An accurate Alzheimer's disease detection using a developed convolutional neural network model

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ABSTRACT

Alzheimer's disease indicates one of the highest difficult to heal diseases, and it is acutely affecting the elderly normal lives and their households. Early, effective, and accurate detection represents an important blueprint for minimizing Alzheimer's progression risk. The modalities of brain imaging can assist in identifying the abnormalities associated with Alzheimer's disease. This research presents a developed deep learning scheme, which is designed and implemented to classify the brain images into multiclass, namely very mild, moderate, mild, and non-demented. The proposed convolutional neural network (CNN) based detection model attained a high performance with an accuracy of 99.92%, considerably enhancing the results achieved via the pre-trained 16 layers in the visual geometric group (VGG16) model and the other related learning models. Consequently, this developed model can assist medical personnel by providing a facilitating tool to identify Alzheimer's disease stage and establishing a suitable medical treatment platform.

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1. INTRODUCTION

Dementia is indicated as gradual cognitive damage and disability that significantly requires assistance and supervision for day-to-day life activities, necessitating a considerable economic and social burden, and dramatically affects the persons and their families [1]-[3]. Alzheimer's disease comprises the leading reason of dementia, which concerns 80% of the affected cases. Alzheimer's disease progression states extend over several years, and these states' alterations can be measured by utilizing various modalities [4]-[6]. There are various effective modalities of medical image scans, such as magnetic resonance imaging (MRI), computed tomography (CT), and others which include information regarding Alzheimer's disease impacts on the functional and structural aspects [7]. In clinical practice, MRI represents the widely available and extremely standardized imaging modality that works on providing a possibility for tracking various clinical stages of Alzheimer's disease. But, analyzing MRI images takes a lot of time for doctors and other medical personnel since these images include lots of tremendous and voxels information [8].

Recently, deep learning models have been rapidly widespread in dealing with various applications, especially in medical images applications [9]-[12]. Safuan *et al*. [13] presented a novel deep learning-based system, which uses several pre-trained convolutional neural networks (CNNs) to detect acute lymphoblastic leukemia (ALL). The authors used the size of malignant and immature white blood cells to identify a potential ALL. Their results showed that the proposed system achieved high-quality detections.

Mia *et al*. [14] suggested two algorithms to discover diseases in cucumbers. The first algorithm is based on machine learning, while the second algorithm uses CNN. Their conducted results demonstrated that the CNN-based method achieved better results than the machine learning-based algorithm in terms of accuracy. Since a few years ago, deep learning models have gained substantial attention in Alzheimer's disease detection research. These models have been stated to be more accurate in this area than general techniques of machine learning [10], [11]. However, the detection of Alzheimer's disease is a burdensome task. It needs considerably discriminatory features representation for the classification process to recognize Alzheimer's patterns in the brain image [15]-[18]. Many researchers have recently performed several studies for Alzheimer's disease diagnosing by utilizing the models of deep CNNs [19], [20]. CNNs are fully trainable deep learning models in which datasets are manipulated without the need for experts, extreme learning machines (ELM), genetic algorithm (GA), and the features are extracted automatically [21], [22].

Song *et al*. [23] implemented and tested a graph CNN classifier for Alzheimer's disease classification into four classes: Alzheimer's disease, cognitively normal, early mild cognitive impairment, and late mild cognitive impairment. This presented model includes nine convolutional layers, two dense layers, and a softmax layer. The Alzheimer's disease neuroimaging initiative (ADNI) dataset was utilized in this model, and the obtained average accuracy was 89%. Puente-Castro *et al*. [24] presented a hybrid learning model for the detection of Alzheimer's disease in MRI brain images. In this model, the features were extracted with ResNet, and the classification was accomplished using the support vector machine (SVM). The hybrid learning model was tested using the open-access series of imaging studies (OASIS) dataset and ADNI dataset. The obtained results of average accuracy were 86.47% and 78.72%, respectively.

Baglat *et al*. [25] suggested several hybrid machine learning-based models, including SVM, Random Forest, and logistic regression for Alzheimer's disease diagnoses. Their proposed models used the OASIS dataset of MRI patient scans. Salehi *et al*. [26] analyzed several related proposals for Alzheimer's Disease. They concluded that the prediction of Alzheimer's disease in its earlier stages could be further enhanced with the aid of the deep learning approach. The authors used different datasets, namely ADNI and OASIS. Fu'adah *et al*. [27] presented a CNN classification model based on the architecture of AlexNet with five convolutional layers and three dense layers for diagnosing Alzheimer's disease. The experiment was achieved using an Alzheimer's dataset of MRI images, and the accuracy obtained was 95%.

Murugan *et al*. [28] presented a CNN model to diagnose Alzheimer's disease. The proposed CNN model includes two convolutional layers, one max-pooling layer, and four dementia network blocks for extracting the discriminative features. Each block encompasses one batch normalization, two convolutional layers, and one max-pooling layer. Three dense layers succeed these layers with a softmax activation layer for classifying Alzheimer's disease stages. The ADNI dataset of MRI images was utilized in this model, and the obtained accuracy was 95.23%. Salehi *et al*. [29] employed CNN for the earlier diagnosis and classification of Alzheimer's disease, in which MRI images were used. Moreover, three ADNI classes were used to test the performance of the proposed method. The CNN model achieves an average accuracy of 84.83%.

Several deep CNN models for detecting Alzheimer's disease are available in the above-mentioned related works. However, the CNN architecture and the number of parameters used to affect the detection accuracy scores which considered an open research issue. In this paper, we proposed and developed a new CNN model for improving the accuracy of predicting Alzheimer's disease. Subsequently, we compared the obtained results from the proposed CNN model with the results of the VGG16, AlexNet, and CNN models to show the performance efficiency of the proposed model.

The introduction section has presented a brief overview of the recent related works in Alzheimer's disease detection based on deep learning algorithms. The next section explains in detail the developed CNN model. The third section presents the empirical results and provides a comparative analysis of the tested models. Finally, the last section draws some conclusions and offers future research suggestions.

2. METHOD

The utilized dataset and most common measurements for evaluating the goodness-of-fit of the proposed model are presented in this section. Furthermore, an accuracy comparison is demonstrated between the developed CNN model and the VGG16 model with the other related learning models.

2.1. Deep learning CNN model

The proposed deep learning is the CNN model. This model is made up of multiple layers. It includes eight two-dimensional convolutional layers (Conv2d) of 3×3 kernel size, three max-pooling layers, and five dense (fully-connected) layers to attain the results, as shown in Figure 1.

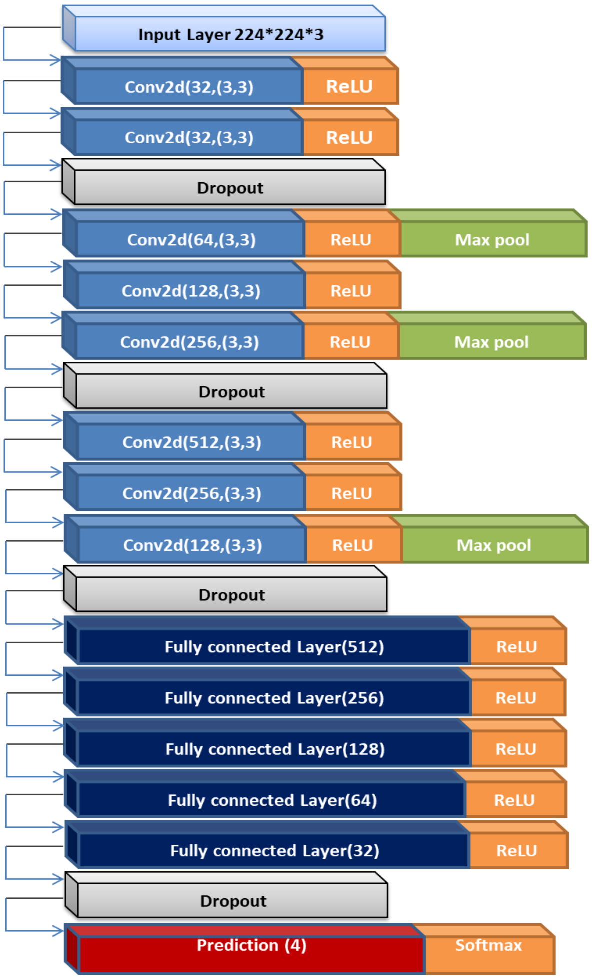


Figure 1. The proposed CNN layers

This CNN model starts with the input layer in which the brain MRI images are resized into 224×224 and then fed into the convolutional layers. The convolutional layers represent the fundamental layers that convolve the input brain MRI image using the learned filters, and these layers are followed by a function of nonlinear activation, which is rectified linear unit (ReLU) for producing suitable feature maps. After the third, fifth, and eighth convolutional layers, the max-pooling layers are employed to down-sampling the feature maps via substituting each non-overlapped block with its maximum. This operation decreases the dimensions of features, the number of utilized parameters, and network computations while holding the significant features further compact in low to higher layers, hence providing robustness against geometric variations and certain distortions.

The developed CNN model's convolutional and max-pooling layers extract features from local brain image patches. The dense layers allow classification utilizing the extracted discriminative features. After eight convolutional and three max-pooling layers, two-dimensional feature maps are flattened into one-dimensional features vectors. Dense layers are then used to connect the features and build nonlinear relationships between the features. Eventually, the softmax activation layer is utilized to classify the tested images into four classes via choosing the largest prediction probabilities for each class label of the images. The details components and parameters of the developed CNN model are shown in Table 1. In the CNN model, various hyper-parameters are utilized. Table 2 shows the setting of the hyper-parameters of the developed CNN model.

Table 1. The proposed CNN parameters

Layers (kinds)	The shape of output	Parameters
Layer-1(Conv2D)	(‘None’, 224, 224, 32)	896
Layer-2(Conv2D)	(‘None’, 224, 224, 32)	9248
Batch-normalization	(‘None’, 224, 224, 32)	128
Dropout (Dropout)	(‘None’, 224, 224, 32)	0
Layer-3(Conv2D)	(‘None’, 224, 224, 64)	18496
Layer-4(MaxPooling2D)	(‘None’, 224, 224, 64)	0
Layer-5(Conv2D)	(‘None’, 112, 112, 128)	73856
Layer-6(Conv2D)	(‘None’, 112, 112, 256)	295168
Layer-7(MaxPooling2D)	(‘None’, 56, 56, 256)	0
Dropout-1(Dropout)	(‘None’, 56, 56, 256)	0
Layer-8(Conv2D)	(‘None’, 56, 56, 512)	1180160
Layer-9(Conv2D)	(‘None’, 56, 56, 256)	1179904
Layer-10(Conv2D)	(‘None’, 56, 56, 128)	295040
Layer-11(MaxPooling2D)	(‘None’, 28, 28, 128)	0
Dropout-2(Dropout)	(‘None’, 28, 28, 128)	0
Fc-1(Flatten)	(‘None’, 100352)	0
Layer-12(Dense)	(‘None’, 512)	51380736
Layer-13(Dense)	(‘None’, 256)	131328
Layer-14(Dense)	(‘None’, 128)	32896
Layer-15(Dense)	(‘None’, 64)	8256
Layer-16(Dense)	(‘None’, 32)	2080
Dropout-3(Dropout)	(‘None’, 32)	0
predictions(Dense)	(‘None’, 4)	132
Total-parameters: 56,608,324, trainable-parameters: 54,608,260, non-trainable parameters: 64		

Table 2. The developed CNN model hyper-parameters

Activation function	ReLU
Batch size	32
Beata1	0.9
Beata2	0.999
Dropout Rate	(0.3,0.4,0.5)
Epsilon	1e–8
Filter size	(3,3) (32,64,128,256,512)
Learning Rate	0.002
Loss function	Binary cross-entropy
No. of convolution layer	8
No. of epoch	25
No. of fully connected layer	5 (512,256,128,64,32)
No. of Max poling layer	3 (2,2) stride 2
Optimizer	Adamax

2.2. Alzheimer's dataset

The dataset includes 6400 MRI images considering four stages of Alzheimer's disease [30]. Figure 2 demonstrates samples for Alzheimer's disease classes in which Figure 2(a) represents moderate demented, Figure 2(b) represents non-demented, Figure 2(c) represents mild demented, and Figure 2(d) represents very mild demented. The term dementia is utilized for explaining the mental decline symptoms that are severe adequate to interfere with social and intellectual capabilities.

2.3. Performance measurements

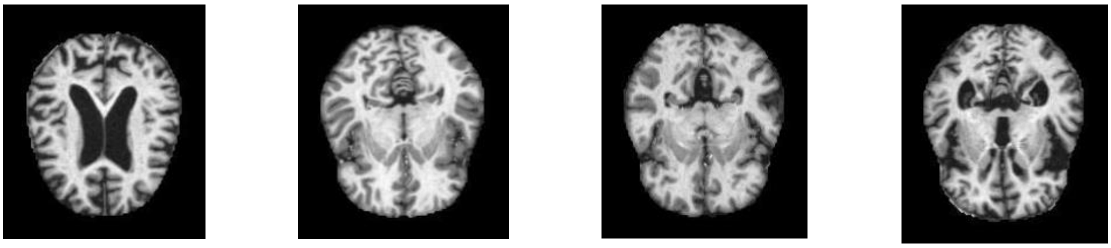
The most common measurements are used to evaluate the goodness-of-fit of the presented models and increase the possibility of comparing the obtained results. The accuracy, recall, precision, and F1-score are depicted in the following formulas. The formulas utilize several terminologies of true positive (T_{po}), true negative (T_{Ne}), false positive (F_{po}), and false negative (F_{Ne}).

$$Accuracy = \frac{T_{po}+T_{Ne}}{T_{po}+T_{Ne}+F_{po}+F_{Ne}} \tag{1}$$

$$Recall = \frac{T_{po}}{T_{po}+F_{Ne}} \tag{2}$$

$$Precision = \frac{T_{po}}{T_{po}+F_{po}} \tag{3}$$

$$F1\_score = 2 * \frac{Recall*Precision}{Recall+Precision} \tag{4}$$

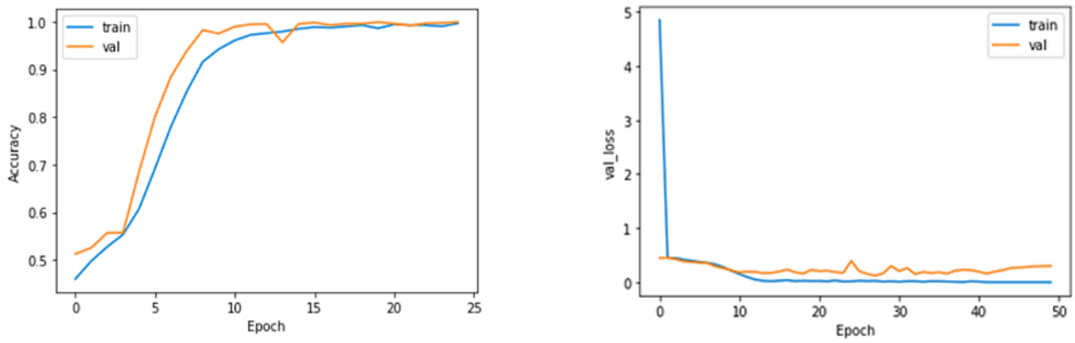


(a) (b) (c) (d)

Figure 2. Samples for Alzheimer's disease classes (a) moderate demented, (b) non-demented, (c) mild demented, and (d) very mild demented

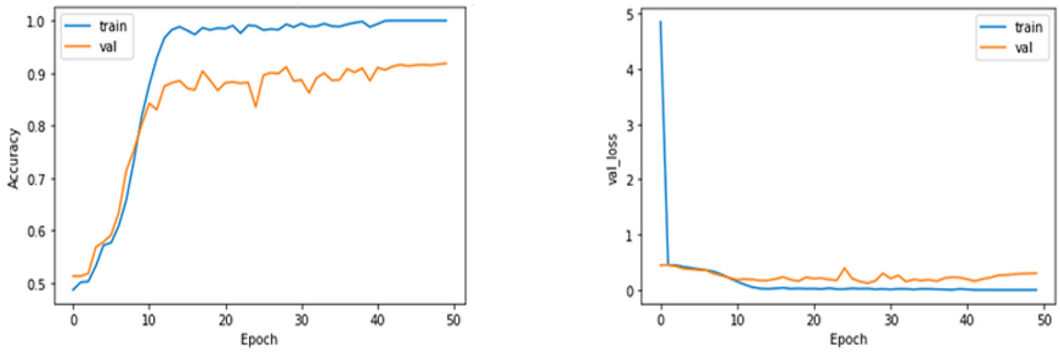
3. RESULTS AND DISCUSSION

The performance of the developed CNN model is checked on four binary classifications. During the experiment, the Alzheimer's dataset of MRI images is split into 80% for training (5121 images) and the remaining 20% for testing (1279 images). In the experiments, the pre-trained VGG16 model is utilized to evaluate the performance efficiency of the developed model. The developed CNN model is capable of recognizing the stages of Alzheimer's disease with 99.92% accuracy and 0.0032 loss. While the obtained accuracy using the pre-trained VGG16 model was 92.03%, and the loss was 0.2943. Figure 3 shows the Alzheimer classification results of the developed CNN model. In Figure 3(a) presents the curves of accuracy and Figure 3(b) presents the curves of loss per epoch of the training (train) and validation (val) tests using the Alzheimer's MRI image dataset. Figure 4 shows the Alzheimer classification results of the VGG16 model. In Figure 4(a) presents the curves of accuracy and Figure 4(b) presents the curves of loss per epoch of the training (train) and validation (val) tests. The results of recall, precision, and F1-score obtained in Table 3 demonstrated that the performance of the developed CNN model outperforms the model of VGG16 in detecting Alzheimer's disease, holding higher values closed to one.



(a) (b)

Figure 3. Alzheimer's disease classification results for the developed CNN model (a) the curves of accuracy (per epoch) and (b) the curves of loss (per epoch)



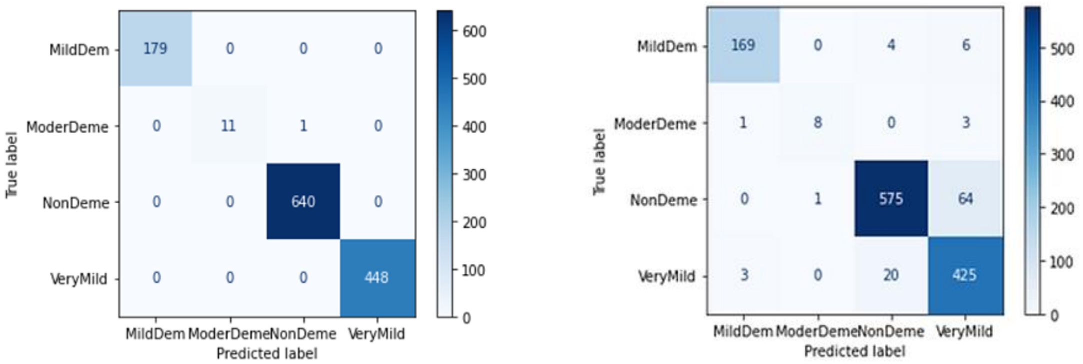
(a) (b)

Figure 4. Alzheimer's disease classification results for the VGG16 model (a) the curves of accuracy (per epoch) and (b) the curves of loss (per epoch)

Table 3. The results of recall, precision, and F1-score of the developed CNN and VGG16 models

Class	VGG16			The proposed model			
	Recall	Precision	F1-score	Recall	Precision	F1-score	Support
MildDem	0.94	0.98	0.96	1.00	1.00	1.00	179
ModerDeme	0.67	0.89	0.76	0.92	1.00	0.96	12
NonDeme	0.90	0.96	0.93	1.00	1.00	1.00	640
VeryMild	0.95	0.85	0.90	1.00	1.00	1.00	448
Average	0.87	0.92	0.89	0.98	1.00	0.99	
Std. Dev.	0.13	0.06	0.08	0.04	0.00	0.020	

Figure 5 demonstrates the confusion matrix of the presented models for detecting Alzheimer's diseases in the testing phase in which Figure 5(a) represents the confusion matrix of the developed CNN model and Figure 5(b) represents the confusion matrix of the developed VGG16 model. The test results of accuracy comparison on the Alzheimer's MRI image dataset depicted in Table 4 demonstrate that the developed CNN model exceeds the VGG16 model and the other related learning models. It has achieved an average F1-score of 99% for predicting Alzheimer's disease. Table 4 shows the comparison results of the developed CNN model with the VGG16 model and the works of Fu'adah *et al*. [27] and Murugan *et al*. [28] as other related recent deep learning models. As the results presented in the table show, the proposed CNN model achieved the highest accuracy of 99.92% and outperformed all the other three models.



(a) (b)

Figure 5. The confusion matrix of (a) the proposed CNN model and (b) the VGG16 model for detecting Alzheimer's diseases

Table 4. The comparison between the deep learning models

Authors	Classification model	Accuracy (%)
Fu'adah *et al.* [27]	AlexNet	95
Murugan *et al.* [28]	CNN	95.23
The proposed CNN models	VGG16	92.03
	Developed CNN model	99.92

4. CONCLUSION

In this research, the proposed CNN model learns the features from MRI brain images and then achieves the task of classification. The experimental results demonstrate that this developed model provides 99.92% of average accuracy for predicting Alzheimer's disease on the MRI image dataset. Performance comparison was made with the pre-trained VGG16 and the other related models. The developed model performance was promising and can be effectively implemented as a decision support system for the medical practitioners in Alzheimer's disease prediction. In future work, the developed model will be implemented as a standalone framework on various open-source datasets to screen the stages of dementia for diagnosing Alzheimer's disease.

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