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# TRANSFER LEARNING MODEL FOR MRI BRAIN TUMOR CLASSIFICATION

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**Abstract**—Transfer learning model is incorporated wherein the last few layers of Alex net architecture are modified to extract the features and then used to predict the class of a new data set. To attain a custom task, TL basically reduces the required data and training time as ImageNet model was trained on millions of images to validate the result. With the proposed TL method an accuracy of 96.25% with sgdm and 97.91% with adam optimizers are obtained for Classification of Tumor images. As the study of this TL model is an important tool and result of this is used for biomedical image processing applications. The classification of brain MRI images and the detection of tumors in the brain are implemented with the TL method as it is simple and beneficial when compared to CNNs. This proposed model is much faster and easier, because this Transfer learning model can be used the learned features to new classification task using 100s of images and 10s of classes.

**Keywords**—Transfer learning model, modified architecture of alexnet, image classification, MRI brain tumor classification, Convolutional neural network**.**

## I.INTRODUCTION

In recent years several studies have been conducted and become a vital job to detect the tumors in the brain via MR images [1] [2] [3]. Human life is threatened by Brain tumors and the chance of patient's survival [4] increases if it is being detected at an early stage. A brain tumor arises when the brain develops a form of abnormal cells from inside. The main two forms of tumorsare: benign tumors and malignant or canceroustumors. Depending on the part of the brain involved and symptoms they produce the types of brain tumors may differ. These consist of symptoms like headaches, seizures, vision problems, vomiting and mental changes.In the volume histological typing of tumors, The World Health Organization (WHO) grading system [2] as controlled by the Central Nervous System, whose first edition dates back to 1979, the second to 1993 and last one to 2007. According to WHO grade, the four kinds of tumors are: Grade I tumors are benign, slow-growing, and has long-term survival. Grade II tumors are comparatively slow-growing but at times recur as higher grade tumors. They are either benign or malignant. Grade III tumors are malignant and frequently recur as higher grade tumors.

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Grade IV tumors are violent malignant tumors and grow rapidly.Transfer Learning (TL) [5][6] is an extension of CNNs[7][8]. Basically to train resources from huge amounts of data Convolutional networks (CNNs) are used but require more time and sufficient amount of pre-trained data (normally ImageNet). The TL model replaces the CNNs by considering the pre-trained CNN model by just removing the last fully-connected layer with the fully-connected custom layer to perform the desired task. For new dataset, the original CNN is treated as a feature extractor and the classifier is trained after replacing the last fully-connected layer. The training period is short because it does not require any iteration. The input weights and connections are both randomly generated as TL method is more efficient.

## II.METHODOLOGY

Alexnet is one of the revolutionary pretrained convolutional neural network and trained on more than one millions of images from the database of ImageNet [1] [7] [9]. The total layers in the alexnet model is 25. Figure 3 represents an interactive visualization of alexnet architecture layers. There are mainly 5 layers in each of this pretrained model convolutional layers, batch normalization, and nonlinear activation function ReLU. There are three layers of max pooling and fully connected layers (dense layer) with two layers of dropout layers, one layer of input softmax and output layer. This model has a depth of eight layers (5-convolutional layers and 3- fully connected layers). It has the capability of classifying 1000 classes because the output layer is having 1000 object categories. Some of the object categories of alexnet are animals, flowers, pencil, mouse, tea cup, jug, keyboard etc. As a result, the rich features are learned by alexnet model to classify the classes for a wide range of images.

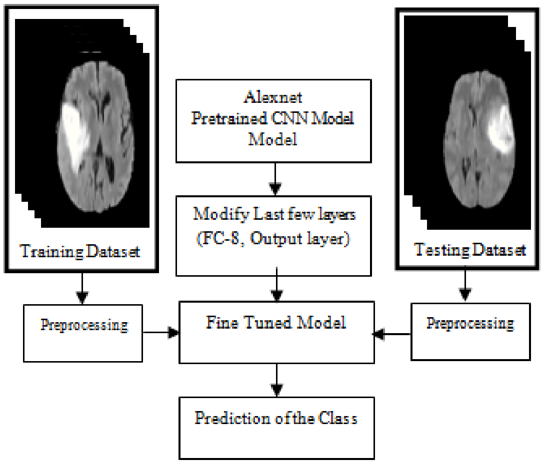


Fig. 1 Frame work of Transfer Learning Model (Fine tuning of Alexnet model)

Input image size of this model is 227*227*3 and alexnet is also used directly to classify a new image. The model is trained to 61 million parameters and has 0.72 billion operations per prediction. Memory size of the alexnet is 245MB.In the ILSVRC imagenet competition, alexnet stood an outperformer with accuracy of 83.6 percentage and reduce the error rate from 26 percentage to 16.4 percentage.The layers of transfer learning model are connected to each other and shown in three dimensional view as shown in figure 2. First and third convolutional filters are of size 11*11 and 5*5 and remaining all convolutional filters are of size 3*3. The number of convolutional filters from first to last are 96,

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96, 256, 256, 384, 384, 256, and 256 and next three layers are dense layers. To retain a pertained alexnet model to predict new images of dataset, a few layers of this model have to be replaced with new layers and adjust according to the new images of dataset. The number of classes must be changed to match new images of dataset. The twenty third layer of the pretainedalexnet, fully connected layer (fc8) should be replaced with new fully connected layer (newfc8) using parameters like output size to the number of classes in the new images of dataset (the number of classes in this paper is 2, benign and malignant) and learning rates are modified to speed up the training process for new dataset

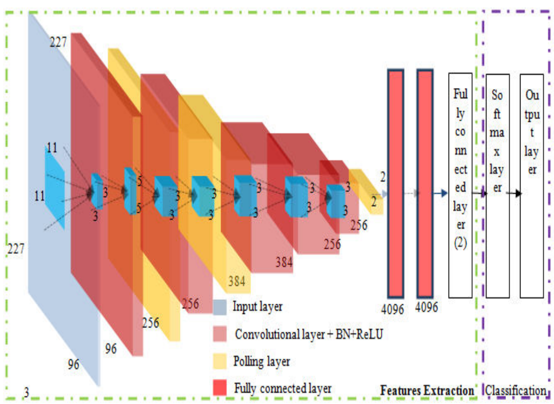


Fig. 2 Architecture of modified Alexnet (Transfer Learning)

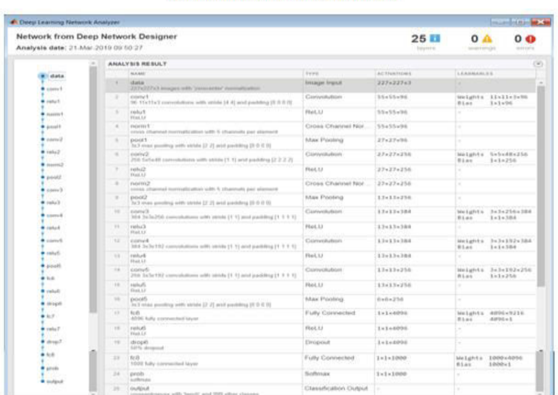

Fig. 3 An interactive visualization of alexnet architecture.

Fig. 4 Modified Last three layers of transfer learning model.

Fig. 5 Training process of Transfer learning model.

The learning rate parameters are weight learn rate factor and bias learn rate factor, both are set to 20. An original classification layer (output) should be replaced with new classification layer (newoutput). This new classification layer is also set to the number of classes i.e. 2. All these modifications can be seen in figure 4 and by now transfer learning model is ready. In the next section, the preprocessing of training dataset, validation dataset, and testing dataset are discussed. The model is trained using training dataset and then classified the images for testing dataset.

## III.EXPERIMENTAL RESULTS

Normally, selecting a data base is very difficult task for image denoising, segmentation [10], and classification. In this paper, a popular database for brain tumor images BraTS 2015 and 2017 database are considered to prepare various datasets like training, validation, and Testing datasets.

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With 660 images including both benign and malignant tumor images, a new database is prepared and named as Brain Tumor Database-660 (BTD-660). In this BTD-660 database, 400 images of training dataset including 200 images of benign tumor images and testing dataset of 120 benign and 120 malignant tumor images. Validation dataset includes benign tumor images of 10 and malignant tumor images of 10. Using data augmentation all the images in the datasets are augmented to appropriate input layer.The transfer learning model is then trained to these datasets of training and validation datasets with training options like optimizer sets to either stochastic gradient descent with momentum (sgdm) or adaptive moment estimation (adam), minibatchsize 20, maxepochs 30, initial learing rate 0.0001, and validation frequency 20. The model is trained with training accuracy of 100 percentage and reached validation accuracy to 100 percentage. Remaining all the information related to training process is shown in figure 5.

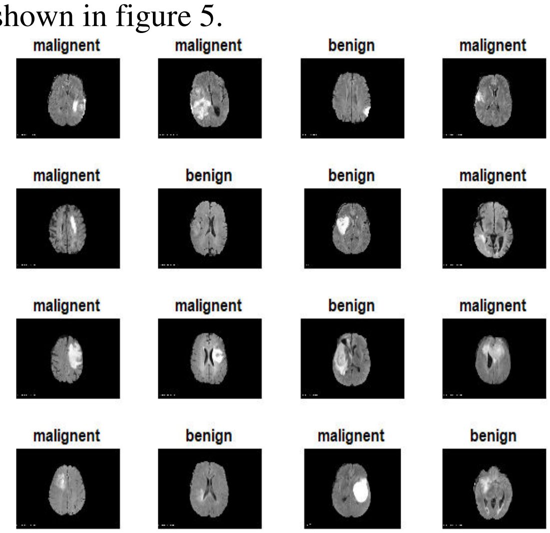


Fig. 6 Training images of 16 random images from Training dataset.

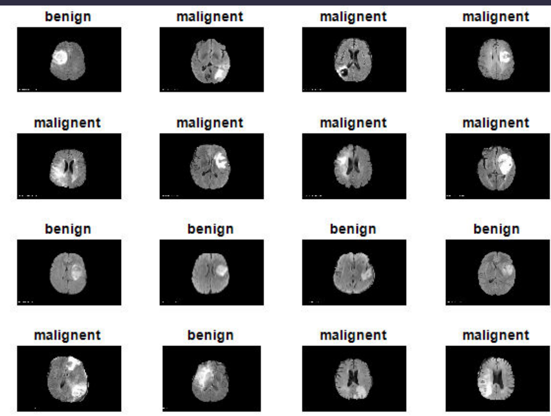


Fig. 7 Testing images of 16 random images from testing dataset.

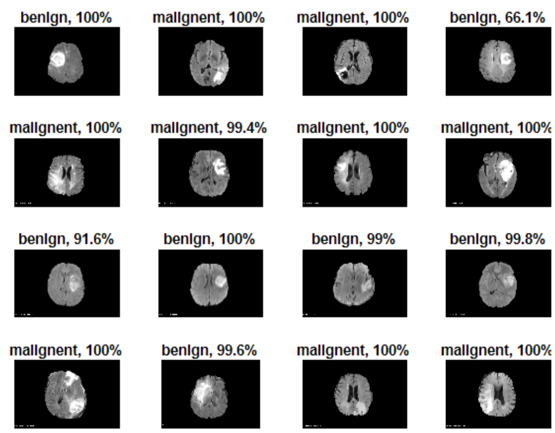


Fig 8 Testing images of 16 random images with prediction percentage from testing dataset

Once training process is reached to the maximum epoch, it shows that the training process has completed. Now it's time to evaluate the trained model with testing dataset. From Fig. 7 and Fig. 8, the proposed model is a predicted class of individual image in the testing dataset with predicted probability

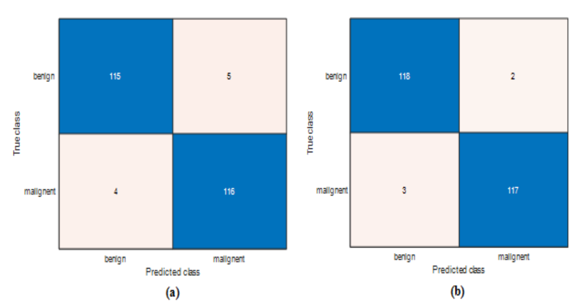


Fig. 9 Confusion matrices of proposed model a) with sgdm optimizer b) adam optimizer.

The proposed transfer learning model is misclassified as 9 images out of 240 images, when sgdm is used as optimizer and five images are misclassified by the model, when adam is used as optimizer. From these confusion matrices, the performance matrices of the proposed model is evaluated. The model has following performance metrics: With sgdm optimizer accuracy is 96.25%, error rate is 3.75 and with adam optimizer accuracy is 97.91%, error rate is 2.08.

## IV.CONCLUSIONS

In this paper, the proposed Transfer learning model is considered for classification of MRI brain tumor images because it is much faster and easier. With sdgm optimizer, the accuracy is 96.25%, error rate is 3.75 and with adam optimizer, the accuracy is 97.91%, error rate is 2.08. From these results, the model with adam optimizer has better performance than that the model with other optimizer. The two optimizers considered in the proposed model for classification purpose performs better compared to alexNet model. Hence the proposed model can be used for biomedical image processing applications.

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