International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 30, No. 2, February, 2025, pp. 457-463
Journal homepage: http://iieta.org/journals/isi

Automatic Alzheimer's Disease Detection Based on Deep Learning Models

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https://doi.org/10.18280/isi.300217

Received: 4 December 2024
Revised: 17 January 2025
Accepted: 14 February 2025
Available online: 27 February 2025

Keywords:
AD, CNN, deep learning, diagnoses, transfer learning

ABSTRACT

Alzheimer's disease (AD) was identified decades before dementia was officially diagnosed, according to a number of medical researches. These studies' development and the identification of numerous ideal biomarkers for Alzheimer's disease symptoms led to the realization that, in order to handle the massive volumes of data involved in an early diagnosis—which gives us a good chance to benefit from treatment—a high-performance computational tool is necessary. This paper's primary goal is to establish a comprehensive framework based on convolutional neural networks (CNNs) and deep learning techniques. Four phases of AD are used: data preparation and preprocessing, data augmentation, deep learning-based classification and feature extraction for medical image classification. Two strategies are used at these phases. A simple CNN architecture is used in the first technique. The second technique used the pre-trained DenseNet169 model, which was trained on the ImageNet dataset and then applied on various dataset.

1. INTRODUCTION

The death of healthy brain cells that leads to Alzheimer's disease (AD) is what causes a steady deterioration in mental, intellectual, and memory functions. It is the most typical cause of dementia, a condition that impairs social and mental abilities [1] This makes it difficult to go about your regular routine and gets worse with time. Nerve cell decline, neurofibrillary development and the gradual shrinkage of brain tissue all contribute to this occurrence [2]. The World Health Organization predicts that in 2021, there will be 55 million cases of dementia worldwide; by 2030, that number is expected to increase to 78 million, and by 2050, it will reach 139 million cases, more than twice as many as in 2021 [3]. While the prevalence of young-onset dementia is only 3% among young persons, which can be brought on by a variety of disorders, most individuals over 65 are at a high risk of developing dementia. Late treatment damages brain cells associated with cognition and memory, leading to loss of brain function, mental skill decline, language issues, and a reduction in the capacity to form coherent thoughts [4].

The illness begins with a slow degeneration of nerve cells and progresses to an acute stage of dementia that makes patients unable of doing basic everyday tasks [5].

As AD develops with time, it is crucial to diagnose it in its early stages. Two approaches are used to diagnose AD: (1) when the patient exhibits symptoms and (2) utilizing neuron imaging technologies. AD appears before any symptoms [6]. This phase, known as "pre-clinical AD," is characterized by the absence of symptoms in both the sick person and others around them Decades or more may pass during this phase of Alzheimer's disease. Whether or not symptoms are evident, amyloid beta deposits, a protein characteristic of AD, may be detected by contemporary imaging methods [7].

Because imaging methods provide a non-invasive interior inspection of the body, they are the most widely used method for identifying AD. When AD could only be identified after death, there was a challenging time in the history of AD therapy [8]. However, modern medical imaging technologies are increasingly crucial to the identification and management of AD. Numerous neuroimaging modalities, including computed tomography (CT), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and magnetic resonance imaging (MRI), are crucial in the identification of brain disorders [9].

Recently, machine learning is attracting the attention of academics in a variety of sectors due to its capacity of learn, enhance an algorithm and forecast the solution to any issue. Deep neural networks are able to use data to detect subtle and complex changes in brain structure, study how Alzheimer's disease progresses, and produce accurate results for the diagnosis of the illness [10]. CNN, auto encoders, recurrent neural networks and deep belief networks are only a handful of the numerous varieties of deep learning. While there are several deep learning models designed to work with two-dimensional image data, CNN is the most well-known of them. These models can also be used with one- and three-dimensional data. In order to train the model with optimal performance, a deep neural network requires a huge dataset [11].

In order to obtain an accurate diagnosis and save many lives, a methodology for detecting AD is suggested in this work. The suggested approach uses the MRI image diagnostic to categorize AD patients. High performance is the goal of this practice. In order to diagnose AD, we suggested a deep learning (DL) model based on the aforementioned concerns.

The aim of this research is to present a convolutional neural network (CNN) based architecture that encompasses a range of processes, from image acquisition to AD classification. Using digital image processing, the proposed machine learning program classifies scanned MRI images and predicts the presence and severity of Alzheimer's disease.

2. RELATED WORK

The argent need for a comprehensive system to detect the Alzheimer disease in its early stage became a big challenge for building such an intelligent model. Many deep learning models conducted for this purpose and the challenge is still open for such a research area.

Alzheimer's disease is a brain ailment that impairs memory and reasoning, making it difficult for those who have it to complete activities [12]. The seriousness of the disease lies in its widespread distribution in aged people and the difficulties of finding a cure for it, that caused an argent need for an early detection of this disorder [13]. The use of deep learning models outperforms many of existing techniques available for the purpose of classification and recognition, The study [12] proposed training model of 12-layes for the binary classification of Alzheimer’s Disease OASIS dataset, the model performed well and obtained 97.75% accuracy. A comparative study is investigated [13] using Res-Net-18 architecture model for the classification of 6 stage of the disease, the performance of the network is comparable and acquired a 97.92% accuracy rate. A classification model is applied using a VGG-16 deep learning model for the purpose of features extraction, the system trained with number of classifiers to achieve 99.95% accuracy [14]. In contrast to their success with the fMRi data, it is evident that the systems have struggled to provide satisfying results with the PET data. The pre-trained Inception version 3 and Xception was experimented [15] for the binary classification task to determine the stage of Alzheimer disease in brain image using OASIS dataset, the result was compared a CNN model build for the same task and the Inception and Xception models outperforms the proposed CNN model. Different six machine learning techniques adopted in order the classification of five stages of the disease, GLM model outperformed the other models and obtained a 88.24% accuracy [16]. Another architecture [17] of deep learning is proposed by adopting the Siamese convolutional neural network (SCNN) model composed of 20 layers, the performance of the proposed system was good and acceptable in relation to the accuracy achieved as 99.05% on the OASIS open access dataset. The studies [18, 19] provided a helpful summary of several studies on the classification of Alzheimer's disease, offering a comprehensive comparison of the classification methods presented by recent researchers. The study [20] focused on Alzheimer's disease, and another study [21] illustrated the use of different machine learning techniques and their impact in developing Alzheimer disease classification. Naik et al. [21] adopted the 3D convolutional neural networks (CNN) for classifying 4 classes of the Alzheimer disease, the four classes were investigated and tested along with the accuracy of the whole system which is 98.96%. Parmar et al. [22] investigated the extent of the effect of the batch size on increasing the accuracy, depending on a set of parameters that were chosen when using the ResNet50 model, their conclusion was decreasing the patch size may enhanced the accuracy of the system. While Fatima et al. [23] used two classifiers (DenseNet169 and ResNet50) for the classification of 4 classes of Alzheimer disease and the results showed that DenseNet169 can performed the task with a highest accuracy. Al Shehri [24] has implemented the classification of multiclass model using three different pre-trained models, GoogLeNet, AlexNet and ResNet18, it is obvious that the ResNet18 was outperformed the other networks. In another attempt [25] to increase the accuracy in the system by balancing the weights for the classes, as well as changing the activation function using the ResNet18 model, the authors obtained an increase in the accuracy in their system, although this can be improved to further enhance the performance. Another study [26] introduced ResNet50 for predicting the multiclass classification of Alzheimer's disease, achieving an accuracy of 91.3%. A number of deep learning models [27] has been investigated and compared to predict the best performance, along with a new architecture of the Dense-Net-121 model to overcome the time loss of it which improve the accuracy from 88.78% to 90.22%. A brief summary of the discussed approaches is illustrated in Table 1.

Table 1. A comparison for number of recent researches of Alzheimer disease according to number of classes and the model based architecture

Reference	Architecture Used	Dataset	Number of Classes	Classification Rate
[12]	CNN model composed of 12 layers	OASIS Dataset	2	97.75%
[13]	ResNet18 architecture model	ADNI fMRi Dataset	6	97.92%
[14]	VGG-16 deep learning model for features extraction with different classifiers	ADNI fMRi and ADNI PET datasets	2	99.95%
[15]	Inception version 3 and Xception and a CNN model	OASIS dataset	2	Multiclass
[16]	k-nearest neighbours (k-NN), decision tree (DT), rule induction, Naive Bayes, generalized linear model (GLM) and deep learning algorithm	ADNI dataset	5	88.24%
[17]	Siamese convolutional neural network (SCNN) model	OASIS Dataset	4	99.05%
[21]	3D convolutional neural networks (CNN)	fMRI dataset	4	98.96%
[22]	ResNet50 model	ADNI dataset	2	The best accuracy of the parameters while using patch size of 16

[23]	DenseNet169 and ResNet50 CNN models	Dataset from Kaggle platform	4	0.8382 and 0.8192
[24]	GoogLeNet, AlexNet and ResNet18	ADNI database	4	96.39%, 94.08% and 97.51%
[25]	Convolutional Neural Network (CNN) method with the (ResNet18) model	ADNI database	multiclass	88.3%
[26]	ResNet50	OASIS-1 dataset	3	91.3%
[27]	DenseNet121	ADNI dataset	3	90.22%

3. THE PROPOSED METHOD

As seen in section 2, many researchers have been developed various diagnostic strategies for AD. On the other hand, some research yielded good findings but required the implementation of a more involved and time-consuming model, while others did not. Therefore, the aim in this study is to minimize the amount of memory and processing power required for the diagnosis procedure while simultaneously improving the model and performance. The purposes of this paper are to: (i) diagnose AD as accurately as possible, (ii) update the previous model we proposed to improve accuracy, (iii) develop a new CNN model, (iv) comparison two suggested models in training and testing using different performance metrics; and (v) emphasize the effectiveness of different optimizers on the same model and compare them based on diagnosis performance. The suggested AD categorizing system show in Figure 1.

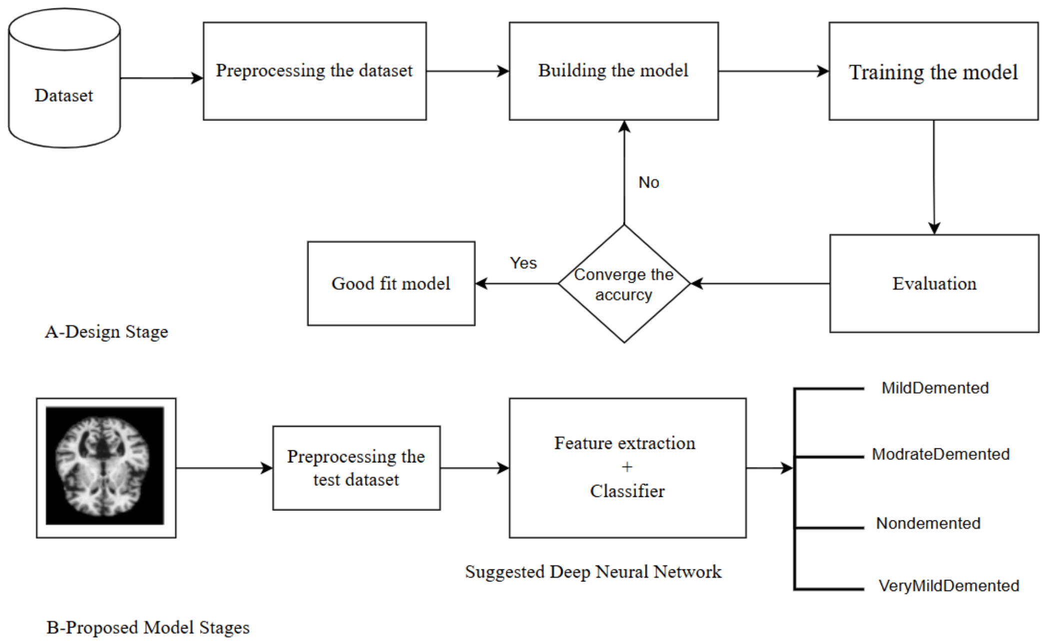

Figure 1. Block diagram of the proposed system

3.1 Dataset

This study's dataset was taken from Kaggle's Alzheimer's classification dataset. 1279 and 5121 scans, respectively, make up the training and testing portions of the dataset. This dataset information is show in Table 2.

Table 2. Information of Alzheimer's dataset

No of Class.	Name of Class	Number of Image
1	Moderately Demented	52
2	Non Demented	2560
3	Mild Demented	717
4	Very Mild Demented	1792

52 Moderately Demented, 2560 Non Demented, 717 Mild Demented, and 1792 Very Mild Demented categories. The file format is jpg, and the image dimensions are 176 × 208. It is a valuable on the website: https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images.

3.1.1 Dataset pre-processing

Preprocessing involves two stages for images: transformation and normalization. During the transformation process, the input image is resized to 224 × 224. Because the model learns more quickly on smaller images, resizing the image is an essential step in the model training process. Normalization is done to each of them following the scaling of the image. The method of normalization is used in this work is max-man method. We adjust the image to normal. The process of normalizing an image involves rescaling each pixel from a given range (0 to 255) to a value between 0 and 1. The updated images are saved in a pickle file once the transformation and normalization have been completed.

3.1.2 Dataset augmentation

The imbalance problem is addressed by the data augmentation process. To address overfitting and image inconsistencies, the proposed technique generates augmented images from original slices using six operations (rotation, translation, gamma correction, random noise addition, scaling, and random affine transformation). We apply augmentation techniques with the following configurations: shearing, zooming, horizontal flipping, 0.1 and 0.2 range width and height adjustments, rotation at 15 degrees. We improved and randomly duplicated photos between classes to balance the collection and increase classification accuracy. Following dataset expansion, Mild Demented has 2519 image, Non Demented 2561, Very Mild Demented 3584, and 364 Modified Demented. The initial training dataset was expanded with the addition of the supplemented data to provide a sufficiently enough sample size.

3.2 The first proposed CNN model

In the proposed CNN model, the images are resized to (224 × 224), with three dimensions. This section will address the construction of the best-proposed model, which consists of four convolutional layers with max-pooling and (0.2) dropout after each conv2D layer. Initially, entered 16 filters convolutional layers were used with a (3 × 3) filter and stride its (1 × 1) with the same padding. Then, a max-pooling layer with a 2 × 2 filter was added to get the image reduced in dimensions with (2 × 2) strides and add dropout with (0.2); at the same point, convolutional layers and filters were increased to 32, 64, and 128 with the same filter size of (3 × 3).

Finally, a dense layer of 1024 neurons and a softmax output layer were used to determine probability scores for each class. Figure 2 shows the basic layers of the proposed CNN model. The run time 7s.

Table 3 illustrates the parameters for each layer of the proposed model. Before training, several hyperparameters may be specified, including the loss function (binary cross-entropy), Adam optimizer, epoch (200), learning rate (0.001), activation function (softmax), kernel regularizer (0.01) is used during model training for preventing overfitting, and batch size (32). The network contains 25,790,626 parameters that may be learnt.

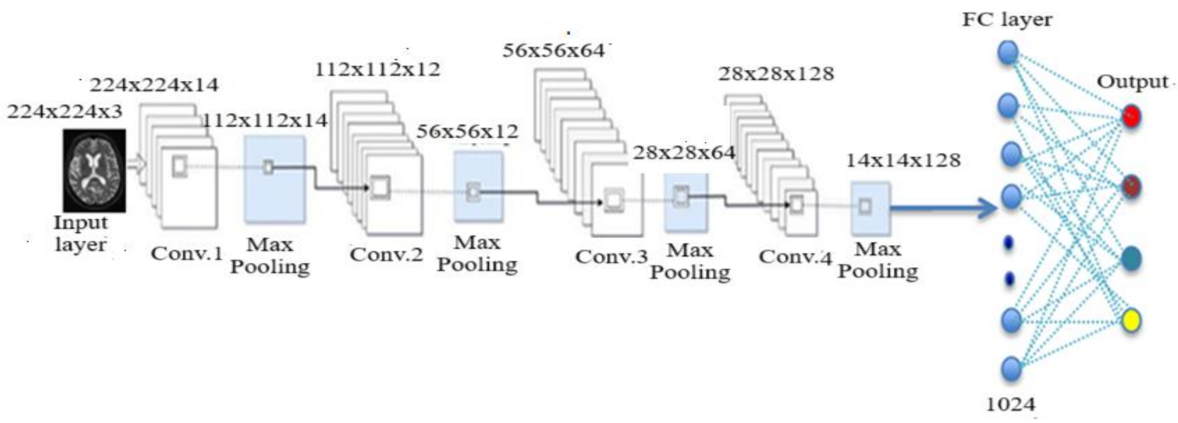

Figure 2. Basic layers of the proposed CNN model

Table 3. Parameters for each layer in the proposed CNN

Layer	Output Shape	Parameters
Conv2D	(None,224,224,16)	448
MaxPooling2D	(None,112,112,16)	0
Dropout	(None,112,112,16)	0
Conv2 D_1	(None,112,112,32)	4640
MaxPooling2D_1	(None,56,56,32)	0
Dropout_1	(None,56,56,32)	0
Conv2D_2	(None,56,56,64)	18496
MaxPooling2D_2	(None,28,28,64)	0
Dropout_2	(None,28,28,64)	0
Conv2D_3	(None, 28,28,128)	73856
MaxPooling2D_3	(None, 14,14,128)	0
Dropout_3	(None, 14,14,128)	0
Flatten	(None,25088)	0
Dropout_4	(None,25088)	0
Dense	(None, 1024)	25691136
Dropout_5	(None,1024)	0
Dense_1	(None, 4)	2050
Total Params: 25,790,626		

3.3 The second pre-trained DenseNet169 model

While it may be used to a variety of datasets, the pre-trained model was developed using the Image Net dataset. Our strategies include fine-tuning and transfer learning. To avoid information loss during transfer learning, a model is trained on a large number of small datasets before freezing the layer. To retain feature extraction, we freeze the convolution and pooling layers and add a new classifier layer that fits our dataset. Using the dataset, we train the layer that recognizes complex patterns, and we freeze the layer that recognizes generic features. Therefore, we used a transfer learning strategy called fine-tuning. Freezing every convolution and pooling layer is not necessary for fine-tuning. The pooling and final convolution layers are no longer frozen.

Table 4. Parameters of each layer for the pre-trained DenseNet169 model

Layer	Output Shape	Parameters
DenseNet169	(None,7,7,1664)	12642880
Dropout (Dropout)	(None,7,7,1664)	0
Flatten(Flatten)	(None, 81536)	0
Bach-normalization	(None,81536	326144
Dense(dense)	(None,2048)	166987776
Bach-normalization_1	(None,2048)	8192
Activation(Activation)	(None,2048)	0
Dropout_1(Dropout)	(None,2048)	0
Dense_1(Dense)	(None,1024)	2098176
Bach-normalization_2	(None,1024)	4096
Activation_1(Activation)	(None,1024)	0
Dropout_2(Dropout)	(None,1024)	0
Dense_2(Dense)	(None, 4)	4100
Total params:182,071,364		
Trainable params:169,259,268		
Non_trainable params:12,812,096		

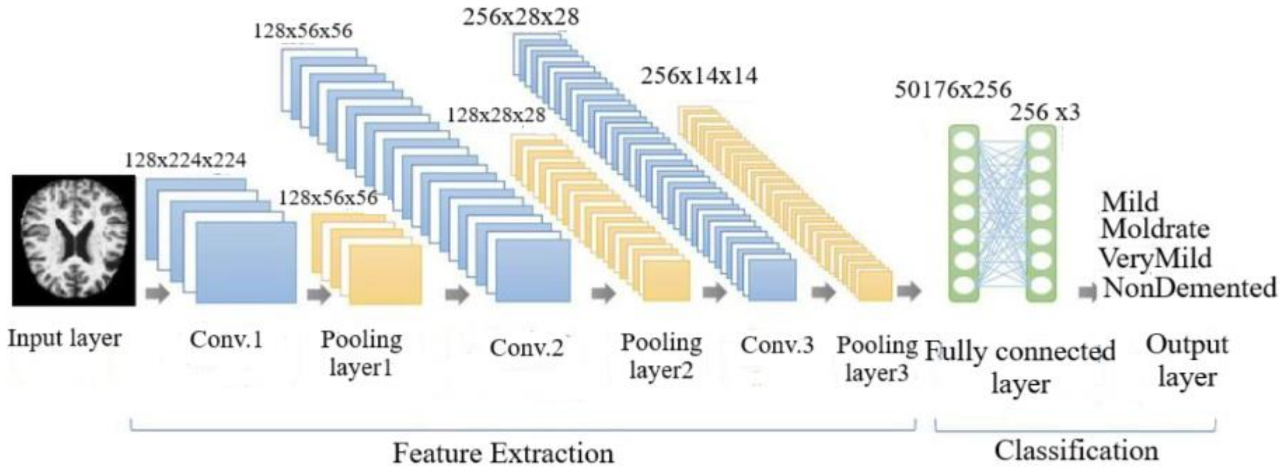

Figure 3. The architecture of the DenseNet169 model

Table 4 shows that just the last convolution and pooling layer was retrained, whereas three fully connected layers were added. The reasons of transfer learning strategy selection, it gives best result from other methods.

The overview of the second suggested DenseNet169 model is displayed in Figure 3 and Table 2. This model was trained using a 224 × 224 preprocessed image. Our data are divided as follows: 20% is for testing, 20% is for validation, and 60% is for training. The dataset with 15 rotation range, 0.1 width and height shift, 0.2 shear, and 0.2 zoom factor is subject to the augmentation procedure. The number of epochs and bach size are used (200 and 32). Adam optimizer achieved the best effective on the data.

4. RESULT AND DISCUSSION

Several tests were conducted to determine the optimum result by varying certain factors such as the number of epochs are increased to 200 and the learning rate when changed from 0.1 to 0.001 obtained best accuracy and balance the model by using regularizer (0.01), the optimizer was replaced with Adam. The activation function softmax used in the end layer. Additionally, adding or removing layers to achieve the best results. The outcomes of model classification report and metrics value in Table 5. The CNN model's confusion matrices are displayed in Figures 4 and 5. Table 6 shows the result of the classification report for the second model. The accuracy of Both the tow method achieved 98%. Accuracy is given by the numper of correctly (TP) samples divided by the total number of samples in the testing dataset. The precision is the number of expected values that were really correct. Recall is the number of correct positive predictions (TP) divided by the total number of positive predictions (TP) yields recall (p) where p= (true positive + false nagative).

Medical image analysis networks for classification over the past few years, learning these frameworks at the ground level has faced some challenges, such as these designs require a huge amount of labeled data for training, especially in the medical image processing domains where it is expensive or sometimes difficult to obtain sufficient information. It also requires a huge amount of computational services including GPUs, hyperparameters, and efficient tuning which may also lead to underfitting or overfitting issues, resulting in a poor prediction model. To address these challenges, analysts have devised an effective process known as transfer learning. Therefore, transfer learning is used to improve the performance of the network as well as to overcome the problem of requiring a huge amount of data to train deep learning models. There is no standard method for selecting the dataset, and this may affect the performance of the classifier.

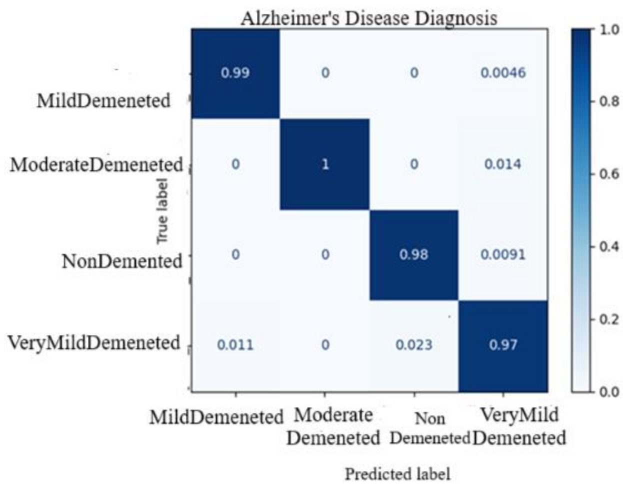

Figure 4. The confusion matrix of the proposed CNN model

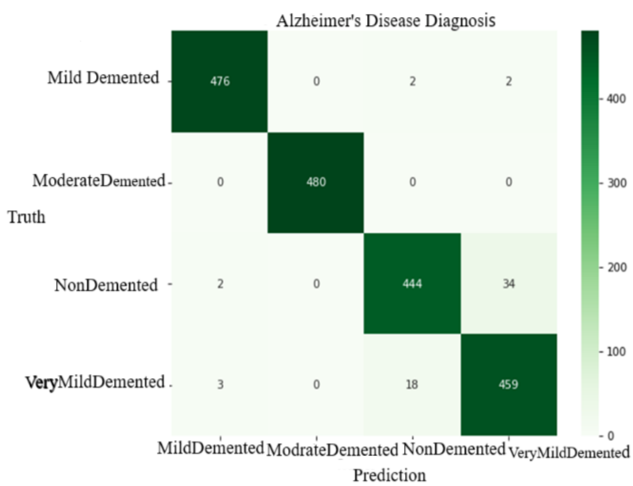

Figure 5. The confusion matrix of the DenseNet169 model

Table 5. Classification report and metrics value of the proposed CNN model

Performance Metrics (%)	Classes			
	MildDemented	**Moderately Demented**	**Non Demented**	**Very Mild Demented**
Accuracy	99%	1.00%	98%	97%
precision	99%	1	98%	97%
Recall	99%	70%	99%	96%
F-Measure	99%	80%	99%	97%
Support	87	9	347	222

Table 6. Classification report and metrics value of the DenseNet169 model

Performance Metrics (%)	Classes			
	Mild Demented	**Moderately Demented**	**Non Demented**	**Very Mild Demented**
Accuracy	0.99	1.00	0.93	0.96
precision	0.99	0.99	0.97	0.97
Recall	1.00	1.00	0.96	0.96
F-Measure	0.99	1.00	0.96	0.96
Support	480	480	480	480

5. CONCLUSIONS

This research proposed a DL and CNN architecture-based diagnostic approach for AD. In this paper, we discuss the approach to classifying Alzheimer's disease using CNN, the types of publicly available datasets, the type of neuroimaging data media available, the type of preprocessing methods used, and the type of data fed into the CNN. The advantages of using multiple media over single-modality and the role of data augmentation and transfer learning for the classification accuracy of the CNN model are discussed. The comparison of accuracy results of the selected studies is affected by many factors, such as that each used a different set of subjects, neuroimaging media, media preprocessing procedures, and different data processing methods. Therefore, it is simply impossible to conclude which approach is best. However, we found some common points:The most widely used method for classifying Alzheimer's disease is magnetic resonance imaging, and multiple methods over a single method provide better accuracy results for classifying Alzheimer's disease. There are two suggested models. Initially, a new CNN model was trained using various dropout ratios by dividing a dataset into distinct training and testing set ratios. Second, we used transfer learning applied to a pre-trained DenseNet169 model to fine-tune and assess the performance of different optimizers (Adam, Adagrad, Adadelta, SGD, and RMSprop) with the model. Two techniques are examined and compared using some performance criteria. Our test findings demonstrate that the recommended designs are appropriate for simple structures with low memory usage, overfitting, computational cost, and controlled time. As we show in the results section, the suggested models outperformed previous researchers in terms of accuracy, with the pro-posed CNN model classifying the AD stage at 99.95%. With optimizations made, the pretrained DenseNet169 model can classify AD stages with 97.44% accuracy. We want to do multi-classification for AD phases and use hyperparameter optimization approaches to each model in the future.

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