Brain Tumor Magnetic Resonance Image Classification: A Deep Learning Approach

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BRAIN TUMOR MAGNETIC RESONANCE IMAGE CLASSIFICATION: A DEEP LEARNING APPROACH

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Abstract:

From the past decade, many researchers are focused on the brain tumor detection mechanism using magnetic resonance images. The traditional approaches follow the feature extraction process from bottom layer in the network. This scenario is not suitable to the medical images. To address this issue, the proposed model employed Inception-v3 convolution neural network model which is a deep learning mechanism. This model extracts the multi-level features and classifies them to find the early detection of brain tumor. The proposed model uses the deep learning approach and hyper parameters. These parameters are optimized using the Adam Optimizer and loss function. The loss function helps the machines to model the algorithm with input data. The softmax classifier is used in the proposed model to classify the images in to multiple classes. It is observed that the accuracy of the Inception-v3 algorithm is recorded as 99.34% in training data and 89% accuracy at validation data.

Keywords: Brain tumor, deep learning, Magnetic resonance images, Softmax

1. Introduction

The developments in the medical field support the medical practitioners to facilitate the patients effectively. With the utilization of artificial intelligence (AI) in the health care helps the medical domain to serve more to the patients [1]. According to the statistics of 2019, most of the deaths in the world are happened due to the cardiovascular diseases and in the next place the cancer diseases are occupied [2]. Brain tumor disease is one of the life threating diseases in the world [3]. Magnetic Resonance Imaging (MRI) is one of the safest imaging techniques that extracts the good images and helps in the process of medical diagnosis. Many researchers are focused on improving the quality of the MR images and also to develop the new methods for quicker and easy medical diagnosis from the MR images. This study concentrated on the brain tumor detection from MR images [4-5].

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The major issues related to the manual diagnosis process is time consuming, interpretation is difficult and costly. To overcome these issues, there is a necessity for computer aided diagnosis (CAD) tool. In the recent years, many automated CAD approaches for brain tumor detection were developed [6]. Approximately, they are classified in to two categories: supervised and unsupervised mechanisms. In most of the cases, supervised mechanisms are performed better when compared against the unsupervised mechanisms. Major brain tumor detection techniques are depend on the segmentation and less importance are given to the feature extraction and classification. This will improve the performance of the CAD process in the MR images. Deep learning mechanism is one of the efficient approaches to classify the tasks. Recently, deep learning approach is employed in the medical diagnosis for classifying the abnormal brain images [7]. Deep learning approaches are important in identifying many diseases like lung cancer and breast cancer [8].

The traditional machine learning techniques are considered as the basics for the proposed deep learning approach. The drawbacks of the prediction models motivate the researchers to focus on the new machine learning mechanisms to improve the accuracy of the image classification. Deep learning is considered as the subset of the machine learning which became more popular with respect to effective prediction from extensive data of text or image. At another side, deep learning is efficient in finding the results from the larger dataset [9]. In medical image processing, the deep learning approaches are considered for identifying the disease effected part in the images. The applications of deep learning approach are not limited to image processing and it can be applied to much object recognition, activity monitoring and many more. The accuracy of the prediction models in deep learning approach depends on the sample data set and its training mechanism which leads to better results. Transfer learning is applied to the deep learning models to reduce the limitations of training the data samples. Transfer learning is a mechanism where the larger dataset features are deployed to the smaller dataset to train them with extracted features [10].

This paper concentrated on developing the deep learning approach for brain tumor detection in MR images. Section 2 deals with the related work regarding the deep learning mechanisms in brain tumor detection. Section 3 explains the convolution neural network and Inception v3 models. Section 4 deals the brain tumor dataset and their properties. Section 5 explains about the result analysis with respect to accuracy. Finally, section 6 concludes the research work.

2. Literature Survey

Machine learning mechanisms play a crucial role in different fields like preventive medicine and medical diagnosis. Only small part of work has been carried in brain tumor detection using the MR images. Most of the researchers concentrated only on the traditional machine learning approaches to deal with MR images. Some of the algorithms used the deep learning mechanisms for brain tumor detection.

In [11], the authors developed the framework called as Convolution Neural Network (CNN) to deal with classification of different type of brain tumor datasets such as VGGNet,

AlexNet and GoogLeNET. The proposed algorithm identifies the region of interests in the brain MR images. It also performs the fine tuning process to the image data set for further classification. The authors achieved 98.6% accuracy in classification of brain tumor images by applying the VGGNet architecture.

In [12], the authors proposed the classification mechanism by using the deep learning approach. The image features are extracted and used in the aggregation and classification process. They used 5-fold mechanism for classification at the patient's side. The proposed mechanism achieved 98% accuracy in the image classification. This work stated that the automated classification models achieved better accuracy compared against the manual classification mechanisms. Another classification mechanism is proposed [13] using the capsule network method (CapsNets). This method improves the classification accuracy in the brain tumor MR images by modifying the convolution layer. This research work claimed that the accuracy has been improved by 86.5% at convolution layer. The CapsNets achieved the accuracy by using the 64 feature map.

In [14], the authors developed the CNN model by adopted the deep learning approach which was applied to the brain MR images. They developed five classification models and among them second model shown better approximation in the classification of MR images. The proposed architecture contains the RELU layer Max Pool layer and contains the 64 hidden neurons. The proposed model achieved 98.5 % accuracy at training phase and 84% accuracy at validation phase. The 2D-DWT [28] and Gabor filter are used for brain MR image classification in [15]. This research work achieved 92% accuracy by applying the back propagation neural networks to the system.

The authors in [16] proposed the classification model based on the neural network mechanism. This model is employs the image segmentation to retrieve the tumor region from the image dataset. The authors employed different noise reduction techniques and transformation mechanisms to improve the prediction accuracy. They considered two data sets to determine the accuracy. The proposed model achieved 90.6% accuracy and classified the data set with different grades. To address the grading mechanism, 3D-CNN model was proposed in [17]. This model automatically grades the glioma from MR images. The proposed model has two functionalities: one is identifying the region of interest and grading the glioma. The 3D-CNN model achieved 89.5% accuracy at whole system and 92.9% accuracy in finding the region of interest.

In [18], the authors developed the hybrid approach by combining the genetic algorithm with convolution neural network to classify the brain MR images. The proposed system uses the genetic algorithm for choosing the CNN structure. This model achieved 90.9% accuracy in classification of Pituitary, Meningioma and Glioma images. In [19], the authors used real time dataset from the United States hospitals. They applied customized classification with the help of Wndchrm tool. This tool uses the deep learning approach for convolution neural networks by measuring the neighbourhood distance. They achieved the accuracy of 92.8% with the proposed setup. The authors in [20] used the CNN models to classify the MR images. They developed the ConvNet mechanisms to slice and patch the MR

images. The authors also considered the existing models like VGGNet to classify the MR images. The proposed model achieved 97% accuracy on different datasets.

3. Dataset

The Brain MR image Dataset contains the 3064 T1-weighted images [5]. The dataset contains three types of tumours such as Glioma, Meningioma and pituitary. The resolution of the images is taken as 512×512. We trained the images though the Inception-V3 CNN model and compared the accuracy with pretrained-VGG16 model and ResNet-50 model. The dataset is spitted in to three segments for training phase, testing phase and validation phase. The dataset for training is used for model learning, the testing data is used for evaluating the model and the validation data set is used for tuning the parameters. Figure 1 shows the sample images of the dataset.

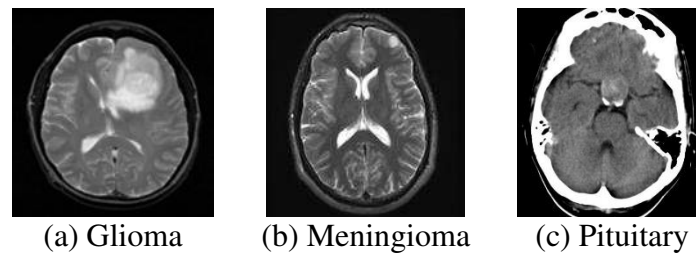(a) Glioma   (b) Meningioma   (c) Pituitary

Figure 1: Different Types of Brain MR images

4. Proposed Model

The proposed model is composed of different layers and pre-training mechanisms. Figure 2 explains about the pre-processing model, training and testing phases and brain tumor prediction. The proposed model uses the deep learning approach and hyper parameters. These parameters are optimized using the Adam Optimizer and loss function. The loss function helps the machines to model the algorithm with input data. Gradually, loss function minimizes the prediction error with the help of some optimization mechanisms. Adam Optimizer is used to optimize the parameters like sparse gradients.
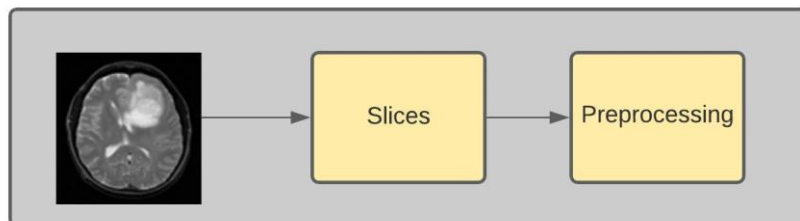

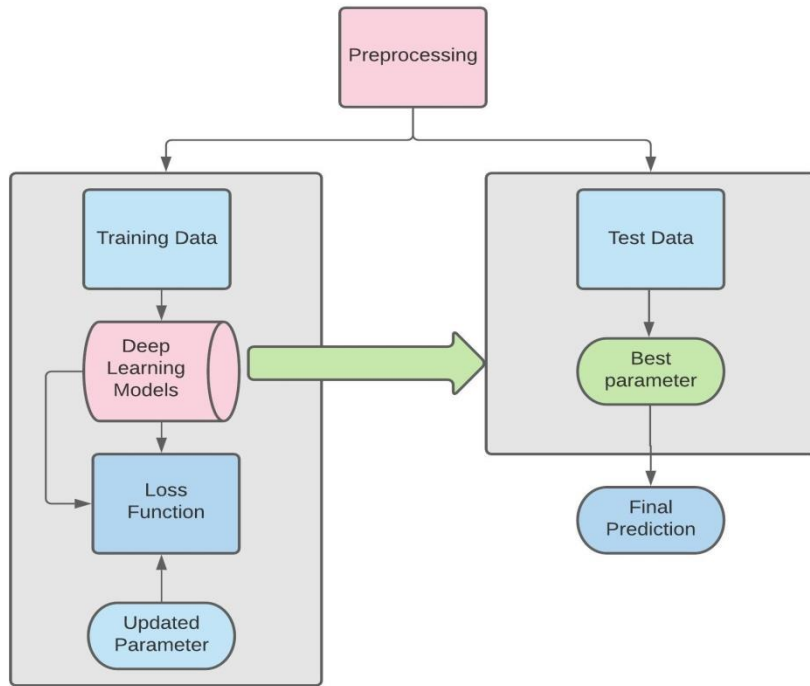Figure 2(a) Pre-processing stage in Proposed Deep Learning Model

Figure 2 (b): Proposed Deep Learning model with Training, Testing and Validation Phase

4.1 Pre-trained Inception-V3

Figure 3 shows the Pre-trained Inception-V3 model which is adapted from GoogleNet [21]. This network consists of 11 modules of inception and each inception module is composed of convolution layer, activation layer, Max pooling layer and Normalization layer. These inception modules help to retrieve maximum number of features from the input images. In the pre-trained Inception-V3 deep learning architecture, some of the inception modules at bottom layers are removed and concatenated the features from the inception modules from the top to perform the classification in the Brain MR Image datasets. The last inception module in the architecture is concatenated with the fully connected layers, global average pooling and extracted features of the images from inception modules. To overcome the over fitting problem in the proposed model, the dropout layer is followed after the global average polling layer. The proposed model extracts the features from the fully connected layer and forwards the extracted features to the classifier. The softmax classifier is used in the proposed model to classify the images in to multiple classes.

4.1.1 ReLU Activation Function

The proposed deep learning model uses the rectified Linear Unit (ReLU) activation model in convolution layer. The functionality of the activation function is to convert the input weights in to the output to the next layer [22]. ReLU is usually employed in the convolution hidden layers. Eq. 1 shows the representation of ReLU in convolution layer.

$$f(x) = \max(0, x) \qquad (1)$$

Where x represents the input value, if x>=0, then it converts the negative input in to 0, if x<0 then the output becomes 1. Hence, if the input value is 0 then we consider that the neuron is dead and it will not be considered.

4.1.2 Loss Function

Loss function is used to compute the error between the true label values and predicted values. Later error is reduced using the optimization mechanism. In this research work, the cross entropy loss function is used to calculate the error [23]. As we are performing the multiclass classification of the MR images so we considered multi class cross entropy. Eq. 2 shows the multi class cross entropy.

$$L(X_i, Y_i) = -\sum_{j=1}^{c} y_{ij} * \log(p_{ij}) \qquad (2)$$

Where X_i represents the input value and the Y_i represents the one-hot encoding target value (y_{i1}, y_{i2},…y_{ic}).

$$y_{i,j} = \begin{cases} 1, & i \in j \\ 0, & otherwise \end{cases} \qquad (3)$$

$$p_{i,j} = f(x_i) \qquad (4)$$

4.1.3 Optimization Mechanism

In the proposed deep learning mechanism, we used adaptive moment estimation (Adam) optimizer to reduce the loss [24]. Adam optimizer is a grouping of stochastic Gradient Descent (SGD) method and RMSprop.

In [25], the SGD method was explained with the Eq. 5.

$$\begin{aligned} K &= K - \eta \times dK \\ g &= g - \eta \times dg \end{aligned} \qquad (5)$$

Where dK represents the derivative of the weights, dg represents the derivatives of bias for every epoch.

Eq. 6 shows the SGD with movement Z, the gradients mean movement is range from 0 and 1.

$$\begin{aligned} Z_{dK} &= \beta \times Z_{dK} + (1 - \beta) \times dK \\ Z_{dg} &= \beta \times Z_{dg} + (1 - \beta) \times dg \end{aligned} \qquad (6)$$
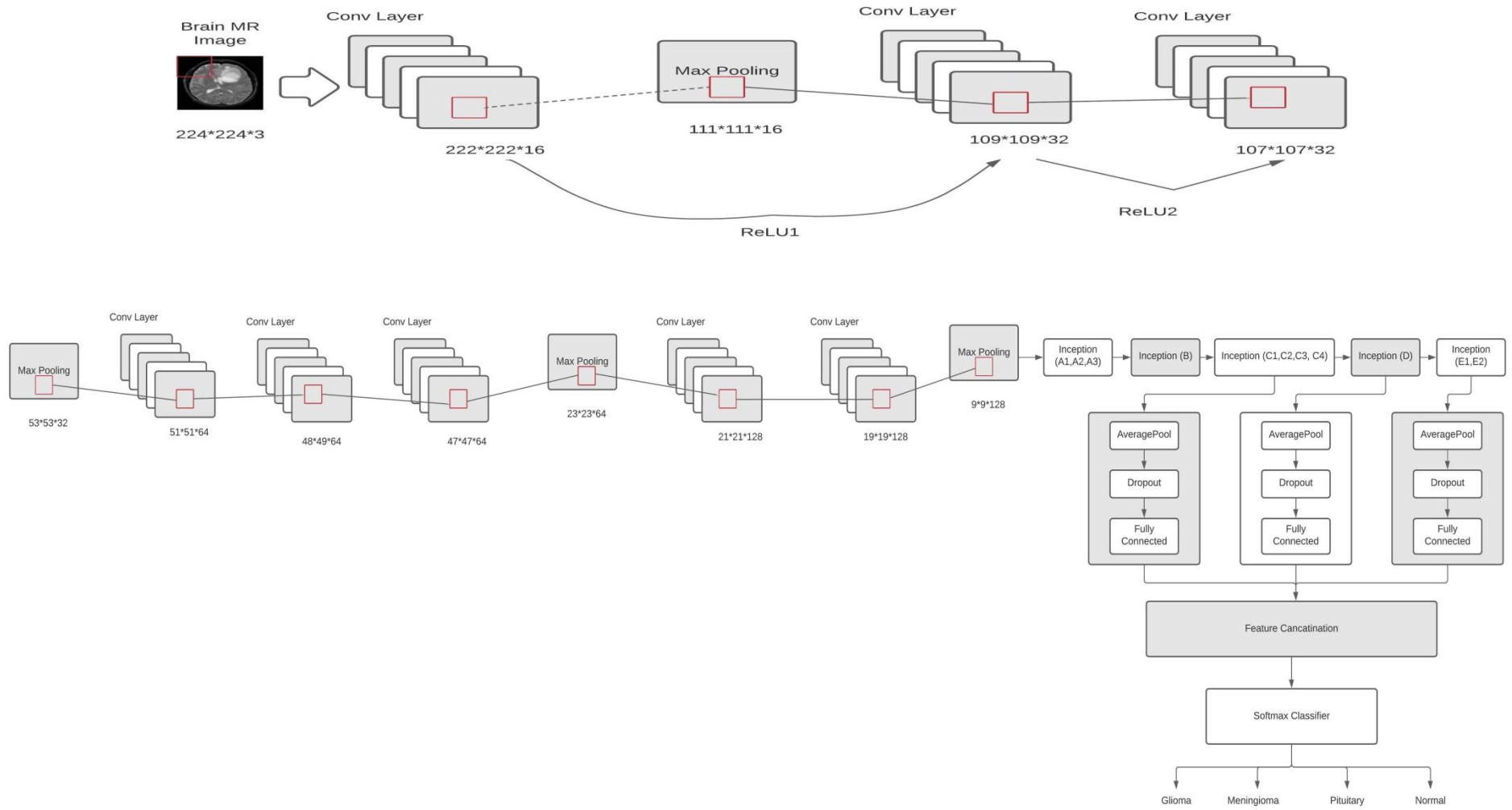
Figure 3: Proposed Inception-V3 Architecture

4.2 VGG-16 Model

The pre-trained VGG-16 CNN model is used in our research work. VGG-16 model is modified by removing some of the layers to overcome the over fitting issue. In this model, we considered 16 convolution layers which are proposed in [26]. The image input size is taken as 224×224×3 and considered 16 convolution layers with 3×3 filter size. This network considered 5 max pooling layer of size 2×2. Figure 4 shows the architecture of the VGG-16 model and it contains 2 fully connected layers along with softmax to classify the images at the top of the model.
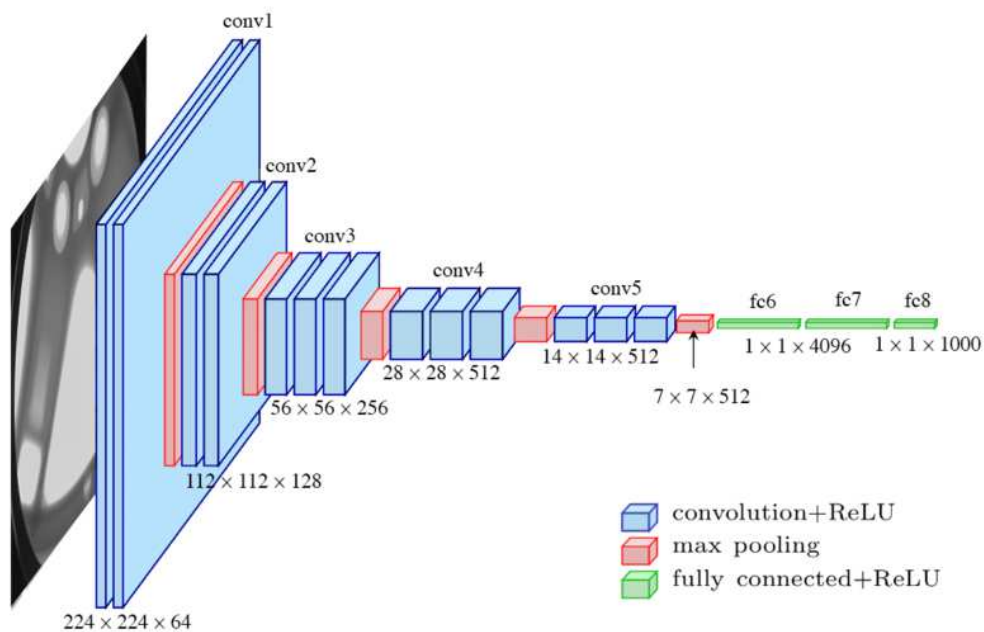

Figure 4: Pre-Trained VGG-16 Architecture [26]

4.3 ResNet50 Architecture

The ResNet50 is a deep CNN model which is developed by Microsoft corporation in 2015 [27]. It contains the 50 layers with 26 million parameters in the network. In ResNet, the learning process is carried out from residuals which are subtracted features from input layers. Figure 5 shows the Resnet 50 architecture where it skip link to forward the information across layers. This research work used the pre-trained ResNet50 architecture to compare the performance with the proposed architecture.
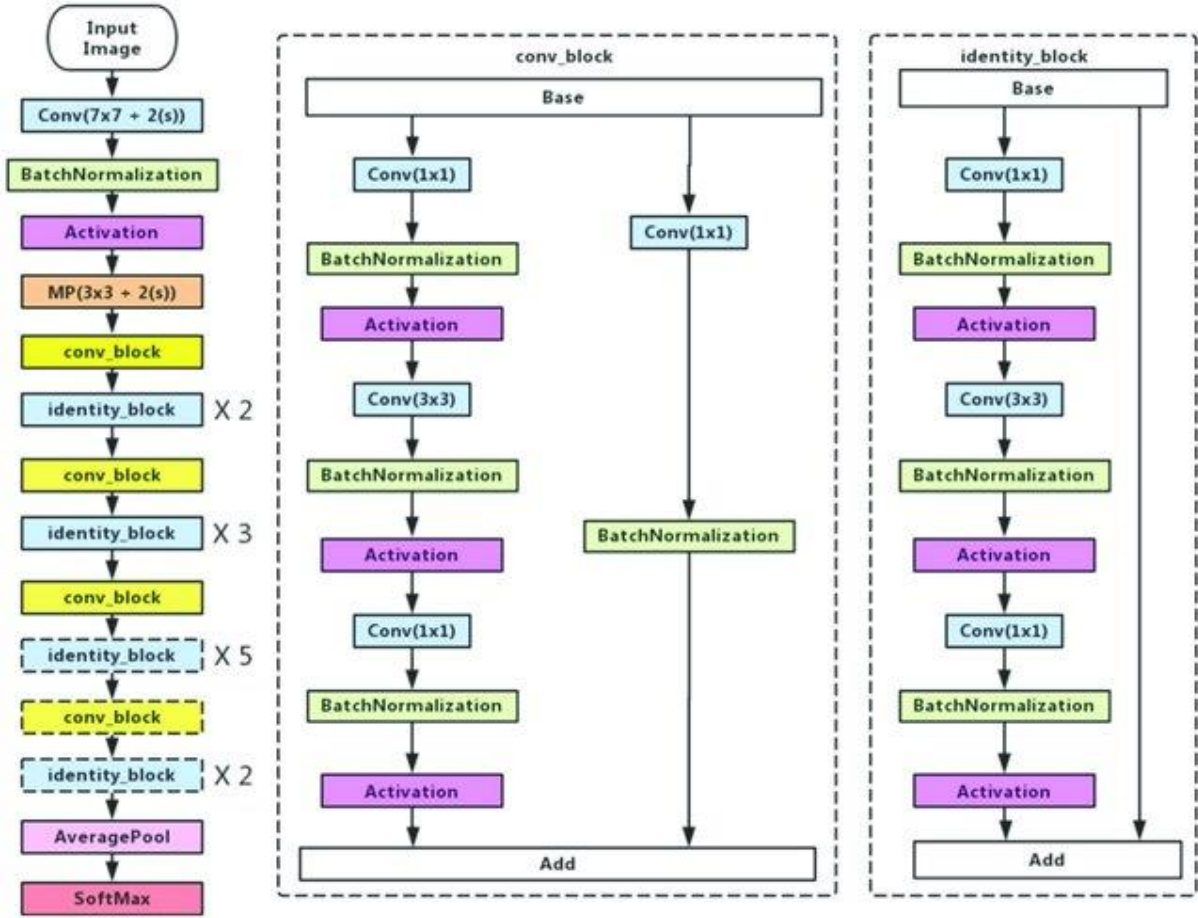
Figure 5: Pre-Trained ResNet 50 Architecture [27]

5. Results and Discussion

To evaluate the performance of the proposed model, we used the following parameters such as accuracy (A), precision (P), recall (R) and F1-score. These parameters measure the predicted and true values from Eqs. 7 to 10 respectively.

$$A = \frac{T_p + T_N}{T_P + F_N + F_P + T_N} \quad (7)$$

$$P = \frac{T_p}{T_P + F_P} \quad (8)$$

$$R = \frac{T_p}{T_P + F_N} \quad (9)$$

$$F1 = 2 \times \frac{P \times R}{P + R} \quad (10)$$

Where T_p represents true positive, T_N represents true negative, F_p represents false positive and F_N represents the false negative.

The proposed model is trained with different hyper-parameters which are given in Table 1. Tensorflow and Keros with backend have been used to train the deep learning model in the proposed architecture. The 80% of the data is allocated for training and 20% data is allocated for testing. The computation of evaluation metric is done by using the ground truth labels and predicted labels.

Table 1: Hyper-Parameters for Model Training

Parameter	Value
Number of Epochs	20
Learning Rate	0.0001
Batch Size	20
Optimizer	Adaptive Moment Estimation
Loss Function	Multi class cross function
Classifier	Softmax

Table 2 shows the precision, recall and F1-score of the different blocks in Inception-v3 model. The blocks available at the bottom layers in the Inception-v3 extracts the features and forwards them to the classifier to classify the brain tumor images.

Table 2: Precision, Recall and F1-score of different blocks in proposed model

Blocks	classes	Precision (P)	Recall (R)	F1-Score
Inception-E	Glioma	98.00	98.00	99.00
	Meningioma	99.00	96.00	98.00
	Pituitary	97.00	100.00	98.00
	Normal	100.00	100.00	100.00
Inception-D	Glioma	100.00	99.00	99.00
	Meningioma	97.00	98.00	97.00
	Pituitary	97.00	98.00	97.00
	Normal	100.00	100.00	100.00
Inception-C	Glioma	100.00	98.00	99.00
	Meningioma	100.00	97.00	98.00
	Pituitary	98.00	99.00	99.00
	Normal	100.00	100.00	100.00

Table 3 shows the comparison of accuracy of proposed and existing algorithms. The proposed Inception-v3 CNN architecture achieved 99.34 % accuracy on the training data and 89% accuracy on the validation data. By using the transfer learning process, the pre-trained VGG-16 model achieved 91% accuracy on the training data and 86% accuracy on the validation data, ResNet-50 achieved 92% accuracy on the training data and 77% accuracy on the validation data. Figs.6 to 8 shows the accuracy of training and validation of Inception-v3, VGG-16 and ResNet-50.
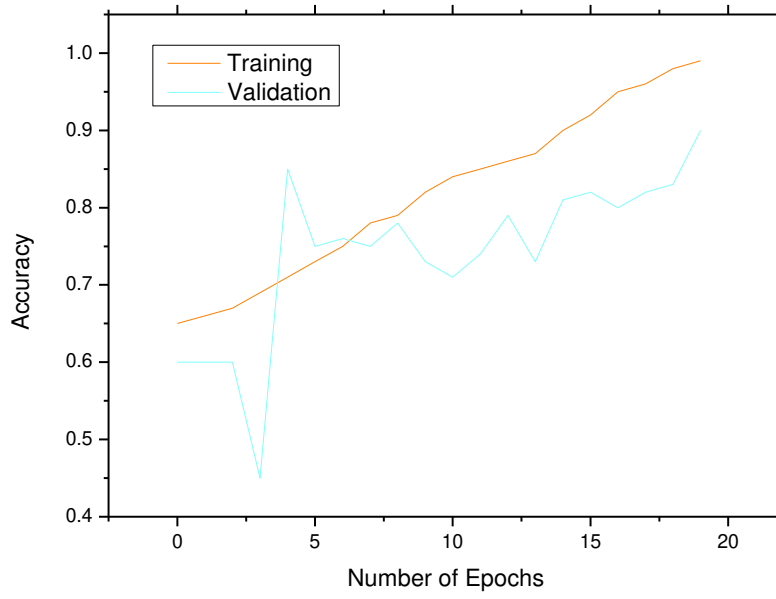
Figure 6: Accuracy of Proposed Inception-V3 model
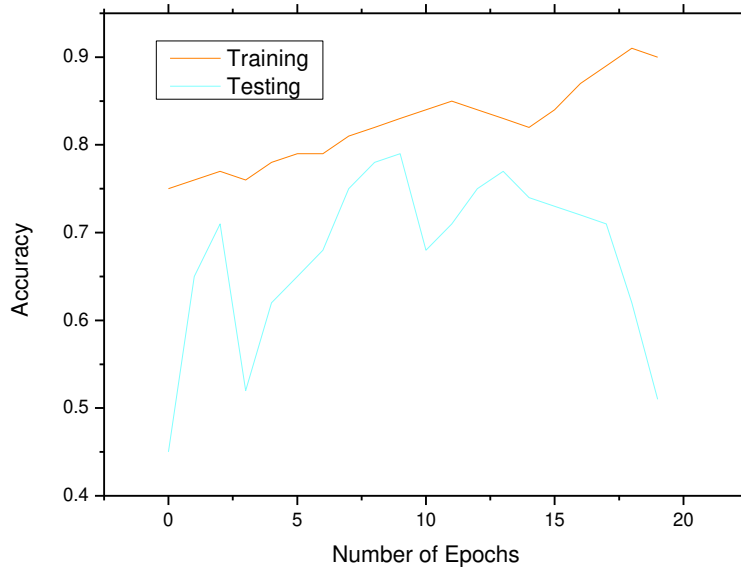

Figure 7: Accuracy of VGG-16 model

Figure 8: Accuracy of ResNet-50 model

Figure 9 shows the region of convergence (ROC) of the proposed and existing models. The ROI of the proposed Inception-v3 model achieved good results for each class of brain tumor (0,1,2,3), class-0 represents the Glioma, class-1 represents the Meningioma, class-2 represents the pituitary and class-3 represents the normal brain.
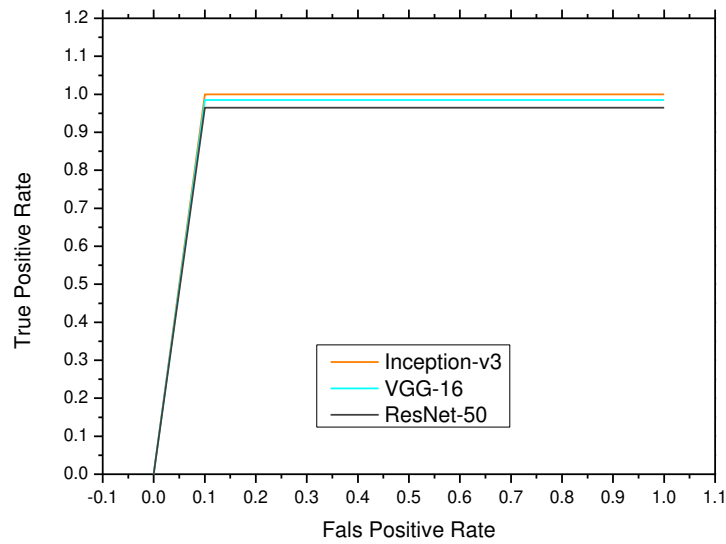

Figure 9: ROC plot for Proposed and Existing models

Table 3: Comparison of Accuracy

Model	Features	Accuracy
CapsNet [13]	Model based Mechanism	86.58
CNN[14]	Model based Mechanism	84.27
DWT-Gabor [15]	Neural Network	89.90
VGG-16 [26]	Log-Based Softmax	91.26
ResNet-50 [27]	Residual	92.17
Proposed Inception-v3 CNN model	Inception Block	**99.34**

6. Conclusion

This paper explained the deep learning mechanism for detection of brain tumors in MR images. In the proposed pre-trained Inception-V3 deep learning architecture, some of the inception modules at bottom layers are removed and concatenated the features from the inception modules from the top to perform the classification in the Brain MR Image datasets. The last inception module in the architecture is concatenated with the fully connected layers, global average pooling and extracted features of the images from inception modules. The proposed model extracts the features from the fully connected layer and forwards the extracted features to the classifier. The softmax classifier is used in the proposed model to classify the images in to multiple classes. Tensorflow and Keros with backend have been used to train the deep learning model in the proposed architecture. The accuracy of the proposed model is recorded as 99.34% which is high compared to the VGG-16 and ResNet-50 models. In the future, we are concentrating on the combination of DensNet model and Inception-v3 model to improve the accuracy.

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