Alzheimer's Disease Prediction using Deep Learning

Mebatsion Sahle Tilahun

A Thesis Submitted to

The Department of Computer Science and Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfilment of the Requirement for the Degree of Master's in Computer Science and Engineering

Office of Graduate Studies

Adama Science and Technology University

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DECLARATION

I hereby declare that this Master's Thesis entitled "**Alzheimer's Disease Prediction using Deep Learning**" is my original work. It has not been submitted for the award of any academic degree, diploma, or certificate at any other university. All sources of materials used in this thesis have been duly acknowledged through proper citation.

Mebatsion Sahle Tilahun _____ _____

Name of Student Signature Date

RECOMMENDATION OF ADVISORS/SUPERVISORS

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "**Alzheimer's Disease Prediction using Deep Learning"** prepared under my guidance by **Mebatsion Sahle Tilahun** submitted in partial fulfillment of the requirements for the degree of Masters of Science in Computer Science and Engineering (CSE). Therefore, I recommend the submission of the revised version of the thesis to the department following the applicable procedures.

Dr. Teklu Urgessa (Ph.D) _____ _____

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APPROVAL OF BOARD OF REVIEWERS

We, the undersigned, members of the Board of Examiners of the thesis by Mebatsion Sahle Tilahun have read and evaluated the thesis entitled "Alzheimer's Disease Detection and Classification using Deep Learning" and examined the candidate during the open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master's of Science in Computer Science and Engineering.

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LIST OF ACRONYMS AND ABBREVIATIONS

AD	Alzheimer's Disease
ADNI	Alzheimer's Disease Neuroimaging Initiative
CNN	Convolutional Neural Network
CT	Computed Tomography
DICOM	Digital Imaging and Communications in Medicine
fMRI	Functional Magnetic Resonance Imaging
GPU	Graphics Processing Unit
MCI	Mild Cognitive Impairment
MRI	Magnetic Resonance Imaging
NC	Normal Control
PET	Positron Emission Tomography
ReLU	Rectified Linear Unit
SMOTE	Synthetic Minority Over-sampling Technique
SVM	Support Vector Machine
VGG	Visual Geometry Group

ABSTRACT

Alzheimer's Disease (AD) represents a significant global health challenge due to its progressive nature and the absence of effective treatments. This study aims to enhance the early detection and classification of AD using deep learning techniques, specifically focusing on MRI data. By addressing the limitations of existing diagnostic models, particularly the issues related to data imbalance, we developed and evaluated two model architectures: a custom Convolutional Neural Network (CNN) and a modified VGG16 model. Our methodology involved the collection and preprocessing of MRI datasets from publicly available sources, ensuring rigorous data handling to maintain quality and relevance. Data augmentation techniques were selectively applied to address class imbalance, notably using the Synthetic Minority Over-sampling Technique (SMOTE). The custom CNN architecture was designed to handle imbalanced datasets effectively, achieving a test accuracy of 99.22%, with precision, recall, and F1 scores all at 99.22%. This model demonstrated robustness and high predictive accuracy across different stages of AD, as validated by its confusion matrix. For balanced datasets, the modified VGG16 model, pre-trained on ImageNet and fine-tuned for our specific task, was utilized. This model achieved outstanding performance with an accuracy of 97.98%, precision of 98.12%, recall of 97.82%, and an AUC of 99.86%. The balanced dataset allowed the VGG16 model to leverage its depth and feature extraction capabilities fully, resulting in a highly effective classification tool for AD stages. Comparative analysis indicated that the modified VGG16 model outperformed the custom CNN in scenarios with balanced data, underscoring the importance of dataset preparation in achieving optimal model performance. The findings from this study highlight the critical role of advanced deep learning models and meticulous data preprocessing in enhancing diagnostic accuracy for Alzheimer's Disease. This research not only contributes to the field of medical imaging and diagnostics by demonstrating effective strategies for adapting pre-trained models but also sets a new benchmark for Alzheimer's disease classification using MRI images. Future work will focus on acquiring more diverse datasets, exploring additional deep learning architectures, and implementing these models in real-world clinical environments to further validate their utility and effectiveness.

***Keywords**: Alzheimer's Disease, Deep Learning, Convolutional Neural Network, VGG16, MRI, Data Imbalance, Synthetic Minority Over-sampling Technique (SMOTE), Medical Imaging,*

Diagnostic Models, Early Detection, Data Augmentation, Healthcare, Neuroimaging, Dementia Classification.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Alzheimer’s disease is an incurable, progressive neurological condition that steadily erodes memory and cognitive abilities, ultimately impairing the ability to perform even basic activities. It is emerging as a major health concern worldwide. Currently, there is no cure for Alzheimer's disease (Hussain et al., 2020). This disease is quickly turning into one of the most common and financially burdensome illnesses on a global scale. Its effects extend beyond the patients themselves, profoundly influencing the lives of caregivers, nurses, and family members involved in their care (Saied et al., 2022).

Alzheimer's Disease (AD) is a serious brain problem that gets worse over time. It slowly damages memory, making it hard to communicate and do everyday things like talking and walking. Sadly, it eventually leads to death. AD is the most common kind of dementia, making up around 60–80% of all dementia cases. It usually starts when people are middle-aged or older, possibly because of the build-up of proteins around brain cells. This causes a gradual decline in memory, connected to problems with brain function, brain shrinkage, and cell death. Changes in the brain happen before memory problems start, and some signs may show up early. Studies suggest that these brain changes related to AD might begin at least 20 years before someone shows any symptoms (Ebrahimighahnavieh et al., 2020).

Alzheimer's disease is a big challenge in healthcare, and it's the main reason behind dementia. About 40 million people around the world are thought to have dementia, and this number might double every 20 years until around 2050. Since dementia is mostly found in people over 60, the longer lifespans we're experiencing mean more and more people are getting dementia, especially AD. This has led to a lot of research to find ways to treat the disease. Unfortunately, even with all the hard work, there are currently no effective treatments for Alzheimer's (Yiannopoulou & Papageorgiou, 2020).

AD represents a significant global health challenge, affecting millions of individuals, particularly among aging populations. AD is characterized by progressive cognitive decline, including memory loss and impaired reasoning. However, the pathogenesis of AD is multifaceted, involving genetic, environmental, and lifestyle factors.

In recent decades, there has been a big change in how brain imaging is used in understanding and dealing with AD. In terms of diagnosis, imaging has become a crucial part, moving from a smaller role to a central one. In research, imaging helps answer important scientific questions about the effects of AD and how it develops over time and space, as outlined by (Johnson et al., 2012).

One of the primary diagnostic tools for AD is Magnetic Resonance Imaging (MRI), which helps detect structural changes in the brain. The use of neuroimaging techniques is becoming more prevalent as a supplementary tool to clinical evaluations for the early detection of AD (Mosconi et al., 2007). However, imbalanced MRI datasets and the quality of local MRI image data have presented challenges in deriving accurate predictions. Additionally, most existing datasets focus predominantly on age-related factors, overlooking critical non-age-influenced variables.

In this study we utilized Python and deep learning techniques to address these challenges, developing a nuanced predictive model that integrates various data types and is attuned to the multifactorial nature of AD.

1.2 MOTIVATION OF THE STUDY

The improvement of detection of AD is the focal point of this study, which seeks to address key challenges within the field. The refinement of data processing techniques, especially in handling imbalanced Magnetic Resonance Imaging (MRI) datasets, is prioritized. The enhancement of accuracy and reliability in detection models for AD. This is seen as vital for the development of more precise and affordable diagnostic tools.

Advanced deep learning methods are utilized in this research to contribute towards early detection strategies for AD. It is anticipated that these strategies will lead to better patient outcomes by facilitating earlier interventions in the disease's progression. The application of

these innovative methods is expected to play a significant role in the early identification of AD indicators.

A broader objective of this study is to revolutionize healthcare practices in AD diagnosis, making them more efficient and effective. This transformation is intended to benefit patients, caregivers, and the medical community at large. The anticipated advancements in diagnostic techniques aim to enhance resource allocation, inform treatment decisions, and overall, improve the quality of care for patients with AD. Additionally, these improvements are expected to provide substantial support to caregivers and family members, who often face significant challenges in caring for loved ones with Alzheimer's Disease.

In conclusion, this research highlights the study's goal to address important issues in how Alzheimer's Disease is currently diagnosed, especially in improving detection and classification across different stages of the disease. The study uses deep learning to help improve the quality of life for people affected by this condition.

1.3 STATEMENT OF THE PROBLEM

The necessity of this research stems from the current limitations in Alzheimer's disease (AD) diagnosis, where existing studies predominantly use public datasets either they use a binary class classification (Arafa et al., 2023) with a single dataset or multi-class classification with multiple datasets with no clear dataset building methodology (Helaly et al., 2022). This gap in data representation, coupled with the prevalent issue of data imbalance (EL-Geneedy et al., 2023), leads to less effective diagnostic models for AD diagnosis. By focusing on addressing data imbalance, this study aims to develop more accurate AD detection models. This approach is vital for advancing global healthcare practices in AD management (Kim et al., 2021), ensuring broader applicability and effectiveness of diagnostic tools across varied populations. This study to addressed these issues by advancing methods in data processing and model adaptation, ultimately striving to improve medical treatment for AD patients through more accurate and ethical use of brain MRI data.

1.4 RESEARCH QUESTIONS

In this study, an attempt will be made to answer the following questions:

1. Which model performs better in the imbalanced four-class detection of Alzheimer disease?
2. What are the optimal preprocessing techniques for handling both even and uneven data distributions in MRI AD datasets?
3. How does the performance of a model in predicting Alzheimer's disease vary with the application of different deep learning algorithms and preprocessing techniques?
4. Which model demonstrates the highest effectiveness in Alzheimer's disease diagnostics for both imbalanced and balanced dataset?

1.5 OBJECTIVE

1.5.1 General Objective

The main objective of the study is to develop a detection model architecture for the early detection of Alzheimer Disease using Deep Learning.

1.5.2 Specific Objectives

The following specific objectives are addressed to achieve the general objective:

- To apply data balancing techniques on the MRI image dataset with uneven class distributions.
- To develop detection models that work well for imbalanced and balanced MRI datasets, ensuring the model is effective and reliable.
- To train, validate, and test the models on both types of datasets, identifying which model performs best based on accuracy and F1-score metrics.
- To analyze how the models, perform on balanced versus imbalanced datasets, focusing on precision, recall, and F1-score metrics.
- To compile a detailed report outlining the techniques used, the outcomes achieved, and a comparative analysis of the performance across the balanced and imbalanced datasets.

1.6 SCOPE OF THE STUDY

The scope of this study centers on enhancing detection models using MRI data, focusing on two main objectives. Initially, it explores the application of data balancing techniques to address class imbalances within MRI datasets, improving the accuracy of detection models. Subsequently, the study aims to identify a robust detection model that delivers consistent performance across both balanced and imbalanced datasets. This involves evaluating various model architectures to determine the most effective in accurately interpreting MRI data.

The limitations of this study are primarily related to resources. Constraints on available data, computational power, and access to advanced analytical tools could potentially affect the outcomes of the predictive models being examined. Additionally, limitations in time for data collection, funding and expert availability might also impacted the depth and scope of the research conducted.

1.7 SIGNIFICANCE OF THE STUDY

The proposed study provides new insights into AD detection, addressing existing challenges. It could lead to better diagnostic tools and contribute to personalized treatment plans for AD patients.

The significance of this study lies in its potential to revolutionize the diagnosis of Alzheimer's disease, the understanding of data balancing techniques is poised to enhance the accuracy of AD diagnostics, which is paramount for early intervention strategies. Furthermore, establishing an effective model for both imbalanced and balanced datasets will not only aid in advancing medical practices contribute valuable insights to the international research community. By adhering to strict ethical guidelines, this study ensures the respectful and responsible use of sensitive medical data, setting a precedent for future research in the field. Ultimately, this work aspires to provide a scalable model for AD diagnosis that can be adapted to other balanced or imbalanced dataset, paving the way for more equitable healthcare solutions worldwide.

CHAPTER TWO

LITERATURE REVIEW

2.1 CONCEPTUAL BACKGROUND

2.1.1 Mental health: Overview

The intersection of physical health and mental well-being is a critical area of focus in contemporary healthcare. As we go deeper into the complexities of aging and neurodegenerative disorders, understanding the link between physical health and mental health becomes increasingly imperative. In this essay, we embark on a journey that begins with exploring the intricate relationship between overall health and mental well-being, traversing through the realm of cognitive decline, and ultimately arriving at a profound understanding of Alzheimer's disease.

Health is not merely the absence of physical ailments but encompasses a holistic state of well-being, including physical, mental, and social dimensions. Mental health, often overshadowed by its physical counterpart, is equally essential for overall well-being. Mental health influences how we think, feel, and behave, impacting our ability to cope with stress, form relationships, and navigate life's challenges. Neglecting mental health can have profound consequences on physical health outcomes, emphasizing the interconnectedness of mind and body.

As individuals age, cognitive function naturally undergoes changes, ranging from mild forgetfulness to more severe cognitive impairment. While aging itself does not inevitably lead to cognitive decline, certain factors, such as genetics, lifestyle, and underlying health conditions, can accelerate the process. Mild cognitive impairment (MCI) represents a transitional stage between normal aging and dementia, characterized by noticeable cognitive changes that do not significantly interfere with daily functioning. Understanding the trajectory of cognitive decline is crucial for early intervention and preventive strategies to mitigate the risk of dementia.

At the heart of cognitive decline lies Alzheimer's disease, a progressive neurodegenerative disorder that robs individuals of their memories, cognitive abilities, and ultimately, their sense of self. Alzheimer's disease is not merely a disorder of aging but a devastating manifestation of cellular dysfunction, characterized by the accumulation of amyloid-beta plaques and tau tangles

in the brain. The journey from initial symptoms to advanced stages of Alzheimer's disease is marked by a gradual erosion of cognitive function, affecting memory, language, executive function, and visuospatial skills. As the disease progresses, individuals become increasingly dependent on others for daily care, underscoring the profound impact of Alzheimer's on both patients and caregivers.

In conclusion, the intricate interplay between physical health and mental well-being sets the stage for understanding neurodegenerative disorders such as Alzheimer's disease. By recognizing the interconnectedness of mind and body, we can adopt a holistic approach to healthcare that addresses both the physical and mental aspects of aging and cognitive decline. Through early intervention, personalized care, and ongoing research, we strive to unravel the mysteries of Alzheimer's disease and pave the way for a future where individuals can age with dignity, resilience, and hope.

2.1.2 Alzheimer’s Disease

AD is a type of neurodegenerative disorder (Tufail et al., 2020). This means it involves the gradual degeneration, or deterioration, of nerve cells in the brain. Classified under dementia, AD causes the brain tissue to atrophy, leading to a decline in memory and cognitive abilities. It affects not only memory but also behavioral, social, and reasoning skills. The disease is primarily caused by the accumulation of abnormal protein fragments in the brain (Tiwari et al., 2019). In essence, AD gradually impairs brain functions, leading to significant changes in a person's ability to think, behave, and interact socially.

Alzheimer's disease, the predominant type of dementia, poses a major health concern in contemporary times (Tatulian, 2022). According to projections by (Brookmeyer et al., 2007), by 2050, over 1% of the global population is expected to suffer from AD or similar conditions, necessitating considerable care. Typically manifesting as a chronic neurodegenerative disorder in middle to old age, Alzheimer's disease can also appear in rare instances as early-onset AD in individuals aged 45–64 years (Loi et al., 2023).

In recent studies, most methods primarily focus on binary classification (Arafa et al., 2022) (Tufail et al., 2020), distinguishing between Normal Control (NC) and AD or multi-class classification for 3 stages (NC, MCI & AD) (M. Liu et al., 2018). However, the model

developed by (Helaly et al., 2022) is capable of diagnosing and differentiating multiple stages of AD, encompassing four stages:

a. Non-Demented: Healthy individuals with no signs of Alzheimer's disease.
    - E.g. Forget where you put your contact glasses
b. Very Mild Demented: Individuals in early stages of Alzheimer's disease with subtle cognitive decline.
    - E.g. Struggling to remember the right word in a conversation
c. Mild Demented: Individuals with mild cognitive and functional impairments due to dementia.
    - E.g. forgetting the way to store
d. Moderate Demented: Individuals with significant cognitive impairments, indicating advanced AD.
    - E.g. S/He may not recognize family members and could have difficulty communicating.

2.1.3 Neuroimaging Techniques in Alzheimer's Research

Identifying the risk and severity of AD during its initial stages is crucial (Nichols & Vos, 2021). Currently, physicians can diagnose early-stage AD using neuro-imaging techniques and computer-aided diagnostic methods, although these approaches have limited accuracy. Neuro-imaging, which encompasses technologies like Computed Tomography (CT) scans, Positron Emission Tomography (PET) scans, and particularly Magnetic Resonance Imaging (MRI) scans, is essential in the diagnosis of medical conditions (Tufail et al., 2020). These methods are non-invasive and provide valuable insights into the body's internal state. Recent advancements in medical diagnostics have significantly fueled research in computer-aided diagnosis (Tiwari et al., 2019), (Fareed et al., 2022), making it a rapidly evolving field.

Neuroimaging techniques such as MRI and PET scans are integral in Alzheimer's research. When combined with deep learning models, these techniques enhance the accuracy of Alzheimer's disease diagnosis and contribute to a better understanding of its pathophysiological mechanisms.

2.1.3 Deep Learning in Alzheimer's Disease Research

The application of deep learning and transfer learning has become increasingly prevalent in Alzheimer's disease research (Gao & Lima, 2022). These models excel in processing and analyzing complex patterns in neuroimaging data, aiding in the early detection and monitoring of disease progression (Zhou et al., 2023).

2.2 RELATED WORKS

Numerous studies have investigated the potential of deep learning in Alzheimer's research, highlighting the value of advanced computational techniques. For instance, some research utilizes Convolutional Neural Networks (CNNs) to classify the stages of Alzheimer's disease using MRI images, showcasing the models' capability to distinguish between different stages of the disease. Other studies focus on integrating neuroimaging data with deep learning algorithms, aiming to predict Alzheimer's progression. This demonstrates the benefits of multimodal data analysis in comprehending the complexities of the disease. These efforts underline the increasing significance of advanced computational methods in improving our understanding and management of Alzheimer's disease.

Research into the genetic architecture of Alzheimer's disease, such as the work by (Neuner et al., 2020), suggests that future studies should consider factors like sex- and ethnicity-specific risks and the complex interactions between genes and the environment. This approach is expected to enhance our comprehension of the genetic factors involved in Alzheimer's.

Deep learning and genetic studies offer valuable insights into Alzheimer's disease, emphasizing the need for comprehensive approaches that consider genetic, environmental, and societal factors in understanding and managing the condition.

In (Helaly et al., 2022b) paper, the research involved a multi-step approach for detecting and classifying AD stages using deep learning. The process began with data acquisition, utilizing the ADNI dataset with 2D T1w MRI modality images, encompassing 300 patients across four classes. The study addressed dataset imbalances through oversampling and under sampling, leading to a balanced set of 24,000 images. Preprocessing included normalization,

standardization, resizing, and denoising using a non-local means algorithm. To augment the dataset, traditional techniques such as rotation and reflection were applied, resulting in 48,000 images. The study then conducted medical image classification using two methods: simple CNN architectures for 2D and 3D MRI scans and transfer learning techniques with models like VGG19. The evaluation was based on nine performance metrics, and the findings were applied to develop a web application for remote AD checking.

Sisodia et al., (2023) study proposed a framework employing deep transfer learning techniques with CNN model architectures like Xception, EfficientNetB7, DenseNet201, ResNet50, and VGG19. The models were initially trained using ImageNet weights with over 14 million images from 1,000 different classes, followed by retraining using the Alzheimer's disease dataset. Fine-tuning of convolutional layer weights and hyperparameter adjustments were made to optimize training. The models were evaluated based on validation accuracy and other metrics, demonstrating their effectiveness in classifying AD stages.

Arafa et al., (2022) research focused on detecting Alzheimer's Disease using deep learning, starting with data acquisition from various neuroimaging modalities. Preprocessing techniques were crucial to enhance data quality and optimize patterns, including removing noise and non-brain tissue from MRI images. The study used Convolutional Neural Networks to detect AD from MRI images, comparing different studies to highlight the effectiveness of deep learning over traditional machine learning methods. This comprehensive approach demonstrated the potential of deep learning in AD detection and classification.

Kavitha et al., (2022) conducted a comprehensive study focusing on early-stage Alzheimer's Disease prediction using machine learning models. Their research involved a detailed analysis of MRI data, utilizing various machine learning algorithms such as Decision Trees, Random Forest, Support Vector Machine, XGBoost, and Voting classifiers. The team aimed to enhance early diagnosis accuracy by applying these models to a dataset that included significant pre-processing steps like feature extraction and data splitting. Their results, with a best validation average accuracy of 83% on test data, signify an improvement in the early-stage diagnosis of Alzheimer's Disease.

Khan et al., (2022) advanced the field of AD diagnostics through a novel transfer learning-based approach for multiclass classification using magnetic resonance imaging (MRI) data. Their methodology involved utilizing pre-trained VGG architectures (VGG16 and VGG19) and implementing a layer-wise transfer learning strategy to fine-tune these models for AD diagnosis. The research team meticulously processed the MRI images, incorporating steps like skull stripping and tissue segmentation, and conducted comprehensive experiments to evaluate the effectiveness of their approach. Their results showed a remarkable accuracy of 97.89% in the 4-way classification of AD stages, significantly outperforming existing diagnostic techniques.

In their innovative research, (Mujahid et al., 2023) developed a sophisticated ensemble approach to enhance the detection of Alzheimer's Disease through the analysis of magnetic resonance imaging (MRI) data. Their study leveraged an adaptive synthetic technique coupled with deep learning algorithms to improve diagnostic accuracy. The researchers meticulously described the dataset, emphasizing the pre-processing steps undertaken to ensure data quality and relevance. The methodology encompassed a comprehensive range of experiments, employing advanced machine learning tools and techniques to analyze the MRI data. The experiments were designed to evaluate the effectiveness of the ensemble approach and to compare its performance against existing methods.

This compilation of research studies highlights the diverse and innovative approaches being employed in the field of AD diagnostics using deep learning and machine learning techniques. A common thread across these studies is the utilization of advanced computational methods, such as Convolutional Neural Networks (CNNs) and transfer learning, to analyze neuroimaging data, particularly MRI images, for the early detection and classification of AD. Studies like those conducted by (Helaly et al., 2022), (Sisodia et al., 2023), and (Khan et al., 2022) demonstrate the application of various deep learning architectures and models to enhance the accuracy of AD diagnosis. These include simple CNNs for image classification, transfer learning with complex architectures like VGG16, and the use of large-scale datasets like ImageNet for training and fine-tuning models.

The significance of this body of work lies in its contribution to the early detection and improved understanding of Alzheimer's Disease. With the increasing prevalence of AD globally, early and accurate diagnosis is crucial for effective management and treatment. The research efforts, such as those by (Kavitha et al., 2022) and (Mujahid et al., 2023), focus on enhancing the predictive accuracy of early-stage AD, addressing the challenges of dataset imbalance, and exploring the genetic architecture and environmental factors influencing the disease. These studies not only provide insights into the progression and stages of AD but also underscore the importance of developing data imbalance issues. By integrating advanced computational techniques with medical imaging and genetic data, these studies pave the way for more personalized and effective approaches to AD diagnostics, contributing significantly to the broader goal of improving healthcare outcomes for individuals affected by Alzheimer's Disease.

In summary, the potential of deep learning in predicting AD offers a transformative approach to diagnostics, where healthcare challenges are unique and resources may be limited. The various studies discussed in this paper, including those by (Helaly et al., 2022), (Arafa et al., 2023), (Sisodia et al., 2023), (Kavitha et al., 2022), (Khan et al., 2022), and (Mujahid et al., 2023), demonstrate the efficacy of machine learning models in the early detection and classification of AD. These models, leveraging advanced techniques such as convolutional neural networks and ensemble methods, can be adapted to suit the specific needs and constraints of the data imbalance issue.

The adaptation of these models to the data balancing context is critical, considering factors like infrastructure limitations, accessibility, and the necessity for cost-effective solutions. The implementation of deep learning models in AD diagnosis promises to enhance the quality of healthcare, making early and accurate diagnosis more accessible.

The incorporation of deep learning in medical diagnostics represents a significant step forward in the management of neurodegenerative diseases. Tailoring these technologies to local healthcare environments ensures that the benefits of innovation reach those most in need. The insights gained from this research advocate for ongoing exploration and application of deep learning in healthcare, highlighting its role in improving patient outcomes and advancing global health initiatives. Ultimately, the integration of these technologies in with different classes of

datasets and other similar contexts is a testament to the evolving landscape of medical diagnostics, underscoring the importance of adapting cutting-edge solutions to meet diverse healthcare challenges worldwide.

Table 2. 1 Summary for Literature Review

No.	Authors	Dataset	Method	Modality	Classification Type	Gap or limitation
1	Deep Learning Approach for Early Detection of Alzheimer's Disease Helaly et al., 2022	ADNI Dataset	CNNs, Transfer Learning	MRI	Multiclass	Expanding dataset and data balance weren't considered
2	Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey Arafa et al.,2022	ImageNet, AD Dataset	Transfer Learning with CNN Architectures	MRI	Multiclass	Expanding dataset and data balance weren't considered
3	A Review of Deep Transfer Learning Approaches for Class-Wise Prediction of Alzheimer's Disease Using MRI Images Sisodia et al., 2023	Various Neuroimaging	Convolutional Neural Networks	MRI, PET, fMRI, CT	Binary/Multiclass	Data balance wasn't considered
4	Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models Kavitha et al., 2022	OASIS	Decision Trees, Random Forest, SVM, XGBoost	MRI	Binary	Expanding dataset and algorithm diversity
5	A transfer learning approach for multiclass classification of Alzheimer's disease using MRI images Khan et al., 2022	MRI Data	Transfer Learning with VGG Models	MRI	Multiclass	Data balance wasn't considered
6	An Efficient Ensemble Approach for Alzheimer's Disease Detection Using an Adaptive Synthetic Technique and Deep Learning Mujahid et al., 2023	MRI Data	Ensemble Deep Learning Approach	MRI	Multiclass	Data balance wasn't considered

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 CHAPTER OVERVIEW

This chapter provides a comprehensive overview of the methodology employed in the development of a deep learning-based model for diagnosing AD. The approach encompasses various stages, ensuring a systematic and thorough execution of the research.

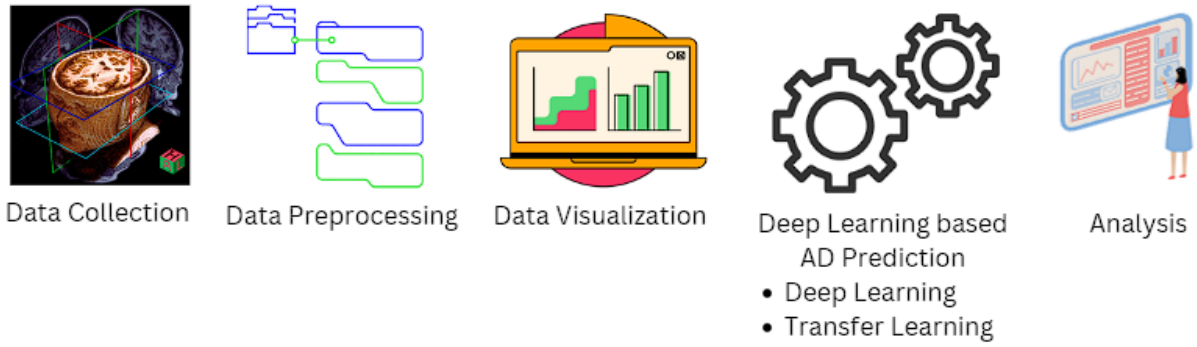

Figure 3. 1 Overall Methodology

The initial step, as depicted in Figure 3.1, involves the collection of datasets related to brain MRI images associated with Alzheimer's. These datasets are sourced publicly available repository known as Kaggle. The inclusion of public datasets enhances the generalizability of the dataset and facilitates the extraction of features from a diverse range of cases. Rigorous curation of these datasets is conducted to ensure their quality and relevance to the study's objectives.

The foundation of the study lies in the comprehensive collection of relevant datasets, essential for training, validating, and testing the proposed model. These datasets are meticulously selected to encompass a broad spectrum of cases, capturing diverse clinical manifestations and stages of AD to enhance the robustness and applicability of the developed model.

Moving forward, the focal point shifts to the development of the proposed model, which leverages deep learning and transfer learning techniques tailored specifically for detecting and diagnosing AD. This development process is segmented into several pivotal processes, starting with the acquisition of medical images, primarily brain MRI scans. The acquisition phase emphasizes sourcing high-quality and high-resolution images, crucial for the model to discern and learn AD-specific patterns effectively.

Subsequently, the collected images undergo preprocessing, where they undergo a series of transformations to prepare them for analysis. These preprocessing steps include data labeling for classification, normalization to ensure uniformity in image intensity, resizing to conform to specific dimensions, and augmentation to address data imbalance issues. By standardizing the input data and maximizing the model's learning potential, these preprocessing techniques play a critical role in enhancing the model's efficacy in AD diagnosis.

3.2 RESEARCH DESIGN

In this study, we developed a deep learning-based model for diagnosing AD through the analysis of brain MRI images. Adopting an experimental research design, the methodology involves collecting datasets from public repository such as Kaggle. The model development phase focuses on leveraging deep learning techniques like deep learning and transfer learning to extract discriminative features from MRI images and accurately classify them as indicative of AD or healthy brains. Through iterative training and evaluation processes, the model's performance is assessed using standard metrics such as accuracy, sensitivity, and specificity. Statistical analyses, including confusion matrices, are employed to validate the model's diagnostic capabilities and assess its generalizability across different populations and imaging protocols. Overall, this research aims to contribute to the development of a robust and reliable tool for early and accurate diagnosis of AD, potentially improving patient outcomes and treatment strategies.

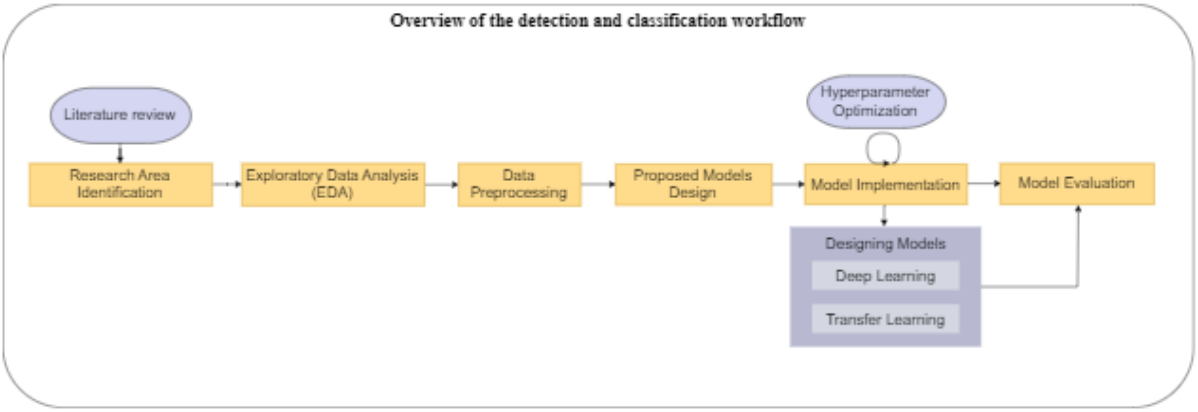

Figure 3. 2 Research methodology workflow

3.3 OVERVIEW OF THE DATASETS COLLECTION

The data collected consists of brain MRI images related to Alzheimer's. The dataset that has been collected is from publicly available source, Kaggle (Arafa et al., 2023). The public dataset used assist in the extraction of features from the dataset. The dataset has been carefully curated to ensure quality and relevance to the study's objectives.

The foundation of this study is the collection of the relevant dataset, crucial for training, validating, and testing the proposed model. The dataset is carefully gathered from credible medical databases of data type known as MRI images. The emphasis is on ensuring that the datasets are comprehensive and representative of the diverse clinical manifestations and stages of AD. The selection of data aims to encapsulate a broad spectrum of cases to enhance the robustness and applicability of the developed model.

The benchmark data for this study is from the Kaggle (Arafa et al., 2023) which encompasses brain MRI images relevant to Alzheimer's disease diagnosis. This data has been widely used for different AD researches.

3.3.1 Dataset source and description

The provided dataset comprises MRI images categorized based on the severity of Alzheimer's disease, with each category reflecting a different stage of the disease progression. The first category, 'Non_Demented' includes individuals who do not show signs of Alzheimer's or significant cognitive impairments. The next category, 'Very_Mild_Demented', consists of individuals with very mild dementia, characterized by subtle cognitive declines and minimal

functional impairments. Following this, the ‘Mild_Demented’ category includes individuals experiencing noticeable cognitive decline and functional impairments, though these symptoms are milder compared to more severe stages. The most severe category in this dataset is ‘Moderate_Demented’, which contains MRI images of individuals with moderate dementia, where significant cognitive and functional impairments are evident.

The arrangement of these categories represents an increasing severity of dementia symptoms within the dataset. It is crucial to recognize that the severity and progression of Alzheimer's disease can vary widely among individuals. The statistical summary of the dataset includes a total of 6430 samples, with the class distribution showing 64 samples for ‘Moderate_Demented’ (approximately 1%), 2250 samples for ‘Very_Mild_Demented (approximately 35%), 3220 samples for ‘Non_Demented’ (approximately 50%), and 896 samples for ‘Mild_Demented’ (approximately 14%).

This dataset is invaluable for researchers and healthcare professionals as it provides a comprehensive view of the continuum of Alzheimer's disease, facilitating a better understanding of its impact on cognitive function and daily activities as the disease progresses.

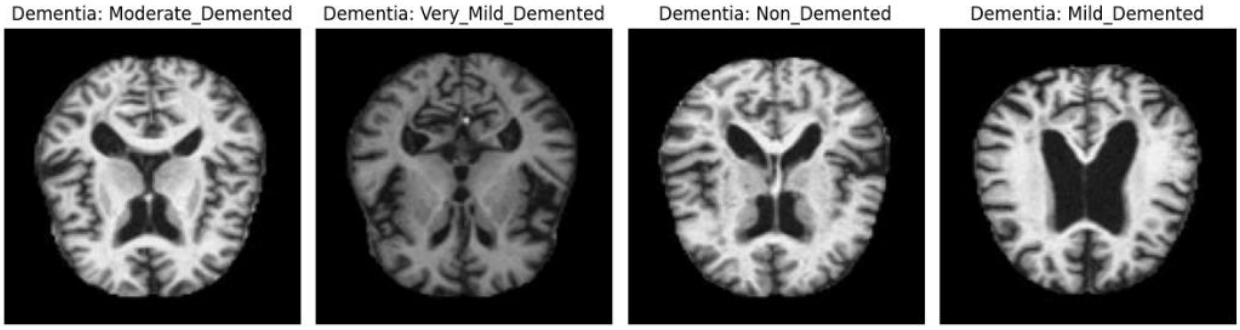

Figure 3. 3 Sample labeled MRI images of dementia

In this research, we focused our efforts on analyzing four specific classes within the dataset: Moderate_Demented, Mild_Demented, Non_Demented, and Very_Mild_Demented. Notably, we chose to use the four classes from our model training due to the expanded classification in the dataset, rendering it statistically significant for our classification task to help patients know which stage of dementia their mind category falls. As a result, our study addressed a four-class classification problem instead of the baseline binary-class scenario.

This decision was inspired by (Helaly et al., 2022a) findings, which underscored the necessity of including the four-classes to the analysis due to its important category to help the patient find which category is the classification belongs to. By streamlining our classification task to these classes, we aimed to enhance the robustness and effectiveness of our model training process, focusing on the most relevant classes for our research objectives.

3.3.2 Data Preprocessing

Data preprocessing is a critical step in preparing datasets for deep learning models. The quality and effectiveness of the model heavily depend on the preprocessing techniques applied to the data. In this report, we discuss the preprocessing techniques used on an image dataset representing different types of dementia. The dataset is divided into training, validation and test sets, and various preprocessing tasks are performed to enhance the quality and balance of the data.

Dataset Loading

The dataset is loaded from a directory specified by the variable `train_dir`. This directory contains subdirectories, each representing a different class of dementia and containing corresponding images. The number of classes is determined by counting the subdirectories. Each image is loaded, converted to RGB format, and resized to specified dimensions (`IMG_WIDTH`, `IMG_HEIGHT`). The preprocessed images are stored in a list along with their associated labels (subdirectory names) and then converted to numpy arrays.

Data Balancing

To address the class imbalance present in the training set, we employed the Synthetic Minority Over-sampling Technique (SMOTE). This method is particularly effective in handling imbalances within datasets by generating synthetic examples rather than by simple over-sampling of the minority class. SMOTE works by selecting samples that are close in the feature space, drawing a line between the samples in the feature space, and drawing a new sample at a point along that line. This approach not only helps in creating a balanced dataset by increasing the number of minority class instances but also introduces variability into the synthesized

examples, thus maintaining the integrity of the dataset without repeating exact copies of minority class instances.

X. Liu et al., (2022) proposed the Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance. SMOTE involves analyzing minority samples, synthesizing new samples based on them, and integrating these samples into the dataset. However, factors such as parameters, data distribution, and other variables may influence the generation of artificial data, potentially causing it to overlap with the majority class. Such occurrences can impact the final classification results.

To effectively utilize SMOTE, we scaled up all classes in the dataset to have 2560 images per class, matching the count of the originally most populous class. This equalization of class sizes is crucial as it prevents the model from developing a bias toward any specific class during training. After applying SMOTE, we plotted visual representations of the class distributions before and after the resampling process. These visualizations clearly demonstrated the effectiveness of the balancing process, showing a uniform distribution across all classes. This strategic approach to data preprocessing ensures that the detection models trained on this dataset have a fair representation of all stages of Alzheimer's disease, thus enhancing the overall predictive accuracy and reliability of the model outcomes.

In conclusion, by strategically addressing class imbalance through random selection and equalization of class sizes in the training set, potential biases were effectively mitigated. The utilization of SMOTE, as highlighted by (X. Liu et al., 2022), underscores the significance of thoughtful consideration and parameter tuning when employing oversampling techniques. This approach contributes to the robustness and reliability of the model training process.

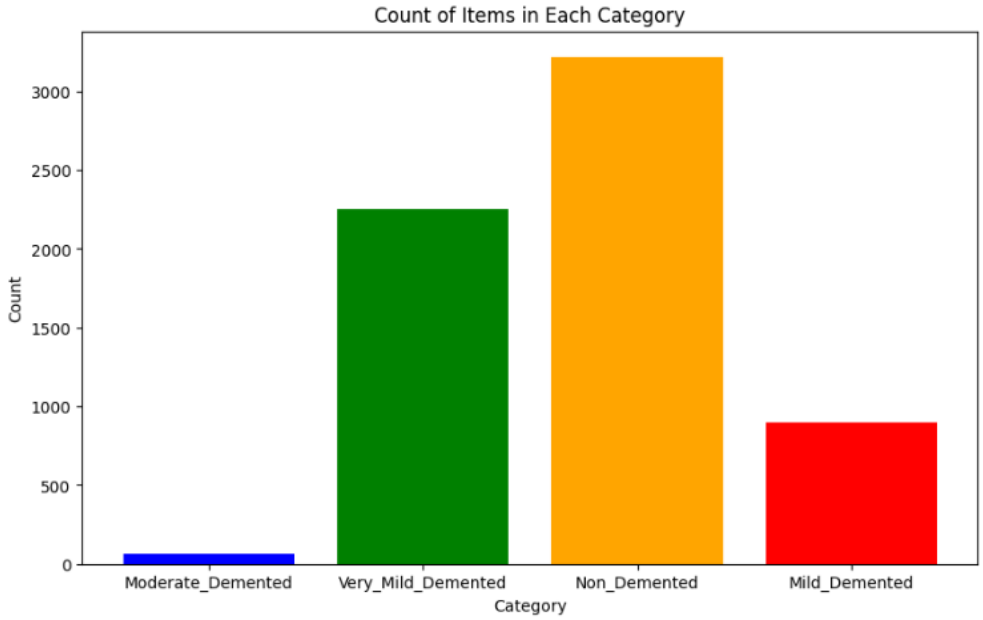

Figure 3. 4 Imbalanced Class Distribution of the Dataset

A segment of code is dedicated to randomly selecting and plotting three images from each dementia type in the balanced training set. This visualization aids in understanding the characteristics of the images that the model will learn from.

The pixel values of the images, originally ranging from 0 to 255, are normalized to lie between 0 and 1. This normalization step is crucial for ensuring that the model's performance is not affected by the scale of the input data.

Similar preprocessing steps are applied to the validation data, including loading, conversion to RGB, resizing, and normalization. However, class balancing is not performed on the validation set to maintain the original distribution. The preprocessed validation images are stored in numpy arrays for model evaluation.

In summary, the preprocessing techniques outlined in this report aim to enhance the quality, balance, and consistency of the image dataset, thus improving the performance of the deep learning model during training and evaluation.

3.4 MODEL SELECTION

The focal point of this research is developing CNN and VGG-16 as indicating by models using deep learning and transfer learning techniques specifically designed for detecting and classifying AD for diagnosis (Arafa et al., 2023). The model development is divided into several pivotal processes:

Convolutional Neural Networks (CNNs) are pivotal in Alzheimer's disease (AD) research due to their adeptness at analyzing complex neuroimaging data. CNNs consist of multiple layers, including convolutional layers that extract intricate features from brain MRI scans and pooling layers that reduce spatial dimensions while preserving relevant information. By leveraging CNNs, researchers can identify subtle structural changes in the brain indicative of AD pathology, facilitating early detection and intervention. The hierarchical feature extraction capabilities of CNNs enable the extraction of meaningful biomarkers from imaging data, aiding in accurate AD diagnosis and prognosis. Additionally, CNNs empower clinicians with critical insights into disease progression and treatment response, ultimately enhancing patient care and management strategies for AD.

VGG16 is a convolutional neural network architecture that was developed by the Visual Graphics Group (VGG) at the University of Oxford. It was introduced in 2014 as part of a paper titled "Very Deep Convolutional Networks for Large-Scale Image Recognition" during the ILSVRC (Imagenet Large Scale Visual Recognition Challenge) competition.

The VGG16 architecture is notable for its simplicity and depth. It consists of 16 layers that have weights. This includes 13 convolutional layers and 3 fully connected layers at the end. The convolutional layers use filters with a very small receptive field (3x3, which is the smallest size to capture the notion of left/right, up/down, center). Additionally, 1x1 convolution filters are used, which can be seen as a linear transformation of the input channels. The network uses the ReLU (Rectified Linear Unit) activation function to introduce non-linearity into the model, helping it to learn more complex patterns in the data. Pooling layers, specifically max pooling, are interspersed between some of the convolutional layers to reduce the spatial size of the representation, thereby decreasing the number of parameters and computation in the network. This also helps in making the detection of features invariant to scale and orientation changes.

VGG16 was one of the first to use such a deep network structure, which significantly improved performance on visual recognition tasks compared to earlier models. The depth of the network allows it to learn a hierarchy of features, from simple to complex, which is useful for a variety of image recognition tasks in fields like computer vision and medical image analysis.

The VGG-16 model is known for its deep structure, which includes 16 layers that aid in detailed image analysis. This depth is advantageous for tasks like Alzheimer's disease (AD) research, where detailed feature extraction from neuroimaging data is crucial. A distinctive feature of VGG-16 is its use of small (3x3) convolution filters, which are effective in capturing subtle variations in images—a key factor in identifying early signs of AD.

VGG-16 also incorporates max pooling layers to reduce the spatial dimensions of image data, thus simplifying the network and reducing the number of parameters. This structure not only deepens the network but also helps manage its computational demands. VGG-16's architecture, characterized by its uniform layer configuration, aids in stabilizing the training process and enhances the model's reliability.

One significant advantage of VGG-16 is its compatibility with transfer learning. Using this approach, the model, pre-trained on large datasets like ImageNet, can be fine-tuned for specific tasks such as AD detection. This strategy decreases the need for extensive training data and reduces the time required to train the model, while still maintaining good performance.

Overall, VGG-16's ability to extract detailed features and its efficiency in training make it suitable for detecting AD through MRI scans. This makes it a practical tool in medical imaging for AD, helping in the development of diagnostic tools and treatment planning, although it requires careful handling due to its size and complexity.

The classification phase is where the model's training culminates in diagnosing AD. During this phase, the model, trained on the extracted features, classifies the images into various categories, such as different stages of AD or normal cognitive function. This classification is based on the model's learned understanding of AD-related patterns, enabling it to detect the disease's presence with high accuracy.

3.5 EVALUATION METHODS

In the realm of machine learning, accurately assessing the performance of a model is paramount to its successful deployment. For tasks such as Alzheimer's disease (AD) classification, where the stakes are high, it becomes imperative to utilize robust evaluation metrics. This section delves into the various evaluation techniques used to measure the efficacy of classification models in AD research.

The performance of a model in machine learning is fundamentally understood through key metrics such as training and validation accuracy and loss. Training accuracy is crucial as it measures the model's ability to correctly classify samples from the training dataset, reflecting how well the model is learning and capturing underlying patterns; a high training accuracy indicates effective fitting to the training data. Conversely, validation accuracy assesses the model's performance on a separate dataset not seen during training, providing insights into the model's ability to generalize and make accurate predictions on new, unseen samples.

Training loss quantifies the discrepancy between the model's detections and the actual labels during training, with lower values indicating a better fit and alignment between predicted and true labels. Validation loss, on the other hand, measures the error between the model's predictions and the true labels on the validation dataset, acting as an indicator of the model's generalization ability and highlighting potential issues like overfitting, lower validation loss values signify more accurate predictions on unseen data.

The confusion matrix is a pivotal tool that provides a detailed breakdown of the model's predictions into true positives, true negatives, false positives, and false negatives, offering a comprehensive view of the model's classification accuracy and its ability to handle different classes, which is especially useful in understanding the strengths and weaknesses of the model.

Metrics such as accuracy provide a simple and intuitive measure of how well the model performs overall, indicating the proportion of correctly classified instances. However, in the context of imbalanced datasets, accuracy might be misleading, hence the need for additional metrics like precision and recall. Precision assesses the proportion of correctly predicted positive instances among all instances labeled as positive, emphasizing the model's ability to

avoid false positives, while recall focuses on the model's capability to capture all positive instances, crucial for scenarios where missing a positive instance can be critical.

The F1-score integrates both precision and recall into a single metric, offering a balanced measure that is particularly valuable in conditions of class imbalance. A high F1-score suggests a robust model that maintains a balance between precision and recall, reflecting improved overall performance. These diverse evaluation techniques enable researchers to gain a nuanced understanding of a model's effectiveness, guiding decisions in AD classification tasks and beyond.

By leveraging these additional evaluation techniques in conjunction with core performance metrics, researchers can gain a comprehensive understanding of a classification model's strengths, weaknesses, and overall effectiveness in AD research. These techniques offer diverse perspectives on model performance, enabling researchers to make informed decisions regarding model suitability and effectiveness in AD classification tasks.

3.6 DEVELOPMENT TOOLS

The development and implementation of the model involve a range of tools catering to different aspects of the model development process:

3.6.1 Design Tools

Design tools are instrumental in creating the architecture of the deep learning model. These tools are used for designing the neural network's architecture, including the number and types of layers (such as convolutional, pooling, and fully connected layers) and the connections between these layers. The use of sophisticated design tools allows for the visualization and fine-tuning of the model structure, ensuring an optimal design conducive to accurate AD detection.

3.6.2 Hardware Tools

Given the computationally intensive nature of training deep learning models, specialized hardware tools, such as high-performance GPUs (Graphics Processing Units), are employed. These tools enable faster processing and computation of complex neural network operations, which is crucial in reducing training time and efficiently handling large datasets.

3.6.3 Software Tools

The model implementation in this study is methodically organized, combining key methods, techniques, and tools essential for developing and validating a deep learning model for Alzheimer's disease detection.

Python is the chosen programming language for its versatility and comprehensive support for deep learning libraries, facilitating the implementation of various techniques crucial for model building and evaluation. Additionally, the study employs advanced deep learning frameworks, specifically TensorFlow and Keras. TensorFlow provides a flexible ecosystem for handling complex model architectures, while Keras offers user-friendliness and modularity, simplifying the model construction and training process.

The robustness of these tools, along with their wide community support, ensures reliable model performance and access to ongoing advancements in the field. Collectively, these components form an efficient system for implementing and validating the model, enhancing accuracy and effectiveness in predicting Alzheimer's disease.

3.7. DESIGN AND DEVELOPMENT TOOLS

3.7.1. Design Tools

Design tools have been used in this thesis to build and design the concepts of the proposed models. Two tools in particular, GitMind and Canva, have been used to design the proposed solution’s various diagrams, flowcharts and the entire architecture.

GitMind is a diagramming software that allows users to create a wide range of diagrams, including flowcharts, mind maps, organizational charts, and network diagrams. It is designed for professionals and businesses that need to create detailed and technical diagrams. It offers a vast library of templates and symbols, and its interface is customizable for specific needs

Canva is a graphic design software that focuses on creating visually appealing designs for social media, marketing, and other purposes. Canva offers an extensive library of templates, images, fonts, and design elements to help users create professional looking designs without extensive

design experience. It is suitable for individuals, small businesses, and marketers who want to create eye-catching designs quickly and easily.

CHAPTER FOUR

PROPOSED SOLUTION ARCHITECTURE

4.1 CHAPTER OVERVIEW

In the previous sections, we explored existing research, outlined our methodology, identified gaps in the literature, framed our problem statement, and raised pertinent research questions. Now, we go deeper into the core part of our solution – the architecture designed to address the identified gap and tackle the research questions. Here, we provide a detailed overview of our proposed approach, including the steps taken and the algorithms chosen. This chapter serves to discuss the architecture used for detecting Alzheimer's Disease, incorporating both data imbalance and data balancing techniques to enhance model performance.

4.2 PROPOSED ALZHEIMER'S DISEASE DETECTION AND CLASSIFICATION ARCHITECTURE

The literature review conducted revealed a significant gap in the understanding of AD detection and classification, particularly concerning the challenges posed by dataset imbalance. Studies by (Helaly et al., 2022), (Kavitha et al., 2022) and (Mujahid et al., 2023) emphasize the importance of early and accurate diagnosis in managing AD, as well as the need to address dataset imbalances and explore genetic and environmental factors influencing the disease. These research efforts contribute valuable insights into AD progression and underscore the significance of addressing data imbalance issues. By leveraging advanced computational techniques alongside medical imaging data (MRI), these studies lead the way for more personalized and effective approaches to AD diagnostics, aligning with the broader goal of improving healthcare outcomes for individuals affected by the disease.

The proposed architecture has two types of techniques to develop the model for the Alzheimer's disease detection and classification.

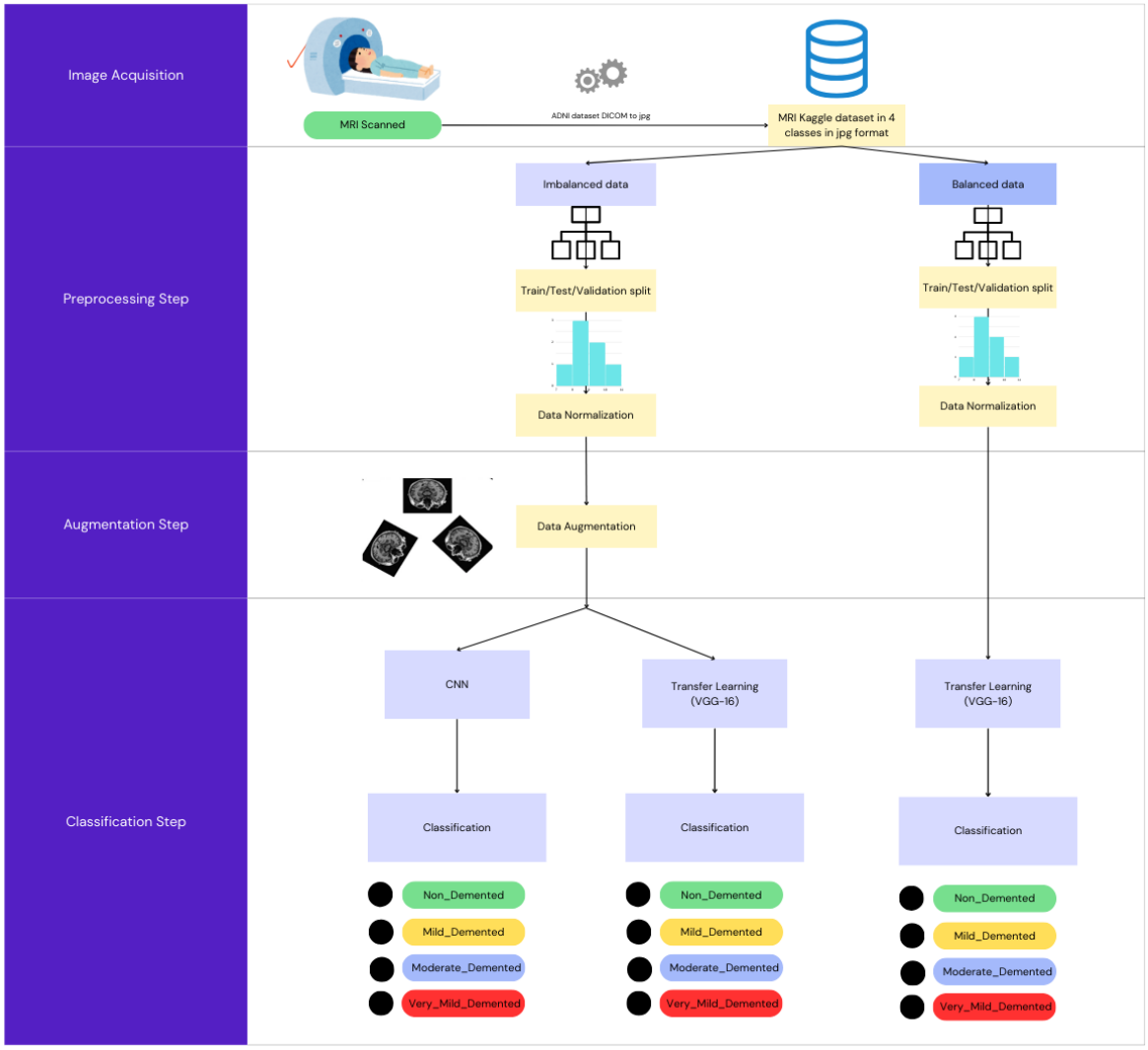

Figure 4. 1 The proposed architecture for Alzheimer's disease detection and classification

The architecture begins with the acquisition of MRI scans, sourced from the ADNI dataset in DICOM format and converted to JPG format, then resulted to the Kaggle datasets containing MRI scans in JPG format. These datasets contain images classified into either 4 classes since the 'Moderate_Dementia' class is only 1% of the total data, this could potentially affect the performance of the model so we removed it and work on the 3 classes. Preprocessing involves balancing the data for both imbalanced and balanced datasets. Next, the images are split into training, validation, and test sets to facilitate model training and evaluation. For imbalanced data, augmentation techniques are applied to increase the dataset size and diversity. Following this, feature extraction is performed using convolutional neural networks (CNNs) and a CNN transfer learning technique such as VGG-16. The extracted features are then inputted into deep

learning models for detection and classification. Finally, the models predict the classes of AD, Mild dementia, and Very Mild dementia based on the input images.

4.3 DATASET

The benchmark data for this study is from the Kaggle (Arafa et al., 2023) which encompasses brain MRI images relevant to Alzheimer's disease diagnosis. This data has been widely used for different AD researches.

The dataset utilized in this study comprises counts of MRI images in jpg format, categorized based on the severity of Alzheimer's disease. During dataset loading, the images are organized into subdirectories for each dementia class. This organizational structure facilitates easy access and categorization of images, allowing for efficient counting and identification of potential class imbalances which could influence the training of models. Identifying the number of images in each category early in the process is crucial for adjusting training strategies and mitigating bias.

In the data visualization phase, both bar graphs and pie charts are employed to illustrate the count of images across different categories. This visualization is essential for a preliminary assessment of the dataset's distribution. It highlights any significant imbalances that may require correction before model training. Visual representations of data distribution not only aid in understanding the dataset's structure but also serve as a critical step in preparing the data for subsequent analysis and modeling efforts. This approach ensures that any initial insights into the dataset can be addressed effectively to improve model performance.

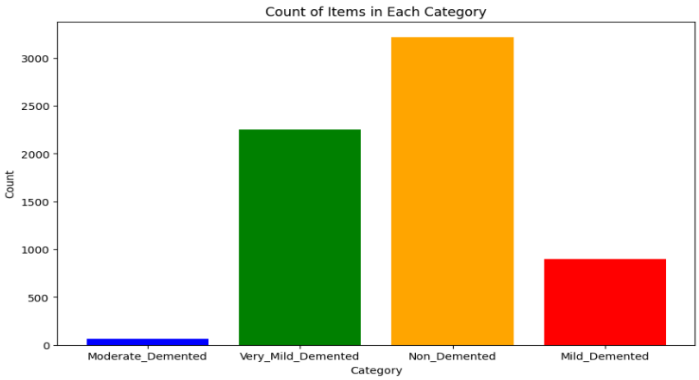

Figure 4. 2 Class distribution of the dataset in bar graph

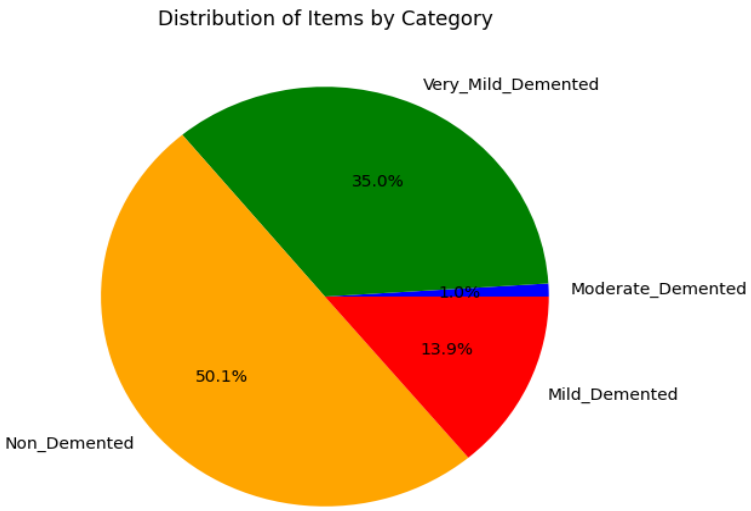

Figure 4. 3 Class distribution of the dataset in pie chart

The provided dataset includes a total of 6,400 MRI images categorized into different classes based on the severity of Alzheimer's disease. The class distribution is as follows: 64 images (approximately 1%) are labeled as 'Moderate_Demented', 2,250 images (approximately 35%) as 'Very_Mild_Demented', 3,220 images (approximately 50%) as 'Non_Demented', and 896 images (approximately 14%) as 'Mild Demented'. This statistical summary offers a clear overview of how the samples are distributed across the categories, reflecting a significant imbalance with a predominance of 'Non_Demented' cases. Such a distribution is critical for informing the data handling strategies, particularly in addressing class imbalances during model training.

The dataset undergoes a structured preparation process, beginning with data splitting. It is divided into training, validation, and test sets following an 80-10-10 ratio. This division is strategic, ensuring that the data is properly segregated to facilitate the training phase, while still reserving separate datasets for validation and testing purposes. Such splitting is essential for assessing the model's performance on data it has not previously encountered, which is crucial for understanding its real-world applicability.

To tackle the issue of class imbalance evident in the initial dataset distribution, the SMOTE (Synthetic Minority Over-sampling Technique) is used. This method enhances the representation of minority classes by generating synthetic samples, thereby equalizing the number of samples across all classes. Addressing class imbalance is fundamental to preventing

the model from developing a bias towards the more frequently represented classes, which could skew its predictive accuracy.

Following the application of SMOTE, visualization after balancing is performed to verify the effectiveness of the balancing process. By visualizing the class distribution post-balancing, it can be confirmed that each class now has an equal number of samples, which is crucial for fair and unbiased model training. This visualization provides a clear and immediate confirmation that the dataset is prepared for more equitable machine-learning operations.

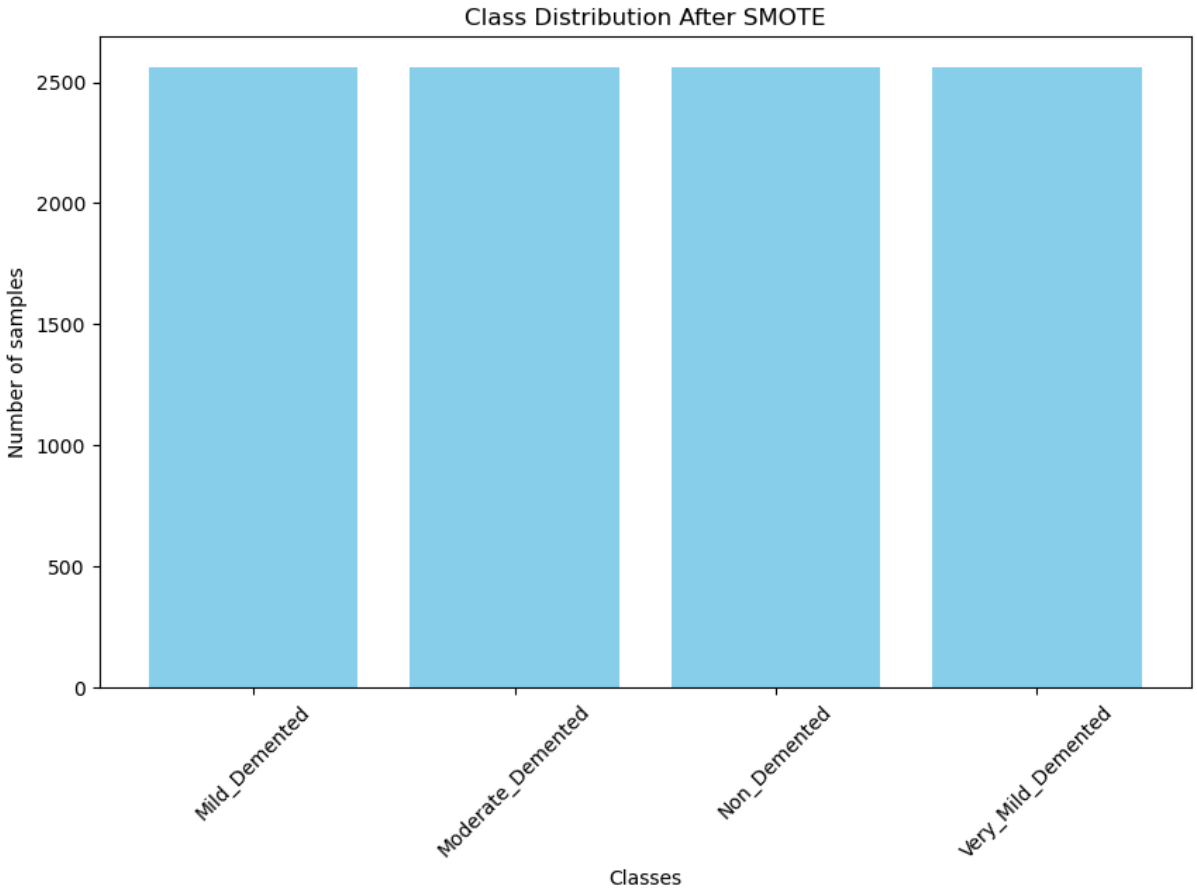

Figure 4. 4 Class distribution after SMOTE

The data preparation continues with normalization, where the pixel values of the images are normalized to range between 0 and 1. This is achieved by dividing each pixel value by 255. Normalization is an essential step in the preprocessing of image data as it ensures that the input data's scale does not adversely affect the model's performance. By normalizing the data,

variations due to differing lighting conditions or color scales in the images are minimized, promoting faster and more stable convergence during the training process.

Following normalization, the images undergo resizing to ensure they meet the specific dimensional requirements of the model. Using TensorFlow's `resize` function, each image is adjusted to have consistent dimensions, defined as IMG_HEIGHT and IMG_WIDTH. This step is critical for maintaining uniformity in the input size, which not only facilitates efficient processing but also ensures compatibility with the model architecture. Ensuring that all input images are of the same size is crucial for the neural network to correctly process and learn from the data without bias or error due to size variations.

4.4 PROPOSED MODEL ARCHITECTURE

In this section, we detail the proposed model architecture designed to tackle the challenges presented by the classification of MRI images related to Alzheimer's disease, which vary in severity from non-demented to moderate demented. Recognizing the distinct characteristics of balanced and imbalanced datasets, we employ two different architectures: a custom Convolutional Neural Network (CNN) and a pre-trained VGG16 model, each tailored to suit specific data conditions.

The custom CNN is specifically developed to effectively handle the imbalanced dataset. This architecture aims to capture the nuanced features of the MRI images through multiple convolutional and pooling layers, followed by dropout layers to combat overfitting, thus ensuring robust performance even when the class distribution is uneven.

For the balanced dataset, we leverage the VGG16 architecture, renowned for its depth and performance in image recognition tasks. The depth and complexity of VGG16 make it particularly suitable for this scenario, as the balanced nature of the dataset allows the model to train effectively without the risk of bias towards the majority class. By adapting VGG16, which includes layers pre-trained on large-scale image datasets, we anticipate enhanced feature extraction and consequently improved classification accuracy.

These architectures are selected and designed with the intention of maximizing the predictive performance on the respective datasets, ensuring that both common and subtle indicators of Alzheimer's disease progression are accurately identified across different stages.

The Custom CNN Model Architecture for the imbalanced data

The model architecture is designed using TensorFlow and Keras to construct a sequential model for image classification. Initially, pixel values are normalized to the range [0, 1] using the `Rescaling` layer to ensure uniform input data scaling, which aids in model training efficiency. The model features three convolutional layers, each followed by max pooling to reduce spatial dimensions and highlight important features. The first convolutional layer has 16 filters with a size of 3x3, using 'same' padding and 'relu' activation, initialized with 'he_normal'. This setup is repeated in the subsequent layers but with an increased number of filters: 32 and then 64, to progressively extract more complex features. Dropout layers with rates of 0.25 and 0.2 are introduced after the second and third convolutional layers respectively, to prevent overfitting by randomly omitting a subset of features during training. The output from the convolutional stack is flattened into a 1D vector before passing through two fully connected layers with 128 and 64 units respectively, both employing 'relu' activation. The final output layer consists of 4 units with a 'softmax' activation function, making it suitable for multi-class classification. The model is compiled with the 'adam' optimizer and uses 'categorical_crossentropy' as the loss function with accuracy as the metric to evaluate performance.

The Custom VGG-16 architecture for the imbalanced data

The architecture uses the VGG16 model as a foundational backbone, tailored for handling image data. This pre-trained model is loaded without its top layer to accommodate custom specifications, specifically an input shape of 128x128x3, and it is set with weights pre-trained on the ImageNet dataset. To prevent alterations to the learned features beneficial for image recognition, the layers of the VGG16 model are frozen, meaning their weights will not be updated during training. On top of the VGG16 base, the architecture incorporates a series of additional layers to enhance learning capability, a Global Average Pooling layer is employed to reduce spatial dimensions, followed by a Batch Normalization layer to stabilize and accelerate the learning process. Several Dense layers with decreasing units (2048, 512, 256,

and 64), all using 'relu' activation, progressively refine the feature representation. The final layer is a Dense layer with 4 units and a 'softmax' activation, suitable for the multi-class classification task at hand. The model is compiled using the Adam optimizer, with 'categorical_crossentropy' as the loss function. Performance metrics include accuracy, precision, and recall, offering a comprehensive evaluation framework for this deep learning model.

The Custom VGG-16 architecture for the balanced data

For the balanced dataset, the model architecture employs the VGG16 network as a base, specifically configured without the top layer to fit an input shape of 128 x 128 x 3,
and initialized with weights from the ImageNet dataset. The layers of the VGG16 base are frozen to maintain the integrity of the pre-trained features, ensuring that these layers do not update during training. Building on this foundation, the model integrates a Global Average Pooling layer to condense the feature maps into a more manageable form, which is followed by a Batch Normalization layer to facilitate faster and more stable training by normalizing the activations. To combat overfitting, a Dropout layer with a rate of 0.5 is introduced after the normalization and between dense layers. The model progresses through a sequence of Dense layers with 2048, 512, 256, and 64 units, each activated by 'relu', enhancing the model's capacity to learn complex patterns from the balanced dataset. Another Dropout layer precedes the final prediction layer, a Dense layer with 4 units and a 'softmax' activation function designed for the multi-class classification task. The model is compiled with the Adam optimizer and 'categorical_crossentropy' as the loss function, alongside metrics such as accuracy, precision, and recall, providing a comprehensive measure of model performance on balanced data.

CHAPTER FIVE

IMPLEMENTATION OF PROPOSED SOLUTION

5.1 CHAPTER OVERVIEW

This chapter provides a comprehensive overview of the implementation process of the proposed solution. It covers the working environment setup, data preprocessing steps, training procedures, and evaluation methods. Each section includes detailed explanations and code snippets to demonstrate the implementation effectively.

5.2 WORKING ENVIRONMENT

The implementation was carried out in a well-equipped computational environment to ensure efficient model training and experimentation. The following tools and libraries were used:

- **Python**: The primary programming language used for implementing the solution.
- **Jupyter Notebook**: An interactive environment for running Python code, visualizing data, and documenting the process.
- **TensorFlow and Keras**: Libraries used for building and training neural network models. TensorFlow provides the underlying framework, while Keras offers a user-friendly interface for model development.
- **Matplotlib and Seaborn**: Libraries for creating visualizations to better understand data distributions and model performance.
- **NumPy**: A fundamental package for numerical computations in Python, crucial for handling and manipulating data arrays.
- **Imbalanced-learn (imblearn)**: A library for addressing class imbalances in datasets, ensuring the model is trained on balanced data.

5.3 DEPLOYMENT ENVIRONMENT

The deployment environment is where the trained model will be used for making predictions on new data. The specifications of the deployment environment are similar to those of the development environment to maintain consistency and ensure optimal performance.

The hardware configuration ensures sufficient computational power and memory for handling large datasets and training complex models efficiently.

- **Operating System**: Windows 11
- **Memory Size**: 32.0 GB (27.9 GB usable)
- **Processor**: AMD Ryzen 5 5600H with Radeon Graphics, 3.30 GHz
- **System Type**: 64-bit operating system, x64-based processor

5.4 DATA PREPROCESSING IMPLEMENTATION

Data preprocessing is a crucial step in preparing the dataset for training the model. The preprocessing steps include loading the dataset, visualizing the class distribution, addressing class imbalance, resizing images, and normalizing pixel values.

5.4.1 Dataset Loading

The dataset is loaded from a directory structure where each subdirectory represents a different class of dementia. The directory structure helps in organizing the images based on their respective categories.

```
# Imports for handling data directories, file operations, and image processing
import os
import pathlib
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import random
```

Figure 5. 1 Imports for loading images from folder to runtime

```
# Set the path to the dataset directory
data_dir = pathlib.Path("../dataset")
```

Figure 5. 2 Define image folder path

```
# Create empty lists to store data from each category
categories = {}


# Iterate over the folders in the "Dataset" directory
for folder in data_dir.iterdir():
    # Get the category name from the folder name
    category = folder.name

    # Count the number of items (images) in each folder
    count = len([name for name in os.listdir(folder) if os.path.isfile(os.path.join(folder, name))])

    # Store the category and count
    categories[category] = count

print(categories)
```

```
{'Mild_Demented': 896, 'Moderate_Demented': 64, 'Non_Demented': 3200, 'Very_Mild_Demented': 2240}
```

Figure 5. 3 Data distribution from the folders

5.4.2 Data Visualization

Visualizing the class distribution helps in understanding the dataset and identifying any class imbalances.

```
# Get the categories and counts from the dictionary
category = list(categories.keys())
num_items = list(categories.values())

# Create a bar graph for the count of each category
plt.figure(figsize=(10, 6))
plt.bar(category, num_items, color=['blue', 'green', 'orange', 'red'])
plt.title('Count of Items in Each Category')
plt.xlabel('Category')
plt.ylabel('Count')
plt.show()
```

Figure 5. 4 Data visualization

5.4.3 Data Splitting

The dataset is split into training, validation, and test sets to ensure that the model is trained on a portion of the data and validated and tested on separate portions.

```
!pip install split-folders
import splitfolders
splitfolders.ratio(path, output="output", seed=1345, ratio=(.8, 0.1,0.1))
```

Figure 5. 5 Data splitting

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Define the image dimensions
IMG_HEIGHT = 128
IMG_WIDTH = 128
BATCH_SIZE = 64

# Define data augmentation for the training data
train_datagen = ImageDataGenerator(
    rotation_range=20,
    horizontal_flip=True
)


# Create the data generators
train_ds = train_datagen.flow_from_directory(
    "./output/train",
    target_size=(IMG_HEIGHT, IMG_WIDTH),
    batch_size=BATCH_SIZE,
    class_mode='categorical',
)

test_ds = tf.keras.preprocessing.image_dataset_from_directory(
"./output/test",
seed=123,
image_size=(IMG_HEIGHT, IMG_WIDTH),
batch_size=BATCH_SIZE,
label_mode="categorical",
)

val_ds = tf.keras.preprocessing.image_dataset_from_directory(
"./output/val",
seed=123,
image_size=(IMG_HEIGHT, IMG_WIDTH),
batch_size=BATCH_SIZE,
label_mode="categorical",
)
```

Figure 5. 6 Loading the split data into runtime environment

```
# Define the path to the directory containing the training data
train_dir = "./output/train"

# Get the list of class folders
class_folders = os.listdir(train_dir)

# Initialize a dictionary to store the count of images for each class
class_counts = {}

# Count the number of images in each class folder
for class_folder in class_folders:
    class_path = os.path.join(train_dir, class_folder)
    num_images = len(os.listdir(class_path))
    class_counts[class_folder] = num_images

# Plot the counts using a bar graph
plt.figure(figsize=(10, 6))
bars = plt.bar(class_counts.keys(), class_counts.values(), color='skyblue')
plt.xlabel('Class')
plt.ylabel('Number of Images')
plt.title('Number of Images in Each Class')
plt.xticks(rotation=15)  # Rotate class labels for better readability

# Add labels on top of each bar
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, height, f'{height}', ha='center', va='bottom')

plt.tight_layout()
plt.show()
```

Figure 5. 7 Data visualization of training data distribution

5.4.4 Class Balancing

Addressing class imbalance is critical to prevent the model from being biased towards the majority class. Using technique named SMOTE ensures that each class has the same number of samples.

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from imblearn.over_sampling import RandomOverSampler, SMOTE
import numpy as np

# Check dataset content manually or with a script
import os
print("Training data by class:")
for class_dir in os.listdir("./output/train"):
    print(f"{class_dir}: {len(os.listdir('./output/train/' + class_dir))} images")


def prepare_dataset_with_smote(ds):
    images = []
    labels = []

    # Extract and prepare images and labels
    for image_batch, label_batch in ds.unbatch().as_numpy_iterator():
        images.append(image_batch)
        labels.append(label_batch)

    images = np.array(images).reshape(len(images), -1)  # Flatten images for SMOTE
    labels = np.array(labels)
    labels_int = np.argmax(labels, axis=1)  # Convert from one-hot to integer labels for SMOTE

    # Apply SMOTE
    smote = SMOTE(random_state=42)
    images_smoted, labels_smoted = smote.fit_resample(images, labels_int)

    # Reshape images back and re-encode labels to categorical
    images_smoted = images_smoted.reshape(-1, IMG_HEIGHT, IMG_WIDTH, 3)
    labels_smoted = tf.keras.utils.to_categorical(labels_smoted, num_classes=labels.shape[1])

    # Reconstruct TensorFlow dataset
    dataset_smoted = tf.data.Dataset.from_tensor_slices((images_smoted, labels_smoted))
    dataset_smoted = dataset_smoted.batch(BATCH_SIZE).prefetch(tf.data.experimental.AUTOTUNE)

    return dataset_smoted
```

```
Training data by class:
Mild_Demented: 716 images
Moderate_Demented: 51 images
Non_Demented: 2560 images
Very_Mild_Demented: 1792 images
```

Figure 5. 8 Class balancing using SMOTE technique

5.4.5 Data Normalization

Normalizing the pixel values of the images to lie between 0 and 1 is essential for consistent model performance. This step ensures that the model is not affected by the scale of the input data.

```
train_ds = train_ds.map(lambda x, y: (x / 255.0, y))
test_ds = test_ds.map(lambda x, y: (x / 255.0, y))
val_ds = val_ds.map(lambda x, y: (x / 255.0, y))
```

Figure 5. 9 Data normalization

5.4.6 Image Resizing

After class balancing, resizing the images to the desired dimensions (IMG_HEIGHT and IMG_WIDTH) ensures consistency in input size for the model.

```
# Resize the images to the desired dimensions
train_ds = train_ds.map(lambda x, y: (resize(x, [IMG_HEIGHT, IMG_WIDTH]), y))
test_ds = test_ds.map(lambda x, y: (resize(x, [IMG_HEIGHT, IMG_WIDTH]), y))
val_ds = val_ds.map(lambda x, y: (resize(x, [IMG_HEIGHT, IMG_WIDTH]), y))
```

Figure 5. 10 Image resizing

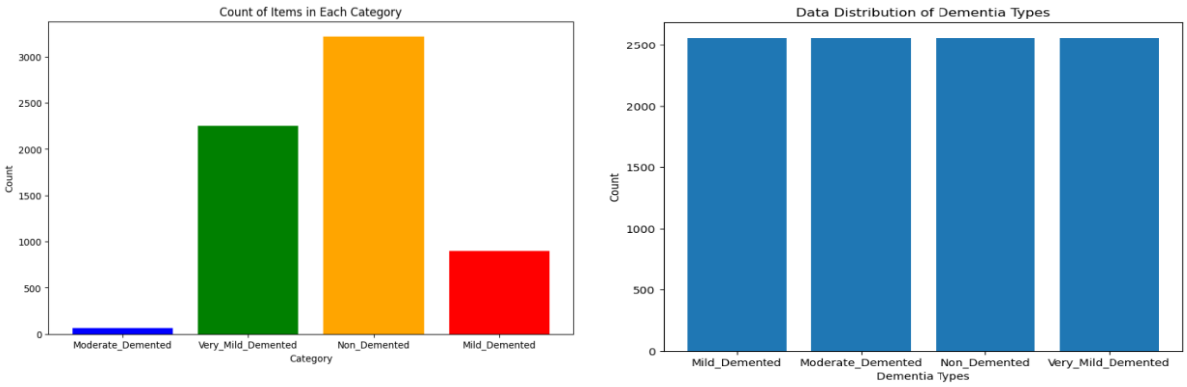

Figure 5. 11 The data visualization before data balancing and after data balancing (the image to the left) before data balancing, (the image to the right) after data balancing

The first image is a bar graph showing an imbalanced distribution of the same four categories, with Non_Demented having the most items and Moderate_Demented having the fewest. The second image is a bar graph showing a balanced distribution of four dementia categories, each with more than 2500 images.

5.5 MODEL TRAINING AND EVALUATION IMPLEMENTATION

The model training and evaluation process is a critical stage in the development of an effective classifier for dementia-related MRI images. Following data preprocessing, the subsequent steps involve creating, training, and evaluating models. Each phase plays a pivotal role in constructing a robust model capable of accurately classifying MRI images into different dementia categories.

5.5.1 Custom Convolutional Neural Network (CNN) Model

A custom CNN model is designed specifically for this task, leveraging its ability to learn spatial hierarchies from the input images.

```
import tensorflow as tf
from tensorflow import keras

# Create a sequential model
model = keras.models.Sequential()

# Preprocessing: Normalize pixel values to [0, 1]
model.add(keras.layers.experimental.preprocessing.Rescaling(1./255, input_shape=(IMG_HEIGHT, IMG_WIDTH, 3)))

# Convolutional layer 1
model.add(keras.layers.Conv2D(filters=16, kernel_size=(3, 3), padding='same', activation='relu', kernel_initializer="he_normal"))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))

# Convolutional layer 2
model.add(keras.layers.Conv2D(filters=32, kernel_size=(3, 3), padding='same', activation='relu', kernel_initializer="he_normal"))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))

# Dropout for regularization
model.add(keras.layers.Dropout(0.25))

# Convolutional layer 3
model.add(keras.layers.Conv2D(filters=64, kernel_size=(3, 3), padding='same', activation='relu', kernel_initializer="he_normal"))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))

# More dropout for regularization
model.add(keras.layers.Dropout(0.3))

# Flatten the output from convolutional layers
model.add(keras.layers.Flatten())

# Fully connected layers
model.add(keras.layers.Dense(128, activation="relu", kernel_initializer="he_normal"))
model.add(keras.layers.Dense(64, activation="relu"))
model.add(keras.layers.Dense(4, activation="softmax"))

# Compile the model with appropriate optimizer, loss function, and metrics
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Print the model summary
model.summary()
```

Figure 5. 12 Custom CNN model

5.5.2 Model Training

Both models are trained using the balanced and preprocessed dataset. The training process involves feeding the data to each model and optimizing their weights over several epochs.

```
hist_1 = model.fit(train_ds,validation_data=val_ds,epochs=5, batch_size=64, verbose=1)
```

Figure 5. 13 Model training

5.5.3 Model Evaluation

The trained models are evaluated on the test dataset to determine their performance on unseen data. Metrics such as accuracy and loss are used to measure the effectiveness of each model.

```
# Evaluate the model on the test dataset
test_loss, test_acc = model.evaluate(test_ds)

# Print the test accuracy and test loss
print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_acc:.4f}")
```

Figure 5. 14 Model Evaluation

5.5.4 Hyperparameter Tuning

Hyperparameter tuning is necessary for optimizing the performance of a neural network model. In this project, we experimented with various hyperparameters, focusing on the number of epochs and the architecture of convolutional layers. We tested epochs ranging from 5 to 100, aiming to find the optimal number of training iterations for convergence. Additionally, we explored different configurations for the convolutional layers, varying the number of filters in each layer from 8 to 2048. By systematically adjusting these hyperparameters and evaluating their impact on model performance, we aimed to enhance the network's ability to learn and generalize from the dataset.

CHAPTER SIX

RESULTS AND DISCUSSIONS

6.1 CHAPTER OVERVIEW

In this section, we present and discuss the results obtained from various experiments using different model architectures and data balancing techniques for classifying dementia-related MRI images. We begin with an overview of the feature engineering approach and the rationale for selectively applying data augmentation. We then detail the results for each experimental scenario, including balanced and imbalanced with data augmentation datasets, using a custom CNN and the VGG16 model.

6.2 FEATURE ENGINEERING

Feature engineering is a critical step in preparing the data for model training. In this study, we performed several preprocessing steps, including resizing images to a uniform dimension of 128x128 pixels and normalizing pixel values to a range between 0 and 1. These steps ensure that the input data is consistent and suitable for training deep learning models. Consistent image sizes facilitate efficient batch processing, while normalization helps in stabilizing and accelerating the training process by keeping pixel values within a similar range.

6.3 DATA AUGMENTATION

Data augmentation techniques, such as rotation, flipping, and zooming, are often used to artificially increase the size of the training dataset and improve model generalization. However, in this study, data augmentation was selectively applied. For experiments involving balanced datasets, augmentation was left out to avoid introducing artificial patterns that might bias the model. In contrast, augmentation was employed in some imbalanced dataset experiments to mitigate the effects of data scarcity and class imbalance. This approach helps to ensure that the model is exposed to a more diverse set of images during training, potentially improving its ability to generalize to new data.

6.4 MODEL DEVELOPMENT AND EVALUATION

Imbalanced Custom CNN

The custom Convolutional Neural Network (CNN) designed using TensorFlow and Keras was trained on an imbalanced dataset comprising 5,000 MRI images classified into different stages of Alzheimer's disease. The model features a sophisticated multi-layer architecture to effectively process and learn from complex image data. It includes three convolutional layers with increasing filter sizes—16, 32, and 64—each followed by max pooling to emphasize essential features and reduce spatial dimensions. Dropout layers with rates of 0.25 and 0.2 were strategically placed after the second and third convolutional layers to prevent overfitting by randomly dropping features during training. The convolutional outputs were flattened and led through two dense layers with 128 and 64 units, respectively, both activated by 'relu', culminating in a four-unit 'softmax' output layer tailored for multi-class classification.

During training, pixel values were normalized to a range of [0, 1] to ensure consistent input data scaling, which enhanced the training efficiency. This setup, combined with a robust layer configuration, was specifically aimed at overcoming the challenges posed by the imbalanced nature of the dataset.

The model's performance was outstanding, as evidenced by a precision, recall, and F1 score of 99.22, and an impressive test accuracy of 99.22 coupled with a low-test loss of 0.0307. These metrics underscore a highly effective model capable of accurately and consistently predicting different stages of Alzheimer's disease from MRI images.

The analysis of the confusion matrix further illuminated the model's accuracy across the classifications. The majority of the predictions were accurately placed within the correct categories, with minimal misclassifications noted across the four classes. Such results demonstrate the model's capability to not only adapt to the majority class but to maintain high accuracy across all classes, which is critical for its application in medical image analysis.

In conclusion, the custom CNN has proven highly efficient and effective in managing an imbalanced dataset, demonstrating robust performance across all evaluated metrics. The architecture and training strategy have equipped the model to handle overfitting effectively and

perform reliably in practical scenarios, particularly in clinical settings where accurate detection and classification of Alzheimer's disease stages are crucial. This model holds significant promise for deployment in healthcare environments, potentially improving patient management and treatment outcomes through early and accurate disease stage detection.

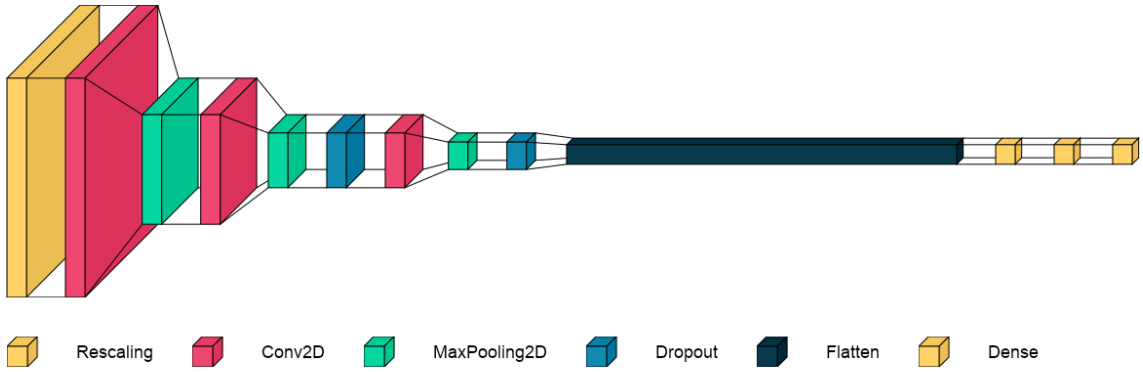

Figure 6. 1 Custom Proposed CNN Model architecture

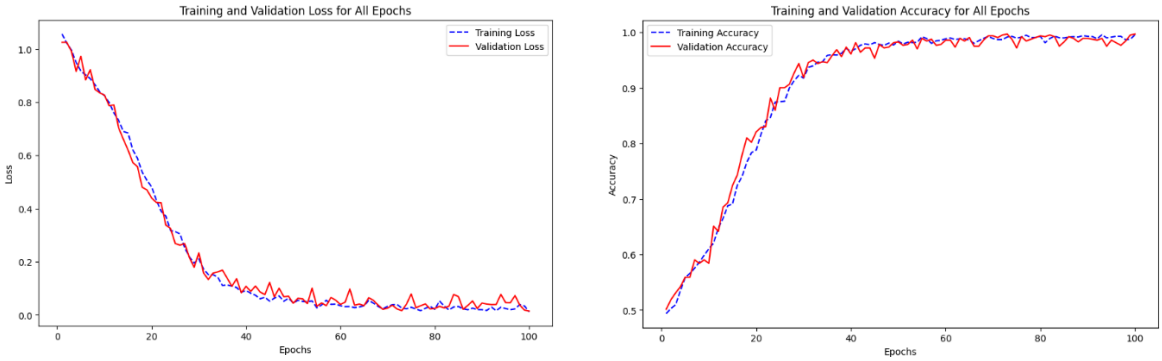

Figure 6. 2 Performance of CNN Custom Architecture - imbalanced dataset with augmentation

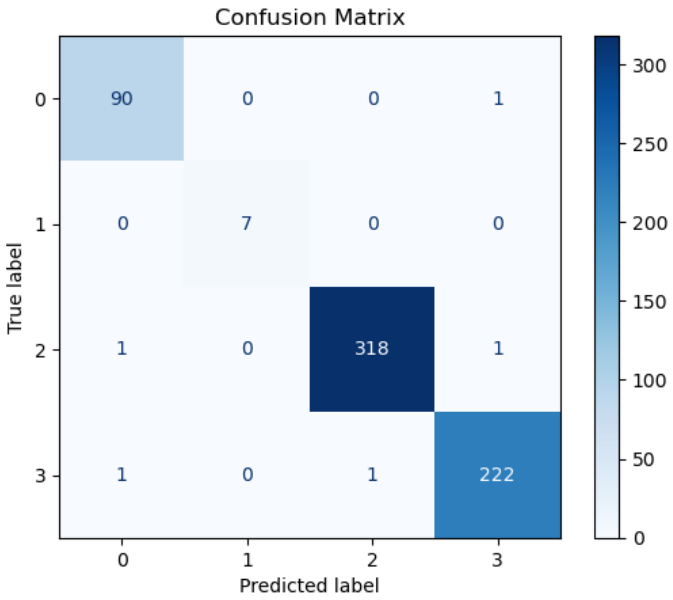

Figure 6. 3 Confusion Matrix of the CNN Custom Architecture - imbalanced dataset with augmentation

Imbalanced VGG16 With Augmentation

We used a modified VGG16 architecture for our deep learning model aimed at tackling a multi-class classification task with an imbalanced dataset. Initially, we configured the VGG16 network to operate without its top layer, adapting the input shape to 128x128x3 to match our image input dimensions, while importing pre-trained weights from ImageNet. To prevent overfitting to the specifics of the ImageNet dataset, we set the layers of the VGG16 base as non-trainable, effectively using it as a feature extractor.

To enhance the model's learning capabilities, we added several layers atop the VGG16 base. This included a Global Average Pooling layer, followed by a series of densely connected layers with units decreasing in size—2048, 512, 256, and 64—each followed by ReLU activation to introduce non-linearity. Batch normalization was employed after the pooling layer to stabilize learning by normalizing the activations. The final output layer consists of a dense layer with four units and a softmax activation function, tailored to our four-class classification problem.

We compiled the model with an Adam optimizer and used categorical crossentropy as the loss function. The model's performance metrics included accuracy, precision, and recall. To address the challenge of class imbalance, we integrated data augmentation strategies during the training

phase, leveraging the `ImageDataGenerator` for real-time data enhancement, thereby helping the model generalize better across under-represented classes.

The training extended over 50 epochs, monitored closely with callbacks like EarlyStopping to prevent overtraining. The resultant metrics were impressive, reflecting the model's efficiency: a test accuracy of 92.06%, precision of 92.18%, and recall of 92.06%, with an F1 score of 92.07%. These figures underscore the model's capability to effectively manage class imbalance while maintaining consistent performance across all categories.

In summary, the enhanced VGG16 model effectively tackled the challenges of an imbalanced dataset in a multi-class classification scenario, achieving high performance metrics and demonstrating robust generalization capabilities. Future directions could explore alternative deep learning architectures, advanced augmentation methods, and specific strategies tailored for handling imbalanced datasets to further elevate the model's performance. This demonstrates the model's robustness and ability to generalize across diverse classes. Future enhancements could include exploring alternative architectures, advanced augmentation techniques, and specialized strategies for imbalanced data to potentially boost performance further.

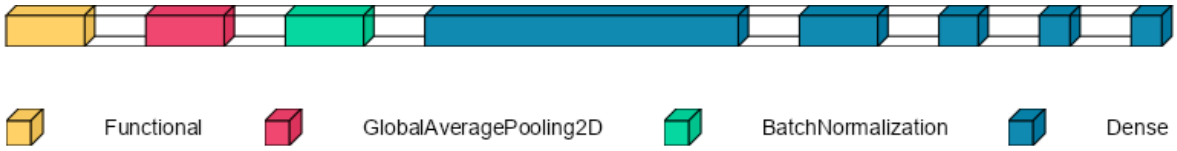

Figure 6. 4 Proposed VGG16 Model Architecture for imbalanced dataset

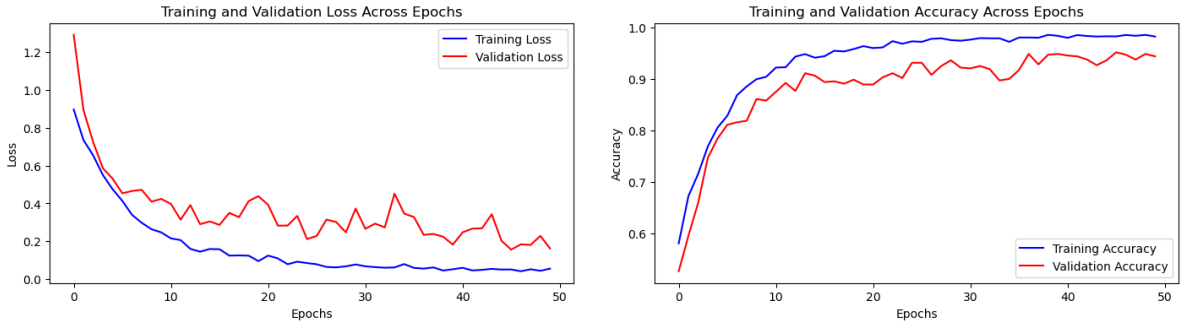

Figure 6. 5 Imbalanced VGG16 With Augmentation

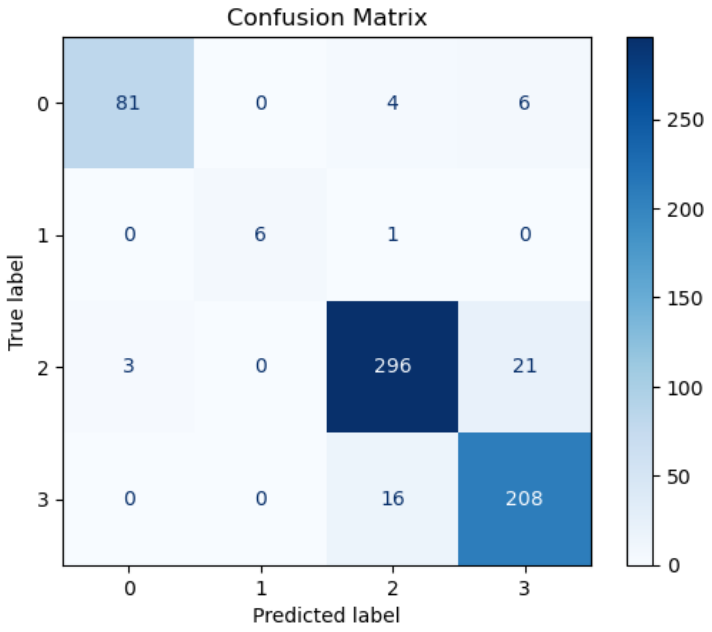

Figure 6. 6 Confusion Matrix for imbalanced VGG16 with augmentation architecture

Balanced data with VGG16

For our case focused on classifying MRI images into different stages of Alzheimer's disease, we used a balanced dataset and designed a modified VGG16 architecture. The VGG16 network was adapted for our specific application by removing its top layer, adjusting the input dimensions to 128x128x3 pixels, and using pre-trained weights from the ImageNet database to harness its powerful feature extraction capabilities. The layers of the VGG16 base were set as non-trainable to preserve the generality of the features learned from ImageNet and prevent the model from becoming too specific to our dataset.

To enhance the model's capacity to learn detailed features relevant to our classification task, we added several layers on top of the VGG16 base. A Global Average Pooling layer was incorporated to reduce the complexity of the output from the convolutional layers, simplifying the input to subsequent layers. This was followed by a series of densely connected layers with units decreasing in number—2048, 512, 256, and 64—all using ReLU activation to maintain non-linearity. Batch normalization was applied after the pooling layer to help stabilize the network's learning by normalizing the layer inputs. Dropout layers with a rate of 0.5 were strategically placed to mitigate overfitting, ensuring the model did not rely too heavily on particular features of the training data.

The architecture was topped off with a softmax-activated dense layer designed to classify the input images into one of four categories, corresponding to different stages of Alzheimer's disease. This setup allows for precise probabilistic classification across multiple classes.

The model was compiled with the Adam optimizer and categorical crossentropy as the loss function, suited for multi-class classification tasks. We tracked several performance metrics during training, including accuracy, AUC (Area Under the Curve), precision, and recall to evaluate the model's effectiveness comprehensively.

Upon completion of the training, the model demonstrated outstanding performance, achieving an accuracy of 97.98%, precision of 98.12%, recall of 97.82%, and an AUC of 99.86%. The loss was notably low at 0.0628, indicating that the model was highly effective in making accurate predictions with minimal error. These results underscore the capability of our tailored VGG16 model to handle a balanced dataset efficiently, making it a robust tool for medical image classification, particularly in identifying the stages of Alzheimer's disease. This setup confirms the potential of deep learning architectures in enhancing diagnostic processes in healthcare, especially when dealing with balanced data in critical domains.

When evaluating the overall effectiveness of the custom CNN architecture versus the modified VGG16 model for classifying MRI images in Alzheimer's disease studies, the modified VGG16 model demonstrates superior performance, particularly with balanced datasets.

The custom CNN architecture was intricately designed to manage imbalanced datasets. It featured progressively complex convolutional layers and integrated dropout layers to prevent overfitting. While this model performed admirably, achieving high precision, recall, and F1 scores, it was primarily optimized for handling variability in class distribution, making it highly suitable for its specific use case.

In contrast, the modified VGG16 model took advantage of the pre-existing robust VGG16 architecture, renowned for its effective deep convolutional networks that excel in feature extraction. This model was adapted for a balanced dataset and further enhanced with additional dense layers and dropout mechanisms to fine-tune its performance. The performance metrics of this model were outstanding, with an accuracy of 97.98%, precision of 98.12%, recall of

97.82%, and an AUC of 99.86%. These metrics indicate that the modified VGG16 model not only excelled in accurate classification but also in maintaining consistency across various stages of Alzheimer's disease with minimal errors.

The superiority of the modified VGG16 model is evident in its ability to leverage a well-established architecture, enhanced to suit the specific requirements of medical image classification. This model offers robustness, reliability, and high precision, making it particularly effective for clinical applications where balanced data is prevalent. Thus, for tasks requiring high accuracy and reliable performance in balanced environments, the modified VGG16 is the preferable choice, providing a strong foundation for further research and practical application in the diagnosis and study of Alzheimer's disease.

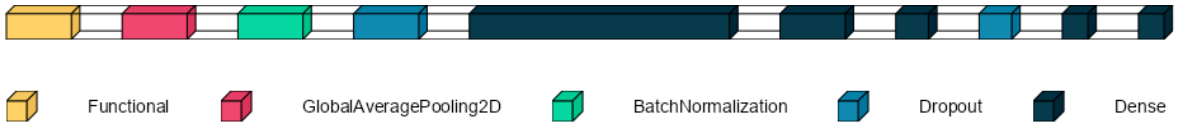

Figure 6. 7 Proposed VGG16 Model Architecture for balanced dataset

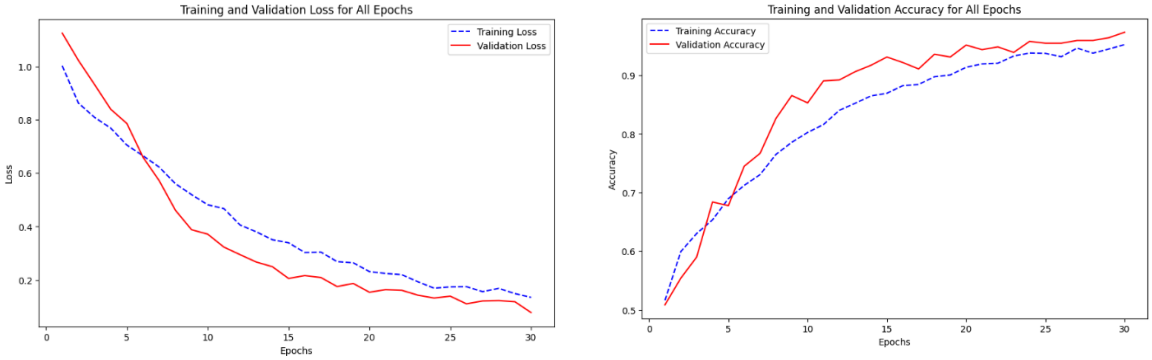

Figure 6. 8 Performance of VGG-16 Custom Architecture - balanced architecture

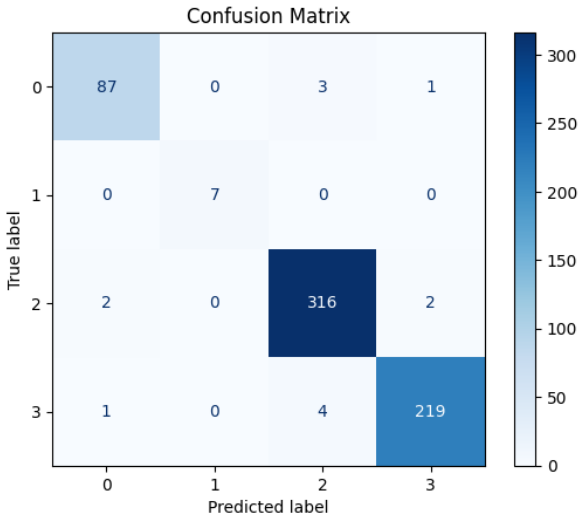

Figure 6. 9 Confusion matrix result of VGG-16 Custom Architecture - balanced

This study explored the implementation and evaluation of custom CNN and VGG16 models for classifying dementia-related MRI images. By comparing balanced and imbalanced datasets, with and without data augmentation, we identified the most effective strategies for this task. The balanced VGG16 model emerged as the best performer. These findings underscore the importance of careful model selection and data preprocessing in developing accurate and reliable classifiers for medical imaging applications.

This study introduces a novel approach by customizing the architecture of CNN and VGG16 models specifically for four-class classification of Alzheimer's disease using MRI images, tailored to handle both balanced and imbalanced datasets effectively. Unlike general-purpose models, these specialized architectures integrate advanced data balancing techniques and adjustments in model depth and complexity, aiming to enhance diagnostic accuracy for dementia-related conditions.

An ablation analysis was performed to evaluate the impact of individual components and modifications within these models. This analysis helped to determine the effectiveness of specific features, such as data augmentation and dropout layers, in improving model robustness and performance. By systematically altering or removing layers within the CNN and VGG16 frameworks, the study highlighted the critical role of these components in optimizing the detection capabilities of the models, particularly in dealing with the challenges of class imbalance.

The contributions of this research are primarily focused on refining detection model architectures for more better multi-class classification of Alzheimer's disease stages from MRI data. These contributions include the development of model architectures that are adept at managing variations in data balance, the successful application of transfer learning and data augmentation to boost model generalization across different clinical scenarios, and providing comprehensive comparative performance analysis under various dataset conditions. This work significantly advances the application of artificial intelligence in medical diagnostics, demonstrating how targeted architectural enhancements can improve the effectiveness of deep learning models in the complex field of healthcare.

To further enhance classification performance, an ensemble approach can be considered. This ensemble method has the potential to improve overall accuracy and provide more reliable classifications, particularly in challenging cases. Ensemble models can benefit from the complementary strengths of different architectures, potentially leading to better generalization and robustness in real-world applications.

6.5 BASELINE EVALUATION

In comparing our study with existing research, the baseline paper by (Arafa et al., 2023) demonstrated impressive results using CNN and VGG16 models on two-class imbalanced data for AD classification, achieving an accuracy of 99.95% with their CNN model and 97.44% with their VGG16 model. Similarly, (Helaly et al., 2022) reported promising results with accuracies of 93.61% using a multi-class approach for AD stage classification with a VGG19 model, which was fine-tuned to reach an accuracy of 97%.

Our study builds on these findings by implementing a modified VGG16 model on a balanced dataset, achieving an accuracy of 97.98%. This result places our model competitively among these established benchmarks, indicating that the modifications we made to the VGG16 architecture effectively enhance its ability to classify AD stages accurately. The slight increase in accuracy compared to the fine-tuned VGG16 model in the (Helaly et al., 2022) study suggests that our approach to balancing the dataset and adjusting the model could be particularly effective.

Furthermore, our results highlight the importance of dataset balance in achieving high accuracy in AD classification. Balancing the dataset helps mitigate the skew introduced by class imbalances, which is a significant challenge in medical imaging analysis, especially in conditions like Alzheimer's Disease where early stages may be underrepresented. By addressing this challenge, our model ensures more reliable classification across all stages of the disease, enhancing its utility in clinical settings.

The consistency of our model's performance with those reported in baseline studies not only validates our methodological adjustments but also points to the potential for further optimization. Fine-tuning the model parameters and exploring additional data augmentation strategies could potentially elevate accuracy even further, particularly for handling the complexities introduced by imbalanced datasets. This indicates a promising direction for future research, focusing on refining deep learning techniques to improve diagnostic accuracy and reliability in the detection of Alzheimer's Disease stages.

6.6 RESEARCH QUESTIONS DISCUSSION

1. Which model performs better in the imbalanced four-class detection and classification of Alzheimer's disease?

The custom Convolutional Neural Network (CNN) performs better in the imbalanced four-class detection and classification of Alzheimer's disease. It achieved a test accuracy of 99.22%, with precision, recall, and F1 scores all at 99.22%. The model's architecture, which includes multiple convolutional layers followed by pooling and dropout layers, is specifically designed to handle class imbalance. Additionally, data augmentation techniques such as rotation, flipping, and zooming enhance the model's ability to generalize across the minority classes, ensuring balanced learning and reducing the risk of overfitting.

2. What are the optimal preprocessing techniques for handling both even and uneven data distributions in MRI AD datasets?

Optimal preprocessing techniques for handling even (balanced) and uneven (imbalanced) data distributions in MRI AD datasets include several key methods. Data augmentation techniques,

such as rotation, flipping, and zooming, artificially increase the dataset size and introduce variability, aiding in better generalization. By scaling pixel values to a range of [0, 1], normalization ensures consistent input data and stability during model training. Resizing images to uniform dimensions, such as 128x128 pixels, maintains consistency in processing across the network. For imbalanced datasets, the Synthetic Minority Over-sampling Technique (SMOTE) effectively balances class distribution by oversampling the minority classes and preventing the model from developing a bias towards the majority class.

3. How does the performance of a model in detecting and classifying Alzheimer's disease vary with the application of different deep learning algorithms and preprocessing techniques?

The performance of models in detecting and classifying Alzheimer's disease varies significantly with the application of different deep-learning algorithms and preprocessing techniques. The custom CNN, designed for imbalanced datasets, leverages its architecture and dropout layers to excel in this scenario. In contrast, the modified VGG16 model, with its pre-trained weights and deep feature extraction capabilities, performs exceptionally well with balanced datasets. This model achieved a high accuracy of 97.98%, with precision at 98.12%, recall at 97.82%, and an AUC of 99.86%. Preprocessing techniques, particularly SMOTE and data augmentation, significantly improve the models' robustness and generalization, particularly in handling class imbalance.

4. Which model demonstrates the highest effectiveness in Alzheimer's disease diagnostics for both imbalanced and balanced datasets?

The highest effectiveness in Alzheimer's disease diagnostics for imbalanced datasets is demonstrated by the custom CNN, which achieves high accuracy and balanced performance across classes. The modified VGG16 model excels for balanced datasets, achieving top-tier performance metrics with an accuracy of 97.98%, precision of 98.12%, recall of 97.82%, and an AUC of 99.86%. Thus, the custom CNN is optimal for imbalanced data scenarios, while the modified VGG16 is highly effective for balanced data conditions.

CHAPTER SEVEN

CONCLUSIONS AND FUTURE WORKS

7.1 CHAPTER OVERVIEW

In this concluding chapter, we revisit crucial aspects of our study, synthesizing the findings and methodologies used to evaluate various machine learning models for classifying Alzheimer's disease stages using MRI images, with a particular focus on handling imbalanced datasets.

7.2 CONCLUSIONS

Our investigation reviewed the effectiveness of both custom-designed CNN architectures and adapted pre-trained models such as VGG16 for medical imaging tasks. Through meticulous testing and fine-tuning, these models proved adept at addressing complex classification challenges, particularly in scenarios involving imbalanced datasets often encountered in medical diagnostics. The findings affirm the importance of precise model selection and the necessity of rigorous optimization processes to enhance diagnostic accuracy in identifying various stages of Alzheimer's disease. This study not only validates the performance capabilities of these advanced models but also highlights the integral role that thoughtful model adjustments play in achieving diagnostic precision.

7.3 CONTRIBUTIONS OF THE STUDY

This research has contributed significantly to the field of medical imaging and diagnostics through several key advancements. First, it has demonstrated effective strategies for adapting and refining pre-trained models to suit specific medical imaging needs, particularly in handling imbalanced data. Second, it has helped establish new benchmarks for the accuracy of Alzheimer's disease classification using MRI images, providing a reference point for future studies. These contributions collectively push forward the practical application of machine learning technologies in medical diagnostics, showcasing the potential to improve diagnostic processes and outcomes.

7.4 APPLICATION OF THE STUDY

The practical applications of this study for clinical practice are substantial, primarily enhancing the accuracy of Alzheimer's disease diagnostics. By improving the reliability of disease stage classification, this research serves as a critical decision-support resource for medical professionals, facilitating earlier and more accurate detection and classification of Alzheimer's disease. Moreover, the empirical data generated from this study can inform and potentially reshape policy and clinical protocols, advocating for the integration of AI technologies to better healthcare outcomes. This aligns with broader healthcare objectives of increasing the effectiveness of diagnostic tools and personalized treatment plans.

7.5 FUTURE WORKS

Looking forward, the study identifies several avenues for further research such as addressing the issue of data scarcity is pivotal thus, acquiring more diverse datasets will be a priority to enhance model robustness and applicability. Additionally, exploring a broader array of machine learning models and integrating various imaging modalities can provide more comprehensive diagnostic tools. Practical implementation of these refined models in real-world clinical environments will also be crucial to assess their usability and acceptance among healthcare professionals. Adding to this, improving the explainability and interoperability of AI models will be essential to ensure that these advanced tools can be effectively understood and integrated into existing healthcare systems, enhancing trust and collaboration among medical practitioners. These initiatives are expected to enrich the foundation laid by this study, propelling advancements in AI applications for Alzheimer's diagnosis and potentially revolutionizing treatment approaches and patient management strategies in the field.

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REFERENCES

Arafa, D. A., Moustafa, H. E. D., Ali-Eldin, A. M. T., & Ali, H. A. (2022). Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey. *Multimedia Tools and Applications*, *81*(17), 23735–23776. https://doi.org/10.1007/s11042-022-11925-0

Arafa, D. A., Moustafa, H. E. D., Ali, H. A., Ali-Eldin, A. M. T., & Saraya, S. F. (2023). A deep learning framework for early diagnosis of Alzheimer's disease on MRI images. *Multimedia Tools and Applications*, *83*(2), 3767–3799. https://doi.org/10.1007/S11042-023-15738-7/TABLES/12

Brookmeyer, R., Johnson, E., Ziegler-Graham, K., & Arrighi, H. M. (2007). Forecasting the global burden of Alzheimer's disease. *Alzheimer's & Dementia*, *3*(3), 186–191. https://doi.org/10.1016/J.JALZ.2007.04.381

Ebrahimighahnavieh, M. A., Luo, S., & Chiong, R. (2020). Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review. *Computer Methods and Programs in Biomedicine*, *187*, 105242. https://doi.org/10.1016/J.CMPB.2019.105242

EL-Geneedy, M., Moustafa, H. E. D., Khalifa, F., Khater, H., & AbdElhalim, E. (2023). An MRI-based deep learning approach for accurate detection of Alzheimer's disease. *Alexandria Engineering Journal*, *63*, 211–221. https://doi.org/10.1016/J.AEJ.2022.07.062

Fareed, M. M. S., Zikria, S., Ahmed, G., Mui-Zzud-Din, Mahmood, S., Aslam, M., Jillani, S. F., Moustafa, A., & Asad, M. (2022). ADD-Net: An Effective Deep Learning Model for Early Detection of Alzheimer Disease in MRI Scans. *IEEE Access*, *10*, 96930–96951. https://doi.org/10.1109/ACCESS.2022.3204395

Gao, S., & Lima, D. (2022). A review of the application of deep learning in the detection of Alzheimer's disease. *International Journal of Cognitive Computing in Engineering*, *3*, 1–8. https://doi.org/10.1016/J.IJCCE.2021.12.002

Helaly, H. A., Badawy, M., & Haikal, A. Y. (2022a). Deep Learning Approach for Early Detection of Alzheimer's Disease. *Cognitive Computation*, *14*(5), 1711–1727. https://doi.org/10.1007/s12559-021-09946-2

Helaly, H. A., Badawy, M., & Haikal, A. Y. (2022b). Deep Learning Approach for Early Detection of Alzheimer's Disease. *Cognitive Computation*, *14*(5), 1711–1727. https://doi.org/10.1007/S12559-021-09946-2/FIGURES/15

Helaly, H. A., Badawy, M., & Haikal, A. Y. (2022c). Deep Learning Approach for Early Detection of Alzheimer's Disease. *Cognitive Computation*, *14*(5), 1711–1727. https://doi.org/10.1007/S12559-021-09946-2/FIGURES/15

Hussain, E., Hasan, M., Hassan, S. Z., Hassan Azmi, T., Rahman, M. A., & Zavid Parvez, M. (2020). Deep Learning Based Binary Classification for Alzheimer's Disease Detection using Brain MRI Images. *Proceedings of the 15th IEEE Conference on Industrial Electronics and Applications, ICIEA 2020*, 1115–1120. https://doi.org/10.1109/ICIEA48937.2020.9248213

Johnson, K. A., Fox, N. C., Sperling, R. A., & Klunk, W. E. (2012). Brain Imaging in Alzheimer Disease. *Cold Spring Harbor Perspectives in Medicine*, *2*(4), a006213. https://doi.org/10.1101/CSHPERSPECT.A006213

Kavitha, C., Mani, V., Srividhya, S. R., Khalaf, O. I., & Tavera Romero, C. A. (2022). Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models. *Frontiers in Public Health*, *10*. https://doi.org/10.3389/fpubh.2022.853294

Khan, R., Akbar, S., Mehmood, A., Shahid, F., Munir, K., Ilyas, N., Asif, M., & Zheng, Z. (2022). A transfer learning approach for multiclass classification of Alzheimer's disease using MRI images. *Frontiers in Neuroscience*, *16*. https://doi.org/10.3389/FNINS.2022.1050777

Kim, E., Baskys, A., Law, A. V., Roosan, M. R., Li, Y., & Roosan, D. (2021). Scoping review: the empowerment of Alzheimer's Disease caregivers with mHealth applications. *NPJ Digital Medicine*, *4*(1). https://doi.org/10.1038/S41746-021-00506-4

Liu, M., Cheng, D., Wang, K., & Wang, Y. (2018). Multi-Modality Cascaded Convolutional Neural Networks for Alzheimer's Disease Diagnosis. *Neuroinformatics*, *16*(3–4), 295–308. https://doi.org/10.1007/s12021-018-9370-4

Liu, X., Guo, L., Wang, H., Guo, J., Yang, S., & Duan, L. (2022). Research on imbalance machine learning methods for MR T1 WI soft tissue sarcoma data. *BMC Medical Imaging*, *22*(1), 1–13. https://doi.org/10.1186/S12880-022-00876-5/FIGURES/6

Loi, S. M., Pijnenburg, Y., & Velakoulis, D. (2023). Recent research advances in young-onset dementia. *Current Opinion in Psychiatry*, *36*(2), 126–133. https://doi.org/10.1097/YCO.0000000000000843

Mosconi, L., Brys, M., Glodzik-Sobanska, L., De Santi, S., Rusinek, H., & de Leon, M. J. (2007). Early detection of Alzheimer's disease using neuroimaging. *Experimental Gerontology*, *42*(1–2), 129–138. https://doi.org/10.1016/J.EXGER.2006.05.016

Mujahid, M., Rehman, A., Alam, T., Alamri, F. S., Fati, S. M., & Saba, T. (2023). An Efficient Ensemble Approach for Alzheimer's Disease Detection Using an Adaptive Synthetic Technique and Deep Learning. *Diagnostics 2023, Vol. 13, Page 2489*, *13*(15), 2489. https://doi.org/10.3390/DIAGNOSTICS13152489

Neuner, S. M., TCW, J., & Goate, A. M. (2020). Genetic architecture of Alzheimer's disease. *Neurobiology of Disease*, *143*. https://doi.org/10.1016/J.NBD.2020.104976

Nichols, E., & Vos, T. (2021). The estimation of the global prevalence of dementia from 1990-2019 and forecasted prevalence through 2050: An analysis for the Global Burden of Disease (GBD) study 2019. *Alzheimer's & Dementia*, *17*(S10), e051496. https://doi.org/10.1002/ALZ.051496

Saied, I. M., Arslan, T., & Chandran, S. (2022). Classification of Alzheimer's Disease Using RF Signals and Machine Learning. *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, *6*(1), 77–85. https://doi.org/10.1109/JERM.2021.3096172

Sisodia, P. S., Ameta, G. K., Kumar, Y., & Chaplot, N. (2023). A Review of Deep Transfer Learning Approaches for Class-Wise Prediction of Alzheimer's Disease Using MRI Images. In *Archives of Computational Methods in Engineering* (Vol. 30, Issue 4, pp. 2409–2429). Springer Science and Business Media B.V. https://doi.org/10.1007/s11831-022-09870-0

Tatulian, S. A. (2022). Challenges and hopes for Alzheimer's disease. *Drug Discovery Today*, *27*(4), 1027–1043. https://doi.org/10.1016/J.DRUDIS.2022.01.016

Tiwari, S., Atluri, V., Kaushik, A., Yndart, A., & Nair, M. (2019). Alzheimer's disease: pathogenesis, diagnostics, and therapeutics. *International Journal of Nanomedicine*, *14*, 5541–5554. https://doi.org/10.2147/IJN.S200490

Tufail, A. Bin, Ma, Y. K., & Zhang, Q. N. (2020). Binary Classification of Alzheimer's Disease Using sMRI Imaging Modality and Deep Learning. *Journal of Digital Imaging*, *33*(5), 1073–1090. https://doi.org/10.1007/S10278-019-00265-5

Yiannopoulou, K. G., & Papageorgiou, S. G. (2020). Current and Future Treatments in Alzheimer Disease: An Update. *Journal of Central Nervous System Disease*, *12*. https://doi.org/10.1177/1179573520907397

Zhou, Q., Wang, J., Yu, X., Wang, S., & Zhang, Y. (2023). A Survey of Deep Learning for Alzheimer's Disease. *Machine Learning and Knowledge Extraction 2023, Vol. 5, Pages 611-668*, *5*(2), 611–668. https://doi.org/10.3390/MAKE5020035

APPENDIX

APPENDIX A: SAMPLE CODE FOR IMBALANCED CNN

```
import tensorflow as tf
from tensorflow import keras

# Create a sequential model
model = keras.models.Sequential()

# Preprocessing: Normalize pixel values to [0, 1]
model.add(keras.layers.experimental.preprocessing.Rescaling(1./255, input_shape=(IMG_HEIGHT, IMG_WIDTH, 3)))

# Convolutional layer 1
model.add(keras.layers.Conv2D(filters=16, kernel_size=(3, 3), padding='same', activation='relu', kernel_initializer="he_normal"))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))

# Convolutional layer 2
model.add(keras.layers.Conv2D(filters=32, kernel_size=(3, 3), padding='same', activation='relu', kernel_initializer="he_normal"))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))

# Dropout for regularization
model.add(keras.layers.Dropout(0.25))

# Convolutional layer 3
model.add(keras.layers.Conv2D(filters=64, kernel_size=(3, 3), padding='same', activation='relu', kernel_initializer="he_normal"))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))

# More dropout for regularization
model.add(keras.layers.Dropout(0.2))

# Flatten the output from convolutional layers
model.add(keras.layers.Flatten())

# Fully connected layers
model.add(keras.layers.Dense(128, activation="relu", kernel_initializer="he_normal"))
model.add(keras.layers.Dense(64, activation="relu"))
model.add(keras.layers.Dense(4, activation="softmax"))

# Compile the model with appropriate optimizer, loss function, and metrics
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Print the model summary
model.summary()
```

APPENDIX B: SAMPLE CODE FOR IMBALANCED VGG16

```
from keras import layers, models
from keras.optimizers import Adam
from keras.applications.vgg16 import VGG16, preprocess_input
from keras.preprocessing.image import ImageDataGenerator


# Load the VGG19 model without the top layer and set it to be non-trainable
input_shape = (128,128, 3)

#Create an instance of the VGG16 model
vgg16 = VGG16(include_top=False, input_shape=input_shape,
                  weights='imagenet')

# Freeze the layers of the VGG16 model
for layer in vgg16.layers:
    layer.trainable = False

# Create a new model with additional layers
global_average_layer = tf.keras.layers.GlobalAveragePooling2D()

prediction_layer = keras.layers.Dense(4,activation='softmax')

model = tf.keras.Sequential([vgg16, global_average_layer,
  keras.layers.BatchNormalization(),
  keras.layers.Dense(2048, activation='relu'),
  keras.layers.Dense(512, activation='relu'),
  keras.layers.Dense(256, activation='relu'),
  keras.layers.Dense(64, activation='relu'),
  prediction_layer
])

model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy',tf.keras.metrics.AUC(),
                       tf.keras.metrics.Precision(),
                       tf.keras.metrics.Recall(),])
```

APPENDIX C: SAMPLE CODE FOR BALANCED VGG16

```
from keras import layers, models
from keras.optimizers import Adam
from keras.applications.vgg16 import VGG16, preprocess_input

# Load the VGG19 model without the top layer and set it to be non-trainable
input_shape = (128,128, 3)

#Create an instance of the VGG16 model
vgg16 = VGG16(include_top=False, input_shape=input_shape,
                  weights='imagenet')

# Freeze the layers of the VGG16 model
for layer in vgg16.layers:
    layer.trainable = False

# Create a new model with additional layers
global_average_layer = tf.keras.layers.GlobalAveragePooling2D()

prediction_layer = keras.layers.Dense(4,activation='softmax')

model = tf.keras.Sequential([vgg16, global_average_layer,
  keras.layers.BatchNormalization(),
  keras.layers.Dropout(0.5),
  keras.layers.Dense(2048, activation='relu'),
  keras.layers.Dense(512, activation='relu'),
  keras.layers.Dense(256, activation='relu'),
  keras.layers.Dropout(0.5),
  keras.layers.Dense(64, activation='relu'),
  prediction_layer
])

model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy',tf.keras.metrics.AUC(),
                       tf.keras.metrics.Precision(),
                       tf.keras.metrics.Recall(),])
```