Detection of Alzheimer's Disease Using Deep Learning Approach

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CERTIFICATE

This is to certify that the thesis entitled **Detection of Alzheimer's Disease Using Deep Learning Approach** submitted by **Sampad Kumar Singha (Roll Number 190133, Registration Number 101849)** to the Pabna University of Science and Technology in partial fulfillment of the Bachelor of Science(Engineering) degree in Computer Science and Engineering is a bonafide record of the research work carried out by him under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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DECLARATION

I affirm that the thesis entitled **Detection of Alzheimer's Disease Using Deep Learning Approach**, submitted in partial fulfillment of the Bachelor of Science (Engineering) degree requirements at Pabna University of Science and Technology, Pabna, is an original work conducted by me under the supervision of Associate Professor S. M. Hasan Sazzad Iqbal. This submission conveys my views in my own terminology, and where other concepts or terminology have been utilized, I have accurately cited and referenced the original sources.

I confirm that I have adhered to the norms of academic honesty and integrity and have neither misrepresented nor faked any data, ideas, facts, or sources in my work.

I recognize that any violation of the aforementioned will lead to disciplinary actions by the institute and/or the university and may also provoke legal consequences from the entities that have not been properly cited or from whom necessary permission has not been obtained. This thesis has not previously been utilized as the basis for awarding any degree, diploma, or comparable title from any other university.

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Abstract

Alzheimer's is a brain disorder that progresses gradually impairing memory and cognitive abilities. Nearly 50 million people is affected by this disease worldwide [1]. It is the most common form of dementia and the fifth-leading cause of death among individuals over 65 years of age. Early detection plays a crucial role in slowing disease progression and facilitating timely interventions. Machine learning (ML) methods have been widely employed in many studies for detection and diagnosis of AD using MRI scans. However, deep learning (DL) models have outperformed traditional ML approaches due to their ability to learn complex and subtle features from provided data without expert intervention, eliminating the need for usual manual feature extraction process needed in ML. Studies have shown that deep learning models, particularly Convolutional Neural Networks, is more capable in AD classification, surpassing conventional methods (Korolev et al., 2017). [2]

In this study, we propose two models for Alzheimer's disease classification: one based on a custom-built Sequential Convolutional Neural Network (CNN) and the other utilizing the pre-trained ResNet50v2 model for automatic feature extraction. The Sequential CNN model demonstrates promising results, achieving an accuracy of 96.01%, which outperforms pre trained ResNet50v2 model, which achieved an accuracy of 94.81%. This performance highlights the potential of deep learning models in providing efficient and accurate solutions for Alzheimer's disease detection, offering valuable insights into the effectiveness of both custom and pre-trained architectures for medical image analysis.

Acknowledgement

I take this opportunity to express my deepest sense of gratitude and sincere thanks to everyone who helped me to complete this work successfully. I express my sincere thanks to Dr. Md. Abdur Rahim, Chairman of the Department, Computer Science and Engineering, Pabna University of Science and Technology for providing me with all the necessary facilities and support.

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Chapter 1

Introduction

1.1 Overview

Our brain is responsible for controlling numerous cognitive functions such as reasoning, solving problems, memorizing and decision making [3]. This organ is the most important part of our body that makes us us. Memory is fundamental to our identity, allowing us to preserve experiences and engage with the environment significantly. However, "Alzheimer's disease (AD) is the most prevalent form of dementia, accounting for approximately 60–70% of cases" [4].—present a considerable obstacle to these activities. Alzheimer's disease progressively deteriorates neurons, resulting in memory impairment, cognitive decline, and finally, the incapacity to execute fundamental daily tasks [5]. "Approximately 50 million people worldwide are affected by dementia" [1], with forecasts suggesting a rise to 152 million by 2050, posing a significant public health concern that necessitates efficient diagnostic instruments [6]. If the disease is detected in an early stage, the patient will get proper treatment which can slow or stop its spread. Magnetic resonance imaging (MRI) has demonstrated its efficacy as a diagnostic instrument, offering comprehensive insights into cerebral atrophy, especially within the temporal and parietal lobes. Nonetheless, manual analysis of MRI data is laborious and susceptible to variability.With the progress of deep learning, clinical image analysis has become far more advanced, with automated methods for extracting various feature and classification. Convolutional neural networks (CNNs) is a new branch of deep learning, that have shown its exceptional capability in numerous image classification tasks, particularly in medical imaging.

1.2 Alzheimer's Disease

According to Selkoe et al., "Alzheimer's disease (AD) is a neurodegenerative disorder that primarily affects older individuals". [7] AD is distinguished from other types of dementia by decline in cognitive

functions, gradual loss of memory, and behavioral changes. The amyloid-beta plaques and tau protein tangles that accumulate in the brain are the cause of AD. These tangles disrupt neural connections and result in cell death. The disease typically commences with mild memory impairments and progresses to severe cognitive and physical disabilities, ultimately preventing individuals from performing fundamental daily activities [8].

Age is the most significant factor contributing to the elderly population's vulnerability. Genetics also contribute to the disease, although it accounts for a reduced proportion of cases [9]. A huge number of people is directly or indirectly are impacted by the disease which poses a significant challenge for both medical and social sectors. Additionally, it has profound emotional and economic consequences.

1.3 Stages of Alzheimer's Disease

Based on the severity of decline in cognitive functions, Alzheimer's disease (AD) is usually classified into five distinct stages. The stages are briefly described below.

1.3.1 Preclinical Stage

Even though tau protein starts to form tiny fibers that clumps together in the brain, the individuals exhibit no clear symptoms in the preclinical stage. "Cerebrospinal fluid analysis, as well as advanced imaging techniques such as magnetic resonance imaging (MRI) and positron emission tomography (PET) scans, are often used to detect AD at this stage" [8].

1.3.2 Moderate Cognitive Impairment (MCI)

Individuals may develop MCI as Alzheimer's disease advances. The phase is a opaque period during which individual may face decline in cognitive functions due to aging. But in can also be a sign of AD. While not all individuals with MCI develop Alzheimer's disease, their risk of developing dementia increases [10].

1.3.3 Mild Dementia

Alzheimer's disease symptoms become more evident and begin to disrupt daily activities in mild cases. Additionally, patients may experience difficulties with recent memory, misplace items, or forget familiar names and words. In addition, behavioral modifications, including anxiety or irritability, may manifest [11].

1.3.4 Moderate Dementia

In this period, decline in cognitive functions becomes prominent. Patients frequently complain of difficulty in remembering their personal history, identifying family members, and managing daily responsibilities. The severity of behavioral symptoms, including aggression, delusions, and wandering, increases, requiring a higher degree of assistance [12].

1.3.5 Severe Dementia

Severe Alzheimer's disease results in a significant decline in cognitive and physical abilities. "Patients are unable to communicate, coordinate their movements, or react to their surroundings. As complications such as difficulty ingesting, loss of bowel and bladder control, and increased susceptibility to infections become prevalent, full-time care is essential at this stage" [13].

1.4 Motivation

"In 2017, the global population aged 60 years or older was 962 million, which is more than twice the number of that in 1980, when there were 382 million elderly people worldwide" [14]. By 2050, the estimation is that the number of elderly people will double once again, reaching nearly 2.1 billion. For developing regions, the number is estimated to be 1.7 billion. Conversely, the number of older individuals in more developed regions is expected to increase by 38% during the same period, from 310 million in 2017 to 427 million in 2050 [15].

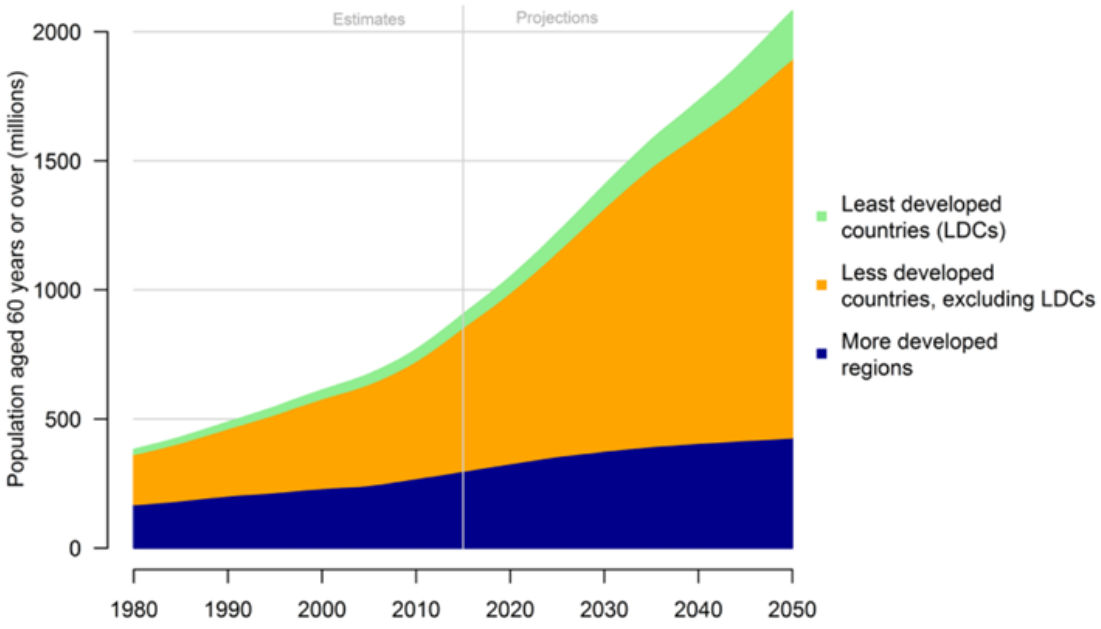

Figure 1.1: Number of people of the age of 60 years or over by years

In 2010, around 36 million individuals globally had been diagnosed with dementia, a figure

expected to rise to 66 million by 2030 and 115 million by 2050. [16] The World Alzheimer Report estimates the global cost of dementia at USD $604 billion for 2010, with one model indicating a 34% increase in costs from 2005 to 2009. [17] A significant portion of the increase will occur in developing nations. Currently, 60% of individuals with dementia reside in low- and middle-income nations; however, this figure is projected to rise to 71% by 2050. The most rapid increase in the older demographic is taking place in China, India, and their neighboring countries in South Asia and the Western Pacific. [18]

This study is motivated by the critical need to develop a model that will detect and classify Alzheimer's accurately and efficiently in an early stage, and will be easily accessible. Leveraging advancements in deep-learning models and clinical imaging, this research seeks to take part in the global cause to mitigate the personal, economical and societal impact of this devastating condition.

1.5 Objective

In this study we seek to develop two deep-learning models to classify various stages of AD using MRI scans. The objective of the study is to evaluate and contrast the effectiveness of the two DL architectures: ResNet50v2 and a sequential model. We will compare their ability to precisely identify and categorize various stages of AD. We will try to improve the impact of Alzheimer's disease classification by detecting it in its early phases. The study also intends to automate the analysis of brain imaging data, thereby reducing the need for manual interpretation and minimizing diagnostic subjectivity. By integrating advanced computational techniques with practical clinical applications, this work aims to advance accessible and scalable diagnostic tools that will contribute to global efforts to address the increasing burden of Alzheimer's disease.

1.6 Thesis Structure

This paper is structured in way that will provide a broad view of the study on Alzheimer's disease (AD) classification using deep learning models, particularly ResNet50v2 and sequential CNNs. The chapters are organized as follows:

- **Chapter 1: Introduction** This is the introductory chapter of the thesis book. Here, we will provide a concise explanation of the objective and motivation behind our thesis. Additionally, we will shortly provide a description of Alzheimer's disease and its classification.
- **Chapter 2: Literature Review** In this chapter, we will study research paper related to our work, discuss their key findings, advantages and challenges.

- **Chapter 3: Background Study** In this chapter, we will discuss theoretical topics related to this study.

- **Chapter 4: Methodology** In this section, we will explain the overall workflow on how we built the model including dataset used, preprocessing steps, and the architectural design of ResNet50v2 and sequential CNN models.

- **Chapter 5: Results and Discussion** In this chapter, we will present the findings from model evaluation, comparing the performance of the two approaches. We will also discuss the implications of the results and potential limitations.

- **Chapter 6: Conclusion** Finally, we will summarize the study's contributions, reiterates its importance, and propose directions for future research in AI-driven Alzheimer's diagnosis.

This structure provides a logical flow, facilitating a clear understanding of the study's objectives, methods, and outcomes.

1.7 Summary

In this chapter, a short description of Alzheimer's disease along with its stages are described. We shortly explained the motivation behind our work which outlines the AD trend and its socio-economic impact. We also described the objective of this study. At last, our thesis structure was briefly described.

Chapter 2

Literature Review

2.1 Introduction

In recent years, we have seen substantial progress in terms of medical image processing, with contributions from domains including deep learning, image analysis, and computer vision. Researchers have been focusing on the utilization of these technologies to enhance the efficacy and accuracy of diagnostics in medical applications. This chapter offers a thorough examination of relevant research articles, delving into the methodologies, datasets, and technologies used in recent studies. We reviewed 18 research papers in order to determine the most advanced and effective methods used in the diagnosis and classification of AD. This review not only emphasizes the extant approaches but also identifies the gaps and challenges that drive the objectives of this thesis.

2.2 Reviews of the related papers

Multiple research studies have investigated the application of various kinds of classification techniques to detect Alzheimer's Disease (AD). This section provides an in-depth review and working procedure of recent research that has implemented both conventional machine learning (ML) and deep learning (DL) methodologies in detection of Alzheimer's disease.

A study by Mehmood et al. [19] says that the first step in finding AD by MRI images is to use structured deep learning to find mild cognitive impairment. This is done by separating brain tissue into multiple layers. The study utilizes the VGG architecture, a branch of deep CNN architecture. The MRI images utilized in this paper are obtained from ADNI (Alzheimer's Disease Neuroimaging Initiative). Various biomarkers, including structural MRI, PET, and MRI, were examined and validated to identify indicators of Alzheimer's disease and to assess the progression of moderate cognitive impairment (MCI). A total of 300 MRI subjects were considered and subsequently classified

as Alzheimer's, late mild cognitive, and initial mild cognitive periods. The techniques employed in this study are CNNs that have a multi-layered structure consisting of a variety of layers, including a convolution layer, a pooling layer, and a softmax layer. Multi-layered CNNs obtained an accuracy of 98.73% without data augmentation.

Using MRI, Liu et al. [20] suggested a "multitemplate-based brain morphometric analysis for the classification of moderate cognitive impairment (MCI) and Alzheimer's disease (AD)". Their method groups subjects into subclasses based on feature representations from numerous templates, in contrast to existing methods that assume simple data distributions. To increase classification accuracy, they used ensemble SVM classifiers and multitask feature selection. When compared to current methodologies, experimental results on the ADNI database indicated encouraging outcomes.

Lazli et al. [21] introduced a computer-aided diagnosis (CAD) system aimed at differentiating Alzheimer's disease (AD) from healthy individuals through the analysis of MRI and PET scans. The system employs a three-step clustering approach that begins with fuzzy c-means (FCM) for initial partitioning, progresses to a possibilistic C-means (PCM) algorithm for tissue mapping, and concludes with segmentation to define brain tissue volumes. A support vector machine (SVM) employing various kernel functions is utilized for classification purposes. The validation of MRI and PET data from 45 Alzheimer's disease patients and 50 healthy subjects revealed enhanced sensitivity, specificity, and accuracy in comparison to alternative methods, achieving accuracy rates of 75% for MRI and 73% for PET scans, even with 20% noise present.

Odusami et al. [22] suggest a deep learning approach for the early detection of Alzheimer's disease. He has suggested a modified ResNet18 model for the extraction of neuroimaging data features from structural magnetic resonance imaging. The investigation included a total of 413 subjects. The database encompasses six categories: normal healthy period, mild cognitive inability, EMCI, notable remembrance, and Alzheimer's. The techniques employed are residual networks with 18 layers. This is a proposal for CNN. It employs a 3x3 sevier, and the phase 1 pooling layer comprises a 1x1 sevier, a softmax layer, and a wholly interlinked layer. The separation rate of accuracy of the fine-tuned CNN, which consisted of 18 layered neural networks, was approximately 99.09%. Active magnetic resonance imaging-imaged sheets of Alzheimer's patients are detectable using CNNs. The preprocessing and fine-tuning, classification and evaluation, and data collection stages comprise the process.

A study conducted by Korolev et al. [2] examined the application of deep learning algorithms in the analysis of neuroimaging data, particularly focusing on the classification of Alzheimer's disease. Their emphasis was on removing the necessity for conventional feature extraction through the

application of residual and plain 3D convolutional neural network (CNN) architectures. This method facilitated the automatic generation of features, enhancing the efficiency of the analysis process. The team implemented their approach to categorize Alzheimer's disease, mild cognitive impairment, and normal controls by utilizing the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, which consists of 3D structural MRI brain scans. The results indicated that this deep learning method could reach performance levels similar to conventional techniques, all while streamlining the entire process.

In a study, Rallabandi et al. [23] created an automated machine learning method to categorize individuals into four distinct groups: cognitively normal aging, early mild cognitive impairment (MCI), late MCI, and Alzheimer's disease (AD). The investigation utilized 1167 whole-brain magnetic resonance imaging (MRI) scans sourced from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. The team concentrated on quantifying regional cortical thickness across both the left and right hemispheres, encompassing a total of 68 features for each participant, which were subsequently utilized to develop a classification model. The study utilized a range of machine learning techniques for classification, finding that a non-linear support vector machine (SVM) classifier with a radial basis function kernel produced the most effective results. The model demonstrated exceptional performance with the highest specificity at 0.77, sensitivity at 0.75, F-score at 0.72, Matthew's correlation coefficient at 0.71, Kappa-statistic at 0.69, and an area under the receiver operating characteristic curve of 0.76. The classification accuracy achieved was 75% through the application of ten-fold cross-validation. The study employed support vector regression to forecast features for the classification of the four groups.

The findings highlighted the promise of machine learning techniques in enhancing the precision and effectiveness of classifying Alzheimer's disease and cognitive impairments through MRI scans, which can support early diagnosis and intervention efforts.

Venugopalan et al. [24] suggested the use of automatic encoders to remove noise from MRI scans in order to evoke properties from provided data. He has proposed a novel 3D CNN method for imaging data, with a particular emphasis on the hippocampus brain area and its features. Oral assessments are extracted through the use of audio. The progression of moderate cognitive impairment is assessed using the ADNI data set, which takes into account biological markers such as MRI, PET, and neuropsychological evaluations. In 18 distinct regions, the cross-sectional magnetic resonance scan image comprised approximately 8209 voxels. In total, 220 patients were under consideration for the examination. The total number of MRI images is 503, while the number of SNPs is 808. The number of HERs is 2004. Each component employs a three-tier automatic encoder, with 199, 99, and 51 nodes utilized in isolation. The initial stage involves the filtering of noise, followed by the extraction of 1680 common features and the conversion of input data to a format of 0's and 1's through shot encoding. The accuracy is 78%.

For the detection of various phases of Alzheimer's disease, Pradhan et al. [25] proposed a model using the VGG19 and DenseNet169 architectures. The source of the data set is Kaggle, an open-source online data set library. Mild, moderate, very mild, and non-demented AD are the classifications of 6000 images. Learning phases comprise eighty percent of the features, while examination phases comprise twenty percent. VGG19 comprises approximately 10–16 convolutional neural network layers. Picture classification employs DenseNet. In this instance, VGG19 achieves an accuracy of 94%, surpassing DenseNet.

In order to classify and identify the initial AD period, Shah et al. [26] implemented hard and flexible voting algorithms. The data set comprises 437 patients between the ages of 60 and 96. Of these, 72 individuals are non-demented, 64 are demented, 70% are utilized to train the algorithm, and 30% are utilized to evaluate the algorithm. There are three classification algorithms: hard voting, soft voting classifiers, and decision trees. SVM serves as a classification methodology. The voting classifier algorithm achieves an accuracy of 84%.

Huanhuan et al. [27] suggested the use of MRI to detect early phases of dementia (ConvNets). The gray color regions and white color regions in the scanned brain images aid in the classification of scan images. The ADNI database is the source of the data. There were a total of 615 MRI images obtained. The proportion of data segregation is 3:1:1. Images are reduced to a size of $192 \times 192 \times 160$, and the patient's head movement is minimized through the use of statistical parameter mapping during the preprocessing stage. The method of detection is based on the eResidual Network, which consists of 50 layers, and the eNeural Architecture Search Network. The addition of a dropout layer resolves the overfitting issue in the completely interconnected layer. Separately, the accuracy rates for MCI AD range from approximately 97.65% to 88.37%.

Razavi et al. [28] emphasized the utilization of unsupervised feature learning, which involves two stages. The initial stage is to extract features from the raw data. The techniques employed are uncontrolled neural layer networks and scattered filtering. Softmax is a term that refers to the classification of healthy and ill individuals through the use of sparse filtering and regression. Distributing the acquired data involves employing a few unsupervised learning techniques, including dispersed coding and Boltzmann machines. This methodology employs ADNI with cerebrospinal fluids as its data set. The total number of patients with Alzheimer's disease is 51, with 43 patients exhibiting moderate symptoms. Utilizing 1.5T scanners, the MRI data were acquired. The softmax regression yields the greatest accuracy at 98.3%.

Islam et al. (2018) [29] employ deep learning CNN to analyze brain MRI images in their research on AD. In addition, this investigation pinpoints the various phases of the illness. The procedure is also

effective with the imbalanced data set. The CNN comprises four layers: a bulk processing layer, a pooling layer, a ReLU layer, and deep neural layers. ResNet, Inception-v4, and MRI data architecture classify the data in accordance with the 3D brain. 416 data samples comprise the data set employed in OASIS. There is a 4:1 ratio between the training and assessing data sets. The performance rates of Inception-v4 and ResNet precision rates are 0.81 and 0.82, respectively.

According to Islam et al. (2019) [30], 3D convolutional neural networks are more effective in the visualization of medical images. Five visualization techniques are implemented in conjunction with brain PET scans to identify Alzheimer's disease through the utilization of 3D CNN. ADNI (adni.loni.usc.edu) is the source of the data sample. A total of 1230 PET scans of Alzheimer's disease patients are accessible. The employed visualization techniques are under the guidance of layerwise relevance propagation and backpropagation brain area occlusion. Training uses 80% of the data set, testing uses 20%, and validation uses the remaining 10%. The objective of the visualization techniques is to emphasize and concentrate on specific brain regions, including the frontal mid, precuneus, postcentral, temporal mid, and precentral areas. Subsequently, the system obtained an efficient classification accuracy of 88.76%.

Thakare et al. [31] proposed the utilization of EEG to identify Alzheimer's disease. Nineteen channels of the EEG database are extracted from Kashi Bhai Hospital in Pune. The initial diagnosis is MSME. This results in the classification of patients as either healthy or having Alzheimer's disease. It is necessary to convert the EEG signals into a .mat file and perform the acquisition using Simulink. Utilizing wavelet transformations, the mean, standard deviation, and mode of these EEG waves are derived. We employ a normalized minimum distance (NMD) classifier algorithm and a support vector machine for the classification. In comparison to the NMD classifier, SVM achieves an accuracy of 95%.

Noor et al. [32] have investigated the most prevalent deep learning techniques for the purpose of identifying the three most prevalent neurological disorders from MRI scan data. The literature has provided an overview of DL methods for the classification of neurological disorders. We have summarized the advantages, disadvantages, and efficacy of these deep learning techniques with respect to neuroimaging data. The primary observation of this investigation was the extensive use of CNN in the detection of Parkinson's disease and Alzheimer's disease. Conversely, the utilization of DNN for the detection of schizophrenia has been particularly prevalent.

Su et al. [33] One of the most prevalent forms of dementia, Alzheimer's disease (AD), has been identified through the integration of magnetoencephalography (MEG) and machine learning techniques. In order to enhance the interpretation of the brain activity captured by magnetometers

and gradiometers, a bimodal recognition system is proposed that is based on an enhanced score-level fusion approach. In this preliminary study, it was determined that the markers derived from the gradiometer generally outperform the magnetometer-based markers. Of the ten regions of interest, the left frontal lobe exhibits a mean recognition rate that is approximately 8% higher than that of the second-best performing region (left temporal lobe) for AD/MCI/HC classification. This is interesting.

2.3 Summary

In this chapter, we examined a total of 12 research articles and analyzed their methodologies. This literature study demonstrates that numerous studies have been conducted on the detection of Alzheimer's disease. Some of the individuals applied traditional classifiers, while others implemented deep learning methods. Certain studies yielded notable outcomes through conventional methods, whereas others did not achieve similar success. After examining these works, it can be asserted that deep learning outperforms traditional classifiers due to its unique learning mechanism and the utilization of memory within the network.

Chapter 3

Background Study

3.1 Neuroimaging in Alzheimer's Disease Diagnosis

Structural and functional neuroimaging techniques like Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) are essential for evaluating brain abnormalities linked to Alzheimer's disease and various cognitive disorders. The use of MRI is prevalent due to its capacity to deliver high-resolution images of the brain's anatomy, allowing for the identification of structural changes that may indicate neurodegeneration.

Studies using MRI have consistently demonstrated that Alzheimer's disease is marked by progressive atrophy, especially in the hippocampus and other parts of the temporal lobe, which are vital for memory and cognitive function (Jack et al., 2010) [34]. The hippocampus, recognized as one of the initial regions to exhibit notable alterations in Alzheimer's disease, is crucial for the processes of memory formation and consolidation. Morphological changes have been extensively utilized as biomarkers for the progression of Alzheimer's disease, with numerous studies suggesting a correlation between the extent of hippocampal atrophy and cognitive decline (McKhann et al., 2011) [11].

Moreover, alterations in cortical thickness have emerged as one of the most dependable markers of Alzheimer's advancement. According to a study conducted by Dickerson et al. (2009) [35], it was observed that cortical thinning in patients with Alzheimer's disease manifests early in the progression of the condition, especially in the entorhinal cortex and hippocampus, prior to the emergence of noticeable clinical symptoms.

Collectively, these neuroimaging methods illuminate the structural and functional brain irregularities linked to Alzheimer's disease and mild cognitive impairment. The results have established a foundational framework for employing neuroimaging as a diagnostic instrument in clinical environments, where the detection of early-stage Alzheimer's via imaging biomarkers can facilitate early interventions and therapeutic approaches (Jack et al., 2010) [34].

3.2 Machine Learning and Deep Learning in Neuroimaging

Machine learning and deep learning are essential tools in analyzing clinical imaging data. Algorithms like support vector machines (SVM) and random forests (RF) are utilized to classify images obtained from MRI, PET, X-ray, and various other forms of brain imaging data. The methods depend on predefined feature engineering and use labeled data to predict outcomes.

In contrast, Deep Learning models learn hierarchical features straight from raw data autonomously. Convolutional Neural Networks (CNNs) are frequently utilized in the examination of MRI and PET scans because of their proficiency in extracting spatial features from images. The architecture of these networks includes various layers, including convolutional, pooling, and fully connected layers, which facilitate the identification of both low- and high-level patterns in data. Besides CNNs, various architectures such as Recurrent Neural Networks (RNNs) and Autoencoders have been applied to neuroimaging tasks, each offering unique advantages for diverse data representation. Recurrent Neural Networks, for instance, are particularly effective for handling temporal data such as longitudinal MRI scans, whereas Autoencoders prove advantageous for the unsupervised learning of intricate features.DL models, particularly those based on ResNet or VGGNet, have demonstrated superior performance in Alzheimer's detection due to their ability to learn complex, high-level patterns without the need for manual feature extraction (Korolev et al., 2017; Liu et al., 2016) [2] [20].

Both ML and DL methods provide notable advancements in Alzheimer's diagnostics through the automation of feature extraction and enhancement of classification accuracy, facilitating a more dependable and efficient identification of patients across different stages of the disease.

3.3 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) have emerged as key element of deep learning models, especially in the field of medical image analysis, including neuroimaging applications such as the detection of Alzheimer's disease, brain tumors, and brain cancer. Convolutional neural networks are structured to autonomously acquire hierarchical features from raw image data, thereby removing the necessity for manual feature extraction, a common constraint in conventional machine learning approaches (LeCun et al., 2015) [36].Convolutional neural networks consist of several layers that collaboratively extract hierarchical features from input images. The main elements of a CNN include:

3.3.1 Convolutional Layers

Convolutional layers in CNNs operate to autonomously extract features from input images through the application of convolutional filters, often referred to as kernels. These filters consist of small matrices that traverse the input image through a process known as convolution. As the filter traverses the image, it performs element-wise multiplication with the segment of the image it covers, producing a feature map highlighting particular patterns like edges, textures, or corners.

3.3.2 Activation layers

Activation layers in Convolutional Neural Networks (CNNs) makes the model non linear, enabling the model to learn and represent more complex patterns, even better than human. Following each convolution operation, the resulting feature map undergoes an activation function, which converts the raw output into a more practical format.

The Rectified Linear Unit (ReLU) is the activation function typically used in convolutional neural networks, defined by the equation:

$$ReLU(x) = max(0, x) \tag{3.1}$$

This function produces zero for all negative inputs and retains positive values unchanged, thereby introducing non-linearity while maintaining computational efficiency.

ReLU effectively addresses the vanishing gradient issue [37] and accelerates the training process, enabling the network to learn more efficiently. Alternative activation functions, such as Sigmoid and Tanh, may be applied; however, their usage is less prevalent in deep networks because of certain limitations, including the issue of vanishing gradients. The selection of an activation function is essential for allowing the model to identify intricate patterns and produce precise predictions.

3.3.3 Fully Connected layers

Fully Connected (FC) layers, often referred to as dense layers, play a critical part in Convolutional Neural Networks (CNNs) by connecting the convolutional layers to the output layer. In these layers, every neuron is linked to all neurons in the previous layer, enabling the network to recognize global patterns from the features identified by the convolutional layers.

The function of fully connected layers is to combine the high-level features generated by the convolutional layers to arrive at the final decision or classification. The layers are generally positioned near the end of the network and use a softmax activation function (for classification tasks) to generate probabilities for each class.

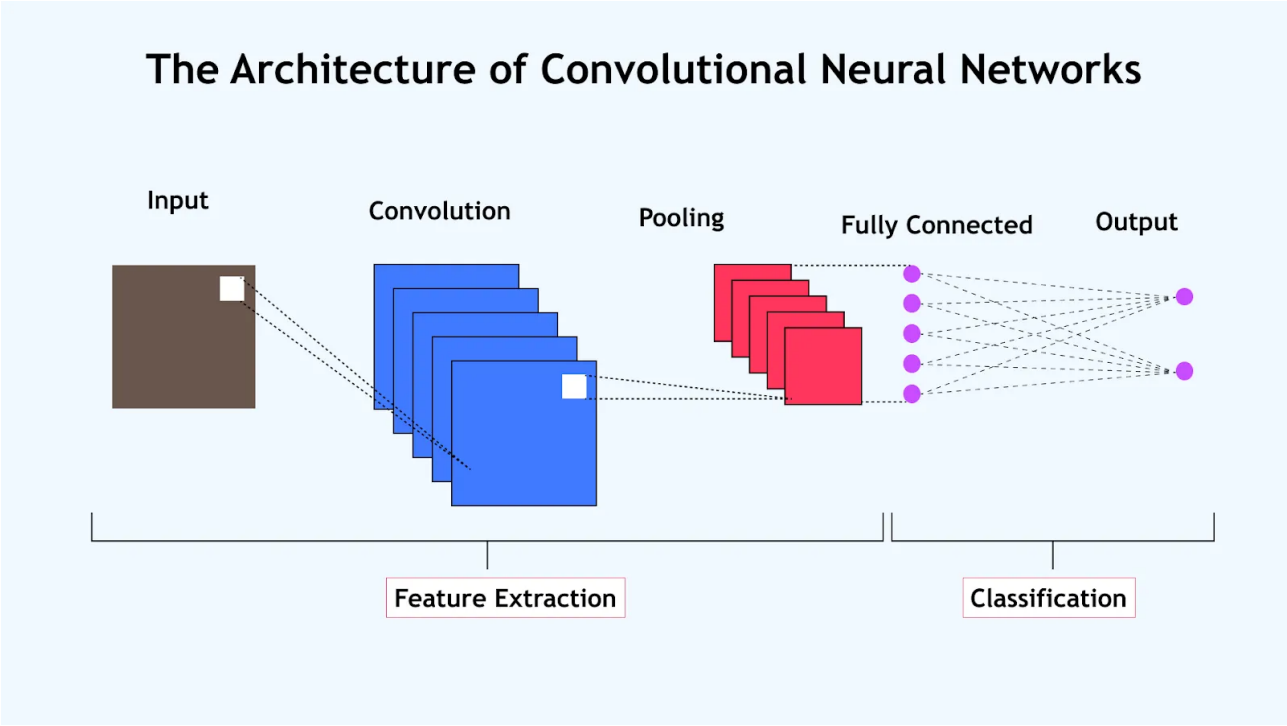

Figure 3.1: Convolutional Neural Network Architecture

3.3.4 Output layer

The output layer of a neural network produces the final predictions, often using an activation function such as softmax for multi-class classification or sigmoid for binary classification. It transforms the high-level features derived from previous layers into either class probabilities or continuous values, based on the specific task at hand.

3.4 Residual Neural Network

A residual neural network, often called a residual network or ResNet, is a deep learning architecture where the layers focus on learning residual functions based on the inputs from the previous layers. It was developed by Microsoft Research in 2015 for the purpose of image recognition. "It achieved victory in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) that same year". [38] [39]Key Components of ResNet Architecture include:

3.4.1 Residual Block

These blocks differentiate a RNN from classical CNN architecture. A classical neural network processes the input in a linear manner where each input is passed through a series of convolution layer and then directed towards the activation layer. A residual network on the other hand incorporates skip connection by placing the input to another block's output, thereby establishing a residual connection.

The representation of the output from the residual block H(x) is as follows:

$$H(x) = F(x) + x \tag{3.2}$$

“F(x) represents the residual mapping learned by the network .The presence of identity term x allows the gradient to flow more easily” [40] .

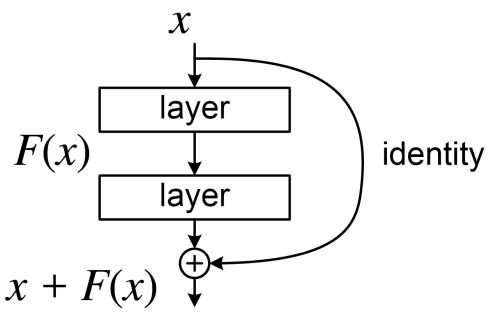

Figure 3.2: A residual block in a deep residual network. Source: LunarLullaby - Own work, CC BY-SA 4.0

3.4.2 Skip Connection

Skip connections contribute to the formation of residual blocks.A Skip Connection bypasses some layers in a neural network, passing the output of one layer as input to subsequent layers rather than solely to the immediate next layer. “This enables the model to learn identity functions, ensuring that the higher layer will perform at least as well as the lower layer, if not better” [41].

3.4.3 Stacked layers

ResNet architectures consist of a series of stacked residual blocks.The integration of multiple residual blocks enables the construction of a significantly deep architecture within the ResNet framework.Variants of ResNet comprising 50, 101, and 152 layers were introduced.

3.4.4 Global Average Pooling(GAP)

Global Average Pooling is the last layer of Resnet architectures before the fully connected layers. GAP shrinks spatial dimensions into a singular value for each feature map, resulting in a compact representation of the complete feature map.

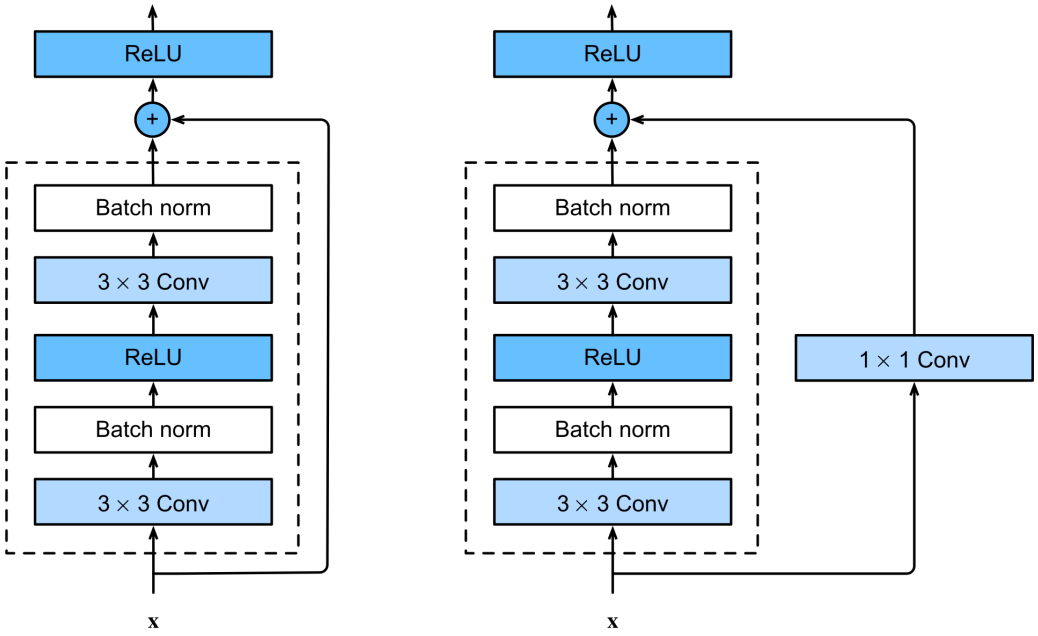

Figure 3.3: Block diagram of ResNet (2015). Source: Zhang, Aston and Lipton

3.5 Summary

In the Background Study chapter, we discussed various important terms related to detection and diagnosis of AD. We explored the role of imaging techniques, such as MRI and PET scans, in identifying brain abnormalities associated with Alzheimer's. We also discussed about machine learning and deep learning in neuroimaging, highlighting the use of Convolutional Neural Networks for analyzing brain scans. Additionally, we looked into the architecture and functionality of Residual Neural Networks (ResNets) and their advantages in handling complex imaging data for Alzheimer's disease classification.

Chapter 4

Methodology

4.1 Introduction

Considering the intricate nature of Alzheimer's disease and its gradual progression that can be detected via neuroimaging, we selected convolutional neural networks as they are able to extract hierarchical features in high-dimensional images autonomously. This eliminates the requirement for manual feature engineering.

This study involves the selection of transfer learning ResNet50v2 alongside a custom Sequential model to classify AD in its different stages, providing a comparative evaluation of both pre-trained and custom architectures. Transfer learning demonstrates superior performance compared to a custom sequential model when applied to smaller datasets. The transfer learning model selected was ResNet50v2, recognized for its proficiency in extracting intricate features [42]. The pre-activation design of the model enhances gradient flow, effectively tackling the vanishing gradient issue in deep networks. Pre-trained weights from ImageNet have been applied to prevent overfitting and to decrease training time. The Sequential model was implemented to create a baseline for comparison. This allows for the creation of a CNN model from the ground up, facilitating exploration of various layer setups, activation functions, and pooling strategies. Training the Sequential model from the ground up requires a large dataset. To achieve improved results, we have augmented the dataset to expand the number of data points. The integration of both models enables an in-depth examination of the trade-offs between the complexity and efficiency of pre-trained and custom-designed architectures. This approach seeks to determine the optimal model for identifying Alzheimer's disease across different phases.

4.2 Dataset

4.2.1 Source of Data

We have used the Alzheimer data from "Open Access Series of Imaging Studies (OASIS)" [43], which is available on Kaggle. The dataset comprises magnetic resonance imaging (MRI) scans. It contains images labeled into four categories: NonDemented (ND), VeryMildDemented (VMD), MildDemented (MD), and ModerateDemented (MoD). This classification aligns with the progressive stages of decline in cognitive functions observed in AD, providing a comprehensive basis for training and evaluating machine learning models.

4.2.2 Data Composition

The dataset is made up of 86,400 MRI images, distributed across four distinct classes that represent various stages of cognitive decline. The composition of the dataset is as follows:

1. **Non-Demented (ND):** 67,200 images, representing individuals without signs of dementia.
2. **Very Mild Demented (VMD):** 13,700 images, indicating the earliest stage of dementia with subtle cognitive decline.
3. **Mild Demented (MD):** 5,000 images, reflecting moderate cognitive impairment and noticeable memory issues.
4. **Moderate Demented (MoD):** 488 images, representing advanced dementia with severe cognitive and functional deficits.

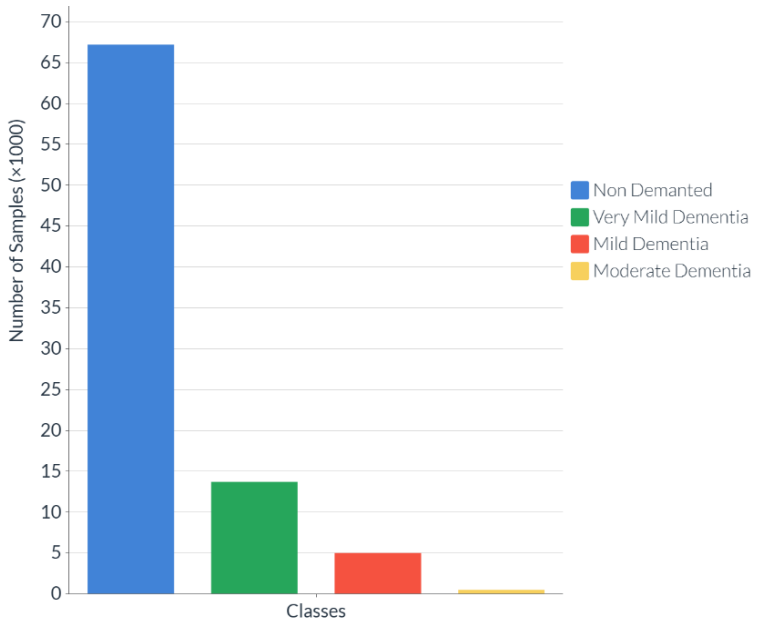

Figure 4.1: Distribution of Data Across Different Classes

Figure 3.1 reveals an imbalance in the representation of all classes. In order to address this issue, we implemented data augmentation methods to achieve class balancing, which ensured a more uniform distribution of data among all categories.

4.2.3 Data Augmentation

Imbalanced datasets can lead to model bias, which causes predictions to favor the majority class and results in suboptimal performance for minority classes. To address this, we picked 1,500 samples from each of the following categories: Non-Demented (ND), Mildly Demented (MD), and Very Mildly Demented (VMD). To address the significant under-representation of the Moderate Demented (MoD) class, data augmentation techniques were employed to artificially increase its data points, thereby achieving class balance.

We performed the augmentation using the ImageDataGenerator from the TensorFlow Keras library. Considering the nature of the neuroimaging data, the transformations were carefully designed to maintain critical structural and diagnostic characteristics. Augmentation methods involved applying random horizontal and vertical flips to create variability in image acquisition, adjusting brightness to address scanning inconsistencies, and modifying contrast to improve image diversity. The objective of these methods was to produce realistic variations while preserving the integrity of the neuroimaging data. This strategy effectively addressed the imbalance in class representation, by which the model is able to learn from all categories uniformly. By ensuring balanced training data, this step increased the reliability and generalization of the model for classifying Alzheimer's disease.

4.2.4 Data Preprocessing

The dataset was carefully preprocessed to improve its applicability for deep learning models, specificly required for medical imaging. The data pipelining framework of TensorFlow allowed efficient handling of large datasets and real-time preprocessing. Key steps included:

- **Grayscale Conversion:** All images underwent conversion to grayscale to highlight structural details pertinent to neuroimaging, removing unrelated color channels that are generally irrelevant in MRI.
- **Image Resizing:** The ResNet50v2 model requires the input images to be the size of 224× 224 pixels. We changed the dimention of the images as per requirement.
- **Normalization:** Pixel values were scaled to the range [-1, 1] to ensure effective result from ResNet50v2 model. But for the Sequential model, the images were not normalized.

- **Label Conversion:** Class labels were transformed into categorical format to enable multi-class classification.

By integrating these steps into TensorFlow's efficient data pipelining workflow, preprocessing and augmentation were streamlined, ensuring the data was prepared for robust and balanced model training.

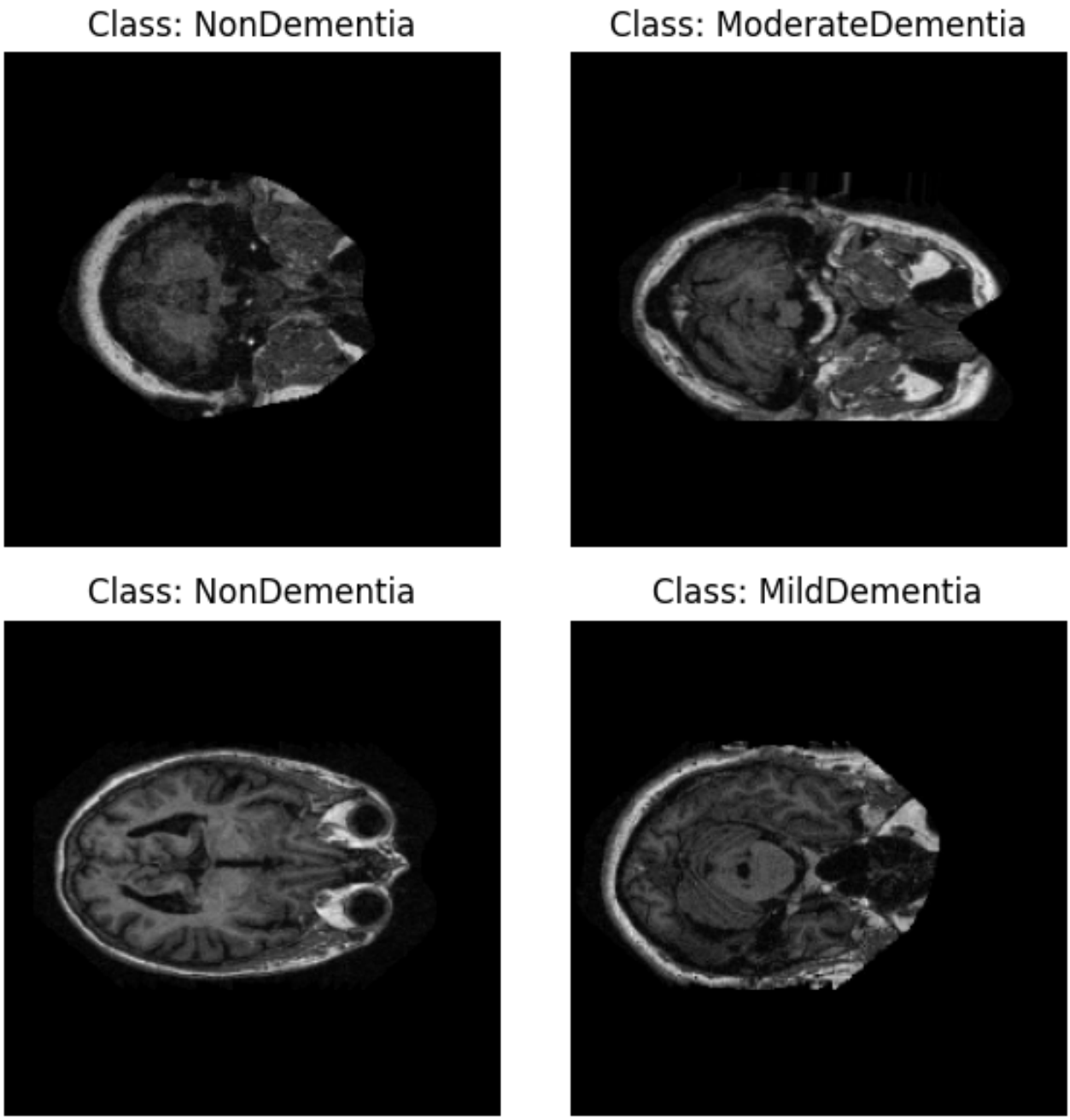

Figure 4.2: Images Before Applying Preprocessing

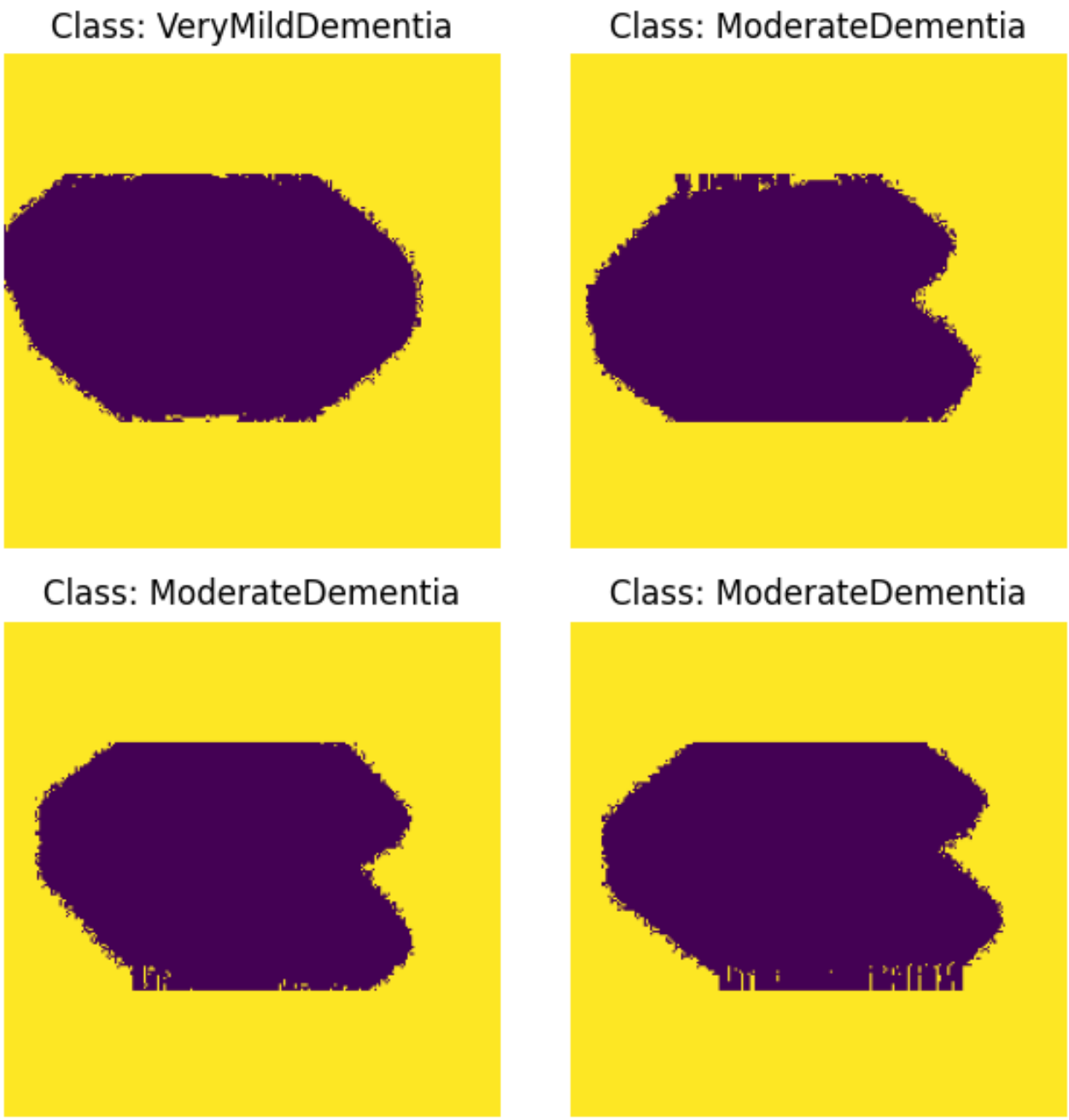

Figure 4.3: Images After Applying Preprocessing

4.3 Proposed Model

In this study, two deep learning models were used to classify AD using neuroimaging data: ResNet50v2 and a custom Sequential model. Both models were selected for their exceptional ability to classify images and identifying complex features within medical imaging.

4.3.1 ResNet50v2 Model

Our proposed model, ResNet50v2, employs the ResNet (Residual Network) architecture. It is an implementation from the Keras Applications library that includes 152 layers with residual

connections. The model is well-suited for transfer learning in medical imaging tasks, such as the classification of AD, due to its use of pre-trained weights from ImageNet.

We developed a Sequential model to customize the ResNet50v2 model for our dataset. To begin, we incorporated a Lambda layer to preprocess gray-scale neuroimaging data into RGB format by duplicating the single channel to three channels, in accordance with the input requirements of the pre-trained ResNet50v2 model. We then incorporated the ResNet backbone and frozen its layers, thereby minimizing the risk of overfitting and preserving the pre-trained features.

In order to refine the learned features and classify the data into four categories, we implemented fully connected layers subsequent to feature extraction. A dense layer with 512 units and ReLU activation was incorporated to capture high-level patterns. Following that, we have added a dropout layer of 50%. Subsequently, a 256-unit dense layer followed by a dropout layer of 20% and a final 4-unit dense layer were added, both of which also utilized ReLU activation. These layers improved the model's capacity to effectively distinguish between the four classes.

In order to guarantee constant convergence during training, we implemented an exponential decay schedule for the learning rate, starting at $lr_i = 0.001$ and decreasing to $lr_f = 10^{-8}$. The equation for scheduling learning rate follows:

$$lr_{epoch} = lr_i \times 10^{-\frac{epoch}{s}} \tag{4.1}$$

epoch = Current epoch count

s = Decay step size

lr_i = Initial learning rate

lr_{epoch} = Learning rate at current epoch

Furthermore, we implemented early stopping to terminate training when validation performance was not improving, thereby avoiding overfitting. In order to optimize the model, we applied the Adam optimizer for its ability to handle complex datasets.

Training Strategy : The dataset has been divided, using 80% for training purposes and keeping 20% for validation. The subsequent parameters were used to train the model. We have used batch size of 32 and total 100 epochs. Loss function was "Sparse Categorical Crossentropy" with optimizer "Adam". We dynamically changed the learning rate using "Exponential Decay" function starting at 0.001, with a decay every 20 epochs. We used pre-trained weights of Imagenet.

ResNet50v2 Model Summary

Total params: 24,681,616 (94.15 MB)

Trainable params: 1,116,816 (4.26 MB)

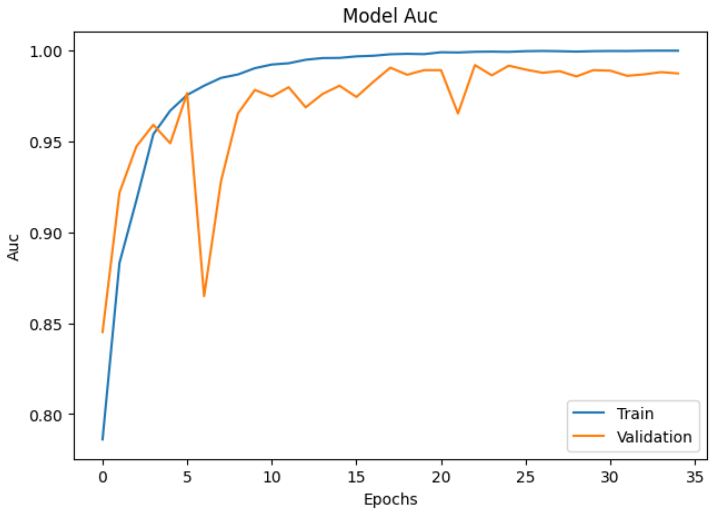

Figure 4.4: Change of AUC During The Training and Validation of ResNet50v2 Model

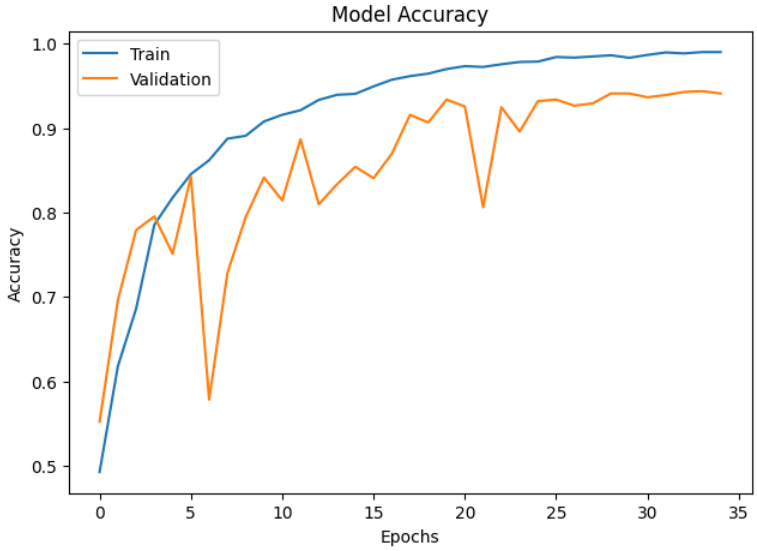

Figure 4.5: Change of Accracy During The Training and Validation of ResNet50v2 Model

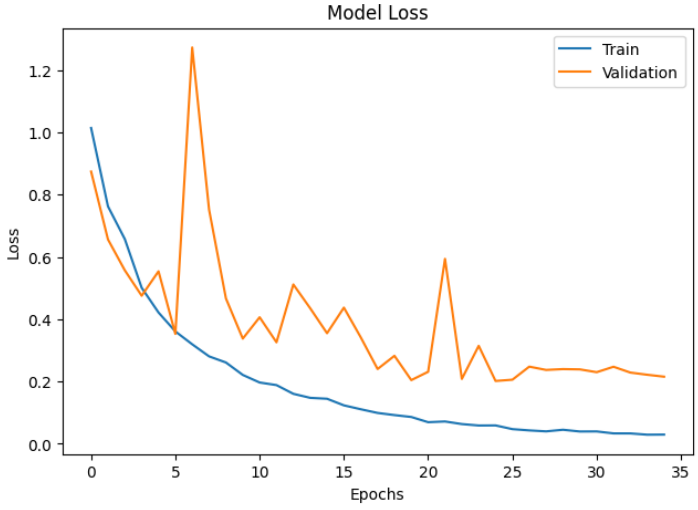

Figure 4.6: Change of Loss During The Training and Validation of ResNet50v2 Model

Layer (type)	Output Shape	Param #
lambda_1 (Lambda)	(None, 224, 224, 3)	0
resnet50v2 (Functional)	(None, 2048)	23,564,800
flatten_1 (Flatten)	(None, 2048)	0
dense_3 (Dense)	(None, 512)	1,049,088
dense_4 (Dense)	(None, 128)	65,664
dense_5 (Dense)	(None, 16)	2,064

Table 4.1: ResNet50v2 model summary.

Non-trainable params: 23,564,800 (89.89 MB)

By combining the powerful feature extraction capabilities of ResNet50v2 with our customized dense layers and training strategy, we built a model that is well-suited for analyzing neuroimaging data and tackling the challenges of multi-class classification in Alzheimer's disease.

4.3.2 Sequential Model

The Sequential model implemented in this study is a Convolutional Neural Network (CNN) defined through TensorFlow's Sequential API. This Sequential model architecture includes convolutional layers, pooling layers, and dense layers, following a systematic pipeline for feature extraction and classification. The model has been customized specifically for multi-class classification tasks.

The process commenced with the establishment of the Sequential model. The input layer defines an RGB image input characterized by a shape of (176, 208, 16). We began by implementing two convolutional layers, each featuring 16 filters and a kernel size of 3, to capture fundamental characteristics such as edges and textures. The subsequent layer implemented max-pooling, effectively reducing spatial dimensions to preserve essential information while minimizing computational demands.

To improve feature extraction, we included custom convolutional blocks, each consisting of two separable convolution layers for efficient computation, batch normalization to stabilize activations, and a max-pooling layer for down-sampling. The blocks functioned in a sequential manner, utilizing filter sizes of 32, 64, 128, and 256, thereby capturing increasingly intricate patterns. Dropout layers were strategically placed to mitigate overfitting, especially following the blocks that utilized a greater number of filters.

After the extraction of features, a flattening layer transformed the 3D feature maps into a 1D vector, facilitating their integration into fully connected layers. The architecture employed tailored dense blocks with diminishing units ($1024 \rightarrow 64$), where each block comprises, a dense layer utilizing ReLU activation, batch normalization to improve stability, and dropout for regularization (which

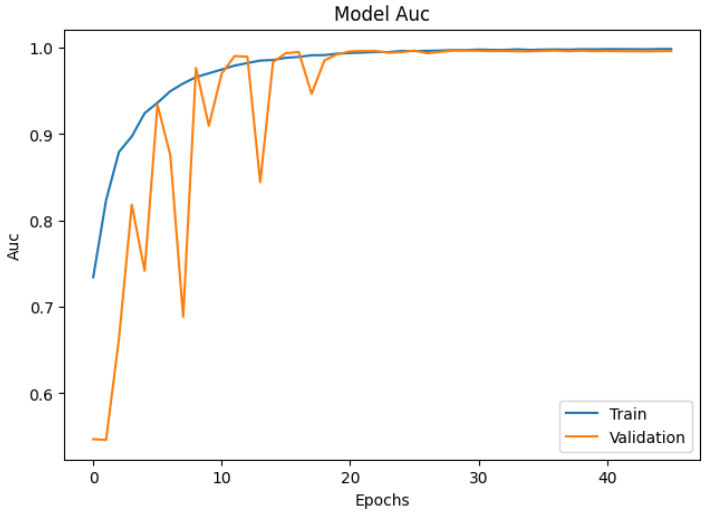

Figure 4.7: Change of AUC During The Training and Validation of Sequential Model

ranged from 0.7 to 0.2). This hierarchy enhanced feature representations and facilitated efficient classification. The concluding output layer employed a dense layer featuring softmax activation to generate probabilities for multi-class classification.

"Adam" was used as the optimizer of the model to facilitate adaptive learning, with categorical crossentropy loss to ensure multi-class accuracy, and metrics such as accuracy and AUC were included for evaluation. Throughout the training process, the learning rate was systematically decreased using an exponential decay schedule, beginning at 0.001 and diminishing every 20 epochs. Callbacks like ModelCheckpoint and EarlyStopping were implemented to guarantee that training concluded at peak performance and the most effective weights were preserved. Ultimately, we conducted training of the model utilizing the supplied dataset, following a specified number of epochs, while ensuring a balance between feature learning and validation performance.

Training Strategy : The dataset has been divided, using 80% for training purposes and keeping 20% for validation. The subsequent parameters were used to train the model.We have used batch size of 32 and total 100 epochs. Loss function was "Categorical Crossentropy" with optimizer "Adam". We dynamically changed the learning rate using "Exponential Decay" function starting at 0.001, with a decay every 20 epochs.

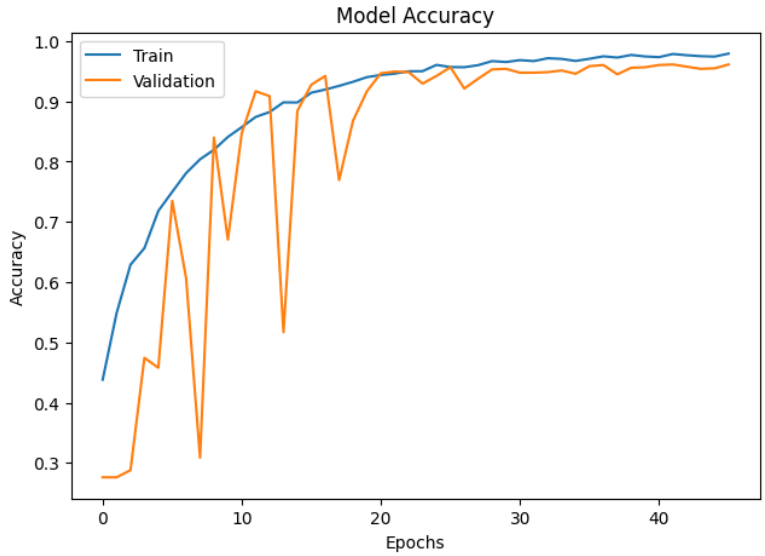

Figure 4.8: Change of Accuracy During The Training and Validation of Sequential Model

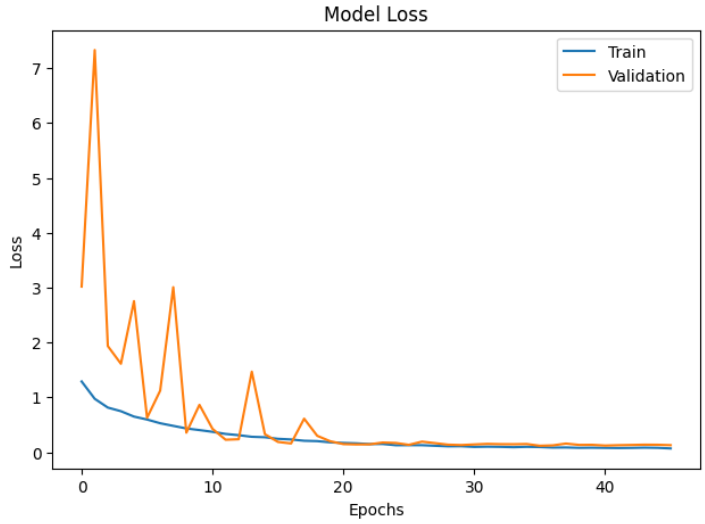

Figure 4.9: Change of Loss During The Training and Validation of Sequential Model

Sequential Model Summary

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 176, 208, 16)	448
conv2d_1 (Conv2D)	(None, 176, 208, 16)	2,320
max_pooling2d (MaxPooling2D)	(None, 88, 104, 16)	0
sequential (Sequential)	(None, 44, 52, 32)	2,160
sequential_1 (Sequential)	(None, 22, 26, 64)	7,392
sequential_2 (Sequential)	(None, 11, 13, 128)	27,072
dropout (Dropout)	(None, 11, 13, 128)	0
sequential_3 (Sequential)	(None, 5, 6, 256)	103,296
dropout_1 (Dropout)	(None, 5, 6, 256)	0
flatten (Flatten)	(None, 7680)	0
sequential_4 (Sequential)	(None, 1024)	7,869,440
sequential_5 (Sequential)	(None, 512)	526,848
sequential_6 (Sequential)	(None, 256)	132,352
sequential_7 (Sequential)	(None, 128)	33,408
sequential_8 (Sequential)	(None, 64)	8,512
dense_5 (Dense)	(None, 4)	260

Table 4.2: Sequential model summary.

Total params: 8,713,508 (33.24 MB)

Trainable params: 8,708,580 (33.22 MB)

Non-trainable params: 4,928 (19.25 KB)

4.4 Summary

This chapter discusses the workflow of developing deep learning models to classify AD from neuroimaging data. We examined the dataset, including its origin, structure, enhancement, and preprocessing methods. Two models were proposed: ResNet50v2, optimized with ImageNet weights, and a bespoke Sequential CNN.

Chapter 5

Results and Discussion

5.0.1 Introduction

This chapter presents and evaluates the performance of two models developed for the classification of Alzheimer's disease. The first model utilizes the ResNet50v2 architecture as its foundation, having undergone pretraining on ImageNet and subsequent fine-tuning to align with the neuroimaging dataset. The second model adopts a comparable architecture, utilizing a more straightforward CNN design that is developed from the ground up, independent of transfer learning techniques. The objective of these models is to categorize neuroimaging data into four distinct classifications: Normal Control (NC), Mild Dementia (MD), Very Mild Dementia (VMD), and Moderate Dementia (MOD).

We conducted comprehensive evaluations of both models, analyzing their performance through multiple metrics including accuracy, specificity, sensitivity and F1-score. The analysis focused on evaluating the performance of each model in managing the imbalanced dataset, assessing the impact of data augmentation, and determining how these models can generalize new unseen data.

Additionally, we will examine the training strategies, focusing on the selection of optimizer, learning rate schedule, and early stopping methods. This chapter aims to offer a detailed analysis of the relative strengths and weaknesses of the two models, illuminating the efficacy of employing a pretrained model in contrast to a custom-built CNN for tasks related to medical image classification.

5.1 Performance Measures

In this analysis, we evaluate both models' performance through various metrics to compare how they accurately classify AD into different classes with imbalanced data. We have briefly discussed about our evaluation metrics.

5.1.1 Confusion Matrix

The confusion matrix is a table that demonstrates how well the model can predict for each class. It consists of the following components:

- **True Positives (TP)**: Number of cases which are correctly identified as positive.
- **True Negatives (TN)**: Number of cases which are correctly identified as negative.
- **False Positives (FP)**: Number of cases which are incorrectly identified as positive.
- **False Negatives (FN)**: Number of cases which are incorrectly identified as negative.

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Class Names	TP	TN	FP	FN
Mild Dementia	153	3249	8	47
Moderate Dementia	3	3438	0	16
Non Dementia	2510	719	49	179
Very Mild Dementia	515	2689	219	34

Table 5.1: Confusion Matrix of Sequential Model

Class Names	TP	TN	FP	FN
Mild Dementia	153	3219	38	47
Moderate Dementia	4	3438	0	15
Non Dementia	2435	708	60	254
Very Mild Dementia	506	2647	261	43

Table 5.2: Confusion Matrix of ResNet50v2 Model

5.1.2 Accuracy

It is the most straight-forward metric of performance which is calculated by dividing the total number of correct predictions by total test cases. In multi-class classification tasks, accuracy provides a broad overview of the model's performance across all classes. However, it is a poor form of metric for imbalanced dataset. The equation for accuracy is as follows:

$$\text{Accuracy} = \frac{\sum_i \text{TP}_i + \sum_i \text{TN}_i}{\sum_i \text{TP}_i + \sum_i \text{TN}_i + \sum_i \text{FP}_i + \sum_i \text{FN}_i}$$

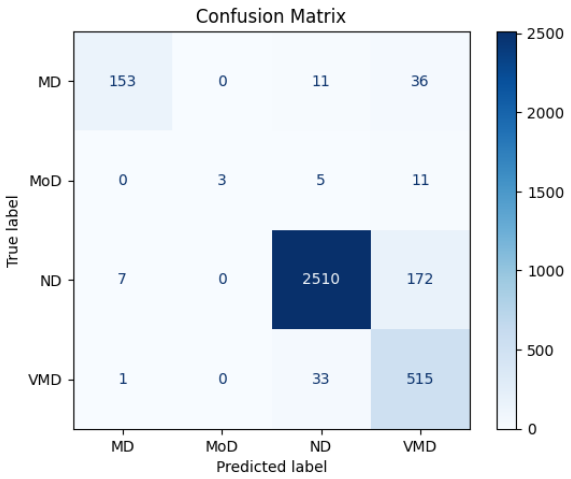

Figure 5.1: Confusion matrix for Sequential model

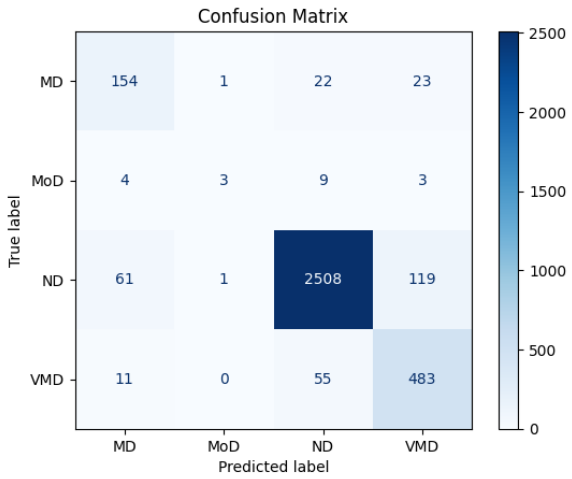

Figure 5.2: Confusion matrix for ResNet50v2 model

5.1.3 Sensitivity

"The sensitivity of a clinical test refers to the ability of the test to correctly identify those patients with the disease." [44] The formula for sensitivity is as follows:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

5.1.4 Specificity

"The specificity of a clinical test refers to the ability of the test to correctly identify those patients without the disease." [44] The formula for specificity is as follows:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

5.1.5 F1-Score

The F1 score is called harmonic mean of precision and recall. It is not affected by class distribution,hence, a better choice if the dataset is imbalanced. The F1 score ranges from 0 to 1, with 1 being perfect precision and recall, and 0 being the worst. The formula for F1-Score is:

$$F1 = 2 \times \frac{\text{TP}}{2 \times \text{TP} + \text{FP} + \text{FN}}$$

Class Names	Sensitivity	Specificity	F1-Score	Accuracy
Mild Dementia	76.5%	99.75%	84.76%	97.67%
Moderate Dementia	15.79%	100.0%	27.27%	99.54%
Non Dementia	93.34%	93.62%	95.66%	93.40%
Very Mild Dementia	93.82%	92.47%	80.28%	92.68%
Overall (Macro)	**69.86%**	**96.46%**	**70.49%**	**96.01%**

Table 5.3: Performance Metrics of Sequential Model

Class Names	Sensitivity	Specificity	F1-Score	Accuracy
Mild Dementia	77.00%	97.67%	71.63%	96.47%
Moderate Dementia	15.79%	99.94%	25.00%	99.48%
Non Dementia	93.27%	88.80%	94.95%	92.28%
Very Mild Dementia	87.98%	95.01%	82.07%	93.90%
Overall (Macro)	**68.51%**	**95.36%**	**68.41%**	**94.81%**

Table 5.4: Performance Metrics of ResNet Model

5.1.6 Performance Summary

Observations

- **Mild Dementia**: The Sequential model showed better results, achieving an F1-score of 84.76% and a specificity of 99.75%, in contrast to ResNet50v2, which recorded an F1-score of 71.63% and a specificity of 97.67%. The sensitivity of both models was similar, with Sequential achieving 76.50% and ResNet50v2 reaching 77.00%.

- **Moderate Dementia** In the Moderate Dementia category, both models encountered difficulties, showing a low sensitivity of 15.79%. The Sequential model achieved a slightly better F1-score of 27.27% compared to ResNet50v2's 25.00%. However, their specificities were almost the same, with Sequential at 100.00% and ResNet50v2 at 99.94%.

- **Non Dementia**: In the Non Dementia class, the Sequential model showed better results compared to ResNet50v2, getting a higher F1-score of 95.66% in contrast to 94.95%, along with a specificity of 93.62% compared to 88.80%. The sensitivities observed were similar, recorded at 93.34% for Sequential and 93.27% for ResNet50v2.

- **Very Mild Dementia**: In cases of Very Mild Dementia, ResNet50v2 showed better results, getting an F1-score of 82.07%, while Sequential reached 80.28%. Additionally, ResNet50v2 exhibited a specificity of 95.01%, in contrast to Sequential's 92.47%. The Sequential model

exhibited a marginally better sensitivity of 93.82%, in contrast to the 87.98% observed in ResNet50v2.

In the evaluation of the overall performance between the Sequential and ResNet50v2 models, certain trends arise that indicate the advantages and drawbacks related to each approach. The Sequential model demonstrates an overall sensitivity (macro-average) of 69.86%, specificity of 96.46%, F1-score of 70.49%, and accuracy of 96.01%. The findings indicate a balance between recognizing true positive cases and reducing false positives, a crucial aspect in the field of clinical decision-making.

The ResNet50v2 model shows a marginally lower macro-average sensitivity at 68.51% and an F1-score of 68.41%. However, it maintains similar levels of specificity at 95.36% and accuracy at 94.81%. The findings suggest that although ResNet50v2 effectively minimizes false positives, it falls short compared to the Sequential model in correctly identifying true positive cases across all classes.

5.1.7 Comparison of performance Among existing models, the proposed model

Table 5.5: Performance comparison of various models for Alzheimer's classification.

Study	**Method**	**Accuracy**	**Specificity**	**Sensitivity**
Liu et al. [20]	Multi-view learning with GM + SVM	93.83%	95.69%	92.78%
Lazli et al. [21]	FPS + SVM	73.00%	-	-
Korolev et al. [2]	ResNet+Softmax	79.00%	-	-
Rallabandi et al. [23]	SVM	75.00%	79.00%	75.00%
Our Proposed Model	Sequential + Softmax	**96.01%**	**96.46%**	**69.86%**
	ResNet50v2 + Softmax	**94.81%**	**95.36%**	**68.51%**

Both of our model exceeds existing approaches with the best accuracy (96.01% and 94.81%) and specificity (96.46% and 95.36%), indicating outstanding Alzheimer's classification dependability.

5.1.8 Summary

This chapter presents an analysis and discussion of the results obtained from our two models: Sequential CNN and ResNet50v2. The Sequential model exhibited superior performance metrics compared to ResNet50v2, showcasing enhanced accuracy and more effective management of the neuroimaging dataset. This underscores the efficacy of a bespoke architecture specifically crafted for the designated task, in contrast to a pre-trained ResNet50v2 backbone. The comparative analysis yielded significant insights into the strengths and limitations of both models, with the Sequential model standing out as the favored solution for Alzheimer's disease classification.

Chapter 6

Conclusion

This thesis studied the application of deep learning models for classifying Alzheimer's disease through neuroimaging data, emphasizing the comparative effectiveness of custom CNN models versus pre-trained models. We examined the performance of custom CNNs, specific for neuroimaging tasks, in comparison to established pre-trained architectures. The investigation demonstrated that customized CNNs demonstrated greater abilities in extracting pertinent features from MRI scans, leading to improved classification accuracy. Through an in-depth analysis of both approaches, we highlighted the benefits and challenges associated with pre-trained models while also emphasizing the promise of custom architectures in meeting particular domain needs. The results provide significant insights into the use of deep learning models for diagnosing AD and indicate potential directions for enhancing model architecture and training methodologies.

6.1 Limitations and Future Scope

Although the results are promising, this study presents a number of limitations. Initially, the dataset utilized for training and evaluation was limited to MRI scans, which might not comprehensively reflect the complicated nature of Alzheimer's disease progression. The performance of the model might improve by utilizing multimodal data, which includes PET or genetic information. Secondly, while pre-trained models such as ResNet50v2 demonstrated impressive outcomes, its reliance on frozen layers might have limited the model's capacity to fully adjust to the unique characteristics of neuroimaging data. Thirdly, the models were trained on a single dataset (OASIS), raising questions about their applicability to other datasets that may have varying imaging protocols or demographic characteristics. Lastly, while we concentrated on enhancing accuracy, additional investigation is required to tackle interpretability, which continues to pose a challenge in deep learning applications within the healthcare sector. Future endeavors may concentrate on utilizing larger and more varied datasets, integrating multimodal imaging data, and enhancing model interpretability.

References

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