14.7	
C-5	0	0	0	0	27	0	0	0	0	2	0	0	2	0	0	0	0	0	0	0	0	0	3	0	0	0	0	1	0	1	0	0	0	0	0	0	75.00	25.0	
C-6	0	0	0	0	0	9	1	0	0	0	0	0	0	1	0	0	0	10	0	0	0	0	0	0	0	0	6	1	0	2	0	0	0	14	0	0	20.45	79.5	
C-7	0	0	0	0	0	1	30	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	2	62.50	37.5		
C-8	0	0	2	0	0	0	1	26	0	0	0	1	0	0	3	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	72.22	27.8	
C-9	0	0	15	1	2	0	0	0	13	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	8	0	1	0	0	0	0	0	0	30.95	69.0	
C-10	0	0	0	0	1	0	0	0	0	19	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	15	0	47.50	52.5	
C-11	26	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32.56	67.4		
C-12	0	0	0	1	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	94.87	5.1		
C-13	0	0	0	0	4	0	0	0	0	5	0	0	10	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	15	0	0	27.03	73.0	
C-14	0	0	0	0	0	2	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	4	0	0	1	0	0	0	0	0	0	0	78.79	21.2	
C-15	0	0	9	4	0	1	1	4	0	0	0	1	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	41.03	59.0	
C-16	0	0	0	0	3	0	0	0	0	10	0	0	6	0	0	0	11	0	0	2	0	0	0	4	0	0	1	1	0	4	0	0	0	0	2	0	25.00	75.0	
C-17	0	0	0	2	0	0	3	3	0	0	0	12	0	0	4	0	17	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40.48	59.5		
C-18	1	0	0	0	0	2	0	0	0	0	0	19	0	0	0	0	0	20	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	44.44	55.6	
C-19	1	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	14	1	0	0	0	1	0	6	0	0	0	0	0	1	0	0	0	2.44	97.6		
C-20	0	0	1	0	0	0	0	1	0	0	0	1	0	0	5	0	0	0	0	0	21	0	0	0	0	0	5	2	0	0	0	0	0	0	0	1	56.76	43.2	
C-21	4	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	1	0	0	0	74.29	25.7		
C-22	2	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	10	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15.00	85.0	
C-23	0	0	2	0	1	0	0	2	0	2	0	0	0	0	0	6	0	0	0	0	0	0	18	0	0	0	0	2	0	0	0	2	0	0	1	0	0	50.00	50.0
C-24	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	31	0	0	0	3	0	1	0	0	0	0	0	1	0	79.49	20.5	
C-25	0	11	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	2	0	0	0	0	0	24	0	0	0	0	0	0	2	0	1	0	0	57.14	42.9	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	2	1	0	0	92.68	7.3	
C-27	0	0	6	0	1	0	0	5	0	0	0	0	0	1	7	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	3	0	0	0	27.50	72.5	
C-28	1	3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	29	0	0	1	0	1	0	0	74.36	25.6	
C-29	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	28	0	0	0	0	0	68.29	31.7		
C-30	0	0	0	0	0	0	6	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	24	0	0	0	3	61.54	38.5		
C-31	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	2	1	0	0	0	0	0	19	0	0	0	51.35	48.6		
C-32	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	3	42	0	0	6.38	93.6		
C-33	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	25	0	0	0	67.57	32.4	
C-34	0	0	0	0	0	11	5	0	0	0	0	1	0	0	0	0	0	1	0	2	0	0	0	2	0	1	5	0	0	0	0	0	8	0	0	22.22	77.8		
C-35	0	0	0	0	3	0	0	0	0	9	0	0	6	0	0	0	0	0	0	0	0	0	2	0	0	0	1	1	0	3	0	0	2	0	6	0	18.18	81.8	
C-36	0	0	0	0	0	0	9	1	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	3	0	0	6	0	0	0	0	13	35.14	64.9		
Positive Classified	53	47	59	45	41	29	60	39	23	47	58	106	25	29	57	11	17	52	7	25	39	9	31	39	53	59	43	29	46	36	26	5	78	34	40	19	Overall Accuracy (%)	49.29	
Precision(%)	33.96	44.68	40.68	64.44	65.85	31.03	50.00	66.67	56.52	40.43	24.14	34.91	40.00	89.66	28.07	100.00	100.00	38.46	0.00	84.00	56.67	66.67	58.06	79.49	45.28	64.41	25.58	100.00	50.87	66.67	73.08	0.00	32.05	23.53	15.00	68.42			
Omission Error(%)	66.04	55.32	59.32	35.56	34.15	68.97	50.00	33.33	43.48	59.57	75.86	65.09	60.00	10.34	71.93	0.00	0.00	61.54	100.00	16.00	33.33	33.33	41.94	20.51	54.72	35.59	74.42	0.00	39.13	33.33	26.92	100.00	67.95	76.47	85.00	31.58			

Figure C.9: Classification Matrix of Proposed Technique using Linear Kernel for UnKnown Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	11	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	4	0	5	0	0	0	0	0	30.56	69.44
C-2	0	12	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	12	0	1	0	0	9	0	0	0	0	0	0	30.00	70.00
C-3	0	0	28	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	4	0	6	0	0	0	0	0	68.29	31.71	
C-4	0	0	2	22	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	64.71	35.29	
C-5	0	0	1	0	20	0	0	1	0	3	0	0	0	0	4	0	0	0	0	0	0	0	2	0	0	0	0	0	0	5	0	0	0	0	0	55.56	44.44	
C-6	0	0	2	0	0	6	0	0	3	0	0	0	0	0	0	0	0	15	0	0	0	0	2	0	0	0	0	0	0	5	0	0	11	0	0	13.64	86.36	
C-7	0	0	0	0	0	0	19	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	1	14	39.58	60.42		
C-8	0	0	18	0	0	0	0	12	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	3	0	0	0	0	0	33.33	66.67	
C-9	0	0	14	0	2	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	7	0	0	0	0	0	33.33	66.67	
C-10	0	0	0	0	1	0	0	0	0	19	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	8	0	47.50	52.50	
C-11	19	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55.81	44.19	
C-12	0	0	0	0	0	12	0	0	0	6	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	61.54	38.46	
C-13	0	0	0	0	0	0	0	0	0	0	6	0	0	6	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	10	0	16.22	83.78	
C-14	0	0	0	0	0	0	1	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	78.79	21.21	
C-15	0	0	13	0	0	0	0	4	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	28.21	71.79	
C-16	0	0	0	0	3	0	0	0	0	9	0	0	0	0	0	1	12	0	0	0	3	0	1	1	0	0	0	0	0	1	10	0	0	1	2	0	27.27	72.73
C-17	0	0	0	1	0	0	5	0	0	0	0	0	0	0	3	0	12	2	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	28.57	71.43	
C-18	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	19	0	0	0	6	0	0	0	0	0	0	4	0	0	0	0	0	42.22	57.78	
C-19	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	27	0	0	0	0	1	0	0	0	0	0	0	9	0	0	0	1	0	0	0.00	100.00
C-20	0	0	5	0	0	0	0	0	0	0	0	3	0	0	12	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45.95	54.05	
C-21	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	11	0	0	0	0	0	57.14	42.86	
C-22	11	0	0	3	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	8	6	0	0	0	0	0	0	1	0	9	0	0	0	0	15.00	85.00	
C-23	0	0	13	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	3	0	0	0	14	0	0	0	0	0	1	0	4	0	0	1	0	0	38.89	61.11
C-24	0	0	1	0	0	7	1	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	1	13	0	0	0	0	0	4	3	0	0	6	0	0	33.33	66.67
C-25	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	18	0	0	0	0	0	0	1	0	0	0	42.86	57.14	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	37	0	0	1	0	0	0	1	0	0	90.24	9.76
C-27	0	3	9	4	0	0	0	0	4	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	1	0	11	0	0	0	0	0	250	97.50	
C-28	0	4	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	3	0	0	0	0	0	76.92	23.08	
C-29	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	63.41	36.59	
C-30	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	61.54	38.46	
C-31	0	12	2	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4	0	0	0	0	0	14	0	1	0	0	37.84	62.16	
C-32	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	3	0	1	0	0	6	0	0	1	31	0	0	2.13	97.87
C-33	0	2	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	4	0	0	0	0	2	0	17	0	0	0	45.95	54.05	
C-34	0	0	0	0	0	14	7	0	0	0	0	0	0	0	0	0	0	5	0	0	0	1	0	0	0	1	0	0	0	1	0	0	7	0	0	19.44	80.56	
C-35	0	0	0	0	12	0	0	0	5	0	0	4	0	0	0	0	0	1	0	0	0	4	0	0	0	0	0	0	0	2	0	0	0	5	0	0	15.15	84.85
C-36	0	0	0	0	0	0	5	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	6	0	0	2	0	21	56.76	43.24	
Positive Classified	42	44	120	36	50	31	54	19	28	42	38	47	10	27	42	12	12	88	3	20	28	12	35	14	41	40	13	35	32	231	17	1	61	31	25	35	Overall Accuracy	40.11
Precision(%)	26.19	27.27	23.33	61.11	40.00	19.35	35.19	63.16	50.00	45.24	63.16	51.06	60.00	96.30	26.19	100.00	100.00	21.59	0.00	85.00	71.43	50.00	40.00	92.86	43.90	92.50	7.69	85.71	81.25	10.39	82.35	0.00	27.87	22.58	20.00	60.00		
Omission Error(%)	73.81	72.73	76.67	38.89	60.00	80.65	64.81	36.84	50.00	54.76	36.84	48.94	40.00	3.70	73.81	0.00	0.00	78.41	100.00	15.00	28.57	50.00	60.00	7.14	56.10	7.50	92.31	14.29	18.75	89.61	17.65	100.00	72.13	77.42	80.00	40.00		

Figure C.10: Classification Matrix of Proposed Technique using RBF Kernel for UnKnown Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	4	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	2	0	0	0	0	0	0	0	0	11.11	88.89
C-2	0	16	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	2	0	0	0	0	2	1	8	0	0	40.00	60.00
C-3	0	0	31	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	75.61	24.39	
C-4	0	0	10	20	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	58.82	41.18	
C-5	0	0	3	0	26	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	72.22	27.78	
C-6	0	0	9	0	0	16	0	2	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	14	0	0	36.36	63.64	
C-7	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50.00	50.00		
C-8	0	0	21	0	0	0	0	7	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	3	0	0	0	0	19.44	80.56	
C-9	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	33.33	66.67	
C-10	0	0	0	0	0	0	0	0	0	19	0	0	1	0	0	0	0	5	2	0	0	2	0	0	0	0	0	0	0	2	0	0	0	0	0	47.50	52.50	
C-11	12	0	0	0	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	72.09	27.91	
C-12	0	0	0	2	0	0	0	0	1	0	0	35	0	0	1	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	89.74	10.26
C-13	0	0	0	0	9	0	0	0	0	8	0	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	13.51	86.49	
C-14	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	84.85	15.15	
C-15	0	0	13	1	0	0	2	16	1	0	0	2	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10.26	89.74	
C-16	0	0	0	4	0	0	0	2	0	0	0	1	0	0	0	28	0	0	0	0	2	0	2	0	0	0	0	0	1	0	0	1	0	0	1	63.64	36.36	
C-17	0	0	0	3	0	0	0	0	0	0	0	2	0	0	0	0	6	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14.29	85.71	
C-18	0	4	0	0	0	1	4	0	0	0	0	16	0	0	0	0	0	10	2	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	22.22	77.78	
C-19	0	1	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	15	5	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	12.20	87.80	
C-20	0	0	6	0	0	0	0	0	0	0	7	0	0	0	2	0	0	0	0	0	9	0	0	1	0	0	0	0	0	0	0	0	0	0	0	24.32	75.68	
C-21	5	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0	3	16.67	83.33
C-22	9	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	10	13	0	0	0	0	0	0	0	0	0	0	0	0	0	32.50	67.50	
C-23	0	0	22	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	13	0	1	0	0	6	1	0	0	0	33.33	66.67	
C-24	0	0	0	0	0	5	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	14	0	0	40.48	59.52	
C-25	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	0	1	0	90.24	9.76	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	35.00	65.00	
C-27	0	0	17	3	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	71.79	28.21	
C-28	0	10	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	7	0	0	0	0	80.49	19.51	
C-29	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	26	0	0	0	0	66.67	33.33	
C-30	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32.43	67.57	
C-31	0	14	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	5	0	0	0	0	12	0	5	0	0	37.43	62.57	
C-32	0	6	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	2	33	0	0	4.26	95.74	
C-33	0	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	8	0	1	0	0	0	0	1	20	0	0	54.05	45.95	
C-34	0	0	2	1	0	17	8	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	0	0	0	3	0	0	8.33	91.67	
C-35	0	0	0	0	7	0	1	0	0	8	0	0	4	0	0	0	0	3	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	6	0	18.18	81.82	
C-36	0	0	0	0	0	5	6	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	37.84	62.16		
Positive Classified	30	58	162	34	47	45	74	32	25	37	64	74	12	31	13	28	6	36	11	12	41	21	34	16	46	43	52	30	41	60	15	4	82	30	25	45	Overall Accuracy (%)	43.08
Precision(%)	13.33	27.59	19.14	58.82	55.32	35.56	32.43	21.88	56.00	51.35	48.44	47.30	41.67	90.32	30.77	100.00	100.00	27.78	0.00	75.00	68.29	61.90	17.65	81.25	36.96	86.05	26.92	93.33	80.49	43.33	80.00	0.00	24.39	10.00	24.00	31.11		
Omission Error(%)	86.67	72.41	80.86	41.18	44.68	64.44	67.57	78.13	44.00	48.65	51.56	52.70	58.33	9.68	69.23	0.00	0.00	72.22	100.00	25.00	31.71	38.10	82.35	18.75	63.04	13.95	73.08	6.67	19.51	56.67	20.00	100.00	75.61	90.00	76.00	68.89		

Figure C.11: Classification Matrix of Proposed Technique using Polynomial Kernel for UnKnown Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	5	0	0	0	0	0	0	0	0	0	21	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	3	0	0	0	0	0	0	0	13.89	86.11
C-2	0	22	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	1	0	0	1	1	4	0	0	0	55.00	45.00	
C-3	0	0	30	2	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	73.17	26.83	
C-4	0	0	6	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82.35	17.65	
C-5	0	0	2	0	27	0	0	1	0	1	0	0	0	0	2	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	75.00	25.00	
C-6	0	0	3	0	0	11	0	0	2	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	2	0	0	2	0	0	14	0	0	25.00	75.00	
C-7	0	0	0	0	0	0	33	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	68.75	31.25		
C-8	0	0	20	0	0	0	0	13	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	36.11	63.89		
C-9	0	0	18	0	2	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	35.71	64.29		
C-10	0	0	0	0	0	0	0	0	0	19	0	0	1	0	0	0	5	1	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	12	47.50	52.50		
C-11	13	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	69.77	30.23		
C-12	0	0	0	1	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	94.87	5.13		
C-13	0	0	0	0	8	0	0	0	0	6	0	0	8	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	11	21.62	78.38		
C-14	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	1	0	0	0	33.33	66.67		
C-15	0	0	13	2	0	0	2	6	0	0	0	1	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	38.64	61.36		
C-16	0	0	0	0	3	0	0	0	8	0	0	4	0	0	4	0	17	0	0	0	3	0	0	1	4	0	0	0	0	0	0	0	0	0	2	23.81	76.19	
C-17	0	0	0	1	0	0	9	0	0	0	0	4	0	0	3	0	10	2	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	33.81	66.19		
C-18	0	0	0	0	0	0	4	0	0	0	19	0	0	0	0	0	0	19	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	42.22	57.78		
C-19	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	19	2	0	0	0	0	0	5	0	0	0	0	0	1	1	0	0	4.88	95.12		
C-20	0	0	4	0	0	0	0	0	0	0	4	0	0	8	0	0	0	0	0	0	19	0	0	0	0	0	1	1	0	0	0	0	0	0	51.35	48.65		
C-21	1	0	0	3	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0	80.00	20.00		
C-22	7	0	0	1	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	10	9	0	0	0	0	0	0	0	0	0	0	0	0	22.50	77.50		
C-23	0	0	17	1	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	13	0	0	0	0	0	1	0	0	0	0	1	36.11	63.89		
C-24	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	19	0	0	0	0	0	6	0	0	6	48.72	51.28		
C-25	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	23	0	0	0	0	0	0	1	0	6	54.76	45.24		
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	1	0	95.12	4.88		
C-27	0	0	15	3	0	1	0	0	5	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	25.00	75.00		
C-28	1	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	0	0	0	0	0	82.05	17.95			
C-29	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	82.93	17.07		
C-30	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	1	69.23	30.77		
C-31	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	5	0	0	0	0	0	1	14	0	0	37.84	62.16		
C-32	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	1	0	0	0	2	39	0	0	4.26	95.74		
C-33	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	6	0	0	0	0	0	0	28	0	0	75.68	24.32		
C-34	0	0	1	0	0	16	7	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	2	0	0	0	0	0	8	0	22.22	77.78		
C-35	0	0	0	0	10	0	0	0	0	6	0	0	3	0	0	0	0	2	0	0	0	0	4	0	0	0	0	0	0	0	3	0	0	5	15.15	84.85		
C-36	0	0	0	0	0	0	9	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	20	54.05	45.95		
Positive Classified	27	54	131	42	50	32	81	21	23	40	67	78	16	29	38	17	10	66	6	22	38	16	28	23	48	48	27	35	48	57	17	3	78	34	31	35	Overall Accuracy (%)	48.32
Precision(%)	18.52	40.74	22.90	66.67	54.00	34.38	40.74	61.90	65.22	47.50	44.78	47.44	50.00	96.55	34.21	100.00	100.00	28.79	0.00	86.36	73.68	56.25	46.43	82.61	47.92	81.25	37.04	91.43	70.83	47.37	82.35	0.00	35.90	23.53	16.13	57.14		
Omission Error(%)	81.48	59.26	77.10	33.33	46.00	65.63	59.26	38.10	34.78	52.50	55.22	52.56	50.00	3.45	65.79	0.00	0.00	71.21	100.00	13.64	26.32	43.75	53.57	17.39	52.08	18.75	62.96	8.57	29.17	52.63	17.65	100.00	64.10	76.47	83.87	42.86		

Figure C.12: Classification Matrix of Proposed Technique using Ensembles of Kernels for UnKnown Signers:OvO

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)		
C-1	20	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55.56	44.4	
C-2	0	17	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	3	0	0	0	0	0	8	1	0	0	0	0	0	1	1	6	0	0	0	42.50	57.5
C-3	0	0	23	0	0	0	0	0	6	0	1	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	56.10	43.9	
C-4	0	0	0	27	0	0	0	2	0	0	0	3	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	79.41	20.6	
C-5	0	0	1	0	25	0	0	0	0	2	0	0	1	0	2	0	0	0	0	0	0	0	0	3	0	0	0	0	1	0	1	0	0	0	0	0	0	69.44	30.6	
C-6	1	0	1	1	0	8	1	0	0	0	1	0	0	0	0	0	0	12	0	0	0	0	0	0	1	0	3	1	0	0	0	0	0	1	13	0	0	18.18	81.8	
C-7	0	0	0	0	0	0	32	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	66.67	33.3		
C-8	0	0	7	0	0	0	1	18	0	0	1	1	0	0	6	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50.00	50.0	
C-9	0	0	17	0	0	0	0	13	0	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	30.95	69.0	
C-10	0	0	0	0	2	0	0	0	0	21	0	0	3	0	0	0	0	0	1	0	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	10	0	52.50	47.5	
C-11	32	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20.93	79.1		
C-12	0	0	0	1	0	0	0	0	0	0	0	36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	92.31	7.7		
C-13	0	0	0	0	5	0	0	0	0	8	0	0	11	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29.73	70.3	
C-14	0	0	0	0	0	2	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	84.85	15.2	
C-15	0	0	13	1	0	0	1	1	0	0	0	1	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	53.85	46.2		
C-16	0	0	0	0	3	0	0	0	0	10	0	0	5	0	1	12	0	0	0	2	0	0	0	0	3	0	2	0	0	0	3	0	0	0	0	3	0	27.27	72.7	
C-17	0	0	0	0	0	0	3	3	0	0	0	8	0	0	6	0	19	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45.24	54.8	
C-18	0	0	0	0	0	4	0	0	0	0	0	12	0	0	0	0	0	20	0	0	0	0	4	0	0	0	0	0	0	0	2	0	0	0	3	0	0	44.44	55.6	
C-19	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	16	2	0	0	0	4	0	5	0	0	0	0	0	0	1	1	0	4	0	4.88	95.1		
C-20	0	0	1	0	0	0	0	1	0	0	0	0	0	0	5	0	0	0	0	0	25	0	0	0	0	0	3	0	0	0	0	1	0	0	0	1	67.57	32.4		
C-21	4	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	77.14	22.9		
C-22	4	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	10	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20.00	80.0		
C-23	0	1	3	0	1	0	0	1	1	1	0	0	0	0	8	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	1	0	0	0	0	52.78	47.2	
C-24	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	32	0	0	2	0	0	0	0	1	0	0	1	0	82.05	17.9	
C-25	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	2	0	0	0	0	0	0	20	0	0	0	0	0	2	0	5	0	0	47.62	52.4		
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	0	3	1	0	0	90.24	9.8		
C-27	1	0	8	5	0	1	1	0	4	0	2	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	3	0	17.50	82.5		
C-28	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	0	0	28	0	0	0	0	0	2	0	0	71.79	28.2		
C-29	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	28	0	0	0	0	0	0	68.29	31.7		
C-30	0	0	0	0	0	0	5	0	0	0	0	3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	29	0	0	0	0	0	74.36	25.6		
C-31	0	7	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	2	0	0	0	0	0	19	0	6	0	0	51.35	48.6		
C-32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	2	43	0	0	4.26	95.7			
C-33	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	3	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	22	0	0	59.46	40.5		
C-34	0	0	0	0	0	11	2	0	0	0	0	2	0	0	0	0	0	3	0	3	0	0	0	4	0	0	4	0	0	0	0	0	6	1	0	16.67	83.3			
C-35	0	0	0	0	5	0	0	0	0	8	0	2	7	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	2	0	0	2	0	5	0	15.15	84.8		
C-36	0	0	0	0	0	1	6	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	7	0	0	0	0	14	37.84	62.2		
Positive Classified	63	36	74	37	41	28	56	26	24	50	46	93	27	28	82	12	19	61	11	31	39	16	38	44	48	52	29	28	37	44	25	3	93	27	33	15	Overall Accuracy (%)	48.73		
Precision(%)	31.75	47.22	31.08	72.97	60.98	28.57	57.14	69.23	54.17	42.00	19.57	38.71	40.74	100.00	25.61	100.00	100.00	32.79	0.00	80.65	69.23	50.00	50.00	72.73	41.67	71.15	24.14	100.00	75.68	65.91	76.00	0.00	23.66	22.22	15.15	93.33				
Omission Error(%)	68.25	52.78	68.92	27.03	39.02	71.43	42.86	30.77	45.83	58.00	80.43	61.29	59.26	0.00	74.39	0.00	0.00	67.21	100.00	19.35	30.77	50.00	50.00	27.27	58.33	28.85	75.86	0.00	24.32	34.09	24.00	100.00	76.34	77.78	84.85	6.67				

Figure C.13: Classification Matrix of Proposed Technique using Linear Kernel for UnKnown Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	9	0	1	4	0	0	1	0	1	0	14	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	1	0	0	0	0	0	0	0	25.00	75.00
C-2	1	21	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	9	2	0	1	0	0	0	52.50	47.50
C-3	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	13	0	1	0	0	0	53.66	46.34		
C-4	1	1	0	23	0	0	0	0	7	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	67.65	32.35	
C-5	0	0	1	0	30	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2	0	0	0	83.33	16.67
C-6	1	0	2	0	0	16	6	0	1	0	1	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	4	0	0	6	0	0	4	0	0	0	36.36	63.64
C-7	0	0	0	0	1	4	25	0	1	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	5	52.08	47.92	
C-8	0	0	16	0	0	0	0	11	3	0	0	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	30.56	69.44	
C-9	0	0	17	0	3	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	8	0	0	0	0	0	28.57	71.43	
C-10	0	0	0	0	1	1	0	0	0	19	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	13	0	47.50	52.50	
C-11	8	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	60.47	39.53	
C-12	0	0	1	0	0	0	0	0	5	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	64.10	35.90	
C-13	0	0	0	0	17	0	0	0	0	8	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	5.41	94.59	
C-14	1	0	1	0	0	1	0	0	1	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	3	0	0	0	0	0	69.70	30.30	
C-15	0	0	17	0	0	0	0	2	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	30.77	69.23	
C-16	0	0	0	0	6	0	0	0	1	10	0	0	2	0	0	3	0	0	0	0	0	0	0	4	0	0	0	0	0	0	6	10	0	0	0	1	1	6.82	93.18
C-17	1	0	0	0	0	1	0	0	4	0	0	0	0	0	0	0	18	0	0	0	7	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	42.86	57.14	
C-18	0	0	0	0	0	2	1	0	0	0	0	13	0	0	0	0	0	15	0	0	0	0	4	0	0	0	0	1	0	0	3	4	0	0	1	0	0	33.33	66.67
C-19	4	1	2	0	0	0	0	0	0	13	0	6	0	0	0	0	0	6	4	0	0	0	1	0	0	0	0	0	0	0	1	0	2	0	0	0	9.76	90.24	
C-20	1	1	7	0	0	0	0	0	0	0	0	3	0	0	3	0	0	0	0	14	6	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	37.84	62.16
C-21	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	65.71	34.29	
C-22	3	0	0	3	0	0	0	0	1	0	6	0	0	0	0	0	0	0	0	0	5	16	1	0	0	0	0	0	0	0	5	0	0	0	0	0	0	40.00	60.00
C-23	0	0	11	0	0	0	0	0	0	2	0	0	0	0	0	3	0	0	0	0	1	0	8	0	0	0	0	0	0	0	0	3	7	0	1	0	0	22.22	77.78
C-24	2	1	0	0	2	0	6	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	2	3	0	0	0	2	1	41.03	58.97
C-25	0	12	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	12	0	0	0	0	0	4	0	0	0	0	0	28.57	71.43
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	1	0	0	97.56	2.44	
C-27	1	1	11	3	1	1	0	0	7	0	0	0	0	0	5	0	0	0	0	1	0	0	0	0	0	0	0	0	3	0	6	0	0	0	0	0	7.50	92.50	
C-28	0	5	0	0	0	0	0	0	3	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	1	0	0	0	0	71.79	28.21	
C-29	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	5	0	0	20	10	0	0	0	0	0	48.78	51.22	
C-30	0	0	0	0	0	1	9	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	25	0	0	0	0	0	64.10	35.90	
C-31	0	14	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0	1	17	0	0	0	0	45.95	54.05	
C-32	0	0	2	0	1	0	0	0	4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	35	0	0	0.00	100.00	
C-33	1	4	11	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	15	0	0	0	40.54	59.46	
C-34	0	0	0	0	0	18	12	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	1	0	0	2.78	97.22	
C-35	0	0	0	0	7	0	0	0	1	6	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	2	0	0	0	13	0	39.39	60.61
C-36	0	0	2	0	1	2	3	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	10	0	0	0	0	14	37.84	62.16	
Positive Classified	36	61	126	33	71	47	63	13	60	59	53	48	6	29	36	3	18	28	5	15	47	21	17	20	18	59	16	28	31	177	36	0	68	8	39	21	Overall Accuracy (%)	41.03	
Precision(%)	25.00	34.43	17.46	69.70	42.25	34.04	39.68	84.62	20.00	32.20	49.06	52.08	33.33	79.31	33.33	100.00	100.00	53.57	0.00	93.33	48.94	76.19	47.06	80.00	66.67	67.80	18.75	100.00	64.52	14.12	47.22	0.00	22.06	12.50	33.33	66.67			
Omission Error(%)	75.00	65.57	82.54	30.30	57.75	65.96	60.32	15.38	80.00	67.80	50.94	47.92	66.67	20.69	66.67	0.00	0.00	46.43	100.00	6.67	51.06	23.81	52.94	20.00	33.33	32.20	81.25	0.00	35.48	85.88	52.78	100.00	77.94	87.50	66.67	33.33			

Figure C.14: Classification Matrix of Proposed Technique using RBF Kernel for UnKnown Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)	
C-1	17	0	0	1	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	5	0	0	0	1	4	0	0	47.22	52.78	
C-2	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	1	1	0	0	0	12	0	2	0	0	50.00	50.00		
C-3	0	2	19	2	0	0	0	4	0	4	0	4	0	0	0	0	0	0	1	0	1	0	0	0	0	0	3	0	0	0	0	0	1	0	0	46.34	53.66		
C-4	0	0	0	25	0	2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	73.53	26.47		
C-5	0	0	1	0	27	0	0	0	0	1	0	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	3	0	0	75.00	25.00		
C-6	0	0	2	0	0	15	3	0	0	0	0	0	1	0	0	0	0	2	1	0	0	0	1	0	0	9	0	1	0	0	0	0	1	8	0	34.09	65.91		
C-7	0	0	0	4	2	6	27	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	56.25	43.75		
C-8	0	0	8	0	0	3	0	18	0	0	0	1	0	0	4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	50.00	50.00		
C-9	0	0	15	0	3	0	0	0	10	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	1	4	0	0	23.81	76.19		
C-10	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	47.50	52.50			
C-11	19	0	0	1	0	0	0	0	0	0	11	0	0	0	0	0	0	0	5	1	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	25.58	74.42		
C-12	0	0	0	1	0	0	0	1	0	0	0	34	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	87.18	12.82		
C-13	0	0	0	0	8	1	0	0	0	11	0	0	4	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	11	0	10.81	89.19	
C-14	0	0	0	0	0	1	0	0	0	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	87.88	12.12	
C-15	0	0	15	1	0	0	2	0	3	2	0	0	0	0	14	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	35.90	64.10		
C-16	0	0	0	3	0	0	0	2	0	11	0	0	0	0	0	9	0	0	0	0	2	0	0	0	5	0	0	0	0	3	3	1	2	0	3	0	20.45	79.55	
C-17	0	1	0	2	0	1	1	0	0	0	0	9	0	0	1	0	17	6	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	40.48	59.52		
C-18	0	0	1	0	0	1	3	0	0	1	0	7	0	0	0	0	0	0	23	2	0	0	0	2	0	0	0	0	0	0	0	0	0	1	3	1	51.11	48.89	
C-19	0	3	0	0	0	0	0	0	0	4	0	3	0	0	0	0	0	0	9	12	0	0	0	1	0	6	0	0	0	0	0	3	0	0	0	29.27	70.73		
C-20	2	9	1	0	0	0	0	0	0	1	0	2	0	0	3	0	0	0	0	16	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	43.24	56.76		
C-21	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	30	0	0	0	0	0	0	0	0	0	0	0	3	0	0	85.71	14.29		
C-22	11	0	0	2	0	1	2	0	0	0	2	0	0	0	0	0	0	7	0	0	4	8	1	0	0	0	0	0	1	0	0	0	1	0	0	20.00	80.00		
C-23	0	2	4	0	0	0	0	0	0	1	0	0	0	0	5	0	0	0	0	0	0	0	9	0	0	0	0	0	3	0	1	8	0	2	0	0	25.00	75.00	
C-24	0	1	0	0	2	0	5	0	0	0	0	0	0	0	0	1	0	1	0	5	0	0	0	0	19	0	0	0	0	0	0	0	1	0	0	48.72	51.28		
C-25	0	11	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	4	0	0	0	0	0	17	0	0	0	0	0	5	1	2	0	0	40.48	59.52	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	100.00	0.00		
C-27	0	2	9	3	2	0	0	1	7	0	1	2	0	0	4	0	0	0	0	0	3	0	0	0	0	0	3	0	0	0	0	0	3	0	0	7.50	92.50		
C-28	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	27	0	0	0	4	0	0	0	69.23	30.77		
C-29	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	4	3	1	0	0	0	0	0	5	0	0	0	18	0	0	0	3	0	43.90	56.10		
C-30	2	0	0	0	0	0	5	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	26	0	0	1	0	0	66.67	33.33		
C-31	1	8	0	1	0	2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	6	2	0	0	0	0	13	0	2	0	0	35.14	64.86		
C-32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	1	0	0	0	0	43	0	0	0.00	100.00		
C-33	0	2	1	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	0	0	0	0	2	1	0	0	0	2	0	0	0	56.76	43.24			
C-34	0	0	2	0	0	14	6	0	0	0	0	1	0	1	0	0	0	4	0	0	0	0	0	0	0	3	1	0	1	0	0	1	0	0	1	2.78	97.22		
C-35	0	0	0	0	2	1	1	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	1	0	5	1	14	0	42.42	57.58
C-36	0	2	1	0	1	8	4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	1	0	9	24.32	75.68	
Positive Classified	54	67	79	46	50	57	59	23	25	56	25	75	4	32	42	10	17	69	27	33	44	15	16	28	40	63	14	38	29	43	54	6	99	14	52	11	Overall Accuracy	43.93	
Precision(%)	31.48	29.85	24.05	54.35	54.00	26.32	45.76	78.25	40.00	33.93	44.00	45.33	100.00	90.63	33.33	90.00	100.00	33.33	0.00	48.48	68.18	53.33	56.25	67.86	42.50	65.08	21.43	71.05	62.07	60.47	24.07	0.00	21.21	7.14	26.92	81.82			
Omission Error(%)	68.52	70.15	75.95	45.65	46.00	73.68	54.24	21.74	60.00	66.07	56.00	54.67	0.00	9.38	66.67	10.00	0.00	66.67	100.00	51.52	31.82	46.67	43.75	32.14	57.50	34.92	78.57	28.95	37.93	39.53	75.93	100.00	78.79	92.86	73.08	18.18			

Figure C.15: Classification Matrix of Proposed Technique using Polynomial Kernel for UnKnown Signers:OvA

Class	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15	C-16	C-17	C-18	C-19	C-20	C-21	C-22	C-23	C-24	C-25	C-26	C-27	C-28	C-29	C-30	C-31	C-32	C-33	C-34	C-35	C-36	Recall (%)	Commission Error(%)
C-1	18	0	0	1	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50.00	50.00
C-2	0	19	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	1	11	1	0	0	0	47.50	52.50
C-3	0	0	23	1	0	0	0	0	6	0	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	1	0	0	0	56.10	43.90
C-4	0	0	0	28	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	3	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	82.35	17.65
C-5	0	0	1	0	32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	88.89	11.11	
C-6	0	0	1	0	0	14	2	0	0	0	0	0	0	0	0	0	8	1	0	0	0	0	0	0	0	7	0	0	0	0	0	0	1	10	0	0	31.82	68.18
C-7	0	0	0	0	0	4	35	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	72.92	27.08	
C-8	0	0	10	0	0	0	0	19	0	0	0	2	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	52.78	47.22	
C-9	0	0	16	0	3	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	1	0	0	0	0	40.48	59.52	
C-10	0	0	0	0	2	0	0	0	0	20	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	50.00	50.00	
C-11	21	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	2	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	34.88	65.12	
C-12	0	0	0	1	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94.87	5.13	
C-13	0	0	0	0	13	0	0	0	0	11	0	0	3	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	81.1	91.89
C-14	0	0	0	0	0	1	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	84.85	15.15	
C-15	0	0	15	0	0	0	3	0	1	1	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46.15	53.85	
C-16	0	0	0	0	4	0	0	0	0	10	0	0	5	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	27.27	72.73	
C-17	0	0	0	0	0	0	3	0	0	0	0	7	0	0	2	0	22	3	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	52.38	47.62	
C-18	0	0	0	0	0	2	1	0	0	0	15	0	0	0	0	0	0	22	0	0	0	0	3	0	0	0	0	0	0	0	1	0	0	0	0	48.89	51.11	
C-19	0	0	0	0	0	0	0	0	0	7	0	6	0	0	0	0	0	14	5	0	0	0	0	1	0	0	0	0	0	0	1	2	0	0	0	0	12.20	87.80
C-20	0	1	1	0	0	0	0	0	0	0	0	1	0	0	4	0	0	0	0	0	24	2	0	0	0	1	3	0	0	0	0	0	0	0	0	64.86	35.14	
C-21	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0	2	0	0	0	0	88.57	11.43	
C-22	10	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	1	0	0	7	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22.50	77.50
C-23	0	1	5	0	0	0	0	0	0	1	0	0	0	0	5	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	63.89	
C-24	0	1	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	26	0	0	0	0	0	1	0	0	1	0	0	66.67	33.33
C-25	0	10	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	22	0	0	0	4	0	0	0	0	52.38	47.62	
C-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-27	0	1	11	4	1	1	0	0	9	0	0	2	0	0	4	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10.00	90.00
C-28	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	3	0	0	0	0	0	1	6	0	0	0	36.11	63.89	
C-29	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	66.67	33.33	
C-30	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	52.38	47.62	
C-31	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00	0.00	
C-32	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10.00	90.00	
C-33	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	18	0	6	0	0	48.65	51.35	
C-34	0	0	0	0	0	21	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.13	97.87	
C-35	0	0	0	0	0	6	0	0	0	0	6	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.56	94.44	
C-36	0	0	0	0	1	2	6	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	2	0	0	36.36	63.64	
Positive Classified	51	45	84	36	63	45	69	19	33	56	42	81	12	29	50	12	22	56	12	34	49	16	19	35	39	65	14	36	34	50	45	5	88	13	40	17	Overall Accuracy (%)	50.99
Precision(%)	35.29	42.22	27.38	77.78	50.79	31.11	50.72	100.00	51.52	35.71	35.71	45.68	25.00	96.55	36.00	100.00	100.00	39.29	0.00	70.59	63.27	56.25	68.42	74.29	56.41	63.08	28.57	91.67	76.47	64.00	40.00	0.00	29.55	15.38	30.00	88.24		
Omission Error(%)	64.71	57.78	72.62	22.22	49.21	68.89	49.28	0.00	48.48	64.29	64.29	54.32	75.00	3.45	64.00	0.00	0.00	60.71	100.00	29.41	36.73	43.75	31.58	25.71	43.59	36.92	71.43	8.33	23.53	36.00	60.00	100.00	70.45	84.62	70.00	11.76		

Figure C.16: Classification Matrix of Proposed Technique using Ensemble of Kernel for Unknown Signers:OvA

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