Developing a Hybrid Model To predict Alzheimer's Disease

Mrs. Thamizharasi M,M.tech
Assistant Professor of Artificial Intelligence and Data Science
Rajalakshmi Engineering College
Chennai, India
[email]@rajalakshmi.edu.in

Prasanna S
Artificial Intelligence and Data Science
Rajalakshmi Engineering College
Chennai, India
221801038@rajalakshmi.edu.in

Sukish M
Artificial Intelligence and Data Science
Rajalakshmi Engineering College
Chennai, India
221801053@rajalakshmi.edu.in

ABSTRACT

Alzheimer's disease is the most prevalent form of dementia in the world: it is a chronic, progressive neurodegenerative disorder that affects memory, cognition, and behavior. The early detection of AD is paramount to patient outcomes. MRI scanning within the entorhinal cortex, a brain region, responsible for memory, provides an opportunity for non-invasive detection of structural changes that prove indicative of Alzheimer's progression We have developed detection of Alzheimer's disease on the basis of deep learning in this paper, using MRI images of the entorhinal cortex. Advanced preprocessing techniques such as grayscale conversion, thresholding, and normalization are applied on MRI scans to enhance the relevant features. Our model consists of two parts, namely: the segmentation model U-Net which divides out the entorhinal cortex followed by an SE-ResNet model for feature extraction and a fully connected neural network for classification. The data set was divided into training, validation, and test sets.

Keywords: Entorhinal cortex segmentation, Alzheimer's, Deep learning, Medical image processing

I. INTRODUCTION

Alzheimer's disease is the most common type of dementia characterized by the gradual annihilation of cognitive and memory functions. It begins with minor memory lapses but leads to a critical inability to perform everyday tasks, maintain conversation, or even react appropriately to the environment. Actually, this disease gradually damages thoughts, language, and memory-the very basic foundation for functioning in everyday life. Current statistics show that 1 in every 9 people who are above the age of 65 suffers from Alzheimer's, constituting 11.4% of the world population. On the other hand, COVID-19 has led to a 16% increase in Alzheimer's cases. Moreover, approximately one-third of those with Alzheimer's die from the disease, more than the combined number of deaths due to breast and prostate cancers. Thus, early, prompt, and efficient diagnosis will help in managing the signs of Alzheimer's disease and retard its process toward improving the quality of care and the lives of such patients.

One of the earliest affected regions is the entorhinal cortex in Alzheimer's disease, which is a part of the brain significantly involved with memory formation and spatial mapping. During Alzheimer's disease progression, the entorhinal cortex shows structure changes that make it an important region for diagnosis based on imaging techniques; in many clinical settings, MRI scans are routinely acquired to obtain images of the brain to be studied by researchers and clinicians for such structural alterations. However, dealing with MRI images is an arduous process and sometimes seems to be subjective, and results may not have consistency, especially in the initial stages of Alzheimer's. Automated processing and machine learning will open very promising avenues in achieving accurate detection and tracking of these subtle changes with promise for an early and reliable diagnosis. Integrating machine learning with medical imaging has revolutionized neurodegenerative disease diagnosis over the past decade. Deep learning models, especially those leveraging Convolutional Neural Networks (CNNs), enable the detection of patterns and subtle abnormalities in medical images that are often imperceptible to the human eye. These models not only speed up the diagnostic process but also enhance accuracy by training on large datasets, making them invaluable tools for identifying early markers of Alzheimer's disease

The work was on developing an automated system for detection of Alzheimer's disease with the use of MRI scans of the entorhinal cortex along with advanced image processing and machine learning techniques. Among these works, the main focus was engineering a robust system that would assist in early detection by undertaking structural changes within the entorhinal cortex, which is affected during the early stages of Alzheimer's disease. The preprocessing begins with images that are to this preprocessing stage where techniques such as grayscale conversion, thresholding, and normalization enhance the critical features. Preprocessed images are fed to a hybrid model comprised of a U-Net for segmentation and an SE-ResNet for feature extraction followed by a fully connected neural network which defines the class of a prognosis about the possibility of the presence of Alzheimer's. This study, therefore, provides a basis for developing robust non-invasive diagnostic tools that can easily be fit into clinical workflows.
The main highlights of this paper are as follows:

- Advanced image processing techniques, including grayscale conversion, thresholding, normalization, and histogram equalization, are applied to enhance MRI images of the entorhinal cortex, focusing on subtle structural changes associated with Alzheimer's disease.

- A hybrid deep learning model is developed for Alzheimer's detection, integrating U-Net for segmenting the entorhinal cortex and SE-ResNet for feature extraction, followed by a fully connected neural network for classification.

- This automated system offers a non-invasive, objective approach to early-stage Alzheimer's detection, in contrast to traditional subjective methods reliant on manual image inspection by experienced professionals.

- The model was evaluated for its effectiveness through metrics such as accuracy, confusion matrix, and ROC-AUC, demonstrating the potential of combining machine learning and deep learning for clinical Alzheimer's diagnosis.

II. RELATED WORKS

Hippocampus segmentation in magnetic resonance images of Alzheimer's patients using Deep machine learning: Alzheimers disease is a progressive neurodegenerative disorder and the main cause of dementia in aging. Hippocampus is prone to changes in the early stages of Alzheimers disease. Detection and observation of the hippocampus changes using magnetic resonance imaging (MRI) before the onset of Alzheimers disease leads to the faster preventive and therapeutic measures. Objective: The aim of this study was the segmentation of the hippocampus in magnetic resonance (MR) images of Alzheimers patients using deep machine learning method. Methods: U-Net architecture of convolutional neural network was proposed to segment the hippocampus in the real MRI data. The MR images of the 100 and 35 patients available in Alzheimers disease Neuroimaging Initiative (ADNI) dataset, was used for the train and test of the model, respectively. The performance of the proposed method was compared with manual segmentation by measuring the similarity metrics. Results: The desired segmentation achieved after 10 iterations. A Dice similarity coefficient (DSC) = 92.3%, sensitivity = 96.5%, positive predicted value (PPV) = 90.4%, and Intersection over Union (IoU) value for the train 92.94 and test 92.93 sets were obtained which are acceptable. Conclusion: The proposed approach is promising and can be extended in the prognosis of Alzheimers disease by the prediction of the hippocampus volume changes in the early stage of the disease.

Assessment of Alzheimer's Disease Based on Texture Analysis of the Entorhinal Cortex : The study was based on the use of texture analysis for differentiation between Alzheimer's disease and Mild Cognitive Impairment from Normal Control subjects differentiated with MRI scans focussed on the atrophied entorhinal cortex. Because entorhinal cortex atrophy has proven very frequently one of the earliest signs of Alzheimer's, but to date texture analysis has not been exhaustively explored in this context. The proposed approach extracted texture features from MRI scans of 194 NC, 200 MCI, 84 MCI patients who converted to AD (MCIc), and 130 AD subjects. ROC curves demonstrated the ability of the texture features to distinguish between the groups: AUCs were 0.872 for NC vs. AD, 0.710 for NC vs. MCI, 0.730 for MCI vs. MCIc, and 0.764 for MCI vs. AD. Including the volume of entorhinal cortex improved the AUCs. Using binary logistic regression, the study estimated conversion from MCIc to AD with average AUCs of 0.760 and 0.764 for the training and validation cohorts, respectively. Texture features, thus, appear to furnish significant information above and beyond traditional volumetric measures for the diagnosis of early Alzheimer's diseases.

MRI-Driven Alzheimer's Disease Diagnosis Using Deep Network Fusion and Optimal Selection of Feature : Alzheimer's disease (AD) is a degenerative neurological condition characterized by cognitive decline, memory loss, and reduced everyday function, which eventually causes dementia. Symptoms develop years after the disease begins, making early detection difficult. While AD remains incurable, timely detection and prompt treatment can substantially slow its progression. This study presented a framework for automated AD detection using brain MRIs. Firstly, the deep network information (i.e., features) were extracted using various deep-learning networks. The information extracted from the best deep networks (EfficientNet-b0 and MobileNet-v2) were merged using the canonical correlation approach (CCA). The CCA-based fused features resulted in an enhanced classification performance of 94.7% with a large feature vector size (i.e., 2532). To remove the redundant features from the CCA-based fused feature vector, the binary-enhanced WOA was utilized for optimal feature selection, which yielded an average accuracy of 98.12 ± 0.52 (mean ± standard deviation) with only 953 features. The results were compared with other optimal feature selection techniques, showing that the binary-enhanced WOA results are statistically significant ($p < 0.01$). The ablation study was also performed to show the significance of each step of the proposed methodology. Furthermore, the comparison shows the superiority and high classification performance of the proposed automated AD detection approach, suggesting that the hybrid approach may help doctors with dementia detection and staging.

Alzheimer's prediction via CNN-SVM on chatbot platform with MRI : Artificial intelligence (AI), consisting of models and algorithms capable of concluding data to produce future predictions, has revolutionary potential in various aspects of human life. One application is an Alzheimer's disease (AD) prediction chat robot (chatbot). Only now has a method provided very accurate findings and recommendations regarding the early detection of AD using magnetic resonance imaging (MRI). Therefore, this research aims to measure AD prediction performance in four stage classes, namely very mild demented, mild demented, moderate demented, and non-demented, using brain MRI images trained in the convolutional neural network (CNN)- support vector machine (SVM) model. The research involved nine combination schemes of dataset proportions and preprocessing in the CNNSVM model. Evaluation shows that scheme 1 produces the highest accuracy, precision, recall, and F1-score, namely 98%, 99%, 98%, and 98%. The chatbot, trained using CNN, achieved 99.34% accuracy in question responses, and was then combined with AD prediction models for improved accuracy. The test results show that the chatbot functionality runs well for each transition, with a functionality score reaching 99.64 points out of 100.00. This success shows excellent potential for early detection of AD. This research brings new hope in preventing AD through AI, with potential positive impacts on human health and quality of life.

Alzheimer's Disease Prediction using Convolutional Neural Network (CNN) with Generative Adversarial Network (GAN) : Alzheimer's is the most common form of dementia in older individuals, which presents a global health challenge with 10 million new cases annually. This neurological disorder causes neurodegenerative alterations in the brain to unfold gradually, commencing with mild memory impairment and then escalating to loss of social interaction and awareness of the environment. Alzheimer Disease International (ADI) believes that 75% of dementia cases globally go undetected, making the early diagnosis challenging. Currently, stopping the development of Alzheimer's disease is difficult since there are no viable diagnosis and treatment solutions available. To overcome these challenges, there is now great interest in using machine learning (ML) for early diagnosis of metabolic disorders such as Alzheimer's. In this work, we propose utilizing a deep convolutional neural network to detect the different phases of Alzheimer's disease using brain MRI structural data analysis. Magnetic resonance imaging (MRI) aids in the early detection of Alzheimer's disease and achieves greater efficacy for initial-stage detection. Clinicians can use the suggested categorization approach to diagnose these disorders much earlier. With these ML algorithms, it is highly advantageous to reduce yearly death rates of Alzheimer's disease in early diagnosis. The suggested technique achieves improved results, with an approved mean score of 96.1% on Alzheimer's Disease test data. Compared to previous efforts, the current score for accuracy is much greater.

A convolutional neural networks approach in MRI image analysis for Alzhei : Artificial Intelligence (AI) and its advancements, particularly in Computer Vision, have narrowed the gap between humans and machines. The Deep Learning techniques, such as Convolutional Neural Networks (CNNs), have revolutionized image analysis by assigning importance to different aspects of an image and enabling accurate differentiation. This paper focuses on applying CNNs to detect structural changes associated with Alzheimer's disease using Magnetic Resonance Imaging (MRI). Currently, the diagnosis of Alzheimer's disease relies on a combination of clinical assessments and neurological tests. This study aims to develop and evaluate various CNN models, including VGG16, VGG19, ResNet50, ResNet101, MobileNet, MobileNetV2, InceptionV3, Xception, DenseNet121, and DenseNet169, to analyze MRI scans for Alzheimer's disease detection. The above models were trained and tested using a dataset comprising MRI scans from healthy individuals and Alzheimer's patients. By comparing the accuracy of the CNN models in detecting Alzheimer's disease from MRI scans, the study demonstrates the potential of CNNs in improving the accuracy and efficiency of Alzheimer's disease diagnosis. The findings suggest that CNN-based analysis of Alzheimer's MRI images holds promise for early detection and treatment of the disease. This research can growing body of knowledge in computer-aided medical diagnostics and underscores the significance of leveraging AI techniques to enhance healthcare outcomes.

A New Deep Learning Model based on Neuroimaging for Predicting Alzheimer's Disease : The psychological aspects of the brain in Alzheimer's disease (AD) are significantly affected. These alterations in brain anatomy take place due to a variety of reasons, including the shrinking of grey and white matter in the brain. Magnetic resonance imaging (MRI) scans can be used to measure it, and these scans offer a chance for early identification of AD utilizing classification methods, like convolutional neural network (CNN). The majority of AD-related tests are now constrained by the test measures. It is, thus, crucial to find an affordable method for image categorization using minimal information. Because of developments in machine learning and medical imaging, the field of computerized health care has evolved rapidly. Recent developments in deep learning, in particular, herald a new era of clinical decision-making that is heavily reliant on multimedia systems. Methods: In the proposed work, we have investigated various CNN-based transfer-learning strategies for predicting AD using MRI scans of the brain's structural organization. According to an analysis of the data, the suggested model makes use of a number of sites related to Alzheimer's disease. In order to interpret structural brain pictures in both 2D and 3D, the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset includes straightforward CNN designs based on 2D and 3D convolutions. Results: According to these results, deep neural networks may be able to automatically learn which imaging biomarkers are indicative of Alzheimer's disease and exploit them for precise early disease detection. The proposed techniques have been found to achieve an accuracy of 93.24%.

Computer-aided diagnosis of Alzheimer's disease based on structural magnetic resonance imaging : Alzheimer's disease (AD) is an irreversible chronic neurodegenerative disease. AD initially affects short-term memory, thinking, and behavior. It then severely disrupts the normal lives of patients and their families and may eventually lead to death. Mild cognitive impairment (MCI) is considered an early stage of AD. Some studies have shown that nearly 20% of patients with MCI are at a risk of developing AD within the next four years.[1] Although there is no impressive way to stop the further development of MCI, only a series of procedures can slow it. Thus, timely and accurate intervention is essential to effectively slow the disease progression. Owing to its non-invasive nature, structural magnetic resonance imaging (sMRI) has become the most commonly used imaging modality for diagnosing AD, because it can capture anatomical information. The application of traditional machine-learning algorithms to sMRI images for AD classification is relatively mature. However, complex preprocessing of sMRI images is usually required to extract more desirable features for classification purposes. In contrast, deep learning algorithms have been more widely employed in recent years because they require no assistance from relevant medical experts for feature extraction and can automatically learn advanced features. Hence, this paper reviews sMRI-assisted AD classification based on various machine-learning algorithms developed in recent years. We also present some prospective approaches to address the shortcomings and problems of the existing research, in addition to providing a reference for future studies in this field. Deep learning methods used for AD classification

Deep Learning Approach to Predict Alzheimer's Disease through Magnetic Resonance Images : Alzheimer's disease is the most common type of dementia that causes many of the functions of the human brain to be severely weakened. To date, there has not been a cure for Alzheimer's disease. Therefore, early diagnosis is needed using MRI images with the help of a classification program. Deep learning using the Convolutional Neural Network (CNN) method is receiving increasing attention because of its excellent performance. Its architecture can be modified according to user needs based on the data to be processed and the approach for classifying, detecting, and segmenting visual objects. In this paper, we offer a classification of Alzheimer's disease using one of the architectures on CNN, namely Visual Geometry Group-19 (VGG-19), with a sagittal view of MRI images with an image size of 229 x 229 pixels. The classification accuracy of the described method is 94% for the validation set

Exploring Deep Learning Models for Accurate Alzheimer's Disease Classification based on MRI Imaging : Alzheimer's disease (AD), a complex neurodegenerative condition, presents significant challenges in early and accurate diagnosis. Early prediction of AD severity holds the potential for improved patient care and timely interventions. This research investigates the use of deep learning methodologies to forecast AD severity utilizing data extracted from Magnetic Resonance Imaging (MRI) scans.
 OBJECTIVES: This study aims to explore the efficacy of deep learning models in predicting the severity of Alzheimer's disease using MRI data. Traditional diagnostic methods for AD, primarily reliant on cognitive assessments, often lead to late-stage detection. MRI scans offer a non-invasive means to examine brain structure and detect pathological changes associated with AD. However, manual interpretation of these scans is labor-intensive and subject to variability.
 METHODS: Various deep learning models, including Convolutional Neural Networks (CNNs) and advanced architectures like DenseNet, VGG16, ResNet50, MobileNet, AlexNet, and Xception, are explored for MRI scan analysis.

Alzheimer’s Disease Detection in MRI images using Deep Convolutional Neural Network Model : Alzheimer's disease (AD) is a neurodegenerative disease that affects cognitive abilities (thinking and memory etc) primarily among the elderly, due to which collective cognitive skills deteriorate, ultimately leading to death. Early detection of Alzheimer's disease is crucial for determining appropriate therapeutic options. This research investigates the use of a Deep Convolutional Neural Network (CNN) for detecting Alzheimer's disease. Due to similar brain patterns and pixel intensities, CNN demonstrates promising results in diagnosing AD through automated feature extraction and characterization. Deep Learning algorithms are designed to perform automated feature extraction and categorization of input image datasets. In this study, a two-way classifier categorizes each image as either Healthy Control (HC) or Alzheimer's disease (AD). Experiments were carried out with the MIRIAD dataset, and the accuracy of disease classification into binary categories was evaluated. The recorded results of CNN with 4- and 5 -layer architectures confirms the effectiveness of the proposed method for AD detection.

III. PROPOSED SYSTEM

The proposed system is an automated deep learning approach with focus on early Alzheimer's detection using MRI images of the entorhinal cortex. This diagnosis incorporates advanced preprocessing, segmentation, and classification techniques for accurate detection about the entorhinal cortex early signs of Alzheimer's-related neurodegeneration. The proposed algorithm improves the MRI images through preliminary steps including grayscale conversion, histogram equalization, normalization, and thresholding. Combining data augmentation through rotation, scaling, and flipping further enriches the model with better generalization toward diverse MRI datasets.

Use the U-Net architecture, isolating the entorhinal cortex, a region crucial for early signs of Alzheimer's disease. The encoder-decoder structure of a U-Net with skip connections ensures accurate segmentation ability by keeping the resolution of detail that is crucially important in medical imaging applications. The regions of the entorhinal cortex are then fed into an SE-ResNet model for feature extraction after segmentation. The SE-ResNet integrates Squeeze-and-Excitation blocks into its architecture that improves the sensitivity for early Alzheimer's markers by adaptively highlighting informative channels. This is a good design for extracting detailed features from segmented MRI images aiming at giving robust representation for successive classification.

It then feeds these features to a fully connected neural network for classification between Alzheimer's cases and non-Alzheimer's cases.

All of these are judged by the performance of the model about accuracy, precision, recall, F1, and ROC-AUC. Grad-CAM visualization tends to give greater interpretations by highlighting where exactly in the entorhinal cortex the model is 'paying attention', which adds transparency of great importance for the clinician. By bringing U-Net and SE-ResNet together in one streamlined pipeline, this system allows for scalable, non-invasive detection of early Alzheimer's disease, with further potential for integration into clinical practice to allow improved patient outcomes.

. the system uses a **fully connected neural network** with binary cross-entropy as the loss function to distinguish between Alzheimer’s and non-Alzheimer’s cases. Binary cross-entropy, a common choice for binary classification tasks, calculates the difference between the predicted probabilities and the actual labels, ensuring that the model learns to optimize its predictions effectively. The formula for binary cross-entropy loss is

$$L_{\text{BCE}} = -\left(y \cdot \log(\hat{y}) + (1 - y) \cdot \log(1 - \hat{y})\right)$$

where y is the true label (0 or 1) and y^ is the predicted probability of the positive class. By minimizing this loss during training, the model learns to improve its predictive accuracy, distinguishing between MRI scans indicative of Alzheimer’s disease and those that are not.

IV. ARCHITECTURE

The proposed architecture of Alzheimer's disease detection uses the U-Net model to carry out accurate entorhinal cortex segmentation, SE-ResNet model to achieve effective extraction of features, and fully connected neural network for the final class prediction. The precise delineation of the very early stage involved in Alzheimer's detection can be guaranteed with the U-Net encoder-decoder structure. SE-ResNet focuses on the most informative features in the image, which involves most of the MRI images necessary for detection, hence improving feature extraction for early-stage neurodegeneration identification. These features are passed on to the final classification layer to predict the respective stages of the disease, namely to classify the case as Normal Control (NC), Mild Cognitive Impairment (MCI), and Alzheimer's (AD). In turn, this hybrid model has utilized proper preprocessing steps, thus enabling superior accuracy in early detection.

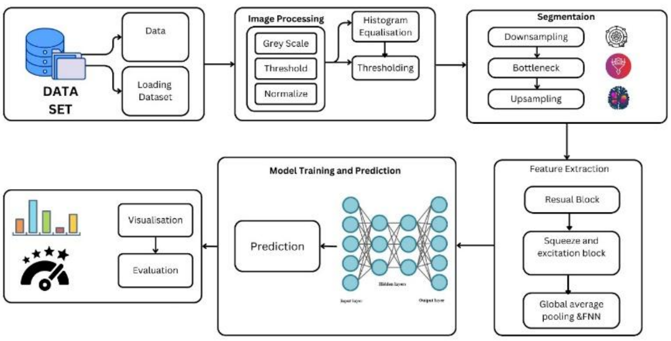

Figure 4.1: Architecture Diagram

Data preprocessing module:

The data preprocessing module plays a critical role in standardizing and enhancing MRI images to optimize their suitability for segmentation and classification tasks in Alzheimer's detection. Mainly, the input MRI images were converted to grayscale to simplify data processing by reducing each image to a single intensity channel while preserving all essential structural information. Further to the grayscale transformation, normalization is applied to have pixel intensity rescaled to a uniform range, of course between 0 and 1, thus minimizing the effects of light and contrast variations. Further, histogram equalization is applied to enhance the contrast for better visibility of subtle features in the entorhinal cortex—the imperatives are to detect those early structural changes that signify Alzheimer's.to previously unseen data during assessment and prediction.Thresholding has further been applied to separate regions of interest where intensities surpass a given threshold, hence permitti ng model training to provide a mechanism for the model to highlight important anatomical structures while thinning out data noisiness. Data augmentation then became an application of techniques like rotation, flipping, and scaling, used to artificially expand the dataset through objectives of model robustness and generalization. All of the above preprocessing stages ensure that the input images are consistent for the segmentation and feature extraction stages and may contribute further to improving the model's ability to detect Alzheimer's-related features within the entorhinal cortex.

Feature extraction and Segmentation module:

The feature extraction module is designed to capture intricate patterns from MRI images of the hippocampus and entorhinal cortex, key brain regions affected by Alzheimer’s disease. To effectively identify structural changes, this module employs a deep learning architecture based on residual learning. In this approach, the network learns to map input features X to output features Y by leveraging a residual function F(X,Y) where W represents the model’s learnable parameters. The residual connection can be mathematically represented as:

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

This equation denotes the addition of the learned features F(X,Y) to the input features X preserving the original information while enriching it with additional extracted patterns. This residual learning strategy improves model training by enabling easier propagation of information and gradients through the network, mitigating the risk of vanishing gradients. By allowing the network to "skip" layers, residual connections help capture both low- and high-level features that are critical for accurate Alzheimer's detection.

In addition to residual connections, this module integrates squeeze-and-excitation (SE) blocks to enhance the representation of critical features by adaptively recalibrating channel-wise feature responses. By combining these advanced techniques, the feature extraction module can detect subtle changes in brain structure related to Alzheimer’s, enabling reliable classification between healthy and affected individuals. This refined feature set is then passed to the classification module, which leverages these features for precise and robust diagnosis.

In the **Segmentation Module** of the proposed system, the goal is to accurately delineate the hippocampus and entorhinal cortex regions in MRI scans, which are vital for identifying structural changes associated with Alzheimer’s disease. Segmentation isolates these specific brain regions, enabling the system to focus on areas of interest and disregard irrelevant background information. This module plays a crucial role in ensuring that the subsequent analysis and feature extraction processes concentrate on the most affected areas in Alzheimer's disease. The segmentation process can be mathematically described as follows:

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

where X represents the input MRI scan, W is the weight matrix learned by the segmentation model, and B is a bias term. Here, Z represents the segmented output, highlighting the targeted brain regions. This operation allows the model to identify and enhance specific features in the scan by assigning higher weights to the regions of interest, while reducing the importance of background areas.

The segmentation module uses a U-Net architecture, which is one of the most popular deep learning networks applied for biomedical image segmentation. In short, a U-Net employs skip connections to preserve features learnt from the upper layers in upsampling processes and also uses an encoder-decoder structure that captures high-level features in the encoder path and further refines these in the decoder path by way of upsampling and skip connections. Focusing on the hippocampus and entorhinal cortex, this module will give clean, accurately segmented regions for feature extraction and classification subsequently, and this improves overall performance in the detection of Alzheimer's disease.

Pseudocode:

```
# 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)
```

pseudocode for the segmentation module discusses workflow in using the U-Net architecture to tackle the task of segmenting images of an entorhinal cortex from MRI images. Here, it begins with the loading and preprocessing of the MRI images followed by the feed through the U-Net model that actually is an encoder for feature extraction followed by a decoder that upsamples the output from segmentation. Optimization is done through backpropagation, and the model is trained using a loss function. Finally, post-processing techniques would be possible for finetuning the results of the segmentation and saving the model obtained so far to reuse for other classification/feature extraction tasks..

Model training module:

The training module of the model is set to train the hybrid deep learning model for the detection of Alzheimer's disease. The MRI dataset is divided between the training and validation sets. For the precise segmentation of the entorhinal cortex, the U-Net model is used, and for feature extraction with efficient use from the segmented regions, SE-ResNet is utilized. These extracted features are then fed into a fully connected neural network (FCNN) classifier to classify the Alzheimer's disease progression within the model. In training, backpropagation will be conducted with some appropriate loss function such as Cross-Entropy Loss and some appropriate optimizer such as Adam. The model will be validated after each epoch for its ability of generalization using a completely independent validation set. The training loop iterates through multiple epochs that refine the parameters of the model for increasing accuracy and decreasing loss. The last trained model is saved for prediction purposes for determining the stages of disease progression, such as NC, MCI, and AD.

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

The equation represents the logistic sigmoid function, often used in binary classification problems, including the training of models in machine learning. Here, y^ s the predicted probability of the positive class (i.e., the likelihood that a given sample belongs to the class of interest), and z is the input to the sigmoid function, typically the weighted sum of features passed through the model. The sigmoid function transforms any real-valued input into a value between 0 and 1, which is interpreted as a probability.

This formulation is particularly useful in training deep learning models-for example, Alzheimer's disease detection, in which the output of the model; that is, probability of disease progression or classification-must lie in between 0 and 1. During training, the model updates its weights so that it predicts a value as close to the true labels as possible on the training set. In particular, the loss function is a quantitative measure of error which may be taken in terms of binary cross-entropy, for example to help guide the optimization process toward an optimal or perfect model fit.

the logistic sigmoid function is crucial for converting raw model outputs into a probabilistic interpretation that can be used for classification tasks, facilitating model training and prediction refinement., which helps identify alterations linked to Alzheimer's disease.

Pseudocode:

```
# 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)
```

The pseudocode of the training module for the model describes step by step the hybrid deep learning architecture to be used in the detection of Alzheimer's disease. It then loads the training and validation datasets, and initializes the segmentation model as U-Net, the feature extraction model as SE-ResNet, and the classification model as FCNN. In the case of each epoch, the operation consisted of segmenting the entorhinal cortex from MRI images using a U-Net model, extracting essential features using an SE-ResNet, and then classifying these features using a fully connected neural network known as FCNN. This compares the model's output with the actual labels with a loss function such as binary cross-entropy, after which backpropagation is used in updating the model weights. Through the optimizer, usually Adam, the weights are modified in such a way as to minimize the loss. The model is validated after each epoch on a set, and then the trained model is saved for further use. This structure of pseudocode ensures that the model learns to make predictive models because it is constantly refining parameters based on the dataset.

Prediction and Evaluation Module :

In the prediction and evaluation module, the accuracy formula determines how well the trained model has been capable of classifying test MRI images as having Alzheimer's or not. After the predictions have been counted, true positives and false positives along with false negatives and true negatives, then the accuracy score is determined, providing an overview of the model at a high level.

Because the greater the accuracy is, the fewer the number of misclassifications, this evaluation is crucial to understand the model's performance, specifically for the early detection of Alzheimer's. However, when the clinical contexts may involve potentially dangerous consequences of misclassifications (false negatives), for example, reliance on accuracy alone may not be acceptable and other evaluation metrics become useful as well.

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

- TP (True Positive): The number of correct predictions where the model correctly identifies a positive case (e.g., correctly diagnosing Alzheimer's).
- TN (True Negative): The number of correct predictions where the model correctly identifies a negative case (e.g., correctly identifying a non-Alzheimer's patient).
- FP (False Positive): The number of incorrect predictions where the model incorrectly classifies a negative case as positive.
- FN (False Negative): The number of incorrect predictions where the model incorrectly classifies a positive case as negative.

Pseudocode:

```
# Pseudocode for Prediction 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')
```

V. RESULTS AND 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

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.

Fig 5.1 performance metrices comparison

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.

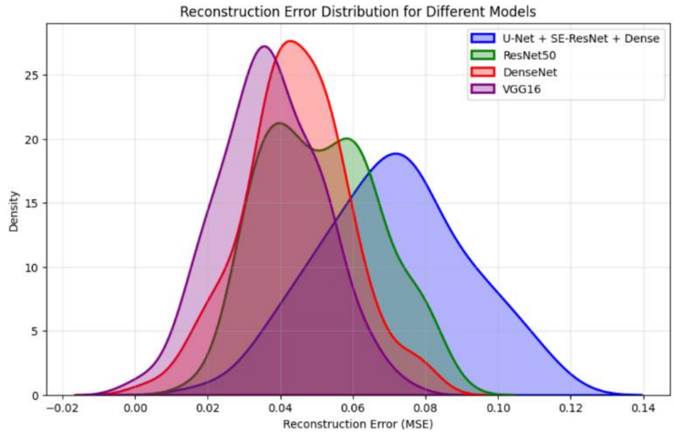

Fig 5.2 Reconstruction Error Distribution

2.FULL FEATURES VS SEGMENTED FEAUTURES

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.

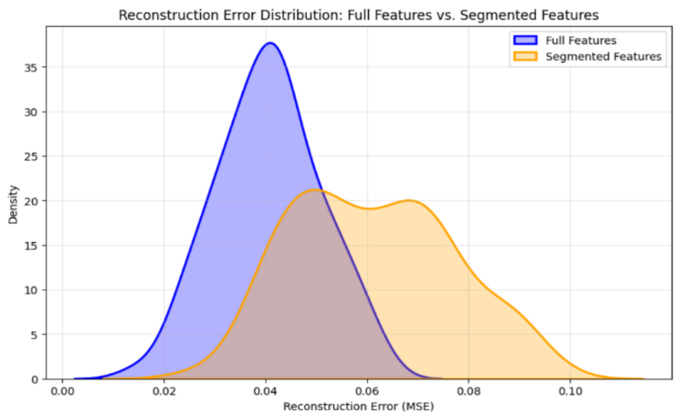

Fig 5.3 Full Features vs Segmented features

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.

VI. 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.

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