Alzheimer Disease Prediction – Deep Learning

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Abstract

The foundation of this project is predicated upon the core idea to stand a solution to Alzheimer's, which is a progressive disease, where dementia symptoms gradually worsen over several years. Early diagnosis of AD is essential for the progress of more prevailing treatments. The application of deep learning to early detection and automated classification of Alzheimer's disease (AD) has proven to be of immense accuracy. We have used a dataset "Alzheimer's Dataset (4 class of Images)" from Kaggle to train and test data A significant accuracy of 92.5 is achieved in which the model performed well as we compared with many other related works 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 using MRI(Magnetic Resonance Imaging) scan brain images, we can detect and predict the disease and classify the AD patients whether they have or may not have this deadly disease in future.

Keywords: Alzheimer's Disease, Deep Learning, Convolutional Neural Network, Magnetic Resonance Imaging, Mild Demented, Non-Demented

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurological brain disease, which is caused due to the damage of nerve cells in parts of the brain [1]. It begins with the loss of memory, difficulty in speaking language and other cognitive functions making a patient unable to perform day-to-day life activities. In particular, [1] researchers found that AD is not only common cause of dementia but eventually leading to death of people, which become a remarkable focus in research (According to Alzheimer's association, it is the sixth leading cause of death in the USA[2]. A survey [3] stated that there will 131.5 million people living with dementia worldwide and most of them with age greater than 65 has higher rate of risk with this disease. The brain region including thinking ability, memory, reasoning of the patient wrinkle up and shrinks in the hippocampus area. This is the main cause of suffering from AD. Genetic mutation is another cause for AD; estimated to affect about 1% or less than 1% people [4]. An early diagnosis of this disease becomes crucial and requires good clinical assessment based on patient's medical history, several neuropsychological tests such as mini-mental state examination (MMSE), neuropsychiatric inventory questionnaire, clinical dementia rating and other pathological evaluations [6]. In addition to these clinical methods, there many other techniques to detect AD such as biomarkers cerebrospinal fluid (CSF) analysis, brain imaging includes magnetic resonance imaging (MRI)/positron emission tomography (PET), analyzing proteins in blood.

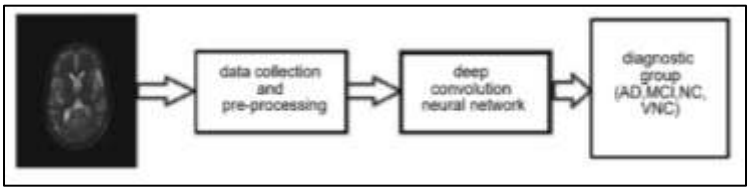

Fig. 1: Proposed deep learning flow for classification of Alzheimer's into AD, MCI and NC, VNC

II. LITERATURE REVIEW

An alternative family of machine learning methods is deep learning algorithms. Deep learning algorithms perform automatic feature extraction without human intervention. Due to the availability of a greater number of hidden layers, deep learning approaches learn the high-level representation from the raw data. This is the reason behind its popularity in the computer vision domain.

Ortiz et al. [7] discussed many deep learning architectures for early diagnosis of AD. Convolutional neural network (CNN) are inspired from human visual cortex and learns the features from simple edges to more complex edges from the dense hierarchical structure. It is building block of convolution and pooling layers.

Convolutional layer provides the feature maps by multiplying the input image with the kernel, and pooling layer down samples the image keeping the similarity features [8]. This stimulated many neuroscience researchers to find their solution to the problem associated with neuroimaging.

Shi et al. [9] described multimodal classification of AD with four classes. Staked autoencoders (SAEs) are used for feature learning for both MRI and PET. These features are fused and trained using SVM, which achieved very less accuracy compared to other available multimode classification.

Cui et al. [10] addressed sequential analysis of MRI image along time axis by measuring the longitudinal progression. Multi-layer perceptron (MLP) is used for spatial features, and to train these features, recurrent neural network (RNN) is used. However, such algorithm requires rigid segmentation as a preprocessing task. The accuracy achieved is 89.69% in two-way classification as AD and NC.

Islam et al. [11] proposed a DCNN model for four classes. In this, five DCNN models have trained and output features are fused to get the prediction of disease. The uniqueness of this approach is that every model gives various features different from one another making the model generalized for unseen data prediction with accuracy 93.18%. There are many works available on CNN method for detection of AD.

Gunawardena et al. [12] addressed the problem for pre-detection of AD for three classes with accuracy achieved is 84.4%. Combination of CNN and RNN is a new approach for AD diagnosis proposed by Liu et al. [13]. 3D PET images sliced into 2D images which trained by CNN and RNN are used to classify the CNN features with accuracy 91.2% for one-vs-all of three classes.

Khvostikov et al. [14] used fusion of structural MRI and mean diffusivity-diffusion tensor imaging (MD-DTI) on hippocampal 590 S. S. Kundaram and K. C. Pathak ROI region for AD diagnosis.

III. METHOD

In this section, we describe the medical dataset used for this study as well as the architecture of the deep learning model used to predict the AD progression and the critical medical scores related to the disease. Moreover, the methods used for data preparation are described at the end of the section.

A. Data Preprocessing

We trained our model on a publicly available Images of MRI Segmentation from Kaggle called the Alzheimer's Dataset (4 class of Images). The data consists of MRI images. The data has four classes of images both in training as well as a testing set:
1) Mild Demented 2) Moderate Demented 3) Non-Demented 4) Very Mild Demented

The data set consists of a total of 6400 images which have been divided into a training and testing set in 80:20 ratio respectively each further divided into 4 classes.

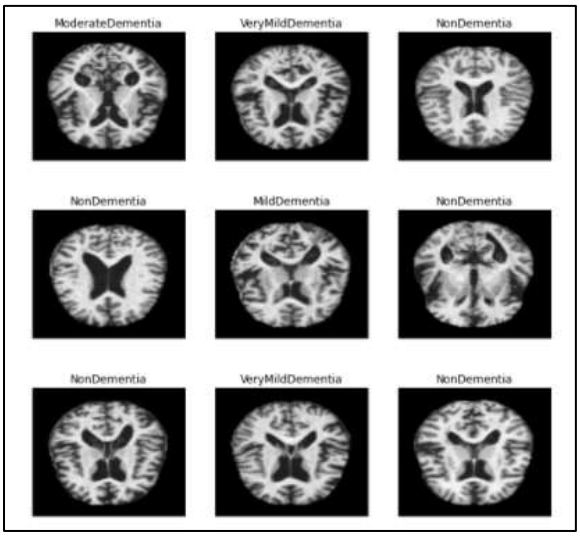

Fig. 2: JPEG slices for each diagnosis class before pre-processing

B. Network Architecture

Convolutional neural networks (CNN) are inspired from human visual system. The visual system has small number of neuron cells sensitive to a specific field, i.e., some neurons in the brain fired only in the presence of edges in particular orientation. Such operation is depicted in CNNs. The functioning of convolution layer is to automatically extract features maps from the input images by using element-wise multiplication with filter along entire image. Pooling layer is generally used to avoid overfitting problem, i.e., when network memorizes the data instead of generalization. Rectified linear unit (ReLU) activation is used to fire the neuron or to determine the output of neural network.
The detail operation of proposed architecture is as follows.

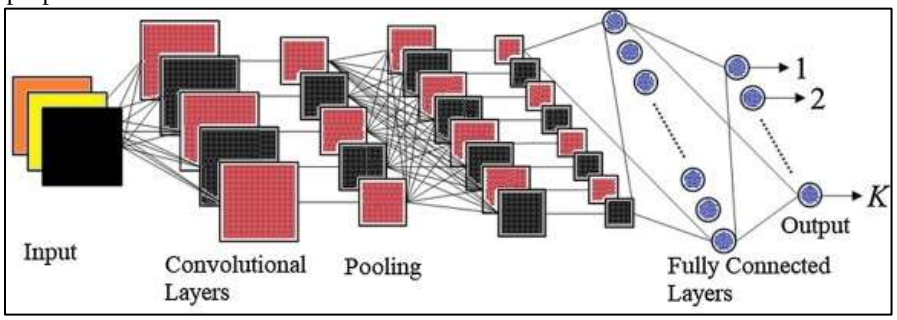

Fig. 3: Architecture of proposed model

Our proposed model shown in Fig-3 is an ensemble of three blocks; each of the individual blocks has several layers performing three basic operations, which are:

- Convolution
- ReLU activation
- Max pooling

The architecture consists of five sets of convolutional and max pooling layers, followed by a flattening convolutional layer features, then four fully connected layers and finally a sigmoid classifier. Output has four classes, which are Alzheimer disease (AD), normal control (NC) and mild cognitive impairment (MCI), Very mild cognitive impairment (VCI).

The input for architecture is a 176 x 208 ×16 gray scale image, which passes through the first convolutional layer with 16 feature maps with filters having size 3 × 3, a stride of two, and pooling is made zero with ReLU activation function. The image dimensions change from 176 × 208 × 1 to 176 x 208 x 16. Next, there is a second convolutional layer with 16 feature maps having size 3 × 3 and a stride of 2, so image dimensions reduced to 176 × 208 × 16, according to the dimension formula given below:

$$n[l] = n[l-1] + 2p[l-1] - f[l] / s[l] + 1 \quad (1)$$

where n is the size of input image or previous layer image, p refers to padding and s refers to stride, l refers to current layer, and F refers to the filter size. Then, the network applies max pooling layer with a filter size 3 × 3 and a stride of two.

The resulting image dimension reduced to 88 × 104 × 16. Next, there is a third convolutional layer with 32 feature maps having size 3 × 3 and a stride of 2, so image dimensions reduced to 88 × 104 × 16. Then again max pooling with filter size 3 × 3, dimension reduces to 44 × 52 × 32. Next, fourth convolutional layer with 64 feature maps having size 3 × 3 and stride 2, dimension reduces to 44 x 52 x 32, and with max pooling, the dimension reduced to 22 × 26 × 64.

Next, fifth convolutional layer with 128 feature maps having size 3 × 3 and stride 2, dimension reduces to 22 x 26 x 64 , and with max pooling, the dimension reduced to 11 x 13 x 128.

Then, total parameters obtained are 7680 by flattening. The eighth layer is a fully connected convolutional layer with 512 feature maps each of size 1 × 1. Each of the 512 units is connected to all the 7680 (5 x 6 x 256) in the eighth layer. The ninth layer is a fully connected layer with 128 units. The tenth layer is a fully connected layer with 64 units. The eleventh layer is a fully connected layer with 4 units. Finally, there is a fully connected sigmoid output layer with 10 possible values corresponding to the digits from 0 to 9. Specification of the proposed model shown in below Table 1.

Table – 1
Specification of proposed model

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 176, 208, 16)      448
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 176, 208, 16)      2320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 88, 104, 16)       0
_________________________________________________________________
sequential (Sequential)      (None, 44, 52, 32)        2160
_________________________________________________________________
sequential_1 (Sequential)    (None, 22, 26, 64)        7392
_________________________________________________________________
sequential_2 (Sequential)    (None, 11, 13, 128)       27072
_________________________________________________________________
dropout (Dropout)            (None, 11, 13, 128)       0
_________________________________________________________________
sequential_3 (Sequential)    (None, 5, 6, 256)         103296
_________________________________________________________________
dropout_1 (Dropout)          (None, 5, 6, 256)         0
_________________________________________________________________
flatten (Flatten)            (None, 7680)              0
_________________________________________________________________
sequential_4 (Sequential)    (None, 512)               3934720
_________________________________________________________________
sequential_5 (Sequential)    (None, 128)               66176
_________________________________________________________________
sequential_6 (Sequential)    (None, 64)                8512
_________________________________________________________________
dense_3 (Dense)              (None, 4)                 260
=================================================================
Total params: 4,152,356
Trainable params: 4,149,988
Non-trainable params: 2,368
_________________________________________________________________
```

C. *Experimental Setup and Evaluation*

Proposed model is implemented with the Keras library with Tensorflow backend. The experiments are conducted on laptop with 6 GB RAM of HP Corei3. Model is trained on Google Colab. Relu activation is applied for each neuron of CNN. Output is classified as AD, MCI and NC and VMC. There are total of 5121 images are used for training the network and 1279 images for testing. Dense activation function used is sigmoid Network is trained for 100 epochs. Table 2 shows the results of the proposed model. Performance is evaluated in terms of accuracy and loss for training as well as validation set. Loss gives the best knowledge of how fit the model is. Out of all the optimizers, Adam proved to give best accuracy with less loss.

Table – 2
Performance of proposed framework

Training accuracy	*Training loss*	*Validation accuracy*	*Validation loss*
0.9250	*0.6354*	*0.8902*	*0.7979*

The accuracy versus epoch and loss versus epoch graph for both training and validation set is shown in Fig-4. And Fig-5 respectively It is seen that for training set as the accuracy reached 92.5 % loss is dropped down to 0.6. This gives the measure of progression during training period of the model. While the validation set gives the measure of the quality of the model. Validation accuracy has reached 89.02%, which describes that with 89.02% accuracy model can predict the detection on new data.

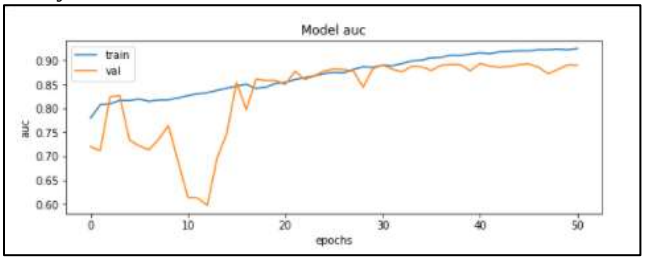

Fig. 4: Accuracy versus epoch graph

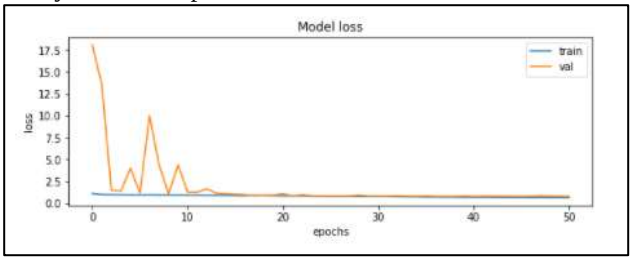

Fig. 5: Loss versus epoch graph

Table – 3
Test Cases

Test Case #	*Test Case Description*	*Test Data*	*Expected Result*	*Actual Result*	*Pass/Fail*
TC1	*Page Load*	*URL*	*page loaded*	*page loaded*	*Pass*
TC2	*Image import*	*v-create*	*image uploaded*	*image uploaded*	*Pass*
TC3	*select file button*	*v-press*	*clicks*	*clicks*	*Pass*
TC4	*results displayed*	*v-show*	*results loaded*	*results loaded*	*Pass*
TC5	*facts displayed*	*v-show*	*facts loaded*	*facts loaded*	*Pass*

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