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DETECTION OF BRAIN TUMOR BASED ON CONVOLUTION NEURAL NETWORK USING MRI IMAGES

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Abstract: Brain tumor is a perilous disease which is brought on by abnormal growth of anomalous cells in the body which limits the functioning of brain. Brain tumors arises in a variety of size, features and shape. Identifying the brain tumor manually with error-prone is a difficult and time-consuming task for the radiologists as there is a good similarity between the normal tissues and brain tumor cells in appearance. In order to decrease the death rate or increase the survival rate of the effected people an early, efficient and accurate detection of brain tumor is required. Automated disease detection has become up-and-coming field in medical diagnostic applications. So, in this project brain tumor is detected automatically using convolutional neural network (CNN) based on Magnetic resonance imaging (MRI). MRI provides detailed information than other imaging techniques. This framework consists of five stages called as input layer, convolution layer, activation layer, pooling layer and fully connected layer. In the results, the loss and accuracy measured, predicted output and actual output are compared and confusion matrix is obtained.

***Index Terms* -** Brain tumor, Convolutional neural network, Magnetic imaging resonance, input Layer, Convolution layer, activation layer, pooling layer and fully connected layer.

I. Introduction

Brain is a convoluted organ that controls human thoughts, emotions, vision, memory, touch, breathing, motor skills, hunger, temperature and every process that regulates our body. In general, new cells will be formed when old cells get old or damaged, but in some instances new cells starts forming even when not required and the damaged cells do not die. This collection of mass tissues is known as brain tumor. Simply, brain tumor is brought on by abnormal growth of unwanted cells in the body. Symptoms of brain tumor includes headaches, vomiting, difficulty with balance, vision problems, gradual loss of sensation and many more. In some cases, there may be no symptoms.

Brain tumors are of two types. They are malignant and benign. Benign tumors are noncancerous. It grows slowly, do not spread into other tissues. It has clear borders. Malignant tumors are cancerous. It grows rapidly and invades healthy brain tissues. It has distorted borders. Some of benign tumors are meningioma, pituitary adenoma, craniopharyngioma. Some of the meningioma tumors are gliomas, germ cell tumors, acoustic neuroma, chordoma. Gliomas develops across nervous system. Germ cell tumors develops from germ cells. Acoustic neuroma affects the hearing nerves. Chordoma presents in the pituitary glands.

Brain cancers have been diagnosed using non-invasive imaging techniques like Magnetic Resonance Imaging (MRI). MRI scans are one of the safest scans.

A convolutional neural network is a type of artificial neural network which is used to recognize image or object. CNN automatically detects the important features without any human supervision. Some of the applications are face recognition, pattern recognition.

2. Abbreviations and Acronyms

CNN	:	Convolution Neural Network
MRI	:	Magnetic Resonance Imaging

3. Theoretical framework

3.1 P. Mohamed Shakeel, this paper explores how infrared sensor imaging technology is used to study the MLBPNN (machine learning-based back propagation neural networks). With the help of the multifractal detection technique, the most important features are chosen after the features have been extracted using the fractal dimension algorithm. Although image segmentation techniques can produce reliable findings, some geometric information is lost in the process.

3.2 Gajendra Raut**,** proposes a CNN model for detection of brain tumor. The images are initially pre-processed to get rid of the noise and make good use of them in the future. The suggested methodology uses pre-processed MRI images for training and distinguishes between normal and abnormal pictures based on features retrieved during training. Back propagation was utilized in this to reduce inaccuracy and produce more accurate findings.

3.3 Sunil Kumar, Renudhi, Nisha Chaurasia, this paper examines various methods which are used to identify brain tumor to overcome the number of issues including accuracy, tumor quality, and tumor detection time. After pre-processing MRI image, median filtering techniques are used and its accuracy is 92%.

3.4 Monica Subashini and Sarat Kumar Sahoo, the MR brain scans as a starting point, for detecting the tumor a method is proposed. They also worked on a variety of techniques, such as backpropagation networks for categorizing tumor cells from brain MRI pictures, pulse-coupled neural networks for strengthening the brain MRI images, and noise removal techniques. In a brain MR image, the backpropagation network facilitates the detection of a tumor, and they noticed picture augmentation and segmentation while using their proposed technique.

3.5 Simonyan and Zisserman, in their study, the depth of the convolutional network's accuracy in the setting of massive picture recognition was examined. Their team's entry to the 2014 ImageNet Challenge was built on these discoveries, and as a result, it won first and second place in the localization and classification categories. Their main contribution was a comprehensive analysis of networks with increasing depth using an architecture with very small convolution filters (33), which shows that increasing the depth to 16–19 weight layers after training smaller variants of VGG with fewer weight layers can significantly outperform existing configurations.

3.6 Szegedy et al., designed an inception, a deep convolutional neural network architecture, became the new standard for detecting and classifying in the 2014 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC14). The key differentiating characteristic of this architecture is the better exploitation of the network's computational capabilities. This was made achievable by a carefully considered design that supports growing the depth and width of the network while keeping a fixed computing budget. His findings appear to provide compelling evidence that optimizing neural networks for computer vision can be accomplished by approximating the desired ideal sparse structure using readily accessible dense building pieces.

3.7 Sathya et al., designed different clustering algorithms, including K-means, C-means, improvised C-means and improvised K-means algorithm. In their paper, they described an experimental analysis for huge datasets made up of original pictures. They conducted a number of parametric tests to examine the results of the findings.

3.8 B. Devkota, identified aberrant tissues using morphological procedures and a computer-aided detection (CAD) technique. The morphological opening and closure operations are chosen among all segmentation methods because they need less processing time while being the most effective at removing tumor areas with the fewest flaws.

4 RESEARCH METHODOLOGY

The above figure describes the block diagram to detect the brain tumor based on CNN using M RI images.

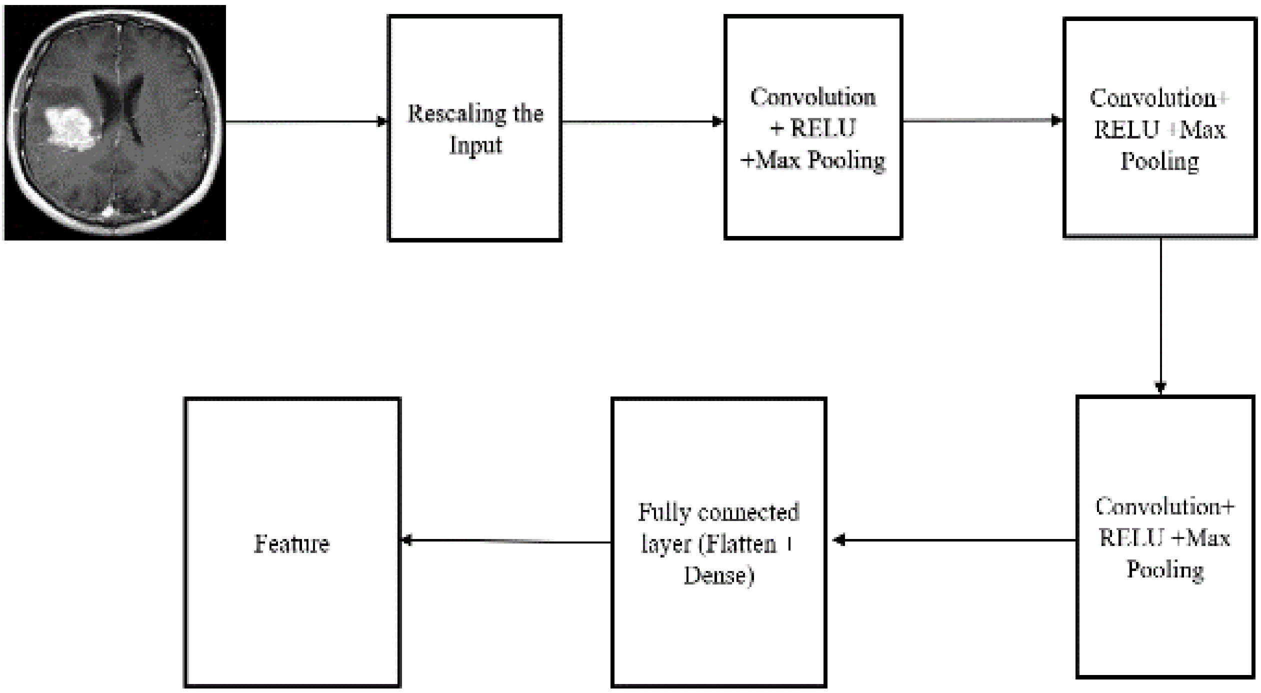


Figure 1. Block Diagram

Step wise Implementation:
Kaggle platform is used to execute the program.

4.1 Importing Libraries
Initially, some important libraries are being imported such as pandas, NUMPY, OS, glob, PIL, matplotlib and tensor flow.

4.2 Importing Dataset from Kaggle software
Kaggle Datasets allows users to create their own custom datasets, to import them into notebooks and to share them with others. In this paper, two data sets are being imported. They are Br35H: Brain Tumor Detection 2020 and Brain Image clean.

Data Set:
Two data sets are extracted using this software. They are mentioned below.
a. Br35H: Brain Tumor Detection 2020
b. Brain Image clean

a. Br35H: Brain Tumor Detection 2020 data:
There are three folders in this data collection. They are yes, no, and pred which together contain 3060 brain MRI images.

Table 1. Br35H: Brain tumor detection 2020 data set

Folder	Description
yes	There are 1500 tumorous brain MRI images in the yes folder.
no	There are 1500 tumorous brain MRI images in the no folder.
Pred	The folder pred contains 60 Brain MRI Images which will be predicted. They might be tumorous or non-tumorous.

b. Image clean data set:
This data set contains 2 folders. They are test and train. Both are again subdivided into two directories known as yes and no. Train contains a total of 2100 Brain MRI Images whereas test contains 900 Brain MRI Images.

Table 2. Brain Image clean data set

Test		Train	
Yes	No	yes	No
457 Images	443 Images	1043 Images	1057 Images

4.3 Model Building
In this step, the model is build using the layers of convolution neural network. The Convolution Neural Network (CNN) consists of five layers such as input layer, convolution layers, activation layer, pooled layer and fully connected layer. The input is given using the input layer. The main work of the convolution layer is, it generates the feature map by convolving on the input image. The output of the convolution layer is down sampled first and then delivered to a nonlinear function. Pooling layer passes the value to the next layer by using defined sliding window technique by taking its maximum or average value. After completion of pooling layer, the image will be flattened and imported into Soft max classifier to obtain the result. The cross-entropy loss function, which will normalise the score to the probability distribution of each label, should be connected to the output of the fully connected data.

The whole process includes five steps mentioned below:

4.3.1 INPUT LAYER:

MRI images are given as an input in this layer. Pre-processing and rescaling is done to achieve better results. The technique called pre-processing is used to transform unclean data from raw data and number of parameters are reduced using rescaling which enables easier to train.

4.3.2 CONVOLUTION LAYER:

The foundation of a convolutional neural network is the convolutional layer (CNN). CNN includes a number of kernel filters which is used to extract the features present throughout the image. Convolution operations are done with different types of kernels at different levels and the feature maps can be obtained from general to advanced during extraction process.

Through the fusion of feature information at the higher levels, CNN is able to gather global information that is equivalent to being fully connected. Set of kernels are convolved with each other and produce a set of images are called feature maps.

Different types of convolution kernels are convolved with the same image and produce a different feature map. To get best results the CNN uses the multi-kernel convolution method and extract the good feature maps and also reduces the corresponding parameters.

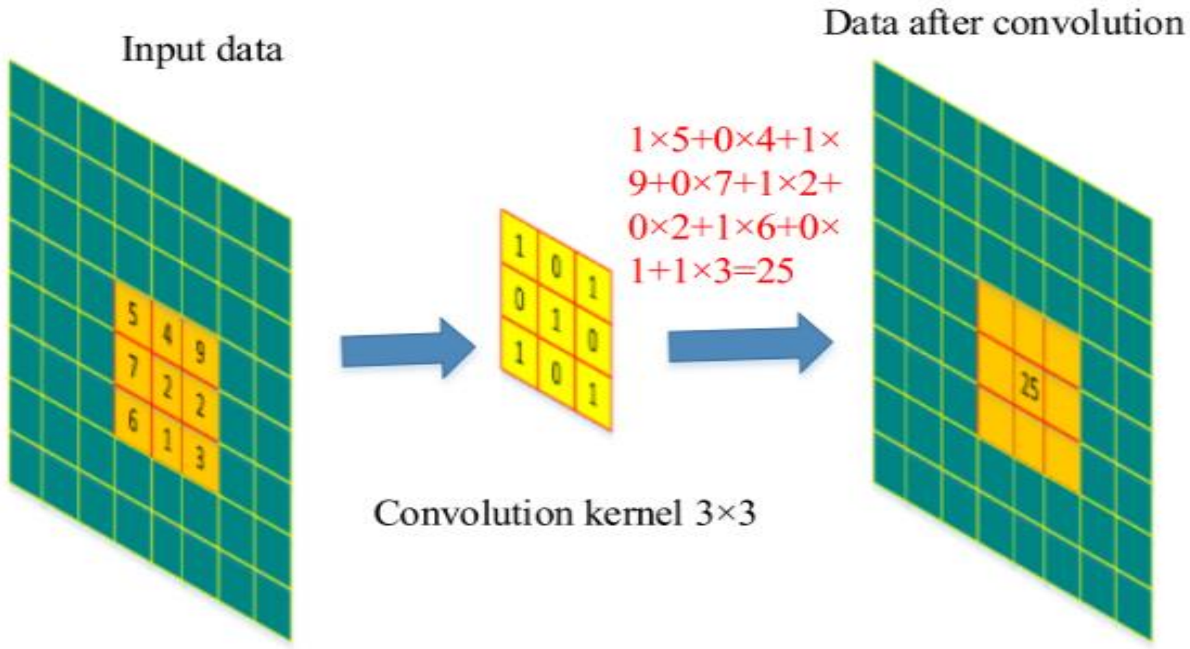


Figure 2. Schematic diagram of CNN convolution operation

Local perception and parameter sharing are the main characteristics in the convolution layer, and these are employed to minimise the amount of training parameters for network models. Local perception is nothing but each neuron node can respond to the certain regions of the global image because the local pixels are closely bonded and the pixels from a distance are weakly bonded.

Parameter sharing means that each feature map corresponds to the same convolution kernels. The number of channels produced by the previous layer determines the number of channels of the convolution kernel. All feature maps get combine to get fully extract features.

4.3.3 ACTIVATION LAYER:

Activation layer is a activation function which introduces non linearity. Common activation functions include Sigmoid, RELU, tanh, and so on.

In this paper we can use the RELU function as the activation function, RELU refers to rectified linear unit. This activation function is more preferrable than other activation functions because they were simple, fast to compute than other activation functions.

$$\mathrm{RELU} = \max(0, x)$$

We can also use the sigmoid function as the activation function. However, because the backpropagation involves a division operation, the derivative steadily approaches zero.

$$\mathrm{Sigmoid} = 1/\left(1 + \exp(-x)\right)$$

4.3.4 Pooling Layer:

Pooling layer remove some redundant information, to speed up the computation and to make the feature map's spatial size less and sends only the important data to the next layer. Moreover, it is used to extract the features independent of their location in an image. In other words, pooling is down sampling of an image.

There are different types of pooling. Some of them are

A. Maximum pooling:

Maximum pooling is a pooling layer which returns the maximum value of the batch selected in the obtained feature map. The term "batch" refers to a collection of pixels that are the same size as the filter, which is determined by the size of the image.

Suppose, there is a 4x4 input after applying maximum pooling the 4x4 input will break down into different regions and produces 2x2.

B. Minimum pooling:

Minimum pooling is a pooling layer which returns minimum value of the pixels in the batch selected in the obtained feature map.

C. Average pooling:

Average is a pooling layer which returns the average value of the pixels in the batch selected in the obtained feature map.

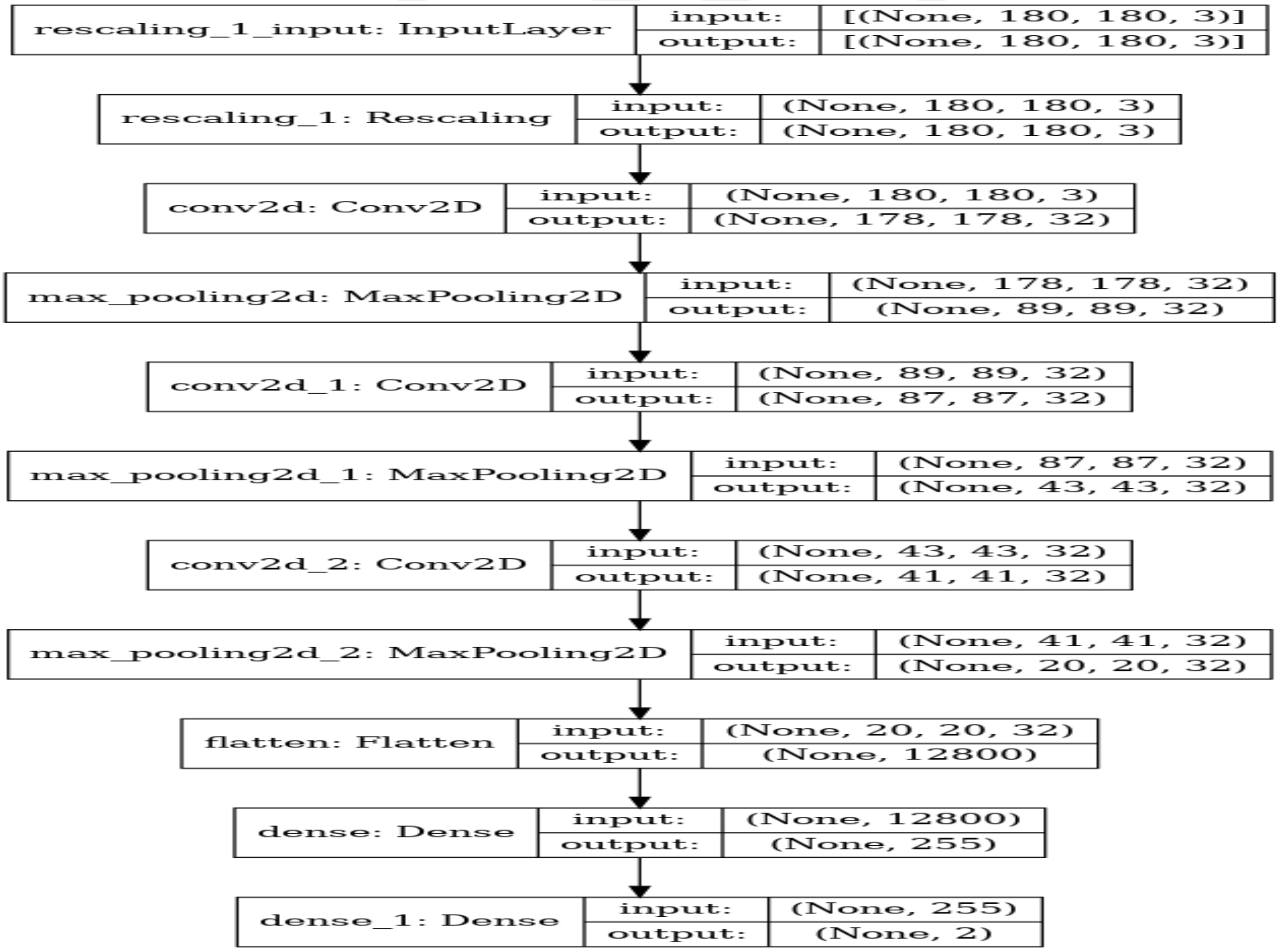
4.3.5 Fully connected layer:

Fully connected layer is also known as hidden layer. It is the last layer in the convolution neural network. Every neuron in one layer is connected to every other neuron in the layer above it, forming a succession of fully connected layers in a neural network. The output acquired from the pooling layer serves as the input to the fully connected layer. In this layer, the matrix is flattened by the flatten function into single long column. The output obtained from the final hidden layer is sent to the soft max function for probability distribution. Then, the dense function returns the output.

4.4 Model testing on test data:

The working of built model is tested using the test data to know whether the predicted output is same as actual output. The loss and accuracy is known using this model testing.

5 Model Analysis:



6 RESULTS AND DISCUSSION

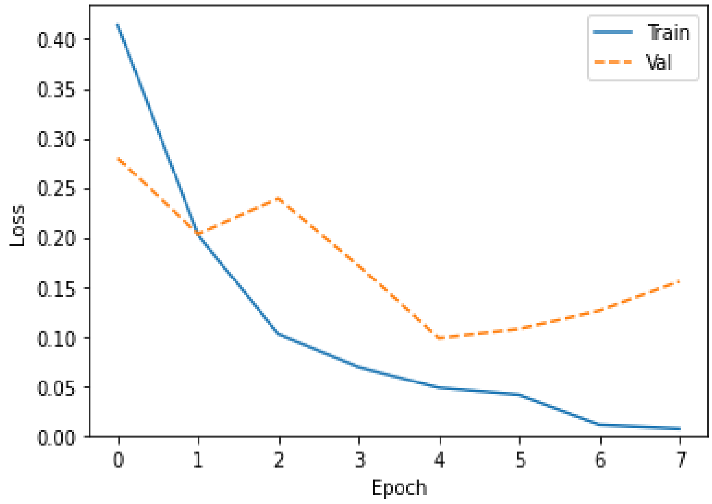


Figure 4. Loss vs Epoch

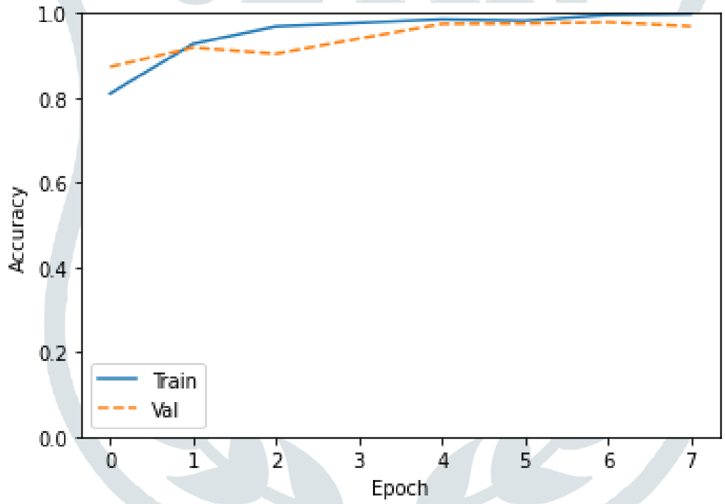


Figure 5. Accuracy vs Epoch

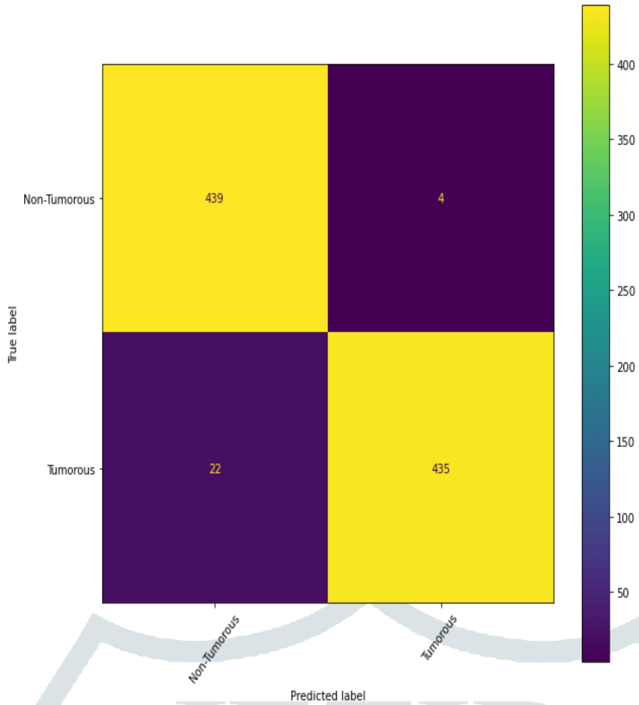
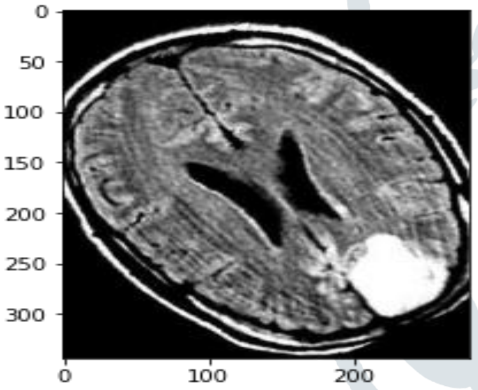
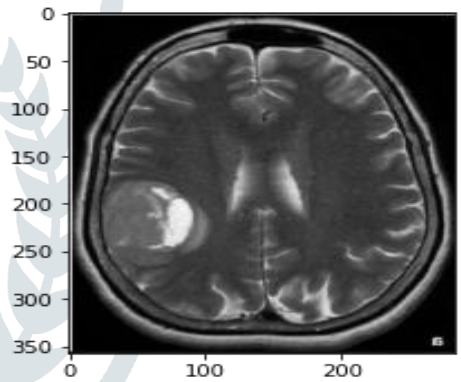


Figure 6. Confusion Matrix



(a)
Actual: no
Prediction: no



(b)
Actual: no
Prediction:no

Fig.7. (a) and (b) Output for Sample Input from data sets

7 Acknowledgment

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