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# Brain Tumour Detection Using CNN And Transfer Learning

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**ABSTRACT:** Brain tumor is a disease that takes many lives each year. During the diagnosis, the patients rely on the expertise of human for brain tumor detection. This process takes the crucial time and can also be erroneous due to human error. In the past decade transfer learning using the pre trained CNN architectures have shown promising results in this type of classifications. We in this paper are exploring various pre trained CNN Models like *ResNet50*, *InceptionV3*, *VGG16* and use them for transfer learning, We also made our custom CNN Model and compared the accuracies of all the models. The best performance is shown by *VGG16* followed by *InceptionV3* and *Resnet50*.

Dataset was taken from Kaggle and preprocessing and Data Augmentation was used to get a larger and a better dataset which can be fed to the network. The accuracies of the models showed that this method is promising and can be used for detecting brain tumor effectively.

**KEYWORDS:** CNN, Brain Tumor, Transfer Learning

## I. INTRODUCTION

The human body is largely controlled by the brain, which acts as the central controlling organ of speech, thoughts and movements. A brain tumour is a lesion inside the skull, which can affect the brain cells by putting high levels of intracranial pressure on them. The mass of the tumour cells is what affects the brain's functionalities. [1].

In the modern era, *Magnetic Resonance Imaging* (MRI) technique is mostly used to detect brain tumours. Early detection of tumours can lead to the possibility of higher survival rate and treatment amongst the patients. MRI does not cause any pain or radiation and is also a non-brain invasive imaging process [2].

MRI if not done and evaluated by an expert are usually not able to precisely detect or classify the brain tumour clearly, which might lead to serious complications that can cause disabilities amongst the patients. Moreover, the cost of Repetitive MRIs is high and needs expert technicians to handle heavy equipment, which makes it less trustworthy. [3]

This research paper proposes the technique of *Convolutional Neural Networks* (CNN) to identify brain tumours using various models with acceptable accuracy for medical grade application. CNN processes closely knitted data used for image classification, processing and face detection.

## II. RELATED WORK

Many approaches have been previously used for detecting and classifying the brain tumour .Some of them are presented in this section:

Hao Dong, Guang Yang et al. [4] proposed a fully automatic method for brain tumour segmentation ,developed using U-Net based deep convolutional network. The model was evaluated on Multimodal Brain Tumour Image Segmentation (BRATS 2015) datasets. The author employed a comprehensive data augmentation process that includes brightness and elastic distortion based transformation and it is coupled with U-Net, which consist of a down-sampling path and an up-sampling path.

Ramy A. Zeineldin et al. [5] proposed a deep neural network framework for automatic brain tumour segmentation using magnetic resonance FLAIR images. It proposes a deep learning architecture called *DeepSeg*. It is modular decoupling framework. This model consist of two connected core parts based on encoding and decoding relationship. Spatial information is extracted using encoder and the resulting semantic map is fed into decode ,which provides the



full resolution probability map. The author used different pretrained CNN Models such as *ResNet*, *Xception*, *MobileNet*, *NasNet*, *VGGNet* for the study. The proposed architectures were evaluated on (BraTS 2019) challenge including 336 cases of training data and 125 cases of validation. The DICE and Hausdorff scores are in range 0.81 to 0.84 and 9.8 to 19.7 correspondingly.

Heba Mohsen et al. [6] used a dataset of 66 Brain MRI images and segmented them into 4 classes namely normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumours.

Author used Fuzzy C-means for image segmentation, and feature extraction was done using discrete wavelet transform. The reduction was carried out using principle component analysis. Dataset consists of 66 Brain MRI images in which 22 are non-tumorous and 44 are tumorous belonging to any of the three tumour categories discussed above. The CNN used contains 7 hidden layer structure.

Mahmoud Khaled Abd-Ellah et al. [7] in their paper discussed about Two-phase multi-model automatic brain tumour detection using MRI images using CNN. In the first phase, pre-processing, feature extraction and feature classification is done. Feature classification is done using error-correcting output codes support vector machine (ECOC-SVM). The first approach is employed to detect and classify the MR into tumour and non-tumour images.

The aim of the second phase was to localize the tumour in abnormal MR images. It is done using the Region based Convolutional Neural Network. First Phase performance was evaluated using *AlexNet*, *VGG-16* and *VGG-19*. *AlexNet* gave the highest accuracy of 99.55%. 804 3D MRI images were used to evaluate the brain tumour localization phase and a DICE score of 0.87 was achieved. A comparison between previous Classical methods and the newly proposed method in paper was also presented.

Arshia Rehman et al. [8] proposed a deep learning based framework for automatic brain tumours classification using transfer learning. In this paper the author conducted studies using three pretrained CNN architectures which includes *AlexNet*, *GoogLeNet* and *VGGNet*. The tumour were classified in three categories such as meningioma, glioma and pituitary. Using Pretrained CNN Architectures transfer learning is used to extract the features from MRI Images. Patterns are classified using SVM. The dataset used was taken from *FigShare*. It contains 3064 samples collected from 233 patients. In 3064 brain MRI slices 708 belonged to meningioma, 930 are of pituitary and 1426 were of glioma tumour category. The effectiveness of proposed system is calculated using the four major outcomes i.e., true positives (tp), true negatives (tn), false positives (fp) and false negatives (fn). In first phase contrast stretching technique is used for enhancing the MRI images. In the next phase pretrained CNN architectures were used. Fine tuning is also done in this stage. In case of freeze layer strategy, linear classifier is used and *log-softmax* is used in case of fine-tune layers strategy. Highest accuracy achieved is 98.69% using the fine-tune VGG16 network.

Digvijay Reddy et al. [9] proposed paper on Brain Tumour Detection using Image Segmentation techniques. Pre-processing using median filter is employed for noise removal. After this clustering using k-means is used and skull portion was scrapped from the image using morphological operations so that tumour could be easily identified. In the last stage image thresholding is applied followed by levelset segmentation for extracting customer cells. The Evaluation is done using four major factors like true positive (tp), true negative (tn), false positive (fp) and false negative (fn). The author stated that results have shown that the stated method is robust for detecting the brain tumour.

### III. METHODOLOGY

#### Convolutional Neural Network

The Proposed method will use CNN as well as pretrained CNN Models which includes *VGG16*, *InceptionV3* and *ResNet50* to detect Brain tumour using the MRI Images. The Dataset is taken from Kaggle. The Dataset have 253 images of brain MRI. It has two folder named as Yes and No. The folder named Yes has 155 Images with tumour and the folder labelled as No contains 98 Samples of MRI Images which does not have tumour. As the number of Images are less we need Data Augmentation for getting a large dataset. Also the images are of different sizes, so we will also need to crop and resize the images.





### Data Pre-processing

#### 1). Data Preparation & Pre-processing

As the images are of different sizes we need to crop the images in such a way that it contains only the brain part, for this operation we have used a cropping technique to find the extreme top, bottom, left and right points of the brain. The Data preparation is done using the following Steps :

- i) Convert the MRI image to greyscale, and make it slightly blur.
- ii) Threshold the image and after that do erosions and dilations for removing noise.
- iii) find contours in image and grab the largest as only it can be the brain image
- iv) find the extreme points and crop new image from original image using these points

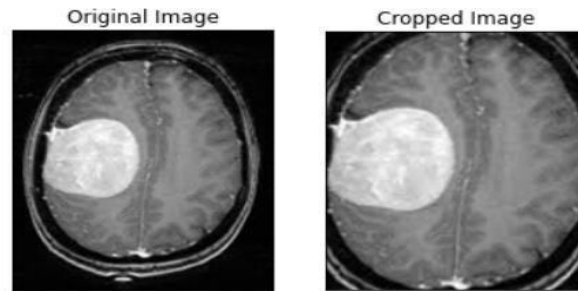


FIG 1. ORIGINAL AND CROPPED IMAGE

#### 2). Data Augmentation

As we have limited number of images , to get a larger dataset and to balance our dataset (as we have 61% data belongs to tumour class) for training our Model we used Data Augmentation technique using the *ImageDataGenerator* provided by *Keras*. The transformations include rotation, width shift, height shift Shear, brightness, horizontal and vertical flip.

This process will surely help the model to detect features accurately. After Augmentation we have got total 2064 images in which 1084 (52.52%) data belongs to tumour class and 980 samples (47.48%) belongs to non-tumour class. In this way we also brought a balance in yes and no classes.

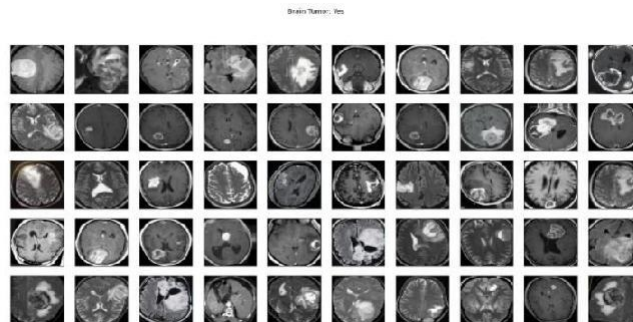


FIG 2. MRI IMAGES HAVING NO TUMOUR

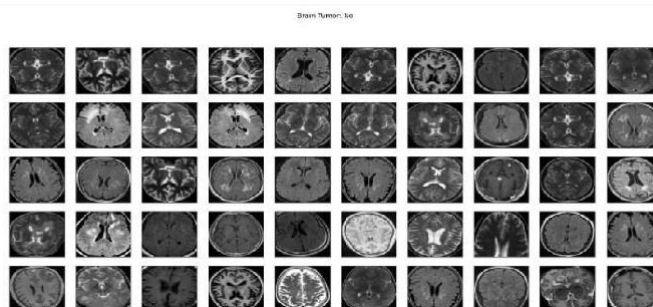


FIG 3. MRI IMAGES HAVING TUMOUR



### 3). Data Split

The Dataset is split in 3 sections for training, validation and testing. 70% of Data is used for training which includes a total of 1444 MRI images, and rest 30 % is equally divided in validation and testing which means 310 Samples for each.

### Convolutional Neural Network

CNN stands for convolutional neural network. It is a deep Learning Technique, in which we feed the input images go through many layers like Convolutional, Max-pooling, Flatten and Dense and accordingly the network adjusts its weights (parameters) in every iteration. [10]

We are using 3 Convolutional, 3 Max-pooling layers in our CNN architecture along with a Flatten Layer and 2 Dense Layers. The activation function being used in the Dense Layer is Sigmoid because of binary classification

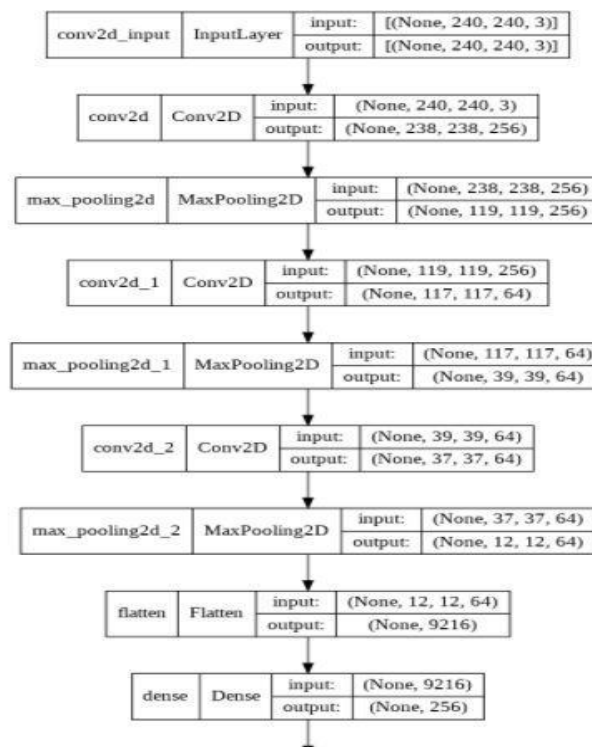


FIG 4. BTDCNN ARCHITECTURE

### Transfer Learning

In Transfer Learning we use the pre-trained deep learning models which are trained on a large dataset and apply this knowledge to our data. This will not only save training time and cost, but also it can improve the accuracy of the model. [11] In our work we have used three pre-trained Models which includes InceptionV3, VGG16, and ResNet50.

### 1). Inception

InceptionV3 is trained on ImageNet dataset and has achieved more than 98.1% accuracy. This model consists of symmetric and asymmetric blocks, like Convolution, Concatenation and Max-pooling, fully connected. [12] The Loss Function is softmax.

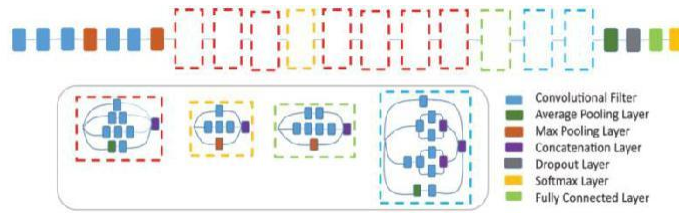


FIG 5. INCEPTIONV3 ARCHITECTURE ADAPTED FROM [16]

## 2).VGG16

VGG16 is a CNN architecture and one of the most efficient model which won ILSVR (ImageNet) Competition in 2014. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter, it is focused on having convolution layers of 3x3 filter with a stride 1, using same padding and max-pool layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max-pool layers consistently throughout the whole architecture. [13]

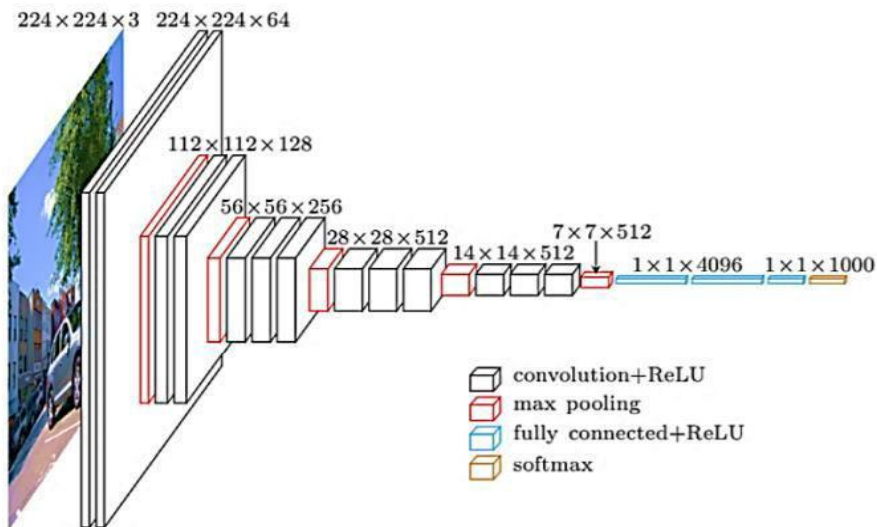


FIG 6. VGG16 ARCHITECTURE ADAPTED FROM [17]



### 3). Resnet50

ResNet50 is a network that corresponds to the 50-layer Residual Network developed in Microsoft Research Centre by Kaiming et al. It has 48 convolution layers, along with 1 Max-Pool and 1 Average-Pool layer.[15]

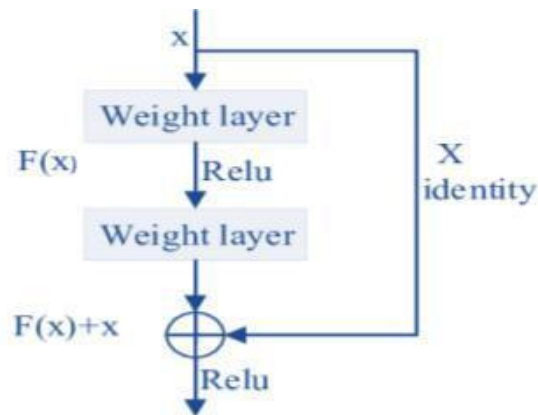


FIG 7 RESIDUAL NETWORK BUILDING BLOCK ADAPTED FROM [14]

## IV. EXPERIMENTAL RESULTS

In this project we have used the f-1 score for measuring the correctness of our model.

F-1 score takes into account the precision and recall. It is the harmonic mean of precision and recall. It is mostly used to evaluate the accuracy of binary system. This score also takes into account the false predictions i.e., false positive and false negative. So it gives us a better understanding of our model.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total}} +$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} +$$

$$\text{F1 Score} = (2 * \text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$

The project was developed using Google-Colab GPU. The *BTD Custom CNN model* was trained For 100 epochs with a batch size of 32. The patience parameter is set to 10 and learning rate was set to 0.001. After 32 epochs the model stopped automatically as there was no increase in accuracy after at least 10 epochs.

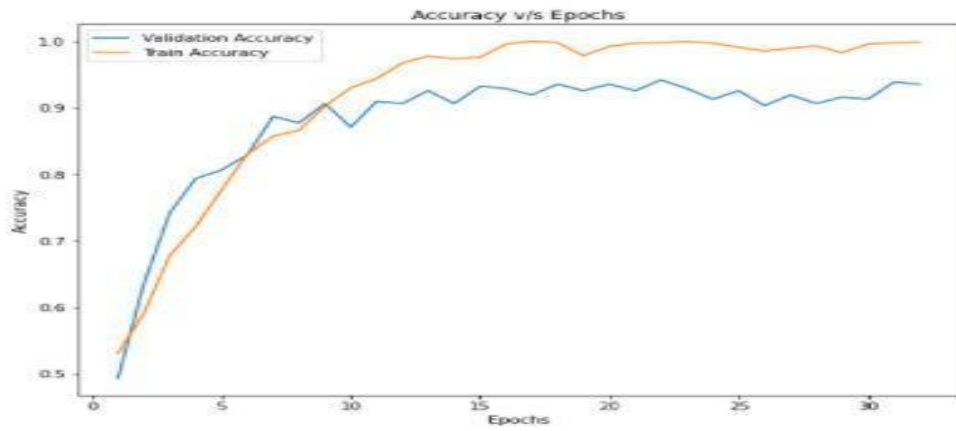


Fig 8. Accuracy vs/ Epochs on Training Data of BTD CNN

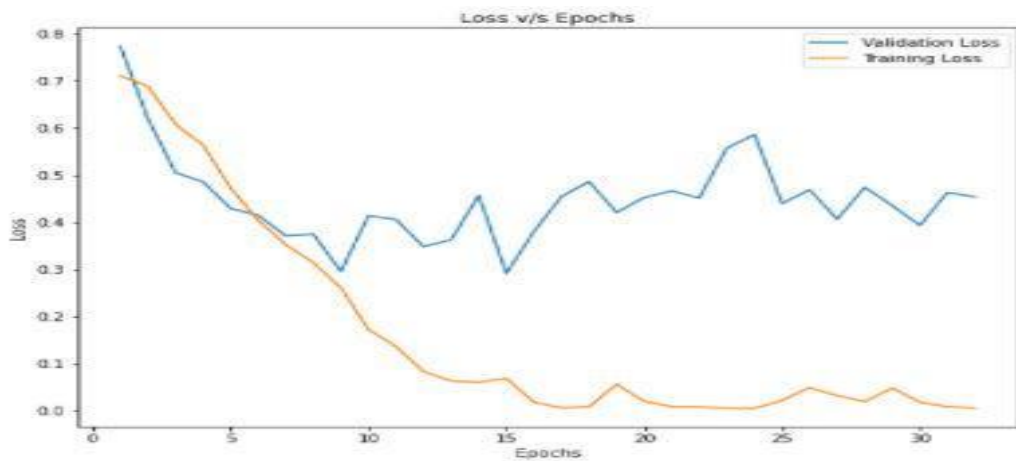


Fig 9. Loss v/s Epochs on Training Data of BTD CNN

The above graphs shows the accuracy and loss changes with epochs. As we can see that with time, the accuracy is increasing while the loss has decreased significantly as compared to the initial stages. The accuracy comes out to be 0.99, 0.94, 0.92 for training, validation and test respectively. Also the Losses were 0.002, 0.45, 0.26 for training, validation and test respectively.



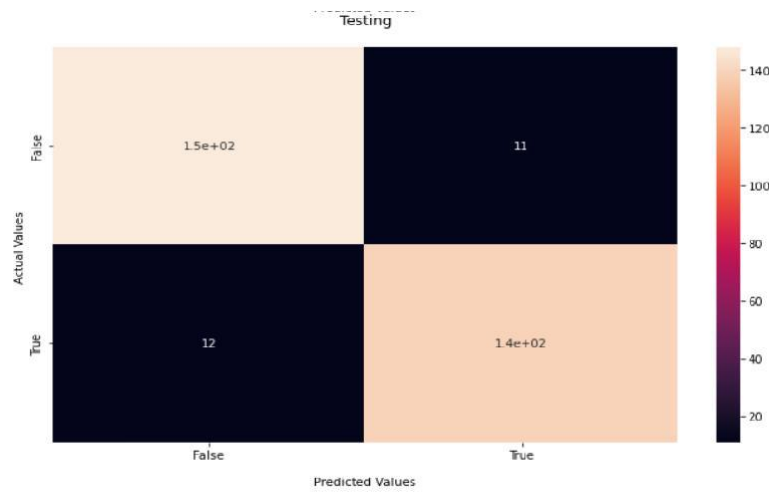


Fig 10. Confusion Matrix for Testing Data of BTD CNN

The confusion matrix shows the following conclusion. The Confusion matrix Shows that the model has detected 140 True positives and 11 False positives. Also the number of True Negatives is 150 and False Negatives is 12

**True Positives:** Tumour class Correctly predicted as Tumour

**True Negatives:** Non-Tumour class Correctly predicted as Non-Tumour

**False Positives:** Non-Tumour class wrongly predicted as Tumour.

**False Negatives:** Tumour-class wrongly predicted as Non-Tumour .

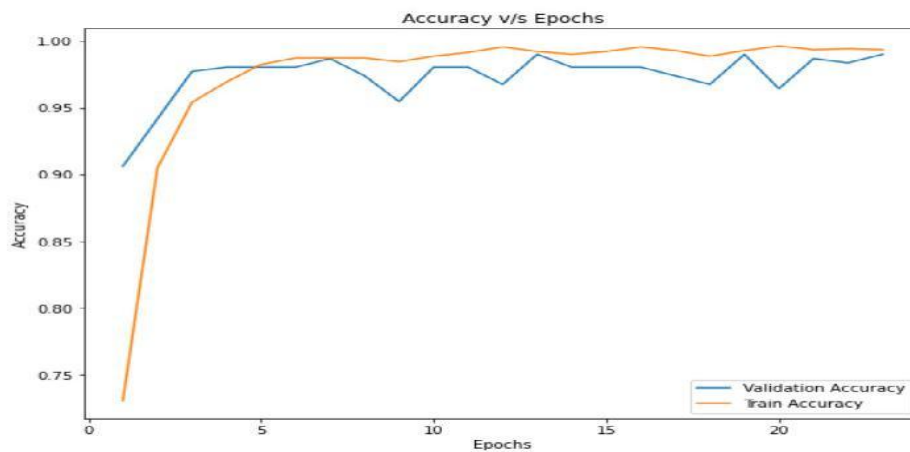


Fig 11. Accuracy vs/ Epochs on Training Data ofVGG16

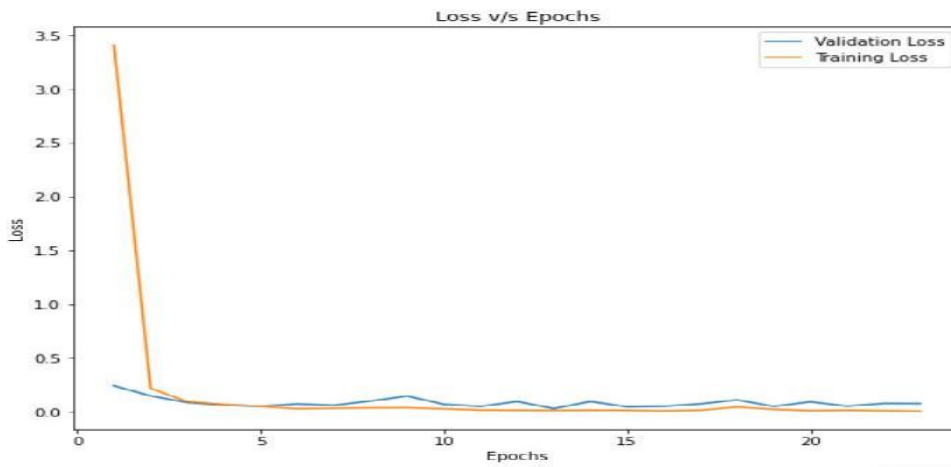


Fig 12. Loss vs/ Epochs on Training Data ofVGG16

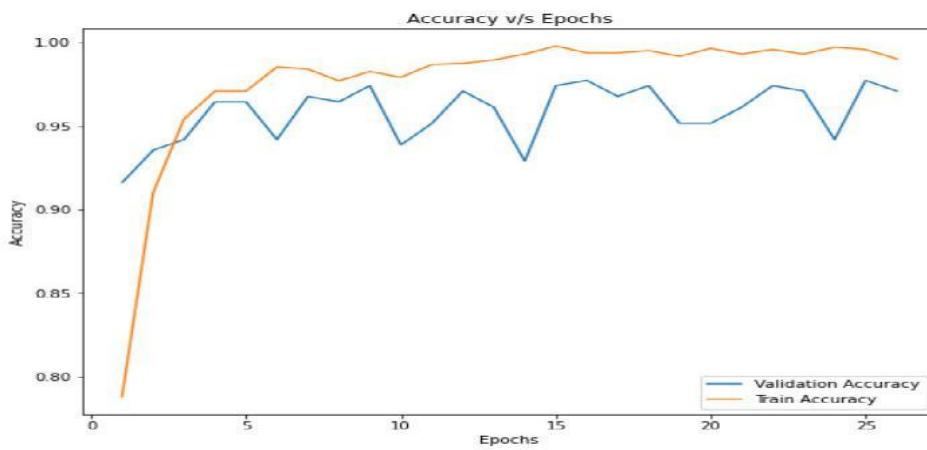


Fig 13. Accuracy vs/ Epochs on Training Data ofInceptionV3

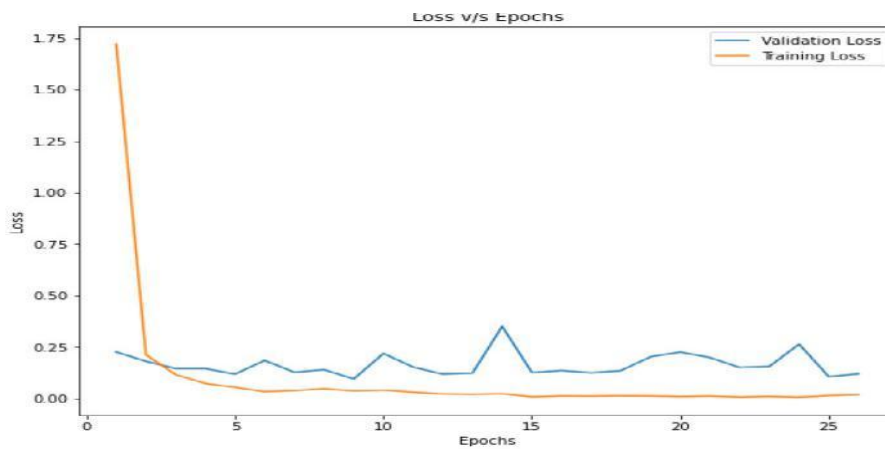


Fig 14. Loss vs/ Epochs on Training Data ofInceptionV3

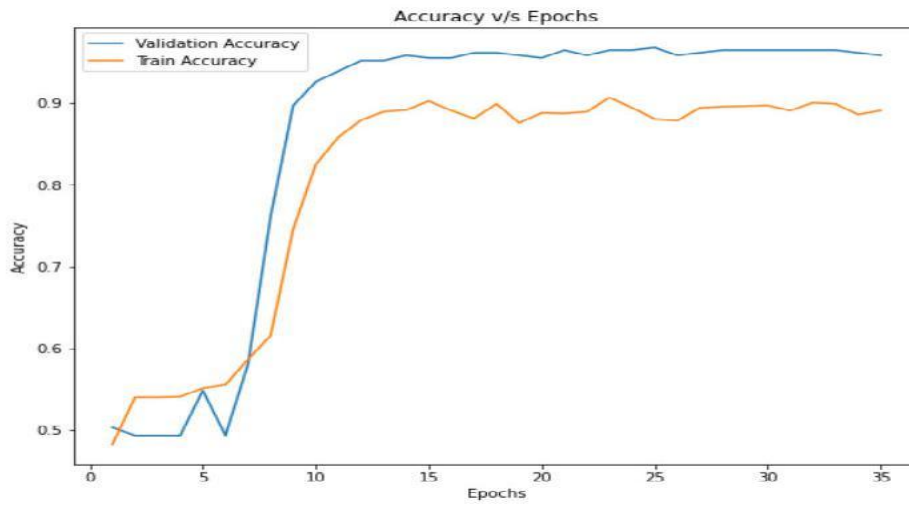


Fig 15. Accuracy vs/ Epochs on Training Data ofResNet50

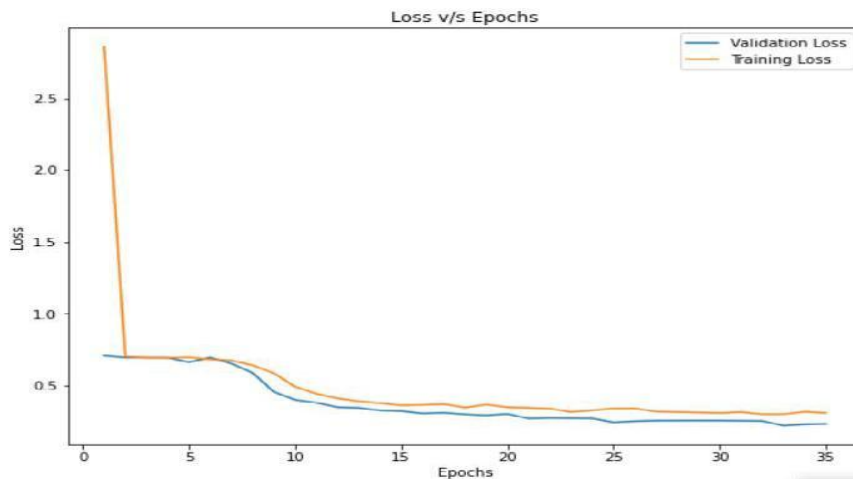


Fig 16. Loss vs/ Epochs on Training Data ofResNet50

Accuracy Table:

	Training	Validation	Testing
BTD CNN	0.999	0.942	0.926
VGG16	0.999	0.990	0.994
InceptionV3	1.000	0.977	0.981
ResNet50	0.981	0.968	0.961

Fig 17. Accuracy Comparison of all the Models



Loss Table:

	Training	Validation	Testing
BTD CNN	0.002	0.451	0.262
VGG16	0.001	0.030	0.049
InceptionV3	0.001	0.136	0.089
ResNet50	0.219	0.243	0.233

Fig 18. Loss Comparison of all the Models

We have tested 4 Models on our Project, in which one is our *Custom BTD CNN Model* and other 3 are pre-trained Models. According to the accuracy and loss calculated on test data, we can conclude that *VGG16* achieved the best results followed by *InceptionV3*, *Resnet50* and *BTD CNN Models*.

Similarly taking the test F1 Score as the concluding factor we have :

**i) BTD CNN**

Classification Report for Testing:				
	precision	recall	f1-score	support
False	0.93	0.93	0.93	159
True	0.93	0.92	0.92	151
accuracy			0.93	310
macro avg	0.93	0.93	0.93	310
weighted avg	0.93	0.93	0.93	310

Fig 19. BTD CNN F1 Scores

**ii) VGG16**

Classification Report for Testing:				
	precision	recall	f1-score	support
False	0.99	1.00	0.99	159
True	1.00	0.99	0.99	151
accuracy			0.99	310
macro avg	0.99	0.99	0.99	310
weighted avg	0.99	0.99	0.99	310

Fig 20. VGG16 F1 Scores



iii )InceptionV3

Classification Report for Testing:				
	precision	recall	f1-score	support
False	0.99	0.97	0.98	159
True	0.97	0.99	0.98	151
accuracy			0.98	310
macro avg	0.98	0.98	0.98	310
weighted avg	0.98	0.98	0.98	310

Fig 21. InceptionV3 F1 Scores

iv) ResNet50

Classification Report for Testing:				
	precision	recall	f1-score	support
False	1.00	0.92	0.96	159
True	0.93	1.00	0.96	151
accuracy			0.96	310
macro avg	0.96	0.96	0.96	310
weighted avg	0.96	0.96	0.96	310

Fig 22. ResNet50 F1 Scores

From the testing F1 Scores we have again got the similar results where F1 Score of *VGG16* is highest followed by *InceptionV3*, *ResNet50* and *BTD CNN*.

V. CONCLUSION

In this paper we showed an efficient approach for brain tumour detection using MRI Images. We Used CNN and transfer learning for it. We were able to get good accuracy with all the models used be it CNN model or pretrained CNN Architectures. Despite of the small Dataset we got good results due to the essential pre-processing and Augmentation. we have used 3 Pretrained Models namely *VGG16*, *ResNet50* and *InceptionV3* and 1 custom CNN Model to Detect Brain Tumour using MRI Images. Among pre-trained CNN Architectures *VGG16* showed the highest accuracy of 99.4%. We have validated our results by using f1 score as well. This shows that the method used in this paper for brain tumour detection can be successfully used for evaluating MRI images of patients for tumour.

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