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Classification and Detection of Brain Tumor through MRI Images Using Various Transfer Learning Techniques

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ABSTRACT

Detection and classification of Brain Tumor in MRI images need exceptionally well expertise. Yet MRI images are mostly used method for imaging structures of interest in human brain. WHO has published data that around 700,000 human beings are suffering from Brain Tumor issues also 86,000 have been treated since 2019. Only 35% is the survival rate of Brain Tumor disease. A systematic and efficient model is needed that can detect and classify the disease. A series of work into this field had been carried out but still robust and more accurate system is needed. There is major scope into Deep Learning by using various transfer learning techniques. Still there is some scope to have very effective and automated model to classify and to detect Brain Tumor at early stage. Various state-of-the-art algorithms have been discussed in this study.

KEYWORDS

Brain Tumor, Transfer Learning, MLP (Base Line), Xception, Inception V3, CNN, VGG16, VGG19, ResNet50, Deep Neural Networks/

Introduction

The cause of brain tumor is a mass or development of unusual cells in the brain. Brain Tumor mainly classified into noncancerous and cancerous [6]. The development rate of brain tumor affects the capacity or working of sensory system of the body [9]. The indications of a brain tumor differ significantly and rely upon the size, area and development pace of brain tumor.

In 2016, World Health Organization (WHO) has given arrangement of tumors of focal Nervous System in both a reasonable and pragmatic development [1]. In the issue of the huge number of patients and the long waiting lines, a robust computerized framework would be of an incredible advantage to both the physician and the patient [8]. Thus, a mechanized identification or classification of Tumor conspire is required [2].

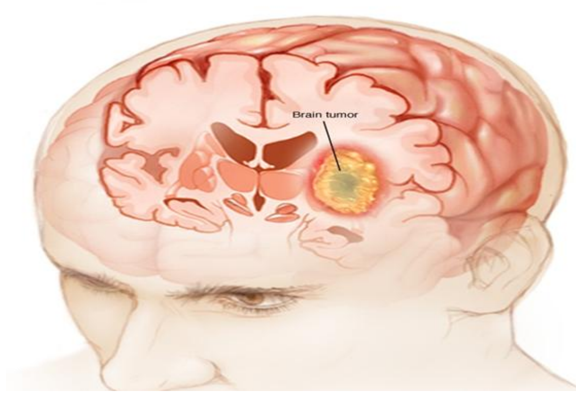

Figure 1. Brain Tumor spot

Division and classification of Brain Tumor utilizing MRI images has extraordinary effect for foreseeing the development pace of Brain Tumor just as contriving the treatment plans [3].

Different systematic approaches have been proposed by many authors. Brain Magnetic Resonance Imaging (MRI) has been one of the reliable techniques for many researchers. A brain tumor can frame in the synapses, or it can start somewhere else and spread to the cerebrum. As the tumor develops, it makes tension on and changes the capacity of

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encompassing brain tissues, which causes signs and manifestations, for example, migraines, queasiness and hearing issue, unexplained queasiness or retching, discourse troubles.

Literature Survey

The brain is most significant piece of a human body so it is important to distinguish cerebrum related illnesses at beginning phase by exceptionally proficient way. Numerous specialists have proposed diverse mechanized framework for disease segmentation. Numerous analysts have utilized various kinds of datasets like MRI, BRATS and CT scan images of cerebrum and some more.

Naik, J., and Patel, S. [7] have proposed work in arrangement and identification of Brain MRI utilizing Naïve Baysian and Decision Tree calculations. They have accomplished some encouraging result in term of exactness with 96% and sensitivity with 93%.

Louis, D. N. et al. [5] have concocted quantitative overview for improved fitting patient treatment and better order for clinical preliminaries and trial studies and more exact arrangement for epidemiological reason. Evaluating of chosen CNS tumors has been utilized as dataset given by World Health Organization (WHO). They have summed up the investigation with nonattendance of atomic information should be plainly assigned.

Isin, A., Direkoglu, C., and Sah, M. [3] have done survey on MRI-based cerebrum tumor picture division utilizing profound learning strategies. They have proposed the diverse cutting edge strategies dependent on profound learning, and a concise review of conventional procedures. They have distinguished some future enhancements and changes in CNN structures and expansion of integral data from other imaging modalities.

Mohsen, H., El-Dahshan, E.- S. A., El-Horbaty, E.- S. M., and Salem, A.- B. M. [6] have proposed a productive strategy which consolidates the Discrete Wavelet Transform (DWT) with Deep Neural Network (DNN) to arrange the cerebrum MRIs into Normal and 3 kinds of harmful brain tumors. They have utilized 66 genuine human cerebrum MRIs with 22 ordinary and 44 irregular pictures as dataset. They have proposed that DWT could be utilized with the CNN for future work.

Amin, J., Sharif, M., Yasmin, M., and Fernandes, S. L. [1] have proposed Deep Convolutional Neural Networks for Big Data Analysis for cerebrum tumor location. They have outlined a model on eight datasets and five MRI modalities.

Shil, S. K., Polly, F. P., Hossain, M. A., Ifthekhar, M. S., Uddin, M. N., and Jang, Y. M. [10] have concocted an improved Brain Tumor Detection and Classification Mechanism. They have applied order utilizing Support Vector Machine (SVM) calculation for characterization and accomplished some encouraging outcomes with arrangement precision of 99.33%, Sensitivity 99.17%, and Specificity 100%.

ARI, A., and HANBAY, D. [2] proposed a Deep Learning based Brain Tumor characterization and identification framework by utilizing ELM-LRF order strategy. Characterization precision of 97.18% was gotten with the proposed ELM-LRF strategy.

Sajid, S., Hussain, S., and Sarwar, A [9] have proposed framework utilizing crossover CNN. They have summed up the examination that hybrid model endeavours the adequacy of profound convolutional neural organizations and takes favourable circumstances of multimodal MRI information to section MR pictures. They have recognized as future degree that improved exhibition can be accomplished with a more noteworthy number of preparing models.

Khan, M. A., Lali, I. U., Rehman, A., Ishaq, M., Sharif, M., Saba, T., et al. [4] have accompanied a system of marker-based watershed calculation and staggered need highlights for Brain Tumor identification and characterization. MICCAL-BRATS 2013 dataset of pictures has been utilized in this examination. They have plot that proposed strategy is executed on profound figuring out how toimprove the framework precision as future degree.
Rehman, A., Khan, M. A., Saba, T., Mehmood, Z., Tariq, U., and Ayesha, N. [8] learned about Microscopic Brain Tumor identification and grouping utilizing 3D CNN and highlight choicedesign. They have reached on resolution that proposed 3D CNN model portions the tumor with high exactness and less mistake rate. Diverse datasets like

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BRATS 2015, BRATS 2017 and BRATS 2018 have been utilized for study. Few have summed up the examination by recommending that a profound fortification learning model can be executed for cerebrum tumor grouping in not so distant future.

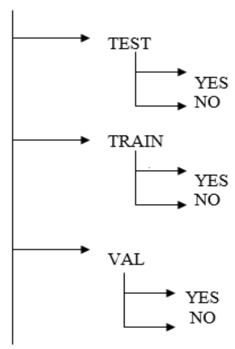
Methodology

The following subsections explain proposed material, methodology and methods.

Dataset

The dataset is available at https://www.kaggle.com/ brain-mri-images-for-brain-tumor-detection.

This dataset has three classes of MRI images like yes, no and pred. There is total 1500 MRI images affected by brain tumor disease and another 1500 samples of images with no brain tumor. Study has used 60 images to predict the outcome. Above classes have been splited into “TRAIN”, “TEST” and “VAL” folders having two classes “YES” and “NO”.



Data Processing

- **Data Augmentation**

The most ideal approach to improve the exhibition of an AI model is to prepare it on more information. The more models the model needs to gain from, the better it will actually want to perceive which contrasts in pictures matter and which don't. More information causes the model to sum up better. One simple method of getting more information is to utilize the information you as of now have. In the event that we can change the pictures in our dataset in manners that safeguard the class, we can show our classifier to overlook those sorts of changes.

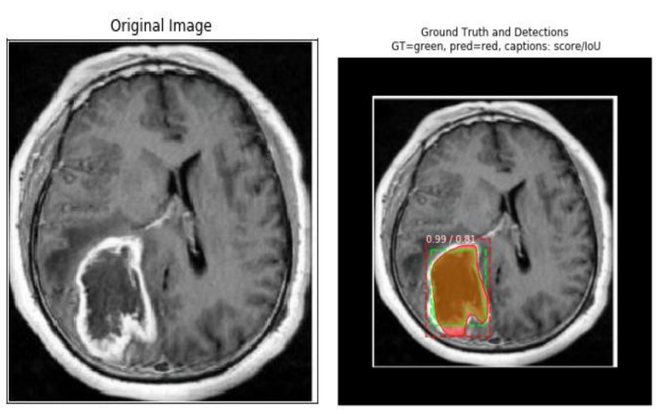


Figure 2. Original image and grounded image

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- **Univariate Analysis**

"Uni" means "one". Univariate analysis is a simplest form of analyzing the data. So in other words if your data has only single variable, is not able to put the causes or relationships. Its main task is to summarize that data and evaluates some patterns in it.

- **Bivariate Analysis**

"Bi" means "two". Bivariate Analysis (BVA) is one of the simplest forms of quantitative analysis. It takes two variables for analysis. Main objective of Bivariate Analysis is to establish empirical relationship between two variables. Bivariate analysis can be helpful in testing simple hypothesis of association.

- **MultivariateAnalysis**

Multivariate analysis (MVA) is based on the principles of multivariate statistics, which involves observation and analysis of more than one statistical outcome variable at a time. Multivariate analysis is very helpful and useful where experimental units and their relationships are important.

Proposed Modeling

For this work, various transfer learning techniques have been studied like MLP, VGG-n, ResNet-n, Xception, Inception V3 and few. We have worked on Keras Library in python version 3.7 to compare the various Transfer Learning Techniques on MRI Images of Brain Tumor.

- **Multilayer Perceptron (MLP)**

The perceptron is the fundamental controlling unit of deep learning concepts. Perceptron and Multilayer Perceptron are the basic foundation to understand the working ethics of Neural Networks.

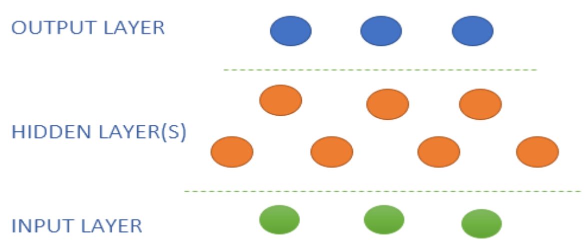

Figure 3. Multilayer Perceptron

MLP is basically built up three different types of layers as we can see in the figure 2. The responsibility of input layer is to receive the input signal. The whole organization needs to have in any case at least one hidden layer. The hidden layer(s) conduct calculations and procedure on the information to create something adequate.

- **VGG-n**

VGG-n stands for Visual Geometric Group for n number of layers. There is series of the convolutional network model from VGG11 to VGG19. The principal goal of the VGG group on profundity was to see how the profundity of convolutional networks influences the precision of the models of enormous scope for image recognition and classification.

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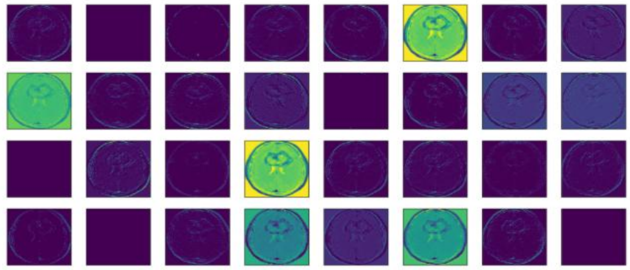

Figure 4. Plot feature map of first conv layer for given image

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure 5. Configuration of VGG 16/19

The base VGG11 has 8 convolutional layers and 3 completely connected layers when contrasted with the most extreme VGG19 which has 16 convolutional layers and the 3 completely connected layers. The various varieties of VGGs are the very same in the last three completely connected layers.

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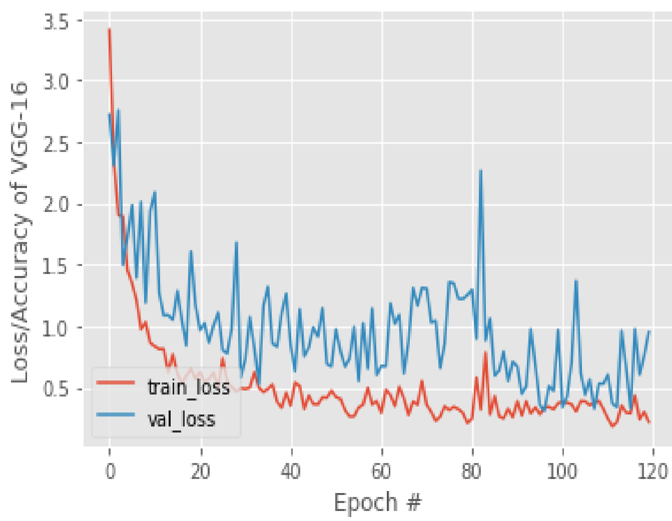

Figure 6. Training Loss and Accuracyon Brain Tumor Classification using VGG16

- **resnet-N**

More profound neural organizations are harder to prepare.ResNet-n stands for Residual Network that is n-layers deep.

ResNet-50 has 48 convolutional layers with attached 1 MaxPool and 1 Average Pool layer. Last two layers are common to every variant of ResNet model.

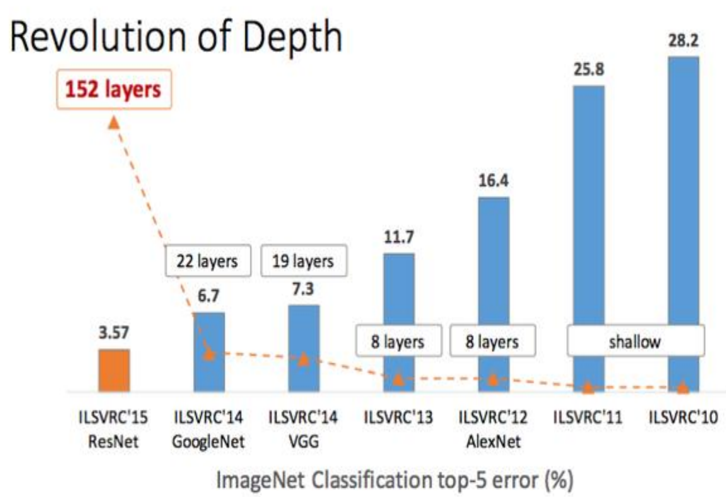

Figure 7. Revolution of Depth

In any case, expanding network profundity doesn't work by essentially stacking layers together. ResNet is an incredible spine model that is utilized every now and again innumerous vision related assignments.

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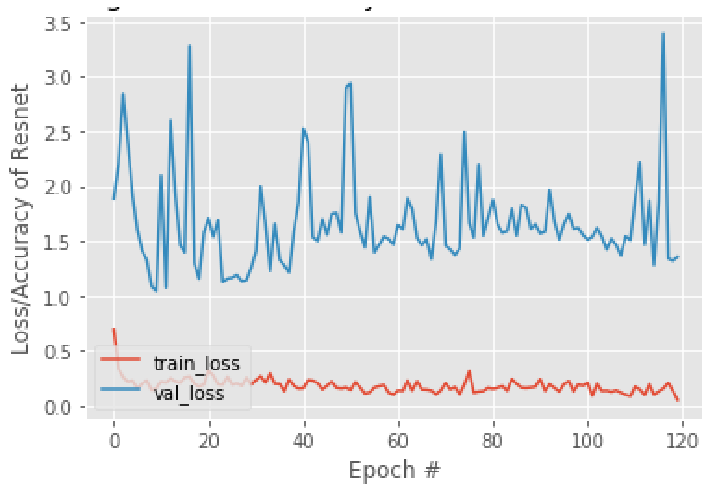


Figure 8. Training Loss and Accuracyon Brain Tumor Classification using ResNet-50

Proposed System based on Proposed Modeling

In proposed work, numbers of different transfer learning techniques have been used along with a CNN. This helps to draw a thin line in terms for classification accuracy of brain tumor images. As depicted in the figure, first and far most a proficient data is required to classify [17]. After acquaint the data, preprocessing starts. In data preprocessing the data augmentation has been done to provide the different caste of images to the models.

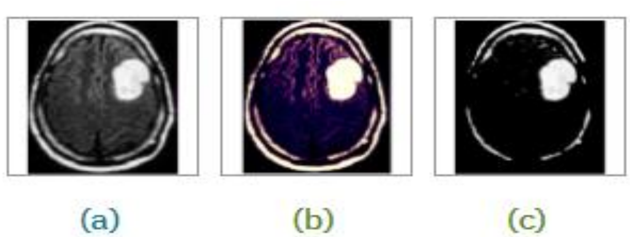
To identify a clear out line of any portion of image, a term wavelet (¥) needs to be calculated. So that we can crop the focused area of any image [14]. A wavelet is a capacity that is characterized throughout a limited time span and has a normal estimation of nothing. The wavelet change strategy is utilized to create capacities, administrators, information, or data into segments of various recurrences, which empowers concentrating every segment independently. All wavelets are produced from a fundamental wavelet by utilizing the scaling and interpretation measure characterized by (1); an essential wavelet is additionally alluded to as a mother wavelet since it is the starting place for different wavelets.

$$¥\,(a,b) = \frac{1}{\sqrt{a}}\,¥\,\frac{t-b}{a} \quad (1)$$

Let us assume that there is only Gaussian Noise present in the image i.e. G(n).

$$G(n) = \frac{1}{2}\int_{\Omega} (\mathrm{n}-\mathrm{c})^2 \qquad (2)$$

where $C(x) \in L^{\infty}(\Omega) \bigcap [0,1]$



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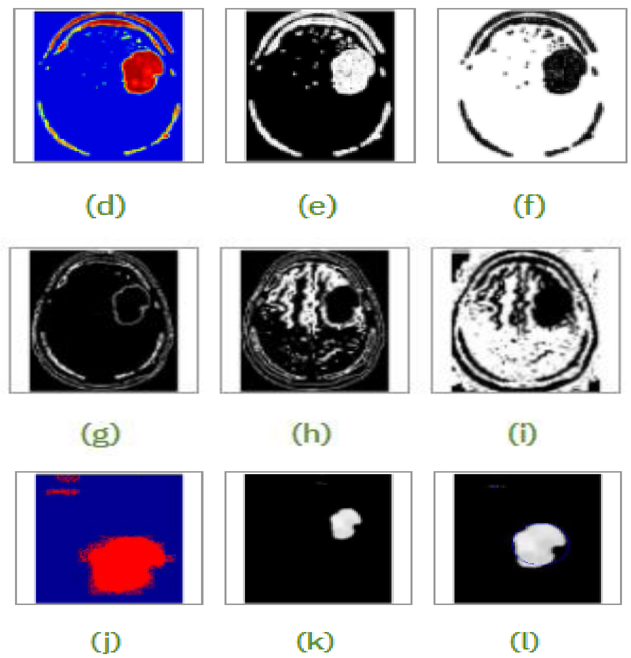

Figure 9. Cropping off the tumor area from image

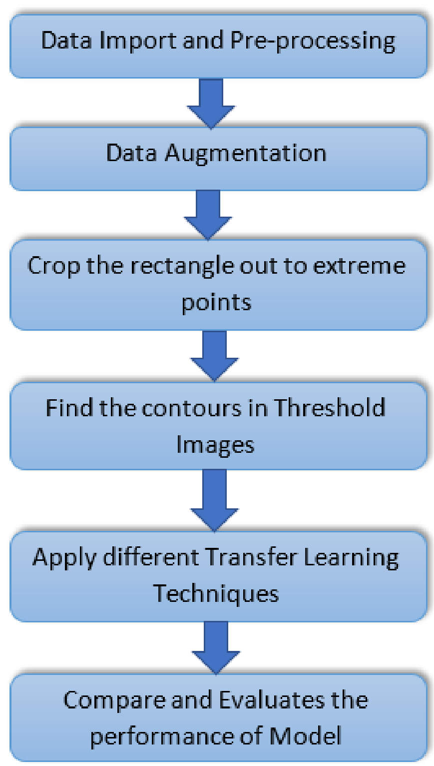

Figure 10. Flow Diagram for Proposed System

After finding the contouring in an image, different transfer learning techniques along with a convolutional neural network have been used to classify the image into two different classes i.e. YES or NO. We have applied number of

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transfer learning techniques like MLP (Baseline), Xception, Inception V3, VGG16, ResNet50, VGG19 and CNN [19]. A comparison chart shows the accuracy attained by different techniques and their summary has been drawn for better comparison.

Results and Discussion

In this segment, the proposed trial results are clarified in mathematical terms. The proposed techniques have been carried out on dataset available athttps://www.kaggle.com/brain-mri-images-for-brain-tumor-detection.

Table 1. Comparative table for accuracy of various Transfer Learning Techniques

Model	Training Accuracy	Val Accuracy	Test Accuracy
MLP(Baseline)	82.78	71.9	60.92
Xception	86.89	-	87.19
Inception V3	93.67	-	92.78
CNN	89.67	91.14	90.67
VGG16	93.71	93.71	95.12
ResNet50	98.09	98.09	89.56
VGG19	97.17	96.89	89.56

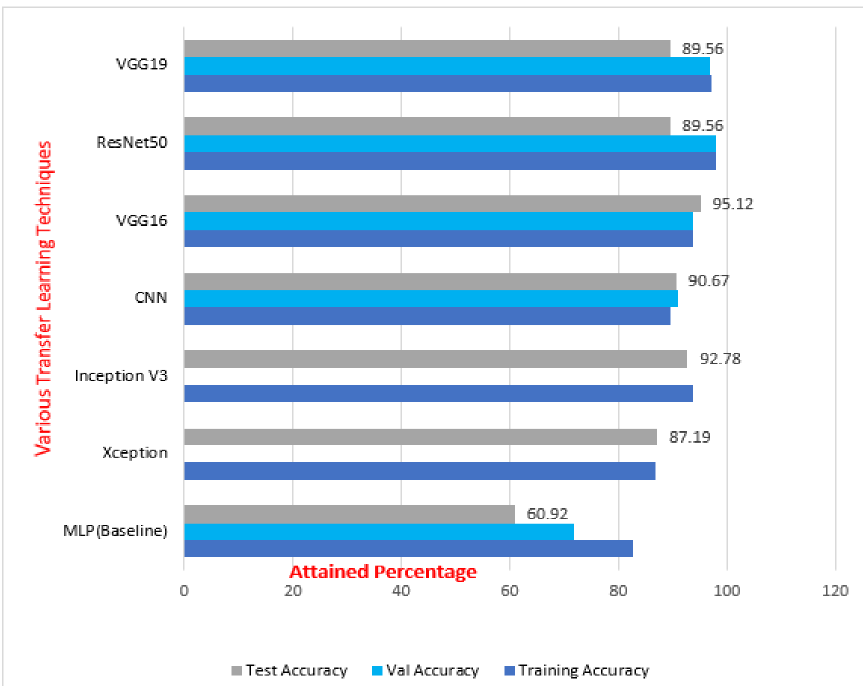

Figure 11. Comparative Line Graph for accuracy of various Transfer Learning Techniques

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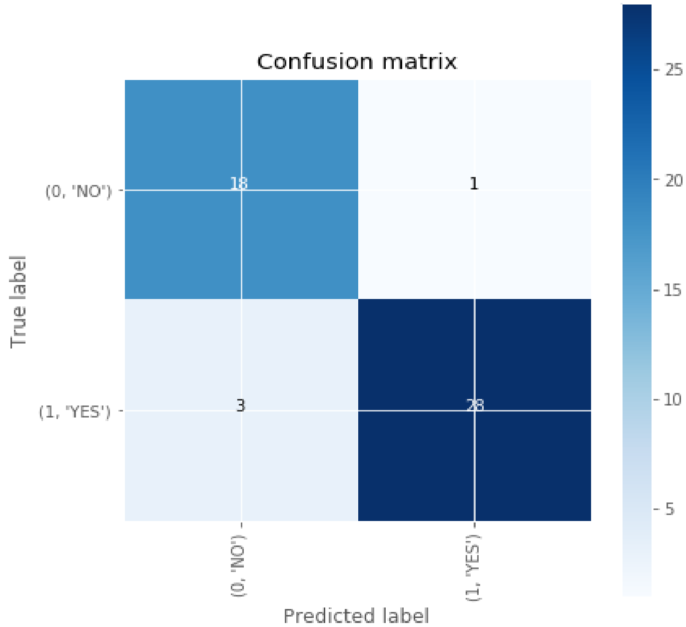

Figure 12. Confusion Matrix

To illustrate the performance of the segmentation or classification by different models, contouring of images has been done to outline the bright spot of brain tumor. The confusion matrix classes ('YES' for having brain tumor and 'NO' for healthy brain) are depicted in figure 12. The results are evaluated on individual modalities and on a convolutional neural network. The confusion matrix for tumor classification results aggregated using all MR images.

Type-I Error has been found on one occasion and at the same time three times TYPE-II Error has been recorded.

Conclusion

This study presents the comparison of accuracy achieved by different transfer learning modalities. The study recorded decent accuracy by using VGG16 transfer learning technique. The performance has been evaluated. Study has proposed a series of different transferlearningtechniques and also study of each modality is summarized. The research work has been carried out on MR images of brain tumor dataset available at www. Kaggle.com. Thiscomparisonmodel can be applied to classify the various images on different diseases on given set of parameters.

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