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Diagnosis and classification of Alzheimer's disease from MRI images using parallel deep convolutional neural networks

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ABSTRACT

Alzheimer's disease, an incurable neurological condition affecting memory, predominantly in the elderly, necessitates precise early diagnosis. While Convolutional Neural Networks (CNNs) are effective in classifying Alzheimer's, they may suffer from overfitting due to random feature collection. To address this, a novel parallel deep Convolutional neural network (PDCNN) architecture is proposed. This architecture extracts global and local features through two parallel paths, mitigating overfitting using dropout regularization and batch normalization. Initial steps involve resizing input images and grayscale transformation for complexity reduction, followed by data augmentation to enhance dataset size. The parallel paths leverage two deep CNNs with identical window sizes, enabling the model to learn both local and global information. Evaluation on a multi-class Kaggle dataset showcases the method's efficacy, achieving 100% accuracy on training data and 98.927% on validation data. The proposed approach not only ensures accuracy but also efficiency by extracting low-level and high-level features, outperforming existing techniques.

Keywords: Alzheimer's disease, convolutional neural networks, parallel deep neural network, overfitting, data enhancement

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INTRODUCTION

Impaired cognitive ability is the main symptom caused by AD. This disease is more common in the elderly and usually affects people over 65 years of age. 10% of premature cases start in people younger than 65 years. AD also affects spoken language, concentration, comprehension, reasoning, and memory. Specialists can care for patients suffering from symptoms of this disease. A decline in cognitive ability occurs due to dementia that affects daily activities. AD is the most common type of dementia, which accounts for about two-thirds of cases due to age factors. In 2020, it was the seventh leading cause of death in the United States. AD has treatments to improve symptoms, but there is no effective cure (1).

Alzheimer's disease is a rapidly growing disease worldwide. It mostly affects the elderly population. Alzheimer's is incurable and is a neurological disease that mostly affects the brain. People face problems related to Alzheimer's due to the lack of early diagnosis due to the absence of symptoms or partial symptoms in the early stages of the disease. In recent years, various methods have been proposed to diagnose Alzheimer's disease by medical imaging data. Various machine learning methods have been used for this purpose (2). Each machine learning method uses its own mechanism to learn this data. Support vector machine methods, decision tree, Bayesian classification and deep learning-based methods are machine learning methods that were used for automatic diagnosis of Alzheimer's disease. Convolutional neural networks have achieved remarkable results in the past decade in various areas recognized by design recognition, from voice recognition to image processing (3). CNN-based automatic coding is also used in various fields such as noise removal, image classification, and pattern recognition (4). New CNN architectures were developed and tested using other CNN architectures for image classification, including: AlexNetet, VGG, DenseNet and ResNet architectures (5). Research has shown that the most widely used methods are support vector machine (SVM) and methods based on deep learning.Ultrasound exams: In some cases, specially trained healthcare providers can perform ultrasounds remotely using portable ultrasound machines and telecommunication technology (6).

METHODS

Statement of challenge

The use of two parallel deep convolutional neural networks, one focusing on local features and the other on global features, is proposed to enhance the accuracy and performance of diagnosing Alzheimer's disease from MRI images. While individual networks have limitations in extracting either local or global features effectively, combining both approaches aim to improve the overall diagnostic accuracy for Alzheimer's disease.

This method improves accuracy and performance in the diagnosis and classification of Alzheimer's disease from MRI images. However, there are challenges such as the lack of training data, the need for powerful hardware and powerful graphics processors, as well as problems such as the interpretability of the results in this method that must be managed. Using local and global parallel deep convolutional neural networks to diagnose Alzheimer's disease from MRI images is an advanced and powerful approach. These methods can improve the accuracy and performance in Alzheimer's disease diagnosis in some cases, but the cases where

their performance is improved depends on the conditions and data used. The advantages of using local and global parallel deep convolutional neural networks are:

1. Local and Global Features: These methods can extract both local and global image features simultaneously to identify crucial information related to Alzheimer's disease in MRI images, aiding in decision-making.
2. 3D Image Utilization: Deep convolutional neural networks have the capability to process 3D MRI images and extract 3D features, offering deeper insights into brain structure and Alzheimer's-related changes.
3. Deep Learning Capability: These networks excel at learning and recognizing complex and irregular patterns present in MRI images, enabling them to detect Alzheimer's disease-related features accurately and enhance diagnostic precision.

However, more studies and experiments on real and large-scale data are needed to accurately compare the performance of different methods. Also, factors such as data composition, sample size, evaluation criteria and comparison criteria can affect the performance of the methods. As a result, to accurately evaluate the performance of the methods, it is better to refer to the relevant studies and researches in this field (7).

Data collection

In this thesis, a dataset from the Kaggle site including MRI images of Alzheimer's patients in 4 classes has been used to train and evaluate networks. This data is collected manually from various websites with each verified label. This dataset contains two files: a training file and a test file. Both of these files contain a total of about 5000 images classified by Alzheimer's disease severity, the Alzheimer's dataset (4 image classes) available on Kaggle contains MRI images used to train and evaluate neural networks. This dataset contains four categories of MRI images of Alzheimer's patients:

- Mild Demented (mild degree of Alzheimer's disease)
- Moderate Demented (moderate degree of Alzheimer's disease)
- Non-Demented (absence of Alzheimer's disease)
- Very Mild Demented (a very mild degree of Alzheimer's disease)

The Alzheimer's dataset (4 classes of images) available on Kaggle is a useful resource for Alzheimer's research and experiments. The number of data in each class is shown in Figure I.

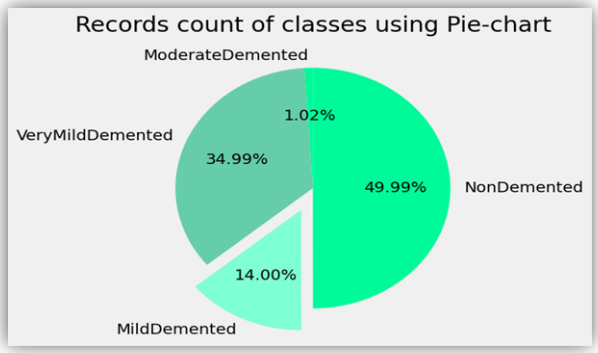

FIGURE I. RECORD COUNT OF CLASSES USING PIE-CHART

Images after pre-processing and labeling in 4 classes randomly can be seen in Figure II.

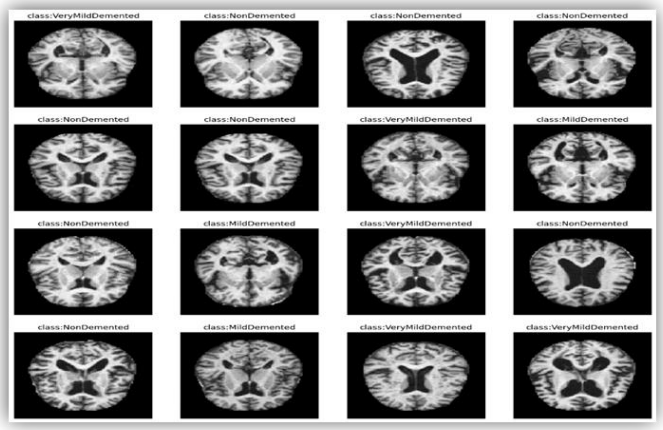

FIGURE II. IMAGES AFTER PREPROCESSING AND LABELING IN 4 CLASSES

Evaluation criteria

In this section, the criteria used to evaluate the performance of the proposed method are explained. These criteria include accuracy, precision, recall and F1 measurement. It is explained what concept each criterion shows in evaluating the performance of the proposed method. To evaluate the performance of the proposed method, the following evaluation criteria have been used:

- Accuracy: the ratio of the number of correctly recognized samples to the total number of samples.
- Precision: the ratio of the number of correctly detected positive samples to the total number of detected positive samples.
- Recall: the ratio of the number of correctly recognized positive samples to the number of real positive samples.
- Measurement (F1-Score): F1 is a measure that is a combination of accuracy and readability and shows how well the method is able to detect the best combination of accuracy and readability.

The reason for choosing the method

The rationale behind choosing local and global parallel deep convolutional neural networks for diagnosing Alzheimer's disease from MRI images. These networks are preferred over traditional methods due to their ability to automate feature extraction, extract complex and structural features, and recognize irregular patterns in images without the need for manual feature design. Additionally, they can simultaneously analyze local and global features in MRI images, boosting diagnostic accuracy. Traditional methods, on the other hand, often rely on manual classification and may struggle with accuracy and performance limitations. While deep convolutional neural networks offer significant advancements, they also come with challenges such as the need for ample training data, powerful hardware, and interpretability issues. Ultimately, the use of local and global parallel deep convolutional neural networks can enhance Alzheimer's disease diagnosis performance compared to traditional methods, though this effectiveness is subject to various conditions and further empirical validation.

Block diagram of the proposed method

Figure III shows a block diagram of PDCNN design. The sequence of events that occur in the proposed structure are: The input layer of PDCNNs receives brain MRI images which are pre-processed to reduce the computational complexity. For training purposes, the input images are converted to 128x128 pixels from different height and width pixels. These input images are converted to grayscale, which helps reduce complexity. Data augmentation is then used to create new images from the old ones. To train the proposed network, the datasets are divided into training and validation. The PDCNN structure is then used to classify the input images, which include local, global, merge, and output paths. In the output path, the softmax function is used to perform the classification process of Alzheimer's disease.

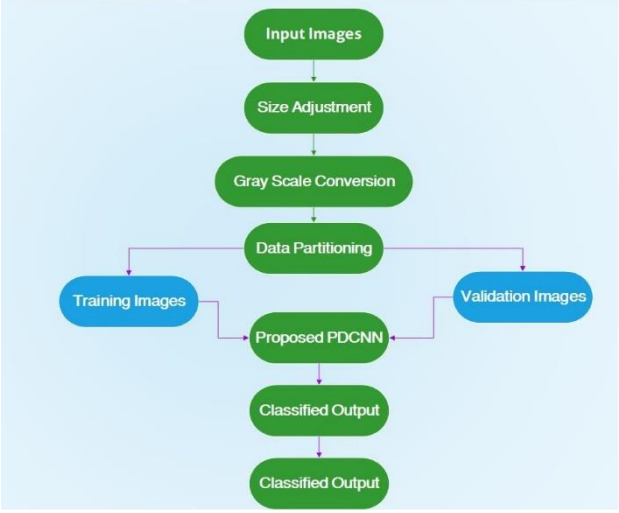

FIGURE III. BLOCK DIAGRAM OF THE PROPOSED METHOD

Details of the proposed method

The details of the proposed PDCNN model are shown in Figure IV.

Architecture of the proposed method

Parallel Deep Neural Network (PDCNN) architecture proposes a new network architecture for Alzheimer's disease diagnosis and classification, which consists of two deep complex neural networks that work simultaneously, as shown in Figure V.

The PDCNN structure is used to classify input images, which includes local, global, fusion, and clustering. To obtain local and global features, local and global routes are used, respectively. In both global local routes, it consists of 3 convolutional layers. These 3 layers have the number of filters respectively (64-128-256), and the average window size of their convolutional layers filters is 5x5 pixels to provide low-level information in the images, and in these convolutional layers padding='Same' and use activation='Relu'. And on the other hand, after each convolution layer, first a BatchNormalization batch normalization layer and then a max-pooling layer have been used in both paths. These two paths are joined by a fusion layer that creates a single path with a cascading link until it enters the final step, classification. The integration stage consists of using the Concatenate function from the class library and a BatchNormalization layer and activation= 'Relu'. And the classification stage

consists of a GlobalAvragepooling2D layer and a Dense layer and a Dropout layer and a Dense layer with Softmax activation.

```
model.summary()
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                Output Shape              Param #   Connected to
==================================================================================================
 input_1 (InputLayer)        [(None, 128, 128, 1)]     0         []

 sequential_1 (Sequential)   (None, 16, 16, 256)       1027840   ['input_1[0][0]']

 sequential (Sequential)     (None, 16, 16, 256)       1027840   ['input_1[0][0]']

 concatenate (Concatenate)   (None, 16, 16, 512)       0         ['sequential_1[0][0]',
                                                                  'sequential[0][0]']

 batch_normalization_6 (Bat  (None, 16, 16, 512)       2048      ['concatenate[0][0]']
 chNormalization)

 activation (Activation)     (None, 16, 16, 512)       0         ['batch_normalization_6[0][0]'
                                                                  ]

 global_average_pooling2d (  (None, 512)               0         ['activation[0][0]']
 GlobalAveragePooling2D)

 dense (Dense)               (None, 512)               262656    ['global_average_pooling2d[0][
                                                                  0]']

 dropout (Dropout)           (None, 512)               0         ['dense[0][0]']

 dense_1 (Dense)             (None, 4)                 2052      ['dropout[0][0]']

==================================================================================================
Total params: 2322436 (8.86 MB)
Trainable params: 2319620 (8.85 MB)
Non-trainable params: 2816 (11.00 KB)
__________________________________________________________________________________________________
```

FIGURE IV. DETAILS OF THE PROPOSED METHOD

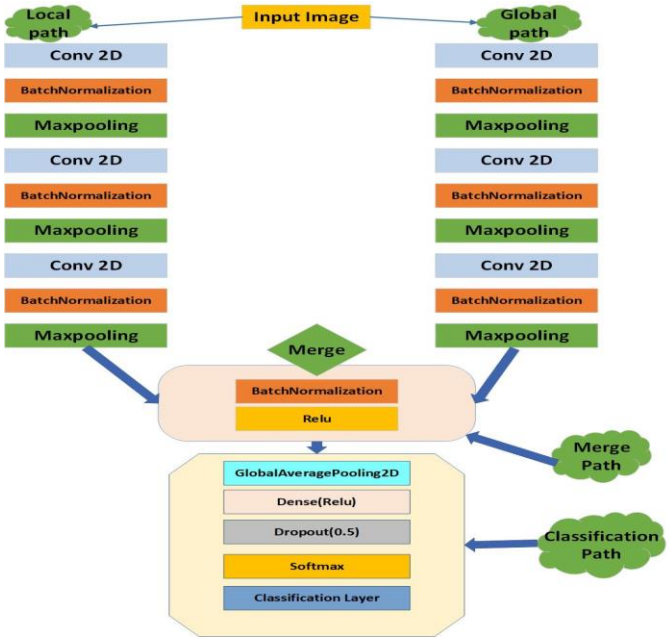

FIGURE V. ARCHITECTURE OF THE PROPOSED METHOD

RESULTS

The results of the simulation

The results obtained from the implementation and execution of the proposed method on the data set include the criteria of precision, accuracy, readability and F1 measurement. These results show that the proposed method is capable of diagnosing and classifying Alzheimer's disease with high precision, accuracy and reproducibility. In addition, F1 measurement also shows that the proposed method is able to achieve a better combination of precision and readability. The data set is first divided into two sets of training data and validation data. The proposed model starts training with the proposed parameters including (batch_size=150, epochs=80) on the dataset data. And after 28 periods or epochs, the model stops and reaches the following results: the accuracy of the model on the training data is 100% and over on the validation data reached 99.024% and the model loss on the training data reached 0.033% and the loss (loss) on the validation data reached 0.591% We will examine and interpret RI using parallel deep convolutional neural networks. Here, the main characteristics of the simulation or implementation results are:

Accuracy

After training on the data set, the model reached 100% accuracy for the training data and 98.927% accuracy on the validation category, and the accuracy graph during 28 periods in the training stages is as follows. The results of the implementation on the training data showed that the proposed model has reached an accuracy of 100%. This result shows that the model has a high ability to diagnose Alzheimer's disease and has correctly classified all training data samples. The accuracy of the model on the validation data is 98.927%. This result shows that the model has a high generalizability and is able to correctly diagnose Alzheimer's disease on new data. The results of the accuracy of the proposed model on the training and validation data are shown in the Figure VI.

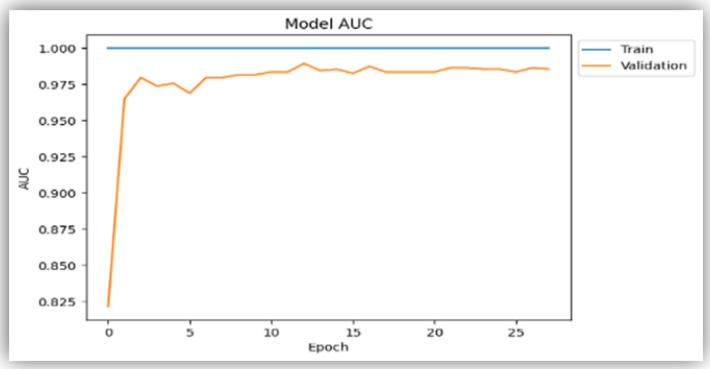

FIGURE VI.. IMAGES AFTER PRE-PROCESSING AND LABELING IN 4 CLASSES

Loss function

After training the model on the dataset data in 28 cycles, it reached a loss of 0.0033 for the training data and a loss value of 0.0362 on the validation data, and the loss graph has been reached during 28 cycles in the training stages. On the training data, the loss of the model has reached 0.33%. This result shows that the model has been learned efficiently and quickly using training data and has been able to extract useful information

about Alzheimer's disease. Based on the validation data, the loss of the model has reached 0.362%. This result shows that the model, even in front of new and unknown data, still performs well and maintains the ability to diagnose Alzheimer's disease. Figure VII shows the amount of loss of the proposed model on the training/validation data.

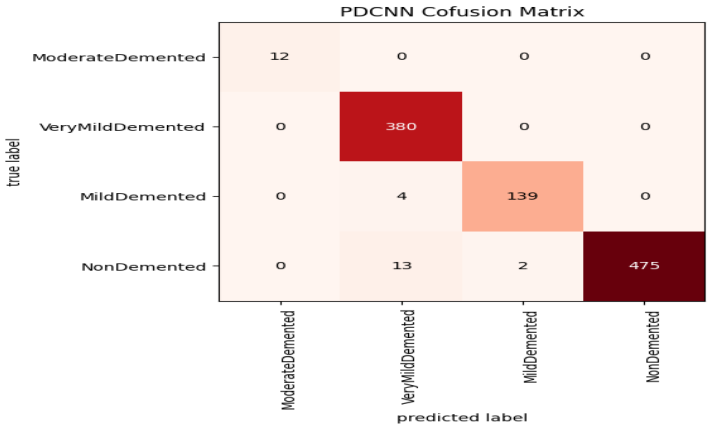

FIGURE VII. AMOUNT OF LOSS OF THE PROPOSED MODEL ON THE TRAINING/VALIDATION DATA

The results of the proposed method in the confusion matrix

By analyzing the confusion matrix, we can assess the model's performance in diagnosing Alzheimer's disease with greater precision. The matrix displays the correct and incorrect identifications made by the model. The columns represent the actual labels of the data, while the rows represent the labels predicted by the model. The provided information indicates that the model's confusion matrix, shown in Figure VIII, details the alignment between the true labels and the predicted labels.

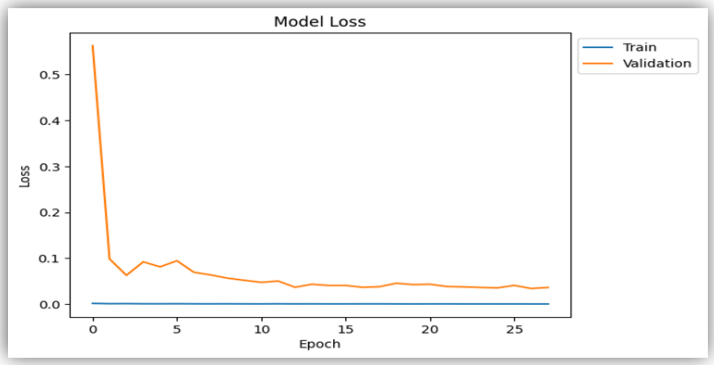

FIGURE VIII.. THE CONFUSION MATRIX

According to the shape of the confusion matrix above, we can conclude that the proposed model performed very well in detecting the "ModerateDemented" class. Because out of all 12 examples of this class, it has recognized all of them correctly. In the "VeryMildDemented" class, out of 380 samples, it correctly identified 372 samples in this class, but misclassified 8 samples in the "NonDemented" class. This result shows that the model performed well in detecting the "VeryMildDemented" class, but

significantly identified the samples of this class as "NonDemented". In the "MildDemented" class, out of 143 samples, it correctly identified 139 samples in this class, but incorrectly classified 2 samples in the "VeryMildDemented" class and 2 samples in the "NonDemented" class. These results show that the model also performed well in detecting the "MildDemented" class, but was wrong in a small number of samples. In the "NonDemented" class, out of 480 samples, it correctly identified 487 samples in this class, but incorrectly classified 3 samples in the "VeryMildDemented" class. This result shows that the model also performed very well in detecting the "NonDemented" class, however, it was wrong in a small number of samples. By examining this information, it can be concluded that the proposed model has generally performed well in diagnosing Alzheimer's disease, however, some errors have occurred. Investigating these mistakes and improving them can be part of the next work to improve the performance of the model. The values of precision and recall and F1 score for each of the classes are presented in Table I.

TABLE I. THE VALUES OF PRECISION AND RECALL AND F1 SCORE FOR EACH OF THE CLASSES

	Precision	Recall	f1-score	Support
ModerateDemented	1.00	1.00	1.00	**12**
VeryMildDemented	0.99	0.98	0.98	**380**
MildDemented	1.00	0.97	0.99	**143**
NonDemented	0.98	0.99	0.99	**490**
accuracy			0.99	**1025**
macro avg	0.99	0.99	0.99	**1025**
weighted avg	0.99	0.99	0.99	**1025**

According to the Table I, we can reach the following results: for "ModerateDemented" class, precision, recall and F1 score are all equal to 1.00. These results show that the model performed very well to correctly recognize the examples of this class. For the "VeryMildDemented" class, the precision is 0.99, the recall is 0.98, and the F1 score is 0.98. These results show that the model performed well in correctly recognizing the examples of this class. However, it identified a small number of samples in this class as "NonDemented". For "MildDemented" class, Precision is 1.00, Recall is 0.97, and F1 score is 0.99. These results show that the model performed well in correctly recognizing the samples of this class. However, it erred in a small number of samples and classified them in the "VeryMildDemented" or "NonDemented" class. For the "NonDemented" class, the precision is 0.99, the recall is 0.99, and the F1 score is 0.99. These results show that the model performed very well in correctly recognizing the examples of this class. However, it identified a small number of samples in this class as "VeryMildDemented". Regarding precision, recall and F1 score for the average of samples (macro avg) and weighted average of samples (weighted avg), the values are equal to 0.99 for all three criteria. Also, the overall accuracy of the model is equal to 0.99, which shows that the model has performed very well in the overall diagnosis of Alzheimer's disease. According to these results, it can be concluded that the proposed model has performed very well in diagnosing Alzheimer's disease, however, in some cases, mistakes have occurred.

Comparison with other deep learning models

TABLE II. COMPARISON WITH OTHER DEEP LEARNING MODELS

Reference/Author	Research method	The performance
Morgan et al (8).	CNN	Accuracy = 95.23% Precision = 96% Recall = 95% F1-score = 95.27%
Ludo et al (9).	Deep ensemble	Accuracy = 97.71% Sensitivity = 96.67% Specificity = 98.22%
Mohammad and colleagues (10).	Pretrained deep model + SVM	Accuracy = 94.80% Sensitivity = 93% Specificity = 97.75%
Balasundaram (11).	Pretrained deep models	Accuracy = 94.10% Precision = 96.50% Recall = 94.75% F1-score = 95.5%
Bangyal et al (12).	CNN	Accuracy = 90% Precision = 91.34% Recall = 87.34% F1-score = 88.09%
Ahmed et al (13).	CNN	Accuracy = 95.93% Precision = 95.93% Recall = 95.88% F1-score = 95.90%
Ahmed Abdul Latif and colleagues (2023) (14).	DenseNet-169	Training AUC = % 97.77 Testing AUC = % 88.70
	ResNet-50	Training AUC = % 83.82 Testing AUC = % 81.98
suggested method	PDCNN	Accuracy =% 99 Precision = %99 Recall = % 99 F1-score = % 99 Training AUC = % 100 Testing AUC = % 98.927

In this section, we will make a comprehensive comparison between our proposed model for Alzheimer's disease diagnosis and other prominent models developed for the same task. This comparison is based on the same multi-class data set and will provide predictions on the relative performance of different models. Table II compares the proposed model for multi-class recognition with previous deep learning methods.

The results of running the proposed algorithm on the experimental data set

In this section, we used parallel deep convolutional neural network for Alzheimer's disease diagnosis and classification and discussed the results and important findings. At first, we implemented the proposed algorithm for the "ModerateDemented" category using experimental data from the dataset. According to the Figure IX, the result shows that the proposed model correctly recognizes this category with 98.46% accuracy. Then, we performed the same process for the "MildDemented" category and achieved an accuracy of 99.15% for this category. The results of this section can also be seen in Figure IX. Also, we performed similar steps for the next category, "VeryMildDemented", and correctly identified this category with 99.99% accuracy. The results of this section can also be seen in the opposite Figure IX. Finally, the algorithm execution results for the "NonDemented" category also reached 99.1% accuracy. These results can also be seen in Figure IX. In general, the use of parallel deep convolutional neural network allows us to detect and classify Alzheimer's disease into different categories with high accuracy and acceptable accuracy.

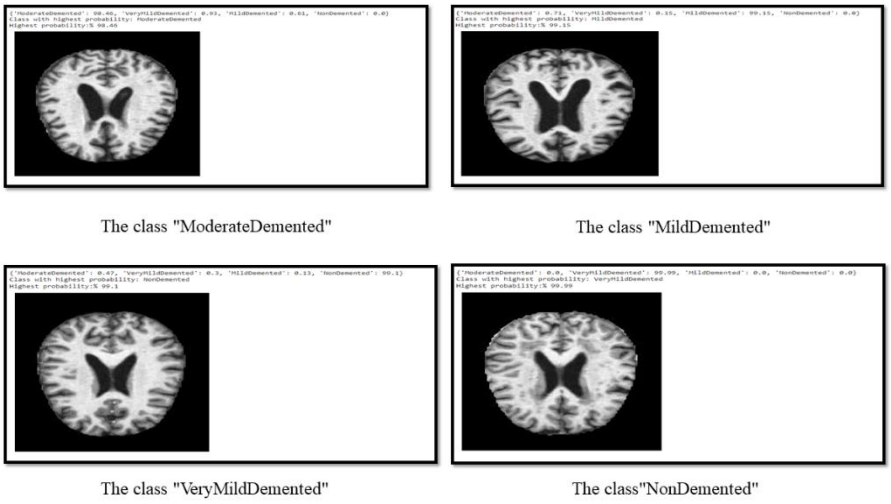

FIGURE IX. THE RESULTS OF THE IMPLEMENTATION OF THE PROPOSED MODEL ON THE DIFFERENT CLASSES

DISCUSSION

The discussion section highlights the effectiveness of the proposed method in accurately diagnosing and classifying Alzheimer's disease using deep convolutional neural networks. The model's high accuracy in identifying patients and non-patients reduces the risk of misdiagnoses. The balanced precision and recall, reflected in the F1 score, enhance the method's utility for early detection and monitoring of Alzheimer's disease. Simulation results demonstrate the model's precision and accuracy in diagnosing Alzheimer's from MRI images, suggesting potential advancements in disease management. The model's strong alignment with training data and its ability to generalize to new data indicate its potential for practical applications. According to table number (1) in the previous sections, the proposed model has better accuracy and performance compared to other similar models. Further evaluation on real-world data is needed to validate the model's performance. Future research should focus on enhancing the

model's stability and adaptability to diverse MRI images and patient profiles to ensure reliability across various diagnostic scenarios. Improving the method's functionality and robustness amidst different patient characteristics and MRI images presents promising avenues for future investigation.

CONCLUSION

The thesis evaluates the performance of a deep learning model, PDCNN, in diagnosing and classifying Alzheimer's disease using MRI images. The model achieved a high accuracy of 98.54% in classifying a four-class dataset, indicating the potential of deep learning for accurate diagnosis and differentiation of Alzheimer's disease stages. The use of specific image data size, enhancement techniques, and activation functions were found to be crucial for achieving these results. The study contributes to the literature on deep learning in disease recognition and classification, with implications for early diagnosis and treatment. However, the study has limitations, including a relatively small dataset and a focus solely on MRI images. Future research is suggested to address these limitations and explore other imaging modalities and deep learning models in medical imaging. Additionally, the development of more interpretable deep learning models is recommended to enhance understanding of the disease's biological mechanisms.

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CONTRIBUTORSHIP STATEMENT

All authors reviewed and commented on the manuscript, as well as all are responsible for the content of the manuscript.

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DECLARATION OF CONFLICTING INTERESTS

The authors declared no conflicts of interest regarding the research, authorship, and publication of this article.

DATA AVAILABILITY STATEMENTS

The data will be made available from the corresponding author on reasonable request.

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