



# DEEP LEARNING APPROACHES FOR BRAIN TUMOR DETECTION

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*Abstract:* The brain is the most important organ in the human body which controls the entire functionality of other organs and helps in decision making. Due to brain tumors, nowadays a large number of patients are in danger. The rapid development of abnormal brain cells that characterize a brain tumor is a major health risk for adults since it can cause severe impairment of organ function and even death. These tumors come in a wide variety of sizes, textures, and locations. When trying to locate cancerous tumors, magnetic resonance imaging (MRI) is a crucial tool. However, detecting brain tumors manually is a difficult and time-consuming activity that might lead to inaccuracies. The medical field needs fast, automated, efficient, and reliable techniques to detect tumors like brain tumors. Detection plays a very important role in treatment. If proper detection of tumor is possible then doctors keep a patient out of danger. Various image processing techniques are used in this application. Using this application doctors provide proper treatment and save a number of tumor patients. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all the nutrients meant for the healthy cells and tissues, which results in brain failure. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming. A tumor is a mass of tissue it grows out of control. We can use a Deep Learning architectures CNN (Convolution Neural Network) and VGG 16(visual geometry group) Transfer learning for detect the brain tumor. The performance of model is predict image tumor is present or not in image. If the tumor is present it return yes otherwise return no.

*Index Terms* – Brain Tumor, Convolutional neural network, Magnetic resonance imaging, Visual Geometry Group.

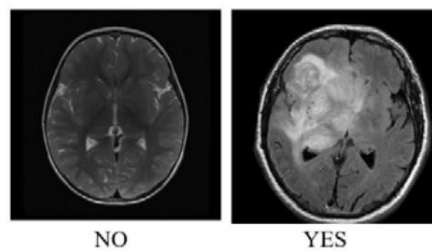
## I. INTRODUCTION

The human brain is incredibly complicated because of its elaborate physical make-up [1]. Stroke, infection, brain tumors, and migraines are only a few examples of CNS illnesses that present considerable difficulties in diagnosis, evaluation, and the development of effective treatments [2]. In terms of early diagnosis, brain tumors—which are caused by the abnormal proliferation of brain cells—present a significant problem for neuropathologists and radiologists. Magnetic resonance imaging (MRI) brain tumor detection is a difficult and error-prone manual process. Brain tumors are characterized by the abnormal development of nerve cells, leading to a mass. About 130 different forms of tumors can develop in the brain and CNS, ranging from benign to malignant and from extremely rare to common occurrences [3]. These malignancies can either form in the brain (primary brain tumors) or spread there from elsewhere in the body (secondary or metastatic brain tumors). Primary brain tumors refer to tumors that originate within the brain itself. These tumors are formed from the brain cells or can be encapsulated within the nerve cells surrounding the brain. Primary brain tumors can exhibit a range of characteristics, including both benign and malignant forms [4]. Secondary brain tumors, also known as metastatic brain tumors, are the most common type of malignant brain tumor. It is important to note that while benign tumors do not typically spread from one area of the body to another, secondary brain

tumors are invariably cancerous and pose a serious threat to health [5]. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming. A Brain Cancer is very critical disease which causes deaths of many individuals. The brain tumor detection and classification system is available so that it can be diagnosed at early stages. Cancer classification is the most challenging tasks in clinical diagnosis. This project deals with such a system, which uses computer, based procedures to detect tumor blocks and classify the type of tumor using Convolution Neural Network

Algorithm for MRI images of different patients. Different types of image processing techniques like image segmentation, image enhancement and feature extraction are used for the brain tumor detection in the MRI images of the cancer-affected patients.

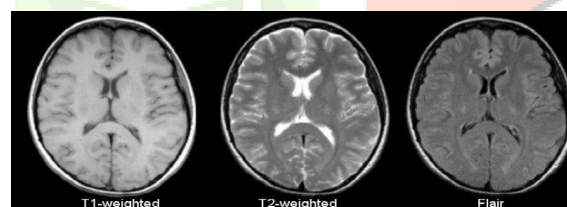
Detecting Brain tumor using Image Processing techniques its involves the four stages is Image Pre-Processing, Image segmentation, Feature Extraction, and Classification. Image processing and neural network techniques are used for improve the performance of detecting and classifying brain tumor in MRI images. Fig.1 shows the images of normal brain and brain with tumor.



**Fig. 1. Normal Brain and Brain with Tumor**

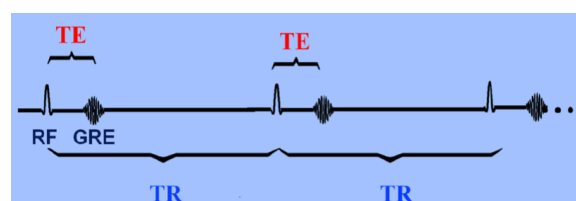
### 1.1 MAGNETIC RESONANCE IMAGING (MRI)

Raymond v. Damadian invented the first magnetic image in 1969. In 1977 the first MRI image were invented for human body and the most perfect technique. Because of MRI we are able to visualize the details of internal structure of brain and from that we can observe the different types of tissues of human body. MRI images have a better quality as compared to other medical imaging techniques like X-ray and computer tomography.[8]. MRI is good technique for knowing the brain tumor in human body. There are different images of MRI for mapping tumor induced Change including T1 weighted, T2 weighted and FLAIR (Fluid attenuated inversion recovery) weighted shown in figure.



**Fig 2: T1, T2 and Flair image**

The most common MRI sequence is T1 weighted and T2 weighted. In T1 weighted only one tissue type is bright FAT and in T2 weighted two tissue types are Bright FAT and Water both. In T1 weighted the repetition time (TR) is short in T2 weighted the TE and TR is long. The TE and TR are the pulse sequence parameter and stand for repetition time and time to echo and it can be measured in millisecond(ms)[9]. The echo time represented time from the centre of the RF pulse to the centre of the echo and TR is the length of time between the TE repeating series of pulse and echo is shown in figure.



**Fig. 3: Graph of TE and TR**

**Table.1: Table of TR and TE time [9]**

	TR (msec)	TE (msec)
<b>T1-Weighted</b> (short TR and TE)	500	14
<b>T2-Weighted</b> (long TR and TE)	4000	90
<b>Flair</b> (very long TR and TE)	9000	114

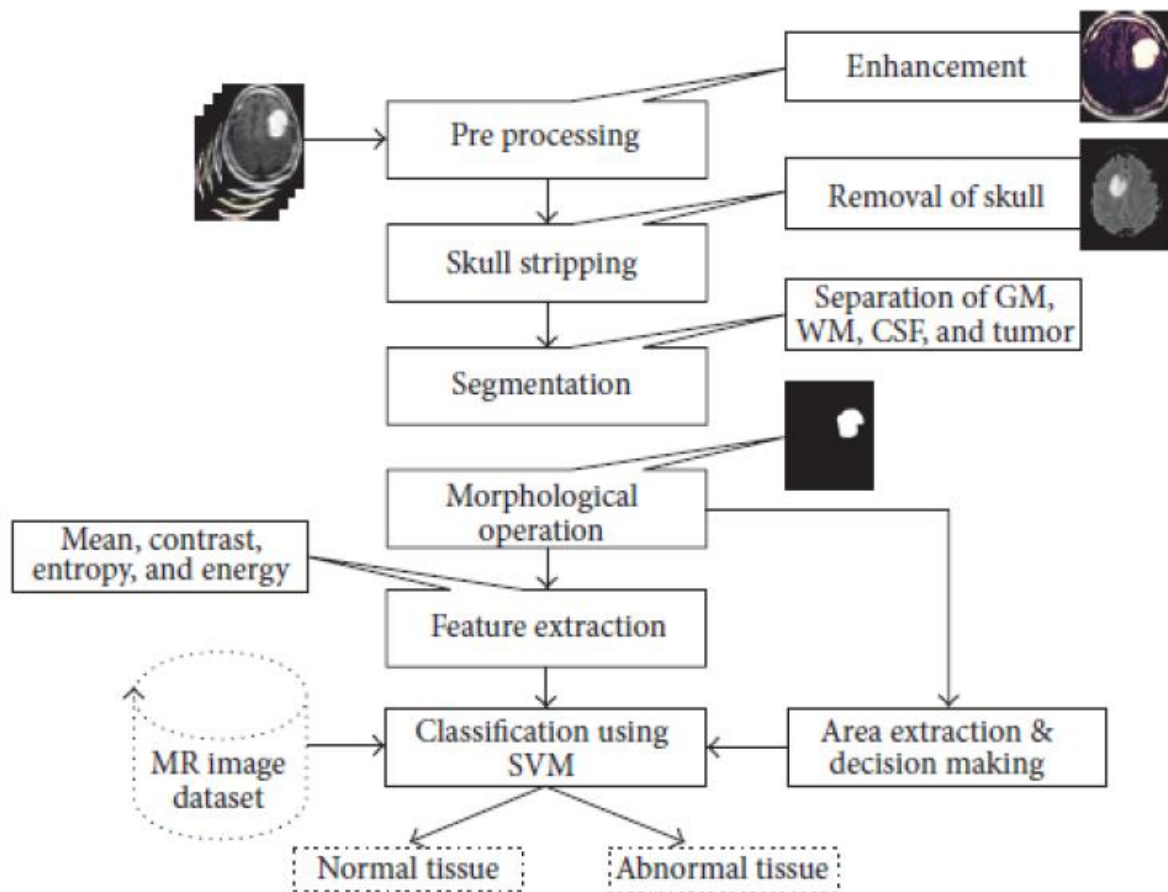
The third commonly used sequence in the FLAIR. The Flair sequence is almost same as T2-weighted image. The only difference is TE and TR time are very long. Their approximate TR and TE times are shown in table.

## II. LITERATURE REVIEW

Abd-Ellah et al. conducted an in-depth study of the available methods for diagnosing brain MRI scans, comparing and contrasting the strengths and weaknesses of traditional machine learning and deep learning approaches. Additionally, the authors presented a new semi-automatic segmentation approach for images of brain tumors [3]. Khan et al. [4] developed a method for classifying and segmenting brain cancers in MRI images using VGG19 CNN architecture and K-means clustering. The suggested method first transformed the input MR modality into slices, then preprocessed the intensities using a statistical normalization strategy. The overall precision of their method was 94%. In 2016, Devendra Somwanshi et.al investigated the different Entropy functions for tumor segmentation and its detection from various MRI images. The different threshold values are obtained depending on the particular definition of the entropy. The threshold values are dependent on the different entropy functions which in turn affects the segmented results. Deepa and Akansha Singh in 2016 proposed a research work on the Brain tumor detection and segmentation is reviewed. Different Techniques used by various researchers to detect the brain Tumor from the MRI images are described. By this review we found that automation of brain tumor detection and Segmentation from the MRI images is one of the most active Research areas. In 2017, Praveen conducted a survey of Identifying brain tumors through MRI images can be categorized into four different sections; pre-processing, image segmentation, Feature extraction and image classification. In 2017, Nilesh e.al. proposed an algorithm using MR images of the brain, segmented brain tissues into normal tissues such as white matter, gray matter, cerebrospinal fluid (background), and tumor-infected tissues. We used pre-processing to improve the signal-to-noise ratio and to eliminate the effect of unwanted noise. We can use the skull stripping algorithm its based on threshold technique for improve the skull stripping performance.

## III. OVERVIEW OF EXISTING METHODOLOGY

Fig.4. shows the existing work flow of brain tumor detection. In the first stage, there is a computer based procedures to detect tumor blocks and classify the type of tumor using Artificial Neural Network Algorithm for MRI images of different patients. The second stage involves the use of different image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations and feature extraction are used for brain tumor detection in the MRI images for the cancer-affected patients. This work is introduced one automatic brain tumor detection method to increase the accuracy and decrease the diagnosis time.



**Fig.4.Existing work flow of brain tumor detection**

**Image Preprocessing:** As input for this system is MRI, scanned image and it contain noise. Therefore, our first aim is to remove noise from input image. As explained in system flow we are using high pass filter for noise removal and preprocessing.

- **Segmentation:** Region growing is the simple region-based image segmentation technique. It is also classified as a pixel based image segmentation technique since it is involve the selection of initial seed points.
- **Morphological operation:** The morphological operation is used for the extraction of boundary areas of the brain images. This operation is only rearranging the relative order of pixel value, not mathematical value, so it is suitable for only binary images. Dilation and erosion is basic operation of morphology. Dilation is add pixels to the boundary region of the object, while erosion is remove the pixels from the boundary region of the objects.
- **Feature Extraction:** The feature extraction is used for edge detection of the images. It is the process of collecting higher level information of image such as shape, texture, color, and contrast.
- **Connected component labeling:** After recognizing connected components of an image, every set of connected pixels having same gray-level values are assigned the same unique region label.
- **Tumor Identification:** In this phase, we are having dataset previously collected brain MRIs from which we are extracting features. Knowledge base is created for comparison.

## IV. PROPOSED METHODOLOGY

The proposed system has mainly five modules. Dataset, Pre-processing, Split the data, Build CNN model train Deep Neural network for epochs, and classification. In dataset we can take multiple MRI images and take one as input image. In pre-processing image to encoded the label and resize the image. In split the data we set the image as 80% Training Data and 20% Testing Data. Then build CNN model train deep neural network for epochs. Then classified the image as yes or no if tumor is positive then it returns yes and the tumor is negative the it.

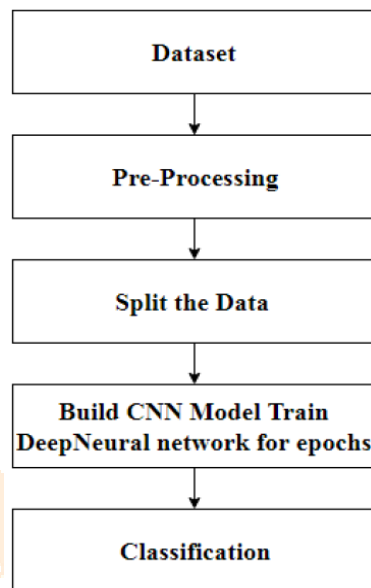


Fig. 5. Proposed work flow of brain tumor detection

### 4.1 CNN model for brain tumor detection

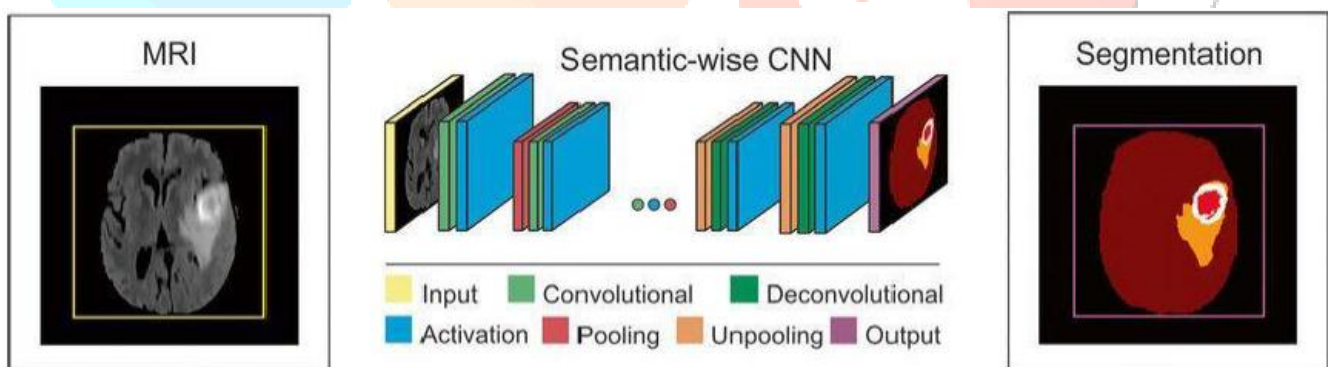


Fig.6. Working of CNN model for brain tumor detection

Layer of CNN model has Convolution 2D, MAX Pooling 2D, Dropout, Flatten, Dense and Activation.

**Convolution 2D:** In the Convolution 2D extract the featured from input image. It given the output in matrix form.

**MAX Pooling 2D:** In the MAX polling 2D it take the largest element from rectified feature map.

**Dropout:** Dropout is randomly selected neurons are ignored during training.

**Flatten:** Flatten feed output into fully connected layer. It gives data in list form.

**Dense:** A Linear operation in which every input is connected to every output by weight. It followed by nonlinear activation function.

**Activation:** It used Sigmoid function and predict the probability 0 and 1.

In the compile model we used binary cross entropy because we have two layers 0 and 1. We used Adam optimizer in compile model.

**Adam:** -Adaptive moment estimation. It used for non-convex optimization problems like straight forward to implement. It is computationally efficient and little memory is used.

## 4.2 VGG16 layered architecture

Transfer learning is a knowledge-sharing method that reduces the size of the training data, the time and the computational costs when building deep learning models. Transfer learning helps to transfer the learning of a pre-trained model to a new model. Transfer learning has been used in various applications, such as tumor classification, software defect prediction, activity recognition and sentiment classification. In this, the performance of the proposed Deep CNN model has been compared with popular transfer learning approach VGG16..



Fig.7. VGG16 layered architecture

VGG16 is a convolutional neural network. The input of the 1 convolution layer is of fixed size  $224 \times 224$  RGB image. The image is passed through a stack of convolutional layers, where the filters are used with a very small receptive field  $3 \times 3$  (which is the smallest size to capture the notion of left/right, up/down, center). In the configurations, it is also utilizes  $1 \times 1$  convolution filters, and it can be seen as a linear transformation of the input channels. The convolution stride is fixed to 1 pixel, and the spatial padding of convolution. Input layer is the spatial resolution is preserved after convolution, i.e. the padding is 1-pixel for  $3 \times 3$  convolution layers. Spatial pooling is carried out by five max-pooling layers, which follow the some convolution layers (not all the conv. layers are followed by max-pooling). Maxpooling is performed over  $2 \times 2$  pixel window, with stride 2.

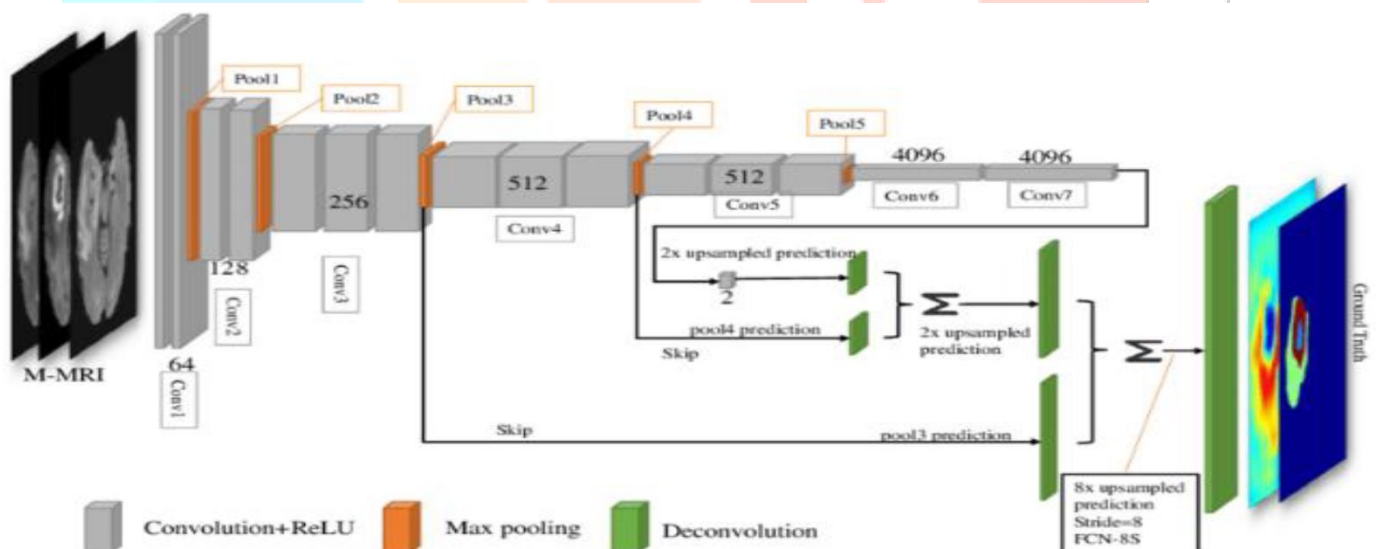


Fig.8. Working of VGG16 model for brain tumor detection

Three Fully-Connected (FC) layers are follow a stack of convolutional layers which has a different depth in different architectures and the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and it contains 1000 channels one for each class. The final layer is the soft-max layer. The configuration of the fully connected layers is same in every network.

All hidden layers are equipped with the rectification (ReLU) nonlinearity. It is also noted that none of the networks (except for one) contain Local Response Normalization (LRN), such normalization does not improve the performance on the ILSVRC dataset, but leads to increased memory consumption and computation time.

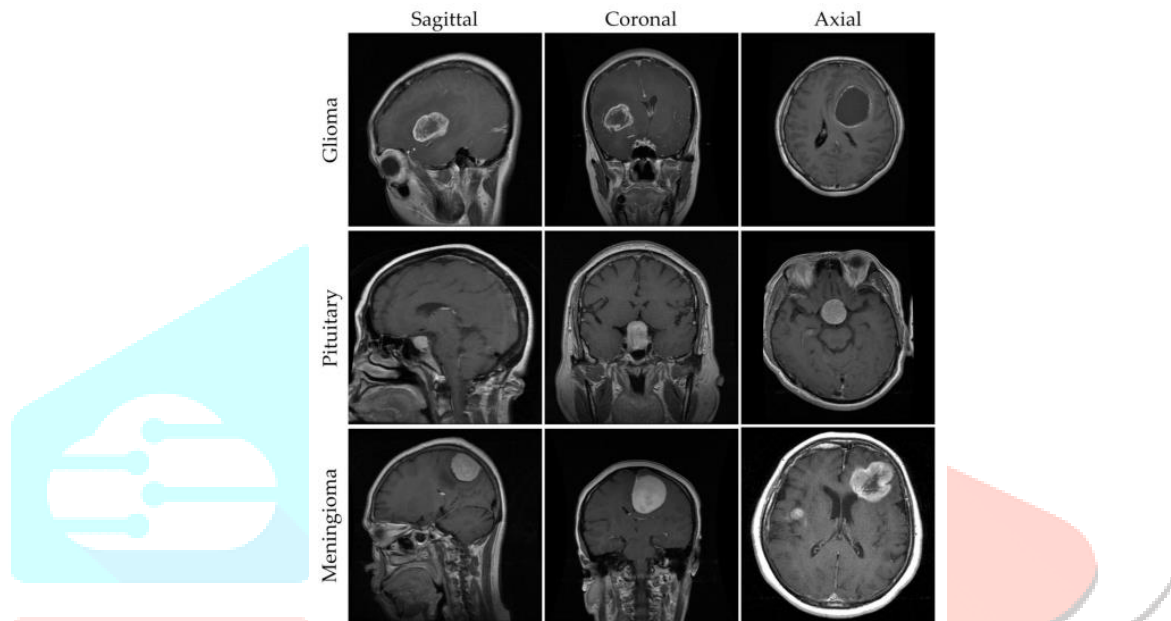
## V. IMPLEMENTATION

The methodology section outline the plan and method that how the study is conducted. This includes Universe of the study, sample of the study, Data and Sources of Data, study's variables and analytical framework. The details are as follows;

### 5.1 Dataset

The dataset has 556 images with different types of tumor and also including images which has tissues of Fat or water.

1. DICOM Samples Image Sets, <http://www.osirix-viewer.com/>.
2. "Brainweb: Simulated Brain Database," <http://brainweb.bic.mni.mcgill.ca/cgi/brainweb1>.



**Fig.9. A sample of MRI images from the brain tumor dataset.**

## 5.2 Tools used

### 5.2.1 Python:

Python was the language of selection for this project. This was a straightforward call for many reasons. Python as a language has a vast community behind it. Any problems which may be faced is simply resolved with a visit to Stack Overflow. Python is among the foremost standard language on the positioning that makes it very likely there will be straight answer to any question. Python has an abundance of powerful tools prepared for scientific computing Packages like NumPy, Pandas and SciPy area unit freely available and well documented. Packages like these will dramatically scale back, and change the code required to write a given program. This makes iteration fast. 3. Python as a language is forgiving and permits for program that appear as if pseudo code. This can be helpful once pseudo code given in tutorial papers must be enforced and tested. Using python this step is sometimes fairly trivial. However, Python is not without its errors. The language is dynamically written and packages are area unit infamous for Duck writing. This may be frustrating once a package technique returns one thing that, for instance, looks like an array instead of being an actual array. Plus the actual fact that standard Python documentation does not clearly state the return type of a method, this can lead to a lot of trials and error testing that will not otherwise happen in a powerfully written language. This is a problem that produces learning to use a replacement Python package or library more difficult than it otherwise may be.

### 5.2.2 Jupiter Notebook:

The Jupyter Notebook is an open-source web application that enables you to make and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modelling, data visualization, machine learning, and much more. Noise Removal and Sharpening: Unwanted data of element are remove using filter and image Can be sharpen and black and white gray scale image is used as a input. Erosion and Dilation: It is applied to binary image, but there are many versions so that can be work on grayscale images. The basic effect of the operator on a binary

image is eroding away to the boundaries of regions for ground pixels. Negation: A negative is an image, usually it used on a strip or sheet of transparent plastic film, in negation the lightest areas of the photographed subject appear darkest and the darkest areas appear lightest.

**Subtraction:** Image subtraction process is the digital numeric value of one pixel or whole image is subtracted from another image. The white part of tumor can be subtracted from another remaining part that is the black portion of the images.

**Threshold:** Thresholding is a process of image segmentation. It converts the gray scale image into binary image.

**Boundary Detection:** Total area or boundary can be form properly using boundary detection method. White part of tumor tissues can be highlighted and there proper boundary can be detected. It is useful method to calculate the size and shape occupy by tumor tissues.

## 5.3 Training and Testing

### 5.3.1 CNN Training and Testing

```
Epoch 245/250
15/15 [=====] - 48s 3s/step - loss: 0.4972 - accuracy: 0.7542 - val_loss: 0.5175 - val_accuracy: 0.8485
Epoch 246/250
15/15 [=====] - 48s 3s/step - loss: 0.5008 - accuracy: 0.7374 - val_loss: 0.5198 - val_accuracy: 0.7879
Epoch 247/250
15/15 [=====] - 52s 3s/step - loss: 0.4825 - accuracy: 0.7879 - val_loss: 0.5250 - val_accuracy: 0.7879
Epoch 248/250
15/15 [=====] - 48s 3s/step - loss: 0.4977 - accuracy: 0.7407 - val_loss: 0.5130 - val_accuracy: 0.8182
Epoch 249/250
15/15 [=====] - 48s 3s/step - loss: 0.4789 - accuracy: 0.7542 - val_loss: 0.5168 - val_accuracy: 0.8788
Epoch 250/250
15/15 [=====] - 48s 3s/step - loss: 0.4849 - accuracy: 0.7441 - val_loss: 0.5262 - val_accuracy: 0.7879
```

**Fig.10. Training CNN**

There are 413 dataset images, which are divided into two parts 330 are in the training part and 83 is the testing part. The images are resized and labelled for proper processing. 150 samples are validated.

```
scores=model.evaluate(xTest, yTest)
print("%s: %2f%%" %(model.metrics_names[1], scores[1]*100))
```

```
3/3 [=====] - 2s 808ms/step - loss: 0.5499 - accuracy: 0.8072
accuracy: 80.722892%
```

**Fig.11. Testing CNN**

Accuracy obtained for convolutional neural network is 80.72%



### 5.3.2 VGG 16 Training and Testing

```

Epoch 65/70
20/20 [=====] - 338s 17s/step - loss: 0.5633 - accuracy: 0.7473
Epoch 66/70
20/20 [=====] - 329s 16s/step - loss: 0.5276 - accuracy: 0.7677
Epoch 67/70
20/20 [=====] - 333s 17s/step - loss: 0.5474 - accuracy: 0.7382
Epoch 68/70
20/20 [=====] - 329s 16s/step - loss: 0.5726 - accuracy: 0.7524
Epoch 69/70
20/20 [=====] - 340s 17s/step - loss: 0.5436 - accuracy: 0.7598
Epoch 70/70
20/20 [=====] - 326s 16s/step - loss: 0.5467 - accuracy: 0.7587

```

**Fig.12. Training VGG16**

```

model.save('braintransfer-VGG70.model')
scores=model.evaluate(xTest, yTest)
print("%s: %2f%%" %(model.metrics_names[1], scores[1]*100))

```

```

83/83 [=====] - 42s 500ms/step
accuracy: 85.542166%

```

**Fig.13. Testing VGG16**

Accuracy obtained for VGG 16 is 85.54%

## VI. RESULTS AND DISCUSSION

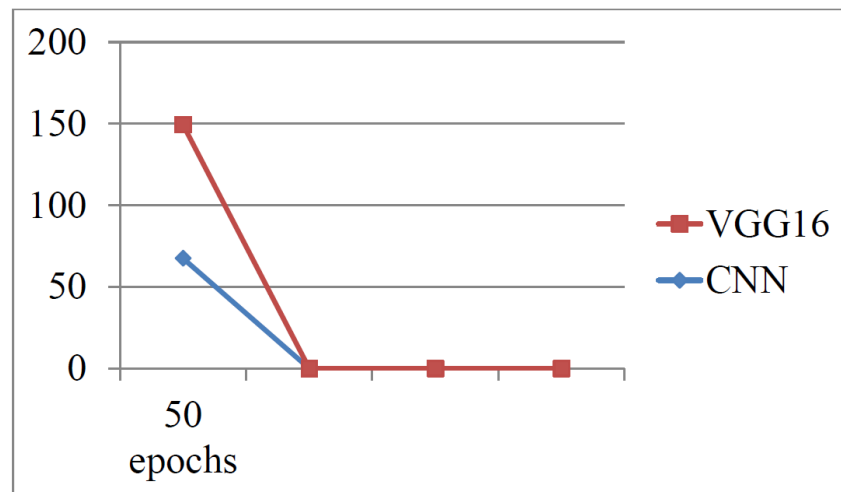
In this system, we have detected whether the tumor is present or not if the tumor is present then the model returns yes otherwise it returns no. and we have compared CNN. with the VGG 16 Model.

### 6.1 Comparison of CNN vs. VGG16

The result of the comparison shows that VGG 16 is more accurate than CNN.

**Table 3. Comparison table of CNN vs. VGG16**

epochs	CNN	VGG 16
30	67.469877%	76.854917%
50	69.87952%	81.927711%
70	72.698794%	85.542166%



**Fig.14. Chart of CNN vs. VGG16**

## VII . CONCLUSION

To reduce global death rates, diagnosis of brain cancers is essential. Brain tumors can be difficult to identify because of their complex architecture, size variability, and unusual forms. In our research, we used a large collection of MRI scans of brain tumors to overcome this obstacle. In brain tumor detection we have studied about feature-based existing work. In feature based we have studied about image processing techniques like image pre-processing, image segmentation, features extraction, classification. And also studied deep learning techniques CNN and VGG16. In this system, we have detected whether the tumor is present or not if the tumor is present then the model returns yes otherwise it returns no. and we have compared CNN. with the VGG 16 Model. The result of the comparison shows that VGG 16 is more accurate than CNN.

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