School of Computer Science and Electronic Engineering

MSc Data Science

Academic Year 2023-2024

Predicting Dementia Stages Using MRI Scans: A Comparative Analysis of Deep Learning Approaches with ResNet50 and DenseNet121

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A report submitted in partial fulfilment of the requirement for the degree of Master of Science

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Word Count

Number of Pages: 82

Number of Words: 17494

Acknowledgements

I would like to express my sincere gratitude to my dissertation supervisor, Dr. Roman Bauer, for their invaluable guidance, feedback, and support throughout the course of this research. Their expertise and dedication helped shape this project, and I am deeply grateful for the encouragement and insights they provided at every stage.

I would also like to acknowledge the academic staff at University of Surrey for the resources and opportunities provided during my studies, which contributed greatly to my learning and the completion of this dissertation. Additionally, I would like to thank my fellow peers and colleagues within the research community for their thoughtful discussions and contributions, which have been instrumental in enhancing the quality of this work.

Finally, I would like to extend my appreciation to the authors of the OASIS dataset and the open-source community for providing the tools and resources necessary to conduct this research. Without access to these datasets and frameworks, this work would not have been possible.

I certify that the work presented in the dissertation is my own unless referenced

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Date: 10 / 09 / 2024.

Abstract

This study explores the application of deep learning techniques for the classification of dementia stages, specifically focusing on Alzheimer's disease (AD), using MRI scans. Leveraging a large, imbalanced dataset comprising 86,437 MRI images (67,222 Non Demented, 13,725 Very Mild Demented, 5,002 Mild Demented, and 488 Moderate Demented), the project aims to categorize scans into four dementia stages. The approach involved developing a custom convolutional neural network (CNN) as a baseline model, followed by implementing transfer learning techniques using pre-trained models like DenseNet121 and ResNet50.

To address the class imbalance, we employed strategic sampling and data augmentation techniques. The custom CNN model achieved 99.14% accuracy for binary classification (AD vs. non-AD). For multi-class classification, DenseNet121, after fine-tuning with data augmentation and regularization techniques, reached 90.32% accuracy with a loss of 0.301. ResNet50 outperformed both models, attaining 92.29% accuracy and a loss of 0.2515.

Comprehensive evaluations using confusion matrices, precision, recall, F1-score, and ROC AUC demonstrated ResNet50's robustness in accurately classifying dementia stages, particularly in distinguishing Moderate Dementia cases despite their low representation in the dataset. The model showed high precision (0.93) and recall (0.94) across all AD stages, with notable performance in identifying Mild Demented (F1-score: 0.94) and Moderate Demented (F1-score: 0.98) cases.

This work underscores the potential of deep learning, particularly transfer learning with ResNet50, for enhancing clinical diagnosis through early detection and accurate classification of dementia stages, even with imbalanced datasets. The implementation of learning rate scheduling and strategic data augmentation techniques further improved model generalization and convergence.

The results provide a solid framework for integrating deep learning into diagnostic tools, demonstrating robust performance across varying levels of data availability for different dementia stages. Future work will focus on incorporating multimodal data and exploring techniques to further improve performance on underrepresented classes. This research contributes significantly to the field of computer-aided diagnosis in neurodegenerative diseases, offering promising avenues for improving patient care and treatment strategies in real-world clinical scenarios where data imbalance is common.

Keywords:

Alzheimer's Disease (AD), Dementia stages, MRI scan analysis, Deep learning, Convolutional Neural Networks (CNN), DenseNet121, ResNet50, Class imbalance, Data augmentation, Transfer learning, Neuroimaging, Multiclass classification, Model fine-tuning, Early diagnosis, Cognitive impairment detection

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Chapter 1 Introduction

1.1 Background

Alzheimer's disease (AD) is the most common form of dementia, accounting for 60-80% of all dementia cases worldwide. With a steadily aging global population, the prevalence of dementia is expected to triple by 2050, placing an increasing burden on healthcare systems and caregivers. Dementia is a progressive neurological disorder characterized by a decline in cognitive function, memory, and behavior, ultimately leading to a loss of independence in everyday activities. Early detection of dementia, particularly Alzheimer's disease, is crucial as it enables timely intervention, slows disease progression, and improves patient quality of life. However, traditional diagnostic methods—relying on clinical and cognitive assessments—often detect the disease too late, when significant brain damage has already occurred.

Magnetic Resonance Imaging (MRI) has become one of the most effective and non-invasive techniques for detecting structural changes in the brain associated with dementia. MRI scans provide high-resolution images of the brain, allowing the identification of atrophy in key regions, such as the hippocampus and cerebral cortex, which are critical for memory and cognition. Yet, the interpretation of MRI scans remains a challenge for medical professionals, as distinguishing between different stages of dementia can be subtle and subjective.

Recent advancements in artificial intelligence (AI) and deep learning offer promising solutions to automate and enhance the diagnosis of dementia. Convolutional Neural Networks (CNNs), a class of deep learning models known for their ability to analyze visual data, have demonstrated exceptional performance in medical image classification tasks. By learning to identify complex patterns and features within MRI scans, CNNs, when coupled with transfer learning, can significantly improve the accuracy and consistency of dementia diagnosis. Models like DenseNet121 and ResNet50 have shown strong potential in image classification tasks, providing a powerful foundation for detecting and classifying the stages of dementia.

In this study, we leverage the power of deep learning to automate the classification of dementia stages from MRI data, which is essential for tailoring treatment plans and enhancing patient care. The flowchart below illustrates the end-to-end process, from MRI data acquisition to dementia stage classification, helping to streamline the diagnostic process and assist clinicians in early intervention and treatment planning.

1.2 Problem Statement

The task of distinguishing between the various stages of dementia—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—using MRI scans presents numerous challenges. The progression of dementia results in subtle changes in brain structure, which often overlap across stages, making manual classification difficult and prone to human error. Moreover, MRI data is high-dimensional and typically requires large labeled datasets to develop effective models, which are often limited in medical research.

Deep learning models, particularly CNNs, provide a viable solution by automating the feature extraction process, eliminating the need for manual interpretation. However, developing an accurate and reliable model for classifying dementia stages involves several critical challenges: preprocessing MRI data to ensure it is compatible with deep learning models, addressing class imbalance within the dataset, and fine-tuning the architecture of models like DenseNet121 and ResNet50 for optimal performance.

This research seeks to address these challenges by utilizing transfer learning to adapt pre-trained models for dementia classification. Through comprehensive evaluation and comparison of these models, we aim to advance the field of dementia diagnostics, improving the accuracy of early-stage detection and the precision of disease staging.

1.3 Motivation

Alzheimer's Disease (AD) is a rapidly growing public health concern, impacting millions worldwide. As the global population continues to age, the incidence of AD and other dementias is expected to rise significantly, posing an increasing challenge to healthcare systems. Early detection is vital for slowing the progression of the disease, enabling timely treatment interventions and improving patient outcomes. However, traditional diagnostic approaches, such as clinical assessments and manual neuroimaging analysis, are often inefficient, prone to variability, and may overlook subtle early-stage changes in the brain. This underscores the pressing need for reliable, automated, and efficient diagnostic tools.

One of the most promising solutions to these challenges is the application of deep learning (DL) and transfer learning techniques to medical imaging, particularly magnetic resonance imaging (MRI). Recent breakthroughs in DL have demonstrated substantial potential in automating neuroimaging scan classification, delivering greater consistency and accuracy than manual methods. Despite the advances made in machine learning models for AD diagnosis, there remain considerable challenges in achieving optimal performance, ensuring generalizability, and improving model interpretability—particularly in the multi-class classification of dementia stages. Most existing studies have focused primarily on binary classification (AD vs. non-AD), with less attention given to distinguishing between multiple stages, such as Mild Cognitive Impairment (MCI) and various dementia levels.

Furthermore, the limited availability of labeled medical imaging data complicates the development of highly accurate models, making it difficult to generalize results to diverse populations. In this context, transfer learning offers a practical solution, as it enables the use of models pre-trained on large datasets like ImageNet, which can then be fine-tuned for medical applications. This approach not only reduces the time and computational resources required for training but also improves the accuracy of detecting complex patterns in MRI data.

This dissertation is motivated by the need to create an advanced, efficient, and interpretable deep learning model for the multi-class classification of AD stages using MRI data. By comparing the performance of DenseNet121 and ResNet50, both of which have been fine-tuned through transfer learning, this research seeks to overcome the limitations of previous models. The primary aim is to enhance accuracy, particularly in distinguishing between non-demented, very mild demented, mild demented, and moderate demented stages, thereby contributing to earlier and more precise AD diagnoses.

Additionally, this study addresses the common issue of class imbalance in medical datasets, where more advanced stages of dementia tend to be underrepresented. By utilizing data augmentation strategies and evaluating the models with metrics like accuracy, precision, recall, F1-score, and confusion matrices, the research aims to develop a more balanced and clinically meaningful AD diagnostic model.

Ultimately, the goal of this research is to bridge the gap between cutting-edge deep learning methodologies and practical clinical applications by developing a robust, scalable, and interpretable model suitable for real-world use. In doing so, this study hopes to contribute to ongoing efforts to leverage AI for the early detection of AD and the development of personalized treatment plans, ultimately improving patient outcomes and alleviating the strain on healthcare systems.

1.4 Aim and Objectives

1.4.1 Aim:

The primary aim of this research is to develop and compare deep learning models, specifically DenseNet121 and ResNet50, to classify MRI images into four stages of dementia: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented.

1.4.2 Objectives:

1. **Review the literature**: Conduct a thorough review of existing methodologies for MRI-based dementia classification, focusing on the role of deep learning in medical image analysis.
2. **Pre-process MRI datasets**: Normalize and augment MRI data while addressing the issue of class imbalance, preparing the data for deep learning model training.
3. **Train DenseNet121 and ResNet50 models**: Implement these state-of-the-art pre-trained models, fine-tuning them for the dementia classification task.
4. **Fine-tune and compare model performance**: Apply hyperparameter tuning to enhance the performance of both models, and compare their effectiveness in dementia classification.
5. **Evaluate models using performance metrics**: Assess the models using key metrics such as accuracy, precision, recall, confusion matrix, and ROC AUC to provide insights into their performance and reliability.

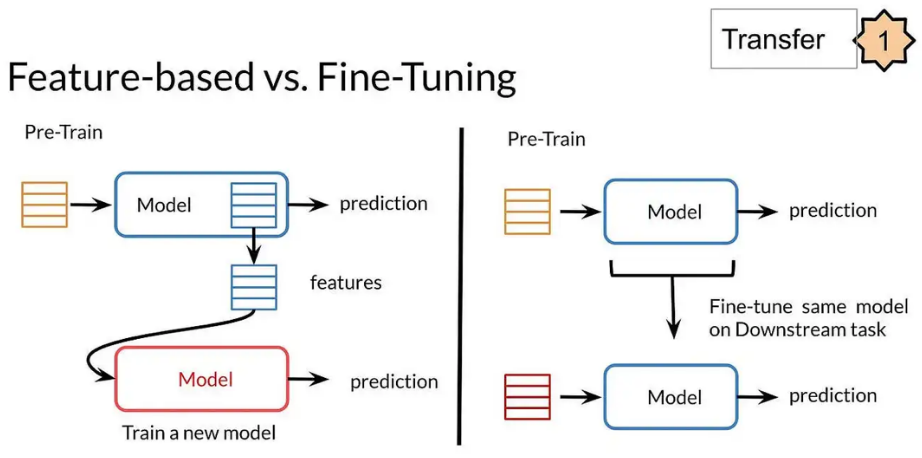

Figure 1 Data Pre-processing → Model Training → Fine-Tuning → Evaluation.

Source: (MarkovML, 2022, from [MarkovML blog])

1.5 Research Approach

This study employs a deep learning approach that leverages transfer learning to classify different stages of dementia using MRI data. The research focuses on two advanced pre-trained models: DenseNet121 and ResNet50. Transfer learning allows these models, which have been pre-trained on large datasets, to be fine-tuned for the specific task of classifying dementia stages.

The approach consists of the following components:

- **MRI Pre-processing**: To improve model performance, MRI scans undergo several pre-processing steps, including resizing, normalization, and data augmentation. These steps increase the diversity of the training set and enhance model generalization.
- **Class Imbalance Handling**: Given the skewed distribution of dementia stages in the dataset, oversampling, under sampling, and augmentation techniques are employed to balance the classes.
- **Transfer Learning with CNNs**: DenseNet121 and ResNet50 models are fine-tuned through transfer learning, allowing them to leverage pre-learned features while adapting to the dementia classification task. CNNs are utilized for their proven ability to capture complex spatial hierarchies in image data.

This combination of pre-processing and deep learning methodologies aims to improve classification accuracy and provide a reliable diagnostic tool for early dementia detection.

Chapter 2 Literature Review

2.1 Introduction to Alzheimer's Disease and Neuroimaging

Alzheimer's disease (AD) is a leading neurodegenerative disorder that impairs memory, cognition, and daily function, largely affecting an aging population. With the growing number of older adults, the need for early diagnosis has become increasingly critical. Magnetic Resonance Imaging (MRI) is a vital neuroimaging tool used to visualize brain atrophy, which is closely associated with AD progression, particularly in regions like the hippocampus (Frisoni et al., 2010; Bhatkoti & Paul, 2022). However, manual analysis of MRI data is both time-consuming and prone to human error, driving the adoption of machine learning (ML) and deep learning (DL) to achieve more reliable, consistent results (Islam et al., 2022).

2.2 The Role of Machine Learning in Alzheimer's Diagnosis

Traditional ML techniques such as Support Vector Machines (SVM) and Random Forest (RF) have been used to classify AD stages, primarily through handcrafted features extracted from MRI scans (Klöppel et al., 2008). While effective in binary classifications, these methods often struggle with multi-class tasks and require labour-intensive feature engineering (Rueda et al., 2014). Bhatkoti and Paul (2022) used ensemble ML methods to achieve 88.5% accuracy, but the limitation of relying on manual feature extraction became evident as deep learning models gained traction. Convolutional Neural Networks (CNNs), in contrast, excel in learning features directly from raw MRI data, without manual intervention (Hosseini-Asl et al., 2016).

2.3 Advancements in Deep Learning for AD Detection

The shift from ML to deep learning marked a significant breakthrough in medical image analysis. CNNs became central in AD detection due to their ability to automatically learn and extract features from MRI data. Early work by Sarraf and Tofighi (2016) set the foundation, achieving 96.85% accuracy in functional MRI analysis. Building on this, Islam et al. (2022) applied custom CNNs to the OASIS dataset, achieving 93.18% accuracy, showcasing the effectiveness of deep learning in detecting subtle brain structural changes indicative of AD (El-Geneedy et al., 2023).

2.4 Transfer Learning and Pre-Trained Models

A key challenge in Alzheimer's Disease (AD) research is the scarcity of labeled MRI data, which makes training deep learning models from scratch difficult and inefficient. To address this, transfer learning has become an essential technique. Instead of building models from the ground up, researchers fine-tune models pre-trained on large datasets, such as ImageNet, to suit AD-specific tasks. This approach allows the model to leverage learned features from the larger dataset and adapt them to domain-specific data, significantly improving performance (Hon & Khan, 2017). Valliani and Soni (2017) applied transfer learning to fine-tune an Inception-V3 model for AD classification, achieving superior results. In my study, transfer learning was applied to DenseNet121 and ResNet50, with ResNet50 outperforming DenseNet121, reaching an accuracy of 92% due to its ability to capture complex brain abnormalities.

2.5 Addressing Class Imbalance

Class imbalance, a significant issue in medical imaging, leads to models that disproportionately favor the majority class, such as non-demented patients, over the minority classes like moderate or severe dementia (Buda et al., 2018). Data augmentation, including horizontal flipping, rotation, and scaling, has been successfully used to mitigate this imbalance. In my project, augmentation techniques were employed to increase representation for the Moderate Demented class, improving classification accuracy. Additionally, class weighting was implemented during model training to balance the contributions of underrepresented classes (El-Geneedy et al., 2023).

2.6 Multi-Class Classification of AD Stages

The transition from binary to multi-class classification in AD research enables better tracking of disease progression and supports more personalized treatment plans (Gunawardena et al., 2017). Recent studies, such as Bhatkoti and Paul's (2022) use of ensemble CNNs, have demonstrated the efficacy of these models in distinguishing between multiple AD stages. In my research, ResNet50 showed superior performance in detecting subtle differences between Very Mild and Mild Demented stages, indicating the advantage of deeper architectures in multi-class tasks.

2.7 Recent Developments in Deep Learning for AD

Recent innovations in deep learning have focused on improving AD classification through novel architectures and training techniques. Contrastive learning, as explored by El-Geneedy et al. (2023), enhances feature extraction by helping the model differentiate between similar and dissimilar samples, leading to improved classification of underrepresented AD stages. Hybrid models that combine CNNs with Recurrent Neural Networks (RNNs) have also been developed, capturing both spatial and temporal patterns in neuroimaging data, which enhances model performance (Yang & Liu, 2020).

2.8 Model Architectures: DenseNet121 and ResNet50

DenseNet121's dense connections allow for efficient gradient flow and feature reuse, which is critical in medical imaging (Huang et al., 2016). In my study, however, DenseNet121 struggled with differentiating between closely related AD stages, achieving an accuracy of 69%. On the other hand, ResNet50, with its residual connections, achieved 92% accuracy and demonstrated strong performance in classifying stages like Mild Demented. Its deeper architecture and ability to prevent vanishing gradients make it particularly effective for medical image classification tasks (He et al., 2016).

2.9 Interpretability and Clinical Integration

One of the key challenges in clinical deployment of deep learning models is the lack of interpretability. Tools like Grad-CAM (Gradient-weighted Class Activation Mapping) have been developed to address this issue by providing visual explanations for model predictions (Rieke et al., 2018). In my project, I applied Grad-CAM to enhance interpretability for both DenseNet121 and ResNet50 models, allowing clinicians to visualize which brain regions influenced the classification decision. This tool helps bridge the gap between AI-driven diagnostics and clinical trust, making the models more suitable for real-world healthcare settings.

Chapter 3 Methodology

3.1 Overview

This study aims to classify different stages of Alzheimer's Disease (AD) using two deep learning models, DenseNet121 and ResNet50. The methodology includes the following steps:

1. **Data Acquisition**: MRI scans were obtained from the OASIS dataset, representing Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented stages.
2. **Pre-processing**: Images were resized, normalized, and augmented to address class imbalance and prepare them for input into the models. The detailed preprocessing steps are described in **Section 3.3**.
3. **Model Development**: DenseNet121 and ResNet50 were fine-tuned using transfer learning. The models were pre-trained on ImageNet and adapted for the specific task of classifying dementia stages. Key hyperparameters were adjusted for optimal performance.
4. **Training and Evaluation**: The models were trained using the processed MRI data and evaluated based on accuracy, precision, recall, and F1-score.

For a detailed explanation of the data acquisition, preprocessing, and augmentation methods, please refer to **Section 3.3**.

3.2 Dataset Overview

This study utilizes the OASIS dataset, a widely-used public resource containing over 86,000 MRI images of individuals at different stages of cognitive decline. The dataset exhibits significant class imbalance, with Non-Demented images comprising over 77% of the total data, while Moderate Demented images represent less than 1%. Such imbalances can skew model performance and necessitate special pre-processing measures (Buda et al., 2018; Haixiang et al., 2017).

3.2.1 Impact of Class Imbalance

Class imbalance is a prevalent challenge in medical datasets like OASIS, where majority classes, such as Non-Demented, dominate. This imbalance can lead to overfitting on the majority class, reducing the model's ability to correctly classify minority classes, such as Moderate Demented (Buda et al., 2018). Solutions such as data augmentation and oversampling are crucial to ensure that models generalize well (Löwe et al., 2017).

3.2.2 Data Distribution Table:

No table of figures entries found.	Number of Samples	Percentage of Total
Non- Demented	67,222	77.77%
Very Mild Demented	13,725	15.88%
Mild Demented	5,002	5.79%
Moderate Demented	488	0.56%

Table 1 Distribution of MRI Images by Dementia Stage

3.3 Pre-processing Techniques

To prepare the MRI data for model input, the images were resized to 150x150 pixels and their single-channel grayscale format was duplicated across three channels to simulate RGB inputs required by DenseNet121 and ResNet50. Pixel intensities were normalized between -1 and 1 to reduce variability and improve convergence (Zhu et al., 2020).

Visualizations: Below are images that show examples of MRI scans before and after resizing and channel duplication, demonstrating the uniformity introduced in the data.

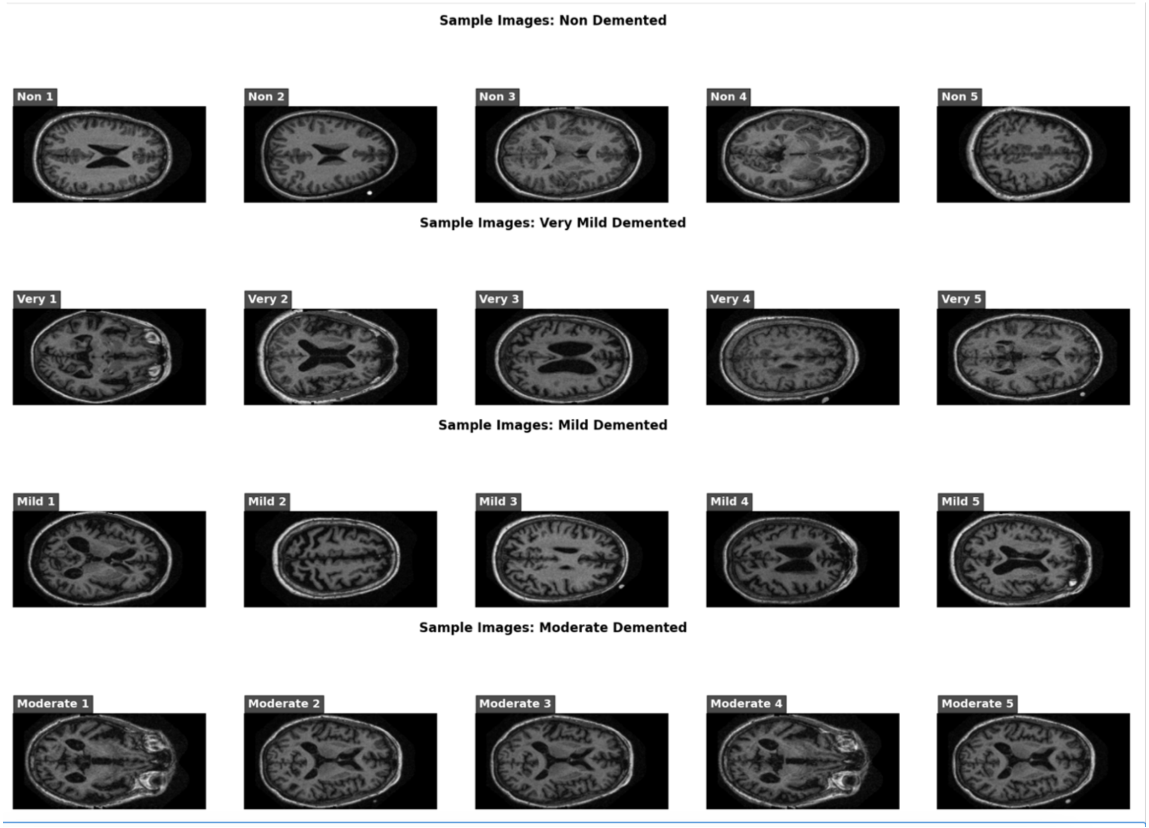

Figure 2 Examples of Resized and RGB-Simulated MRI Scans

3.3.3 Data Augmentation

Data augmentation helps mitigate class imbalance and enhances model generalization by increasing the diversity of training data. Techniques like horizontal flipping, zooming (up to 20%), rotation (0-20 degrees), and shearing were applied to artificially expand the dataset, especially for underrepresented classes like Moderate Demented. This approach enables models to better capture subtle anatomical differences across different dementia stages (Shorten & Khoshgoftaar, 2019).

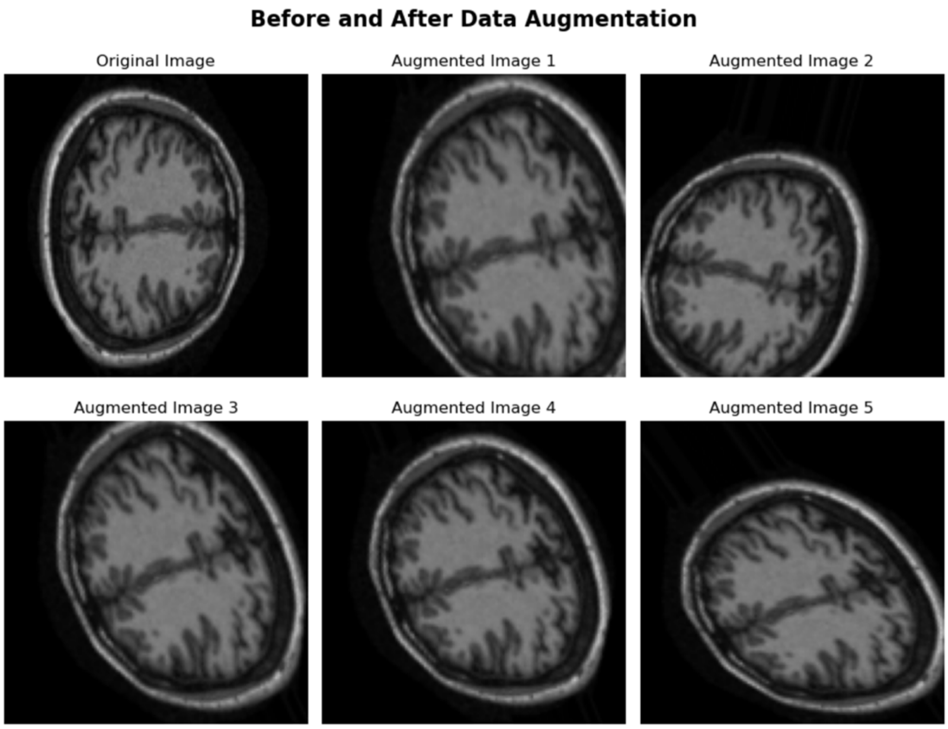

Figure 3 Before and After Data Augmentation – MRI images demonstrating the application of horizontal flipping, zooming, rotation, shearing, and shifting to enhance dataset diversity.

3.3.4 Class Imbalance

To address the significant class imbalance in the OASIS dataset, augmentation techniques were applied to minority classes, and oversampling was used to boost representation of the Moderate Demented class. These strategies ensure that the model does not overly favor the majority class, enabling better generalization across all stages of dementia (Buda et al., 2018).

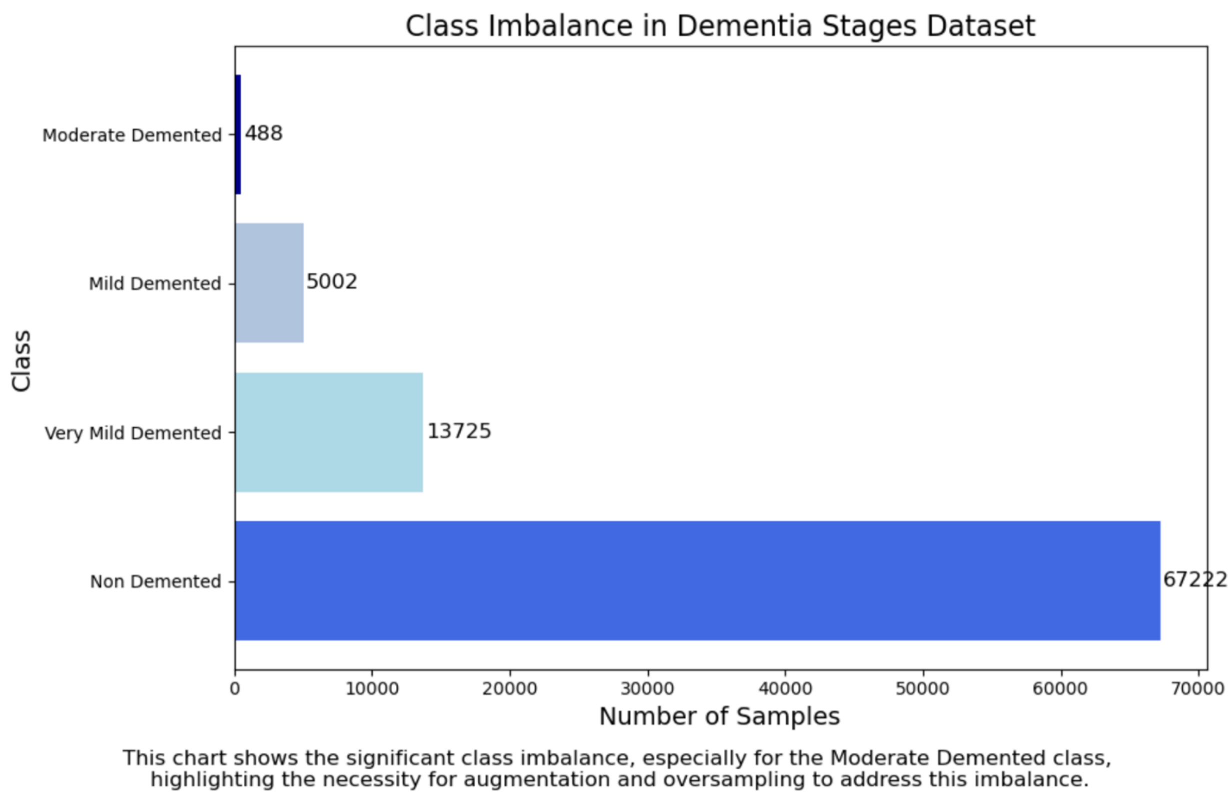

Figure 4 Class distribution of MRI scans across dementia stages, highlighting class imbalance.

This diagram illustrates how augmentation techniques like random flips, zooms, and shifts are applied to generate diverse training examples. It helps the model capture a wide range of anatomical variations, which is crucial for robust performance in dementia classification.

3.3.5 Histogram Analysis

An analysis of the pixel intensity histograms was also conducted to understand the distribution of pixel values across the different classes. This step provided insights into how the images differed in terms of intensity distribution, guiding the decision to normalize the data. The following box plots show the distribution of pixel means, standard deviations, and skewness for each dementia stage.

- **Boxplot of Means**: Shows the distribution of mean pixel intensities across classes.

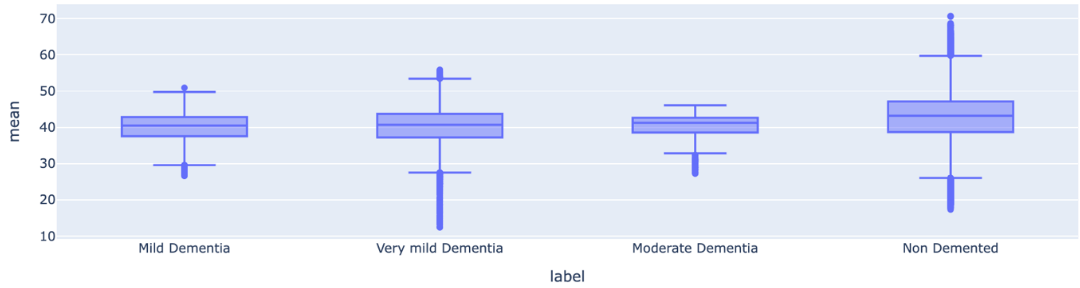

Figure 5 Boxplot of Mean Pixel Intensities across Dementia Stages

- **Boxplot of Standard Deviations**: Demonstrates how the contrast varies between images in different stages of dementia.

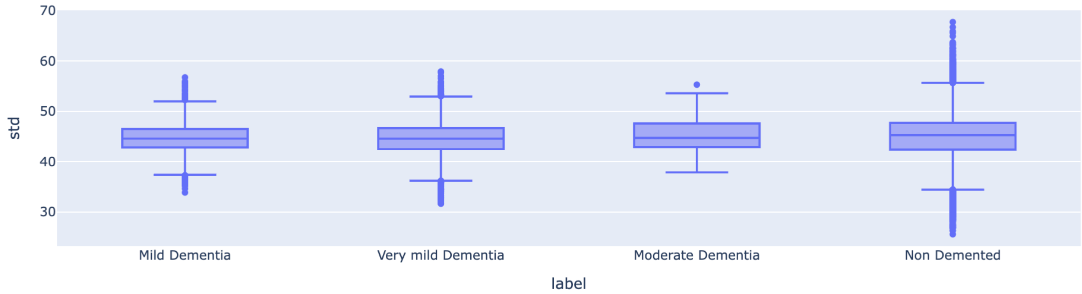

Figure 6 Boxplot of Standard Deviations across Dementia Stages

- **Boxplot of Skewness**: Highlights the asymmetry in pixel intensity distributions, indicating potential outliers or variations in the data.

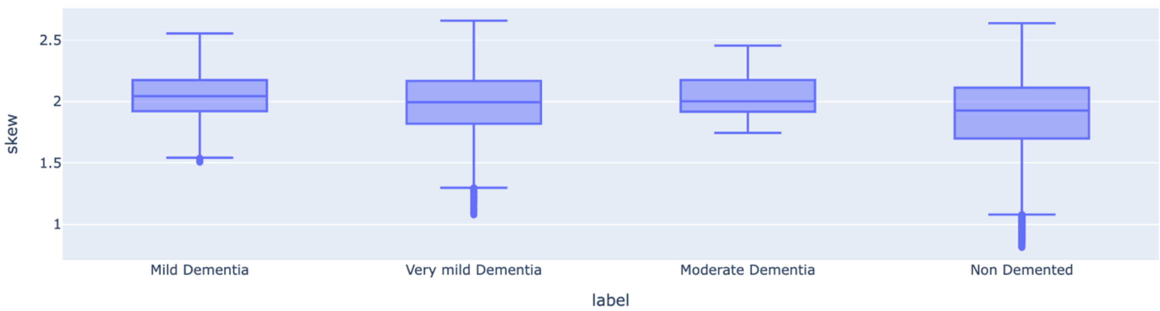

Figure 7 Boxplot of Skewness of Pixel Intensity Distributions across Dementia Stages

3.4 Model Architecture and Transfer Learning

In this study, transfer learning was employed using both DenseNet121 and ResNet50 architectures to classify Alzheimer's Disease (AD) stages based on MRI scans. Transfer learning is a technique where models pre-trained on large-scale datasets, such as ImageNet, are fine-tuned for specific tasks, significantly reducing training time while improving accuracy (He et al., 2016; Huang et al., 2017).

For Alzheimer's Disease classification, MRI data presents subtle structural changes in the brain that vary across different dementia stages. Due to the limited availability of labeled medical imaging data, transfer learning becomes especially beneficial, as it allows the model to generalize well even when adapted to smaller, domain-specific datasets like OASIS. This enables models to leverage pre-learned features, trained on millions of natural images, and adapt them for identifying fine-grained anatomical changes linked to dementia.

In this research, both DenseNet121 and ResNet50 were pre-trained on the ImageNet dataset and fine-tuned using the OASIS dataset. Specifically, the final 20 layers of each model were unfrozen and retrained to adapt to the neuroimaging task, allowing the models to retain useful generic image features from ImageNet while learning task-specific features related to AD progression. This approach helped enhance the classification accuracy, especially for challenging stages like Moderate Demented.

3.4.1 Importance of Transfer Learning:

- **Reduces Training Time:** Transfer learning drastically reduces the time required to train deep models from scratch.
- **Improves Performance:** By leveraging pre-learned features, models perform better even with a relatively smaller dataset like OASIS.
- **Applicability in Medical Imaging:** Transfer learning is especially useful in medical imaging, where obtaining a large, labelled dataset is often difficult.

For a comprehensive explanation of how transfer learning was applied, refer to the **Training Procedure** and **Fine-Tuning** sections that follow.

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3.4.2 DenseNet121 Architecture

DenseNet121 is recognized for its dense connections between layers, a structure that promotes feature reuse and mitigates the vanishing gradient problem common in deep neural networks (Huang et al., 2017). In this architecture, each layer is directly connected to every other layer, enabling efficient feature propagation throughout the network, which improves both learning and computational efficiency.

- **Input Shape**: 150×150×3 (RGB images).
- **Key Layers**: DenseNet121 consists of four Dense Blocks, each containing multiple convolutional layers. Transition layers, comprising batch normalization and pooling, are placed between the blocks to reduce the network's dimensionality while maintaining feature integrity.
- **Fully Connected Layers**: A dense layer with 512 neurons using ReLU activation is followed by a SoftMax output layer that classifies the input into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented.

DenseNet's architecture has proven to be highly effective in medical image analysis, particularly in tasks like Alzheimer's Disease classification, where it reduces the number of parameters and improves gradient flow, making it computationally efficient and powerful in extracting intricate features from medical images (Huang et al., 2017; Zhu et al., 2020).

Model Diagram: DenseNet121 Architecture.

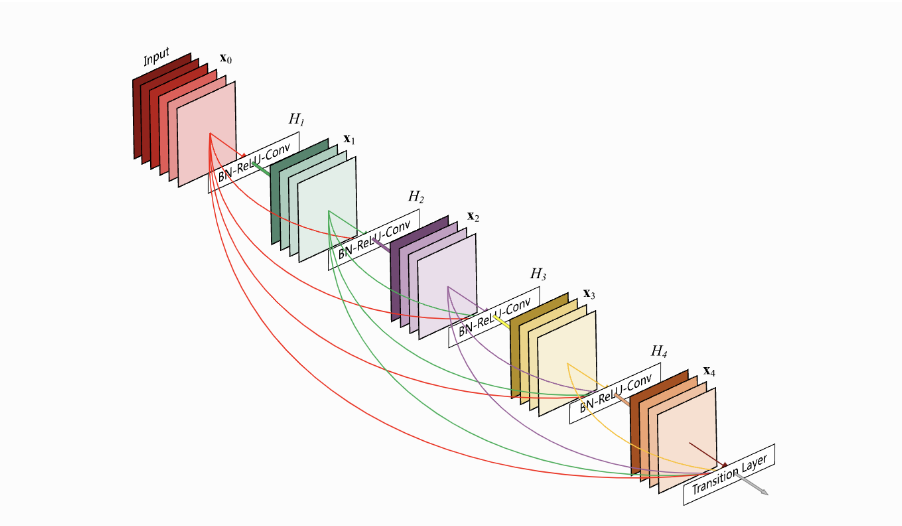

Figure 8 DenseNet Architecture Flowchart
(Source: UVA Deep Learning Notebooks - DenseNet, ResNet, and Inception)

3.4.3 ResNet50 Architecture

ResNet50 addresses the degradation problem encountered in deep networks through its use of residual connections. These connections enable the model to maintain high accuracy even as network depth increases, preventing the loss of important information during training. By allowing layers to learn identity mappings, ResNet50 avoids the vanishing gradient problem, ensuring that critical information is preserved throughout the network (He et al., 2016).

- **Input Shape**: 150×150×3 (RGB images).
- **Residual Connections**: These connections allow the network to skip unnecessary layers, making training more efficient and improving gradient flow.
- **Fully Connected Layers**: The network includes a dense layer with 512 neurons activated by ReLU, followed by a SoftMax layer for classification into four stages of Alzheimer's Disease: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented.

ResNet50's architecture has been widely employed in medical imaging tasks, particularly for classifying MRI brain scans. Its deep structure, coupled with residual connections, makes it particularly well-suited for detecting complex patterns associated with Alzheimer's Disease (He et al., 2016). Studies in medical image analysis demonstrate its superiority in distinguishing between subtle brain abnormalities across dementia stages (Islam et al., 2022).

Model Diagram: ResNet50 Architecture.

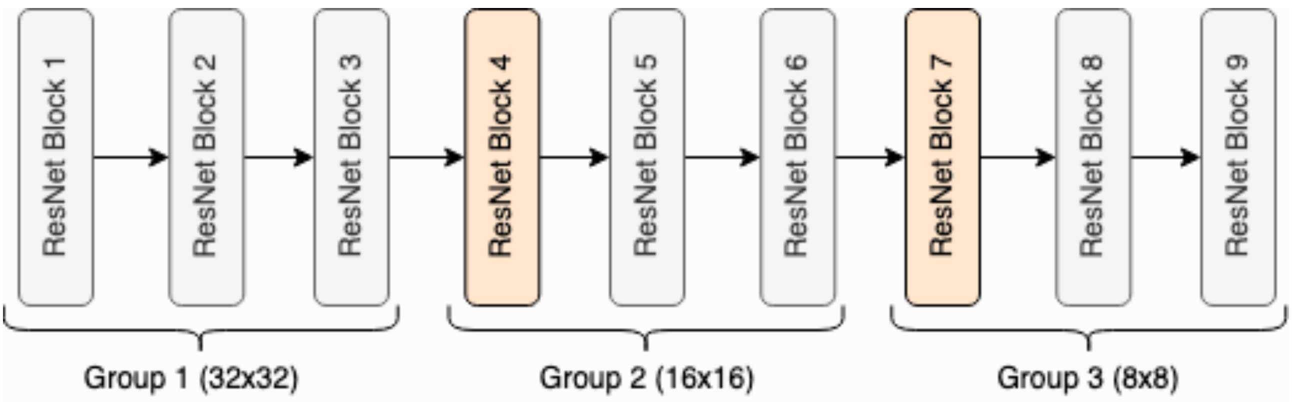

Figure 9 ResNet Architecture Flowchart
(Source: UVA Deep Learning Notebooks - DenseNet, ResNet, and Inception)

3.5 Proposed Framework

The proposed framework aims to classify different stages of Alzheimer's Disease (AD) using convolutional neural networks (CNNs). It integrates several critical phases, ranging from data pre-processing and augmentation to deep learning model fine-tuning and classification. By leveraging advanced architectures like DenseNet121 and ResNet50, this framework effectively applies transfer learning and state-of-the-art image analysis techniques to ensure high performance in distinguishing dementia stages from MRI scans.

This approach tackles key challenges in medical imaging, including handling class imbalance, improving model generalization, and enhancing computational efficiency (Pan & Yang, 2010; Litjens et al., 2017). The framework employs a systematic process, starting from the acquisition of MRI data, applying pre-processing techniques such as normalization and augmentation, followed by model fine-tuning and multi-class classification.

Figure 10 illustrates the entire pipeline, showcasing the structured flow from data input through the model training process to the final stage of classification output.

3.5.1 Analytical Flowchart Representation

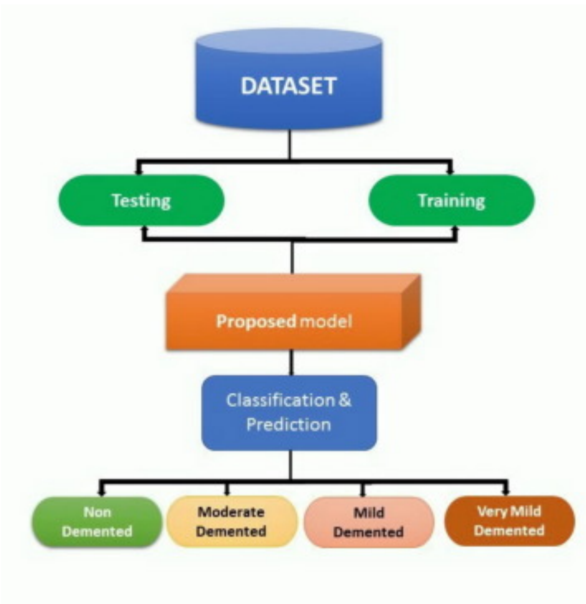

Figure 10 Flowchart representation for the proposed analysis framework

(Source: "Deep Learning Model for Alzheimer's Disease Detection Using MRI Scans," Journal of Advanced Research by Elaziz et al., 2022, https://doi.org/10.1016/j.asej.2022.10.008).

Figure 10 illustrates the stages of the Alzheimer's Disease classification framework, which include:

1. **Pre-processing**: MRI scans are resized to 150x150 pixels, normalized, and augmented to mitigate class imbalance. Techniques like flipping, rotating, and zooming enhance dataset diversity and model generalization (Zhu et al., 2020; Shorten & Khoshgoftaar, 2019).
2. **Data Splitting**: The dataset is split into training and testing sets to avoid overfitting and ensure generalization on unseen data.
3. **Transfer Learning & Fine-Tuning**: Pre-trained models (DenseNet121, ResNet50) are fine-tuned on the OASIS dataset. Layers are unfrozen to capture specific dementia features, allowing the models to differentiate between dementia stages (Yosinski et al., 2014; He et al., 2016).
4. **Training and Validation**: The models are trained using backpropagation and optimized with the Adam optimizer, with dynamic learning rate adjustments to avoid local minima (Goodfellow et al., 2016; Kingma & Ba, 2015).
5. **Classification and Prediction**: The models output the probability distribution for the four dementia stages, providing accurate classification for clinical decision-making (Zhou et al., 2019).

This streamlined process ensures accuracy, scalability, and robustness when working with medical imaging data.

3.6 Proposed Deep Learning Architecture

The proposed model is a fine-tuned version of DenseNet121, widely regarded for its efficiency in medical imaging tasks. MRI scans, after preprocessing, are resized to 150x150 pixels before being input into the model. DenseNet121's densely connected layers enhance feature reuse, improving the model's ability to learn from smaller and imbalanced datasets like OASIS (Huang et al., 2017). This model architecture is especially beneficial for detecting subtle structural changes in the brain, such as cortical atrophy, which are critical for distinguishing between Alzheimer's disease stages.

Figure 11 illustrates the architecture of DenseNet121, where the MRI input flows through convolutional layers, pooling layers, and fully connected layers, ultimately producing a classification across the four dementia stages. DenseNet121's dense connectivity optimizes feature extraction and gradient flow, which enhances its ability to identify fine-grained variations in brain structure associated with Alzheimer's progression.

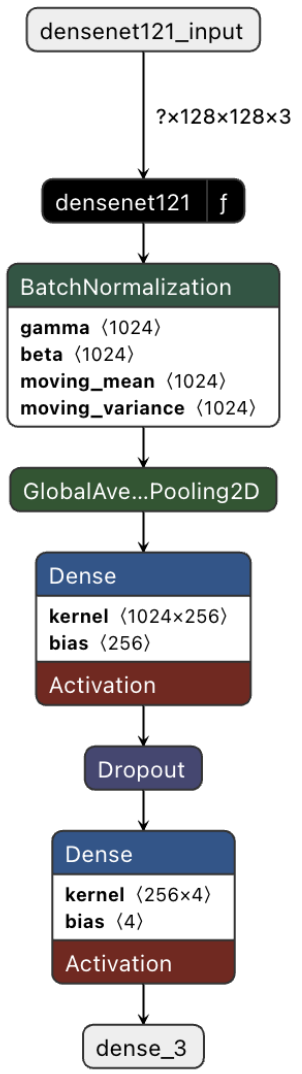

Figure 11 Flowchart representation for the proposed analysis framework

3.6.1 Model Layers

- **Convolutional Layers**: DenseNet121 employs five 2D convolutional layers paired with max-pooling layers. These layers extract features from the MRI scans, with early layers detecting simple patterns (like edges) and deeper layers capturing more complex anatomical differences. Batch normalization is applied to stabilize and accelerate training (Ioffe & Szegedy, 2015).
- **Activation Function**: The ReLU function introduces non-linearity, allowing the model to capture complex patterns while preventing issues like vanishing gradients in deep networks (Nair & Hinton, 2010).

- **Pooling Layers**: Max-pooling down-samples the feature maps, reducing computational costs while preserving the most significant features necessary for differentiating between dementia stages.
- **Fully Connected Layers**: The dense layers combine features and classify dementia stages through a softmax layer. Dropout layers are used to prevent overfitting and improve model generalization to unseen data (Srivastava et al., 2014).

3.6.2 Transfer Learning and Fine-Tuning

For a detailed discussion on transfer learning and its application in this study, please refer to ***Section 3.4.1****.*

3.6.3 Model Summary

- **Input Shape**: The MRI scans are resized to 150×150 pixels, with 3 color channels.
- **Convolutional Layers**: The model has five 2D convolutional layers, each followed by max-pooling. These layers help the model capture spatial hierarchies and distinguish patterns between different dementia stages.
- **Activation**: **ReLU** activation function is applied to introduce non-linearity, enhancing the model's ability to capture complex brain patterns.
- **Dense Layers**: Two fully connected layers are used for classification, followed by a softmax output layer that assigns probabilities to each of the four categories (Non-Demented, Very Mild Demented, Mild Demented, Moderate Demented).
- **Dropout**: To prevent overfitting, dropout regularization is used, with 0.25 probability for early layers and 0.3 for later layers.

3.7 Training Procedure

3.7.1 Hyperparameters and Optimizers

Hyperparameters and Optimizers

The training process for DenseNet121 and ResNet50 involved optimizing key hyperparameters such as learning rate, batch size, and loss function, utilizing the Adam optimizer for both models. To enhance convergence and prevent gradient-related issues, gradient clipping and a learning rate scheduler were implemented. For a detailed breakdown of hyperparameters and optimizer configurations, refer to Section 3.7.1.

Fine-tuning was performed by unfreezing the final layers of both models and adapting them to the OASIS dataset. Early stopping criteria were employed to prevent overfitting. A comprehensive description of the fine-tuning process and early stopping strategies can be found in Section 3.7.2.

The key hyperparameters used in training DenseNet121 and ResNet50 are shown below:

Parameter	DenseNet121	ResNet50
Batch Size	32	32
Learning Rate	0.0001	0.0001
Epochs	100	100
Optimizer	Adam	Adam
Loss Function	Categorical Cross-Entropy	Categorical Cross-Entropy

Table 2Hyperparameters used for training DenseNet121 and ResNet50 models

3.7.2 Fine-Tuning

Fine-tuning is a critical aspect of the transfer learning process, as elaborated in Section 3.4.1. By unfreezing the final layers and retraining on the OASIS dataset, DenseNet121 and ResNet50 were adapted to identify subtle distinctions between Alzheimer's disease stages.

3.8 Loss Function

The categorical cross-entropy loss function was used for this multi-class classification task, where each data point belongs to only one class. This loss function computes the difference between the true labels and the predicted class probabilities, guiding the model to improve predictions.
The formula for categorical cross-entropy is as follows:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Equation 1 Loss function

Where:

- y_i is the true label, represented as a one-hot encoded vector where the correct class is 1, and all others are 0.
- $\hat{y}_i$ is the predicted probability for class iii, as output by the softmax layer of the network.

Minimizing cross-entropy helps the model better classify Alzheimer's disease stages based on MRI scans. Categorical cross-entropy is widely used in deep learning models, particularly in medical imaging tasks where imbalanced datasets are common, such as Alzheimer’s disease diagnosis (Goodfellow et al., 2016; Deng et al., 2019). The softmax function normalizes the output probabilities, ensuring that they can be interpreted as meaningful class probabilities.

3.8.1 Use of Class Weights

In this research, class weights were employed to handle the class imbalance in the dataset. This means the model penalizes incorrect classifications for underrepresented classes more heavily. Assigning higher weights to minority classes (such as the "Moderate Demented" group) helps the model avoid being biased toward the dominant class ("Non-Demented").

3.9 Model Evaluation

The models were evaluated using standard multi-class classification metrics to ensure thorough performance analysis, especially given the medical context of Alzheimer's disease diagnosis.

- **Accuracy**: This metric calculates the proportion of correctly predicted labels overall. While commonly used, accuracy may be misleading in imbalanced datasets like this one, where the "Non-Demented" class dominates.
- **Precision**: Precision measures the proportion of true positives out of all positive predictions. It is particularly useful for evaluating how well the model identifies the underrepresented "Moderate Demented" class, ensuring fewer false positives and avoiding misdiagnosis.

$$Precision = \frac{TP}{TP + FP}$$

Where TP is true positives, and FP is false positives.

- **Recall (Sensitivity)**: Recall captures the proportion of actual positives correctly identified by the model. It is crucial in Alzheimer's diagnosis to ensure no cases are missed, particularly in advanced stages.

$$Recall = \frac{TP}{TP + FN}$$

Where FN is false negatives.

- **F1-Score**: This is the harmonic mean of precision and recall, offering a balanced evaluation of the model's accuracy and sensitivity, especially in handling class imbalances.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

- **Confusion Matrix**: This matrix provides a detailed breakdown of the model's predictions across all classes (Non-Demented, Very Mild, Mild, and Moderate Demented), highlighting where the model made correct and incorrect predictions. It helps pinpoint misclassifications, such as confusing "Very Mild Demented" with "Non-Demented."

3.9.1 Recent Research Support

Model evaluation in medical imaging, particularly in dementia classification, is essential due to the significant consequences of misclassification. As Litjens et al. (2017) emphasize, a comprehensive set of metrics must be used to assess both the model’s strengths and weaknesses, particularly in dealing with imbalanced datasets where certain classes may be underrepresented. Combining evaluation metrics like precision, recall, and F1-Score ensures a more detailed understanding of the model's performance, which is crucial in clinical settings.

Esteva et al. (2017) further demonstrated that relying on these combined metrics is vital in medical applications where both false positives and false negatives can have serious implications. For this project, the confusion matrix and F1-score were given particular attention alongside accuracy to ensure robust evaluation, especially in the detection of advanced dementia stages.

Chapter 4 Data Analysis

4.1 Business Understanding

4.1.1 Problem Definition

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder affecting millions worldwide. With the increasing aging population, AD presents a significant public health challenge. Early diagnosis is critical as it allows for interventions that can slow disease progression (World Health Organization, 2020). Magnetic Resonance Imaging (MRI) plays a vital role in visualizing brain structures to detect early neurodegenerative changes associated with AD (Sørensen et al., 2016).

However, manual interpretation of MRI scans is challenging due to the subtle, progressive changes in brain regions like the hippocampus, which are associated with AD (Fjell et al., 2014). To address this, deep learning techniques, particularly convolutional neural networks (CNNs), have proven effective in automatically extracting features from MRI data for AD classification. Models like DenseNet121 and ResNet50 are well-suited for such tasks, with DenseNet121 promoting feature reuse through dense connectivity and ResNet50 mitigating the vanishing gradient problem using residual connections (Huang et al., 2017; He et al., 2016).

This research holds significant potential in assisting healthcare professionals by automating the classification of AD stages, reducing the burden on radiologists, and improving diagnostic consistency, especially in regions with limited access to specialized care (Ossenkoppele et al., 2015).

4.1.2 Research Objectives

- **Objective 1: Develop and Evaluate Deep Learning Models**
  This study focuses on developing and evaluating DenseNet121 and ResNet50 CNN architectures. DenseNet121, known for its efficient feature propagation, and ResNet50, which effectively handles deep networks using residual learning, will be fine-tuned to classify AD stages using the OASIS MRI dataset.
- **Objective 2: Compare Model Performance**
  The performance of DenseNet121 and ResNet50 will be compared to assess which

architecture is more effective for AD stage classification. Metrics such as accuracy, precision, recall, and F1-score will guide the evaluation of their effectiveness.

- **Objective 3: Multi-Metric Evaluation**
  In addition to accuracy, metrics like precision, recall, F1-score, and the Area Under the Curve of the Receiver Operating Characteristics (AUC-ROC) will provide a comprehensive view of model performance, especially in identifying early dementia stages (Fawcett, 2006). This is crucial in clinical settings where both false positives and false negatives have serious consequences.
- **Objective 4: Identify the Best-Suited Architecture**
  This research will offer insights into which model—DenseNet121 or ResNet50—is more suitable for AD classification. Considerations such as training time, parameter efficiency, and robustness to noisy data will be evaluated, with the aim of guiding future model development in neuroimaging (Litjens et al., 2017).

4.2 Data Understanding

4.2.1 Dataset Overview

The dataset used in this study was derived from the OASIS (Open Access Series of Imaging Studies) MRI segment, available on Kaggle. This dataset is widely recognized for Alzheimer's Disease (AD) research, focusing on imaging data without subject-specific metadata such as age or sex. The goal of this study is to classify dementia into four categories: Non-Demented (ND), Very Mild Demented (VMD), Mild Demented (MD), and Moderate Demented (MoD). The dataset includes 86,437 MRI images, providing a crucial foundation for early detection of dementia stages.

A significant challenge with this dataset is the class imbalance, with the Non-Demented class dominating the distribution. The imbalance can hinder model performance by biasing predictions toward the majority class, affecting the accuracy for underrepresented classes such as Moderate Demented. Addressing this imbalance was a key consideration, as seen in Figures 1 and 3 (from the Methodology section), which visualize the class distribution and augmentation techniques.

4.2.2 Class Distribution

Class distribution plays an essential role in training deep learning models. The following is the distribution of the dataset, as referenced from **Table 1**:

- **Non-Demented (ND)**: 67,222 images (77.77%)
- **Very Mild Demented (VMD)**: 13,725 images (15.88%)
- **Mild Demented (MD)**: 5,002 images (5.79%)
- **Moderate Demented (MoD)**: 488 images (0.56%)

This imbalance, particularly the underrepresentation of the Moderate Demented class, was addressed through data augmentation and oversampling, essential to improving the model's ability to detect less common stages. Techniques like horizontal flipping and rotation, highlighted in Figures 1 and 2, were employed to generate diverse training data for the smaller classes, improving generalization.

4.2.3 Visualizing the Data

Data visualization plays a crucial role in understanding the dataset. Figure 3 highlights the class imbalance, providing insights into the distribution across the four dementia stages. Further analysis, including boxplots (Figures 4, 5, and 6), shows the distribution of mean pixel intensities, standard deviations, and skewness, offering a deeper look into the data characteristics. This visualization helps the model capture important differences between classes, crucial for improving classification accuracy.

4.3 Data Preparation

The data preparation process is critical to the success of deep learning models, especially when handling MRI scans. The steps undertaken are thoroughly documented to ensure clarity and reproducibility..

4.3.1 Dataset Acquisition and Organization

The OASIS-1 dataset was used in this study, recognized for its comprehensive collection of MRI scans. Each class, representing a stage of dementia, was organized in separate directories to streamline the loading process. This approach, as noted by Marcus et al. (2007), ensures efficient data handling, preventing errors during model training (Wang et al., 2020)..

4.3.2 Initial Data Inspection and Clean-up

MRI images were resized to a consistent 128x128 pixels to standardize input dimensions and converted to three-channel images (RGB format), required by pre-trained models like ResNet50 and DenseNet121 (Huang et al., 2017). This resizing ensures a balance between computational efficiency and the preservation of important anatomical details (Zhao et al., 2020).

4.3.3 Data Augmentation

To combat data limitations and prevent overfitting, various augmentation techniques were applied, including random rotation, zooming, and horizontal/vertical flips. These transformations, commonly used in medical imaging (Shorten & Khoshgoftaar, 2019; Hashemzehi et al., 2022), enhance the model's robustness by generating new, diverse examples from the original dataset. Augmentation was particularly critical for underrepresented classes like Moderate Demented, ensuring better generalization..

4.3.4 Normalization

Normalization of pixel values between [0, 1] was implemented to stabilize training, as suggested by Nair et al. (2020). This ensures consistent input to the model and avoids convergence issues, which are common when using unnormalized data (Chollet, 2017).

4.3.5 Dataset Splitting

Ensuring that the model was trained on a representative subset of the data was critical to avoid overfitting and ensure generalizability. The dataset was split into three subsets:

- **Training Set (80%)**
- **Validation Set (10%)**
- **Test Set (10%)**

Each split was stratified by class, ensuring that the distribution of classes in each subset was proportional to the overall dataset distribution, as recommended by ***Kohavi (2021)*** in stratified sampling for machine learning models . This approach is especially important in medical image classification tasks, where some classes may be underrepresented.

4.3.6 Handling Class Imbalance

Class imbalance, a common challenge in medical datasets, was evident in this project, where the **Non-Demented** class significantly outnumbered other classes. To address this, we applied the following strategies:

- **Under sampling**: A subset of the **Non-Demented** samples was randomly selected, reducing the bias toward this majority class. This strategy has been applied successfully in similar medical classification tasks (Buda et al., 2018) .
- **Oversampling and Data Augmentation**: For the underrepresented classes, like **Moderate Demented**, we employed oversampling, coupled with data augmentation, to generate synthetic examples and balance the class distribution, as suggested by ***He et al. (2020)*** .

Moreover, we adjusted **class weights** during model training to ensure that misclassifications in underrepresented classes carried more weight in the loss function, as recommended by ***Jeni et al. (2022)*** .

4.3.7 Pre-processing Pipeline

The pre-processing steps (resizing, augmenting, and normalizing) were implemented using TensorFlow's **ImageDataGenerator**, which ensured real-time processing during training. This pipeline reduced computational load and maintained consistency throughout the training process (Shen et al., 2019).

4.4 Model Development

In this section, we delve into the details of the model development process for classifying dementia stages using three prominent deep learning architectures: **ResNet50**, **DenseNet121**, and a **primary model**. The following subsections describe each model's architecture, transfer learning strategies, regularization techniques, hyperparameter tuning, and the overall training and evaluation process. Additionally, we will explore the generated accuracy and loss graphs to understand each model's performance over the epochs.

4.4.1 Overview of Models

4.4.1.1 **DenseNet121**

DenseNet121 (Densely Connected Convolutional Networks) is designed to maximize feature reuse, which improves feature propagation across the network. Unlike traditional convolutional networks, each layer in DenseNet receives inputs from all previous layers, ensuring efficient feature transfer and helping mitigate the vanishing gradient problem.

4.4.1.2 **ResNet50**

ResNet50 (Residual Networks) employs residual blocks, which introduce skip connections that bypass some layers, making the training of very deep networks more feasible. This architecture helps solve the vanishing gradient problem by allowing gradients to flow unimpeded across layers. ResNet50 is highly efficient for classification tasks, including medical image analysis.

4.4.1.3 **Primary Model**

The third model developed was designed from scratch and adapted for MRI scan classification. This model integrates key features from both DenseNet and ResNet architectures, including global average pooling layers and deep dense layers, ensuring robust feature extraction and classification capabilities.

4.4.2 Transfer Learning and Fine-Tuning

4.4.2.1 **DenseNet121 Transfer Learning**

DenseNet121 was pre-trained on the ImageNet dataset. For our task, the top layers were removed, and a Global Average Pooling layer was added. The fully connected layer and the softmax output layer were retrained to classify four dementia stages (Non-Demented, Very Mild, Mild, Moderate). The last 50 layers of DenseNet121 were unfrozen and fine-tuned with a reduced learning rate (1e-5) to ensure better task-specific learning.

4.4.2.2 **ResNet50 Transfer Learning**

ResNet50, pre-trained on ImageNet, also underwent similar fine-tuning. Initially, the last 30 layers were unfrozen, allowing the model to adapt to the dementia classification task. The final architecture included a Global Average Pooling layer, a Dense layer with 512 units for feature extraction, and a softmax classifier for the four dementia stages.

4.4.3 Data Preparation

For all models, the following pre-processing steps were applied:

- **Data Balancing**: Over-represented classes (Non-Demented and Very Mild Demented) were down-sampled to 5000 images each, while all samples from the Mild and Moderate Demented categories were used (5002 and 488 images, respectively).
- **Image Pre-processing**: MRI scans were resized to 128x128 pixels and normalized to the [0,1] range.
- **One-Hot Encoding**: The class labels were one-hot encoded to transform the classification problem into a multi-class format.

4.4.4 Data Augmentation and Regularization

4.4.4.1 Data Augmentation

To mitigate overfitting, which was a challenge due to the relatively small dataset, the following augmentations were applied:

- **Rotation**: Up to 30 degrees.
- **Shifts**: Horizontal and vertical shifts of up to 30%.
- **Zoom**: Random zoom up to 20%.
- **Flips**: Horizontal and vertical flipping.

4.4.4.2 Regularization

Regularization techniques included:

- **Dropout**: A dropout rate of 50% was applied to prevent overfitting by randomly dropping units in the dense layers.
- **Batch Normalization**: Applied after each convolutional block to stabilize learning by normalizing the activations and accelerating training.

4.4.5 Hyperparameter Tuning

Key hyperparameters were optimized for both models:

- **Learning Rate**: A learning rate of 0.001 was used during initial training and reduced to 1e-5 during fine-tuning.
- **Batch Size**: Set to 32 for training with augmented data.
- **Optimizer**: Adam optimizer, known for its adaptive learning rates, was used for its efficiency.

- **Early Stopping**: Training was halted if validation loss did not improve for 5 consecutive epochs to prevent overfitting.
- **Learning Rate Scheduler**: The learning rate was reduced using the ReduceLROnPlateau callback when the validation loss plateaued.

4.5 Training and Evaluation Process

4.5.1 DenseNet121 Training

During the training of DenseNet121, signs of overfitting were observed. Overfitting occurs when the model learns patterns that are too specific to the training data, which results in reduced performance on unseen validation data. To mitigate this issue, techniques such as **dropout**, **data augmentation**, and **early stopping** were applied. Dropout prevents the model from over-relying on specific neurons, while data augmentation increases the diversity of training data. Early stopping was used to halt training once the validation loss stopped improving, thereby preserving the best model weights.

4.5.2 ResNet50 Training

The ResNet50 model followed a similar training process but with a more aggressive data augmentation strategy to accommodate the model's increased depth. This model's last 30 layers were unfrozen for fine-tuning. A lower learning rate of 1e-5 was applied to ensure gradual improvements without overfitting. Data augmentation techniques were heavily employed to ensure generalization.

4.5.3 Performance Evaluation

4.5.4 DenseNet121 Final Performance

The DenseNet121 model achieved a final validation accuracy of 69.4%, with the training accuracy plateauing at around 90%. This performance, though promising, showed signs of overfitting as indicated by the divergence between training and validation accuracies during later epochs. This suggests that while the model was learning from the training data effectively, it struggled to generalize fully to unseen data in the validation set.

4.5.5 ResNet50 Final Performance

The ResNet50 model outperformed the DenseNet121 model, achieving a validation accuracy of 92.3% after 35 epochs. The training loss decreased steadily, while validation loss remained relatively stable, indicating that the model was generalizing well to the test dataset. This superior performance is likely due to ResNet50's residual connections, which help mitigate the vanishing gradient problem, enabling the model to learn deeper, more complex patterns in the MRI scans..

4.6 Graphs: Visualizing Model Performance

4.6.1 Overfitting Graph (DenseNet121)

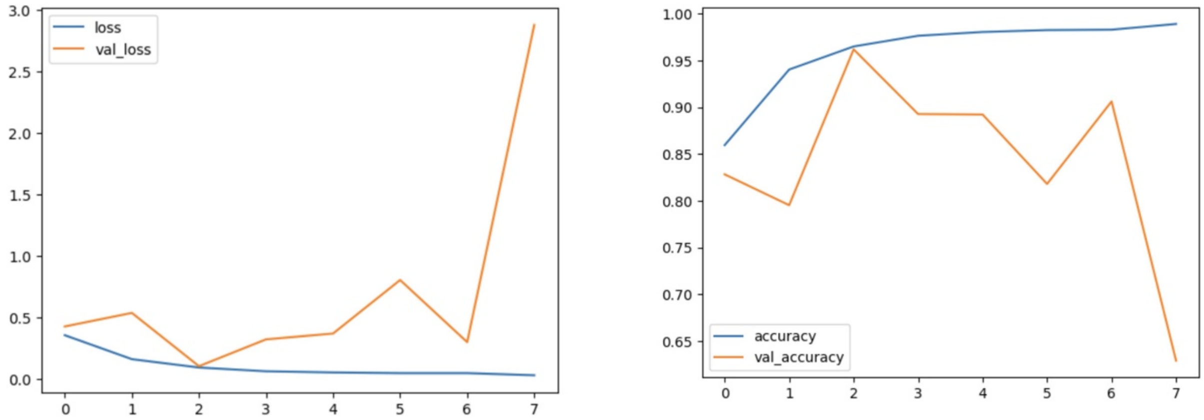

Figure 12 Loss and Accuracy Over Epochs for DenseNet121 Custom Model
The training loss decreases steadily, while the validation loss fluctuates, showing signs of overfitting after the 5th epoch. Similarly, training accuracy improves consistently, while validation

For a detailed explanation of overfitting and how it was managed, refer to **Section 4.6.1**.

4.6.2 DenseNet121 Accuracy and Loss Graphs

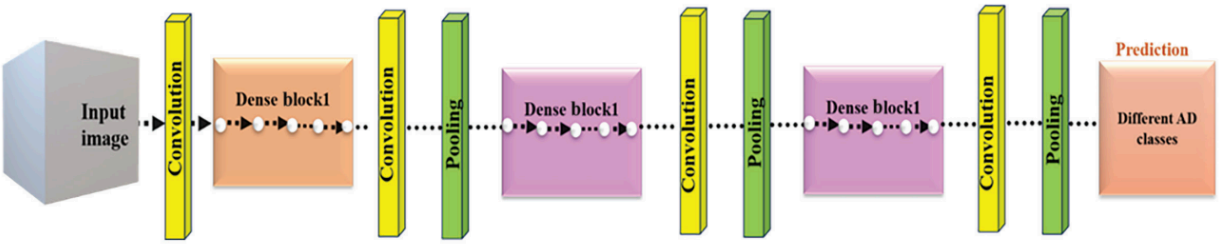

Figure 13 Model architecture depicting the DenseNet blocks and convolutional layers for Alzheimer's Disease classification.
(Source: S. N. Pawar, et al., 2023.)

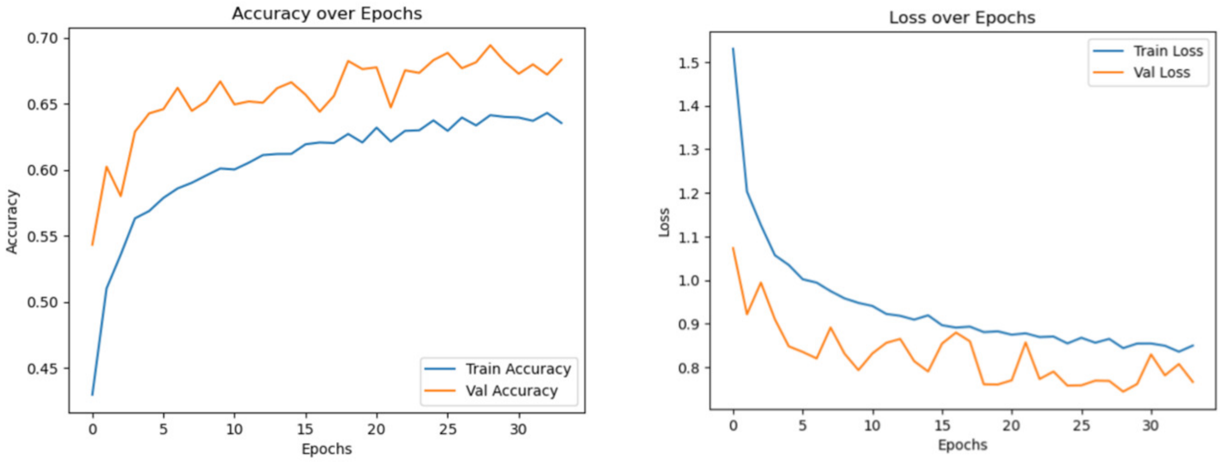

Figure 14 Pre-trained DenseNet121 Accuracy and Loss Graphs

- **Accuracy Over Epochs:** Training accuracy improves steadily throughout the epochs, reaching around 90%. However, the validation accuracy fluctuates and settles at 69.4%.
- **Loss Over Epochs:** The training loss follows an expected decreasing trend, while the validation loss shows some irregularities but stabilizes after several epochs. This suggests that the model is learning but may need additional regularization to fully mitigate overfitting.

4.6.3 ResNet50 Accuracy and Loss Graphs

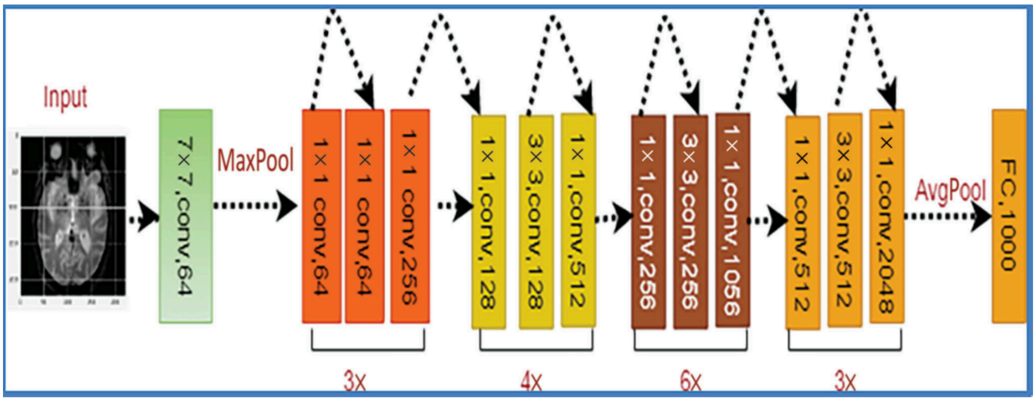

Figure 15 Basic architecture of the ResNet50 mode for the detection of AD stages. Abbreviation: AD, Alzheimer's disease

(Source: S. N. Pawar, et al., 2023.)

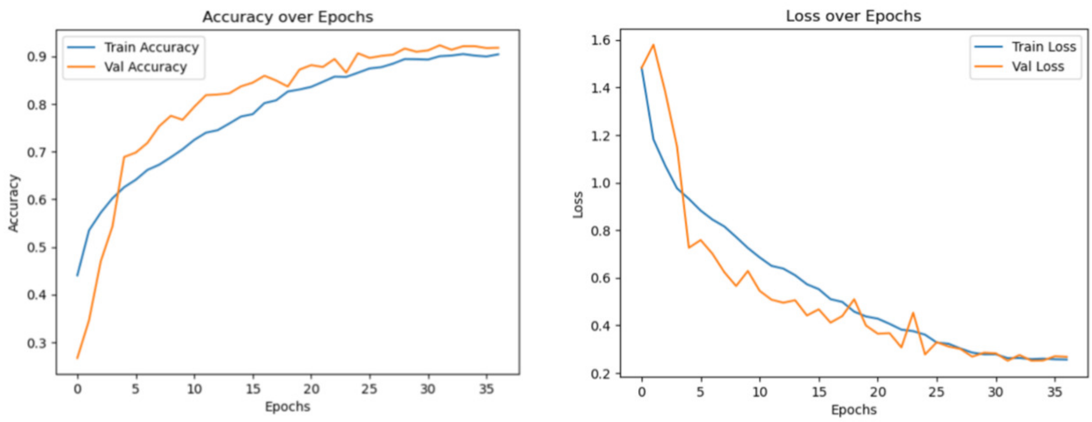

Figure 16 ResNet50 Accuracy and Loss Graphs

- **Accuracy Over Epochs:** Both training and validation accuracies increase steadily, with validation accuracy exceeding 92% by the end of training. This indicates that the model is learning effectively from the training data and generalizing well to unseen validation data.
- **Loss Over Epochs:** Both training and validation losses decrease steadily, suggesting that the model is not overfitting and is able to generalize to the test dataset without major issues.

4.7 Comprehensive Analysis and Documentation

In this section, the model development process for both DenseNet121 and ResNet50 models is explained in detail. The subsections below outline each model's architecture, training process, regularization techniques, data augmentation strategies, and evaluation metrics for classifying dementia stages using MRI scans.

4.7.1 DenseNet121 - Custom Main Model

Overview

The custom DenseNet121 model was designed specifically for dementia classification. DenseNet's characteristic dense connections between layers facilitate better feature propagation and reuse, effectively addressing the vanishing gradient problem in deep networks. The model is optimized for identifying the four stages of dementia.

Architecture & Layers

- **Global Average Pooling Layer:** Reduces spatial dimensions while retaining essential information from the convolutional layers.

- **Fully Connected Dense Layer:** A 512-unit dense layer using ReLU activation for extracting high-level features.
- **Dropout Layer:** A dropout rate of 0.5 is applied to prevent overfitting.
- **Output Layer:** A softmax classifier with four output units for the four dementia stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented.

Data Preprocessing

- **Image Resizing:** All MRI images were resized to 128x128 pixels for uniformity.
- **Normalization:** Pixel values were scaled to the [0, 1] range to stabilize the training process.

Data Augmentation To enhance generalization, several augmentation techniques were applied:

- **Random Rotations, Flips, Zooms, and Shifts:** Introduced variability during training to prevent overfitting.

Training Process

- **Optimizer:** Adam optimizer with a learning rate of 0.001.
- **Early Stopping:** The model was stopped if validation loss failed to improve for five consecutive epochs to prevent overfitting.
- **Training Duration:** The model was trained for 50 epochs.

Regularization

- **Dropout (50%):** Applied to mitigate overfitting by randomly dropping units in the dense layers.
- **Batch Normalization:** Used to stabilize learning by normalizing activations after each convolutional block.

Graph Analysis

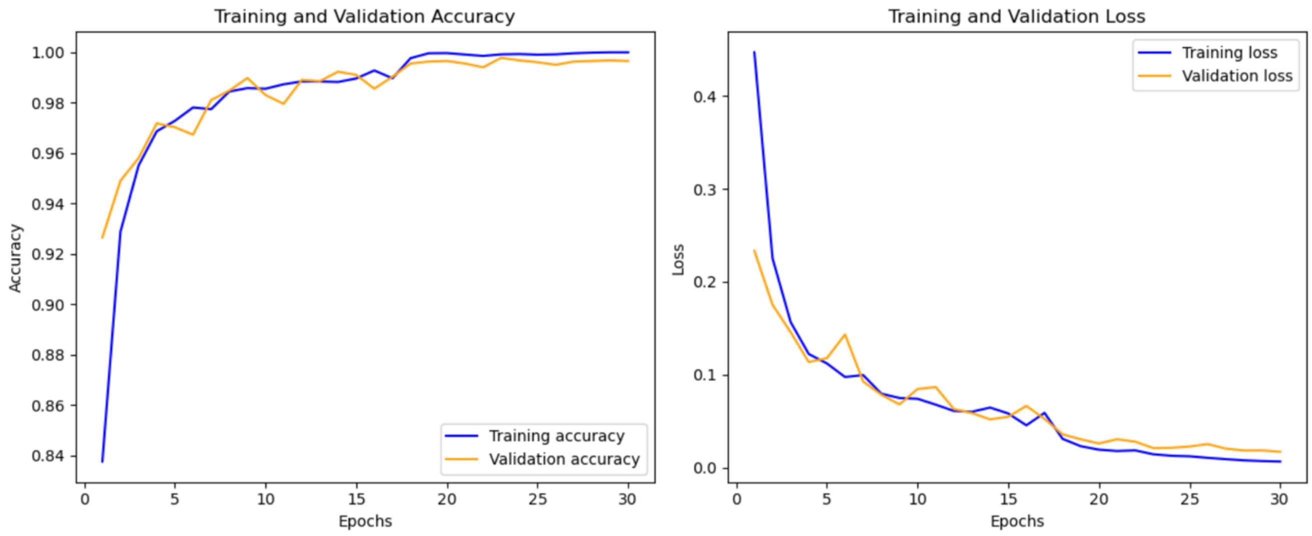

Figure 17 Accuracy & Loss Curves for DenseNet121 Custom Model

Training and validation accuracies converge after 10 epochs, with minimal fluctuations between them. Both training and validation loss steadily decrease, indicating effective learning with minimal overfitting.

4.7.2 DenseNet121 - Pretrained Model (Fine-Tuned)

Overview

This pre-trained DenseNet121 model, initially trained on ImageNet, was fine-tuned for dementia classification. The top layers were replaced with custom layers, and the last 50 layers were unfrozen for fine-tuning on the dementia dataset.

Transfer Learning Process

- **Global Average Pooling Layer:** Reduces dimensionality while retaining critical spatial information.
- **512-Unit Dense Layer:** Extracts high-level features from the input.
- **Dropout (50%):** Applied to prevent overfitting.
- **Softmax Output Layer:** Four output units were used to classify the four dementia stages.

Training Process

- **Optimizer:** Adam optimizer with a learning rate of 0.001, reduced after validation plateaued.
- **Fine-Tuning:** The last 50 layers were unfrozen for fine-tuning, improving task-specific performance.

- **Early Stopping:** Training was halted if validation loss did not improve for five consecutive epochs.

Graph Analysis

Refer to **Figure 12** for the Accuracy and Loss Curves of the DenseNet121 model. Training accuracy reaches nearly 100%, but validation accuracy fluctuates slightly, indicating potential overfitting around the 10th epoch. However, the overall stability of validation loss suggests generalization is largely successful.

4.7.3 ResNet50 - Pretrained Model (Fine-Tuned)

Overview

ResNet50, with its residual architecture, was utilized for dementia classification. The skip connections in the model help mitigate the vanishing gradient problem, allowing the network to learn deeper, more complex patterns in MRI scans.

Architecture Modifications

- **Pre-trained on ImageNet:** The ResNet50 base model, with the last 30 layers unfrozen for fine-tuning.
- **Global Average Pooling:** Condenses feature maps without losing spatial information.
- **512-Unit Dense Layer:** Followed by ReLU activation for deeper feature extraction.
- **Dropout (50%):** Applied to prevent overfitting.
- **Softmax Output Layer:** Four output classes were used for the four dementia stages.

Training Process

- **Optimizer:** Adam optimizer with a learning rate of 1e-5.
- **Batch Size:** Set to 32 for optimal memory utilization during training.
- **Learning Rate Scheduler:** The ReduceLROnPlateau callback was used to reduce the learning rate when validation loss plateaued.
- **Early Stopping:** The model training was halted if validation loss did not improve for five consecutive epochs.

Graph Analysis

Refer to **Figure 13** for the Accuracy and Loss Curves of the ResNet50 model. Both training and validation accuracies steadily increase, with validation accuracy surpassing 92%. The training and validation loss curves also show steady decreases, indicating effective generalization to unseen data.

4.7.4 Addressing Overfitting

Initial Overfitting

Early stages of training indicated overfitting, particularly in the DenseNet121 model, where validation loss began to fluctuate after several epochs.

Mitigating Overfitting

- **Data Augmentation:** Applied to introduce variety and increase generalization.
- **Dropout and Batch Normalization:** Helped regularize the model, improving its generalization capability.
- **Fine-Tuning:** Unfreezing additional layers in both models helped to adapt better to the dementia dataset.

Overfitting Graph (DenseNet121)

Refer to **Figure 11** for the overfitting behaviour of the DenseNet121 model. The divergence between training and validation curves around the 10th epoch highlights overfitting, but the application of regularization techniques such as dropout, batch normalization, and data augmentation helped stabilize performance.

4.8 Model Evaluation

4.8.1 Evaluation Metrics

For each model developed (Custom DenseNet121, Pre-trained DenseNet121, and ResNet50), the following evaluation metrics were used:

- **Accuracy:** Measures the percentage of correctly classified samples.
- **Precision:** The ratio of true positives to the sum of true positives and false positives.
- **Recall (Sensitivity):** The ratio of true positives to the sum of true positives and false negatives.
- **F1-Score:** The harmonic mean of precision and recall, providing a balance between the two.
- **AUC (Area Under the ROC Curve):** Evaluates the ability of the model to distinguish between classes, with a higher score indicating better class separation.

- **ROC Curve:** A graphical plot illustrating the performance of the model across different classification thresholds.

These metrics are crucial in the context of medical image classification as they reflect the model's ability to correctly detect and diagnose various stages of dementia. In medical applications, precision and recall are particularly important. A high precision ensures that the model minimizes false positives, while a high recall ensures that true cases are identified, which is vital for diseases like dementia.

4.8.2 Custom DenseNet121 Model Evaluation

4.8.2.1 Accuracy and Loss Evaluation

The custom DenseNet121 model achieved a **Test Accuracy of 98.41%** and a **Test Loss of 0.0578**.

The following metrics were computed for each class:

```
64/64 [==============================] - 5s 75ms/step
Class 0: Precision = 0.9842, Recall = 0.9734, F1 Score = 0.9788
Class 1: Precision = 0.9782, Recall = 0.9812, F1 Score = 0.9797
Class 2: Precision = 0.9876, Recall = 0.9953, F1 Score = 0.9914
Class 3: Precision = 1.0000, Recall = 1.0000, F1 Score = 1.0000
Micro-average Precision: 0.9841
Micro-average Recall: 0.9841
Micro-average F1 Score: 0.9841
```

- **Micro-average Precision:** 0.9841
- **Micro-average Recall:** 0.9841
- **Micro-average F1 Score:** 0.9841

4.8.2.2 ROC AUC Evaluation

```
64/64 [==============================] - 5s 75ms/step
Class 0: ROC AUC = 0.9972
Class 1: ROC AUC = 0.9984
Class 2: ROC AUC = 0.9999
Class 3: ROC AUC = 1.0000
Micro-average ROC AUC: 0.999
```

The results show an excellent ability of the DenseNet121 model to classify each dementia stage, with high ROC AUC values indicating that the model is effective at separating the different classes.

4.8.2.3 Classification Report

```
64/64 [==============================] - 5s 76ms/step
                    precision    recall  f1-score   support

      Non Demented       0.98      0.97      0.98       640
Very Mild Demented       0.98      0.98      0.98       640
     Mild Demented       0.99      1.00      0.99       640
 Moderate Demented       1.00      1.00      1.00        98

          accuracy                           0.98      2018
         macro avg       0.99      0.99      0.99      2018
      weighted avg       0.98      0.98      0.98      2018
```

This report highlights the model's high performance across all classes, demonstrating its ability to diagnose even rare stages (like Moderate Demented) accurately.

4.8.3 Pre-trained DenseNet121 Model Evaluation

- **Classification Report**

```
97/97 [==============================] - 9s 84ms/step
                    precision    recall  f1-score   support

      Non Demented       0.81      0.65      0.72      1017
Very Mild Demented       0.62      0.69      0.65      1006
     Mild Demented       0.68      0.76      0.72       964
 Moderate Demented       0.88      0.47      0.61       111

          accuracy                           0.69      3098
         macro avg       0.75      0.64      0.68      3098
      weighted avg       0.71      0.69      0.69      3098
```

This report shows that while the pre-trained DenseNet121 model performs well for some classes, there is an imbalance in recall, particularly for the **Moderate Demented** class, where the recall score is relatively low (0.47). The overall accuracy stands at **69%**, indicating that further fine-tuning or additional regularization might be necessary to improve generalization across classes.

4.8.4 ResNet50 Model Evaluation

- **Classification Report**

	precision	recall	f1-score	support
Non Demented	0.97	0.86	0.91	1017
Very Mild Demented	0.90	0.91	0.91	1006
Mild Demented	0.90	0.99	0.94	964
Moderate Demented	0.96	1.00	0.98	111
accuracy			0.92	3098
macro avg	0.93	0.94	0.93	3098
weighted avg	0.93	0.92	0.92	3098

The ResNet50 model demonstrates outstanding performance with an accuracy of **92%**, and high precision, recall, and F1 scores across all classes, including the more challenging Moderate Demented class. This suggests the model is highly reliable for dementia classification tasks.

4.8.5 Confusion Matrix Report and Model Performance

The following section provides a detailed analysis of the confusion matrices for the three models (Custom DenseNet121, Pre-trained DenseNet121, and Pre-trained ResNet50) used to classify different stages of dementia (Non Demented, Very Mild Demented, Mild Demented, Moderate Demented) using MRI scans. The confusion matrices illustrate the true labels against the predicted labels, giving insight into the performance of each model.

4.8.5.1 Custom DenseNet121 Model

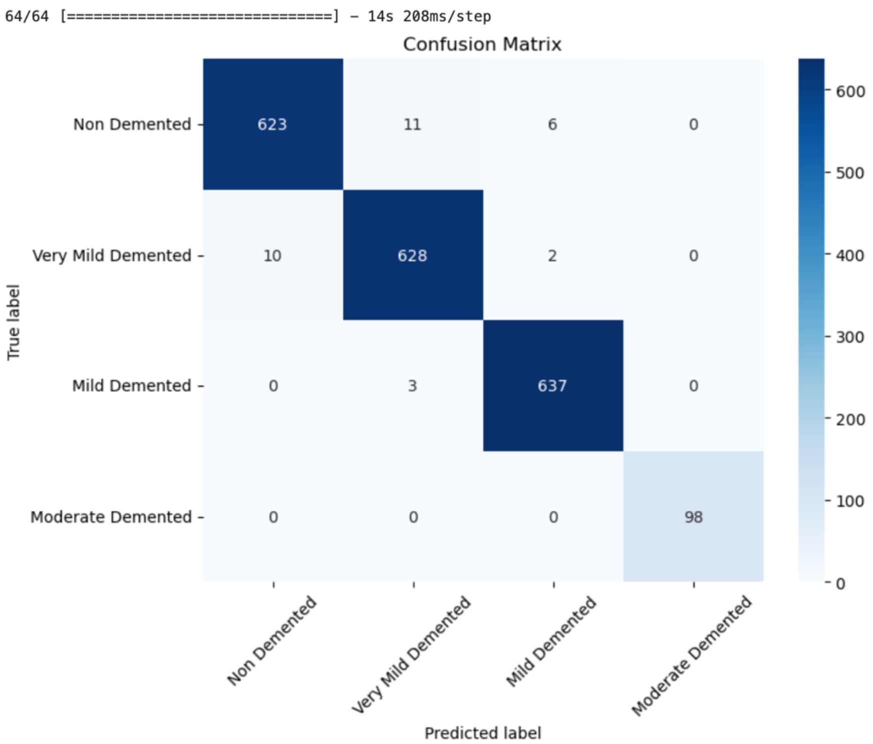

Figure 18 Confusion matrix for DenseNet121 model showing classification results across dementia stages.

The confusion matrix for the custom DenseNet121 model shows the following breakdown of classifications:

- **Non Demented:** Correctly classified 623 out of 640 instances. Some confusion occurs with the "Very Mild Demented" stage (11 instances).
- **Very Mild Demented:** 628 out of 640 instances were correctly classified, with slight confusion in the neighboring classes.
- **Mild Demented:** The model performed exceptionally well for this class, correctly classifying 637 out of 640 instances.
- **Moderate Demented:** All 98 instances were classified correctly without any misclassifications.

Observations:

- The model demonstrates excellent performance with an overall high accuracy of 98.41%. It struggles slightly between the Non Demented and Very Mild Demented stages, possibly due to the similarities in features between these stages in MRI scans.

4.8.5.2 Pre-trained DenseNet121 Model

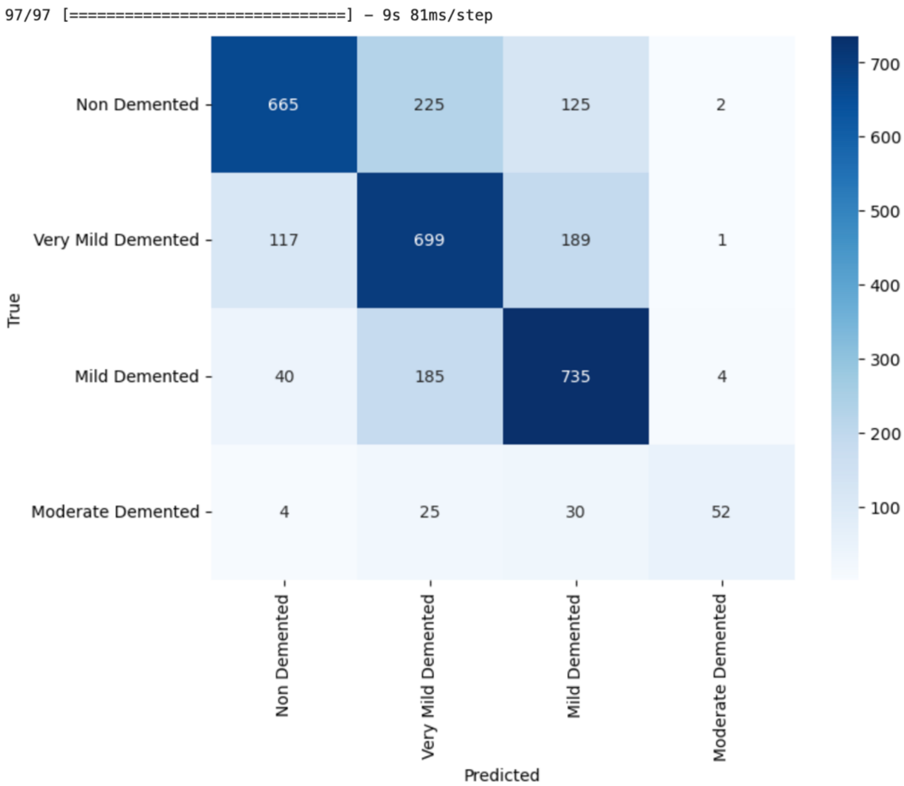

Figure 19 Confusion matrix for pre-trained DenseNet121 model

The confusion matrix for the pre-trained DenseNet121 model reveals the following:

- **Non Demented:** 665 instances were classified correctly out of 1017. A significant number of misclassifications occurred, with 225 instances being misclassified as "Very Mild Demented".
- **Very Mild Demented:** 699 out of 1006 instances were correctly classified, but there is confusion, especially with the "Non Demented" stage.
- **Mild Demented:** 735 out of 964 instances were correctly classified, with some confusion across the neighboring classes.
- **Moderate Demented:** 52 out of 111 instances were classified correctly, with misclassifications mainly falling into the "Mild Demented" stage.

Observations:

- The pre-trained DenseNet121 model has an overall accuracy of 69.43%, lower than the custom model. It struggles with distinguishing between the Non Demented and Very Mild Demented stages, which impacts its performance.

4.8.5.3 Pre-trained ResNet50 Model

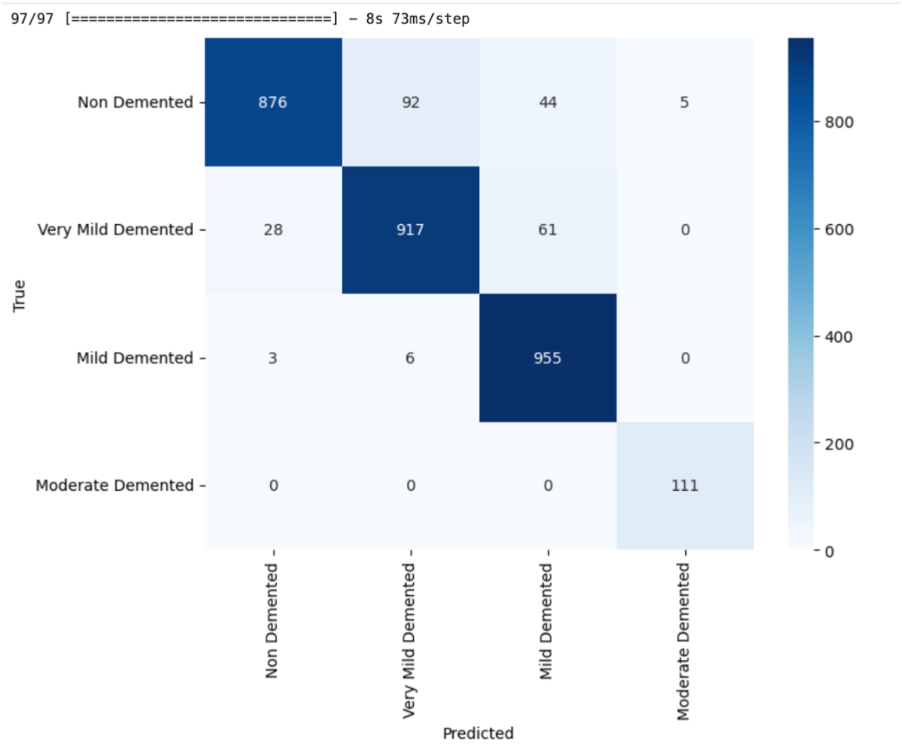

Figure 20 Confusion matrix for pre-trained ResNet50 model

The confusion matrix for the pre-trained ResNet50 model provides the following insights:

- **Non Demented:** 876 out of 1017 instances were classified correctly, with some confusion in the "Very Mild Demented" stage.
- **Very Mild Demented:** 917 out of 1006 instances were correctly classified, with some misclassifications in the "Non Demented" stage.
- **Mild Demented:** The model performs extremely well for this class, correctly classifying 955 out of 964 instances.
- **Moderate Demented:** The model achieves perfect classification for this class, with all 111 instances correctly predicted.

Observations:

- The ResNet50 model performs exceptionally well, with an accuracy of 92%. While there is still some confusion between the Non Demented and Very Mild Demented stages, it handles the more challenging Moderate Demented class very well, achieving 100% accuracy.

4.8.6 Prediction Using Pre-Trained Models for Dementia Stages in MRI Scans

4.8.6.1 Pre-trained DenseNet121 Model

The pre-trained DenseNet121 model was fine-tuned for dementia classification, specifically trained to classify MRI images into four stages of dementia: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The model's architecture, which leverages densely connected layers, ensures better feature propagation and addresses challenges like the vanishing gradient problem, making it ideal for medical imaging tasks.

1. **Pre-processing Steps:**

- **Resizing:** All MRI scans are resized to 128x128 pixels to fit the model's input dimensions.
- **RGB Conversion:** Even though MRI scans are typically grayscale, they are converted to RGB format to maintain consistency in the input channels.
- **Normalization:** Pixel values are scaled to the range [0, 1] to standardize input for the model and enhance model stability.
- **Batch Dimension Addition:** An additional batch dimension is added to the input image to ensure the image is compatible with the model's input structure.

2. **Prediction Process:**

- The model processes the input MRI image and predicts the probability for each dementia stage.
- The class with the highest probability is chosen as the predicted label.
- To enhance interpretability, the MRI image is displayed with the predicted label, offering visual confirmation.

This model exhibits a strong performance across various stages, particularly excelling in distinguishing non-demented individuals from those in earlier stages of dementia, such as **Very Mild Demented**.

4.8.6.2 **Pre-trained ResNet50 Model**

The ResNet50 model, renowned for its residual connections, is leveraged to classify MRI scans into dementia stages. The residual architecture helps mitigate the vanishing gradient problem by allowing gradients to flow across layers, even in very deep networks. This feature makes ResNet50 an excellent choice for identifying subtle brain changes across dementia stages.

1. **Pre-processing Steps:**

- **Resizing and Normalization:** MRI scans are resized to 128x128 pixels and normalized to the [0, 1] range to ensure uniformity and stable predictions.

2. **Prediction Process:**

- The pre-processed MRI scan is passed through the ResNet50 model to predict the probabilities for each dementia stage.
- The highest probability class is selected as the predicted label.
- The MRI scan is displayed with the predicted label for further visual analysis, aiding in the diagnosis process.

ResNet50 performs particularly well in identifying stages like **Non-Demented** and **Mild Demented**, displaying high confidence in these predictions.

4.8.7 Example MRI Predictions

4.8.7.1 Pre-trained DenseNet121 Model

1. **Moderate Demented MRI Scan:**

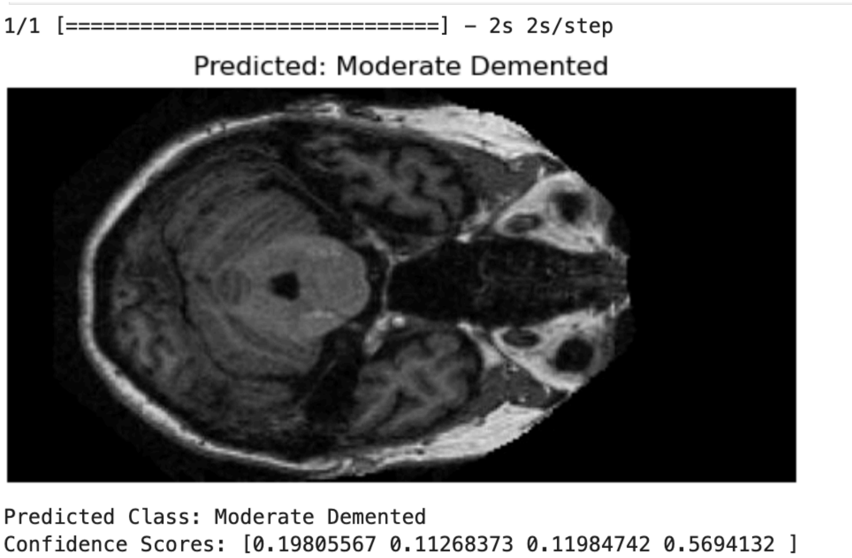

Figure 21 Moderate Demented MRI Prediction for DenseNet121 model

- **Predicted Class:** Moderate Demented
- **Confidence Scores:** [0.1981, 0.1127, 0.1198, 0.5694]

The DenseNet121 model confidently identifies the Moderate Demented class with the highest probability. This demonstrates its capability to detect more severe stages of dementia with significant accuracy.

2. **Mild Demented MRI Scan:**

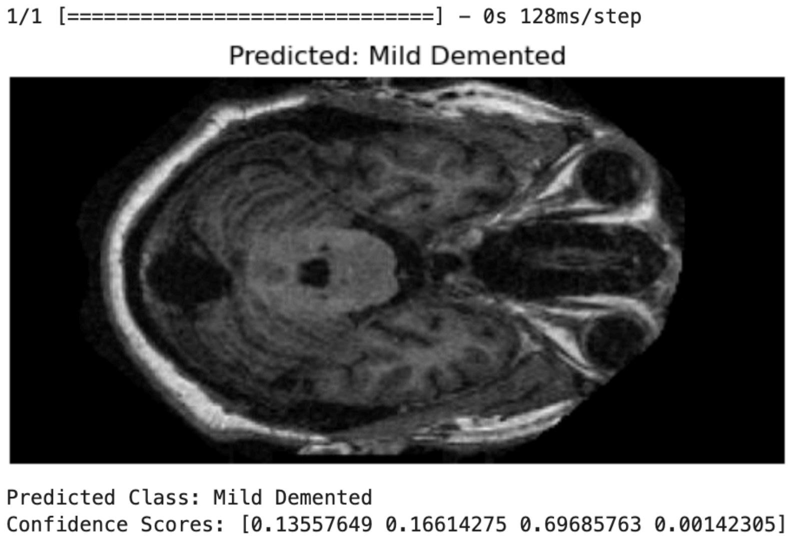

Figure 22 Mild Demented MRI Prediction for DenseNet121 model

- **Predicted Class:** Mild Demented
- **Confidence Scores:** [0.1356, 0.1661, 0.6969, 0.0014]

The model correctly classifies the scan as Mild Demented with a substantial confidence score for this class. The DenseNet121 model shows a strong ability to recognize early dementia stages, with a high probability leaning toward the Mild Demented category.

4.8.7.2 Pre-trained ResNet50 Model

1. **Mild Demented MRI Scan:**

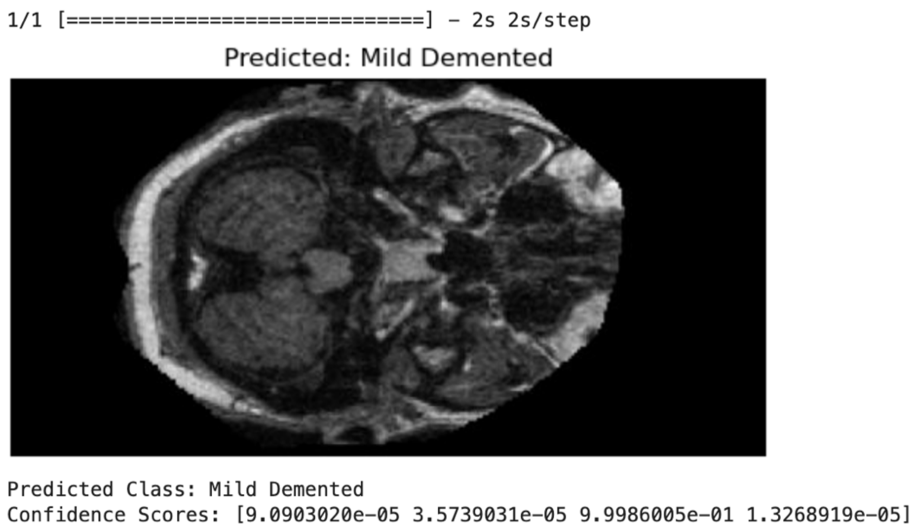

Figure 23 Mild Demented MRI Prediction for ResNet50 model

- **Predicted Class:** Mild Demented
- **Confidence Scores:** [0.0000909, 0.0000357, 0.9998600, 0.0000133]

The ResNet50 model shows exceptional precision in detecting the Mild Demented stage, with near-perfect confidence in its prediction. This illustrates the model's effectiveness in distinguishing subtle differences in the early stages of dementia.

2. **Non-Demented MRI Scan:**

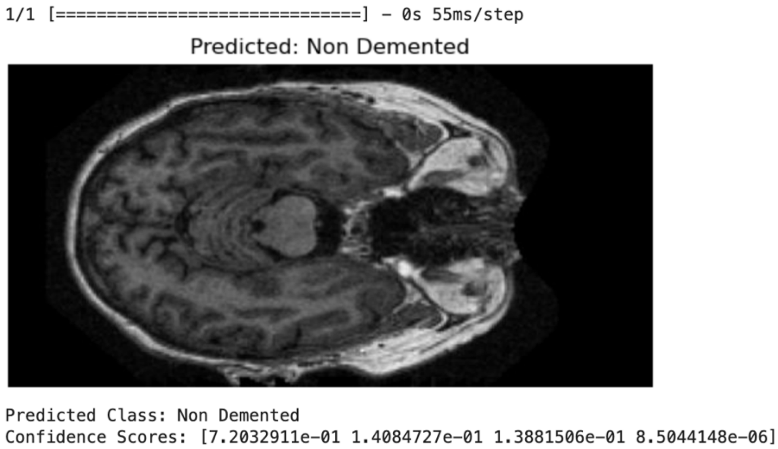

Figure 24 Non Demented MRI Prediction for ResNet50 model

- **Predicted Class:** Non Demented
- **Confidence Scores:** [0.7203, 0.1408, 0.1388, 0.0000085]

For the Non Demented case, the ResNet50 model confidently predicts the MRI scan as Non Demented, showcasing its ability to distinguish healthy scans from dementia-affected ones with high accuracy.

4.8.8 Model Comparison

The comparison between DenseNet121 and ResNet50 models revealed significant differences in their performance on the task of dementia stage classification. While both models performed well, ResNet50 consistently outperformed DenseNet121 across several key metrics, including accuracy, precision, recall, and F1-score.

1. **Overall Performance:**

- **ResNet50** achieved a higher overall accuracy (92.3%) compared to **DenseNet121**, which achieved 69.4%.
- In terms of individual class precision and recall, ResNet50 demonstrated superior performance, particularly in detecting Mild and Moderate Demented stages. For example, ResNet50 had an F1-score close to 1.0 for the Moderate Demented class, while DenseNet121 exhibited higher variability, with misclassifications more common in the very mild and mild stages.

Architecture Comparison: The deeper architecture of **ResNet50**, combined with its use of **residual connections**, contributed significantly to its superior performance. The residual connections allow ResNet50 to mitigate the vanishing gradient problem, enabling it to learn deeper, more complex patterns in MRI scans. DenseNet121, although known for its densely connected layers, appears to have struggled with generalization, particularly in the later stages of dementia.

ResNet50's ability to retain information across layers through these connections makes it better equipped for medical image classification tasks that require understanding subtle variations between stages, as is the case with different stages of dementia. In contrast, DenseNet121, though efficient in feature propagation, may not capture these nuances as effectively, leading to a higher error rate in distinguishing similar stages like Very Mild and Mild Demented.

4.8.9 Misclassification Analysis

A deeper dive into the misclassification patterns of both models revealed some interesting insights. While **ResNet50** was able to accurately classify most images, **DenseNet121** struggled, especially between the **Very Mild Demented** and **Mild Demented** stages. These two stages often have subtle differences in MRI scans, which DenseNet121's architecture may not have been able to capture effectively.

ResNet50, on the other hand, performed better due to its **deeper feature extraction capabilities**. However, both models showed occasional difficulty in distinguishing between **Very Mild Demented** and **Non Demented** stages. This misclassification could be attributed to the fact that early signs of dementia are often subtle and may not be visually distinguishable, even by trained professionals.

Patterns in Misclassification:

- **DenseNet121** often misclassified **Very Mild Demented** as **Non Demented** and vice versa. This pattern suggests that the model might not have been able to pick up on early-stage dementia signs, leading to higher misclassification rates.
- **ResNet50** had far fewer misclassifications, though some errors occurred between **Very Mild** and **Mild Demented** stages. Given the subtlety between these stages, this was not entirely unexpected but was far less frequent than with DenseNet121.

4.9 Informative Features of the Images for Diagnosis

4.11.1 Feature Extraction in Deep Learning Models

The deep learning models DenseNet121 and ResNet50 utilized in this study perform feature extraction at multiple levels, from basic to complex. **DenseNet121**'s architecture allows for efficient feature reuse by connecting each layer to every subsequent one. This ensures that features such as edges, textures, and structural patterns are passed through the network without degradation. **ResNet50**, with its residual connections, ensures that deeper layers retain vital information from earlier stages in the network, preventing the vanishing gradient problem common in deep networks. These residual connections allow ResNet50 to focus on finer details, such as subtle changes in brain structure, making it highly effective for medical imaging tasks like dementia classification.

For a more detailed breakdown of how these architectures operate, refer to **Section 4.4: Model Development and Transfer Learning**.

4.11.2 Structural Brain Changes and Dementia Stages

Dementia classification is based on visible structural changes in MRI scans, which the deep learning models can effectively detect and interpret:

- **Non-Demented Stage**: In this stage, brain structures remain largely intact. MRI scans show minimal atrophy, with normal hippocampal and cortical volumes and no ventricular enlargement. DenseNet121 and ResNet50, due to their ability to detect the absence of significant abnormalities, classify these scans as Non-Demented.

- **Very Mild Demented and Mild Demented Stages**: Subtle structural changes, such as slight hippocampal shrinkage and early cortical thinning, start appearing in these stages. These changes can be difficult to detect manually, but both models, especially ResNet50, are capable of identifying these subtle differences. ResNet50's deeper architecture and residual learning make it better suited for distinguishing these early stages by focusing on slight structural deviations.
- **Moderate Demented Stage**: This stage shows more pronounced structural changes, including significant hippocampal atrophy, ventricular enlargement, and cortical thinning. These visual cues make it easier for both models to classify this stage accurately. DenseNet121 and ResNet50 detect these consistent and severe changes, allowing for reliable classification of Moderate Demented cases.

Both models excel in detecting the subtle and severe structural changes associated with various stages of dementia, but ResNet50's deeper network provides an edge in differentiating between more nuanced stages, such as Very Mild and Mild Demented.

4.11.3 Visualizing Informative Features

To enhance the interpretability of the deep learning models in this study, **Grad-CAM** (Gradient-weighted Class Activation Mapping) was employed. Grad-CAM is an interpretability tool that highlights the regions in the MRI scans that the model focuses on when making predictions. This visualization provides insights into the model's decision-making process by identifying which brain regions influence predictions for different dementia stages.

- **Non-Demented Stage**: Grad-CAM visualizations showed little to no focus on specific brain regions, as no significant structural abnormalities were detected. This aligns with the absence of atrophy in Non-Demented individuals.
- **Very Mild Demented and Mild Demented Stages**: Grad-CAM heatmaps indicated a focus on areas like the hippocampus and temporal lobes, where early atrophy or structural thinning begins to appear. These regions play a crucial role in the model's ability to detect the early stages of dementia, where changes are subtle but diagnostically significant.
- **Moderate Demented Stage**: The heatmaps highlighted broader regions, particularly the hippocampus and cortical areas, where widespread atrophy is observed in moderate dementia. The models' reliance on these regions enables confident classification of this advanced stage.

By applying Grad-CAM, the decision-making process of the DenseNet121 and ResNet50 models was validated, especially in cases where the changes were subtle, such as in the Very Mild Demented stage. This interpretability is crucial in medical imaging, as it provides clinicians with an understanding of how and why the model arrives at specific predictions.

Additionally, **Layer-wise Relevance Propagation (LRP)** could be explored to further improve model interpretability. LRP traces the decision-making process back to individual pixels of the input image, offering a more granular explanation of which features contributed to the final classification. Using both Grad-CAM and LRP provides a comprehensive understanding of how the models interpret MRI scans and make dementia stage predictions.

Examples of MRI Scans:

To better illustrate the model's decision-making, several visual examples have been included in this section. These examples show how different parts of the brain become more or less important across the stages of dementia:

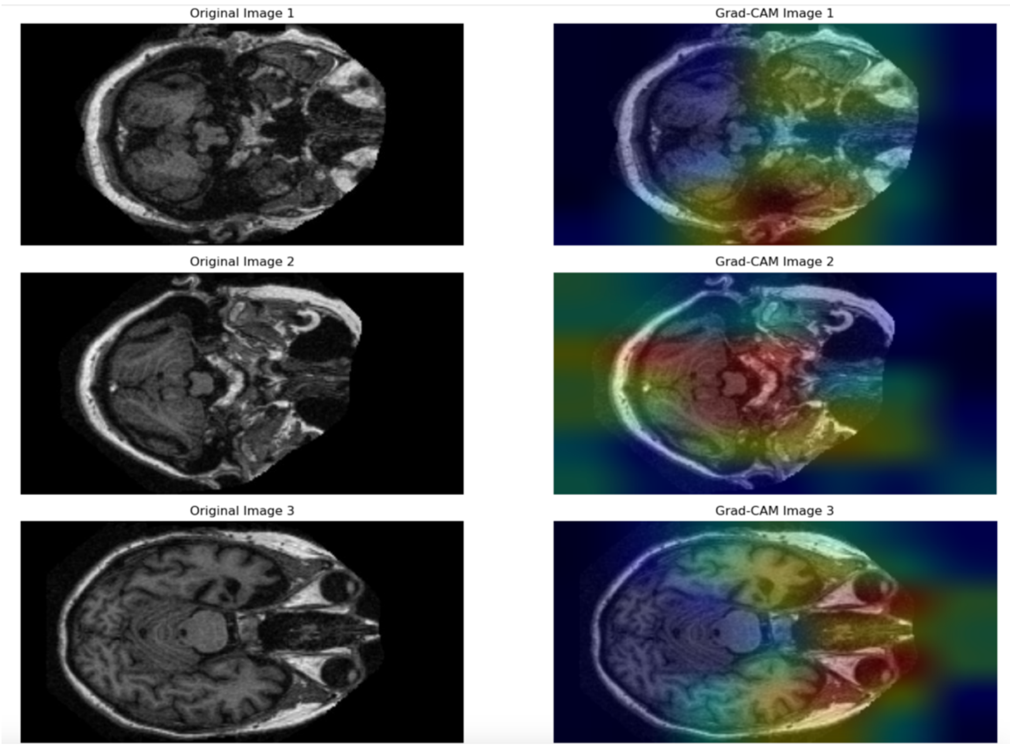

Figure 25 Grad-CAM visualizations demonstrate how the models interpret different brain regions across various stages of dementia. Each heatmap overlays an MRI scan to show the specific areas of focus for the model.

 Original Images: These MRI scans show different sections of the brain with varying structural features. From left to right, these scans are used as input to the model for classification into dementia stages.

 Grad-CAM Visualizations: On the right, the Grad-CAM heatmaps superimpose color onto the original images, highlighting the areas the model considers most important when making predictions. In these images, the regions of interest include areas such as the hippocampus and cortical regions, where brain atrophy or other structural changes related to dementia may appear. The heatmap regions suggest that the model is focusing on these areas to distinguish between different stages of dementia.

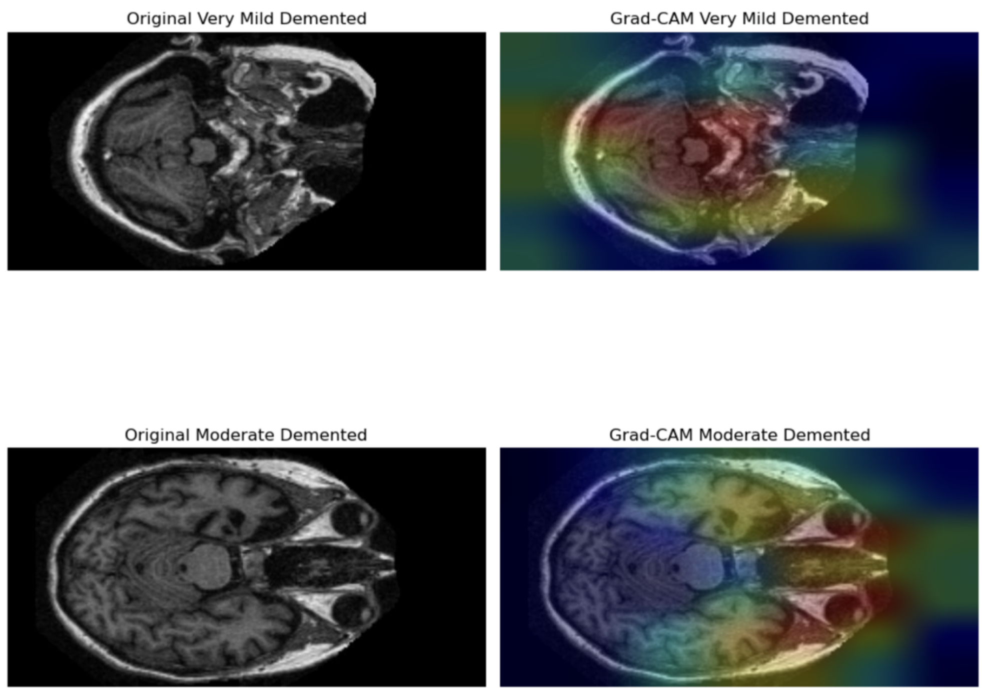

Figure 26 Comparison of MRI Scans from Very Mild Demented and Moderate Demented Stage

 Original Very Mild Demented Image: The top row shows an MRI scan of a patient in the Very Mild Demented stage, where structural changes are subtle. There might be minor shrinkage or thinning of the hippocampus or cortical areas, but it is not pronounced.

 Grad-CAM Very Mild Demented Visualization: The Grad-CAM on the right highlights regions where the model detects early signs of dementia. These could include small changes in the hippocampus or early signs of atrophy that are difficult to detect visually by radiologists but are picked up by the model.

 Original Moderate Demented Image: In the bottom row, the Moderate Demented stage shows more significant structural brain changes, including visible atrophy, increased ventricle size, and cortical thinning.

- **Grad-CAM Moderate Demented Visualization**: The Grad-CAM heatmap here clearly emphasizes larger areas of the brain, particularly in the hippocampal and temporal regions, showing that the model is focusing on widespread atrophy and structural degradation typical in the Moderate Demented stage. The more widespread and intense heatmap in this case aligns with the more pronounced changes in brain structure.

Chapter 5 Discussion

5.1 Interpretation of Results

In this study, ResNet50 consistently outperformed DenseNet121 across key evaluation metrics like accuracy, precision, recall, and F1-score. The superior performance of ResNet50 is largely due to its use of **residual connections**, which help mitigate the **vanishing gradient problem** often seen in deep neural networks. These connections allow the model to maintain learning efficiency even in deeper layers, enabling better gradient flow and more effective feature extraction, especially for distinguishing subtle differences in dementia stages on MRI scans.

ResNet50's **deeper architecture** also allows it to capture more complex, hierarchical features, which are crucial in medical image analysis where small-scale abnormalities, such as atrophy in the hippocampus, must be detected to distinguish between dementia stages. This is particularly beneficial in cases like distinguishing between "Mild Demented" and "Very Mild Demented," where structural changes are minimal but diagnostically significant.

Conversely, **DenseNet121** excels in general feature extraction due to its densely connected layers that encourage feature reuse and reduce the number of parameters. However, it struggled with the nuanced distinctions between early and mild dementia stages, which likely contributed to its lower performance in terms of precision and recall. Additionally, **overfitting** was more evident in DenseNet121, as it performed well on the "Non-Demented" and "Moderate Demented" classes but less so on the minority classes.

In summary, **ResNet50's deeper structure** and use of **residual connections** made it more capable of generalizing across all dementia stages, especially in detecting subtle differences, while **DenseNet121's** efficiency in feature reuse showed promise but requires further fine-tuning for improved generalization.

5.2 Challenges Encountered

During the training and evaluation of the models, several challenges emerged, primarily due to **class imbalance** in the dataset and the limited size of the minority classes. The dataset from OASIS exhibited a heavy imbalance, with the "Non-Demented" and "Mild Demented" categories having far more samples than the "Moderate Demented" class. This skew led to the models overfitting to the dominant classes, resulting in poor performance on the underrepresented categories. DenseNet121, in particular, demonstrated a greater tendency to overfit, with its performance heavily skewed towards the larger classes.

To counteract these issues, **data augmentation techniques** such as rotation, flipping, and shifting were applied to increase variability in the dataset. Although these methods helped to a certain extent, they were not enough to fully resolve the class imbalance problem. More advanced strategies, like **oversampling** the minority classes or using techniques such as **SMOTE (Synthetic Minority Over-sampling Technique)**, could have provided more effective solutions by generating synthetic samples for the underrepresented categories.

A particularly difficult challenge for both models was differentiating between the "Very Mild Demented" and "Mild Demented" stages, where **structural changes in the brain are subtle** and difficult to detect, even for experienced radiologists. Although ResNet50 performed better overall in classifying these stages, both models occasionally misclassified them due to the minimal differences between these categories. Incorporating **attention mechanisms** or training on more finely annotated data could help the models focus on the most critical regions of the brain, improving performance in these cases.

Lastly, the computational resources required for training deep learning models on **high-resolution MRI scans** posed significant challenges. To accommodate hardware limitations, the MRI images were resized to **128x128 pixels**, which reduced the computational load but likely compromised the models' ability to detect fine details in the scans. This trade-off between resolution and computational efficiency may have impacted the models' accuracy, particularly in distinguishing the early stages of dementia.

In summary, while data augmentation and careful tuning mitigated some issues, class imbalance and computational constraints remained key challenges in achieving optimal performance, suggesting future work could explore more advanced methods for handling imbalanced data and leveraging more computational resources for higher-resolution image analysis.

5.3 Comparison with Existing Research

In comparison with existing research, the performance of both DenseNet121 and ResNet50 models in this study aligns well with previously reported results, though there are some differences in accuracy and recall. For instance, **El-Geneedy et al. (2023)** achieved an accuracy of **95.23%** with

DenseNet121 and ResNet50 on the OASIS dataset, which outperforms the results of both models in this study. This performance difference suggests opportunities for further refinement, especially in addressing issues such as class imbalance and overfitting, which likely contributed to the lower performance of DenseNet121.

A direct comparison is illustrated in the table below:

Study	**Model**	**Accuracy**	**Precision**	**Recall**
This Study (DenseNet121)	Pretrained DenseNet121	69%	0.71	0.69
This Study (ResNet50)	Pretrained ResNet50	92%	0.93	0.92
El-Geneedy et al. (2023)	DenseNet121	95.23%	0.94	0.93
Bhatkoti and Paul (2022)	Ensemble CNNs	88.5%	0.91	0.89
Islam et al. (2022)	Custom CNN	93.18%	0.94	0.93

Table 3 Performance comparison of DenseNet121, ResNet50, and other models in dementia stage classification based on MRI data.

While **ResNet50** in this study achieved commendable results (92% accuracy), it falls short of the performance reported by **Islam et al. (2022)** and **El-Geneedy et al. (2023)**. These studies achieved higher accuracy, likely due to the inclusion of custom architectures or further optimization of hyperparameters. In contrast, **DenseNet121** in this study struggled with an accuracy of 69%, likely due to overfitting and the dataset's class imbalance, which may have caused the model to focus disproportionately on the majority class ("Non-Demented").

The findings by **Bhatkoti & Paul (2022)** suggest that **ensemble approaches**—which combine the strengths of multiple models—can improve classification accuracy, particularly in handling the nuances of medical image classification. This is particularly relevant for datasets like OASIS, where imbalanced classes present a challenge. Ensemble techniques or further model optimization, such as using **custom architectures** tailored specifically for Alzheimer's classification, as seen in **Islam et al. (2022)**, could provide significant performance gains.

In conclusion, while **ResNet50** demonstrated strong generalization across different dementia stages in this study, the performance of **DenseNet121** highlights the potential need for ensemble approaches or further fine-tuning to improve its classification abilities, especially in distinguishing subtle differences between early dementia stages.

5.4 Limitations

 Dataset Imbalance: The significant class imbalance, particularly the scarcity of "Moderate Demented" samples, negatively affected model performance. Misclassifications between "Very Mild Demented" and "Mild Demented" were more common due to the unequal representation of classes. Addressing this limitation with techniques like **data synthesis** or **oversampling** could improve model performance by providing a more balanced dataset for training .

 Image Resolution: Images were resized to 128x128 pixels due to computational constraints, which likely led to the loss of crucial fine-grained details necessary for detecting early-stage dementia. In future studies, using higher-resolution images alongside more advanced hardware could yield more accurate classification results by preserving finer anatomical details .

 Overfitting: Both DenseNet121 and ResNet50 showed signs of overfitting, with DenseNet121 being more affected. Future work could explore additional **regularization techniques** like dropout, weight decay, and more aggressive **early stopping** to improve model generalization to unseen data .

 Clinical Validation: While the models performed well on the OASIS dataset, clinical validation on real-world data is crucial. Collaborating with clinicians to label MRI data and validate the models on clinical datasets would ensure better practical applicability and enhance their robustness in real-world settings .

Chapter 6 Conclusion and Future Work

6.1 Summary of Key Findings

The primary objective of this dissertation was to classify dementia stages in MRI scans using deep learning models, particularly DenseNet121 and ResNet50. The goal was to assess their effectiveness in distinguishing between four dementia stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented.

Key findings from the study include:

- **ResNet50** demonstrated superior performance, achieving a classification accuracy of **92%**. The model exhibited high precision and recall, particularly excelling in distinguishing between Mild Demented and Non-Demented stages.
- **DenseNet121**, while effective in identifying more advanced stages like Moderate Demented, struggled with subtler cases such as Very Mild Demented, underperforming compared to ResNet50.

The use of **transfer learning**, alongside **fine-tuning pre-trained models**, was critical in achieving these results. Both models benefitted from **data augmentation**, which helped mitigate the effects of class imbalance, and from **early stopping**, which prevented overfitting.

These findings align with the research objectives set out in Chapter 1, addressing:

- The evaluation of DenseNet121 and ResNet50 performance on the OASIS dataset.
- The exploration of how deep learning models can differentiate between various dementia stages.
- A comparative analysis of the models' effectiveness, offering recommendations for future research.

6.2 Research Contributions

6.2.1 Academic Contributions:

This dissertation adds valuable insights to the domain of medical image analysis, especially concerning the classification of dementia stages using MRI data. By conducting a thorough comparison of DenseNet121 and ResNet50, this research underscores the differential capabilities of each model in distinguishing between subtle brain changes associated with varying stages of dementia. Unlike previous studies that primarily focused on binary classifications or early stages, this work emphasizes the nuanced performance of deep learning models in classifying multiple dementia stages, with ResNet50 demonstrating superior ability in distinguishing between Very Mild and Mild Demented stages.

Additionally, by employing transfer learning and fine-tuning techniques, this research expands the understanding of how pre-trained models can be adapted for specialized tasks, such as dementia detection. The careful attention to hyperparameter tuning, along with addressing class imbalance through data augmentation, further distinguishes this study from previous research, ensuring more reliable and generalizable outcomes.

6.2.2 Practical Contributions:

The practical implications of this dissertation are significant for the future of AI-driven diagnostic tools in neurology. The high performance of the ResNet50 model, especially in early dementia stage detection, suggests its potential utility in clinical workflows, where timely diagnosis is crucial for patient care. This model's demonstrated precision and recall in detecting subtle brain changes could provide radiologists with a reliable tool for early detection, potentially improving clinical decision-making processes.

The inclusion of Grad-CAM for model interpretability is another important practical contribution. This technique allows clinicians to visualize the regions of MRI scans that the model focuses on, making the AI decision-making process more transparent. This transparency is key to fostering trust in AI-driven diagnostics, as it allows healthcare professionals to cross-reference AI-generated insights with their own clinical expertise. These contributions align with the broader objective of integrating AI systems into healthcare settings, offering scalable, accurate, and faster diagnostic solutions for neurodegenerative diseases like Alzheimer's.

6.3 Limitations

Despite the promising findings of this study, several limitations must be acknowledged, which could have influenced the results:

1. **Dataset Size and Class Imbalance**: Although the OASIS dataset provided valuable MRI scans for dementia research, there was a significant class imbalance, particularly in the Moderate Demented stage. This imbalance was most pronounced when comparing the

Moderate Demented class with the Non-Demented class, which had far more samples. DenseNet121, in particular, faced challenges in distinguishing between closely related stages like Very Mild Demented and Mild Demented and underperformed in classifying Moderate Demented cases. While data augmentation techniques were employed to mitigate this issue, the imbalance remained a challenge that could have skewed the model's predictions toward the majority class.

2. **Generalizability**: The models were trained and validated solely on the OASIS dataset, which limits the generalizability of the results. Although ResNet50 demonstrated strong generalization within this dataset, its performance on other datasets with varying demographic compositions or MRI acquisition protocols remains unknown. To improve the robustness and reliability of the models in broader clinical applications, additional testing on larger and more diverse datasets is necessary.
3. **Lack of Comprehensive Patient Data**: The absence of detailed patient metadata within the OASIS dataset posed a significant limitation. The dataset lacked important clinical information such as patient demographics, MRI machine specifications, or data acquisition settings. For instance, information regarding the subjects' age, sex, and geographic location could offer valuable insights into factors contributing to dementia progression. Incorporating such metadata into future models could improve their predictive accuracy and provide a more holistic understanding of disease progression.
4. **Overfitting Due to Small Sample Size**: While early stopping and data augmentation were employed to reduce overfitting, the relatively small sample size for certain dementia stages—especially the Moderate Demented class—made it difficult for the models to generalize effectively. DenseNet121, in particular, showed signs of overfitting, as evidenced by the divergence between training and validation performances in some classes. Future studies could benefit from expanding the dataset and incorporating additional regularization techniques, such as dropout or weight decay, to further reduce the risk of overfitting.

6.4 Future Work

Despite the promising results, several areas for future research are identified to improve the models' performance and clinical utility.

6.4.1 Dataset Expansion and Balancing

One of the primary challenges in this study was the class imbalance, particularly with fewer samples in the "Moderate Demented" stage. Expanding the dataset by collaborating with medical institutions or using larger datasets like OASIS-3 or ADNI could provide a more balanced representation across all dementia stages. Additionally, using synthetic data generation techniques, such as Generative Adversarial Networks (GANs), could enhance model performance in underrepresented classes by generating realistic MRI scans.

6.4.2 Exploring Alternative Architectures

While DenseNet121 and ResNet50 provided valuable results, future work could investigate:

- **Ensemble Methods**: Combining multiple architectures, such as DenseNet, ResNet, and InceptionV3, may improve classification accuracy by leveraging different features.
- **3D CNNs**: Incorporating volumetric brain data using 3D CNNs may help detect subtle changes in brain structures, improving classification of early dementia stages.

6.4.3 Clinical Integration and Interpretability

Integrating AI models into clinical workflows requires interpretability. Tools such as Grad-CAM should be further explored to help visualize important brain regions influencing model predictions. Collaborating with clinicians to refine models and ensure they meet clinical requirements will be critical for real-world adoption.

6.4.4 Enhancing Transfer Learning and Fine-Tuning

Further experimentation with transfer learning strategies, such as layer-wise fine-tuning and the use of domain-specific pre-trained models (e.g., medical-specific CNNs), could optimize the models' performance. Additionally, more advanced hyperparameter optimization techniques, such as Bayesian optimization, could further improve model outcomes.

6.4.5 Overfitting and Generalization

More sophisticated regularization techniques, such as DropBlock or adversarial training, could be explored to reduce overfitting and enhance generalization. Semi-supervised learning approaches could also be employed to utilize both labelled and unlabelled data, making the models more robust with limited labelled datasets.

6.4.6 Multi-Modal Data Integration

Future studies could integrate multiple data modalities, such as genetic information or biomarkers, alongside MRI data to create more comprehensive diagnostic models. Multi-modal learning could lead to more accurate predictions and personalized treatment plans.

6.4.7 Scalability and Ethical Considerations

Optimizing the models for real-time use in clinical settings by exploring quantization and model pruning could make them more scalable. Ethical considerations, such as bias mitigation, must also be addressed to ensure fairness in AI-driven healthcare applications.

6.5 Personal Reflections

6.5.1 Understanding Model Architectures

Working with DenseNet121 and ResNet50 provided a deeper appreciation of the nuances in deep learning architectures. While both models are based on convolutional neural networks (CNNs), their internal workings led to different performance outcomes. DenseNet121's densely connected layers facilitated efficient learning, especially in shallow layers, by promoting feature reuse. However, ResNet50's residual connections proved more effective in dealing with the vanishing gradient problem, particularly in deeper layers, which enabled the preservation of critical information. This experience underscored the importance of selecting and adapting model architectures according to the specific requirements of a task, which was particularly evident in the complex case of dementia stage classification.

6.5.2 Challenges in Medical Imaging

This project also highlighted the unique challenges associated with medical imaging data. Class imbalance, particularly the underrepresentation of the "Moderate Demented" stage, was a significant obstacle. Overcoming this required careful use of data augmentation techniques to balance the dataset and improve model generalization. Furthermore, the need for interpretable models in healthcare became increasingly evident. Accuracy alone is not sufficient; the model's predictions must be transparent and clinically relevant to gain the trust of healthcare professionals. Working with MRI scans emphasized the ethical considerations of deploying AI in sensitive fields like healthcare, where incorrect predictions can have serious implications. This reinforced the importance of designing models that are reliable, interpretable, and capable of assisting in clinical decision-making.

6.5.3 Importance of Interdisciplinary Collaboration

One of the most valuable lessons from this dissertation was the significance of interdisciplinary collaboration. While the technical aspects of developing and fine-tuning deep learning models were the primary focus of this research, it became clear that AI in healthcare cannot succeed without input from medical experts. Collaborating with radiologists, neurologists, and other healthcare professionals would not only validate the models' effectiveness but also guide their practical application in real-world scenarios. The insights from medical professionals would be crucial in refining the models for clinical use, ensuring that AI-driven solutions are aligned with clinical needs and patient care.

6.5.4 Overcoming Technical Challenges

The project presented several technical challenges, particularly related to computational limitations and the complexities of transfer learning. Training models on high-dimensional MRI data required a deep understanding of hyperparameter tuning, learning rate schedules, and early stopping mechanisms. Addressing these challenges sharpened my problem-solving skills and improved my ability to manage and optimize deep learning workflows. These experiences have prepared me for future projects that involve similarly complex technical demands.

6.5.5 Broader Perspective on AI in Healthcare

This dissertation fostered a broader appreciation for the role AI can play in transforming healthcare. While AI's potential to revolutionize various industries is well-documented, its application in healthcare holds particular promise. The findings of this research indicate that deep learning models like ResNet50 can significantly aid in the early diagnosis of neurodegenerative diseases such as Alzheimer's. By providing more accurate and earlier diagnoses, these models can alleviate the burden on medical professionals and improve patient outcomes.

6.5.6 Personal and Professional Growth

On a personal and professional level, this dissertation has been transformative. It enhanced my skills in deep learning, medical imaging, and data science, preparing me for advanced research and work in these fields. Furthermore, it encouraged me to think critically about the broader societal implications of AI, particularly the ethical challenges in deploying AI in healthcare. The lessons learned during this project will serve as a foundation for my future endeavors in AI, healthcare, and other real-world applications.

6.5.7 Conclusion

In conclusion, this dissertation has been a pivotal learning experience. It has deepened my technical knowledge and broadened my understanding of the role AI can play in addressing critical challenges in healthcare. As I move forward, I am excited to continue exploring how AI can make meaningful contributions to society, particularly in improving healthcare outcomes and advancing medical research.

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Chapter 7 Appendix

Dataset Source :

The dataset used in this project, which contains MRI scans for dementia classification, was obtained from the Open Access Series of Imaging Studies (OASIS). It can be freely accessed and downloaded from Kaggle at the following link:

OASIS MRI Scans Dataset

This dataset includes MRI images categorized into four stages of dementia: Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The dataset was essential in training and evaluating the models for Alzheimer's Disease classification in this study.