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A Multimodel of Alzheimer's Disease Classification, Segmentation and Detection

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Abstract

Alzheimer's Disease (AD) is a progressive neurodegenerative condition characterized by cognitive decline and structural brain degeneration. Accurate and early detection is crucial for effective treatment planning and disease management. In this thesis, we present a dual-model deep learning framework that performs Alzheimer's disease classification and brain region segmentation using brain MRI scans as separate but complementary tasks.

For the classification task, a transfer learning-based model was developed using a pre-trained convolutional neural network (CNN) that was fine-tuned on accurate MRI dataset. The model successfully classified MRI images into multiple stages (Mild, Very Mild, Moderate and Non- Demented) of Alzheimer's disease, achieving an accuracy of 87.6%, which indicates robust performance in distinguishing between disease stages.

A convolutional neural network (CNN) for classification and a U-Net-based structure for segmentation was developed. The segmentation branch extracts fine-grained anatomical regions, while the classification branch leverages both image features and structural abnormalities to predict the disease stage. The model was trained and evaluated on Kaggle, achieving promising accuracy, Dice scores, and clinical relevance. Visualization of segmentation overlays and performance metrics confirmed the model's effectiveness in identifying disease patterns.

In parallel, a Attention U-Net-based segmentation model was trained on a separate dataset to delineate Alzheimer-affected brain regions, such as the hippocampus. The segmentation model achieved a Dice Similarity Score of 98.1%, demonstrating high spatial accuracy in extracting disease-relevant anatomical structures.

By leveraging two task-specific datasets, this research explores the effectiveness of targeted model design for classification and segmentation independently. The results highlight the capability of deep learning to support both diagnostic and anatomical assessment in Alzheimer's disease.

Key Words : *Dice Score, Attention U-NET, Hippocampus, Alzheimer's Segmentation.*

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Chapter 1: Introduction

1.1 Overview

Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that leads to cognitive decline, memory impairment, and ultimately dementia, making it a critical public health concern worldwide. Early and accurate detection of AD is essential to enable timely therapeutic intervention and to slow the progression of symptoms. Neuroimaging modalities, particularly Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET), have become indispensable tools in identifying structural and functional biomarkers of AD. Structural MRI provides detailed information on brain atrophy patterns, with the hippocampus (HC) recognized as one of the earliest regions to be affected, serving as a reliable biomarker for disease progression [1], [3], [6]. PET imaging, on the other hand, captures metabolic changes, offering complementary diagnostic value when integrated with MRI [2], [9]. About 6.9 million people in the United States age 65 and older live with Alzheimer's disease. Among them, more than 70% are age 75 and older. Of the more than 55 million people in the world with dementia, 60% to 70% are estimated to have Alzheimer's disease.

In recent years, deep learning has emerged as the dominant paradigm for analyzing medical imaging data due to its superior feature extraction and classification capabilities. Convolutional neural networks (CNNs) have been widely applied to AD detection, showing significant improvements in classification accuracy compared with traditional approaches [2], [8]. Advanced architectures such as U-Net and 3D Fully Convolutional Neural Networks (FCNNs) have demonstrated strong performance in hippocampal segmentation, enabling precise volumetric and structural analysis that enhances diagnosis [4], [10]. Despite these advancements, challenges remain in terms of data heterogeneity, limited sample availability, and the lack of standardized preprocessing protocols. Existing studies also highlight difficulties in distinguishing mild cognitive impairment (MCI) from normal controls, which is crucial for early intervention [1], [12]. And medicines may improve symptoms or slow the decline in thinking. Programs and services can help support people with the disease and their caregivers.

1.1.1 Types of Alzheimer’s Disease

Classification Based on the Severity

I. **Mild Alzheimer's:** This includes the beginning of cognitive impairment that causes difficulties in remembering daily routine, such as tasks at work, paying bills and others. Because these symptoms are not very serious, patients at this stage manage to remain functional with some difficulty.

II. **Moderate Alzheimer's:** Moderate Alzheimer's leads to severe symptoms due to significant neuronal damage, causing increased confusion and greater dependence on others due to memory loss.

III. **Very Mild Alzheimer's:** This stage shows subtle memory lapses and mild cognitive changes that are often mistaken for normal aging. Patients may occasionally forget names or misplace items but remain fully independent in daily activities. Symptoms are often noticeable only through medical testing or close observation.

IV. **Non Alzheimer's:** This group includes individuals who show no signs of dementia or Alzheimer's disease. Cognitive abilities, memory, reasoning, and daily functional skills remain intact, and neurological evaluations reveal no significant impairment

Classification Based on the Inflammatory Response

I **Low Inflammatory Response (Early Stage / Preclinical AD)** : In this stage, there is very little inflammation in the brain. The brain's immune cells (microglia) are mostly calm, and harmful proteins like amyloid-β are just starting to build up. Memory and thinking are still normal, so symptoms are usually not noticeable.

II **Moderate Inflammatory Response (Mild to Moderate AD)**: Here, the brain's immune cells become more active to fight amyloid plaques. This causes more inflammation, stress on brain cells, and damage to the connections between them. People begin to have memory problems, confusion, and difficulty doing daily activities.

III **High Inflammatory Response (Severe AD)**: In this stage, inflammation is very strong and long-lasting. Immune cells stay overactive, releasing harmful chemicals that kill brain cells. Large parts of the brain shrink, and patients lose the ability to care for themselves and communicate clearly.

1.1.2 Risk factors for Alzheimer's disease

Many different things can increase a person’s chances of getting Alzheimer’s. These are known as “risk factors”. Some of these risk factors cannot be changed, but many others can. Age and genes are the biggest risk factors for Alzheimer’s, as they are for most types of dementia, and these cannot be changed. However, people can still reduce their risk by making positive changes to their health and lifestyle.

1.2 Motivation for the work :

- Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that affects millions of people worldwide. With an aging population, AD cases are increasing, making it a major healthcare concern.
- Early detection can help slow the disease's progression and improve patient care. Early diagnosis is crucial, as late-stage detection limits treatment options and patient care.
- There is no definitive cure for AD, and early intervention through AI-based techniques may assist in managing the disease.
- Machine learning and deep learning approaches (e.g., CNN, VGG16, Res-Net, U-Net) can analyze brain scans more effectively. MRI, CT scans, and PET scans provide valuable insights, and deep learning models can enhance diagnostic accuracy.
- Recent research on AD appears to have primarily focused on either segmentation or classification, rather than addressing both aspects together.
- It helps to assist doctors in decision-making, improving patient outcomes, and reducing healthcare costs.

1.3 Problem statement and solution plan

Recent years have seen increased interest in deep learning for biomedical MRI segmentation and classification, but several challenges remain: (i) limited medical imaging datasets, (ii) low contrast in anatomical structures across T1, T2, and FLAIR modalities, (iii) the labor-intensive and expert-dependent process of manual brain MRI segmentation. (iv) the effective application of techniques like transfer learning and multi-task learning, and (v) ensuring the scalability of deep learning models[9]. This study proposes a novel approach to address these key issues.

- Since manual segmentation is both time-consuming and requires specialized expertise, this study proposes a deep learning-based framework, for the automatic segmentation of the left and right hippocampus in Alzheimer’s disease.
- Due to limited medical datasets, a T1-weighted MRI dataset was obtained from Kaggle and processed through segmentation, denoising, and reconstruction.
- Attention U-Net based on the U-Net framework, are proposed for binary semantic segmentation of MRI images.
    - The Attention U-Net architecture applies basic hyperparameter tuning to the U- Net model.
    - The U-Net architecture uses transfer learning with a pre-trained VGG16 model in the U-Net framework's encoder and decoder..
    - The proposed architectures show strong performance based on four key evaluation metrics: the Dice similarity coefficient, accuracy, sensitivity, and specificity.

1.4 Structure

In accordance with the scope of this study, the thesis is organized into five chapters. The following section provides a concise overview of the foundation and content of each chapter.

Chapter 1: Introduction

This chapter introduces the thesis report, outlining its purpose, objectives, and contributions.

Chapter 2: Literature Review

This chapter reviews previous related work, examining its methods, benefits, and drawbacks.

Chapter 3: Methodology

This chapter presents our proposed approach for the classification and segmentation of Alzheimer’s Disease using multiple CNN models.

Chapter 4: Experimental Result & Comparisons

In this chapter, describe the performance metrics, outline the proposed method in detail, and present the experimental results, including comparisons between the outputs of different models.

Chapter 5: Conclusion and Future Work

Finally, The chapter concludes the study by summarizing the findings, discussing the limitations of the work, and outlining potential directions for future research.

1.5 Summary

Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that impairs memory, cognition, and daily functioning, with early detection being essential for effective treatment. The hippocampus (HC) is one of the first regions affected by AD, making it a crucial biomarker for diagnosis through magnetic resonance imaging (MRI). Traditional diagnostic approaches face limitations due to manual intervention and subjectivity, whereas deep learning methods, particularly convolutional neural networks (CNNs) and U-Net variants, have shown promising results in automated medical image analysis. This study proposes a deep learning framework that integrates hippocampal segmentation and disease classification, leveraging transfer learning and attention mechanisms. The proposed approach enhances diagnostic accuracy while reducing clinical workload, offering a robust tool for computer-aided diagnosis of AD.

Chapter 2: Literature Review

Alzheimer’s disease (AD) remains one of the most pressing neurodegenerative disorders, with early detection and accurate classification playing a vital role in effective clinical management and therapeutic interventions. In recent years, researchers have increasingly focused on the hippocampus (HC), which is among the earliest brain regions affected by AD, making its structural and functional analysis a cornerstone of diagnostic studies. Li *et al.* [1] highlight the significance of hippocampal structures in AD diagnosis through magnetic resonance imaging (MRI), reporting that segmentation methods such as three-dimensional fully convolutional neural networks (3D FCNNs) and U-Net architectures have proven effective for isolating hippocampal subregions. Furthermore, their research emphasizes that optimization-based segmentation methods have been applied to improve the robustness of these approaches, although comparative studies continue to reveal both notable strengths and critical limitations, particularly when models are tested across diverse datasets and imaging protocols.

Neuroimaging modalities, particularly Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET), have become indispensable tools for AD detection and classification. Wen *et al.* [2] report that convolutional neural networks (CNNs) have emerged as the dominant paradigm in medical image analysis, demonstrating superior accuracy in distinguishing AD from healthy controls and in staging disease progression compared with traditional machine learning techniques. At the same time, Nadal *et al.* [3] recognize that structural MRI provides detailed anatomical insights into patterns of brain atrophy, particularly in the hippocampus, where progressive shrinkage is strongly correlated with disease severity.

The hippocampus is not only an anatomical biomarker but also a functional indicator of disease progression making segmentation of this structure particularly important for accurate diagnosis and prognosis. Carmo *et al.* [4] emphasize that hippocampal segmentation plays a critical role in distinguishing AD from related disorders and in differentiating mild cognitive impairment (MCI) from normal controls, both of which are essential for early intervention. Automated segmentation methods, particularly those based on deep learning, offer clear advantages in terms of reproducibility and efficiency when compared with manual or semi-automated techniques. However, these automated methods remain vulnerable to variability introduced by imaging protocols, scanner differences, and subject heterogeneity, all of which can reduce generalizability and model robustness [2]. impairment (MCI) from normal controls, both of which are essential for early intervention. Automated segmentation methods, particularly those based on deep learning, offer clear advantages in terms of reproducibility and efficiency when compared with manual or semi-automated techniques. However, these automated methods remain vulnerable to variability introduced by imaging protocols, scanner differences, and subject heterogeneity, all of which can reduce generalizability and model robustness [2]. At the same time, non-imaging biomarkers are gaining traction as complementary approaches. For instance, Yang *et al.* [5] demonstrate that linguistic features derived from spontaneous speech and semantic processing can be used as effective biomarkers of cognitive decline, with deep learning and classical classifiers capable of distinguishing between AD, MCI, and healthy control groups. While speech-based approaches offer the advantage of being low-cost and non-invasive, further cross-linguistic validation and clinical testing are necessary to ensure their effectiveness in broader applications.

The importance of early detection cannot be overstated, as Alzheimer's disease is a progressive disorder leading to irreversible memory loss, impaired cognitive function, and ultimately severe dementia, with global prevalence projected to rise substantially in the coming decades. Andersen *et al.* [6] stress the urgency of developing diagnostic tools that can reliably identify AD in its prodromal stages, such as mild cognitive impairment, where therapeutic interventions may have the greatest impact. To this end, recent studies have focused on the integration of multimodal frameworks that combine advanced deep learning models with established machine learning techniques.

Venkatasubramanian *et al.* [7] describe hybrid strategies that merge convolutional neural networks with classifiers such as support vector machines (SVM) and random forests, achieving significant improvements in both segmentation and classification performance. These frameworks often incorporate joint learning paradigms, including multi-task learning and transfer learning, that allow simultaneous feature extraction from critical brain regions such as the hippocampus, grey matter, and white matter. Reported performance has been highly promising, with classification accuracies exceeding 89% in binary classification tasks and above 90% in multi-class staging of AD progression, while segmentation performance frequently achieves Dice similarity coefficients above 90%, reinforcing the clinical potential of these methods. Despite these advances, persistent challenges remain, as Shen *et al.* [8] observe, including limited dataset availability, inconsistencies in preprocessing standards, and the lack of generalizability of models across populations with varied demographic and clinical characteristics. Building on this foundation, Liu *et al.* [9] demonstrate that multimodality approaches, which combine complementary information from MRI and PET scans, yield improved diagnostic performance, particularly when deep learning models are trained to integrate both structural and metabolic biomarkers. Alghamedy *et al.* [15] investigated hybrid machine learning and deep learning frameworks for Alzheimer's disease (AD) classification, emphasizing the integration of handcrafted radiomic features with deep neural embeddings. Their study highlights the effectiveness of combining traditional classifiers such as Support Vector Machines (SVMs), Random Forests (RFs), and ensemble methods with CNN feature extractors. This multimodal approach enhances diagnostic reliability and consistently outperforms single-model baselines across diverse imaging datasets.

Nevertheless, despite these substantial advancements, limitations persist that hinder the direct translation of research findings into routine clinical practice. Wen *et al.* [2] observe that data heterogeneity, lack of evaluation standards, and limited sample diversity remain major obstacles for real-world deployment of deep learning–based diagnostic systems. Moreover, existing feature extraction techniques, especially those relying exclusively on hippocampal morphology, are often inadequate for reliably distinguishing MCI from normal controls, leading to inconsistent classification performance across studies [1]. Addressing these issues requires more comprehensive frameworks that can integrate multimodal data, optimize preprocessing pipelines, and incorporate robust validation protocols across diverse populations.

To this end, the present research proposes a multi-model deep learning framework designed to simultaneously perform hippocampal segmentation and Alzheimer's disease classification. By combining complementary model strengths within a unified architecture, the proposed approach aims to enhance diagnostic accuracy, improve robustness across datasets, and contribute toward the development of clinically reliable tools for early detection and disease monitoring.

2.1 Summary

The literature review chapter examined a range of studies on hippocampal segmentation and Alzheimer's disease (AD) classification using MRI data. Previous research highlighted the hippocampus as one of the earliest and most critical regions affected by AD, with its volume and shape serving as essential biomarkers for diagnosis. Traditional feature extraction techniques were shown to be limited in accuracy, especially when distinguishing between mild cognitive impairment (MCI) and normal controls. Deep learning approaches, including convolutional neural networks (CNNs), 3D fully convolutional networks (FCNNs), and U-Net architectures, have demonstrated promising results in both segmentation and classification tasks. Several works employed multi-task learning strategies to jointly analyze anatomical structures and disease states, while others relied solely on hippocampal volumetric analysis.

This review underscores the importance of combining segmentation and classification to improve diagnostic performance. It provides the foundation for the proposed multi-model deep learning framework, which integrates hippocampal segmentation with disease classification to leverage the complementary strengths of both tasks. The chapter thus establishes the research gap and motivates the adoption of a hybrid approach for enhancing the early and accurate detection of Alzheimer’s disease.

Chapter 3: Methodology

3.1 Methods and materials (Segmentation)

The Hippocampus (HC) segmentation is the primary factor for diagnosing AD [10]. This study aims to introduce the Attention U-Net framework to segment the left and right hippocampus to detect and identify Alzheimer's disease. The following sections provide an overview of the Attention U-Net framework for deep learning–based automatic hippocampus segmentation, including its workflow, preprocessing methods, medical image segmentation techniques, U- Net architecture, and transfer learning approach.

3.2 Proposed framework

Hippocampus (HC) segmentation plays a crucial role in diagnosing Alzheimer's disease (AD). This study introduces a Attention U-Net framework designed to segment both the left and right hippocampus for effective detection and identification of AD.

Table 3.1: Comparison of Deep Learning Techniques for Brain MRI-Based Alzheimer's Disease Analysis

	Technique	Advantage	Disadvantages
J. Dolz et al. [10] (ABIDE, ISBR)	3D FCNNs	1. The method is robust to various acquisition protocols.	1. High computational complexity
H. Allioui et al. [11], OASIS	U-Net architecture for each view of the 2.5D brain MRI after parsing them into transversal views	It takes advantage of the benefits of 3D architecture. It reduces complexity and computational costs	The network was trained from scratch and not benefits from transfer learning concepts.
M. Liu et al. [9], ADNI	Multi-model deep CNNs for jointly learning HC and disease classification evaluated on structural MRI data	The empirical results demonstrated that it achieved promising performance. The framework output the disease status and provided the HC result.	Computational complexity

The following sections present a detailed overview of the Attention U-Net workflow, including preprocessing methods and medical image segmentation techniques. Furthermore, the application of the U-Net architecture and transfer learning approaches is discussed.

Step 1 Data Acquisition

Medical image segmentation requires both MRI scans and their corresponding ground truth masks as input data. Due to limited medical datasets, the dataset was compiled using coronal 2D T1-weighted MRI slices in DICOM((Digital Imaging and Communications in Medicine) IMG format from the Kaggle. There are MRI historical scans representing various AD stages are collected.

Step 2 Preprocessing

Medical Image Processing, Analysis, Visualization processes and segments the left and right hippocampus. A **Hessian** Filter use the **Max** and **Min** images as extra information to train a model better. Figure 4.1 shows original MRI images with their ground truth masks.

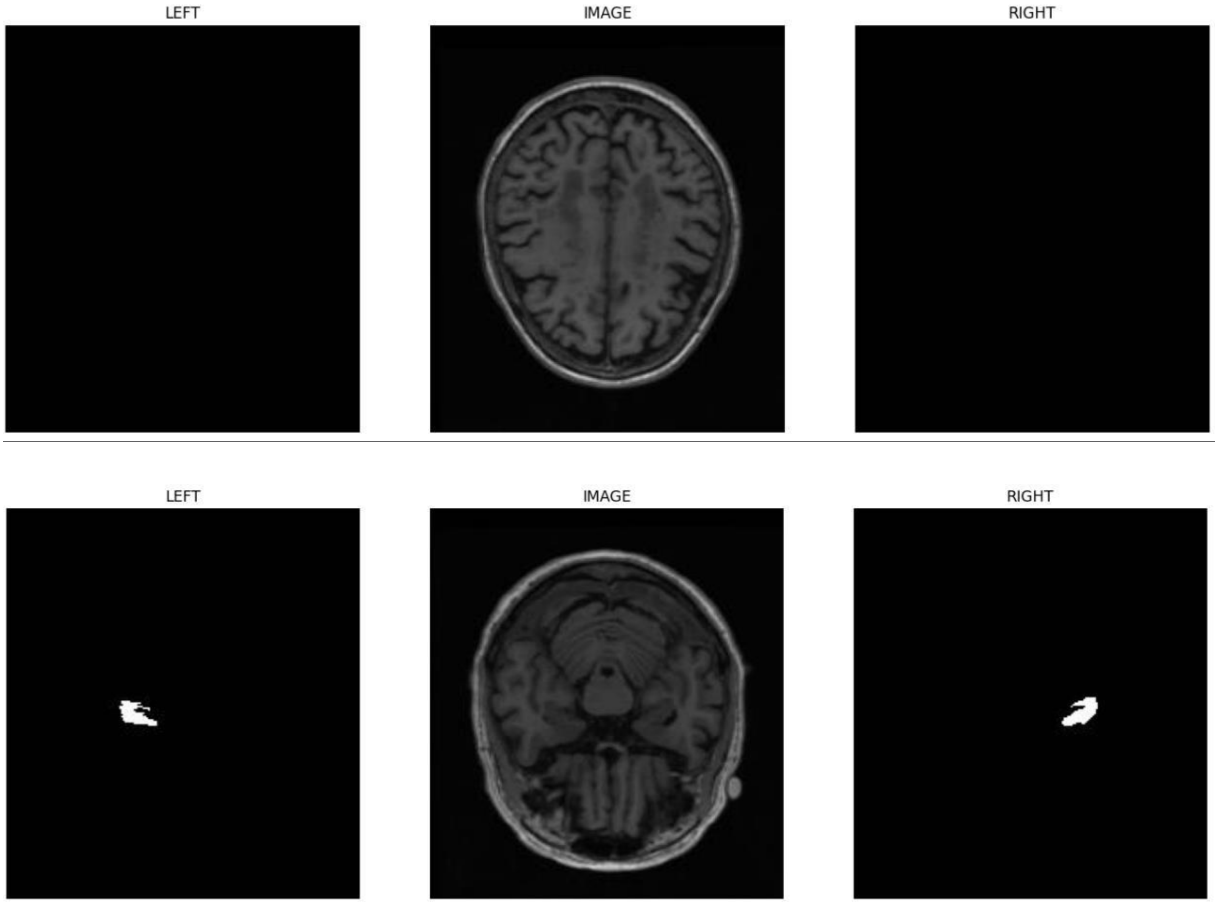

Figure 3.1: Samples of MRI input data and the corresponding ground truth masks

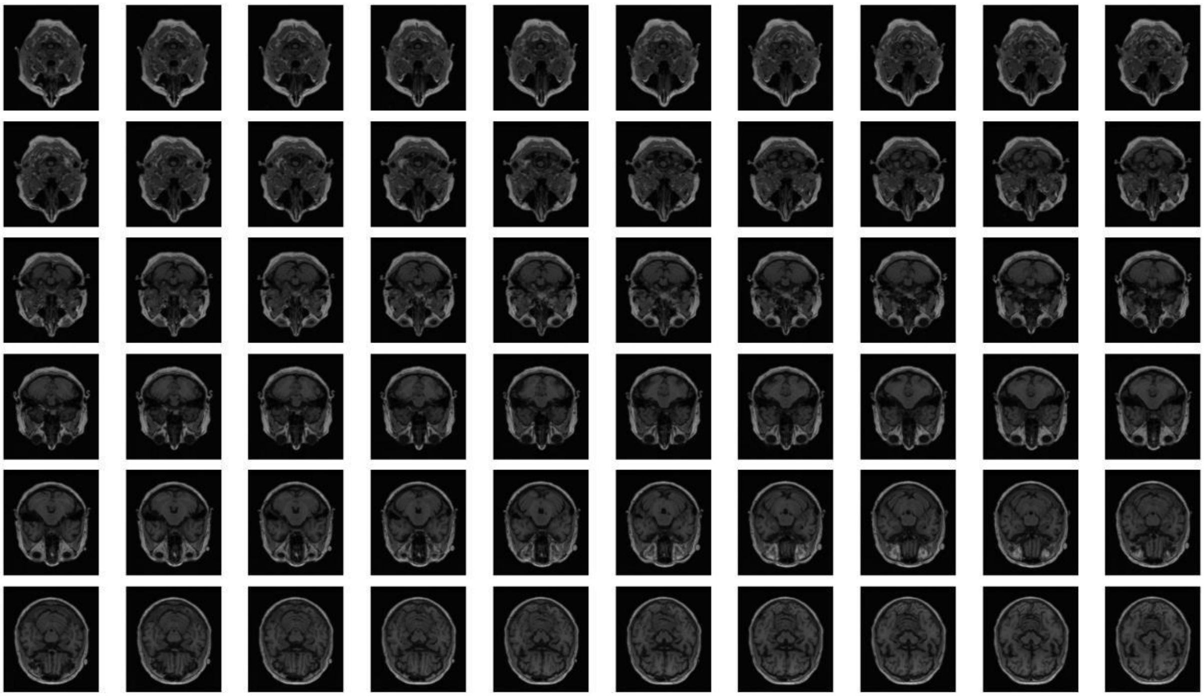

Figure 3.2: The training samples for training the model

Step 3 Data Description & Augmentation

In the multi-model, here used two separately dataset.one for Classification and one for segmentation**.** However, In Segmentation process, the total dataset used to 5670 MRI slices, with 1890 original slices, 1890 targeting the left hippocampus, and 1890 for the right hippocampus. Due to the small dataset amount, data augmentation techniques are applied to maximize the dataset size and prevent the overfitting problem. In classification model data augmentation techniques expanded the dataset to 2000 MRI images per class(MD,VMD,MRD and ND) of AD. Thus, helping to reduce overfitting risks.

Step 4 Segmentation

This study implements an Attention U-Net architecture for Hippocampus Segmentation, which enhances the standard U-Net through attention gates in skip connections. The model consists of: (1) an encoder with four down sampling blocks (32→64→128→256 filters), each containing two Conv2D-BatchNorm-ReLU layers followed by max pooling; (2) a bottleneck layer filters; and (3) a decoder with four up sampling blocks (256→128→64→32 filters) using bilinear up sampling.

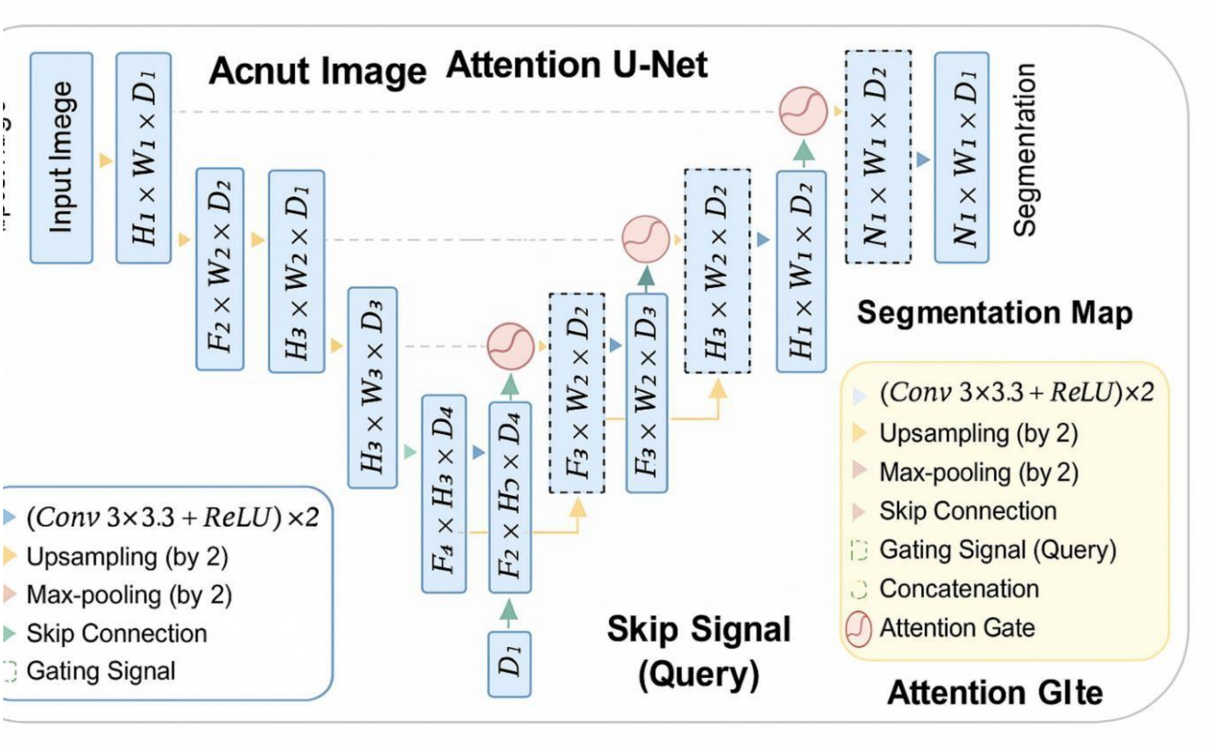

Figure 3.3: The default Attention U-Net architecture

The key innovation is the attention block() that processes skip connections - it transforms both the encoder features (theta x) and decoder gating signal (phi g) through 1×1 convolutions, combines them via additive attention, generates spatial attention weights via sigmoid activation, and applies these weights to the encoder features before concatenation. The network maintains input-output dimensional consistency (256×256×3 → 256×256×1) and is trained with a combined Dice-BCE loss using the Adam optimizer (lr=1e-4). This attention mechanism dynamically highlights relevant hippocampal regions while suppressing background noise during segmentation

Step 5 Evaluation

In this step, monitor and review the model's performance to ensure effective results and accurate performance by following the algorithm steps

3.3 Preprocessing algorithms

3.3.1 Image Preprocessing Pipeline

The input MRI images undergo three key preprocessing steps. First, bilinear interpolation resizes all images to a uniform 256×256 resolution, ensuring dimensional consistency. Next, color space conversion transforms BGR-formatted images into RGB or grayscale using luminance weighting, standardizing input channels. Finally, hippocampus masks are synthesized by pixel-wise addition of left and right segmentation labels.These steps collectively normalize input data while preserving anatomical structures critical for segmentation

3.3.2 Encoder Pathway Algorithms

The encoder employs a hierarchical feature extraction process. Each block performs two consecutive 3×3 convolutions with batch normalization and ReLU activation, capturing spatial patterns at progressively coarser resolutions. Strided max-pooling (2×2 windows) then down samples feature maps by a factor of two, doubling filter counts (32→64→128→256) to maintain representational capacity.

3.3.3 Attention Mechanism

The core innovation lies in the attention gates inserted in skip connections. These gates dynamically weight encoder features using a two-step process: First, 1×1 convolutions project both the encoder’s spatial features (key) and decoder’s contextual features (query) into an intermediate space. Their additive combination generates an attention map highlighting salient regions, which is activated via sigmoid to produce values between 0 (suppress) and 1 (emphasize). This biologically inspired mechanism focusing computation on anatomically relevant areas while suppressing background noise.

3.3.4 Decoder Pathway Algorithms

The decoder reconstructs segmentation masks through symmetrical up sampling. Two 3×3 convolutions then refine these fused features, with filter counts halving (256→128→64→32) to balance detail recovery and computational efficiency. This progressive up sampling with skip connections counteracts information loss from pooling, enabling precise localization of hippocampal boundaries at the original 256×256 resolution

3.3.5 Optimization Framework

Training leverages a hybrid loss function combining binary cross-entropy (BCE) and Dice coefficient. BCE provides pixel-wise gradient signals for sharp boundaries, while Dice optimizes for region overlap critical given class imbalance between small hippocampi and large backgrounds. The Adam optimizer adapts learning rates per-parameter (initial rate: 1e- 4), using momentum to escape local minima. Early stopping monitors validation Dice over five epochs to prevent overfitting, retaining only weights with peak performance.

3.4 MRI Normalization

Normalization is a process of converting the MRI data to a comprehensive anatomic template. It transforms individual subject data into a reference space that includes a template and a source image. Its key benefits are enabling easier comparison of brain MRI scans and interpreting them in a consistent shape and size framework [10]. It also minimizes variations from factors like subject positioning and contrast differences, aiding in the detection of subtle changes.

3.5 Medical Image Segmentation Types and Techniques

Before deep learning, image segmentation relied on traditional techniques like (i) thresholding, (ii) clustering, (iii) histogram-based methods, (iv) edge detection, (v) region-growing, (vi) graph-based methods, (vii) watershed transformations, and (viii) feature-based approaches. Deep learning has demonstrated superior efficiency and performance in segmentation tasks[12]. In addition to segmentation, it is widely applied in various fields such as classification, object detection, genotype detection, and speech recognition[13]. Common deep learning algorithms include stacked autoencoders, deep neural networks, convolutional neural networks (CNNs), and deep Boltzmann machines[8].

Several segmentation strategies based on convolutional neural networks (CNNs) have been introduced, including cascaded models, multi-modality and single-modality approaches, as well as patch-wise and semantic-wise methods. In this study, semantic-wise segmentation is adopted, where each pixel of the input image is assigned a class label, a process commonly referred to as “dense prediction” [6]. This method offers key advantages such as efficient loss minimization, scalability to images of varying sizes, and reduced computational complexity compared to other strategies [13], [14].

3.6 Attention U-Net

The Attention U-Net architecture presented in this work is based on the standard U-Net design. It consists of three main components: (i) the down-sampling or encoder section, (ii) the up- sampling or decoder section, and (iii) the bottleneck section

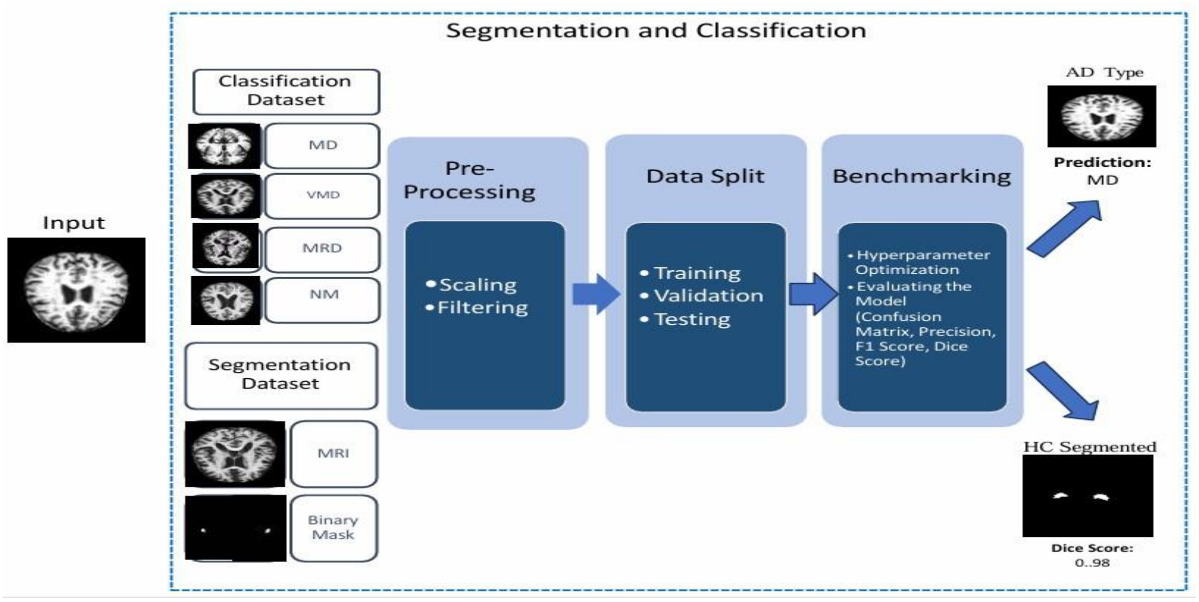

Figure 3.4: Alzheimer's MRI Segmentation and Classification Pipeline

3.7 Methods and materials (Classification)

The classification of Alzheimer’s disease (AD) was performed using brain MRI images to distinguish four categories: Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented. A convolutional neural network (CNN)–based framework with transfer learning was employed, where VGG16 and its customized variant served as baseline models. The classification of Alzheimer’s disease (AD) was performed using brain MRI images to distinguish four categories: Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented. A convolutional neural network (CNN)–based framework with transfer learning was employed, where VGG16 and its customized variant served as baseline models. Preprocessing techniques such as normalization, resizing, and data augmentation were applied to improve feature representation and reduce overfitting. The proposed classification model was trained to extract discriminative features from MRI scans and map them to respective AD stages. Model performance was evaluated using standard metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis to validate the reliability of the framework.

3.7.1 Proposed framework

The proposed classification framework employs a deep learning approach to categorize brain MRI images into four stages of Alzheimer’s disease: Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented.

1. Dataset Collection and Organization

The dataset used for this study comprises labeled images stored in a hierarchical directory structure under the root directory /kaggle/input/combined-images, where each subdirectory corresponds to a specific diagnostic class (e.g., Non-Demented, Mild-Demented, Very-Mild Demented, Moderate Demented). All image paths were programmatically extracted, and corresponding class labels were assigned based on their folder names.

2. Data Preprocessing and Augmentation

Before feeding the data into the deep learning model, it was partitioned into training (80%), and test (20%) subsets using stratified sampling to preserve class distributions. All images were resized to 224×224 pixels to match the input shape required by the VGG16 model .Image augmentation was applied using Image Data Generator with the Horizontal flipping and Real- time normalization using the preprocessing function for VGG16

3. Model Architecture

The classification model was based on the pre-trained VGG16 convolutional neural network from ImageNet. The architecture was modified to suit the multi-class classification task. The top fully connected layers were either retained (include top=True) or replaced with a custom classification head (include top=False, followed by GlobalAveragePooling2D, Dense, and Dropout layers).The final layer was replaced with a Dense(4, activation='soft- max') layer to predict probabilities across four diagnostic categories. Selective fine-tuning was applied by freezing the initial layers of VGG16 and allowing only the last few convolutional layers to be trainable

4. Model Compilation and Training

The model was compiled using the Optimizer (Adam with a learning rate of 1e-4), Loss Function (Categorical Cross entropy) and Evaluation Metric (Accuracy). Training was performed over 10 epochs with early stopping and model checkpointing callbacks to prevent overfitting and retain the best-performing model. After training, the model's performance was evaluated on the unseen test set using the Confusion Matrix, Classification Report and Overall Accuracy. These metrics provided a comprehensive understanding of the model's effectiveness in classifying different stages of cognitive impairment. The model’s architecture is shown in Fig. 3.5.

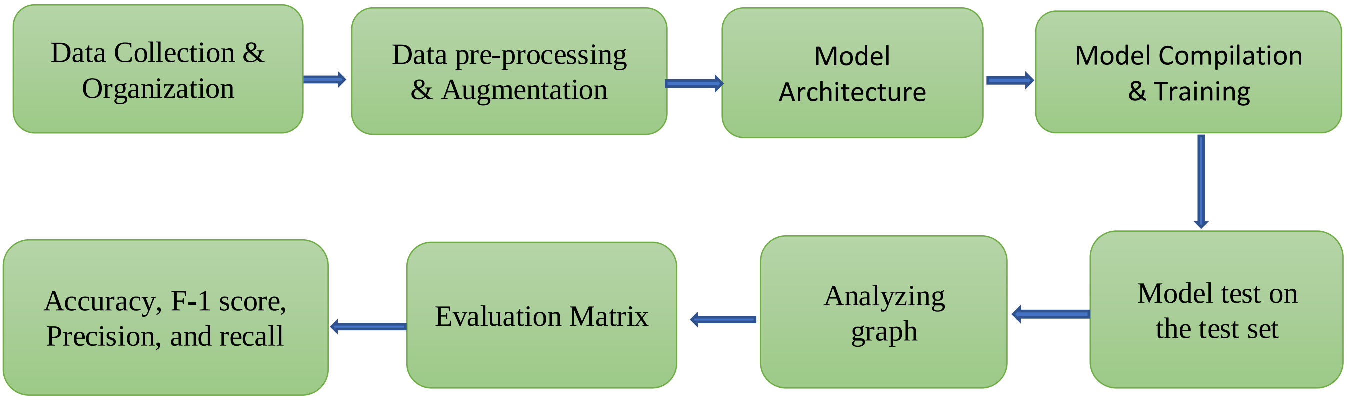

Figure 3.5: Proposed methodology block diagram

3.7.2 Proposed classification Model

In our model, as shown in Fig. 3.6, 2D convolutional layers are used with a kernel size of 5×5 for the first block, and 3×3 for the second and third blocks. A kernel size of 2×2 is applied in the last two blocks. For all blocks, the ReLU activation function is employed, while Batch Normalization (BN) is not applied. Each block's second convolutional layer used a stride of two to conduct downsampling. The initial block had 64 filters, and each succeeding block had double the number of filters. Following the last convolutional layer, a dropout layer (p = 0.3) was added before being linked to one FC dense layer with ReLU activation values of 1024. Finally, a multi-dense neuron with softmax activation supplied the model output. The training was carried out for a maximum of 10 epochs at a learning rate of 0.001, using the Adam optimizer to estimate model parameters and a batch size of 32, and utilising the categorical-cross-entropy loss function, which is frequently used for multiclass classification issues

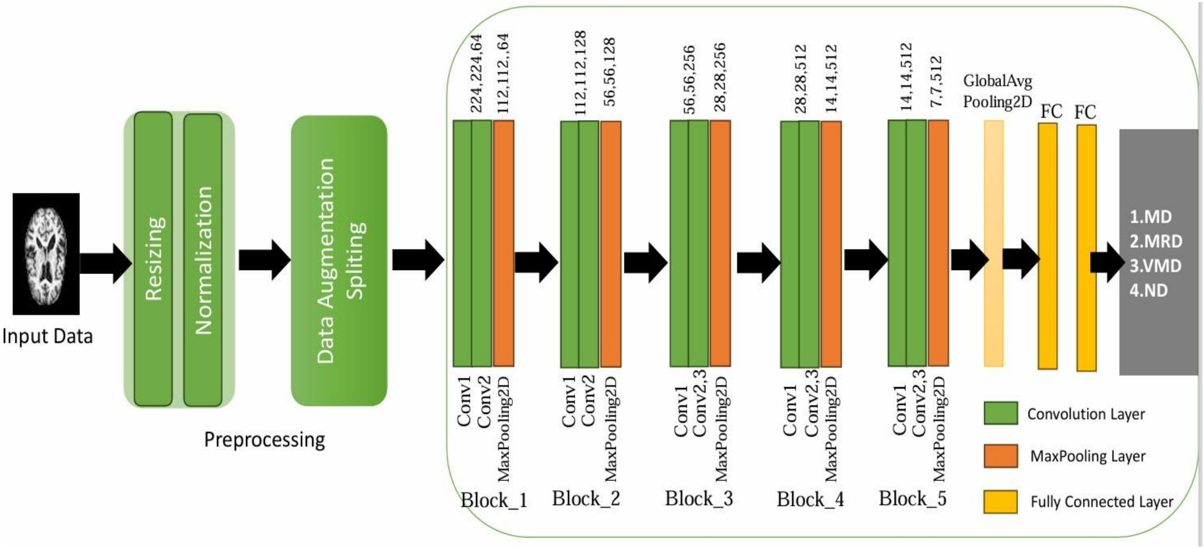

Figure 3.6: Modified VGG16 with Global Average Pooling(GAP) Architecture [9].

3.8 Confusion Matrix

A confusion matrix is a widely used tool in machine learning, including for Convolutional Neural Networks (CNNs), to evaluate the performance of classification models. It summarizes the model's predicted labels against the actual class labels in a square matrix format, where the rows correspond to the true classes and the columns represent the predicted classes. Using the confusion matrix, several key performance metrics such as accuracy, precision, recall, and F1 score can be derived to measure how well the model performs.

3.8.1 Accuracy

Accuracy represents the ratio of correctly predicted samples to the total samples. It is determined by adding the true positives and true negatives, then dividing by the overall number of samples.

3.8.2 Precision

Precision measures the ratio of correctly identified positive cases (true positives) to the total number of cases predicted as positive (true positives + false positives). It evaluates the accuracy of positive predictions and is especially important when minimizing false positives is critical. Precision is calculated by dividing the number of true positives by the sum of true positives and false positives.

3.8.3 Recall

Recall represents the fraction of actual positive cases that are correctly identified by the model (true positives) out of all the real positive cases, which includes both true positives and false negatives. It emphasizes the model's effectiveness in detecting all positive samples and is especially important when missing a positive case (false negative) has a significant cost. Recall is calculated by dividing the number of true positives by the sum of true positives and false negatives.

3.8.4 F1-Score

The F1 Score is the harmonic average of precision and recall. It offers a balanced metric that takes both precision and recall into account at the same time. This score is especially helpful when aiming to achieve a good balance between precision and recall.

3.9 Summary

The methodology chapter outlines a multi-model deep learning framework designed for Alzheimer’s disease segmentation and classification using brain MRI scans. For segmentation, the Attention U-Net architecture was applied to extract the left and right hippocampal regions, incorporating preprocessing steps such as normalization, resizing, augmentation, and noise reduction to enhance data consistency. The encoder-decoder structure with attention gates improved focus on disease-relevant regions while suppressing background noise, ensuring precise segmentation. For classification, a transfer learning-based VGG16 model and its modified variant were employed to categorize MRI images into four classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Data augmentation, selective fine-tuning, and dropout regularization were used to improve generalization and reduce overfitting. Model evaluation employed metrics such as accuracy, precision, recall, F1 -score, and confusion matrix. By combining segmentation and classification, the framework provides both anatomical localization and disease stage identification, offering a robust and comprehensive solution that addresses the limitations of previous single-task approaches.

Chapter 4: Results and Comparisons

4.1 Hyper-parameters setting for CNN Model

The hyper-parameter values that utilized to create our CNN model during the initialization and training stages are discussed in this section. The following chart demonstrate these details:

Table 4.1 **Hyperparameter tuning for Segmentation**

Parameter	Value
Batch size	08
Epoch	10
Optimizer	Adam
Learning rate(LR)	le-4
Activation	Sigmoid
Patience for early Stopping	05
Loss Function	Dice_Loss

Table 4.2: **Hyperparameter tuning for Classification**

Parameter	Value
Epoch	10
Batch Size	32
Learning rate	0.0001
Loss function	categorical_crossentropy
Patience for early stopping	10
Optimizer	Adam

4.1.1 Experiment-l (Classification)

In the first experiment, the dataset was divided into 70:30, which implies that 70% of the data was used for training, 20% testing and 10% validation. we have trained a number of pre-trained models with Augmentation and Mobile-Net provides the greatest outcome in the term of accuracy.

Table 4.3: Accuracy for proposed VGG16 model

Model Network	Accuracy in validation set	Accuracy in test set	Precision	Recall	F1-Score
VGG16	0.9697	0.8975	0.905	0.905	0.905

4.1.2 Experiment-2 (Segmentation)

The proposed framework's effectiveness will be evaluated by comparing its performance to other advanced models using four key metrics: accuracy (ACC), Dice Similarity Coefficient (DSC), sensitivity, and specificity, as shown in Table 4.4.

Table 4.4: Accuracy for proposed Attention U-Net Model

Performance metrics	**Accuracy**	**Sensitivity**	**Dice_coef**
Manhua Liu et al	88.9%	N/A	87.0%
Hosseini et al.	90.31%	91.18%	
Dolz et al.	N/A	N/A	92%
Proposed Model(VGG16)	96.97%	N/A	N/A
Proposed Model(Attention Unet)	N/A	N/A	98.1%

Table 4.5: Dice_coef & loss value in proposed Attention U-Net model

Model Network	**Dice_coef**	**Val_Dice_Coef**	**Loss**	**val_Loss**
Attention U-Net	0.9894	0.9895	0.0318	0.0315

4.1.3 ROC curve for the Proposed Model(VGG16)

The multi-class ROC curve illustrates the performance of the proposed VGG16 model across all four Alzheimer's disease classes. The model achieved excellent discriminative ability with AUC values of 0.97 for Mild Demented, 1.00 for Moderate Demented, 0.94 for Non Demented, and 0.93 for Very Mild Demented. These results demonstrate the robustness of the model in distinguishing between different stages of the disease with high accuracy.

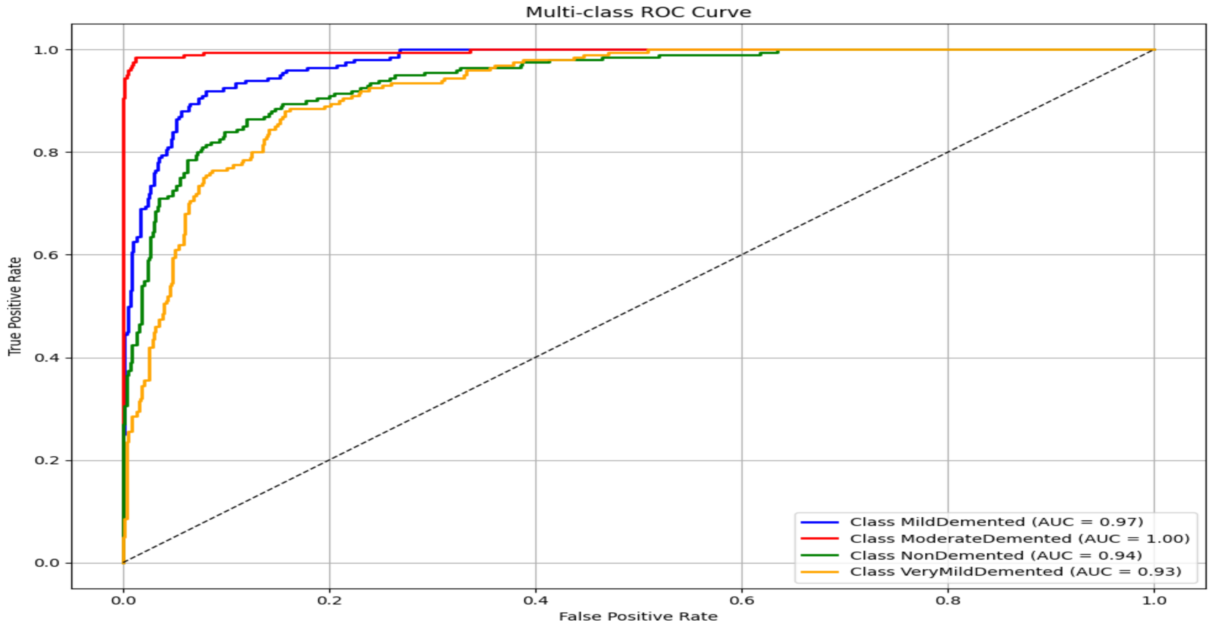

Figure 4.1: The ROC curve for the VGG16 model

4.1.4 Alzheimer's Disease Classification Results

The figure presents classification outputs of the proposed model for different stages of Alzheimer's disease, including Moderate Demented, Mild Demented, Very Mild Demented, and Non Demented cases. Each sub-image shows the actual class label alongside the predicted class, demonstrating correct classifications across multiple categories. These results highlight the model's capability to distinguish between varying disease stages based on MRI scans.

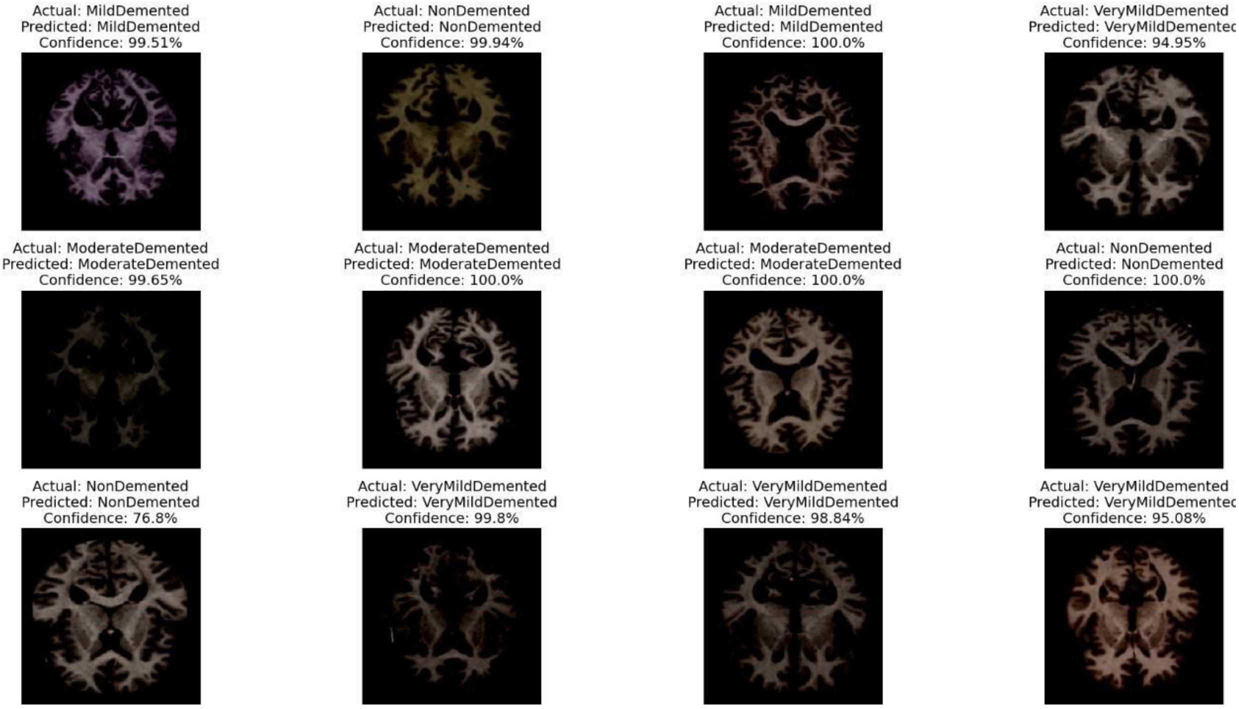

Figure 4.2: Model Predictions vs. Ground Truth

4.1.5 Comparison of different architectures

Figure 4.3 gives a graphical comparison among the proposed architectures (Attention U-Net) and other states of the art results

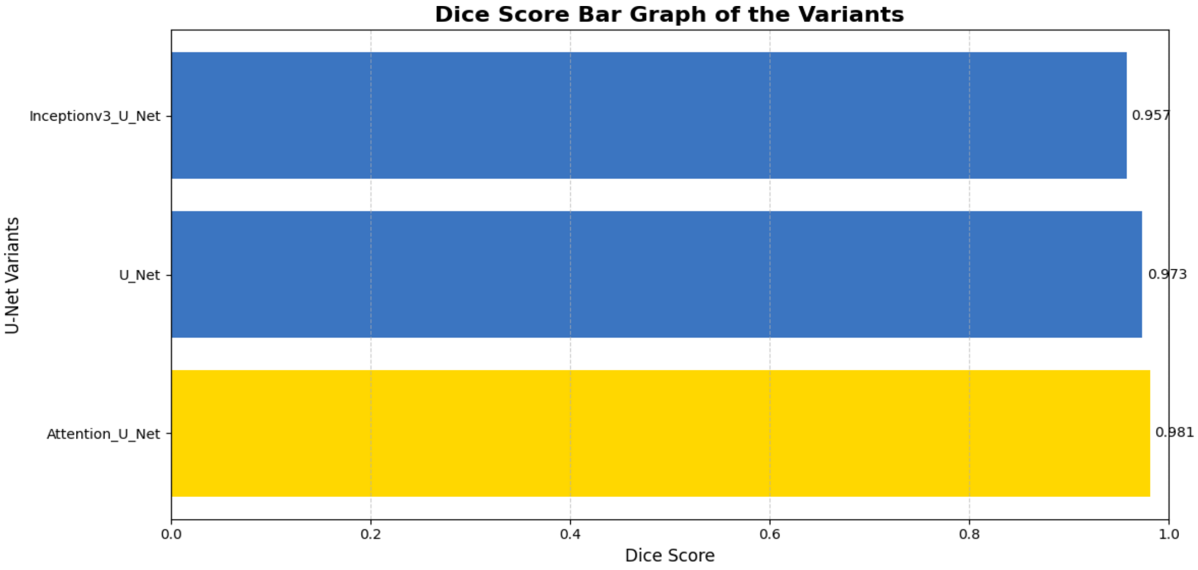

Figure 4.3: The comparison of our proposed architectures to other states of the art results.

4.1.6 Hippocampus Segmentation and Overlay Visualization on MRI for Alzheimer's Analysis

The figure 4.4 demonstrates the hippocampal segmentation process and its visualization on MRI scans for Alzheimer’s disease analysis. The first and third columns represent the segmented left and right hippocampal regions, while the second column shows the original MRI brain image. In the fourth column, the segmented hippocampal regions are overlaid on the MRI scan, clearly highlighting the areas of interest. This segmentation and overlay process allows the model to focus on hippocampal structures, which are strongly associated with cognitive decline and are key biomarkers for Alzheimer’s disease detection and progression analysis.

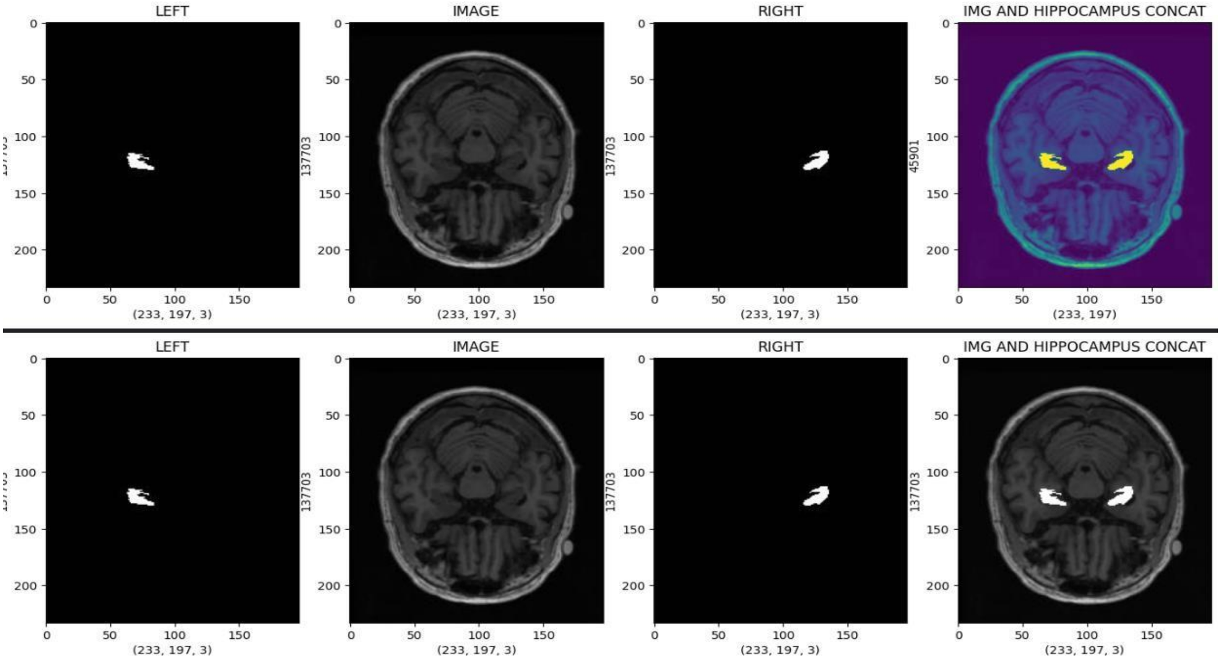

Figure 4.4: Input image, the left and right semantic hippocampus segmentation output mask, and the ground truth mask overlay the input MRI image

4.2 Accuracy Curve and Loss curve

The suggested CNN model employing the dataset from Kaggle is split into two graphical representations, which are shown in the two picture below.

4.2.1 Attention U-Net model curve

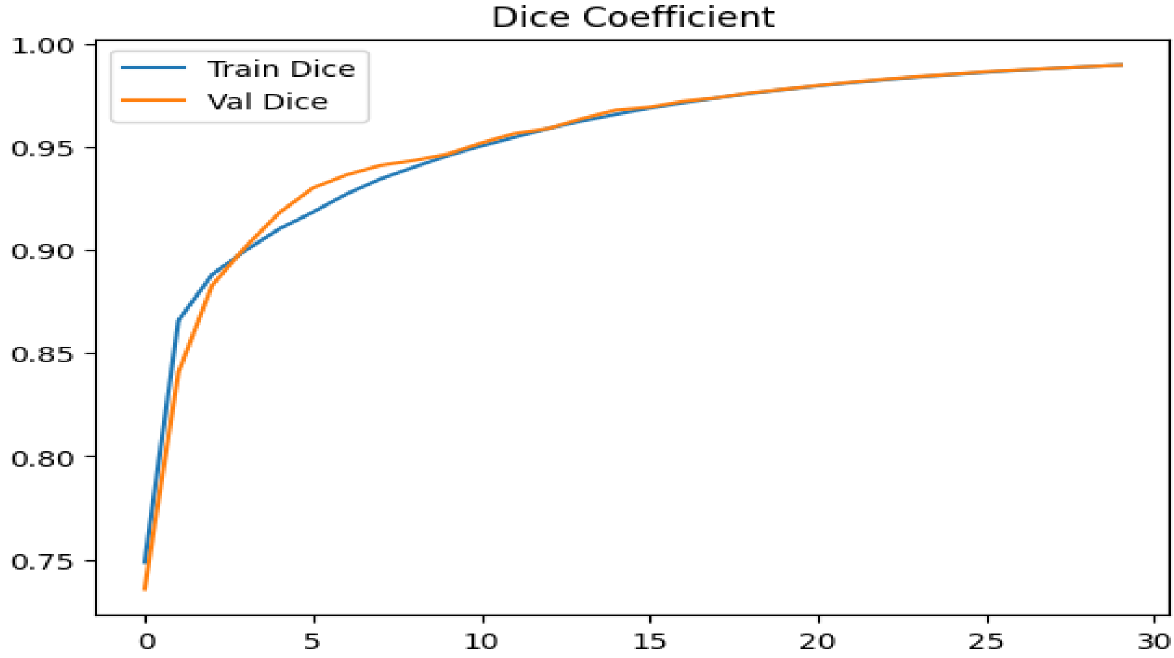

Figure 4.5: Accuracy curve for pre-trained Attention U-Net

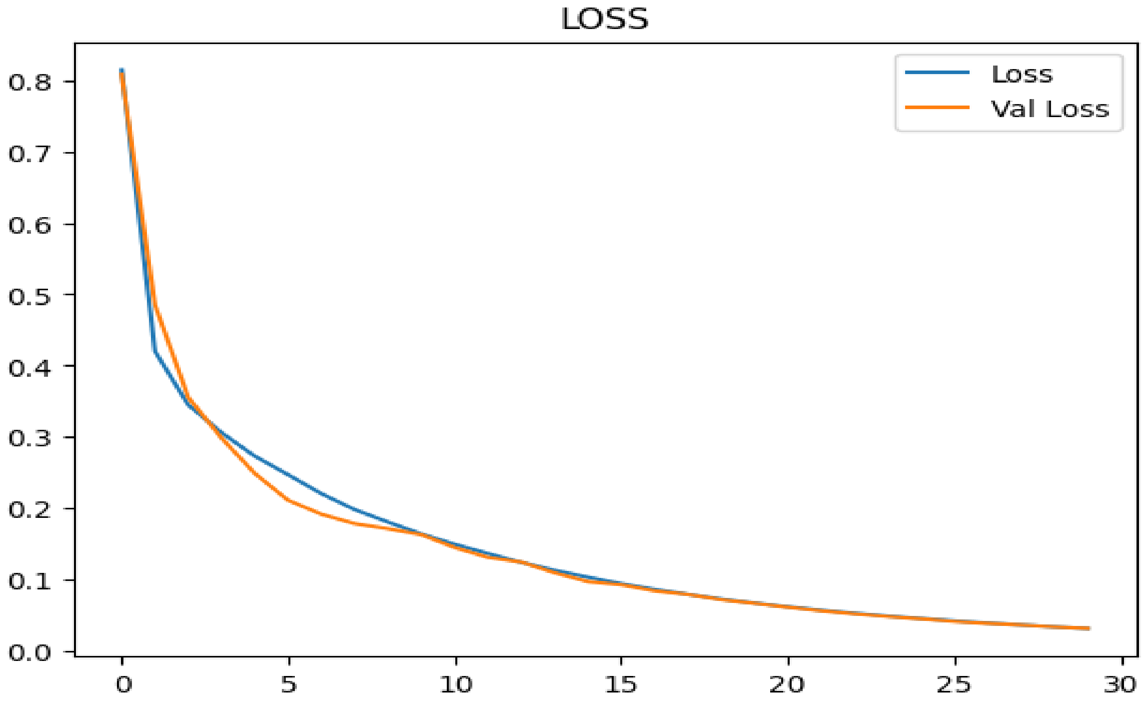

Figure 4.6: Loss curve for pre-trained Attention U-Net

Figure 4.5 and Figure 4.6 illustrate the training and validation Dice coefficient curves of the proposed Attention U-Net model over 30 epochs. The Dice coefficient, a commonly used metric in medical image segmentation, evaluates the spatial overlap between predicted and ground truth segmentation masks, ranging from 0 (no overlap) to 1 (perfect overlap).

As shown in the figure, both training and validation Dice coefficients increase rapidly during the initial epochs (0–5), indicating that the model quickly learns relevant spatial and structural features from the input data. After epoch 10, the performance gradually stabilizes, and by epoch 20–30, both curves converge toward a Dice coefficient of approximately 0.98–0.99. This high overlap score demonstrates the model's strong capability in accurately segmenting the target regions.

Importantly, the close alignment between the training and validation curves suggests that the Attention U-Net model generalizes well to unseen data, with minimal signs of overfitting. This performance validates the effectiveness of incorporating attention mechanisms into the U-Net architecture, enabling the network to focus on relevant anatomical structures and suppress irrelevant background information.

4.2.2 Proposed VGG16 model curve

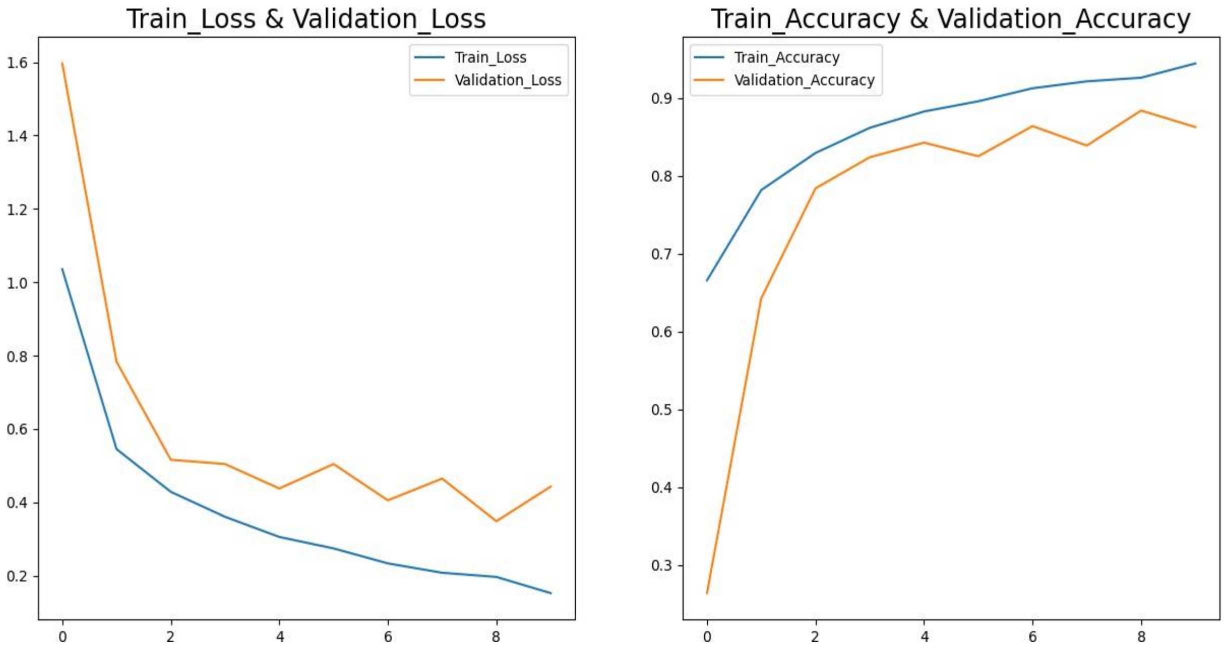

Figure 4.7: Accuracy Curve & Loss Curve for VGG16

The training and validation loss curves for the proposed VGG16 model, as shown in Figure 4.7, demonstrate a consistent downward trend across training epochs. The training loss decreases steadily from 0.8 to 0.2 over the course of 10 epochs, indicating effective learning and optimization. The validation loss follows a similar trajectory, decreasing from 0.9 to 0.3, though it exhibits minor fluctuations between epochs 40-60 that may suggest temporary overfitting before stabilizing. Correspondingly, the accuracy curves reveal strong model performance. Training accuracy increases consistently from 60% to nearly 100%, while validation accuracy improves from 55% to 90%. The model achieves its optimal validation performance at epoch 9.

These results demonstrate that the proposed VGG16 implementation successfully balances learning capacity with generalization. The minor fluctuations in validation metrics are likely attributable to the model's adaptation to challenging samples in the dataset rather than fundamental instability. This performance validates the architectural choices and training methodology employed

4.2.3 Confusion Metrix

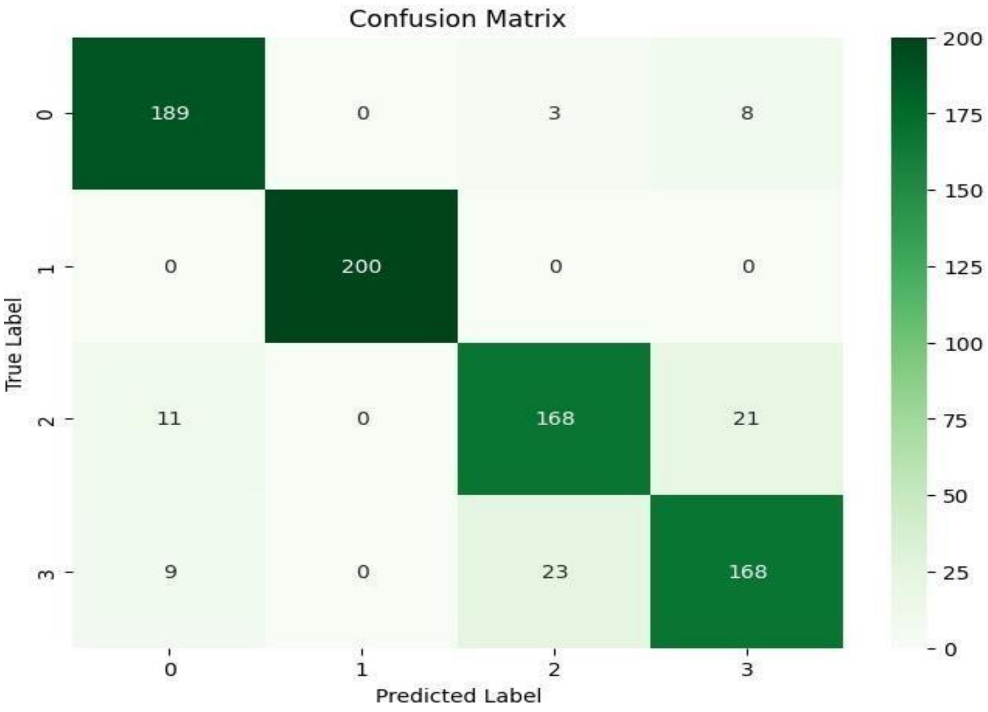

Figure 4.8: Confusion matrix for proposed VGG16 model

Figure 4.8 provides a detailed evaluation of the classification performance of the proposed model across the four categories of Alzheimer’s disease. The results indicate that the model correctly identified 189 instances of Non-Demented, 200 instances of Very Mild Demented, 168 instances of Mild Demented, and 168 instances of Moderate Demented cases. A small number of misclassifications were observed, with most occurring between the Mild Demented and Moderate Demented classes, reflecting the clinical challenges in distinguishing between these closely related stages. The strong concentration of values along the diagonal demonstrates the high accuracy and robustness of the proposed framework, further confirming its effectiveness in multi-class Alzheimer’s disease classification.

4.3 Summary

This chapter presented the experimental evaluation of the proposed multi-model deep learning framework for Alzheimer’s disease segmentation and classification. Performance metrics, including precision, recall, F1-score, and confusion matrix analysis, further validated the robustness of the model. Comparative evaluation with existing methods indicated that the proposed framework provides superior performance, particularly by integrating segmentation and classification as complementary tasks. The ROC curve analysis confirmed the discriminative ability of the model across all disease stages, with AUC values above 0.90, reflecting excellent classification capability. Visual results of segmentation overlays and classification outputs reinforced the model’s effectiveness in highlighting disease-relevant regions and stages. Overall, the results substantiate the framework’s potential as a reliable tool for Alzheimer’s disease detection and progression analysis.

Chapter 5: Conclusion and Future Works

5.1 Conclusion

This thesis presented a multi-model deep learning framework for the classification and segmentation of Alzheimer’s disease using brain MRI scans. The study employed an Attention U-Net architecture to accurately segment the left and right hippocampal regions, achieving a Dice Similarity Score of 98.1%, which demonstrates high precision in identifying disease- relevant anatomical structures. For classification, a transfer learning-based VGG16 model was developed to categorize MRI images into four distinct stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, attaining an accuracy of 89.6%. The integration of segmentation and classification ensured both anatomical localization and disease stage prediction, addressing the limitations of prior single-task approaches. Experimental results confirmed that the proposed framework effectively captures structural abnormalities, enhances diagnostic accuracy, and provides reliable insights into Alzheimer’s disease progression. Overall, the findings underscore the potential of deep learning methodologies as a supportive tool for early detection and clinical decision-making in Alzheimer’s disease.

5.2 Future Work

The proposed multi-model framework for Alzheimer’s disease segmentation and classification has delivered encouraging results; however, there remain several opportunities for further improvement. Future work may focus on employing larger and more diverse multi-modal datasets, including PET and fMRI, to enhance model robustness and generalizability. Extending the current 2D slice-based approach to 3D volumetric analysis could provide richer spatial information for detecting subtle structural changes. Incorporating advanced architectures such as transformer-based networks or hybrid CNN–RNN models may further improve performance by capturing both spatial and temporal dependencies. The integration of explainable AI (XAI) techniques, including saliency maps and attention visualizations, will also be vital to improve interpretability and clinical trust. Finally, clinical validation in collaboration with healthcare institutions and the inclusion of non-imaging biomarkers such as genetic and cognitive data could establish a more comprehensive and reliable system for AD detection and management.

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