PERFORMANCE ANALYSIS OF IMAGE SEGMENTATION TECHNIQUES IN MEDICAL IMAGES

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CERTIFICATE

This is to certify that the thesis entitled, **“Performance Analysis of Image Segmentation Techniques in Medical Images”** submitted by **Tripti Singhal (2K11/ISY/20)** in partial fulfillment of the requirements for the award of Master of Technology Degree in Information Systems during session 2011-2013 at Delhi Technological University is an authentic work carried out by her under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.

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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. In recent years, Magnetic Resonance Imaging (MRI) is the most widely used imaging technology, because of widespread availability and ability to produce high resolution images. MR imaging is a powerful visualization tool that permits to acquire images of internal anatomy of human body to be acquired in a secure and non-invasive manner. MRI of brain has become one of the major areas of medical research in order to segment brain tumor. Early detection and accurate treatment based on truthful diagnosis are the major concern to cure brain tumor. The important task in the diagnosis of brain tumor is to determine the exact location, orientation and area of the abnormal tissues. Detection of anatomical brain structure plays a major role in the planning of treatment. This study involves comparative analysis of three image segmentation techniques for detection of brain tumor from sample MRI images of brain. The image segmentation techniques involve namely, K-Means Clustering, Fuzzy C-Means Clustering and Region Growing. A comparative analysis of the above mentioned image segmentation techniques, is done on the images taken from Rajiv Gandhi Cancer Institute & Research Centre, Delhi, India (RGCI&RC).

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Chapter 1

INTRODUCTION

1.1 Preliminaries

Brain tumor is one of the most widespread brain diseases, which has affected and devastated many lives. According to International Agency for Research on Cancer (IARC) it is estimated that people diagnosed for brain tumor per year around the world are comparatively more than mortality [1]. The statistics shows low survival rate of brain tumor patients even though brain tumor disease has been the center of attention of thousands of researchers for many decades, around the world. In recent years, researchers from different disciplines ranging from medical to mathematical and computer sciences have combined their knowledge and efforts to better understand the disease and to find more effective treatments. 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 detection and segmentation of brain tumor from brain MR images offer a mechanism for overcoming the effort involved in the manual segmentation of large datasets. Pursuing automatic tumor segmentation methods is alleviating the manual work and reducing the variability associated with defining radiation therapy target areas. This is especially important with respect to new technologies such as radio surgery and intensity-modulated radiation therapy that allow more precise treatment options than traditional technology.

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. Accurate automatic methods would be advantageous since they are not subject to this variation and thus the significance of changes in volumes could be more easily assessed.

1.2 Literature Survey

Medical image analysis is one of the most significant studies in area of medicine, since results achieved by the analysis direct radiologists for diagnosis, treatment planning, and verification of results of treatment. Medical images require sequential application of several image post-processing techniques in order to be used for quantification and analysis of intended features. Medical image segmentation has received significant attention, due to the many practical applications of segmentation results in medical imaging. An impressively large amount of research effort has even 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 have designed a multithreaded framework using k-means clustering and morphological operations in parallel to segment multiple MRI images [2]. Kiran Thapaliya et al have proposed an effective algorithm to detect brain tumor using morphological gradient and morphological operations [3]. Ishita Maiti et al have presented a color based brain tumor segmentation method based on combination of watershed method and edge detection algorithm [4]. Dr. M. Karnan et al have made use of ant colony optimization along with fuzzy c-means algorithm for brain MRI image segmentation [5].H. B. Kekre et al have developed a vector quantization segmentation method along with morphological operations to find out cancerous mass from MRI images [6]. Sudipta Roy et al have presented a fully automatic algorithm for detection of brain tumor using symmetric analysis and watershed segmentation [7]. Rajendran et al have proposed a region based fuzzy c- means clustering for brain tumor segmentation in [8]. 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 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 in [9]. R. B. Dubey et al have explored the comparison of level set method; modified watershed approach and modified region growing method for extraction of tumor from brain MRI images [10]. Ming–Ni Wu et al 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 [11]. N.Nandha Gopal et al have presented an intelligent system to diagnose brain tumor using Fuzzy C means along with optimization techniques [12].

Then tumor is detected by applying fuzzy classification method or symmetry analysis and some morphological operations. A supervised hybrid fuzzy ANN based for tumor detection is proposed in [13] by Pradhan et al. Thresholding based tumor detection and segmentation methods [14, 15] which integrated with watershed and histogram analysis have been proposed. Kadam D. B. et al [16] have used eight textural features to train the MLP network in segmenting brain tumor. Automated brain tumor segmentation with two phases is proposed by Khontalou et al in [17]. In first phase tumor is detected and segmented by combining of histogram analysis with symmetry analysis using morphological operations. A comparative study of adaptive network based fuzzy inference system (ANFIS), k-nearest neighbors (KNN) and fuzzy c-means (FCM) for brain tumor segmentation is conducted in [18] by Khalid et al.

1.3 Thesis Outline

Chapter 1: Introduction

Chapter 2: **Medical Imaging:** This chapter discusses about the medical imaging and its most widely used technique namely magnetic resonance imaging (MRI) along with pros and cons. We have also explained about the anatomy of brain in detail, classification of brain tumor and role of imaging in diagnosis of brain tumor.

Chapter 3: **Image Segmentation:** This chapter briefly describes the image segmentation and techniques that we have used for brain tumor detection namely region growing, K-means clustering and FCM clustering. We have also mentioned the applications of image segmentation techniques to medical imaging.

Chapter 4: **Brain Tumor Detection:** This chapter presents steps involved in brain tumor detection from sample MRI images with different segmentation techniques.

Chapter 5: **Results and Comparative Analysis:** Results of all the three approaches for detecting tumor is shown in this chapter along with the comparison on the basis of error percentage.

Chapter 6: **Conclusion and future work**: Conclusion of the thesis is presented in this chapter. Also the scope and areas in which future investigation can be done are discussed.

Chapter 2

MEDICAL IMAGING

2.1 Introduction

Medical imaging is the general name given to the group of techniques and processes developed for creating anatomical or functional images of human body (partially or as a whole), which are used for both clinical and scientific purposes. Medical image analysis is one of the most critical studies in field of medicine, since results gained by the analysis lead field professionals for diagnosis, treatment planning, and verification of administered treatment. Medical imaging is the general name for the widely-used techniques developed in order to create images of human body for medical purposes. As acquired images could involve complete human body, they can span it partially. Medical imaging data is used for revealing normal or abnormal physiological and anatomical structures. Medical imaging techniques are also employed in diagnosis and treatment planning processes of patients suffering from many health problems. Professionals from field of medicine make use of medical imaging data in order to guide or avoid medical intervention. Quantitative analysis of medical images is crucial for diagnosis and prognosis stages of many diseases and abnormalities. Quantification of radiographic information includes various features such as linear measurements, estimation of cross section and surface areas, volume quantization, estimation tissue density, monitoring tumor growth, verification of treatment, and comparison of patient's data with anatomical atlases [**19, 20].**

A variety of medical imaging techniques are used to study parts of human body, including computed tomography (CT), magnetic resonance (MR) imaging, and single photon emission computed tomographic (SPECT) imaging, positron emission tomographic (PET) scanning, and cerebral angiography. At this moment, CT and MR imaging are the most widely used techniques, because of their widespread availability and their ability to produce high resolution images of normal anatomic structures and pathological tissues. CT is the fastest modality, making it the preferred examination for imaging critically ill or medically unstable patients. SPECT and PET imaging serve smaller roles, although their ability to provide information on tissue biology and physiology can be greatly helpful. PET scanning is also used to evaluate tumor grade. Magnetic Resonance Imaging (MRI) is a powerful visualization tool that permits to acquire images of internal anatomy of human body to be acquired in a secure and non-invasive manner and is discussed in detail in section 2.2. It is the most frequently used neuroimaging technique for the evaluation and follow up review of patients with brain tumors for many reasons. Brain tumor and its anatomy have been described in Section 2.3 and 2.4.

2.2 Magnetic Resonance Imaging

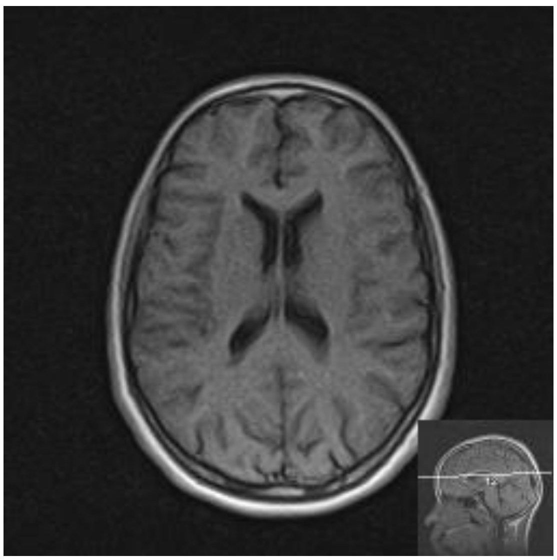
A variety of imaging techniques that are used to study brain tumors, such as: magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), single photon emission computed tomography (SPECT) imaging and cerebral angiography. In recent years, CT and MR imaging are the most widely used techniques, because of their widespread availability and their ability to produce high resolution images of normal anatomic structures and pathological tissues [21].

- It does not use ionizing radiation like CT, SPECT and PET.
- Its contrast resolution is higher than other techniques mentioned above.
- Ability of MRI devices to generate 3D space images enables them to have superior tumor localization.
- Its ability in acquisition of both functional and anatomical information about the tumor during the same scan.

Magnetic resonance imaging (MRI) is a method used to visualize pathological or other physiological alterations of living tissues and is commonly used for brain tumor imaging because of the following reasons. MRI is based on the principles of Nuclear Magnetic Resonance (NMR), and allows a vast array of different types of visualizations to be performed. This imaging medium has been of particular relevance for producing images of the brain, due to the ability of MRI to record signals that can distinguish between different 'soft' tissues (such as gray matter and white matter)[22].

The intensity values seen on an MRI scan for a particular brain depends primarily on the content of that pixel versus neighboring tissue and on other factors including the presence of abnormality. In normal brain MR images intensity level of brain tissues in the order of increasing brightness is CSF, GM, WM in T1-weighted (T1-w) and WM, GM and CSF in T2-weighted (T2-w) image, as shown in Figure 2.1.

Despite of several advantages there are some limitations to MRI that must be acknowledged. The most important being the lack of specificity. Although, enhancement does not always correspond to histologic tumor grade, in general, higher grade tumors will frequently show enhancement on MR imaging. However, an exception can be seen in a very slow-growing tumor which will frequently show contrast enhancement regions within the tumor. Similarly, some higher grade tumors will not enhance [23]. Hence, although MR features of a lesion can be helpful, but sometimes histologic verification is necessary to perform a diagnosis. MR imaging is also not able to distinguish the edge of a tumor, or determine the full extent of disease. Possible tumor cells are known to exist beyond the borders of abnormal contrast enhancement [23]. Hence, MRI alone cannot be applied to determine whether tumor is present or not following such a therapy. In spite of these limitations, MRI remains the standard imaging technique in human neurooncolgy.

(a) 

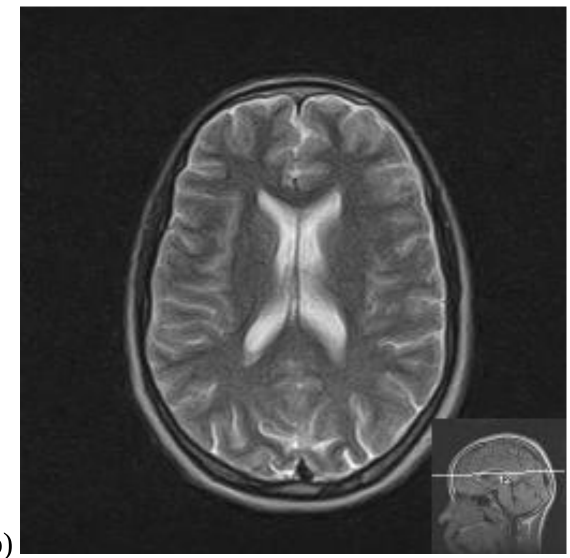
(b) 

Fig 2.1: MRI image. a) T1-w axial scan image, b) T2-w axial scan image.

2.3 Brain Anatomy

Brain is extremely focused organ of the human body which helps us to cope with the environment. Human brain serves as the manager for all the functions performed by the body such as words, actions, thoughts, and feelings that are centered in the brain. In this section we describe the brain tissue structure and its anatomical parts.

The brain mainly comprises of two types of tissue: gray matter (GM) and white matter (WM). Gray matter consists of neuronal and glial cells, also known as neuroglia or glia and the basal nuclei. The former controls brain activity and the later are the gray matter nuclei located deep within the white matter. The basal nuclei are made of caudate nucleus, putamen, pallidum and claustrum. White matter fibers are myelinated axons which connect the cerebral cortex with other brain parts. The corpus callosum, a thick band of white matter fibers, joins the left and right hemispheres of the brain [24].

The brain also contains cerebrospinal fluid (CSF) that consists of glucose, salts, enzymes, and white blood cells. This fluid circulates through ventricles around the brain and the spinal cord to protect them from injury. There is also another tissue called meninges used as membrane for covering the brain and spinal cord [24].

Anatomically the brain is composed of the cerebrum, the cerebellum and the brain stem as shown in Figure 2.2. The largest part of the brain is the Cerebrum which helps in controlling conscious thought, movement and sensation of human body. It comprises of two halves, the right and left cerebral hemispheres, each managing the opposite part of the body. Each hemisphere is divided into four lobes: the frontal, temporal, parietal, and occipital lobes. The second largest part of the brain is the cerebellum which helps in controlling motor functions such as walking, balance, posture, and coordination of movement of human body. It is situated at the back of the brain and is connected to brain stems. Both cerebrum and cerebellum have a thin outer cortex of gray matter, internal white matter and deeply situated masses of gray matter. The brainstem is located at the bottom of the brain and connected to spinal cord. It controls many vital functions including motor and sensory pathways, cardiac and repository functions, and reflexes. It has three structures: the midbrain, pons and medulla oblongata [24].

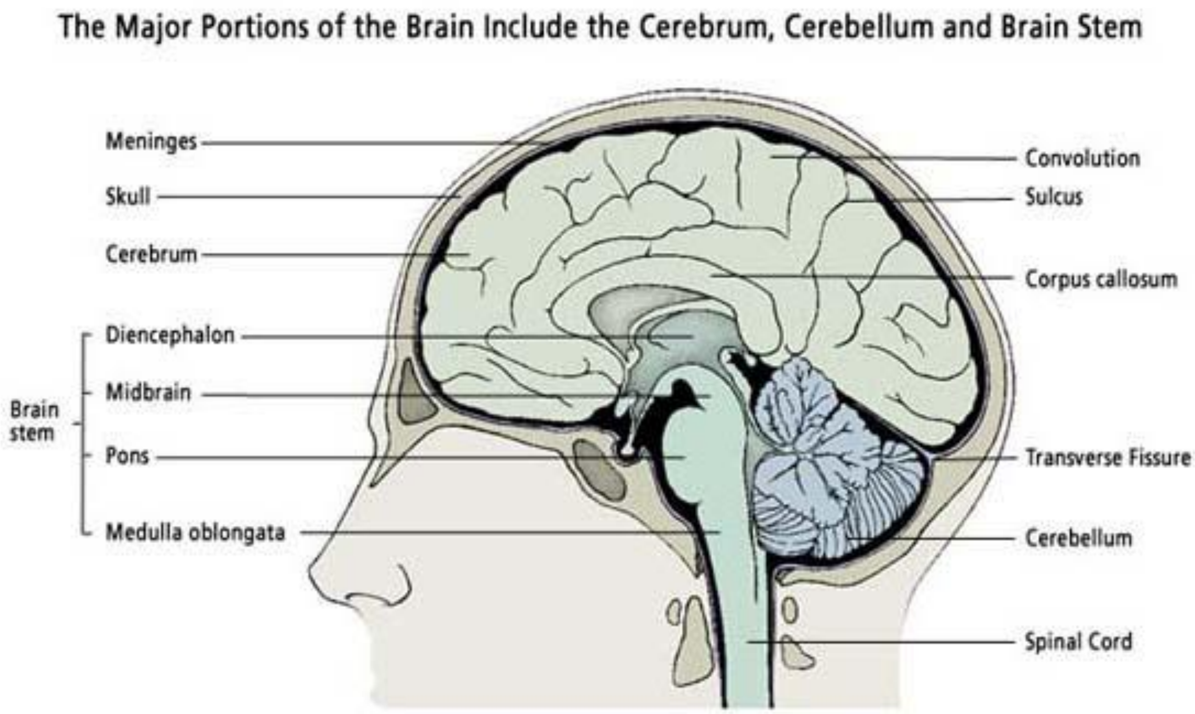


Fig 2.2: Anatomy of human brain

2.4 Brain Tumor

A brain tumor is the mass of tissue that grows abnormally due to uncontrollable cell multiplication. The growth of a tumor takes place within the skull and interferes with normal brain functions. Tumor can harm brain by increasing pressure inside it, pushing against the skull, and by attacking and damaging nerves and healthy brain tissues [25].

Brain tumors are classified depending on the location of the tumor, the type of tissue, whether they are noncancerous (benign) or cancerous (malignant) and site of origin (primary or secondary). World Health Organization (WHO) classifies brain tumors into more than 120 types. According to WHO the classification of brain tumor is done on the basis of by cell origin and behavior of the cells from benign to malignant. Types of tumor are also assigned a grade, ranging from Grade I to IV depending on the rate of growth of malignant; though there are variations in grading systems depending on the tumor type [25].

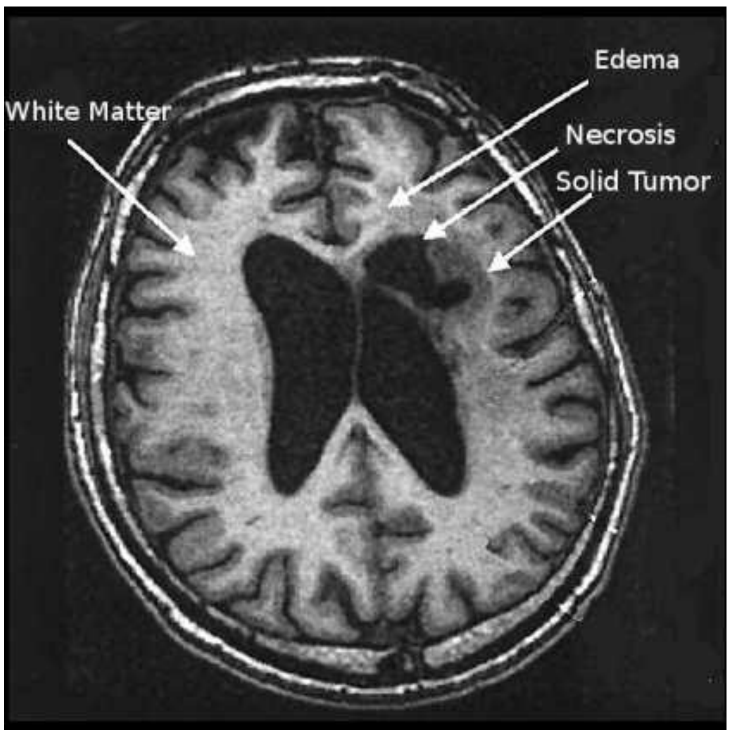


Fig 2.3: Brain MRI image showing tumor areas

The tumors that originated in the brain and are named for the cell types from which they originated are known as primary brain tumors. Benign tumors grow slowly and do not spread elsewhere or affect the surrounding tissues. However, growing in a limited space, a benign tumor can put pressure on the brain and compromise its function. On the other hand, malignant tumors grow quickly and can invade the surrounding tissues. Each of these tumors has unique clinical, radiographic and biological characteristics. Secondary brain tumors originate from another part of the body. These tumors are actually composed of cancer cells from somewhere else in the body that have metastasized, or spread, to the brain. The secondary brain tumors are commonly caused by lung cancer, certain sarcomas, breast cancer, melanoma, bladder cancer, and testicular and germ cell tumors [25].

Imaging plays a vital role in treatment of brain tumor patients at different stages and usually has a significant job in each of them. Several phases of management can be considered:

- detection or confirmation that a structural abnormality is present,
- localization and assessment of the extent of any abnormality,
- characterization of the abnormality,
- assessment of the nature of a tumor,
- facilitation of additional diagnosis procedures, and planning for surgery or other types of therapy,
- intraoperative control of rejection progress,
- monitoring of response to therapy.

Chapter 3

IMAGE SEGMENTATION

3.1 Introduction

Image segmentation is one of the most important tasks of image analysis. Segmentation is defined as a technique which subdivides an image into its constituent regions or objects depending on the problem being solved [26]. The process of image segmentation should stop when the object of interest is found. Every pixel in an image is allocated to one of the regions. The main objective of image segmentation is to divide an image into regions having high degree of correlation with objects of significance in the image. A good segmentation is typically one in which pixels in the same category have similar grey scale of multivariate values and form a connected region and neighboring pixels which are in different categories have dissimilar values.

3.2 Techniques of Image Segmentation

On the basis of different properties of an image, the approaches to image segmentation can be classified into discontinuity based segmentation and similarity based segmentation [27].

In discontinuity based segmentation the image is divided on the basis of sudden change in intensity. This includes techniques like edge detection. Edge detection based segmentation attempts to resolve image segmentation by detecting the edges or pixels between different regions that have abrupt changes in intensity [27]. This results in a binary image. 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 but effective technique for segmenting images having light objects on dark background. Thresholding algorithms are fast and economical in computation but require prior knowledge about image. Region based segmentation is relatively simple and has higher noise immunity as compared to edge detection method [28]. Region based segmentation is used to divide an image into regions that are similar according to some predefined criteria [27]. Clustering is an unsupervised learning algorithm, where one needs to identify a finite set of categories known as clusters to classify pixels. Clustering use no training stages rather train themselves using available data.

3.2.1 Region Growing

Region growing is a region-based image segmentation technique [29] in which the pixels in whole image are grouped into sub regions or larger regions on the basis of some predefined criterion [26]. Region based segmentation is relatively simple and has higher noise immunity as compared to edge detection method [28]. 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 neighboring pixels of initial "seed points" and determining to which region the neighboring pixels belong. The process is repeated on till the image is divided into regions. In the implementation of region growing 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 [30].

Seed point selection is based on the criteria defined by the user. The initial region starts as the accurate position of these seed points. The regions are then developed from these initial seed pixels to neighboring points depending on a region membership criterion. The criteria for growing of region can be pixel intensity, color information or gray level texture. Hence, the prior image information is very important in this technique. For example, if the criterion were a pixel intensity threshold value, knowledge of the histogram of the image would be of use, as one could use it to determine a suitable threshold value for the region membership criterion.

Region growing can be achieved by performing the following steps:-

- Select a group of seed pixels in original image.
- Select a set of similarity criterion such as gray level intensity or color and set up a stopping rule.
- Grow regions by appending to each seed those neighbouring pixels that have predefined properties similar to seed pixels.
- Stop region growing when no more pixels met the criterion for inclusion in that region.

Advantages of Region Growing:

- Region growing methods can correctly separate the regions that have the same properties we define.

- Region growing methods can provide the original images which have clear edges the good segmentation results.
- The concept is simple. We only need a small numbers of seed point to represent the property we want, then grow the region.
- We can determine the seed point and the criteria we want to make.
- We can choose the multiple criteria at the same time.
- It performs well with respect to noise.

Disadvantages of Region Growing:

- The computation is consuming, no matter the time or power.
- Noise or variation of intensity may result in holes or over segmentation.
- This method may not distinguish the shading of the real images.

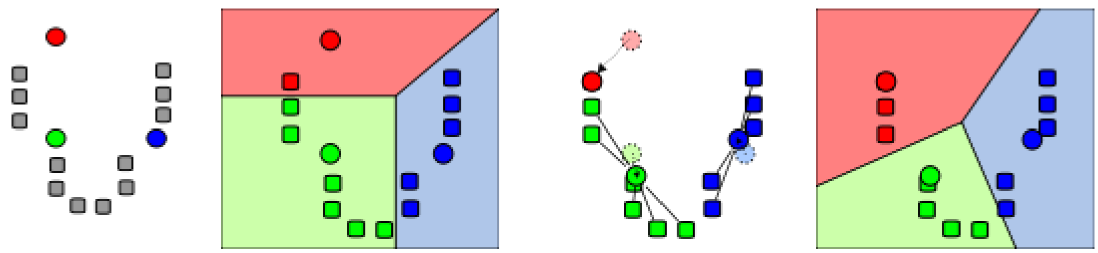
We can conquer the noise problem easily by using some mask to filter the holes or outlier. Therefore, the problem of noise actually does not exist.

3.2.2 Clustering

Cluster analysis or clustering is the process of grouping a set of objects in such a way that objects in the same group (called cluster) are more similar to each other than to those in other groups. 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. It is a main task of explorative data mining, and a common technique for statistical data analysis used in many fields, including pattern recognition, image analysis, information retrieval, and bioinformatics. In image analysis, Clustering is the process of grouping pixels according to some characteristics such as intensity. In hard clustering, data is divided into distinct clusters, where each data element belongs to exactly one cluster with a degree of membership equal to one and well defined boundaries between them. In soft clustering, data elements can belong to more than one cluster, and associated with each element is a set of membership levels.

K-means Clustering

K-means is a type of hard clustering algorithms. K-means clustering 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. The process of K-means clustering is illustrated in figure 3.1 with some random data points.



a) b) c) d)

Fig 3.1: a) Initial clusters (k=3) b) all observations assigned to corresponding cluster c) calculation of new cluster centers d) steps 2 and 3 repeated until convergence.

Steps of the algorithm are:

Step 1: Cluster centroids are initialized with random values. These observations represent temporary cluster centers.

Step 2: For each observation, calculate sum of square of distance between centroid and the observation. Based on this distance, assign each observation to closest cluster. Mathematically it can be given by equation (1)

$$\min \sum_{i=1}^{k} \sum \| x_j - u_i \|^2 \quad \text{……………….. (1)}$$

Where u_i are the cluster centroids and x_j represents other observations.

Step 3: A new centroid is calculated for each cluster and is replaced with previous cluster centroid.

Step 4: repeat steps 2 and 3 until no cluster centroid changes.

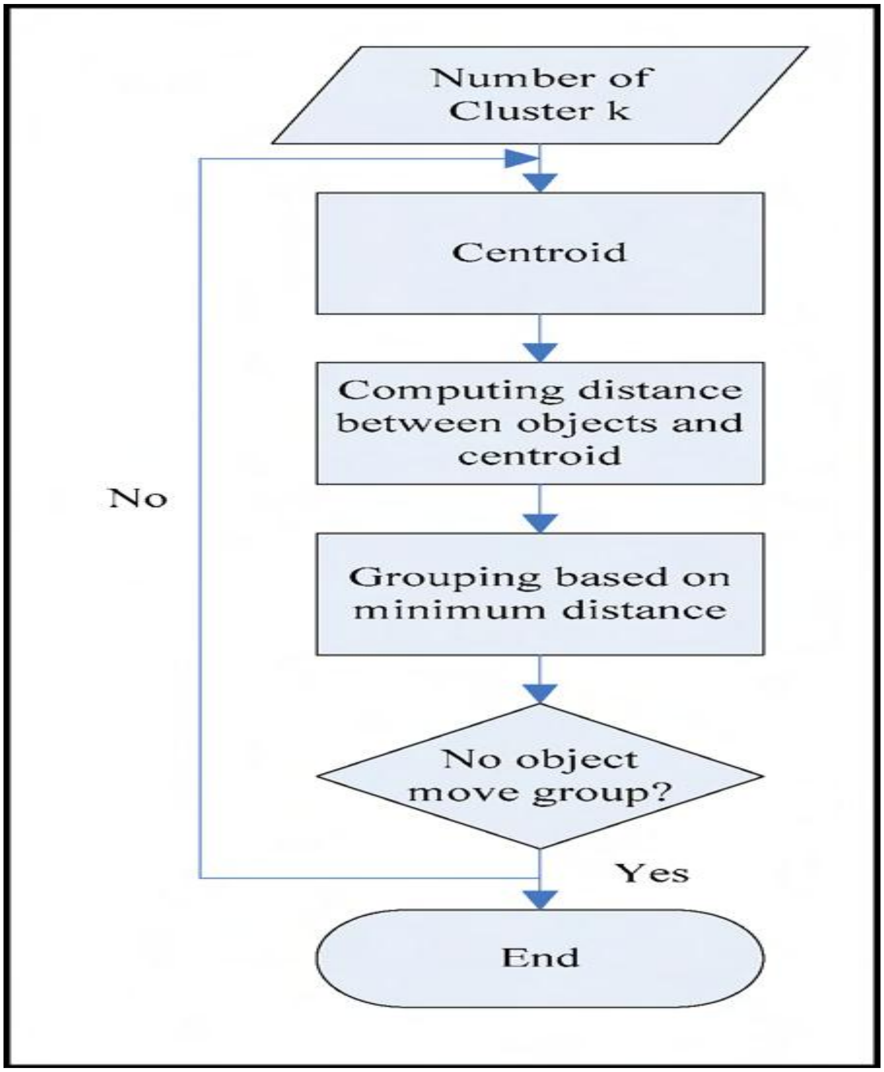


Fig 3.2: Flowchart of K-means Clustering

Fuzzy C Means Clustering

As discussed in previous section clustering assigns observations into different groups (clusters) such that observations belonging to the same cluster are more similar to one another than observations belonging to different clusters [31]. A large number of clustering schemes are proposed in literature. One major classification of schemes is hard clustering and the fuzzy clustering (or soft clustering). In hard clustering each observation or point in the dataset either belongs to a particular cluster or does not belongs. This leads to very crisp segmentation results. i.e., each pixel of the image belongs to exactly one class. Hard segmentation does not provide satisfactory results in images with issues like poor contrast, limited spatial resolution, overlapping intensities etc. Fuzzy clustering on the other hand is a soft clustering technique which allows partial belongingness of pixels into different clusters. 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. Dunn et al [1] first introduced FCM which was later extended by [31].

The algorithm finds c clusters by minimizing the objective function given by equation (1).

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

where X = {x1, x2, …, xn} 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 i_{th} cluster is represented as u_{ik}, q is a weighting exponent on each fuzzy membership, vi represents the centre of cluster i, d2 (x_k, v_i) is a distance between data point x_k and cluster centre v_i. Objective function is minimized using iterative process as follows:

Step 1: Initialize parameters like c, q.

Step 2: Initialize the fuzzy partition matrix U = [u_{ik}].

Step 3: Initialize the loop counter b= 0.

Step 4: Calculate the c cluster centers v_i^b with U using equation (2):

$$v_i^{(b)} = \frac{\sum_{k=1}^{n} (u_{ik}^{(b)})^q x_k}{\sum_{k=1}^{n} (u_{ik}^{(b)})^q} \text{..............(2)}$$

Step 5: Calculate the membership U $^{(b+1).}$ For k = 1 to n, calculate the following:

$I_k = \{i \mid 1 \le i \le c, d_{ik} = \| x_k - v_i \| = 0\}$; For the kth column of matrix, compute new membership values.

$$a)\quad if\, I_k \ne \phi, then$$

$$u_{ik}^{(b+1)} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{\frac{2}{(q-1)}}}$$

$$b)\ else\quad u_{ik}^{(b+1)} = 0\ for\ all\ i \notin I\ and \sum_{i \in I_k} u_{ik}^{(b+1)} = 1; next\, k.$$

Step 6: If $\| U^{(b)} - U^{(b+1)} \| < \varepsilon, stop; otherwise, b = b + 1 and\ go\ to\ step\ 4.$

3.3 Medical Applications of Image Segmentation

Medical imaging techniques are used in order to gain information on specific organs or parts of human body, physiological abnormalities such as tumors and cysts, or any other structures like bone, cartilage, and vessels. In general, analysis of medical images requires segmentation of the images. Image segmentation is methods are in practical use in field of radiology in order to assist or automate multiple procedures. Significant roles of image segmentation applications in the following areas and this can be observed from references [32].

- Anatomical research on regular body structure,

- Quantification of tissues in several metrics like distance, cross-sectional and surface area, and volume,
- Classification of several special tissues like white matter and gray matter of brain,
- Diagnostic radiology,
- Localization of abnormalities, malfunctions, and pathologies,
- Prognosis and treatment planning,
- 2D and 3D registration of imaging data acquired at various times,
- Computer-aided surgery, and
- Volume correction in functional imaging data.

Chapter 4

BRAIN TUMOR DETECTION

In this thesis, a framework for an automatic brain tumor detection and segmentation based on fuzzy co-clustering for images algorithm is proposed. The designed system consists of two main components: preprocessing 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 preprocessing 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.

4.1 Preprocessing

The input of preprocessing block is MRI brain image. In preprocessing part of the system the image is first processed in order to remove noise and inhomogeneity and then intracranial mask of image is extracted to process further. 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 preprocessing 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 we have used automatic threshold value selection using Otsu's algorithm to automatically choose threshold value. Then, mathematical morphology operations on a binarized image are applied stage by stage to get the intracranial mask from input MRI image.

4.2 Segmentation

The second section of our framework is the segmentation. The input consists of the preprocessed images (reduced noise, registered and segmented brain) and some information on the tumor provided by the preprocessing section. 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 study 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. All of the segmentation methods used in this study is selected so that there are very few user-defined parameters required. We have used 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 operation are applied to get the exact shape of the tumor. The tumorous region is mapped on the input MRI image and area is calculated for quantification.

4.3 Algorithms for brain tumor detection

The algorithms for detecting brain tumor using image segmentation techniques are described below in Section 4.3.1 and 4.3.2.

4.3.1 Region Growing based tumor detection

- Give MRI image of brain as input
- Convert color image into gray scale image
- Resize the image in 400*400
- Apply median filter to enhance the quality of image
- Compute threshold using Otsu's threshold method
- Apply region growing and morphological operation for segmentation of image
- Final output will be a tumor region

4.3.2 Clustering based tumor detection

- Give MRI image of brain as input
- Convert color image into gray scale image
- Resize the image in 400*400
- Apply median filter to enhance the quality of image
- Choose no of clusters
- Apply clustering algorithm whether k-means or fcm clustering
- Display clustered images
- Find appropriate image from clustered image in which tumor is present
- Remove noise and other particles from final image
- Final output with tumor is found

CHAPTER 5

RESULTS AND COMPARATIVE ANALYSIS

The following system configuration has been used while conducting the experiments:

Processor: Intel Pentium

Clock Speed: 2.0 GHz

Main Memory: 2 GB

Hard Disk Capacity: 512 GB

Software Used: MATLAB 7.9.0 (2009b)

The comparative analysis is carried out on MRI image real time database taken from RGCI&RC, Delhi. We have shown some results for quantitative analysis for all three methods of segmentation. The 10 input MRI images of brain tumor detection are illustrated in figure 5.1 with the tumor mapped on input images by all methods of segmentation. The results of the comparison are validated by the radiologist from RGCI&RC. The quantitative analysis of MRI images is shown in tables 5.1, 5.2 and 5.3 with segmentation techniques region growing, k-means clustering and fuzzy c-means clustering respectively. This analysis is done on the basis of the segmentation results analyzed from the images shown in figure 5.1. Parameters used for quantitative analysis are ground truth, true positive, and error value and error percentage shown in tables 5.1-5.3. 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.

As shown in table below error value and percentage value are lowest with FCM clustering. The value of the error value and error percentage of all three techniques illustrates that the Fuzzy C-Means Clustering outperforms other techniques. Table 5.1-5.3 summarizes the performance measures for different segmentation techniques.

S.No.	Ground Truth	True Positive	Error Value	Error Percentage
1	1928	2376	448	0.23
2	4360	4867	507	0.12
3	2324	1866	458	0.20
4	514	683	169	0.33
5	5212	4170	1042	0.20
6	5680	5031	649	0.11
7	4794	4983	189	0.04
8	5028	4676	352	0.07
9	4913	5231	318	0.06
10	5295	3833	1462	0.28

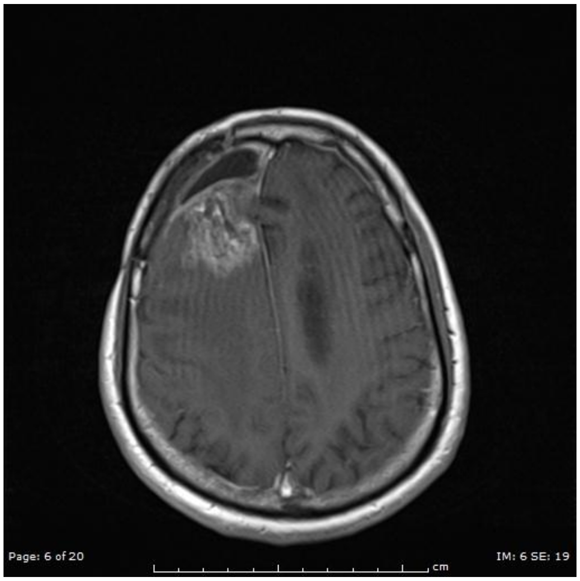
Table 5.1 Quantitative Analysis of MRI images with region growing

S.No.	Ground Truth	True Positive	Error Value	Error Percentage
1	1928	1786	142	0.07
2	4360	5990	1630	0.37
3	2324	1765	559	0.24
4	514	528	14	0.03
5	5212	4023	1189	0.23
6	5680	3805	1875	0.33
7	4794	4126	668	0.14
8	5028	4342	686	0.14
9	4913	4451	462	0.09
10	5295	5371	76	0.01

Table 5.2 Quantitative Analysis of MRI images with K-means clustering algorithm

S.No.	Ground Truth	True Positive	Error Value	Error Percentage
1	1928	1600	328	0.17
2	4360	4142	218	0.05
3	2324	2301	23	0.01
4	514	514	0	0.00
5	5212	4278	934	0.18
6	5680	5112	568	0.10
7	4794	4794	0	0.00
8	5028	4526	502	0.10
9	4913	4451	462	0.09
10	5295	5182	113	0.02

Table 5.2 Quantitative Analysis of MRI images with fuzzy c-means clustering algorithm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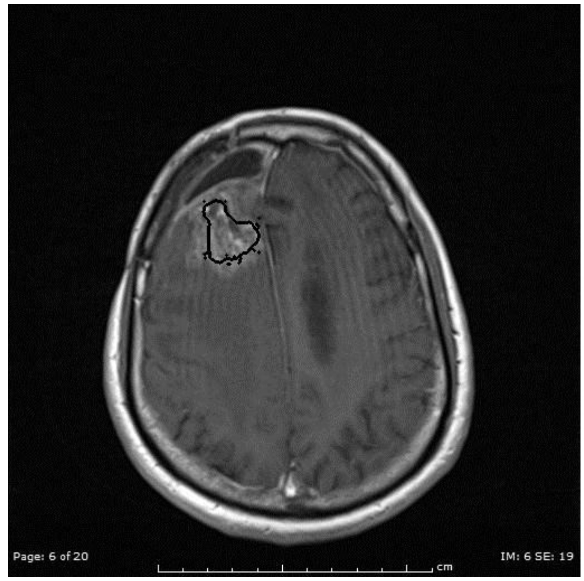
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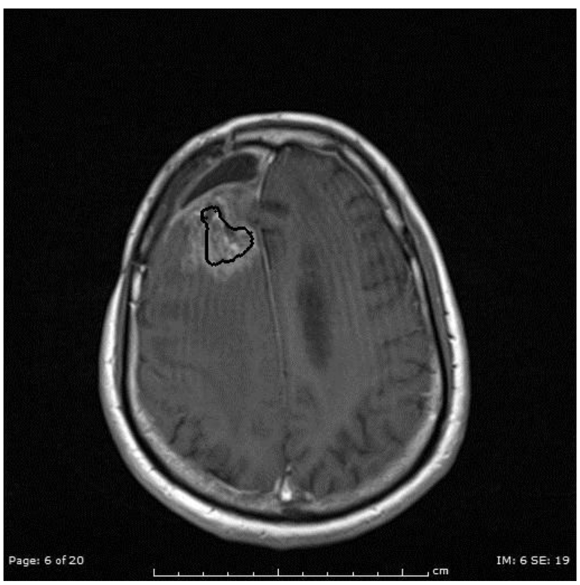
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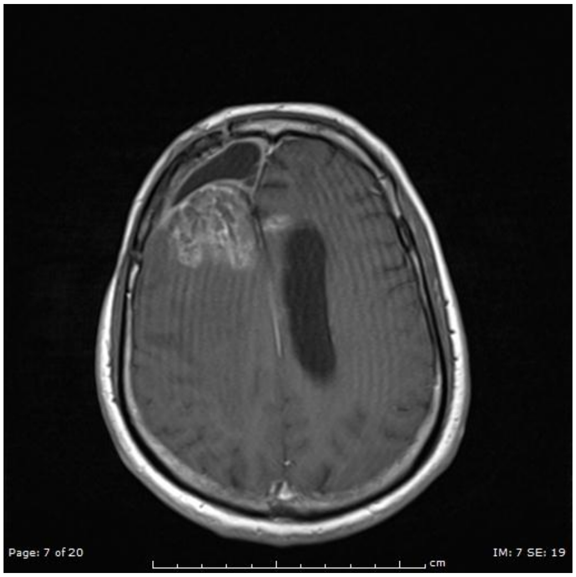
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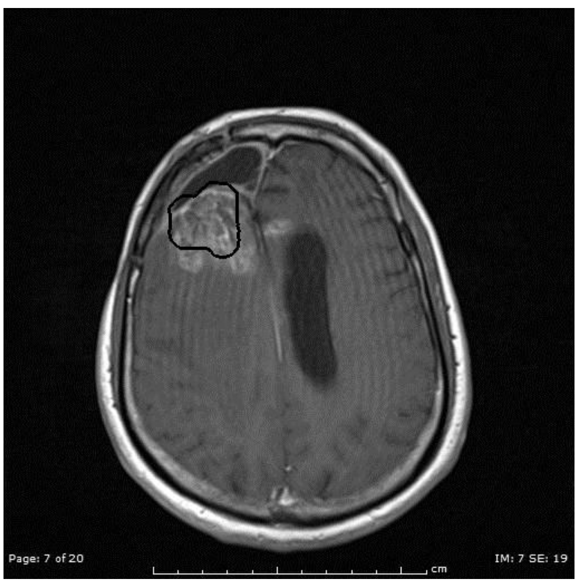
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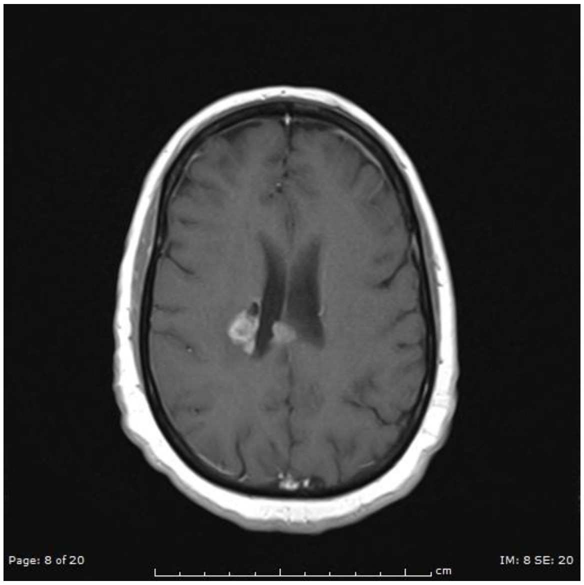
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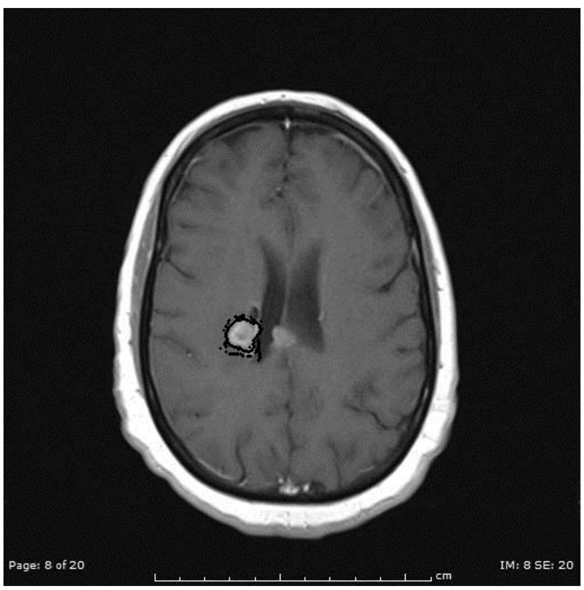
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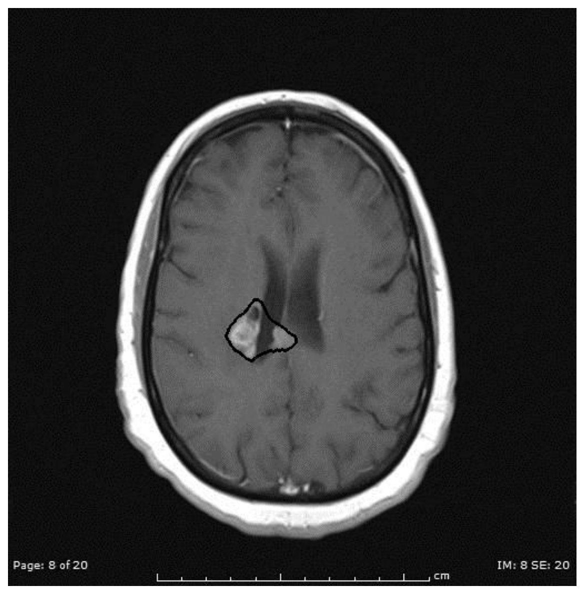
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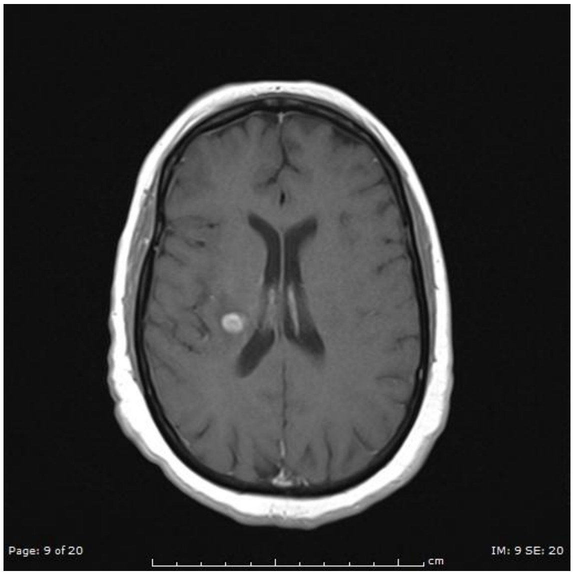
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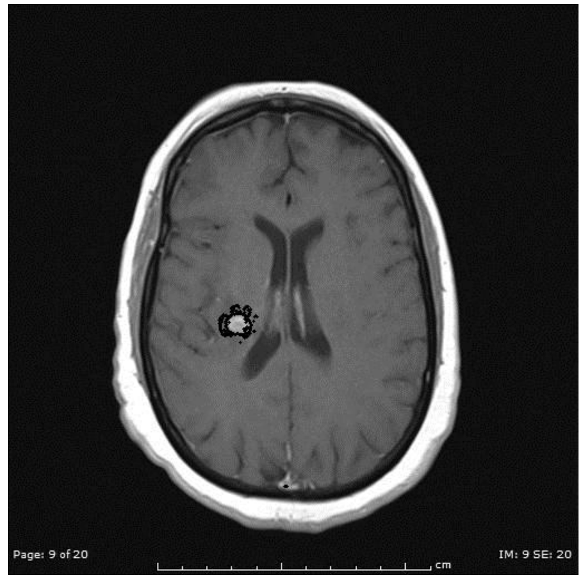
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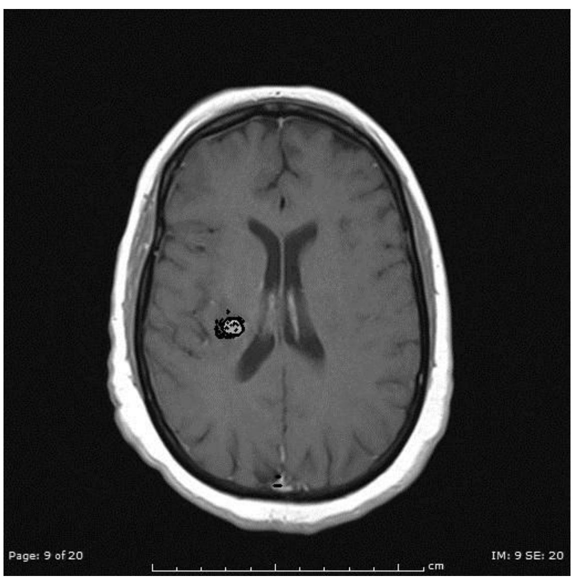
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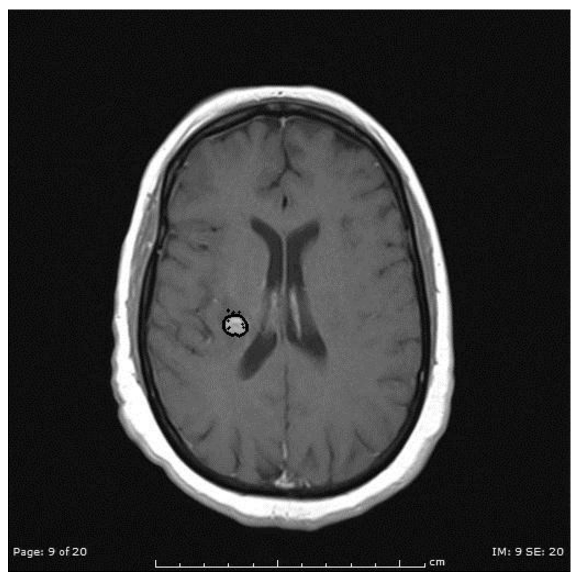
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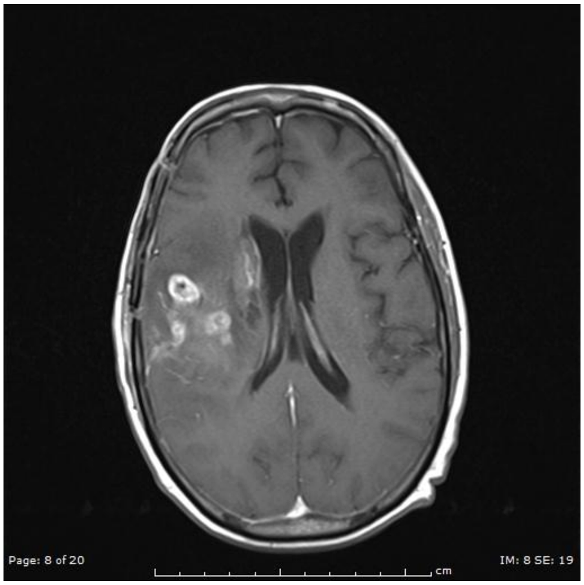
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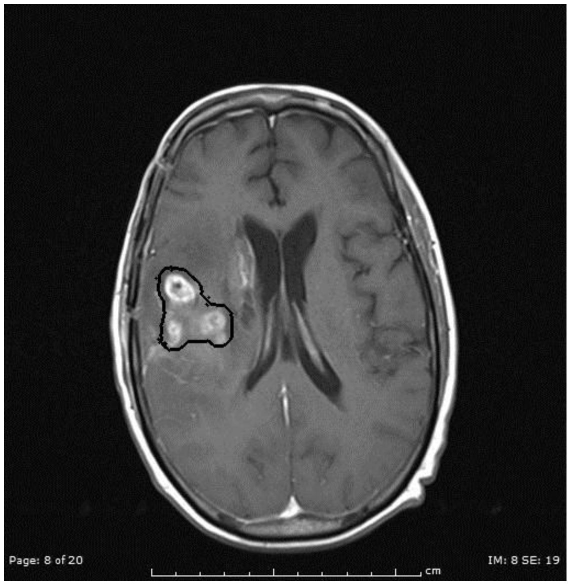
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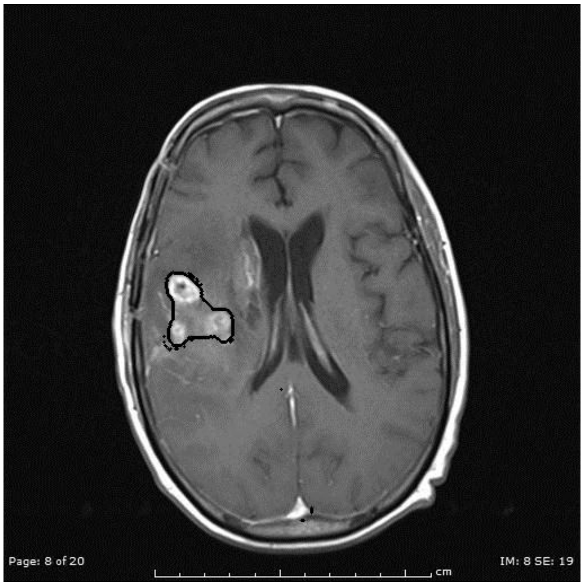
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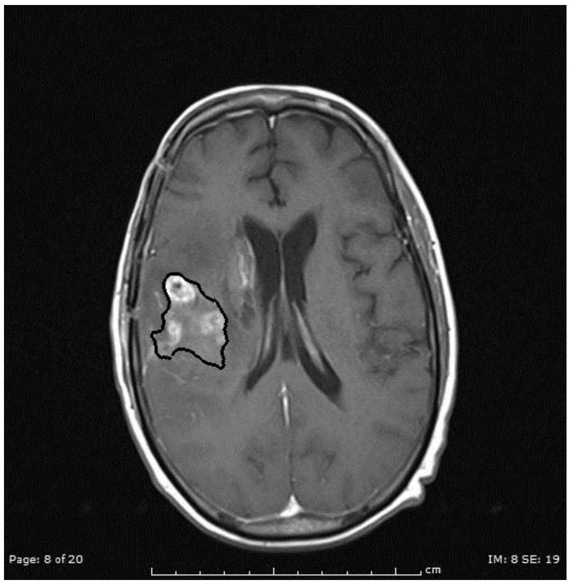
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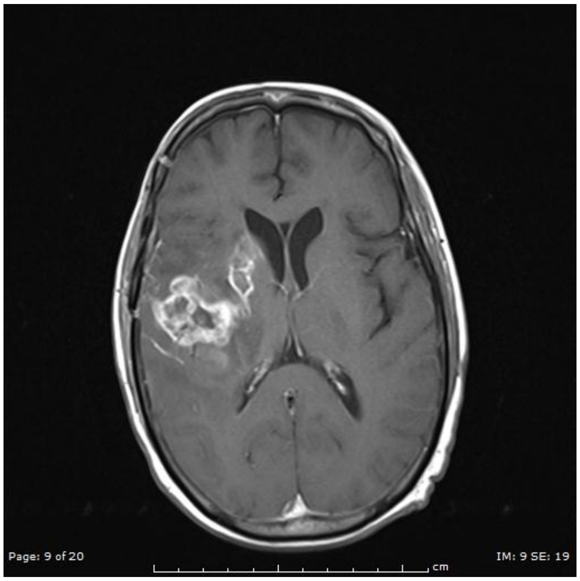
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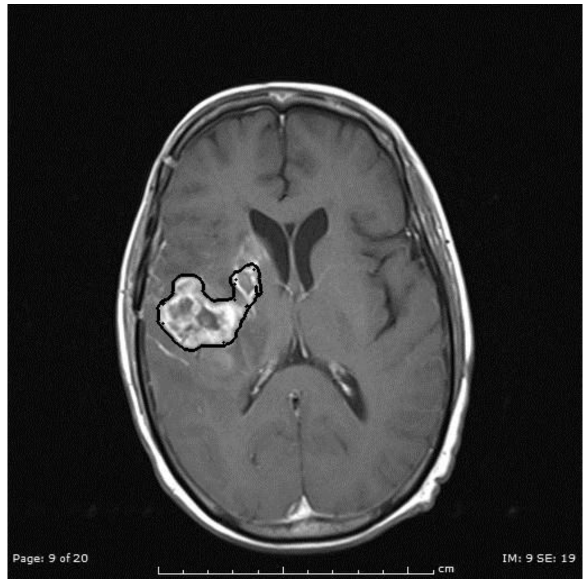
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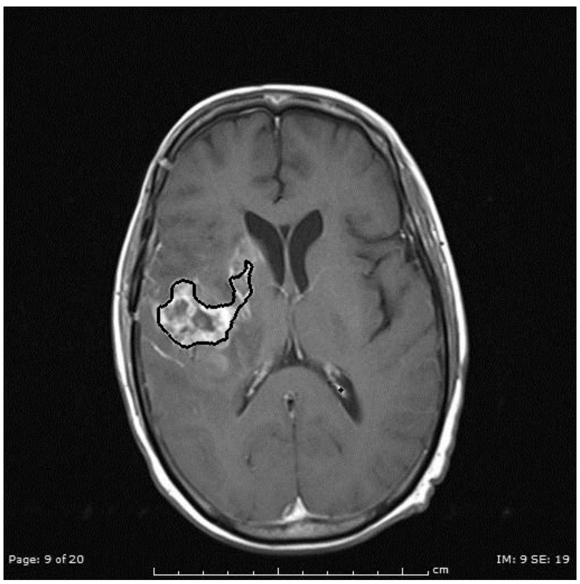
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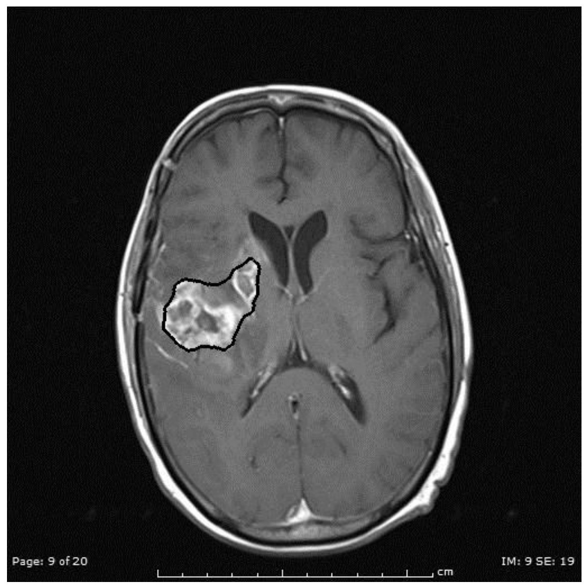
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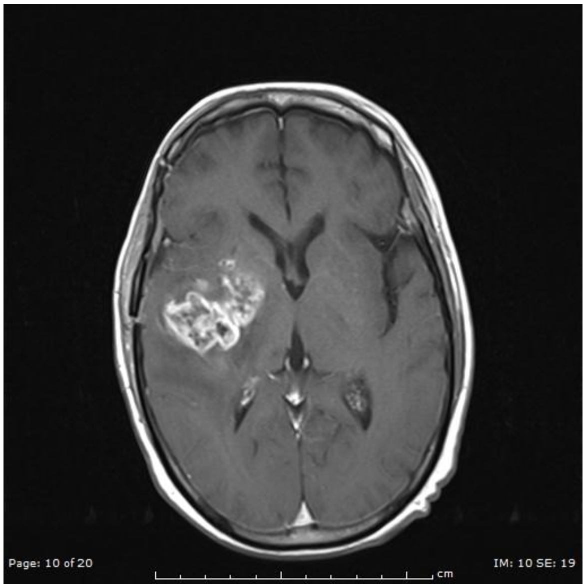
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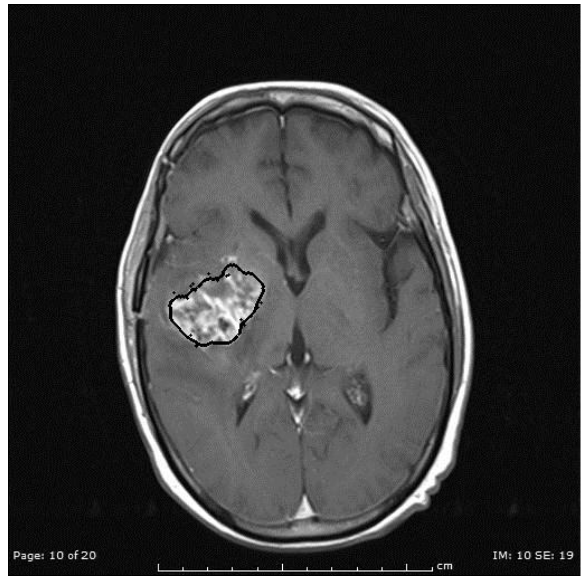
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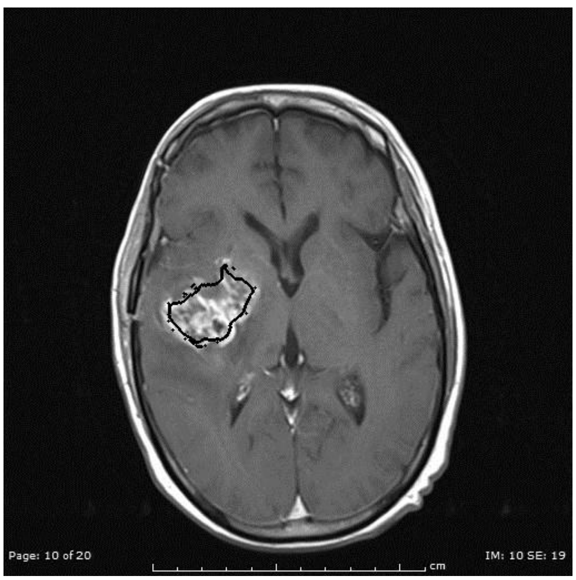
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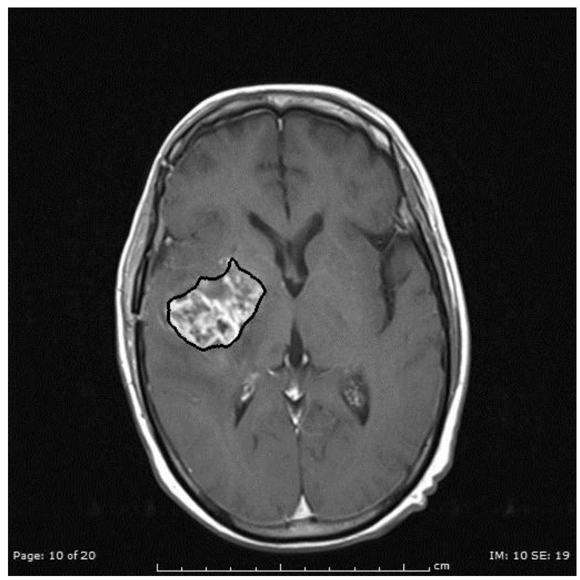
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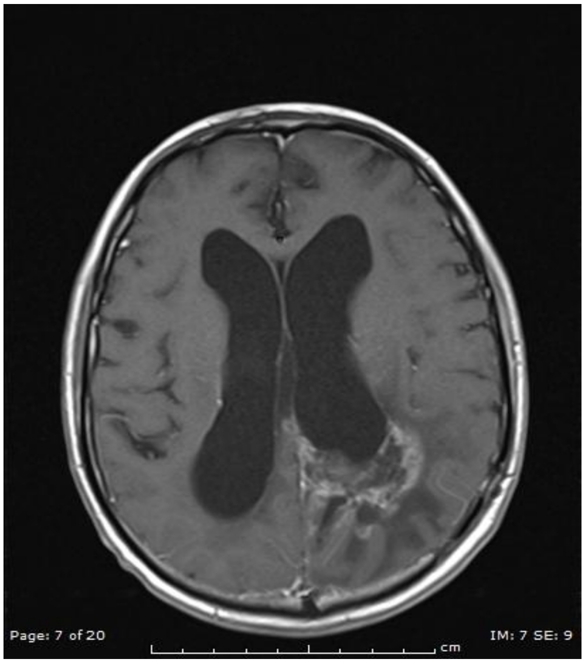
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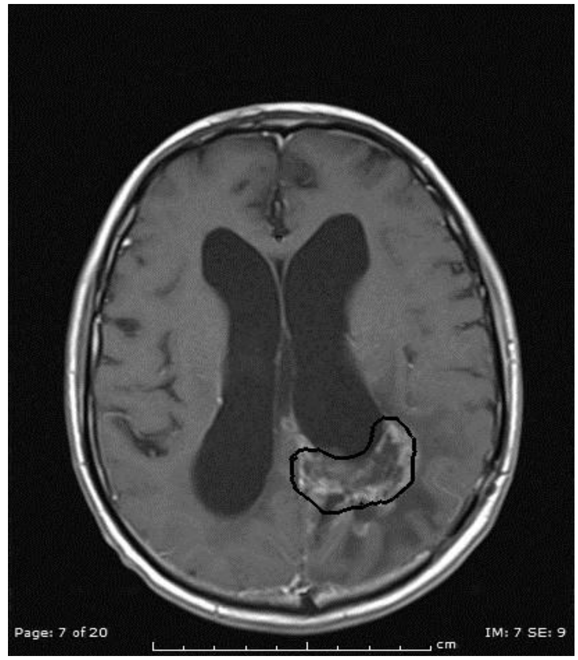
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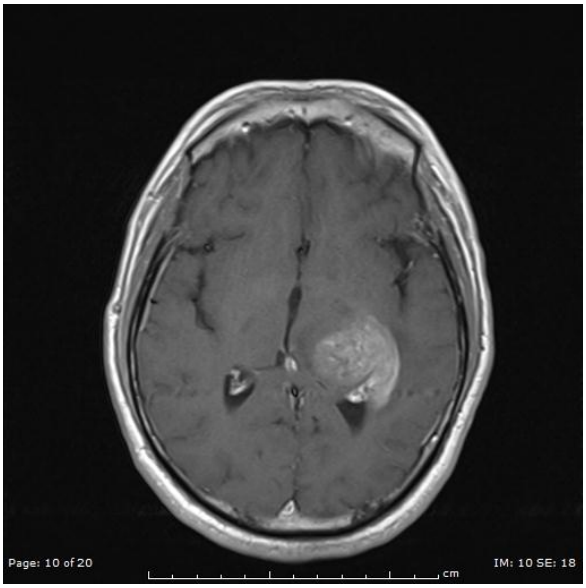
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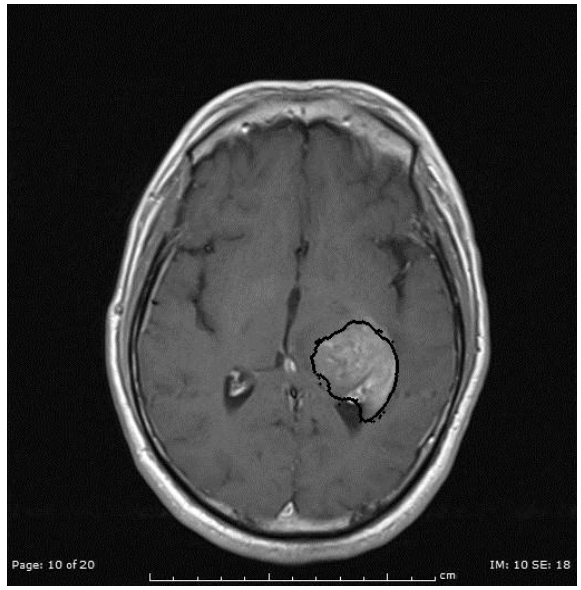
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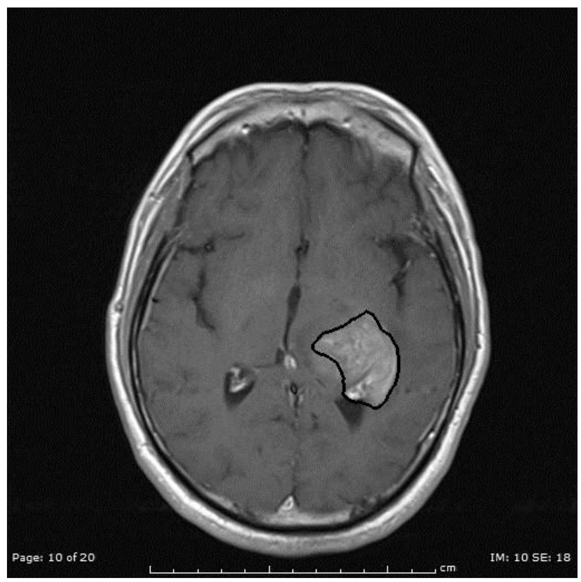
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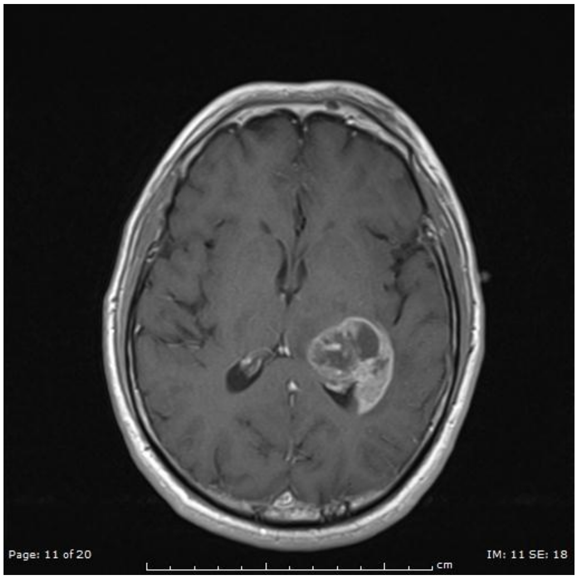

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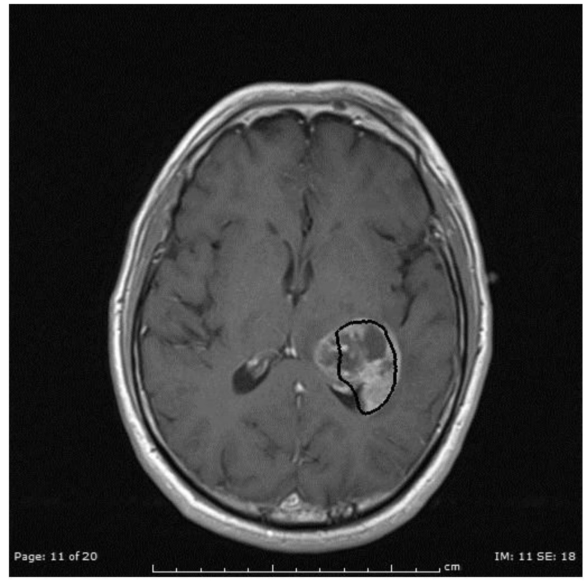

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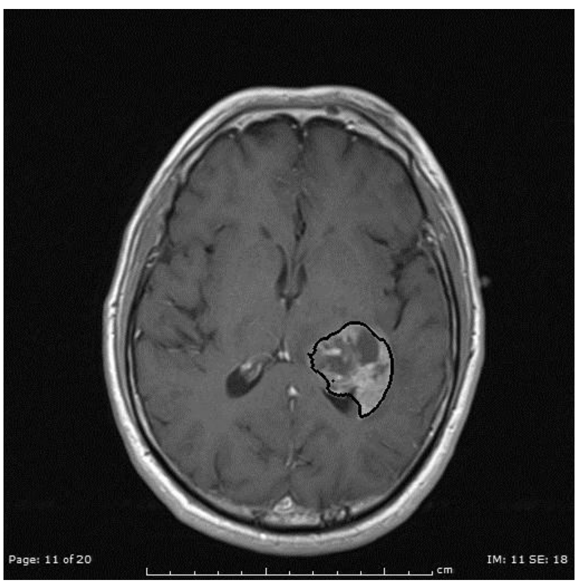

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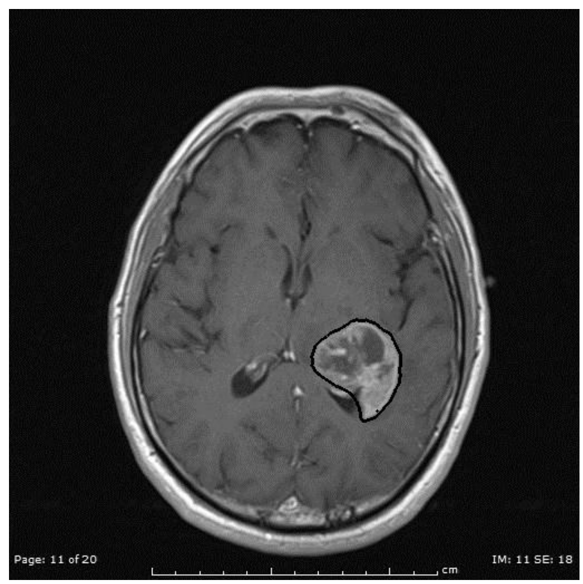

(d)

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

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

In this thesis, we have evaluated the performance of three different segmentation methods to detect brain tumor from sample MRI image database taken from RGCI&RC. Performance calculation of segmentation techniques is a tough task as different parameter settings can affect the results considerably. We have applied three most commonly used traditional methods for image segmentation, namely region growing, k-means and fuzzy c-means clustering based segmentation. We have evaluated the efficiency of these techniques on the basis of how well the detected tumor matches up with the true shape of the tumor. This quantitative analysis is done efficiently with the help of Error Percentage; low value of error percentage is desirable for better system performance. The value of the error percentage of all three technique shows that the Fuzzy C-Means Clustering outperforms other techniques. However, no image segmentation technique is as accurate as manual segmentation but Fuzzy C-Means Clustering can be used for tumor detection to compensate for the time and effort put in manual segmentation. In future, further improvement can be done in segmentation techniques in order to increase the detection accuracy. We can also optimize the parameters of the techniques used with the help of multi objective evolutionary algorithms to get better segmentation results. Texture information of MRI images can also be incorporated to increase the effectiveness of system.

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