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EARLY DETECTION OF BRAIN TUMOR USINGMRI IMAGES

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ABSTRACT:

Brain diseases are mainly caused by abnormal growth of brain cells that may damage the brain structure, and eventually will lead to malignant brain cancer. An early diagnosis to enable decisive treatment using a Computer- Aided Diagnosis (CAD) system has major challenges, especially accurate detection of different diseases in the magnetic resonance imaging (MRI) images. In this, a three step preprocessing is proposed to enhance the quality of MRI images, along with a new Deep Convolutional Neural Network (DCNN) architecture for effective diagnosis of tumor and no tumor. The architecture uses batch normalization for fast training with a higher learning rate and ease initialization of the layer weights. The proposed architecture is computationally light model with a small number of convolutional, max-pooling layers and training iterations. An outstanding competitive accuracy is achieved of 97.72% in detecting the tumor images when tested on a dataset with 300 MRI images. Experimental results prove the robustness of the proposed architecture which has increased the detection accuracy of a variety of brain diseases in a short time.

KEYWORDS: Brain Tumors, Deep Convolutional Neural Network, Computer Aided Diagnosis, Image Processing, MRI images.

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. 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 the 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. This process pursues the disorder identification and management. This process creates a data bank of the regular structure and function of the organs to make it easy to recognize the anomalies. This process includes both organic and radiological imaging which used electromagnetic energies (X-rays and gamma), sonography, magnetic, scopes, and thermal and isotope imaging.

1.2. OVERVIEW OF BRAIN AND ITS STRUCTURE

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.

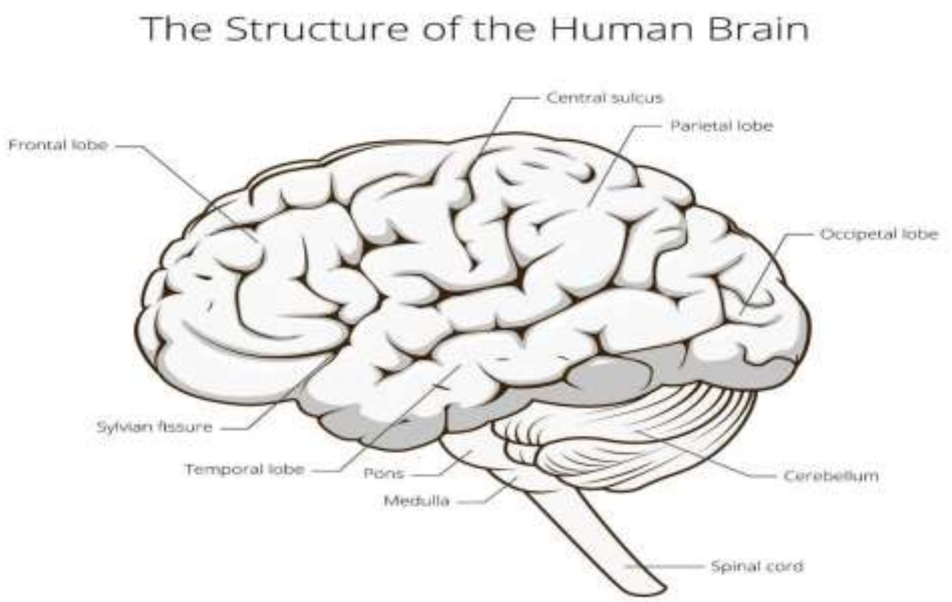

Fig.1.1 Basic Structure of Brain Tumor

A brain tumor is an abnormal growth or mass of cells in or around your brain. Together, spinal tumors and brain tumors are called central nervous system (CNS) tumors. Brain tumors can be malignant (cancerous) or benign (noncancerous). Some tumors grow quickly, while others are slow growing. Only about one-third of brain tumors are cancerous. But whether they're cancerous or not, brain tumors can impact brain function and your health if they grow large enough to press on surrounding nerves, blood vessels and tissue.

Tumors that develop in your brain are called primary tumors. Tumors that spread to your brain after forming in a different part oy your body are called secondary tumors. 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 on the brain and because of that, brain stops working properly.

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

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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.

1.3. 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 weare 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 ascompared to other medical imaging techniques like X-ray and computer tomography. 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.

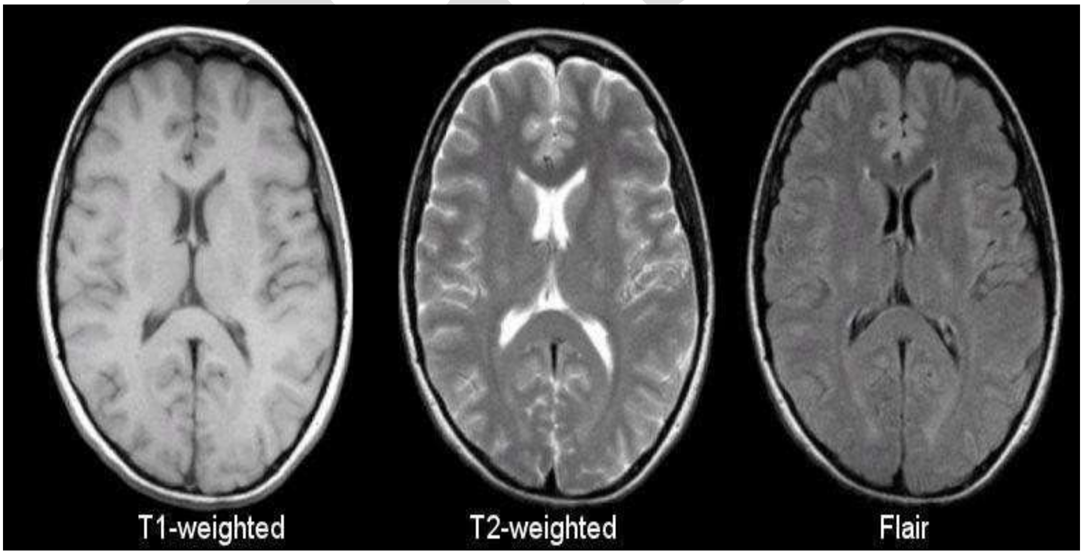

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Fig.1.2 T1, T2 and Flair image

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). The echo time representedtime from the center of the RF pulse to the center of the echo and TR is the length of time between the TE repeating series of pulse and echo is shown in figure.

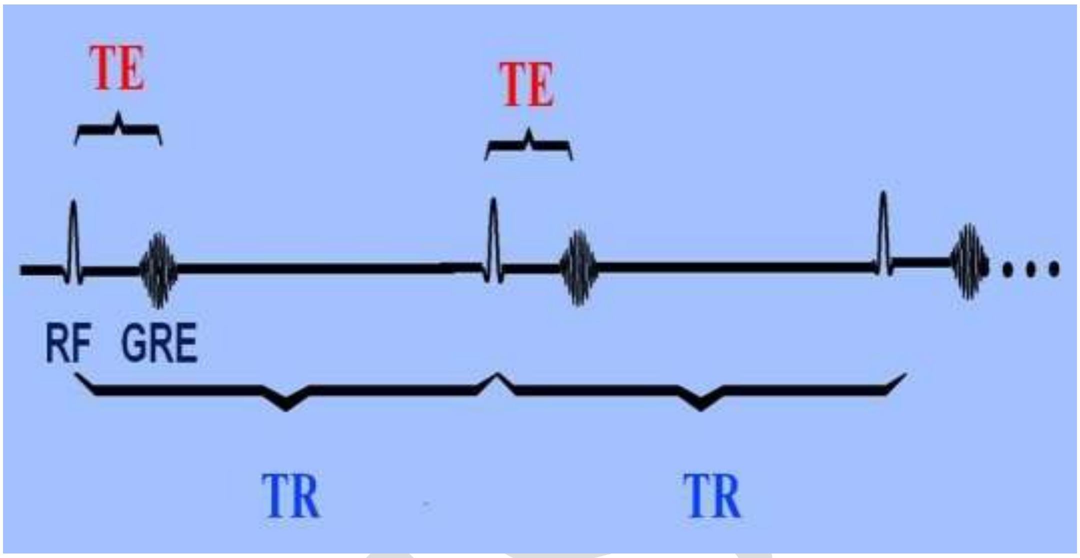

Fig.1.3 Graph of TE and TR

2. EXISTING MODEL:

2.1: VGG16

VGG-16 [1] is a convolutional neural network that is 16 layers deep. You can load a pretrained version of the network trained on more than a million images from the Image Net database. The pretrained network can classify images into 1000 object categories. The number 16 in the name VGG refers to the fact that it is 16 layers deep neural network. This means that VGG16 is a pretty extensive network and has a total of around 138 million parameters.

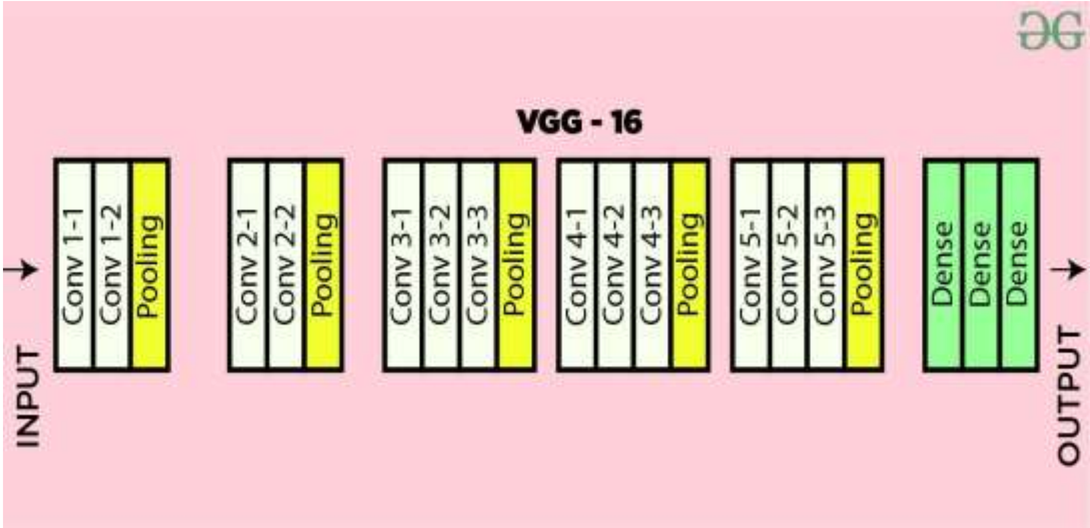

Fig.2.1 VGG16 Architecture.

2.2. WORKING OF VGG16 MODEL

2.2.1. CONVOLUTIONAL LAYER:

It is considered to be one of the excellent vision model architecture till date. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filter with a stride 1 and always used same padding and max-pooling layer of 2x2 filter of stride 2.

This method that reduces the size. It 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.

It follows this arrangement of convolution and max-pool layers consistently throughout the whole architecture. In the end it has 2 FC(fully connected layers) followed by a soft-max for output. The 16 in VGG16 refers to it has 16 layers that have weights. This network is a pretty large network and it has about 138 million (appr) parameters.

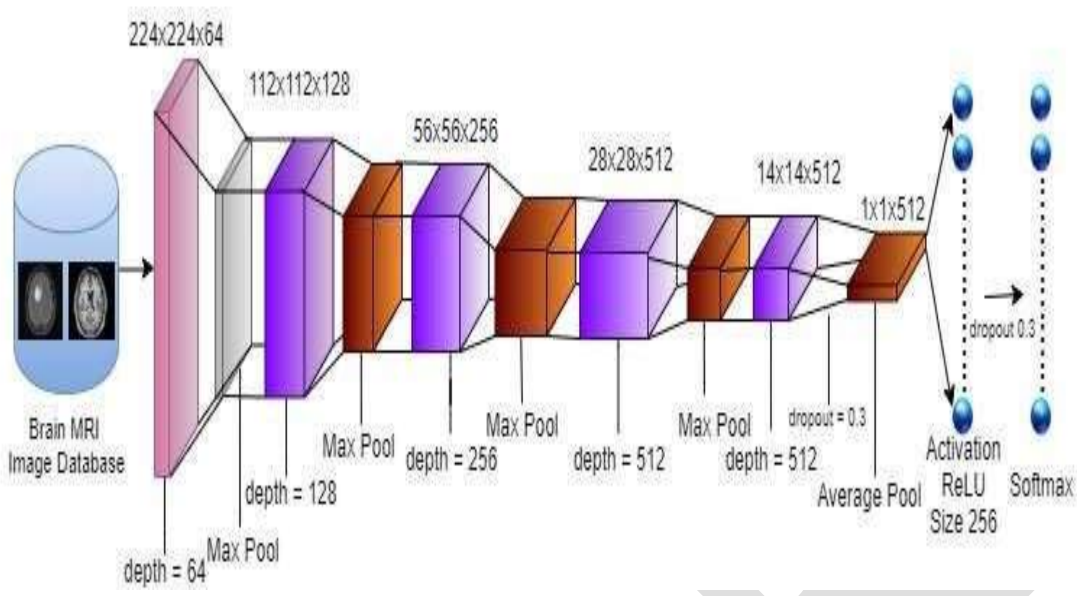

Fig.2.2 VGG16 layered diagram.

VGG16 is a convolutional neural network.The input of the 1 convolution layer is of fixed size 224x224 RGB image .The image is passed through a stack of convolution layers,where the filters are used with a very small receptive field 3x3. In the configurations,it is also utilizes 1x1 convolution filters,and it can be seen as a linea transformation of the input channels.The convolution stride is fixed to 1 pixel ,and the spatial padding of convolution and saptial padding of cnvolution.Input layer is the spatial resolution is preserved after convolution ,i.e.the padding is 1-pixel for 3x3 convolution layers.

3. PROPOSED MODEL:

3.1. STEPS IN PROPOSED MODEL

In this model we are going to use the pre-processing steps. Here there are three pre-processing steps. They are:

- Removing the confusing objects.
- De-noising the images with filter.
- Histogram Equalization.
- Along with these steps we are proposed the DCNN [3] model.

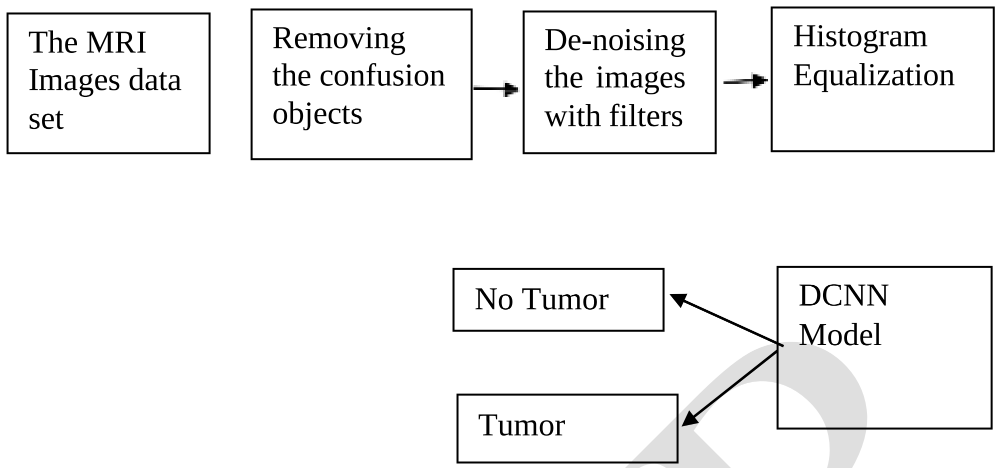

Fig.3.1 Block Diagram of Proposed Model

3.2.WORKING OF PROPOSED MODEL:

In this paper, the program code has been written and modeled of the brain tumor in MATLAB. Here we have to implemented the four important stages of processing steps that include the Input image, Image processing, Threshold Segmentation and then Feature Extraction.

3.2.1. INPUT IMAGE (MRI IMAGE):

The first stage i.e, the image acquisition stage which start with taking a collection of images from the dataset [4]-[5]. Images will be displayed in MATLAB as a gray scale image. As our MRI dataset was in desktop, we have extracted the images by MATLAB code.

We have collected our MRI image dataset from : https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection/code.

This dataset consists of different MRI images. They may contain tumor or may not contain tumor.

3.2.2. IMAGE PRE-PROCESSING:

This is the second step of image processing where the images are used to enhances the chances of detecting the suspicious region. Finer details of the images are enhanced and noise are removed from the images. Clinical MRI when corrupted by the noises reduces the accuracy of the images. So various filters are used to remove the noises [6]. It aims to improve the image data by suppressing the undesired distortions and enhances the some of the images features that will be helpful in future processing. The goal of pre-processing is to remove the noise and to provide Contrast Enhancement to improve the image quality. The functions performed by pre-processing process is-

- Removing the confusion objects.
- Noise-Removal.
- Histogram Equalization.

3.2.2.1. Removing confusion objects:

Pre-processing is a method to remove the noise, film artifacts in MRI image. The MRI image consists of the some film artifacts such as patient details, image information and some of the unwanted information in it. In some image processing techniques such as segmentation and enhancement is based on the intensity value of the pixel.

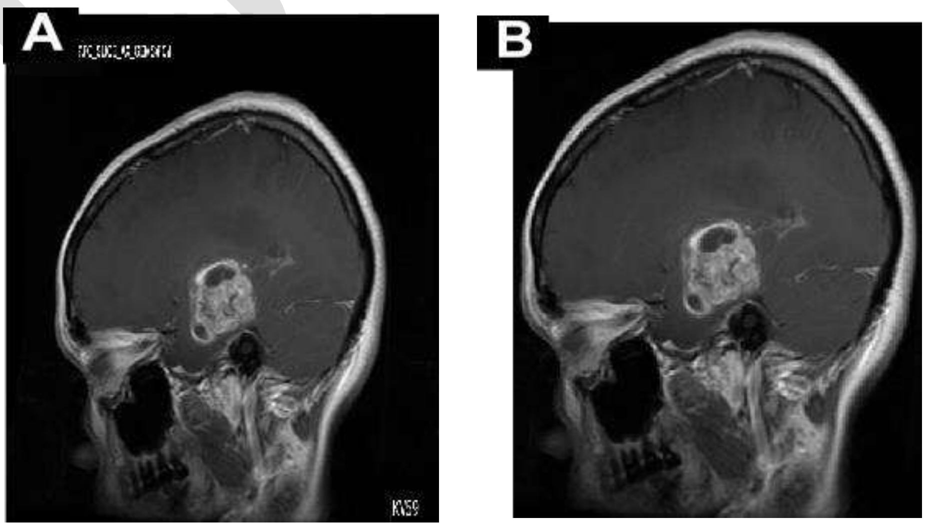

Fig.3.2 A) An example of MRI images before cropping the process. B) The same

image after the cropping process.

Conversion to Gray Scale:

A grayscale image consists of only gray scale values, but MRI images consists of primary colors (RGB) content. A gray color is the one in which the Red, Green, Blue components all have equal intensity in RGB space and so it is only necessary to specify a single intensity value for each pixel, as opposed to the three intensity values needed to be specified for each pixel in a full color image. When MRI images are viewed, they look like black and white but they contain some primary colors (RGB).So, for further processing of MRI brain image, it must be converted to perfect gray scale image.

An RGB image can be viewed as three images(a red scale image, a green scale image and a blue scale image) stacked on top of each other. In MATLAB, an RGB image is basically a M*N*3 array of colour pixel, where each colour pixel is a triplet which corresponds to red, blue and green colour component of RGB image at a specified spatial location.

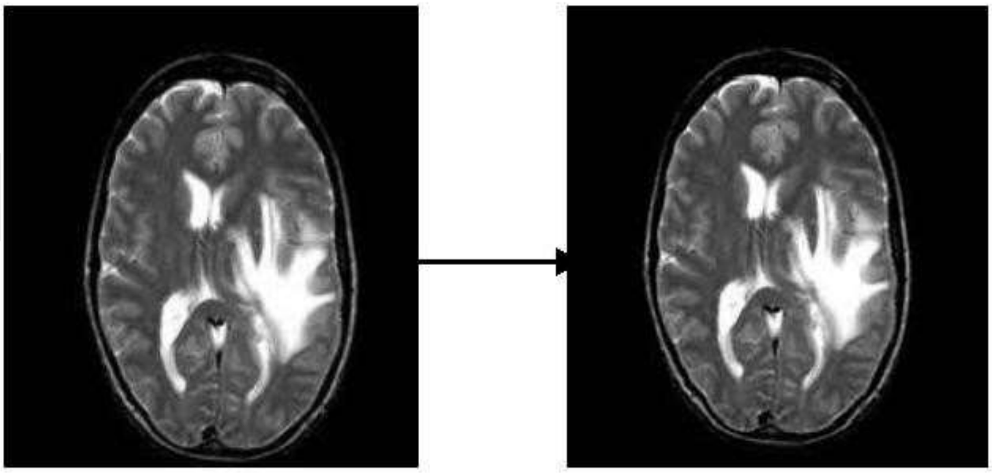

Fig.3.3 Gray scale conversion

3.2.2.2. De-Noising the images:

Filtering is a technique for modifying or enhancing an image. Image processing operations implemented with filtering include smoothening, sharpening and edge enhancement. Filtering is a neighborhood operation ,in which the value of any given pixel in the output image is determined by applying some algorithms to the values of the pixels in the neighborhood of the corresponding input pixel.

There are different types of filters to remove the noise from the images.

a) Median Filter:

In image processing, it is very important to perform some kind of noise reduction method in order to extract maximum information from the image. In pre-processing module we have proposed median filter. Median filter is very widely used in digital image processing because under certain condition, it preserves edges while removing noise [7]. Median filter is used for noise reduction in general and removal of salt and pepper noise in specific, Usually MRI images contain salt and pepper noise present due to motion artifacts (movement of patient during scan) and it is desirable to use median filter. It is done for smoothening of MRI brain image. Here we are using median filter to eliminate salt and pepper noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of the neighboring pixels. The pattern of neighbors is called the "window", which slides pixel by pixel, over the entire image. In MATLAB we have used "imfilter" command to remove the noise from the image.

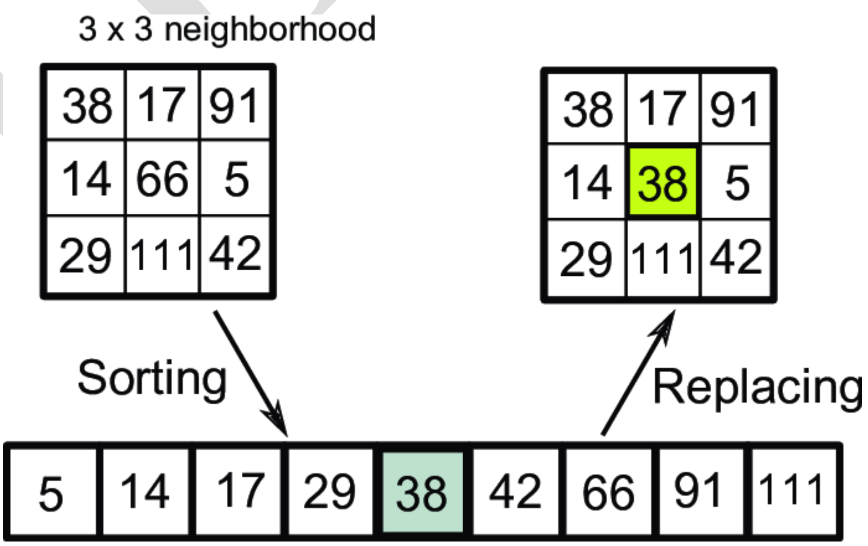

Fig.3.4 Example of Median filtering

b) Anisotropic Filtering:

In our proposed system we used the Anisotropic filter. In image processing and computer vision anisotropic diffusion, also called **Perona–Malik diffusion**, is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. Anisotropic diffusion [8] resembles the process that creates a scale space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process.

Each of the resulting images in this family are given as a convolution between the image and a 2D isotropic Gaussian filter, where the width of the filter increases with the parameter. This diffusion process is a linear and space-invariant transformation of the original image. Anisotropic diffusion[8] is a generalization of this diffusion process: it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. As a consequence, anisotropic diffusion is a non-linear and space-variant transformation of the original image.

In its original formulation, presented by Perona and Malik in 1987, the space-variant filter is in fact isotropic but depends on the image content such that it approximates an impulse function close to edges and other structures that should be preserved in the image over the different levels of the resulting scale space. This formulation was referred to as anisotropic diffusion by Perona and Malik even though the locally adapted filter is isotropic, but it has also been referred to as inhomogeneous and nonlinear diffusion or Perona- Malik diffusion by other authors.

A more general formulation allows the locally adapted filter to be truly anisotropic close to linear structures such as edges or lines: it has an orientation given by the structure such that it is elongated along the structure and narrow across. Such methods are referred to as space-adapted smoothening or coherence enhancing diffusion. As a consequence, the resulting images preserve linear structures while at the same time smoothing is made along these structures. Both these cases can be described by a generalization of the usual diffusion equation where the diffusion coefficient, instead of being a constant scalar, is a function of image position and assumes a matrix (or tensor) value.

Although the resulting family of images can be described as a combination between the original image and space-variant filters, the locally adapted filter and its combination with the image do not have to be realized in practice. Anisotropic diffusion is normally implemented by means of an approximation of the generalized diffusion equation: each new image in the family is computed by applying this equation to the previous image. Consequently, anisotropic diffusion is an iterative process where a relatively simple set of computation are used to compute each successive image in the family and this process is continued until a sufficient degree of smoothing is obtained.

The anisotropic diffusion filter (ADF) was proposed to adaptively remove the noise, maintaining the image edges. However, as quantified in this paper for the first time, ADF methods still produce unsatisfactory results.

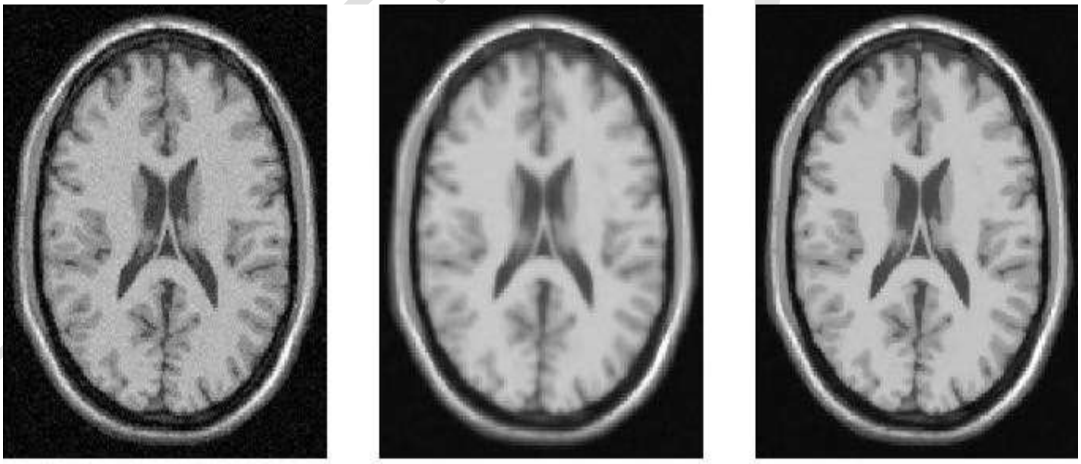

Fig.3.5 Anisotropic diffusion filtering image

Applications of Anisotropic filter:

Anisotropic diffusion can be used to remove noise from digital images without blurring edges. With a constant diffusion coefficient, the anisotropic diffusion equations reduce to the heat equation which is equivalent to Gaussian blurring.

This is ideal for removing noise but also indiscriminately blurs edges too. When the diffusion coefficient is chosen as an edge avoiding function, such as in

Perona-Malik, the resulting equations encourage diffusion (hence smoothing) within regions of smoother image intensity and suppress it across strong edges. Hence the edges are preserved while removing noise from the image.

Along the same lines as noise removal, anisotropic diffusion can be used in edge detection algorithms. By running the diffusion with an edge seeking diffusion coefficient for a certain number of iterations, the image can be evolved towards a piecewise constant image with the boundaries between the constant components being detected as edges.

c) Sobel Gradient:

The Sobel operator is a derivate mask and is used for edge detection. It is used to detect two kinds of edges in an image.

1. Vertical Direction
2. Horizontal Direction

In Sobel operator the coefficients of mask are not fixed and they can be adjusted to our requirement unless they do not violate any property of derivative masks. The mask will prominent the horizontal and vertical edges in an image. It works on the principle of mask and calculates difference among the pixel intensities of a particular edge.

4. RESULTS & DISCUSSIONS:

CASE 1: IF TUMOR IS PRESENT

4.1. INPUT MRI IMAGE

STEP 1: First we given the input image from the collected data set.

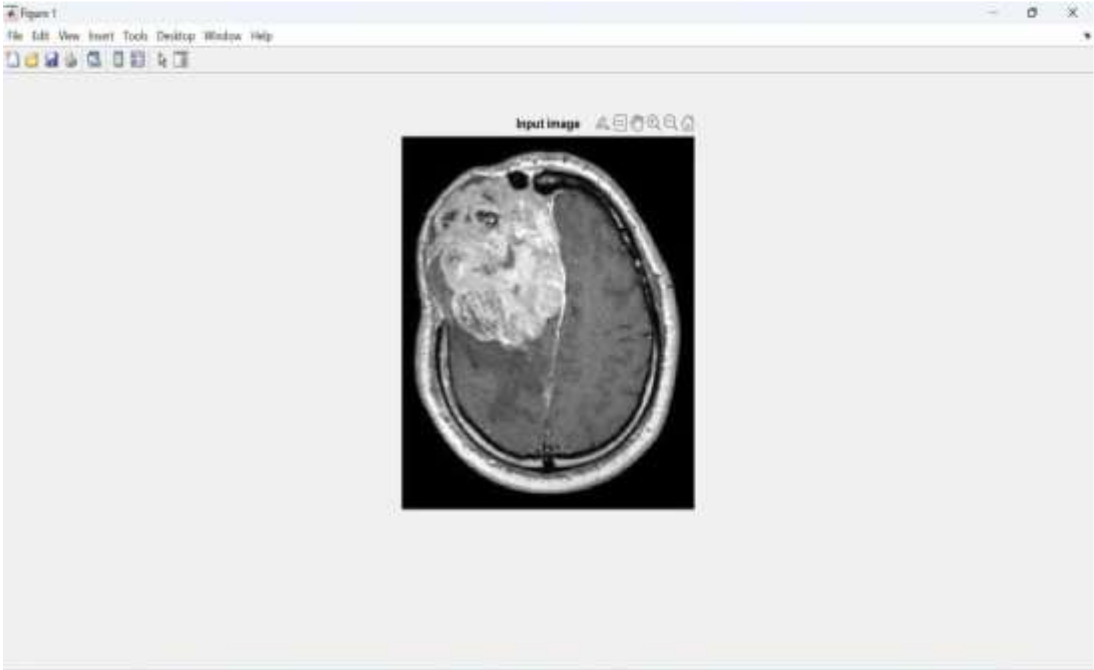

Fig.4.1 Input image

4.2. PRE-PROCESSING USING ANISOTROPIC FILTER AND SOBEL EDGE DETECTION, HISTOGRAM EQUALIZATION

STEP 1: De-noising using Anisotropic filter.

Fig.4.2 Filtered Image

STEP 2: Sobel edge detection method.

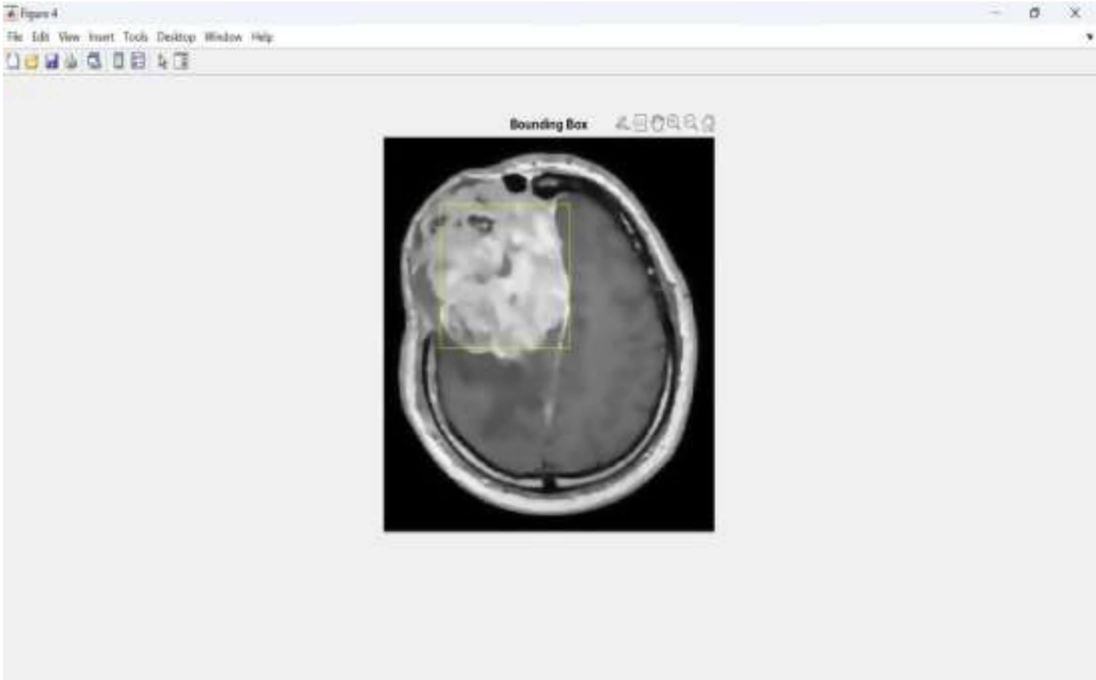

Fig.4.3 Bounding image

STEP 3: Histogram Equalization.

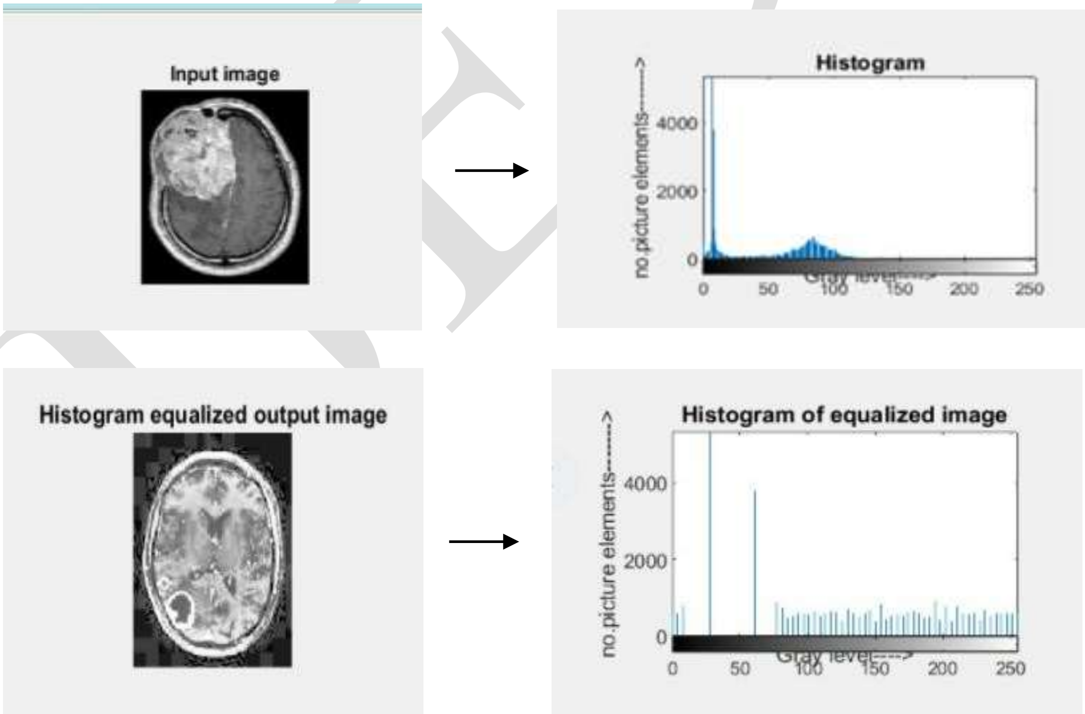

Fig.4.4 Histogram Equalized image

4.3. THRESHOLD SEGMENTATION

STEP 1: Segmentation of the tumor by Threshold Segmentation.

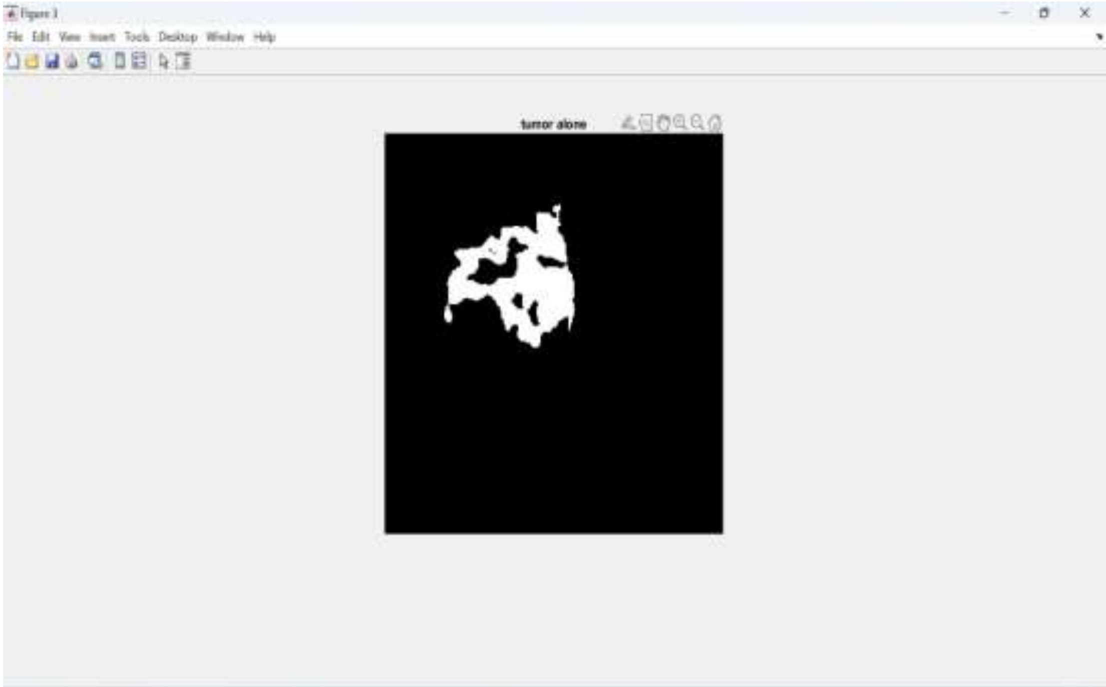

Fig.4.5 Segmented Image

STEP 2: Outline of the segmented tumor.

Fig.4.6 Outlined Image

4.4. FEATURE EXTRACTION

STEP 1: The tumor was highlighted or indicated by some features like shape, color.

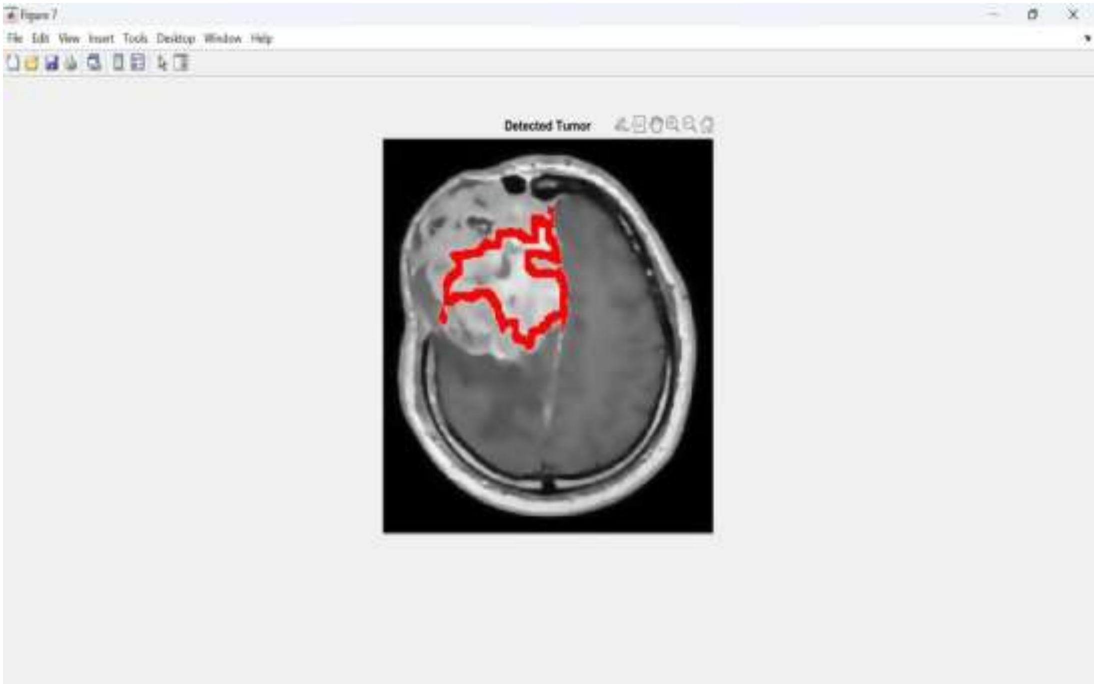

Fig.4.7 Tumor detected Image.

4.5 : ANALYSIS OF AN IMAGE

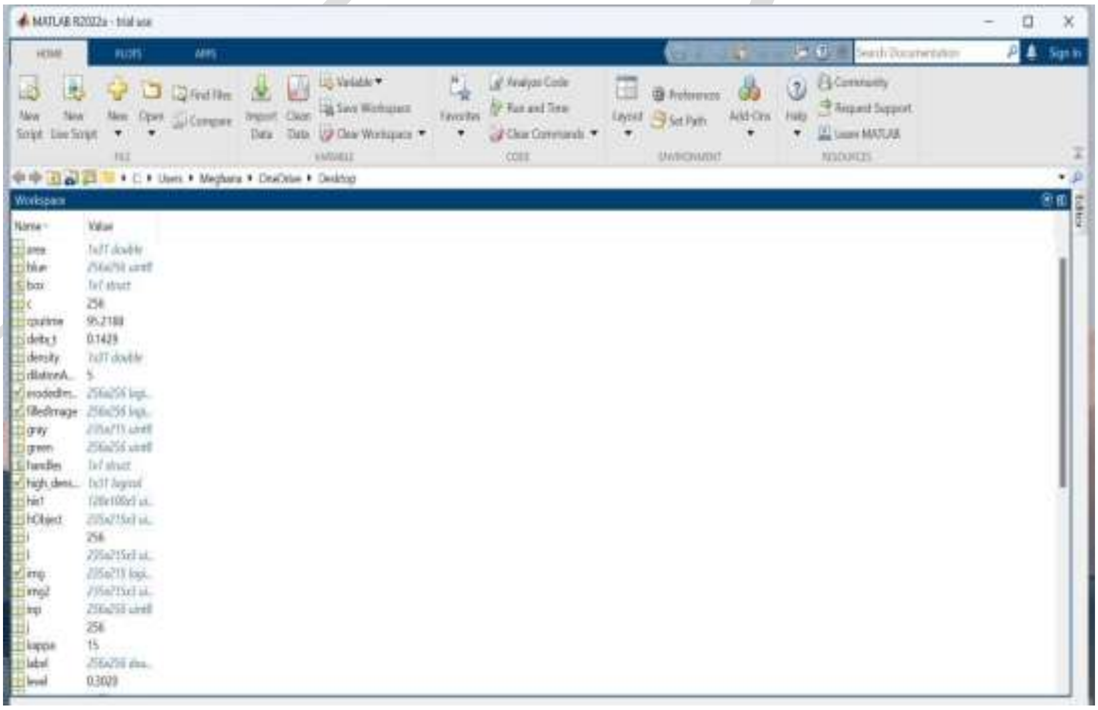

Fig.4.8 Tumor analysis

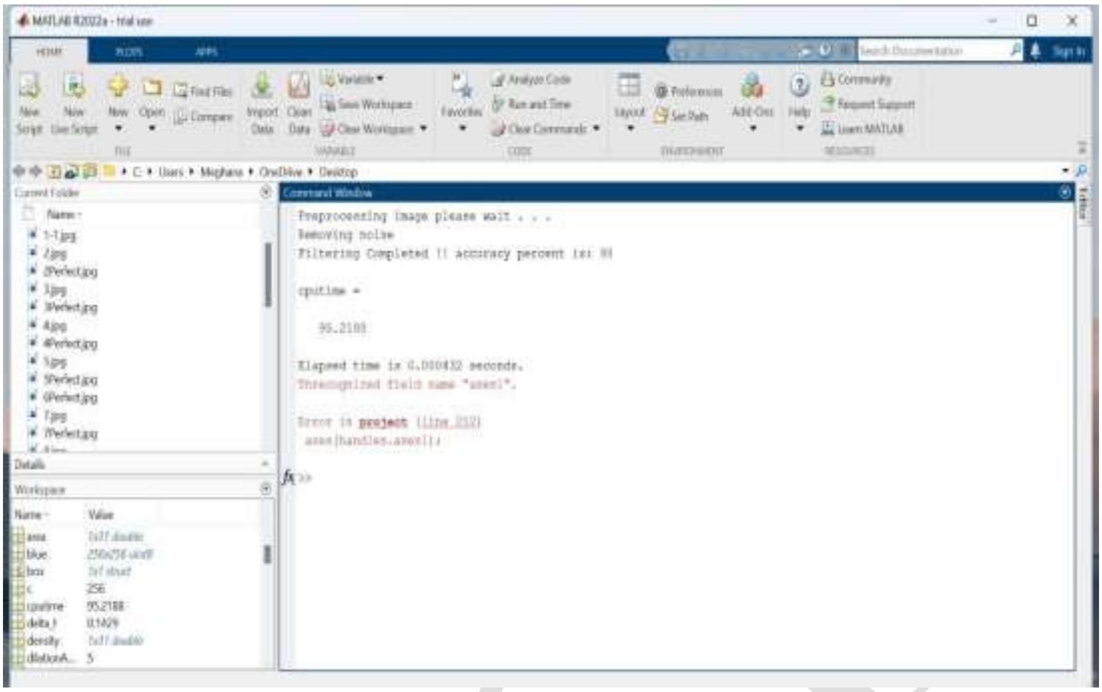

Fig.4.9 Command outputs

<u>CASE 2:</u> IF TUMOR IS NOT PRESENT

4.6 : INPUT IMAGE

STEP 1: The input image is given from the dataset.

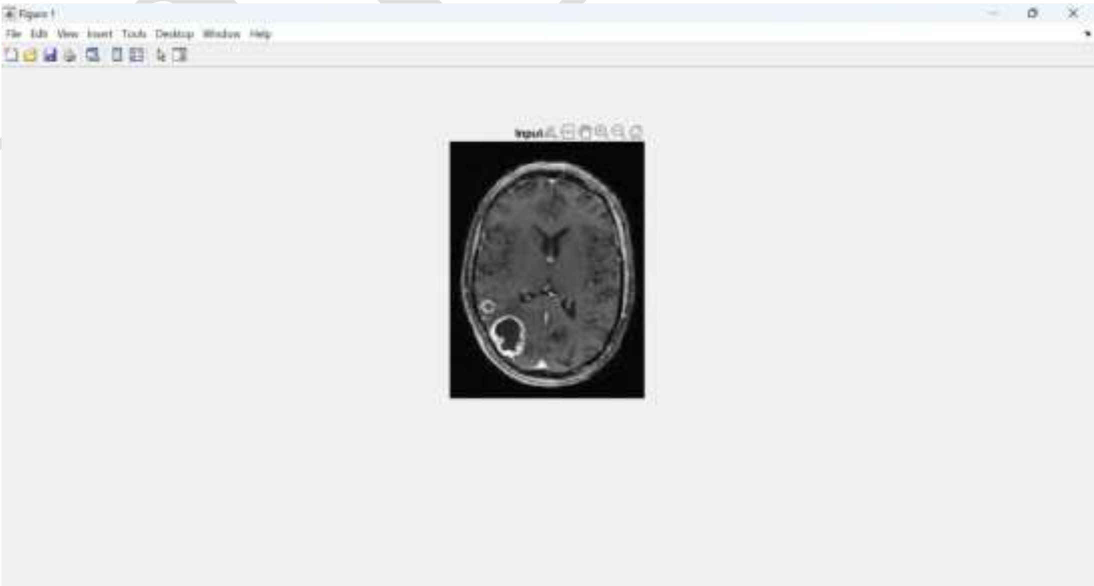

Fig.4.10 Dataset Image

4.7 : DENOISING THE IMAGE

STEP 1: Filter the image using Anisotropic filter.

Fig.4.11 Denoised Image

4.8 : STATUS OF THE IMAGE

STEP 1: Status of the input MRI image is obtained.

Fig.4.12 Status of the image

5. CONCLUSION & FUTURE WORK:

5.1. CONCLUSION

MRI Images are best suitable for brain tumor detection. In this study Digital Image Processing Techniques are important for brain tumor detection by MRI images. The pre-processing techniques include different methods like Filtering, Histogram Equalization, Edge Detection is used for image smoothing. The pre-processed images are used for post processing operation like threshold and then features are extracted and classification is done by Deep Convolutional Neural Network where we have obtained 97.72% of accuracy when run on a dataset of 300 images in classifying tumor and non-tumor images. This work help in detection of tumor which in turn save the precious time of doctor and pathologist to diagnose the tumor automatically in short span of time.

5.2. FUTURE WORK

In our project we have successfully implemented all the steps of image processing that is Pre-Processing steps, Segmentation, Feature extraction and Classification using various algorithms as we have mentioned above. As we have received 97.72% of accuracy in our project, for future we are going to increase the MRI images in the used dataset to improve the accuracy of the proposed model. Moreover, applying the proposed approach to other types of medical images such as X-ray, computed tomography (CT) and ultrasound may constitute a principle to future studies.

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