# Diagnosis System for the Detection of Abnormal Tissues from Brain MRI

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**Abstract:** The brain tumor is widely disseminating disease all over the world and causing the increasing death rates. If the tumor is diagnosed at early stages, the increasing death rate can be decreased to some extent. Manual segmentation of brain MR images by experts is very expensive, non-repeatable and time consuming task. The computer-aided diagnosis system assists experts to take the opinion to diagnose the disease severity. The diagnosis process can be affected if the images are low contrast or poor quality and wrong diagnoses chances become high. The objective of this paper is to establish an automatic, accurate, fast and reliable diagnosis system which could be able to diagnose the brain tumor and also extract the region of the brain tumor from brain MR images. The median filter is used for enhancing the poor quality image, fuzzy c-means clustering technique for segmentation of images and mathematical morphological operations are performed to extract the abnormal portion from images. The proposed technique is applied on different brain MR images for both visual evaluations and quantitative. Experimental results of the proposed method showed, the proposed approach provides a fast, effective and promising method for the brain tumor extraction from MR images with high accuracy.

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**Keywords:** Image segmentation; mathematical morphological operators; fuzzy c-means clustering

## 1. Introduction

Image segmentation refers to as partitioning a digital image into significant and non-overlapping regions with respect to a particular problem. There are four regions in the brain image which are gray matter, white matter, cerebrospinal fluid and background. These four regions can also be considered as four different classes in the brain. The input image therefore needs to be partitioned into these four classes. The segmentation of the medical image is an important issue in medical imaging. Segmentation is a primary step for medical image analysis. The human brain is the kernel part of the body and controls the functionality of the overall body. The brain has a very complex structure which contains billions of nerves that can concurrently process information from the body, operate internal organs, generate emotions and thoughts, recall and store memories, and also it controls the movement (http://www.inborn-talent.in/know-brain). The brain tumor is rapidly increasingly disease in the different countries of the world. The brain can be affected by a problem that cause changes in its normal structure and its normal behavior . This problem is known as the brain tumor. The Brain tumor is the leading cause of solid tumor cancer death in human beings. Nowadays, the death rate is increasing due to the tumor. According to the research of the National Cancer Institute and National Brain Tumor Foundation United State (http://www.cancer.gov/cancertopics/types/brain/), almost 42000 people including men and women in the US suffer from the brain tumor each year. About 29000 people are diagnosed and 13000 die. According to the latest survey of 2013 in the United States, new tumor cases reported are 23130 (including men and women), and deaths reported are 14080 (http://www.cancer.gov/cancertopics/types/brain/). Diagnosis of the brain tumor is a serious task because a wrong diagnosis can lead to severe results. If the tumor is diagnosed at early stages, then life of a person can be saved for some extend. Brain tumor surgery is also a crucial task because the brain has a very complex interrelated structure. Each brain cell is bounded together in a very complex way.

Magnetic Resonance Imaging (MRI) is a medical imaging technique and radiologist used this for the purpose of visualization of the internal structure of the body (Bandhyopadhyay, 2013). MRI is a type of scan that is used mostly to help diagnose health conditions that affect bone, organs and tissue. MRI provides rich information about the human soft tissues anatomy. MRI can also be used to visualize almost all parts of the body, but it is most often used to study the blood and heart vessels, the spinal cord and brain, other internal organs such as liver or lungs, joints, bones and breasts (Aly, 2011).

In the most recent few years, several computer-aided diagnosis (CAD) systems have been developed using different methods and techniques to diagnose the brain tumor which provide the accuracy of correct detection at different accuracy scales.

The major objective of this study is to develop an automatic, fast and reliable approach which identify the brain tumor and also extract the region of the brain tumor from brain MR images with high accuracy rate.

The rest of the paper is managed as the following: Section 2 represents some related work which is closely related to current work and find out the problems. The methodology of the proposed method is described in Section 3. Implementation note is given in section 4. In section 5, results and discussion are explained. Conclusions are included in the section 6.

**2. Literature Review**

Ahmed (2008) proposed a method for the segmentation of brain MR images by using the k-means clustering algorithm and perona malik anisotropic filter. In this technique some mathematical morphological operations are performed to separate the abnormal portion. This method showed good visual results, but the accuracy of results have not been calculated and validated. Held (1997) proposed an algorithm using Markov random fields for brain image segmentation This algorithm is built upon the information of non-parametric distribution of tissue intensities, neighborhood correlation and signal inhomogeneities that comes at the time of capturing MR images. The main disadvantage of this model is that the results achieved are based on an iterative conditional model overlaps some white matter regions with the gray matter regions. Leemput (1999) proposed a segmentation method of brain images based on intensity that segments the voxels of the brain. It determines the partial volume of every voxels of the image. On the basis of this information, segmentation of the brain MR image is achieved by using the Markov Random Field. The voxels which lies between the overlapping regions of the tissues classes of the brain does not accurately specify the partial volume because this model just deals with voxels that belong to specific one class. Bazi (2007) proposed histogram based thresholding segmentation method. This method is global histogram based thresholding. This technique uses expectation-maximization algorithm to segment background and objects assuming these two classes follow generalized Gaussian distribution. The initialization of the parameters is done using the Genetic algorithm (GA) strategy which is its main limitation because this initialization takes more time. Vasuda (2010) proposed a tumor detection method from MR images. In this method, fuzzy c-means algorithm is used for segmentation purpose. The main drawback of this technique is that the computation cost is greater.

The major problem with some of the former methods is that if the noise in the images exists then it affects on the segmentation process as well as reduces the accuracy. Further, most of the former methods are computationally very costly and takes some large time to perform the segmentation process.

**3. Methodology**

For segmenting the MR image accurately, the entire system is divided into several phases to perform the segmentation process. Since the presence of noise affects the segmentation process, so the preprocessing step is performed first on to the input image, then post processing step is performed. In the last tumor portion is detected. The complete flow of the proposed method is given in the figure 1. The following subsections describes the detail of the major components one by one.

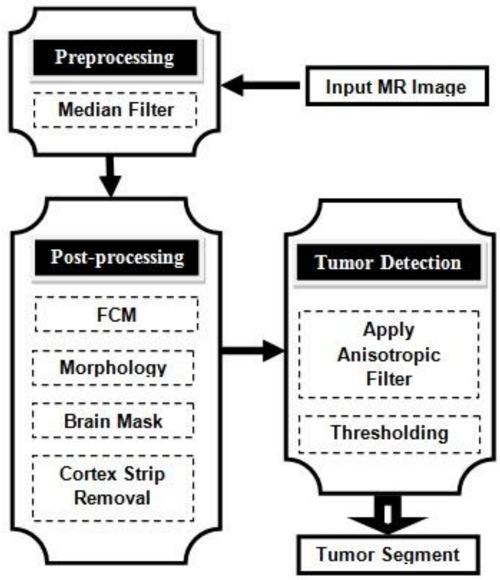
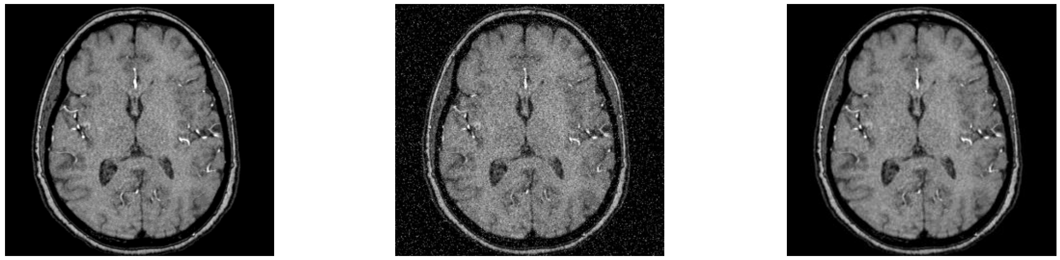


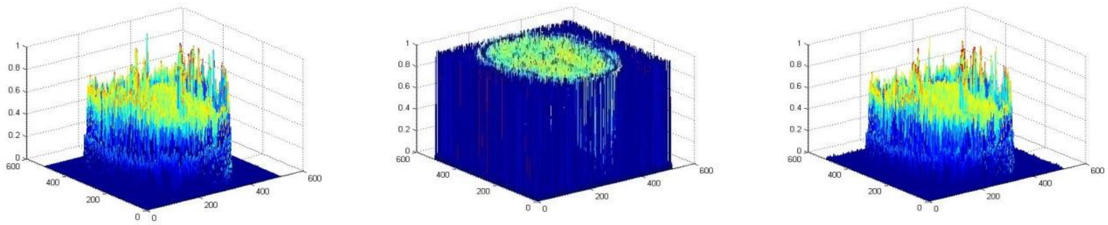

**Figure 1:** System process flow diagram

***3.1 Preprocessing Step***

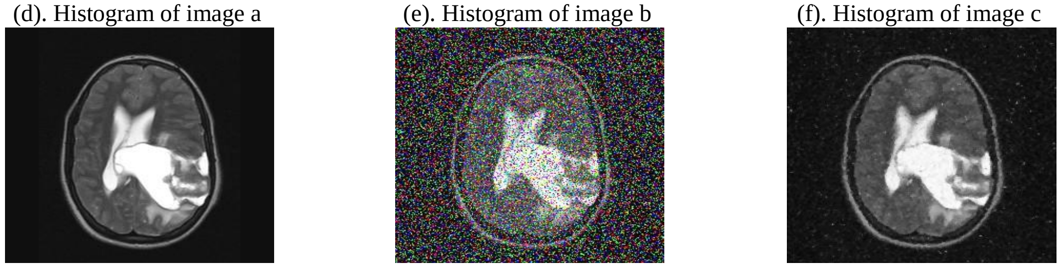
For achieving best possible diagnose it is necessary that the medical image should be sharp, distinct and noise free. Since now-a-days technologies of digital medical image acquisition are improving tremendously, which gives images of high quality and resolution, but the noise on the images is still an issue. For achieving the best quality of the image, first preprocessing step is performed to enhance the image quality. A median filter is applied to improve the image quality. It considers the neighborhood of a pixel and sorts the values of these neighboring pixels, then it chooses the median value. The median is a more robust average than the mean and so for a single very unrepresentative pixel in a neighborhood it does not affect the median value significantly (Marion, 1991). The median filter preserves the edges of the image. A 5 x5 square window was used throughout this work. The noise is added first in the image and then the image is enhanced by the median filter. Figure 2 shows the image enhancement with the median filter.



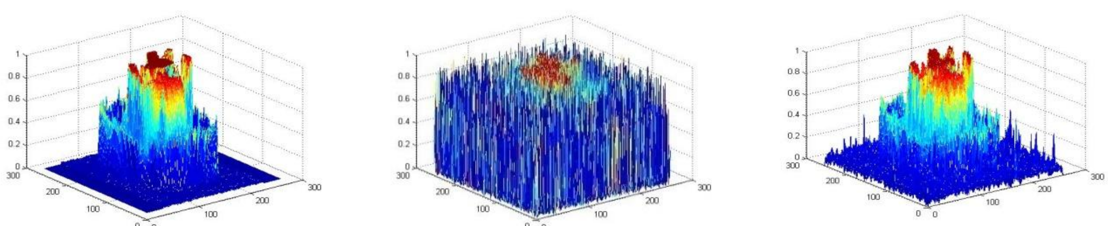
(a) (b) psnr = +15.85 dB (c) psnr = +32.11 dB



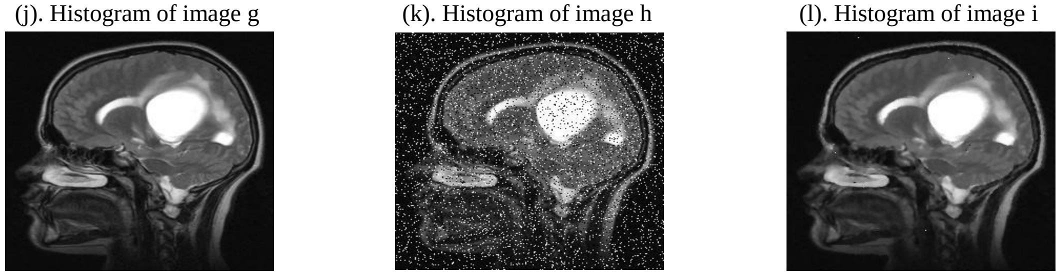
(d). Histogram of image a (e). Histogram of image b (f). Histogram of image c



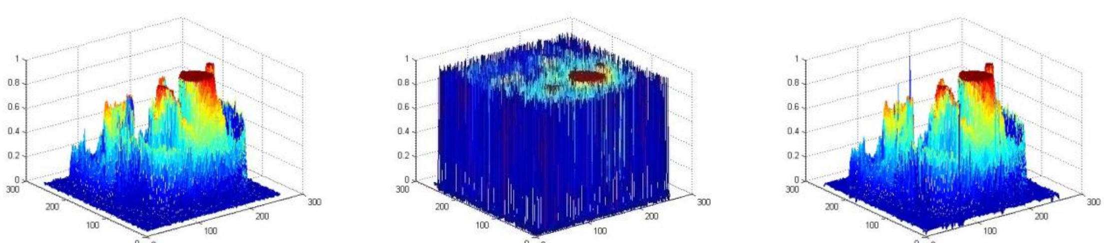
(g) (h) psnr = +12.16 dB (i) psnr = +28.05 dB



(j). Histogram of image g (k). Histogram of image h (l). Histogram of image i



(m) (n) psnr = +13.43 dB (o) psnr = +31.41 dB



(p). Histogram of the image m (q). Histogram of the image n (r). Histogram of the image o

**Figure 2:** (a, g, m). Original image (b, h, n). Noisy image (c, i, o). The De-noised image with median filter

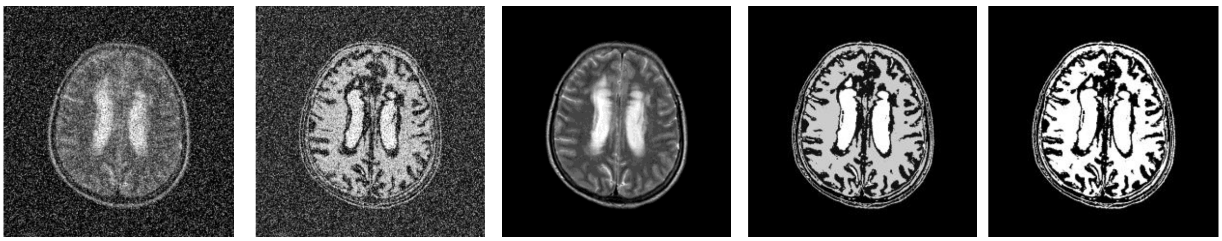
### *3.2 Post-processing*

*3.2.1 Fuzzy C-Means Clustering (FCM)*

For the segmentation of the image, fuzzy c-means (Christ, 2011; Ahmed, 2002) clustering algorithm is applied. This algorithm assigns membership degrees to each point of the image between 0 and 1. Cost function is minimized iteratively that is dependent on the distance of the pixel to the cluster centers in the feature domain for achieving clusters. By using fuzzy memberships FCM algorithm assigns pixels to each group. FCM starts with an initial guess for the center of each cluster. FCM converges to a solution for representing the local minimum or Convergence can be perceived by evaluating the changes in the membership function or the cluster center at two successive iteration steps. The cost function of FCM is given as:

$$J_m = \sum_{j=1}^{k}\sum_{i=1}^{n} U_{ij}^{m} \left\| x_i - c_j \right\|^2, \qquad 1 \le m < \infty$$

Where $\left\| x_i - c_j \right\|$ is the measure of the distance between data point $x_i$ and cluster center $c_j$, $U_{ij}^{m}$ is the membership matrix and m is the fuzzification factor. Figure 3 shows the binary segmented image by applying the fuzzy c-means algorithm before and after image enhancement.



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

**Figure 3:** (a). Input image (b) Segmented by FCM before enhancement (c). Enhanced image (d)**.** Segmented by FCM after enhancement (e). Binary image

*3.2.2 Mathematical Morphological Operations*

Mathematic morphological operations are performed to remove the imperfections during the segmentation process. The basic purpose of applying these operations is to disjoint of background to foreground objects and separation of non-brain parts. After applying morphological operations, a brain mask is prepared and then this mask is mapped with the original image to remove the hard tissues and brain cortex strip removal from the brain which are not the region of interests. As a result of this, only soft tissues remained which are the important. The tumor exists in the soft tissues. The following mathematical morphological operations are performed:

Opening Operation: $A \circ B = (A \ominus B) \oplus B$

Closing Operation: $A \bullet B = (A \oplus B) \ominus B$

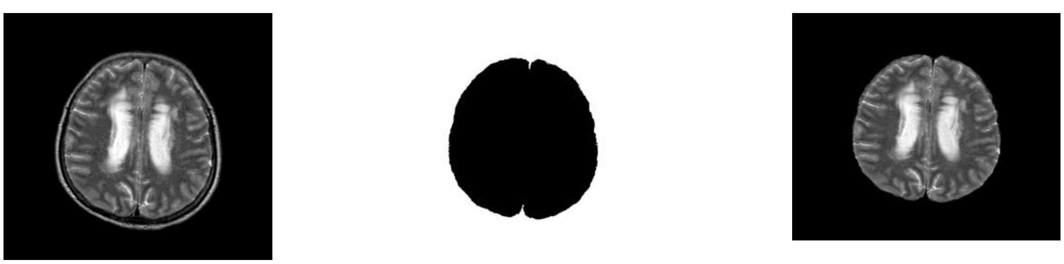
Erosion Operation: $A \ominus B$

Dilation Operation: $A \oplus B$

Where A is the image and B is the structuring element. A disc shaped structuring element having radius 7 is used throughout this work. The effect of morphological operations is shown in figure 4.

### *3.3 Tumor Detection*

After the removal of skull tissues and brain cortex strip, the Perona Malik anisotropic diffusion filter (Pietro, 1987) was applied to make the image smoother. This filter smoothes the image and gives the better preservation of the edges of the image objects. This filter smoothes the edges without loosing any finer and important detail of the image. After that, a global threshold method was used to extract the tumor segment. The extracted tumor segment from the brain is shown in figure 5.



(a) (b) (c)

**Figure 4:** (a). Input image (b). Brain mask after morphology operations (c). Skull removed image

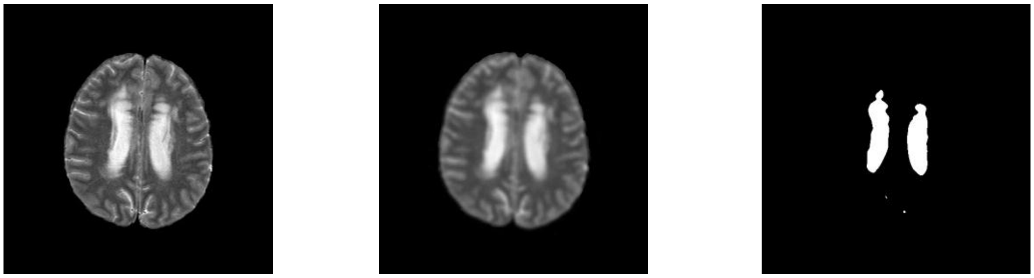

(a) (b) (c)

**Figure 5:** (a). Skull removed image (b). Anisotropic filtered image (c). Tumor extracted

**4. Implementation**

The proposed system is implemented in matlab® 7.8 (R2009a) installed on Pentium 4, i5, 4GB of RAM with the windows 7 operating system. The complete flow of the proposed method is given in figure 1.

First, the brain MR image is given as input to the system. Median filter is applied on to the input image to reduce the noise and enhancing the quality of the image. After reducing the noise, fuzzy c-means clustering algorithm was applied for segmenting the image and then this segmented image is converted in binary format. Some mathematical morphology operations are performed to remove the imperfections occurred during the segmentation process. After removing non-brain parts, a brain mask is prepared. Then this mask is mapped with the original image to remove the skull, the brain cortex strip and hard tissues. Perona Malik Anisotropic diffusion filters is applied to make the image as smoother. Since the tumor exists in the high intensity region, so finally by applying the global thresholding method, the tumor segment is extracted from the brain.

**5. Results and Discussion**

Though the proposed method is tested on a wide variety of brain MR images with a varying complexity, however, the experimental results are shown only for few images. Figure 7 shows the visual results of the proposed system. The experimental results are calculated with the help of ground-truth (GT) by using the knowledge-based (KB) validation method. For this purpose, a database was formed by selecting the suitable images having the data of six patients. Then these selected images were sent to two experts to draw the manual boundary of the tumor portion.

***5.1. Knowledge Based (KB) validation method***

To measure the segmentation results of the proposed method with the ground-truth (GT), the knowledge based (KB) (Clark, 1998) method was used. The results are calculated on the basis of Correspondence Ratio (CR) and Percent Match (%Match) between the proposed system detected tumor portion and ground-truth tumor labeled. The Correspondence Ratio (CR) and Percent Match (%Match) are defined as:

$$\mathrm{CR}_{\mathrm{average}} = \frac{\text{True Positive} - (0.5 * \text{False Positive})}{\text{No.of Ground Truth pixels}}$$

Where the True Positive are tumorous pixels indicated both by system and ground-truth, False Positive: the system indicates the tumorous pixels while ground-truth not. The CR value estimates that how far is the segmentation from the ground truth. 1 is the ideal value for CR.

$$(\%\mathrm{Match})_{\mathrm{avg}} = \frac{\sum_{i=1}^{\text{slices in set}} (\%\mathrm{match})_i * (\text{No. of GT pixels})}{\sum_{i=1}^{\text{slices in set}} (\text{No. of GT pixels})_i}$$

The Higher values for percent match (PM) indicate the greater similarity of segmented areas between the system generated and ground-truth.

Table 2 indicates the calculated experimental results of the proposed method. The average %match between the extracted tumor portion and ground-truth is 97.58 and average CR is 0.86. The average %match of the system presented by Clark (1998) is 90 and the average %match of the presented method by Alegro (2012) is 94 (see figure 8). Table 1 shows the tumor detection time of the proposed method which is average 1.253 seconds and figure 6 shows the time performance of the proposed method graphically. Figure 2 shows the image enhancement which is measured with the help of standard criteria for the image quality measurement peak signal to noise ratio (PSNR). If the PSNR of any image is between 25-35 dB, then that image is considered to be of best quality. The proposed method improves the noisy image within the standard range. The experimental results of the proposed method showed that the performance found to be a fast, efficient, accurate and improved.

**6. Conclusion**

In this paper an automatic, robust and effective method is developed which gives maximum accuracy and extract the tumor segment from the brain MR image. This method provides support and opinion the experts to diagnose the abnormalities in the brain.

First, the image of poor quality is enhanced using the median filter which updates each pixel of the image by considering the neighborhood of the pixel and selecting the median value. Then the fuzzy c-means clustering technique is applied to segment the image. By applying some mathematical morphological operations and thresholding method, tumor segment is separated from the brain MR image.

Analysis are performed on the extracted abnormal portion of the brain by considering the ground-truth. The area of the detected tumor portion is compared with the ground-truth and results are calculated for efficiency and accuracy measurement. From the analyzed results, efficiency and accuracy of the proposed method found to be amazingly very promising and good.

**Table 1:** Time performance of the proposed method

| **Dataset** | **Dataset size** (Pixels) | **Detection time** (Seconds) |
|---|---|---|
| **#1** | 512 x 512 | 1.45 |
| **#2** | 512 x 512 | 1.49 |
| **#3** | 204 x 204 | 1.05 |
| **#4** | 448 x 448 | 1.30 |
| **#5** | 256 x 256 | 1.14 |
| **#6** | 225 x 225 | 1.09 |
| Total Average time | | **1.253** |

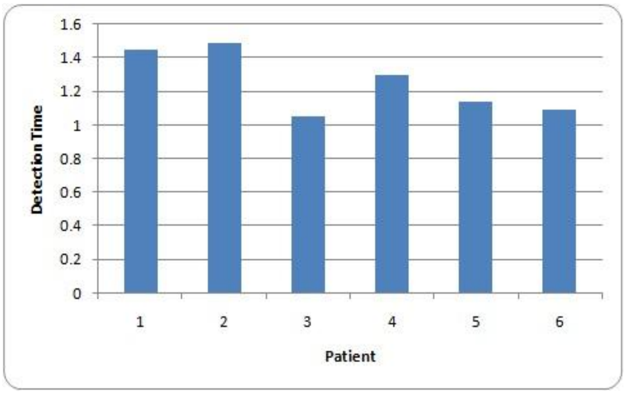



**Figure 6:** System time performance graphically

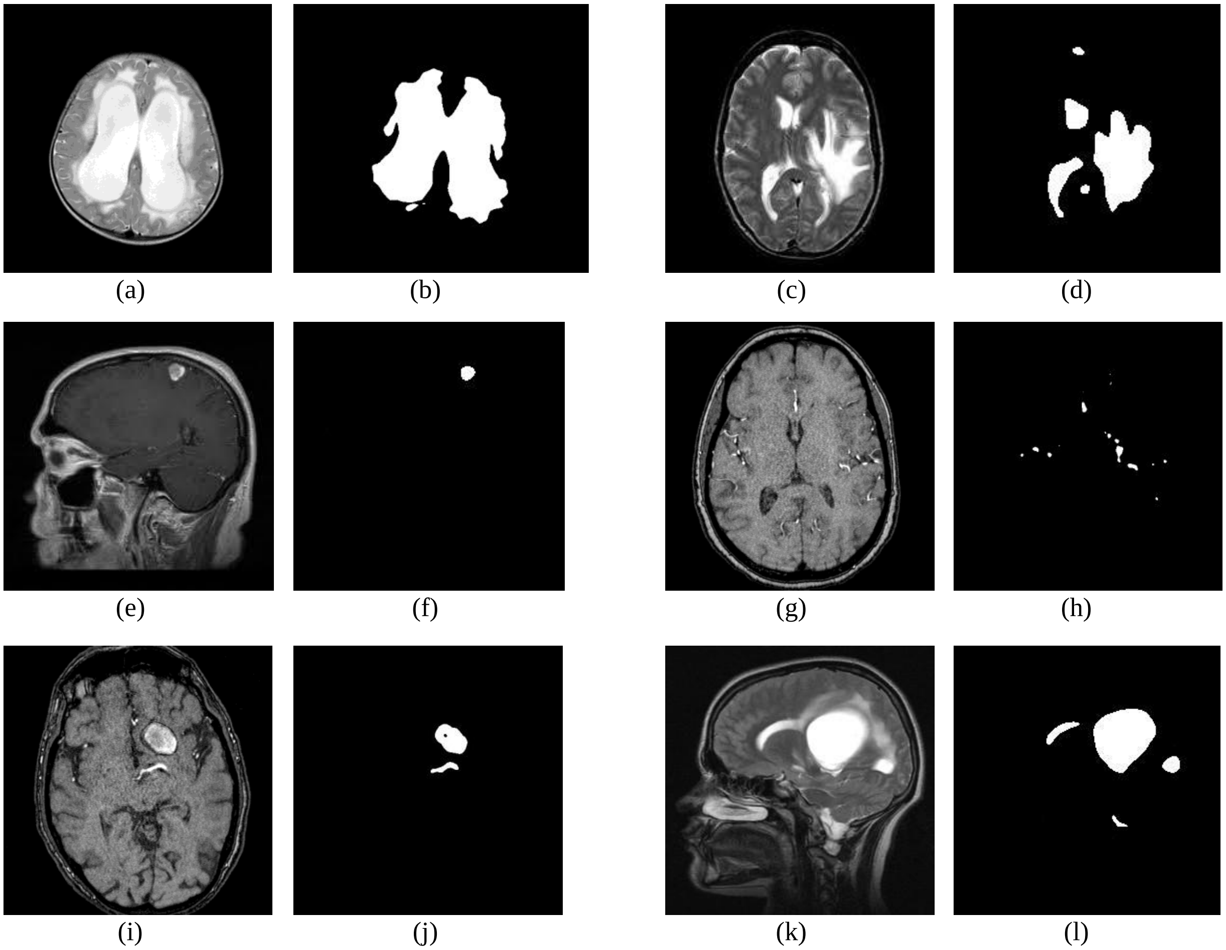



**Figure 7:** Visual Results of the Proposed Method (a, c, e, g, i, k). Input images, (b, d, f, h, j, l). Tumor extracted images by the proposed method

**Table 2:** Results of the proposed method by using KB method

| Patient | GT by Expert 1 | | GT by Expert 2 | | Mean of Expert 1 & 2 | |
|---|---|---|---|---|---|---|
| | PM | CR | PM | CR | PM | CR |
| #1 | 98.46 | 0.86 | 99.04 | 0.81 | 98.75 | 0.84 |
| #2 | 96.84 | 0.82 | 97.27 | 0.84 | 97.06 | 0.83 |
| #3 | 93.94 | 0.87 | 96.23 | 0.83 | 95.09 | 0.85 |
| #4 | 97.77 | 0.91 | 98.40 | 0.93 | 98.08 | 0.92 |
| #5 | 98.83 | 0.89 | 98.34 | 0.79 | 98.59 | 0.84 |
| #6 | 96.19 | 0.79 | 99.61 | 0.93 | 97.90 | 0.86 |
| Total Average | | | | | **97.58** | **0.86** |

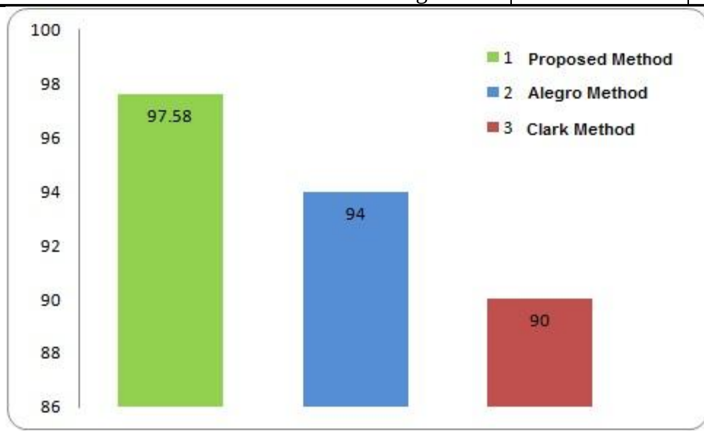



**Figure 8:** Accuracy Comparison of the proposed method

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