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A CNN Model: Earlier Diagnosis and Classification of Alzheimer Disease using MRI

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***Abstract*— Alzheimer's Disease (AD) is the most common form of dementia that can lead to a neurological brain disorder that causes progressive memory loss as a result of damaging the brain cells and the ability to perform daily activities. Using MRI (Magnetic Resonance Imaging) scan brain images, we can get the help of Artificial intelligence (AI) technology for detection and prediction of this disease and classify the AD patients whether they have or may not have this deadly disease in future. The main purpose of doing all this is to make the best prediction and detection tools for the help of radiologists, doctors, caregivers to save time, cost, and help the patient suffering from this disease. In recent years, the Deep Learning (DL) algorithms are very useful for the diagnosis of AD as DL algorithms work well with large datasets. In this paper, we have implemented Convolutional Neural Network (CNN) for the earlier diagnosis and classification of AD using MRI images, the ADNI 3 class of images with the total number of 1512 mild, 2633 normal and 2480 AD were used. A significant accuracy of 99% achieved in which the model performed well as we compared with many other related works. Furthermore, we also compared the result with our previous work on which ma-chine learning algorithms were applied using OASIS dataset and it showed that when dealing with large amount of data like medical data the deep learning approaches can be a better option over the traditional machine learning techniques.**

Keywords*— *Alzheimer's Disease, Deep Learning, Convolutional Neural Network, Magnetic Resonance Imaging, ADNI.

I. Introduction

The Alzheimer's disease is a common cause of dementia which is a progressive brain disorder that can cause brain cell damage and a patient affected with this dis-ease can decline in their behavior, thinking, and social activities skills [1]. According to the previous study it was estimated that in the year 2050, 1 out of 85 people could be affected by this AD disease [2]. It is important to diagnose and take prevention in the earlier stages of AD patients. There are several tools present for the detection and prediction of this dementia with the use of MRI, PET (Positron Emission Tomography), and CT (Computed Tomography) scans but the diagnosis of AD patients with the use of MRI scans is the most affected and popular neuroimaging method. In most of the previous research papers they are using MRI based classification methods using the machine and deep learning algorithms [3]. The objective of our paper is to make the best prediction and detection tools for the help of radiologists, doctors, caregivers to save time, cost, and help the patient suffering from this disease [4].

Deep learning is a subset of machine learning in artificial intelligence that allows the machine to learn classification tasks from raw data because of its multiple layered and or ordered structure network [5], [6]. In a neural network, CNN is used to extract high-level features from image classification and prediction, and it is also the most widely used algorithm of deep learning because of its high success achieved in analysis and image classification [7], [8].

In our previous work [9], we proposed a various machine learning algorithm for classification of AD patients using T1-weighted MRI data from the OASIS (Open Access Series of

Imaging Studies) dataset using different models such as Logistic Regression, Decision Tree, Random Forest classifier, Support Vector Machin (SVM), and AdaBoost. However, in this research work, we are using the CNN algorithm to classify Alzheimer's disease brain and healthy brain using MRI scans data. The other part of this paper included Material and methods, results and discussion, and conclusion.

II. Materials and Methods

A research plan was created for each step that customized to our needs and the steps includes MRI data collection, preparing of collected data, , training, and testing of the data. Lastly the model development is given.

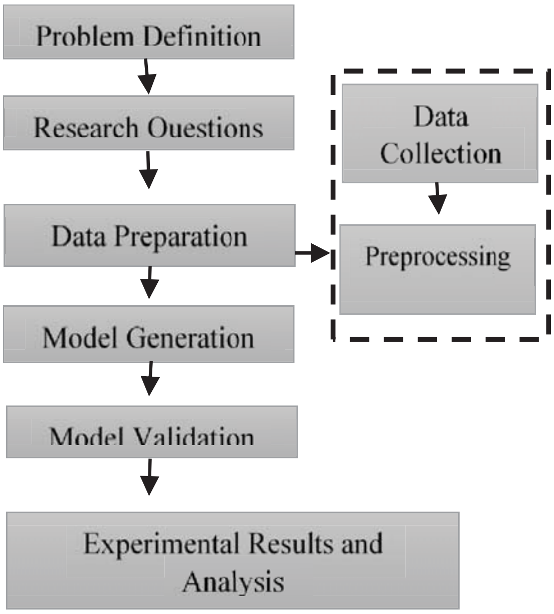
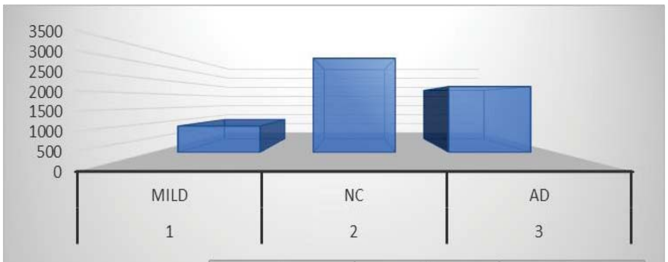


Fig. 1. Flow chart

A. Data Acquisition

ADNI researchers collect, validate, and make use of data, containing PET and MRI images, cognitive tests, genetics, CSF, and blood features as predictors of AD disease [10]. In this work, we have taken the data from two sources. In which the combination of two data sources have three classes which are namely Mild, Normal Control and Alzheimer Disease images in which both training along with testing set containing a total of 7635 number images. For accessing the MRI images from ADNI website an authenticated user ID and password is required for that I have login to the ADNI website with an authenticated username and download 1290 MRI images of ADNI1 Annual 2 Yr 3T and ADNI1 Baseline 3T in which all the images were in nii extension format.

One of the main reasons why we combined two data sources of images is to increase the number of images and to utilize data from different sources in order to improve the performance of the model. The implementation of model has been done using Anaconda for Python and TensorFlow with 8 GB RAM and Graphics Intel HD 6000 1536 MB.



	1	2	3
	Mild	NC	AD
Total Number of Images	896	3200	2240

Fig. 2. Number of cases in each stage category

B. Data Preprocessing

As for as we are given input to the CNN model the jpg image format so the images must be in the form of jpg. The data we downloaded from ADNI website the images were in the form of nii extension format and for that we needed to convert all those images from nii format to jpg.

For doing this task we have used a software called DICOM converter which is a windows application used for converting nii files or DICOM files to common images formats and converting popular image files to DICOM format. Like DICOM to PNG, JPEG, BMP format. Which then can be easily viewable with any kind of image viewer.

C. Method and Classification Algorithm

CNN is a type of feedforward neural networks [11] are used for the image processing, pattern recognition and classification problem [12]. This architecture is inspired by the biological process by the visual cortex [13]. Convolutional Neural network is made up of neurons that contain weights and biases to the various objects in the image. The core operations performed in this CNN model are detailed below.

Convolutions

Convolution operations are done on the image of size 8 blocks with a kernel size of 45*45*45, stride 1,2,3 have used 2 convolutional layers with first filter having 32 kernels of 3*3. The kernels behave as feature finders, convolved with the image, so to produce a set of convolved features. In neural network, the size of the kernel indicates a neuron receptive field, therefore enforcing regional connectivity of the neurons to the pervious volume. Final configuration is in figure 3 which is depicting the CNN architecture [14].

Rectified Linear Unit and Softmax

The Activation function of ReLU is defined as bellow [15] and the Softmax function let the model to express the inputs as a discrete probability distribution. In ReLUs the training time is significantly faster as compare to sigmoid units and hyperbolic tangent [16].

ReLU: $$f(x) = \max(0, x) \tag{1}$$

Sofmax: $$\sigma\left(\vec{z}\right)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_i}} \tag{2}$$

Pooling Layer

And aggregation function is max-pooling which is used in a region to get the maxi-mum value, specified by k which is the kernel size, an input h x w size, and s stride. Pooling technique is not only reduce the inputs dimensions but efficiently summarizes the outputs of neighboring groups of the inputs as well [17]. This layer is actually performs down sampling operation which reduces the spatial dimensions but retains useful information and also reduces the number of parameters when the image size is very large [18] in this work 1 max pooling layer is used.

Dropout

Dropout layers are used in the hidden layers to set the output of neurons with a prob-ability of r, which is called ratio dropout, into 0. The dropped-out neurons do not contribute to the backpropagation steps and the forward pass. In the architecture we propose, 2 dropout layers have been added one after pooling layers. , with the ratios of 0.25 and 0.5.

Full Connected Layer

The last one is fully connected layer which we call as FC layer in that layer each neurons are connected to the previous layer and also it improves the training performance of the CNN models because in this we flattened our matrix into the vector form and feed it into the fully connected layer [19]. This layer has complete connections to all activations in previous layer of it.

TABLE I
CNN MODEL GENERATION

Layer	Output	Kernel size	Activation Function	Ratio
Conv2D-1	32	3, 3	ReLU	
Conv2D-2	64	3, 3	ReLU	
Max-pooling2D		Pool-size = 2, 2		
Dropout				0.25

Before training the CNN model, we have reduced the size of MRI images in to 45, 45, 3 shape due to its large size for the purpose of speeding up the performance of the model. The below figure shows the python code used for reducing the image size.

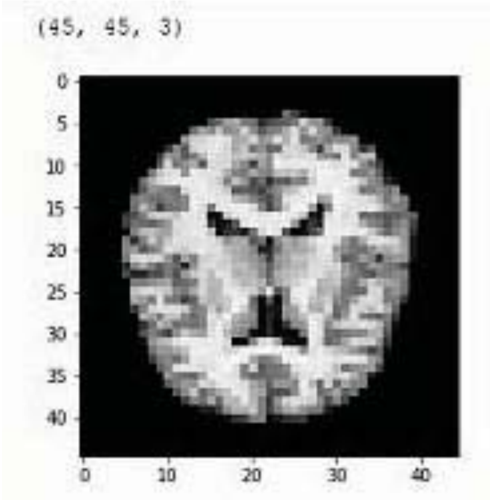


Fig. 3. Reducing the size of MRI images

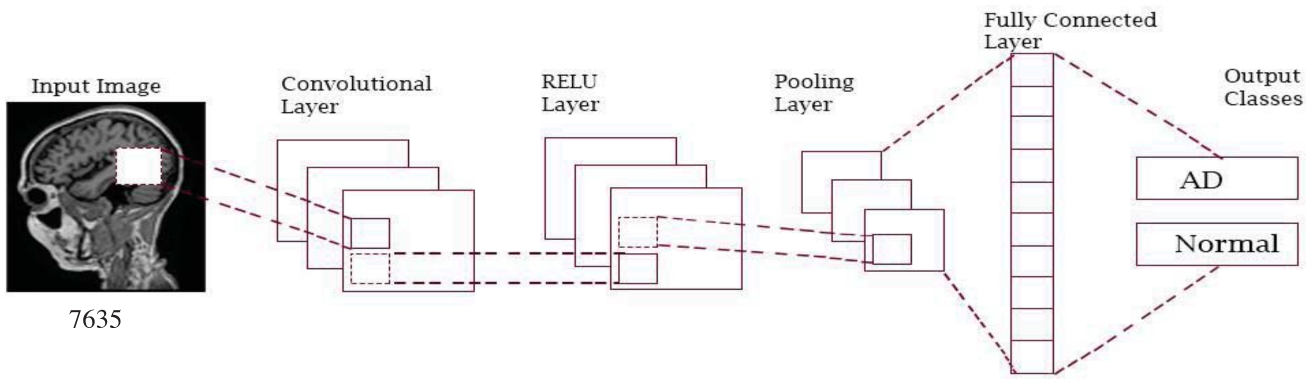


Fig. 4. CNN Architecture

In this work, we have taken MRI scans images that have classified into mild dementia, non-dementia, and very mild dementia and when we train our data, we randomly select 80% of training data and 20% remaining data is used for validation of the model.

There are different layers in the CNN network such as convolutional, activation, pooling, and fully connected layer. In which the first layer is Convolutional layer which takes the input image using a kernel (ReLU) or filter and identifies the relationship between the image and their features (to identify whether the image is of Alzheimer's patient or Normal) and second layer is the activation layer which applies the Rectified Linear Unit (ReLU) to increase the nonlinear properties in the CNN model because of its training speed. In the end fully connected layer which improves the training performance of the models because in this we flattened our matrix into the vector form and feed it into the fully connected layer.

TABLE II
PROPOSED MODEL FOR PREDICTION OF AD IN COMPARISON WITH OTHER PREVIOUS TECHNIQUES

References	TECHNIQUES	Modalities	Source	Accuracy
[24]	CNN	sMRI	OASIS dataset	93.18%
[25]	DSA- 3D CNN	MRI	ADNI	3-Class 94.8%
[19]	-Softmax -Stacked Autoencoders	PET and MRI images	ADNI	- Four class classification= 47.42% - Binary classification= 87.76%
[26]	CNN	MRI	ADNI	Classification accuracy- - EMCI/LMCI = 93.00% -CN vs LMCI = 94.54% -CN/EMCI = 93.96%
Proposed Model	CNN	MRI	ADNI	Mild, NC, AD 99%

III. RESULT AND DISCUSSION

In this work, we used CNN for the detection and prediction of AD by using MRI scans. With this model we achieved the test accuracy rate of 0.99% and low percentage of test loss with rate of 0.0571 and the train and test the model using 7635 images.

We have train and test the model using four different epoch size such as 25, 15 and 10 to compare the results to get the more accurate result. Out of all four epochs we achieved more accurate accuracy by using 25 epochs as well as better test loss. Figure 3 depict the output and the number of epochs used in CNN.

TABLE III
COMPARISON OF RESULTS WITH THREE DIFFERENT EPOCH SIZE

SN	EPOCHS SIZE	Test Loss	Test Accuracy
1	25	0.0571	0.9933
2	15	0.0446	0.9865
3	10	0.2639	0.8971

The following graphs are representing the accuracy and the loss of training and validation of the model. In the figure 5, The training set is used for training the model , while the validation set is used in this model for evaluating the performance of the model. The figure number 6 demonstrate the training and validation loss of the model. The loss is calculated on both training and validation and its interpretation is based on how well the proposed model is doing in two sets and the loss values present how poorly or well the model behaves after each iteration of optimization. And in the last figure 7, as the graph shows that there is a significant increase in terms of test accuracy of the model and with lower rate of test loss.

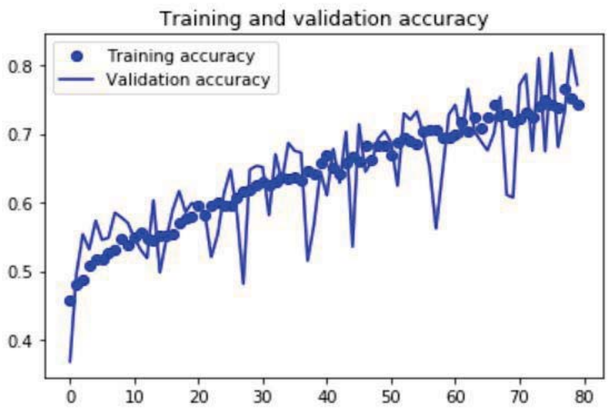


Fig. 5. Training and validation accuracy of the model

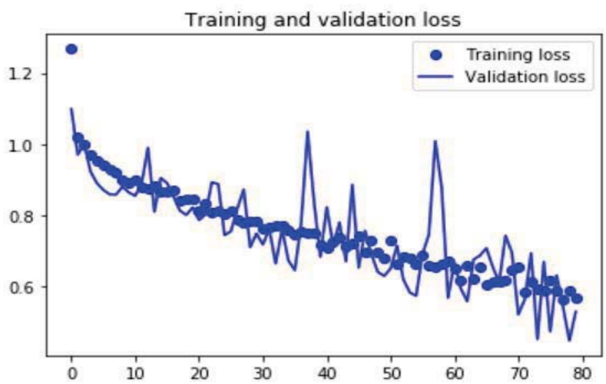


Fig. 6. Training and validation loss of the model

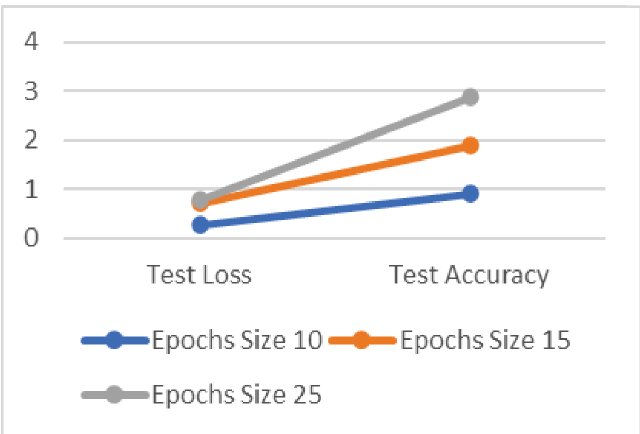


Fig. 7. Comparison of the result in terms of 3 different epoch sizes

IV. Conclusion

The recent advancements in the course of biomedical engineering the study and analysis of medical images has become one of the key research areas [20], [21]. One of the reasons for this development in analyzing of medical images is the use and application of DL [22]. In the past year's classification using DL has been mostly used and for automatic diagnosis of AD in its early stage is the AI-based techniques to satisfy clinicians primary goals [23]. So, an automated framework and classification for AD using MRI scans is very vital for the early detection of the AD patients. In this study, we have proposed convolutional neural network classification algorithm for AD using MRI images, the three classes of images are with total number of 1512 mild, 2633 normal and 2480 AD were used in this study. A significant accuracy of 99% has been achieved. Out of all the results with different epochs, a considerable result obtained when dealing with epoch size of 25 with the accuracy rate of 99%.

In future we are looking forward and aiming at encouraging of future work. Hence, the result could be further improved by carrying out deep convolutional neural network which has recently shown its potentiality in neuroimaging investigations. Therefore, the use of deep CNN using huge MRI scan images would significantly improve the ability of the algorithm in the detection of AD. Furthermore, this deep learning approach not only helps doctor, caregivers, and radiologist and patient suffering from this disease but also it provides precious information to the researcher to diagnosis the other type of disease.

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