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Deep Learning for Alzheimer's Diagnosis: MRI-Based Preprocessing and Classification

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Abstract— **Alzheimer's disease (AD) is the most common type of dementia, a neurological condition that causes progressive memory loss and difficulty completing daily tasks owing to brain cell death. Artificial Intelligence (AI) technology can be used to diagnose and predict this disease using MRI (Magnetic Resonance Imaging) brain scans, classifying patients as having or not having Alzheimer's disease. The main purpose of all of this is to provide the best prediction and detection tools for radiologists, doctors, and caregivers to save time and money while also assisting patients suffering from this ailment. Deep Learning (DL) algorithms have been increasingly useful in the diagnosis of Alzheimer's disease in recent years. In this article, we developed a deep convolutional neural network (CNN) model for diagnosing Alzheimer's disease using the two datasets Oasis (Open Access Series of Imaging Studies) and the Alzheimer's Disease Neuroimaging Initiative (ADNI). The ADNI dataset is preprocessed to produce a 2D image with a total of 21324 MRI scans divided into three classes: MCI (Mild Cognitive Impairment) with 7572 slices, CN (Control Normal), and AD (Alzheimer's Disease). The trained model outperformed multiple other comparable studies, with a significant accuracy of 99.67 percent on the Alzheimer's Disease Neuroimaging Initiative (ADNI) and 99.06 percent on the Open Access Series of Imaging Studies (OASIS). The model produces good results on the Oasis and ADNI datasets. So, the proposed technique deals with massive amounts of data.**

Keywords— **Alzheimer’s, Deep Learning, Transfer Learning, ADNI (Alzheimer's Disease Neuroimaging Initiative)**

I. INTRODUCTION

This Alzheimer's disease (AD) is a progressive neurodegenerative disorder that is characterized by the loss of cognitive function, including memory and reasoning. Early diagnosis of AD is crucial for the development of effective treatment strategies, as it allows for the initiation of interventions at an early stage when they are likely to be most effective. Magnetic resonance imaging (MRI) is a commonly used technique for the diagnosis and monitoring of AD, as it provides detailed images of the brain's structure and function.

Around 50 million people worldwide suffer from neurological disorders, and we are expected to reach 82 million in 2030, according to the World Health Organization. Alzheimer’s disease, the most common form of dementia, can contribute to 60-70% of cases. Alzheimer's disease (AD) is a neurological illness that leads to dementia in the elderly. By 2050, one out of every 85 individuals will be affected by the disease [1]. Early detection of Alzheimer's disease can be performed by using machine learning by analysing MRI data. Machine learning algorithms have recently been proven to predict AD better than doctors in some circumstances [2], There is currently no cure for Alzheimer’s disease, but studies have shown that deep learning can improve the ability of brain imaging to predict Alzheimer’s disease class before a real diagnosis, this would allow us to find better ways to slow down or even stop the disease process. The patient's cerebral cortex shrinks dramatically, with substantial shrinkage occurring in the hippocampal region in general. This area is involved in reasoning, remembering, and creating new memories. In Alzheimer's disease, the brain ventricles that create cerebrospinal fluid enlarge as well. A timely diagnosis of this disease is critical, and it necessitates clinical evaluation based on the patient's medical history, multiple neuropsychological tests, such as the mini-mental state examination (MMSE), neuropsychiatric inventory questionnaire, clinical dementia rating, and other pathological assessments. The Alzheimer's Association and the National Institute of Aging developed the first clinical criteria for diagnosing AD [3]. Modern procedures employ a variety of imaging technologies in addition to these clinical methods. The non-invasive techniques of magnetic resonance

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imaging (MRI) and positron emission tomography (PET) are widely used to characterize the brain structure. In practice, cerebrospinal fluid (CSF) analysis is also used.

Tong et al. [4] suggested a cross framework that uses a stochastic graph fusion method to aggregate similarities from diverse modalities into a unified graph for categorization. Similarly, Sorenson et al. [5] used a combination of MRI biomarkers for multi-class categorization, including cortical thickness measurements, volumetric measurements, hippocampus shape, and hippocampal texture. Zhang et al. [6] classified AD and normal Alzheimer's Disease using a mixed kernel method and SVM classifier. The mixed kernels were mainly composed of features from the three techniques listed previously.

II. RELATED WORKS

Using a deep convolutional network CNN can achieve the process of classification of AD, some approaches can be detailed below:

In [7], they proposed a model based on transfer learning using VGG16 architecture to classify Alzheimer's Disease into 3 categories based on the ADNI dataset, the accuracy of the model achieve 95.73 % after validation. Bumshik Lee et al. [8] suggested using sMRI to classify Alzheimer's Disease with a deep convolutional neural network data permutation technique. On the ADNI dataset, Alex Net's architecture is chosen for this work. Their strategy enhanced overall classification accuracy, the classification accuracies for binary achieved 98.74 % and 98.06 % for the 3 classes (AD, CN, MCI). Traditional learning algorithms including SVM and feed-forward neural networks have been effectively used to identify Alzheimer's disease using structural MRI data [9], [10]. A dual-tree complex wavelet transform is employed to extract features, and a feed-forward neural network is utilized to categorize pictures in one recent technique.[8] contains a detailed explanation and comparison of findings with other common classical approaches. CNN has gotten a lot of attention as the most widely used Deep learning (DL) design because of its success in image classification and prediction [11]. However, due to limited acquisition and inaccuracies in preprocessed medical pictures, researchers have a significant hurdle in diagnosing AD using a deep learning approach [12].

DL approaches have already outperformed techniques by a wide margin. A. Gupta, M. Ayhan, and A. Maida employed a mix of patches extracted from an autoencoder and convolutional layers for feature extraction [13]. Payan and G. Montana used a 3D convolution to improve the approach[14].

In previous research, stacked autoencoders followed by a softmax layer were used for classification by S. Liu in [15]. In [16], popular CNN architectures including LeNet and the Inception model were employed. While these deep learning (DL) approaches have produced high accuracy results, in their study, a null masking method was used to preserve all of the information and features, and stacked autoencoder networks (SAE) were used to extract higher-level features. Additionally, SVM classification and multimodal feature extraction techniques were utilized. The best result of their study was an accuracy rate of 87 percent. While using SVM classifiers in fMRI (functional magnetic resonance imaging) situations can improve the classifier's accuracy, it may not always be the most efficient approach. This may be due to the fact that fMRI data is considered "big data," which can require more time and resources to process. In addition, the feature selection process for SVMs can be time-consuming, as noted in [18].

III.METHODOLOGY

The proposed pipeline consists of two steps: preprocessing and training, as depicted in Figure 1. These steps are described in more detail in the following subsections.

A. A. Pre-processing

The ADNI (Alzheimer's Disease Neuroimaging Initiative) datasets are a collection of imaging data from individuals with Alzheimer's disease (AD) and other forms of dementia, as well as healthy controls. The data is stored in NIfTI-1 (Neuroimaging Informatics Technology Initiative) format, which is a standard file format for storing medical imaging data. NIfTI files contain the image array as well as metadata such as the affine data, dimension, and other information. Once the data has been preprocessed, it may be segmented using techniques such as Otsu thresholding or the HMRF (Hidden Markov Random Field) Tissue Classifier. Segmentation involves dividing the images into different regions or "segments" based on certain criteria, such

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as intensity or texture. This can be useful for identifying specific structures or regions of interest in the images. Below we describe the mentioned steps.

Fig.1: The suggested deep learning model for Alzheimer's disease 3-way classification

Skull stripping: Skull stripping is a preprocessing step that involves removing non-brain tissue from 3D images of the brain. This is often necessary because the presence of non-brain tissue, such as the skull, can cause noise and interfere with the analysis of the brain images. One way to perform skull stripping is to use the Extractor class from the dipy library, which is a well-maintained tool for deep brain extraction. To use the Extractor class, an instance of the class is first created, and the run() method is then executed on the instance. This method returns a set of probabilities for each pixel in the image, indicating whether the pixel is likely to be part of the skull or not. Using these probability values, a mask containing only the brain tissue can be created. This mask can then be applied to the 3D image, setting all pixel values outside the mask to 0 and leaving only the brain tissue. The resulting brain image can be saved in 3D format using the nibabel library's Nifti1Image function, which allows the affine data to be included as one of its parameters.

Bias Correction: Bias correction in MRI scans is important because it can affect the accuracy of image analysis and interpretation. Non-uniform intensity in an MRI scan can be caused by a number of factors, including the magnetic field inhomogeneity, the receiver coil sensitivity, and patient motion. Bias correction algorithms attempt to correct these intensity variations by estimating the intensity field that would have been present in the absence of these factors, and then applying a correction to the actual intensity field to remove the bias.

he N4-Bias-Field-Correction algorithm is a popular method for bias correction in MRI scans. It is based on a non-parametric, iterative approach that estimates the bias field by minimizing the difference between the corrected image and a reference image, which is typically a histogram-equalized version of the original image. The algorithm uses the mask generated from thresholding to identify the regions of the image that need to be corrected, and then applies the correction to these regions. Overall, bias correction is an important step in the preprocessing of MRI scans, as it helps to improve the accuracy and reliability of image analysis and interpretation.

Segmentation and 2D Image Extraction :In neuroimaging, three-tissue probability segmentation is a method for dividing the brain into three different tissue types: Grey Matter (GM), White Matter (WM), and Cerebro Spinal Fluid (CSF). This segmentation is typically performed using the Tissue Classifier HMRF class in the "dipy" library. The Tissue Classifier HMRF class takes three inputs: the real data (i.e., the MRI scan), the class size (i.e., the number of tissue types being Before using the ADNI data for analysis, it is often necessary to perform several preprocessing steps to ensure that the data is of high quality. These steps may include skull stripping, which involves removing non-brain tissue from the images, and bias correction, which is used to remove noise and normalize the intensity of the images .

B. Network architecture

Classification of MRI slice as input entails a classifier dividing different objects into various classes. The approach of CNN is nearly identical to that of classic supervised learning methods: they take input pictures and process the transforming raw data into numerical features in order to train the classifier. It uses convolution filtering processes to accomplish template matching. The first stage uses numerous convolution kernels to pass filters on the image and provide "feature maps," which are then normalized (using an activation function to help the network learn complex patterns). The output feature map values are concatenated into a vector. This output is the input of the second block permitting the classification of the image into 3 classes if we use the ADNI dataset and four classes for the Oasis dataset.

The CNN architecture of the model consists of four convolutional layers, after each layer a max-pooling is performed. As input, the CNN takes tensors of shape (256, 256, color channels=1) and passed the input to the convolutional layers, A (16, 16, 128) outputs were flattened into vectors of shape (32768) before going through two dense layers to provide the output array of shape (none, 512) and (none, 3); ReLU activation

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function is added to the first dense layer and a Softmax activation function with the second applied to NUM_LABELS =3 or 4 depending on the preprocessed dataset.

III. RESULTS

In this section, we provide the results after training and validating the model. A confusion matrix, also known as a contingency table, is a tool used to measure the performance of a machine learning model in classification tasks. It shows how often the model's predictions are accurate in relation to the true labels of the data. The confusion matrix is particularly useful for identifying patterns in the model's errors, such as misclassifying one class more frequently than others. In the context of the results provided in Fig. 2 and Fig. 3, it appears that the model has been trained and validated on two different datasets: the ADNI dataset with three classes, and the Oasis dataset with four classes. The confusion matrices in these figures show the performance of the model on each of these datasets, with the rows representing the true labels of the data and the columns representing the predicted labels. Overall, the confusion matrices can be used to evaluate the accuracy of the model's predictions and identify areas where it may be performing poorly. This information can then be used to improve the model's performance through techniques such as fine-tuning the hyperparameters or adding more data to the training set.

Fig.2: Confusion matrix for ADNI dataset

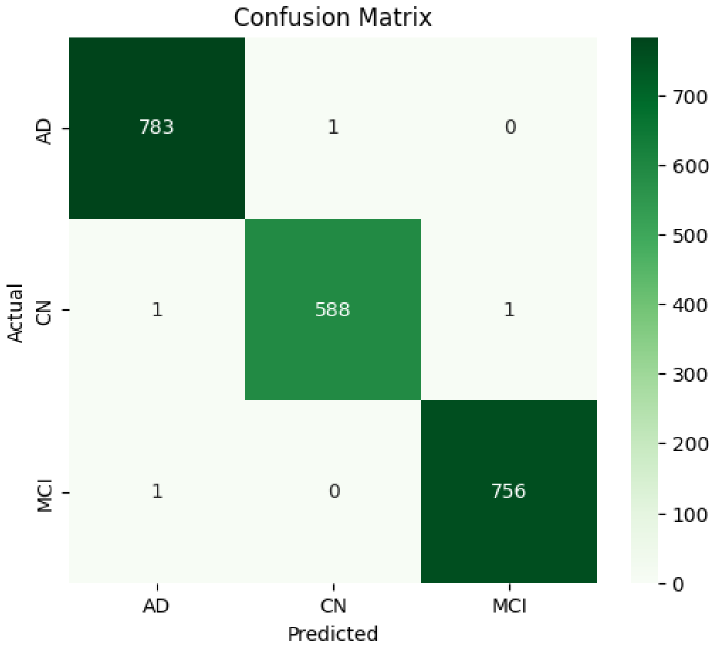

Fig.3 Confusion matrix for Oasis dataset

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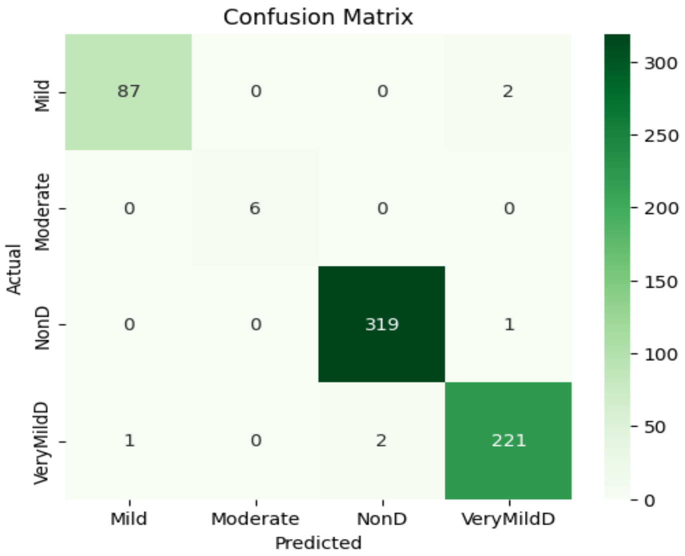

To evaluate the performance of a machine learning model, it is common to calculate a set of metrics known as confusion metrics. These metrics include accuracy, precision, recall, and F1 score, and they can be used to understand how well the model is performing on a given dataset. Tables I and II provide the interpretation of these performance measures, which can be used to evaluate the model's performance and identify areas where it may be underperforming. Accuracy measures the overall correct predictions made by the model, while precision measures the proportion of correct positive predictions to total positive predictions. Recall measures the proportion of correct positive predictions to total actual positive cases, and F1 score is a balance between precision and recall. Together, these metrics provide a comprehensive view of the model's performance, which can be used to identify areas for improvement and optimize the model's performance. Table I and Table II show the interpretation of performance measures.

TABLE I: PERFORMANCE MEASURES WITH OVERALL ACCURACY = 99.81%, ADNI 3 CLASSES

Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
AD	**785**	**784**	**99.86%**	**1.0**	**1.0**	**1.0**
CN	**589**	**590**	**99.86%**	**1.0**	**1.0**	**1.0**
MCI	**756**	**756**	**99.91%**	**1.0**	**1.0**	**1.0**

TABLE II: PERFORMANCE MEASURES WITH OVERALL ACCURACY = 99.06 %, OASIS 4 CLASSES.

Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
Mild	**88**	**89**	**99.53%**	**0.98**	**0.99**	**0.98**
Moderate	**6**	**6**	**100%**	**1.0**	**1.0**	**1.0**
NonD	**321**	**320**	**99.53%**	**1.0**	**0.99**	**1.0**
VeryMildD	**224**	**224**	**99.06%**	**0.99**	**0.99**	**0.99**

A model accuracy and loss curve (Fig.5) is a plot that shows how the accuracy and loss of a model change over time, typically during the training phase. The accuracy of the model is a measure of how well the model is able to correctly classify or predict the output for a given set of inputs. The loss of the model is a measure of how far the model's predictions are from the true values. Both the accuracy and loss are calculated using a metric or loss function, which is a mathematical equation that is designed to capture the performance of the model.

FIG.4 PERFORMANCE CURVE OF THE PROPOSED MODEL (ADNI) APPLIED TO THE ADNI SMALL DATA SIZE DATASET

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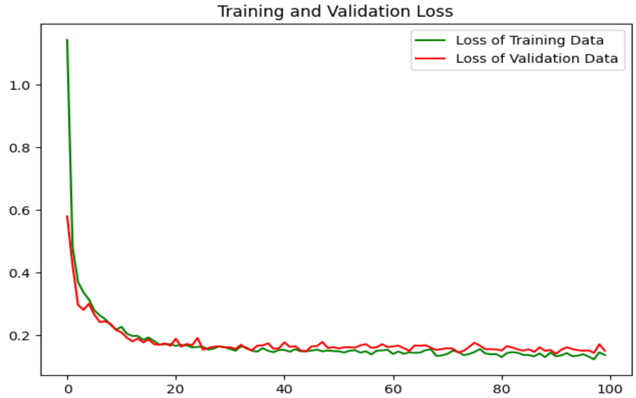
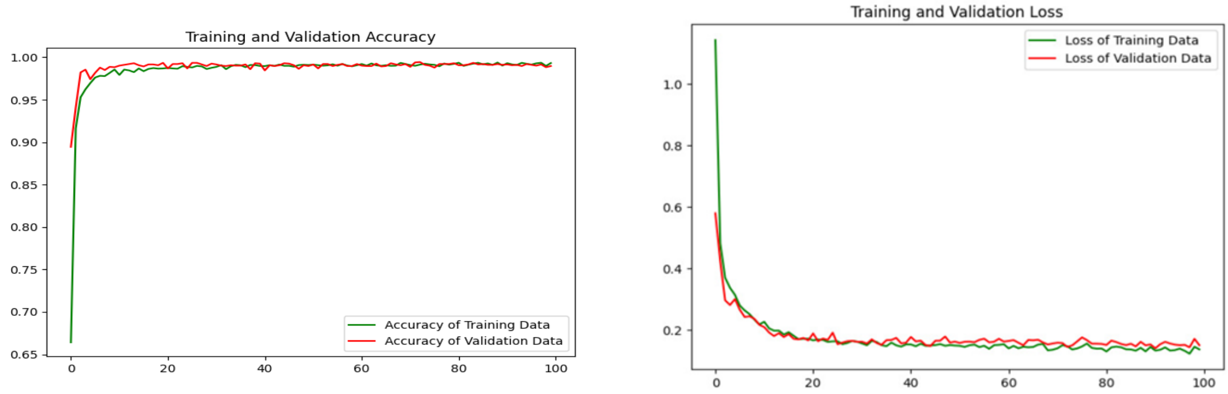


FIG.5: TRAINNG AND VALIDATION ACCURACY AFTER 100 EPOCHS APPLIED ON ADNI 21000 MRI SCAN



In all of our studies, we were able to get very high accuracy. We kept track of the loss in the training and testing datasets during the learning process, in addition to accuracy. After conducting training experiments, we found that the model was able to achieve an average accuracy of 99 percent. This high accuracy was consistently achieved across all of our studies. In addition to tracking accuracy, we also monitored the loss in the training and testing datasets during the learning process.These results demonstrate the effectiveness of the model in accurately classifying MRI scans into different tissue types.
To address the issue of overfitting, we added a kernel regularizer (l2 = 0.001) to the last three dense layers of the model. This helped to optimize the model's loss and improve its generalization to the testing dataset . As a result, the model was better able to handle new data and perform more accurately on the testing dataset. The use of kernel regularization was a successful method for enhancing the model's performance and decreasing the possibility of overfitting.

IV. DISCUSSION

The results of the proposed model were very promising, indicating that it was able to effectively learn from the data and make accurate predictions. This is an important finding, as it suggests that the proposed model has the potential to be a valuable tool for the diagnosis of Alzheimer's disease. By accurately classifying AD patients, the model can help radiologists, doctors, and caretakers to make informed decisions about treatment and care, ultimately improving the quality of life for those suffering from this condition. The proposed model used around 21324 MRI scan from ADNI for training, and 6400 from the OASIS dataset. Tables III and IV present a comparison in terms of accuracy with other methods.

With a dropout of 0.4 and a weight decay of 0.02 the suggested model has the least training and validation loss and the greatest training and validation accuracy.

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Table IV presents a comparison of the accuracy of the proposed method with the state-of-the-art in terms of accuracy on the ADNI dataset. The table includes the modality, method, and database used in each study, as well as the reported accuracy. The proposed method, which uses a CNN model on MRI data, achieved an accuracy of 99.67% on the ADNI dataset. This accuracy is higher than the accuracy reported in several other studies, including those that used PET and MRI data (53.8% accuracy), 2D-SAE on MRI data (89.47% accuracy), 3D-CAE on MRI data (89.1% accuracy), vgg16 on MRI data (95.73% accuracy), AlexNet on sMRI data (98.06% accuracy), LeNet-5 on fMRI/MRI data (96.86% accuracy), 3D-CNN on sMRI (T1) data (97.52% accuracy), and CNN on EEG data (83.33% accuracy). These results suggest that the proposed method is a promising approach for the diagnosis of Alzheimer's disease using MRI data.

TABLE III: COMPARISON WITH THE STATE - OF - THE - ART IN TERMS OF ACCURACY (ADNI DATASET)

Ref	Modality	Method	Database	Accuracy
19	MRI	2D-SAE	ADNI	89,47%
7	MRI	DL (vgg16)	ADNI	95,73%
8	sMRI	DL(AlexNet)	ADNI	98,06%
21	fMRI/MRI	LeNet-5	ADNI	96,86%
22	sMRI(T1)	3D-CNN	ADNI	97.52%
23	EEG	CNN	ADNI	83,33%
P	MRI	CNN	ADNI	99,67%

The proposed method, which uses a CNN model, achieved an accuracy of 99.06% on the OASIS dataset. The results in Table V show that the proposed method is an effective approach for the diagnosis of Alzheimer's disease using MRI data. The proposed method outperformed several other methods, including a sparse autoencoder with convolutional layers (94.74% accuracy), a hybrid deep CNN (95.23% accuracy), a standard CNN (83.18% accuracy), 3D convolutional layers (95.39% accuracy), stacked autoencoders (87.76% accuracy), and the Inception model (98.84% accuracy).
One interesting finding is that the proposed method had a higher accuracy than the other methods despite using a smaller training size. This suggests that the proposed method is able to effectively learn from the data and make accurate predictions even with a limited amount of training data. This is an important consideration for real-world applications, where it may not always be possible to access large amounts of data for training.

TABLE IV: COMPARISON WITH THE STATE - OF - THE - ART IN TERMS OF ACCURACY (OASIS DATASET)

Ref	Modality	Training Size	Accuracy
13	Sparse autoencoder + conv	103,683	94.74%
21	CNN		83,18%
14	3DConv	117,708	95.39
15	Stacked autoencoders	21,726	87.76
16	DeepAD (Inception)	46,751	98.84
Proposed	CNN	6,400	99.06%

VI. CONCLUSION

AD is a degenerative disease affecting the brain that is the leading cause of dementia in the elderly. AD causes nerve cell death and tissue degeneration, massively reducing brain size over time and compromising the majority of its activities. As a result, we provide a Deep Learning algorithm technique for reliably identifying AD using CNN. We discuss details of similar work and evaluated the proposed CNN. In this work, we preprocess the ADNI data to create a database of 200 000 images. In this study, 21000 images are used for training. The algorithm achieves the highest accuracy of 99.81 percent compared with other methods. We also use the CNN model on the Oasis Dataset, which we achieve an accuracy of 99.06 percent. Our results demonstrated that the given technique was successful in identifying AD with high accuracy on two different databases. In the future, we intend to expand our work by including more data and more optimization approaches to increase the algorithm's accuracy.

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