# CHAPTER - 1
# INTRODUCTION

## 1.1 BRAIN TUMOR DETECTION SYSTEM

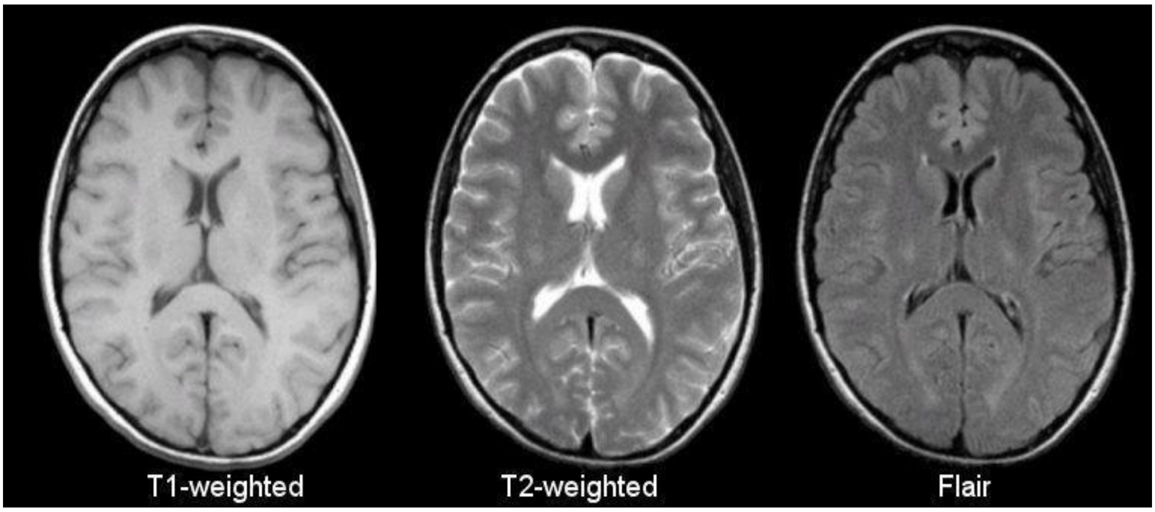
The human body is made up of many organs and brain is the most critical and vital organ of them all. One of the common reasons for dysfunction of brain is brain tumor. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all 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 Brain Cancer is very critical disease which causes deaths of many individuals. The brain tumour 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.

## OVERVIEW OF BRAIN AND BRAIN TUMOR

Main part in human nervous system is human brain. It is located in human head and it is covered by the skull. The function of human brain is to control all the parts of human body. It is one kind of organ that allows human to accept and endure all type of environmental condition. The human brain enables humans to do the action and share the thoughts and feeling. In this section we describe the structure of the brain for understanding the basic things [4]. The brain tumors are classified into mainly two types: Primary brain tumor (benign tumor) and secondary brain tumor (malignant tumor).The benign tumor is one type of cell grows slowly in the brain and type of brain tumor is gliomas. It originates from non neuronal brain cells called astrocytes. Basically primary tumors are less aggressive but these tumors have much pressure onthe brain and because of that, brain stops working properly [6]. The secondary tumors are more aggressive and more quick to spread into other tissue. Secondary brain tumor originates through other part of the body. These type of tumor have a cancer cell in the body that is metastatic which spread into different areas of the body like brain, lungs etc. Secondary brain tumor is very malignant. The reason of secondary brain tumor cause is mainly due to lungs cancer, kidney cancer, bladder cancer etc [7].

## 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.




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 an 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.

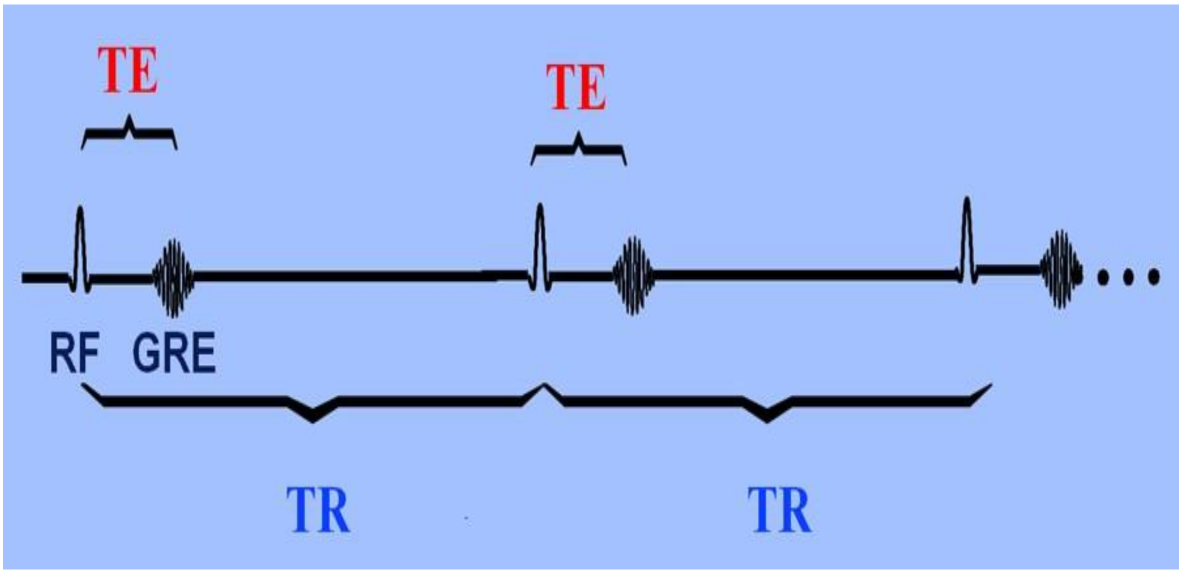



Fig. 3: Graph of TE and TR [10]

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.

## 1.2 APPLICATION

- The main aim of the applications is tumor identification.
- The main reason behind the development of this application is to provide proper treatment as soon as possible and protect the human life which is in danger.
- This application is helpful to doctors as well as patient.
- The manual identification is not so fast, more accurate and efficient for user. To overcome those problem this application is design.
- It is user friendly application.

## 1.3 OBJECTIVE

- To provide doctors good software to identify tumor and their causes.
- Save patient’s time.
- Provide a solution appropriately at early stages.
- Get timely consultation.

## 1.4 MOTIVATION

The main motivation behind Brain tumor detection is to not only detect tumor but it can also classify types of tumor. So it can be useful in cases such as we have to sure the tumor is positive or negative, it can detect tumor from image and return the result tumor is positive or not. 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.

## 1.5 ORGANIZATION OF REPORT

Chapter 1 gives the brief introduction of Brain tumor Detection and Classification using Deep Learning, its applications, objective of the system and motivation.

Chapter 2 contains literature survey that provide summary of individual paper.

Chapter 3 provides overview of existing work for Brain tumor detection and classification that has been done using done using CNN.

Chapter 4 presents Implementation and its results, tools and technology used to achieve this and dataset detail.

Chapter 5 contains conclusion about Brain tumor detection using deep learning.

# CHAPTER - 2

# LITERATURE SURVEY

## Paper-1: Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM

- **Publication Year:** 6 March 2017
- **Author**: Nilesh Bhaskarrao Bahadure, Arun Kumar Ray, and Har Pal Thethi
- **Journal Name:** Hindawi International Journal of Biomedical Imaging
- **Summary:** In this paper using MR images of the brain, we 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 used the skull stripping algorithm its based on threshold technique for improve the skull stripping performance.

## Paper-2: A Survey on Brain Tumor Detection Using Image Processing Techniques

- **Publication Year:** ***2017***
- **Author:** Luxit Kapoor, Sanjeev Thakur
- **Journal Name:** IEEE 7th International Conference on Cloud Computing, Data Science & Engineering
- **Summary:** This paper surveys the various techniques that are part of Medical Image Processing and are prominently used in discovering brain tumors from MRI Images. Based on that research this Paper was written listing the various techniques in use. A brief description of each technique is also provided. Also of All the various steps involved in the process of detecting Tumors, Segmentation is the most significant.

## Paper-3: Identification of Brain Tumor using Image Processing Techniques

- **Publication Year:** 11 September 2017
- **Author:** Praveen Gamage
- **Journal Name:** Research gate
- **Summary:** This paper survey of Identifying brain tumors through MRI

  images can be categorized into four different sections; pre-processing, image segmentation, Feature extraction and image classification.

## Paper-4: Review of Brain Tumor Detection from MRI Images

- **Publication Year**: *2016*
- **Author:** Deepa, Akansha Singh
- **Journal Name:** IEEE International Conference on Computing for Sustainable Global Development
- **Summary:** In this paper, some of the recent research work done 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.

## Paper-5: An efficient Brain Tumor Detection from MRI Images using Entropy Measures

- **Publication Year:** December 23-25, 2016
- **Author:** Devendra Somwanshi , Ashutosh Kumar, Pratima Sharma, Deepika Joshi
- **Journal Name:** IEEE International Conference on Recent Advances and Innovations in Engineering

**Summary:** In this paper, we have investigated the different Entropy functions for tumor segmentation and its detection from various MRI images. The different threshold values are obtained depend on the particular definition of the entropy. The threshold values are dependent on the different entropy function which in turn affects the segmented results

# CHAPTER - 3

# EXITING WORK
# &
# PROPOSED WORKFLOW

## 3.1 OVERVIEW OF EXITING WORK

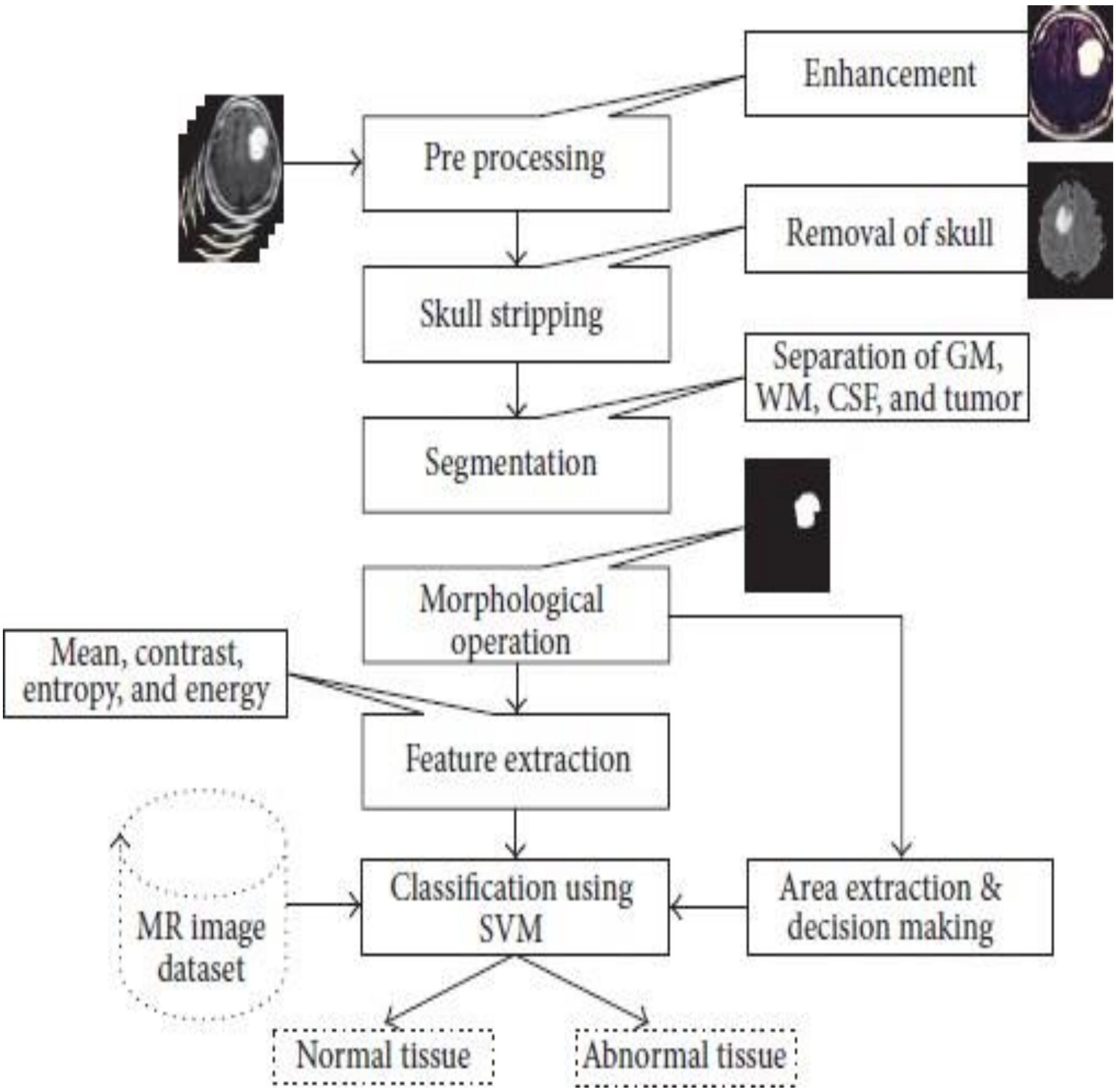



Fig.5.Existing work flow of brain tumor detection. [12]

- In the first stage, there is a computer based procedures to detect tumor blocks and classify the type of tumor using an 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 iss introduced one automatic brain tumor detection method to increase the accuracy and decrease the diagnosis time

- **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.

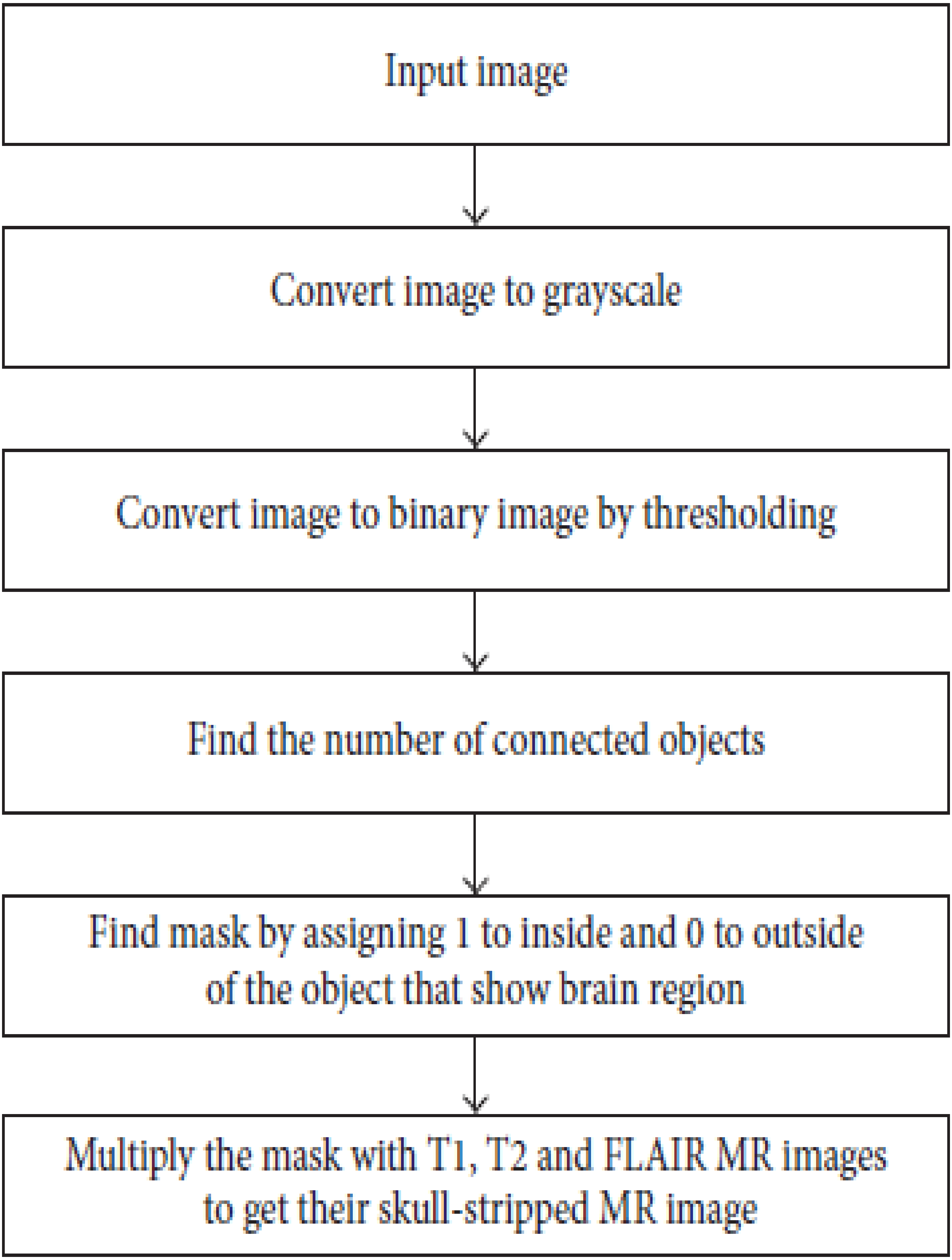



Fig. 6. Steps used in skull stripping algorithm.[12]

- In the first step we can take image as input. In the image we used tumor in the image and only fat and water tissues in the images.
- In the second step convert image to grayscale
- Signal to noise
- Complexity of the code
- Learning image processing
- Difficulty of visualization
- Color is complex
- Then we convert image to binary image by thresholding.

  Thresholding is the simplest method of image segmentation and the

  most common way to convert a grayscale image to binary image.

  In thresholding we select threshold value and then gray level value .below the selected threshold value is classified as 0.and equal and greater then the threshold value are classified as 1.

- Find the number of connected object
- Find mask by assigning 1 to inside and 0 to outside of the object that show brain region.
- Multiply the mask with T1,T2 and FLAIR MR images to get their skull stripped MR image
- T1 & T2: weighted MRI
  - FLAIR: fluid attenuated inversion recovery weighted MRI.

Types of MRI images

- T1: one tissue type is bright-FAT
- T2: two tissue types are bright-FAT and water

## 3.2 PROPOSED WORKFLOW

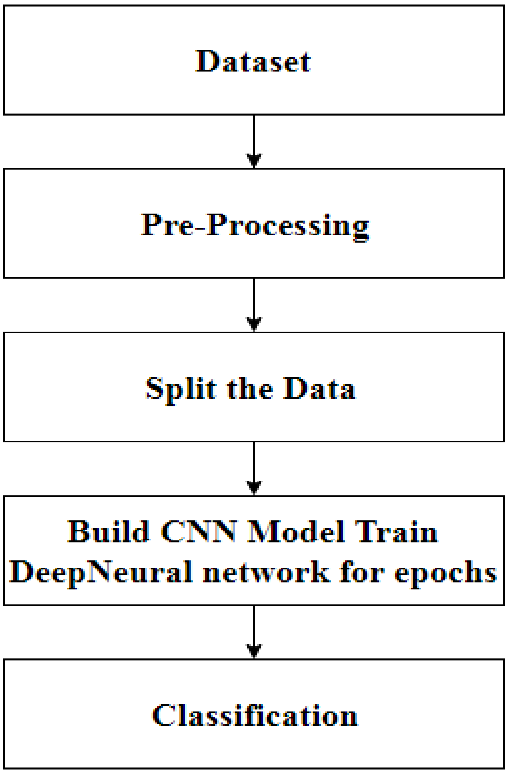



Fig. 7.Proposed work flow of brain tumor detection

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 returns no.

### 3.2.1 Working of CNN model

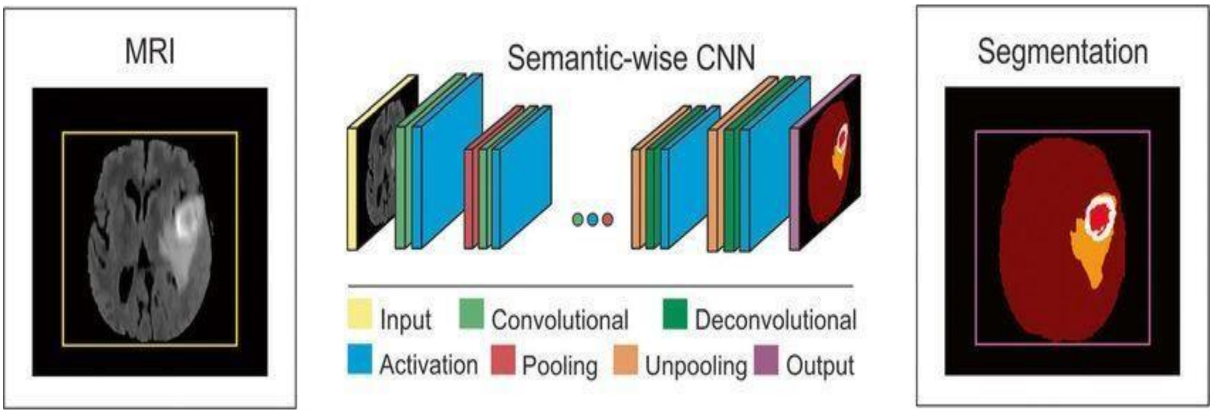



Fig.8.Working of CNN model for brain tumor detection [14]

***Layer of CNN model:***

1. Convolution 2D
2. MAX Poolig2D
3. Dropout
4. Flatten
5. Dense
6. Activation

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

**MAX Poolig2D:** In the MAX polling 2D it takes 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 problem like straight forward to implement.

Computationally efficient.

Little memory requirement.

### 3.2.2 Working of VGG16 model

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.

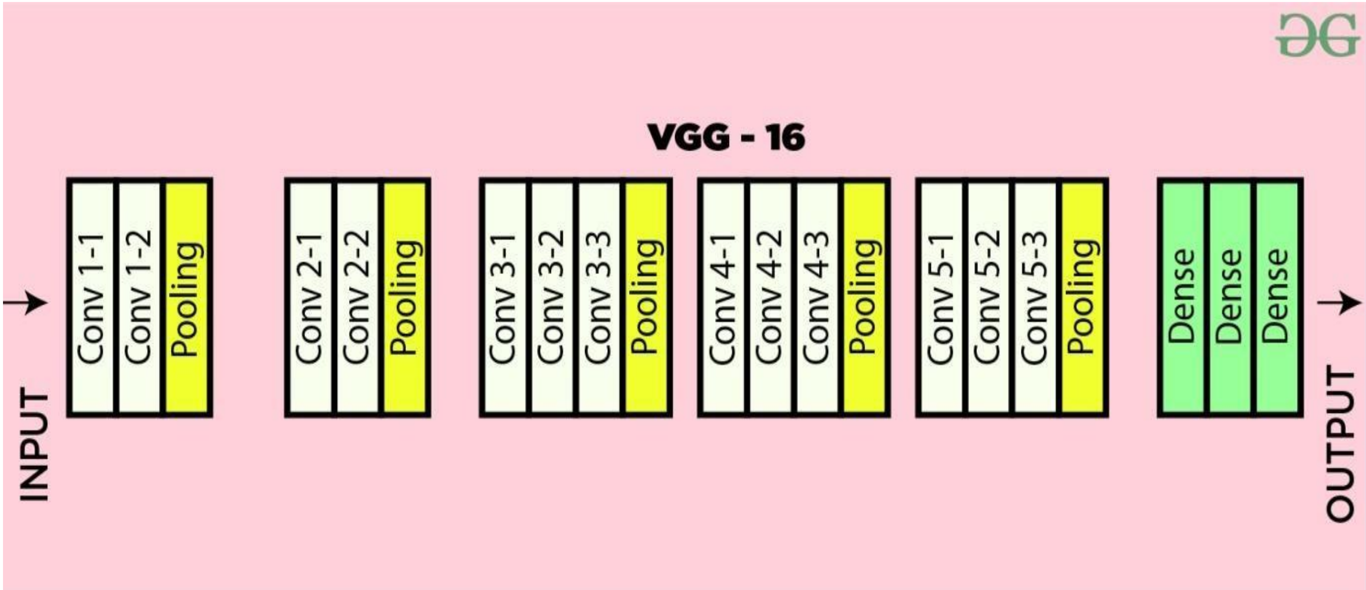



Fig.9. VGG16 layered architecture[20]

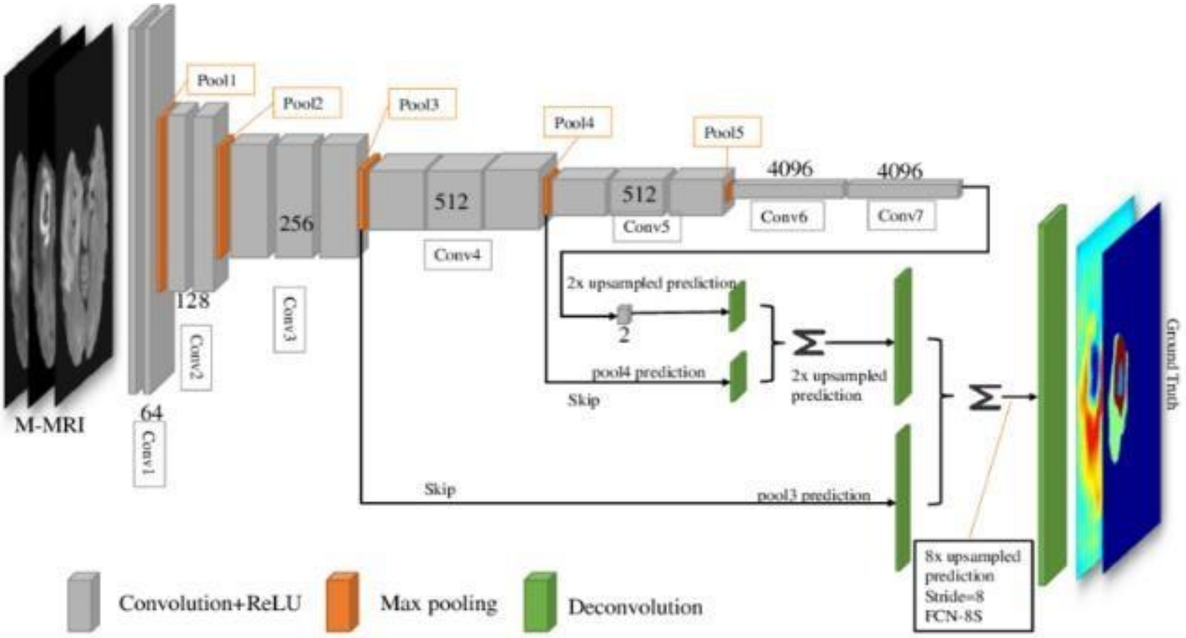



Fig.10.Working of VGG16 model for brain tumor detection [14]

VGG16 is a convolutional neural network. The input of the 1 convolution layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional layers, where the filters are used with a very small receptive field 3×3 (which is the smallest size to capture the notion of left/right, up/down, centre). In the configurations, it also utilizes 1×1 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 3×3 convolution layers. Spatial pooling is carried out by five max-pooling layers, which follow some convolution layers (not all the conv. layers are followed by max-pooling). Max- pooling is performed over 2×2-pixel window, with stride 2.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.

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 3×3 convolution layers.

# CHAPTER 4
# DATASET, IMPLEMENTATION AND RESULT

## 4.1: DATASET DETAIL

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/.[3]

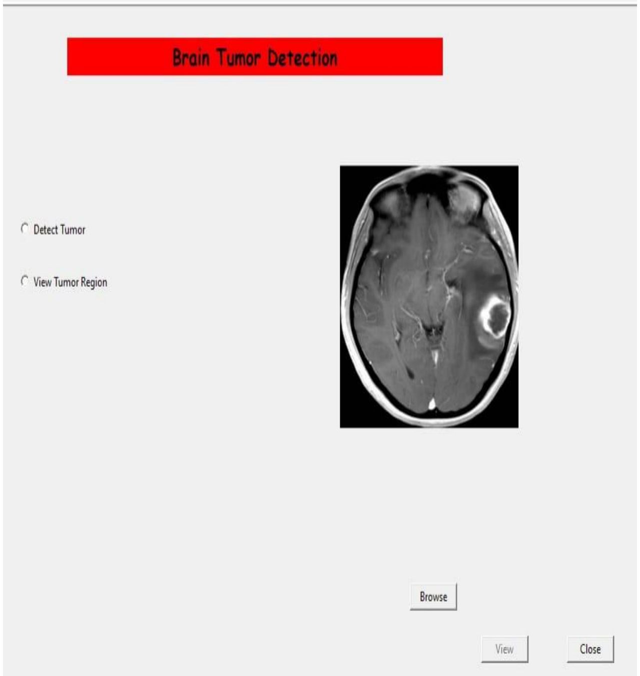
2."Brainweb:SimulatedBrainDatabase,"

http://brainweb.bic.mni.mcgill.ca/cgi/brainweb1.[4]

## 4.2: TOOLS & TECHNOLOGY USED

- **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.
- 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.

## 4.3 RESULTS



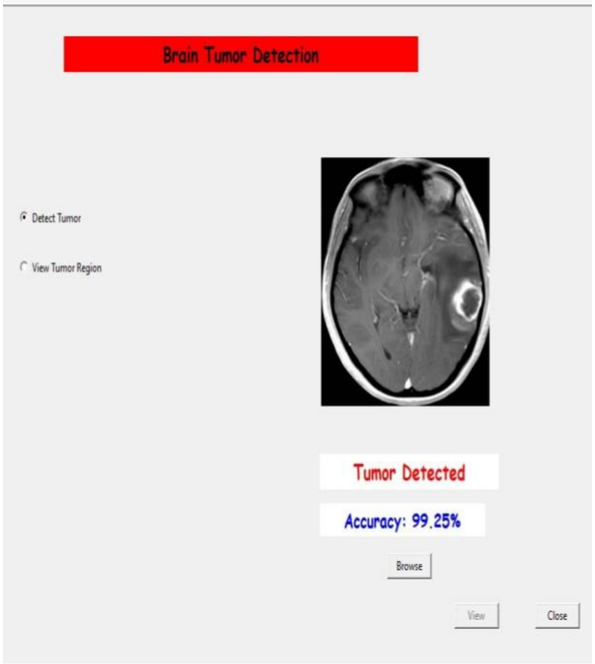




*Fig – 1 shows the input image*

*Fig-2 shows the Tumor Detected & Accuracy*

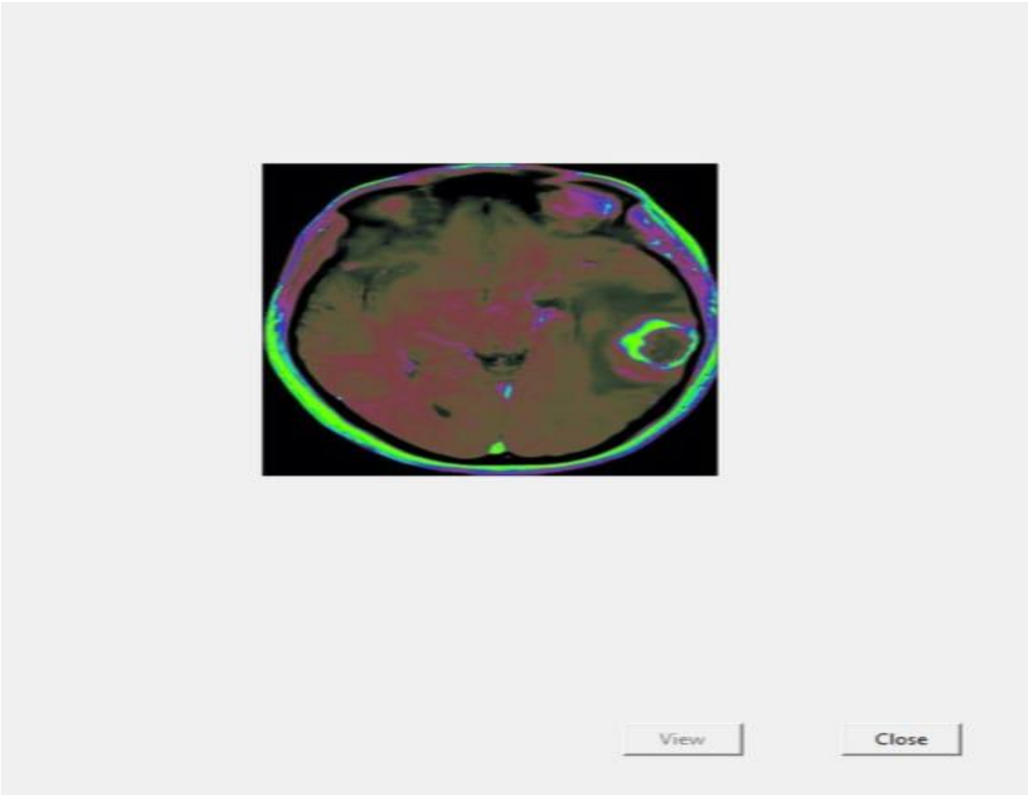
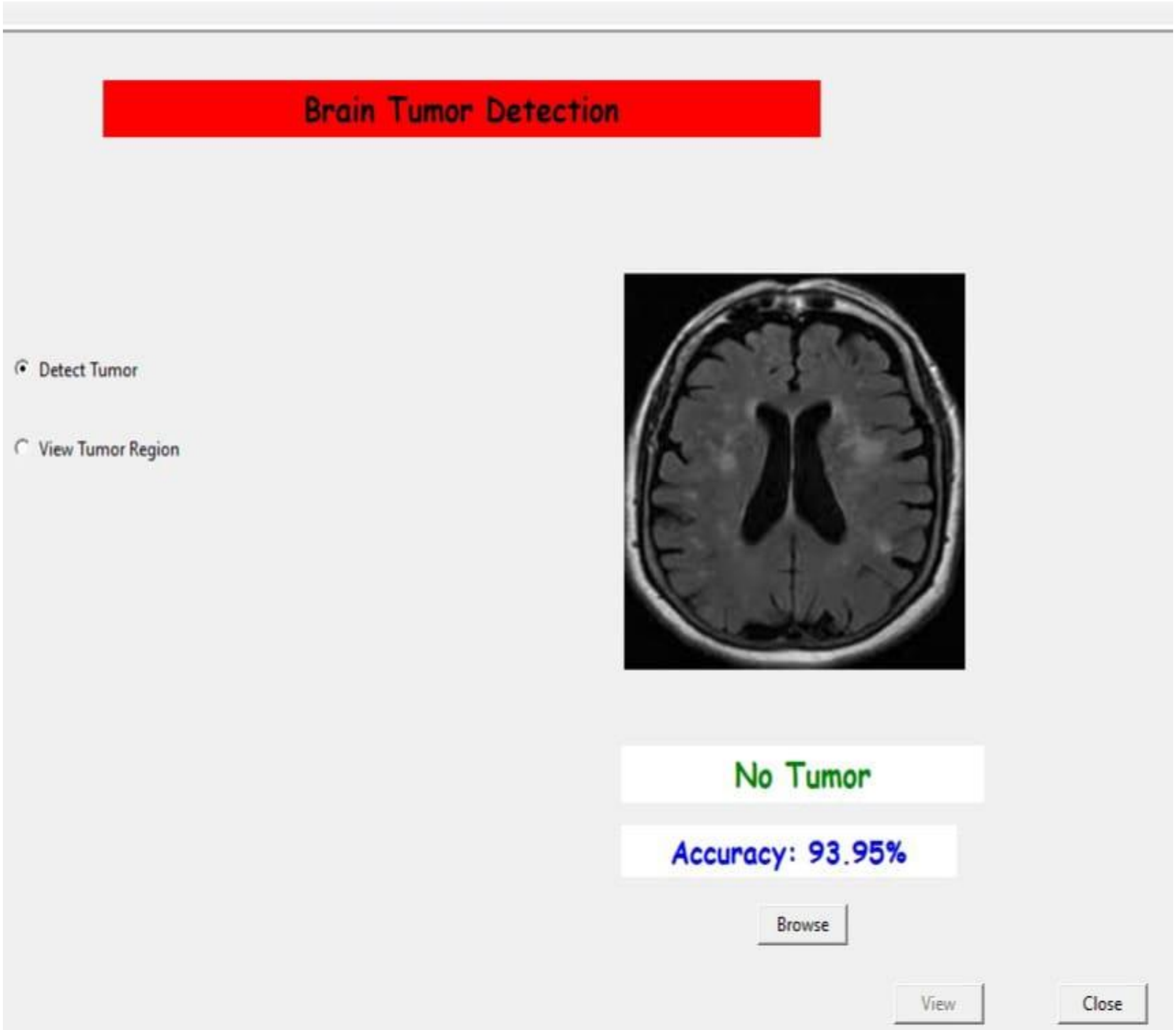



*Fig- 3 shows the Tumor region of Brain*


Brain Tumor Detection
Detect Tumor
View Tumor Region
No Tumor
Accuracy: 93.95%
Browse
View
Close

# CHAPTER 5

# CONCLUSION

## 5.1 CONCLUSION

In brain tumor detection we have studied about feature based existing work. In feature based we have study about image processing techniques likes image pre-processing, image segmentation, features extraction, classification. And also study about deep learning techniques CNN and VGG16.In this system we have detect the tumor is present or not if the tumour is present then model return's yes otherwise it return no. and we have compared CNN with the VGG 16 Model. The result of comparison VGG 16 is more accurate than CNN. However, not every task is said to be perfect in this development field even more improvement may be possible in this application. I have learned so many things and gained a lot of knowledge about development field. Brain tumor detection using deep learning has significantly improved the accuracy and efficiency of diagnosing tumors from medical imaging, particularly MRI scans. Deep learning models, such as Convolutional Neural Networks (CNNs), have demonstrated superior performance in automatic feature extraction, reducing the need for manual intervention by radiologists. The integration of deep learning in brain tumor detection offers several advantages, including faster diagnosis, improved precision, and the potential for early detection, which is critical for effective treatment planning. However, challenges such as dataset limitations, class imbalance, and the need for high computational power still exist. Future research should focus on enhancing model generalization, incorporating explainable AI techniques, and ensuring real-world applicability through clinical validation. Overall, deep learning presents a promising approach for brain tumor detection, contributing to advancements in medical imaging and improving patient outcomes

# CHAPTER 6
# FUTURE SCOPE & ADVANTAGES & DSIADVANTAGES

## 6.1 FUTURE SCOPE of Brain Tumor Detection Using deep Learning

Higher Accuracy Models – Development of more advanced deep learning models with better accuracy by incorporating hybrid architectures like CNN with Transformers or GANs.

3D MRI Analysis – Implementation of 3D CNNs to analyze volumetric MRI scans for more precise tumor localization.

Automated Diagnosis Integration – Combining CNN models with AI-based decision support systems to assist radiologists in faster diagnosis.

Edge AI for Real-Time Detection – Deploying CNN-based tumor detection models on IoT-enabled edge devices for real-time screening in remote areas.

Multi-Modal Imaging – Integrating CT, PET, and MRI scans to improve detection beyond a single imaging modality.

Explainable AI (XAI) – Enhancing interpretability by visualizing CNN decision layers to gain insights into tumor classification.

Cloud-Based Diagnosis – Developing cloud-integrated CNN models for remote access by medical professionals worldwide.

Early Prediction Models – Training CNNs with longitudinal patient data for predicting tumor growth progression over time.

## 6.2Advantages :

✅ High Accuracy – CNNs provide superior image recognition and feature extraction, leading to high detection accuracy.

✅ Automation & Speed – Reduces manual effort and speeds up diagnosis by processing large MRI datasets efficiently.

✅ Non-Invasive Detection – Unlike biopsies, CNN-based MRI image analysis allows non-invasive tumor diagnosis.

✅ Early Detection – Helps in detecting tumors at an early stage, improving treatment outcomes.

✅ Reduces Human Error – Minimizes diagnostic errors by eliminating subjective variations in radiologists' interpretations.

✅ Scalability – Can be deployed in hospitals, research labs, and AI-powered diagnosis centers.

✅ Cost-Effective – Reduces the need for expensive manual evaluations, making MRI analysis more affordable.

**Disadvantages :**

❌ Need for Large Datasets – CNN models require large and diverse datasets for effective training, which may not always be available.

❌ Overfitting Issues – Models can memorize training data rather than generalizing well to new, unseen images.

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## ABBREVIATIONS

| Sr No. | Abbreviation | Meaning |
|---|---|---|
| 1 | CNN | Convolutional neural network |
| 2 | MRI | Magnetic resonance imaging |
| 3 | FLAIR | Fluid attenuated in version recovery weighted |
| 4 | TR | Time repetition |
| 5 | TE | Pulse sequence parameter |
| 6 | VGG 16 | Visual Geometry Group |
| 7 | FC | Fully connected layer |
| 8 | ReLU | Rectified linear unit |
| 9 | LRN | Local response normalization |
| 10 | SVM | Support vector machine |
| 11 | KNN | K nearest neighbor |