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A Study of CNN Based Brain Tumor Detection Using Deep Learning

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ABSTRACT

Necessarily, most of the humans are suffered by an abnormal growth of cells in the body called cancer. There is various sort of cancer diseases are prevailed among the human. So, among a few infections, quite possibly the most thorough issues people are confronting today is Brain Tumour. Tumour is a bundle tissue that is made by a development of irregular cells. Tumour cells develop quickly paying little mind to the body need not bother with them. They don't kick the bucket like ordinary cells. Along these lines, identification of tumour cells is an incomparable errand. Manual location is a drawn-out task. At Present, Artificial Intelligence is helpful for diminishing manual work and furthermore work like a human. Despite the fact that we had a modest quantity of dataset, we can without much of a stretch distinguish the Tumour cells utilizing Transfer learning. It is one of the primary benefits of AI. A portion of the calculations are there, yet it has low precision and requires more pre-handling strategies. A large portion of the customary mind tumour identification having low exactness issue. The principle point of this work is to arrange and anticipate the tumours a piece of the MRI picture by utilizing Transfer learning. The results created by this methodology will build the precision and lessen the quantity of cycles.

Keywords: Brain Tumour, Magnetic Resonance Imaging (MRI), Transfer Learning

Introduction

All the necessary functions of the body are controlled by brain. The brain is most important part of the central nervous system (CNS) which is the most complex organ in human body. The people in the developed countries are died due to brain tumours has increased 300% over the last three decades which is reported by National Brain Tumour Foundation (NBTF). It is one of the Menacing diseases in the world. Tumour is an uncontrollable cell proliferation in the brain. It can be benign or malignant. The benign and malignant tumour types classification is scaled from grade I to grade IV where benign tumours categorized under grade I and II glioma and malignant tumours categorized under grade III and IV glioma. One of the brains tumour analysis based on imaging data. Analysis through experts may vary by experience which can influence the accurate examination of image. Therefore, how accurately the algorithms show only 90% to 96% of accuracy in detection.

Detect the tumours in the brain is the foremost thing. Magnetic Resonance Imaging can provide detailed information about the human tissues and organs including its contour, volume and location without high ionizing radiation. Computed Tomography (CT) uses radiations to check for abnormalities in the tissues and have the potential to affect the living tissues. The advantage of MRI over CT image is that it is not harmful to human health. The results derived from MRI scans are very clear and precise. Here MRI Images are used for detecting the brain tumour parts.

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Literature Review

For the past few decades, a numeral number of algorithms have been developed for recognition and segmentation. Some of the algorithms show only 90% to96%accuracy in detection.

Nasrulloh et al. [2] proposed an enhanced region mounting approach to eliminate the integrate the gradient information and volume effect. This work obtained more accuracy and had a certain filling of the seepage gap that may occur after detection.

The Template-based K means and improved Fuzzy C Means clustering algorithm for an automatic brain tumor detection in MRI image was proposed by Md ShahariarAlam et. al.[3]. This algorithm produced 97.5% accuracy.

Convolutional Neural Network (CNN) based lung tumor detection was proposed by Sasikala et. al. [8]. This system predicts and classify the lung tumor as malignant or benign. The accuracy of this system is 96%. It is more efficient than traditional neural network systems. In addition to that, the specificity of this system is 100% which shows that there is no false positive detection.
However, this existing method of tumor detection generally have the following problem

- Low accuracy
- It requires more data preprocessing
- Need a greater number of images to train

The major aid of this work can be concluded as follows:
This work proposes an algorithm of brain Tumor detection based on Transfer learning with a small amount of dataset. Mainly, it improves the accuracy of detection.

Transfer Learning

Transfer learning is mainly used for, instead of learning from scratch, leverage or transfer the knowledge learnt from the past. Fig1 shows the schematic representation of the transfer learning.

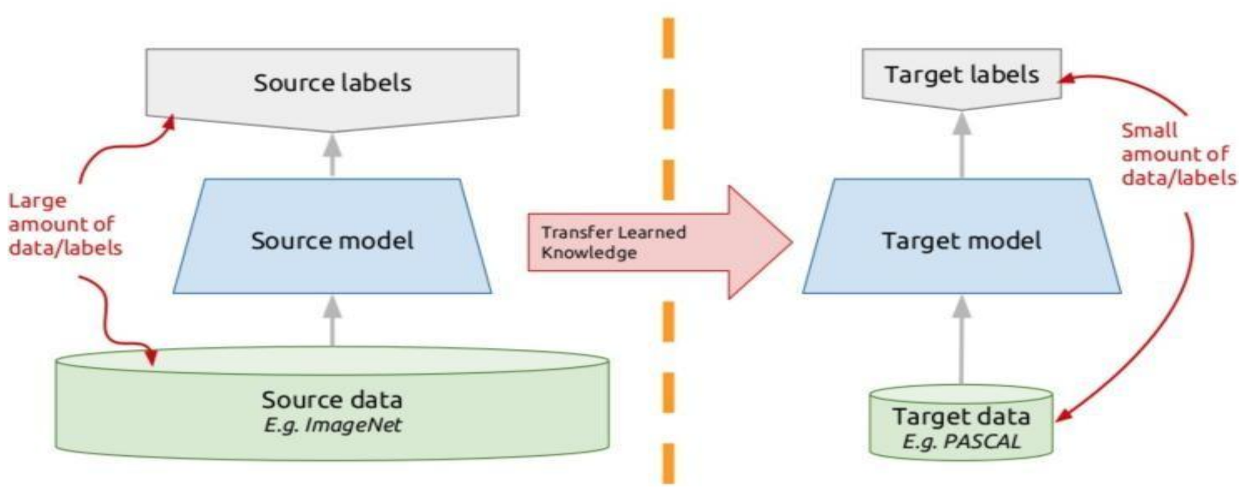

Fig1.SchematicdiagramofTransferLearning

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It is one of the research problems in Machine Learning. When we have a smaller dataset than the large dataset, then we can use the transfer learning.

a) Vgg16

A convolutional neural network model named as VGG16 was developed by K.Simonyan and A. Zisserman in their ―Very Deep Convlutional Networks for Large-Scale Image Recognition work at University of Oxford. It is having multiple 3 x 3 kernel sized filters one after another which replaces large kernel-sized filters in AlexNet. Hence, VGG16 outperforms well rather than AlexNet.It was one of the famous models submitted to ILSVRC-2014.

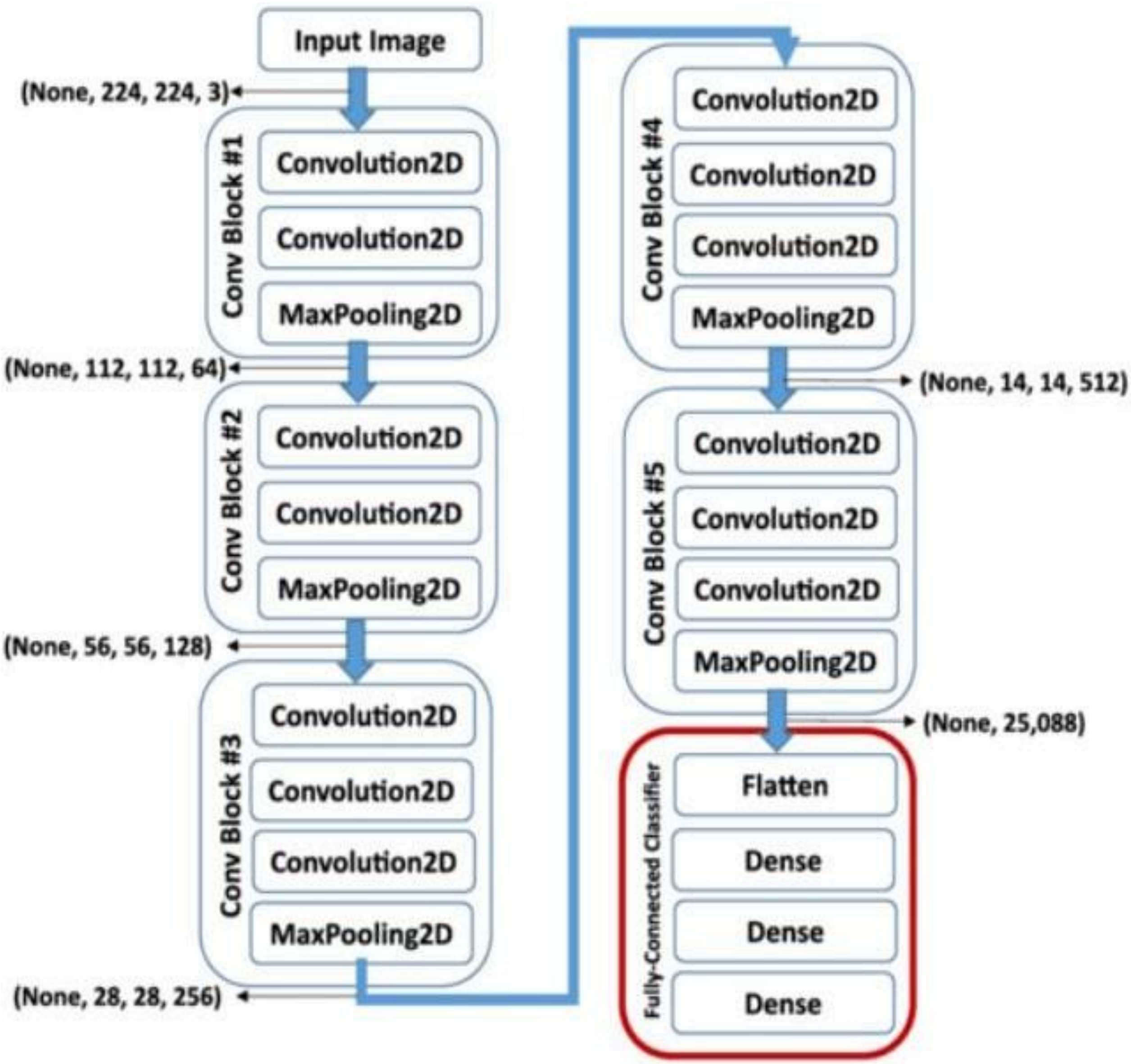

Fig2. Architectural Diagram of Vgg16

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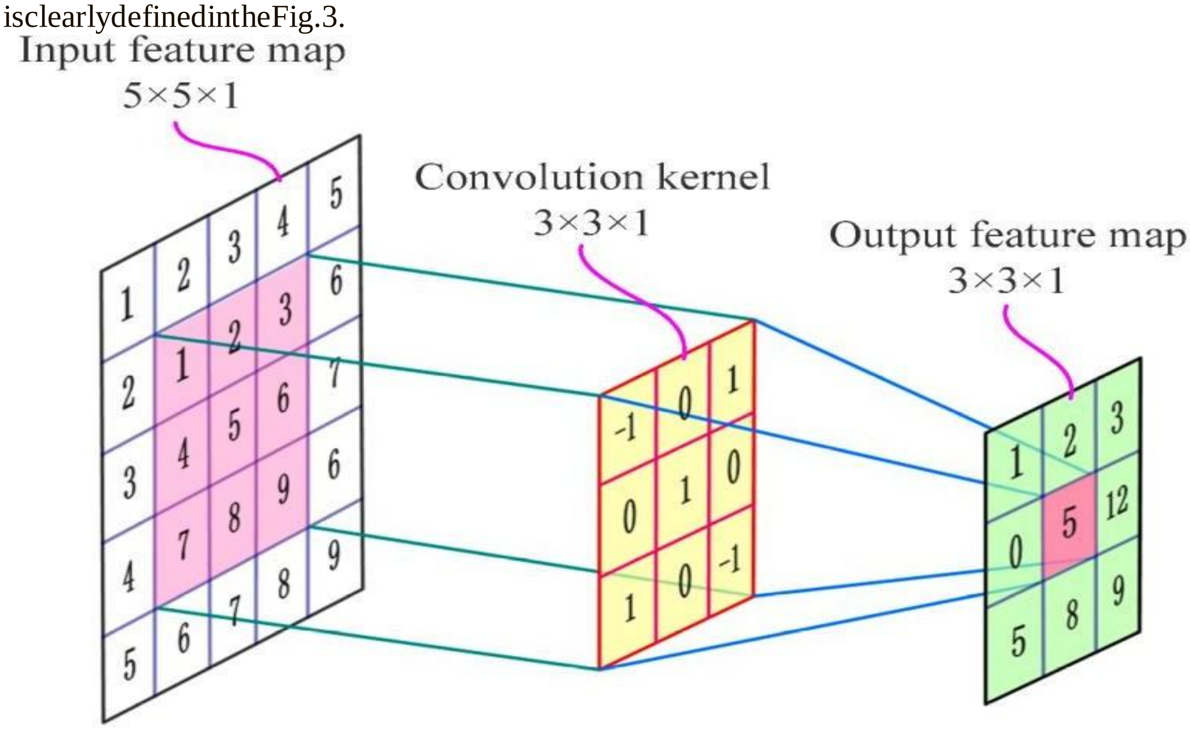
This model achieved 92.7% test accuracy in ImageNet. ImageNet is the large dataset of over 14 million images available with 1000 different classes. NVIDIA Titan Balck GPU was used for training VGG16 model for week. The architecture of VGG16 model is shown in Fig.2. This model consists of 13 convolutional layers, 5 Max Pooling layers and 3 dense layers, where out of 21 layers 16 layers are having weights in VGG16.c) SMOTE (Synthetic Minority Oversampling Technique)

Layers

a) Convolution Layers

Convolution layeristhe first layerin the VGG16Model. This layer mainly comprises of set of filterswhich areconvolved with an input image. The mainaim this layer is to extract the high-level features ofthe inputimageviz.edges. During training, CNN learns and updates filters or kernel values. The richer features of the images can be extracted by using CNN with multi-kernel convolution mechanism. The convolution operation of the layer isclearlydefinedintheFig.3.



$$-1\times1+0\times2+1\times3+0\times4+1\times5+0\times6+1\times7+0\times8+(-1)\times9=5$$

Fig3. Schematic diagram of CNN convolution operation

b) Pooling Layer

The spatial size of the convolved feature is reduced using pooling layer which is computationally in expensive one. There are two different types of pooling function viz Max pooling and Average pooling. The maximum value from the convolved matrix as the result of

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max pooling method. whereas an average value from the convolved matrix as the result of average pooling method.The average and max pooling operations are shown in Fig.4

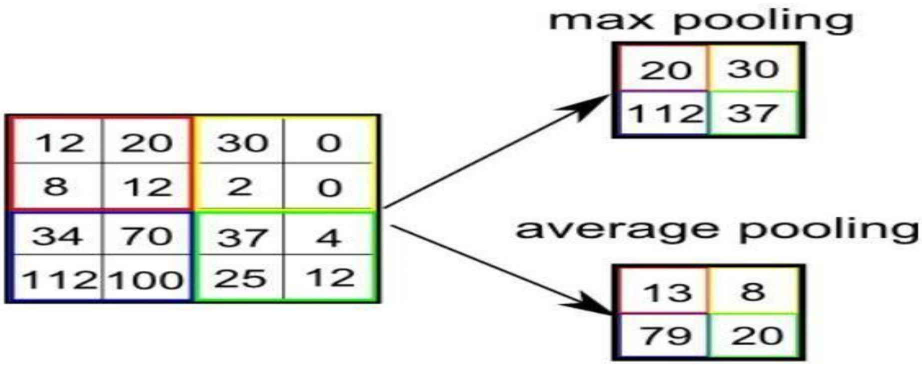

Fig4. SchematicDiagramofPooling Operation

Max pooling is used to remove the Noisy activation and also perform de-noising along with dimensionality. So, Max pooling outperforms well rather than Average pooling. Once the pooling operation is completed, the model can be learned the feature of input image.In this work the Relu activation function has been used because of its advantage which is it does not activate all the neurons at the same time.

c) **Activation Function**

Activation functions are significant to construct sense of something really complicated and Non-linear complex functional mappings. If we use the network, without activation function then, the network does not perform good most of the times. Some of the activation functions used in CNN model are ReLu, Sigmoid, tanh which is mentioned in the Fig 5. In this work the Relu activation function has been used because of its advantage such as it does not activate all the neurons at the same time.

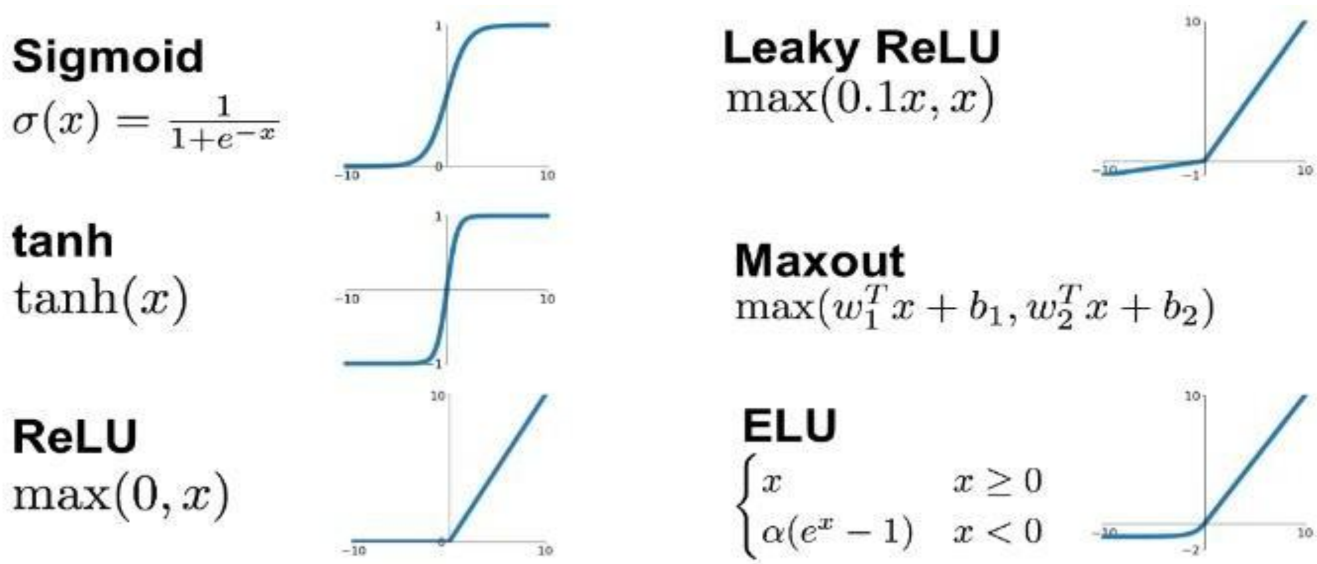

Fig5. TypesofActivationFunction

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In this work, we used densely connected or fully connected layer where each neuron in layer received an input from all the neurons present in the previous layer. This densely connected layer provides learning features collected from all the combinations of features from previous layer. But where as in the convolution layer relies only consistent features with a small repetitive field.In order to obtain the classification result, the image is imported to softmax classifier through the densely connected layer after the convolution kernel imaged.

Proposed Methodology

Flow Diagram

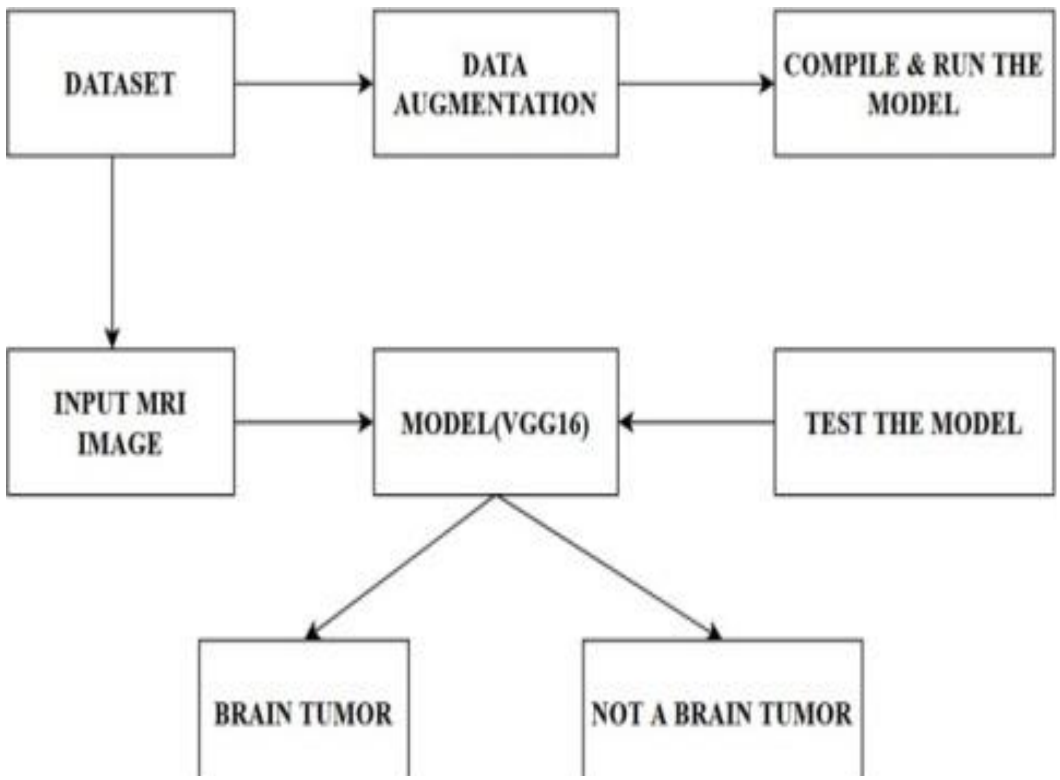

Fig6 :Flow diagram of the workflow System

Working

Initially, the original small dataset was augmented using ImageDataGenarator() function. There is no need for training for this model VGG16. But we can also use our own layer as a last layer. Here, 2 dense layers with 1024 neurons and activation function are ReLu. Finally, one more layer which is a Prediction layer with 2 Neurons because we have to classify between 2 Categories and add Softmax Activation Function which is for Probability Distribution. After all this modification simply compiles and runs the entire model. Compile the model using model.compile() function which has taken two parameters Optimizer and loss function.

Adam optimizer and categorical cross entropy is used as a loss function. Run the model using model.fit_generator(). The main parameter of this function is no. of epochs and batch size. Now, this model can successfully recognize and categorize images into either a Brain Tumor(tumorous) or a Not a Brain Tumor(non-tumorous).

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Experimental Results

Dataset:
The experimental data set consists of Yes and No for Tumor Detection, which have a total 253 MRI image of the Brain. Folder yes contains 155 MRI images and No contain 98 MRI images. In this work, existing data set is augmented with the limited source of images. Then images will be converted as numpy arrays to process the data.

Confusion Matrix:
The summary of prediction result on a classificationproblem is carried out by using confusion matrixwhere count values of correct and incorrect prediction on each class is summarized. It shows the ways in which our classification model is confused when it makes predictions. Table1 shows the General Confusion Matrix and where as in Table2 shows the Calculated Matrix for this work.

Table1: General Confusion Matrix

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Calculations

Table2: Calculated Confusion Matrix

		Actual	
		Positive(1)	Negative(0)
Predicted	Positive(1)	7 (TP)	0 (FP)
	Negative(0)	1 (FN)	6 (TN)

Total Image given as input for test =14

1. **<u>TPR</u> (True Positive Rate)**

   TPR = TP/P = TP/(TP+FN)TPR =7/(7+1)=0.875

2. **<u>TNR</u> (True Negative Rate)**

   TNR=TN/N=TN/(TN+FP)TNR=6/(6+0)=1.000

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Training Loss and Accuracy

The Experimental result of this network is out performed. This work produced 98.74% training accuracy over 8 epochs. Below the diagram is the graph for Training loss. This method takes around 3.5minutes to train the dataset with 98% accuracy.

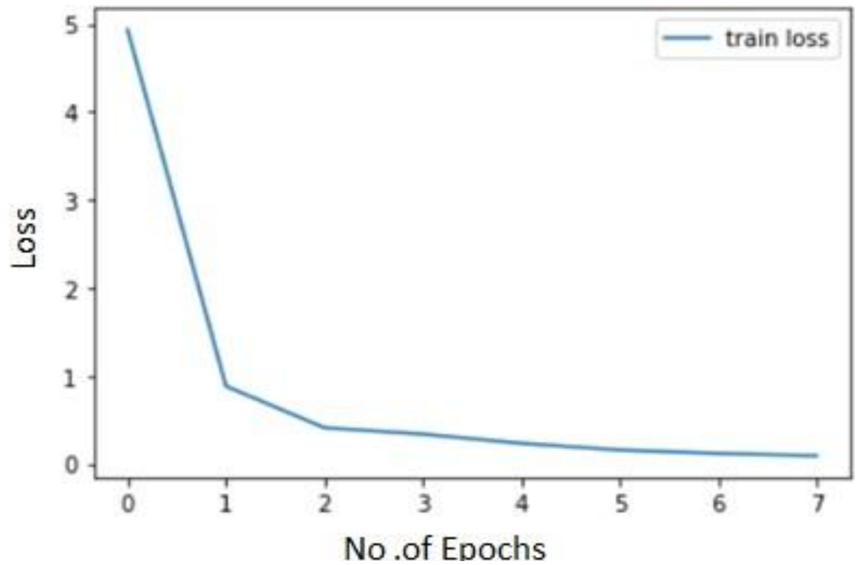

Fig7. Result of Training Graph

The above graph Fig7 represents the Training loss of the model. Here X axis represents No of epochs and Y axis represent the loss value of the model.

Conclusion and Future Enhancement

In this study, a 2D MRI brain tumor detection using the VGG16 model was proposed. It is very useful to predict the Brain Tumor‖ or Not a Brain Tumor image with more accuracy. The main advantage of this approach is with the help of small dataset, system can easily predict the tumor cells with 98% accuracy. For future scope, I will analyze the multimodality of the brain and detect the tumor lesions area very effectively using CNN combining with Multimodal fusion information using Literature [1].For further we will consider life quality attributes to which will identify the most influencing factor and to identify the best classification technique for predicting the brain tumor.

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