Classification of Magnetic Resonance Lesions Using Support Vector Machines

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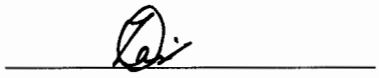

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Bismillah

In the name of Allah, the Most Gracious and the Most Merciful.

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All praise and glory goes to Almighty Allah (Subhanahu Wa Ta'ala) Who gave me the courage and patience to carry out this research work. Peace and blessings of Allah be upon His last Prophet Muhammad (Sallulaho-Alaihihe-Wassalam) and all his Sahaba (Razi-Allaho-Anhum) who devoted their lives for the prosperity and spread of Islam.

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May Allah help us in following Islam according to Quran and Sunna! (Ameen).

ABSTRACT

The classification and segmentation of brain tumor images have always been challenging tasks in medical imaging consisting of classification and extraction procedure of tumorous lesions in images of different subjects. In general, medical doctors and radiologists manually perform these steps because they are doubtful as much similarity is always there in between tumorous and non tumorous lesions along with the highly diverse appearance of tumors. Thus, automated classification and segmentation of images has always been a challenge and therefore, has gained attention of medical researchers in past few years. In this research, focus will be on the classification and segmentation of magnetic resonance brain images (MRI). The idea behind this research is to consider the problem as a classification problem between tumorous and non tumorous pixels dependent upon many features which are textures. On the other hand, support vector machine (SVM) has been proposed for classification purpose as it is a very popular and dependable technique. The experimental research will be carried on subset of tumor namely gliomas dataset having non uniform tumor shapes, complex locations in skull, different sizes and random image intensities and textures.

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CHAPTER 1

INTRODUCTION

Medical imaging represents a field of different techniques and methodologies used for creation and acquisition of images of human anatomy. The acquired images are used in clinical methods as in medical processes in order to detect or identify the disease. It is also used in medical sciences to study internal human body comprising of structures and design of different structures in living organisms and in physiology to study mechanical, physical and biochemical processes occurring in living things. Medical imaging can also be considered to be a part of different imaging techniques which usually are known as radiology, radiological sciences, thermography, medical photography etc. Moreover, medical imaging also represents other techniques used to obtain high risked data represented as maps in electro encephalography (EEG), magneto encephalography (MEG) and electro cardiography (ECG) etc.

Medical imaging also deals with the scientific investigations as in biomedical engineering and medical physics etc. The developments, advancements and ongoing research in the instrumentation, acquisition of images and the modeling are also considered to be the part of engineering in biomedical, medical physics. The specified working for images acquisition along with description of the human body is a part of radiology. Many of above mentioned

techniques are also having some industrial and scientific applications which are in practice nowadays.

1.1 Motivation

Normal adult body forms new cells whenever there is a need of division or replacement of old and damaged cells. Children and infants produce new cells for the completion of the development along with those that are needed for repairing. A tumor forms when normal or damaged cells divide at the time where there is no need.

Brain tumor is defined to be a mass of unnecessary/damaged abnormal cells which multiply out of proportion in brain. Also known as neoplasm or lesion, tumor is categorized as primary and secondary.

Primary tumors grow and usually halt in brain. On the other hand, secondary brain tumors comprise of dead cells that produce/grow in different organs in body and spreads towards brain. Mostly, secondary tumors spread from lung and breast.

Whenever doctors diagnose brain tumors, they normally identify them either as "Malignant" or "Benign". Such details discussed above provide the degree of severity or aggressiveness in growing tumor. Classification of brain tumor as "Malignant" or "benign" is a complex task as many factors are involved apart from pathological features which contribute towards the outcome and growth of tumor. Basic difference between "Malignant Tumors" and "Benign Tumors" is that malignant brain tumors grow abruptly affecting other cells while benign brain tumors normally do not grow as much, but sometimes even benign tumors can also be a threat to life.

A tumorous cell that forms inside the brain can be defined as primary. Some of the primary tumors are glioblastoma, multiforme, astrocytoma, medulloblastoma and ependymoma. Primary brain tumors are categorized either as malignant or benign.

The properties of a benign brain tumor are that they slowly grow having discrete outlines and rarely disperse. Tumorous cells have normal like appearance when visualize under the microscope. Surgery is referred to be the preferable treatment for such tumor. A brain tumor that is comprised of less damaged cells, but formed in a sensitive region, can be a threat to life even though tumorous cells will only be considered as benign.

The properties of malignant brain tumor are that their growth is abrupt, severe and a threat to life. Malignant brain tumors sometimes are known to be cancer though primary tumors mostly do not spread out of brain and so not exactly considered to be generalized definition of cancer. Thus below mentioned is a small comparison between cancer and brain tumor as:

Cancer is a disease that is being caused by:

- Abnormal growth of damaged cells
- Damaged cells, that grows in different organs in the body and creates hurdles because of the normal functions.
- Propagation in remote organs of the body.

Brain Tumors are considered as severe only when they

- Possess the properties of cancerous cells.
- Forms in sensitive region of the brain.
- Cause threat to life.

Malignant brain tumors are severe and abruptly displaces in brain. They affect other body parts very rarely. Such tumors don't have defined borders as they tend to spread "roots" in neighboring normal tissue. They can also affect moving cells.

Cancer cells which grow in other parts within the body and moves towards the brain forms metastatic tumors in brain which include lung cancers, colon, breast and skin (melanoma) mostly spreading towards the brain either by the blood circulation or attracting other organs inside the human body.

1.2 Problem Statement

Initial detection of brain tumor is an important constituent that determines prospect of malignant or benign tumor. This process generally is performed manually by medical doctors and radiologists who are sometimes doubtful because of the similarities in tumorous and non tumorous tissues along with the complexity in the visualization of tumors. In this regard, computer aided diagnosis systems (CAD) have potential to aid and have attracted attention of the medical experts and researchers. A key in developing such computer aided diagnostic system that can assist medical experts is dependent upon appropriate algorithm for the classification of tumorous and non tumorous lesions.

1.3 Objectives

The goal of this research is to develop a computer aided diagnostic system that successfully classifies between doubtful tumor and non tumor candidates and also segment magnetic resonance brain images. Moreover, a selection methodology has been proposed which helps in selecting only those features out of total calculated which shows significant variance

between tumor and non tumor values. Comparison of Non Linear SVM, Linear SVM and Artificial Neural Networks has also been carried out to determine which classifier is suitable for tumor classification.

1.4 Scope

Different softwares and tools have been used which include:

- Medical image conversion utility (MEDCON) software, for reconstruction of 2-D images into a 3-D volume of images [44].
- Statistical parametric mapping (SPM) tool, for co registration and template registration [45].
- Medical image processing and visualization (MIPAV) tool, for extraction of slices of interest [46].
- Anisotropic filtering technique, for removal of noise from given images.
- Intensity and haralick texture features, for characterization of given images.
- Support vector machines (SVM), for classification of tumorous and non tumorous lesions [47].

Experiments have been conducted under complex environments on different subjects using the available software package MATLAB R2011b.

1.5 Contribution of Thesis

Research in this thesis will contribute in supervised segmentation of MR brain images which will enhance the automated detection and classification of brain tumor. Detection and classification of brain tumor will be minimal complex, dependable, more accurate and

alternative way for classification instead of conventional diagnostic procedure in the field of medical sciences.

1.6 Thesis Organization

Chapter 2 is divided into two sections. First section discusses medical imaging and its applications, brain tumor and its features along with different tumor grades in detail. Second section discusses medical imaging techniques which are used for brain abnormalities especially magnetic resonance imaging.

Chapter 3 is the literature review of existing techniques in segmentation, features and classification methodologies.

Chapter 4 discusses the proposed system which mainly comprises of four phases namely preprocessing phase different processes involve in preprocessing, feature extraction phase, training and testing phase which is basically the classification and segmentation phase.

Chapter 5 contains simulation results of model of system build on proposed classification algorithm formulated for magnetic resonance brain tumor images.

Chapter 6 presents the summary of results obtained using proposed algorithm and also illustrates potential future directions as well.

CHAPTER 2

MEDICAL IMAGING

Medical imaging is a methodology by which images of parts of the body and its functions are examined in clinical settings to seek or diagnose various diseases. This technique is also used as a part of sciences in medicine to examine structures and physiology. Although medical imaging is carried out on removed organs and tissues for medical reasons, when it is, it comes under the branch of pathology which deals with the laboratory examination of the samples for diagnostic or forensic purposes.

Medical imaging is considered as biological imaging incorporating radiological techniques, nuclear medicine techniques, endoscopy, (medical) Thermography and microscopy to investigate human pathology.

Forms of medical imaging include measuring and recording techniques, such as electroencephalography (EEG), magneto encephalography (MEG), electrocardiography (ECG) etc. These are not meant for producing images but they instead yield information to be represented as maps as these contain information of the position which helps in the diagnostic processes [1].

2.1 Overview of Medical Imaging

Medical imaging is also considered as clinical imaging i.e. acquisition of images which is basically a technical aspect of medical imaging. The related people which acquire such images are known radiologists (radiology technologists). The radiologists are responsible for acquiring medical images which are expected to be of high quality so that the disease or the affected area can easily be diagnosed.

Medical imaging also deals with the scientific investigations such as biomedical engineering and medical physics etc. The developments, advancements and ongoing research in the instrumentation, acquisition of images and the modeling happen to be the part of biomedical sciences, medicine of physics and also computer science. The specified acquisition and interpretation of acquired human body images is a part of radiology. Many of above mentioned techniques are also having some industrial and scientific applications.

As a whole, we can say that medical imaging constitutes all those techniques that are used to create and acquire images of the living organisms. At the same time, medical imaging provides information of the chemical and physical changes that are happening in the normal body along with the abrupt changes which usually causes internal disorders and lead to malignant and benign diseases [2].

2.2 Brain Tumor

Brain tumor is the buildup of abnormal mass of tissues in the intracranial portion of the skull. It is caused by cells dividing at an increased speed but still, early detection can usually increase the chance of survival. These abnormal cells can invade surrounding tissues and travel towards different parts from blood stream to the body or also through the white blood.

The abnormal cells can also erode healthy tissues as they don't have much in common with the healthy cells; this is known as a malignant or a cancerous tumor. If caught, early the malignant tumor cells have a low chance of destroying healthy brain tissue and thus spreading. The common cases of malignant tumors arise from other existing malignant cancerous cells which have moved from other parts towards the brain and are known as metastases or secondary tumors and in adults 20-40% of malignant cancers are as a result of metastatic lesions in the brain originating from existing malignant cancers elsewhere in the body [3].

The origination of tumors inside skull is unknown, but it can happen to individuals who usually get exposure to vinyl chloride, have blood relation with cancerous patients and has gone through renal transplantation who are treated with immunosuppressant medication. Symptoms of tumor are often those having headache continuously, nausea, vomiting on regular basis, papilledema, lethargy, and disorientation though sometimes depends upon the sight.

Identification of a brain tumor usually involves a neurological test, scans of the brain and/or analyzing the tissues. Doctors require information after diagnosis for the classification of tumor as malignant or benign. Diagnostic measures include field visualization and electroencephalography, x rays of the skull to examine, spinal fluid studies, computed tomography and magnetic resonance imaging. Gliomas, mostly astrocytomas tumors are the most common type of malignant tumor. Medulloblastomas tumor normally occurs in children. Mostly, brain tumor is named on its origination of cell or its exact presence in the brain. Identification of the tumor type supports the doctors for the determination of the most appropriate treatment. Normally, surgery is recommended as treatment for the tumors of the brain. Radiotherapy treatment is usually recommended when there are inoperable tumorous

lesions, medulloblastomas, tumors having different foci and also for the postoperative treatment of residual tumor tissue. [4].

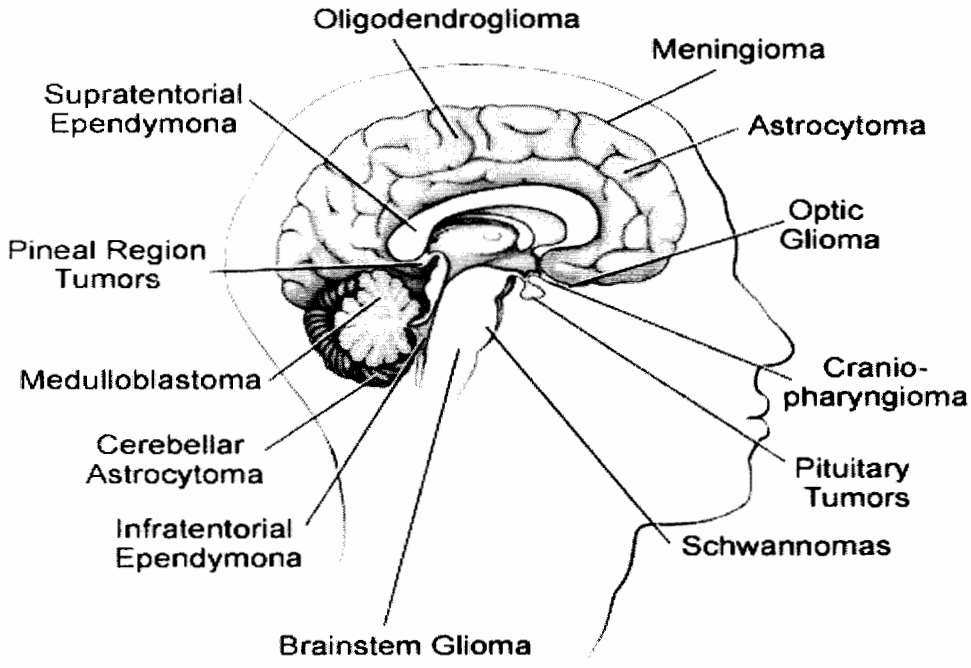


Figure 2.1: Major regions of Brain.

Figure 2.1 gives the detailed view of tumor occurring regions. From here, it is quite obvious that mostly occurring tumor in different parts of human skull is gliomas tumor which as stated is 90% of all malignant tumor cases.

2.2.1 Grading Criteria

Tumors grading is defined for the facilitation of communication, planning the required treatment and prediction of outcome. The degree of malignancy is being indicated by the grade of its tumor.

The assignment of grades is based on the microscopic appearance of the tumor upon following criteria:

- Similarity with non tumorous cells (atypia)
- Growth rate (mitotic index)
- Signs of unstoppable growth
- Presence of dead tumorous cells inside the tumor (necrosis)
- Potential to invade and/or spread (infiltration) dependent upon having a definitive margin (diffuse or focal) or not
- Blood supply (vascularity)

According to world health organization (WHO) grading system [5], tumors in grade I as shown in Figure 2.2 (a), are considered as lowest malignant and are considered to survive long term. Growth of these tumors is very slow having normal visualization whenever seen under a microscope. Surgery itself is referred as a recommended treatment for such tumor type. Pilocytic astrocytoma, craniopharyngioma and different other tumors of neurons which are gangliocytoma and ganglioglioma are considered to be part of grade I tumors.

Grade II tumors as shown in Figure 2.2 (b), have an abnormal microscopic view as they grow slowly. Few of them may spread in a neighboring normal tissue and grow. These tumors are considered as an upper grade tumor sometimes.

Grade III tumors as shown in Figure 2.2 (c), are malignant even though much difference in grade II and grade III tumor is not there. Tumorous cells reproduce abnormal cells abruptly which then grows affecting the nearby tissues. Such tumors often have the tendency to grow as a higher graded tumor.

Grade IV tumors as shown in Figure 2.2 (d), are an extremely severe tumors. They reproduce very actively and their visualization is very bizarre whenever viewed under the microscope.

This rapid production results in growth of tumor in nearby tissues. They formalize new blood streams for the maintenance of abrupt growth. The most common type is glioblastoma multiforme.

The grading system [5], [6] can be summarized as:

Grade I Tumor

- Cells grow slowly
- Appears normal in microscope
- Less malignant
- Can survive for long period of time

Grade II Tumor

- Cells grow relatively slow
- Impartially abnormal visualization under a microscope
- Chances of invading neighboring tissue
- Chances to be diagnosed higher grade

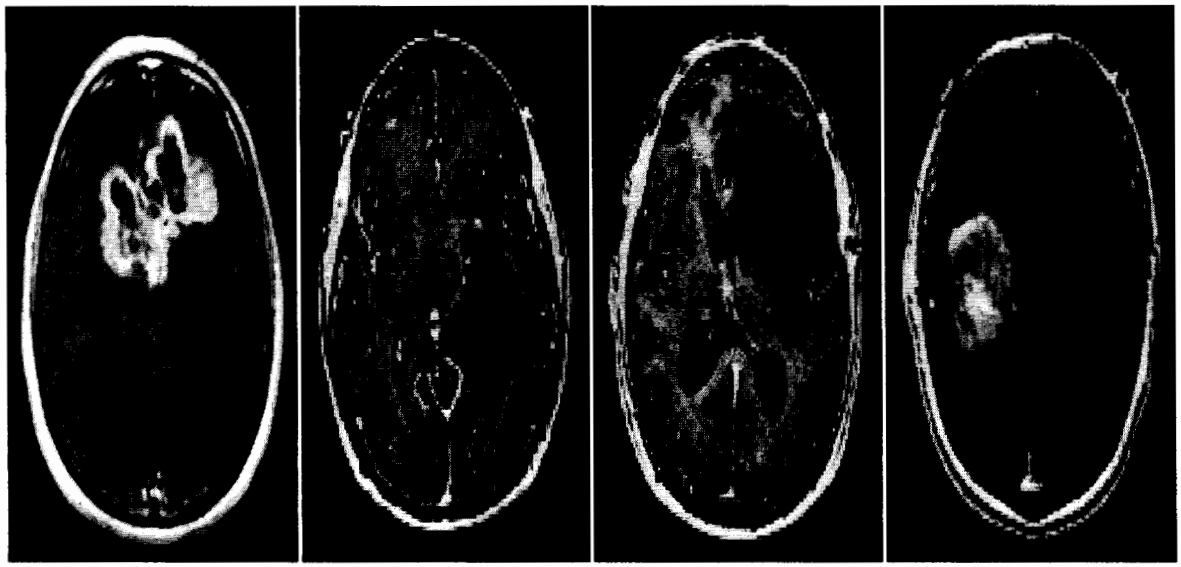
Grade III Tumor

- Active reproduction of tumorous cells
- Completely abnormal visualization under a microscope
- Effect neighboring tissues
- Often recurred as upper grade

Grade IV Tumor

- Tumorous cells reproducing actively
- Complete abnormal appearance under a microscope
- Maintains active growth by forming its own blood vessels
- Mostly dead cells.

There are cases where tumor sometimes contains many grades of dead cells. The presence of the highest grade of tumorous cells determines the aggressiveness and eventually final grade even if majority of the tumorous cells are low graded tumor.



(a) (b) (c) (d)

Figure 2.2 Grades of tumor. (a) Grade I tumor. (b) Grade II tumor. (c) Grade III tumor. (d) Grade IV tumor.

Some of the dead cells can change from diagnosis, even a non malignant tumor becoming a severe tumor. In few cases, a benign tumor might become a higher graded tumor. This all can only be discussed with the relevant doctor if the effected tumor has this potential or not. Thus, all graded systems have inherent complexities and criticalities [7], they are not accurate or precise.

- Criteria used for the grading assignments are related to the interpretation by expert pathologists.
- Tumors are never one dimensional and the examined lesion may not represent complete tumor.

2.3 Medical Imaging Techniques

There are many medical imaging techniques available. Some of them are discussed below:

2.3.1 Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) uses powerful magnetic fields to acquire images of inside of the brain. It produces detailed images of brain without using ionizing radiation as the former does [8]. The patient is told to lie down in a cylinder shaped magnet. Radio waves thousands time powerful than magnetic field of the earth are passed through the body. This affects the bodies atoms enforcing the nuclei into a different position and as they move back into place they send out radio waves of their own. The scanner then picks up these signals and through a computer turns these signals into images. Again, the quality of these pictures depends on the location and strength of the incoming signal. The tissue that has the least hydrogen atoms (such as bones) turns out dark, while the tissue that has many hydrogen atoms (such as fatty tissue) looks much brighter. By changing the timing of the radio-wave pulses it is possible to gain information about the different types of tissues that are present [9].

MRI scan gives a very detailed picture making it the best technique when it comes to finding tumors in the brain. If a tumor is present the scan can also be used to find out if it has spread

into nearby brain tissue. This technique is safe and shows the detailed images of injury, disease or abnormality of the anatomy in a non-invasive way making it ideal.

The MR scanner may take loud knocking and tapping noises during the procedure; therefore earplugs are used to prevent problems that may occur with the processed noise [10].

MRI is now the preferred procedure for diagnosing large number of abnormal conditions or potential problems in different parts of the body. Generally, MRI produces pictures that can differentiate between healthy and unhealthy tissues. Therefore, MRI is preferred by the physicians to examine brain, spine, abdomen, joints (knee, shoulder, hip, ankle and wrist), breast, blood vessels, heart and other body parts.

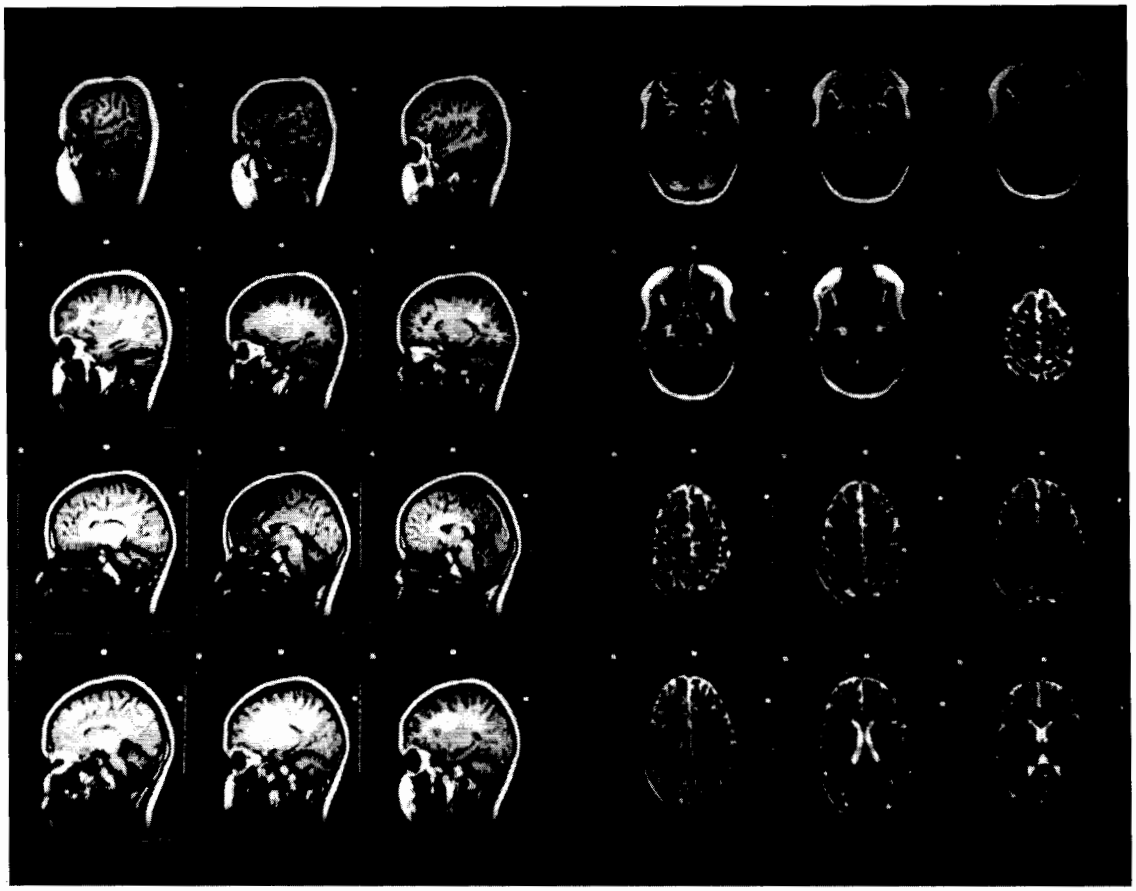


Figure 2.3: Magnetic resonance images.

Figure 2.3 comprises of magnetic resonance images in different planes shown on the screen as a volume. All these images provide detailed information of skull and rest of the structure of human skull.

2.3.2 Overview of Other Medical Imaging Techniques

Below are other imaging techniques for the acquisition of images of human body.

2.3.2.1 Nuclear Medicine

Nuclear medicine is a pain-free cost effective way to image the body and therefore treat the disease. It is a unique and provides doctors with information on both the structure and the function of the imaged parts and a way to gather medical information which would otherwise be unavailable, require surgery or necessitate further expensive diagnostic tests.

Nuclear medicine imagery procedures often identify abnormalities at a very early stage of the progress of the disease, long before many medical problems associated with the disease are apparent through other diagnostic tests. It uses very small amounts of radioactive materials (radiopharmaceuticals) to diagnose as well as treat disease.

In the imaging, the radiopharmaceuticals are detected by special cameras that work with computers to provide precise images about the part of the body being examined. In treatment the radiopharmaceuticals travel directly to the organ being treated thus reducing the chance of side effects to other organs. The amount of radiation in a nuclear imaging procedure is comparable to that received during an x-ray and the amount received in a typical treatment procedure is kept within the safe limits.

Figure 2.4 are some images acquired using nuclear medicine technique. The tumor is somewhat visible in the skull but the images entirely are of very low brightness which may be

because of very less x rays passed through human skull to avoid any exposure. Here, it is quite clear that this technique does not provide detailed and proper view of the skull as dark regions might contain some tumor which has not been detected due to low quality of images acquired.

Figure 2.4: Nuclear medicine images.

Below are some nuclear medicine methodologies for diagnosing diseases inside human body:

2.3.2.1.1 X-Rays

The usage of X-rays for acquiring images is the first imaging procedure that was commercially available to Science. X-rays are used in two different image acquisition techniques which are fluoroscopy and projection radiographs. Both these techniques are acquiring 2-D Images but still they are widely used in many developing countries due to their low cost, high resolution and low radiation [11].

2.3.2.1.2 Fluoroscopy

X-rays are consistently used in fluoroscopy which basically provides run time x-ray scans. This scanning is pretty useful in diagnosing severe and moderate diseases. Fluoroscopy provides a display motion where almost 25-30 images are produced in a second's time.

While acquiring one fluoroscopic image, one should make sure that the exposure time required to produce fluoroscopic image should be low as compared to radiograph. If the exposure will be high, it will result large series of images which will be mixture of several fluoroscopic processes and thus will not be the desired images. Hence, the total exposure to the patient for fluoroscopic image is primarily dependent upon time which we call as the total fluoroscopic time.

Moreover, two factors must be considered and should be handled very carefully while patient if exposed to the radiations in order to acquire images. One is the area of interest which usually is the skin and the organs as they are always the most exposed by the beam in order to get maximum absorbed dose. Other is the radiation energy that is being imparted on the patient's body. This energy is easily measureable and is known as kerma area product [12].

In fluoroscopy, the formation is dependent upon the image information requirements. Moreover, one, before acquiring images from a fluoroscopic system, should be careful as the system is highly sensitive that is the exposure required for the production of images. Recent advancements in this field leads better results but still, the exposure to the patients is very risky as the issue of optimizing the patient exposure with image quality. The optimization is done in order to avoid the patient getting exposed to the unnecessary radiation that takes place while acquiring images as it can be very harmful.

2.3.2.1.3 Projection Radiographs (X-Rays)

Projection radiographs are normally called x-rays. They are used for detection with type and the extent of any physical injury like bone swelling and fracture etc as shown in Figure 2.5. They are also used for the detection of pathological changes that takes place in lungs.

Recent advancements have led the use to x-rays in order to view internal structures in the body like stomach and liver etc. x-rays technology is associated to radio opaque media namely barium. The visualization with barium can help in diagnosing cancer and ulcers which mostly effect stomach and intestines very severely [13].

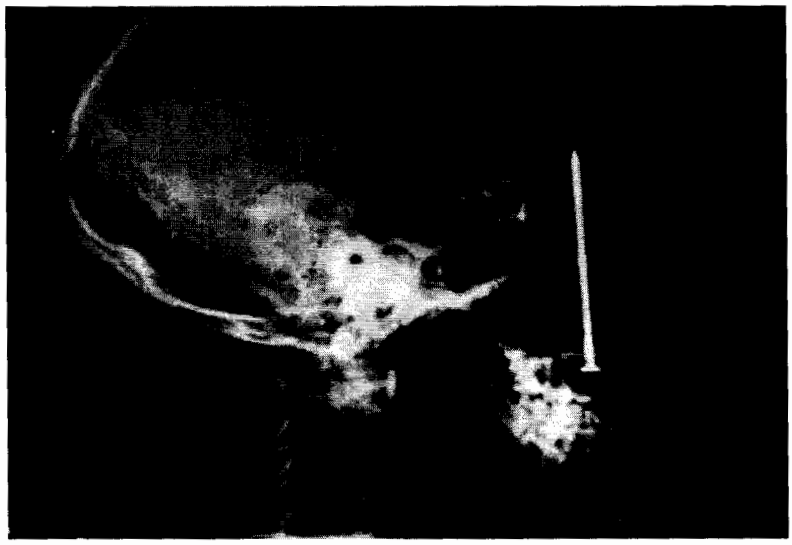


Figure 2.5: X-ray image.

Figure 2.5 is an x ray image. From here it can be observed that x rays only provide details of outer structure. It cannot be trusted for the detection of brain tumor or any tumor detection because of their in ability to acquire images in details of the skull from inside.

2.3.2.1.4 Computed Tomography (CT)

Computed tomography is also called CT scanning. It requires ionizing radiations of x-rays to acquire images of patient. When applied, the two dimensional images are acquired by having

different angles, these 2-D images are then combined producing a 3-D image using different predefined algorithms as shown in Figure 2.6. CT scanning is a cheap source for acquiring three dimensional images.

The reason behind using CT scanner is low cost and easy usage. But at the same time, it has different disadvantages like it requires high intensity x-rays that are injurious to human body. Moreover its resolution and image quality is very low [14].

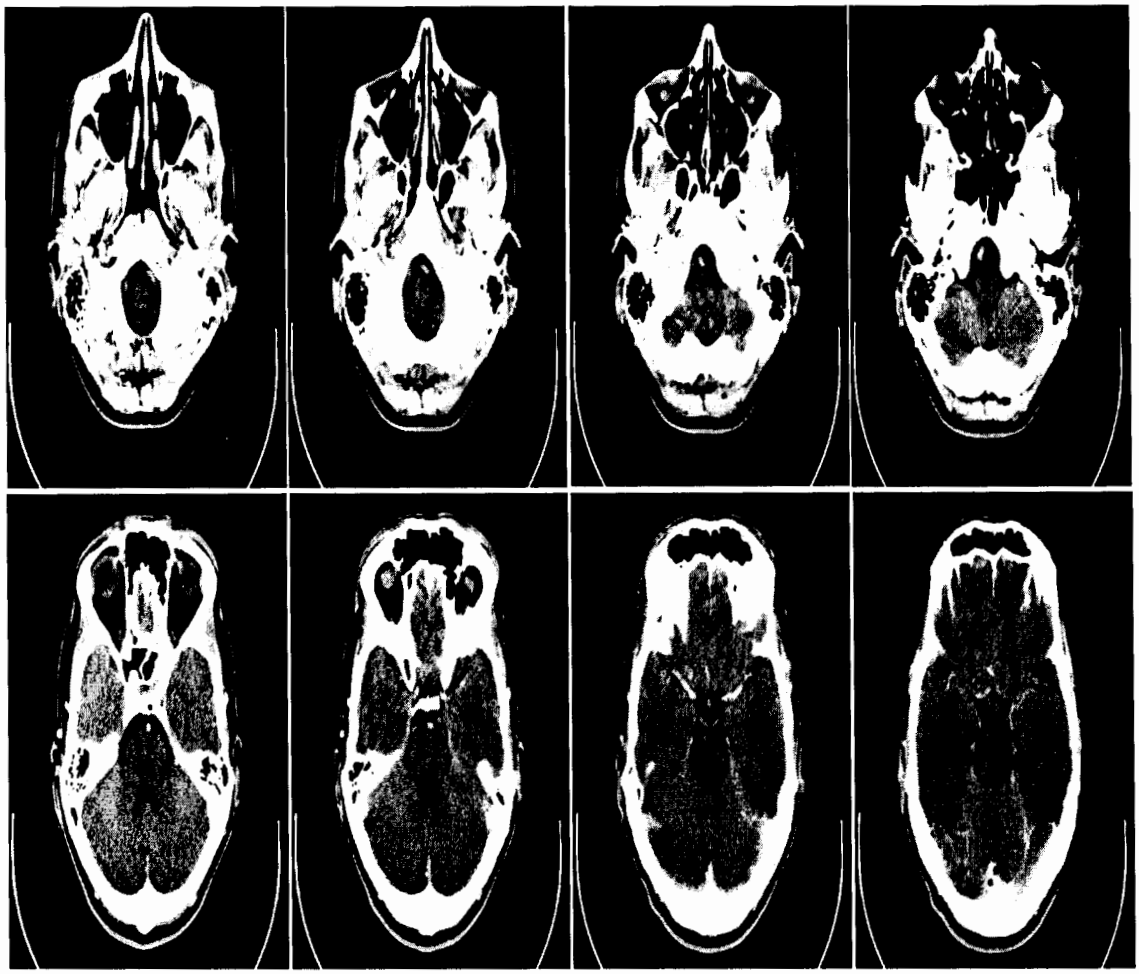


Figure 2.6: Computed tomography scan images.

Figure 2.6 comprises of computed tomography scans. The images acquired are of low quality and does not provide proper details of the skull. Therefore, no risk can be taken because brain

is a very sensitive part of the human body and such details are not enough to conclude the presence or absence of tumor or any other benign disease inside human skull.

2.3.2.2 Ultrasound or Ultra-Sonography (US)

Ultrasound is being used in medical ultra-sonography (US). The usage of ultrasound was developed in last 25-30 years. In the beginning, ultrasound images were two dimensional and static but with the passage of time, research and advancements in modern science has lead quite a success and now three dimensional images can also be acquired keeping in view of the limitations in ultrasound as shown in Figure 2.7, which will be discussed in the later part of this topic.

Ultrasound is basically very high frequency sound waves which are used in the visualization of soft tissue structures present in the living bodies. With the presence of high frequency sound waves, we can expect the frequency ranges to be in megahertz. The procedure that is adapted while acquiring images in ultrasound is that the sound waves are reflected by the tissue to varying degrees and thus images are produced. Such imaging is mostly found with the pregnant women biopsies. Moreover, such procedure is also adapted while acquiring images of the heart, breast, muscles, arteries and veins etc.

The major drawbacks in using ultrasound are that they provide less anatomical details in the images as compare to magnetic resonance imaging, computed tomography scanning and mammography (in breast examinations). Another worth mentioning drawback is that the ultrasound is unable to retrieve image through air (lungs, bowell loops) and bones. The reason behind less anatomical details in the acquired images is basically its dependence upon the quality of images. More information can be acquired if better the quality of the images is. Hence, the quality of image is highly dependent upon the skills of the practitioner. If the

practitioner is skillful, better results can be obtained else not. In developed countries, skilled practitioners can be found but in developing countries, it is very rare.

Beside the drawbacks, ultrasound has many advantages making it preferable such as it supports the function of non uniform structures making it easier to differentiate normal and abnormal characteristics. It does not emit ionizing radiations and also produces a speckle noise which is extremely useful in elastography, which is the non-invasive method in which stiffness or strain images are taken of soft tissue and are used to identify and classify cancerous growths such as a tumor. Computed tomography scanning is very safe, cheap and quick to use and does not appear to have any adverse effects but on the other hand, the ultrasound scanners can be taken to serious patients in intensive care units, avoiding the danger of moving the patients to radiology department for x-rays. Ultrasound provides real time images and is used in drainage and biopsy procedures. Veins and arteries can also be visualized by using doppler capabilities in advanced scanners [15].

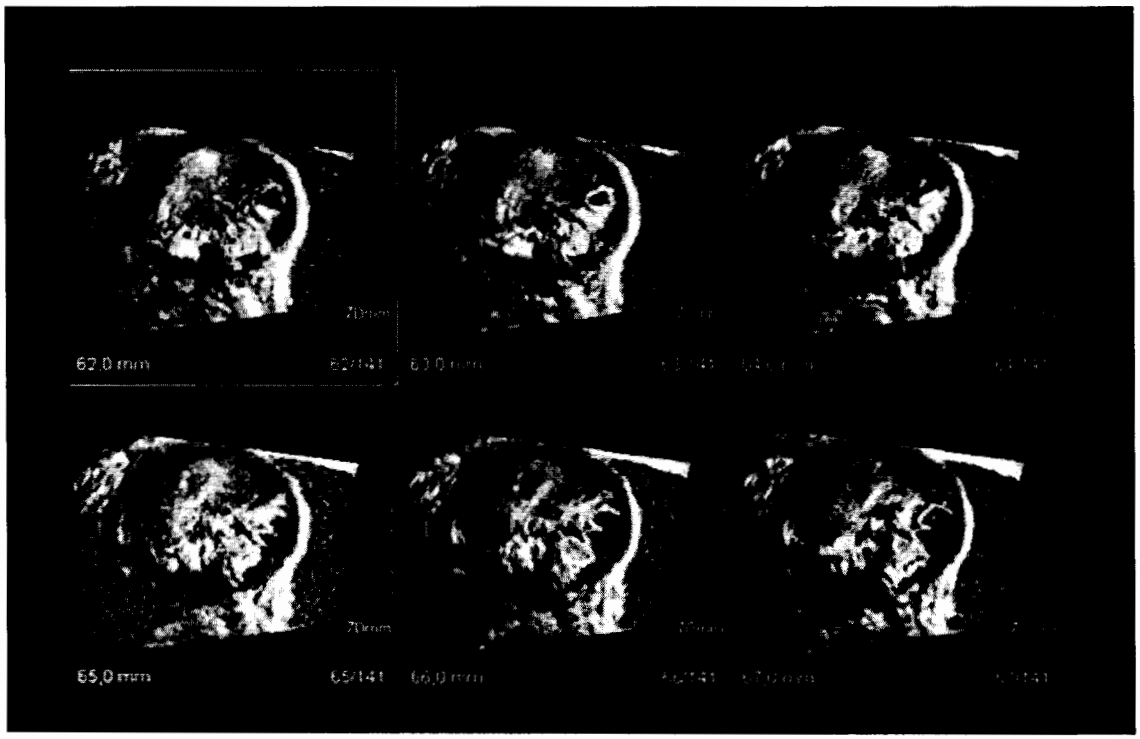


Figure 2.7: Ultrasound images.

Figure 2.7 comprises of a set of ultrasound images. The quality of images acquired using ultrasound is very blur and nothing can be detected from such images. Therefore, this image acquisition technique is not recommended for brain tumor detection.

2.3.3 Why Magnetic Resonance Imaging?

While the cost of other methodologies is relatively low, their sensitivity is not ideal. Neither, the x-ray based technology is completely benign. Therefore, research is still in progress to develop an authentic and proper screening tool in magnetic resonance imaging as in recent years, it has become the most advanced technology available and useful in medical imaging which include:

- Detection of anatomical areas in images for their diagnosis, treatment or surgery.
- Image Registration.
- Improving the correlation with localized functional metrics of anatomical areas of interest.

CHAPTER 3

LITERATURE REVIEW

In last few years, many segmentation methodologies [16] and classification techniques [17] have been introduced to deal with brain tumor. Some segmentation methodologies and classification techniques have been discussed below.

3.1 Magnetic Resonance Images Segmentation Techniques

The segmentation of MR images requires some preprocessing phases as shown in Figure 3.1. It shows basic processes of computer vision system. In segmentation, preprocessing basically enhances quality of given data by making less complex artifacts. Then, sets of features extracted from the images also play vital role in ensuring error free segmentation.

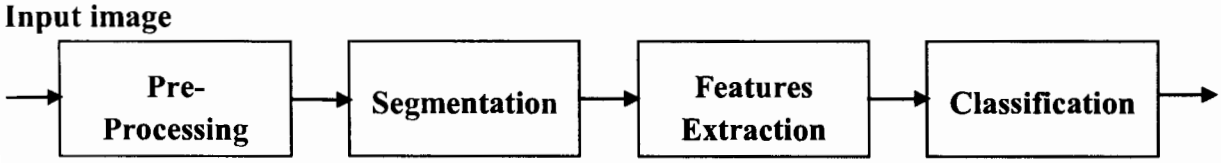


Figure 3.1: Image Processing System.

The literature on image segmentation is distributed in two categories which are:

- Single contrast segmentation, having 2-D or 3-D images as input.

- Multispectral image segmentation, having magnetic resonance images with variations in gray scale contrasts as input.

3.1.1 Single Contrast Segmentation

The single contrast segmentation methods are further divided into categories as discussed below.

3.1.1.1 Thresholding-based Segmentation Techniques

Thresholding method is the simplest technique for image segmentation. Binary images are also created from gray scale images using thresholding.

Global thresholding is one of the most intuitive methods of segmentation that is mostly applied on x-ray computed tomography images. The issue mostly encountered in this methodology is the determination of value of the threshold for the region of interest. The selection of operator of threshold for intra cranial region has only been reported.

Knowledge guided is another method of thresholding which determines the global thresholds by using a "goodness function". This function describes the separation of background. This technique only proposes skull and brain for thresholding [18].

Local thresholding is use in other modalities [19] which includes MRI data combined with morphological filtering. But, similar problems have been anticipated which stimulate the interest of radiologists and engineers in the applications of other methodologies.

3.1.1.2 Edge-based Segmentation Techniques

Edge detection techniques mostly endure from wrong edges especially when noise is present, complete or under segmentation and invariable threshold selection in an image. Bomans et al, [20] proposed a technique which required the combination of edge detection with

morphological filtering. This method involves manually labeled edited regions to generate 3-D displays.

3.1.1.3 Boundary tracing Segmentation Techniques

The Boundary tracing segmentation technique itself discovers a point from boundary of interested region and follows from that interested point where an operator identifies a pixel and outlines. Different techniques are available for the operator in optimization of the result for non ideal images (if any).

Some researchers propose boundary tracing technique in dynamic programming of brain parts having noise and indeterminate boundaries. Still, proper application that can be used to segment MR images remained to be explored since a closer initial guess for the presence of boundaries is required. Therefore, boundary tracing techniques are only restricted for large and properly defined structures segmentation e.g. Brain Parenchyma, though it cannot differentiate individual types of tissue.

3.1.1.4 Seed Growing Segmentation Techniques

There was not much research conducted in seed growing segmentation methods though technique is available as a program namely ANALYZE which was introduced by the mayo foundation [21] and allergo system (ISG technologies, Toronto, Canada), both use subject technique for segmentation and reconstruction of 3-D images. Early work was conducted by cline by using seed growing for extraction of brain surface. This technique basically needs an operator which considers seeds and the required thresholds empirically.

Pixels surrounding seeds are observed and included in that part if they lie in the thresholds with the assumption that they are almost similar to pixels present in the region. Thus, every pixel becomes a seed if its neighbors are considered in the region. Few researchers have

included seed growing and other related algorithms to operate on the data that has been segmented for the post processing to reduce noise in segmentations and improvement of 3-D reconstruction [22]. Results gathered by using seed growing mostly depend upon the settings of operator. In all single image methodologies, defined regions can be identified robustly.

3.1.1.5 Other Segmentation Methods

A powerful technique known as associative memory technique has been proposed [23]. It has limited practical applications due to the work required necessarily for acquisition and transformation of geometry of the normals in slice to match each other. Also, it is limited to a specific type of magnetic resonance acquisition. This technique can be used for identification of abnormal areas in complex pathology but it cannot distinguish the boundaries present in between normal and abnormal tissues.

Random field techniques [24] are proposed in different modalities which include simulated annealing as well as iterated conditional nodes. Markov random field is another good classifier but major drawback in using markov random field is use of complex energy function making it computationally intensive and prohibiting the practical usage [25].

The gray scale segmentation techniques can offer important information with limitations. Therefore, for complex data, more information is needed, which can be extracted in multispectral magnetic resonance imaging data.

3.1.2 Multi Spectral Segmentation

Common technique used in multi spectral magnetic resonance imaging segmentation is known as pattern recognition. This technique is generally considered as successful especially for brain images but more research is required in validation. Many publications propose these methodologies to normal [25], while some offers neuro-psychiatric disorders with

magnetic resonance parametric distributions having similar features as of normal. More difficult problems arise by segmenting glioblastomas along with tumor necrosis when radiation necrosis and tissue can modify because of chemotherapy [26].

3.1.2.1 Unsupervised Segmentation Methods

Unsupervised segmentation methods are also known as clustering. These methods themselves find structure in given inputs. A cluster is basically an area in feature space having higher density. Unsupervised methods are applied for magnetic resonance image segmentation including k means and related fuzzy, fuzzy c means (FCM).

Unsupervised methodologies are ideal but they cannot provide required segmentations requiring long computation. To avoid these limitations, different fully unsupervised methods were proposed which use validity guided re clustering algorithm. An example included a partial supervision which requires Semi supervised fuzzy c-means for implementation. It had some anatomical results with fewer requirements for operator time which could be achieved by partial supervised methodologies. Here, given input simply directs the process for the detection of structure. Over all, unsupervised or partial supervised methodologies have scope in further research.

3.1.2.2 Supervised Segmentation Techniques

Below are the supervised segmentation techniques:

3.1.2.2.1 Pattern Recognition Techniques

Supervised techniques include many pattern recognition methodologies. Some assume specific features and are called parametric methods. For example, the maximum likelihood method is based on multivariate gaussian distributions [22]. For each tissue, the mean and covariance matrices are formed from training set which is obtained from regions of interest.

Other pixels are distributed by the calculation of likelihood for every tissue and considering the type having maximum probability. These parametric techniques can only useful when distribution is known for the features but this case is not necessarily in magnetic resonance images. Non parametric methods like k nearest neighbors (kNN) never depends upon predefined distributions. They are dependent upon the actual distribution of the trained samples. kNN as compare to other parametric methods has provided better outputs in accuracy and duplicability. Artificial neural networks and decision tree approach (ID3) are other non parametric methods [27].

3.1.2.2.2 Algebraic Methods

Algebraic approaches are relatively different from the field of pattern recognition. They give proper result on volumetric measurements. These techniques have become useless on images having complexities as they apply only on feature vectors. Therefore, the required features especially uncorrelated for the determination of eigen images becomes huge, leading to improper segmentation [28]. These approaches are only applicable on orthogonal vectors.

3.1.2.2.3 Manual Feature Space Segmentation Methods

Other methodologies utilize decision boundaries defined by operator. Researchers obtained features in some multi dimensional graph by emphasizing on feature selection and extraction procedure. The regions of interest are those which are having high density tissue.

3.1.2.3 Supervised Segmentation Methods vs. Unsupervised Segmentation Methods

The difference between supervised segmentation methods and unsupervised segmentation methods is because of consistent results. Unsupervised approaches are automatic though sometimes operator maybe required completing the process but results are operator

independent. The input data simply contains selected features where unsupervised methods simply define regions in the image which have no anatomical meaning.

On the other hand, supervised methods always require training or input for segmentation. This is done by the selection of training pixels or the training regions of the images. There are few methods where training is done automatically that are slice to slice but still, it is considered as supervised segmentation. Supervised segmentation methods therefore give better or desired results as compare to unsupervised segmentation methods.

3.2 Features

Magnetic resonance images classification is always based on set of features that are extracted from the given images due to the fact that every pixel exhibit characteristics which can be used for the differentiation between the tumorous part and the normal part of the image [29] [30].

There are great varieties of features that can be computed for each pixel which include edges and texture-based features, gabor features [31], features based on wavelet transform, principal component analysis, minimum noise fraction transform, decision boundary feature extraction, non parametric weighted feature extraction, discriminant analysis, spectral mixture analysis and also existing works combine many of them relating to the nature of problem. Pixel intensities can be used to calculate other features which include edges and texture. Instead of using all information at once for the given image, selecting and extracting feature simply breaks down the segmentation problem to the group of feature vectors. The selection of good features is the key to successful segmentation of images [32].

3.2.1 Haralick Texture Features

In image processing algorithms and machine vision, texture plays an important role in analyzing and drawing major conclusions on given images for the identification of interested objects or regions in given images. Hence, texture can be defined as function of spatial variation in pixel intensities. The use of texture has proved to be very effective in different applications; one of them is the recognition of image regions, identifying homogenous regions and production of classification map of input with identified classes.

Haralick has described texture as one of the fundamental types of feature that are used researchers to differentiate regions in a given image [33]. Apart from texture, tone and context are other two fundamentals type of features. Haralick noted that tone and texture cannot be completely separated. In small image with large variations in tone, texture is the dominant feature, whereas in small area with large variations in texture, tone is dominant [34]. But, an area consisting of one pixel, it is impossible to identify texture and tone as texture is property of spatial variations in tone and there is no spatial variation in a pixel [35].

Haralick introduced the co-occurrence matrix and texture features in 1973. These features and matrix are recommended for automated classification of rocks in six categories. Some of the proposed features include angular second moment, contrast, correlation, sum of squares variance, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information of measure of correlation 1 and information measure of correlation 2 and are used in different images.

3.2.2 Overview of different Features

Different features have been introduced by researchers; some of them are discussed below:

3.2.2.1 Edges and Texture-based Features

Few researchers have used either 2-D or 3-D magnetic resonance image as they possess non uniform attributes. In this regard, a global function is unable to segment the given data and requires different other features for data to be uniquely identified [20]. Therefore, few researchers have proposed edge detection techniques using marr-hildreth operator, 2^{nd} derivative of a gaussian. Moreover, quality of edge detection can be improved using canny edge detector [23].

Another feature used for segmentation is textures. These features are used for classification of different regions. Texture features are calculated from different pixels and have been recommended for classification of pixels. This technique is a promising technique as different features can uniquely identify given pixels and hence, proposed for magnetic resonance images by many researchers.

3.2.2.2 Gabor Features

Gabor filter is used for edge detection. It is basically a linear filter which is self similar and generated from wavelets. These filters are related to gabor wavelets designed for dilations and rotations. Gabor features are used in different applications of image processing which include iris recognition, fingerprint recognition [31].

3.2.2.3 Features based on Wavelet Transforms

Features based on wavelet transforms are mostly used in computer vision to get frequency and time description of input data. This technique can be considered as robust feature extractor but it is limited to edge and corner detection therefore not much work been done in this field.

3.3 Classification of Medical Images

Extraction of information from images is a very complex task besides acquiring and creating images. The extraction is basically done in order to diagnose and reveal the disease along with its severity. Magnetic resonance imaging, as discussed earlier is considered to be the best screening tool available. Therefore, development of a computer aided diagnosis system is needed to support the skilled radiologists for analyzing the images that is of classifying the images into tumorous and non tumorous. By developing computer aided system, complexity of the data can be reduced and easily analyzed by radiologists. Selection of a proper algorithm for classification of tumorous and non tumorous lesions of any body part will be the key in computer aided system.

3.3.1 Support Vector Machines

Support vector machines belong to supervised learning methodologies for pattern recognition, classification and non linear regression. It is a one dimensional machine with some very useful applications. The idea behind using this technique is that they perform being a computer aided diagnostic classifier for viewing magnetic resonance images. In this context, we can say that they have performed in separating the tumorous and non tumorous magnetic resonance images [36].

Support vector machine constructs a hyper plane in by maximizing the margin in separation between positive and negative attributes. This property is being achieved by following a standard scope of statistical learning theory. Therefore, support vector machine may offer extrapolated performance on problems related to pattern classification.

Support vector and vector from input space forms the structure of support vector machine algorithm by inner product kernel. The algorithm extracts training data having small subsets known as support vectors. Many different learning machines can be constructed by generating different inner-product kernels and characterizing their own non linear decision surfaces. Following three types of machines will be implemented in our classification.

- Linear Machines
- Polynomial Machines
- Radial-basis Function

For each feed forward networks given above, we may use support vector learning algorithm to apply the classification process by using a given training data, automatically determining the required number of hidden units [37].

3.3.2 Overview of different Classification Techniques

Significant research has been conducted on many classification techniques on magnetic resonance images. Some most common approaches are discusses as under:

3.3.2.1 Artificial Neural Networks

Artificial neural networks (ANN) are also known as neural network. It is a mathematical used to imitate the functional and tangible prospects of any neural networks. Artificial neural networks basically comprise neurons and process the information by using connective procedure to process. Moreover, it also can be considered as an adaptive system as it updates itself with the flow of internal and external information during the learning phase [38].

Classification in artificial neural networks first requires training. Training a neural network model means the selection of a specific model from different proposed models. The selection

is done with this condition that it proposed model reduces the cost factor. Many algorithms are proposed for training neural network models.

The advantages of using ANNs are their ability to be based on a function trains from given data. ANNs are not easy to understand and one must get into details before employing.

- Proposed Model. It is dependent upon the data representation. Complex models can lead to complex problems with learning.
- Choosing Algorithm. It is another important phase in ANN. There are several tradeoffs between choosing algorithms. Majority of the algorithms will work on proper parameters for training but selection of an ideal algorithm for unseen data requires much experimentation.
- Robustness. Results can be very robust on selection of proper model, algorithm and cost function.

Neural networks are used in the following application:

- Regression analysis for time serious prediction and modeling.
- Data processing for filtering, separating and compressing
- Robotics for Computer numerical control direction
- Classification which includes pattern recognitions (radar systems, face identification, object identification and medical images) sequence recognitions and sequential decision making.

The major problem in artificial neural networks while employing in classifications is the selection of algorithms. There is no specified algorithm for classification. The given algorithms are very complex and are very time consuming. Moreover, due to complexity of

algorithms, they are not robust and hence not recommended by researchers to be used in classification purposes.

3.3.2.2 Linear Discriminant Analysis

Linear discriminant analysis is implied in statistics and machine learning to observe features combining in one dimensional and evenly separating different classes of events and objects. Resulting combination either becomes a linear classifier or reduces the dimensions for classification.

Linear discriminant analysis can be associated with principal component and factor analysis as both seem variables having combinations in one dimension and explain data comprehensively. It can also be used to project the dissimilarities between data explicitly [39].

CHAPTER 4

PROPOSED SYSTEM

Preprocessing and features extraction are important phases for noisy, irregular real time data.

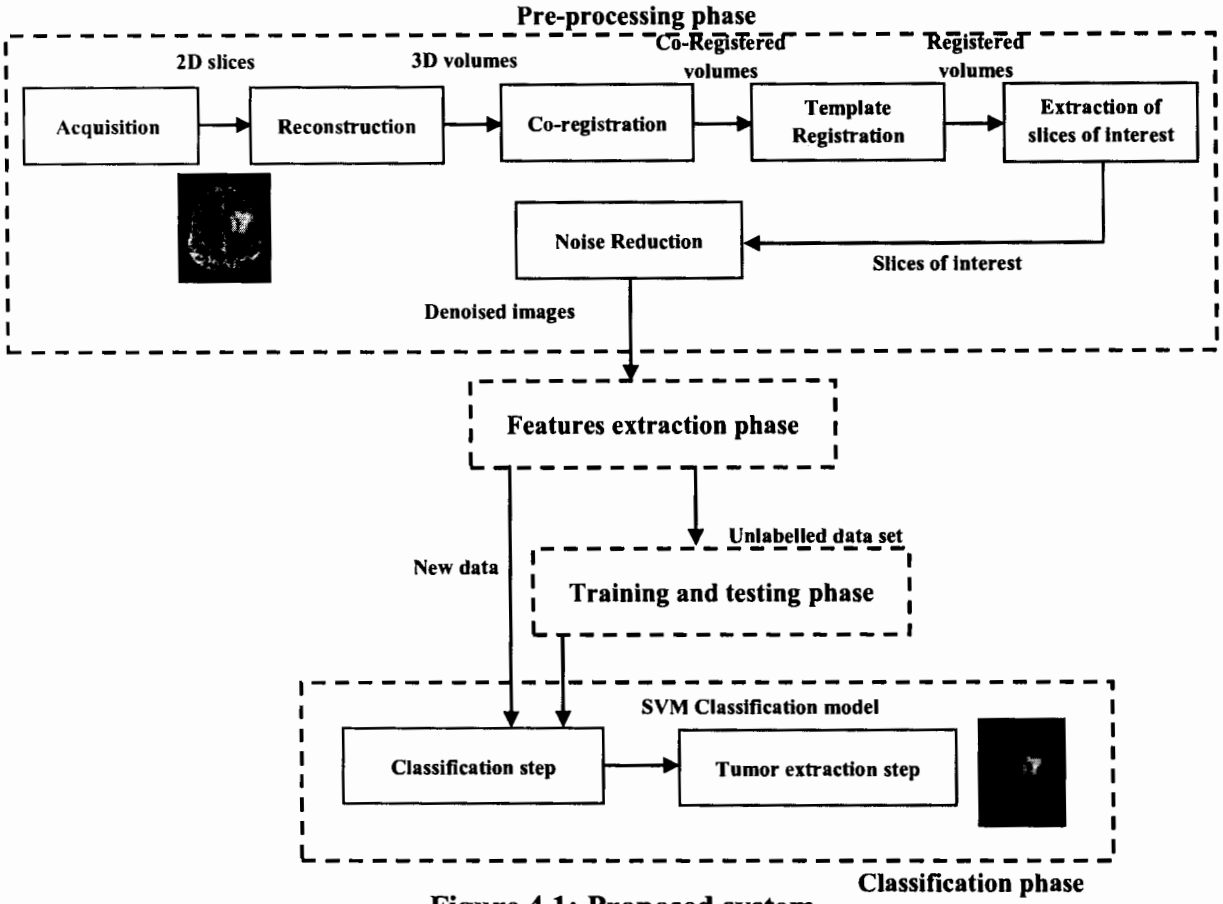


Figure 4.1: Proposed system.

Figure 4.1 is the proposed system for classification of brain tumor images. It comprises of four phases namely pre processing phase, features extraction phase, training and testing phase, and segmentation phase. Each image will undergo all the processes mentioned. Results will contain all the classified and segmented lesions as tumorous and non tumorous.

4.1 Pre-processing

The steps mentioned above in pre processing phase in Figure 4.1 enhance the quality of images for visualization and detection of interested regions for segmentation and classification. Moreover, using preprocessing steps, an image can be transform into different types of image if that is more suitable for machine analysis.

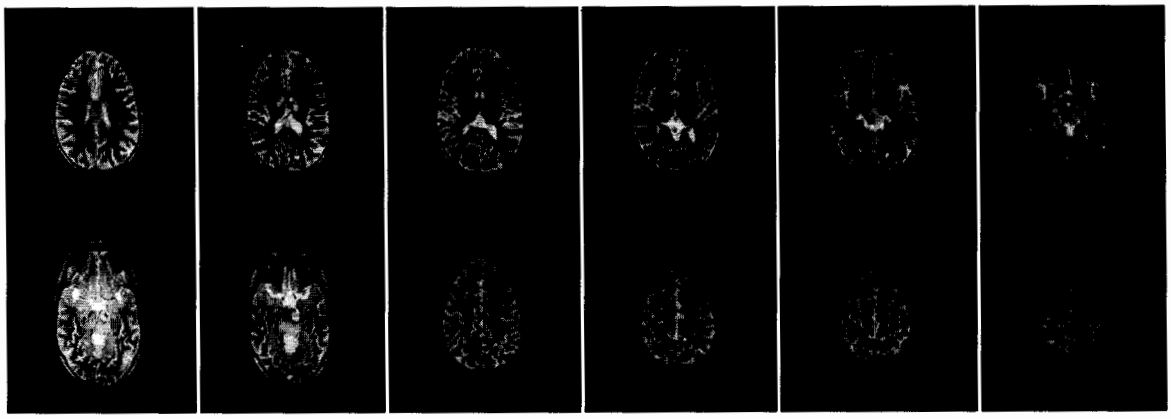
4.1.1 Image Acquisition

First step is the acquisition of images which has been done by magnetic resonance imaging (MRI) which provides internal images of body in a safe and non incursive manner. When acquired, it generates axial, coronal and sagittal 2-D images for each patient. The standard of images is digital imaging and communications in medicine (DICOM) standard known as international standard for communication of biomedical diagnostic using digital images [40].

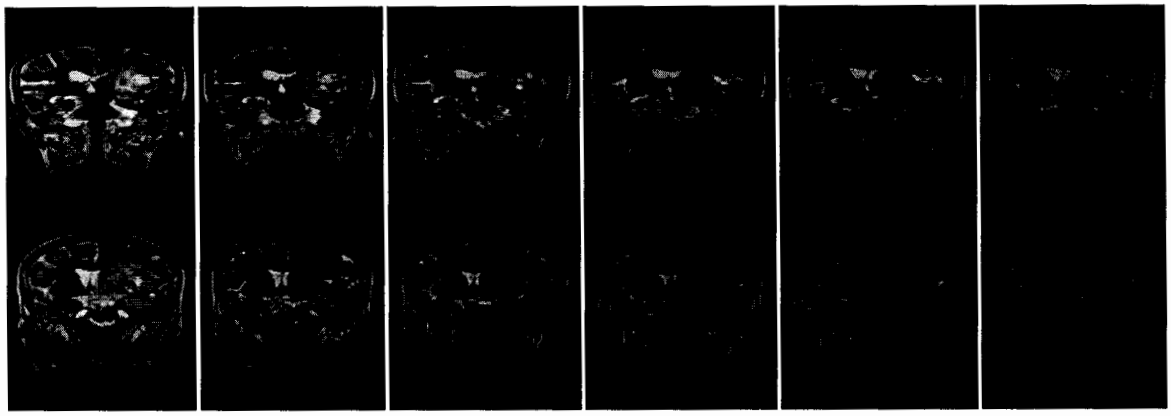
Magnetic resonance imaging (MRI) provides many visualizations by combination of different built in parameters (repetition time (TR), echo time (TE)) and handles T1, T1 after injection of contrast agent and T2 images. T1 images are acquired by short repetition and short echo time sequence while T2 images are produced in more repetition and long echo time sequence.

Majorly focus is on tumorous images as their classification is a difficult problem requiring different indicators like tumor localization, shape, volume, homogeneity and closeness. With so much diversity, a unique classification cannot generalize all tumors [41]. So, gliomas

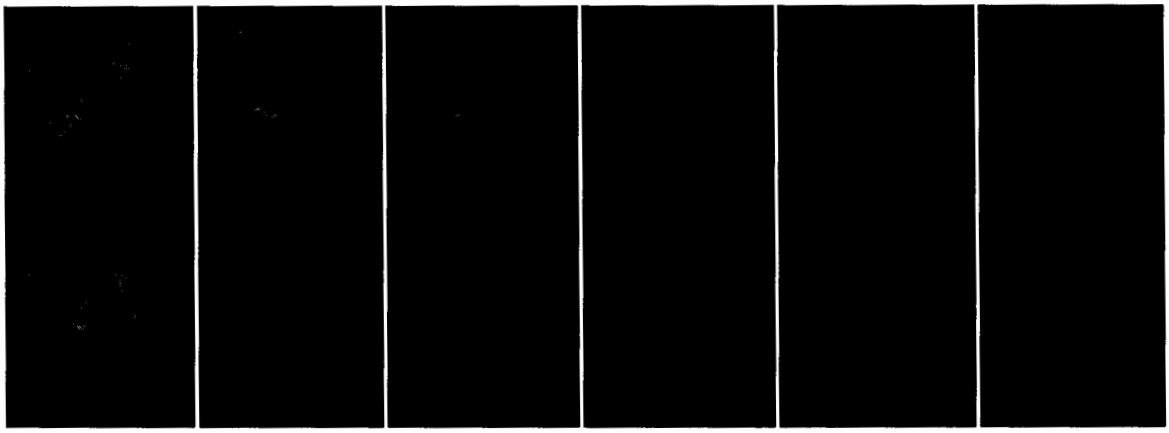
tumor developing from glial cells has been chosen. Gliomas are present in almost 90% cases of tumor and its importance cannot be ignored. Thus, above steps are primal, dependent upon the quality of images and ensured via MRI.



(a)



(b)



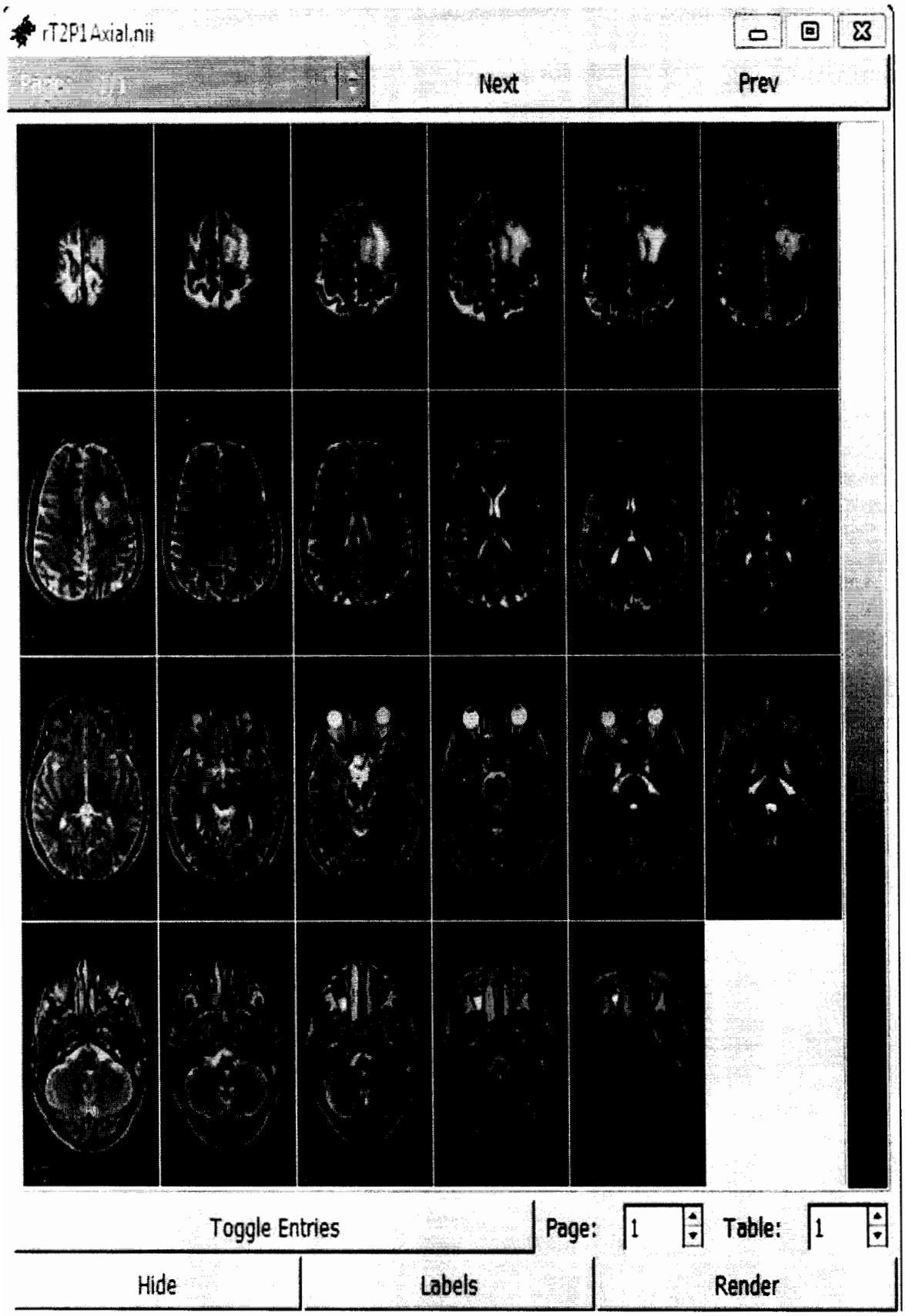
(c)

Figure 4.2: MR images. (a) Axial images. (b) Coronal images. (c) Sagittal images.

Figure 4.2 is the complete set of acquired images in greater details from magnetic resonance imaging machine. The images are sliced in three planes namely axial, coronal and sagittal. Figure 4.2 (a) is the 2-D axial plane images. Figure 4.2 (b) is the 2-D coronal plane images and Figure 4.2 (c) is the sagittal plane images. The contrast of the images can be increased after adding contrast agent which adds more details and makes easier for the radiologists and doctors to detect tumor and its roots. Moreover, images can also be modified as per requirement of the medical experts. All images are of different angles which help in detection and finding out exact location of the tumor inside the skull.

4.1.2 Image Reconstruction

Image reconstruction is essential before image registration as registration is only possible in 3-D image. Therefore, complete set of images for every patient has been acquired so that all planes combined can generate 3-D images. Here, 2-D sequential slices of each patient are mapped into a complete 3-D volume for axial as shown in Figure 4.3 (a), coronal as shown in Figure 4.3 (b) and sagittal as shown in Figure 4.3 (c). This process of mapping 2-D images into complete 3-D volume has been done by using MEDCON software. These volumes are then used for co registration and template registration in order to align all the images with each other. These volumes are also projected on the screen to choose the interested slices where tumor is suspected to be present. So, in this way reconstruction of images plays an important role in pre processing as individual co registration and template registration are very time consuming tasks.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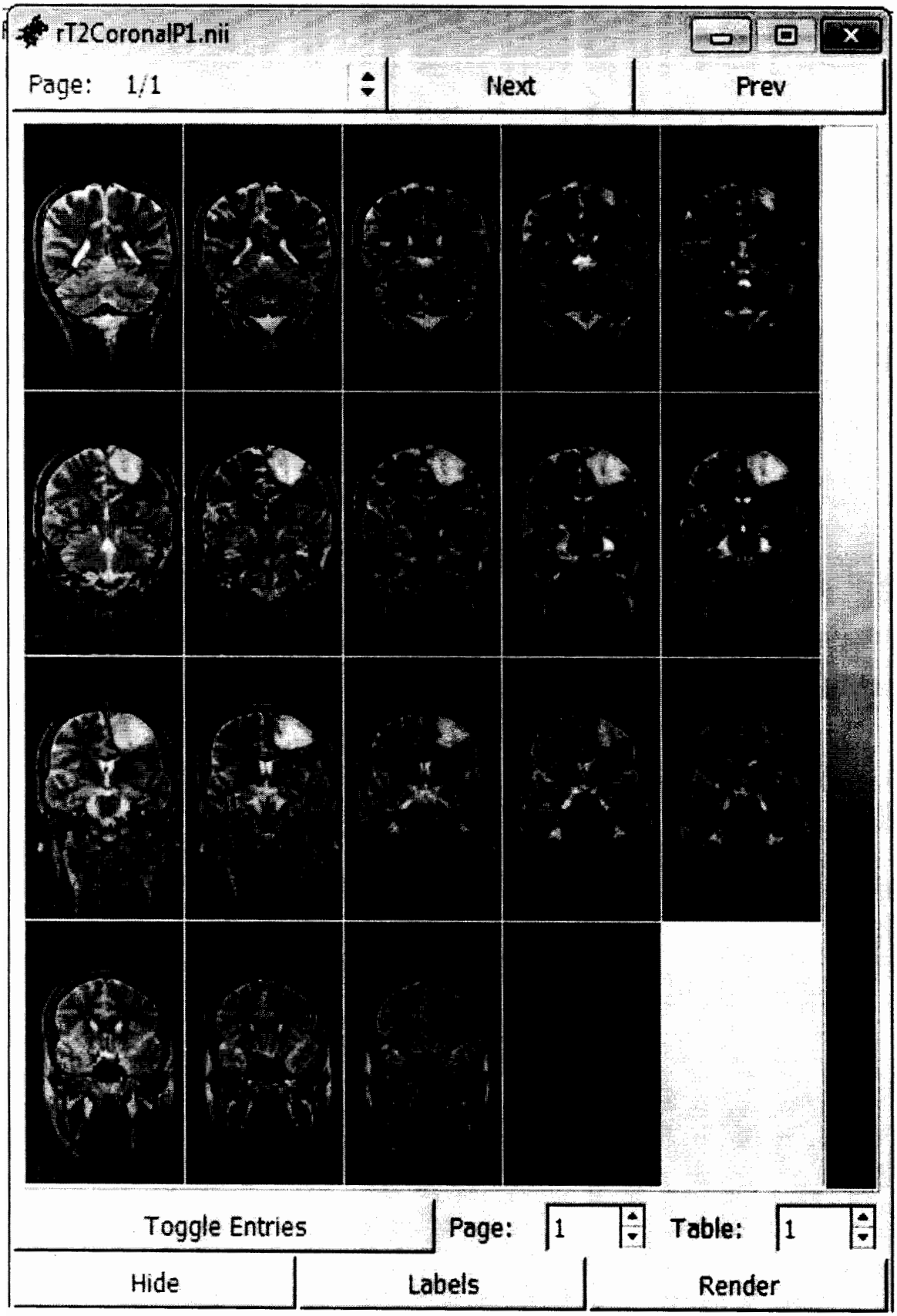
(a)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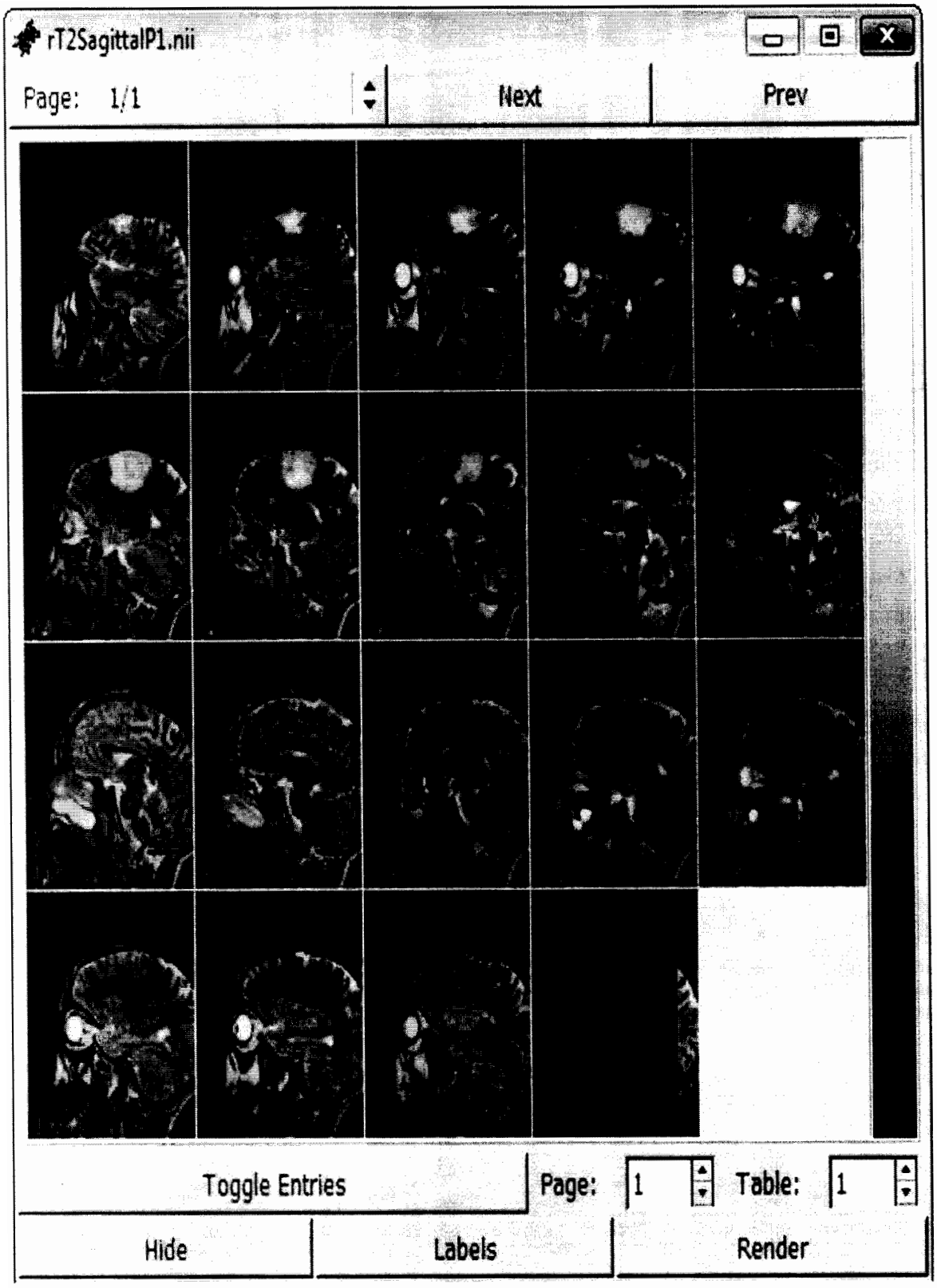
(b)



(c)

Figure 4.3: Magnetic resonance images reconstruction. (a) 3-D axial volume. (b) 3-D coronal volume. (c) 3-D sagittal volume.

4.1.3 Image Registration

Image registration is the procedure of positioning two images spatially by calculating a transformation employed on an input image so that it can be matched with the template image assumed to be stationary. The problem associated with this step is the definition of a quantitative measurement which assesses spatial alignment. After definition, the next step is simply to find a set of transformations parameters for the optimization. The transformations either are affine, rigid or curved. The rigid transformations are type of affine transformation comprising translations and rotations processes. The affine transformation simply adds scaling and shearing processes. The objective function to be maximized here is the normalized mutual information (NMI) as it a popular co registration measure [42].

Two registration techniques have been used as they are dependent upon modality and subject. Modality technique involves co-registration as shown in Figure 4.4, done by involving different modalities of same patient including images type (T1, T1 with contrast, T2). This step is essential if used modalities are not perfectly aligned, which mostly the drawback of real data is.

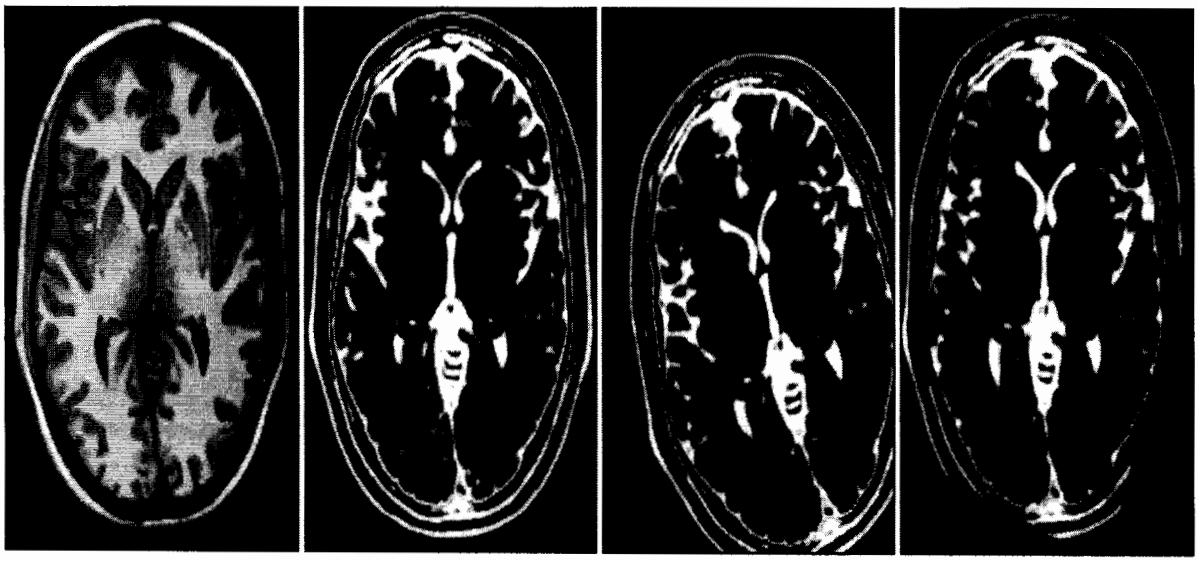


Figure 4.4: Magnetic resonance images co-registration.

SPM tool has been used to spatially align volumes of each patient with different modalities (T1, T1 with contrast & T2).

The second registration technique involves template for the alignment of the modalities over an image used as template in predefined coordinate system. This technique can be used by mapping given images in a recognized coordinate system which in this case is brain. The measure used here is sum of squared difference. A well known technique Montreal Neurological Institute (MNI) coordinate system has been chosen and used as it works on templates with different modalities T1, T1 with contrast and T2 with respect to translation, rotation, scaling and shearing.

Having input as co-registered volumes, statistical parametric mapping software has been used again so that alignment of different modalities T1, T1 with contrast and T2 along with template could be possible in the MNI standard coordinate system to cancel variations of signals in images of all patients as shown in Figure 4.5 where first image is the original image and rest are registered with the original image accordingly.

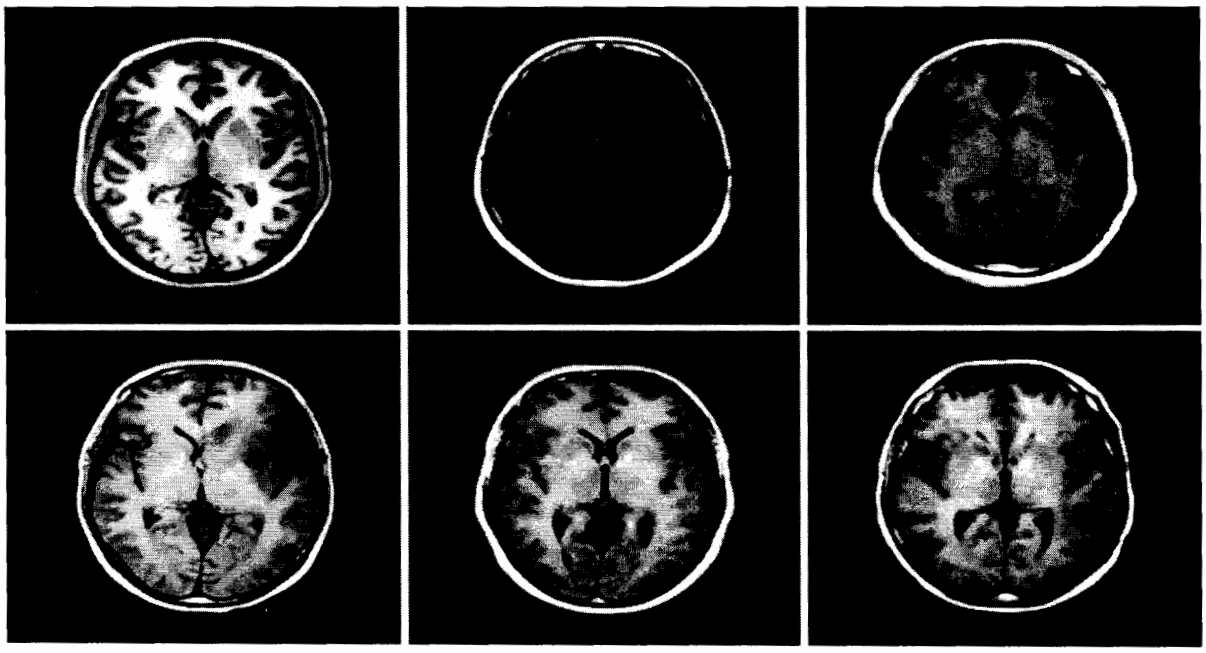


Figure 4.5: 3-D Magnetic resonance images template registration.

4.1.4 Extraction of Slices of Interest

After reconstruction and co-registration, interesting slices has been chosen from the registered volumes. Figure 4.6 shows the extraction of slices of interest where Figure 4.6 (a), Figure 4.6 (b) and Figure 4.6 (c) are original images. Tumor has been chosen in Figure 4.6 (d), Figure 4.6 (e) and Figure 4.6 (f). The output is 2-D tumorous images. MIPAV software has been used though different softwares are available to perform this step.

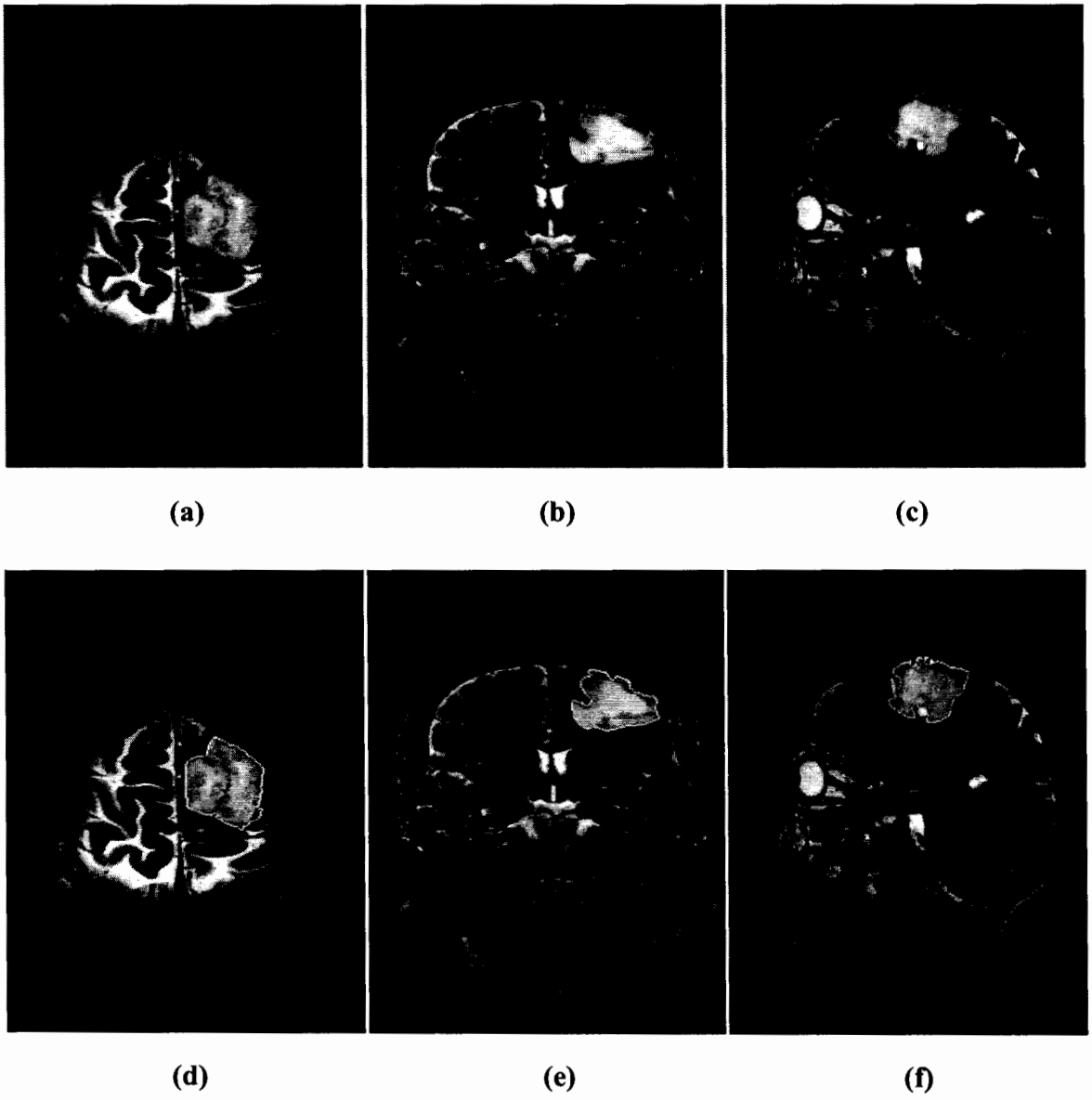
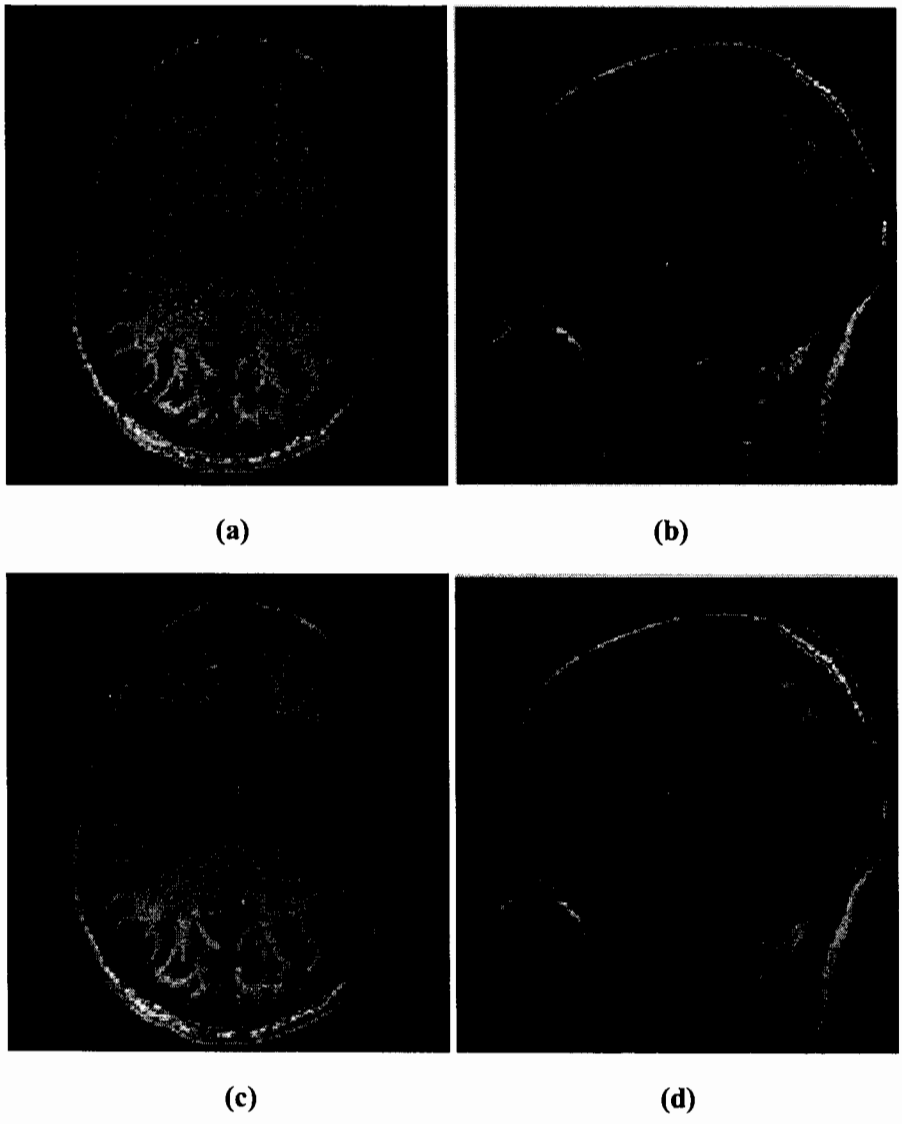


Figure 4.6: Extraction of slices of interest. (a), (b), (c) Original image. (d), (e), (f) Interesting slices.

4.1.5 Noise Reduction

This step is very essential as noise if present could corrupt the signal of all pixels or can also remove the signal completely or partially. With all successfully known methods, anisotropic diffusion method proposed [43] has been used to suppress the noise. It basically performs an easy method which reduces the local noise without model. The filter strengthens the dissimilarities of regions by removing noise, increasing homogeneity and preserving edges.



(a) **(b)**

(c) **(d)**

Figure 4.7: Denoising using anisotropic filtering. (a), (b) Original Images. (c), (d) Denoised Images.

Figure 4.7 is the denoising of brain MR images. Figure 4.7 (a) and Figure 4.7 (b) are the original images with noise. Figure 4.7 (c) and Figure 4.7 (d) are the denoised images. Here, it is clearly visible that anisotropic filtering not only minimizes the noise but also smooth the edges of the images.

4.2 Features

Extraction and calculation of features is a vital process because each pixel itself should have different properties that can be used to differentiate between the tumorous and non tumorous pixels. There are numerous features available that can be used in every image which include intensities, textures, distance to labels, spatial tissue prior probabilities, all related with type of image [30].

4.2.1 Overview of Other Features

Different types of features are used to represent patterns in images. Selection of optimized features is dependent upon nature and information gathered of images.

Boundary descriptors are calculated on binary images and provide description of the shapes which include chain code, shape number, major and minor axis etc.

Geometrical features for area and centroid are used to calculate ratios. Area is total number of pixels in a region and centroid is balance point of image.

Texture features are dependent upon smoothness, regularity, uniformity and the complexity of textures in images characterized by neighborhood. However, in brain tumor, features to be considered are those which reflect properties of discrimination between normal and abnormal pixels. For that, Intensities and texture features have been adapted as they are the proposed features for segmentation of brain tumor [42]. The first order features are the intensities

obtained in given modalities. Second level features are dependent upon such calculations that can identify patterns in region variations.

4.2.2 Texture Features

As discussed in previous section about first order parameters, they are also known as statistical moments which are not dependent upon any spatial information. Therefore, they have been used to obtain properties of local histogram. Many parameters have been calculated which include all first order features. The second order features are used to obtain textures is called Haralick features.

The above Haralick features are calculated from a gray level spatial co occurrence matrix [63] which is formed by estimating likelihood of two pixels with intensities i and j occurring at a distance d having angle θ in neighborhood. Moreover, d and θ have the following values: d = 1, 2 etc and θ = 0, 45, 90, and 135 respectively.

For above features, a co occurrence matrix has been calculated which involves using the values in d and θ. Different frequencies have been calculated for pixels with intensity values.

First order histogram features do not require spatial information. Therefore, gray level co occurrence matrix (GLCM) features known as texture features have been considered.

4.2.2.1 Gray Level Co occurrence Matrix

A co occurrence matrix is defined upon an image having co occurring values at specific offset. Mathematically, co occurrence matrix C is an n x m image I, with offset (Δx, Δy) as:

$$C_{\Delta x,\Delta y}(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{n}\begin{cases}1, & if\ I(p,q)=i\ and\ I(p+\Delta x,q+\Delta y)=j\\ 0, & otherwise\end{cases} \quad (4.1)$$

Value of the image will be gray scale value of given pixel. Moreover, the value would be binary offset or 32 bit. Having 32 bit value the matrix will be $2^{32} \, x \, 2^{32}$ matrix.

The co occurrence matrix as shown in Figure 4.8 can also be used to calculate texture by taking various metrics to get useful set of features which can uniquely identify a given image. These set of features are computed on the pixels having joint probability distribution. Distance d and angle θ is applied to calculate joint probability distribution of given image pixels. The values for distance are d = 1, 2 and for angle are $\theta = 0^0, 45^0, 90^0 and \, 135^0$ for calculation. These features are known as Haralick features. Below is the set of Haralick features used to calculate image features.

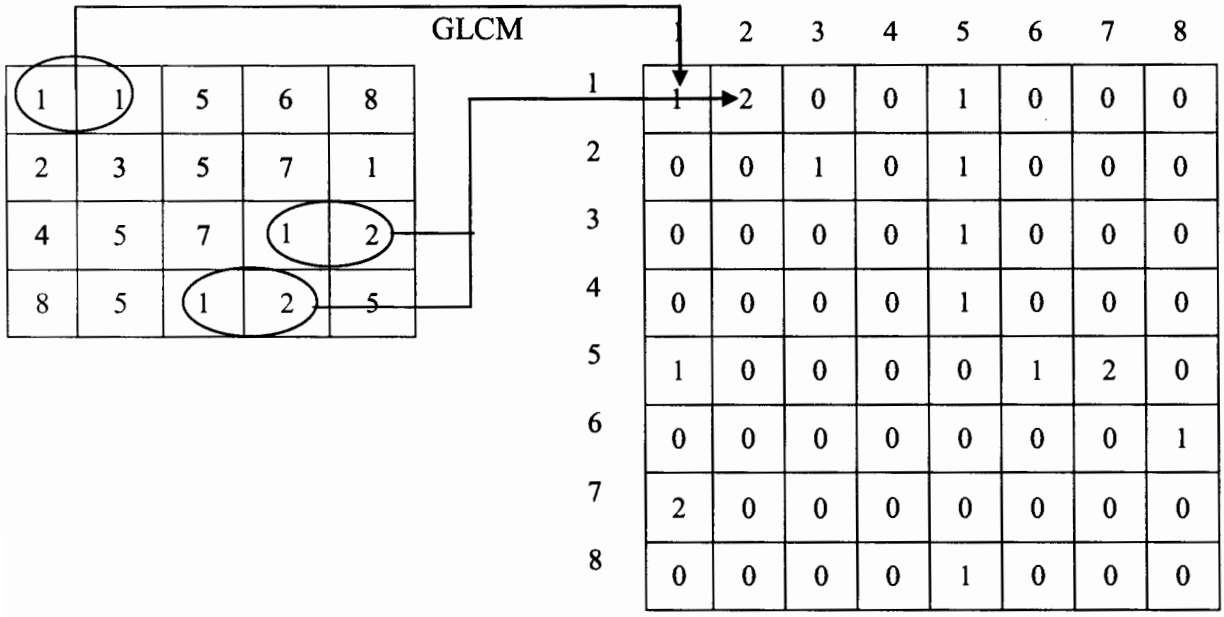


Figure 4.8: Gray level Co-occurrence Matrix.

4.2.2.2 Angular Second Momentum

Angular second momentum is also known as energy, uniformity or uniformity of energy. It provides the sum of squared values in gray level co occurrence matrix.

$$F_{ASM}^{Har} = \sum_{i=1}^{n} \sum_{j=1}^{n} \left(p(i,j)\right)^2 \quad (4.2)$$

4.2.2.3 Contrast

Contrast is also known as inertia and variance. It provides the value of intensity contrast between a pixel and neighbors in an image.

$$F_{Con}^{Har} = \sum_{i=0}^{n-1} i^2 \begin{bmatrix} \sum_{i=1}^{n} \sum_{j=1}^{n} p(j,k) \\ |j-k=i| \end{bmatrix} \quad (4.3)$$

4.2.2.4 Correlation

Correlation provides values of similarity between a pixel and its neighborhood in an image.

$$F_{Cor}^{Har} = \frac{1}{\sigma_x \sigma_y} \left(\sum_{i=1}^{n} \sum_{j=1}^{n} (i\,j) p(i,j) - \mu_x \mu_y \right) \quad (4.4)$$

4.2.2.5 Sum of Squares Variance

It is defined as sum of squared deviations representing sum of squared differences from the mean. The sum of squares gives rise to variance.

$$F_{SSV}^{Har} = \sum_{i=1}^{n} \sum_{j=1}^{n} (i-\mu)^2 P(i,j) \quad (4.5)$$

4.2.2.6 Inverse Difference Moment

It is also known as homogeneity and measures the closeness in distribution of pixels in gray level co occurrence matrix or gray level co occurrence matrix diagonal.

$$F_{IDM}^{Har} = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{1}{1+(i-j)^2} P(i,j) \quad (4.6)$$

4.2.2.7 Sum Average

It provides value by adding all the average intensities of an image.

$$F_{SAv}^{Har} = \sum_{i=2}^{2n} i\, p_{x+y}(g) \quad (4.7)$$

4.2.2.8 Sum Variance

It provides value by adding all the variations of intensities around the mean values.

$$F_{SVa}^{Har} = \sum_{i=2}^{2n} (g - F_{SAv}^{Har})^2\, p_{x+y}(g) \quad (4.8)$$

4.2.2.9 Entropy

It provides the statistical measure of randomness around an image.

$$F_{Ent}^{Har} = -\sum_{i=1}^{n} \sum_{j=1}^{n} p(i,j) log\, \{p(i,j)\} \quad (4.9)$$

4.2.2.10 Sum Entropy

It provides value by adding all the statistical measures of randomness around an image.

$$F_{SEn}^{Har} = -\sum_{i=2}^{2n} p_{x+y}(g) log\, \{p_{x+y}(g)\} \quad (4.10)$$

4.2.2.11 Difference Variance

It provides value by computing the variance of samples then their difference is taken.

$$F_{DVa}^{Har} = \sum_{i=0}^{n-1} (p_{x-y}(g)(g - \sum_{j=0}^{n-1} j\, p_{x-y}(j))^2 \quad (4.11)$$

4.2.2.12 Difference Entropy

It provides value by computing the entropy and then difference of samples to show difference in the randomness of given samples.

$$F_{DEn}^{Har} = -\sum_{i=0}^{n-1} p_{x-y}(g) log\, \{p_{x-y}(g)\} \quad (4.12)$$

4.2.2.13 Information Measures of Correlation

It provides value showing how much mutual the samples are with each other.

$$F_{IC1}^{Har} = \frac{HXY - HYX1}{max\ \{HX, HY\}} \tag{4.13}$$

$$F_{IC2}^{Har} = (1 - exp[-2.0|HXY2 - HXY|])^{1/2} \tag{4.14}$$

4.2.2.14 Autocorrelation

It is used to identify the repeating patterns in an image.

$$F_{autoc} = \sum_{i=1}^{n} \sum_{j=1}^{n} (ij) p(i,j) \tag{4.15}$$

4.2.2.15 Maximum Probability

It calculates the most frequent motif in an image.

$$F_{mp} = {}^{MAX}_{i,j} p(i,j) \tag{4.16}$$

4.2.2.16 Cluster Prominence

Cluster prominence basically calculates the skewness of the matrix. When high, image is not symmetric. When low, there is a peak around the mean values of the matrix.

$$F_{cp} = \sum_{i=1}^{n} \sum_{j=1}^{n} (i + j - \mu_x - \mu_y)^2 \, p(i,j) \tag{4.17}$$

4.2.2.17 Dissimilarity

It computes the differences between different pixels of an image.

$$F_{Dis} = \sum_{i=1}^{n} \sum_{j=1}^{n} |i - j| . p(i,j) \tag{4.18}$$

4.3 Classification

In classification phase, the extracted features are separated into decision regions and identified as class labels. Decision regions are partitioned by decision boundaries. An individual lesion, object or set of objects can be identified as belonging or not belonging to a certain class on the basis of its characteristics or attributes. Lesions or objects are deputed to the respective classes by the distinguishing features and comparison with different features of models of same class.

Classification algorithms are preferred only on their ability to overcome the non linear features of lesions or objects to differentiate the variations between regions. It does not matter how much optimized features have been computed, inadequate classification design results in poor performance of whole system.

In the following section, proposed support vector machines the best classification technique available has been discussed.

4.3.1 Support Vector Machines (SVM)

Support vector machines belong to supervised learning methodologies for pattern recognition, classification and non linear regression. It is a one dimensional state of the art classification technique that successfully classifies binary data. The idea behind using this technique is that they perform as a computer aided diagnostic classifier for viewing magnetic resonance images. In this context, we can say that they have performed to separate the tumorous and non tumorous magnetic resonance images [36].

Having 'S' linearly separable training sample

$$S = ((x_1 , y_1), \dots , (x_l , y_l)), \text{ where } y_i = \pm 1 \tag{4.19}$$

Support vector machines draw a decision surface on a separate hyper plane

$< w . x^{+} > + b = +1,$

$< w . x^{-} > + b = -1,$

where $x \in R^{l}$ $w \in R^{l}$ and $b \in R$. For linear data, support vector machines draw a hyper plane (w , b) that solves the optimization problem

$minimise_{w,b} \ < w . w >,$

subject to $y_i \ (< w . x_i > + b) \geq 1$, i = 1, 2 ...l.

maximizes the margin hyper plane with geometric margin $\gamma = 1/||w||_2$.

Optimum hyper plane for non linear data is drawn after addition of slow variables ϵ_i = 1, 2.., n and a conditional parameter C. Now the optimization difficulty is defined as:

$minimise_{w,b} \ < w . w > + C \sum_{i=1}^{n} \epsilon_i$

subject to $y_i \ (< w , x_i > + b) = 1 - \epsilon_i$, i = 1, 2,...$l$

Applying lagrangian transformation, the optimization problems are resolved by adding an undefined scalar variable, α_i known as lagrange multiplier defined for every constraint forming linear combinations having multipliers as coefficients.

$$L (w, b, \alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} y_i y_j \alpha_i \alpha_j <x_i . x_j> \qquad (4.20)$$

The points with α_i are the specific data (x_i , y_i) are known as support vectors. They draw the decision function and rest of the data is omitted.

In non linear data, the surface for both classes is not linear, so data points will be transformed into a high dimensional space where it comes linearly separable. For high dimensional space φ, lagrangian function is defined as:

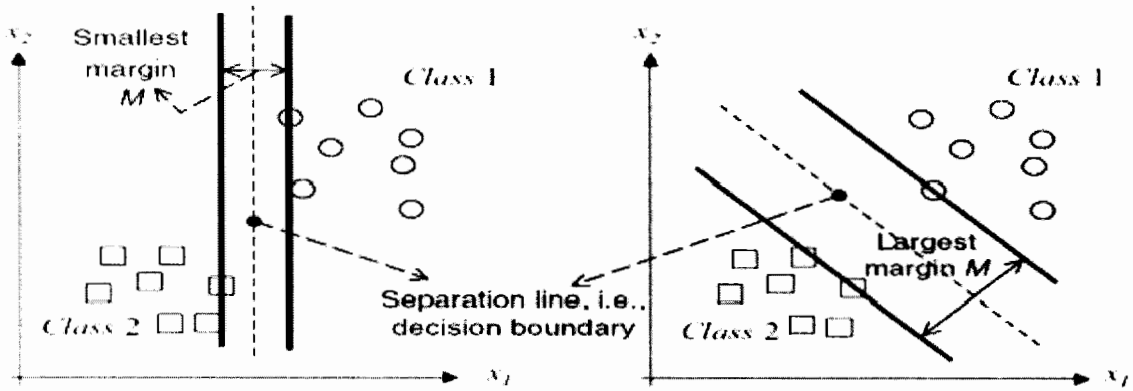
$$L(w, b, \alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} y_i y_j \alpha_i \alpha_j \varphi(x_i)\varphi(x_j) \quad (4.21)$$

The dot product $\varphi(x_i)\varphi(x_j)$ in high dimensional space defines kernel function $k(x_i \cdot x_j)$. The common kernels used in support vector machines are defined as:

- **Linear kernel**: $x_i \cdot x_j$,
- **Polynomial of degree "d" kernel**: $(x_i \cdot x_j + 1)^d$,
- **Radial Basis Function (RBF) kernel**: $\exp\left(\frac{-||x_i - x_j||^2}{2\sigma^2}\right)$.

After computing support vectors, the decision function becomes

$$f(x) = \sum_{j=1}^{SV} \alpha_j y_j K(x_j, x) \quad (4.22)$$



(a) (b)

Figure 4.9: Two out of many separating lines. (a) A less acceptable separating line with a small margin. (b) A good one with a large margin.

Figure 4.11 shows the two hyper planes drawn by support vector machines. In Figure (a) the difference between the data is less. Therefore, hyper plane drawn between the two is a narrow

line. In Figure 4.11 (b), the difference between two classes is more and so margin in between the two is large.

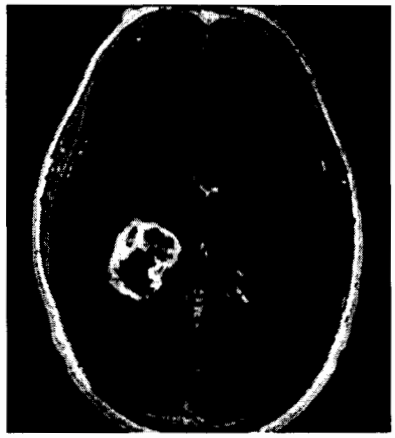
4.4 Segmentation

Segmentation technique is basically subdivision of image into regions or objects. System always rely on good segmentation technique as finally segmented image shows the performance of all the processes, techniques and algorithms employed on given images. Segmentation in medical imaging is a highly complex task as there are different variations of regions in images taken at different angles along with the limitations imposed on radiation level to avoid exposure of humans. Therefore, image acquired are low in contrast because of less radiation exposure.

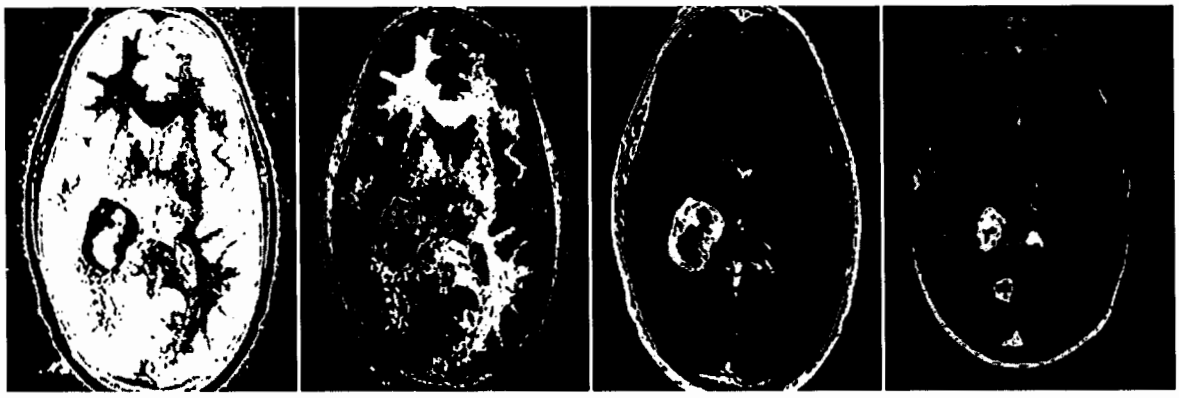
Segmentation algorithms are mostly dependent upon discontinuity and similarity. Discontinuity in intensity values is the abrupt changes in intensities which are responsible for formation of edges in images and so edge based segmentation is opted. Moreover, for those regions where intensity values are almost same, they are grouped on predefined criteria called region based segmentation. Few segmentation techniques are based on intensities in images.

4.4.1 Gray level Slicing

It is a very simple method for segmentation. Slices are obtained at varying intensity levels. Gray level slicing partitions different lesions or objects based upon their intensity levels. Thresholds are set at different levels varying from 0 – 255. In case of brain MR images, background and shadowing regions have been obtained correspondingly to values of gray levels. Slices are corresponding to high values of gray levels. Tumor is detected in slices corresponding between different gray levels of images.



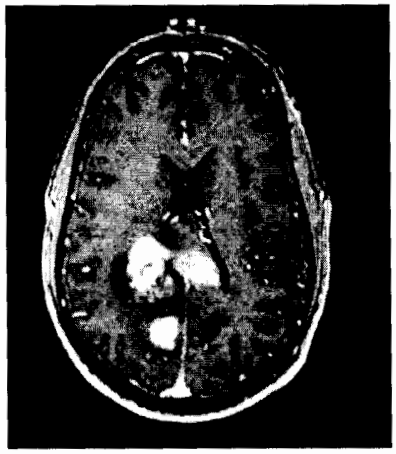
(a)



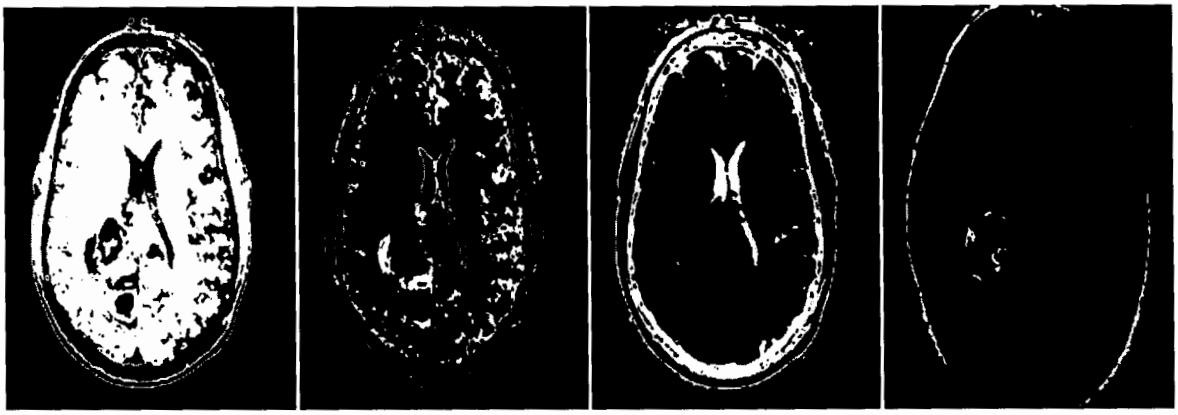
(b) (c) (d) (e)

Figure 4.10: Gray level slicing at four levels. (a) Original image. (b) Slice of gray level from 0 to 90. (c) Slice of gray level from 90 to 120. (d) Slice of gray level from 120 to 230. (e) Slice of gray level from 230 to 255.

Gray level slicing has been applied on image for segmentation. Figure 4.13 (a) is the original image. Figure 4.13 (b) ranges from 0 to 90 intensity levels, Figure 4.13 (c) ranges from 90 to 120 intensity levels, Figure 4.13 (d) ranges from 120 – 230 intensity levels and Figure 4.13 (e) ranges from 230 – 255 intensity levels. Results show that every image contains some part of the tumor and no specific image contains complete tumor which concludes that its performance is poor on brain tumor images. Therefore, this technique is not favorable for brain tumor segmentation.



(a)



(b) (c) (d) (e)

Figure 4.11: Gray level slicing at four levels. (a) Original image. (b) Slice of gray level from 0 to 90. (c) Slice of gray level from 90 to 120. (d) Slice of gray level from 120 to 230. (e) Slice of gray level from 230 to 255.

Gray level slicing has been applied on another image for segmentation. Figure 4.14 (a) is the original image. Figure 4.14 (b) ranges from 0 to 90 intensity levels, Figure 4.14 (c) ranges from 90 to 120 intensity levels, Figure 4.14 (d) ranges from 120 – 230 intensity levels and Figure 4.14 (e) ranges from 230 – 255 intensity levels. Here tumor is not detected or identified. So, this technique is not valid for brain tumor segmentation.

4.4.2 Region based segmentation

Region based segmentation is used to divide images into segments. This technique basically identifies pixels having similar intensity values according to pre defined rules. Sometimes, thresholds are defined according to pixel intensity values or location. If pixels fall within the defined threshold, they are grouped and formed into one group. Many approaches are used in region based segmentation which is original seed pixel, region statistics, neighbor in region, similarity. In brain tumor case, the focus is mainly upon the tumor intensity and its texture. There are variations in intensity values for tumor as compare to non tumor and therefore proposed methodology in tumor case is fuzzy c means segmentation technique as it employees both hard and fuzzy ways on image at the same time to segment tumor from the original image.

4.4.2.1 Fuzzy C Means Clustering

Fuzzy clustering is based on clusters. It basically determines the similarity of a pattern with other patterns based upon the measure of distance of patterns towards the center of clusters. This similarity or relationship between patterns is defined as soft membership. This technique is improved by the introduction of fuzzifier parameter k, where $1 \leq k \leq \infty$. FCM reduces the cost function below:

$$J(U,W) = \sum_{i=1}^{n} \sum_{j=1}^{c} (\mu_{ij})^k ||x_i - w_j||^2 \quad (4.23)$$

Where: $X = \{x_1 x_2 \ldots x_n\}$ is the data set and $W = \{w_1 w_2 \ldots w_c\}$ is the group of cluster centers. Moreover, μ_{ij} is the degree of pattern x_i towards the center of cluster w_j and should meet following conditions:

$$\mu_{ij} = [0,1], \text{ for } i = 1,\ldots, n, j = 1,\ldots, c, \quad (4.24)$$

$$\sum_{j=1}^{c} \mu_{ij} = 1 \qquad (4.25)$$

Where m is known as fuzzifier and applied to balance the extent of fuzziness on any data point. Theoretically there are no defined criteria for m, but normally m = 2 values are used. Euclidean distance between data x_i and cluster centers w_j is given by $\|x_i - w_j\|$. The matrix formed U = $(\mu_{ij})_{nxc}$ includes the values of membership from all data points towards the center of cluster matrix known as fuzzy partition matrix. FCM algorithm basically is:

1. Initialize U with some random values to fuzzy partition matrix that it satisfies the conditions (4.24) (4.25), and limit the number of clusters c, while $2 \leq 2 < n$.
2. Calculate fuzzy centers w_j by:

$$w_j = \frac{\sum(\mu_{ij})^m x_i}{\sum_{i=1}^{n}(\mu_{ij})^m}, \quad \forall j = 1,...,c \qquad (4.26)$$

3. Update the FP matrix U using following relation,

$$\mu_{ij} = \frac{1}{\sum_{h=1}^{c}(\frac{d_{ij}}{d_{ih}})^{\frac{2}{m-1}}} \qquad (4.27)$$

where $d_{ij} = \|x_i - w_j\|$, i =1,…,n and j = 1,…,c.

4. Repeat step (2) and (3) as long as pre defined stopping criterion meets.

Stopping criteria can be increased by increasing the number of iterations over the difference of current and previous values of cost function less or equal to the value obtained in previous iteration.

CHAPTER 5

EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

Results of different techniques that have been preferred for the different steps of proposed system for the detection of brain tumor are compared. Moreover, performance of proposed system has also been evaluated in this chapter. MATLAB R2011b has been used as simulation tool in this research. Complete experimental work discussed in this chapter includes pre-processing of magnetic resonance brain tumor images, segmentation, selection of interested regions, extraction of intensity and texture features and classification of tumorous and non tumorous lesions. Proposed system has been tested for its ability to differentiate among brain tumor images that is either presence of tumor or not.

5.1 Image Acquisition

The screening protocol used is as follows. Simultaneous bilateral MRI was performed using a 1.5 T magnet (GE Signa, ver. 11.4). Sagittal images were obtained with a phased-array coil arrangement using a dual slab interleaved bilateral method. This provided a 3-D volume data

over each breast obtained with a radio-frequency (RF) spoiled gradient recalled sequence (SPGR, scan parameters: TR/TE/angle = 18.4/4.3/30^0, 256 x 256 x 32 voxels, field of view (FOV): 18 x 18 x 6 – 8 cm). Imaging is performed before and after a bolus injection of 0.1mmol/kg of Gd-DTPA. Each bilateral acquisition was obtained in 2 min and 48 s. Slice thickness was 2-3mm.

A total of 50 magnetic resonance imaging brain examinations of high risk patients were obtained containing lesions pathologically proven to be malignant or non malignant. Images have been collected from Dr. Abrar Diagnostic center. For every patient, 25 tumorous images (15 Axial, 5 Coronal and 5 Sagittal) related to gliomas tumor in different grades, for three modalities (T1, T1 after injection of contrast agent, T2) have been selected. For training of classification algorithm, 10 axial slices have been chosen for every patient in different modalities and rest of the slices has been used for testing purpose. Acquired database includes full history of patients with their age ranging from 16 – 64 years. Expert radiologist assessed all acquired images as tumor and non tumor along with location of tumor and its severity which helped in verifying and analyzing the performance and results of the proposed classification system.

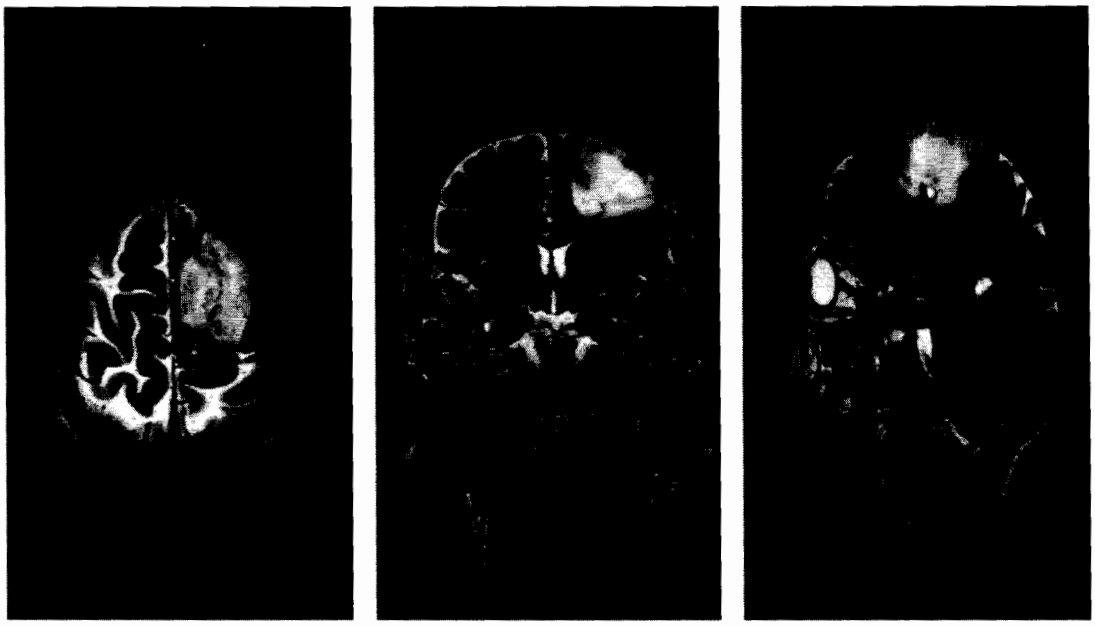
5.2 Preprocessing

Brain magnetic resonance images under gone from preprocessing phase which included different processes. Reconstruction of images of each patient has been done on medical conversion software (MEDCON) which constructs 2-D set of images into complete 3-D volume of images. A specialized doctor's help has been taken for the verification of images sequence.

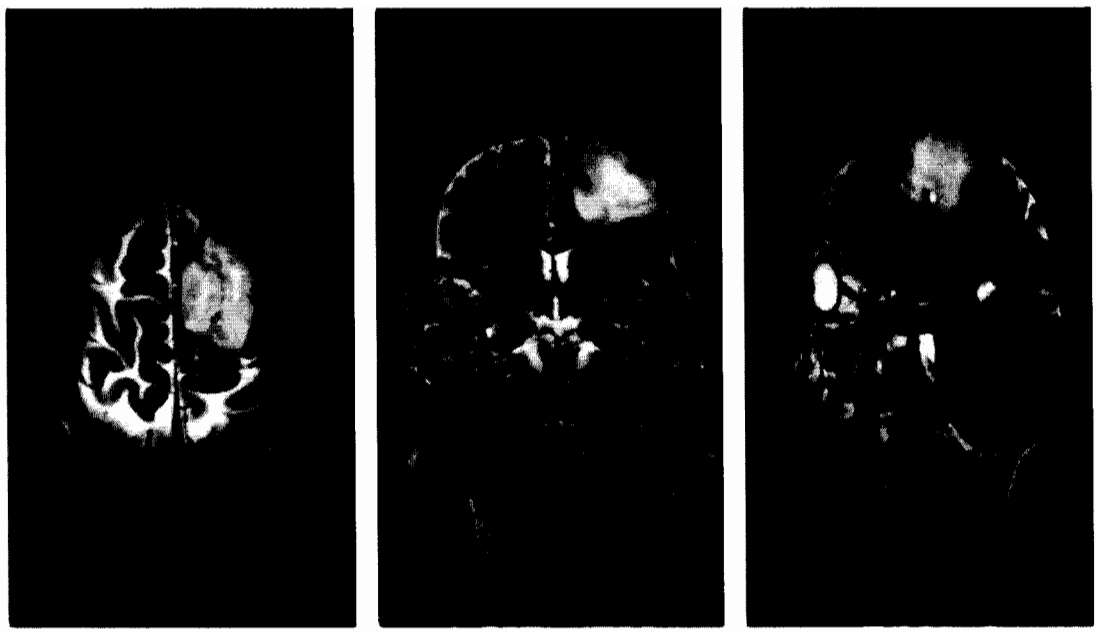
Co registration technique has been performed using statistical parametric mapping tool in MATLAB R2011b. All images having different modalities of same subject have been registered with each other by maximizing the normalized mutual information measure.

Template registration technique has also been done using SPM in MATLAB R2011b. Images of different modalities of different subjects have been registered with a template image by using measure of sum of squared difference.

Interested slices after assessment of expert radiologist have been extracted using MIPAV as shown in Figure 5.1 (a), Figure 5.1 (b) and Figure 5.1 (c). Slices of brain tumor have been passed through proposed filter namely anisotropic filters which can either be applied in MIPAV or in MATLAB R2011b for strengthening the differences between different regions of tumorous and non tumorous lesions and minimizing the effects of present noise by increasing homogeneity of the regions and keeping the edges preserved.



(a) (b) (c)



(d) (e) (f)

Figure: 5.1 Anisotropic filters applied on interesting slices where tumor is visible. (a), (b), (c) Original brain slices in three planes. (d), (e), (f), Slices after applying filter on original images.

5.3 Features extraction

In this research, for every slices of each patient, Gray level co occurrence matrix has been computed for all the texture features. 16 texture features have been chosen for every tumorous and non tumorous lesion. Here, the aim is to identify those features which can evaluate the difference of values in tumor and non tumor pixels. In total, there are 16 features per slice. All the features need to be normalized so that no specific feature dominates the others. The comparison of outputs of tumor and non tumor lesions using different texture features with recommendations have been discussed below:

5.3.1 Angular Second Momentum

Figure 5.2 shows the energy of non tumors and tumors images. Here the difference is quite obvious between tumorous and non tumorous pixel values.

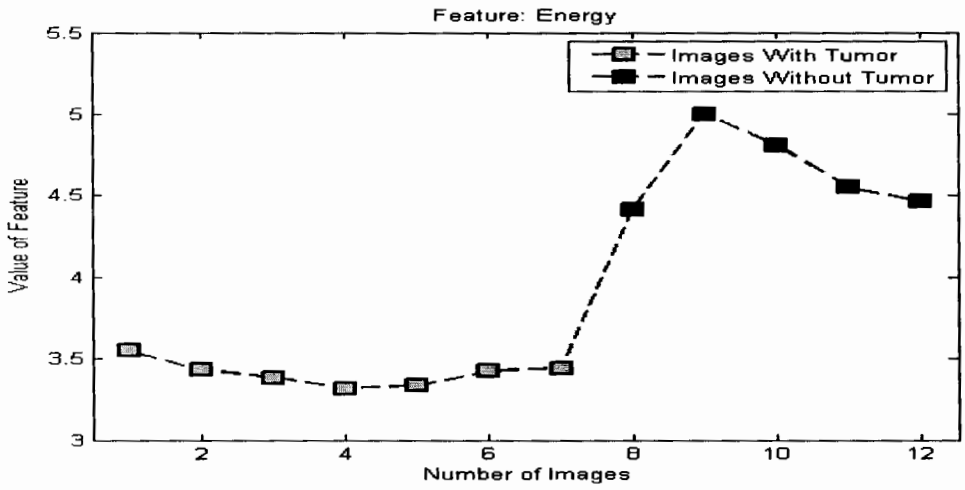


Figure: 5.2 Energy of images.

5.3.2 Contrast

In Figure 5.3, there is slight variation in results after using contrast feature which implies that this feature cannot be used for complete classification of images.

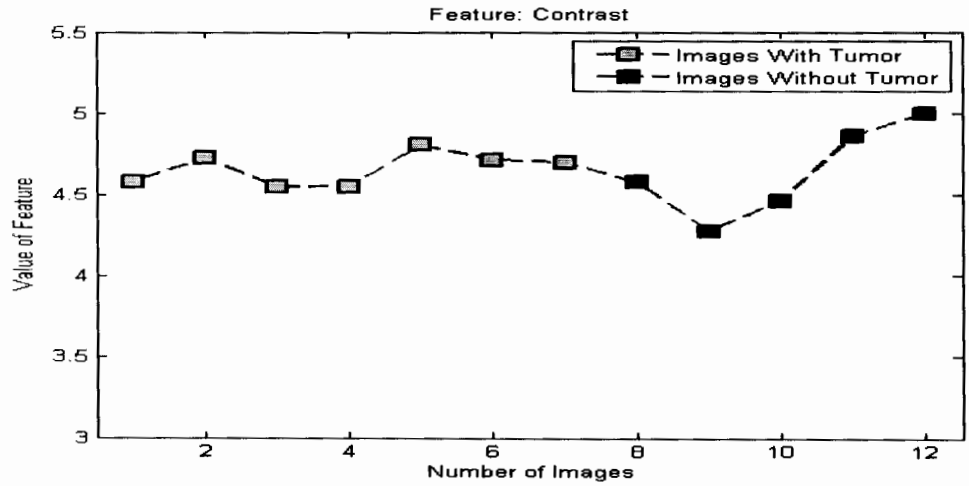


Figure: 5.3 Contrast.

5.3.3 Correlation

Results in Figure 5.4 shows that there is not much difference in values after using correlation feature as variations between different images are almost similar.

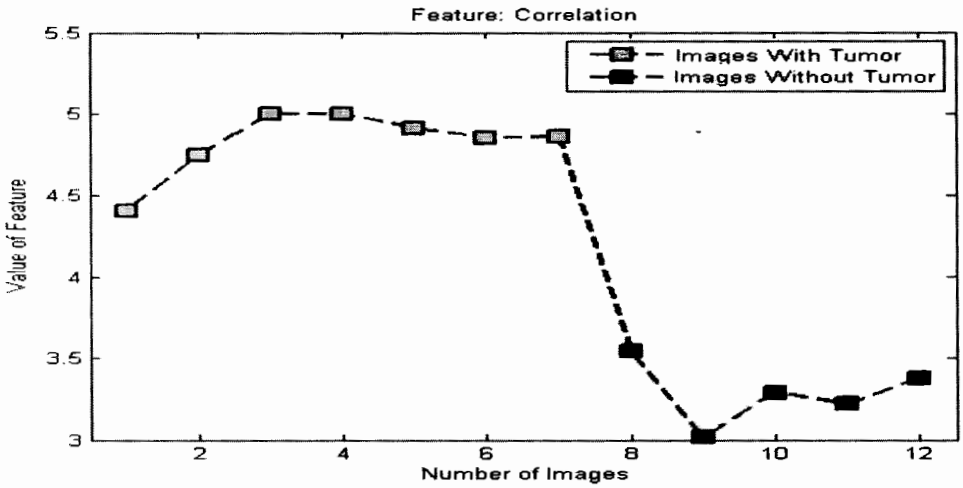


Figure: 5.4 Correlation.

5.3.4 Sum of Squares Variance

From Figure 5.5, it is clear that non tumorous images have same variations and same goes for tumorous but there is quite a difference in variations between tumor and non tumorous images and so this feature is highly recommended for classification.

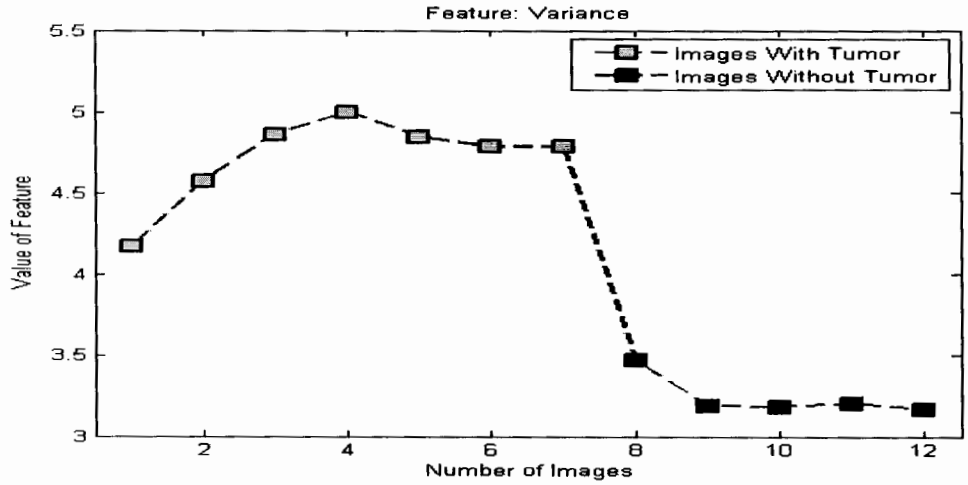


Figure 5.5: Sum of squares variance.

5.3.5 Inverse Difference Moment

In Figure 5.6, no variation between images. This feature has been discarded.

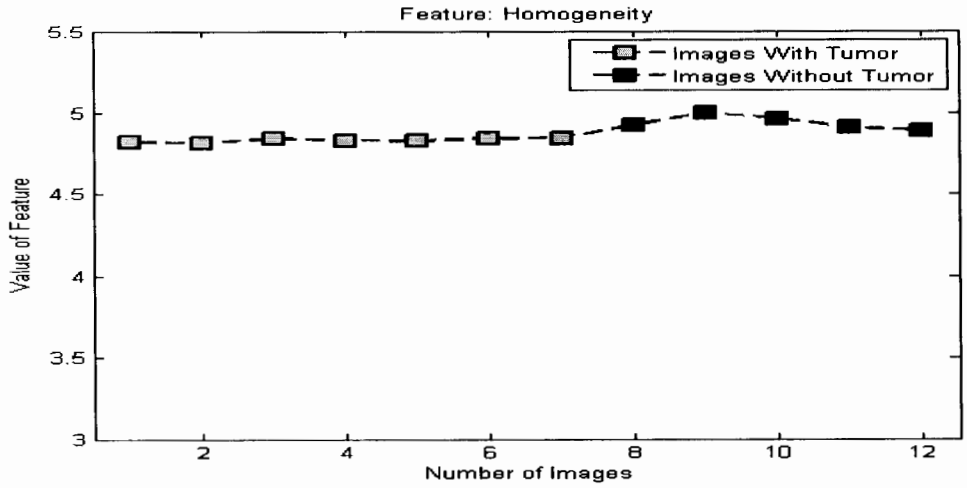


Figure: 5.6 Inverse difference moment.

5.3.6 Sum Average

In Figure 5.7, there is reasonable difference between the values of tumor and non tumor. Therefore, this feature is recommended for classification.

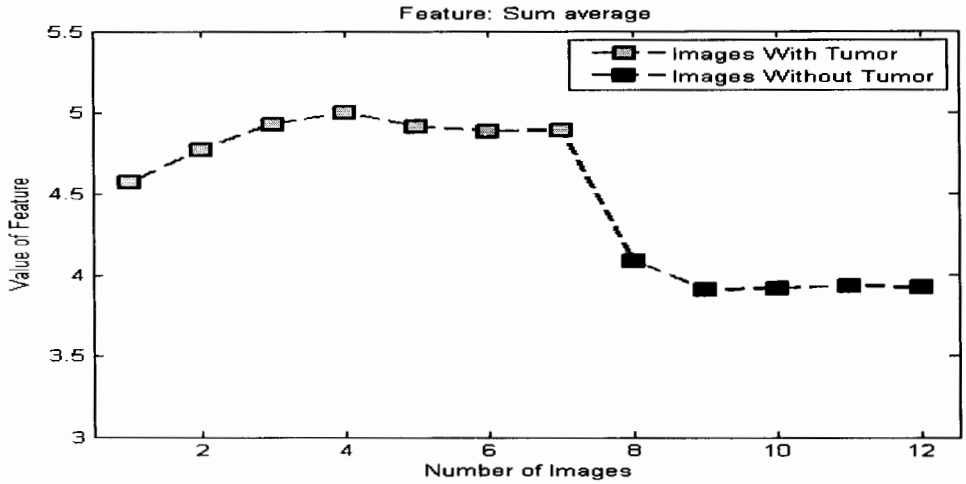


Figure: 5.7 Sum average.

5.3.7 Sum Variance

In Figure 5.8, there is huge difference between the values of tumor and non tumor. Therefore, this feature is recommended for classification as difference is on the increasing side.

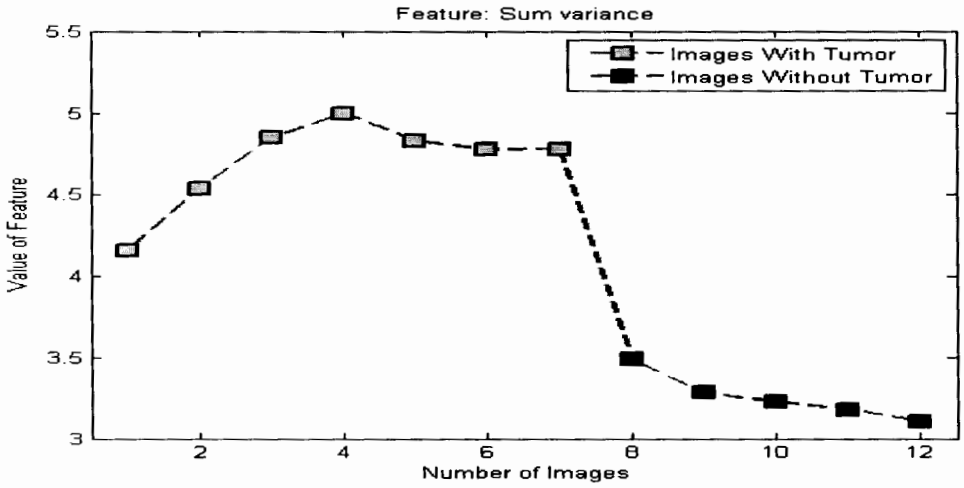


Figure: 5.8 Sum variance.

5.3.8 Entropy

In Figure 5.9, there is reasonable difference between the values of tumor and non tumor. Therefore, this feature can also be considered for classification.

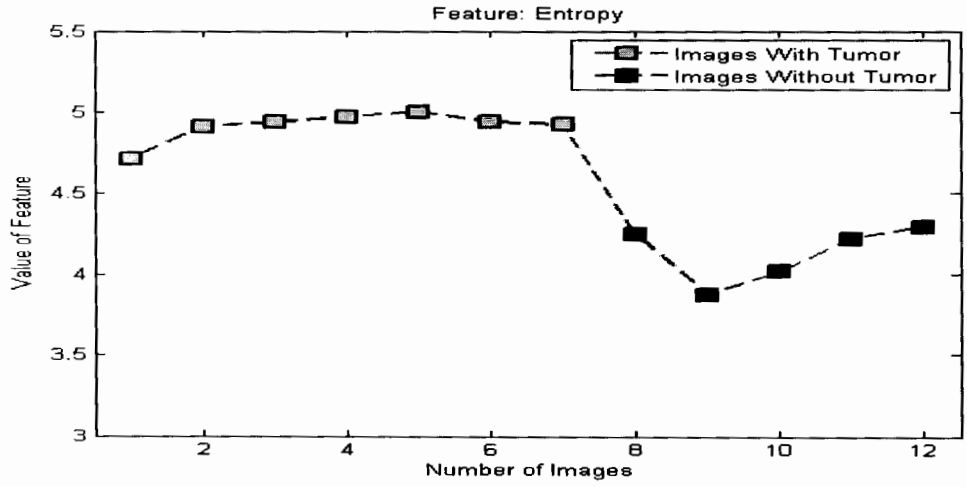


Figure: 5.9 Entropy.

5.3.9 Sum Entropy

In Figure 5.10, there is reasonable difference between the values of tumor and non tumor. Therefore, this feature is also highly recommended for classification.

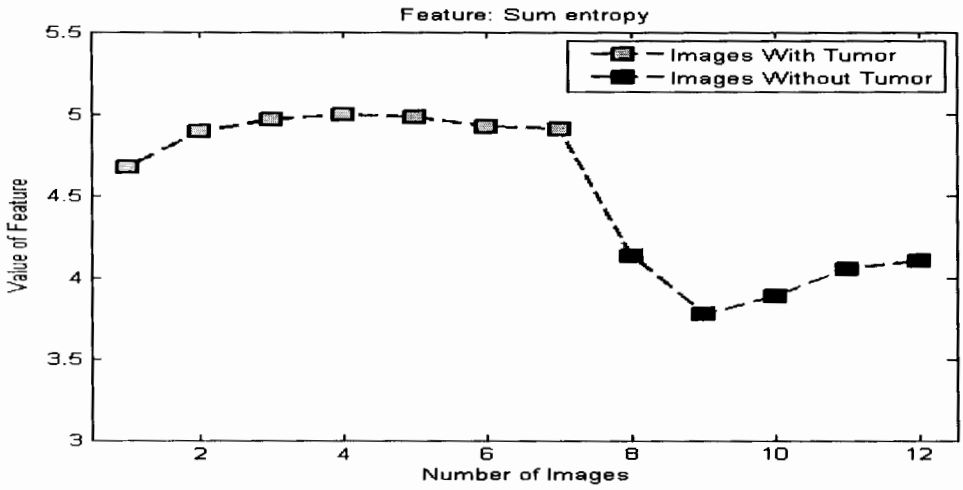


Figure: 5.10 Sum entropy.

5.3.10 Difference Variance

In Figure 5.11, not much difference between the values of tumor and non tumor can be viewed. The variations are same for both and so it is not recommended for classification.

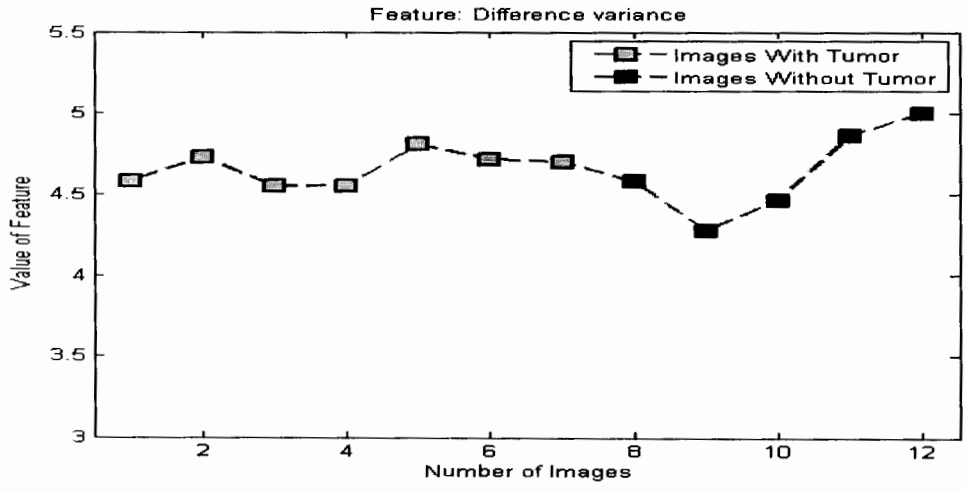


Figure: 5.11 Difference variance.

5.3.11 Difference Entropy

In Figure 5.12, there is a slight difference between the values of tumor and non tumor. Therefore, this feature can be considered for classification.

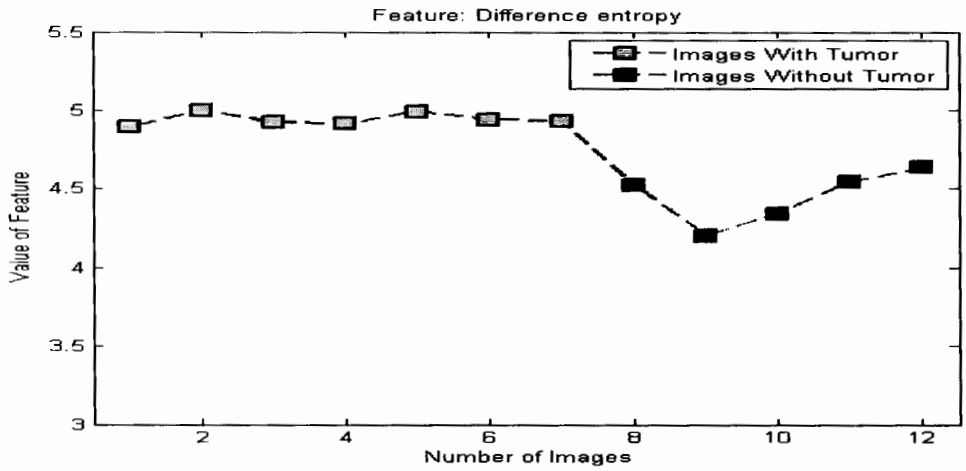


Figure: 5.12 Difference entropy.

5.3.12 Information Measures of Correlation

In Figure 5.13, there is a huge difference between the values of tumor and non tumor. Therefore, this feature is highly recommended for classification.

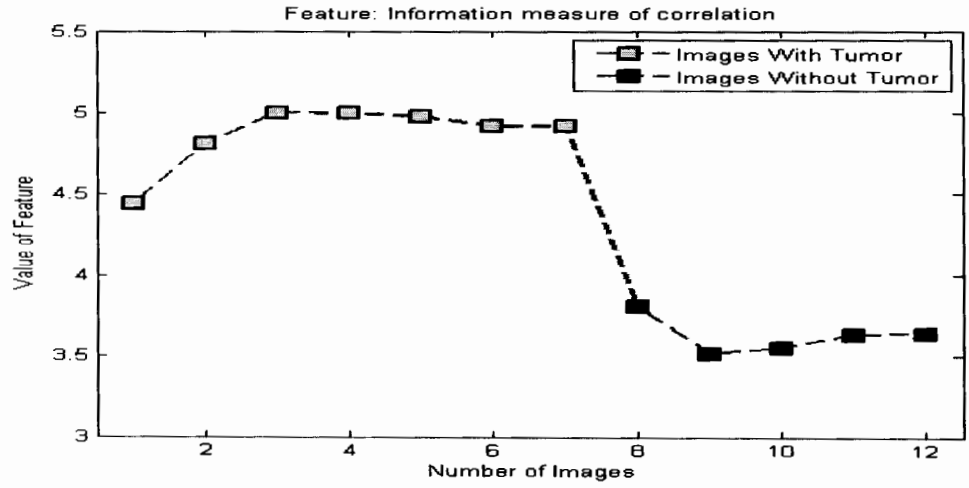


Figure: 5.13 Information measure of correlation.

5.3.13 Autocorrelation

In Figure 5.14, there is a huge difference between the values of tumor and non tumor. Therefore, this feature is also highly recommended for classification.

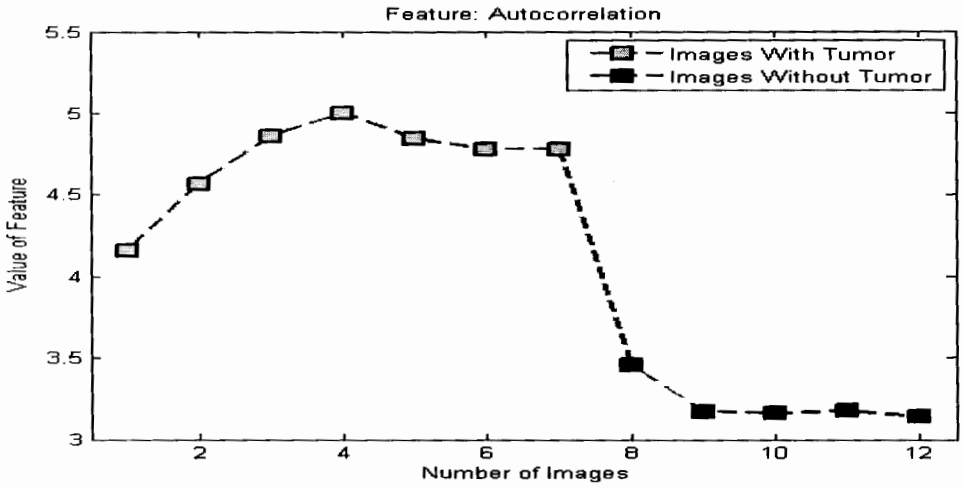


Figure: 5.14 Autocorrelation.

5.3.14 Maximum Probability

In Figure 5.15, there is quite a difference between the values of tumor and non tumor. Therefore, this feature is recommended for classification.

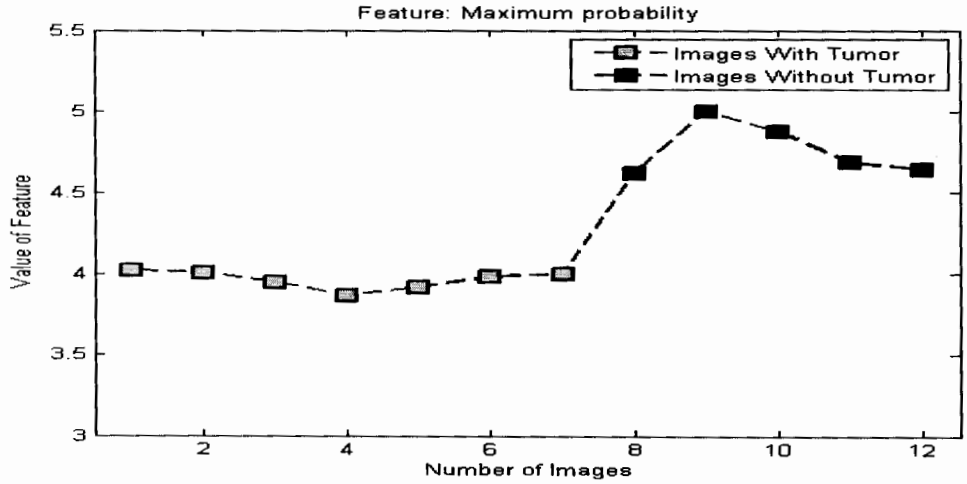


Figure: 5.15 Maximum probability.

5.3.15 Cluster Prominence

In Figure 5.16, there is a slight increasing difference between the values of tumor and non tumor. Therefore, this feature is can be for classification.

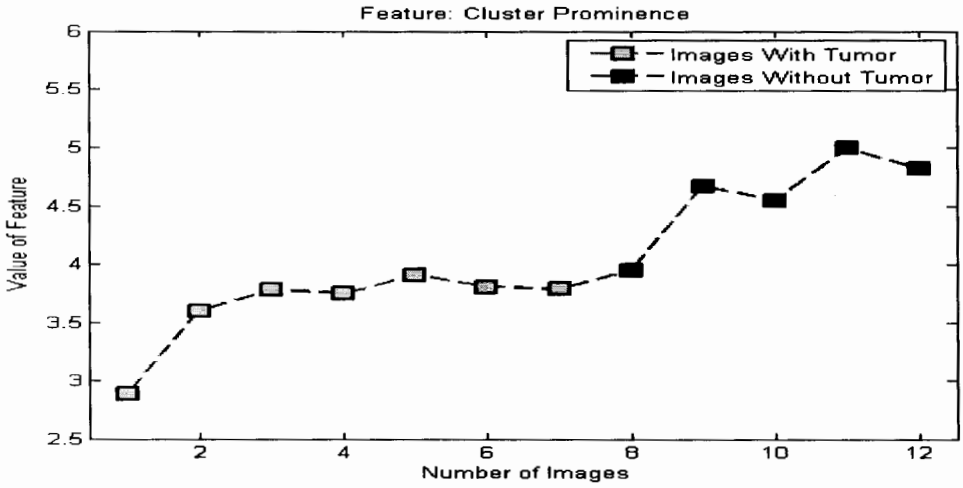


Figure: 5.16 Cluster prominence.

5.3.16 Dissimilarity

In Figure 5.17, there is a slight difference between the values of tumor and non tumor. Therefore, this feature can also be for classification.

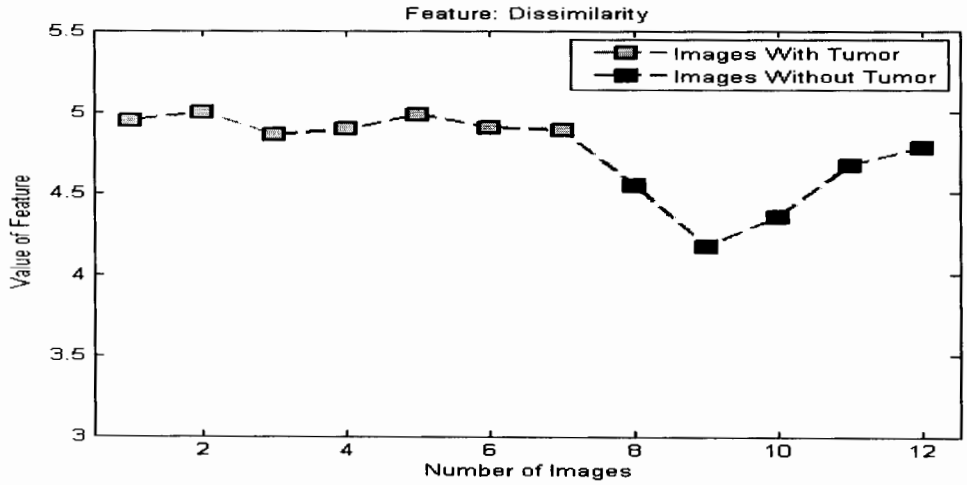


Figure: 5.17 Dissimilarity.

5.4 Selection of features

Out of 16 texture features computed for all tumor and non tumor slices, only those features have been selected which showed greater variance between tumor and non tumor images. Features like Autocorrelation, Energy, Entropy, Sum Average and Variance were selected in order to perform training of support vector machines. The data of these selected features is normalized so that no particular feature shows its dominance over others.

In the following figure normalized values of these features are shown.

	1	2	3	4	5
1	4.1618	3.5504	4.7174	4.5723	4.1702
2	4.5703	3.4336	4.9121	4.7745	4.5770
3	4.8626	3.3840	4.9397	4.9272	4.8639
4	5	3.3180	4.9704	5	5
5	4.8432	3.3372	5	4.9135	4.8486
6	4.7823	3.4265	4.9395	4.8853	4.7868
7	4.7828	3.4452	4.9245	4.8866	4.7871
8	4.0635	3.4686	4.6995	4.5085	4.0882
9	4.4972	3.4075	4.8698	4.7711	4.5051
10	4.8283	3.3246	4.9302	4.9203	4.7671
11	4.9416	3.3158	4.9106	4.9680	4.9469
12	4.8325	3.2947	4.9529	4.8604	4.8160
13	4.6917	3.3953	4.8699	4.8198	4.7763
14	4.6949	3.4291	4.8545	4.8459	4.7260
15	4.3600	3.7321	4.8352	4.7362	4.3522
16	4.7433	3.5596	5.0544	4.8779	4.7488
17	4.9970	3.5435	5.0491	5.0341	5.0608
18	5.1584	3.4203	5.1303	5.1320	5.1531
19	4.9540	3.4798	5.1471	5.0666	4.9811
20	4.9730	3.5578	5.1091	5.0507	4.8974
21	4.9708	3.5614	5.0944	5.0274	4.9482
22	4.1600	3.5321	4.6352	4.5362	4.1522
23	4.5433	3.3596	4.8544	4.6779	4.5488
24	4.7970	3.3435	4.8491	4.8341	4.8608

Figure: 5.18 Selected feature values

5.5 Classification

After successfully extracting and choosing required features, training and testing phase requires support vector machines to be properly trained with selected features.

5.5.1 Classifier

The MRI slices were classified using MATLAB R 2011b/ SVM for SVM classification with both linear and RBF kernels. Various parameters have been selected for the classifiers through pilot runs. In SVM – classifier, the value of standard deviation (σ) for Gaussian RBF kernel was chosen as 0.1.

5.5.2 Performance Measures

All classification results could have a misclassification rate and on any occasion can either generate false result to identify an abnormality, or it may also classify an abnormality which is not present. Usually misclassification rate is described by the correct and false positive and correct and false negative parameters as follows:

Correct Positive (C_p): the result of our classifier is positive and the abnormality is also present as per indicated by an expert.

Correct Negative (C_n): the result of our classifier is negative and the abnormality is not present as per indicated by an expert.

False Positive (F_p): the result of our classifier is positive and the abnormality is not present as per indicated by an expert.

False Negative (F_n): the classification result is negative and the abnormality is not present as per indicated by an expert.

Based upon the above mentioned rules, the accuracy of classifier can be tested with the help of following formula.

$$Accurate\ \ Classification = \left(\frac{C_p + C_n}{C_p + C_n + F_p + F_n} \right) \times 100\% \tag{5.1}$$

Below table is the contingency table which defined various terms used to describe the clinical efficiency of a classification based on terms above and

$$\text{Sensitivity} = C_p / (C_p + F_n) * 100\% \tag{5.2}$$

$$\text{Specificity} = C_n / (C_n + F_p) * 100\% \tag{5.3}$$

$$\text{Positive Predictive Value} \quad PPV = \frac{C_p}{C_p + F_p} \times 100 \tag{5.4}$$

$$\text{Negative Predictive Value} \quad NPV = \frac{C_N}{C_N + F_N} \times 100 \tag{5.5}$$

are used to measure the performance of the classifiers.

Table 5.1: Contingency table

	Predicted Class	
Actual Class	**Normal**	**Abnormal**
Normal	C_n	F_p
Abnormal	F_n	C_p

5.6 Comparison of Performance of Classifiers

In order to verify the effectiveness and robustness of SVM classifier, experiments were performed on magnetic resonance brain images. In this work, two different training and test sets have been considered. The experiments were carried out on HP ProBook 4520s laptop

having Intel ® Core ™ i3 CPU M 380 @ 2.53GHz, 2533 MHz, 2 Core(s), 4 Logical Processor (s) and 2 GB RAM.

The performance of classifier using support vector machine was evaluated using RBF and linear kernels. For comparative analysis, SVM Linear and SVM RFB were used on data sets. Two different sets have been taken for comparing the results. The formulation is to test the generalization and adaptability of the two classifiers. The first training set is more biased towards the abnormal class. In the second set, equal number of training samples from both classes has been chosen in order to have an unbiased training of the two classifiers.

5.6.1 SVM Results:

Based upon these five selected features, SVM algorithm with linear kernel and with Radial Basis Function kernel were trained. The outputs of SVM training results were observed with all the combinations of selected features, since SVM can only classify between two classes at a time. By performing these combinations, it was noticed that Autocorrelation and Energy feature provided the maximum marginal width required for correct classification than the rest. Therefore for training and classification the SVM linear kernel and Non Linear kernel these two features were used.

Following figures shows the training result with the first set having total of 53 images, out of which 28 were tumor and 25 were non tumor.

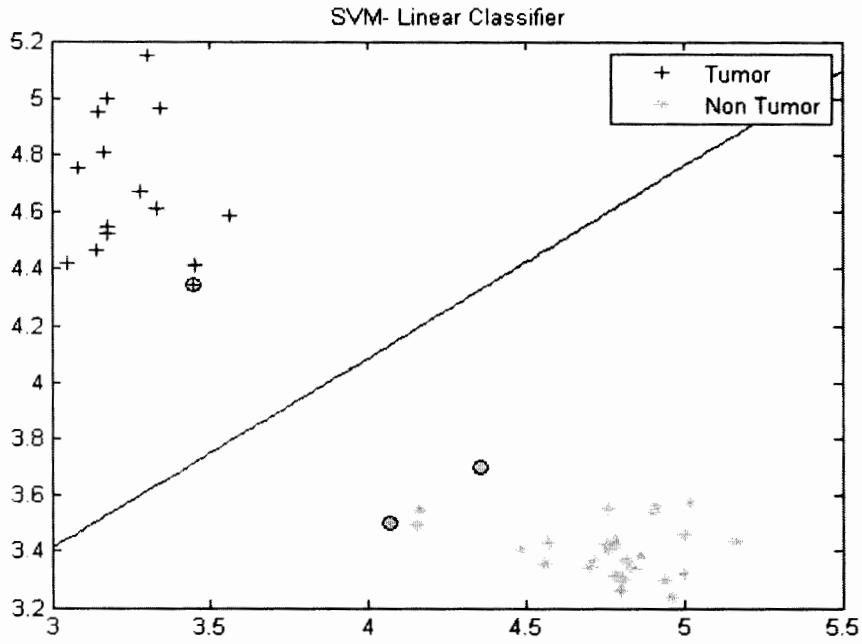


Figure 5.19: Training of Set 1 using SVM linear classifier

Similarly the SVM-RBF kernel was trained upon this data and the following figure shows the training results.

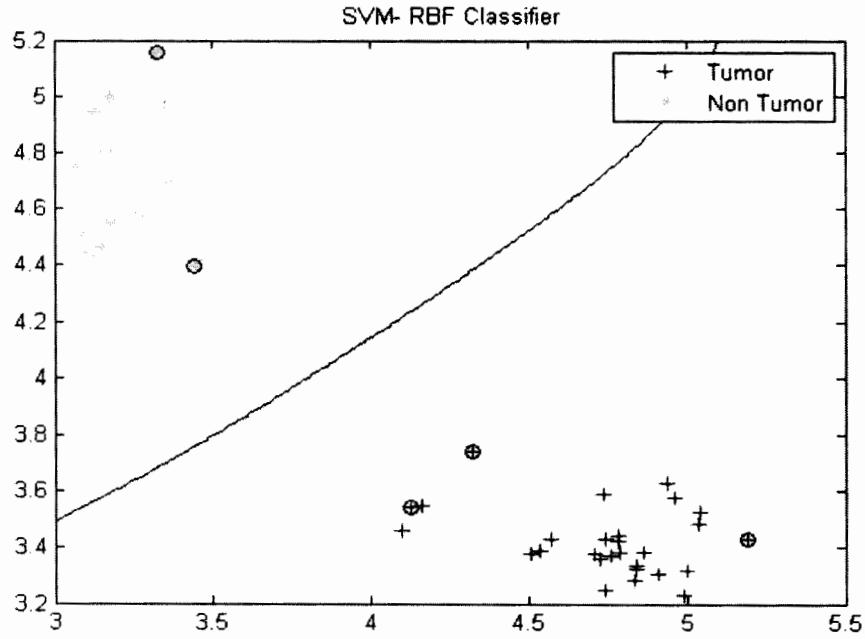


Figure 5.20: Training of Set 1 using SVM RBF Classifier

Furthermore the images were extended to 91 out of which 54 were containing tumor and 37 were without tumor images. Again SVM linear kernel and RBF kernels were trained by using these images.

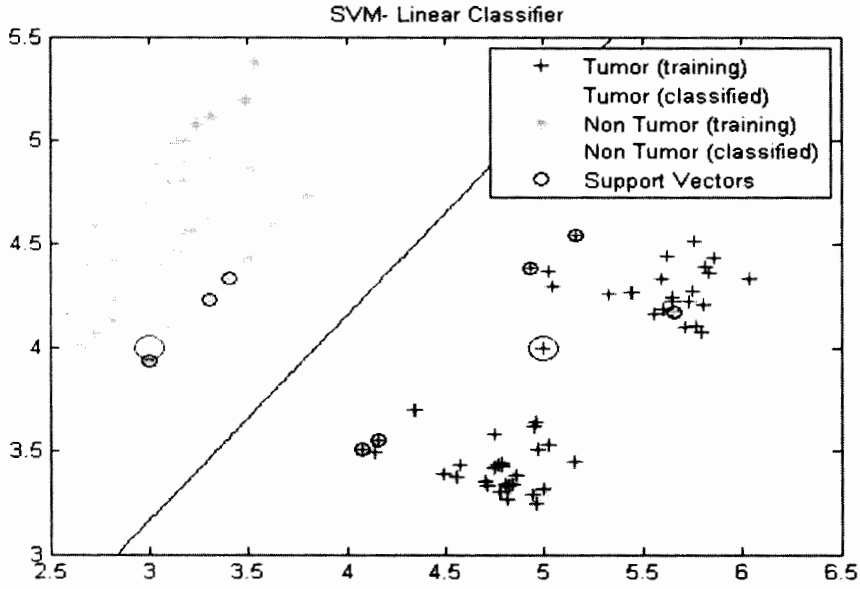


Figure 5.21: Testing of Set 1 using SVM linear classifier

Here in this image it can be seen that SVM linear classifier has been trained and then tested for multiple values. The results show that due to proper training the SVM linear kernel was successful in correct classification.

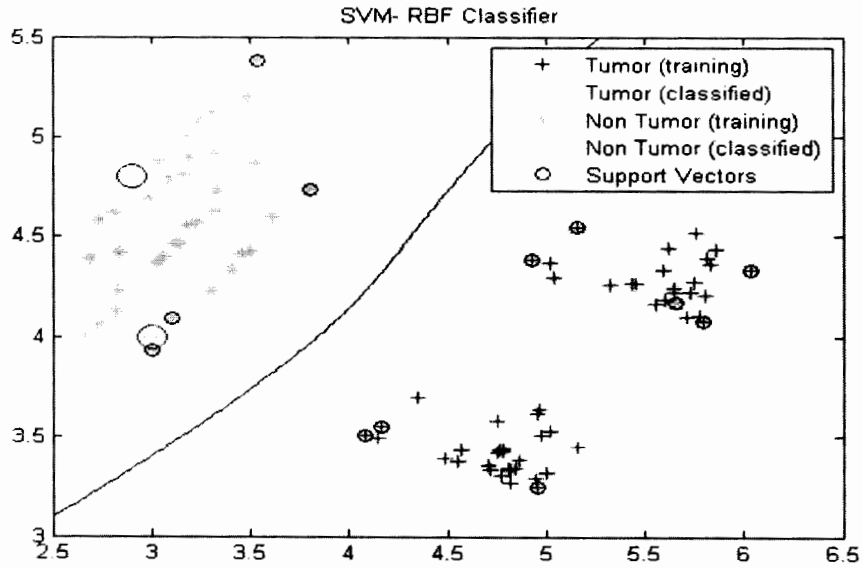


Figure 5.22 Testing of Set 1 using SVM RBF classifier

Here in this image it can be seen that SVM RBF classifier has been trained and then tested for multiple values. The results show that due to proper training the SVM RBF kernel was successful in correct classification.

5.7 Comparison of Classifier's Performance

In this table we have shown the quantitative analysis of our trained classifiers. Comparison has been drawn between linear SVM, non linear kernel SVM and of Artificial Neural Network (ANN) classifier. In ANN, a general three layered perceptron neural network and the back propagation learning rule are used. For training of Test Set 1 a total of 91 test images were used, out of which 54 were tumor images and 37 were non tumor images. The given table shows comparison between above mentioned classification techniques by evaluating figure of merits such as accuracy, sensitivity, specificity, positive predictive value and negative predictive value. By observing the table it can be seen that in our problem, non linear SVM with RBF kernel has come up with better accuracy.

Table 5.2: Results for Test Set 1

Classifier Type	C_p	C_n	F_p	F_n	Accurate Classification	Sensitivity	Specificity	PPV	NPV
SVM-RBF	54	36	01	00	98.9%	100%	97.29%	98.18%	100%
SVM-Linear	52	36	01	02	96.7%	96.29%	97.29%	98.11%	94.73%
ANN	46	31	09	05	84.62%	90.19%	77.5%	83.63%	86.11%

These results show that RBF has performed better than the conventional linear classifier for this specific application area. Out of total 91 test images RBF has shown consistency in accurate classification.

Furthermore these classifiers were tested upon a wider range of test data including total of 450 images, in which there were 170 tumor images and 280 non tumor images. Based upon this test data again the classifiers were tested and the results are shown in table given below.

Table 5.3: Results for Test Set II

Classifier Type	C_p	C_n	F_p	F_n	**Accurate Classification**	**Sensitivity**	**Specificity**	**PPV**	**NPV**
SVM-RBF	165	267	07	11	96%	93.75%	97.44%	95.93%	96.04%
SVM-Linear	153	257	12	28	91.11%	84.53%	95.5%	92.7%	90.17%
ANN	131	235	27	57	81.33%	69.68%	89.69%	82.91%	80.47%

These results show that RBF has performed better than the conventional linear classifier for this specific application area. Out of total 450 test images RBF-SVM has shown consistency in accurate classification.

Table 5.4: Simulation Results Comparison

	Classifier Type	True Positive	False Positive	Sensitivity
Case I	Proposed Method-RBF kernel	314	271	97.5%
	SVM-RBF [48]	290	268	93%
Case II	Proposed Method-Linear kernel	378	212	98.3%
	SVM-Linear [48]	353	202	92.5%

Finally results of our proposed technique is compared with [48], in which author has performed brain tumor classification by using GLCM features and SVM classifier. In that paper a total of 59 images have been used, this is clearly insignificant amount for such vital diagnosis system. A comparison of our proposed method has been presented with [48] based upon sensitivity parameter, ideal value of this parameter should reach unity. Our database contains 450 images with normal and tumor affected tissue, when same approach, as given [48], is applied on this database our method has shown better Sensity as compared to other since feature selection criteria has improved our SVM based classification system. Comparison has been made with both Linear and RBF kernel and results have been shown in Table. 5.4.

5.8 Segmentation

In segmentation phase, we have performed two steps. First step is basically referred to classification step performed in previous section where pixels have been identified as tumorous and non tumorous. In this regard, previous model generated will be used to differentiate between tumorous and non tumorous pixels.

Second step is the tumor extraction. Here, the set of pixels which have been identified as tumor has been grouped together to form complete tumorous region. For the final segmentation result, binary image has been proposed for every segmented image where black portion will be the non tumorous part and the white portion will be the tumorous part.

Region based segmentation techniques have been used on classified lesions for the separation of different clusters, gray level slicing of gray level images at different thresholds and fuzzy c means clustering.

5.5.1 Segmentation by Fuzzy C Means

Results of three images with four clusters have been shown in Figure 5.23. 2-D slices have been taken. Tumorous region can be seen in the third cluster for three images in all planes.

For the verification of efficiency, fuzzy c means technique has been applied on 120 brain tumor images acquired from different patients with varying ages. After applying this technique, tumorous regions have been consistently observed in the third cluster.

Figure (a), (b) and (c) are the original images whilst Figure (d), (e) and (f) after 1^{st} cluster where tumor cannot be seen. Figure (g), (h) and (i) after 2^{nd} cluster where tumor can be distinguish impartially. Figure (j), (k) and (l) after 3^{rd} cluster where tumor can be seen clearly differentiated. Figure (m), (n) and (o) after final 4^{th} cluster where tumor is purely visible.

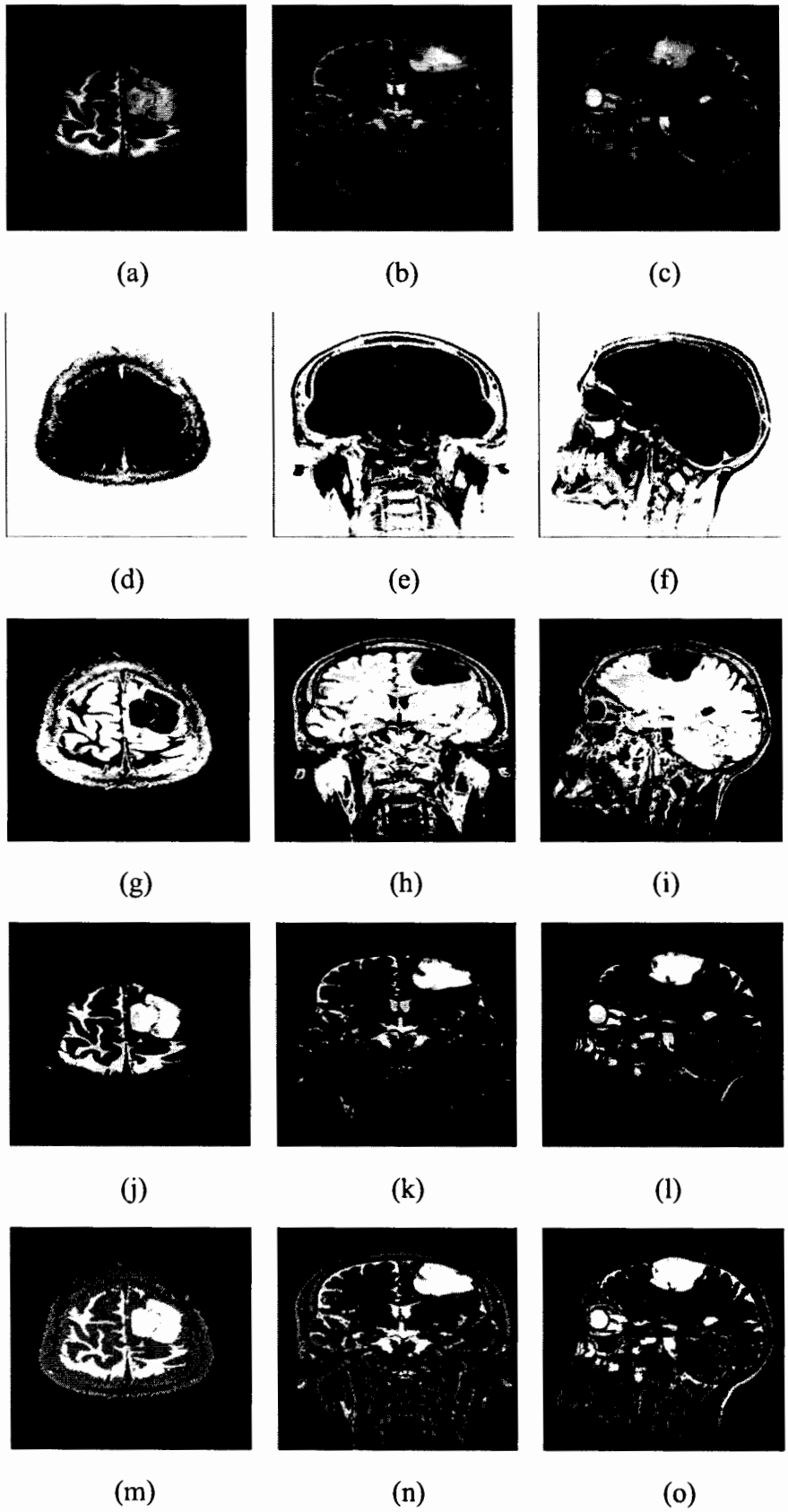
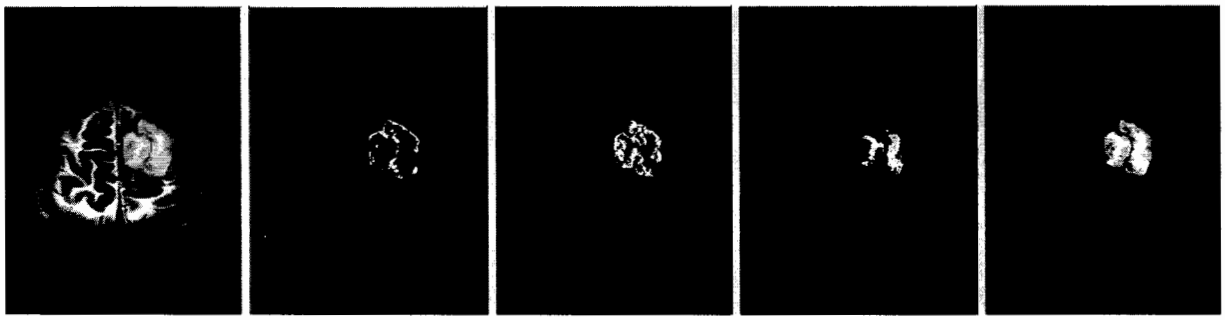
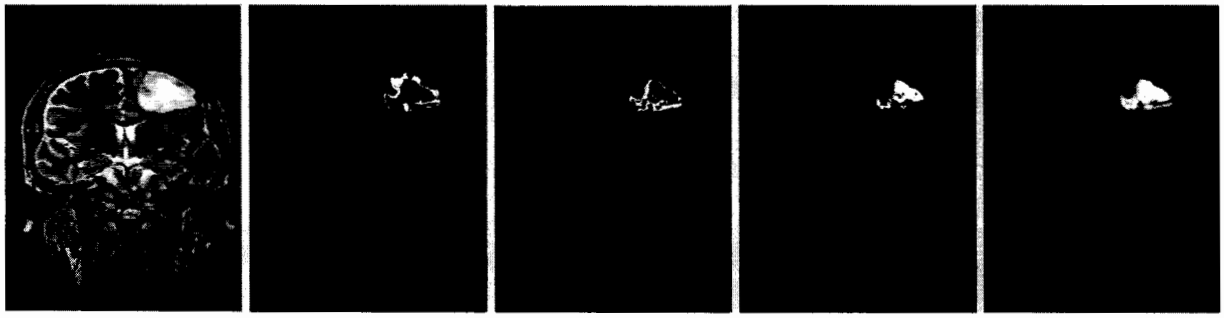


Figure 5.23: FCM segmentation. (a), (b), (c) Original images. (d), (e), (f) First cluster. (g), (h), (i) Second cluster. (j), (k), (l) Third cluster. (m), (n), (o) Fourth cluster.

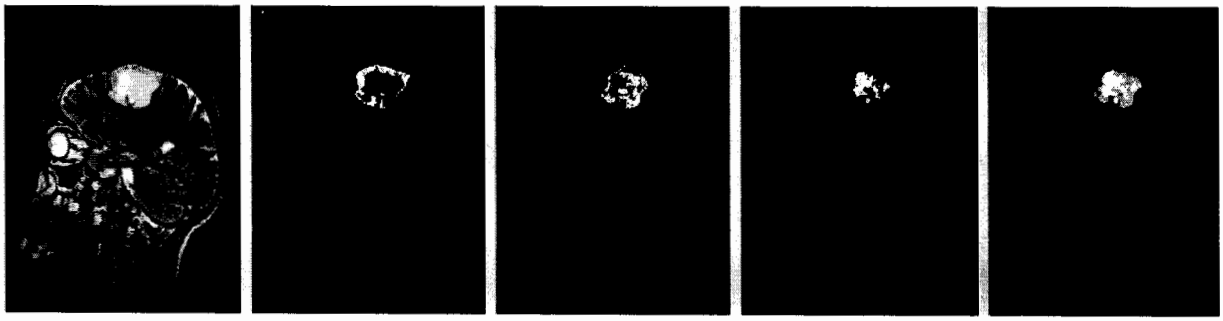
The region where tumor has been identified is selected by eliminating the surrounding regions which are in the neighborhood of those regions. Segmentation results obtained in last section showed tumor along with parts of skull visible. These are removed by applying the same segmentation technique on regions where tumor is visible as shown in Figure 6.5.



(a)



(b)



(c)

Figure: 5.24 FCM applied on tumorous regions. (a) Axial plane. (b) Coronal plane. (c) Sagittal plane.

CHAPTER 6

CONCLUSION AND FUTURE DIRECTIONS

Medical image classification and segmentation tools have shown their performance in different research applications in medical sciences and they are in practice for computer aided diagnosis and radiotherapy planning. These tools are going to be more effective in those fields of medical sciences where visualization of human anatomy is a compulsory task that is computer integrated surgery.

Proposed system is a user interactive tool used for the classification and segmentation of magnetic resonance images. Focus given in this research is only on brain tumor images of different subjects acquired from magnetic resonance device.

Proposed system primarily classifies between the tumorous and non tumorous images of different subjects. Once, tumor is classified by support vector machines, it incorporates the segmentation process as classification by support vector machines comparatively from other classification techniques is fast due to robustness in its properties and the capacity of handling loads of data at once.

6.1 Conclusion

System is based upon four phases, which are pre-processing phase, features extraction phase, training and testing phase and the segmentation phase. Pre-processing phase basically registers images of dissimilar features and also registers upon a template image in MNI co ordinate system. Then, denoising of images is another important step which is ensured using anisotropic filtering technique. Moreover, extraction of features determines a specific feature vector for each lesion characterized either upon the texture features. After that, proposed support vector machines build an algorithm which allows discrimination between tumorous and non tumorous lesions. At the end, this system is used to distinguish new pixels for the extraction of tumorous regions. The choice of proper parameters can optimize the results and accuracy in system as it requires many steps with the usage of different tools and softwares. Up till now, the experimental study offers a proper way and results obtained are highly encouraging which can surely be improved and more diversified by adding more real data, which always is another challenge because there is not much real data available in brain tumor imaging.

6.2 Future Work

This presents the initial line of research. The proposed system in this research is capable of brain tumor detection. It can also be used on different set of images for the construction of automated 3-D tumor volume. The proposed system can be optimized at each step of whole proposed system on better choice. Precisely, the selection of features can be improved by selecting more appropriate features which may include characteristics of tumor, location of tumor and even some personal features of patients themselves which extends the system processes and becoming a complete decision support system. With some modification, this system may also be used on breast and many other organs for cancer detection. Interested

researchers in this field may further include brain tumor images and their grades identified by doctors to enable more features and the ability to distinguish between different grades of tumors.

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