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Brain Tumor Segmentation on MR and CT Images Using Fuzzy C-Means and Active Contour Methods

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ABSTRACT

A brain tumor is a dangerous brain disease that can attack anyone. It can be described as the abnormal growth of cells in or around the brain, leading to impaired brain function. The first step in diagnosing a brain tumor is to perform an MRI (Magnetic Resonance Imaging) scan. The research aims to analyze the segmentation results of brain tumor MRI and CT (Computed Tomography) images using the Fuzzy C-Means and Active Contour methods. The evaluation is based on ROC parameters, including accuracy, dice score, precision, and sensitivity. The methodology involves analyzing data from secondary image sources, using MATLAB for the segmentation process, and evaluating the results of image segmentation by radiologists. Four ROC measurements were used for each method. The segmentation evaluation results for MRI images show that the Fuzzy C-Means method achieved a precision of 0.92; sensitivity of 0.64; dice score of 0.76; and accuracy of 0.61. The Active Contour method, on the other hand, obtained a precision of 0.97; a sensitivity of 0.99; a dice score of 0.98; and an accuracy of 0.96. For CT images, the Fuzzy C-Means method yielded a precision of 0.72; sensitivity of 0.98; dice score of 0.83; and accuracy of 0.71. The Active Contour method obtained a precision of 0.96; a sensitivity of 0.95; a dice score of 0.96; and an accuracy of 0.92. These results indicate that the Active Contour method, especially with MRI images, provides better segmentation performance. In conclusion, the segmentation results from the Active Contour method can be used as additional information for doctors in diagnosing the presence of tumors.

INTRODUCTION

The International Agency for Cancer Research at the WHO reported that in 2020, brain tumors occurred in 168,346 male patients and 139,756 female patients worldwide. The highest incidence of brain tumors is found in developed countries, which is related to better registration systems [1]. In medicine, the term "tumor" refers to the abnormal proliferation of cells in the human body. There are two main types of brain tumors: primary and secondary [2,3]. Primary brain tumors originate in the brain, While secondary, or metastatic tumors, originate elsewhere in the body and spread to the brain. Although the exact cause of brain cancer is difficult to determine, it is advisable to avoid substances associated with cancer formation. Symptoms of brain cancer may include sleepiness, seizures, disorientation, and behavioral abnormalities [3]. Brain tumors can be detected through imaging and histopathological diagnosis, which help determine the type of tumor, appropriate therapy, and prognosis [4]. MRI scans are highly sensitive and provide detailed imaging making them particularly useful in distinguishing between soft and hard tissue in the brain [5].

In treating brain tumors, medical image processing can be carried out. Non-invasive imaging methods, such as Positron Emission Tomography (PET), Computed Tomography Scanning (CT-Scan), Ultrasound (USG), Single Photon Emission Tomography (SPECT), Magnetic Resonance Imaging (MRI), and X-ray, are commonly used to

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determine non-invasive treatment solutions [6]. This research utilizes MRI and CT images. Image processing in brain imaging is an important method for diagnosing the presence of brain tumors at an early stage [7].

MRI is a commonly used neuroimaging modality for the diagnosis and treatment of brain tumors due to its high contrast-to-noise ratio, lack of ionizing radiation, and ability to provide multi-modal 3D image sequences with versatile tissue contrast for better visualization [8]. The basic planes of MRI for visualizing brain structures are axial, sagittal, and coronal. The most commonly used MRI sequences for brain analysis are Tl-weighted, T2-weighted, and FLAIR [9].

Radiation refers to the emission of energy through matter or space in the form of heat, electromagnetic particles, waves, or light (photons). There are two types of radiation: ionizing and non-ionizing, depending on the type of ionization involved. A modality that uses ionizing radiation is the Computed Tomography (CT) scan [10]. CT is a diagnostic imaging method that employs highly ionizing radiation [11,12]. It produces cross-sectional images of the body based on X-ray absorption, which can be displayed on a computer screen. The term "computed tomography" refers to the calculated or reconstructed images in CT, while "tomography" is derived from the Greek words "tomo" (meaning "cut" or "cut" in Greek) and " graphy" (meaning in Greek "to describe"). One of CT’s advantages is its excellent low-contrast resolution, making it widely used for detecting the presence of tumors in the brain [13].

An image is a visual representation of an object, which can include photographs, X-rays, or satellite images [14]. Segmentation refers to the process of extracting contours from an image or dividing it into segments that collectively cover the entire image [15]. The purpose of segmentation is to extract the area of interest in an image, and many methods are based on attributes such as color, gray value, depth, motion, texture, discontinuity, and similarity [16]. In medical imaging, segmentation plays a crucial role in various applications, including tumor identification [17].

The clustering method has proven successful in distinguishing various regions within images, particularly for segmentation. In cases where boundaries between regions are unclear, the concept of membership in the regions becomes vague. Classical set theory, or “hard clustering”, determines whether an object belongs to a specific cluster or not by dividing data into mutually exclusive subsets. In contrast, fuzzy clustering allows objects to belong to multiple clusters simultaneously, each with varying degrees of membership [18]. Fuzzy C-Means (FCM) is a clustering method that allows one data sample to be part of two or more clusters: Each data point has a degree of membership (or probability) of each cluster [19].

The Active Contour method is a technique that focuses on using curves or contours to adapt to the boundaries of objects within an image [20]. The contour outlines the area of interest in the image and consists of a collection of interpolated points. These curves can be adjusted using polynomial, linear, or spline interpolation methods [21]. The contour method is considered an image classification technique that uses a set of variable parameters and geometric properties to classify different regions in the image [22]. Active Contour utilizes closed and smooth curves to mark target boundaries, which is usually achieved by minimizing the associated energy function through standard descent algorithms [23].

Previous research [15,21,24] used a greedy snake model, which estimates new tumor boundaries by optimizing the segmentation using the Fuzzy C-Means algorithm to produce accurate segmentation output. The approach demonstrated improved performance for various types of tumors, such as Meningioma, Glioma, and Pituitary Tumor with respective dice scores of 0.78; 0.59, and 0.49. The corresponding sensitivity values were 0.67; 0.51 and 0.44, while the specificity values were 0.96; 0.94, and 0.91, respectively [24]. Additionally, according to research on image segmentation using Fuzzy C-Means, a comparison between K-Means and Fuzzy C-Means, Fuzzy C-Means clustering showed a greater accuracy value than the K-Means clustering technique in segmenting brain tumors. The overall segmentation accuracy for the K-Means and Fuzzy C-Means techniques was 90 % and 94 %, respectively [15]. The use of research on the Active Contour method can quickly segment brain MRI images at a level of precision sufficient for various applications [21].

Based on previous research described above [15,21,24], studies on brain tumor segmentation using the Fuzzy C-Means and Active Contour methods show that each method has its advantages. Therefore, it is necessary to carry out further research regarding segmentation. However, the ROC measurement values and research methodologies used in these studies differ, so this research aimed to process CT and MR images of brain tumors to segment areas as a step in detecting brain tumors using the Fuzzy C-Means and Active Contour methods.

METHODOLOGY

The data consisted of 150 brain tumor MR images sourced from the following website: https://www.cancerimagingarchive.net/collections/, and 150 brain tumor CT images from the website: https://radiopaedia.org/search?q=Brain+tumors. The general stages of this research included pre-processing, segmentation, and evaluation.

The pre-processing stage was the first step in this research. At this step, image enhancement and filtering techniques were applied to MR and CT images to filter out noise [25]. Since the images were obtained from different sources with varying contrast levels, they had to be normalized before segmentation and further processing. The next step was the process of segmentation using MATLAB.

Image segmentation involves separating coherent regions of an image based on the boundaries of the region of interest (ROI) [26]. In this research, Fuzzy C-means clustering and the Active Contour method were used. The Fuzzy C-Means method applies the FCM clustering algorithm, which focuses on minimizing the following objective function on Eq. (1):

$$Q(A,B) = \sum_{i=1}^{n} \sum_{j=1}^{c} N_{i\,j}^{m} \left\| x_i - r_j \right\|^2 \tag{1}$$

where r_j Is the centroid point, c is the number of features extracted from the image tool set, x_i is the position of the data point, n is the number of clusters, m is the fuzzification algorithm coefficient, and N is the representative matrix for the membership of each element in each cluster [27].

The Active Contour method utilizes a closed and smooth curve to delineate the target boundary, typically achieved by minimizing the associated energy function through standard reduction techniques. The energy acting on the Active Contour is a continuous total energy expressed by the following Eq. (2) [21]:

$$E_{snake} = \int_0^1 (E_{in}(v(s)) + E_{ex}(v(s)))ds \tag{2}$$

where E_{in} represents the internal energy, which is influenced by the curve of the object, and E_{ex} refers to the external energy, which adjusts the contour to either wider or narrower towards the target object. Meanwhile, $v(s)$ is a curve in two-dimensional space [23,28]. Active Contour operates on the principle of energy minimization. The total energy is defined by the internal energy, which is based on the initialized contour, and the external energy, which is determined by the image properties of the target object. Generally, external energy is derived from the edge maps that stop at the boundaries of an object [29].

The segmentation results were evaluated by a doctor, with evaluation carried out using Receiver Operating Characteristic (ROC) analysis. ROC graphs are a technique for visualizing, organizing, and selecting classifiers based on their performance [24]. Sensitivity, precision, and dice scores were used as performance segment metrics for the segmentation test. Precision indicates how close the measurement results are to each other. Sensitivity measures how well a technique correctly identifies brain tumor images. The dice score quantifies the accuracy of segmentation by comparing the proposed output with the actual field conditions. The formula for precision, sensitivity, and dice score were as follows Eqs. (3-5) [24,31]:

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{4}$$

$$Dice\ score = \frac{2\times TP}{FN+2\times TP+FP} \tag{5}$$

The segmentation results were compared with the ground truth to determine the values for TN (True Negative); TP (True Positive); FN (False Negative) and FP (False Positive). The definitions used in this research were as follows [32]. TP (True Positive), the image was detected and diagnosed as having a tumor by the program and doctor. TN (True Negative), the detected image and diagnosis was normal (no tumor) by the program and doctor. FP (False Positive), the image detected was normal (no tumor) by the program, but diagnosed as having a tumor by the doctor. FN (False Negative), the image was detected as having a tumor by the program, but was diagnosed as normal by the doctor.

This research also used an accuracy parameter. Accuracy represents the proportion of correct results provided by the technique compared to the actual situation (the similarity between the program’s results and the doctor's diagnosis). The accuracy formula is given by Eq. (6) [30]:

$$Accuracy = \frac{TP}{TP+FP+TN+FN} \tag{6}$$

After completing the evaluation and ROC measurement stages, the research process was considered complete.

RESULTS AND DISCUSSION

This research used 150 MR and 150 CT images. The MRI images included various visual fields: axial with T1 FLAIR (Fluid Attenuated Inversion Recovery Magnetic Resonance Imaging) contrast, T1 Mprage (Magnetization Prepared Rapid Acquisition Gradient Echo), 3D Mprage T1, T2-weighted, and perfusion MRI contrast. The color intensity of these contrasts affected the segmentation results.

Figure 1 shows the segmentation results of the Fuzzy C-Means and Active Contour Methods applied to MR images, while Fig. 2 displays the results for CT images. The Fuzzy C-Means method segments the images into two clusters: the tumor area and other parts of the brain. The clusters are further divided into gray matter and white matter, based on the basic tissue classification of the human brain. The white matter is observed to highlight the tumor area. The Active Contour method segments brain tumor images by initializing a contour influenced by internal and external energies, allowing it to outline the tumor.

In the first stage of the Fuzzy C-Means algorithm, the image is processed to search for fuzzy membership patterns with two clusters as centroids. The resulting images are divided into gray matter and white matter. Iterations are carried out to determine the centroid for each cluster until convergence is achieved (i.e., the centroid no longer changes). Meanwhile, In the active Contour method, segmentation begins by outlining an initial contour that adjusts to its shape widening or narrowing by minimizing the energy function based on external energy and image features such as lines or edges. The contour moves to match the shape of the brain tumor, reflecting changes in energy between pixels around the contour line.

In the MR image segmentation process, errors can occur in evaluating brain tumors due to the similarity between tumor areas and other parts of the brain. The results of MR imaging are influenced by the amount of water molecules in the human body, which affects the image brightness. High water content produces predominantly white images, while lower water content results in darker images. Therefore, the segmentation process might identify areas as normal (no tumor) when, in fact, there is a tumor, or vice versa, as diagnosed by a doctor. Meanwhile, CT images, that use ionizing radiation and X-rays, face different challenges. Error in CT imaging can be caused by artifacts and the relatively short scanning time compared to MRI. This shorter scan duration can make it difficult for CT to capture detailed images of soft tissue anatomical areas in the brain.

This research builds on the work described in [22]. In the image segmentation process, contours are represented by thick red lines to delineate the tumor area, making the segmentation results more distinct. The contour marking improves the accuracy of the object's (tumors) identification. The segmentation results of brain tumor patients are evaluated by radiologists. Additionally, this research also uses four ROC measurements for each method, including precision values, sensitivity values, dice score values, and accuracy values.

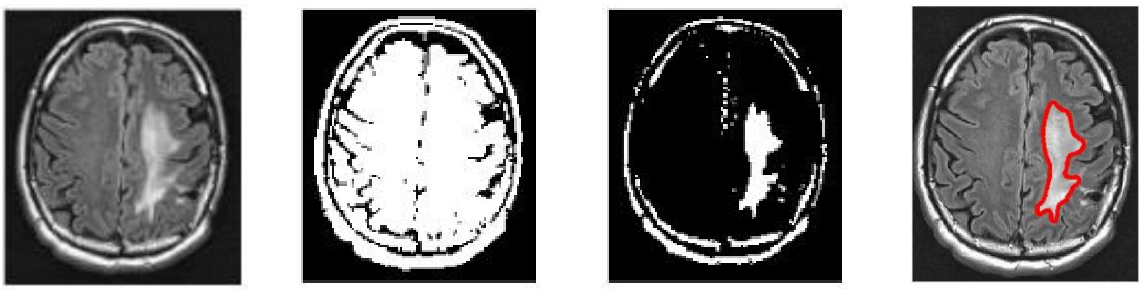

Fig. 1. Segmentation of fuzzy C-Means and active contour methods in MRI.

Fig. 2. Segmentation of fuzzy C-Means and active contour methods in CT-Scan.

The results of segmentation evaluation for MRI images indicate that the Fuzzy C-Means method achieved a precision value of 0.92; a sensitivity value of 0.64; a dice score value of 0.76; and an accuracy value of 0.61. The Active Contour method obtains a precision of 0.97; sensitivity of 0.99; dice score of 0.98; and accuracy of 0.96. The results of segmentation evaluation on CT images show that the Fuzzy C-Means method shows a precision value of 0.72; a sensitivity value of 0.98; a dice score value of 0.83; and an accuracy value of 0.71. The Active Contour method obtains a precision of 0.96; sensitivity of 0.95; dice score of 0.96; and accuracy of 0.92. Based on the segmentation results, the Active Contour method demonstrates better performance compared to the Fuzzy C-Means method in this research. The Active Contour method is more effective in handling noise, such as black or white spots, in the image, allowing it to accurately outline the shape of the object (brain tumor). Additionally, the Active Contour method yields better segmentation results when applied to MRI images compared to CT images.

The results of the ROC measurements in this study are strengthened when compared with other studies which are shown in Tables 1 and 2. Table 1 presents a comparison of the ROC parameter values from the MR images used in this research with those from other studies. Research A refers to the study from [24], and research B refers to the study from [33]. This research has shown a higher value for all four ROC parameters compared to the two other studies. The ROC parameters are obtained from the results of the doctor's evaluation. Table 2 displays a comparison of the ROC parameter values from the CT images used in this research with those from other studies. Research C and D correspond to the research from [34,35].

Research C uses CT images of brain hemorrhage, while Research D analyzes CT images of the lungs to assess damage. In this research, the CT images and ROC parameters exhibited higher values compared to these previous studies, despite the differences in the cases being segmented.

The evaluation results from doctors regarding the Fuzzy C-Means and Active Contour methods, as well as the use of MRI images and CT images, demonstrate that the Active Contour methods provide better segmentation. This conclusion is on the alignment between the program results and the doctor's diagnosis, and the effectiveness of the method in producing accurate segmentation. Specifically, the Active Contour method using MRI images yields superior segmentation results based on ROC measurements.

Table 1. ROC Value of Active Contour Method on MR images from 3 Researches.

Parameter	This Research on MRI	Research A [24]	Research B [33]
Accuracy	0.96	-	0.945
Dice Score	0.98	0.78	-
Precision	0.96	-	-
Sensitivity	0.99	0.67	0.9695

Table 2. ROC Value of Active Contour Method on CT images from 3 Researches.

Parameter	This Research on CT	Research C [34]	Research D [35]
Accuracy	0.92	0.8540	0.80
Dice Score	0.96	-	-
Precision	0.96	-	-
Sensitivity	0.95	0.7991	-

CONCLUSION

Based on the results and data analysis, the segmentation results using the Fuzzy C-Means and Active Contour methods show that the Active Contour method provides more accurate results. This method can be valuable as additional information for doctors in diagnosing the presence of brain tumors, especially glioblastoma. The Active Contour method aligns well with the similarity between the program results and the doctor's diagnosis and demonstrates superior accuracy in detecting brain tumors. The Active Contour method for MR image segmentation achieves a precision value of 0.97; a sensitivity value of 0.99; a dice score value of 0.98; and an accuracy value of 0.96. Besides, the Active Contour method for CT image segmentation obtains a precision of 0.96; sensitivity of 0.95; dice score of 0.96; and accuracy of 0.92. As technology develops, it is recommended that further research use deep learning algorithms to detect abnormalities, such as brain tumors, to make the segmentation process easier [36].

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AUTHOR CONTRIBUTION

Meilinda, E. R. Putri, and S. H. Intifadhah initiated and contributed together as the main contributors to this paper as well as A. Mu'ti contributed to evaluating the segmentation results from the research section.

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