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Alzheimer Disease Classification Using Transfer Learning

Ms.Heta Acharya
PG Research Scholar,
Information Technology
Parul University, Vadodara,
Gujarat, India
heta.acharya14507@paruluniversity.ac.in

Prof. Rutvik Mehta
Assistant Professor,
Information Technology
Parul University, Vadodara,
Gujarat, India
rutvik.mehta@paruluniversity.ac.in

Prof. Dheeraj Kumar Singh
Assistant Professor,
Information Technology
Parul University, Vadodara,
Gujarat, India
dheeraj.singh@paruluniversity.ac.in

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Abstract— **In recent years, transfer learning has gained huge popularity in solving problems from various fields including the medical image analysis. Clinical picture examination has altered medical services in the course of recent years, permitting specialists to discover disease earlier and improve patient recovery. Imaging has assumed a significant role in the finding of Alzheimer disease (AD). AD is a progressive neurological issue that gradually destroy memory and thinking skills of human. Initially, Computed Tomography scan (CT) and then Magnetic Resonance Imaging (MRI) were utilized to discover reasons of dementia in AD patients. This research aims to classify MRI of Alzheimer disease patients into multiple class by using VGG16, ResNet -50 and AlexNet as transfer learning models along with convolution neural networks. There are some stages of AD like mild cognitive impairment, mild Alzheimer's, moderate Alzheimer's and severe impairment. The proposed strategies show results with an accuracy of 95.70%, this represents a substantial improvement in accuracy over previous studies, demonstrating the efficacy of the proposed method.**

Keywords— Alzheimer's disease prediction; Alzheimer's stage classification; brain MRI; transfer learning; convolution neural network; Alexnet; ResNet 50; and VGG16.

I. INTRODUCTION

Alzheimer's disease is a neurodegenerative disease that has affected nearly 50 million people worldwide [1]. The disease causes an irreversible damage to the brain that affects cognition, memory and other function. In case of brain failure, it may lead to the death of the individual. Alzheimer can unfavorably influence the functionality of normal health such as writing, speaking and reading due to loss of nerve cell throughout the brain. Now and again AD patients may have issues distinguishing their relatives. Patients in the cognitive stage are more inclined to abnormalities, yet patients in the last phase of AD experience the ill effects heart failure [1]. Because of the slow onset of symptoms, proper diagnosis of Alzheimer's disease is difficult [2, 4]. However, its early-stage diagnosis and treatment can improve a patient's health [3]. Based on damage of brain and patient's condition AD can be classified in four stages: Mild Cognitive Impairment, Mild Alzheimer's, Moderate Alzheimer's and Severe Impairment. [11]. In clinical research, MRI analysis is most preferable practice for Alzheimer's disease diagnosis.

Convolution neural networks (CNNs) have made significant progress in automated medical image analysis. Therefore, many CNN models are offered for object detection and segmentation such as VGG, and AlexNet, Residual Network (ResNet). Although CNNs have been widely recognized as a reliable deep learning approach, lack of a large amounts of medical imaging training data, hamper's their performance. In case of smaller data, transfer learning is one of the most powerful technique for training deeper networks without any over fitting [17]. Transfer learning is based on the use of a pre-trained network. Instead of training a particular CNN without preparation, the proposed learning approach can learn the most effective features. The proposed research work has implemented on Basic CNN and three pretrained networks such as CNN, VGG 16, ResNet and AlexNet to classify AD into four classes.

II. RELATED PAPER WORKS

Hina Nawaz & Muazzam Maqsood [1] have worked on computer aided diagnostic system that requires real time diagnosis of Alzheimer's disease. They have proposed on a classification of AD stages. For some deep features model and extraction, they have used machine learning classifiers such as KNN (K-nearest neighbor), RF (Random Forest), and SVM (Support Vector Machine) using machine learning methods. For classification and deep features extraction they required large dataset to overcome over fitting issues. They have suggested in real time the depth and transmission of learning models in comparison with other methods to achieve the highest accuracy of early Alzheimer's diagnosis.

Early diagnosis of Alzheimer's disease, as well as protein symptoms, which are usually used in AD categories (Alzheimer's disease), is extremely difficult, and there is no cure for AD at this stage using any medical reasoning techniques. Ketki Tulpule, V.P. Subramanyam Rallabandi [2] they created an automated machine learning method for classifying Alzheimer's disease stages, focusing on nonlinear SVM for the radial basis function to achieve high accuracy.

U. Rajendra Acharya & Steven Lawrence Fernandes [3] they created a CABD (Computer Aided Brain Diagnosis) system that decides whether or not a normal brain scan would reveal any signs of Alzheimer's disease. Mohamed Mahyoub, Martin Randles [4] Alzheimer's disease can be diagnosed at different stages depending on factors such as lifestyle, medical history, and demography, as well as other factors. Lihua Wang and Zhi-Ping Liu [5] combined genetic data from six brain regions with SVM machine learning to identify AD biomarkers.

Goo-Rak Kwon, Yubraj Gupta [6] developed machine learning-based methods to distinguish AD (Alzheimer's disease) from MCI (Mild Cognitive Impairment) using a combination of four different types of biomarkers, such as FDG-PET (Fluorodeoxyglucose positron emission tomography), MRI (magnetic resonance imaging), CSF protein levels, and the Apolipoprotein-E (APOE) genotype. To increase the outcome of early AD prediction, a new kernel-based multiclass SVM classifier was used.

Yong-Kui Ma, Ahsan Bin Tufail [7] they created a deep 2D convolutional neural network (2D-CNN) to investigate the different characteristics of the brain images that were combined to make the diagnosis of Alzheimer's disease. Amir Ebrahimi-Ghahnavieh, Suhuai Luo [9] they utilized transfer learning on brain MRI scan to detect AD. First, they trained various CNNs in binary and multiple class classification on the same dataset. The Recurrent Neural Network was then fed with characteristics extracted from the CNN model (RNN). Despite the recent success of deep learning in computer science, such algorithms are limited to a large number of training images.

Naimul Mefraz Khan,Nabila Abraham[10] The state-of-the-art VGG model was implemented with large data for natural images to solve these problems using transfer learning. They propose using MRI imaging to diagnose Alzheimer's disease using a transfer learning technique. Muazzam Maqsood, Faria Nazir [11] explore a transfer learning method to transmit Alzheimer's disease. They proposed categorizing each AD class into several categories.

III. TRANSFER LEARNING

By using pre-trained networks, transfer learning is used to reduce the training time for a neural network model. When dataset available to train the model is relatively small, but using a pre-trained network trained in a large data set and optimizing it for a specific task is effective. Convolutional neural network (or ConvNet) is a class of Deep Neural Networks (DNN), most commonly used for any medical image analysis. Figure 1, illustrates a basic architecture of the CNN. In literature, different transfer learning techniques has been proposed. This paper has used VGG 16, ResNet 50 and AlexNet.

VGG16 is also called as an Oxford Net which is a convolutional neural network name after the Visual Geometry Group from oxford. Initially, it was trained on the ImageNet dataset. VGG 16 consists of 16 layers that can classifies the images into 1000 categories [9].

The ResNet model contains a large number of remaining blocks, each block being rotated by a stack of flexible layers. This design reduces the problem of CNN disappearance. ResNet 50 is a classical is a CNN mainly used in computer vision tasks. ResNet 50 consist of 50 layers [8].

AlexNet is first deep neural network to achieve ImageNet classification accuracy by a significant stride in comparison to other CNNs. Five convolutional layers and three fully connected layers make up the AlexNet architecture. It utilizes two GPU for training initially that directly reduces the training time. To avoid over fitting Problem, data augmentation and drop out layer has been introduced [11].

MODIFIED ALEXNET ARCHITECTURE

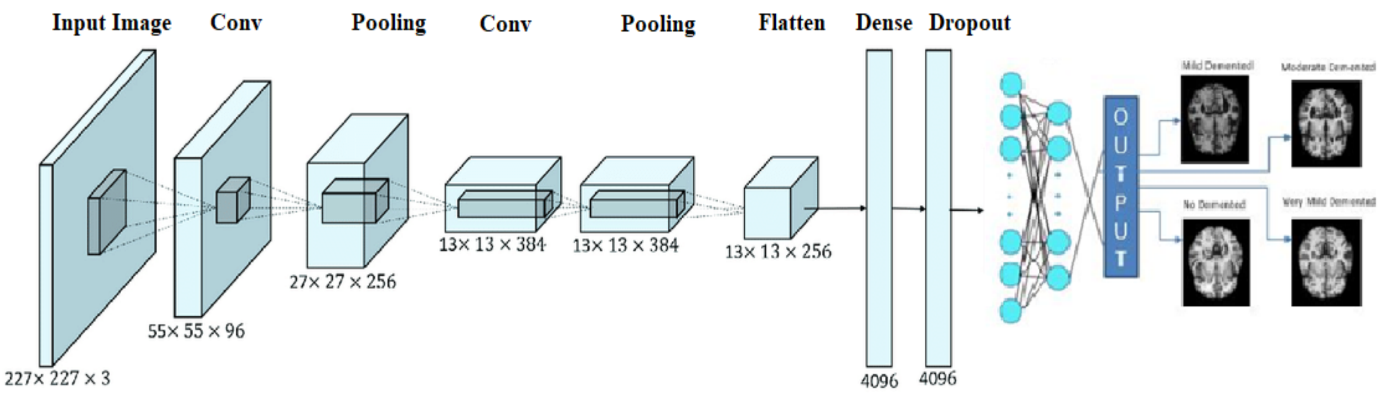

Fig. 1. Basics CNN

IV. EXPERIMENTAL SETUP

This paper has used MRI images, which are publicly available on Kaggle repositories. This dataset consists of 6,400 images, each of size 227 x 227. Table 1 shows the details of each AD stage's images.

TABLE I. Dataset statistics

AD Stage	Number of Images in Dataset		
	Train	**Test**	**Total**
Mild Demented	717	179	896
Moderate Demented	52	12	64
Non-Demented	2560	640	3200
Very Mild Demented	1792	448	2240

As shown in figure.1 the modified AlexNet architecture block diagram includes total 8 layers from that 5 are specification and 3 are that fully connected. Here, in modified means, conv-pooling layer has been inserted on behalf of conv-conv-pooling layer. However, this is not something that converts AlexNet special; here some of the features were utilized as new methods of CNN:

Pseudocode

```
[NonTest, Test] =split (Dataset);
for S = [Class-1, Class-2, Class-3, Class-4]
    for i = 1:10
    [train (), valid ()] = split (NonTest),
    Model (S, i) = Train Network (AlexNet, train (), valid (i),
Setting = S),
    PertValid(S,  = Predict(Model(S, i), valid()),
    end
    PertValid(S)  = mean (PedValid(S, i)),
End
S= argmax (Performance(S)),
for i = 1:10
    [train (i), valid (i)) = split (NonTest),
    Model (S., i) = Train Network (AlexNet, train (1), valid (),
Setting = S)
    PerfTest(S., i) = predict(Model(S., i), Test),
End
PerfTest(S") = mean (PerfTest(S., i)),
Output PerfTest(S.)
```

A. ReLU Function:

AlexNet utilizes the Rectified Linear Units (ReLU) behalf of tanh work, which was common at that time. ReLU benefits are in training time; CNN which utilizing ReLU was able to access 25% error in the AD stage database 6 times faster than CNN utilizing tanh.

B. Scattered Pooling:

The effects of CNN's "pool" according to the culture of neighboring groups of non-dispersing neurons. Saw lift is a decrease in mistake of around 0.5% then it has been originating that models by interlocking combinations often find it harder toward pass.

C. Skipping Problematic:

AlexNet ought to 60 squillion restrictions, a key problem with overtime. Two methods are utilized to reduce cost:

D. Multiple GPUs:

Graphical Process Unit were unmoving roaming with three gigabytes of memory (these days those types of memory can stand recruit numbers). This was even worse since the exercise usual contained 1.2 squillion pictures. AlexNet permits multi-Graphical Process Unit exercise through placing semi of the model neurons in one graphic unit and one component in another GPU. This not only means that a larger model can be trained, but it also reduces training time.

E. Added Data:

Paper used a change that keeps the label to make their data very different. In particular, they have produced horizontal rendering of images and displays, which has increased the training set by the 2048 element. They also perform RGB pixel values and Principal Component Analysis (PCA) to reverse the strength of RGB channels, which reduced the top-1 error by more than 1%.

F. Drop out:

This strategy includes "turning off" neurons at foreordained freedoms (e.g., half). This implies that each emphasis utilizes an alternate example of model boundaries, driving every neuron to have solid qualities that can be utilized with other irregular neurons. Notwithstanding, exiting school additionally expands the preparation time needed for model reconciliation. AlexNet can see medium items and the greater part of its main four classes for each picture bode well.

V. RESULTS AND ANALYSIS

Dataset having of 2 files - Testing and Training both having a total of 6400 images, each separated into the severity of Alzheimer's stage. The dimension of images is 227x227. In this experimental different Transfer learning techniques: Pretrained-CNN, VGG, ResNet, and Modified AlexNet with parameters tuning which will give a classification of Alzheimer's disease four stages with high accuracy.

Pretrained-CNN Model, contain three layers of convolution is applied to input image size (227x227) which converted into (127x127) and the feature matrix is 58 dense layer output. As shown in figure 2 of Pretrained-CNN Accuracy plot after 10 epochs getting 88.89% accuracy. As shown in figure 4 loss plot after 8 epoch's loss is decreases exponentially.

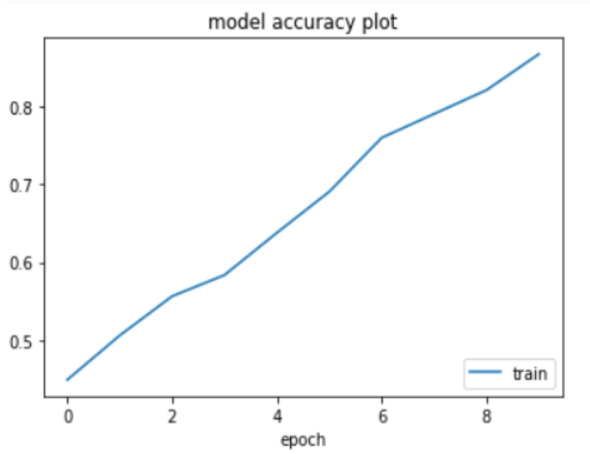

Fig. 2. CNN Accuracy Plot

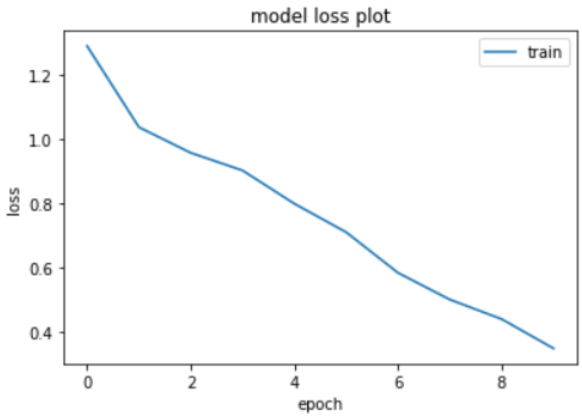

Fig. 3. CNN Loss Plot

VGG16 Model contain sixteen layers of convolution is applied to input image size (227x227) which converted into (7x7) and the feature matrix is 4 dense layer output. As shown in figure 4 of Accuracy plot after 25 epochs getting 85.07% accuracy. As shown in figure 7 loss plot after 10 epoch's loss is decreases exponentially.

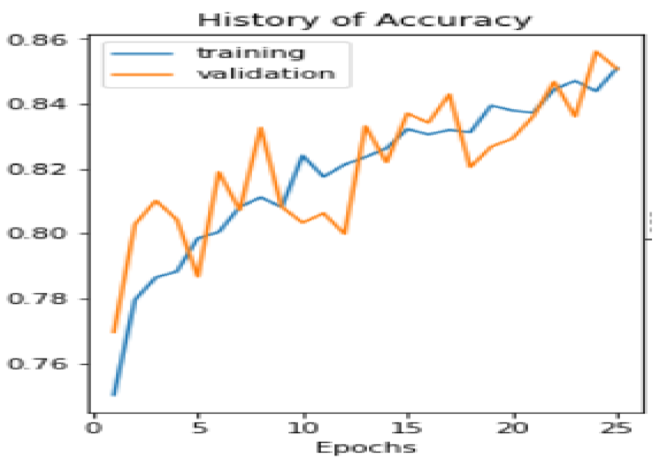

Fig. 4. VGG16 Accuracy Plot

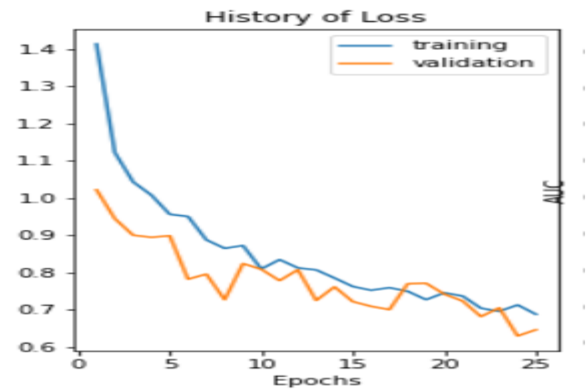

Fig. 5. VGG16 loss Plot

RESNET50 Model, contain fifty layers of coevolution is applied to input image size (227x227) which converted into (7x7) and the feature matrix is four dense layer output. As shown in figure 9 of Accuracy plot after 20 epochs getting 75.25% accuracy. As shown in figure 6 loss plot after 10 epoch's loss is decreases exponentially.

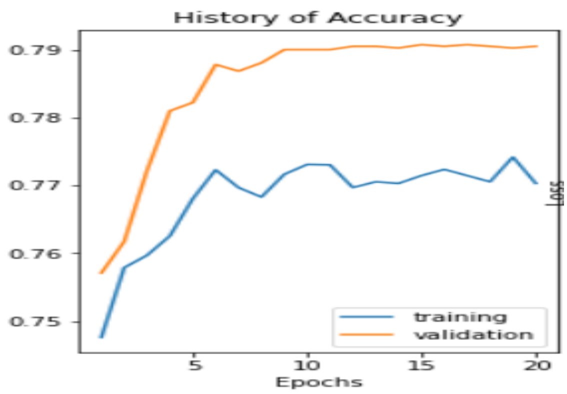

Fig. 6. RESNET50 Accuracy plot

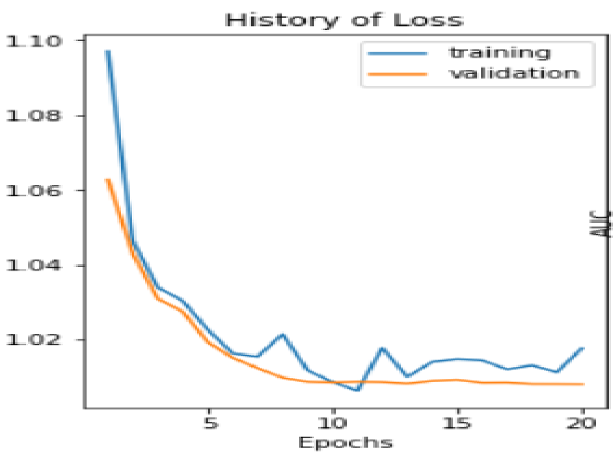

Fig. 7. RESNET50 Loss plot

Modified AlexNet Model, contained eight layers of convolution is applied to input image size (227x227) and the feature matrix is four dense layer output. Here, modified means has use used only two convolutions instead of five. Also, optimization function is changed as Adam optimization. As shown in figure 8 of Accuracy plot after 20 epochs, it obtains a 95.70% accuracy. As shown in figure 13 loss plot, after 5 epochs, loss gets decreased exponentially.

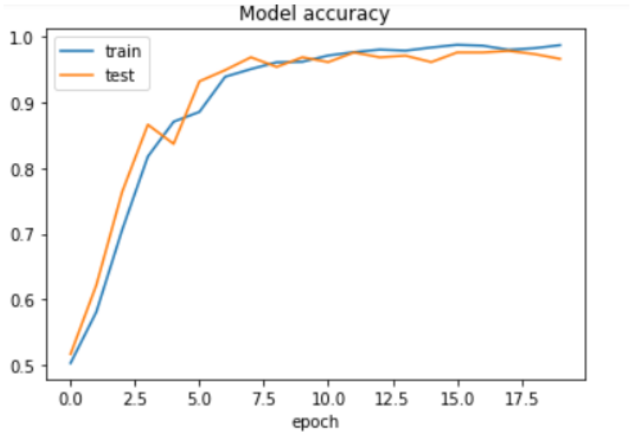

Fig. 8. AlexNet Accuracy plot

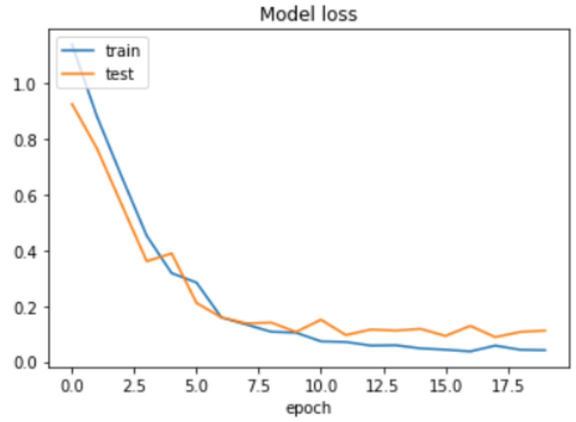

Fig. 9. AlexNet Loss plot

In this part discuss about different parameters definition and also showcase results. At the end comparative analysis is done with existing methods.

$$\text{Accuracy}=(TN+TP)/\ (FP+TP+FN+TN) \quad (1)$$

$$\text{Precision}=TP/\ (FP+TP) \quad (2)$$

$$\text{Recall}=TP/TPFN \quad (3)$$

$$\text{F1-Score}=(2*TP)/(2*TP+FN+FP) \quad (4)$$

Where, true negative (TN), true positive (TP), false negative (FN) and false positive (FP).

In above experiment 6400 images taken from Kaggle each separated into the severity of Alzheimer's groups. For Evolution overall data is split into training data 75% (375 images) and testing data 25% (125 images). Below Table Shows the Different parameters calculated from different models testing results.

TABLE II. ANALYSIS

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Transfer Learning				
CNN	88.89%	82.23%	86.36%	78.34%
VGG-16	85.07%	73.19%	63.60%	68.06%
ResNet-50	75.25%	56.56%	43.78%	79.41%
Modified AlexNet	95.70%	91.90%	92.30%	94.70%

As shown in table II of Accuracy, F-score, Recall and Precession among all Modified AlexNet gives best accuracy.

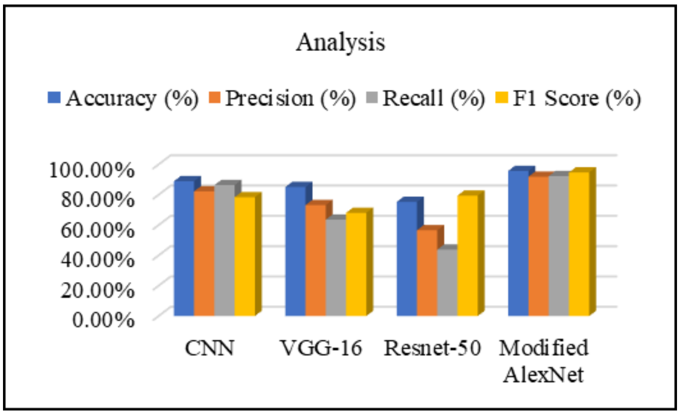

Fig. 10. Analysis of All Models

CONCLUSION

Proposed learning modes to predict Alzheimer's disease stage were investigated in this study. Proposed model work for data testing at the Kaggle warehouse, where the MRI image is in four categories such as demented (VMD), demented (MD), moderate AD (MAD) and demented (ND) used to determine the highest accuracy of the model as 95.70%. The analysis has investigated the reduction of overcrowding and the adjustment of the model effect on the performance of our application. To this end, the research used familiarity and finally compared proposed strategies to the three existing networks CNN, VGG16, and RESNET50 advanced systems, and the proposed model has performed much better than others. After that, it has been seen that the proposed model offers a 12% to 18% improvement in multi-level differentiation compared to modern technology strategies. In future work, examine whether the same model can be applied to other computer-assisted diagnostic problems. Also, examine the progress of the intelligent classification of real-time programming training data.

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