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Brain Tumor Detection Using Image Processing and Convolutional Neural Network MATLAB

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Abstract

Even with the tremendous advancements in medical technology, detecting brain tumours is still a time-consuming and difficult endeavour for doctors. Brain tumours may be treated more effectively and efficiently if they are detected early and accurately. An improved level of predictability in the diagnosis and categorization of brain tumours may be achieved by using automated systems. As a result, it is well documented that the accuracy performance of automated detection and classification approaches varies from technique to technique and tends to be reliant on the picture modality used. This study examines the current detection methods and outlines their advantages and disadvantages. As one of the most frequent illnesses in the world, brain tumours may be described as the unchecked growth of abnormal cells in the brain, which presents a diagnostic difficulty. When paired with a well-established image processing technology, identification of this condition becomes much simpler. The goal of this research is to propose a feasible approach for fast determining the size and location of a tumour from an MRI image utilising area splitting, merging, and growth based segmentation. A total of five phases are involved in the whole process, including input in the form of MRI pictures, pre-processing and enhancement, image segmentation and feature extraction. In order to identify the tumour, MRI images were enhanced using contrast enhancement and median filtering, which was followed by a segmentation technique. Graphical user interfaces and MATLAB algorithms have been used to organise input and output data.

Keywords: MRI, GUI, Segmentation, Brain Tumor, Filtering, Enhancement, MATLAB.

I. INTRODUCTION

The human body is made up of a variety of cells, but the brain is the most important. [1] The central nervous system's kernel is also known as the nucleus. When abnormal cells sprout in the brain without being controlled by the usual processes that govern development, this is known as a brain tumour. Any ontogenesis inside the small confines of the skull, which surrounds the brain, might lead to serious complications. Tumors in the brain may be malignant or not. Even whether tumours are malignant or noncancerous, they may lead to brain damage, such as a halt in the brain's capacity to function properly, or they can even be life-threatening [2].

Brain tumours have risen to the status of one of the most frequent medical conditions. Brain tumours are one of the leading causes of death in both adults and children. Complex brain tumours may be divided into two main types based on variables such as the tumor's origin, development style, and aggressiveness. A primary brain tumour is one that forms from the brain's cells or covering; secondary or metastatic brain tumours, on the other hand, originate when cancer cells travel to the brain from a primary malignancy elsewhere in the body [4]. Tumors of the brain affect people of all ages, genders, and races equally. There are now more than 700,000 persons in the United States who have a brain tumour, and about 80,000 of them are receiving treatment this year for primary brain tumours. Primary brain and central nervous system cancers have been diagnosed in more than 120 different ways. Brain tumours claim the lives of over 16,000 individuals each year [2]. Detecting tumours via image processing is now simpler than ever before. All of these factors have a role in determining whether or not a patient has a brain tumour. MRI, CT, and PET are some of the most often used imaging modalities for identifying tumours in the human body. In order to examine the tumor's anatomy, MRI and CT scans have been the most used [1]. There are a number of factors that affect the detection and processing time, as well as the segmentation outcome, such as screen brightness and contrast. Medical research relies heavily on automated brain tumour detection [3]. Automated identification of tumours improves their chances of survival. Numerous studies are being conducted in order to diagnose brain tumours with more precision, exactness, and speed of calculation by eliminating the need for manual intervention. There is a possibility to improve the automated identification of tumour size and location from MRI images in a short period of time and with greater accuracy, according to this article. Segmentation algorithms have been used to find the optimal combination of information based on the criteria used for this project. A total of five phases are involved in the whole process, including input in the form of MRI scans, image enhancement, picture segmentation and feature extraction. As soon as an MRI image has been taken and contrast enhancement has been applied, noise will be reduced using median filtering to make the pictures clearer to see. The pixel-based technique of segmentation has been used to divide, merge, and increase pixels. The morphological procedure was then used to isolate the tumour from the MRI picture.

ASSESSMENT STRUCTURE

A flowchart of the suggested approach for identifying brain tumour cells automatically is shown in figure 1. Detection of a brain tumour involves a series of five processes.

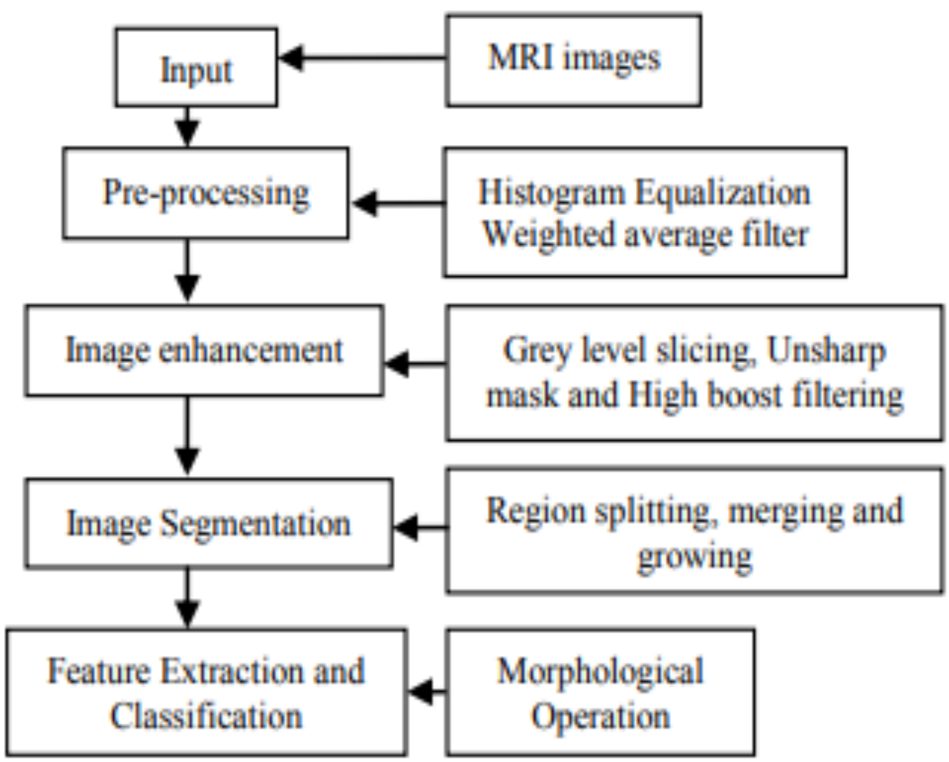

Figure 1: depicts a proposed approach for automatically detecting brain tumour cells.

An MRI picture

Magnetic resonance imaging (MRI) scans (interaction of magnetic field and radio waves) have produced a 3-D comprehensive image of the brain anatomy, which is painless and noninvasive. Following figure 2, sounds are generated by the MRI machine in order to collect MRI pictures.

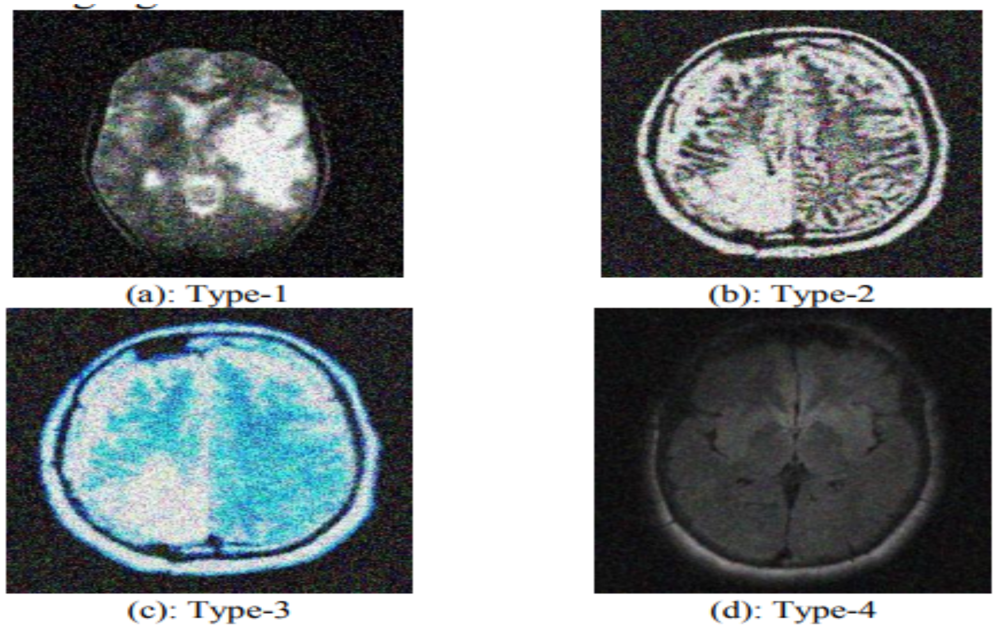

Figure 2: Various MRI machine images

B. Preparation

By executing image filtering methods such as histogram equalisation, which distributes the intensity evenly, and then using a weighted average median filter to enhance the picture details, noise has been eliminated from the MRI images. q indicates the normalised grey levels in Figure 3, which may be expressed as a variable.

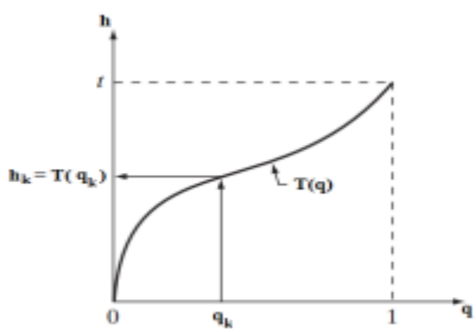

Figure-3: Histogram equivalence transformation

C. Image processing

There was no obvious difference between the brain and the tumour. High-boosting filtering and contrast stretching have been used to improve the MRI images' distinct properties. Grey level slicing has been employed for contrast stretching in the MRI images as seen in figure 4.

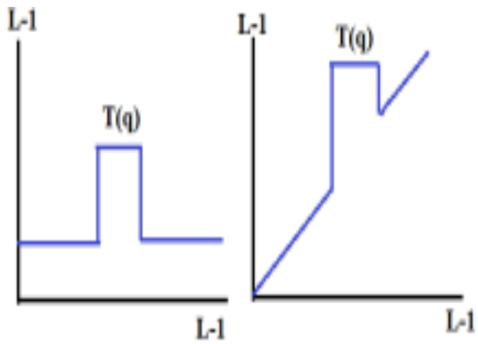

Figure 4: Contrast slicing at the grey level

Using a digital computer to process digital photos using an algorithm is known as digital image processing. There are several benefits to digital image processing as a subdivision or topic of digital signal processing. Input data may be processed using a larger variety of algorithms, avoiding issues such as the buildup of noise and distortion throughout the process. It is possible to represent digital image processing in the form of multidimensional systems since pictures are specified in at least two dimensions. As computers and mathematics (particularly discrete mathematics theory creation and improvement) advance, so does demand for a broader range of applications in fields such as agriculture, military, industry, and medicine. These factors all combine to influence digital image processing generation and development.

Image sensors

Mohamed Atalla and Dawon Kahng at Bell Labs invented the MOSFET (MOS field-effect transistor) in 1959, which is the underlying technology for contemporary image sensors. [6] CCDs and then CMOS sensors were developed in response to this trend, which led to the creation of digital semiconductor image sensors. Willard S. Boyle and George E. Smith of Bell Labs devised the charge-coupled device in 1969. They discovered, while studying MOS technology, that an electric charge could be compared to the magnetic bubble and stored on a small MOS capacitor. It was easy to make a series of MOS capacitors in a row, so they linked them to a voltage that would allow the charge to be stepped up and down. Digital cameras for television broadcasting made use of the CCD, which is a semiconductor circuit.

As far back as the 1980s, Olympus in Japan developed the NMOS active-pixel sensor (APS). Increasingly tiny micron and eventually sub-micron scaled downMOSFET device manufacture allowed this to happen. [9] Tsutomu Nakamura's team at Olympus developed the NMOS APS in 1985. In 1993, Eric Fossum's team at NASA's Jet Propulsion Laboratory created the CMOS active-pixel sensor (CMOS sensor). [12] The sales of CMOS sensors have overtaken the sales of CCD sensors by 2007.

Medical imaging

A British engineer, EMI Housfield, devised the X-ray computed tomography equipment for head diagnostics in 1972, which is often referred to as CT, in the United Kingdom (computer tomography). Based on projection of the human head section and computer processing, a CT nucleus technique called image reconstruction is used for cross-sectional image reconstruction. CT scanners for the whole human body were invented by EMI in 1975 and were able to provide clear images of diverse body areas. This method of diagnosis was awarded the Nobel Prize in 1979. [4] In 1994, the Space Foundation's Space Technology Hall of Fame welcomed medical image processing technology into its hall of fame.

Image Segmentation

It is the goal of image segmentation to break up a medical picture into distinct sections and identify the area of interest. Components may be isolated from the rest of the picture so that they can be seen or identified as separate objects.

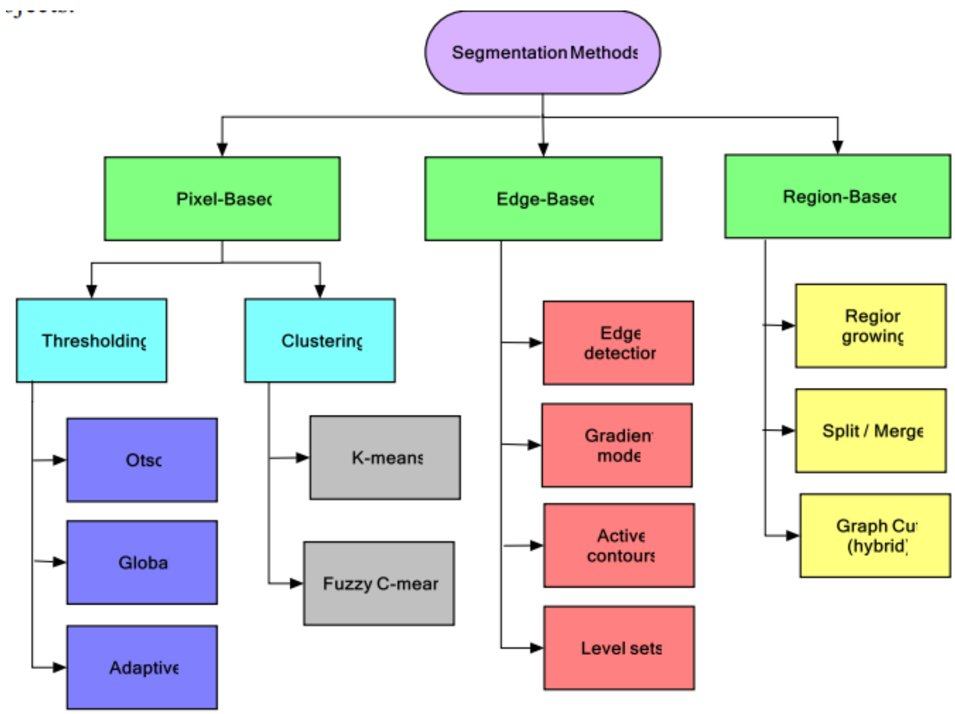

Fig. 5. Segmentation categories

As indicated in Figure 3, Alireza et al. [2] classified picture segmentation into pixel approaches, region-based methods, and edge-based methods. [2] Another two broad studies of picture segmentation have also been published by Alireza et al [2] and Yu Jin [3]. [4] [5] Some reviews focused on MRI picture segmentation in particular. MRI image segmentation methods were compared directly by Zhang [6] and Clarke et al [7].

An MRI picture is segmented based on colour or texture in order to identify certain features, such as lines or curves. This simplifies further processing. An MRI picture is made up of a series of separate images that are reunited. Segmentation techniques such as region splitting, merging, and growing were used to identify the tumour area directly. Using the zone splitting process, the whole picture is divided down into a collection of distinct and distinct regions.

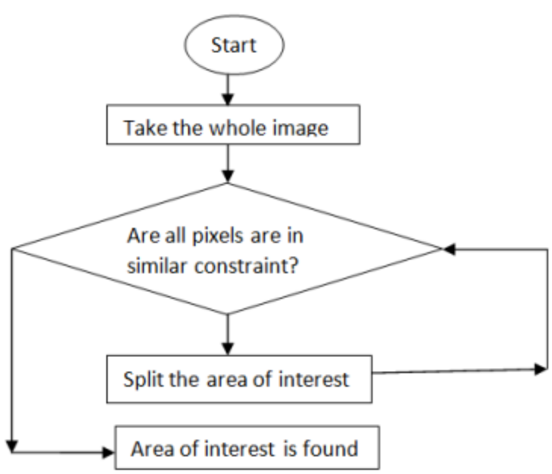

Figure 6: Region splitting based segmentation process

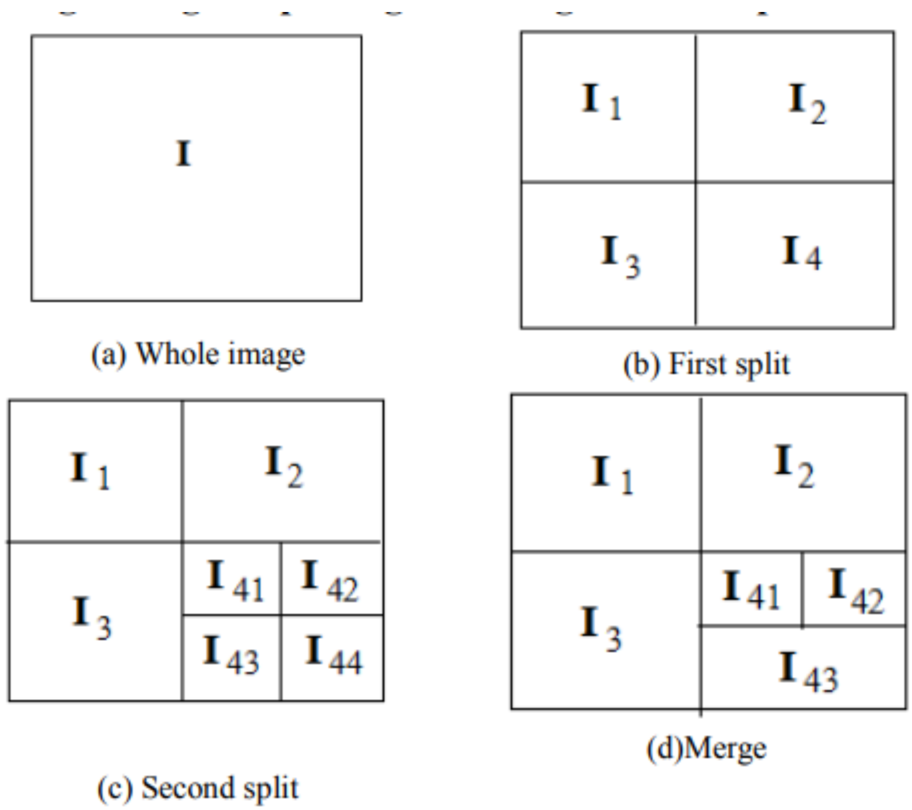

Figure 7: Region splitting approach

Feature Extraction and Selection

According to Nassiri et al. [8], feature extraction is the reduction of the original data set by calculating certain features or qualities that may be used to categorise and distinguish various input patterns. An image's dimensionality may be reduced to a compact feature vector as part of the feature extraction process, which finds interesting components of a picture. This approach is beneficial for applications involving huge pictures, such as image matching and retrieval, in which feature representation must be decreased in order to speed up the completion of these tasks.

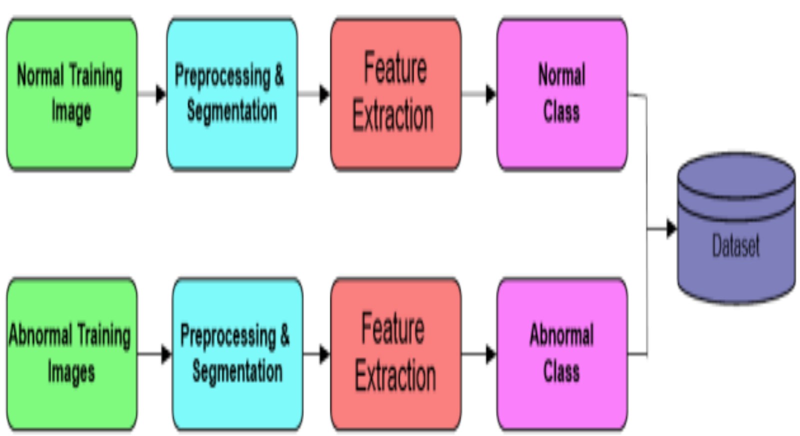

Figure 8: Block diagram of feature extraction stage

Figure 6 shows a block schematic of the feature extraction step. [9] showed that the most often used feature extraction methods are LBP, GLCM, Canny edge detection, and a bag of words (BoW). To assess the advantages and disadvantages of various extraction methods, a large number of studies have been carried out. Unrelated and unneeded characteristics are eliminated from input records in order to build powerful classifiers via feature selection, which is the primary goal. This phase is likely to boost the final classifier's construction speed and accuracy. A thorough search of all possible feature subsections is required for optimum feature selection in supervised learning tasks, according to theory.

It's just not feasible to look at every feature in order to come up with the best possible feature set for a large number of features or models. Rather than trying to find the exact best characteristics for a particular classifier, a supervised learning method is used to analyse a reasonable approximation an ideal combination.

Result & Discussion

Experiment outcomes from this project are discussed here. Figure 7 depicts the first graphical user interface (GUI) designed to make a programme more user-friendly. There are two sections to the GUI, one for the MRI picture and one for the tumour detection.

MRI images may be selected by selecting the "input MRI image" button, and then the user can click the "detected tumour" button to execute the area splitting, merging, and growth-based segmentation procedure.

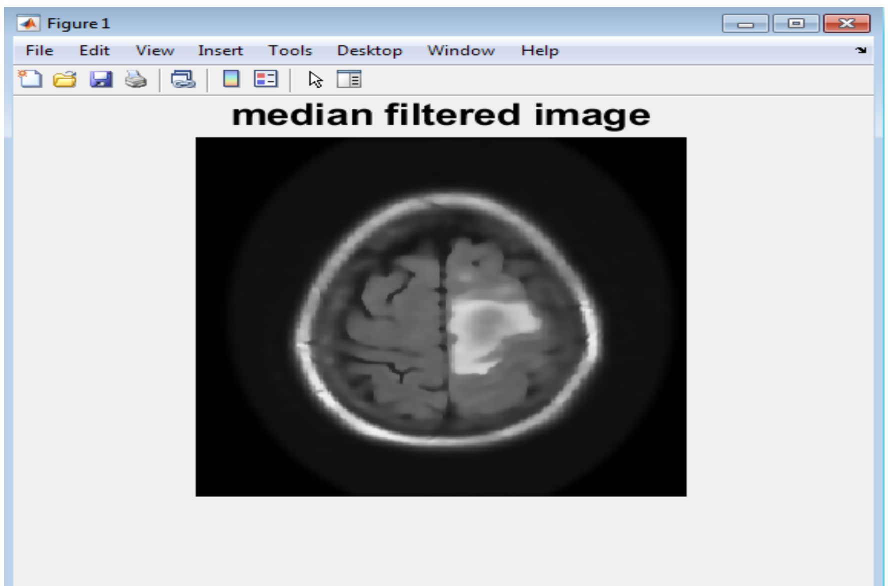

Figure 9: Median Filtered image

Figure 10: Types of tumor

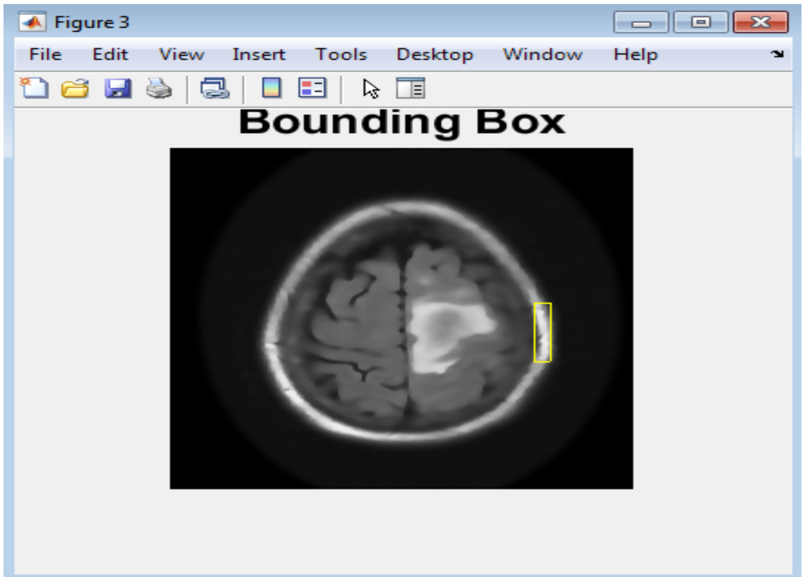

Figure 11: Bounding box in tumor

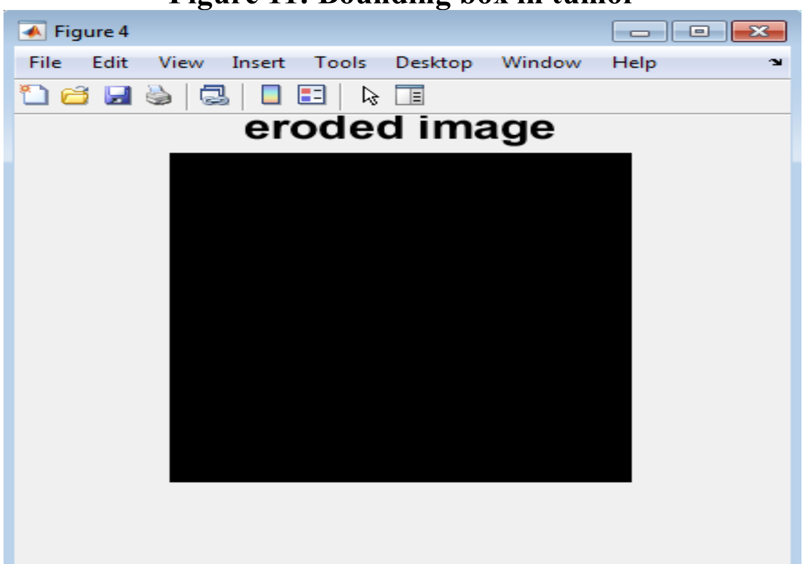

Figure 12: eroded image

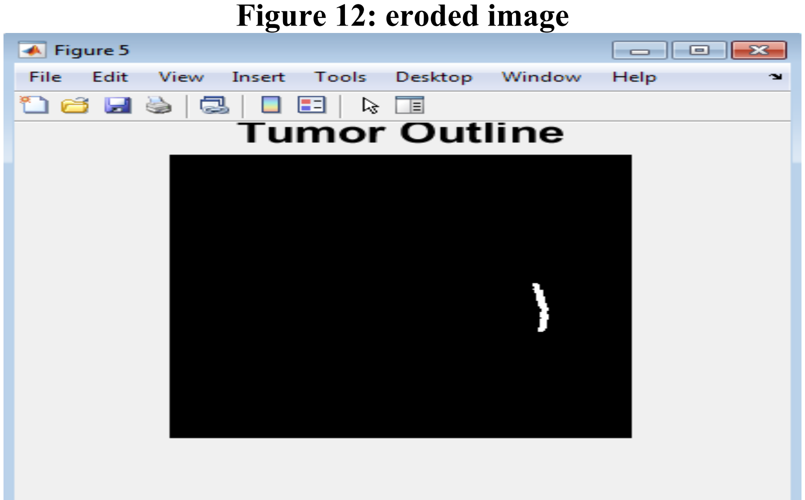

Figure 13: Tumor outline

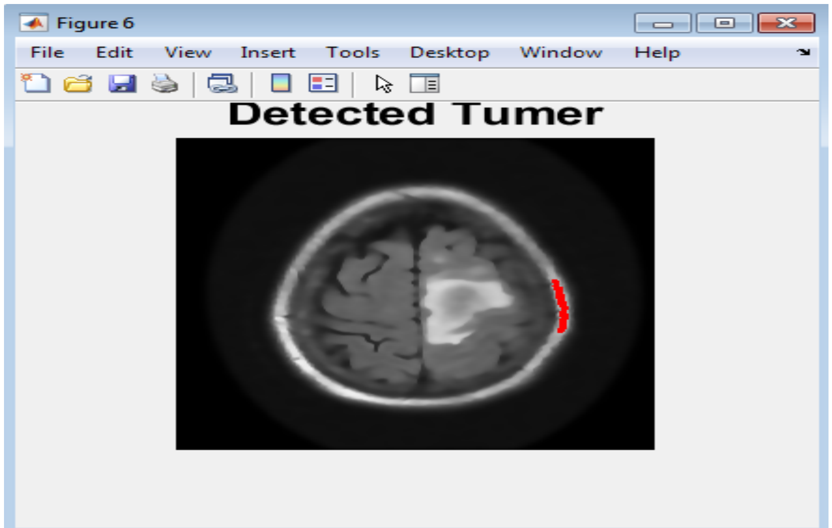

Figure 14: Detected Tumor

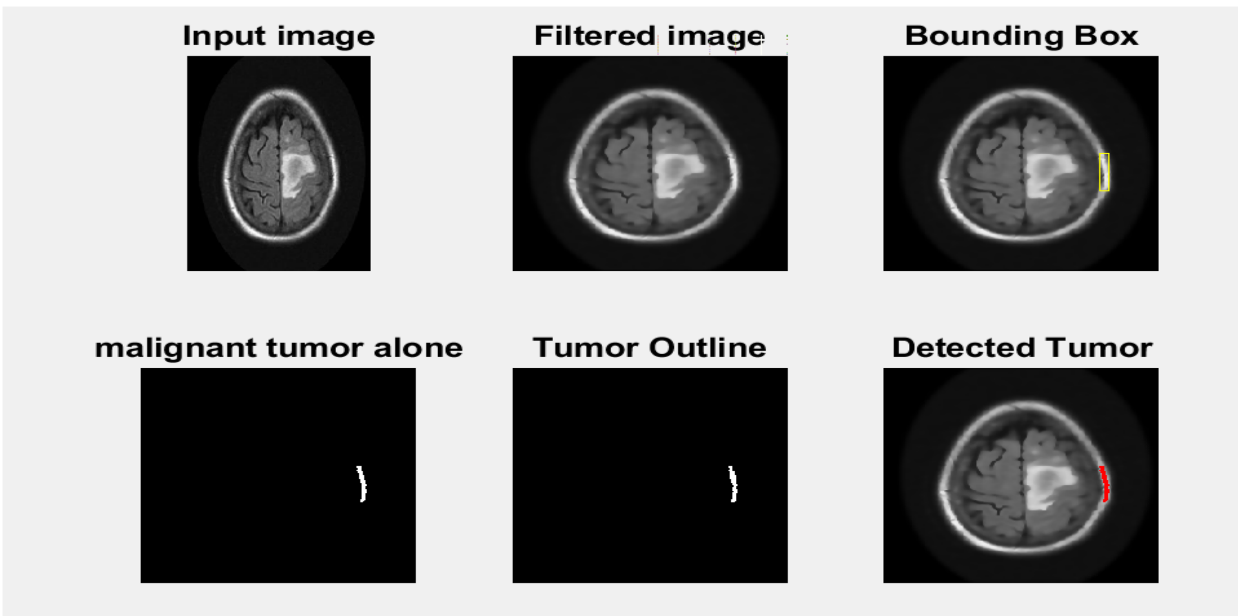

Figure 15: Brain tumor complete images Segments

In the field of image analysis, data is extracted from pictures, usually digital images, using image processing methods. Bar code reading is a basic image analysis activity, but facial recognition software may be smart enough to identify a person only by looking at them.

If you need to analyse big volumes of data, do difficult computations, or want to extract quantitative data, you'll need a computer. In contrast, the human visual brain is an effective picture analysis apparatus, particularly for extracting higher-level information, and for many applications—such as health, security, and remote sensing—human analysts still cannot be substituted by computers in these areas. Human visual perception models have inspired several significant image analysis technologies, such as edge detectors and neural networks.

Conclusion

The area of biomedicine relies heavily on image processing for a variety of reasons. The authors of this research outlined a strategy for swiftly detecting tumours in MRI scans. The MRI picture was treated to an area splitting, merging, and growing-based segmentation procedure to remove noise and improve image quality before being used to locate the tumor's location. It is possible to use this technique to quickly and accurately identify brain tumours using MRI images acquired by MRI equipment. Processes such as histogram equalisation, weighted average filter, contrast stretching, and unsharp mask high boost filtering have all been used to enhance the picture quality before it can be used in further processing. Finally, an image segmentation procedure using area splitting, merging & growing was used to identify and name the tumor's location, as well as extract its attributes. The new approach has virtually reached 100% accuracy in the identification of tumours in the middle and end stages. Correlation and neural networks may be used in future efforts to identify pre-stage tumours with 100 percent accuracy using this technique.

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