GSJ: Volume 12, Issue 3, March 2024, Online: ISSN 2320-9186
www.globalscientificjournal.com

MRI IMAGE PROCESSING FOR DETECTING BRAIN TUMOR

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KeyWords
Image enhancement, feature extraction, segmentation, tumor detection, tumor properties.

ABSTRACT

A brain tumor exhibits an abnormal growth of tissues within the brain. Physicians ascertain the tumor's location and malignancy status based on its cellular origin. The National Brain Tumor Society classifies brain tumors as Benign, Malignant, Primary, or Metastatic. With over 10,600 people diagnosed with brain tumors in England annually, there is a critical priority for early detection. This underscores the urgency of identifying brain tumors promptly. This project focuses on algorithms implemented through image processing techniques to detect brain tumors. Employing CAD (Computer-Aided Diagnosis) on MRI (Magnetic Resonance Imaging) images stands out as the most efficient and straightforward method for diagnosing cancer. Early and precise tumor detection can mitigate the mortality rate associated with cancer. Mass clusters serve as early indicators of potential brain cancers, aiding in early cancer prediction. Images utilized in this project will be sourced from internet datasets “Kaggle.com”. MATLAB software will be utilized to enhance images for tumor region detection within a region of interest (ROI). Extracted features will undergo various analyses to improve mass identification.

1. INTRODUCTION

A tumor arises from abnormal cell growth resulting from dysfunctional cell growth mechanisms. Tumors can be classified as either malignant or benign. Both types represent abnormal growth; however, malignant tumors originate in a specific organ and can spread via the bloodstream to form secondary tumors in other organs, a process known as metastasis. Conversely, benign tumors typically remain localized within their original organ.

Detection of this condition often involves clinical examinations and radiographic imaging. Identifying abnormal areas that are not obvious presents challenges in traditional detection methods. Therefore, employing image processing and feature extraction techniques can significantly aid in tumor detection. This study focuses on utilizing image processing techniques for the detection of brain tumors. images used in the study are MRI images, and the process for tumor detection will involve several steps, including pre-processing, segmentation, feature extraction, and getting information regarding the extracted region.

2. LITERATURE REVIEW

Current tools and methods used for analyzing tumor and their attitude are the most used. Image processing techniques are used to detect brain tumor. Image processing techniques convert images into digital images then operate it using different procedures to get a better and enhanced image. In 2012, Mokhled S. introduced several procedures to detect tumor, including image segmentation to extract tumor out of the background. This was done using 'Gabor filter' to classify cancer cells in a better way. In 2013, H. G. Zahed proposed additional procedures, these procedures included image extraction and segmentation to diagnose cancer cells. The "Gaussian smoothing concept was proposed for filtering purposes, before applying 'Fast Fourier Transform' (FFT)" [1].

In the year 2014, X. Chen proposed a new technique called the "gene counting technique", but this technology was suitable for the complex formation of gene selection [2]. In the year 2015 K. Sudharani et al proposed an "Advanced morphological technique for automatic brain tumor detection and evaluation of statistical parameters", The main objective of this paper is to present the automatic segmentation method which separates non-enhancing brain tumors from healthy tissues in MR images by locating tumor position in the brain and to give a complete statistical analysis of the tumor. By applying the algorithm presented in this paper we can determine the area of the tumor in the brain along with the area length in the vertical and horizontal planes, sensitivity of the tumor, specificity, and similarity index can also be found. [3]

In the year 2017, T. Chithambaramet al. proposed "Brain Tumor Detection and Segmentation in MRI Images Using Neural Network", this research presented two techniques for the detection purpose; the first one is Edge detection and segmentation instant is Artificial Neural Network proficiency. The aimed Neural Network technique comprises some stages, namely, feature extraction, dimensionality reduction, detection, segmentation, and classification. In this research, the proposed method is more accurate and effective for brain tumor detection and segmentation. [4]

In the year 2019, Parasuraman Kumar, B. Vijay Kumar proposed "Brain Tumor MRI Segmentation and Classification Using Ensemble Classifier", in this paper, four processes are done to identify brain tumors. The first process is preprocessing the image data from the collection of the database using median filtering, second stage is segmentation using Fuzzy C-means Clustering Algorithm [6], third stage is feature extraction using Gray Level Co-Occurrence Matrix (GLCM), [1] and the fourth stage is classification using ensemble classifiers is the combination of neural network, Extreme Learning Machine (ELM) and Support Vector Machine classifier (SVM)[6].

In May 2019, Md Shahariar Alamet al. proposed "Automatic Human Brain Tumor Detection in MRI Image Using Template-Based K Means and Improved Fuzzy C Means Clustering Algorithm"[5]. Due to previously mentioned techniques, and using different techniques, this project will focus on identifying brain tumors using image processing [7].

Machine Learning for tumor detection using Neural Networks, Fuzzy logic, and C-mean algorithms were proposed to detect tumor cells, this required less computations but was less accurate in detection [8]. Deepa and Arunadevi [9] have proposed a technique of an extreme learning machine for the classification of brain tumors from 3D MR images. This method obtained an accuracy of 93.2%, a sensitivity of 91.6%, and a specificity of 97.8%.

3. Methodology

The proposed study utilizes MATLAB software to detect tumors in multi-echo magnetic resonance imaging (MRI) brain images. Figure 1 shows the steps followed for the detection of tumor existence.

Steps followed in the experiment:

1. Input the image: either with or without tumor.
2. Pre-processing:
   a. Converting the image to grayscale
   b. Resizing the image.
3. Enhance the image to clarify parts of the image using "*anisodiff*" function.
4. Segment the image to specify if there is an odd part using "Thresholding and Morphological Operations".
   a. NO: if there is no detection of a tumor a message will be displayed.
   b. YES: if detected then proceed to the following step.
5. Extracting the odd part (tumor) in a separate image.
6. Surround the odd part with a box to distinguish it.
7. Specify the ROI in a surrounding line.
8. Specifying tumour properties. See Figure 1, figure 2.

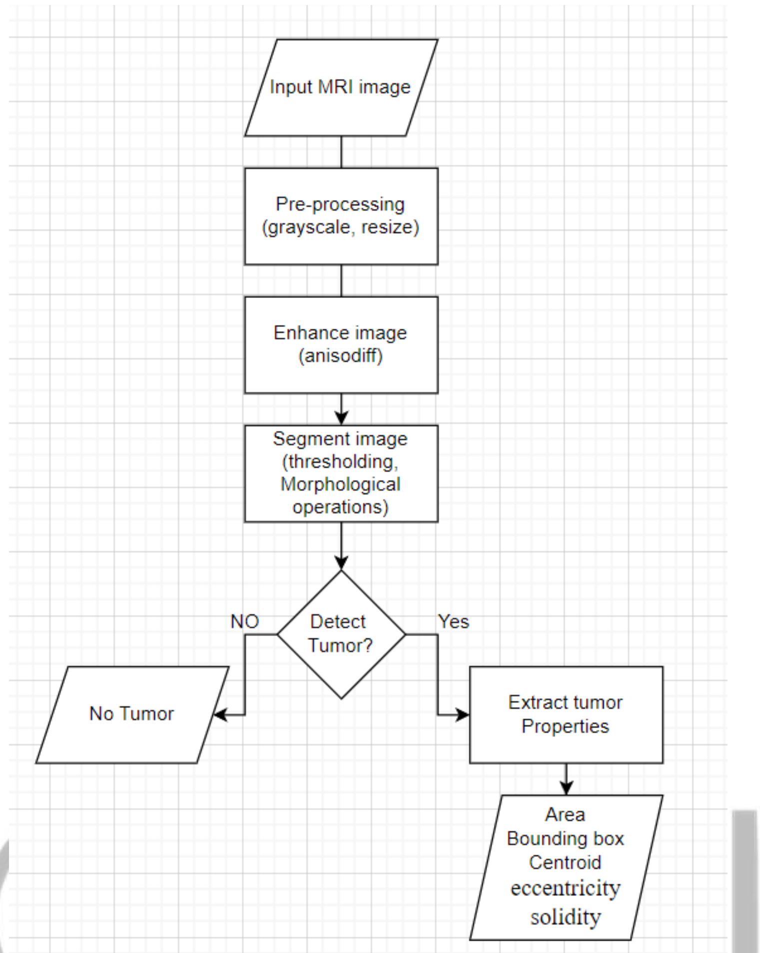


Figure 1: Steps for tumor detection

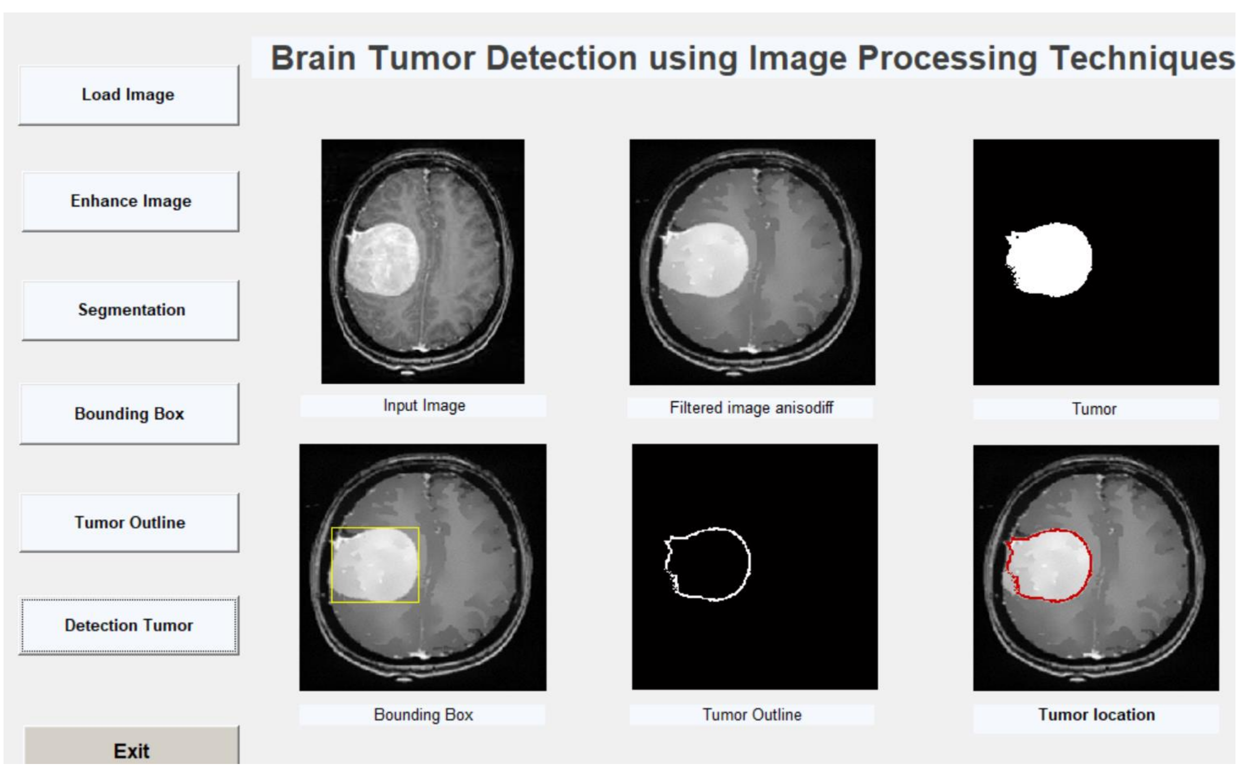


Figure 2: Steps for tumor extraction

Two online databases, "brain-mri-images-for-brain-tumor-detection," consist of images: one containing tumor and the other free from such abnormalities. [10].

3.1 Pre-Processing

This step includes:

- **Grayscale**: Converting an image to grayscale is a common preprocessing step in image processing and computer vision tasks. There are several reasons why converting to grayscale can be advantageous such as simplicity, focus on structure, and Reduced Computational Cost. Grayscale images contain only intensity information, representing each pixel with a single value ranging from black to white. This simplification reduces the complexity of the image data, making it easier to process and analyze. This step is done using "*rgb2gray*" function.

- **Resizing**: resizing an image to an appropriate resolution can be beneficial for enhancing processing speed and reducing computational complexity, especially if the original image is large. However, care should be taken to preserve important details during resizing. This step is done using "*imresize*" function.

3.2 Enhancement

Deciding on the image processing method can be challenging. Before initiating any image processing, it's crucial to eliminate any unnecessary artifacts the image might contain. Once these artifacts are removed, the image is prepared for processing. The initial step of pre-processing involves converting the image from color, if it was in color, to grayscale, followed by noise reduction and image reconstruction.

Noise removal is achieved through a filtering technique aimed at enhancing the image. Anisotropic filtering (AF) is employed for this purpose. Anisotropic diffusion is utilized to analyze the image based on selective smoothness while enhancing local features such as region boundaries. In its standard form, anisotropic diffusion promotes smoothness within regions while preventing diffusion across different regions. This behavior makes it particularly suitable for enhancing MRI images.

Another filtering technique commonly employed for noise reduction is the Median Filter. It is widely used to eliminate "Salt and Pepper noise" from grayscale images. The Median Filter, being a "non-linear" technique, operates by computing the median value of pixels. Additionally, it is effective in reducing Speckle noise while preserving edges and boundaries. However, it comes with drawbacks such as complexity and higher time consumption compared to other filters.

In our proposed study, we used anisotropic Diffusion Filtering which smooths the image while preserving edges. It iteratively diffuses the image with a diffusion coefficient that depends on the image gradient. See Figure 3.

$$\frac{\partial I}{\partial t} = div\ (c(x,y,t), \nabla I) = \nabla c . \nabla I$$

Equation 1: Anisotropic diffusion equation

MRI_filtered = anisodiff(MRI, niter, kappa, lambda, option);

Through try and error, we found that the following values for the variables gave the best results in the enhancement stage: niter = 30, kappa = 5, lambda = 5/7, and options = 1.

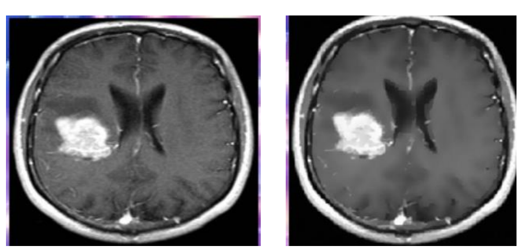


Figure 3: Original image (left), and Enhanced image (right)

3.3 Segmentation

Segmentation plays a vital role in preprocessing images for feature extraction by partitioning the image into distinct, non-overlapping regions. This method divides the image into subsets of pixels, enabling focused analysis and extraction of meaningful information.

The primary objective of segmentation is to delineate boundaries or distinguish objects within the image, creating segments that cover the entirety of the image. Segmentation algorithms commonly rely on either similarity or discontinuity properties to achieve this task. In the segmentation process both thresholding and morphological operation were implemented, see Figure 4:

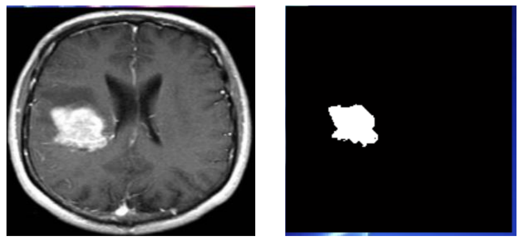


Figure 4: Enhanced Image (left), Extracted Tumor (right)

3.2.1 Thresholding

Thresholding methods can be used to separate different tissue types based on their intensity values. In our experiment, we utilize thresholding as the method to segment the image for tumor extraction. After segmentation, we draw a bounding box to outline the tumor's position in the image, defining the surrounding area known as the region of interest (ROI). See Figure 5.

Figure 5: Bounding Box

3.2.2 Morphological Operation

Feature extraction is a pivotal stage in pattern construction. Extracting specific features helps determine whether an image contains a tumor. Upon tumor detection, an outline is generated using a morphological operation such as erosion, which subtracts the tumor, thereby delineating the contour of the selected area. Overall, morphological operations complement the segmentation process by addressing common challenges encountered in MRI images, leading to more accurate and reliable tumor extraction results. See Figure 6.

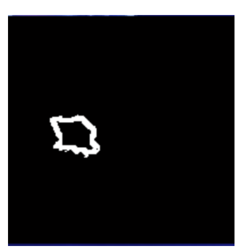


Figure 6: Tumor Outline

3.4 Tumor Information

The segmented and delineated region provides valuable insights into the tumor's size, area, and position. Employing the '*rgionprops*' function, we extracted key tumor properties including area, perimeter, centroids, and pixel index values. These pixel index values correspond to the physical dimensions of each pixel within the image, specific to each scan. Converting these properties into millimeters facilitates their interpretation in real-world units. This empirical data, tailored to each MRI scan, offers crucial information for assessing the tumor's dimensions, position, and characteristics, empowering users to analyze the tumor.

- The area property represents the number of pixels in the labeled (segmented) region. In the context of tumor segmentation, the area indicates the size of the tumor region, typically measured in square pixels.

- The bounding box property specifies the smallest rectangle that contains the labeled region. It is represented as a vector [x y width height], where (x, y) denotes the coordinates of the upper-left corner of the bounding box, and width and height represent the dimensions of the box. In tumor segmentation, the bounding box can help localize and visualize the tumor region within the image.

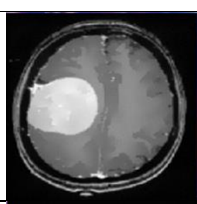
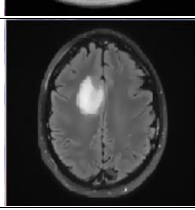
- The centroid property denotes the center of mass of the labeled region, calculated as the mean coordinates of all pixels in the region. It is represented as a vector [x y], where (x, y) represents the coordinates of the centroid. In tumor segmentation, the centroid provides a central reference point for the tumor region.

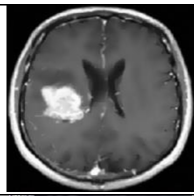
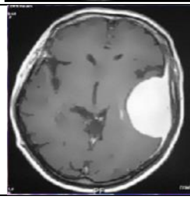
- The eccentricity property quantifies the elongation or flatness of the labeled region. It is a scalar value ranging from 0 to 1, where 0 represents a perfect circle (minimum eccentricity) and 1 represents a line segment (maximum eccentricity). In tumor segmentation, the eccentricity can indicate the shape of the tumor region, with values closer to 0 suggesting a more circular shape and values closer to 1 suggesting a more elongated shape.

- The solidity property measures the convexity of the labeled region, calculated as the ratio of the area of the region to the area of its convex hull (the smallest convex polygon that encloses the region). It is a scalar value ranging from 0 to 1, where 1 represents a completely solid and convex region. In tumor segmentation, solidity can provide information about the irregularity or complexity of the tumor shape, with higher solidity values indicating a more compact and convex shape.

Table 1 illustrates the details associated with some MRI images.

Table 1: properties related to the extracted tumor in the relevant image.

MRI enhanced image	Area	Bounding Box	Centroid	Eccentricity	Solidity
	5451	33.5 87.5 91 77	80.47679 125.6821	0.51679	0.93531
	2689	128.5 39.5 79 95	179.0338 75.70844	0.91576	0.64131
	996	98.5 80.5 33 47	114.2008 106.0884	0.69587	0.88691

	1841	49.5 111.5 55 48	77.32863 134.2977	0.69034	0.87045
	4167	165.5 79.5 62 112	200.0967 138.8455	0.70251	0.89884

4. RESULTS AND DISCUSSION

This research aimed to extract tumors from MRI images and characterize the properties of the identified segments. These segments could potentially represent either benign or malignant tumors, a distinction that will be addressed in future work through the training of a neural network, as outlined in an upcoming paper. The current study utilized image processing techniques to enhance the MRI images, facilitating the segmentation of tumors. The obtained results demonstrate satisfactory outcomes.

Conclusion

The utilization of computer software for diagnosing medical conditions is on the rise; however, it should never substitute medical expertise in decision-making processes. Nonetheless, it plays a crucial role, particularly in handling large volumes of data efficiently. Image processing stands out as a pivotal domain within information technology, facilitating rapid and accurate diagnosis across various scenarios. The outcomes of our experiments are promising, closely mirroring real-world scenarios, thereby potentially aiding physicians in their diagnostic endeavors.

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