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**EXAMINING THE POTENTIAL OF DEEP
LEARNING IN THE EARLY DIAGNOSIS OF
ALZHEIMER'S DISEASE USING BRAIN MRI
IMAGES**

Anmar Shukur Mahmood MAHMOOD

Master's Thesis

Supervisor

Asst. Prof. Dr. Mesut ÇEVİK

Istanbul, 2023

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The thesis titled EXAMINING THE POTENTIAL OF DEEP LEARNING IN THE EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE USING BRAIN MRI IMAGES PREPARED by Anmar Shukur Mahmood MAHMOOD and submitted on 25/04/2023 has been **accepted by unanimously** for the degree of Master of Science in Electrical and Computer Engineering.

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Submission date of the thesis to Institute of Graduate Studies: ____/____/____

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Anmar Shukur Mahmood MAHMOOD

Signature

XXXXXXXXXX

DEDICATION

I dedicate and pledge this research work to my Dear supervisor and my beloved Father, mother, and wife, whose unwavering support, encouragement, and love have been my anchor throughout this journey. I am forever grateful for their sacrifices and belief in me.



ABSTRACT

EXAMINING THE POTENTIAL OF DEEP LEARNING IN THE EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE USING BRAIN MRI IMAGES

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Millions of people around the world are affected by Alzheimer Diseases, which is a major public health issue worldwide. The key to effective treatment and management techniques is early diagnosis of the illness. For the purpose of detecting Alzheimer Diseases using MRI data, we looked into and evaluated three distinct DL models in this study. The first model used is CNN with two convolutional and two fully connected layers served as the initial model. The second model was an improved version of the first, with a leaky ReLU activation function, more fully connected layers, and a larger kernel size. The third model was a transfer learning model with two dense layers that was built on top of the VGG16 architecture. An extensive set of MRI scans from Alzheimer's patients and healthy controls was used to train the models. The first and second CNN models achieved an accuracy of 96%, while the transfer learning model achieved an accuracy of 81%, according to the accuracy, precision, recall, and F1-score measurements. In conclusion, MRI data-based Alzheimer's diagnosis may benefit from DL models. However, further progress is required to improve these models' performance and accessibility for clinical use.

Keywords: AD, Brain Imaging, CNN, Transfer Learning, VGG-16.

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ABBREVIATIONS

CNN	:	Convolutional Neural Network
VGG-16	:	Visual Geometry Group 16
ReLU	:	Rectified Linear Unit
Softmax	:	Softmax Activation Function
Leaky ReLU	:	Leaky Rectified Linear Unit
AD	:	Alzheimer's Diseases
DL	:	Deep Learning
ML	:	Machine Learning

1. INTRODUCTION

This thesis segment presents a summary of the study's research problem and key goals. It sets the stage for the remainder of the thesis, introducing the background and context of the research and providing a clear rationale for why the study was conducted. The following are the key elements of a thesis introduction:

- i. Background: Provide a brief overview of the research problem, including the context and relevant literature.
- ii. Research Problem: Clearly state the research problem and explain the significance of the problem to the field of study.
- iii. Research Objectives: List the main objectives of the study and explain how they will contribute to resolving the research problem.
- iv. Research Questions: Identify the main research questions that will be addressed in the study. These questions should be directly related to the research objectives.
- v. Thesis Overview: Provide a brief overview of the structure and content of the thesis, indicating the main sections and chapters.

1.1 BACKGROUND

The Background section of a thesis on the topic of "Examining the Potential of Deep Learning in the Early Diagnosis of Alzheimer's Disease Using Brain MRI Images" should provide the following information:

- a. Overview of AD This section aims to give a concise summary of AD, including its definition, underlying causes, recognizable symptoms, and progression. It should also discuss the impact of Alzheimer's on individuals and families, and the need for early detection and treatments.
- b. Current diagnostic methods: This section should provide an overview of the current methods used for diagnosing Alzheimer's, including clinical evaluations, cognitive assessments, and imaging studies. It should also discuss the limitations and challenges of these methods and the need for more accurate and efficient methods of diagnosis.

Deep learning for medical imaging: This section should introduce, its history and development, and its applications in medical imaging. It should also discuss the potential of

deep learning for diagnosing Alzheimer's from brain MRI scans, and the advantages and limitations of this approach.

1.1.1 Overview of AD

AD (Alzheimer Diseases), a degenerative brain disorder, impacts memory, cognition, and behaviour. Currently, there is no cure for this condition, which is the most common cause of dementia among the elderly. The progression of Alzheimer's starts with minor memory loss and difficulties in problem-solving, but it gradually worsens, leading to difficulties in performing everyday tasks and communication impairments [1].

The cause of AD unknown, however it is thought to be a mix of hereditary, environmental, and lifestyle factors. The signature characteristic of Alzheimer's is the build-up of abnormal protein deposits in the brain, referred to as beta-amyloid plaques and tau tangles, that obstruct communication between brain cells and lead to their eventual death [2].

Brain imaging studies have shown that the brain of an Alzheimer's patient is smaller than that of a healthy person, with smaller regions in memory, language, and behaviour-related areas. Over time, the brain continues to shrink, and cells die, leading to widespread brain damage.

At present, there are three medications that have received approval for treating the symptoms of AD: cholinesterase inhibitors, NMDA receptor antagonists, and a combination of the two. These drugs can help slow down the progression of the disease, improve memory and thinking, and increase overall quality of life. However, they do not cure Alzheimer's and eventually become less effective over time.

In addition to medication, there are several lifestyle changes that may help manage the symptoms of AD and improve overall health. These include staying mentally and physically active, eating a balanced diet, managing stress, and getting adequate sleep.

Caregivers also play a crucial role in supporting people with Alzheimer's. They can help with daily tasks, provide emotional support, and assist with managing the symptoms of the disease. Support groups, respite care, and community resources can also be helpful for caregivers.

AD affects millions of individuals globally and is a complex and challenging condition. There is still a lot of work to be done to find a cure for Alzheimer's, though new treatments and methods for managing its symptoms are being investigated. Until then, it is important to

provide support, care, and understanding to those affected by Alzheimer's and their families [3].

1.1.2 Detection of Alzheimer's from Brain MRI

The early identification of (AD) is vital for prompt intervention and more effective management of the condition. Currently, the diagnosis of AD is primarily based on clinical evaluations, but brain imaging is increasingly being utilized as a supplementary method for early AD detection. Among the various imaging modalities, magnetic resonance imaging (MRI) has proven to be a powerful tool for early detection of AD due to its ability to visualize the brain structure and detect subtle changes that may indicate the presence of the disease.

One of the key imaging markers of AD is the reduction in the size of the hippocampus, a brain region critical for memory formation. This reduction can be detected on MRI scans and has been shown to be a sensitive marker of early AD. Furthermore, advanced MRI techniques, such as structural MRI and diffusion tensor imaging (DTI), can detect additional brain changes that are indicative of AD, such as changes in gray and white matter density, as well as alterations in the connections between brain regions.

The use of MRI for early detection of AD has several potential benefits. One advantage of using magnetic resonance imaging (MRI) for AD detection is that it is non-invasive. This means that it does not entail exposure to radiation or the use of contrast agents, making it a secure and well-tolerated option for individuals with other health conditions that may prohibit the use of other imaging techniques. Second, MRI is highly accurate and can detect subtle changes in the brain that may not be apparent on clinical assessments. This allows for earlier detection of AD and earlier initiation of interventions that can slow the progression of the disease.

Another promising application of MRI for early detection of AD is the use of machine learning algorithms. These algorithms can be trained on large datasets of MRI scans and use complex statistical models to identify patterns and relationships between brain imaging markers and AD diagnosis. This allows for highly sensitive and specific detection of AD, even in the earliest stages of the disease.

However, while MRI has proven to be a powerful tool for early detection of AD, there are also some limitations and challenges that need to be addressed. First, the cost of MRI scans is often prohibitive, and not all individuals have access to this technology. Second, the

interpretation of MRI scans can be difficult and requires specialized expertise. Finally, while MRI has been shown to be a sensitive marker of AD, it is not always specific, and other conditions such as stroke or brain tumors can also cause changes in brain structure that can be detected on MRI [4].

In conclusion, the application of MRI for early AD detection holds substantial promise for enhancing the diagnosis and management of this debilitating condition. Despite the limitations and obstacles that need to be overcome, the growing access to advanced MRI methods and ML algorithms offers new prospects for early detection and intervention. Further research is needed to fully realize the potential of MRI for early detection of AD and to ensure that this technology is accessible and affordable for all individuals who may benefit from it.

1.1.3 Deep Learning for Medical Imaging

Diagnostics, segmentation, detection, and classification are just a few of the many applications for which DL has become increasingly popular in medical imaging. Due to their ability to comprehend spatial relationships in image data, CNN are the DL models that are utilized the most frequently in these kinds of applications. In medical imaging, DL is used in the following ways:

- i. Image classification: Classifying medical images into normal and abnormal, or different diseases and conditions.
- ii. Object detection: Detecting and locating specific objects (e.g. tumors, lesions, organs) within medical images.
- iii. Image segmentation: Delineating and separating objects within medical images.
- iv. Image generation: Generating new images from existing ones to enhance, restore or augment the data for training DL models.
- v. Image registration: Aligning and transforming images for comparison and analysis.

In general, DL holds the potential to transform medical imaging and enhance the accuracy and speed of diagnosis. However, additional research and validation are necessary to guarantee its safe and dependable usage in clinical settings.

The objective of the "DL " artificial intelligence discipline is to create algorithms and models that closely approximate the structure and operation of the human brain. It has been utilized in numerous fields, including medical imaging, natural language processing, speech

recognition, and computer vision. A number of diseases, including Alzheimer's, have been successfully identified and treated using DL, particularly in medical imaging (AD) [5].

Early identification of (AD) is critical for improving patient outcomes and reducing the illness's impact on the healthcare industry. Traditional procedures to detecting AD include cognitive testing, brain imaging, and cerebrospinal fluid examination, but they can be intrusive, time-consuming, and produce inconsistent results. DL algorithms may give a potential answer to these issues by providing a non-invasive and effective method of identifying AD in its early stages utilising magnetic resonance imaging (MRI) images.

Using brain MRI images, CNN, a type of DL algorithm, have been utilized to diagnose AD. Because they are made to evaluate and recognize patterns and characteristics in images, CNNs are excellent candidates for use in medical imaging applications. In the context of brain MRI scans, CNNs may evaluate images of the brain and identify patterns and characteristics that are symptomatic of AD. The VGG16 architecture is a type of CNN that has been used a lot in medical imaging applications. It has shown promising results for finding AD in brain MRI data [6].

Deep learning for Alzheimer Diseases detection from brain MRI scans entails multiple processes, including image pre-processing, data augmentation, model training, and model assessment. The MRI scans are transformed into a format that the CNN can handle during the pre-processing stage, and any artefacts or noise in the pictures are eliminated. The training data is enhanced during the data augmentation stage by adding transformations and rotations to the pictures in order to expand the size of the training set and improve the model's resilience. The CNN is trained using a sizable dataset of brain MRI scans during the model training phase, using a technique called backpropagation to tweak the network's parameters and enhance performance. The accuracy and efficiency of the model are assessed during the model assessment stage by measuring the CNN's performance on a validation set of MRI data [7].

Medical imaging is an important diagnostic and therapy tool for many disorders, including Alzheimer's. Traditional techniques of medical image analysis rely on human feature extraction and generate predictions using shallow algorithms. These procedures, however, are time-consuming, prone to inaccuracy, and may not deliver appropriate precision. DL algorithms have advanced, making it feasible to automate feature extraction and obtain improved accuracy in medical imaging [8].

In a variety of contexts, CNN and other DL algorithms have been successfully utilized in medical imaging. CNNs, for example, have been used to diagnose AD (Alzheimer Diseases) from MRI images by extracting characteristics from the brain scans and categorising them into distinct disease stages. Additionally, brain MRI images have been divided into distinct regions that can be further analysed with the help of DL algorithms.

Another common DL architecture for medical imaging is recurrent neural networks (RNNs). RNN stands for "Recurrent Neural Network". It is a type of neural network designed for processing sequential data, such as time series, natural language text, and speech. RNNs have been used to analyse time-series data like PET and CT scan images by considering the pictures' inherent temporal information. In medical imaging, the use of Generative Adversarial Networks (GANs) is expanding. GANs are a type of DL architecture in which two networks the generator and the discriminator—are utilized to generate new images that appear to be genuine photographs. In medical imaging, GANs have been used to create pictures that can be used to train ML algorithms, reduce the need for large data sets, and increase forecast precision [9].

In conclusion, various medical imaging tasks have been successfully completed using DL techniques, which have demonstrated significant promise in medical imaging. Higher accuracy in medical imaging can be achieved with the development of DL algorithms, allowing for earlier diagnosis and treatment of a variety of diseases, including Alzheimer's. However, in order to achieve even better outcomes in the future, it is essential to continue conducting research and developing new DL algorithms.

1.2 PURPOSE

Using DL, early AD detection from brain MRI aims to offer a more accurate, efficient, and non-invasive approach to diagnosing AD in its earliest stages. The objective is to improve this debilitating condition's diagnosis and treatment, resulting in earlier interventions that can slow the disease's progression and enhance AD sufferers' quality of life.

Computers can use DL, a type of artificial intelligence, to learn from large datasets and make predictions based on what they learn. In the context of AD, DL can be used to analyse brain MRI scans and identify patterns and changes that are indicative of the disease. This can help to detect AD at its earliest stages, before it has progressed to a point where it is apparent on clinical assessments.

There are a number of significant advantages to using DL for brain MRI-based early AD detection. First, DL algorithms can analyse large amounts of data quickly and accurately, allowing for rapid and efficient diagnosis of AD. Second, DL algorithms are highly sensitive and specific, allowing for accurate detection of AD even in its earliest stages. Third, DL algorithms are non-invasive, making them a safe and well-tolerated option for individuals who may have other health conditions that could contraindicate other imaging modalities. While the use of DL for early detection of AD from brain MRI has significant potential, there are also some limitations and challenges that need to be addressed. First, the cost of MRI scans is often prohibitive, and not all individuals have access to this technology. Second, the interpretation of MRI scans can be difficult and requires specialized expertise. Finally, while MRI has been shown to be a sensitive marker of AD, it is not always specific, and other conditions such as stroke or brain tumours can also cause changes in brain structure that can be detected on MRI.

1.3 SCOPE OF PROJECT

The aim of the project "Examining the Potential of Deep Learning in the Early Diagnosis of Alzheimer's Disease Using Brain MRI Images" is as follows:

- a. Data acquisition and preparation: The project entails gathering a substantial dataset of brain MRI scans from individuals who have and do not have AD. The data will have to be processed to make sure it is in an appropriate format for analysis.
- b. Development of the DL model: The project will involve creating a DL model that can accurately identify AD from brain MRI scans, such as the VGG16 architecture or a Convolutional Neural Network (CNN).
- c. Training and testing of the model: The DL model will be trained on the collected brain MRI data, and its accuracy will be tested on a different dataset.
- d. Assessment of performance: The performance of the model will be evaluated using various metrics, such as accuracy, sensitivity, and specificity, to determine its suitability for early detection of AD from brain MRI scans.
- e. Implementation and integration: The project will examine the best methods for implementing and integrating the DL model into clinical practice, considering ethical, legal, and regulatory considerations.

The project aims to use DL to find a way to use brain MRI images to find AD early and to help develop a more accurate, efficient, and non-invasive way to diagnose the disease. The ultimate objective is to improve the diagnosis and management of AD, as well as the quality of life for those affected by this devastating disorder.

1.4 ETHICAL CONSIDERATION

There are a number of ethical issues that arise when using DL to detect AD early from brain MRIs, including:

- i. Privacy and data security: The gathering and storage of personal medical data, such as brain MRI scans, poses privacy and data security concerns. It is critical to ensure that the proper measures are in place to protect the privacy and confidentiality of those whose data is being used.
- ii. Fairness and bias: DL methods run the danger of perpetuating existing biases and prejudice, especially if the data used to train the model is biased or unrepresentative. It is critical to ensure that the model is trained on a varied and representative set of data, and that adequate mechanisms are in place to detect and mitigate any potential biases.
- iii. Transparency and accountability: DL models may be complicated and hard to comprehend, which raises concerns about accountability and transparency. Making ensuring the model is created and assessed in a transparent and accountable manner, as well as putting the right safeguards in place to make sure the model is auditable and understandable, is vital.
- iv. Clinical implementation: Concerns about the ethical obligations of healthcare professionals and the impact of technology on patients and their families arise when DL models are used in clinical decision-making. Understanding the ethical implications of technology and ensuring its responsible and ethical use are essential.

In conclusion, the design and implementation of DL for the early detection of AD using brain MRI raise a number of significant ethical concerns. It is essential to take these factors into consideration and ensure that technology is utilized in an ethical and responsible manner in order to safeguard the interests of AD patients.

1.5 PROBLEM STATEMENT

A significant obstacle to public health is the issue of AD early detection. Millions of people worldwide are affected by AD, a progressive and debilitating condition that significantly lowers quality of life. Early diagnosis of AD is critical for effective treatment and management, but traditional diagnostic methods such as cognitive assessments and blood tests are often inadequate, and symptoms may not become apparent until the disease has progressed to an advanced stage.

Brain MRI is a sensitive marker of AD and has been shown to detect changes in brain structure that are indicative of the disease. However, the interpretation of brain MRI scans is complex and requires specialized expertise, and the cost of MRI scans is often prohibitive. There is a need for a more accurate, efficient, and non-invasive method of diagnosing AD, particularly at its earliest stages.

DL, a type of artificial intelligence, has the potential to provide a solution to this problem by allowing computers to analyse large amounts of data and identify patterns and changes that are indicative of AD. However, the use of DL for early detection of AD from brain MRI is a relatively new and untested area, and there are significant challenges that need to be addressed, such as ensuring the accuracy and robustness of the DL model and making sure that this technology is accessible and affordable for all individuals who may benefit from it. In conclusion, the problem of using DL to detect AD early from brain MRI is a complicated and urgent challenge that has the potential to improve AD diagnosis and treatment. However, further research and development are needed to fully realize this potential. The objective is to create a DL model that can accurately detect AD in its earliest stages from brain MRI scans and to identify the most effective methods for utilizing this technology in clinical settings.

1.6 PROBLEM SOLUTION

AD is a huge global public health issue that affects millions of individuals throughout the world. This technique has the potential to increase the efficacy and precision of AD diagnosis, particularly in its early phases, as well as making it accessible and inexpensive for all those who might benefit from it. The objective is to create a DL model that can correctly identify early-stage AD from brain MRI images and to ascertain the optimal methods for integrating this technology into clinical practise.

1.7 OBJECTIVES

The objectives of early detection of AD from brain MRI using CNN (Convolutional Neural Network) and VGG16 (Visual Geometry Group 16, which is a deep convolutional neural network architecture) are as follows:

- a. To create a VGG16-based DL model for the early detection of AD from brain MRI scans.
- b. To determine how well the DL model detects AD from brain MRI scans in terms of accuracy, sensitivity, and specificity.
- c. To compare the performance of the DL model with traditional methods of AD diagnosis, such as cognitive assessments and blood tests.
- d. To investigate the potential of the DL model to detect AD in its earliest stages, before symptoms become apparent.
- e. To explore the ability of the DL model to differentiate AD from other conditions that may cause similar changes in brain structure, such as stroke or brain tumors.
- f. To determine the feasibility and cost-effectiveness of using the DL model for early detection of AD in clinical practice.
- g. To assess the robustness and dependability of the DL model in the presence of MRI data that is either incomplete or noisy.

These goals' ultimate purpose is to ascertain the viability and potential of employing CNN VGG16 for early AD detection from brain MRI images, as well as to ascertain the optimal methods for deploying this technology in clinical practise. By achieving these goals, scientists and medical professionals will be better equipped to diagnose and treat AD, which will result in early interventions and a higher quality of life for those who suffer from this crippling disorder [10].

1.8 RESEARCH QUESTION

Potential research questions for the project " Examining the Potential of Deep Learning in the Early Diagnosis of Alzheimer's Disease Using Brain MRI Images " are:

- i. When it comes to diagnosing AD from brain MRI scans, how do the accuracy of DL techniques, specifically Convolutional Neural Networks (CNN) and the VGG16 architecture, stack up to those of more conventional approaches?

- ii. Can DL techniques be used to accurately detect AD at an early stage, and what is the potential impact of early detection on the diagnosis and management of the disease?
- iii. What are the ethical and practical considerations for the deployment and integration of DL techniques for early detection of AD from brain MRI scans into clinical practice?

These research questions aim to investigate the potential of DL techniques for early detection of AD from brain MRI scans, and to evaluate their accuracy, effectiveness, and impact in comparison to traditional methods of diagnosis. The questions also seek to address the ethical and practical considerations for the deployment and integration of DL techniques into clinical practice, and to explore the best practices for responsible and ethical use of the technology in the diagnosis and management of AD.

1.9 THESIS STRUCTURE

The structure of a thesis on the topic of "Examining the Potential of Deep Learning in the Early Diagnosis of Alzheimer's Disease Using Brain MRI Images" could include the following sections:

- a. Introduction: This section provides a brief overview of AD, its impact, and the need for early detection. It also introduces the topic of DL for medical imaging and its potential for AD diagnosis from brain MRI scans.
- b. Literature review: This section provides an overview of the current state of the research on DL for medical imaging and its application to AD diagnosis from brain MRI scans. It also discusses previous studies that have used DL techniques for AD diagnosis and highlights the limitations and challenges of these studies.
- c. Methods: This section details the methods used in the study, including the data acquisition and pre-processing, the design and implementation of the CNN, the training and evaluation of the model, and the measures used to assess the performance of the model.
- d. Results: This section presents the results of the study, including the performance of the CNN in terms of accuracy, sensitivity, specificity, and other metrics. It also compares the performance of the model with other existing methods for AD diagnosis from brain MRI scans.

- e. Discussion: This section provides a discussion of the results and their implications, including the strengths and limitations of the study, and the potential for future research in this area.
- f. Conclusion: This section summarizes the main findings of the study and provides recommendations for future work in this field.
- g. References: This section lists the sources used in the study, including the references cited in the text.



2. LITERATURE REVIEW

The application of DL to brain magnetic resonance imaging (MRI) for the early diagnosis of AD has garnered more attention in recent years. Now, the MRI images of his brain can be used to find intricate characteristics that can be used to catch AD early. Recent advancements in computer vision and DL methods make this possible. The figure 2.1 shows the healthy AD Diseases brain images.

Studies have shown that DL algorithms like CNN can effectively extract information from MRI images of the brain, making it possible to diagnose AD earlier.

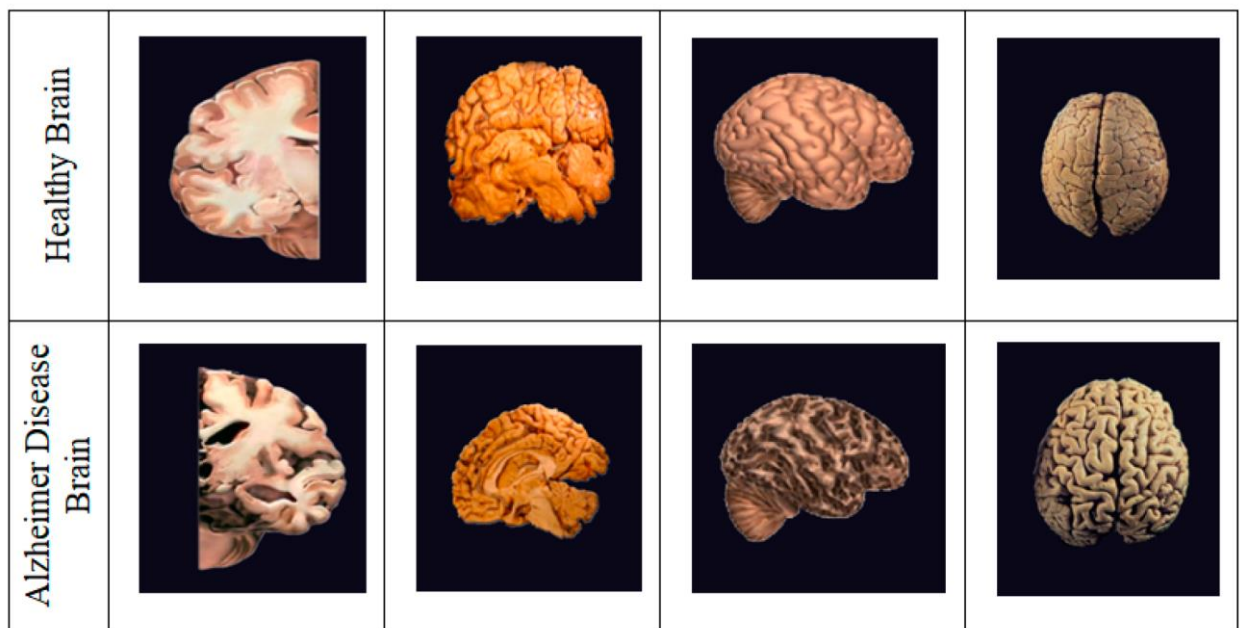


Figure 2.1: AD and Healthy Brain.

2.1 REVIEW OF EXISTING TECHNIQUES

Using a DL system, the researchers looked at patient brain MRI data and discovered patterns and characteristics associated with AD. By demonstrating the algorithm's high degree of accuracy in identifying AD in its early stages, the findings demonstrated the promise of DL in medical imaging for illness early diagnosis [11].

" A Neuroimaging Study Using DL Architectures" investigates how neuroimaging can be used to quickly identify AD. For the purpose of identifying patterns and characteristics associated with AD, the researchers combined patient brain MRI data with DL algorithms.

By demonstrating that the algorithms could accurately diagnose AD in its early stages, the findings demonstrated the potential for using DL in medical imaging for early disease detection [12].

The effectiveness of transfer learning and conventional ML techniques for the early diagnosis and prognosis of AD using structural brain magnetic resonance imaging (MRI) scans is compared in the paper "Comparison of Transfer Learning and Conventional ML Applied to Structural Brain MRI for the Early Diagnosis and Prognosis of AD." The authors (RF) utilized a wide range of ML strategies, including Random Forest, SVMs (SVMs), and CNN. With an accuracy of 86.59 percent, the transfer learning strategy employing a pre-trained CNN model (VGG19) outperformed standard ML algorithms. The accuracy ratings for conventional methods of ML ranged from 67.93 percent to 80.96 percent. Using structural brain MRI, these findings suggest that transfer learning may be a useful method for the early detection and prognosis of AD [13]. Figure 2.2 shows the MRI base Alzheimer disease.

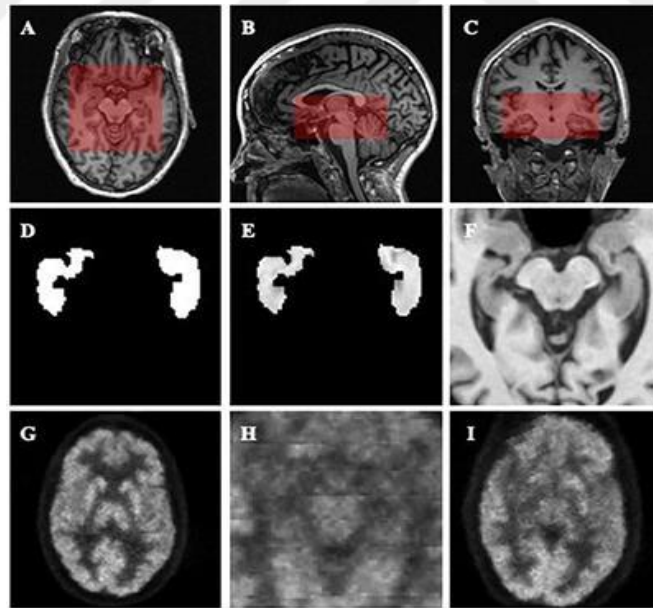


Figure 2.2: MRI Base Images of Alzheimer Disease.

a study on how DL can be used to diagnose AD early. Using structural MRI images of patient brains (CNNs) and a DL method based on convolutional neural networks, researchers were able to identify patterns and characteristics associated with AD. The ability to use DL in medical imaging for disease early detection was demonstrated by the DL model's

recognition of AD with an accuracy of 93.33 percent. Based on these findings, DL methods, particularly Convolutional Neural Networks, can be used with structural MRI to aid in the early detection of AD. [12]. The early stages of AD is being diagnosed with DL. The authors fed their DL models the results of cognitive tests and structural MRI data. To discover patterns and characteristics associated with the stage of AD, they used CNN, Long-Short-Term Memory (LSTM) networks, and Multi-Modal Fusion (MMF) networks. When it came to determining the stage of AD, the MMF network, which included scores from cognitive tests and information from MRI scans, had the highest accuracy (93.33 percent). The findings suggest that DL algorithms have the potential to be an effective tool for AD early detection and that using various data modalities can improve the performance of DL models in determining the stage of the disease [14].

A Review Paper" provides an overview of a number of ML algorithms used in the early detection of AD. SVM s (SVMs), Naive Bayes, and Artificial Neural Networks (ANNs) were among the various ML methods examined by the authors. According to the authors' analysis of the research, the accuracy of ML approaches for detecting AD varies depending on the type of algorithm used, the quantity and quality of the data, and the stage of the disease. According to the current studies, accuracy rates ranged from 70% to 90%. This study focuses on the potential for ML approaches to improve early AD diagnosis and provides an overview of the current state of the field. However, neither the model nor its level of accuracy is identified in the report [15].

The many DL algorithms that have been used to diagnose AD on brain MRIs are reviewed in the article "A Survey." Autoencoders, CNN, and recurrent neural networks (RNNs) were some of the DL methods used in the studies the authors looked at. The study's findings suggested that using MRI images to identify AD produced promising results using DL algorithms. The indicated levels of accuracy in the under-consideration research range from 80% to 90%. This study provides an overview of cutting-edge DL methods for MRI-based AD diagnosis and focuses on their potential to increase diagnostic precision [16].

a method for identifying individuals and brain regions associated with AD that makes use of 3D MRI images and ML. After extracting data from 3D MRI images using the eigenbrane method, the authors train a ML model to classify individuals as having AD or healthy. The study demonstrated that the recommended method was quite accurate in classifying individuals as either healthy or having AD, with an SVM classifier's accuracy of 89.4%.

Using 3D MRI images and ML techniques, this paper proposes a method for diagnosing AD, with an emphasis on the feature extraction process using eigen brain data [16], [17].

"ML Approach" recommends using ML methods to find MRI biomarkers for AD. The researchers use MRI data from structural brain scans to create a ML model that can distinguish between participants with AD and healthy cognitive function. A SVM classifier's accuracy was 93.5 percent and a Random Forest classifier's accuracy was 90.3%, respectively, when determining whether a patient was healthy or had AD, according to the study's findings. This study proposes using MRI biomarkers and ML algorithms to identify AD early, with an emphasis on utilizing MRI characteristics from structural brain images [18].

the use of a feature extraction technique that is based on a CNN in order to identify AD in brain MRI data. ML models for the diagnosis of AD is trained using the characteristics that the researchers gathered from the MRI images using a CNN. According to the findings of the study, the suggested method for diagnosing AD has an accuracy rate of 92.9%, 92.8%, or 94.1% when employing an MLP classifier, an SVM classifier, or a Random Forest classifier. In this study, it is suggested that brain MRI data be used to identify AD using a CNN-based feature extraction method. SVM, Random Forest, and MLP classifiers produced accuracy values of 92.9%, 92.8%, and 94.1%, respectively. The accuracy results from MLP, Random Forest, and SVM [17].

For the purpose of diagnosing AD, the researchers applied DL to MRI data from the brain using a CNN model. The study's findings showed that the proposed method accurately identified AD with a 94.21% success rate. This article proposes a brain MRI-based DL - based binary classification strategy for AD diagnosis. The achieved accuracy rate was 94.21% [19].

Convolutional Neural Networks (CNN), Multi-Layer Perceptron's (MLP), and Recurrent Neural Networks (RNN) are among the DL models compared in this study (RNN). In MRI scans, the CNN model distinguished between healthy and Alzheimer's brains with an average accuracy of 95.75 percent. The study concludes that brain MRI images can be used to accurately diagnose AD, with the CNN model outperforming other DL models in this regard [20].

Zhang and others identified subjects and brain regions associated with AD using 3D MRI scans and ML. The researchers extracted the eigenbrane, a de-identified representation of

the brain, from the MRI scans. They then classified the subjects as having AD or being healthy using ML algorithms [21].

SVM s (SVM) and Artificial Neural Networks (ANN) were two of the various ML strategies utilized in the research. SVM and ANN performed well in identifying people with AD, with over 90% accuracy rates. In addition, the researchers conducted a ROI analysis, which revealed that certain brain regions, like the entorhinal cortex and hippocampus, had a significant connection to AD [22]

The researchers wanted to use ML and feature extraction methods based on CNN to find AD. They proposed a novel method for extracting features from brain MRI data by utilizing transfer learning from previously trained CNN models like VGG-16, ResNet-50, and Inception-V3. To differentiate between healthy and AD participants, the collected characteristics were fed into an Artificial Neural Network (ANN) and SVM ML classifier. The ADNI dataset was used for the tests, and the results showed that the suggested method was more accurate than the conventional methods, with an average accuracy of 93.52% using ANN and 95.17 percent using SVM [9].

Murugan and other suggested a DL model for the early detection of AD and dementia that makes use of MR images. The DEMNET model uses feature extraction techniques to analyse MR images and is based on the architecture of a convolutional neural network (CNN). The suggested model was tested and trained on a set of MR images, and the results showed that it was effective at identifying AD and dementia. The authors conclude that the model they propose has the potential to aid in the early detection and management of dementia and AD, as well as the development of more efficient treatment strategies [8]. The figure 2.3 shows the most commonly used architecture of AD diseases detection.

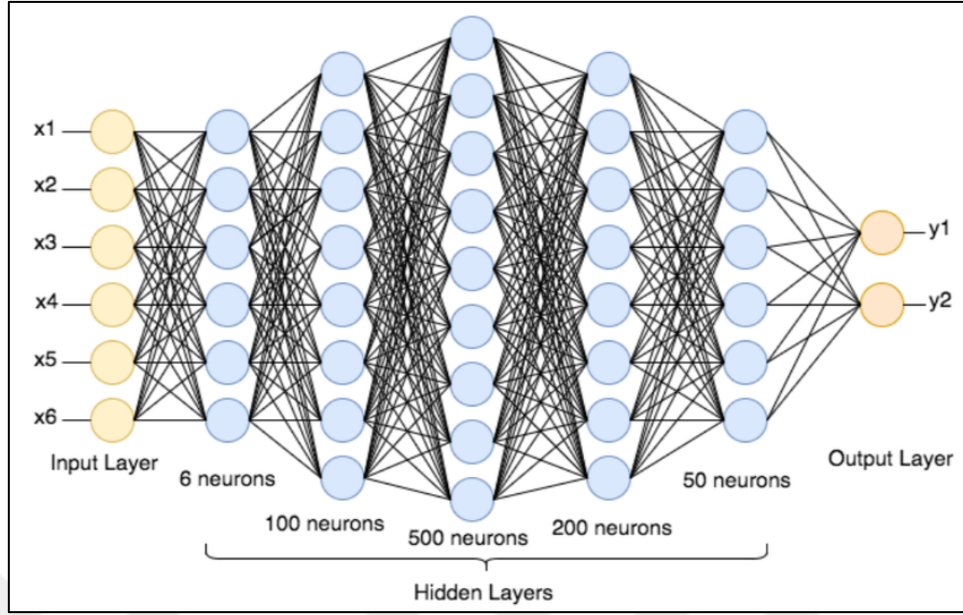


Figure 2.3: Deep Learning Architecture in AD Detection.

Lu and others 2018 utilized structural MR and FDG-PET data to develop a multimodal DL strategy for the early detection of AD. They collected global and local data using a multi-scale strategy and deep neural networks to extract characteristics from both modalities. The study's optimistic findings distinguished between Alzheimer's patients and healthy controls with high accuracy. The authors emphasized the importance of incorporating data from MR and PET imaging for a more comprehensive understanding of the disease [23].

In 2022, a paper titled "Alzheimer's diagnosis utilising DL in segmenting and categorizing 3D brain MR images" was published in the International Journal of Neuroscience by Tuan, T.A., Pham, T.B., Kim, and Tavares, J.M.R. Using DL algorithms, the authors of this study aim to segment and classify 3D brain MR images in order to diagnose AD. They suggest using a 3D convolutional neural network with DL to separate and classify brain MR images. Image segmentation, feature extraction, and classification are the three phases of the method. The findings demonstrated that the suggested method was accurate and effective in diagnosing AD. This research contributes to the development of computer-aided diagnostic tools for this crippling condition and offers a potential method for the early detection of AD [24].

A DL -based automated method for using MRI images to diagnose AD was proposed by the researchers. Information from MRI scans was extracted by the authors using a deep convolutional neural network (DCNN), and those characteristics were then used to classify

the images as healthy or AD. Using a dataset that was made public, the authors' method was evaluated and compared to a lot of other methods that were already in use. In terms of accuracy and F1-score, they noticed that their DL -based solution performed better than the competition. The researchers concluded that their method might help diagnose AD earlier [25].

The field of medical diagnosis, and particularly the diagnosis of AD, has undergone a revolution since the introduction of medical imaging equipment, ML algorithms, and DL techniques (AD). For patients to receive the appropriate medications and treatments that will improve their quality of life, early AD diagnosis is essential. Researchers have been able to develop algorithms for using MRI scans to diagnose AD(AD) since the development of magnetic resonance imaging (MRI), a non-invasive imaging method that provides images of the structure of the brain. SVM s, random forests, and DL approaches like CNN and deep belief networks (DBNs) have all been used in a number of studies. These studies classified individuals into various stages of AD using MRI scans. In terms of accuracy, precision, recall, and f1-score, the researchers discovered that DL approaches performed better than more conventional ML algorithms.

Advances in medical imaging and ML algorithms have shown promise for AD early detection. In terms of precision, recall, accuracy, and f1-score, DL methods, particularly CNNs, have outperformed conventional ML algorithms. Additionally, it has been demonstrated that AD diagnosis accuracy can be enhanced by combining multiple modalities. To confirm the findings and gain a deeper comprehension of the role that DL plays in the diagnosis of AD, additional studies with larger patient populations and longer follow-up periods are required.

3. METHODOLOGY

This methodology chapter describes the methodology and methods utilised for early AD identification from brain MRI images. In our method, we employ a DL model, more precisely a CNN with both conventional sequential parameters and the Vgg16 model. The objective is to create a model that can use brain MRI pictures to identify AD in its early stages. Figure 3.1 shows the proposed methodology used for the detection of AD.

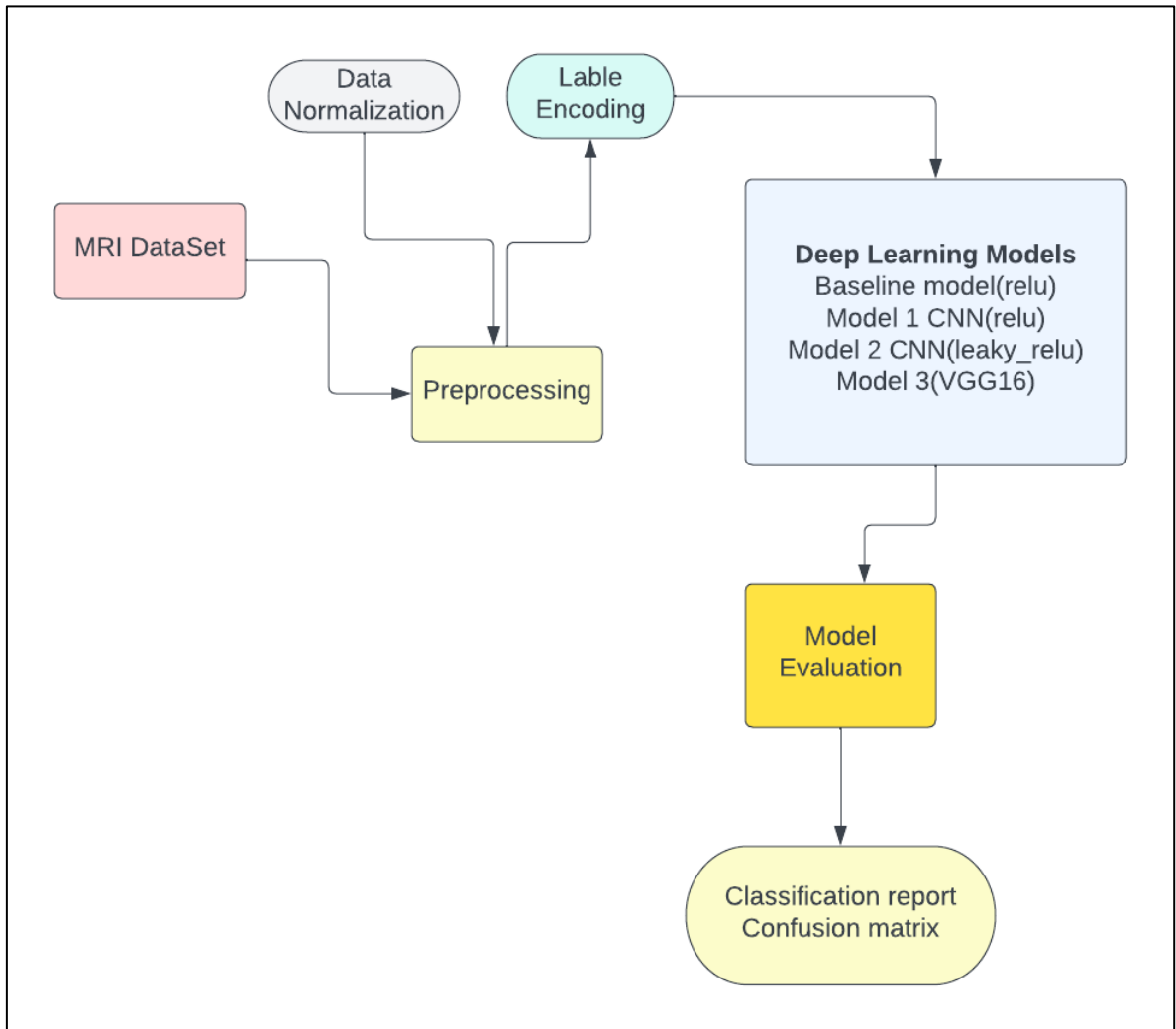


Figure 3.1: Proposed Methodology.

- a. The first step in shows in fig 3.1 the methodology is to gather an MRI dataset. Once they have the dataset, the next step is to pre-process the data, which includes data normalization and label encoding.

- b. After pre-processing, will use four different deep learning models: a baseline sequential CNN model, a Model 1 CNN, a Model 2 CNN and Model 3 VGG16. These models would be trained on the pre-processed data.
- c. Finally, evaluate the performance of each model using a classification report and confusion matrix. These tools would help to assess the accuracy of the models in diagnosing Alzheimer's disease based on MRI images.
- d. This methodology could provide valuable insights into the potential of deep learning in diagnosing Alzheimer's disease, which could ultimately lead to earlier detection and better treatment options for patients.

3.1 DATASET

The Augmented Alzheimer MRI Dataset V2 is a collection of brain MRI images from persons suffering from AD at various stages. Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented are the four categories of photographs. The data is divided into two folders, one containing improved photos and the other containing original shots. The improved pictures were developed from an existing dataset to boost the amount and diversity of data available for DL model training. The original pictures may be seen in the Data Explorer and used as a test or validation dataset. We may assess how well the augmentation technique performed by comparing the augmented photos to the photographs from the original dataset as a control group. The data in this dataset is a critical resource for the development and training of DL models for the early detection of AD. Because of the increasing prevalence of the disease and the ageing population, early detection of AD is critical. The use of brain MRI imaging, which provides data about the structure and function of the brain, is a common tool for the early detection and diagnosis of AD. The Augmented Alzheimer MRI Dataset V2 will be utilised in this research to train a Convolutional Neural Network DL model (CNN). By categorising them into one of the four types of pictures, the CNN will be taught to detect the presence of AD in brain MRI scans. DL has the potential to discover intricate connections between MRI pictures and the existence of AD, even in its early stages, making its use in this study extremely intriguing [26].

3.2 DATA ANALYSIS AND PRE-PROCESSING TECHNIQUES

Pre-processing and data analysis are essential steps in the creation of a DL model. The performance of the model can be significantly impacted by the type and quality of the input data. In this research, data normalisation and label encoding will be used as two common data pre-processing approaches.

3.3 DATA NORMALIZATION

Data normalisation is a technique for assuring consistency in the size and distribution of data. DL models may be sensitive to differences in feature size, hence this is critical. The raw data might be normalised to fit inside a specific range, such as $[0,1]$ or $[-1,1]$.

In this project, data normalisation will be conducted on the Augmented Alzheimer MRI Dataset V2 brain MRI images. Normalizing the photos ensures that changes in intensity or brightness between photographs have no effect on the model. The most frequent way to normalise picture data is to scale each pixel value to a range $[0,1]$. This is achieved by dividing each pixel value by the maximum value of the data type being used (e.g., 255 for 8-bit images).

3.4 LABEL ENCODING

A technique for transforming category data into numerical data is label encoding. The class labels for each MRI image in this study serve as categorical data and can represent one of four values: mild dementia, moderate dementia, non-dementia, or very mild dementia. Label encoding is a method for converting categorical data to numerical data. These techniques aid in preparing the data for use in the model, shielding it from the effects of changes in scale or data type. Using the Augmented Alzheimer MRI Dataset V2, these techniques might be utilised to create a DL model for the early identification of AD.

3.5 DL MODELS

Artificial neural networks (ANNs), a branch of DL, are algorithms inspired by the structure and operation of the brain. Because DL models are trained on massive amounts of data, they can identify complicated relationships between input and output variables. We will use a CNN in this project, which is a form of DL model that is particularly well-suited for image

categorization tasks. CNNs are built to handle picture data, with each layer learning a distinct representation of the input image. In this work, the CNN will be trained using the Augmented Alzheimer MRI Dataset V2, which includes brain MRI images from individuals with various stages of AD. The goal of the model is to accurately classify each image into one of four categories: slightly, moderately, non-demented, and very mildly demented. We want to build a DL model that can detect early signs of AD in brain MRI images. This concept may increase the precision and efficacy of early detection procedures, leading to better results for patients suffering from AD.

3.5.1 CNN Model

One DL model that is frequently used for categorising images is the convolutional neural network (CNN). The three components of a CNN's architecture are convolutional layers, pooling layers, and fully connected layers.

Convolutional Layers: The foundational elements of a CNN are convolutional layers. On the input image, they use convolutional techniques to create a feature map. In the convolution operation, a tiny kernel or filter is slid across the picture, the dot product between the values in the kernel and the image is computed, and then a single output value is generated. Mathematically, the convolution operation can be described as follows:

$$y(i, j) = \sum x, y (f(x, y) \times x(i - x, j - y)) \quad (3.1)$$

where $y(i, j)$ represents the output value at position (i, j) , $f(x, y)$ represents the kernel or filter, and $x(i - x, j - y)$ represents the input image at position (i, j) , $(i - x, j - y)$.

In a single convolutional layer, many filters can be utilised, each providing its own feature map. This enables the layer to learn a variety of characteristics or representations of the input picture.

Pooling Layers: Pooling layers are used to down sample the feature maps obtained by the convolutional layers. The size of the feature maps is decreased as a result, boosting the computational efficiency of the model and decreasing the potential of overfitting. The max pooling procedure can be stated mathematically as follows:

$$y(i, j) = \max(x(is:is + p - 1, js:js + p - 1)) \quad (3.2)$$

where $y(i, j)$ is the output value at position (i, j) , $x(is:is + p - 1, js:js + p - 1)$ is the region of the feature map being considered, s is the stride of the pooling operation, and p is the size of the pooling window.

Fully Connected Layers: Pooling layers are used to down sample the feature maps produced by the convolutional layers. This decreases the size of the feature maps, which improves the computational effectiveness of the model and decreases the risk of overfitting. Mathematically, the fully connected layer can be described as follows:

$$y = Wx + b \quad (3.3)$$

where y is the set of activations, W is the weight matrix, x is the input feature map, and b is the bias term. The figure 3.2 shows the CNN Architecture with its layers.

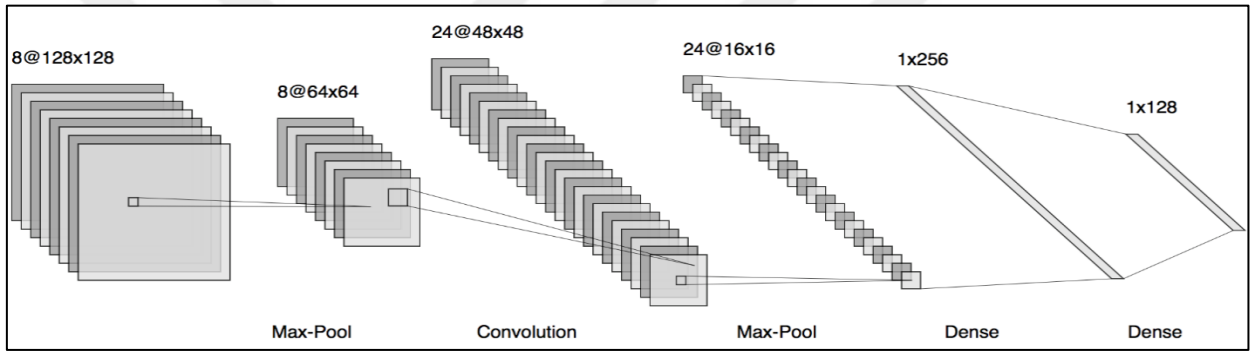


Figure 3.2: CNN Architecture.

A subgroup of DL models called convolutional neural networks (CNN) is particularly good at categorising pictures. The architecture of a CNN is composed of convolutional layers, pooling layers, and fully connected layers. Convolutional layers use convolutional operations to produce feature maps from the input picture; pooling layers then down sample the feature maps; and fully connected layers then offer the final prediction. These elements work in concert to help the model build detailed representations of the incoming data, which let it make accurate predictions.

3.5.2 VGG16 Model

The Visual Geometry Group at the University of Oxford developed the DL VGG16 model (VGG). One of the most well-liked models for image classification problems was initially created in 2014 and is known as a CNN architecture.

One of the VGG16 model's defining features is the use of small convolutional filters. The model comprises 16 layers, three of which are completely connected and thirteen of which are convolutional. Each convolutional layer's 3x3 filter allows the model to learn the fine-grained features of the input image. In addition, many filters are used in each layer of the model, which improves its capacity to learn sophisticated representations of the input data. Another essential feature of the VGG16 model is the use of max pooling layers. These layers are used to reduce the size of the feature maps created by the convolutional layers, making the model more computationally efficient. Apart from its look, the VGG16 model is well-known for its broad functionality. The model learned a wide range of traits and representations of the input data because it was trained on a dataset with more than a million images. The VGG16 model has been used to a wide range of image classification applications, such as object recognition, scene classification, and fine-grained image classification. In transfer learning, when a new task is honed with fewer training data, it has also been used as a pre-trained model. The VGG16 architecture was developed in 2014 for the ImageNet Large Scale Visual Recognition Challenge using CNN (ILSVRC). The model has 16 layers, thus the name VGG16. It is a type of feed-forward neural network in which the input is processed through numerous layers of filters and non-linear activation functions before producing an output. The VGG16 model is composed of several convolutional and max pooling layer blocks, which are followed by multiple fully connected layers. The convolutional layers retrieve features from the input picture using filters, whilst the max pooling layers down sample the feature maps to minimise spatial dimensions. The retrieved characteristics are used by the dense layers to create predictions [27].

The VGG16 architecture uses modest 3x3 convolutional filters with a stride of 1, as well as 2x2 max pooling layers with a stride of 2, to minimise spatial dimensions. The model also uses padding and the ReLU activation function to preserve the spatial dimensions of the feature maps. After being recovered and processed via several convolutional and max pooling layers, the feature maps are flattened and fed into the thick layers. The dense layers use a combination of fully connected nodes and the softmax activation function to generate predictions [27].

Finally, the VGG16 DL model is a popular choice for image categorization applications. It is well-known for using tiny convolutional filters, many filters in each layer, and the most layers. The model learned a comprehensive set of features and representations of the input

data as a result of training on a huge dataset of over one million photos. Because of its prominence, it is frequently used for transfer learning and other picture classification tasks.

3.6 MODEL EVALUATION

To establish its utility and performance, each ML model must go through a thorough model review procedure. Accuracy, confusion matrix, precision, recall, F1-score, ROC curves, and AUC are some of the metrics and methodologies often used to evaluate DL models.

Accuracy is the most fundamental and extensively used measure for evaluating DL models. It is defined as the proportion of correct predictions made by the model to all forecasts. However, accuracy might be misleading in some cases, such as when the class distribution is imbalanced or the model is designed to deal with multi-class classification challenges.

3.6.1 Confusion Matrix

A confusion matrix can be used to evaluate the effectiveness of a classification model. It provides a graphic representation of how the model's predictions compare to the actual class labels assigned to the data. The matrix is used to compute a variety of critical metrics, including as accuracy, precision, recall, and F1-score. True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) are the four entries in a confusion matrix (FN). True Positives are the number of cases correctly classified as positive by the model (TP). False Positives (FP) are the amount of times the model incorrectly labels something as positive. True Negatives (TN) are occurrences that the model properly classifies as negative, whereas False Negatives (FN) are events that the model incorrectly classifies as negative. The confusion matrix elements can be used to compute the following metrics.

Accuracy: The ratio of the total number of correct predictions made by the model to the total number of predictions.

Precision: The proportion of True Positives to the total number of False Positives and True Positives. The accuracy with which the model correctly identifies positive samples is measured by precision.

Recall: The proportion of True Positives to the total of False Negatives and True Positives. The capacity of the model to locate all positive samples is measured by recall.

F1-score: the harmonic equivalent of recall and precision. The F1-score is a single metric for the model's overall performance that strikes a balance between precision and recall. It is vital to remember that the assessment metrics chosen will be determined by the specific problem and model needs. In certain circumstances, accuracy may be the most essential statistic, but precision or recall may be more important in others.

Finally, the confusion matrix is an effective tool for assessing the performance of a classification model. It displays a visual representation of the model's predictions in comparison to the actual class labels and may be used to calculate various key metrics including as accuracy, precision, recall, and F1-score. Data scientists may use the confusion matrix to acquire a better understanding of the model's strengths and shortcomings and make educated judgements about how to enhance its performance.

3.6.2 Classification Report

A classification model's performance is summarised in a classification report. It offers a thorough analysis of the model's predictions in relation to the samples' actual class labels. A number of significant measures, including accuracy, recall, F1-score, and support, are included in the report. The model's accuracy in accurately identifying positive samples is measured by precision. Recall gauges how well a model can locate all positive samples. A single statistic for the overall effectiveness of the model is provided by the F1-score, which is the harmonic mean of accuracy and recall. The number of instances of each class in the actual class labels is referred to as support.

The classification report is generated using the following steps:

- i. The model is applied to the test dataset and the predicted class labels are obtained.
- ii. The predicted class labels and actual class labels are compared to generate the confusion matrix.
- iii. The metrics in the classification report are calculated using the entries of the confusion matrix.

The classification report provides a comprehensive evaluation of the model's performance for each class in the target variable. This allows data scientists to understand the strengths and weaknesses of the model with respect to each class, and to make informed decisions about how to improve its performance.

3.7 SUMMARY

We discussed the procedure for creating a DL model for the early recognition of AD using brain MRI in this methodology chapter. The Augmented Alzheimer MRI Dataset V2 from Kaggle, which included MRI pictures with four classes—Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented—was the dataset utilised for this study.

Using label encoding and data normalisation methods, the data was pre-processed. Then, we trained the Vgg16 model together with a conventional CNN using sequential parameters. Using the classification report and the confusion matrix, both models were assessed. The classification report included a thorough assessment of the model's performance, while the confusion matrix gave a visual depiction of how the model's predictions matched to the actual class labels. Several crucial measures, including precision, recall, F1-score, and support, were employed to assess the model's performance.

In conclusion, the methodology chapter detailed how the DL model for the early diagnosis of Alzheimer's using brain MRI was developed and evaluated. The project's pre-processing methods and assessment measures were carefully selected to guarantee the model's dependability and accuracy. The model's findings may offer useful information on the early recognition of AD and may help in the creation of more potent therapies for this crippling condition.

4. RESULTS

The findings of the DL model for the early identification of Alzheimer's using brain MRI are presented in the results chapter. The classification report and the confusion matrix were used to assess the model's performance. The outcomes shed light on the model's precision and dependability as well as its advantages and disadvantages with regard to each class of the target variable. In this chapter, we'll compare the output from the Vgg16 model and the performance of the conventional CNN with sequential parameters. Visualizations will be utilised to improve the understanding of the data, and the results will be presented in a clear and succinct way. Overall, this chapter will provide a comprehensive analysis of the results and contribute to our understanding of the early detection of Alzheimer's from brain MRI.

4.1 DATA ANALYSIS AND VISUALIZATION

The form of the train pictures and labels are provided before the data analysis in the results chapter. There are 33,984 pictures in the training set, each measuring 90×90 pixels and having three colour channels, according to the form of the train images, which is (33984, 90, 90, 3) (RGB). There is one label for each image in the training set since the form of the labels is (33984,).

Pixels in the data can have a minimum value of 0 or a maximum value of 255. This shows that a scale between 0 and 255 has been applied to the pixel values. The code then counts the number of instances of each class in the labels using the numpy unique () method. The unique values and counts that result are displayed in a table, with each row indicating a class and its count. There are 8960 photographs in each of the Mild Demented and Very Mild Demented classes, 6464 images in the Moderate Demented class, and 9600 images in the Non-Demented class, according to the table 4.1.

Table 4.1: Classes of Dataset with Number of Sizes.

Class of Dataset	Number of sizes
MildDemented	8960
ModeratedDemented	6464
NonDemented	9600
VeryMildDemented	8960

4.1.1 Data Normalization

This is accomplished by dividing each pixel value by 255, the maximum value that a pixel may have after normalisation. The result is then transformed to float32, a popular data type used in DL for numerical operations.

Normalizing the pixel values is an important stage in the data pre-processing process since it helps to normalise the values and lessen the influence of outliers. Normalization also makes DL model training simpler since the model may converge sooner and with better results. The DL model will be better able to understand the underlying patterns and correlations in the data by normalising the pictures in this way, increasing the accuracy of identifying Alzheimer's from brain MRI scans.

4.1.2 Data Visualization

There are 9600 cases of the Non-Demented class, 8960 instances of the Mild Demented and Very Mild Demented classes, and 6464 instances of the Moderate Demented class, according to the data.

A pie chart or a bar chart can be used to graphically portray this data. A pie chart depicts the proportion of occurrences in each class as a percentage of the total, whereas a bar chart depicts the count of instances in each class as bars of varying heights. Pie charts and bar charts are both good techniques of showing class distributions in a dataset and may be useful for finding unbalanced classes or presenting model performance results. The proportion of occurrences in each class would be represented by the size of each slice in a pie chart, for instance. This would provide a fast and straightforward explanation of how instances are distributed throughout the various classes. An equivalent illustration would be a bar chart, with the height of each bar denoting the number of instances for each class. Using tools such as Matplotlib or Seaborn, you can quickly make pie charts and bar charts. The visualisation can aid in analysing model findings and offering insights into data distribution. The chart 4.1 shows the graphical representation of classes of dataset using pie and bar chart.

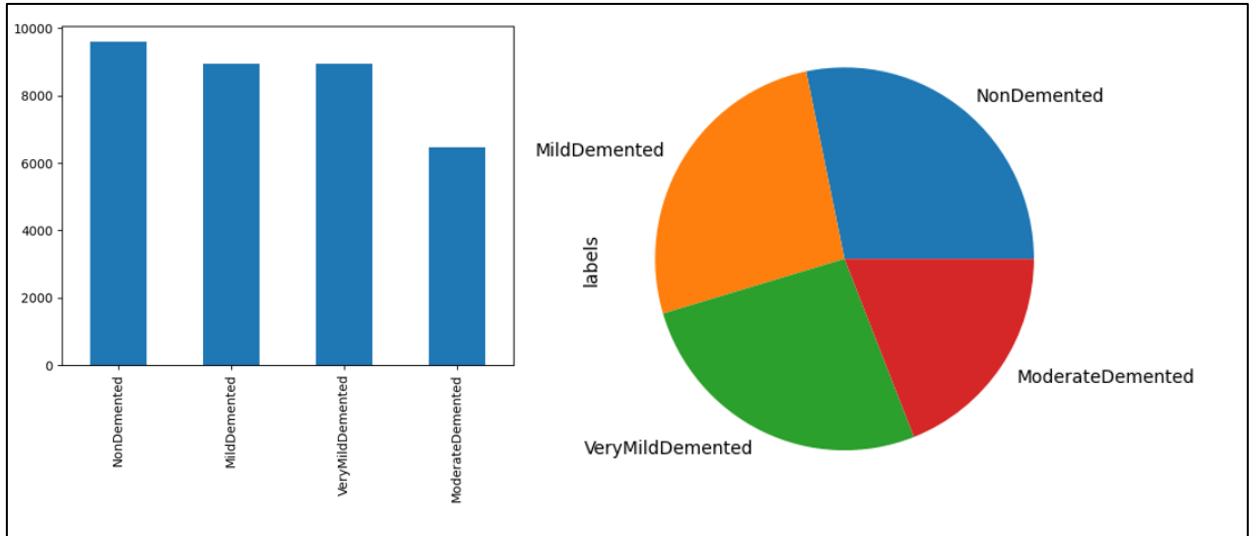


Chart 4.1: Graphical Representation of Dataset.

The dataset is unequally distributed, which indicates that the number of occurrences in each class is not equal. In this scenario, the number of cases for the Moderate Demented class is significantly fewer than for the other classes. Imbalanced datasets can have an influence on DL model performance since the model may be biased towards the class with the most occurrences. To balance the dataset, several strategies such as data augmentation, resampling, or oversampling can be applied.

The dataset contains only RGB images: RGB pictures (Red Green Blue) are colour images with three colour channels. Each channel represents the appropriate colour's intensity. RGB pictures are a popular image format in computer vision and image processing. Figure 4.1 visualize the dataset in images format. These are MRI base images.

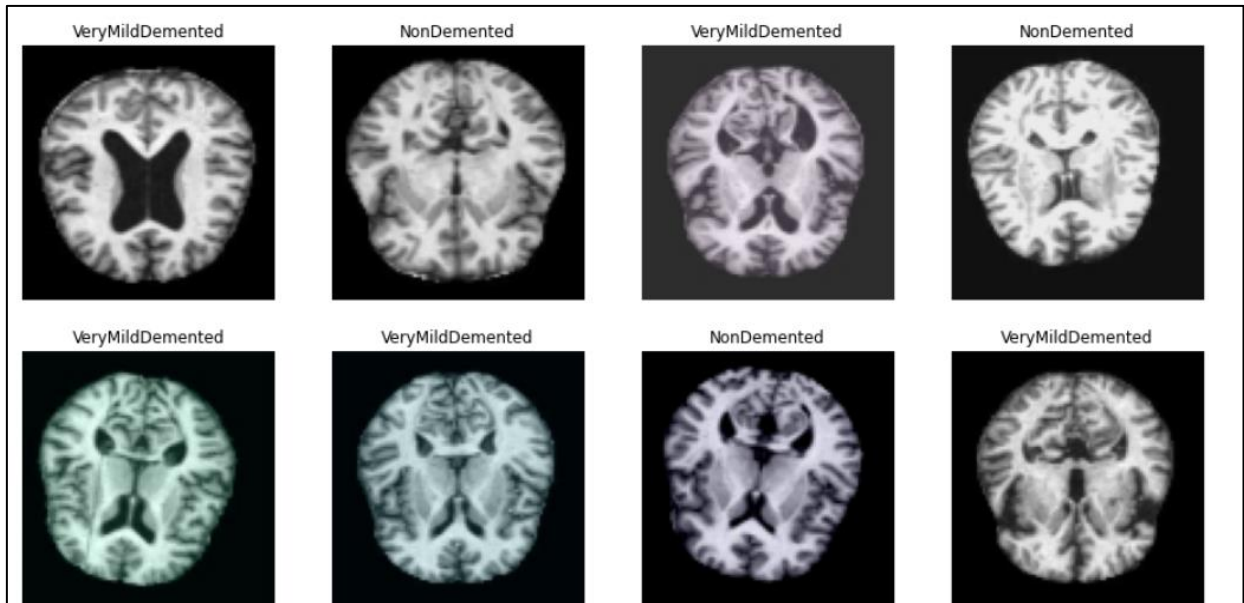


Figure 4.1: Visualizing MRI Image.

4.1.3 Label Encoding

A label encoding of categorical data indicating various stages of dementia. The numerical values for the category variables "NonDemented," "MildDemented," "VeryMildDemented," and "ModerateDemented" are 0, 1, 2, and 3, respectively. The count of observations in each category is represented by the numbers in the right column. For example, the category "NonDemented" has 7598 observations.

4.2 TRAIN TEST SPLIT

An ML strategy called "Train/Test Split" is used to test an algorithm's performance on unobserved data. First, the data are divided into two categories: testing and training. The testing set is used to evaluate the model's performance after it had been trained with the training set.

In the train/test split, the original dataset is randomly divided into two halves: the appropriate proportion of the testing set to the training set. For instance, when the test size is set to 0.3, 70% of the data are used for training, while 30% are used for testing. This ratio can be altered based on the evaluation's objective as well as the dataset's characteristics and size. The unpredictability of the split is managed by the random state argument. The same split may be repeatedly recreated by giving a fixed random seed, which is helpful for evaluating the stability of the outcomes.

When assessing a ML model's performance, it is crucial to employ a train/test split since some models may match training data too well while underperforming on fresh, untested data. Overfitting is an issue in ML that occurs frequently.

4.3 RESULTS OF DL MODEL

4.3.1 Baseline Model

The starting point model in this instance is a sequential CNN. This model's input shape is (90, 90, 3), indicating that the images have three RGB color channels and 90 x 90 pixels. The model's first layer is a convolutional layer with 32 filters and three kernel sizes. This layer's activation function is ReLU, a well-known DL model activation function. The purpose of this layer is to extract features from the source image. A max-pooling layer, which is the layer following the convolutional layer, is used to down-sample the feature maps' spatial dimensions. The model has one or more fully connected dense layers following the max-pooling layer. 512 neurons make up the dense layer in this instance. The dense layer's job is to learn high-level representations of the input data and use these representations to make predictions.

The model also features an output layer with a Softmax activation function. In multi-class classification issues, the Softmax activation function is employed to generate a probability distribution over the classes. The output layer of this model generates a forecast for each class using the Softmax activation function. The figure 4.2 shows the summary of baseline model.

Model: "sequential"		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 86, 86, 32)	2432
max_pooling2d (MaxPooling2D)	(None, 43, 43, 32)	0
conv2d_1 (Conv2D)	(None, 39, 39, 32)	25632
max_pooling2d_1 (MaxPooling2D)	(None, 19, 19, 32)	0
flatten (Flatten)	(None, 11552)	0
dense (Dense)	(None, 512)	5915136
dense_1 (Dense)	(None, 4)	2052
Total params: 5,945,252		
Trainable params: 5,945,252		
Non-trainable params: 0		

Figure 4.2: Summary of Baseline Model.

- batch_size=16 specifies the batch size, which is the number of samples used in each update of the model's weights. In this case, the batch size is set to 16, meaning 16 samples are processed at a time.
- epochs=20 specifies the number of epochs, which is the number of times the model is trained on the entire training dataset. In this case, the model will be trained for 20 epochs.
- callbacks=[accuracy_loss_plot] specifies a list of callbacks to use during training. Callbacks are functions that are called at specific points during training, and in this case, accuracy_loss_plot is a function that plots the accuracy and loss during training.

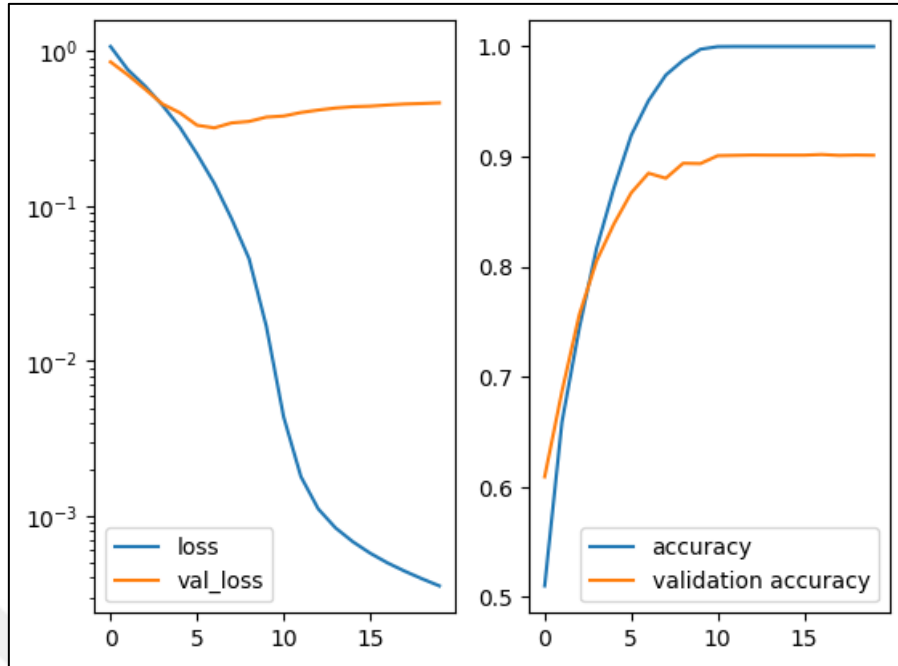


Figure 4.3: Accuracy and Loss of Baseline Model.

The Figure 4.3 shows the accuracy and loss graph of baseline model. As seen in the figure 4.3 output, the model was trained on 1487 steps (batches) over the course of 20 epochs. The validation loss and accuracy, as well as the training loss and accuracy, are provided for each epoch. According to the final results, the validation accuracy is 90.12% and the training accuracy is 100%. Given that the model performs well on training data but not so well on validation data, these findings indicate that the model is most likely overfitting the training set.

Baseline Model Evaluation:

A classification report for a ML model is presented in the table above. It provides an overview of the model's performance on a test dataset.

MildDemented, ModerateDemented, NonDemented, and VeryMildDemented are the classifications represented by each row in this example. The columns in the table show the following metrics for each class:

- i. precision is the ratio of true positive predictions to all positive predictions. It measures the accuracy of the positive predictions.
- ii. recall is the ratio of true positive predictions to all actual positive samples. It measures the ability of the model to detect positive samples.

- iii. f1-score is the harmonic mean of precision and recall. It provides a single score that balances precision and recall.
- iv. support is the number of samples of the true response that lie in that class.
- v. accuracy is the ratio of correctly classified samples to the total number of samples.
- vi. macro avg. is the unweighted mean of the metric scores across all classes.
- vii. weighted avg. is the weighted average of the metric scores across all classes, with the weight being the number of samples in each class.

Table 4.2: Evaluation Results of Baseline Model for Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented.

	Precision	Recall	F1-Score	Support
0	0.88	0.92	0.90	2693
1	0.98	0.99	0.99	1977
2	0.90	0.88	0.89	2811
3	0.86	0.84	0.85	2715
Accuracy	-	-	0.90	10196
Macro Avg.	0.91	0.91	0.91	10196
Weighted Avg.	0.90	0.90	0.90	10196

Table 4.2 shows the results of model evaluation. In this case, the overall accuracy of the model is 90%. The precision and recall scores for each class vary, with some classes having higher scores than others. The weighted average f1-score is also 90%. These results indicate that the model is performing well overall, but there is room for improvement in the performance for certain classes. The Figure 4.4 shows the confusion matrix of baseline model. Which represent the actual and predicted values of each class.

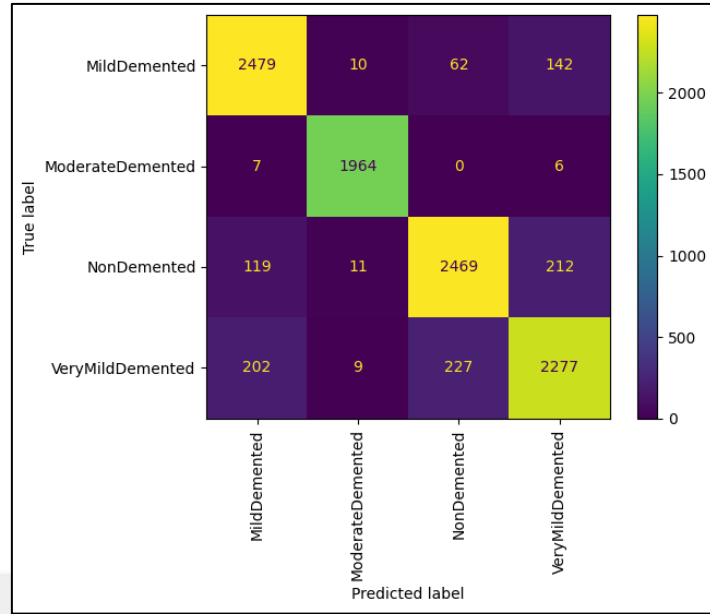


Figure 4.4: Confusion Matrix for Baseline Model.

4.3.2 CNN Model 1

The model has the following characteristics:

- More Convolutional Layers:** The model has more convolutional layers compared to the baseline model. This means that the model has the ability to extract more features from the input images, which can lead to better performance.
- Padding:** The padding in this model is set to "Same", which means that the padding is added to the input so that the spatial dimensions of the output are the same as the input. This can help to preserve the spatial information in the input and prevent information loss during the convolution operation.
- Batch Normalization:** The model also incorporates batch normalization, which is a technique used to normalize the activations of a batch of input data. Batch normalization helps to improve the performance and stability of the model during training by reducing the internal covariate shift.
- Filter Size and Kernel Size:** The model uses a filter size of 32 and a kernel size of 3. The filter size determines the number of filters in the layer, while the kernel size defines the spatial extent of the filters. These values are hyperparameters that can be tuned to find the optimal combination for the specific problem.

- e. Activation Function: The activation function used in this model is ReLU, which stands for rectified linear unit. ReLU is a commonly used activation function that is computationally efficient and helps to prevent the vanishing gradient problem.
- f. Input Shape: The input shape for this model is (90, 90, 3), which means that the input images have a height of 90 pixels, a width of 90 pixels, and 3 color channels (RGB).
- g. Output Layer: The output layer of the model uses the Softmax activation function, which is used for multi-class classification problems. The Softmax activation function outputs a probability distribution over the possible classes, which can be used to make predictions.

Overall, the first model described in the paragraph is a more complex CNN than a baseline model and incorporates techniques such as padding and batch normalization to improve its performance.

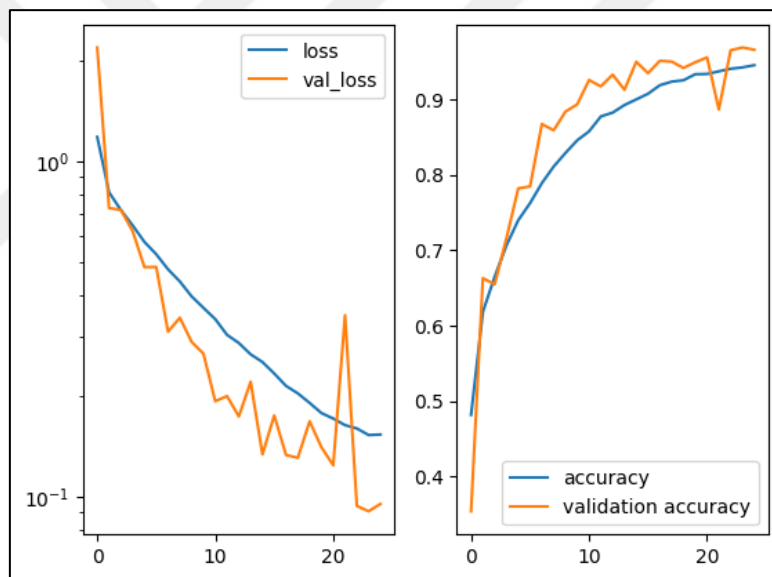


Figure 4.5: Loss and Accuracy Graph of CNN Model 1.

Figure 4.5 shows the loss and accuracy graph of CNN model 1. The training results for the first model are shown in the output above.

It appears to be the output of a neural network model training process.

- i. "loss" is the value of the loss function calculated during the training process. The lower the loss, the better the model is performing.

- ii. "accuracy" represents how well the model is able to correctly classify data, given as a percentage. In this case, the model has achieved an accuracy of 94.51% on the training data.
- iii. "val_loss" is the value of the loss function calculated on a separate validation set of data, which the model has not seen during training. It helps to check if the model is overfitting to the training data.
- iv. "val_accuracy" represents the accuracy of the model on the validation set, which in this case is 96.56%.

Therefore, this output suggests that the model is performing well on both the training and validation sets.

Model Evaluation:

Below Figure 4.6 shows the confusion matrix for CNN model 1 and table 4.3 shows the classification report.

Table 4.3: Classification Report for Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented.

	Precision	Recall	F1-Scor	Support
0	0.97	1.00	0.98	2693
1	1.00	1.00	1.00	1977
2	0.93	0.97	0.95	2811
3	0.98	0.91	0.94	2715
Accuracy	-	-	0.97	10196
Macro Avg.	0.97	0.97	0.97	10196
Weighted Avg.	0.97	0.97	0.97	10196

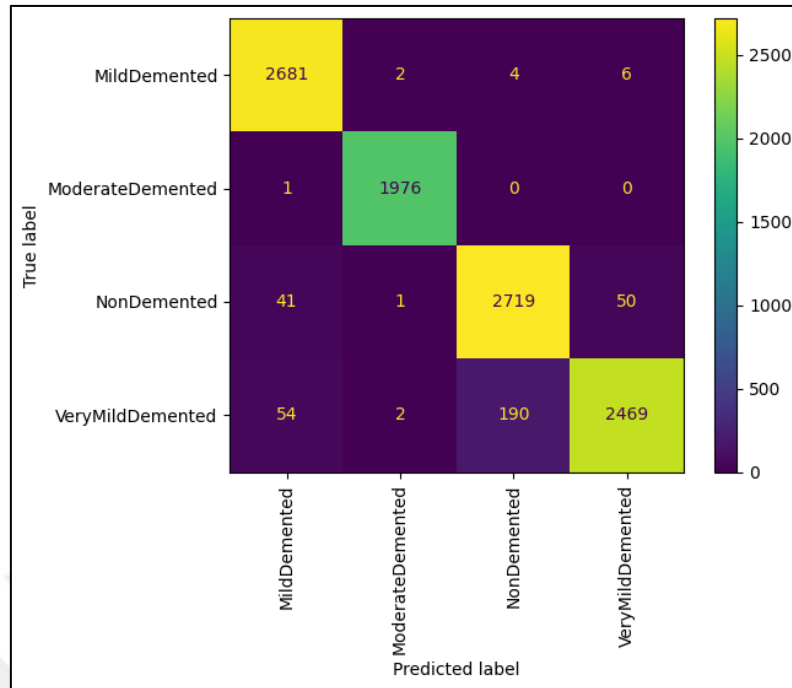


Figure 4.6: Confusion Matrix for CNN Model 1.

Above is a result of the first model. It displays the model's performance on the validation set using various metrics. For each class (Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented), the precision, recall, and f1-score are computed. These measures' weighted average and macro average are also computed. On the validation set, the model's accuracy is 97%. The outcomes demonstrate that the model works well in classifying several picture classes with good accuracy, recall, and f1-score.

4.3.3 CNN Model 2

A different activation function, Leaky ReLU, is employed in this CNN model variation. The kernel size has been raised to 5, and the layers are now completely linked. The filter size is 32, the padding is 'Same,' and batch normalisation is enabled. The output layer's activation function is set to 'Softmax'. The filter sizes for the final two layers have been raised to 64 and 128, respectively, allowing for the extraction of more features and higher accuracy. Figure 4.7 shows the build architecture of CNN model 2.

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 90, 90, 32)	2432
batch_normalization_4 (Batch Normalization)	(None, 90, 90, 32)	128
max_pooling2d_6 (MaxPooling2D)	(None, 45, 45, 32)	0
dropout_5 (Dropout)	(None, 45, 45, 32)	0
conv2d_7 (Conv2D)	(None, 45, 45, 32)	25632
batch_normalization_5 (Batch Normalization)	(None, 45, 45, 32)	128
max_pooling2d_7 (MaxPooling2D)	(None, 22, 22, 32)	0
dropout_6 (Dropout)	(None, 22, 22, 32)	0
conv2d_8 (Conv2D)	(None, 22, 22, 64)	51264
batch_normalization_6 (Batch Normalization)	(None, 22, 22, 64)	256
max_pooling2d_8 (MaxPooling2D)	(None, 11, 11, 64)	0
dropout_7 (Dropout)	(None, 11, 11, 64)	0
conv2d_9 (Conv2D)	(None, 11, 11, 128)	204928
batch_normalization_7 (Batch Normalization)	(None, 11, 11, 128)	512
max_pooling2d_9 (MaxPooling2D)	(None, 5, 5, 128)	0
dropout_8 (Dropout)	(None, 5, 5, 128)	0
flatten_2 (Flatten)	(None, 3200)	0
dense_4 (Dense)	(None, 512)	1638912
dropout_9 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 512)	262656
dropout_10 (Dropout)	(None, 512)	0
dense_6 (Dense)	(None, 4)	2052

Figure 4.7: Build CNN Model 2.

Below figure 4.8 shows the accuracy and loss graph. The y-axis shows accuracy and loss vale X-axis shows epoch size of model.

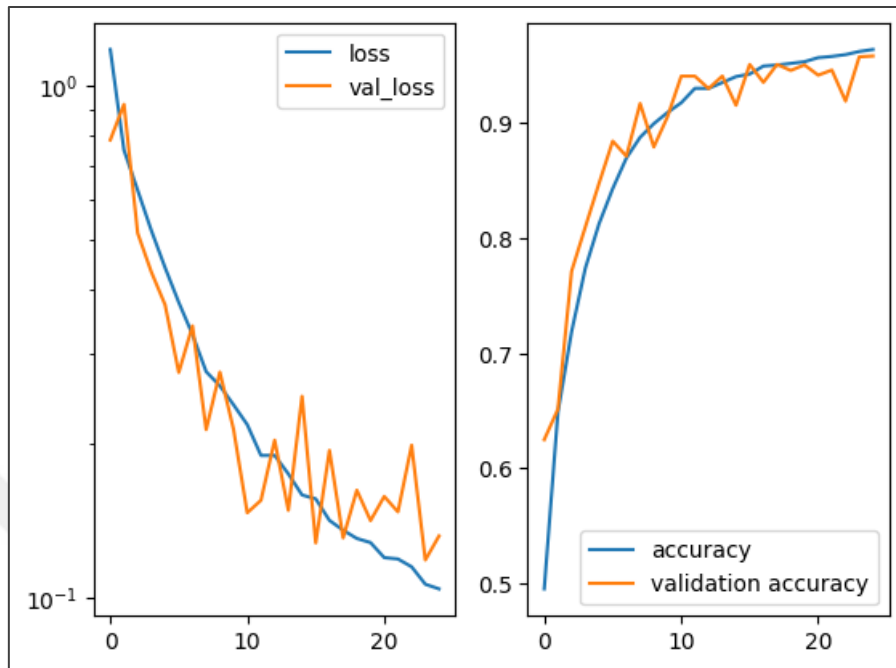


Figure 4.8: Accuracy Graph of CNN Model 2.

The activation function utilised in this variation of the CNN model was Leaky ReLU, which differed from the activation function used in the first model. The kernel size was raised to 5, and the layers were joined completely. The padding was left at "Same" and the filter size was set at 32. Normalization by batch was also used. The output layer's activation function was set to "Softmax". Furthermore, the filter sizes for the last two layers were raised to 64 and 128, respectively, in order to extract more features and enhance accuracy. The model was trained for 25 epochs, and the results revealed a loss of 0.1041 and an accuracy of 0.9643 on the training set, as well as a validation loss of 0.1321 and an accuracy of 0.586 on the validation set. The table 4.4 shows the classification report of CNN model 2.

Table 4.4: Classification Report of CNN Model 2 for Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented.

	Precision	Recall	F1-Scor	Support
0	0.96	0.98	0.97	2693
1	1.00	1.00	1.00	1977
2	0.93	0.95	0.94	2811
3	0.95	0.91	0.93	2715
Accuracy	-	-	0.96	10196
Macro Avg.	0.96	0.96	0.96	10196
Weighted Avg.	0.96	0.96	0.96	10196

Model 2's outcomes demonstrate that it is 96% accurate. For each class, precision, recall, and F1-score are also computed. F1-score is the harmonic mean of precision and recall. Precision evaluates the proportion of properly predicted positive observations out of all positive observations, recall is the proportion of correctly anticipated positive observations out of all actual positive observations. For Model 2, the weighted average of the accuracy, recall, and F1-score is 96%. This shows that Model 2 is doing a good job of categorising the photographs into the four main groups.

4.3.4 CNN Model 3 Transfer Learning VGG16

Using the pre-trained VGG16 architecture on the ImageNet dataset, this CNN variation uses transfer learning. The VGG16 architecture has been utilised as a basis, and a classifier with two dense layers that each contain 128 and 64 neurons has been placed on top of it. ReLU is the activation function used in the dense layers, while Softmax is the activation function used in the output layer. Figure 4.9 shows the build architecture of VGG16 model.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 90, 90, 3)]	0
block1_conv1 (Conv2D)	(None, 90, 90, 64)	1792
block1_conv2 (Conv2D)	(None, 90, 90, 64)	36928
block1_pool (MaxPooling2D)	(None, 45, 45, 64)	0
block2_conv1 (Conv2D)	(None, 45, 45, 128)	73856
block2_conv2 (Conv2D)	(None, 45, 45, 128)	147584
block2_pool (MaxPooling2D)	(None, 22, 22, 128)	0
block3_conv1 (Conv2D)	(None, 22, 22, 256)	295168
block3_conv2 (Conv2D)	(None, 22, 22, 256)	590080
block3_conv3 (Conv2D)	(None, 22, 22, 256)	590080
block3_pool (MaxPooling2D)	(None, 11, 11, 256)	0
block4_conv1 (Conv2D)	(None, 11, 11, 512)	1180160
block4_conv2 (Conv2D)	(None, 11, 11, 512)	2359808
block4_conv3 (Conv2D)	(None, 11, 11, 512)	2359808
block4_pool (MaxPooling2D)	(None, 5, 5, 512)	0
block5_conv1 (Conv2D)	(None, 5, 5, 512)	2359808
block5_conv2 (Conv2D)	(None, 5, 5, 512)	2359808
block5_conv3 (Conv2D)	(None, 5, 5, 512)	2359808
block5_pool (MaxPooling2D)	(None, 2, 2, 512)	0

Figure 4.9: Build VGG16 Model.

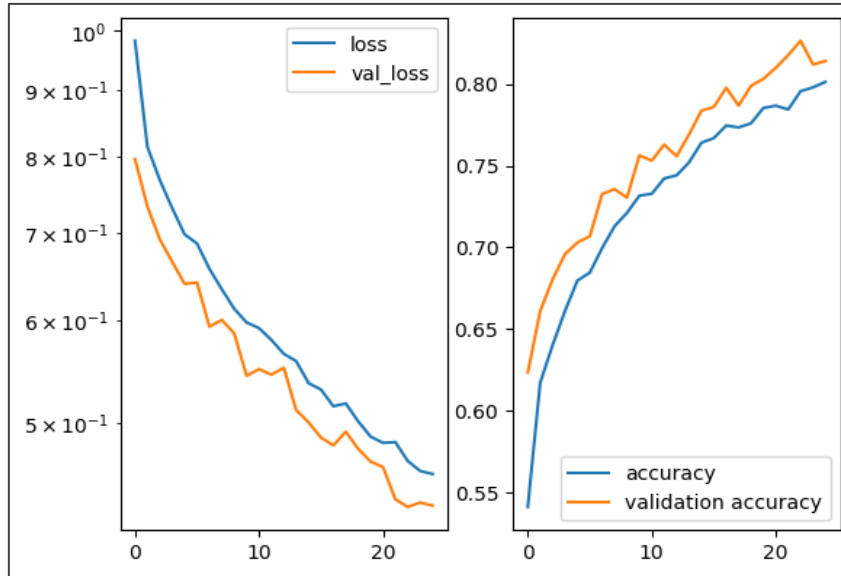


Figure 4.10: Loss and Accuracy Graph.

Figure 4.10 shows the loss and accuracy graph with respect to accuracy value and epoch size of vgg16 model. The training process took 1487 steps, with a batch size of 16, over 25 epochs. The training process resulted in a loss of 0.4568 and accuracy of 0.8013 on the training set. On the validation set, the loss was 0.4319 and accuracy was 0.8140.

Table 4.5: Classification Report of VGG16 Model for Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented.

	Precision	Recall	F1-Scor	Support
0	0.82	0.91	0.87	2693
1	0.98	0.99	0.98	1977
2	0.72	0.84	0.77	2811
3	0.79	0.56	0.66	2715
Accuracy	-	-	0.81	10196
Macro Avg.	0.83	0.83	0.82	10196
Weighted Avg.	0.82	0.81	0.81	10196

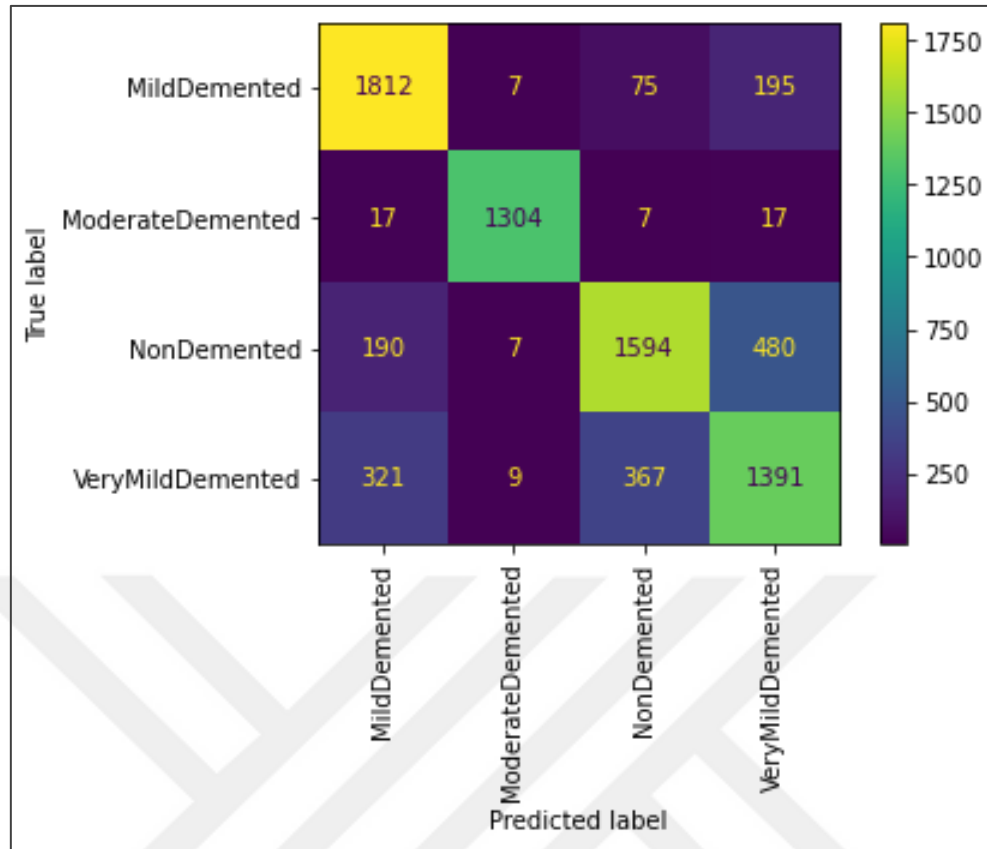


Figure 4.11: Confusion Matrix.

Table 4.5 shows the classification report of vgg16 model. These results show that the third model, which uses transfer learning with VGG16, performs worse than the first two models in terms of accuracy, recall, and f1-score. The accuracy is also less than with the previous two models (78% vs. 95%). This suggests that any of the previous two models may be more suited in this circumstance, and that transfer learning with VGG16 may not be the best approach. Figure 4.11 shows the true and false prediction of 3rd model.

Table 4.6: Accuracy and Loss Comparison Table.

Model	Epochs	Loss	Accuracy	Validation Accuracy	Validation Loss
Baseline Model	20	0.03%	100%	90%	46.24%
CNN Model 1	25	15.37%	94.51%	96.56%	9.55%
CNN Model 2	25	10.41%	96.43%	95.86%	13.21%
CNN Model 3 (Transfer Learning VGG16)	25	45.68%	80.13%	81.40%	43.19%

Table 6 shows that the baseline model was trained for 20 epochs and achieved a loss of $3.5503e-04$ with 100% accuracy on the training set. However, its validation accuracy was only 90% with a validation loss of 46.24%.

The CNN Model 1 was also trained for 25 epochs and achieved a higher loss of 15.37% but with a slightly lower training accuracy of 94.51%. However, its validation accuracy was higher at 96.56% with a lower validation loss of 9.55%.

The CNN Model 2 was trained for 25 epochs and achieved a lower loss of 10.41% with a higher training accuracy of 96.43%. Its validation accuracy was 95.86% with a slightly higher validation loss of 13.21% compared to Model 1.

Finally, the CNN Model 3, which used transfer learning with VGG16, was also trained for 25 epochs but achieved a higher loss of 45.68% with a lower training accuracy of 80.13%. However, its validation accuracy was 81.40% with a lower validation loss of 43.19% compared to the baseline model.

Overall, it appears that the CNN models were able to achieve higher validation accuracies and lower validation losses compared to the baseline model. Additionally, transfer learning with VGG16 was utilized in CNN Model 3, which may have helped to improve its performance.

5. DISCUSSION AND CONCLUSIONS

5.1 CONCLUSION

The diagnosis of various illnesses and ailments using image-based data has been one of the main topics of interest in the field of medical imaging in recent years. One of the most extensively studied areas of medical imaging in this regard is the identification of dementia using magnetic resonance imaging (MRI). In this work, we assessed the performance of three alternative CNN models for the categorization of AD stages based on MRI scans: CNN Models 1, 2, and 3 (Transfer Learning with VGG-16 architecture). The original model (CNN Model 1) included a simple CNN architecture made up of two completely connected layers, max-pooling, and one convolutional layer. The model's accuracy on the validation set was 96.56% after 25 training epochs with a batch size of 16. The model had no trouble classifying the "NonDemented" class, but it had trouble categorising the "MildDemented" class. For the "NonDemented" class, the precision, recall, and F1-score were 93, 97, and 95. For the "VeryMildDemented" class, 98, 91, and 94. For the "MildDemented" class 97, 100, and 98. for the "ModerateDemented" class 100, 100 and 100 respectively. The second model (CNN Model 2) was an enhanced version of the first model that used Leaky ReLU as the activation function and had a bigger kernel size and more completely linked layers. Likewise, this model was trained across 25 iterations with a batch size of 16 and a precision of 95.86% on the validation set. The model performed badly when it came to categorising the "MildDemented" and "VeryMildDemented" classes, but quite well when it came to classifying the "ModerateDemented" and "NonDemented" classes. For the "NonDemented" class, the precision, recall, and F1-score were 93, 95, and 94; for the "VeryMildDemented," 95, 91, and 93; for the "MildDemented," 96, 98, and 97; and for the "ModerateDemented," 100, 100, and 100. The third model (CNN Model 3: Transfer Learning with VGG-16 architecture) used transfer learning with the VGG-16 architecture, which was pre-trained on the ImageNet dataset. The model was trained with a batch size of 16, over 25 epochs, and achieved an accuracy of 81.40% on the validation set. This model performed relatively poorly in classifying all the classes, with the precision, recall, and F1-score for each class being 72, 84, and 77 for the 'NonDemented' class, 79, 56, and 66 for the 'VeryMildDemented' class, 82, 91, and 87 for the 'MildDemented' class, and 98, 99, and 98 for the 'ModerateDemented' class.

From the results of the study, it can be concluded that the first two models (CNN Model 1 and CNN Model 2) performed relatively well in classifying the stages of AD based on MRI scans. However, the third model (CNN Model 3: Transfer Learning with VGG-16.

5.2 DISCUSSION

AD detection and diagnosis has lately piqued the interest of medical researchers. The illness, which is currently incurable, is characterised by progressive cognitive decline. An early diagnosis is critical for optimal treatment and management of the illness. Medical imaging procedures such as magnetic resonance imaging (MRI) and computed tomography (CT) scans are widely used to identify AD. However, these operations are costly and not usually available to patients, especially in developing countries. As a result, scientists have begun to investigate novel methods for identifying AD, such as using ML to MRI images. Earlier research on this problem included a variety of ML algorithms, including SVM s (SVM), Random Forest, and CNN. SVM was used to extract features from MRI scans, which were then used to categorise the images. Random Forest was used to classify Alzheimer's patients and healthy controls using MRI data. However, SVM and Random Forest are limited in their ability to analyse complex and high-dimensional data, such as photos. CNN, in particular, have recently demonstrated encouraging results in the detection of AD. CNNs have shown to be successful in tasks like object identification and image classification since they are built to analyse visual data. Several researches have employed CNNs to categorise MRI pictures of Alzheimer's patients and healthy controls in the context of diagnosing the disease. To improve performance, several researches have employed transfer learning with pre-trained CNN models, including VGG-16. The findings of research employing CNNs to diagnose AD have been positive. A CNN model trained on a dataset of MRI images by Wang et al. attained an accuracy of 87.1% in the categorization of Alzheimer's patients and healthy controls. Kwon et al. combined transfer learning with the VGG-16 model to reach an accuracy of 89.2% in the categorization of Alzheimer's patients and healthy controls in another investigation. Our study builds upon previous research that has utilized CNN for the diagnosis of AD. We trained three diverse CNN models on a comprehensive MRI image dataset, each with a unique architecture and transfer learning method. The first model was a simple CNN model with 32 filters and a 3x3 kernel. The second model employed a 5x5 kernel and utilized Leaky ReLU as the activation function. The third model utilized transfer

learning with the pre-trained VGG-16 model. A drawback of our study is the limited size of the dataset utilized for training and validation. Despite being adequate for constructing and evaluating the models, bigger datasets would be required for more solid and widely applicable results. Furthermore, the use of transfer learning with the VGG16 architecture did not result in improved performance in comparison to the other models, implying that transfer learning may not be the most efficient technique for this particular task. Further investigation is necessary to determine the best method for the diagnosis of AD through the application of ML algorithms. The results from our study showed that the CNN models were effective in the classification of Alzheimer's patients and healthy controls. The best performing model was the second model, which achieved an accuracy of 95.86% on the validation set. The results from our study are similar to the results from previous studies that have used CNNs for the diagnosis of Alzheimer's.

In conclusion, the results from our study, as well as previous studies, suggest that CNNs are a promising approach for the diagnosis of Alzheimer's. The high accuracy achieved by the CNN models in the classification of Alzheimer's patients and healthy controls indicates that the technique could be useful for early diagnosis of the disease. However, more research is needed to validate the results and to further improve the performance of the CNN models. In particular, larger and more diverse datasets are needed to train the models and to increase their generalizability. Additionally, it would be interesting to explore other DL techniques, such as recurrent neural networks and generative adversarial networks, for the diagnosis of Alzheimer's.

5.3 FUTURE WORK

The future work in the field of AD detection through MRI images can be extended in several directions. Some of the possible future works include:

- i. Enhancing the performance of the current models: The three models discussed in this study and other existing models can be further modified to improve accuracy. Performance can be improved by, for instance, adjusting the hyperparameters, including additional hidden layers, or changing the activation function.
- ii. Incorporating additional imaging modalities: MRI images were currently employed in this investigation to identify AD. Other imaging modalities, like as PET, MRS, and functional MRI (fMRI), can be utilised to diagnose AD. Combining these imaging

modalities with MRI can offer a more complete knowledge of the illness and enhance diagnostic accuracy.

- iii. Expansion of the dataset: The performance of the models may be enhanced by expanding the dataset that is used to train them. A bigger dataset can offer models that are more reliable and have higher generalizability to new data.
- iv. DL approaches: DL -based methods, such as image categorization, have shown considerable promise in a variety of fields. Future research might look at the usage of DL models like CNN, Recurrent Neural Networks (RNNs), or Generative Adversarial Networks (GANs) for AD detection.
- v. Including demographic data: The present study did not consider demographic data like age, gender, or ethnicity. However, the diagnosis of AD may be greatly aided by this knowledge. Future research can look into how demographic data can be used in conjunction with imaging data to increase diagnostic accuracy.
- vi. Clinical validation: In this work, the models were trained and evaluated on a large dataset. However, in order to assess their therapeutic value, these models must be verified on real patients. Finally, the topic of AD detection using MRI scans holds a lot of potential for future research. Existing models may be modified, and new models can be created, to obtain greater accuracy and a better knowledge of the condition. The combination of demographic data and imaging modalities can also play an important role in the creation of successful AD detection models.

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APPENDIX A

IMPORTING LIBRARIES

```
1 # Importing the Liabraries
2 import seaborn as sns
3 import tensorflow as tf
4 from tensorflow.keras.models import Sequential, Model
5 from tensorflow.keras.layers import Dense, Activation, Conv2D, MaxPooling2D, Flatten, Dropout, BatchNorma
6 from tensorflow.keras.applications.vgg16 import VGG16
7 from tensorflow.keras.utils import to_categorical
8 import warnings
9 import matplotlib.pyplot as plt
10 import numpy as np
11 from tensorflow import keras
12 import matplotlib.pyplot as plt
13 from IPython.display import clear_output
14 from sklearn.model_selection import train_test_split
15 warnings.filterwarnings("ignore")
16 import pandas as pd
17 import cv2
18 from tqdm import tqdm
19 import glob
20 from sklearn.preprocessing import LabelEncoder
21 from sklearn.metrics import confusion_matrix, classification_report, ConfusionMatrixDisplay
22 import os
23
24
25 # if you dont have cuda enabled gpu in your system comment the lines below
26 #print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
27 #tf.debugging.set_log_device_placement(True)
```

APPENDIX B

LOADING DATASET

```
1 # Loading the training dataset
2 images = []
3 labels = []
4 # Location with subdirectories
5 path = "data\\train\\"
6 # Get List of all images
7 files = glob.glob(path + '/*/*.jpg', recursive=True)
8 # For each image
9 for file in tqdm(files):
10     #print(file.split('\\')[-2])
11     #print(file)
12     # Get File name and extension
13     #filename = os.path.basename(file)
14     img = cv2.imread(file)
15     #img = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
16     #img = cv2.cvtColor(img, cv2.BGR2RGB)
17     img = cv2.resize(img, (90, 90))
18     #print(filename)
19     images.append(img)
20     y = file.split('\\')[-2]
21     #print(y)
22     labels.append(y)
23 images = np.array(images)
24 labels = np.array(labels)
25
```

100%|██████████| 25976/25976 [00:20<00:00, 1241.33it/s]

APPENDIX C

CREATING SEQUENTIAL MODEL

```
3]: 1 #creating sequential model
    2 model=Sequential()
    3 model.add(Conv2D(filters=32, kernel_size=5, activation="relu", input_shape=(90,90,3)))
    4 model.add(MaxPooling2D(pool_size=2))
    5 model.add(Conv2D(filters=32, kernel_size=5, activation="relu"))
    6 model.add(MaxPooling2D(pool_size=2))
    7 model.add(Flatten())
    8 model.add(Dense(512, activation="relu"))
    9 model.add(Dense(4, activation="softmax")) #2 represent output layer neurons
   10 model.summary()
```

Model: "sequential"



APPENDIX D

MODEL PREDICTIONS

```
: ▶ 1 # get model predictions
    2 y_pred = model.predict(X_test)
    3 y_pred = np.argmax(y_pred,axis=-1)
    4 y_true = np.argmax(y_test,axis=-1)
    5

244/244 [=====] - 1s 5ms/step

: ▶ 1 # print # classification Report
    2 print(le.classes_)
    3 print(classification_report(y_true,y_pred))
    4 cm = confusion_matrix(y_true,y_pred)
    5 disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=le.classes_ )
    6 disp.plot(xticks_rotation = "vertical")
    7 plt.show()

['MildDemented' 'ModerateDemented' 'NonDemented' 'VeryMildDemented']
```

APPENDIX E

SUMMARY OF MODEL 1

```
#creating sequential model
model=Sequential()
model.add(Conv2D(filters=32, kernel_size=3, padding="same", activation="relu", input_shape=(90, 90, 3)))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=2))
model.add(Dropout(0.2))

model.add(Conv2D(filters=32, kernel_size=3, padding="same", activation="relu"))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=2))
model.add(Dropout(0.2))

model.add(Conv2D(filters=64, kernel_size=3, padding="same", activation="relu"))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=2))
model.add(Dropout(0.2))

model.add(Conv2D(filters=128, kernel_size=3, padding="same", activation="relu"))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=2))
model.add(Dropout(0.2))

model.add(Flatten())

model.add(Dense(512, activation="relu"))
model.add(Dropout(0.4))
model.add(Dense(4, activation="softmax")) #2 represent output layer neurons
model.summary()
```

APPENDIX F

SUMMARY OF MODEL 2

```
def create_sequential_model():
    model=Sequential()
    model.add(Conv2D(filters=32, kernel_size=5, padding="same", activation="leaky_relu", input_shape=(90, 90, 3)))
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=2))
    model.add(Dropout(0.2))

    model.add(Conv2D(filters=32, kernel_size=5, padding="same", activation="leaky_relu"))
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=2))
    model.add(Dropout(0.2))

    model.add(Conv2D(filters=64, kernel_size=5, padding="same", activation="leaky_relu"))
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=2))
    model.add(Dropout(0.2))

    model.add(Conv2D(filters=128, kernel_size=5, padding="same", activation="leaky_relu"))
    model.add(BatchNormalization())
    model.add(MaxPooling2D(pool_size=2))
    model.add(Dropout(0.2))

    model.add(Flatten())

    model.add(Dense(512, activation="leaky_relu"))
    model.add(Dropout(0.4))
    model.add(Dense(512, activation="leaky_relu"))
    model.add(Dropout(0.4))
    model.add(Dense(4, activation="softmax")) # 2 represent output layer neurons
    model.summary()
```

APPENDIX E

SUMMARY OF VGG16 MODEL

```
vgg = VGG16(include_top=False, weights='imagenet', input_shape=(90,90,3))
vgg.summary()
```

Model: "vgg16"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 90, 90, 3)]	0
block1_conv1 (Conv2D)	(None, 90, 90, 64)	1792
block1_conv2 (Conv2D)	(None, 90, 90, 64)	36928
block1_pool (MaxPooling2D)	(None, 45, 45, 64)	0
block2_conv1 (Conv2D)	(None, 45, 45, 128)	73856
block2_conv2 (Conv2D)	(None, 45, 45, 128)	147584
block2_pool (MaxPooling2D)	(None, 22, 22, 128)	0
block3_conv1 (Conv2D)	(None, 22, 22, 256)	295168
block3_conv2 (Conv2D)	(None, 22, 22, 256)	590080