A Transfer Learning Approach for Predicting Alzheimer's Disease

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***Abstract*—Alzheimer's disease(AD) is a human brain disorder that gradually damages the memory and cognitive skills of an individual. The prediction of this condition was often laborious and time consuming. In order to reduce these constraints, different deep learning algorithms were investigated to automate the AD detection and prediction. In this study, the potency of transfer learning approach was analyzed in detail by fine tuning the deeper layers of Transfer Learning models like VGG-19, VGG-16, Resnet-50 and Xception. In prior work, VGG-16 model was experimented on the ADNI datasets to get an accuracy of 97% and a precision of 96%. From this study, it is analyzed that the overall classification accuracy and precision of VGG- 19 is exceptionally high (98%) when compared to other models. This shows that the automated method can be a true guide in Alzheimer's detection and prediction, especially when an early stage diagnosis may help to get the benefit of treatment.**

***Index Terms*—Transfer Learning, Alzheimer's Disease, ADNI, Deep Learning**

I. Introduction

Human brain is a complex organ with millions of neurons transmitting information through different electrical and chemical signals. AD is an irreversible neurological disease that interrupts this communication, resulting in gradual cell death [1]. Initially, the brain region responsible for memory like hippocampus gets affected and later it spreads to other parts like cerebral cortex that focus on reasoning, social behavior and language. Over time, the person with AD will lose his ability to work independently. Studies are underway to find the molecular changes that results in Alzheimer's disease. As per the data from National Center for Health, about 84,767 people died from Alzheimer's disease in 2013 [2]. A follow up study on this disease in India is given in [3].

In Alzheimer's disease the beta–amyloid protein may get collected between neurons in different molecular layers. An abnormal level of this protein will collect together to form plagues and damage the cells. As neurons are damaged extensively throughout the brain, the network connections may break causing shrinkage of brain regions. The final stage of Alzheimer's disease results in brain atrophy. Studies are now going on to diagnose the early stage detection of this disease before an irreversible brain disruption occurs. Different strategies like Biomarkers, Brain/Neuro Imaging, Cerebro Spinal Fluid biomarkers etc were adopted for the early stage detection [4]. A study on the brain function during a squeeze task as a biomarker is specified in [5].

Neuro Imaging is the most favorable area focused on the detection of AD [6]. It uses different imaging technologies like Functional Imaging, Structural Imaging and Molecular Imaging. Functional Imaging shows the working of brain regions. It includes PET, fMRI etc. Structural Imaging retrieves information about the volume and shape of brain tissue. It includes MRI, CT etc. Molecular Imaging reveals the cellular changes associated with specific diseases. It includes PET, fMRI, SPECT etc. In this study, Magnetic Resonance Imaging of brain regions were used to predict the Alzheimer's disease due to its moderate cost and high resolution. A secure diagnosis is possible with an automated analysis of these images.

Artificial Intelligence especially Machine Learning, has given remarkable contribution in the detection and prediction of Alzheimer's Disease. In a related work, Generalized Linear Model was used for the detection of AD [7]. The study showed that the algorithm classified the different stages of AD with an accuracy of 88.24%. Support Vector Machine is the most commonly used model for classifying these images. A related study [8] presented the classification of AD, healthy control and mild cognitive impairment with SVM, Import Vector Machine and Regularized Extreme Learning Machine(RELM). RELM exhibited high classification accuracy when compared to other two models. Decision tree [9], Gaussian Mixture Model [10], Naive Bayesian Classifier [11] etc were the other traditional machine learning classifiers used to detect the disease. But traditional machine learning algorithm still suffers from the problem of learning deep and relevant features of the clinical data in detail. To overcome these difficulties an emerging approach, Deep Learning, can be used on the raw Imaging data. Features of medical images can be automatically learned through this on –the –fly learning approach. In recent years, deep learning made a big leap in classifying the Alzheimer's MRI images. Among the deep learning algorithms used, Convolutional Neural Network [12] has drawn a lot of attention in image analysis and

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classification. The studies had proved that CNN outperforms traditional machine learning algorithms in many ways [13]. In CNN, several pre-trained models can be used partially or fully to improve the training. The Transfer Learning models used in the previous studies were Alexnet [14] giving an accuracy of 92.85%, Resnet-18 and GoogleNet [15]. In a related study [16], a 16-layered VGGNet was used in detection and classification of MRI images in ADNI datasets. The overall accuracy was found to be 95%.

In this paper, apart from analyzing the above models and results, experimentation has been done on the transfer learning models like VGG-19, VGG-16, Resnet and Xception. From the result it is observed that, by fine tuning the deeper layers of VGG-19, the precision and accuracy measures of the model can be improved to 98%, which is relatively high when compared to VGG-16 with precision 96% and accuracy 97%, Resnet with an accuracy of 71% and Xception with 84%.

II. Methods

A. Transfer Learning Approach

In Transfer Learning approach [17], a pre-trained model is reused by freezing the dense layers or the final layer to train large and complex data. An architecture of a transfer learning model is given in Fig. 1. The input images are pre-processed before introducing the models.

Initially the transfer models were loaded with weights trained on Imagenet dataset. The model is freezed in the middle of the layers to retrain the deep convolution layers and it has been done with the expectation to improve speed of convergence and learning. The outputs from the intermediate layers are flattened and feed into a dense layer(fc1). The output from fc1 is a 1024 dimensional vector which is finally connected to a softmax layer with 2 neurons. Since updation of weights occur only upto last two layers, gradients are not allowed to back propagate till the first hidden layer. The convergence speed and model accuracy has been examined. The analysis has been done with the help of confusion matrices, graphs and tables.

B. CNN Algorithms used

In this study, the different CNN transfer learning models like VGG-19, VGG-16, Resnet-50, Xception have been experimented on ADNI datasets.

Convolutional Neural Network (CNN) is very popular in image classification and has wide range of applications in many areas. Their capability to identify local features has been used in the medical domain for the analysis of volumetric MRI [18], Alzheimer's detection etc. The 3 basic units of CNN are Convolutional layers, Activation Functions and Max-pooling layers.

VGG [19] is one of the most popular CNN model designed to classify ImageNet datasets. It has multiple blocks with 3×3 convolution layer and 2×2 max-pooling layer. The variants of VGG model are VGG-16 and VGG-19 .VGG-19 has 16 convolutional layers, 3 Fully connected layers, 5 MaxPool layers and a softmax layer. In VGG-16, entire model is divided into five different blocks. Blocks 1 and 2 have two convolutional layers and one pooling layer. Similarly blocks three, four, five have three convolutional layers and a pooling layer. The dense layer has two fully connected layers with 4096 neurons and finally a softmax layer with 1000 neurons. Resnet-50 [20] is another transfer learning architecture which uses repeated block of 3×3 convolutions. During back propagation, this residual layer will allow easy flow of gradients using identity mapping. Here, one pooling layer is used in the initial stage and the other pooling layer (Global Average Pooling) is used before the final layer.

Xception [21] is a 71 layered deep Convolutional Neural Network. This pre-trained model can classify images into 1000 different classes. It is capable of training millions of data from the ImageNet dataset.

C. Alzheimer's Disease Neuroimaging Initiative (ADNI)

ADNI datasets [22] help in the study of early stage detection of AD. The first phase of ADNI started in 2004. A total of 6100 brain MRI images were taken for this study. A progression of AD in human brain is tracked by researchers at different sites for finding the clinical trials for the prevention of this disease .

III. Results and Discussions

Based on the methods detailed in section 2, the results are discussed here. As mentioned above, the datasets used for the study are ADNI brain MRI images. In order to avoid the skewing of this model, it was assured that the train and test splits contains the same percentage distribution of data from each class. Ten fold cross validation is used to evaluate the model. 80% of the data was taken for training and 20% for testing.

TABLE I
CONFUSION MATRIX OF VGG-19 MODEL

	AD	***Normal***	***Rate(%)***
AD	571	15	98
Normal	12	622	98
Precision(%)	98	98	

The models were trained for 20 epochs using SGD optimizer and binary cross entropy loss with a learning rate of 0.0001 and batch size of 16. It was observed that these parameters helps the model VGG-19 to converge to a high accuracy of 98% in ten epochs itself with a continuous decrease in loss compared to other models. The accuracy

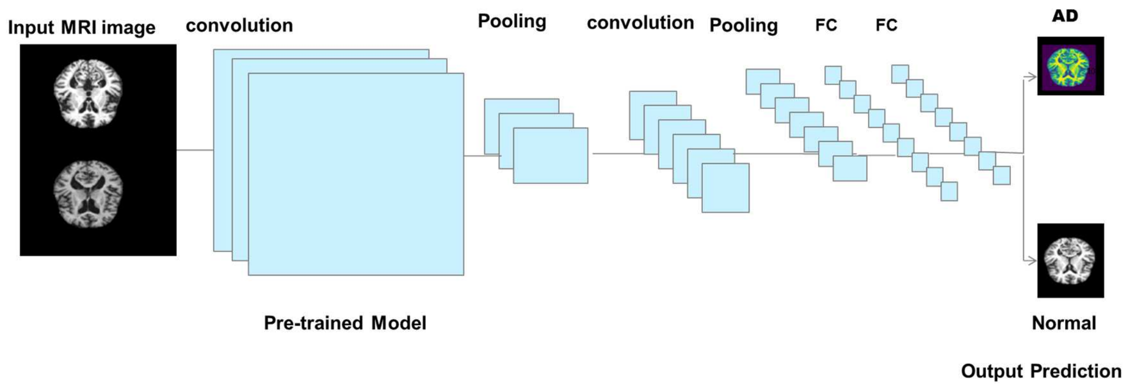

Fig. 1. Architecture of Transfer Learning Models

TABLE II
COMPARISON OF PRECISION MEASURES OF VGG-19 WITH OTHER MODELS

Models	***AD***	***Normal***
VGG-19	98	98
VGG-16	96	98
Resnet-50	61	84
Xception	86	85

graph is shown in Fig. 2 and ROC curve is shown in Fig 3. A detailed analysis of this result is presented with the help of a confusion matrix shown in Table. 1. Further studies were extended to other models like VGG-16, ResNet-50 and Xception using the same parameters.

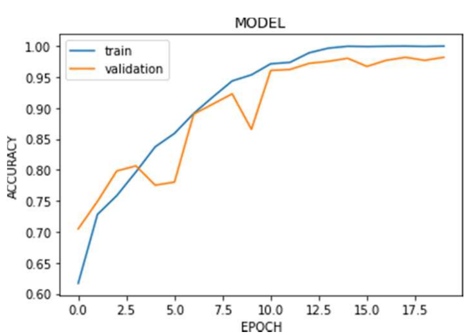

Fig. 2. Learning trend of model VGG-19 giving an accuracy of 98%

The model accuracies of VGG-16, Xception and ResNet-50 are shown in Fig. 4, Fig. 5 and Fig. 6 respectively. The model evaluation metrics like precision and recall were used to evaluate the model. The precision measure gives the amount of samples classified correctly from each class.

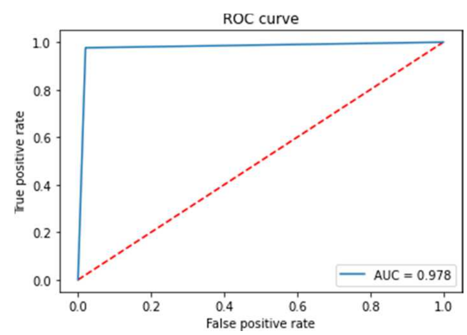

Fig. 3. ROC curve of Vgg-19

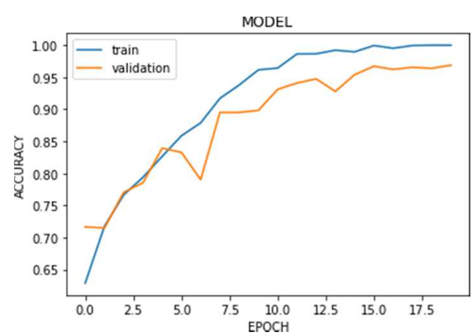

Fig. 4. Learning trend of model VGG-16 giving an accuracy of 97%

To check the performance of these models the corresponding precision measures are compared in Table. II. Recall and F1- Measures are also analyzed in Table. III and Table. IV

It was observed that VGG-16 exhibited a classification accuracy of 97%. Since the accuracy measures of two VGG

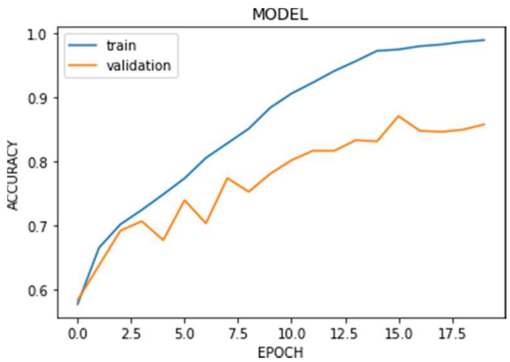

Fig. 5. Learning trend of model Xception giving an accuracy of 86%

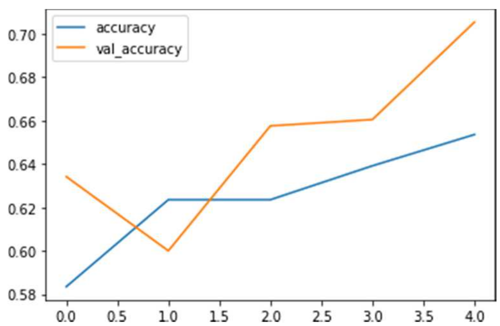

Fig. 6. Learning trend of model Resnet-50 giving an accuracy of 71%

variants were comparable, further analysis was done on the precision measures of these two models. It was found that VGG-16 had a precision measure of only 96% compared to VGG-19 with 98%. This result was further compared with Resnet-50 giving an accuracy of 71% and Xception with 86%. Eventually, the result shows that VGG-19 yields a high accuracy of 98% with a steady decrease in loss.

TABLE III
COMPARISON OF RECALL MEASURES OF VGG-19 WITH OTHER MODELS

Models	*AD*	*Normal*
VGG-19	97	98
VGG-16	98	96
Resnet-50	84	61
Xception	86	86

TABLE IV
COMPARISON OF F1-MEASURES OF VGG-19 WITH OTHER MODELS

Models	*AD*	*Normal*
VGG-19	98	98
VGG-16	97	97
Resnet-50	71	71
Xception	86	86

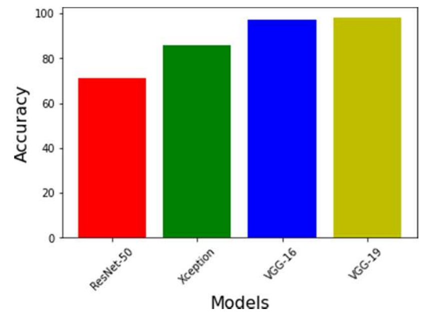

Fig. 7. Accuracy Comparison

IV. Conclusion

In this work, a Transfer Learning approach for the automation of Alzheimer's disease prediction is presented. The experiment was conducted with different Transfer learning models like VGG-19, VGG-16, ResNet and Xception on ADNI dataset. From the result, it was observed that VGG -16 and VGG-19 performs well in this dataset. But it was also analyzed that, on fine tuning the deeper layers of VGG-19, the model can exhibit exceptionally high accuracy and precision(98%) when compared to other Transfer Learning models. Thus an efficient and automated prediction of Alzheimer's disease is possible using this approach.

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