International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 10 Issue: 03 | Mar 2023 www.irjet.net p-ISSN: 2395-0072

Deep Learning based Multi-class Brain Tumor Classification

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Abstract - *A brain tumor is a kind of cancer that can impact people, sometimes fatally or with significant quality of life impairment. Using Deep learning techniques, researchers can identify tumors and treat them more efficiently. Brain MRI pictures can be used in a variety of ways to find malignancies. Deep learning techniques have significantly outperformed the rest of these techniques. Within the framework, comparison of the models has been employed for tumor detection from brain MRI scans. Among the Convolutional Neural Network (CNN) architectures that can be employed are Custom CNN, DenseNet169, MobileNet, VGG-16, and ResNet152 models. The same hyper-parameters can be used to train these models on MR images that have undergone the same dataset and preprocessing procedures. The goal is to develop an architecture that will compare various models to classify the Brain Tumor MRI. Machine learning and deep learning algorithms can be used to directly scan and determine the presence and type of tumor. Therefore, it is useful for analyzing brain tumor detection performance using various methods. The dataset used for Brain Tumor Detection consists of approximately 5000 Brain MR Images.*

Key Words: Classification, Neural Networks, Brain Tumor Classification, Deep Learning, Artificial Intelligence

1.INTRODUCTION

A relatively large number of people are diagnosed with secondary neuropathy. Although the exact number is unknown but this type of brain tumor is on the rise. With the use of extremely effective clinical imaging tools, early detection can always speed up the process of controlling and eliminating tumors in their early stages. A patient with the tumor may become immobile because a tumor may place pressure on the part of the brain that regulates movement of the body [6] [14] [15]. The aim of this study is to improve the detection accuracy of brain tumors on MRI picture using image processing and machine learning algorithms, as well as to develop a framework for rapidly diagnosing brain tumors from MRI images [19]. Amin et al. proposed [3] a three-step method for distinguishing between cancerous and non-cancerous brain tissue MRI. Among the steps involved are image processing, feature extraction, and image classification. This framework is useful not only for the medical staff but also for the other employees of the company because there is a chance that teams will need to divide the images into various categories. In such circumstances, this can be used to distinguish between the images and keep patient records secure. This could be a crucial tool that is helpful for any hospital employee because medical images are delicate and must be handled with extreme care. The objective is to identify and classify different types of tumors and most importantly to save time of doctors/patients and provide a suitable remedy at an early stage and to identify and supply good insights to doctors [20]. Examining the Brain tumor MRI images in the Healthcare industry implies the process of identifying tumors in the early stage. The framework will help in automatic detection of images containing tumors and searching for correlations between neighboring slices along with it can also do automatic detection of symmetrical axes of the image [13]. Furthermore, this framework can be used to create a full-fledged application to detect any type of Cancerous Polyps.

2. BACKGROUND

2.1 Convolutional Neural Network

Convolutional Neural Networks (ConvNet/CNN) is a deep learning technique that can accept input images and assign gist to various elements and objects (learnable weights and biases), and be able to distinguish between them. ConvNets, by comparison, depends upon approximately less preprocessing than other classification techniques. ConvNets can learn from filters and properties, but primitive techniques create the filters manually. To classify multi-grade brain tumors, a novel convolutional neural network (CNN) is proposed [2]. Individual neurons perceive stimuli only in this restricted area of the visual field.

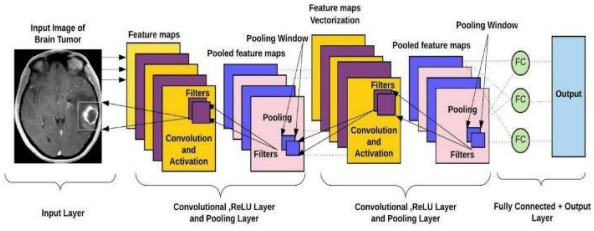

Fig - 1: CNN Architecture

A layer that receives model inputs is called an input layer. The total number of features in the data is the same as the number of neurons (pixels in the case of images) in that layer. Input Layer: The hidden layer receives the input from the input layer [1] [7]. Depending on our model and the volume of the data, there may be numerous hidden levels as shown in Fig 1. The number of neurons in each hidden layer varies, but usually exceeds the number of features. The output of each layer is computed by multiplying the output of the layer below by a learnable weight, adding a learnable bias, and then computing an activation function that makes the network nonlinear [21]. The output from the hidden layer is then passed into the output layer, where it is converted into the probability score for each class using a logistic function like sigmoid or SoftMax. Applications for CNN include decoding facial recognition, understanding climate, and gathering historical and environmental data [10].

2.2 Transfer Learning

Transfer learning is a term used in machine learning to describe the use of a previously trained model for another task. In transfer learning, machines use information gathered from previous work to improve predictions about new tasks [16]. For instance, if a user trains a classifier to determine if an image contains food, the learned knowledge can be used to distinguish between drinks. Transfer learning applies the expertise of trained machine learning models to unrelated but closely related problems. For example, in this case, if user trained a simple classifier to predict whether an image contains tumor, user can use modeling data to determine whether the tumor in the image are present or not.

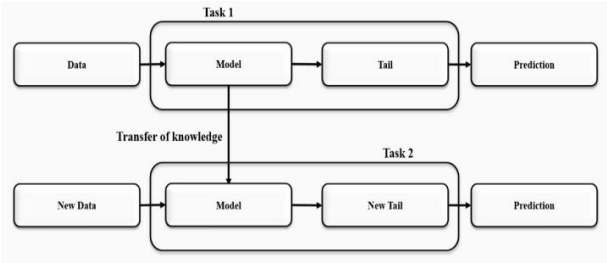

Fig - 2: Transfer Learning

Shows how transfer learning basically uses what the machine or user has learned in one task to try to better understand the concepts of another task. The weights are automatically transferred from the network that performed "task B" to the network that performed "task A". Because of high CPU power requirement, transfer learning is usually used in computer vision.

2.3 VGG-16

The key difference between the networks and the deeper networks of 2014 is that some designs are flashier and perform even better. The 16-layer VGG 16 architecture consists of his two layers of convolutions, a layer for pooling, and a fully connected layer. The concept of a much deeper network with much smaller filters is known as a VGG network. It currently has VGGNet models with 16 to 19 layers. One crucial aspect of these models is that they consistently used 3 x 3 convolutional filters, which are the smallest convolutional filter sizes capable of examining some of the nearby pixels. All the way across the network, they just maintained this basic structure of 3 x 3 convs with periodic pooling. Because VGG had fewer parameters, it layered more of them rather than using larger filters. Instead of using huge filters, VGG uses smaller and deeper filters. With a 7 x 7 convolutional layer, it now has the same effective receptive field as that layer. Convolutional layers, a pooling layer, a few other convolution layers, a few more pooling layers, and so on are present in VGGNet. Fig 3 VGG architecture has 16 fully connected

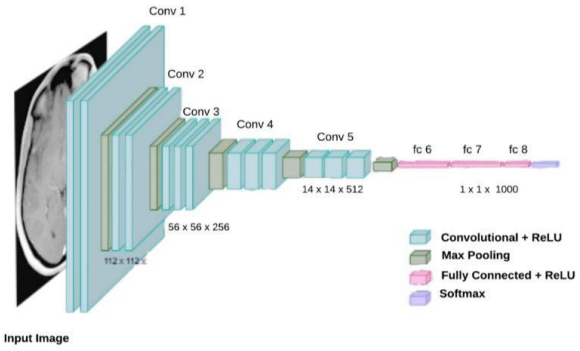

Fig - 3: VGG-16

Convolution layers. In this case, VGG 16 contains 16 and VGG 19 contains 19, which means basically the same architecture, but with some extra layers of convolution.

2.4 MobileNET

The MobileNet model, as its name suggests, is TensorFlows first mobile computer vision model and is intended for use in mobile applications.

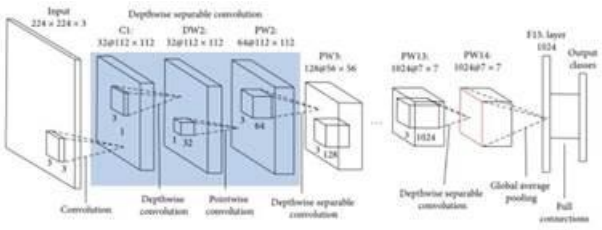

Fig - 4: MobileNET

Fig 4 shows Depth-separable folding is used in MobileNet. When compared to conventional convolution nets with equal depth folds, the number of parameters is significantly reduced. As a result, a lightweight deep neural network has

been created. Two processes are used to create a depthwise separable convolution.

1. Depthwise convolution.
2. Pointwise convolution.

The convolution described above is an excellent starting point for training ridiculously small and extremely fast classifiers. Google offers an open-source CNN class called MobileNet.

2.5 ResNET-152

The residual block serves as ResNet's primary base component. The complexity of processing increases as delve further into the network with several levels. Stack of these layers on top of one another is done, with each layer attempting to uncover some underlying mapping of the desired function. However, instead of using these blocks, user try to adjust the remaining mapping.

Because the input to these blocks is simply the incoming input, classes are used directly to adjust the remainder of the function H(X) - X rather than the predicted function H(X). Basically, the input is just taken and passed through as an identity at the end of this block, where it takes the skip connection on this right here. If there were no weight layers between, the input would simply be the identity. If further weight layers are not employed

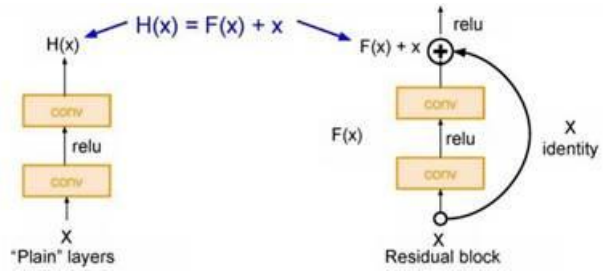

Fig - 5: ResNET-152

to learn some delta from residual X, the result would be the same as the output. In a word, while moving further into the network, learning H(X) becomes increasingly difficult due to the high number of layers. As a result, F(x) direct input of x as the outcome in this case and employed skip connection. So F(x) is referred to as a residual as shown in Fig 5. All of these blocks are very closely stacked in ResNet. Another benefit of this extremely deep architecture is that it allows for up to 150 levels of this, which gets periodically stack. Additionally, stride two is used to down sample spatially and double the number of filters. Only layer 1000 was ultimately fully connected to the output classes.

2.6 DenseNET-169

As demonstrated in the Fig 6, a forward pass in a conventional convolutional neural network involves passing an input image through the network to obtain a predicted label for the output.

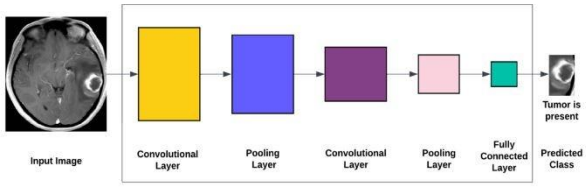

Fig - 6: DenseNET-169

Except for the first convolutional layer, which uses the input image, all subsequent convolutional layers build the output feature map that is passed to the next convolution layers using the output of the previous layer. The L layers have L direct connections, one from each layer to the next. Each layer in the DenseNet architecture is connected to every other layer, thus the term densely connected convolutional network. For L classes, there are L(L+1)/2 direct connections. Each layer uses the feature map from all layers before it as input, and its own feature map is used as input for each layer after it. DenseNet layers take input as a concatenation of features Map from previous level.

3 RELATED WORKS

Techniques based on deep learning have recently been used to classify and detect brain tumours using MRI and other imaging methods.

[4] A custom CNN algorithm was created, which improved the model by training with additional MRI images to distinguish between tumor and non-tumor images. This paper only proposes to determine if an image contains a tumor and introduces a mobile application as a medical tool.

A computer-based method for differentiating brain tumor regions in MRI images. The algorithm uses NN techniques to complete the appropriate phases of image preprocessing, image segmentation, image feature extraction, and image sorting [5].

[12] suggests developing an intelligent mechanism to detect brain tumours in MRI images using clustering algorithms such as Fuzzy C Means and intelligent optimization tools. A CAD system was used, and the results showed that PSO improved classification accuracy as well as typical error rate accuracy to 92.8 percent.

An automated system for real-time brain tumor detection was proposed by two distinct deep learning-based methods for the detection and classification of brain tumors [11].

Sasikala and team [18] presented a genetic algorithm for selecting wavelet features for feature dimension reduction. The best feature vector that can be fed into a selected classifier, such as an ANN, is the foundation of the method. The findings demonstrated that the genetic algorithm was able to achieve an accuracy of 98 percent by only selecting four features out of a total of 29.

Sajjad et al. [17] suggested a CNN method for data augmentation for the classification of brain tumors. The method used to classify brain tumors based on MRI images of segmented brain tumors. For classification, they utilized a pre-trained VGG-19 CNN architecture and achieved accuracies of 87.39 percent and 90.66 percent for the data before and after augmentation, respectively.

A sophisticated method for classifying and categorising brain tumors from Magnetic Resonance Imaging (MR) images has been proposed [9]. The operation of the two image restoration filters, the active use of the adaptive mean filter on the MR images, and the appropriate image enhancement and clipping steps required for tumor recognition are essential parameters needed to evaluate image quality. The established technique is primarily focused on tumor detection, specifically detecting abnormal mass accumulation and significantly influencing the pixel-wise intensity distribution of the image.

4. METHODOLOGY

4.1 About Dataset

The dataset contains a total of about 5000 MR images divided into three different tumor types (Glioma, Meningioma and Pituitary) and one class of healthy brain depicting No tumor.

Sample MR Images of all classes are represented in Fig - 7:

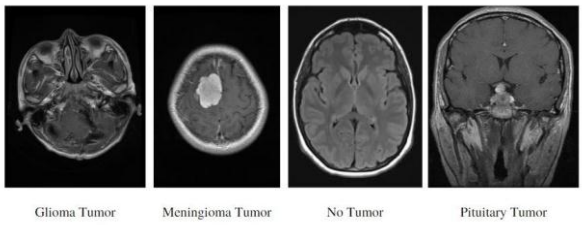

Fig - 7: Sample Input Images

4.2 Flow of the Project

In contrast to the existing architecture, the proposed system addresses all its disadvantages and limitations. Fig 8 is a more detailed explanation of the proposed system: First, the system will access the image, then prepare it. To ensure that the image will stand up for the algorithm to predict accurately, the image will be enlarged during preprocessing. The image will then be scaled to meet a specific need. After scaling, the image will then be reshaped into required dimensions so that it can fit in the algorithms that it is going to pass through. The image will then be transformed into an array for additional modeling. After all preprocessing is complete, the image is run through five different best models which predicts effective output. Now since the model is trained for predicting tumor from the existing four classes, the type tumor that is present in the image will be predicted based on the probability from the softmax activation function. The tumor type that is associated with maximum probability will be given as output. Because five strong and robust models are used to test the same input, this design's unique feature is that it offers significant reliability of the presence of tumor and its type. As a result, a detailed comparison can be made between all five model outputs based on the accuracy of the output as well as the predicted output using a web-based interface.

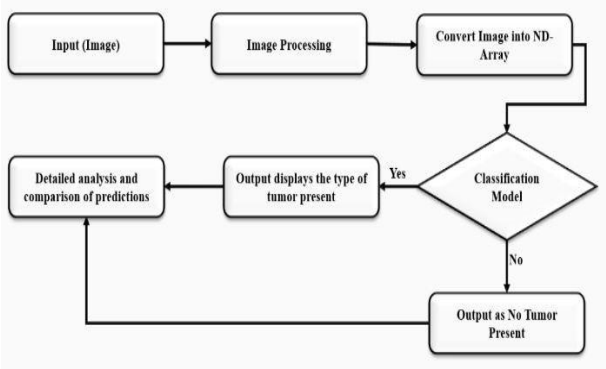

Fig - 8: Proposed Methodology Architecture

Input Image

The first and foremost step is to collect the brain MRI images.

This data can be collected from websites like Kaggle, UCI repository etc. A lot of brain MRI images are required to train and test our model it to check the accuracy and precision of the proposed model.

Image Processing

After getting the data, data processing is done. It is a very important step as if the image size is very large then the model will take a very long time to train the model. As a result, input images are resized to lower dimensions so that the model does not take a lot of time to train. Sometimes the number of images will be very less, which is very bad for deep learning models as it is data hungry. Further, data augmentation is performed to increase the number of images. Brain MRI images are basically GrayScale images so the value ranges from 0 to 255. So, normalization is done on this data in the range of 0 to 1. Normalization is basically done on top of images so that training the model becomes

much faster. The entire preprocessing of all the images can be done at once by using the keras ImageDataGenerator function in which custom parameters are provided and it will automatically convert set of images into desired processed image and also it will convert data into desired batches so that it can be passed directly through the convolution neural network or transfer learning model. Once the image processing is done then it will be passed through next stage which is converting image to ND Array and based on classification model predicts whether tumor is present or not.

Convert Image into N-D array

Images are basically in the form of pixels. It is basically a GrayScale image so it has 1 single channel. The pixel values range between 0 to 255. The images are represented in the form of 2D matrix. Models like an ANN could not take 2D matrix as input, as a result there is need to convert the images into N-D array so that ANN could take this as an input. This section is optional if ImageDataGenerator function is used. Because the function ImageDataGenerator will automatically convert the set of images into suitable format for CNN and store it in a variable for further processing.

Classification model

After converting images into N-D arrays, the next step is to train the model. Before training the model, since this is a classification problem and the data is in the form of images, CNN and transfer learning methodologies can be used to train the model. In the proposed system five different ideologies are been used i.e. Custom CNN with 6-layered architecture, MobileNET transfer learning model, VGG- 16 transfer learning model, ResNET-152 transfer learning model and DenseNET-169 transfer learning model. These were proven to be the best as far as robustness and accuracy are concerned. Once the model is trained and analyzed, the same trained model can be used for any new unseen images to predict the type of tumor that is present inside it. For testing new unseen images, the same ideology of preprocessing will be applied on it and then it will be passed through these trained models and finally the prediction whether the MRI contains the pituitary tumor, glioma tumor, meningioma tumor or no tumor is present. Currently only these four classes are available and in future more classes can also be integrated with the existing data to extend the scope of the project.

Detailed analysis and comparison of prediction

Since the work have used five robust models, after the image is passed through all the five models, the output can be seen and finally a detailed comparison of each model's output is made with graphs and accuracies associated with each as shown in Fig 9.

5. RESULT AND ANALYSIS

The obtained results are presented in the Fig 9 below. In this figure, one can see the accuracy of 98.32 percentage with the custom CNN 6-layered model with some preprocessing on the unseen images. One can also see that usage of the transfer learning Mobile Net architecture with preprocessing has brought an accuracy of 98.63 percentage. Using ResNET-152 and VGG-16 architecture one can see a great accuracy of 97.71 percentage and 98.62 percentage respectively on testing data. With the usage of Transfer learning DenseNET architecture, an accuracy of 96.56 percentage has been obtained on the unseen images of brain tumor MRI.

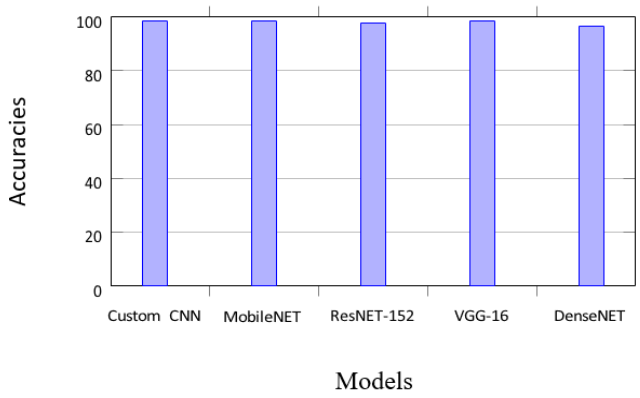

Fig - 9: Comparison of Model Accuracies

5.1 Custom CNN

6-layered architecture of CNN has given pretty good accuracy on unseen images [8].

Accuracy: 98.32 percentage as represented in Table 1. Accuracy and Loss graph comparison can be seen in Fig 10 and 11 respectively.

	TP	TN	FP	FN	Precision	Recall	f1-score
Glioma Tumor	288	1010	12	0	1.00	0.96	0.98
Meningioma Tumor	300	991	6	11	0.96	0.98	0.97
No Tumor	404	902	1	4	0.99	1.00	0.99
Pituitary Tumor	297	1008	3	3	0.99	0.99	0.99
Accuracy							0.98
Macro avg					0.98	0.98	0.98
Weighted avg					0.98	0.98	0.98

Table - 1: CNN Model Performance

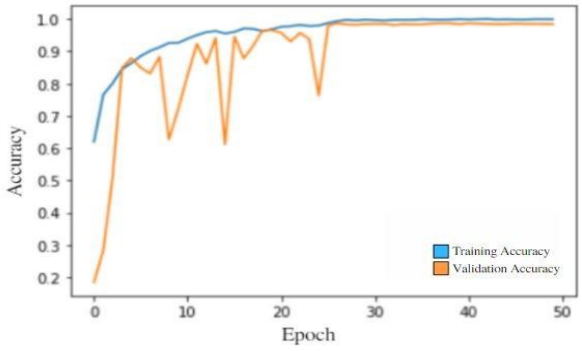

Fig - 10: Accuracy Comparison of CNN Model

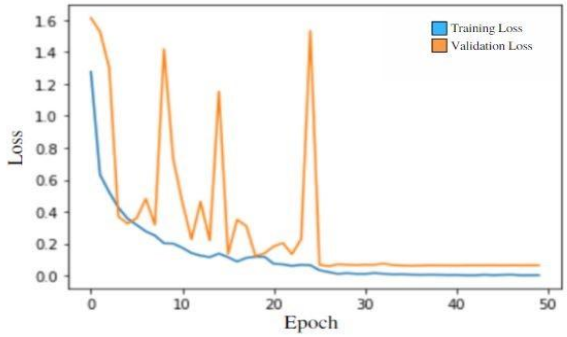

Fig - 11: Loss Comparison of CNN Model

5.2 MobileNET

Pre-trained architecture of MobileNET has given great accuracy on unseen images.

Accuracy: 98.63 percentage as represented in Table 2.

Accuracy and Loss comparison is shown in Fig 12 and 13 respectively.

	TP	TN	FP	FN	Precision	Recall	f1-score
Glioma	290	1008	10	0	0.98	0.97	0.97
Meningioma	303	995	3	10	0.94	0.99	0.97
No Tumor	403	906	2	0	1.00	1.00	1.00
Pituitary	290	999	10	1	1.00	0.97	0.98
Accuracy							0.98
Macro avg					0.98	0.98	0.98
Weighted avg					0.98	0.98	0.98

Table - 2: MobileNET Model Performance

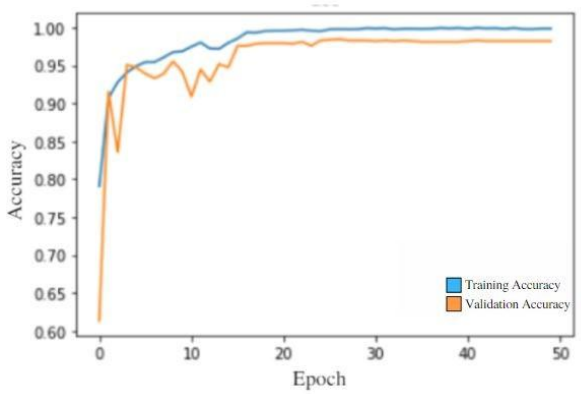

Fig - 12: Accuracy Comparison of MobileNET Model

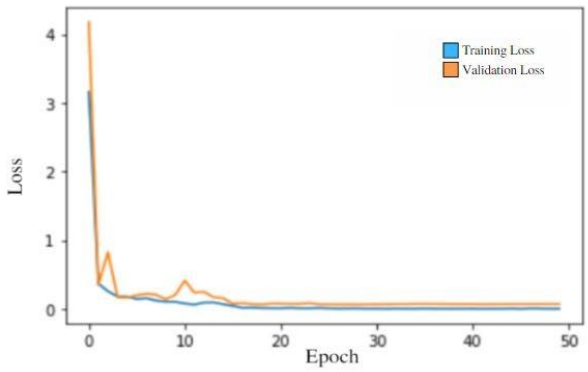

Fig - 13: Loss Comparison of MobileNET Model

5.3 ResNET-152

Pre-trained architecture of MobileNET has given great accuracy on unseen images.

Accuracy: 97.71 percentage as represented in Table 3. Accuracy and Loss graph comparison of ResNET-152 can be seen in Fig 14 and 15 respectively.

	TP	TN	FP	FN	Precision	Recall	f1-score
Glioma Tumor	284	1002	9	16	0.97	0.95	0.96
Meningioma Tumor	295	998	17	11	0.95	0.96	0.95
No Tumor	405	905	1	0	1.00	1.00	1.00
Pituitary Tumor	297	1008	3	3	0.99	0.99	0.99
Accuracy							0.98
Macro avg					0.98	0.98	0.98
Weighted avg					0.98	0.98	0.98

Table - 3: ResNET-152 Model Performance

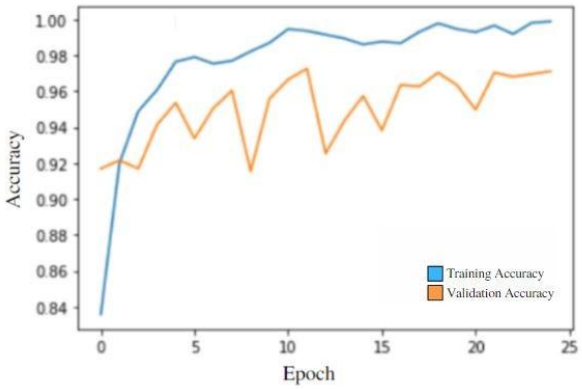

Fig - 14: Accuracy Comparison of ResNET-152 Model

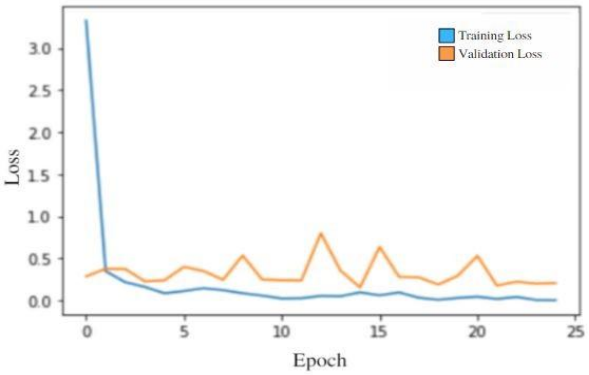

Fig - 15: Loss Comparison of ResNET-152 Model

5.4 VGG-16

Pre-trained architecture of VGG-16 has given great accuracy on unseen images.

Accuracy: 98.62 percentage as represented in Table 4. Accuracy and Loss graph comparison can be seen in Fig 16 and 17 respectively.

	TP	TN	FP	FN	Precision	Recall	f1-score
Glioma Tumor	286	1009	2	14	0.99	0.95	0.97
Meningioma Tumor	302	991	14	4	0.96	0.99	0.97
No Tumor	405	905	1	0	1.00	1.00	1.00
Pituitary Tumor	300	1010	1	0	1.00	1.00	1.00
Accuracy							0.99
Macro avg					0.99	0.99	0.99
Weighted avg					0.99	0.99	0.99

Table - 4: VGG-16 Model Performance

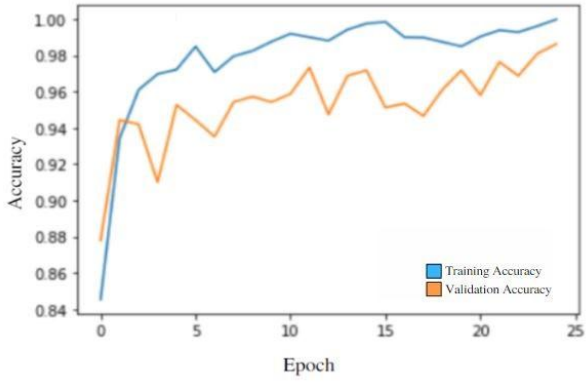

Fig - 16: Accuracy Comparison of VGG-16 Model

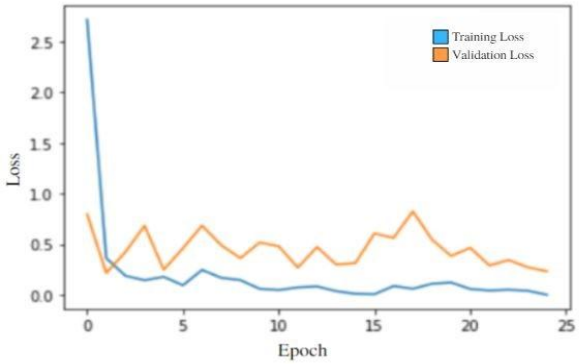

Fig - 17: Loss Comparison of VGG-16 Model

5.5 DenseNET-169

Pre-trained architecture of DenseNET-169 has given a nice accuracy on unseen images.

Accuracy: 96.56 percentage as represented in Table 5. Accuracy and Loss graph comparison can be seen in Fig 18 and 19 respectively.

	TP	TN	FP	FN	Precision	Recall	f1-score
Glioma Tumor	273	1009	27	0	0.99	0.91	0.95
Meningioma Tumor	290	978	16	25	0.91	0.95	0.93
No Tumor	404	900	1	6	0.99	1.00	0.99
Pituitary Tumor	299	1001	1	10	0.97	1.00	0.98
Accuracy							0.97
Macro avg					0.97	0.96	0.96
Weighted avg					0.97	0.97	0.97

Table – 5: DenseNET-169 Model Performance

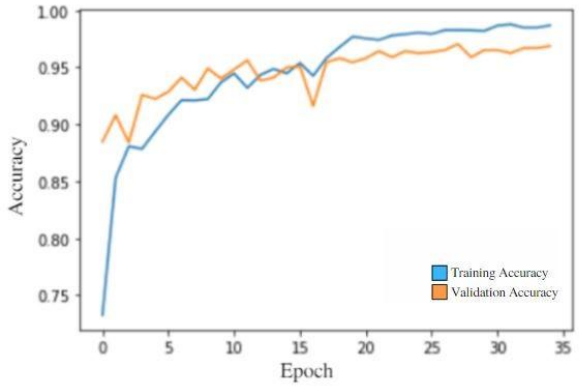

Fig - 18: Accuracy Comparison of DenseNET-169 Model

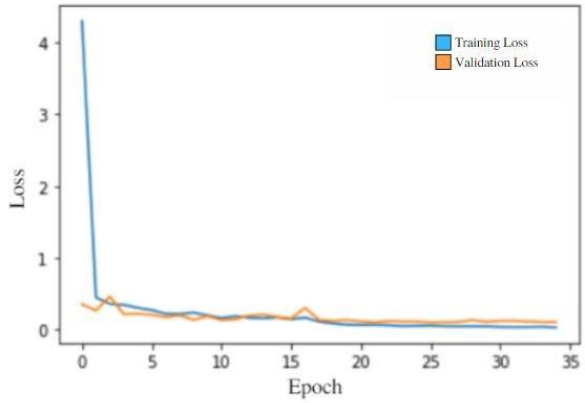

Fig - 19: Loss Comparison of DenseNET-169 Model

6. CONCLUSION

In this report, a peculiar brain tumor detection architecture has been developed that is beneficial for the characterization of four MRI modalities. It implies that each modality has distinctive qualities to effectively aid class distinction by the network. CNN model (the most popular deep learning architecture) can achieve performance close to that of human observers by processing only the portion of the brain image that is close to the tumor tissue. It has also been suggested to use an easy-to-use but effective cascade CNN model to extract local and global characteristics in two separate methods utilising extraction patches of various sizes. The patches are chosen and fed into the network whose centres are situated in the predicted region of the tumour following the extraction of the tumour utilising our method. Because a considerable number of useless pixels are eliminated from the image during the preprocessing stage, calculation time is decreased and the capacity for quick predictions for clinical image classification is increased. The comparative study of various techniques mentioned above is presented in this report.

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