A Comparative Analysis of Deep Neural Networks for Brain Tumor Detection

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***Abstract*—The technological advancement in the field of medical science for the detection, classification and identification of several diseases is making the diagnosis process easier and efficient at the same time, provides a helping hand for medical practitioners in saving life. Health experts are making use of these most advanced technological practices for reaching at conclusions in the area of health care. Brain tumor detection is one of the key major challenges in medical field. Early detection of tumor plays the most important role in fixing the most efficient treatment techniques for increasing the survival rate of patients. Manual detection of tumors for diagnosing cancer from data generated from clinical instruments is a time consuming task and the efficiency depends upon the radiologist. So through this paper, we are proposing methods for automating the detection process which can help the radiologist reaching at a faster conclusion in an efficient manner. We are proposing methods based on the pre-trained network models like ResNet and its variants for brain tumor detection. The obtained results shows that ResNet-152 is the most efficient one among them for brain tumor detection and we can automate the process more effectively.**

***Index Terms*—Brain Tumor Detection, ResNet, transfer learning, MRI**

I. Introduction

A tumor is any mass caused by the abnormal or uncontrolled growth of cells inside living organisms. Different types of tumors are there according to the size, position and growth of the cells inside human body. Tumors present inside human brain are known as brain tumor. Brain tumor accounts for 85% to 95% of all the primary Central Nervous System (CNS) tumors. As they are dangerous and can cause death, they should be detected as early as possible and should be diagnosed. There are several methods available for capturing and diagnosing the affected area. Computer Tomography (CT) scan, Neurological examination, Magnetic Resonance Imaging (MRI) scan, Spinal tap, Biopsy etc. are some of them. MRI can capture the affected area inside human brain more clearly than CT scan as it is suitable for soft tissues, ligaments or organs.

Brain tumor is one of the leading causes of deaths related to cancer in many of the countries. Also it is the second leading cause of deaths, related to cancer, in children under the age of 20 as well as males of age 20 to 29. The five year survival rate means what percentage of people live at least five years after detecting the presence of tumor inside their body. The five year survival rate for people with cancerous brain is almost 36%. The five year survival rate of patients under the age group of 15 is greater than 74%, that in between 15 to 39 years is about 71% and that of greater than 40 years is about 21%. The ten year survival rate means what percentage of people live at least ten years after detecting the presence of tumor inside their body. The ten year survival rate is almost 31%. Survival rate decreases with increase in age. Also it may vary widely depends on several factors like age, food intake, adaptation, etc.

There are several methods available for brain tumor detection and classification based on deep learning (DL) technology. So many pre-trained classification models like Alexnet [1], VGGnet [2], Googlenet [3], Squeezenet [4], ResNet [5], Inception [6], Xception [7], etc are also available. In [8], Palash Ghosal et al. discussed about brain tumor classification system using ResNet-101 model. They classified tumor area into three different classes like Glioma, Meningioma and Pituitary tumor and got an overall accuracy of 93.83%. In [9], Rajat Mehrotra et al. proposed a comparative approach for brain tumor classification as benign and malignant based on transfer learning techniques. They have used five unique DL models like AlexNet, GoogLeNet, ResNet-50, ResNet-101, and SqueezeNet. They got an overall accuracy of 99.05% for a dataset consists of only 696 MRI images.

In [10], Prayash et al. did a comparative study of ResNet-50, VGG-16 and Inception-v3 and proved that ResNet50 outperforms all others. They got an overall accuracy of 95% for ResNet-50 model. But they have used a dataset containing only 253 images. In [11], Ahmet et al presented a network created from ResNet50 and compared it with the existing models like Alexnet, Resnet50, Densenet-201, Inception-v3 and Googlenet. They got an accuracy of 97.2%. According to the literature, ResNet-152 is more accurate than other ResNet models. So we are proposing retrained models, created via the method of transfer learning, from different versions of ResNet.

The main contribution of this work is to make use of existing classifiers like ResNet and its variants for brain tumor detection purpose via classification with more than 10000 images. The section 2 describes the proposed networks for brain tumor detection followed by the implementation of them in section 3. The section 4 explains the results obtained with detailed analysis and finally concluding in section 5.

II. Proposed Method

If we can develop automated systems for detecting the presence of brain tumor inside human brain, it will help the doctors as well as the radiologists to diagnose it more effectively and accurately. This paper deals with a comparative analysis of the possibility of the existing classifiers like ResNet-50, ResNet-101 and ResNet-152 for brain tumor detection via the method of classification. Here, we have used transfer learning for making the networks compatible for brain tumor detection detection.

The block schematic of the proposed method is shown in fig. 1. Here, the first block indicates the images used for training the deep learning network. The dimension of the input images may not be equal to the size of the input layer of the existing network. Therefore, we need to resize the original images in accordance with the size of the input layer of the network. For example, if we are using ResNet architecture as the existing model then we need to resize the original images to a dimension equal to 224x224x3 in order to make it process by that network. The pre-processing block is doing this resizing. After this step, all the training images are given to the deep learning network for training the network. Here, we have used stochastic gradient descent momentum optimization function for training the network. After the training process, the trained network is tested by using the query images which should be of size 224x224x3. So the query should be pre-processed before giving as input to the network. As the last stage, we have used a segmentation process for segmenting out the tumor area using the algorithm mentioned in [14]. It is a simple global thresholding algorithm used for segmenting out the soft tissues.

III. Network Implementation

Residual Network, or ResNet in short, is an efficient classifier which introduced the concept of skip connection. ResNet introduces a new structure called residual learning units which has different variants that differ in depths. Residual unit is having a feedforward network structure with skip connections which adds somewhat previous inputs into the network to generate new outputs. The main advantage or the fundamental breakthrough of this model was this allowed the user to train very deeper neural networks with more than 150 layers more efficiently. Different types of ResNet architectures are available in the literature. ResNet-18 is a Convolutional Neural Network (CNN) with 18 deep layers. Similarly ResNet-34, ResNet-50, Resnet-101 and ResNet-152 has 34, 50, 101 and 152 deep layers respectively. The number of layers is more when compared to other architectures like Alexnet, VGGnet, etc. but it is faster. The ResNet produces better classification accuracy without increasing the complexity of the network model. ResNet architectures are using batch normalization for increasing the performance of the network.

The basic architecture of ResNet-50 in [12] is shown in Fig. 2. This architecture consists of different stages. Each stage

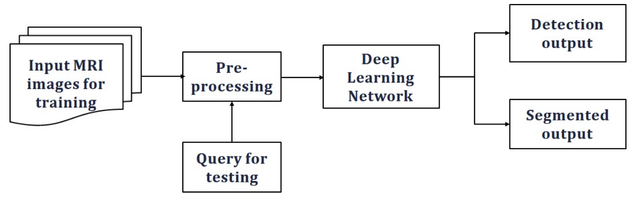


Fig. 1: Block schematic of the proposed method

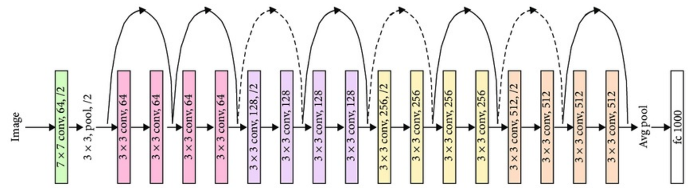


Fig. 2: Basic architecture of ResNet-50

has a convolution block and an identity block. Each of these blocks has 3 convolution layers. This has a total of 50 layers and over 23 million trainable parameters. The convolutional layers are using filters of size 3x3 and 1x1. ResNet-101 is more deeper than ResNet-50 with 101 layers. The basic architecture is shown in Fig. 3. The filter dimensions are same as that of ResNet-50, but the number of filters is more. Thus more amount of features will be extracted and accuracy will be more when compared to ResNet-50. ResNet-152 is more deeper and efficient than the previous ones with a total of 152 layers. Thus it is eight times deeper than VGGnets. The basic architecture is shown in Fig. 4. This is also using the same size filters, but number of filters is more. Resnet architectures became the winner of the ILSVRC 2015 [5]. All these networks are

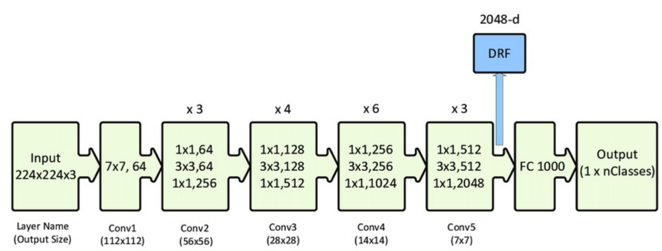


Fig. 3: Basic architecture of ResNet-101

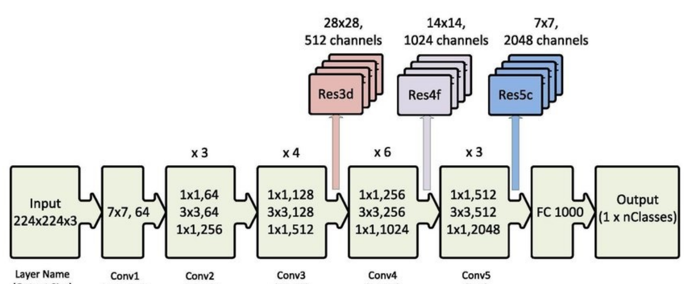


Fig. 4: Basic architecture of ResNet-152

basically 1000 class classifiers.

The proposed network architecture is created via the method of transfer learning. The last 3 layers are replaced from all the above models to handle two classes, normal and tumor, and retrained. That means, we have adopted the method of classification of the input data into two classes for detection purpose. We have used batch normalization size of 200 for 20 epochs and initial learning rate as 0.0001. After training, the retrained network is validated and tested with MRI data. Here the networks are classifying the input data into one with tumor and the other without tumor. That means, the network is acting as a two class classifier. Thus we can detect the presence of tumor area in a particular image. All these are implemented using the Deep Network Designer toolbox in MATLAB 2020b. Image resizing, training and testing are done using the same toolbox.

A. Dataset

We used a dataset consists of 11722 MRI images downloaded from BRATS2017 challenge and Oasis Dataset. Different images are of different sizes. We have resized all images according to the size of the input layer of the corresponding network. Among these, 3250 are normal images and 8472 are tumor images. A total of 80% images are used for training, 10% for validation and remaining 10% for testing

IV. Results and Discussion

A total of 1172 images are used for testing, 325 normal and 847 tumor images. The plot corresponding to the training process of ResNet-50, Resnet-101 and ResNet-152 obtained from the Deep Network Designer toolbox are shown in Fig. 5, 6 and 7 respectively. In all these figures, the first part is showing the accuracy of the training process (blue line) and validation (black dotted line) process respectively. The second part is showing the loss occurred during training process (red line) and validation process (black dotted line) respectively. From these, it is evident that training accuracy is starting from 30% and reaching to100% for ResNet-50. For Resnet-101, it is starting from 50% and reaching to 100%. For ResNet-152, it is starting from 60% and reaching to 100%. The corresponding losses are reaching to minimum.

Segmentation stage is incorporated with all the retrained networks. The segmented output of that of ResNet-152 is shown in Fig. 8. After training and validation, all these networks are tested. The confusion matrices of the testing processes are shown in Fig. 9, 10 and 11. Table. 1 shows the parameters like precision, recall, specificity, F1 score, validation accuracy, error rate and testing accuracy used for evaluating the performance of the network. These are obtained directly from the confusion matrices. From the table, it is evident that ResNet-152 is the most efficient one among the variants of ResNet. Since the validation accuracy and testing accuracy are somewhat closer, we can say that overfitting problem is not there with these models.

TABLE I: Performance of Proposed Detection Networks

Parameters	**ResNet-50**	**ResNet-101**	**ResNet-152**
True Positive (TP)	786	805	812
True Negative (TN)	261	275	287
False Positive (FP)	64	50	38
False Negative (FN)	61	42	35
Precision, P = TP/(TP+FP) (in %)	92.5	94.2	95.5
Recall (Sensitivity), R = TP/(TP+FN) (in %)	92.8	95	95.9
Specificity = TN/(FP+TN) (in %)	80.3	84.6	88.3
F1 score = 2RP/(R+P)	0.93	0.95	0.96
Validation Accuracy (in %)	92.5	94.3	95.9
Error rate (testing) = False/Total (in %)	10.7	7.8	6.2
Testing Accuracy (in %)	**89.3**	**92.2**	**93.8**

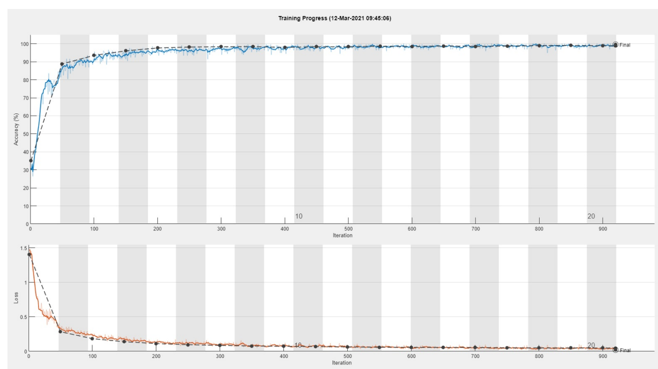


Fig. 5: Training accuracy and loss curves of ResNet-50

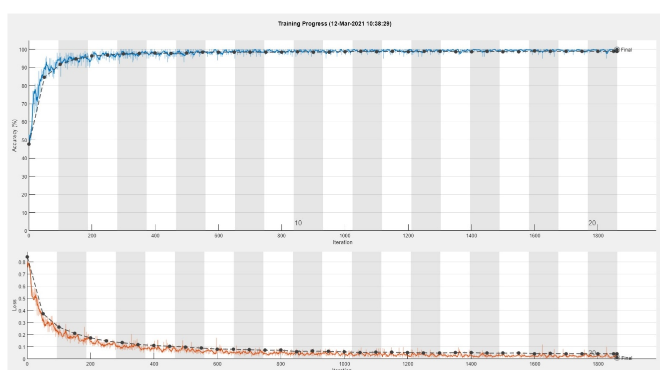


Fig. 6: Training accuracy and loss curves of ResNet-101

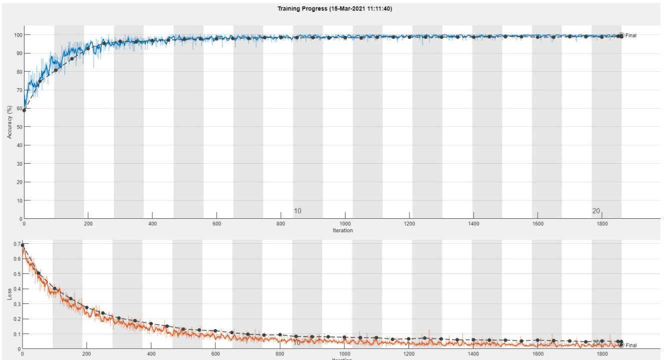
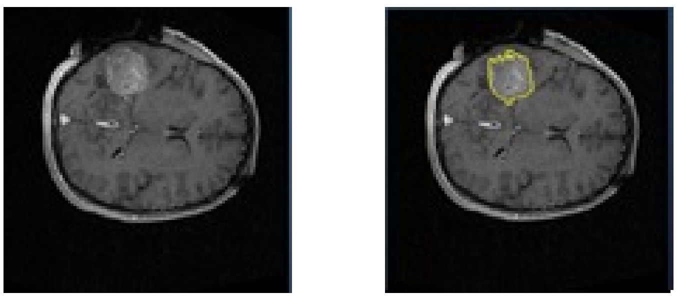


Fig. 7: Training accuracy and loss curves of ResNet-152



(a) (b)

Fig. 8: (a) Input Tumor Image and (b) Segmented output

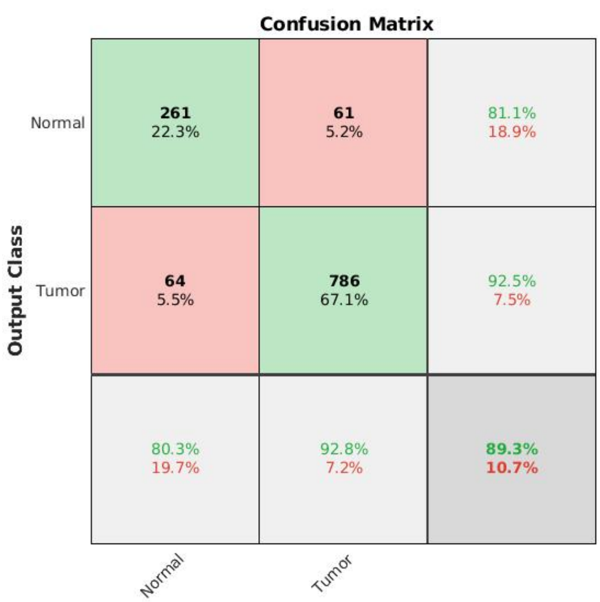


Fig. 9: Confusion matrix of ResNet-50

Fig. 10: Confusion matrix of ResNet-101

Fig. 11: Confusion matrix of ResNet-152

V. Conclusion

In this paper, we proposed a comparative analysis of different variants of ResNet like ResNet-50, ResNet-101 and ResNet-152. All the networks are modified by the method of transfer learning by replacing the last three layers of the existing models. Then all are retrained for verifying whether they are suitable for brain tumor detection. From the obtained results, we can conclude that ResNet-152 retrained model outperforms all the others. These networks can be used for automating the brain tumor detection process. As a future work, we can have an analysis of other efficient classifiers with them and make use of these networks for classifying other diseases. Also, we can check whether these can be directly used for analyzing real time data. These networks can be used as a base for developing new efficient networks for brain tumor detection and classification.

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