Exploiting Customized Explainable Artificial Intelligence Driven Deep Architectures for Improved Alzheimer's Disease Classification

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2025

DISSERTATION

A dissertation submitted to the Department of Electrical and Computer Engineering, International Islamic University Islamabad as a partial contentment of the requirements for the honor of the degree.

Department of Electrical and Computer Engineering

Faculty of Engineering and Technology

International Islamic University Islamabad

2025

DEDICATION

I dedicate research work to my cherished parents, esteemed educators, siblings and all those who anticipated my success.

"Alhamdulillah for everything, we can never thank Allah enough for the countless blessings he blessed us with"

CERTIFICATE OF APPROVAL

Title of Thesis: Exploiting Customized Explainable Artificial Intelligence Driven Deep Architectures for Improved Alzheimer's Disease Classification

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I certify that research work titled "Partially Adaptive Optimization driven Spatial Focused CNN with Gompertz Non-Linearity for Interpretable Alzheimer's Disease Diagnosis" has been completed by me and it has not been done before and presented anywhere for evaluation. Furthermore, I have properly acknowledged the material taken from related sources.

ACKNOWLEDGEMENT

First, I would like to thank ALLAH (SWT) for giving me a great family, supportive teachers, and cooperative friends. Without their assistance, I couldn't have finished my research work.

This work is completed with the help of two people. I would like to express my admiration to my supervisor Dr. Ihsan Ul Haq for his continuous assistance, motivation, strength and insightful direction. I would also pay my sincere affection to my co-supervisor Dr. Zeeshan Aslam Khan for his sincere devotion, valuable time, and suggestions throughout the work.

In the last, I am very thankful to my beloved parents for their continuous encouragement, unconditional love. They have always given me the moral and spiritual support and motivation to achieve my goals.

ABSTRACT

Recently, deep learning has revolutionized various scientific disciplines. Strategies based on deep learning have consistently surpassed traditional methods, proving extraordinary efficiency in the healthcare environment. Alzheimer's disease (AD) is one of the major global health threats due to its rapid increase and late diagnosis. Originating from complicated neuroanatomical variations, AD is caused by the brain's accumulation of amyloid and tau proteins. Various deep learning methods have been proposed in the literature, yet these models demand significant time and computational resources due to their multi-layered architectures. Therefore, a solution providing a good balance between accuracy and computational efficiency is a dire need of time. The proposed research contributes in the following directions, (1) The transformer-inspired spatial attention mechanism-driven a compact and lightweight CNN structure has been proposed to produce an accurate and efficient solution for Alzheimer’s disease diagnosis, (2) Furthermore, a non-linear activation function named Gompertz Linear Unit (GLU) is exploited in the proposed network for capturing complex relationship in the given data and to overcome the issues of dead neuron and vanishing gradient faced in existing activation operations, (3) To address the challenges of over adaptiveness in existing techniques, a Partially adaptive variant of Adam optimizer (Padam) is utilized in this study. Moreover, the incorporation of Padam provides flexibility to fine-tune the model as needed which improves the performance in terms of accuracy and speedy convergence, (4) Explainable Artificial Intelligence (XAI) is exploited to produce an interpretable diagnostic insight which will be valuable for healthcare professionals to make the informed clinicals decisions. The proposed model achieves a substantial test accuracy of 99% on OASIS database. Moreover, the proposed approach outclasses the existing benchmark models in terms of both accuracy and computational cost. The proposed solution has the potential to serve as a smart healthcare system for detection and classification of Alzheimer’s disease at premature stages

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter provides an overview of deep learning techniques for classification of Alzheimer's disease, highlighting their importance and significance in medical image processing. It devils different machine learning techniques employed to distinguish and differentiate different classes and stages of Alzheimer's disease. This chapter also explain different stats regarding Alzheimer's disease as it is one of leading causes of death worldwide. Lastly, the chapter introduces a Deep Neural Network approach for classification of Alzheimer's diseases.

1.2 Inspiration and Background

AI has recently demonstrated promising results in medical diagnostics. These advancements play a key role in enhanced accuracy and precision [1]. The effectiveness of the treatment relies on the availability of medical data like health surveys and other reports. AI-based models have the power to visualize and analyze the complexity of medical data which is not a normal task for humans [2]. AI and deep learning techniques have contributed to detecting different brain ailments like EEG signal analysis and pattern detection. For Alzheimer's disease, accurate and early detection is crucial & important as it leads to an appropriate medical treatment.

AD is a progressive neurodegenerative disorder. According to World Alzheimer's Report 2020, over 50 million people are living with dementia. This number will be increased to 131.5 million by 2050 due to the aging population. In the US, about 5.8 million people are surviving with AD. AD mainly is the sixth leading cause of death. It leads to the destruction of cognitive processes &

cognizance. Data in Fig 1 [3] is a graphical demonstration of this. Research indicates that AD has no effective treatment. However, early detection may help in early intervention & control of the symptoms of AD.

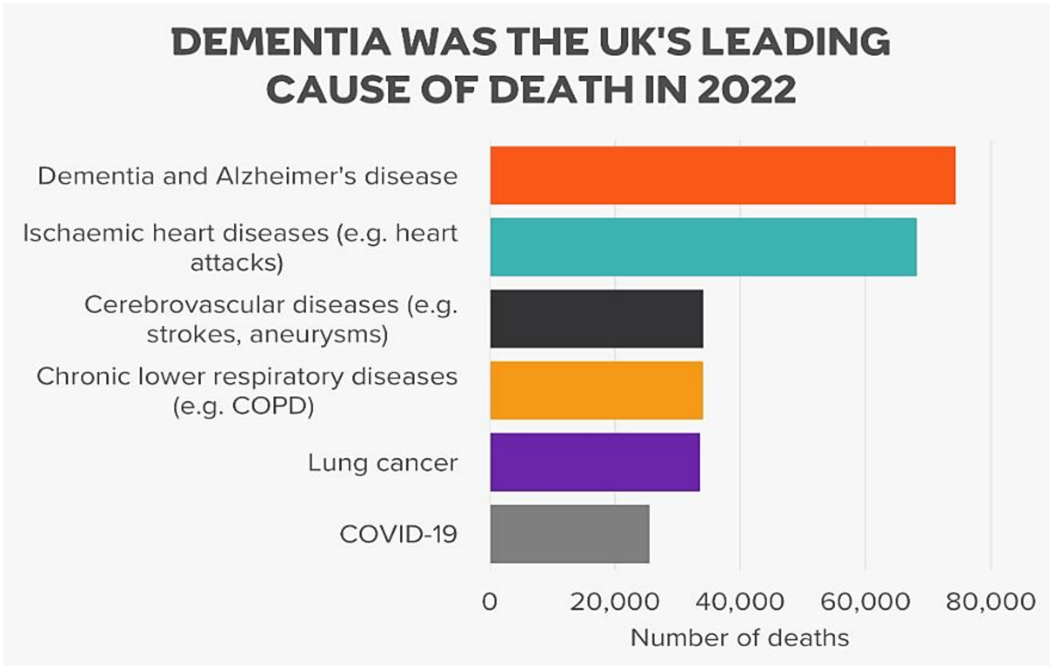


Fig 1: Alzheimer's Disease Stats

There are numerous factors for AD-like age, genetic, and medical history. It seems that age is a major risk factor for AD as its value is 5% for people between 65-74, while it increased exponentially to 50% above the age of 85 [4]. It is also observed that people having cardiac-related issues have a higher rate of AD. Biomedical assessments are used to identify different stages of AD. But this is time-consuming as well as it depends upon the expertise of a person. In recent decades, various approaches have facilitated the prediction of AD through the assessment of MRI images. These techniques yield more effective & accurate results. Research focuses on different factors like cortical thickness, grey matter density, ventricular expansion, etc. Studies show the relationship between reduced gray matter and AD, especially affecting the hippocampus in the early stages, it is shown in Fig 2**.**

There are different ML methods like SVM used for AD detection. DL methods like auto-encoders and CNN have been used for AD diagnosis [5]. However, these approaches' significant computational cost and time requirements stem from their intricate architecture. To get around these problems, we modified CNN in addition to PADAM (optimizer). This lowers the model's weight parameter and shortens the testing and validation period. Additionally, this aids in overfitting.

The goal of this research is to distinguish between AD and normal MRI pictures using a customized CNN that makes use of optimizers and X-AI. This will assist with the features and characters that are key factors of classification as well as the decrease in computation. The main aim is to create a robust and automated model that can precisely predict the AD symptomatic images.

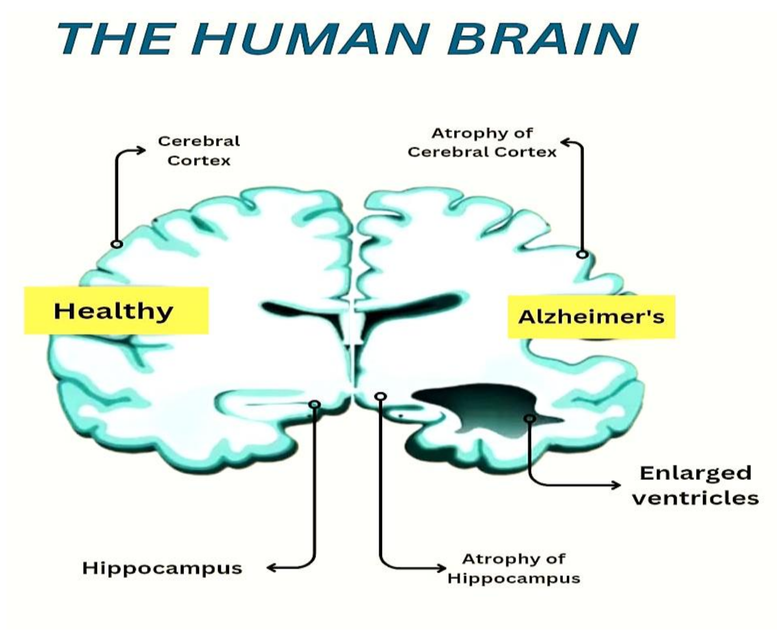


Fig 2: Human brain overview

1.3 Problem Statement

Deep learning has profoundly revolutionized various scientific disciplines in recent years. Strategies based on deep learning have consistently surpassed traditional methods, proving extraordinary efficiency in the healthcare environment. Alzheimer's disease (AD) is one of the major global public health threats due to its rapid increase and late diagnosis. Originating from complicated neuroanatomical variations, AD is caused by the accumulation of amyloid and tau proteins in the brain. Auspiciously, developments in AI techniques have facilitated the early detection/diagnosis of AD using different datasets that help in both cost & time savings. In literature, various deep learning methods have been proposed, yet these models demand significant time and computational resources due to their multifaceted structure. In this study, Padam is used to fine-tune the parameters of along with spatial attention mechanism-based CNN model to target the major contributing features for classification and also the indication of affected areas using explainable AI (X-AI). Introducing a state of art descriptive approaches, the proposed model achieves a remarkable 95% accuracy while testing and validating using the OASIS dataset. Moreover, this method transcends complicated algorithms with respect to time & cost. Its performance is assessed by different metrics including precision, recall, & F1 score.

1.4 Goals and Objectives

The primary objectives of this research work are

- To develop an enhanced and customized CNN model integrated with spatial attention mechanism to (a) Focus most Effective Regions (b) Avoid Computational Complexity (c) Classify Alzheimer’s Disease Images Accurately.

- An unexplored Partially Adaptive Momentum Estimation (PADAM) optimizer will be exploited to accelerate convergence speed for efficient classification.
- To address the problem of dead neurons and vanishing gradient problem of activation functions.
- Explainable Artificial Intelligence will be exploited for making the model's predictions interpretable and human understandable.

1.5 Thesis Organization

The chapter-wise organization of the research work is presented below.

Chapter 1 gives a conceptual summary of the entire thesis, including research gaps, statements, and definitions that explicitly outline the objectives of the study, as well as the background information and reasons for the identification of significant issues and the formulation of the research topic.

Chapter 2 discusses the benefits and drawbacks of previously proposed techniques in the literature to give a detailed overview of the work completed thus far.

Chapter 3 explains the suggested deep learning model's research process by expanding on the suggested strategy. The description of the various procedures employed in our proposed model is also included.

Chapter 4 includes hyper-constraints selection details. Moreover, it provides simulation results in terms of tables and learning curves for a detailed analogy of the proposed deep learning model with the state of art algorithms using OASIS benchmark datasets.

Chapter 5 highlights future research directions for the potential extension of a current study as well as the findings reached from the research endeavor.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter includes the basic concepts, key limitations and differences of deep learning methods specific to Alzheimer's disease classification, which describes how different scientist have used deep learning networks to classify this disease. Additionally, this chapter also includes our contributions and a summary at the end.

2.2 Algorithms for Classification of Alzheimer's Disease

The following section includes an explanation of algorithms that are used for the classification of mental disorder i.e. dementia.

Various AI-based approaches [6] are introduced for diagnosing Alzheimer's disease. In [7] the transfer Learning technique was proposed for AD classification. Researchers have utilized sagittal MRI images from benchmark datasets, i.e. ADNI & OASIS. They utilize ResNet for feature extraction from the input dataset and concatenated with age & gender characteristics. Furthermore, the SVM that was specifically trained for this problem classified the input into different labels. An accuracy of about 86.47% was reached. The study [8] has suggested innovative modifications in capsule networks for the detection of AD by using OASIS dataset. The modified Capsule Network takes the data as input and forms a parent vector by considering different features in the dataset. The suggested model was Computationally effective due to the incorporating the Squash activation function in Capsule Net. Overall, this proposed method has achieved an accuracy of 92.39%. In [9] ensemble learning technique was introduced for the classification of

AD. Authors have applied image segmentation on MRI images to isolate the brain's hippocampus region. The model was trained on these segmented images and compared with the model trained on complete images. The accuracy obtained though segmented approach outperforms the other one by achieving an accuracy of 94.1%. Gopi and Nali [10] have utilized a convolutional neural network (CNN) for the categorizing of AD on the OASIS dataset. They trained a CNN model with Adam optimizers along cross entropy as a loss operator which shows satisfactory efficiency by accomplishing the AD classification task with an accuracy score of 83.33%. In [11] a deep learning-based algorithm named as long short-term memory (LSTM) was proposed for the diagnosis of dementia. LSTM was used to create a memory component that was both for the short and long term as compared to traditional RNNs. For feature selection part Brouta algorithm based on Clinical Dementia rating CDR and mini mental status examination MMSE was exploited. The accuracy of this method was 95% on the test dataset. Abdulkareem and Ebrahim [12] have recommended two deep learning algorithms based on ResNet-50 and AlexNet for AD classification on the OASIS dataset. AlexNet with 25 layers achieves an accuracy of 92.2% while 177-layered ResNet50 reaches an accuracy of 93.1%.

In [13] Researchers have proposed a 3-way hybrid analysis using clinical and MRI images for the classification of AD. In this study to extract and classify features hybrid technique that was consisted of four algorithms AlexNet-MLP, AlexNet-NB, AlexNet-ETC, and AlexNet Adaboost. Researchers have tested these on three different datasets OASIS, ADNI, and EEG. Different accuracies such as 95.32% for OASIS by using AlexNet-ETC, 97.7% for ADNI, using AlexNet-MLP, and 92.5% for EEG using AlexNet-MLP have been achieved. Island and Zhang [14] have proposed an ensemble learning technique for the categorization of AD. In this research, their proposed model was also able to predict different stages of AD. Three different convolutional networks with different configurations were used which include convolution, batch normalization, Relu, and pooling. An accuracy of 93% was achieved. Residual-based multistage deep learning architecture was proposed by Hassan and Shin. [15]. This model comprised five stages for feature enhancement while maintaining model depth. To reduce overfitting, they used deep learning-based feature selection techniques as well. This model was tested on Three different datasets ADNI, OASIS, and MIRAID. Accuracy rates of 99.46. 99.7 and 99.1% respectively was achieved.

In [16] a 2D convolutional network was proposed for the detection of AD. In this method, the model has learned various features from brain images. Two transfer learning architectures Inception Vision 3 and Xception for feature learning along with separable CNNs were developed for AD diagnosis task. Overall, 93% accuracy was achieved by fivefold cross-validation. Moreover, Atif and Moazzam [17] have designed a deep Siamese CNN (SCNN) for the detection and classification of AD. This model was inspired by VGG16 and OASIS dataset was used for testing and training purposes. A test accuracy of 98% was attained in this study. Additionally, researchers have also suggested a transfer learning-based approach for early detection and diagnosis of different stages of AD [18]. AlexNEt was Alex Net pre-trained on segmented and non-segmented images. The progress of the recommended model was evaluated on the OASIS dataset with an accuracy of 92.85%.

Table 1: Summarized Literature Review

Study	**Methodology**	**Dataset**	**Accuracy**	**Key Findings**
Sarraf & Tofighi (2016)	Transfer Learning (ResNet + SVM)	ADNI, OASIS	86.47%	ResNet for feature extraction, concatenated with age & gender, classified with SVM.
Hinton et al. (2018)	Modified Capsule Network	OASIS	92.39%	Squash activation function improved computational efficiency.
Liu et al. (2019)	Ensemble Learning (Image Segmentation)	MRI Images	94.1%	Segmented hippocampus region outperformed full-image approach.

Gopi & Nali (2020)	CNN (Adam optimizer, Cross-Entropy)	OASIS	83.33%	CNN with Adam optimizer achieved satisfactory performance.
Zhang et al. (2021)	LSTM + Brouta Algorithm	CDR, MMSE	95%	Memory component improved short- and long-term feature learning.
Abdulkareem & Ebrahim (2021)	Deep Learning (ResNet-50 & AlexNet)	OASIS	92.2% (AlexNet), 93.1% (ResNet-50)	AlexNet (25 layers) and ResNet-50 (177 layers) tested.
Lee et al. (2022)	3-Way Hybrid (AlexNet-MLP, AlexNet-NB, AlexNet-ETC, AlexNet-Adaboost)	OASIS, ADNI, EEG	95.32% (OASIS), 97.7% (ADNI), 92.5% (EEG)	Hybrid approach using clinical and MRI images.
Island & Zhang (2022)	Ensemble Learning (3 CNN Variants)	-	93%	Predicted different AD stages using CNN variations.
Hassan & Shin (2022)	Residual-Based Multistage Deep Learning	ADNI, OASIS, MIRAID	99.46% (ADNI), 99.7% (OASIS), 99.1% (MIRAID)	Deep learning-based feature selection and five-stage architecture reduced overfitting.
Kim et al. (2023)	2D CNN + Transfer Learning (Inception Vision 3, Xception)	Brain Images	93%	Fivefold cross-validation approach.
Atif & Moazzam (2023)	Deep Siamese CNN (SCNN)	OASIS	98%	SCNN model inspired by VGG16 for AD classification.
Patel et al. (2023)	Transfer Learning (AlexNet on Segmented & Non-Segmented Images)	OASIS	92.85%	Evaluated early detection performance using segmented images.

2.3 Our Work

The rise of deep learning in the medical industry has significant and lasting influence on detection and classification of different diseases. In the medical sector the understanding of complex structures of medical images and prediction of disease is always challenging. To overcome this, researchers are working in this area of research. The early detection of Alzheimer’s disease is necessary so patients can get enough medical treatment to get rid of this early. Thus, designing a deep learning algorithm for classification of Alzheimer's disease will help medical experts for their decisions.

Some noticeable features of the proposed study are stated as follows:

- The transformer-inspired spatial attention mechanism integrated with compact CNN framework is suggested to produce an accurate and efficient solution for Alzheimer's disease diagnosis
- A non-linear activation function named Gompertz Linear Unit (GLU) is exploited in the proposed network for capturing complex relationship in the given data and to overcome the issues of dead neuron and vanishing gradient faced in existing activation operations.
- The Partially adaptive variant of Adam optimizer (Padam) is utilized in this study, to address the challenges of the over adaptiveness in existing techniques. Moreover, the incorporation of Padam provides flexibility to fine-tune the model as needed which improves the performance in terms of accuracy and speedy convergence.
- Explainable Artificial Intelligence (XAI) is exploited to produce an interpretable diagnostic insight which will be valuable for healthcare professionals to make the informed clinicals decisions.

2.4 Summary

This chapter has described the basic concepts and literature review of Deep learning algorithms along with their limitations. The next Chapter provides the detailed description of the proposed methodology and Auto-encoders.

CHAPTER 3

PROPOSED METHODOLOGY

3.1 Introduction

This portion delves with a general summary of the proposed partially adaptive optimization driven spatial focused CNN with Gompertz non-linearity for interpretable Alzheimer's disease diagnosis. It includes detailed overview of proposed methodology containing simulation environment, dataset description, proposed CNN model, local interpretable model-agnostic explanation, Padam and Gompertz Linear Unit. Fig 3 displays the overall methodology for the proposed research.

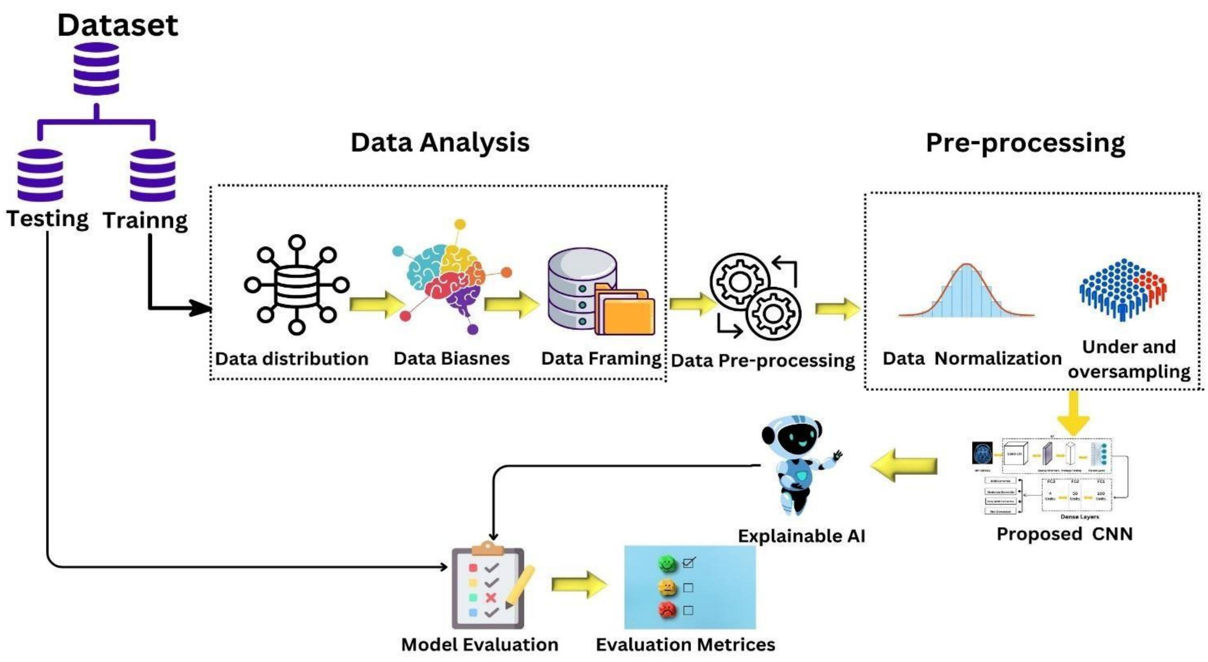


Fig 3: General Work-flow of the Proposed Study

3.2 Database Description

An OASIS database [19] is utilized consisting of more than 80000 MRI (brain) images of the people effected and not effected by the Alzheimer's disease. The dataset contains four classes of brain MRI images such as very mildly demented (VMD) containing 13.7k images with high degree of AD, moderately demented (MOD) containing 488 images with initial stage AD, mildly demented (MID) involving 5002 images with more severe AD, and non-demented (NOD) comprising of 67.2k images without AD. To improve the performance of the model, necessary preprocessing steps such as data balancing and data normalization were performed. Training, validation and testing are done by splitting the dataset in the ratio of 85:10:10 respectively.

3.3 Proposed Model

Convolutional Neural Networks (CNNs) are being widely used in computer vision problems for feature identification and extraction in images. Recently, due to their outstanding accomplishments in dimension reduction and extraction of attributes, CNNs are extensively used in imagery in healthcare problems. This research suggested a customized CNN architecture for Alzheimer's disease diagnosis. The general block schematic for the suggested architecture is in Fig 4**.** The architecture comprises three blocks. The firsttwo blocks consist of two convolutional layers with Gompertz non-linear activation function to reduce parameters complexityand increase training speed. Additionally, spatial attention mechanism is exploited within CNN model to focus on specific features for enhanced prediction. The final block includes a flatten layer that alters the 3D feature map to 1D. Then this is followed by a fully connected dense layer and two further dense layers along with a Gompertz non-linear activation function for the classification of Alzheimer's patients and normal ones. The detailed architecture of the proposed model is shown in Table 1.

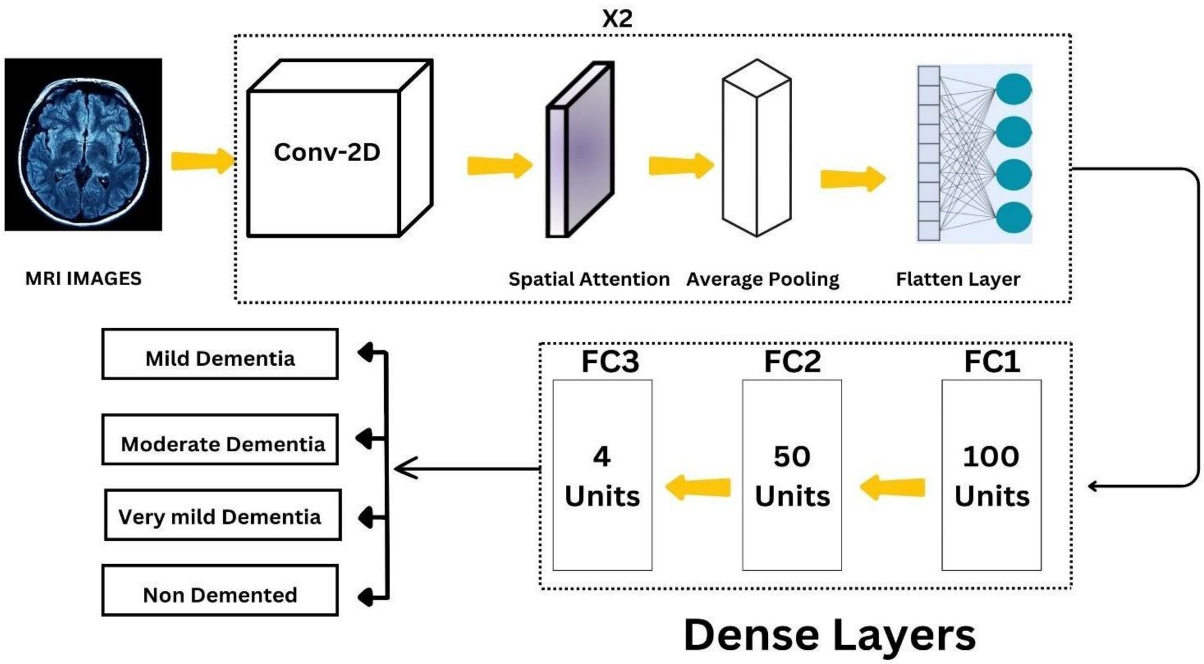


Fig 4: Block Diagram of the Proposed Spatial Focused CNN Model

3.4 Spatial Attention

The CNN model has been exploited with a special attention mechanism [20] that helps in complexity reduction and also enhances the value of major contributing factors in the classification. The layered representation of the incorporated mechanism is shown in Fig 5. This attention mechanism has enhanced the accuracy of the model as well. By ensuring the

utilization of interrelationships between different features a spatial attention map is created. In contrast with channel attention, spatial attention only concentrates on the informative part where this is located. We initially perform max pooling that will result in an output of effective feature descriptor before the computation of spatial attention. This pooling technique effectively highlights informative regions. The input tensor block relates to a specific input image given to the module. There is a Conv2D layer that is also known as the attention block is responsible for the calculation of attention weights. There are trainable parameters in this module which implies that there is automatic adjustment of different parameters like weight and biases. Additionally, attention weights that have been calculated match the significance of every region, and then element-wise multiplication between input and attention weights is carried out to get weighted output. This weighted output refers to the original input after channel-wise attention mechanism operation, where sections with prominent features within provided images are given spatial attention weights. This model benefits from spatial attention when it comes to focusing on comprehensive information, giving task-relevant critical position information a higher weight, and reducing the importance of irrelevant noise information. By highlighting the channel that is most important for the given prediction, it provides insightful information about the process by which the suggested model make decisions.

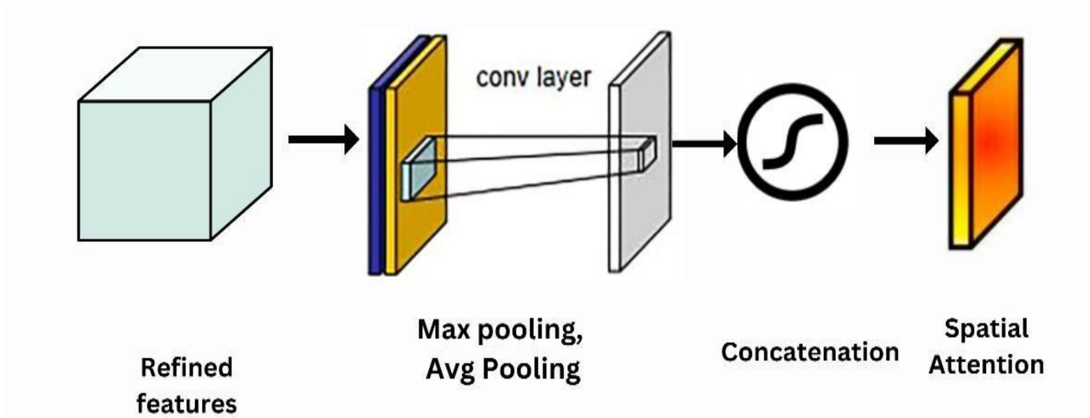


Fig 5: Layered Representation of Spatial Attention

3.5 Gompertz Non-Linearity (GNL)

In this study, we have introduced an unexplored activation function in the proposed CNN model which is inspired by a mathematical model named as 'Gompertz Function (GF)' mainly utilize [21] to elaborate the progression the process. GNL is designed to offer a mix of linear and non-linear transformations [22]in the deep neural network for capturing latent feature characteristic in the complex data like medical imaging. The mathematical expression for Gompertz function is given below, which results in a curve similar to sigmoid:

Where γ refers to the growth rate and μ is the point of inflection. However, the above expression

$$g(i) = e^{-e^{-\gamma(i-\mu)}} \tag{1}$$

is further modified for simplified computations and making it compatible with the neural activations. The scaled sigmoid transformation is exploited to leverage the capabilities of Gompertz function into a neural activation.

$$GNL(i) = i.\,\sigma(\mu.\,i + \alpha) \tag{2}$$

Where i is the input, σ () refers to the sigmoid operation, μ and α are the learnable parameters which will be automatically adjusted during the training of deep network. The dot product of an input i and a non-linear sigmoid term permits the deep model to scale the operations on the basis of learnable parameters for making a smoother balance between linear and non-linear activation operation in the deep neural networks.

3.6 Partially Adaptive Moment Estimation (Padam)

Padam an evolved version of Adam [23], designed to improve the balance between convergence and generalization of the optimizer. It introduces a new factor p, which adjusts the adaptivity level in the optimization technique. The pseudo code and mathematical basis behind the proposed partially adaptive moment estimation (Padam) are detailed in **Algo-1**.

Algo-1: Padam - Pseudo Code-based Mathematical Intuition

Input:

Preliminary point: $\omega_1 \in Z$, momentum terms: $\beta_{1t}, \beta_2,$ partially adaptive term: $\rho \in [0,1]$,step size: s_t

To begin with, $m_0 = 0, e_0 = 0, \hat{e}_0 = 0$

For t = 1..........., T

$c_t = \nabla h_t(\omega_t)$

$m_t = \beta_{1t} m_{t-1} + (1 - \beta_{1t})c_t$

$e_t = \beta_2 e_{t-1} + (1 - \beta_2)c_t^2$

$\hat{e}_t = \max(\hat{e}_{t-1}, e_t)$

$\omega_{t+1} = \pi_Z, diag(\hat{e}_t^{\rho})(\omega_t - s_t . n_t / \hat{e}_t^{\rho})$

end

Table 2: Architecture Parameters of Proposed Model

Layer (type)	Output-Shape	Parameters
Conv-2D	(None,126,126,200)	5602
Spatial attention	(None,126,126,200)	19
Average_pooling-2D	(None,63,63,200)	0
Conv-2D-2	(None,61,61,100)	180102
Spatial_attention-1	(None,61,61,100)	19
Average_pooling-2D_1	(None,30,30,100)	0
Flatten	(None,90000)	0
Dense	(None,100)	9000102
Dense-1	(None,50)	5052
Dense-2	(None,4)	204
Total-params: 9191049 (35.06 MB) **Trainable-params**: 9191049 (35.06 MB) **Non-trainable-params**: 0 (0.00 B)		

In Algo-1 c_t is the resultant stochastic gradient, and $\hat{e}_t$ is the moving average of 2nd degree momentum for the computed stochastic gradient. The main difference between Algo-1 and regular Adam [23] is the insertion of the "partially adaptive term (ρ) " by the second-degree momentum.

$$\omega_{t+1} = \omega_t - s_t \frac{n_t}{\hat{e}_t^{\rho}}, \tag{3}$$

where $\hat{e}_t = \max(\hat{e}_{t-1}, \hat{e}_t)$

Padam modifies the basic Adam optimizer by adjusting the second momentum studied in adaptive learning rate. The general updating rules for both regular Adam and suggested Padam are listed below:

$$\omega_{t+1} = \omega_t - \sigma . \frac{m_t}{\sqrt{\hat{e}_t + \varepsilon}} \quad \text{(Adam)} \tag{4}$$

Where, m_t and e_t are 1st and 2nd order momentum estimate, σ is learning rate (LR) and ε is constant term.

$$\omega_{t+1} = \omega_t - \sigma . \frac{n_t}{\sqrt{\hat{e}_t^{\rho} + \varepsilon}} \quad \text{(Padam)} \tag{5}$$

In Eq (5), $\hat{e}_t$ is raised to the power of ρ (0≤ρ≤1), making the learning rate somewhat adaptive. Eq (4) employs $\sqrt{\hat{e}_t}$ for flexible learning rate, which sometimes results in poor generalization outcomes. Padam offers a partially adjustable term (ρ) to tune the supremacy of $\hat{e}_t$. This addition can reduce the adaptiveness of learning trends while improving generalization features. Padam proposes bridge the convergence-generalization gap using adaptive control. Exploration of partially adaptive terms (ρ) allows for a more supervised convergence method, avoiding excessive adaptiveness, which can impede convergence. For the Tensorflow implementation of the recommended Padam, we essentially change the conventional Adam optimizer's update_step. Algo-2 presents the TensorFlow-like pseudocode for the suggested Padam.

Algo-2: Padam – TensorFlow code-like pseudocode

Import TensorFlow as tf
# define the custom Padam class which inherits the tensorflow optimizer class 	
Class Padam(tf.keras.optimizers.Optimizer)
    # Initialize the hyperparameters for optimizer class
    def__ init__ (self, learning_rate=0.01, beta1=0.9, beta2=0.999, epsilon=1e^-9, $\rho = 0.125$):
    …..
    # make slots for 1st moment (n), 2nd moment (e) and max 2nd moment (ecap)
    def_create_slots(self, variable_list):
    …..
    # For computational Compatibility with tensorflow convert specified parameters to tensors
    def_prepare(self):
    …..
    # update-rule
    def_apply_dense(self, gradient, variable):
    …..
    # obtain bias corrected LR
    LR= self._LR*sqrt(1-beta2_power)/(1-beta1_power)
    …..
    # modify 1st moment approximation

```
n_t=beta1*n + (1-beta1)*gradient

…..

# modify 2nd moment approximation

e_t= beta2*e + (1-beta2) *(gradient*gradient)

…..

#Modify maximum 2nd moment approximation

ecap_t=max (e_t, ecap)

…..

# Utilize update-rule

variable_update= variable – LR*n_t / (ecap_t^ ρ +epsilon)

…..

return variable_update

…..

# to hold sparse gradient

def_apply_sparse(self, gradient, variable):

…..

# Modify power accumulators

def_finish (self, modified_ops, name_scope):

…..

# compilation

model= Padam(learning_rate=0.005, ρ = 0.225)

end
```

3.7 Convergence Evaluation of Partially Adaptive Moment Estimation (Padam)

This section goes into the convergence analysis of the suggested Padam optimizer in an online optimization context [24]. The primary goal is to lower the aggregated objective value for a set of loss operators $h_1, h_2, \dots \dots, h_T$.. Furthermore, the Padam optimization technique computes a point $\omega_1 \in Z$, where Z represents the reachable group for each step time t. Beyond this, a loss operator g_t is formed, and the technique incurs loss of $g_t(\omega_t)$.. Assuming ω^* as the optimal outcome, the aggregated objective operator is:

$$\omega^* \in argmin_{\omega \in Z} \sum_{t=1}^{T} h_t(\omega) \tag{6}$$

In this case, Z is an achievable group for every step t. The regret approach is also used to evaluate the proposed strategy. It measures the number of previous loss values $h_t(\omega_t)$in relation to the optimal parameter $\omega^*$from the achievable group (Z). The following is a summary of the regret approach:

$$K_T = \sum_{t=1}^{T} (\, h_t(\omega_t) - h_t(\omega^*)) \tag{7}$$

From the above equation (36), the main aim is to predict ω_t and reduce overall regret (K_T). The analysis is performed with convex loss functions along certain assumptions.

Assumption-Each $h_t(\omega)$ are convex operators on Z for $0 \leq t \leq T$ with each a, b ∈ Z.

$$h_t(b) \geq h_t(a) + \nabla h_t(a)^T (b - a) \tag{8}$$

This presumption serves as a benchmark for online optimization-learning and is also used by standard optimizers like Adam[24] and Adagrad [25]. Under above assumption, if convex attainable group Z has bounded span i.e., $||\omega - \omega^{*}||_{\infty} \leq E_{\infty}$ for each $\omega \in$ Z, and h_t has confined gradients like $||\nabla h_t(\omega)||_{\infty} \leq L_{\infty}$ for each $\omega \in$ Z, $1 \leq t \leq T$. Moreover, assuming $s_t = \frac{s}{\sqrt{t}}$, $\beta_{1t} = \beta_1 \gamma^{t-1}$, where $\gamma \in [0,1]$ and $0 \leq \beta_{1,}\beta_2 \leq 1$, $\rho \in [0,1]$, the regret approach for Algo-1 will be:

$$K_t \leq \frac{{E_{\infty}}^2}{2\beta(1-\beta_1)} \sum_{i=1}^{d} \sqrt{T} \, . \, \hat{e}_{T,i}^{\rho} + \frac{s{L_{\infty}}^{(1-2\rho)}\sqrt{1+logT}}{(1-\beta_1)^2(1-\Omega)(1-\beta_2)^{\rho}} \sum_{i=1}^{d} \left|\left|c_1 : T, i\right|\right|_2 + \frac{\beta_1 d {E_{\infty}}^2 {L_{\infty}}^{(2\rho)}}{2s(1-\beta_1)(1-\gamma)^2} \tag{9}$$

Where $\Omega = \frac{\beta_1}{\sqrt{\beta_2}} < 1$. Similar to Adam [4], the aforementioned discussion demonstrates that partially adaptive moment estimation (Padam) regrets are significantly better than current online gradient descent techniques. Additionally, it is shown that despite the limited moment delay $\beta_{1t} = \alpha_1/t$, the regret bound still remain same. For each $T \geq 1$, the regret operation for Padam fulfills $K_T = O^{\sim}(\sqrt{T})$, which shows that Padam converges to ideal outcome when loss functions are convex as given by $lim_{T\to\infty} K_t/T \to 0$. This detailed discussion concluded with a fact that the suggested Padam optimizer resulted a regret operations of $O^{\sim}(\sqrt{T})$, which is the optimal known parameter for any convex learning problem.

3.8 Local Interpretable Model-Agnostic Explanation (LIME):

In the healthcare sector, the accountability of the solution is crucial for fostering confidence in AI-based analytical tools. Thisis why the application of explainable AI to transparent, approachable, and user-friendly solutions is utilized for comprehensible Alzheimer's disease categorization. As the complexity of algorithms increases, XAI [26] is needed for critical identification, especially in the field of medical imaging. This can help medical experts understand the model and then predict different patterns and diseases. Various XAI methods, such as gradient weighting class activation mapping (Grad-CAM), local interpretable model-agnostic explanation (LIME), and Shapley adaptive explanation (SHAP), exist, which illustrate promisingresults in explaining the conclusive behavior of the AI-based models. However, we have utilized LIME [27] for the interpretability of our solution. LIME selects a particular case that demands elaboration. To create a collection of comparable but marginally different examples, this instance is disrupted. The predictions of the complicated model are then obtained for this modified dataset. The third phase involves training a more easy-to-understand interpretable model like a decision tree on the perturbed occurrences and the predictions that go along with them. It teaches how the model works by weighing different features and inputs [28]. In the area of the selected instance, this interpretable model serves as a substitute for the complex model. Finally, the original forecast is explained in a way that is understandable by humans using the coefficients of the interpretable model to describe the contribution of various aspects. The LIME [29] technique essentially provides important insights into the decision logic of deep learning algorithms by bridging the gap between interpretation and complicated models.The graphic diagram of LIME-based explainable AI is given in Fig 6.

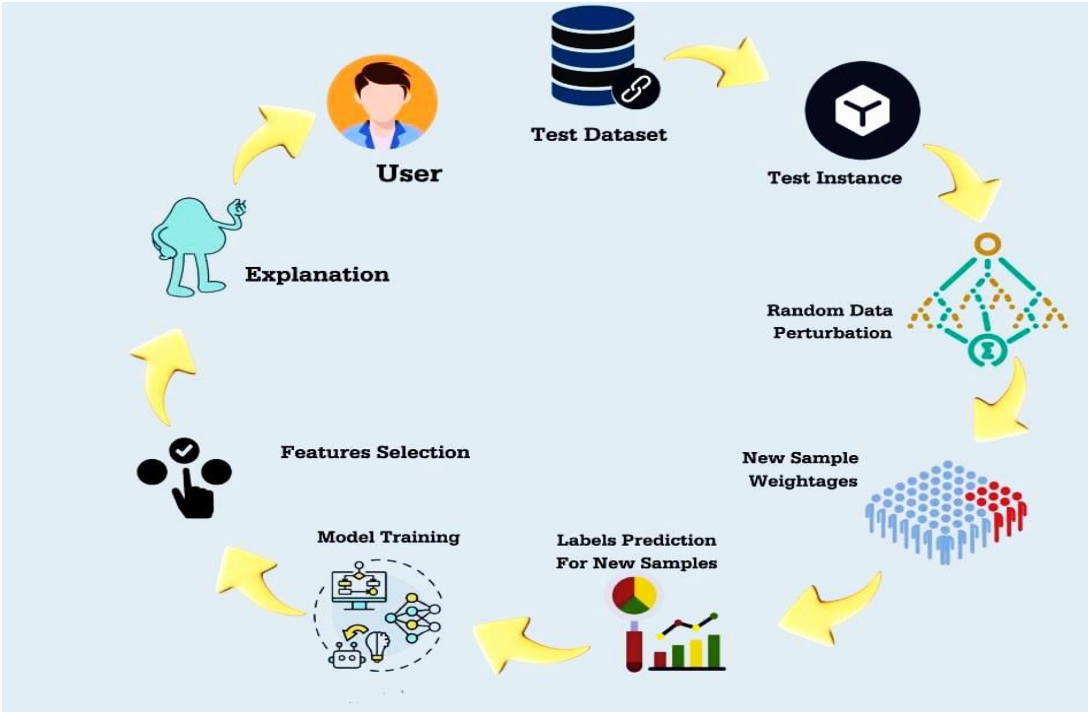


Fig 6: Working Process of LIME for Interpretable Predictions

3.9 Summary

This chapter has described the proposed methodology of research. The description of different terminologies and dataset has been discussed. The next chapter will briefly explain the results and simulations of the proposed architecture.

CHAPTER 4

SIMULATIONS AND ANALYSES

4.1 Introduction

This portion of the research assessment explains the implementation of the suggested customized CNN architecture along with the spatial attention mechanism for the identifying and categorizing of Alzheimer's disease on the benchmark OASIS database. Following comprehensive hyperparameter adapting, the suggested model is implemented with ideal parameters which contain the range of learning rate (LR) and partial adaptivity (**p**) values of the Padam optimizer i.e. trade-off between robustness and simplicity. All the possible variations were carried out to fine-tune the hyperparameters. Three case studies that represent various modifications and variations in optimization methodologies to get the best forecast feasible for the given assignment make up the overall result part.

4.2 Simulations and Results

This section includes subsections like data manipulation, datasets particulars, simulation description, simulation setting, ranking-based evaluation metrics, results and discussion and detailed analysis.

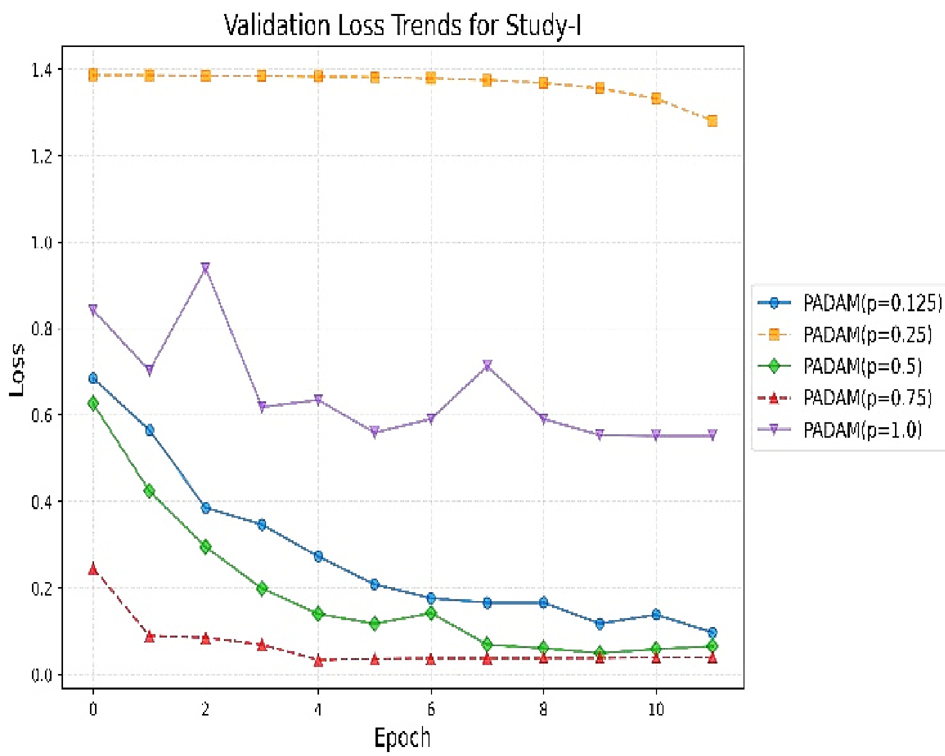
4.2.1 Study-I (With LR =0.00001 and p = (0.125 to 1)):

To begin with, the proposed model is executed with a partial adaptive (Padam) optimizer. The value of partial adaptivity p varies from 0.125 to 1 with a difference of 0.25. The learning rate for this case study was 0.00001. For this learning rate, the model has been evaluated with different performance parameters like accuracy, F1-Score, etc. The overall performance of various p values with a learning rate of 0.00001 can be evaluated from Table 2. It can be seen that at p =0.25 model performancewas worst with the lowest accuracy of about 39%, while the model performed well at p=0.75 and reached an accuracy of 99%. The learning behaviors of the proposed model associated with variations of study-I can be seen in Fig 7(a) & 7(b). It is concluded from the study-I, that with a learning rate of 0.0001, the proposed model shows best assessment outcomes on p=0.75 which can be illustrated by the mean of confusion matrix shown in Fig 7 (c).

Table 3: Performance Evaluation of the Proposed Model with LR=0.00001 ((Precision as PR, Recall as RE, F1-Score as FS, Loss as LS and Accuracy as AC (%))

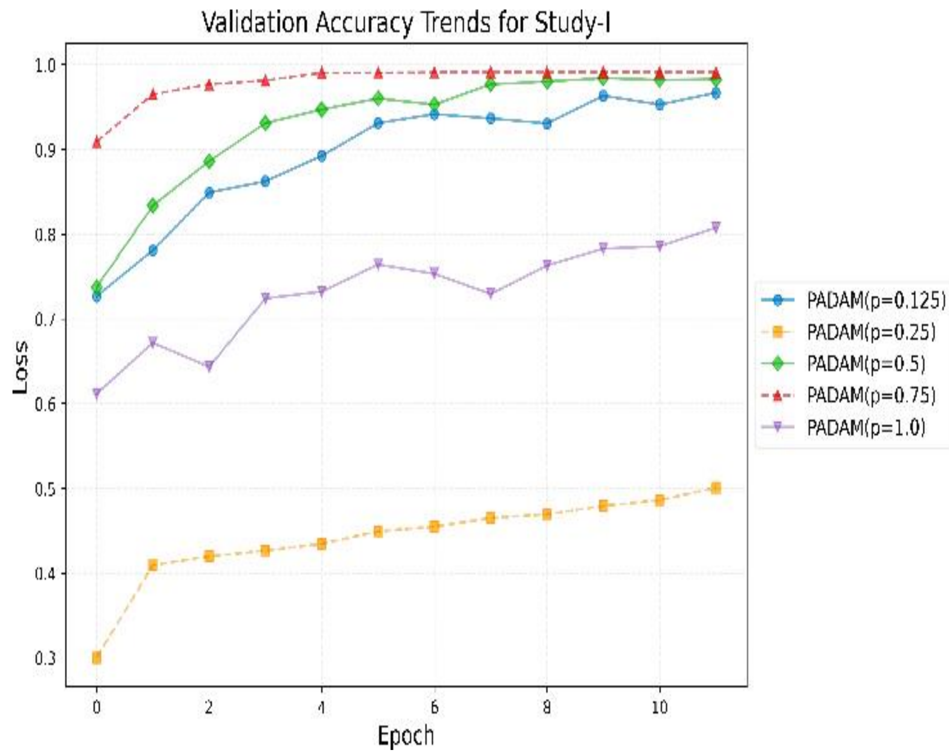
Optimizer	**Labels**	**Training Set**					**Validation Set**					**Testing Set**				
		PR	**RE**	**FS**	**LS**	**AC**	**PR**	**RE**	**FS**	**LS**	**AC**	**PR**	**RE**	**FS**	**LS**	**AC**
Padam (p=0.125)	Non-Demented	0.96	0.98	0.97	0.06	0.98	0.93	0.95	0.94	0.09	0.96	0.91	0.96	0.94	0.09	0.96
	Very Mild Demented	0.98	0.96	0.97			0.97	0.92	0.94			0.97	0.91	0.94		
	Mild Demented	0.99	1.00	1.00			0.98	1.00	0.99			0.98	0.99	0.99		
	Moderate Demented	1.00	1.00	1.00			1.00	1.00	1.00			0.99	1.00	0.99		
Padam (p=0.25)	Non-Demented	0.49	0.44	0.46	1.27	0.51	0.46	0.42	0.44	1.28	0.50	0.48	0.43	0.46	1.31	0.39
	Very Mild Demented	0.43	0.19	0.26			0.47	0.21	0.28			0.50	0.19	0.27		
	Mild Demented	0.47	0.47	0.47			0.46	0.46	0.46			0.46	0.46	0.46		
	Moderate Demented	0.57	0.93	0.71			0.56	0.94	0.70			0.17	0.96	0.29		
Padam (p=0.5)	Non-Demented	0.99	1.00	1.00	0.01	0.99	0.97	0.96	0.97	0.06	0.98	0.98	0.97	0.97	0.07	0.98
	Very Mild Demented	1.00	1.00	1.00			0.97	0.98	0.98			0.97	0.99	0.98		
	Mild Demented	1.00	0.99	1.00			0.99	0.99	0.99			1.00	0.99	0.99		
	Moderate Demented	1.00	1.00	1.00			1.00	1.00	1.00			0.97	1.00	0.98		
Padam (p=0.75)	Non-Demented	1.00	1.00	1.00	0.00	1.00	0.99	0.97	0.98	0.03	0.99	0.99	0.98	0.99	0.03	0.99
	Very Mild Demented	1.00	1.00	1.00			0.98	0.99	0.98			0.99	0.99	0.99		
	Mild Demented	1.00	1.00	1.00			1.00	1.00	1.00			1.00	1.00	1.00		

	Moderate Demented	1.00	1.00	1.00			1.00	1.00	1.00			0.99	1.00	0.99		
Padam (p=1.0)	Non-Demented	0.90	0.90	0.90	0.16	0.94	0.69	0.66	0.68	0.55	0.80	0.66	0.69	0.67	0.58	0.72
	Very Mild Demented	0.91	0.89	0.90			0.70	0.66	0.68			0.66	0.66	0.66		
	Mild Demented	0.96	0.97	0.97			0.84	0.91	0.88			0.82	0.78	0.80		
	Moderate Demented	1.00	1.00	1.00			0.99	1.00	1.00			0.89	0.90	0.89		

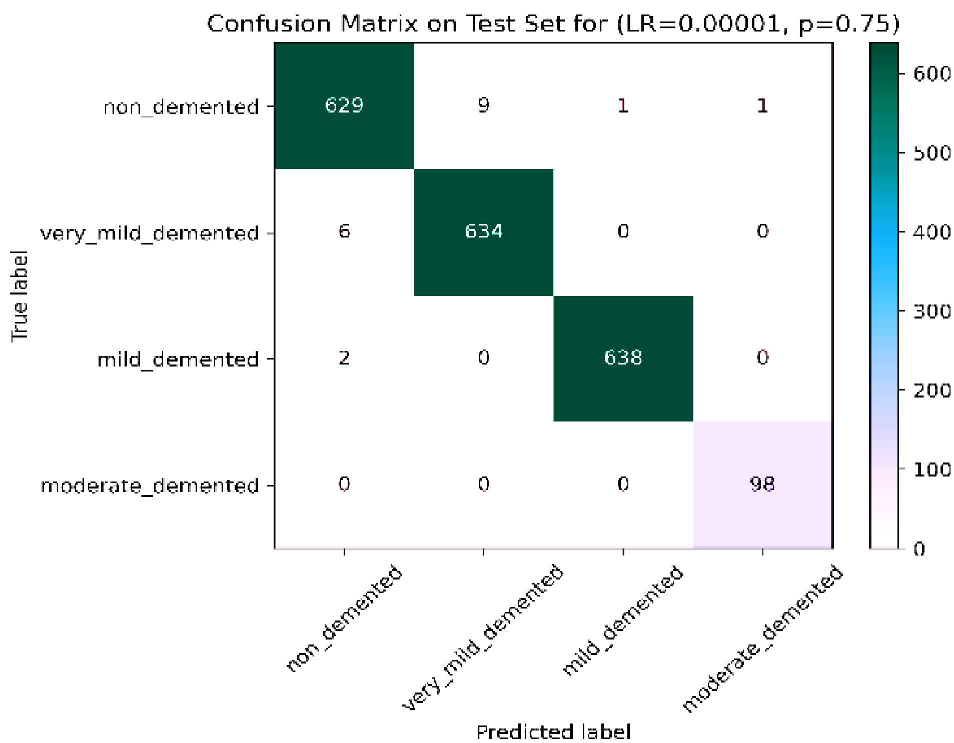


(a)

Fig 7: Performance Evaluation of Proposed Model in Study-I (continue)



(b)



(c)

Fig 7: Performance Evaluation of Proposed Model in Study-I

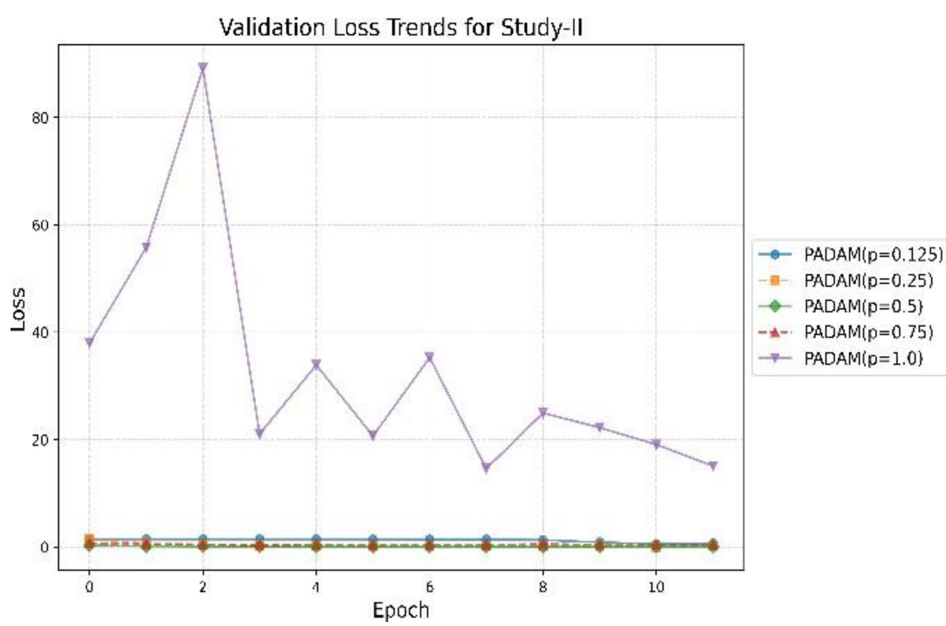
4.2.2 Study-II (With LR =0.0001 and p = (0.125 to 1)):

The learning rate was increased to 0.0001 for evaluating the accuracy level of the model. This study with a higher learning ratefrom the previous case has been studied and assessed with different values of partial adaptivity p. After the implementation ofvarying p values the model has shown the lowest accuracy with a p-value of 1, and the model has achieved an accuracy of 59%.Conversely, the model performance was extraordinary at p=0.5 with the highest accuracy of 99%. The performance of the proposed model with variations of study-II is given in Table 3**.** The learning behaviors of the recommended model associated withdeviations of study-II can be seen in Fig 8(a) & 8(b). It is concluded from the study-I, that with learning rate of 0.0001, the proposed architecture shows best classification performance on p=0.5 which can be verified by means of confusion matrix shown in Fig 8(c).

Table 4: Performance Evaluation of the Proposed Model with LR=0.0001 ((Precision as PR, Recall as RE, F1-Score as FS, Loss as LS and Accuracy as AC (%))

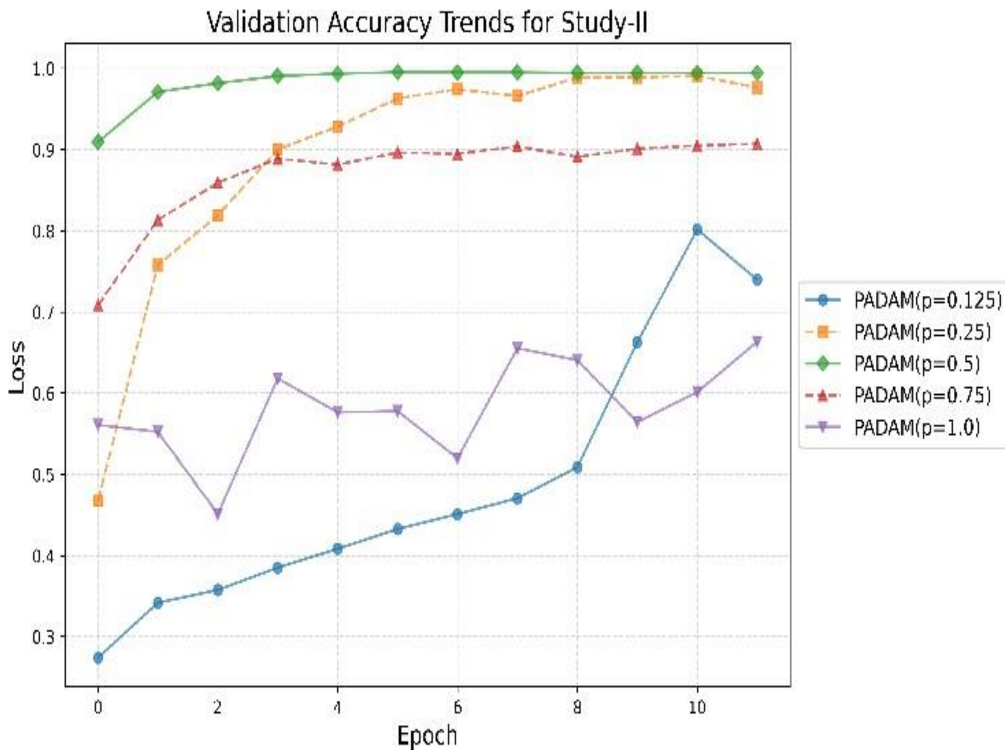
Optimizer	Labels	Training Set					Validation Set					Testing Set				
		PR	RE	FS	LS	AC	PR	RE	FS	LS	AC	PR	RE	FS	LS	AC
Padam (p=0.125)	Non-Demented	0.81	0.64	0.72	0.56	0.76	0.77	0.59	0.67	0.59	0.73	0.80	0.63	0.71	0.60	0.70
	Very Mild Demented	0.79	0.44	0.56			0.77	0.42	0.54			0.80	0.43	0.56		
	Mild Demented	0.59	0.97	0.74			0.57	0.96	0.72			0.59	0.97	0.74		
	Moderate Demented	0.98	1.00	0.99			0.98	1.00	0.99			0.88	1.00	0.93		
Padam (p=0.25)	Non-Demented	1.00	0.96	0.98	0.03	0.98	0.99	0.93	0.96	0.08	0.97	0.99	0.93	0.96	0.08	0.97
	Very Mild Demented	0.98	1.00	0.99			0.95	0.98	0.97			0.96	0.98	0.97		
	Mild Demented	0.99	1.00	0.99			0.97	0.99	0.98			0.97	1.00	0.98		

	Moderate Demented	1.00	1.00	1.00			1.00	1.00	1.00			0.96	1.00	0.98		
Padam (p=0.50)	Non-Demented	1.00	1.00	1.00	0.00	1.00	0.99	0.99	0.99	0.02	0.99	0.99	0.98	0.98	0.02	0.99
	Very Mild Demented	1.00	1.00	1.00			0.99	0.99	0.99			0.98	0.99	0.99		
	Mild Demented	1.00	1.00	1.00			1.00	1.00	1.00			1.00	1.00	1.00		
	Moderate Demented	1.00	1.00	1.00			1.00	1.00	1.00			1.00	1.00	1.00		
Padam (p=0.75)	Non-Demented	1.00	1.00	1.00	0.01	0.99	0.83	0.83	0.83	0.39	0.90	0.82	0.81	0.82	0.40	0.86
	Very Mild Demented	1.00	1.00	1.00			0.85	0.83	0.84			0.83	0.85	0.84		
	Mild Demented	1.00	1.00	1.00			0.95	0.97	0.96			0.93	0.91	0.92		
	Moderate Demented	1.00	1.00	1.00			0.99	1.00	1.00			0.98	0.95	0.96		
Padam (p=1.00)	Non-Demented	0.60	0.55	0.57	12.9	0.68	0.55	0.51	0.53	15.1	0.66	0.60	0.54	0.57	16.1	0.59
	Very Mild Demented	0.50	0.73	0.59			0.49	0.71	0.58			0.48	0.71	0.58		
	Mild Demented	0.85	0.47	0.60			0.82	0.44	0.57			0.83	0.43	0.57		
	Moderate Demented	0.93	1.00	0.97			0.92	1.00	0.96			0.63	1.00	0.77		

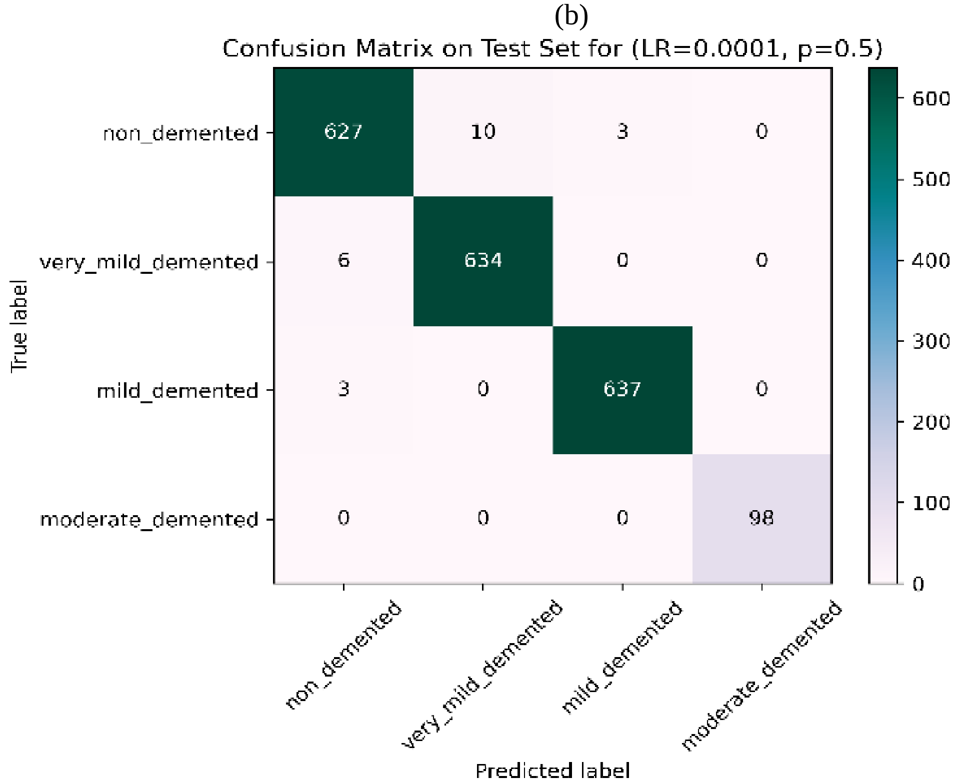


(a)

Fig 8: Performance Evaluation of Proposed Model in Study-II (continue)



(b)



(c)

Fig 8: Performance Evaluation of Proposed Model in Study-II

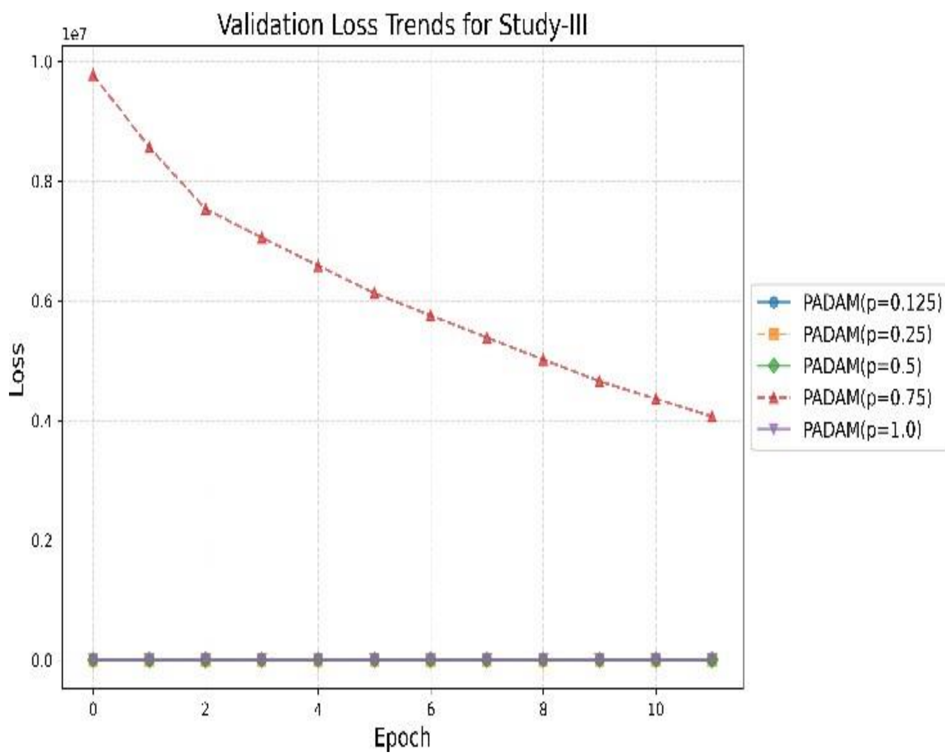
4.2.3 Study-III (With LR =0.001 and p =0.125 to 1):

The learning rate was further increased to 0.001 and the model has been trained and validated on various values of p. The model performance with this learning rate was best in all of the cases under this study. The overall model has shown a poor performance with an accuracy of 59% while using a value of p=1. However, the model achieved the highest accuracy of 99.35% when it was trained and tested with p=0.25. The model's overall behavior and performance are shown in the Table 4. The learning behaviors of the proposed model associated with variations of study-III can be seen in Fig 9(a) & 9(b). It is concluded from the study-I, that with learning rate of 0.0001, the suggested model shows best categorization performance on p=0.25 which can be illustrated using the provided confusion matrix. shown in Fig 9(c).

Table 5: Performance Evaluation of the Proposed Model with LR=0.001 ((Precision as PR, Recall as RE, F1-Score as FS, Loss as LS and Accuracy as AC (%)).

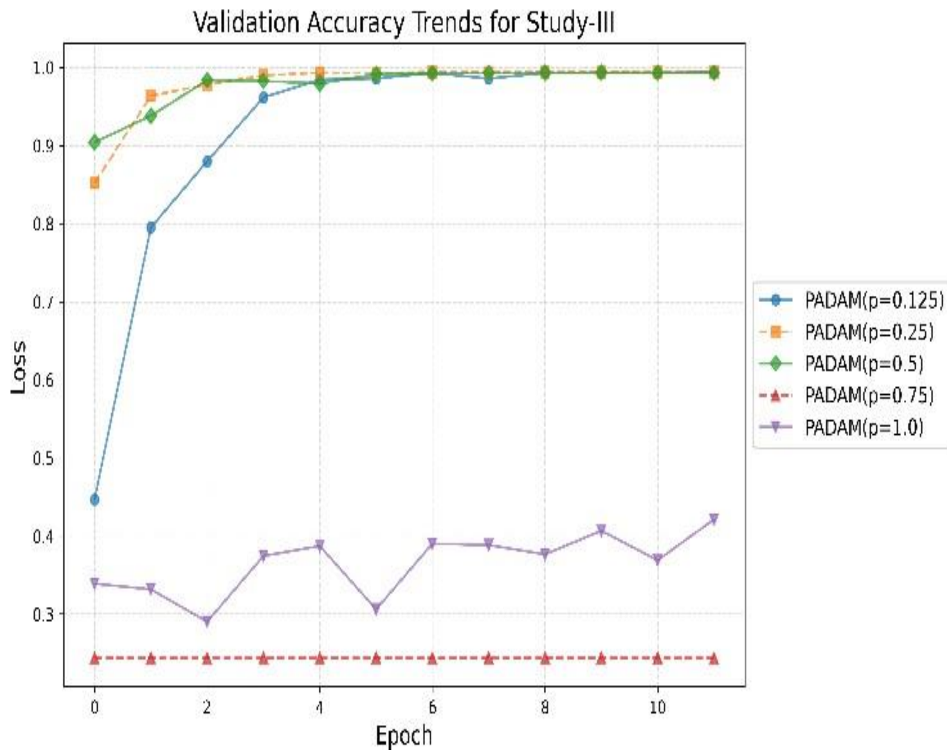
Optimizer	Labels	Training Set					Validation Set					Testing Set				
		PR	RE	FS	LS	AC	PR	RE	FS	LS	AC	PR	RE	FS	LS	AC
Padam (p=0.125)	Non-Demented	1.00	1.00	1.00	0.01	1.00	1.00	0.98	0.99	0.02	0.99	0.99	0.98	0.99	0.02	0.99
	Very Mild Demented	1.00	1.00	1.00			0.98	1.00	0.99			0.99	0.99	0.99		
	Mild Demented	1.00	1.00	1.00			1.00	1.00	1.00			1.00	1.00	1.00		
	Moderate Demented	1.00	1.00	1.00			1.00	1.00	1.00			0.99	1.00	0.99		
Padam (p=0.25)	Non-Demented	1.00	1.00	1.00	0.00	1.00	1.00	0.98	0.99	0.02	0.99	0.99	0.98	0.99	0.02	0.99
	Very Mild Demented	1.00	1.00	1.00			0.98	1.00	0.99			0.98	0.99	0.99		
	Mild Demented	1.00	1.00	1.00			1.00	1.00	1.00			1.00	1.00	1.00		
	Moderate Demented	1.00	1.00	1.00			1.00	1.00	1.00			1.00	1.00	1.00		
Padam (p=0.5)	Non-Demented	1.00	1.00	1.00	0.00	1.00	0.99	0.98	0.99	0.03	0.99	0.99	0.98	0.98	0.03	0.99
	Very Mild Demented	1.00	1.00	1.00			0.98	0.99	0.99			0.98	0.99	0.99		
	Mild Demented	1.00	1.00	1.00			1.00	1.00	1.00			1.00	1.00	1.00		

	Moderate Demented	1.00	1.00	1.00			1.00	1.00	1.00			0.99	1.00	0.99		
Padam (p=0.75)	Non-Demented	0.00	0.00	0.00	nan	0.25	0.00	0.00	0.00	nan	0.24	0.00	0.00	0.00	nan	0.05
	Very Mild Demented	0.00	0.00	0.00			0.00	0.00	0.00			0.00	0.00	0.00		
	Mild Demented	0.00	0.00	0.00			0.00	0.00	0.00			0.00	0.00	0.00		
	Moderate Demented	0.25	1.00	0.40			0.24	1.00	0.39			0.05	1.00	0.09		
Padam (p=1.0)	Non-Demented	0.41	0.12	0.19	1.63	0.43	0.41	0.13	0.19	1.81	0.42	0.41	0.14	0.20	1.89	0.30
	Very Mild Demented	0.36	0.38	0.37			0.36	0.38	0.37			0.38	0.38	0.38		
	Mild Demented	0.54	0.29	0.38			0.49	0.28	0.36			0.55	0.29	0.38		
	Moderate Demented	0.44	0.91	0.59			0.44	0.90	0.59			0.10	0.87	0.18		

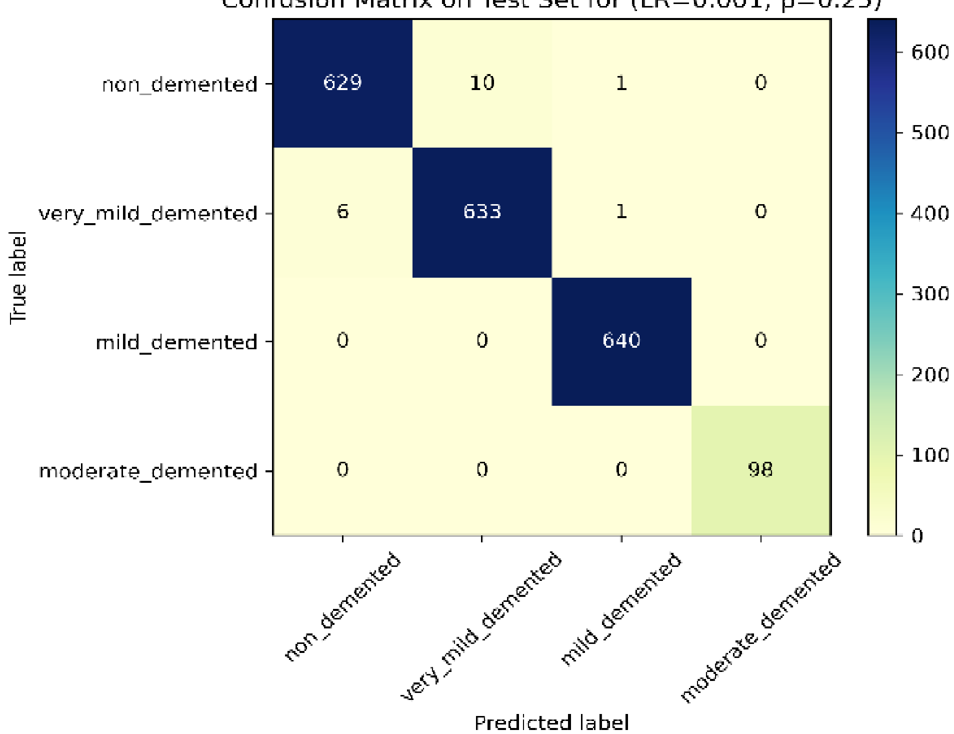


(a)

Fig 9: Performance Evaluation of Proposed Model in Study-III (continue)



(b)



(c)

Fig 9: Performance Evaluation of Proposed Model in Study-III

4.3 Discussion

It is evident from all of these case studies that the partial adaptivity (p) value is a key factor in determining the model's performance; as p rises above 0.5, the model shows a downward trend in accuracy, indicating a negative impact on its learning ability; this decline in performance is consistent across a range of p values, indicating that higher levels of partial adaptivity may impede effective convergence; the analysis also shows that model stability is dependent on the choice of suitable parameters, highlighting the necessity of optimizing p to achieve better generalization and efficiency.

With a learning rate (LR) of 0.001, the optimal performance among the tested configurations is attained at p = 0.25 p = 0.25. This combination effectively improves model learning by producing the maximum accuracy while reducing loss. This conclusion is corroborated by additional evaluation criteria, which demonstrate that the model continues to behave optimally in these particular circumstances. These findings highlight the significance of meticulous parameter tweaking in deep learning models, where overall performance and predicted accuracy are greatly improved by striking the ideal balance between stability and adaptability.

4.3.1 Comparison with benchmark models:

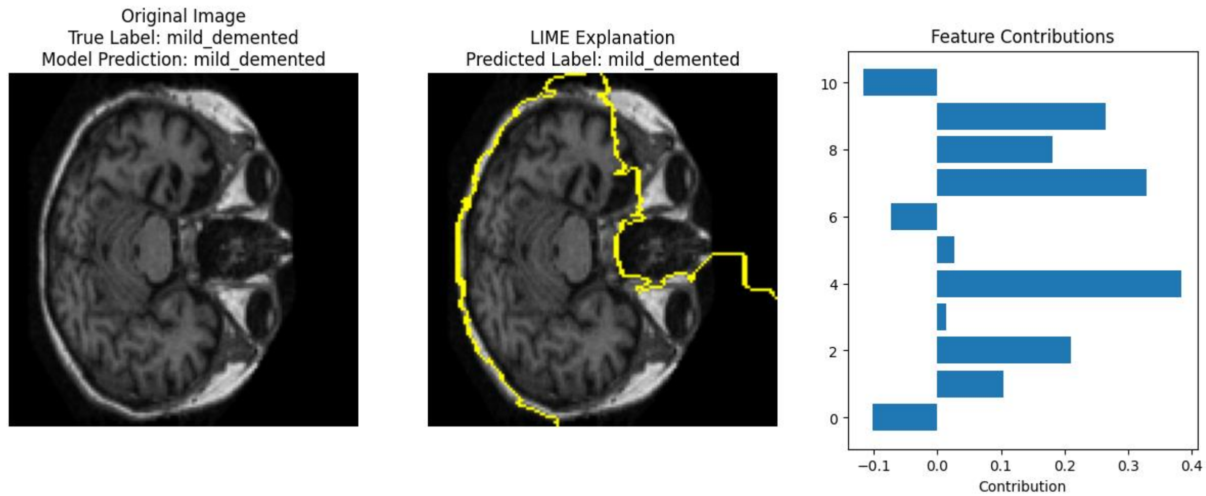
The suggested model demonstrates significant performance by achieving test accuracy of 99%, which confirms the model's durability and universality, according to the results and discussion section. Additionally, by achieving such great accuracy the proposed solution outperforms the existing state-of-the-art (SOTA) models in terms of accuracy, efficiency and interpretability. In Table 5, an extensive performance comparison of suggested models with standard solution is given which gives insightful information about the noteworthy results achieved by the recommended solution.

The proposed CNN [30] model demonstrates the efficient and accurate classification of AD. The proposed solution is designed through CNN architecture integrated with an attention mechanism that focuses on critical and most weighted regions of the human brain. The model was trained by using benchmark data i.e. OASIS. The model evaluation was performed using key metrics i.e. accuracy, F1 score, recall, etc. After in-depth training and testing of the model, it is observed that the model has outperformed the existing models in terms of efficiency and accuracy. The model was reliable and capable of detecting different stages of AD. To make the model more interpretable the explainable AI i.e. LIME was employed to visualize important and effective features. This capability improved the trust in the model's output, making it suitable for clinical applications where explainability is crucial. The projected outcomes by the suggested model on the test data

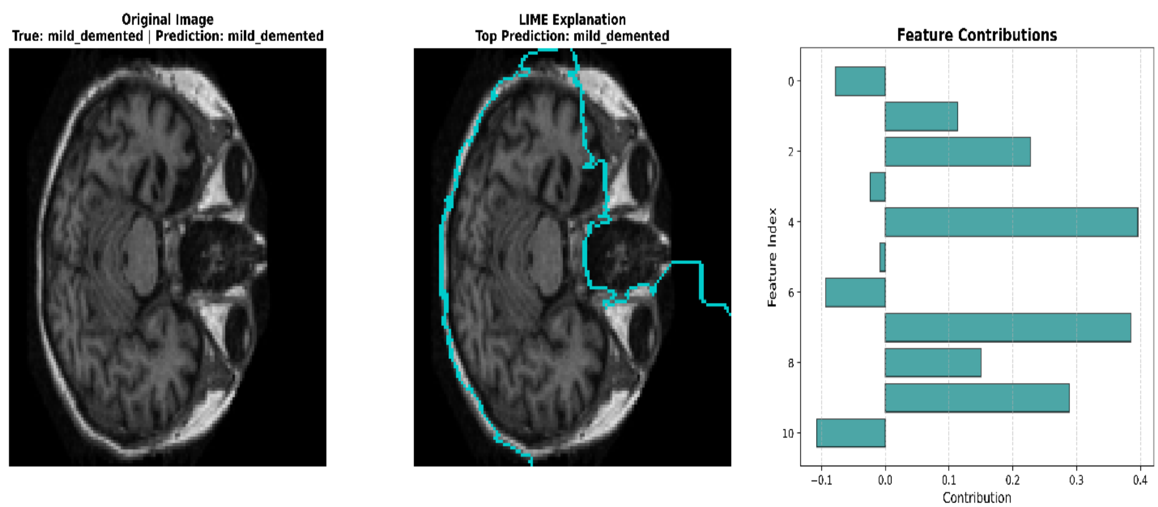
with LIME-based explainability is given in Fig 10(a1) to 10(h3), which provides valuable insights about the regions of the MRI on the basis of which decision is taken with graphical representation of top features.

Table 6: Performance Comparison of Proposed Model with Existing Solutions

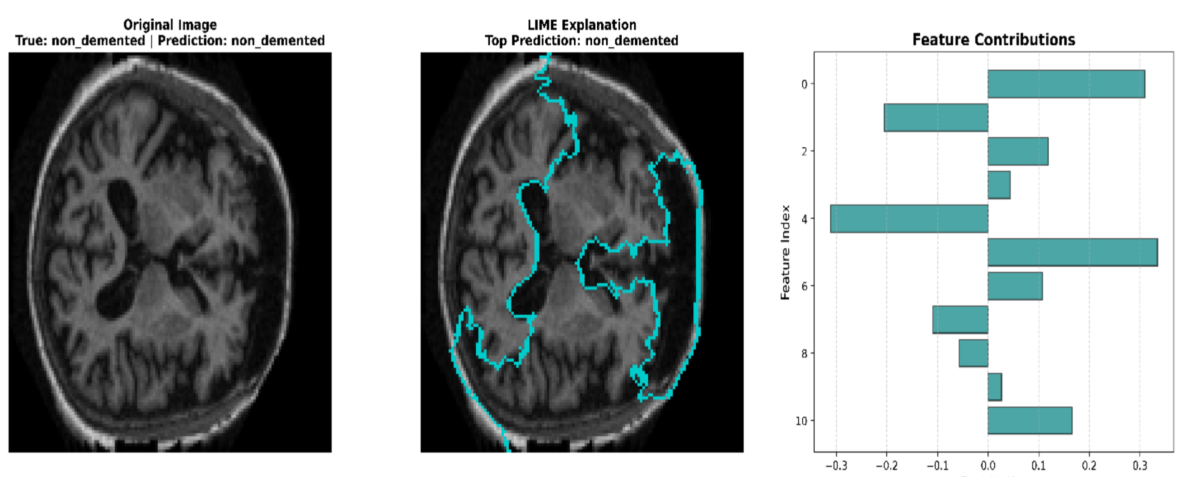
Ref	Approach	Interpretability	Epoch	Model Parameters	Model Size (MB)	FLOPs (Billion)	Accuracy (%)
[7]	Transfer Learning	X	300	25,625,741	102.41	40	78.72
[8]	Capsule Network	X	1000	18,361,136	70	13.33	92.39
[9]	Deep Neural Network	X	30	14,634,372	58.3	9.47	94
[10]	CNN	X	80	11,850,634	47.2	7.83	83.3
[11]	LSTM	X	175	-	-	-	94
[12]	AlexNet + SVM	X	10	19,763,200	75	19.64	94.8
[13]	AlexNet-ETC Hybrid Model	X	-	62,472,951	238	94.81	95.32
[14]	Ensemble Learning	X	-	128,648,641	488	162.83	93.18
[15]	Transfer Learning	X	30	-	-	-	96.7
[16]	Transfer Learning	X	10	62,378,344	249	98.62	92.85
[17]	Deep Siamese CNN	X	20	138,947,624	555	183.74	99.05
Proposed Model	**Spatial Focused CNN with Gompertz non- linearity**	✓	**12**	**9,191,100**	**35.06**	**1.55**	**99.35**



(a1) (a2) (a3)

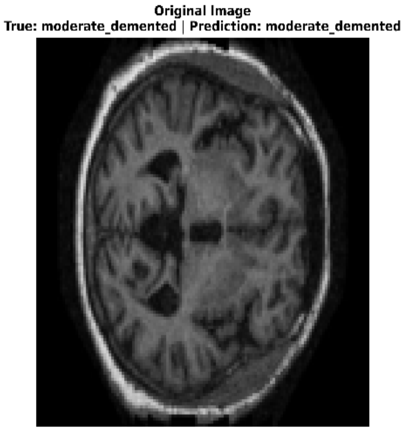


(b1) (b2) (b3)

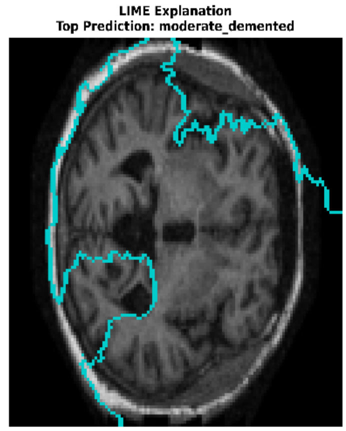


(c1) (c2) (c3)

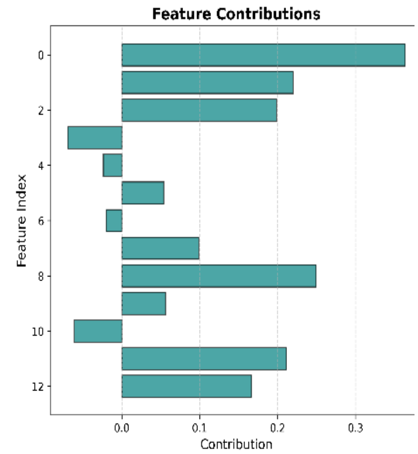
Fig 10: Interpretable Predictions by the Proposed Model (Continue)



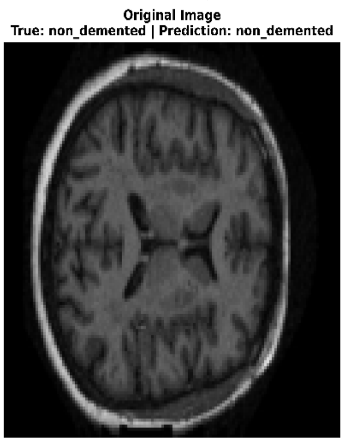
(d1)



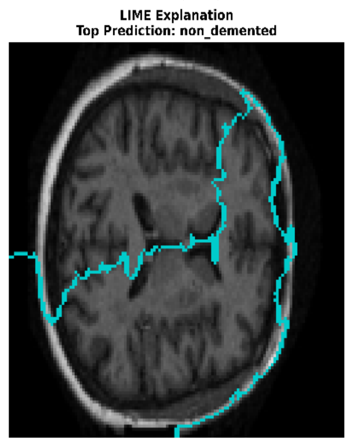
(d2)



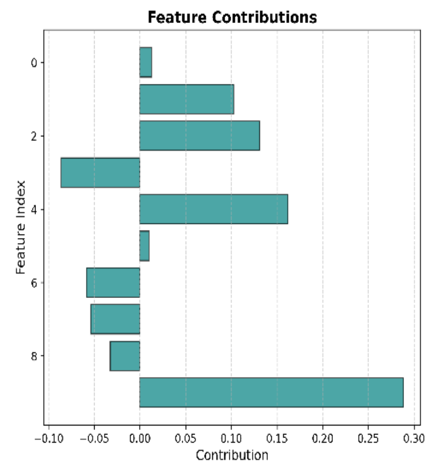
(d3)



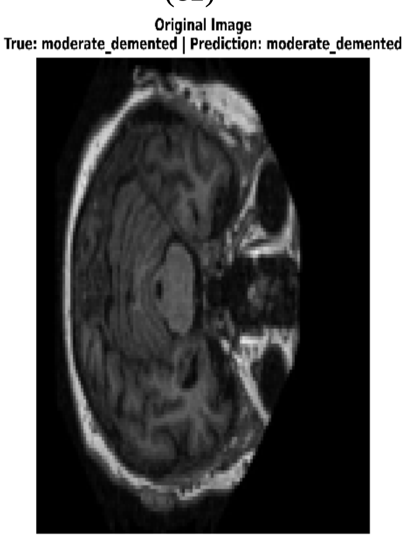
(e1)



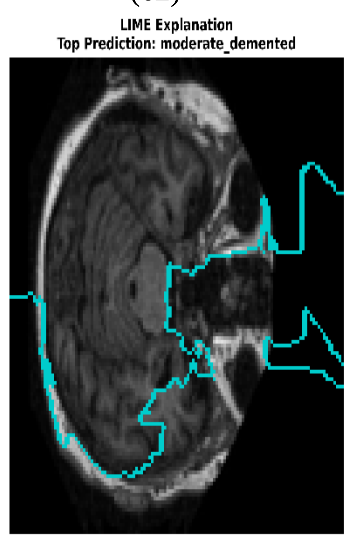
(e2)



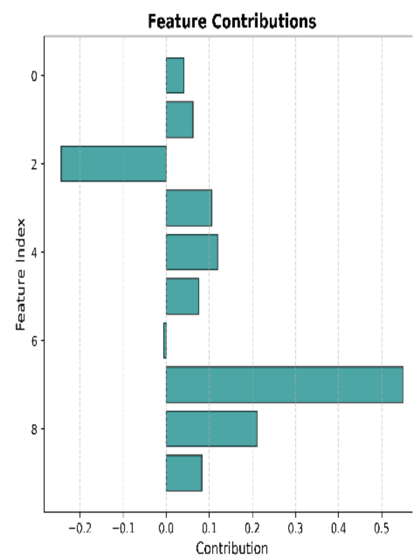
(e3)



(f1)



(f2)



(f3)

Fig 10: Interpretable Predictions by the Proposed Model (Continue)

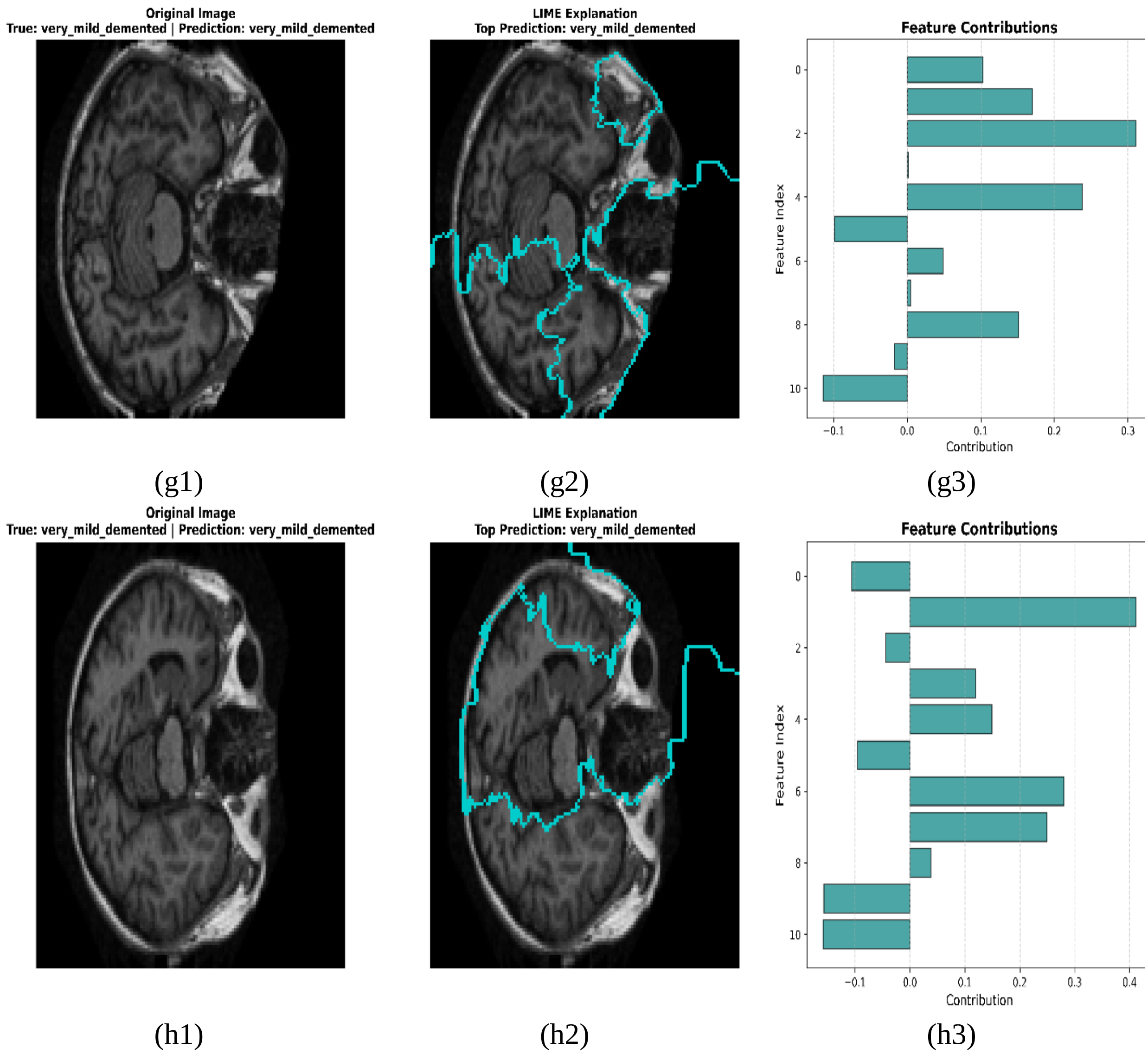


Fig 10: Interpretable Predictions by the Proposed Model

4.4 Summary

The simulation of proposed architecture has been discussed in this section. The different case studies have been discussed according to different hyperparameters and their effects on models have been presented. The results and future work will be briefly described in the next chapter.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1 Introduction

As discussed in the previous chapters, these conclusions have been derived from the suggested algorithm for Alzheimer’s disease classification. Besides from conclusion, this chapter also provide recommendation for researchers who wish in doing future research by implementing proposed methodology or adopting proposed methods in different domain.

5.2 Conclusions

The major findings of the proposed study are:

- The exploration of spatial attention module within CNN architecture is a useful approach to design an accurate andefficient model for tasks at hand.
- Furthermore, the exploitation of Gompertz non-linearity in neural activation operation results in smooth trainingprocess by intelligently overcoming the problem of dead neurons and vanishing gradients.
- The incorporation of partial terms within standard Adam optimizer is beneficial for controlling the over-adaptiveness factor and providing more flexibility in fine-tuning the optimization as per the model needs.
- Overall, the proposed model is reliable in the early diagnosis of AD which is truly visible through its generalized test accuracy and other evaluation metrics.

5.3 Future Work

Although the accomplishment and efficiency of the proposed model for Alzheimer's disease classification and identification is encouraging, there are a few extents that need more research to improve its performance and effectiveness:

- **Multi-Modal Data Integration**: To provide a more complete diagnosis tool, the model is being extended to incorporate multi-modal data, such as genetic information, biomarkers, and clinical records.
- **Hardware Acceleration**: Using GPU-based training to speed up processing and make it possible to test out bigger datasets and more intricate model architectures.
- **Personalized Diagnostics**: Investigating methods to include patient-specific data into the classification process to personalize it and produce more precise and customized predictions.
- **Explainable AI (XAI):** Improving the model's explainability by incorporating sophisticated interpretability methods, like Grad-CAM++ or SHAP values, to give physicians a better understanding of the model's decision-making process.
- **Cross-Population Validation:** To assess the model's generalizability and robustness across a range of demographic and clinical contexts, validation studies are carried out on a variety of datasets from distinct populations.
- **Development of Real-Time Applications:** Creating real-time diagnostic systems that can be integrated into healthcare environments while guaranteeing the model's scalability and usability in clinical workflows.
- **Longitudinal Data Analysis:** This method helps with early intervention methods by using longitudinal data to monitor the course of the disease and forecast its future stages.

By addressing these areas, the suggested model can advance into a more robust, adaptable, and impactful tool for the timely detection and categorization of Alzheimer's disease.

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