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# Brain Tumor Detection Using Multi-Task-Inductive Deep Transfer Learning On MRI Images: An Analysis

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**Abstract**

Deep Learning improves the process of recognition, classification, detection, forecasting and diagnosis of various healthcare domains like pathology breast cancer brain tumor etc. It helps to automate the manual processing of medical images obtained from different modalities like MRI, CT scans and X-ray etc. This paper implements various pre trained deep learning models that is Le Net, Alex Net, inception, convolution neural network (CNN), VGG 16, VGG 19 and analyze their performance for brain tumor detection. The performance is evaluated by computing the performance para meters like accuracy, loss, F1 score, precision, and recall.

**Keywords:** Deep Learning, Brain Tumor, MRI, Transfer Learning

## 1. Introduction

An uncontrolled growth of brain cells has been considered as brain tumor, which results into abnormal functioning of brain and eventually affect the health of the person[1]–[3]. Brain tumors are broadly classified into ten categories that is benign which arenon-cancerous and malignant which are cancerous in nature. WHO has furtherclassified brain tumors into Grade I to IV. In other words, WHO has provided the grading mechanism for brain tumor classification. According to this grading system, the low-grade tumors (i.e., Grade I & II) are non-cancerous in nature while & high-gradetumors (i.e. Grade III & IV) are considered as cancerous in nature (malignant) [4]. Therefore, it is very necessary to have early detector & diagnosis of the brain tumor.

The advance the advancement in medical imaging techniques like CT scan, MRI, X Ray, ultrasound facilitate the diagnosis and treatment procedure [1], [2], [4]–[7]. TheMRI scan of brain consists of multiple sequences known as multi-modality. These are T1- weighted (T1), T1- weighted contrast-enhanced (T1c),T2- weighted (T2) and T2- weighted Fluid Attenuated Inversion Recovery (FLAIR) and diffusion weighted imaging (DWI) and gives the complete anatomy of brain and helps in brain tumor detection.

Further, the manual detection and classification of brain tumor is a tedious an errorprone

task. Therefore there is a need to automate the manual procedure. Deep learningmodel has shown a great potential for this problem including both 2D and 3D images [8]–[15]. In the initial stages it is mostly used for image recognition and detection but nowadays it is widely used for segmentation, prediction, survival rate prediction [16]–
for brain tumors. But one of the major issues of using deep learning is that it requires a lot of data which is scare in case of medical applications. So, to address thisissue in this paper we are using transfer learning. In transfer learning, the objective is to improve the learning of task in target domain by using the learning results, also known as pre-trained model of source domain. Formally, transfer learning is that field of machine learning in which the information is transferred from source domain to target domain. As per the definition of transfer learning there can be three categories of transfer learning namely, inductive, transductive and unsupervised. In case of inductive

learning the task for both source and target is different irrespective of source and target domain. Further, if a lot of labelled data is available in the source domain then this typeof transfer learning is known as multi-task inductive transfer learning which the case inthis work is. Therefore, this paper investigates the performance of various transfer learning based pre-trained deep learning models for brain tumor detection and highlights the effect of transfer learning on the performance of various models.

The rest of the article has been organized as follows. Section 2 provides existing work related to brain tumor detection and classification. Section 3 comprises of the methodology followed and the CNN models implemented, Followed by results and discussions in Section 4. The conclusion and future work is given in Section 5.

## 2. Literature Review

This section summarizes the recent work for brain tumor detection. The author in
use extreme learning in conjunction with deep learning for brain tumor detection and achieves the accuracy of 97.18% by denoising the data. In [21] and [22] the authorsused pre-trained VGG models along with ELM on BRATS dataset for classification ofbrain tumor and achieves an accuracy of 97%. The authors in [17] and [23] uses fuzzylogic and dragon fly algorithms respectively for BRATS dataset. Deepmedic [24] deeplearning-based model has been proposed for BRATS dataset provides an dice coefficient of 0.81 as result. In [25] the authors used LSTM and UNET on pre-processed data obtained by applying intensity normalization and inhomogeneity alteration on BRATS 2015 dataset for brain tumor classification.

In articles [19], [35] CNN is used and some additional methods were also incorporates with CNN like, in [26] the feed forward CNN is used while in [29] CNNis incorporated with Whale Harris Hawks optimization, CA-CNN [31], Goog Le Net [32], Brain MR Net-CNN[27], DWT [34]. Stack encoder with contrast enhancement gives an accuracy of 97% for BRATS dataset [28] and auto-encoder with wavelet transform has been used in [33] for brain tumor detection. A comparison of various machine learning classifier with feature fusion has been discussed in [30].

It has been observed that CNN is most widely used deep learning model for brain tumor detection and classification. Further, the most commonly used dataset is BRATSand in order to improve the performance of deep learning models and to reduce the effect of overfitting different methods have been used by the researchers during preprocessing phase and the most commonly used method is transfer learning. Therefore, in this study the most widely used and the current popular CNN models namely Le Net, Alex Net, X Ception, VGG-16 and VGG19 has been implemented for detecting the brain tumor using MRI images.

## 3. Methods and Materials

The overall block diagram is shown in Figure 1 and the details related to each module is provided in the subsequent subsections.

### 3.1. Dataset Description and Preprocessing

The dataset for brain tumor detection has been taken from https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection which consists of 253 images out of which 155 images are of class 0 that are for normal brainand 98 in class 1 that is for abnormal brain. Further, as the images are of different sizes,so in order to maintain the uniformity all the images are rescaled to a size of 224 x 224.

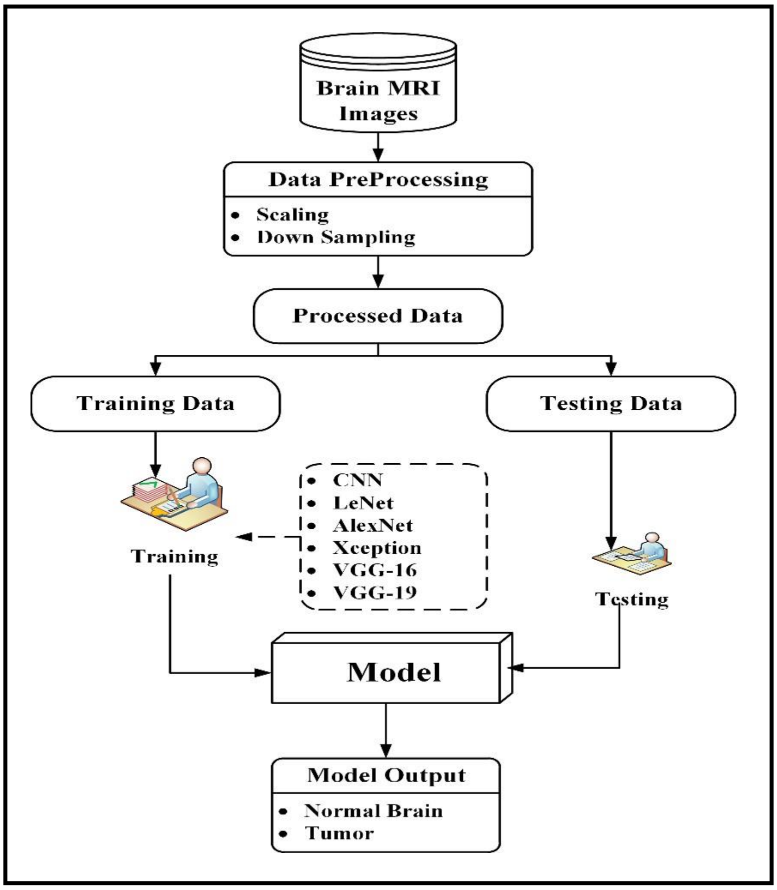


**Figure 1: Block Diagram Brain Tumor Detection**

### 3.2. Inductive Transfer Learning and Deep learning (DL)

In case of deep learning both the target and source domain are same while in case of transfer learning the information is transferred from source to target. In this work, firstly, the basic deep learning models have been trained using ImageNet data after thatthe information is transferred to the target domain which is the MRI images of brain tumor. The various deep learning models used in this wor are explained in thissubsection.

There are a number of deep learning models but among these CNN models are mostwidely used with medical images due too there tremendous success in this field. Therefore, in this work following pre-trained models have been implemented that is Le Net, Alex Net, VGG-16 without transfer learning, pre-trained Xception, VGG-16 andVGG-19 models. Along with this a CNN model has also been designed with three convolution layers that is each convolution layer consists of a convolution layer and a Max pooling layer followed by a dropout layer and four fully connected or dense layers.Le Net consists of 7-layers with three convolution layer, two pooling layers and two fully connected layers. It has been widely used for handwritten digit recognition. Alex Net is the deeper version of Lenet-5 and consists of 5 convolution, 3 pooling and 3 fully connected layers and is most widely used for object detection. Xception stands for extreme Inception which replaces the inception modules with depth wise separable convolutions. It has 36 convolution layers which are structured into 14 modules, givinga look of linear stack of convolution layers with residual connections. VGG-16 has 16layers that has weight and accordingly VGG-19 has 19 layers having weights. In other words, VGG-16 has 13 convolution, 3 fully connected and 5 pooling layers while VGG-19 has 16 convolution layers.

## 4. Results and Discussion

One of the issues with deep learning implementation for medical image analysis is lack of labelled data which leads to the overfitting of data. Therefore, in order to overcome this issue transfer learning, batch normalization and dropout layers are used.Transfer learning is the technique in which the pre-trained weight of a neural network are used which are trained on similar data rather than creating and training a model from scratch. Batch normalization is helpful in normalizing the layers according to theinput values. It is also helpful in training the model quickly and in stable manner. In addition to this dropout technique is also used which drops or ignore some neurons during training.

The deep learning models are implemented with the following hyper-parameters, learning rate 1e-6, epoch 50, dropout value 0.5 and categorical cross entropy as the lossfunction.

### 4.1. Performance Parameters

In order to evaluate the performance of the model accuracy, precision, recall and f1-score are used. Accuracy defines the degree of correct classification rate. It is computed as ratio of correct predictions and total predictions. This metric is very usefulfor evaluation when all the classes are equi-important. Precision specifies the probability to test the positive screening of the tumor rate. In other words, it measures the accuracy of a model to classify any sample as positive. It is computed as the ratio of correct positive prediction and total number of positive predictions.

Recall calculates the degree of how much the model is sensitive to measure the tumor detection rate. It measures the ability of model to detect positive samples. It is calculatedas the ratio of the correct positive prediction to the total number of positive samples.

F1-score is the parameter which is used to provide a balance between precision and recall and is an efficient metric when the data is suffering from class imbalance problem. It is computed as the harmonic mean of precision and recall.

## 5. Results and Analysis

This section provides the experimental results and their analysis. The accuracy plotand the loss plots for all the implemented models,i.e., Le Net, Alex Net , VGG-16 andCNN (basic model) and pre-trained X Ception, VGG-16 and VGG-19 models are shownin Figure 2 and Figure 3 respectively. It has been observed that in case of basic models(without transfer learning) the maximum accuracy has been achieved by Alex Net and for pre-trained models, the best performance has been shown by VGG-19.

It can be seen that the pre-trained models although starts with approximately same accuracy as that of traditional deep models at epoch1 but there performance is gradually improving with each epoch.

This is quite expected as with transfer learning a lot of data is available for trainingwhich results in improvement of accuracy.

Further, it also has been observed that the pre-trained models converges fast than the traditional models at around 15 epochs.

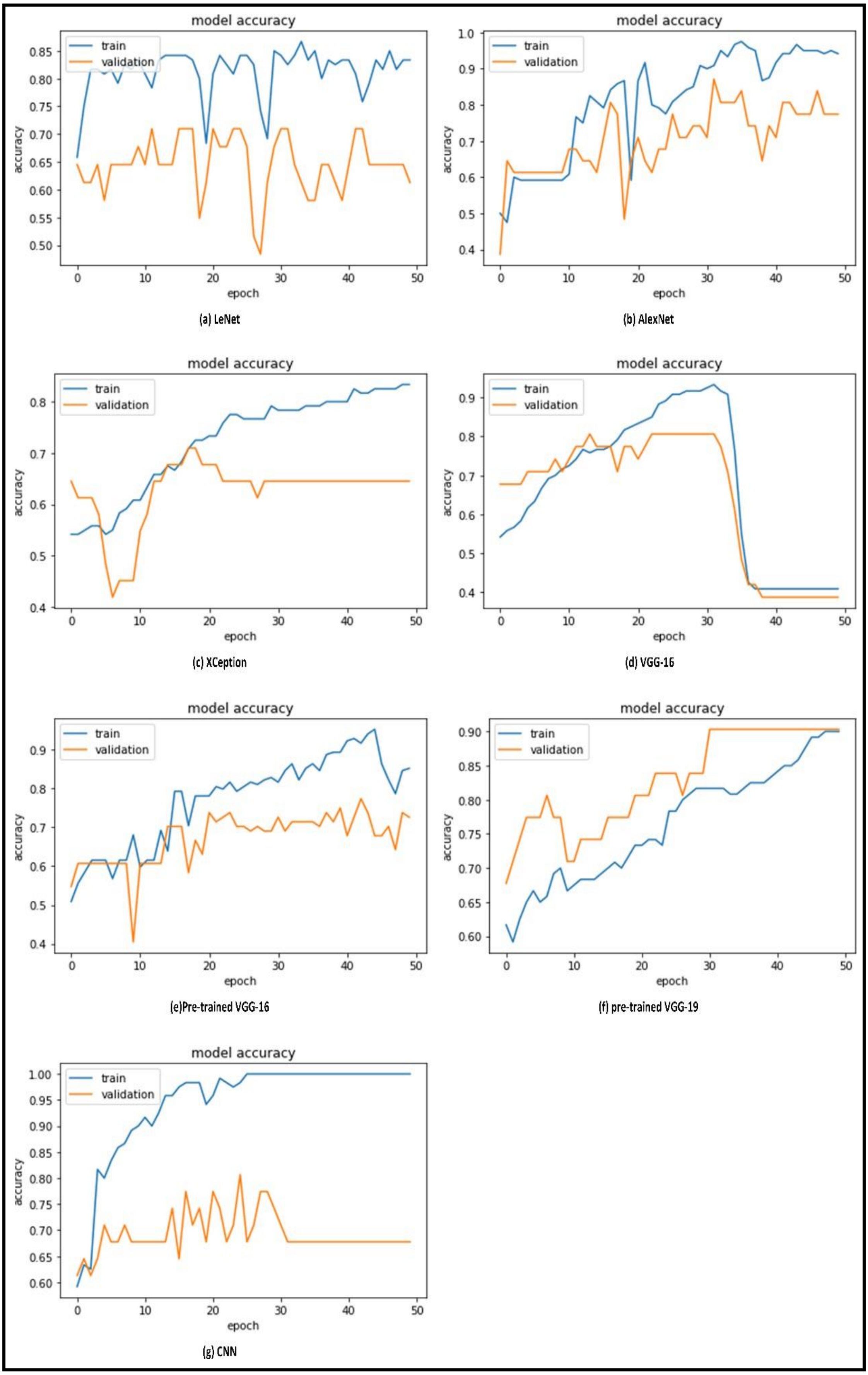


**Figure 2: Accuracy Plot for Deep Learning Models**

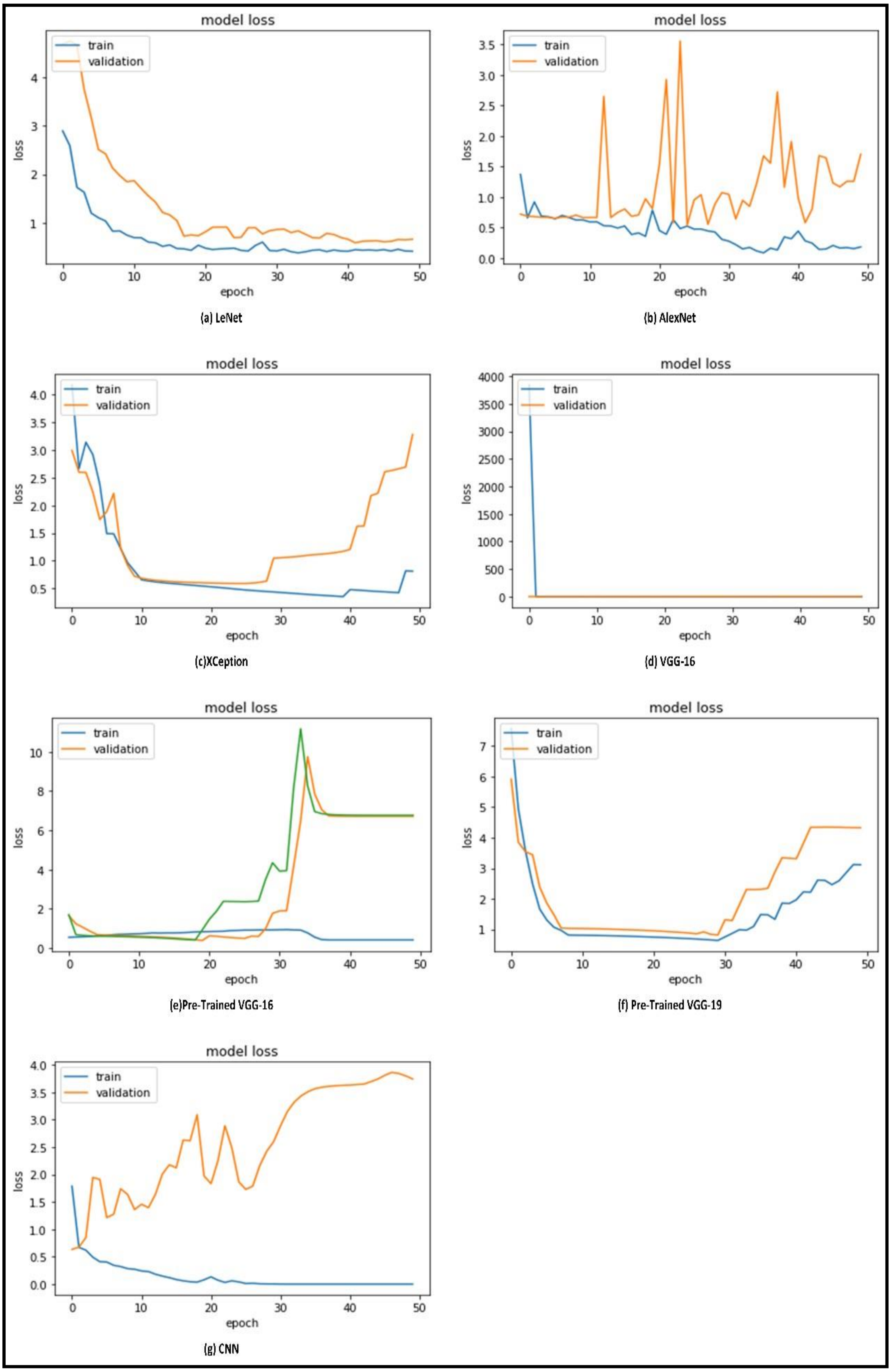


**Figure 3: Loss Plot for Deep Learning Models**

The performance metrics precision, recall, F1-score and accuracy for the implemented models has been summarized in Table 1- Table 3.It can be observed thatin case of basic models Alex net proven to be the best, in terms of accuracy and as wellas F1-score.

In case of pre-trained models VGG-19 is most accurate model and as the data is imbalanced, so from F1-score measure the performance for both VGG-16 and VGg-19is comparable.

**Table 1: Summary of Performance Parameters for Basic Models (Without Transfer Learning)**

| **Model** | **Le Net** | | | | **Alexnet** | | | | **VGG-16** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **class 0** | **class 1** | **macro Avg** | **Weighted Avg** | **class 0** | **class 1** | **macro Avg** | **Weighted Avg** | **class 0** | **class 1** | **macro Avg** | **Weighted Avg** |
| **precision** | 0.61 | 0.75 | 0.68 | 0.7 | 0.72 | 0.75 | 0.74 | 0.74 | 0.86 | 0.7 | 0.78 | 0.76 |
| **recall** | 0.54 | 0.8 | 0.67 | 0.71 | 0.49 | 0.89 | 0.69 | 0.75 | 0.36 | 0.96 | 0.66 | 0.73 |
| **F1-score** | 0.57 | 0.78 | **0.67** | 0.7 | 0.58 | 0.82 | **0.7** | 0.73 | 0.51 | 0.81 | **0.66** | 0.69 |
| **Accuracy** | 0.71 | | | | 0.75 | | | | 0.73 | | | |

**Table 2: Summary of Performance Parameters for Pre-trained Models (With Transfer Learning)**

| **Model** | **XCeption** | | | | **VGG-16** | | | | **VGG-19** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **class 0** | **class1** | **macro Avg** | **Weighted Avg** | **class 0** | **class1** | **macro Avg** | **Weighted Avg** | **class 0** | **class1** | **macro Avg** | **Weighted Avg** |
| **precision** | 0.53 | 0.72 | 0.62 | 0.65 | 0.86 | 0.7 | 0.78 | 0.76 | 0.65 | 0.85 | 0.75 | 0.78 |
| **recall** | 0.49 | 0.75 | 0.62 | 0.66 | 0.36 | 0.96 | 0.66 | 0.73 | 0.76 | 0.77 | 0.76 | 0.76 |
| **F1-score** | 0.51 | 0.74 | **0.62** | 0.65 | 0.51 | 0.81 | 0.66 | 0.69 | 0.7 | 0.81 | 0.75 | 0.77 |
| **Accuracy** | 0.66 | | | | 0.73 | | | | 0.76 | | | |

**Table 3: Summary of Performance Parameters for CNN**

| Model | CNN | | | |
|---|---|---|---|---|
| | **class 0** | **class1** | **macro Avg** | **Weighted Avg** |
| **Precision** | 0.79 | 0.81 | 0.8 | 0.8 |
| **Recall** | 0.62 | 0.91 | 0.76 | 0.8 |
| **F1-score** | 0.7 | 0.86 | 0.78 | 0.8 |
| **Accuracy** | 0.84 | | | |

The Figure 4 and Figure 5 shows that how the models predict the class of MRI images during the testing phase.

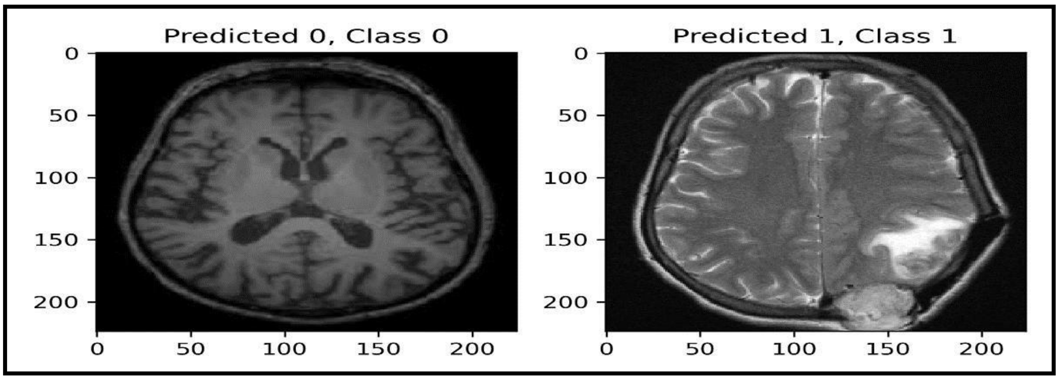


**Figure 4: Correctly Predicted by VGG-19**

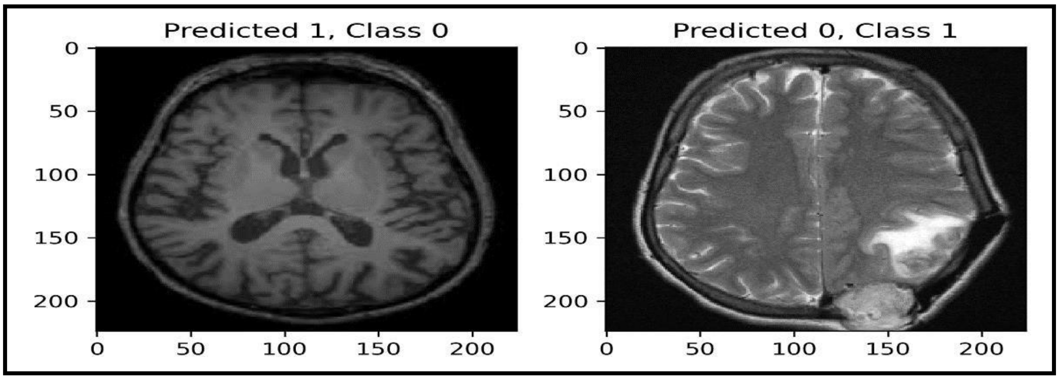


**Figure 5: Incorrectly Predicted by Alex Net**

## 6. Conclusion and Future Work

Transfer learning is one of the machine learning methods, which is designed for onetask and can be reused for another task. In this work, Le Net, Alex Net, VGG-16, VGG-19, X Ception and CNN models are implemented with and without using transfer learning for brain tumor detection through MRI images of brain and it will classify theimages into two classes that is normal and abnormal. This work also highlights the benefit of transfer learning when we have less data. So, it will helpful in handling overfitting of data and speed up the process of training. The results show that pre-trained VGG-19 model obtained the highest accuracy among the basic deep learning models while the CNN model that has been designed from scratch gives the best performance overall in terms of accuracy (84% accuracy). But as the data is imbalanced, so considering F1-score value the pre-trained VGG-19 models gives the best performance (81%). In this work, only a small dataset has been considered, so as future scope, this work will explore various data augmentation techniques for handling class imbalance problem and will extend this work from detection to multiclass classification problem.

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