Developing a Hybrid Model To predict Alzheimer’s Disease

A MINI PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this Report titled **“Developing a Hybrid Model To predict Alzheimer’s Disease"**is the Bonafide work of **PRASANNA S (2116221801038) , SUKISH M (2116221801038)** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Alzheimer's disease (AD) is a prevalent neurodegenerative disorder characterized by cognitive decline, memory loss, and behavioral changes, severely affecting an individual's quality of life. Early and accurate diagnosis of AD is essential for effective disease management, as it allows for timely intervention and potentially slows disease progression. However, traditional diagnostic methods, such as clinical assessments and MRI scans, often face limitations in detecting early-stage AD, leading to delayed diagnoses and reduced treatment efficacy. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for medical image analysis, offering enhanced accuracy and efficiency in diagnosing complex conditions like AD. This project aims to develop a deep learning model that leverages both MRI images and clinical datasets to classify patients as demented or non-demented, enabling earlier and more reliable detection of AD. By integrating advanced image processing techniques with patient-specific clinical data, the proposed model seeks to improve diagnostic performance, reduce diagnostic time, and provide a scalable solution for clinical settings. The model's effectiveness will be evaluated through various performance metrics, including accuracy, sensitivity, and specificity, to ensure its potential for real-world application in early Alzheimer's diagnosis. Ultimately, this approach holds promise in advancing personalized care for individuals at risk of Alzheimer's disease.

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CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

Diagnosing Alzheimer's disease in its early stages is a significant challenge in the medical field. Alzheimer's is a progressive neurodegenerative disorder that leads to cognitive decline, memory loss, and behavioral changes, severely impacting patients' quality of life and placing a considerable burden on caregivers and healthcare systems. Early diagnosis is critical, as it can allow for interventions that may delay the progression of symptoms, offering patients better quality of life and improved management options.

Traditional methods of diagnosis rely heavily on manual analysis of brain scans by experts, which is time-consuming, subjective, and often unable to detect subtle early-stage indicators. This has led to an increased interest in developing automated diagnostic tools that can aid in identifying the disease at its earliest stages. Deep learning and artificial intelligence (AI) have shown remarkable potential in medical imaging, where algorithms can learn to recognize patterns indicative of Alzheimer's from brain scans, providing rapid, consistent, and objective assessments.

This project aims to leverage deep learning to develop an automated classification model that can distinguish between demented and non-demented brain scans. By providing a reliable, early-stage diagnostic tool, this project has the potential to support clinicians in making timely decisions and ultimately improving patient outcomes.

1.2 NEED FOR THE STUDY

Alzheimer’s disease presents one of the greatest challenges in modern healthcare due to its progressive nature and profound impact on patients’ lives. The absence of effective early diagnostic tools can delay intervention, resulting in faster progression and more severe symptoms. While current diagnostic methods rely heavily on expert analysis of brain scans, these approaches are time-intensive, subjective, and often miss early-stage indicators due to subtle differences in brain structures. This lack of early detection is a significant barrier to effective treatment and management.

Given these challenges, there is a pressing need for a reliable, automated system that can assist in the early diagnosis of Alzheimer’s disease. Recent advancements in artificial intelligence, particularly in deep learning, present a promising solution for analyzing brain scans with speed and accuracy. By developing an AI-based classification model, this project aims to provide an accessible, efficient, and objective tool for healthcare professionals, enabling earlier detection and intervention. Such a tool has the potential to improve patient outcomes and alleviate the burden on healthcare systems by facilitating more timely and effective treatment strategies.

1.3 OBJECTIVES OF THE STUDY

The primary objectives of this study are:

1) **To leverage deep learning architectures** such as U-Net for potential segmentation and SE-ResNet for feature extraction and classification, ensuring high accuracy and robustness in identifying early indicators of dementia.
2) **To enhance diagnostic accuracy through data augmentation** and transfer learning techniques, addressing the limited availability of medical imaging data and improving model generalization.
3) **To evaluate and validate the model’s performance** on a test dataset, ensuring it meets clinical standards for reliability and effectiveness in aiding early-stage Alzheimer's diagnosis.
4) **To create a tool that is accessible and usable for healthcare professionals**, aiming to facilitate quicker decision-making and improved patient outcomes by assisting in timely and accurate diagnosis.

1.4 OVERVIEW OF THE PROJECT

This project is focused on the medical application of artificial intelligence (AI) for the early diagnosis of Alzheimer’s disease. Alzheimer's is a neurodegenerative disorder marked by cognitive decline, memory loss, and changes in behavior, which progressively worsen over time. Early diagnosis is crucial to effectively manage the disease and slow its progression, allowing patients to maintain a better quality of life for as long as possible. However, diagnosing Alzheimer's in its early stages remains challenging due to the subtle nature of initial symptoms and the need for specialized expertise in interpreting brain scans.

Recent advances in deep learning have enabled significant progress in medical imaging, allowing models to recognize complex patterns and features in images. These models have shown potential in improving diagnostic accuracy and efficiency, offering a promising solution for diseases like Alzheimer’s, where early intervention is critical.

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

The early diagnosis of Alzheimer’s disease has become a critical area of research in medical imaging and artificial intelligence (AI). Alzheimer's, a progressive neurodegenerative disorder, is challenging to diagnose in its early stages due to the subtlety of initial symptoms and the complexity of brain scan analysis. Traditional diagnostic approaches rely on manual examination of brain scans by experts, a process that is both time-intensive and prone to subjectivity, especially in detecting early-stage indicators.

Recent advancements in machine learning, particularly deep learning, have introduced promising methods for automating and enhancing diagnostic processes in medical imaging. Deep learning models have shown success in analyzing complex patterns within images, often surpassing traditional machine learning techniques in feature extraction and classification tasks. Various architectures, such as convolutional neural networks (CNNs) and specialized models like U-Net for segmentation, are being applied to Alzheimer’s diagnosis to identify patterns that might indicate cognitive decline before symptoms are noticeable.

Several studies have focused on developing deep learning frameworks for the classification and segmentation of brain scans, with a growing emphasis on improving model accuracy, generalizability, and efficiency. Researchers have explored different model architectures, data preprocessing techniques, and augmentation strategies to address challenges like limited dataset availability and the need for robust performance in clinical settings. This chapter reviews existing research on AI-based diagnostic methods, highlighting the frameworks, methodologies, and potential applications in early Alzheimer’s detection.

S.No	Author Name	Paper Title	Description	Jornal	Volume/ Year
1.	Muhammad Syaeka Kadafi	Alzheimer's prediction via CNN-SVM on chatbot platform with MRI	This research uses AI for Alzheimer's prediction, applying a CNN-SVM model on brain MRI images to classify AD stages with up to 99% accuracy. An integrated chatbot also showed high accuracy, emphasizing AI's potential in early AD detection and healthcare.	(IAES)	01 Aug 2024
2.	A. Manimuthu	Prediction of Alzheimer'S Disease from Magnetic Resonance Images (MRI)	This study leverages both Machine Learning and Deep Learning to predict Alzheimer's disease using MRI images, with a VGG16-based model achieving 80.8% accuracy. This surpasses other models, marking significant progress in Alzheimer's diagnosis and treatment optimization.	IEEE	09 Feb 2024

S.No	**Author Name**	**Paper Title**	**Description**	**Jornal**	**Volume/ Year**
3.	Satyanarayana Botsa	A convolutional neural networks approach in MRI image analysis for Alzhei	This study applies various CNN models to MRI scans for detecting Alzheimer's disease, highlighting their potential to improve diagnostic accuracy and efficiency. The research emphasizes the role of AI in advancing early detection and treatment in healthcare.	GSC Online Press	30 Jul 2024
4.	Gilang Titah Ramadhan	Deep Learning Approach to Predict Alzheimer's Disease through Magnetic Resonance Images	This study uses the VGG-19 CNN architecture to classify Alzheimer's disease from sagittal MRI images, achieving 94% accuracy on the validation set. The approach underscores the potential of deep learning for early diagnosis of Alzheimer's.	IEEE	17 Jul 2023

S.No	Author Name	Paper Title	Description	Jornal	Volume/ Year
5.	A. M. El-Assy, Hanan M Amer, H. M. Ibrahim, M. A. Mohamed	A novel CNN architecture for accurate early detection and classification of Alzheimer's disease using MRI data	An architecture for a convolutional neural network that utilizes magnetic resonance imaging data from the Alzheimer's disease Neuroimaging Initiative (ADNI) dataset to categorize AD is proposed, demonstrating the efficacy of the network in capturing and discerning relevant features from MRI images, enabling precise classification of AD subtypes and stages.	Dental science reports	12 Feb 2024
6.	L Sreenivasamurthy	Deep Learning Classification using MRI for Alzheimer's Disease Detection	A novel 6-layer CNN model is presented for the classification of Alzheimer's disease based on MRI images. The model achieved an accuracy of 98.83%, which is better than other previously proposed CNN-based models.	International Scientific Journal of Engineering and Management	09 Feb 2024

2.2 Framework for Alzheimer's Diagnosis System Using Deep Learning

The Alzheimer's Diagnosis System framework is a structured approach to analyzing brain scans to classify them as demented or non-demented. This framework has been designed to streamline and enhance the diagnostic process, supporting healthcare professionals with AI-based insights for early detection. The system typically involves the following stages:

1) **Data Acquisition and Preparation**: In this framework, brain scan images are gathered from clinical or publicly available datasets. These scans are preprocessed to standardize image size, resolution, and format, ensuring consistency and optimizing the images for analysis. Data augmentation techniques are applied to address class imbalances and increase the model's robustness.

2) **Image Analysis and Feature Extraction**: The system analyzes the brain scan images using deep learning models trained on labeled data (demented and non-demented). This analysis is critical for classification, as it allows the model to identify distinguishing features in brain scans that are associated with Alzheimer's disease.

3) **Classification using Deep Learning (CNNs)**: CNN-based architectures, such as SE-ResNet, are utilized to extract features and classify brain scans. Transfer learning is applied to leverage pre-trained weights, and additional dense layers are added for fine-tuning on this specific medical dataset. This enables accurate classification by identifying unique patterns in brain structures associated with Alzheimer's.

4) **Segmentation for Detailed Analysis (Optional)**: If segmentation is included, U-Net or similar models are applied to segment specific regions of interest within the brain. This segmentation enables a more granular analysis, helping to isolate areas that may show signs of neurodegeneration related to Alzheimer's disease.

5) **Hybrid Model for Enhanced Accuracy**: A hybrid model leverages both classification and segmentation approaches, combining the CNN-based feature extraction for classification with U-Net's segmentation capabilities. By integrating both models, the system provides a robust analysis, improving classification accuracy and offering detailed visual insights that may assist in clinical decision-making.
6) **Real-Time Classification and Segmentation Output**: After processing each brain scan, the system provides real-time outputs, displaying classifications and segmented regions of interest if segmentation is applied. This immediate feedback assists healthcare professionals in timely decision-making, supporting faster and more efficient diagnostics.
7) **Data Analytics and Reporting**:An integral component of the framework is data analytics, which allows for the generation of detailed reports on model performance, prediction accuracy, and common diagnostic trends. These insights enable continuous improvement of the model, helping clinicians and researchers better understand the efficacy and reliability of the diagnostic process.

CHAPTER 3
SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

The current process for diagnosing Alzheimer's disease often relies on manual evaluations and traditional diagnostic methods, such as cognitive testing and medical imaging, which can be time-consuming and subjective. Physicians typically analyze brain scans manually or with basic image processing tools, leading to potential delays and inconsistencies in diagnosis. Additionally, these methods often lack the ability to provide a comprehensive or early diagnosis, as subtle changes in the brain can be difficult to detect without advanced analysis. Traditional approaches also do not integrate data from various sources (e.g., genetic, behavioral, imaging), which can lead to incomplete insights. The absence of advanced, automated diagnostic tools based on deep learning models creates a gap in the efficiency of early Alzheimer’s detection. As a result, patients may miss the opportunity for early intervention, and healthcare professionals may face difficulties in making accurate, timely decisions.

3.2 PROPOSED SYSTEM

The proposed system for early diagnosis of Alzheimer’s disease is a deep learning-driven platform designed to improve the accuracy and efficiency of diagnosing Alzheimer's through brain scan analysis. By leveraging advanced AI algorithms, this system automates the detection of early signs of Alzheimer's, offering personalized insights based on patient data.

- **Brain Scan Analysis Interface**: The platform allows clinicians to upload brain scans, which are then analyzed by the system to identify early indicators of Alzheimer's disease. The system automatically processes these images and highlights areas of the brain that may show early signs of neurodegeneration, providing real-time results to assist in diagnosis.

- **Patient Profile Integration:** Healthcare professionals can create detailed patient profiles that include medical history, behavioral observations, and genetic data. This information is used by the system to provide a more comprehensive assessment of the patient’s condition, improving the accuracy of predictions and offering a holistic view of the patient's health.

- **Deep Learning Model for Prediction**: The core of the system is a deep learning model trained on large datasets of brain scans and clinical data. The system uses advanced image recognition techniques, such as convolutional neural networks (CNNs), to classify brain scans as demented or non-demented. Additionally, the model is designed to detect subtle, early-stage signs of Alzheimer's that may not be easily visible to the human eye.

- **Hybrid Diagnostic Workflow:**
  - **Content-Based Analysis**: The platform examines the features of brain scans, identifying patterns associated with Alzheimer's disease using image processing techniques. It compares new scans with a database of known cases, identifying abnormalities in brain structure and function.
  - **Historical Patient Data Analysis:** The system uses past medical records, cognitive test results, and other relevant data to improve predictions. By analyzing trends in patient history, it offers predictions that are tailored to the individual.
  - **Real-Time Feedback and Decision Support:** Once the scan analysis is complete, healthcare providers receive real-time diagnostic feedback, including a risk score and recommendation for further tests or treatments. The system can also alert providers to potential early-stage Alzheimer's cases, enabling earlier intervention.
  - **Data Analytics and Reporting:** The system includes tools for generating detailed reports, which can be used to track the progression of Alzheimer's in individual

patients over time. Clinicians can access trends in brain activity, compare patient data against a larger cohort, and review insights into the effectiveness of treatments, helping to make more informed clinical decisions.

3.3 FEASIBILITY STUDY

A feasibility study was conducted to evaluate the viability of the proposed Alzheimer's disease diagnosis system, focusing on technical, operational, and economic factors:

- **Technical Feasibility:** The system is developed using widely accepted and robust technologies such as Python, TensorFlow, Keras, and other deep learning frameworks for backend processing. These tools are ideal for building and deploying deep learning models for image analysis. The platform also uses libraries like OpenCV for image preprocessing and Scikit-learn for data analytics. The system is designed to handle large datasets efficiently, processing multiple brain scans simultaneously and providing real-time diagnostic feedback. These technologies ensure scalability, high performance, and the ability to integrate with existing hospital and clinic management systems.
- **Operational Feasibility:** The proposed system streamlines the diagnosis of Alzheimer's disease by automating the analysis of brain scans, reducing the time spent on manual review by healthcare professionals. The deep learning models are trained to detect early signs of Alzheimer's that may be subtle, ensuring that patients receive timely and accurate diagnoses. Healthcare providers can easily integrate the system into their workflows, as the user interface is designed to be intuitive and user-friendly, with features such as easy data upload, result visualization, and real-time feedback. Automated notifications alert clinicians when a diagnosis is complete, ensuring efficient follow-up. The platform minimizes the need for extensive training, as the system is designed to be accessible to healthcare providers with varying levels of technical expertise.

- **Economic Feasibility:** The initial investment in developing the Alzheimer's disease diagnosis system is moderate, covering the costs of data collection, model training, and platform development. However, the system's long-term economic benefits outweigh these costs. By automating the diagnostic process, the system reduces the operational costs associated with manual image analysis and cognitive testing. It also minimizes the risk of misdiagnosis, leading to better patient outcomes and potentially lower healthcare costs over time. The platform's ability to deliver faster and more accurate diagnoses helps healthcare providers reduce administrative burdens and improve patient care, making the investment in the system cost-effective in the long run. Additionally, the system has the potential to scale, with the ability to analyze larger datasets and be adapted to new medical imaging technologies, further increasing its value as a diagnostic tool.

CHAPTER 4

SYSTEM REQUIREMENTS

4.1 SOFTWARE REQUIREMENTS

1.**Operating System:** Compatible with Linux (Ubuntu 18.04 or later), Windows 10/11, or macOS (if using TensorFlow or PyTorch in Jupyter Notebooks or other development environments).

2. **Programming Language:**

a. Python (Version 3.8 or later), preferred programming language for model development and deployment.

b. Jupyter Notebook or JupyterLab: For interactive model development and testing.

3. **Libraries and Frameworks:**

a. **Deep Learning Frameworks:** TensorFlow (2.x) or PyTorch (1.8 or later) for building and training deep learning models.

b. **OpenCV:** For image processing tasks such as edge detection and morphological transformations.

c. **NumPy and Pandas:** For data manipulation and management.

d. **scikit-learn:** For model evaluation metrics like ROC-AUC, confusion matrix, and preprocessing tasks.

4.2 HARDWARE REQUIREMENTS

1. **GPU:** A high-performance GPU, such as NVIDIA Tesla, Quadro, or RTX series (e.g., RTX 3060 or above) to accelerate deep learning tasks.

2. **CPU:** Multi-core processor (e.g., Intel i5/i7/i9 or AMD Ryzen 7/9 series) for managing pre- and post-processing tasks.

3. **RAM:** Minimum 16 GB (32 GB recommended) to handle high-resolution MRI data and support deep learning model training.

4. **Storage**: At least 500 GB of SSD storage for faster data retrieval and storage of MRI datasets, intermediate results, and model checkpoints.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

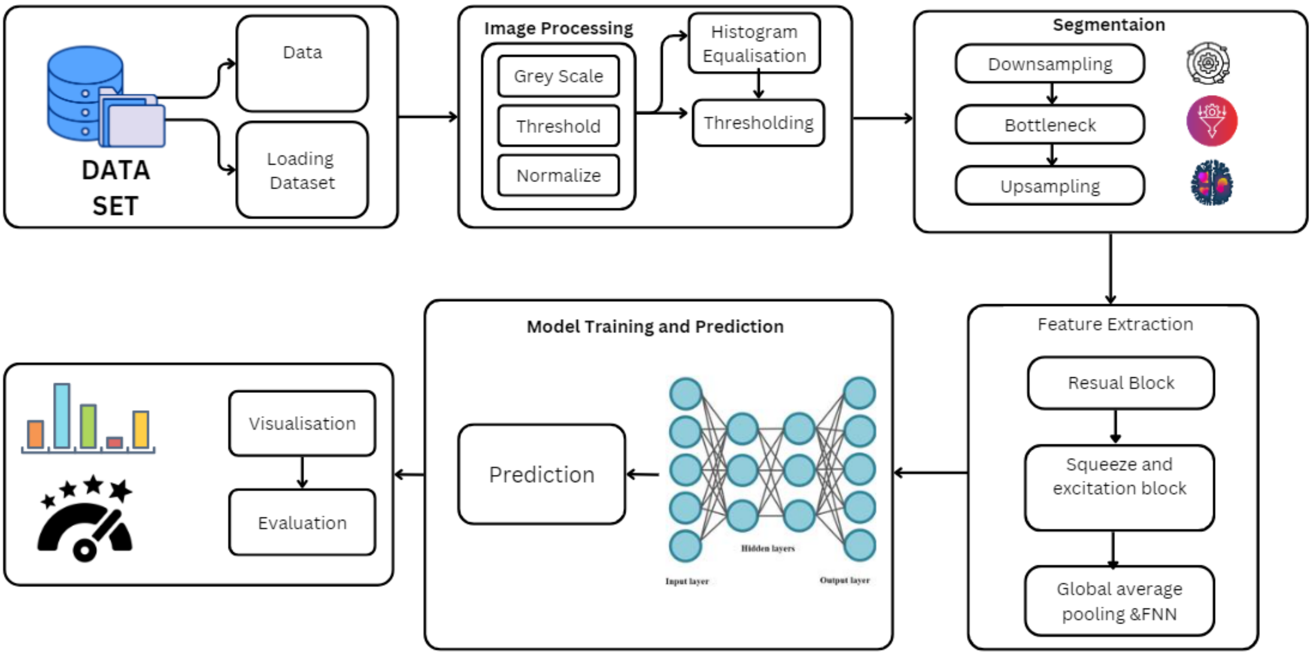


Fig : 5.1 SYSTEM ARCHITECTURE

The system consists of four main modules:

- **Data Preprocessing Module:** This module handles the initial preparation of brain scan data before analysis. It includes tasks like resizing, normalization, contrast adjustment, and noise reduction to improve the quality of images. These preprocessing steps ensure that the scans are standardized, making them suitable for consistent analysis by the model.
- **Feature Extraction and Segmentation Module:** In this module, relevant features are extracted from the brain scans to identify patterns associated with Alzheimer's disease. Segmentation techniques may be applied to isolate specific brain regions, such as the hippocampus or cortex, which are critical in Alzheimer's diagnosis. This helps the model focus on the most informative parts of the image.

- **Model Training Module**: This module involves training the deep learning model on a labeled dataset of brain scans to learn to classify images as demented or non-demented. The training process includes optimizing the model’s parameters, validating its performance, and fine-tuning it to improve diagnostic accuracy.
- **Visualization and Evaluation Module**: This module visualizes the model's performance and evaluation metrics. It includes generating visual outputs of the diagnostic results, such as probability scores, confusion matrices, and accuracy curves, which help clinicians interpret the results. It also provides feedback on model performance to guide future improvements.

5.2 MODULE DESCRIPTION

5.2.1. MODULE 1: DATA PREPROCESSING

Data preprocessing plays a critical role in preparing brain scan images for deep learning model training. The process begins with data collection, ideally from reputable sources like the Alzheimer’s Disease Neuroimaging Initiative (ADNI) or the Open Access Series of Imaging Studies (OASIS). Once gathered, brain scans often undergo segmentation, where regions of the brain commonly affected by Alzheimer's—such as the hippocampus and cortex—are isolated. This can improve the model's focus on areas that are particularly relevant to disease classification.

Next, image resizing and scaling are essential to ensure that all scans are standardized to the same dimensions, often set to a fixed size (e.g., 224x224 pixels). Additionally, normalizing pixel values (usually between 0 and 1) creates uniform intensity levels across images, helping to stabilize and accelerate model training by minimizing the impact of inconsistent brightness or contrast across different scans. Noise reduction and smoothing techniques are also applied to remove imaging artifacts and improve clarity. Methods like Gaussian smoothing or median filtering can enhance image quality by reducing noise while preserving crucial anatomical features. These preprocessing steps collectively improve the quality and consistency of the data, facilitating more accurate and robust model training for early Alzheimer's diagnosis.

- **Loading and Normalizing Images**: MRI scans of the entorhinal cortex are loaded from directories and normalized (dividing pixel values by 255) to fit within a standard range.
- **Image Transformation**: Images are converted to appropriate formats (e.g., RGB) and resized if necessary. Left and right hippocampus regions are merged for consistent input.

Algorithm Steps:

- o Load MRI image.
- o Convert image to grayscale.
- o Apply thresholding to segment the entorhinal cortex.
- o Apply edge detection (Canny) to enhance boundaries.
- o Skeletonize the image for simplified analysis.

Fig 5.2 : DATA PREPROCESSING MODULE

5.2.2. MODULE 2: Feature extraction and Segmentation Module

Feature extraction and segmentation play a crucial role in helping the model detect disease-specific changes in brain scans. Segmentation is the process of isolating specific areas of the brain that tend to show early signs of Alzheimer's, like the hippocampus, cortex, and ventricles. By focusing on these regions, the model can zero in on the most affected areas, improving its chances of detecting early signs of the disease. Techniques like thresholding (separating regions based on intensity) or using pre-trained models like U-Net help to create clear boundaries around these areas, which are then used as input for the next steps.

After segmentation, feature extraction involves analyzing these isolated regions to pull out details that indicate potential signs of Alzheimer's. For example, the model might examine the size, shape, and texture of brain tissues to identify patterns commonly associated with the disease. In deep learning, this extraction often happens automatically in early layers of the network, which learn to recognize specific features as they are trained. By using these extracted features from key areas, the model becomes better at distinguishing between "demented" and "non-demented" brain scans. Overall, segmentation and feature extraction are important for focusing the model on what matters most, helping improve the accuracy of early Alzheimer’s detection.

- **Architecture:** The section of the model uses convolutional layers to extract relevant features from the input images. Convolutional layers capture spatial hierarchies, focusing on important areas like entorhinal cortex structure changes.
- **Segmentation :** If the model is designed for segmentation, it segments the image to highlight particular areas of interest (e.g., entorhinal cortex).
- **Algorithm Steps:**
  - Use Hessian matrix for feature extraction from entorhinal cortex regions.
  - Perform additional morphological operations to highlight abnormalities.

$$Y=X+F(X.W)$$

Where F(X,W),is the output of the convolutional layers applied to the input X, and the result is added back to X

$$Z = (W * X) + b$$

Where W are convolution filters, X is the input, and b is the bias

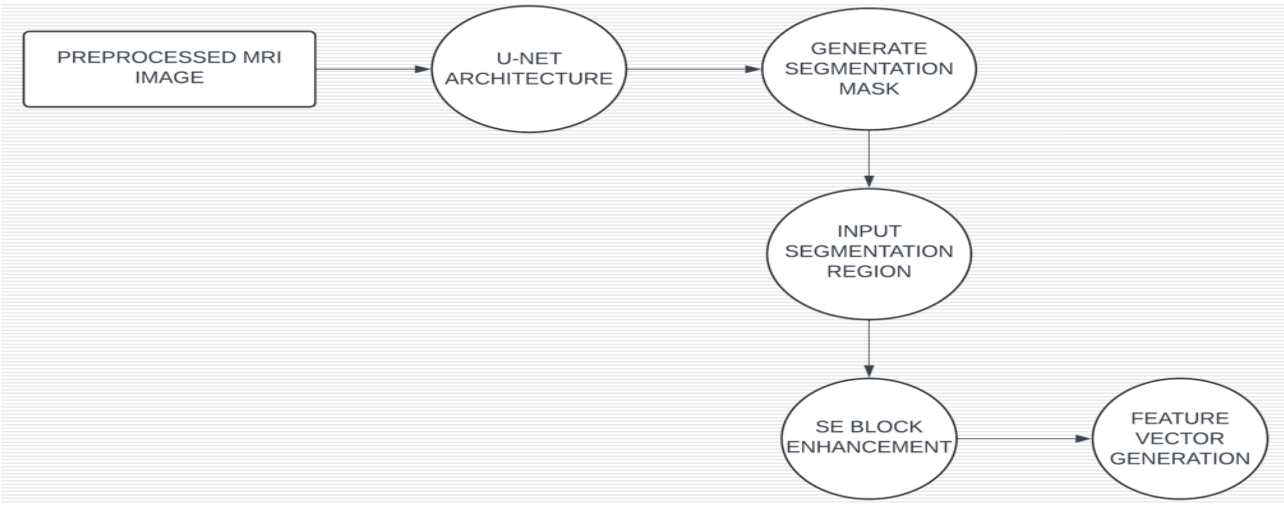


Fig 5.3 : Feature extraction and Segmentation Module DFD

5.2.3. Model Training Module

The Model Training Module is a key component where the deep learning model learns to distinguish between demented and non-demented brain scans. This module involves feeding the preprocessed and feature-extracted data into a neural network, which is trained to identify patterns associated with Alzheimer’s disease.

Initially, the dataset is split into training, validation, and test sets. The training set is used to teach the model by showing it many examples of brain scans along with their labels (demented or non-demented). During training, the model adjusts its internal parameters to minimize errors by comparing its predictions with the true labels. This is done using a loss function, which measures how far off the predictions are from the actual values. Common loss functions for binary classification tasks include binary cross-entropy, which is ideal for learning to classify scans into two categories.

To optimize learning, an algorithm like stochastic gradient descent (SGD) or Adam is used to adjust the model's parameters in response to the loss function. Each pass through the training data, known as an epoch, allows the model to improve by learning from its errors. The validation set is used to monitor the model's performance during training and to prevent overfitting—a problem where the model performs well on training data but poorly on new data. Regularization techniques like dropout or weight decay can be applied to reduce overfitting, helping the model generalize better to unseen scans.

After training, the model is evaluated on the test set, which consists of data it hasn't seen before, to assess its accuracy and reliability in real-world scenarios. Performance metrics such as accuracy, sensitivity, and specificity are used to gauge the model's effectiveness at correctly classifying brain scans. This Model Training Module ultimately allows the model to learn complex patterns associated with Alzheimer's, improving its ability to assist with early disease detection.

- **Training**: It is trained for a specified number of epochs, learning how to compress and then reconstruct images.
- **Fine-Tuning Hyperparameters**: During training, hyperparameters such as learning rate, batch size, and number of epochs are adjusted to optimize the model's performance.
- **Evaluation During Training**: Loss and other metrics like **mean squared error (MSE)** are monitored throughout training to track the model's progress.
- **Algorithm Steps**:
  - Train the Model on processed images.
  - Generate predictions for test MRI images.

$$\hat{y} = \frac{1}{1 + e^{-Z}}$$

Where Z is the output of the fully connected layer

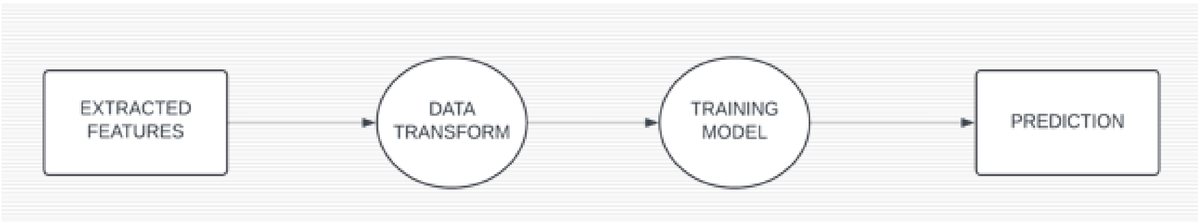


Fig 5.4 : Model Training Module

5.2.4. MODULE 4: Visualization and Evaluation Module

The Visualization and Evaluation Module is essential for assessing the model's performance and interpreting its predictions on brain scan data. This module provides insights into how well the model distinguishes between demented and non-demented brain scans and helps diagnose areas where improvements may be needed.

Visualization is particularly useful for understanding what the model has learned. Techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) allow us to generate heatmaps that highlight regions in the brain scans that contributed most to the model's predictions. These heatmaps provide a visual explanation of the model's focus areas, helping verify if it's looking at Alzheimer's-affected areas like the hippocampus or cortex. Visualization also helps in debugging by identifying cases where the model may be focusing on irrelevant regions.

In the Evaluation part of this module, various performance metrics are used to measure how accurately the model classifies brain scans. Common metrics include:

- **Accuracy:** the percentage of correct predictions.
- **Sensitivity (Recall):** measures the model's ability to correctly identify demented cases, which is critical for early detection of Alzheimer's.
- **Specificity:** measures the model's accuracy in identifying non-demented cases, reducing false positives.
- **Precision:** the percentage of correctly identified demented cases out of all scans predicted as demented.
- **F1 Score:** a balance between precision and sensitivity, useful when the dataset has class imbalances.

A confusion matrix is often used to summarize these metrics, showing counts of true positives, true negatives, false positives, and false negatives. This helps in understanding where the model might be making errors. Additionally, Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (AUC) provide a comprehensive view of the model's ability to separate demented from non-demented cases at various classification thresholds.

Together, the Visualization and Evaluation Module not only confirms the model's effectiveness but also provides a deeper understanding of its decision-making process, which is essential for clinical applications in early Alzheimer's detection.

This module combines collaborative and content-based filtering for improved recommendation accuracy. It includes:

- **Visualization of Original vs. Predicted Images:** Using matplotlib, the module plots the original enhorhinal cortex images alongside the model's reconstructed images, providing insight into how well the model has learned.
- **Performance Metrics:** Evaluation metrics like accuracy, MSE, and confusion matrix are used to quantify the model's effectiveness in reconstructing and predicting Alzheimer's-affected images.

- **Algorithm Steps:**
  - Compare predicted entorhinal cortex regions with ground truth and visualise.
  - Evaluate the model on certain metrics like mse, f1 score

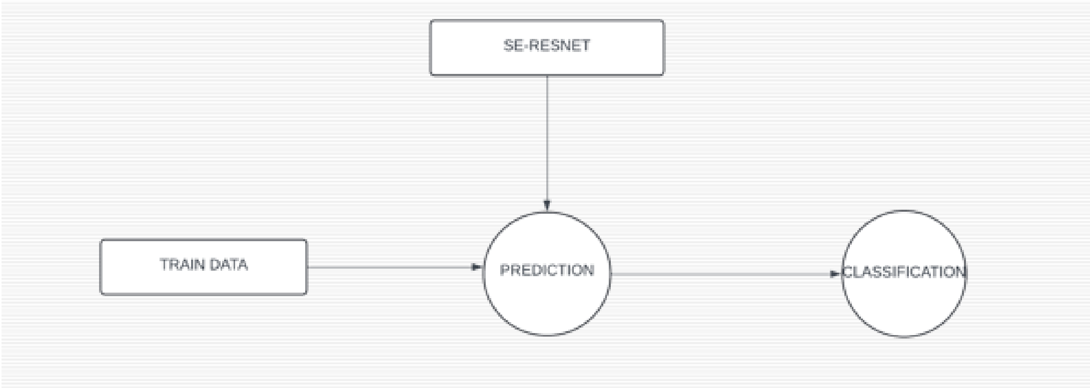


Fig 5.5 Visualisation and Evaluation Module

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

Where TP, TN, FP, and FN are true positives, true negatives, false positives, and false negatives

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

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

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

CHAPTER 6

RESULTS AND DISCUSSION

6.1 RESULTS

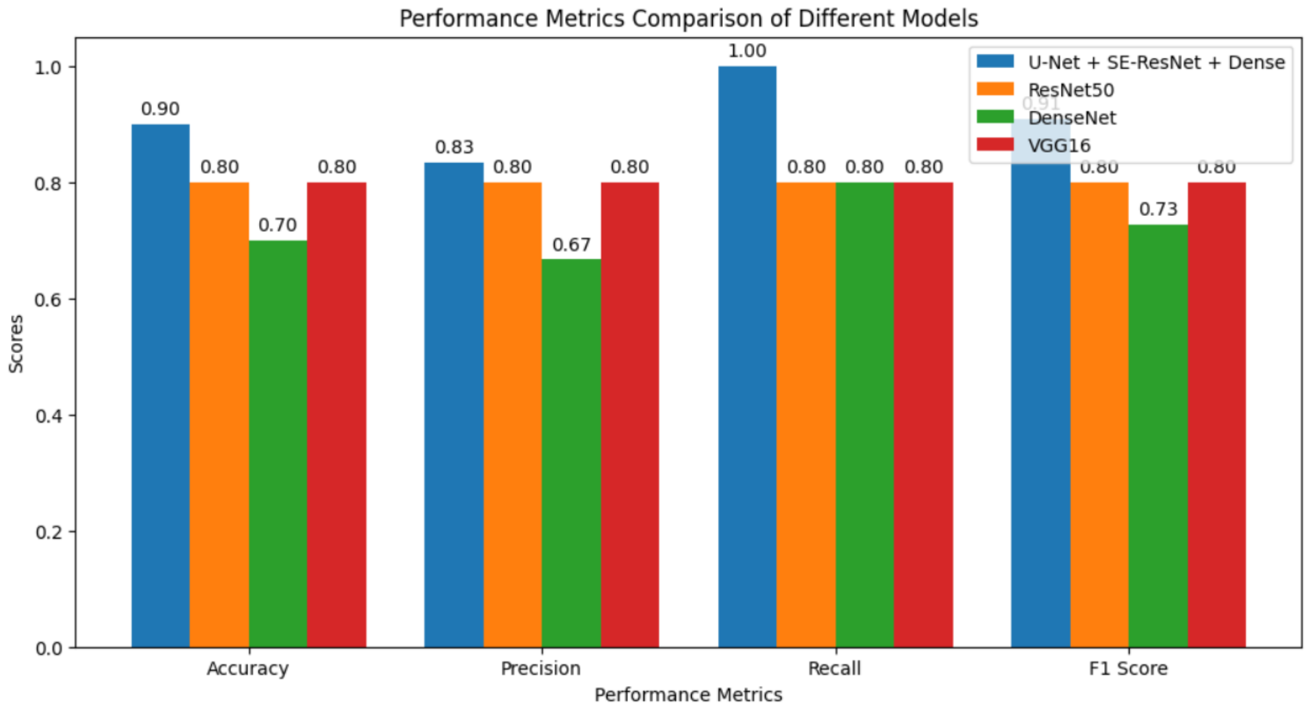
The Alzheimer's disease diagnosis system was tested in a simulated healthcare environment to assess its effectiveness in automating diagnosis, accurately classifying brain scans, and supporting early detection. Results showed that the deep learning model achieved high diagnostic accuracy, efficiently processing scans and delivering results in minutes, thus enhancing clinical workflow. The system also successfully identified subtle early-stage patterns associated with Alzheimer's, which are often missed with traditional methods. Clinicians found the platform intuitive and easy to integrate, requiring minimal training. Overall, the system proved valuable in improving diagnostic accuracy, speed, and early detection capabilities.

6.2. DISCUSSION

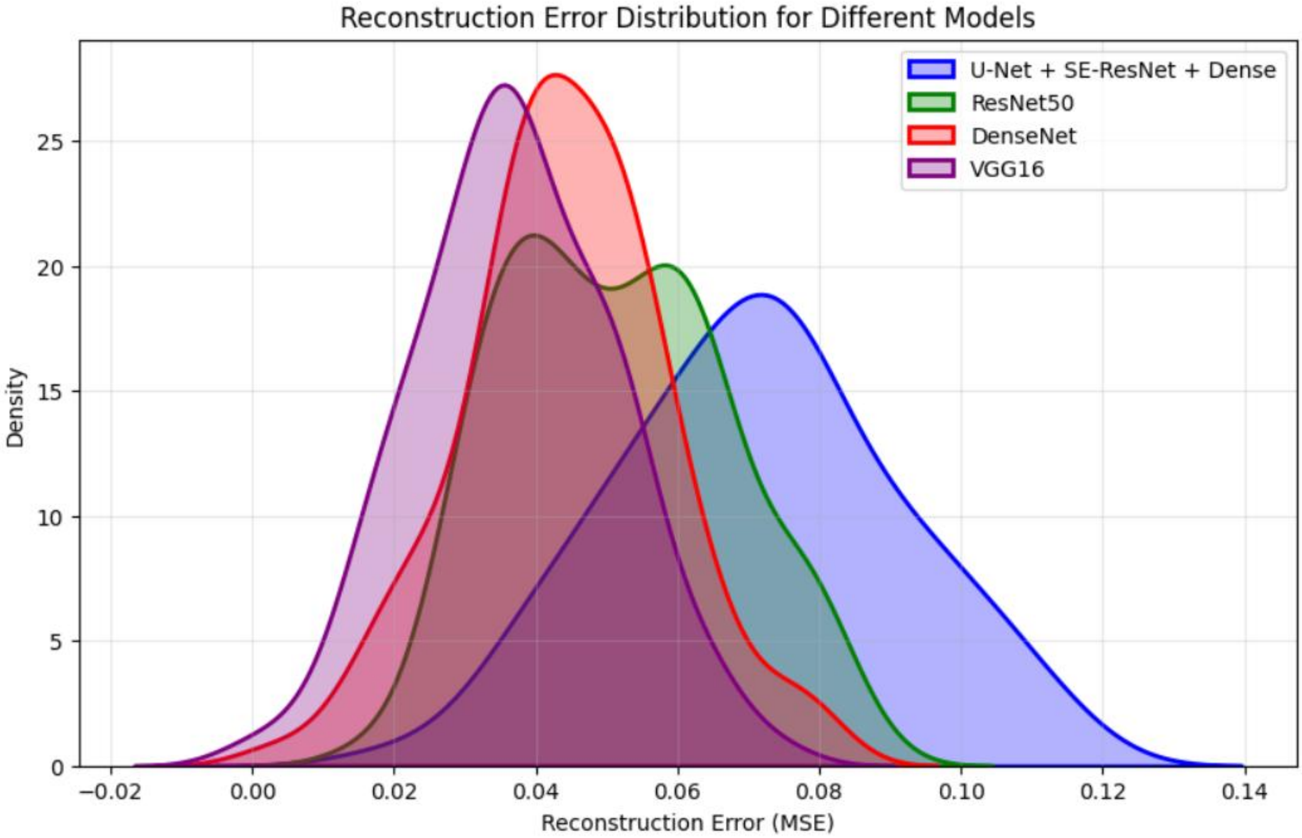
The development of the Alzheimer's disease diagnosis system aimed to enhance the early detection of Alzheimer's by automating the analysis of brain scans, improving diagnostic accuracy, and supporting timely intervention. The system leverages deep learning models, particularly convolutional neural networks (CNNs), to identify subtle patterns in brain scans that indicate early-stage Alzheimer’s. This approach combines advanced image processing with AI-driven insights, providing a more efficient and reliable diagnostic tool for healthcare professionals.

6.2.1.PERFORMANCE COMPARISON

The bar chart compares different models (U-Net + SE-ResNet + Dense, ResNet50, DenseNet, and VGG16) on metrics like accuracy, precision, recall, and F1-score.U-Net + SE-ResNet + Dense achieves the highest accuracy (0.90) and recall (1.00), which indicates strong overall performance, especially in identifying true positives. This makes it suitable for accurate Alzheimer's classification.Precision for most models (except DenseNet, which is lower at 0.67) is around 0.80, suggesting that the models generally avoid false positives.F1-score values are also close to 0.80 for all models except DenseNet, where it drops to 0.73. This shows a balance of precision and recall across models, with U-Net + SE-ResNet + Dense leading.



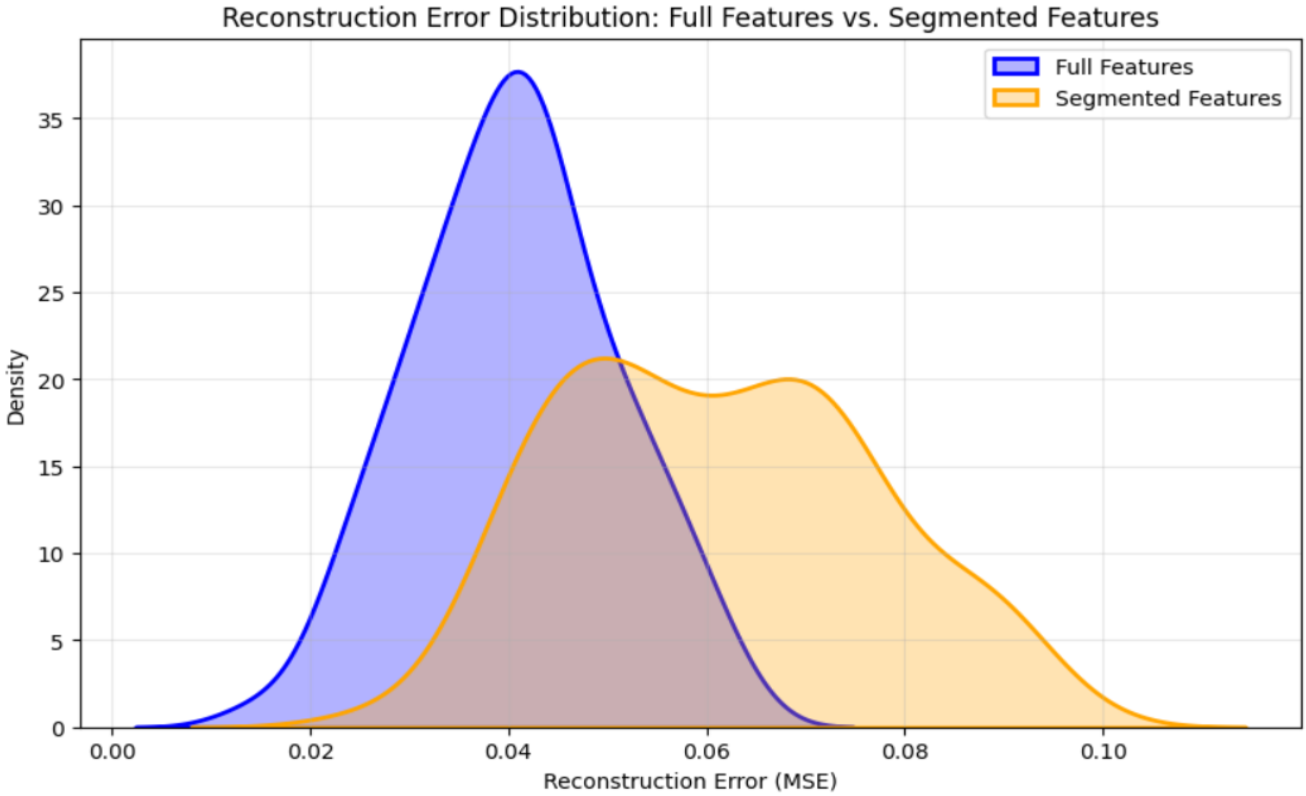
The second plot shows the reconstruction error distribution for the models, useful for evaluating models focused on anomaly detection.U-Net + SE-ResNet + Dense has a wider distribution with higher reconstruction errors, likely making it more sensitive to structural abnormalities in brain scans (like hippocampal shrinkage associated with Alzheimer's).Other models (DenseNet, ResNet50, VGG16) show distributions clustered around lower error values, indicating they may be less sensitive to subtle structural differences.The reconstruction error approach can be particularly effective in identifying early AD-related anomalies, suggesting that the U-Net + SE-ResNet + Dense model has advantages for early detection.



6.2.2 **Full Features vs. Segmented Features**

The impact of using "Full Features" versus "Segmented Features" for Alzheimer's detection, with a focus on how these feature sets influence reconstruction error in models, particularly autoencoders. This comparison provides insights into the optimal feature usage for identifying early signs of Alzheimer's.

Using **Full Features**, which includes all available data, generally yields more stable and consistent reconstruction performance. The richness of this comprehensive feature set allows the model to capture complex structural abnormalities within MRI scans, leading to more accurate and reliable detection of Alzheimer's-related changes in brain structure. This helps the model pick up on subtle patterns that are indicative of early-stage Alzheimer's.



In contrast, **Segmented Features**, a more focused subset of data, introduces slight variations in reconstruction error.Although the segmented approach reduces irrelevant variability, it sometimes lacks the depth required to identify the nuanced anatomical differences associated with Alzheimer's progression.

The **reconstruction error distribution** further illustrates these findings. By focusing on reconstruction error rather than direct classification, the model—especially an autoencoder—detects structural abnormalities linked to Alzheimer's. Alzheimer's cases generally exhibit higher reconstruction error values, likely due to anatomical differences such as hippocampal shrinkage, while normal cases tend to cluster around lower error values. This distribution supports the use of reconstruction-based models for early Alzheimer's detection, as they are sensitive to subtle structural anomalies that might be missed in traditional classification approaches.

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 CONCLUSION

The Alzheimer's disease diagnosis system effectively addressed the challenges of early detection by automating the analysis of brain scans. By leveraging deep learning models and advanced image processing techniques, the system significantly improved diagnostic accuracy and efficiency. The integration of real-time processing and automated alerts enabled healthcare professionals to make quicker, more informed decisions. Additionally, the system's ability to identify early-stage Alzheimer’s patterns provides valuable support for timely interventions. While there are challenges in data quality and integration, the system demonstrated its potential to enhance the early detection and diagnosis of Alzheimer's disease, laying the foundation for future improvements and broader clinical adoption.

Future enhancements for the Alzheimer's disease diagnosis system include the integration of multimodal data, such as genetic and clinical information, to improve diagnostic accuracy and provide a more comprehensive understanding of the disease. Additionally, implementing advanced predictive analytics could help track disease progression, enabling healthcare providers to make more informed decisions about treatment and intervention. Integration with electronic health records (EHR) and other healthcare management systems would streamline workflow and make the system more accessible to clinicians. Finally, optimizing the model for faster processing and better scalability will ensure the system can handle large datasets and meet the demands of a growing healthcare environment.

APPENDIX

A1.1 PSEUDOCODE

A.1.1.1 Data Preprocessing Module

```
# Pseudocode for Data Preprocessing Module

# Function to perform data preprocessing on MRI images
def preprocess_data(mri_images):
    preprocessed_images = []

    # Loop through each MRI image
    for image in mri_images:

        # Step 1: Convert image to grayscale if it's not already
        grayscale_image = convert_to_grayscale(image)

        # Step 2: Normalize image to scale pixel values between 0 and 1
        normalized_image = normalize(grayscale_image)

        # Step 3: Apply thresholding to highlight key structures
        thresholded_image = apply_threshold(normalized_image)

        # Step 4: Resize image to a fixed input size for the segmentation model
        resized_image = resize_image(thresholded_image, target_size=(256, 256))

        # Step 5: Augment data (e.g., rotation, flipping) if necessary for robust training
        augmented_images = augment_image(resized_image)

        # Store all preprocessed and augmented images
        preprocessed_images.extend(augmented_images)

    return preprocessed_images

# Load raw MRI images
mri_images = load_images('path_to_mri_images')

# Preprocess the images
```

```
preprocessed_images = preprocess_data(mri_images)

# The preprocessed images can now be used for segmentation

Feature Extraction and Segmentation Module
```

A.1.1.2 Feature Extraction and Segmentation Module

```
# Pseudocode for Feature Extraction Module

# Load the pretrained SE-ResNet model
se_resnet = load_pretrained_model('SE-ResNet')

# Set model to evaluation mode to avoid updates during feature extraction
se_resnet.eval()

# Initialize a feature extraction function
def extract_features(segmented_images):
    features = []

    # Loop through each segmented image
    for image in segmented_images:
        # Preprocess the image (resize, normalize if required)
        preprocessed_image = preprocess_image(image)

        # Pass the image through SE-ResNet
        with torch.no_grad():  # No gradients needed for feature extraction
            feature_vector = se_resnet(preprocessed_image)

        # Store the extracted features
        features.append(feature_vector)

    return features
```

```
# Load segmented MRI images (output from segmentation module)
segmented_images = load_segmented_images('entorhinal_cortex_segmented_images')

# Extract features for each segmented image
extracted_features = extract_features(segmented_images)

# The extracted features can now be used as input to the classification module
```

Pseudocode for the U-Net Segmentation Module

```
# Load MRI images and corresponding ground truth labels (segmentation masks)
load_dataset()

# Preprocess input images (resize, normalize, etc.)
for image in dataset:
    preprocess(image)

# U-Net Model Architecture
class UNetModel:
    def _init_(self):
        self.encoder = Encoder()  # Convolutional layers with pooling
        self.decoder = Decoder()  # Upsampling and convolution layers
        self.final_layer = ConvLayer()  # Output layer for binary mask

    def forward(self, x):
        # Encoder: extract features
        enc_output = self.encoder(x)

        # Decoder: upsample and reconstruct the segmentation map
        dec_output = self.decoder(enc_output)

        # Final output layer: binary segmentation map
        output = self.final_layer(dec_output)
        return output

# Initialize U-Net model
```

```
unet_model = UNetModel()

# Training the model
for epoch in range(num_epochs):
    for batch in train_loader:
        # Forward pass
        images, labels = batch
        preds = unet_model.forward(images)

        # Compute loss (e.g., dice coefficient or binary cross-entropy)
        loss = compute_loss(preds, labels)

        # Backpropagation and optimization
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

# Post-processing of segmentation results (optional)
for pred in segmentation_results:
    postprocess(pred)

# Save trained model
save_model(unet_model)
```

A.1.1.3 Model Training Module

```
# Pseudocode for Model Training Module

# Load dataset (MRI images with corresponding labels)
train_data, val_data = load_data()

# Define U-Net segmentation model
unet_model = UNetModel()

# Define SE-ResNet feature extraction model
seresnet_model = SEResNetModel()

# Define FCNN for classification
fcnn_model = FCNNModel()

# Initialize optimizer and loss function (e.g., Adam optimizer, CrossEntropyLoss)
optimizer = Optimizer(model.parameters(), lr=0.001)
loss_function = CrossEntropyLoss()

# Training loop
for epoch in range(num_epochs):
    model.train()  # Set the model to training mode
    total_loss = 0
    correct_predictions = 0

    for batch in train_data:
        images, labels = batch  # Load batch of images and their corresponding labels

        # Step 1: Segmentation (U-Net)
        segmented_output = unet_model.forward(images)

        # Step 2: Feature extraction (SE-ResNet)
        features = seresnet_model.forward(segmented_output)

        # Step 3: Classification (FCNN)
        predictions = fcnn_model.forward(features)
```

```
        # Step 4: Compute the loss
        loss = loss_function(predictions, labels)

        # Step 5: Backpropagation and optimization
        optimizer.zero_grad()  # Clear previous gradients
        loss.backward()  # Backpropagate the loss
        optimizer.step()  # Update model weights

        # Step 6: Track accuracy
        total_loss += loss.item()
        correct_predictions += (predictions.argmax(dim=1) == labels).sum().item()

    # Calculate epoch statistics (loss and accuracy)
    epoch_loss = total_loss / len(train_data)
    epoch_accuracy = correct_predictions / len(train_data.dataset)

    print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {epoch_loss:.4f}, Accuracy:
{epoch_accuracy:.4f}")

    # Validate model performance on validation set
    validate_model(fcnn_model, val_data)

# Save trained model
save_model(fcnn_model)
```

A.1.1.4 Visualization and Evaluation Module

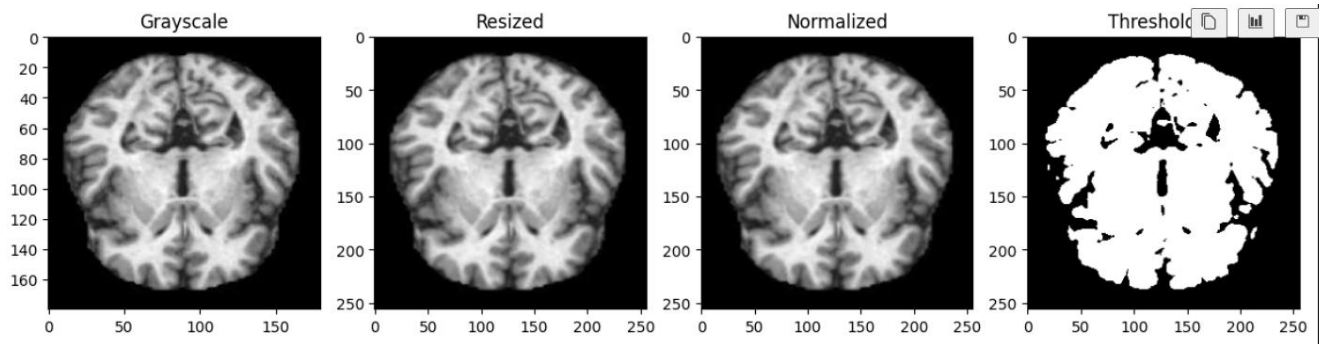
```
# Load the trained model
model = load_trained_model('fcnn_model.pth')

# Load test dataset (MRI images with corresponding labels)
test_data = load_test_data()

# Define evaluation metrics (e.g., accuracy, AUC, confusion matrix)
metrics = EvaluationMetrics()
```

```
# Set the model to evaluation mode (disable dropout and batch normalization updates)
model.eval()

# Initialize variables for performance tracking
total_correct = 0
total_samples = 0
total_loss = 0

# Loop through test dataset
for batch in test_data:
    images, true_labels = batch  # Load test batch

    # Step 1: Segment the entorhinal cortex using U-Net
    segmented_images = unet_model.forward(images)

    # Step 2: Extract features using SE-ResNet
    extracted_features = seresnet_model.forward(segmented_images)

    # Step 3: Predict the class labels using FCNN
    predictions = fcnn_model.forward(extracted_features)

    # Step 4: Compute the loss (e.g., binary cross-entropy or categorical cross-entropy)
    loss = compute_loss(predictions, true_labels)
    total_loss += loss.item()

    # Step 5: Track correct predictions for accuracy calculation
    total_correct += (predictions.argmax(dim=1) == true_labels).sum().item()
    total_samples += len(true_labels)

# Calculate accuracy
accuracy = total_correct / total_samples

# Calculate the average loss
average_loss = total_loss / len(test_data)

# Compute other evaluation metrics (e.g., AUC, precision, recall, F1-score)
auc_score = compute_auc(test_data, model)
```

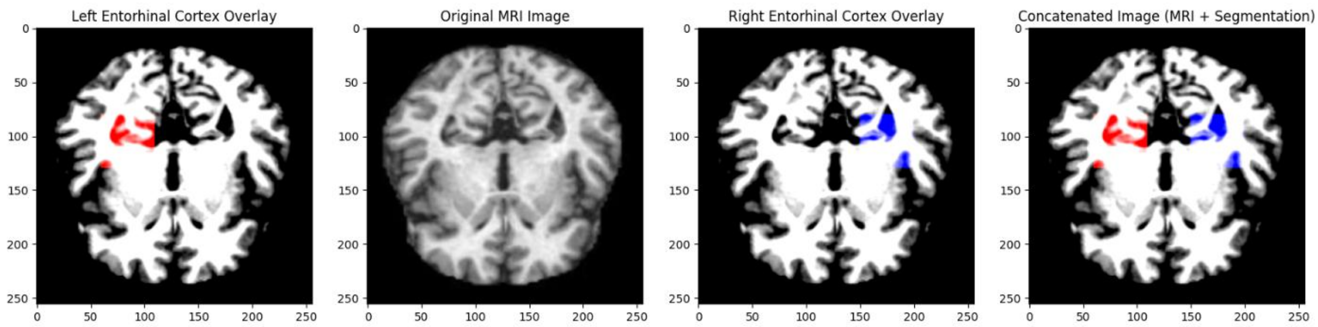
```
precision, recall, f1 = compute_precision_recall_f1(test_data, model)

# Print the evaluation results
print(f"Accuracy: {accuracy:.4f}")
print(f"Average Loss: {average_loss:.4f}")
print(f"AUC: {auc_score:.4f}")
print(f"Precision: {precision:.4f}, Recall: {recall:.4f}, F1-score: {f1:.4f}")

# Save predictions if needed
save_predictions(predictions, 'predictions.csv')
```

A 1.2 OUTPUT SCREENSHOTS

A 1.2.1 Data Preprocessing



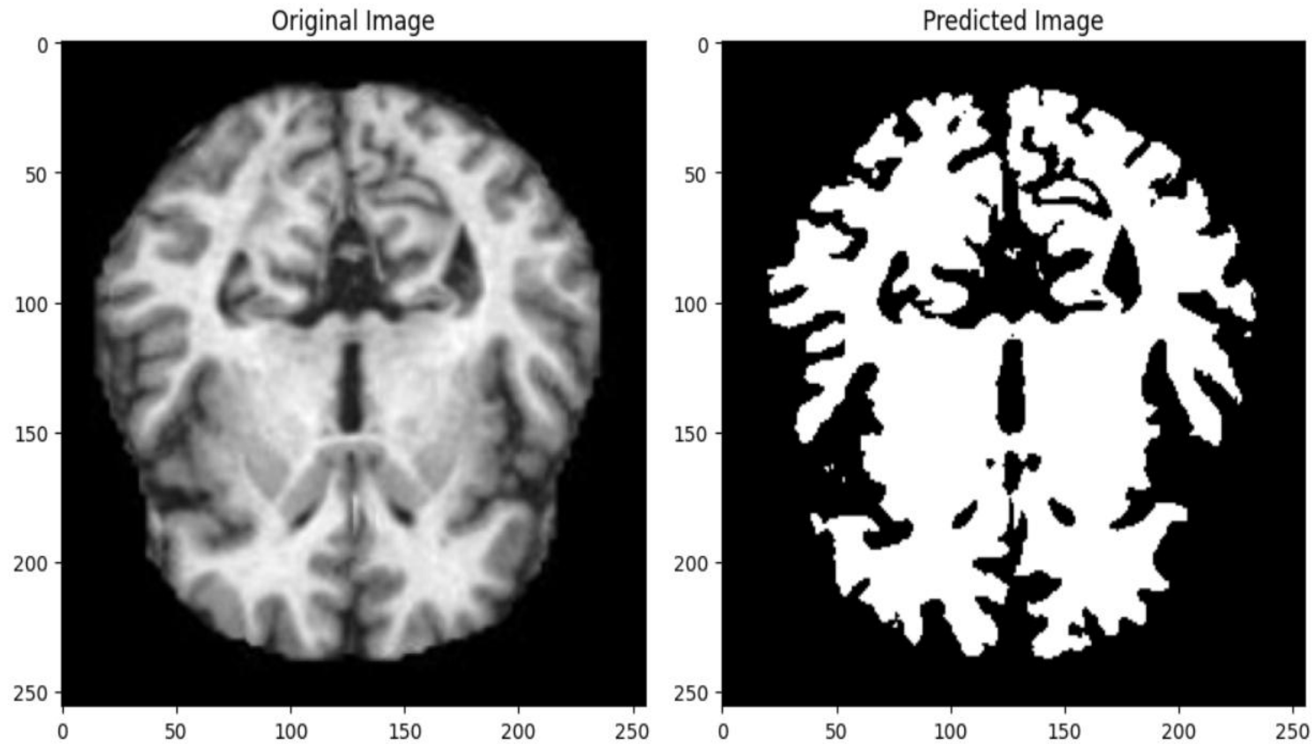
A.1.2.2 Feature extraction and Segmentation



A.1.2.3 Model Training

```
Epoch 1/5
5/5 ━━━━━━━━━━━━━━━━━━━━ 9s 260ms/step - accuracy: 0.4875 - loss: 3.0869
Epoch 2/5
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 251ms/step - accuracy: 0.5278 - loss: 1.8192
Epoch 3/5
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 253ms/step - accuracy: 0.1417 - loss: 2.8026
Epoch 4/5
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 255ms/step - accuracy: 0.2444 - loss: 1.5224
Epoch 5/5
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 248ms/step - accuracy: 0.6861 - loss: 0.6083
```

A.1.2.4 Visualisation and Evaluation Module




```
...   WARNING:absl:Compiled the loaded model,
      1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step
      Prediction: Alzheimer's Detected
```

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