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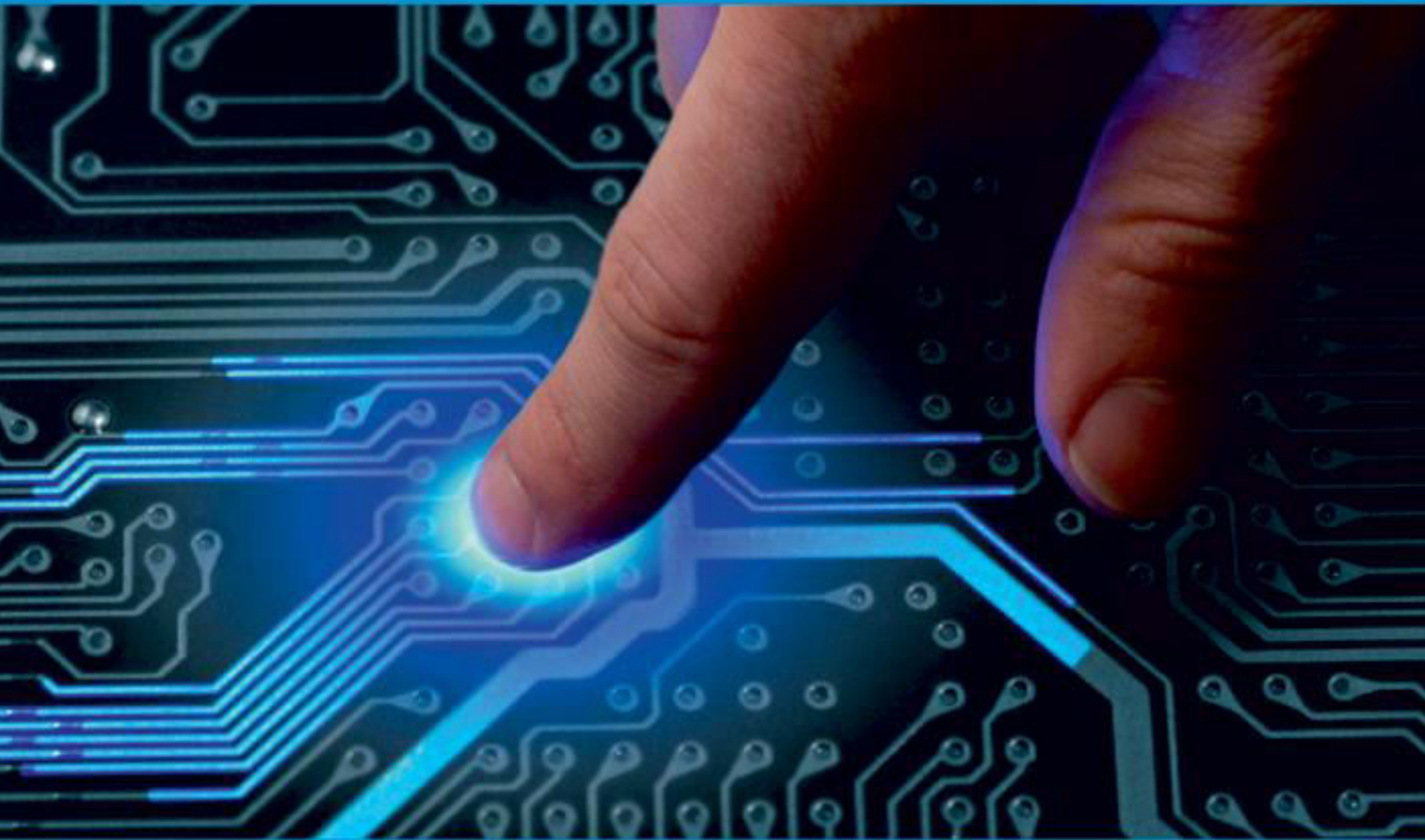

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Brain Tumor Detection Using Vgg16 Convention Neural Network

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ABSTRACT: A cancerous or non-cancerous mass or growth of abnormal cells in the brain is known as brain tumor. It is life threatening hence it is important to recognize and identify the presence of brain tumors. The brain tumors are identified by MRI images. Magnetic resonance imaging(MRI) is a medical image processing technique that uses radio waves to scan the body. In medical world, the detection of brain tumors by reading of MRI images is still done manually by doctors and radiologists. And relying on human visual vision was insufficient to detect quickly and accurately from these MRI images. Current technological support is undoubtedly beneficial for various fields of life especially in medical area with the development of digital image processing. The detection of brain tumor is done by applying deep learning algorithms. It takes extremely little time to forecast a brain tumour when these algorithms are applied to MRI pictures, and the better accuracy makes it easier to treat patients.These also helps the radiologist in making quick decisions. In the proposed work, a self defined convolution neural network (CNN) is applied in detecting the presence of brain tumor and their performance is analyzed.

KEYWORDS:CNN,MRI,Deep Learning,Tumor,VGG 16.

I. INTRODUCTION

The brain is the most important and significant organ among the numerous that make up the human body.A tumour is nothing more than an accumulation of cells that are growing out of control. Brain failure occurs as a result of the growth of brain tumour cells, which eventually consume all the nutrition intended for healthy cells and tissues. Brain cancer is a serious condition that claims many lives every year. Several exclusionary strategies rely on generic edge-based data rather than being focused on the brain tumour domain. Deep learning algorithms have recently been applied for tumour segmentation tasks because to their effectiveness in recognising aspects of photos.

We can see the internal features of the brain's structure thanks to MRI, and we can utilise that information to observe the several sorts of human bodily tissues. When compared to other medical imaging methods like X-ray and computer tomography, MRI images are of higher quality.For mapping tumor-induced change, various MRI images, such as T1 weighted, T2 weighted, and FLAIR (Fluid attenuated inversion recovery) weighted images, are available.

II. LITERATURE SURVEY

The existing method focuses on creating an self defined architecture of ANN and CNN model and finally the performance of ANN and CNN is compared when applied on brain tumor MRI dataset.

ANN and CNN are used in the classification of normal and tumor brain. ANN(Artifical Neural Network) works like a human brain nervous system, on this basis a digital computer is connected with large amount of interconnections and networking which makes neural network to train with the use of simple processing units applied on the training set and stores the experiential knowledge. It has different layers of neurons which is connected together. The neural network can acquire the knowledge by using data set applied on learning process. There will be one input and output layer whereas there may beany number of hidden layers. In the learning process, the weight and bias is added to neurons of each layer depending upon the input features and on the previous layers(for hidden layers and output layers). A model is trained based on the activation function applied on the input features and on the hidden layers where more learning happens to achieve the expected output.

The ANN model used here has seven layers. First layer is the flatten layer which converts the 256x256x3 images into single dimensional array. The next five layers are thedense layers having the activation function as relu and number of neurons in each layers are 128,256,512,256 and 128 respectively. These five layers act as the hidden layers and the last dense layer having the activation function is sigmoid is the output layer with 1 neuron representing the two classes.

The CNN sequential model is generated by implementing different layers. The input image is reshaped into 256x256. The convolve layer is applied on the input image with the relu as activation function, padding assame whichmeans the output images looks like the input image and the number of filters are 32,32,64,128,256 for different convolve layers. The max pooling applied with the 2x2 window size and droupout function is called with 20% of droupout. Flatten method is applied to convert the features into one dimensional array. The fully connected layer is done by calling the dense method with the number of units as 256 and relu as the activation function. The output layer has 1 unit to represent the two classes and the sigmoid as activation function.path and send RREP. Optimization function uses the individual node's battery energy; if node is having low energy level, then optimization function will not use that node.

III. METHODOLOGY

The proposed system:

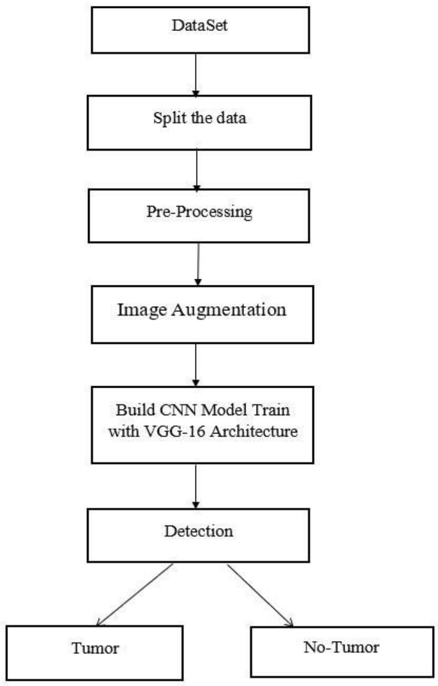

Fig.1.Proposed Work Flow of Brain Tumor Detection

1.Data Set: Dataset is taken from Kaggle. This dataset contains MRI scans of the brain and the dataset is divided into three folders. They are namely YES, NO, PRED FOLDERS. There will be 1500 tumorous brain MRI images in the YES folder. The NO folder contains 1500 brain MRI images that are non-tumorous. The folder pred contains 60 unlabelled Brain MRI scans for testing purpose. ***Brain_Tumor_Detection_MRI:***https://www.kaggle.com/datasets/abhranta/brain-tumor-detection-mri.

Split Data:In split the data we split the datset as 60% Training Data, 20% Validation Data and 20% Testing Data. In each splitting we consider yes and no folders. Pred folder is used only for testing purpose.

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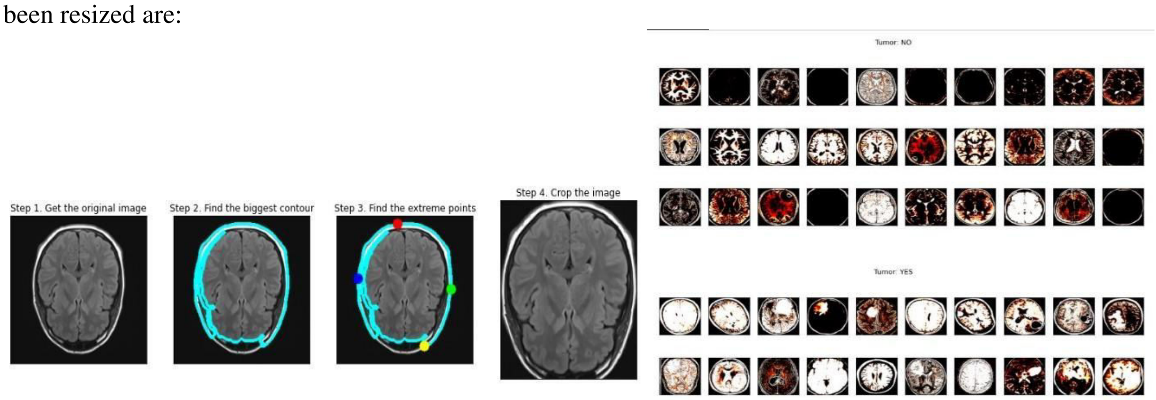
Fig.2.Splitting the data

3.Pre-Processing: Image pre-processing are the steps taken to format images inference. The main aim is to improve the quality of the image so that we can analyse it in a better way. Pre-processing allows us to eliminate unwanted distortions and improve specific qualities that are essential for the application we are working on.

A. Cropping: The images we have are of different sizes. But our model accepts images of size (224*224*3) as input. To achievethis, we have to resize the images. Blindly resizing the images can lead to extreme distortions in the images. Hence, we will first crop their images and then resize them. This will minimize the issue of distortions. This cropping is done by finding contours in the images using the OpenCV Library.

B. Resizing: Resizing an image entail altering its proportions, whether by adjusting just the width, just the height, or both. When the total number of pixels needs to be increased or decreased, an image must be resized. The photos must be resized after being cropped in order to prevent severe distortions or resizing artefacts. The photos must be scaled to (224,224) and pre-processed for input into the VGG-16 model. Some of the photographs from the dataset that have been resized are:



(a) (b)

Fig.3.Pre-Processing
a. Cropping
b. Resizing

Augmentation: Image data augmentation refers to altering per-existing image by making changes to it and including the change version in the training datasets for the neural network.

IV.CONSTRUCT A CNN MODEL USING VGG-16 STRUCTURE

Operating CNN Model A CNN is a particular type of network design for deep learning algorithms that is utilised for tasks like image recognition and pixel data processing. Applications of CNN include natural language processing, picture classification, medical image analysis, and image and video recognition. The term "Convolution" is used in CNN to refer to this mathematical operation. Pretrained VGG-16 model with ImageNet weights from Keras will be used in this instance. For this activity, transfer learning will be used. The loss function will be binary cross entropy, and the monitoring metrics will be accuracy andAUC.Building deep learning models requires less time, money, and

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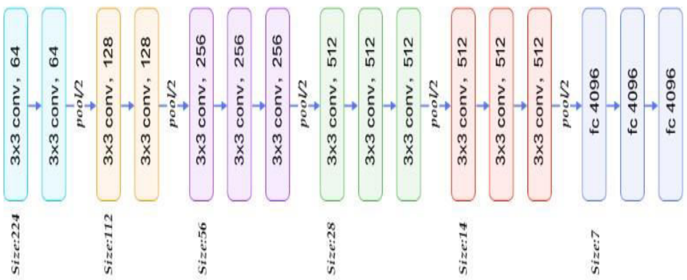
computer resources thanks to the knowledge-sharing technique known as transfer learning.A pre-trained model's learning can be transferred to a new model with the use of transfer learning. Transfer learning has been applied to a variety of tasks, including sentiment analysis, activity recognition, software error prediction, and tumour categorization.



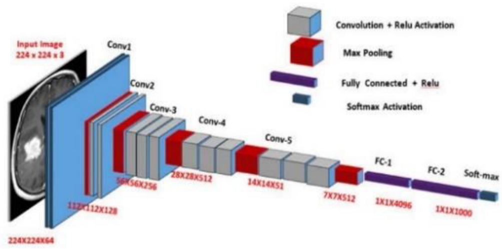


Fig.4.VGG16 layered architectureFig.5.Working of VGG16 model for brain tumor detection

A convolutional neural network with 16 layers is called VGG-16. It is a well-liked technique for classifying images and is simple to employ with transfer learning. The ImageNet dataset, which consists of more than 14 million photos divided into 22,000 categories, was used to train the convolutional neural network VGG16.The 16 in VGG16 stands for 16 weighted layers. Thirteen convolutional layers, five Max Pooling layers, three Dense layers, and a total of 21 layers make up VGG16, but only sixteen of them are weight layers, also known as learnable parameters layers. The most distinctive feature of VGG16 is that it focuses on having convolution layers of a 3x3 filter with stride 1 instead of having a lot of hyperparameters, and italways uses the same padding and maxpool layer of a 2x2 filter with stride 2.Convolution and max pool layers are positioned consistently across the architecture. There are 64 filters in the Conv-1 Layer, 128 filters in Conv-2, 256 filters in Conv-3, and 512 filters in Conv-4 and Conv-5.A stack of convolutional layers is followed by three Fully-Connected (FC) layers, the third of which conducts 1000-way ILSVRC classification and has 1000 channels.
The first two FC layers have 4096 channels each (one for each class). The soft-max layer is the last one.

IMPLEMENTATION OF VGG16 USING KERAS:
Keras is an open source deep learning framework for python. The open source machine libraries TensorFlow, Theano, or Cognitive Toolkit are built on top of Keras (CNTK). The most well-known symbolic math library used to build neural networks and deep learning models is called TensorFlow. and of the original Keras model represents the real neural network model. There are two models Sequential and Functional. Here we are using Sequential Model. The actual neural network model is represented by the Keras model. Sequential and functional models are the two available. Here we are utilising Sequential Model.
Sequential Model: The majority of ANN also have layers in sequential order, and the data flows from one layer to another layer in the given order until the data finally reaches the output layer.
Functional Model: Layer-by-layer models are built using a sequential API. An alternate method for building more complicated models is to use functional API. To access input and output for the model, we first build an instance of the model and link to the layers.

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Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	224 x 224 x 3	-	-	-
1	2 X Convolution	64	224 x 224 x 64	3x3	1	relu
	Max Pooling	64	112 x 112 x 64	3x3	2	relu
3	2 X Convolution	128	112 x 112 x 128	3x3	1	relu
	Max Pooling	128	56 x 56 x 128	3x3	2	relu
5	2 X Convolution	256	56 x 56 x 256	3x3	1	relu
	Max Pooling	256	28 x 28 x 256	3x3	2	relu
7	3 X Convolution	512	28 x 28 x 512	3x3	1	relu
	Max Pooling	512	14 x 14 x 512	3x3	2	relu
10	3 X Convolution	512	14 x 14 x 512	3x3	1	relu
	Max Pooling	512	7 x 7 x 512	3x3	2	relu
13	FC	-	25088	-	-	relu
14	FC	-	4096	-	-	relu
15	FC	-	4096	-	-	relu
Output	FC	-	1000	-	-	Softmax

Fig.6.Layers of VGG16 Architecture

V. RESULT

```
<ipython-input-33-2c0dd213ad9d>:7: UserWarning:

`Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.

Epoch 1/5
50/50 [==============================] - ETA: 0s - loss: 0.3961 - accuracy: 0.8439 - auc: 0.9134 WARNING:tensorflow:Early stopping conditioned on m
50/50 [==============================] - 739s 15s/step - loss: 0.3961 - accuracy: 0.8439 - auc: 0.9134 - val_loss: 0.3552 - val_accuracy: 0.9075 -
Epoch 2/5
50/50 [==============================] - ETA: 0s - loss: 0.2153 - accuracy: 0.9188 - auc: 0.9723 WARNING:tensorflow:Early stopping conditioned on m
50/50 [==============================] - 762s 15s/step - loss: 0.2153 - accuracy: 0.9188 - auc: 0.9723 - val_loss: 0.2260 - val_accuracy: 0.9500 -
Epoch 3/5
50/50 [==============================] - ETA: 0s - loss: 0.1787 - accuracy: 0.9283 - auc: 0.9812 WARNING:tensorflow:Early stopping conditioned on m
50/50 [==============================] - 745s 15s/step - loss: 0.1787 - accuracy: 0.9283 - auc: 0.9812 - val_loss: 0.1143 - val_accuracy: 0.9675 -
Epoch 4/5
50/50 [==============================] - ETA: 0s - loss: 0.1362 - accuracy: 0.9480 - auc: 0.9891 WARNING:tensorflow:Early stopping conditioned on m
50/50 [==============================] - 760s 15s/step - loss: 0.1362 - accuracy: 0.9480 - auc: 0.9891 - val_loss: 0.0716 - val_accuracy: 0.9775 -
Epoch 5/5
50/50 [==============================] - ETA: 0s - loss: 0.1278 - accuracy: 0.9550 - auc: 0.9899 WARNING:tensorflow:Early stopping conditioned on m
50/50 [==============================] - 759s 15s/step - loss: 0.1278 - accuracy: 0.9550 - auc: 0.9899 - val_loss: 0.1211 - val_accuracy: 0.9650 -
```

Fig.7.output

Model Accuracy

The plot between the epochs and accuracy of the training set and validation sets is shown in the graph below. The model's accuracy is indicated by the training set accuracy from the graph below, which is marked as 96.5.

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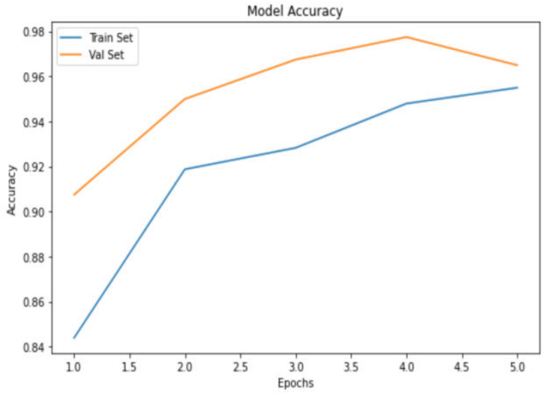

Fig.8.Model Accuracy

Model Loss

This is the plot between epoch and loss of the training and validation sets.

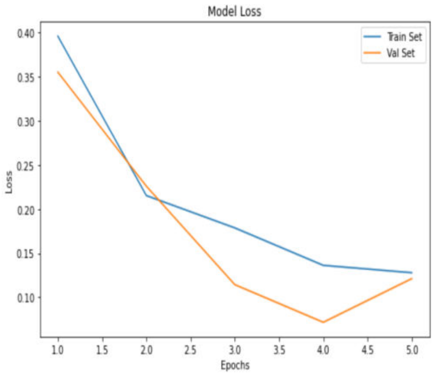

Fig.9.Model Loss

Confusion Matrix

A confusion matrix helps visualize the results of a classification task by presenting a table arrangement of the various outcomes of the prediction and findings. It presents a table of all the anticipated and actual values of a classifier.

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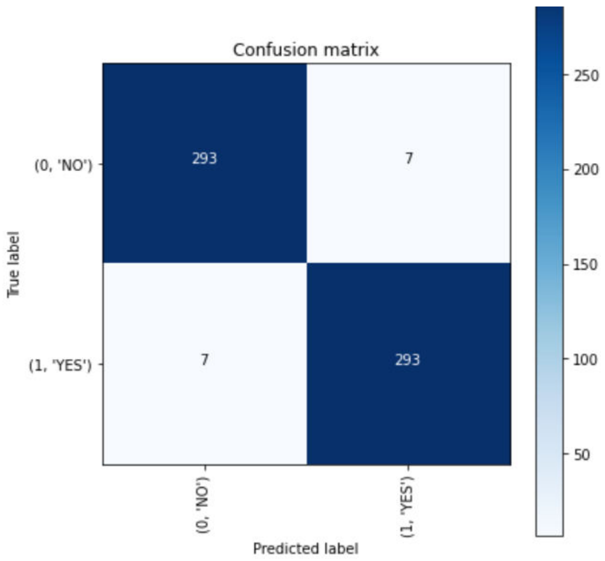
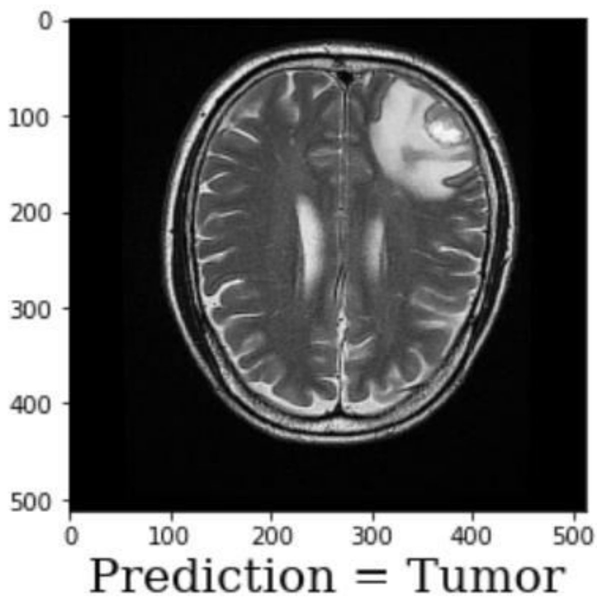


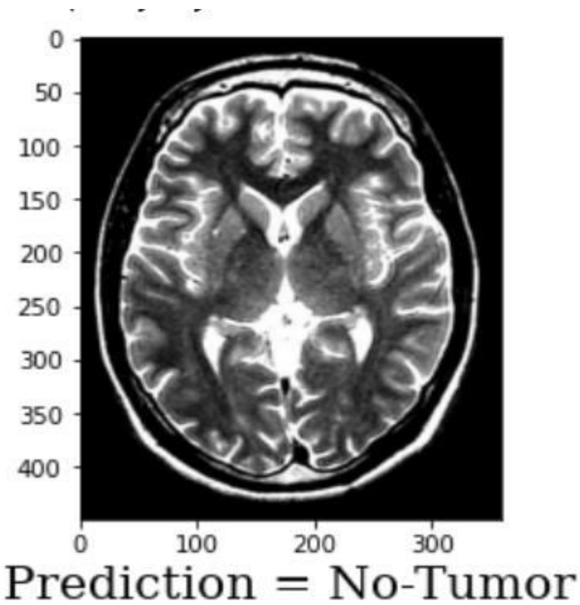
Fig.10.Confusion Matrix

Brain Tumor Prediction

The figures (a) and (b) display the results of our model's predictions both with and without a tumour.



(a)



(b)

Fig.11. prediction of tumor

(a) Tumor present

(b) No-Tumor

VI. CONCLUSION

This research introduces deep learning model for identifying brain tumors. The "VGG 16" architecture is designed to work for detecting the brain tumor. Our experimental results demonstrated that models enhance the prediction performance of diagnosis of brain tumors. We achieved 96.5% prediction accuracy for dataset.

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