Comparative Study of Deep Learning Approaches for Improving Alzheimer's disease Classification

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Abstract

The rise of Deep Learning in the past two decades has prompted research into solutions to help improve Alzheimer's diagnosis based on neuroimaging data. As such, a wide variety of different techniques have been used, but a clear turn towards the use of Convolutional Neural Networks (CNN) has been observed in the last decade. In this study, we built two deep learning-based MRI data classifiers to predict AD and infer the brain regions that contribute to disease development and progression. We then systematically compared the two distinct classifiers, which were constructed based on 3D-Convolutional Neural Networks and sparse autoencoder with 3D-CNN. The classification accuracy for AD subjects from elderly control subjects was 80.6 % and 87.8% for the 3D-CNN and sparse autoencoder with 3D-CNN respectively. Overall, our comparisons suggested that the using sparse autoencoder with 3D-CNN model provided the best classification performance compared to using 3D-CNN alone.

Keywords:*Alzheimer's disease, Convolutional Neural Network, Sparse autoencoder, Magnetic Resonance Imaging (MRI).*

1. Introduction

According to the World Health Organization (WHO), Alzheimer's disease (AD) is the most common form of dementia, accounting for 60 to 70 percent of senile dementia cases and affecting 47.5 million people worldwide in 2015 [1]. The median survival duration after the onset of dementia ranges from 3.3 to 11.7 years [2]. Alzheimer's disease (AD) is a severe, chronic, and incurable neurodegenerative illness characterized by memory loss, cognitive impairment, aberrant behavior, and personality changes [3]. For prevention and early diagnosis of Alzheimer's disease, sensitive and specific biomarkers are essential. Structural MRI is commonly utilized in neuroimaging analysis because it shows morphometric differences and structural changes in the brain [4]. MRI image analysis of Alzheimer's disease may provide insight into which structures are involved in the disease's development as well as long-term structural changes induced by the disease.

Because of the good results obtained in numerous visual identification tasks in recent years, a novel ML technique from the computer-vision area has attracted the interest of the scientific community [5]. Deep learning is a technique that allows learning representations of data with several degrees of abstraction, resulting in a dramatic gain in performance over traditional classification algorithms [6]. Deep learning has shown considerable promise in assisting in the detection of Alzheimer's disease using MRI scans. CNN and other deep learning approaches have been shown to outperform existing machine learning methods [7]. It

has made significant progress in the field of image processing, owing to the availability of big, labelled datasets like ImageNet that allow for more accurate and efficient model learning. Around 1.2 million natural photos are available in Image Net, with over 1000 unique classes. The accuracy of medical image categorization improves when CNN is trained on such images.

Deep learning algorithms are capable of automatically learning the latent features of data and are well-known for their high accuracy in learning significant features for classification tasks, particularly image classification.

In this study, we constructed and compared two classification models for AD prediction and disease region identification based on 3D-CNN and sparse auto encoder based 3D-CNN, respectively, to overcome the shortcomings in current AD classification. In first model, we propose a deep 3D-convolutional neural network that can identify Alzheimer'sdisease and classify the current disease stage with accuracy 80.6%. In the second model we improved the performance by training sparse auto encoder (SAE) approach to perform unsupervised feature leaning and prediction of AD. We spot the light on developing a SAE model to learn effective features from the AD dataset and then perform classification using the learned features. The model is optimized using the adaptive moment estimation (Adam) algorithm to achieve dynamic adjustment of different parameters, and a batch normalization technique is applied to avoid over fitting and to improve the performance, speed, and stability of the model. The second stage involves using 3D-Convolutional Neural Network (3D-CNN) to predict the health status based on the learned records.

This article is organized as follows. Section 2 presents the first model. Section 3 proposes the second model. Section 4 reports the experimental details and the results. Section 5 offers the comparative study between the two proposed models Finally; Section 5 gives conclusion of our work and the future work.

2. Methods

2.1. The overall structure scheme

Our AD classification comprised of three major steps: (i) data acquisition and pre-processing including data normalization and resizing; (ii) deep learning algorithms with feature selection automatically and (iii) 3D-CNN and sparse autoencoder based models were used in the deep learning as classifier. (See figure 1).

2.2.3D-Convolutional Neural Network model

The purpose of the model is to develop a model technique which efficaciously discriminates AD from MCI and NC; in this work, we intended to develop an effective classification system for AD by using the 3D Convolutional Neural Network (3D-CNN).

2.3.Data Acquisition

We used the structural brain MRI scans from the ADNI dataset [8]. The ADNI was launched in 2003 as a public private partnership, led by Principal Investigator Michael W. Weiner, MD. The primary goal of ADNI has been to test whether serial MRI, positron emission tomography, other biological markers, and clinical and neuropsychological assessment can be combined to measure the progression of MCI and early AD. For up-to-date information, see WWW.ADNI-INFO.ORG. A total of 3013 subjects (955 patients with probable AD, 835 patients with MCI, and 1223 healthy controls) were considered in this study. Standard 3 T baseline T1-weighted images were included from the ADNI dataset.

2.4.Data Preprocessing

The preprocessed MRI data included were loaded into memory using a similar approach to any other format, but the data was used as a Numpy Array, hence the usage of the library Numpy and OpenCV for the manipulation of the used images such as resizing and reshaping, and then the data is loaded to the variables and split into train and test and validation for each of the images and the labels , image size is 96x96 each of 62 channels as the 3rd dimension of the image of total 2109 subject for training (130,758 images) and 435 for validation (26,970 images) and 469 for testing (29,078 images) these are assigned to the appropriate variables in the memory , then fed to the training process of our model , with number of epoch = 55 , base learning rate =0.01 and batch size of 16 per batch , the training process was done on Google Collaboratory servers to insure that the hardware is sufficient for the training process 70% of the data was assigned for the training and validation processes while 30% is for the testing process and the results for 25 epoch gave us 91% of training accuracy, 71% of validationaccuracy and 70.70% of total accuracy (testing accuracy), but after increasing the epoch number to the 55 epochs, training accuracy reached to 96.6%, 79% for validation and 80.60% of total accuracy (testing accuracy).

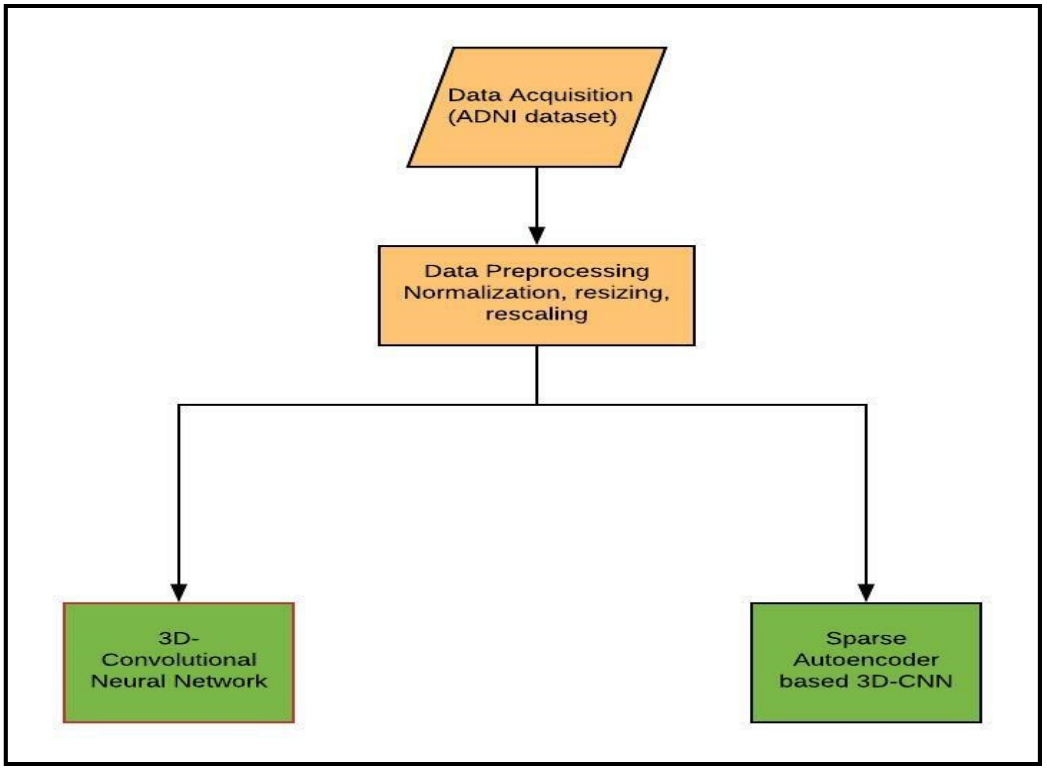

Figure 1The overall framework of the model

2.5. Architecture Model

Our proposed model is a deep convolutional neural network were written and evaluated in Python 3 using both tensor flow and Keras**[35]** packages as shown inFigure 2.

The input layer size is the (96x96x62x1) saved from the data processing step. First, a (3x3x3) 3D-convolution layer with ReLU activation function was used to create 162 feature maps. This was followed by (2x2x2) maximum pooling. This process was repeated with two (3x3x3) 3D-convolution layers with kernel size 128, 256 consequentially and the

ReLUactivation function and another max pooling layer. After that, there are two (3x3x3) 3D-convolutional layers with kernel size 324, (2x2x2) max pooling and (3x3x3) 3D-convultional layer with 512 kernel size and (2x2x2) max pooling. The last 162 feature maps were attended and were fully connected to neural nodes. This was tracked by flatten layer which is responsible for transforming the data into a 1-dimensional array for inputting it to the denselayer to feeds the output of pervious layer to all it is neurons. Finally, a layer with softmax activation was employed to yield probabilities for each zone.

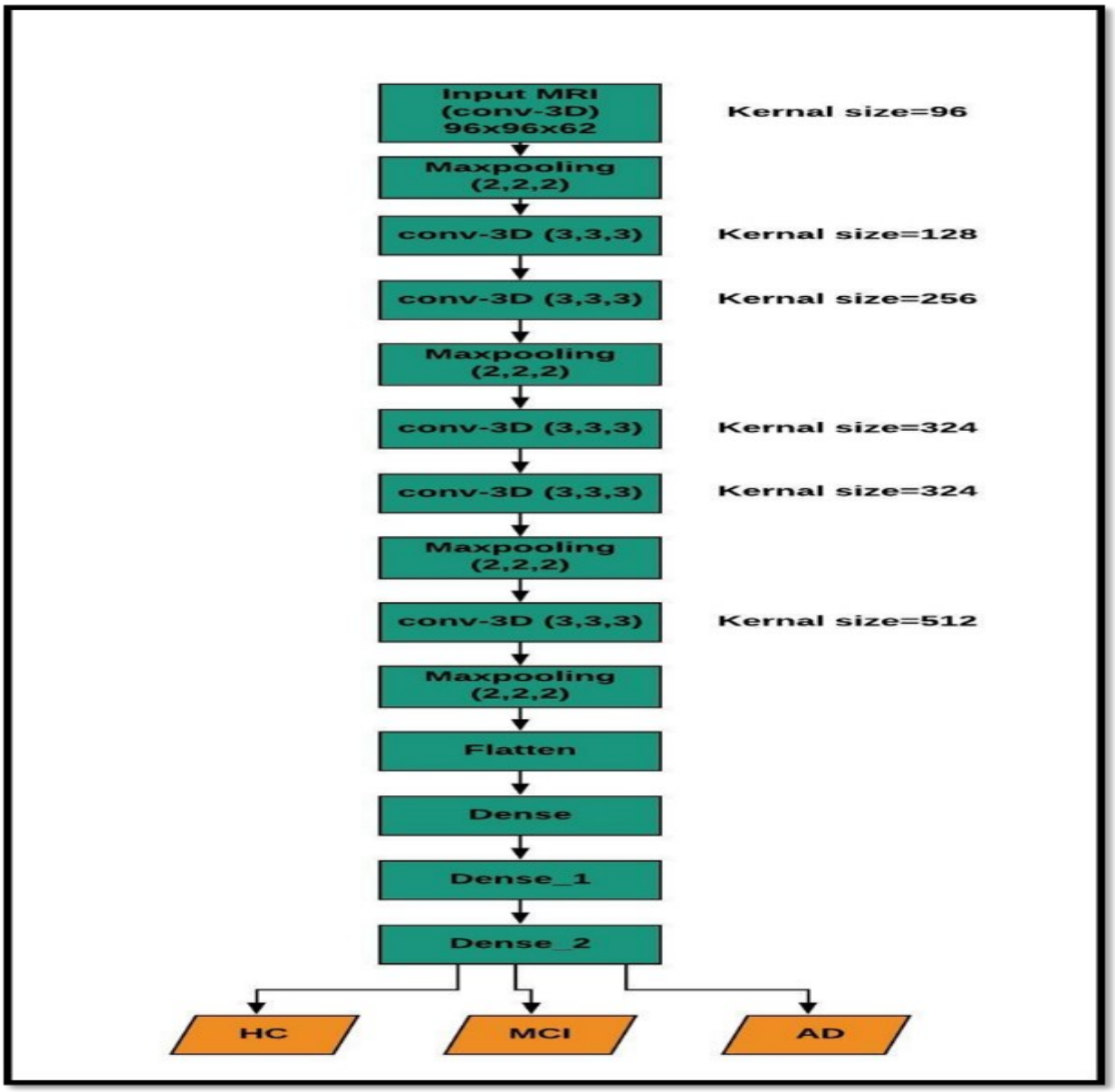

Figure 2Block diagram of proposed Alzheimer's disease diagnosis framework

3. Sparse auto encoder based 3D-CNN model

The objective of this model is to employ sparse autoencoders to create an effective filter for convolution, and then a 3D-Convolutional neural network with softmax function to achieve classification. For this study, we obtained MRI scans from the Alzheimer's disease Neuroimaging Initiative (ADNI). A total of 3888 subjects were considered in this study.

The images are imported from the backup folder using Collaboratory framework, the resizing and normalization processes has been applied to all of the data before putting them in any classes, after that the data was merged into 3D as the size was (256x256x48) Length Width and no. of scans for each patient to create a 3D image to feed to the model. After finishing this step, a process of collecting random patches of the data is started to get 1000 random patch of each picture of the patients we have and feed it later on to the model to increase the model reliability and keep the to control the model and prevent bias.

3.1. Training Sparse autoencoder

The sparse autoencoder model is a Sequential model consist of three layers: the first layer is the dense1 layer of value 343, the second layer (dense 2) is with 410 with sigmoid activation function and the third layer (dense 3) with 343 with sigmoid activation function as show in figure 3. This autoencoder uses regularizes to hold the best weights for the current model to be used lateron in another model as initial weights and to learn a sparse representation in the first layer. So, we can control the influence of these regularizes by setting various parameters: L2 Weight Regularization controls the impact of an L2 regularize for the weights of the network.

In our approach, we train an autoencoder on a set of selected 3D objects extracted from the MRI scans. We extract 1000 random patches from 3888 scans in the training set. Adam optimizer was used to optimize the model output and Mean Absolute Error was used as loss function. The model succeeded in getting a loss of 23% which gave us an average of accuracy of 75% for this model.

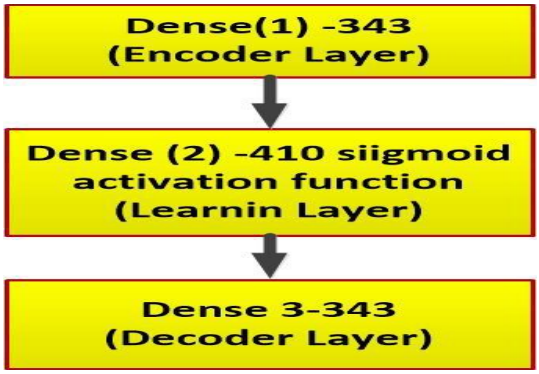

Figure 3 Block diagram of sparse auto encoder

3.2. Training 3D-CNN model

In this model, we use ADNI dataset publicly available on [7]. A total of 897 subjects (297 patients with probable AD, 300 patients with MCI, and 300 healthy controls). The architecture of the network contains: 3d-conv input layer with shape (1, 48, 96, 96) and mask (410, 7, 7) with 50 kernels of size 5×5×5 with alternating stride (6, 7, 7), a Rectified LinearUnit (activation layer); a max pooling 3d with size (6, 7, 7) , two dropout layers with 50% and 50% respectively, flatten layer, dense layer and dense output layer with softmax activation and three classes: HC, MCI, AD. Figure 4 provides an illustration of the 3D-CNN model.

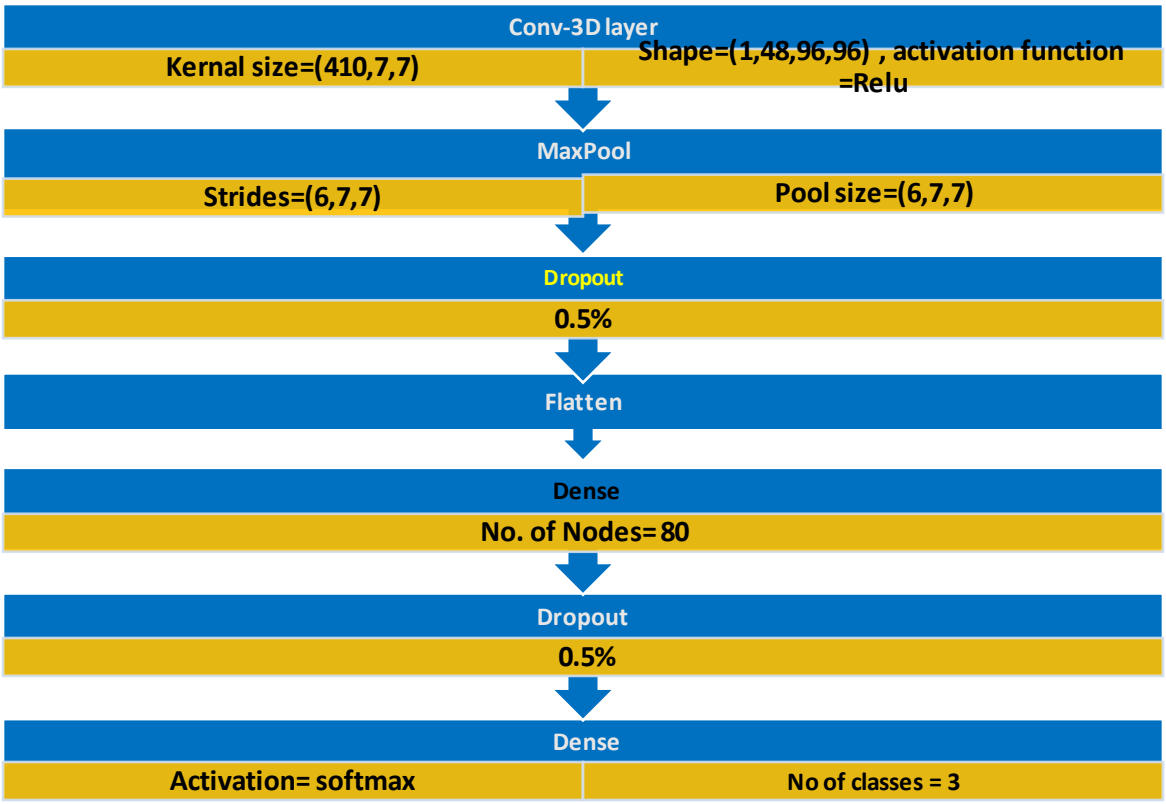

Figure 4 3D-CNN Model

Our model is trained by Adam optimization with a learning rate of 0.001. Our classifier is trained with 45 epochs. We used it to perform multiclass classification. Multiclass classification was performed by the trained classifier, using AD-MCI-CN images which achieved 93% training accuracy and 87% for testing accuracy. Show figure 5

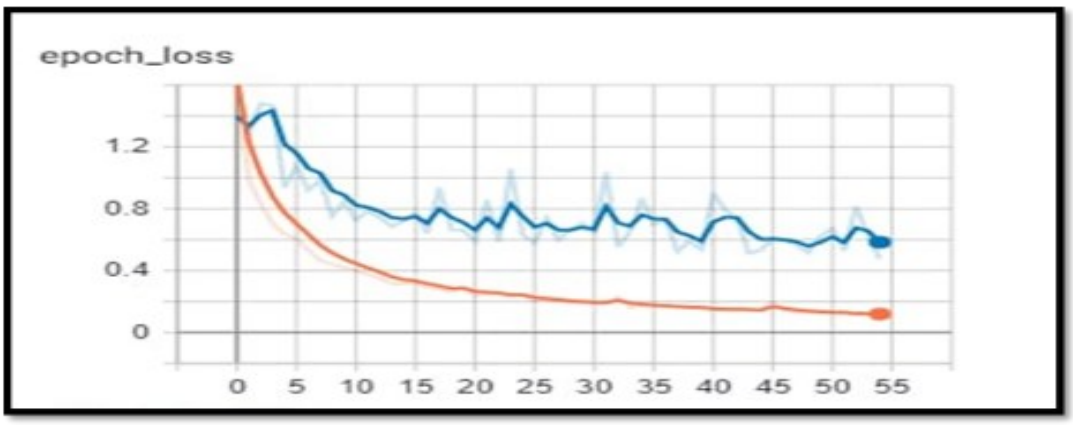

Figure 5.The categorical cross entropy loss shown for the 3D-CNN training as function for ecpoch number

4. Results

In the first model, The 3D-CNN training process took approximately 666 seconds per epoch for a total time of 9 hours on Google collapse (25.5 Gigabytes RAM, GPU is NVIDIA tesla k80 and 2VCPU @ 2.2GHZ) . First, the network was trained using 25 epochs and the trainingaccuracy reached to 91%. After that the network was trained with 55 epochs and the

accuracy achieved 97.8%. It is clear that overfitting is not an issue for the CNN, since both the training and validation losses follow the same decreasing curve. This is further supported by the fact that the testing set had the exact same loss when it was evaluated after the CNN was trained. The network only took 666 seconds to train on Google collapse, and yielded extraordinary results even after epoch-24: 93%

In the second model, the classification included three steps: (i) training with 897 patients with 93% accuracy (ii) validation with 100 patients with 94% accuracy and (iii) testing with 300 patients with 87, 87% accuracy. Training, validation accuracy, and loss graphs are shown in figure 6 and figure 7.

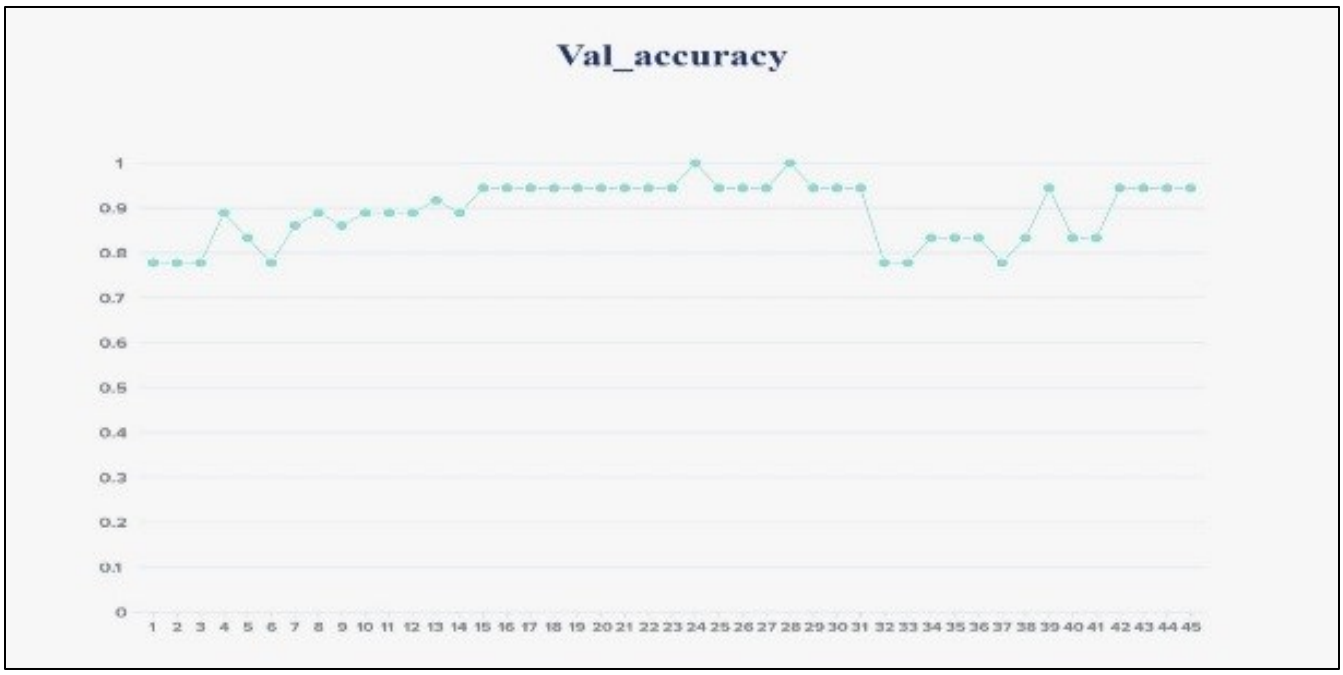

Figure 6.Accuracy and loss calculation of model during training

Figure 7.Accuracy and loss calculation of model during validation

5. Comparison to State-of-the-Art Approaches

5.1.Comparison between SAE-3D CNN model and 3D CNN model

In this section, we will compare between this work and our previous work which develop 3d-cnn model without sparse autoencoder. Using deep learning approaches to diagnosis AD is very important specially 3d-cnn. 3D-CNN plays an effective role due to its ability to save the time and 3D-Convolutional Neural Networks are specially build on the basis of the explicit assumption that raw data are two-dimensional (images) enabling us to encode those properties and also to decrease the amount of hyper parameters. The 3D-CNN topology uses spatial structures to minimize the number of parameters which must be learned and thus develops upon general feed-forward back propagation training. In the previous study, we proposed model to predict the AD with a deep 3D convolutional neural network (3D-CNN), which can learn generic features capturing AD biomarkers, classify Alzheimer's brain from normal healthy brain based on MRI scans of the brain. We successfully classified MRI data of Alzheimer's subjects from normal controls using ADNI data set using 3013 scans where the accuracy for training data reached to 96.5% and for test data reached 80.6%. In this chapter, we apply pre-training step with sparse autoencoders to improve classifying possibility of MRI modality. AD was classified using ADNI MRI data set by using a total of 897 subjects where the accuracy for the training data reached to 93% and for the test data reached to 87, 87%. (See table 1).

Table 1.Result of Proposed and Previous Models

Method	Precision			Recall			F1–score			Accuracy		
	HC	MCI	AD	HC	MCI	AD	HC	MCI	AD	HC	MCI	AD
Simple 3D-CNN	0.78	0.76	0.91	0.92	0.80	0.70	0.84	0.78	0.79	0.92	0.80	0.69
SAE+3D-CNN	**0.91**	**0.85**	0.91	**0.94**	**0.85**	**0.88**	**0.93**	**0.85**	**0.89**	**0.93**	**0.94**	**0.87**

5.2.Comparative study

Furthermore, the proposed approach is compared with some recent scholarly works as shown in Table 2, and it shows better performance than those reported in the literature.

Table 2.Comparison between the proposed approach and some recent scholarly work

Reference	Methodology	Way-classification	Accuracy	Precision (%)	Recall (%)
[9]	KNN-Decision tree- Deep learning	5- way (CN-EMCI-LMCI-SMC-AD)	88.24%	89%	86%

[10]	Deep CNN	4 way (AD, EMCI, LMCI, NC)	73.75%	-	-
[11]	Deep Learning methods (sparse autoencoders and 3D CNNs)	3-way (AD vs HC, AD vs MCI, HC vs MCI)	89.47%	-	-
Our approach	Deep Learning methods (sparse autoencoders and 3D CNNs)	3-ways (CN,MCI,AD)	87.8%	91%	88%

From the results obtained so far, it can be grasped that the proposed method shows significant enhancement compared to the other methods in terms of classification performance. And it is clear that the proposed sparse autoencoder improves the accuracy of the CNN compared to a case where the CNN alone was used to make predictions. The results also show that improved performance can be achieved not only by improving the structure of the neural network, but also by improving the preprocessing stage of the classification process. Figure 8 shows performance comparison of algorithms comparison.

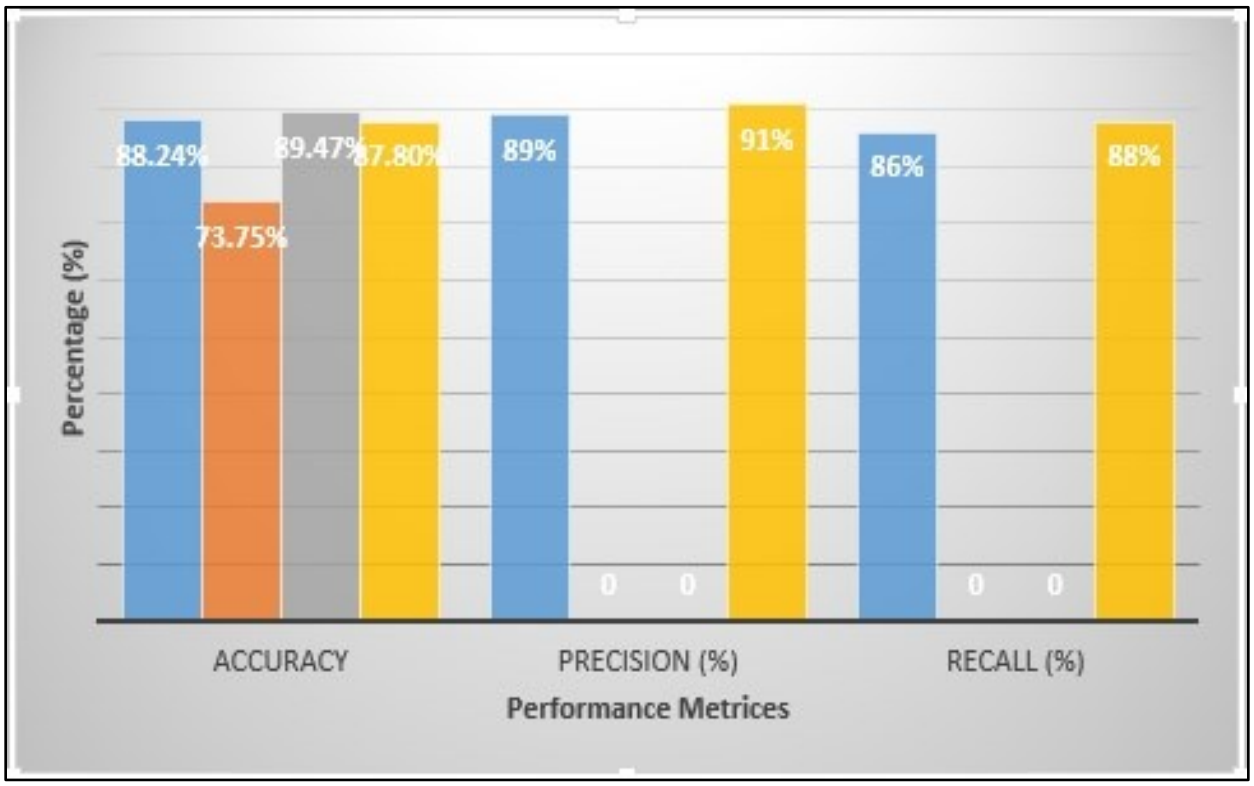

Figure 8.Performance comparison of the proposed system.

6. Conclusion

In this paper, we presented two models based on deep learning approaches. In, the first model, we presented 3D-CNN model in order to diagnosis AD patients from healthy patients and outperform good accuracy. In the second model, to enhance the performance of the previous model, we propose an enhanced sparse autoencoder-based 3D-CNN for Alzheimer's disease prediction. The sparse autoencoder was used to learn the optimum data representation, and the 3D-CNN was utilized to create predictions based on the learned records. The SAE was optimized with the Adam method and batch normalization. This model yielded accuracy better than the previous model with 87.8%. We introduced a comparison between two models

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