2014 IEEE International Conference on Advanced Communication Control and Computing Technologies (ICACCCT)

Brain Tumor Segmentation: A Performance Analysis using K-Means, Fuzzy C-Means and Region Growing Algorithm

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***Abstract*-Medical imaging is a technique that is extensively used to create images of human body for medical and research purposes. Magnetic Resonance Imaging (MRI) is a powerful visualization tool that permits to acquire images of internal anatomy of human body in a secure and non-invasive manner. Automatic brain tumor detection from MRI images has become one of the major areas of medical research. The important task in the diagnosis of brain tumor is to determine the exact location, orientation and area of the abnormal tissues. This paper discuss the performance analysis of image segmentation techniques, viz., K-Means Clustering, Fuzzy C-Means Clustering and Region Growing for detection of brain tumor from sample MRI images of brain. The performance evaluation of the above mentioned techniques is done on the basis of error percentage as compared to ground truth. The real time database is taken from Rajiv Gandhi Cancer Institute & Research Centre, Delhi, India (RGCI&RC).**

Keywords: Medical imaging; brain tumor segmentation; region growing; clustering.

I. INTRODUCTION

According to International Agency for Research on Cancer (IARC), the rate of diagnosis of brain tumor is estimated to be comparatively greater than the mortality rate [1]. Medical imaging techniques play a vital role in detection of brain tumor and development of new techniques allow us to use them in several domains of medicine. Automatic brain tumor detection helps in easy and accurate segmentation of tumor from large MR image datasets. Pursuing automatic tumor segmentation methods is alleviating the manual work and reducing the variability associated with defining radiation therapy target areas. Although manual segmentation by qualified professionals remains superior in quality to automatic methods, it has two drawbacks. The first drawback is that producing manual segmentations is extremely time consuming, with higher accuracies on more finely detailed volumes demanding increased time from medical experts. The second problem with manual segmentations is that the segmentation is subject to variations both between observers and within the same observer.

An impressively large amount of research effort has been focused on specific areas of the body or specific modalities, such as the segmentation of images of the brain in MR images. Vidhya S. Dessai et al [2] have designed a multithreaded framework using k-means clustering and morphological operations in parallel to segment multiple MRI images. Kiran Thapaliya et al [3] have proposed an effective algorithm to detect brain tumor using morphological gradient and morphological operations. Ishita Maiti et al [4] have presented a color based brain tumor segmentation method based on combination of watershed method and edge detection algorithm. Dr. M. Karnan et al [5] have made use of ant colony optimization along with fuzzy c-means algorithm for brain MRI image segmentation. H. B. Kekre et al [6] have developed a vector quantization segmentation method along with morphological operations to find out cancerous mass from MRI images. Sudipta Roy et al [7] have presented a fully automatic algorithm for detection of brain tumor using symmetric analysis and watershed segmentation. Rajendran et al [8] have proposed a region based fuzzy c- means clustering for brain tumor segmentation. The method uses the tumor class output of fuzzy clustering to initialize the region based algorithm, the region based moves towards the final tumor boundary. M.A. Jaffar et al [9] have proposed an automatic brain MR image segmentation method using curvelet transform for noise removal and FCM for the automatic segmentation of brain MR images. R. B. Dubey et al [10] have explored the comparison of level set method; modified watershed approach and modified region growing method for extraction of tumor from brain MRI images. Ming–Ni Wu et al [11] have proposed a color based segmentation algorithm using k-means clustering and histogram clustering to segment the position of tumor from other objects from input MRI images. N. Nandha Gopal et al [12] have presented an intelligent system to diagnose brain tumor using Fuzzy C means along with optimization techniques.

The paper is structured as follows: Various techniques for image segmentation are described in section 2. The algorithm for brain tumor detection is explained in section 3. The experimental results and comparison of the segmentation algorithms used is done in section 4. The paper is concluded in section 5.

II. IMAGE SEGMENTATION

Image segmentation is defined as a technique which partitions an image into different regions having high degree of similarity with objects of significance in the image. Depending on different properties of an image, the techniques for image segmentation can be categorized into discontinuity based segmentation and similarity based segmentation [13]. The image is divided on the basis of abrupt change in intensity in discontinuity based segmentation. This includes methods like edge detection that segments an image by detecting the edges or pixels between dissimilar regions that have abrupt variation in intensity. Edge based techniques do not require a priori information about the image content and is comparatively faster in computation. In similarity based segmentation the image is divided into regions which are similar depending on a set of predefined criteria. This includes techniques like thresholding, region growing and clustering. Thresholding based segmentation is easy and effective technique but require prior knowledge about image. Region based segmentation is relatively simple and has higher noise immunity as compared to edge detection method [13]. Region based segmentation is used to partition an image into regions that have similar properties according to some predefined criteria. Clustering is an unsupervised learning algorithm which identifies a finite set of class known as clusters. Clustering based segmentation does not make use of training stages rather train themselves by making use of the available data.

A. Clustering

Cluster analysis or clustering based segmentation technique groups a set of objects in such a way that objects in the same cluster have higher degree of similarity to each other than to those in other clusters. Clusters may be defined as contiguous regions of a multidimensional space containing relatively high density of points, separated from other such regions containing relatively low density of points. In image analysis, Clustering is the process of grouping pixels according to some characteristics such as intensity. In hard clustering, data elements belong to one cluster only and the value of membership of belongingness to a cluster is exactly one. In soft clustering, data elements belong to more than one cluster, and the value of membership of belongingness to a cluster range from 0 to 1.

1) K-means Clustering

K-means clustering is a type of hard clustering algorithms. This technique belongs to the category of unsupervised cluster analysis algorithms. Given 'n' number of observations, this algorithm groups these observations into clusters [11]. The observations that belong to same cluster are alike in nature and those belonging to different clusters are different in nature. The number of clusters 'k' is assumed to be fixed. Each cluster has a leader called 'centroid'. Cluster centroids are initialized with random values. The sum of squares of distance between observation and cluster centroid is minimized iteratively. Centroid is then recalculated until convergence.

2) Fuzzy C-means Clustering

Fuzzy C-means clustering is a soft clustering technique which allows partial belongingness of pixels into different clusters [15]. This partial membership is calculated using membership functions. The sum of all membership degrees for any given data point is equal to 1. This method has better applicability to segmentation applications than hard clustering algorithm. The algorithm finds 'c' clusters by minimizing the objective function given by equation (1).

$$J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q d^2(x_k, v_i) \qquad (1)$$

where, $x_k = \{x_1, x_2, \ldots, x_3\}$ are the data points, n is the number of data items, c represents the number of clusters, the degree of membership of x_k in the ith cluster is represented as u_{ik}, q is the weighting exponent on each fuzzy membership, v_i represents the centre of cluster i, $d_2(x_k, v_i)$ is the distance between data point x_k and cluster centre v_i.

B. Region Growing

Region growing is a region-based image segmentation technique [14] in which the pixels in whole image are grouped into sub regions or larger regions on the basis of some predefined criterion. Region based segmentation is relatively simple and has higher noise immunity as compared to edge detection method. It can also be termed as a pixel-based image segmentation technique which incorporates the selection of initial seed points from the image. This method of segmentation is performed by observing neighbouring pixels of initial seed points and determining to which region the neighbouring pixels belong. The process is repeated on till the image is divided into regions. In the implementation of this algorithm, there are three important aspects. The first and the most important one is to select the group of initial seed pixels by which we can accurately represent the required region; second one is to choose the criteria by which adjacent pixels can include in the growth process and third one is to select conditions to terminate the growth process.

III. PROPOSED WORK

In this paper, a framework for an automatic brain tumor detection and segmentation is proposed. The designed system consists of two main components: pre-processing and segmentation. Initially, the MRI images are processed before being fed as an input to the system. In the real time database, there are some problems that need to be resolved before performing segmentation operation. The problems like intensity inhomogeneity correction, background noise removal are removed in the pre-processing section. The non brain tissues such as skull and fat from head MRI scans are also removed in this section. The second component of the framework is segmentation in which the tumorous slice is detected. It includes image registration, tumor extraction and tumor mapping.

A. Pre-processing

The major sources of degradation of images in MRI are the sensitivity inhomogeneity of the receiver coils, coil tuning, gradient eddy currents, RF standing wave effects, and RF penetration effects. A common problem that arises due to these sources is intensity inhomogeneity (bias field), image corruption with a slowly varying multiplicative spatial field across the images. Intensity inhomogeneity is not always visible to human observer, but it causes significant tissue misclassification problems when intensity based segmentation is used. Therefore, it is required to correct intensity inhomogeneity in the brain MR image prior to tumor detection and segmentation. The noise is reduced by passing the images through median filter. Median filter is more effective when one wants to reduce noise and preserve edges simultaneously. The intention of doing pre processing is to ensure that we can identify the exact shape of the tumor without any loss of information.

The next step in the pre-processing stage is to isolate the intracranial mask from the entire image. The extra cranial region consists of bones which do not contain the tumor and hence its inclusion is insignificant in the detection of tumor. There is significant difference in the intensity of intracranial and extra cranial region. This difference can be used as a measure to remove the extra cranial mask from the MRI images. In this paper we have used automatic threshold value selection using Otsu's algorithm to automatically choose threshold value. Then, mathematical morphological operations on a binarized image are applied stage by stage to get the intracranial mask from input MRI image.

B. Brain Tumor Segmentation

The automated segmentation method is composed of two phases: tumor detection and mapping. Three commonly used techniques for autonomous image segmentation are applied in this paper and their results are compared. Performance evaluation of segmentation methods is a tough task as different parameter settings can affect the results significantly. The problem of over-segmentation and under-segmentation is also quite crucial in this context. We have applied three most commonly used traditional methods for image segmentation, namely k-means clustering, fuzzy c-means clustering and, region growing based segmentation. In detection of tumor each segmentation technique is applied to the image obtained and then morphological operations are applied to get the exact shape of the tumor. The tumorous region is mapped on the input MRI image and area is then calculated for quantification.

The algorithm for detecting brain tumor using image segmentation techniques are described below:

Step1: Give MRI image of brain as input

Step2: Convert color image into gray scale image

Step3: Resize the image in 400*400

Step4: Apply median filter to enhance the quality of image

Step 5: Apply image segmentation algorithm whether k-means, fuzzy c-means or region growing

Step 6: Find appropriate image from segmented images in which tumor is present

Step 7: Remove noise and other particles from final image using morphological operations

Step 8: Final output with tumor is found

IV. RESULTS

The algorithm is implemented on personal computer (2.0 GHz CPU, 2GB RAM) using MATLAB 7.9.0 (2009b). The performance analysis is carried out on MRI image real time database taken from RGCI&RC, Delhi. The quantitative analysis of 10 MRI images is shown in table 1 with segmentation techniques k-means clustering and fuzzy c-means clustering and region growing respectively. This comparison is done on the basis of the segmentation results analysed from the images shown in figure 2.

Parameters used for quantitative analysis are ground truth, true positive, and error value and error percentage shown in table 1. 'Ground truth' is the tumor area manually mapped by the radiologist. The area accurately measured by the system is termed as 'True Positive' whereas the variation between ground truth and true positive termed as 'Error Value'. 'Error percentage' is the ratio of error value to ground truth. Error value and error percentage values should be low, as low values of these indicate that system is corresponding well with ground truth and performing well.

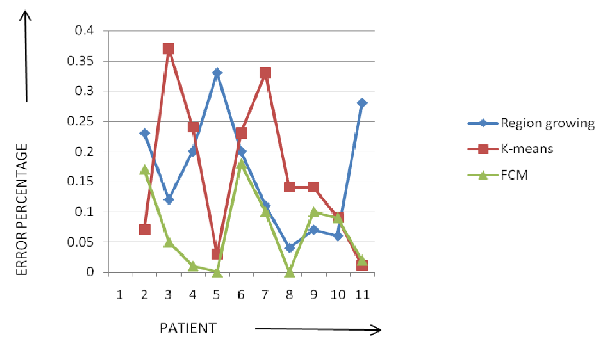

Fig 1: Performance Analysis of Image Segmentation Techniques

V. CONCLUSION

In this paper, we have compared image segmentation techniques viz., K-Means Clustering, Fuzzy C-Means Clustering and Region Growing for detection of brain tumor from sample MRI images of brain taken from RGCI&RC, Delhi. The area of the detected tumor is compared with the area calculated by the algorithms and the results are evaluated on the basis of error percentage. As it can be seen from table 4.1 and figure 4.1 error percentage value is lowest with FCM clustering and it outperforms other segmentation algorithms.

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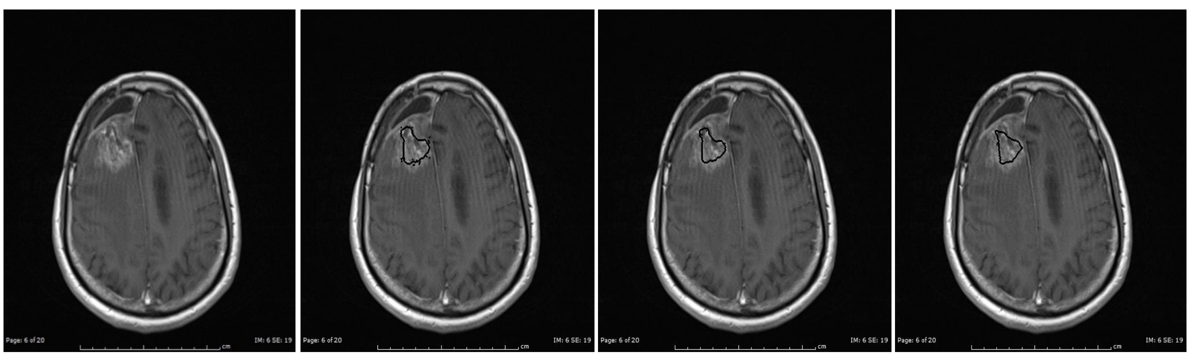
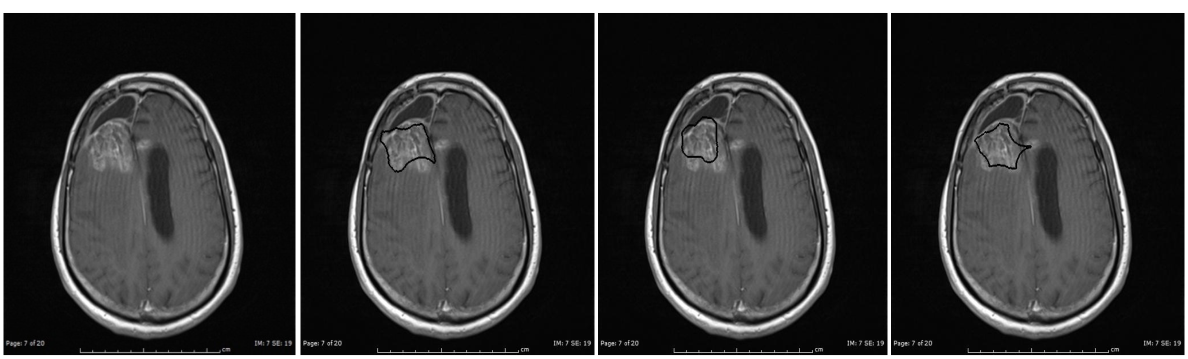
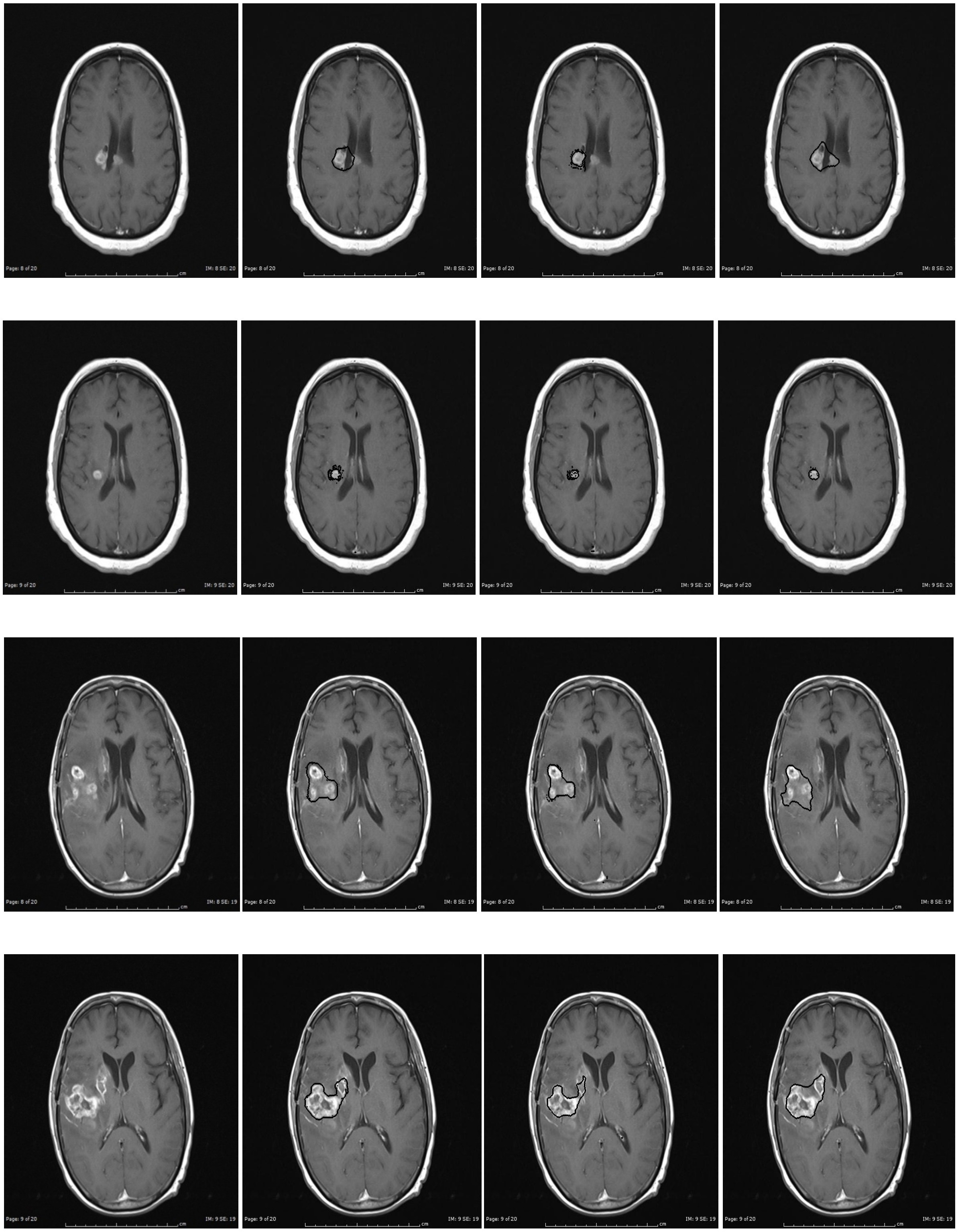
TABLE 1: PERFORMANCE ANALYSIS OF IMAGE SEGMENTATION TECHNIQUES

		REGION GROWING			K-MEANS			FUZZY C-MEANS		
S.No.	Ground Truth	True Positive	Error Value	Error Percentage	True Positive	Error Value	Error Percentage	True Positive	Error Value	Error Percentage
1	1928	2376	448	0.23	1786	142	0.07	1600	328	0.17
2	4360	4867	507	0.12	5990	1630	0.37	4142	218	0.05
3	2324	1866	458	0.20	1765	559	0.24	2301	23	0.01
4	514	683	169	0.33	528	14	0.03	514	0	0.00
5	5212	4170	1042	0.20	4023	1189	0.23	4278	934	0.18
6	5680	5031	649	0.11	3805	1875	0.33	5112	568	0.10
7	4794	4983	189	0.04	4126	668	0.14	4794	0	0.00
8	5028	4676	352	0.07	4342	686	0.14	4526	502	0.10
9	4913	5231	318	0.06	4451	462	0.09	4451	462	0.09
10	5295	3833	1462	0.28	5371	76	0.01	5182	113	0.02

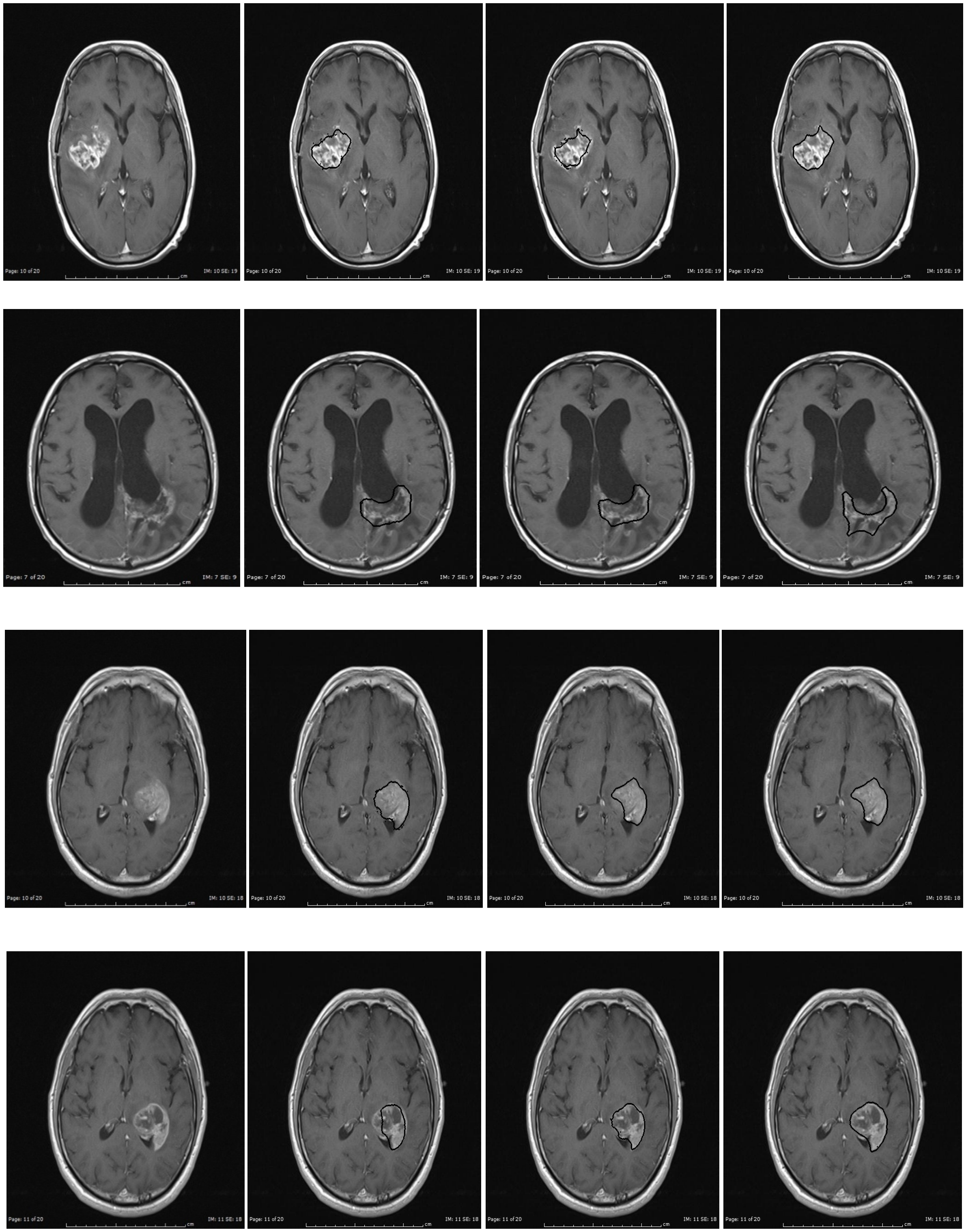




(a) (b) (c) (d)



(a) (b) (c) (d)



(a) (b) (c) (d)

Fig 5.1: (a) Input MRI image, Tumor mapping with (b) Region Growing (c) K-means clustering (d) Fuzzy c-means clusterin