Provably Efficient and Fast Technique for Determining the Size of a Brain Tumor in T1 MRI Images

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***Abstract*—This work proposes an efficient and effective technique for determining the size of neoplasms in the brain using image processing. The cerebral hemispheres make up the largest part of the human brain, and abnormal growth of cells within them can lead to the development of neoplasms, or brain tumors. Many tumors are believed to occur for unknown reasons, which highlights the importance of annual check-ups to detect any early signs of a tumor. Image processing is a crucial component of these annual check-ups, as it can identify any changes that may have occurred in the brain since the previous check-up. This work proposes a new method that can segment the tumor through the skull and estimate its size using MRI images. The proposed method involves three steps: first, extracting the brain from the skull; second, applying thresholding to identify abnormal cells and segment the neoplasm; and finally, estimating the size of the neoplasm in a fast manner. To validate the results, a comparison with other techniques such as K-means and C-means is performed. Overall, this proposed method provides a promising approach to detecting and measuring neoplasms in the brain, which could ultimately improve the diagnosis and treatment of these potentially life-threatening conditions.**

***Index Terms*—Brain Tumor, Size estimation, Image processing, Segmentation, Neoplasm**

I. Introduction

The human brain serves as the central part of the nervous system and is responsible for managing and controlling various bodily functions such as vision, hearing, speech, fine motor control, posture, and balance [1]–[4]. Brain tumors arise from the growth of abnormal cells within the brain tissue. Unlike many other types of cancer, brain tumors typically spread locally and rarely metastasize outside the brain. Two types of brain tumors have been identified in studies: primary brain tumors and secondary brain tumors, also known as brain metastases. Primary tumors develop in the anatomical location where tumor growth began and progresses to create a malignant mass. Secondary tumors, on the other hand, result from cancer that originates in other parts of the body and spreads to the brain. It is important to note that secondary brain tumors are distinct from primary brain tumors [5]–[7]. Fig 1 illustrates the differences between these two types of tumors.

Brain tumors can occur at any age, and the main cause of these tumors is not yet known. The symptoms of brain tumors depend on their size, location, and type, with different locations causing different functional disorders. Common symptoms of brain tumors include early morning headaches, tingling in the arms or legs, seizures, balance and walking problems, changes in speech, vision, or hearing, memory loss, and others [8], [9]. Studies have shown that children between the ages of 3 and 12 are more likely to develop brain tumors than individuals

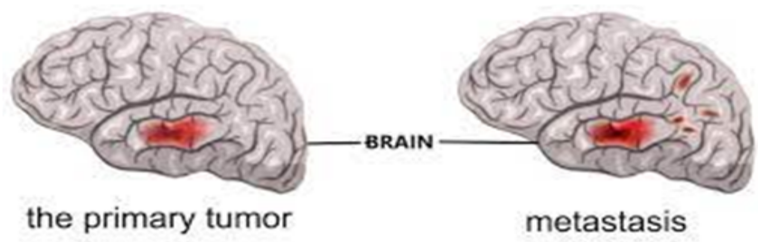

Fig. 1. The primary and Secondary Tumors.

of other ages. Additionally, adults aged 55-65 are the second most common age group to be diagnosed with brain tumors. Primary brain cancer is the second leading cause of cancer-related deaths in children under the age of 34, and the fourth leading cause of cancer-related deaths in males aged 35 to 54 [10]. In 2012, it was estimated that approximately 23,000 new cases of brain cancer would be diagnosed in the United States alone. According to the World Health Organization, an estimated 400,000 people worldwide are diagnosed with brain tumors each year [11].

Early identification of brain tumors is critical for effective treatment planning. However, due to the various characteristics of tumors in images, such as size, shape, location, and intensities, diagnosing a brain tumor can be challenging and requires the expertise of trained neuroradiologists. In recent years, several research studies have employed various image processing approaches to address these difficulties and improve the early identification and treatment of brain tumors.

Research has been carried out to detect brain tumors using various clustering and histogram techniques. For example, one study used Fuzzy C-Means clustering and histogram techniques for brain tumor detection [12], while others have investigated automatic brain tumor detection using K-Means clustering [13]. There have been several studies that have investigated the detection of brain tumors using various techniques such as clustering and histogram methods. A comprehensive review that discusses the application of artificial intelligence tools in brain tumor segmentation from MRI images has been conducted in [14]. The review covers various deep learning techniques, including convolutional neural networks (CNNs), autoencoders, and generative adversarial networks (GANs), which have been used for brain tumor segmentation. Some recent studies have explored the application of deep learning approaches to MRI brain tumor segmentation, such as the Znet approach proposed in [15]. In addition, researchers have investigated the use of rough-fuzzy c-means and shape-based properties for MRI brain tumor segmentation and analysis, as reported in [16].

other studies have focused on specific techniques, such as Otsu's thresholding technique, which has been used for MRI image brain tumor segmentation [17]. Meanwhile, the effectiveness of the finite differences method on physical and medical images has also been studied [18]. Although most

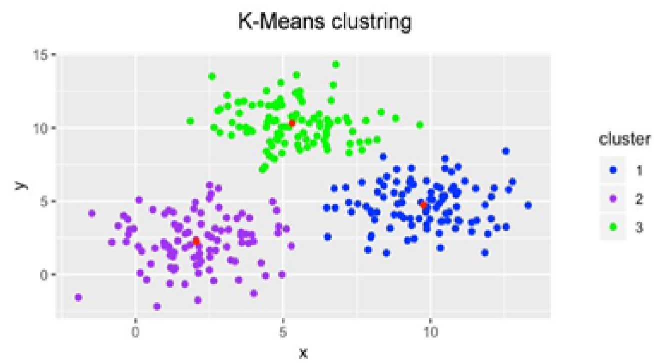

Fig. 2. The K-Means clustering.

studies have focused on brain tumor detection, image processing techniques have also been explored for the early diagnosis of breast cancer, as reported in [19]. These approaches have shown promising results, suggesting that artificial intelligence tools can be useful for accurate and efficient brain tumor detection and segmentation in medical images. Another recent study that investigated the automatic detection of brain tumors using clustering techniques is [20]. The authors proposed a template-based approach that combines K Means and Improved Fuzzy C Means clustering algorithms for human brain tumor detection in MRI images. The fundamental distinction between K-Means clustering and Fuzzy C-Means clustering is that K-Means clustering divides all data points into K clusters, each of which contains only one data point. Fuzzy C-Means, on the other hand, creates K clusters and assigns each data point to each cluster, but there is a factor that determines how strongly the data belongs to that cluster. Fuzzy C-Means takes less computing time than K-Means when there are a large number of clusters, but the time to convergence for Fuzzy C-Means is longer, and K-Means is faster in obtaining its optimal performance overall. Fig 2 and Fig 3 below illustrate these two types of clustering K-Means and Fuzzy C-Means respectively on some random data. The rest and contributions of the paper is constructed as follows. In Section 2, we present a new three-step technique for determining the size of a brain tumor in T1 MRI images. This technique includes image input and preprocessing, image thresholding, segmentation by thresholding, and tumor size calculation. We describe each

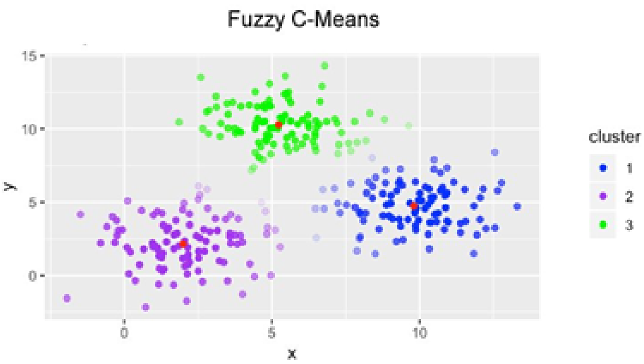

Fig. 3. The C-Means clustering.

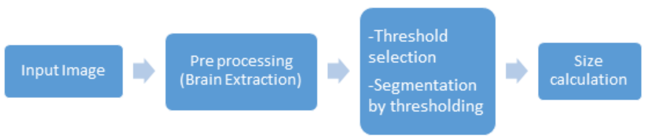

Fig. 4. The flow chart of the proposed method.

of these steps in detail and explain how they contribute to the overall accuracy and efficiency of our proposed method. In Section 3, we evaluate the performance of our proposed method and compare it with other commonly used methods for tumor size estimation. We calculate the tumor volume using our proposed method, as well as other methods, and compare the results with the exact tumor volume. We also measure the processing time required for each method to determine the efficiency of our proposed method.
The results and discussion presented in Section 3 demonstrate the effectiveness of our proposed method in accurately determining the size of a brain tumor in T1 MRI images, while also reducing the processing time. Our contribution to the field of medical image processing is the development of a new and efficient technique that can aid in clinical decision-making and patient care.

II. MATERIALS AND METHODS

In this section, we present a novel method for brain tumor segmentation and its size calculation. The computer-aided system can process it with various image processing techniques like morphological operations, histogram thresholding segmentation and size calculation. Fig 4 shows the steps involved in the proposed method. Before we start explaining the proposed method, we recall the algorithm of the Fuzzy C-Means [21]–[24], which starts by attempting to split a finite collection of the elements $(y_1, y_2, \dots, y_n)$ into a collection of C fuzzy clusters based on several criteria. We are here having a set of elements, then the output of this algorithm is the set of c cluster $(c_1, c_2, \dots, c_n)$ and a matrix $S = s_{k,l} \in [0,1], k = 1, \dots, n, l = 1, \dots, c$, where every point $s_k l$ gives the degree of the corresponding cluster c_l and the belonging element y_k.

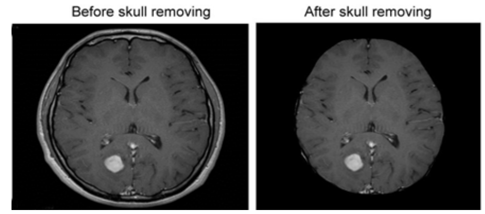

Fig. 5. MRI of a brain before and after skull removal.

Therefore, the Fuzzy C-Means goal is to minimize the needed function:

$$argmin_c \sum_{k=1}^{n} \sum_{i=1}^{c} S_{ki}^{p} \parallel Y_k - C_i \parallel^2, \tag{1}$$

where

$$S_{ki} = \frac{1}{\sum_{m=1}^{c} \left(\frac{\|Y_k - C_i\|}{\|Y_k - C_{cm}\|} \right)^{\frac{2}{p-1}}} \tag{2}$$

On the other hand, the algorithm of K-Means aims to minimize the within-cluster sum of squares and to find

$$argmin_S \sum_{k=1}^{p} \sum_{y \in S_k} \parallel y - \mu k \parallel^2, = argmin_S \sum_{k=1}^{p} \mid S_k \mid Var S_k, \tag{3}$$

Where μ_k is the mean of points in S_k. This is equivalent to minimizing the pairwise squared deviations of points in the same cluster

$$argmin_S \sum_{k=1}^{p} \frac{1}{2 \mid S_k \mid} \sum_{y,z \in S_k} \parallel y - z \parallel^2 \tag{4}$$

A. Image input and preprocessing

The MRI scan images of brain are acquired. These scanned images are either color or gray-scale images. If it is a color image, then a grayscale converting technique is applied. Preprocessing is done for improving the quality of optical vision. Skull removing is the preprocessing step done here. It is the process of segmenting brain tissues from non-brain tissues in the whole-head magnetic resonance images. The skull is removed by morphological operations like erosion which is followed by opening by reconstruction. Then dilation is carried out and opening closing by reconstruction is followed Finally Otsu's thresholding is done to obtain skull-removed brain [21], [25], [26]. Fig 5 shows the brain MRI before and after skull removal.

B. Image thresholding

In image processing, thresholding is considered the most directed and the simplest method when it comes to image segmentation. In fact, we can start from the grayscale image and do the processing of thresholding which can be dedicated to creating the so-called binary images. Initially the threshold value is selected from histogram. To differentiate the pixels (ROI) from the rest, a threshold is chosen, and that value is compared with each pixel value of brain image. If the threshold

Fig. 6. Segmented brain tumor.

value is lower than a pixel value of the image, then retain that pixel in the image, which means it will remain as it is. If the threshold value is greater than a pixel value of an image, then that pixel is removed from the image. After thresholding we get a binary image, and it has only two values binaries, either (0), which is a value of zero, or binary value (255), which is a value of one. The pixel values which are greater than the threshold value are set to binary one (255), and the remaining are set as binary zero (0). The output image obtained is defined as a tumor with dark background. The weight is obtained by modified values which are defined by:

$$W_k^2(S) = \frac{1}{P_k(S)} \sum_{k=0}^{n} (g - \mu_k(S))^2 f(g) \tag{5}$$

$$Y_k(S) = \frac{1}{Q_k(S)} \sum_{k=0}^{n} f(g) \tag{6}$$

where $Y_k(S)$ is the total mean and $W_k^2(S)$ is the total variance, and the weight here is given by $(1 - Q_k(S)/2)$.

C. Segmentation by thresholding

Morphological operations like erosion, opening closing by reconstruction is performed to segment the tumor in brain image. Two pieces of data are sent into the erosion operator. The first is the degraded skull picture, and the second is the structural element, which is a series of co-ordinate points. After that filling and region closing through morphological operation is applied to that eroded image. This operation fills the small holes and gaps in a single pixel object. Closing protects coarse structures by closing small gaps and rounding off concave corners. Fig 6 shows the segmented tumor in brain MRI image of Fig 5.

D. Tumor size calculation

The segmented tumor is the region of interest, the size of which is to be found. The number of pixels in this region is obtained to find the size of tumor. For the manually cropped tumor images, the images are first converted to binary ones and then the size is found.
The proposed method involves all the steps mentioned earlier, and a visual representation of the method is provided in Fig **??**, which presents an extended flowchart of the process.

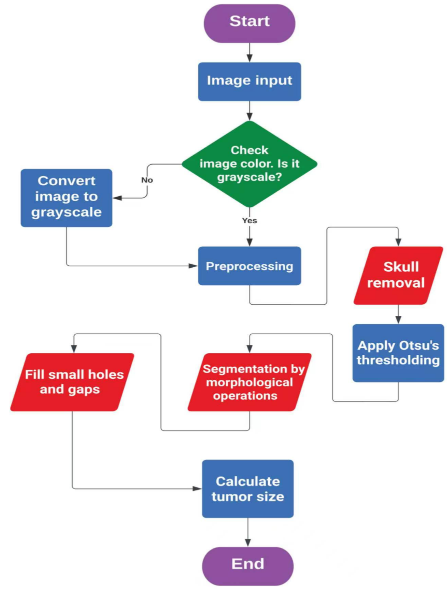

Fig. 7. The extended flow chart of the proposed method.

III. RESULTS AND DISCUSSION

MATLAB 2020b was utilized to carry out all the necessary experimental results and generate figures. The computations were performed on a desktop machine that runs on Windows 10 Pro (64-bit) operating system. The computer is equipped with an Intel(R) Core(TM) i3-4170 CPU that runs at a speed of 3.70GHz, and it has a total installed memory of 10.00GB RAM. The system configuration provided ample resources to ensure a smooth and efficient execution of the MATLAB algorithms used in the study.
Brain images on which experiments were performed were taken from the whole brain Atlas [27].The proposed method is applied on the selected T1 weighted images. The results are obtained as shown in Fig 8 and Tab I. Fig 8 shows the size of tumors. Initially MRI images are obtained; preprocessing is done to remove the skull in the images. Morphological operations are done to segment the brain tissues from the non-brain tissues. Histogram thresholding is then carried out to segment the tumor portion in the brain image. Finally, tumor size is calculated to find the size of the tumor.
The MRI images of tumor affected brain taken are subjected to Fuzzy C-Means, K-Means, histogram thresholding and manual cropping techniques for segmenting the tumor. Then, the tumor size is calculated. The results given in Table 1 show that the histogram-based thresholding technique applied to brain tissues after removing the skull is more accurate than Fuzzy C-Means, K-Means techniques.
This method is simple and efficient, and involves only a few steps. The run time is lower when compared to other methods like Fuzzy C-Means and K-Means.

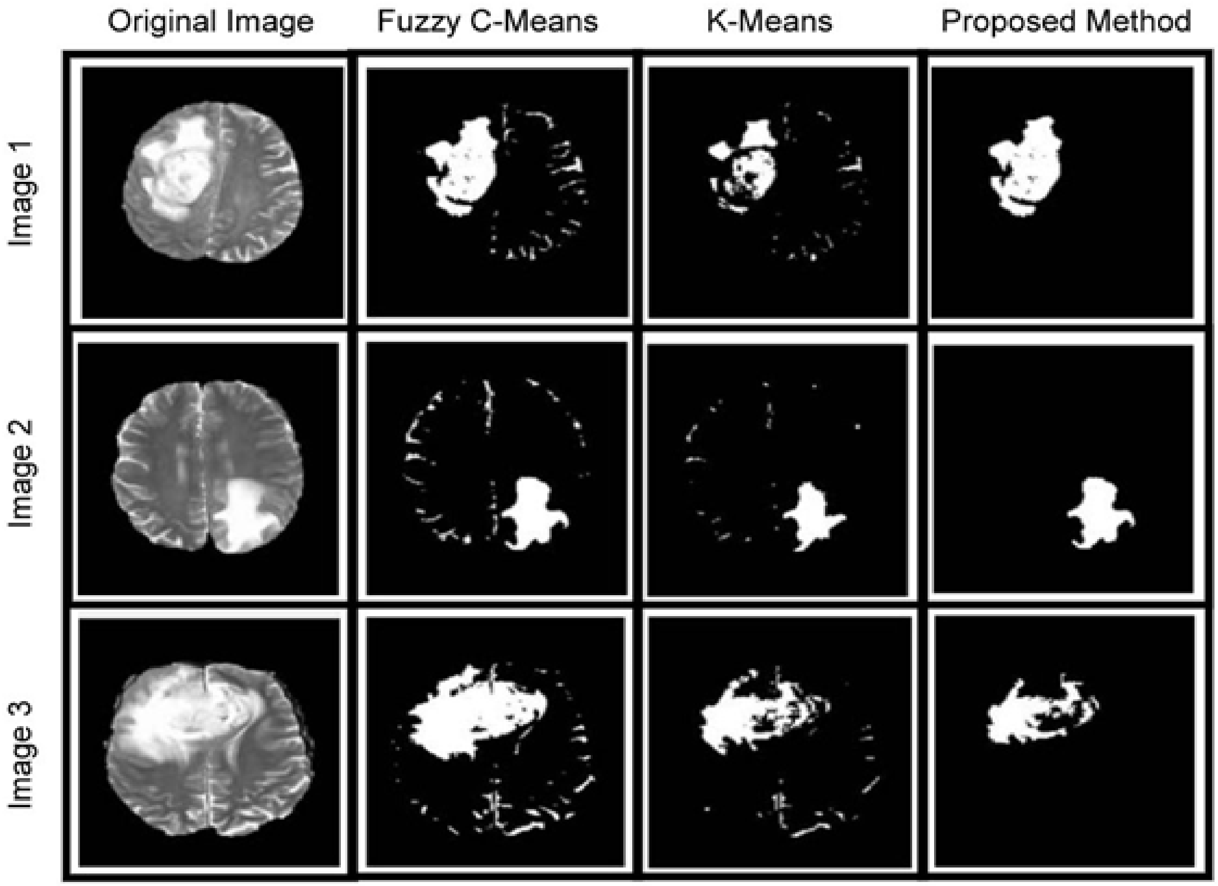

Fig. 8. The results of the proposed method compared with other methods.

TABLE I
THE SIZE OF TUMORS AND TIME SPENT IN EACH METHOD

	Fuzzy C-Means		k-Means		Proposed Method		Extract volume of extracted tumor
	Time (S)	Volume	Time (S)	Volume	Time (S)	Volume	
Image 1	88.23	1003	112.21	934	79.03	696	782
Image 2	72.45	516	101.09	476	66.39	351	396
Image 3	97.01	1287	124.33	1157	86.87	879	954

IV. CONCLUSION

In conclusion, we have proposed a novel three-step computer-based method for effectively extracting brain images, segmenting tumor cells, and calculating tumor size using various image processing techniques. It is important to note that our method is currently applicable only to T1 weighted MRI images, and future modifications should be made to extend its use to T2 weighted MRI images. This new method can significantly contribute to the early detection and diagnosis of brain tumors, leading to better treatment planning and improved patient outcomes. In addition, further research could explore the application of our method to other medical imaging modalities and the potential integration with artificial intelligence and machine learning techniques to enhance its accuracy and efficiency.

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