

# AN IMPROVED SEGMENTATION APPROACH USING LEVEL SET METHOD WITH DYNAMIC THRESHOLDING FOR TUMOR DETECTION IN MRI IMAGES

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## Abstract:

In this paper an improved approach for segmentation of brain tumor using MRI images has been presented. This approach consists of three steps, namely: preprocessing, segmentation and post processing. The preprocessing has been carried out using skull stripping and histogram equalization techniques. The region of interest is segmented by applying conventional Level Set method to the preprocessed image. The segmented image consists of distortions at the boundaries which lead to boundary leakage problem. This can be minimized by applying dynamic Thresholding technique and region localization method. The proposed method achieved better accuracy of segmentation as compared to the conventional level set segmentation method.

## Keywords:

Image Segmentation, MRI sample, Level Set coding, Region Detection of MRI sample.

## I. Introduction

Image segmentation is an important task of image processing. Properly segmented image provides the basis of further very high level image understanding, subsequent planning for diagnosis. Through manual clustering by human experts is a tedious task due to very slight variations, similarity among affected and original biological tissues and larger data set for analysis. These problems go more complicated in general and brain tumor in particular. A brain tumor is a disease in which tissues grow irresistibly in the brain. Brain tumors are classified into two types namely: benign and malignant. In the case of benign tumors, they are incapable of unfolding outside the brain and their growth is self-limited. Due to their location sometimes tumors creates problem. They are curable using radiation or surgery method. In the case of malignant tumors, they are called brain tumors; these tumors can spread not only in the brain as well as other parts of the body at faster rate. Malignant brain tumors create problem if it is not treated.

In order to treat, early detection and complete removal is the best solution, if not any, proven method of treating deadly tumor growth. The only way to “cure” a tumor is to find and treat it early before symptoms arise. In order to early detection of tumors there are different techniques are available in the literature such as

## MRI image segmentation

MR imaging is a very powerful technique and able to access and monitor various parameters of physiological, pathological and morphological importance. MRI imaging has advantage of being more sensitive than CT Scan to detect even small tumors that may be missed by CT Scan and often used in the initial diagnosis of tumors, while CT imaging is suitable for accurate identification of bone and better computation of radiation dose. MRI is better for soft tissue contrast. The main challenge of medical image analysis is the inherent uncertainty and imprecision of the image objects. In many situations it is difficult to find the same class of pixel as the features used to determine the homogeneous segmented regions may not have sharp variations at region boundaries. Mistakes made in this stage affect all the further activities.

## Brain image segmentation

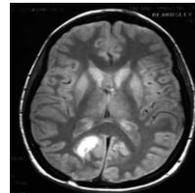


Figure 1: MRI of Brain showing Tumor

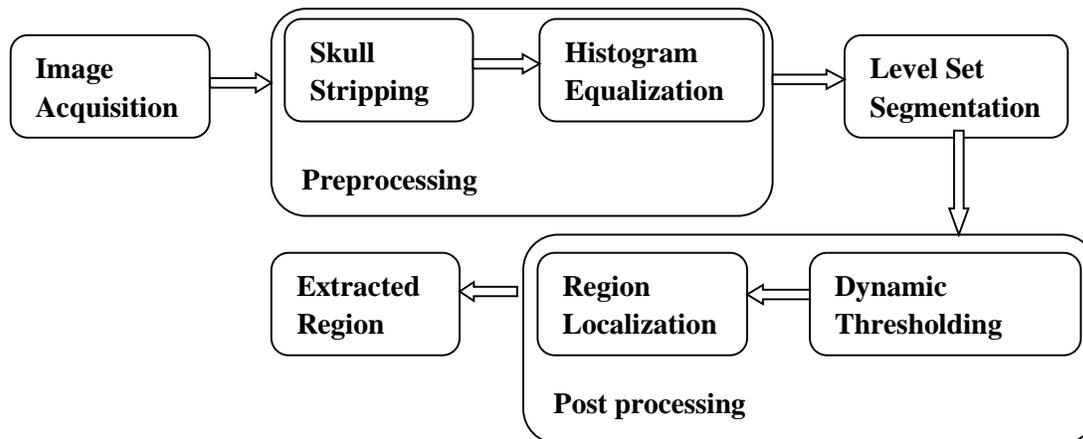
A substantial methodological framework including new data analysis method was developed in [10] to meet the challenge of working with big data. Effected imaging phenotypes determined by MRI providing a mean of panoramic and noninvasive surveillance of oncogenic pathway activation for patient’s treatment was presented. In [11], to summarize and compare the

methods of automatic detection of brain tumor through Magnetic Resonance Image (MRI), different stages of Computer Aided Detection (CAD) system was presented. In [12] a method to segmentation EEG signal for detection of primary brain tumor detection, in combination of wavelet transform is presented. Uncertainty in the EEG signals is measured by using the Approximate Entropy. This observation leads to the process of tumor detection based on EEG analysis. [13,14] Describes a Matlab implementation, to identify & extract tumor from MRI images of the brain. Contained with noise eradication functions, segmentation methods and morphological operators which are used for MRI image coding. The approach of automated segmentation of the proposed approach was outlined in this work. In [15] an artificial neural network (ANN) approaches by probabilistic neural network (PNN) and Back propagation neural network (BPNNs) was presented. This classification method is used to find Astrocytoma (type of brain tumor) in MRI images. Wherein most methods were developed for segmentation of regions from a given MRI sample, less focus is made on its localization. Localization of

the mass elements in the MRI sample could minimize the overhead coming for processing the whole sample. With this objective a simpler however robust approach of mass localization in MRI sample using recursive Morphological approach with its fusion is suggested. In the approach of segmenting such region, a walker based approach was suggested in [16]. This logic presents a simpler approach of region segmentation via boundary region tracking. In this paper, a new region detection approach was proposed for MRI image segmentation based on the Level Set coding and dynamic Thresholding algorithm. The proposed approach obtains the exact regions with perfect boundaries because of LS coding and also achieves improved segmentation accuracy due to the Thresholding and region localization logic. Simulations are carried out in various MRI images to show the performance of proposed approach. The rest of this paper outlines the MRI processing in section 2. Section 3 outlines the proposed approach of recurrent morphological coding. Section 4 presents the experimental result obtained. A conclusion is given in section 5.

**II. Materials and methods**

This section briefly explains the techniques used in proposed method for brain tumor segmentation. It has four steps namely acquisition of data, Pre-processing, Segmentation and post processing.



**Fig 2: Architecture of the proposed work**

**1. Image Acquisition.**

The proposed method uses databases of BRATS 2013 & BRATS 2015. In BRATS for every patient four sequences of MR images are available, namely, Weighted T1 (T1), T1 with contrast (T1C), Weighted T2 and FLAIR. There are three types of datasets available in BRATS 2013, Training, Leaderboard &

Challenge, consisting of 65 MR images from various Patients diagnosis. In the database of BRATS 2015 training samples include 220 & 54 images the Training set comprises 220 and 54 images of High Grade Glioma (HGG) and Low Grade Glioma (LGG).

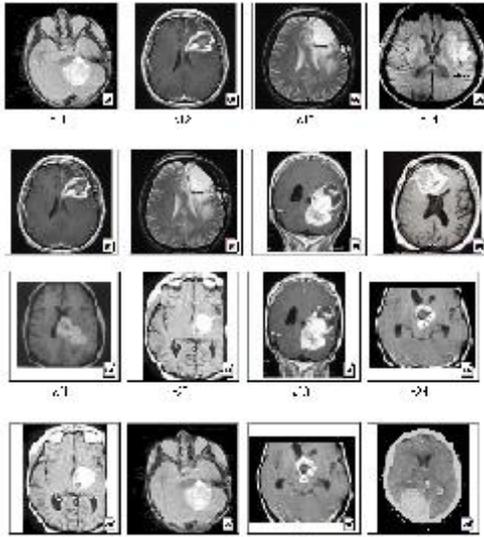


Fig.3. A typical MRI database

## 2. Preprocessing

In the proposed method preprocessing is carried out using following two methods.

### a. Skull stripping

Skull stripping is used as preliminary step in many MRI sequences to remove extra-meningeal tissues from the MRI volume of head. This algorithm employs a edge detector to find the boundary between the brain and skull. In T1 scan there exists a dark space between Cerebral Spinal Fluid (CSF). This algorithm employs Morphological operators to enhance the edge detection result and gives better separation of tissues. Finally, the result is improved by the application of Anisotropic Diffusion filter.

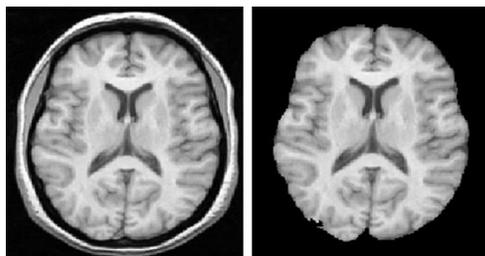


Fig 4: (a) original image (b) Skull Stripped image

### b. Histogram Equalization

The occurrences of various gray levels and the relative frequency of the image is represented in the histogram. Histogram equalization provides a standard technique for altering the contrast and dynamic range of picture by modifying that picture such that histogram of picture's intensity has desired appearance. Comparing to contrast stretching, operators of histogram modeling may use nonlinear and non-monotonic transfer

functions to use between the values of input pixel intensity and output picture. This technique makes use of monotonic, nonlinear mapping in which the intensity of pixel in the picture is reassigned such that the uniform distributions of intensities are accommodated in the output. The result of this method on MRI image is shown below.

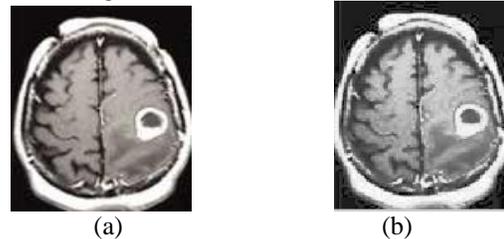


Fig 5. a) The input MRI image b) Histogram Equalized image.

## 3. Level Set Segmentation:

This segmentation algorithm's work is to represent the given curve or surface at a particular time  $t$  as the zero level set of a certain function  $u(t, \mathbf{x})$ , that is called as levelset function. Thus the initial surface is the set  $\{\mathbf{x} \mid u(0, \mathbf{x}) = 0\}$ . The speed of point on the surface will be represented by  $F(t, \mathbf{x})$  and is denoted as the speed function. For points on the zero level set it is usually determined by physical models. The speed function  $F(t, \mathbf{x})$  usually dependent on the space and time variables.

The surface at a later time  $t_1$  is also the zero level set of the function  $u(t, \mathbf{x})$ , namely  $\{\mathbf{x} \in \mathbb{R}^n \mid u(t_1, \mathbf{x}) = 0\}$ . This gives rise to the level set equation

$$u_t + F(t, \mathbf{x}) \|\nabla_{\mathbf{x}} u\| = 0,$$

$$u(0, \mathbf{x}) = u_0(\mathbf{x}) \text{ Given,}$$

In the unknown variable  $u$ , where  $u(0, \mathbf{x})$  determines the initial surface. Now in order to use the level set method a necessary initial function  $u(0, \mathbf{x})$  has to be determined first. The obvious choice for initialization is the signed distance function of a point from the given surface. This function is the common distance function multiplied by  $-1$  or  $+1$  depending on which side of the surface the point lies in. The common distance function of a point  $\mathbf{x}$  from a set  $M$  is then defined by  $d(\mathbf{x}, M) := \inf_{y \in M} d(\mathbf{x}, y)$ , where  $d$  is usually the Euclidean metric.

**Extending the Speed Function**

The results of the speed function at the zero level set must be covered to the entire area of the active points such that the level set function retains the shape of the signed distanced function. This can be ensured by requiring

$$\nabla_{\mathbf{x}}u \cdot \nabla_{\mathbf{x}}F = 0.$$

Assuming that  $F$  and  $u$  are smooth, it is straightforward to show that the signed distance function is retained at all times under this requirement [122,154]. Initially we have  $\|\nabla u(0, \mathbf{x})\| = 1$ . Using the level set equation  $u_t = -F\|\nabla u\|$ , the calculation

$$\frac{d\|\nabla u\|^2}{dt} = 2\nabla u \cdot \frac{d\nabla u}{dt} = -2\nabla u \cdot \nabla F\|\nabla u\| - 2\nabla u \cdot \nabla\|\nabla u\|F = 0$$

shows that  $\|\nabla u\| = 1$  always holds. Indeed the first term is zero because of the assumption and the second term is zero since  $\|\nabla u(0, \mathbf{x})\| = 1$ . Thus one solution is  $\|\nabla u\| = 1$  and a uniqueness result for this differential equation implies that  $\|\nabla u\| = 1$  always holds.

**4. Thresholding**

Thresholding is a way of segmenting the image based on the intensities present in the image as well as the colors of the image. Thresholding technique works on both grayscale & color image. The output of the Thresholding will always be a segmented binary image. The black pixels in the binary image represents background of the image and white pixels corresponds to foreground. In many implementations of Thresholding the segmentation is based on the intensity threshold parameter. In every pass of Thresholding algorithm each pixel is compared to the threshold, if pixels intensity is greater than threshold value the pixel is set to white in the output image else it is set to black.

**III. Proposed Approach**

The proposed work enforces an effective system for the recognition of tumor from a input brain MRI and identifies the data extracted for many applications. This proposed work can be used in the area of medical imaging such as Computer assisted diagnosis and radiology etc. This work will be useful under hospitals for predicting early brain tumor cells using levelset and edge segmentation. The complete details of the proposed approach is explained in the below sections.

**Image Segmentation**

Segmentation is a process of dividing the images into its constituent regions; the level of division depends on the problem under investigation. i.e., the division of the image should cease when the boundary of the tumor is able to be identified. The main intention of segmentation is to separate the tumor from its background. The biggest problem in the tumor edge detection process is that the tumor cells near the boundary of the MRI is very fatty, thus looks very dark on the MRI, which is very confusing in the edge detection process. To overcome the problem, preprocessing to the acquired image was performed. First, Skull Stripping was applied for removal of extra-meningeal tissues from the MR Images. In the proposed approach, the Level Set coding was used to obtain the exact boundaries which were the main problem with conventional approach. The proposed approach applies a Thresholding and a region localization approach to obtained increased segmentation accuracy.

Segmentation technique to separate the tumor cells from the background image and Image enhancement technique to improve the contrast between the Tumor regions and the MRI of the brain.

**1. Thresholding**

Thresholding is a sort of segmentation in which labelling of the pixels is done either as object of interest or background image based on the binarized gray level. Before segmenting the image Thresholding converts the image into binary image. Thresholding divides the image regions into objects and image background. Segmentation techniques detect edges; these edges comprise of both normal edges as well as tumor edges. But tumor edges are always characterized by higher intensity. So by choosing suitable threshold value one can remove the background image from the object of interest. In every scan of algorithm, a dynamic threshold value is calculated, denoted as  $T$ . this  $T$  is calculated by solving an equation on collection of pixels in the image (mask). A mask equation is obtained by using two mask operators and then each pixel threshold value is calculated for every 3 X 3 mask (sub-band). Usually dynamic Thresholding technique gets dissimilar target threshold for dissimilar masks of the image.

Each block  $e_s$  is then correlated to  $T$  to get a binary image ( $e$ ).

The threshold  $T$  is determined by

$$T = \frac{\sum(e_s(i,j)Xs(i,j))}{\sum s(i,j)} \dots\dots\dots (5)$$

Where

$$s(i, j) = \max(|g_1 ** e_s(i, j)|, |g_2 ** e_s(i, j)|)$$

and

$$g_1 = [-1 \ 0 \ 1], g_2 = [-1 \ 0 \ 1]^t$$

2-Dimensional linear convolution is represented by “\*\*” in equation 5. A 5 X 5 sub mask ( $e_s$ ) of the image is shown in figure 6. The masked matrix element S(P8) is determined as shown in Equation 6.

$$\begin{pmatrix} p_1 & p_2 & p_3 & p_4 & p_5 \\ p_6 & p_7 & p_8 & p_9 & p_{10} \\ p_{11} & p_{12} & p_{13} & p_{14} & p_{15} \\ p_{16} & p_{17} & p_{18} & p_{19} & p_{20} \\ p_{21} & p_{22} & p_{23} & p_{24} & p_{25} \end{pmatrix}$$

Figure 6.5x5 image sub-band ( $e_s$ )

$$s(p_8) = \max(|p_9 - p_7|, |p_{13} - p_3|) \dots\dots (6)$$

Seeking similar operations to each pixel, all S (i, j) elements can be determined for each detail component sub-band. Using Equation 5, threshold ‘T’ can then be computed and the binary edge image ( $e$ ) is then given by

$$e(i, j) = \begin{cases} 255, & \text{if } e_s(i, j) > T \\ 0, & \text{otherwise} \end{cases} \dots\dots (7)$$

**2. Region localization**

The basic improvement required in the MRI image is an increase in contrast of the image. Human eye cannot percept the contrast present between the brain and the tumor region. Thus, in order to increase the contrast between the tumor region and normal brain, a segmentation filter is used to the MRI image, which produces perceptible improvement in the contrast of the image. Segmentation filters work to emphasize the changes, i.e. by expanding image intensity at the boundaries to emphasizing fine sharp details and enhancing the blurred detail. Most of the segmentation filters uses a mask of 3 \* 3 size pixel neighborhood. For every resulting pixel mask estimates the weighted addition of respective input pixel in the image and its surrounding eight pixels. The weight of the middle pixel is positive and for the bordering pixels it is negative. The entire intensity of the image is unspoilt by organizing their sum of the weights equal to one. In order to extract the tumor region, we use morphological operators and logical operators. The non-tumor regions are characterized by separate

vertical edges, diagonal edges and horizontal edges. Where-in tumor regions all the edges are inter mixed together. The edges of the tumors are generally short and interconnected with each other in various orientations. To connect isolated tumor edges in each block of the image morphological erosion and dilation operators are used. The morphological operators are mainly used on the binary images. Erosion operator is used to weaken the edges of the prominence pixels. This operator basically shrinks the size of foreground pixels and results in holes for the larger area. Erosion operator expects two tuple data as input, such as input image and structuring element (Kernel). The structuring element is made up of a pattern represented as the co-ordinates values of various discrete sets of points with respect to any origin.

1	1	1
1	1	1
1	1	1

Fig 7: Structuring element

Figure 7 shows an example of structuring element. In every computation the origin of the image is indicated by a circular shaped ring surrounding any point. The origin needs not to be present in the middle of the structuring element but in most of the cases it is. The most commonly used structuring element is 3 \* 3 grids with origin present at the center. The morphological operation translates each pixel position in the image in turn to the origin of the structuring element and then compares with underneath image pixel values. The comparison details and outcome depends on which morphological operator used.

**IV. Results and Discussion**

This section illustrates the performance evaluation of proposed approach. To test the proposed approach, various MRI images were used. For each and every MRI image, the proposed approach tends to segment the region with exact tumor. The obtained results are shown below:

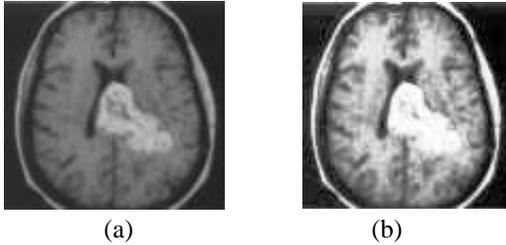


Figure 8. (a) Original Test sample (b) Histogram equalized image

Figure.8 (a) represents the original MRI image used for testing. Initially, to enhance the illumination and to eliminate the noise effect, the histogram equalization is applied and the obtained histogram equalized MRI image is shown in figure.8 (b).

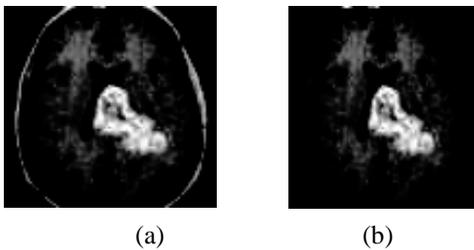


Figure 9. (a) Intensity Mapped Image (b) Boundary region extraction

Figure.9 (a) shows the intensity mapped MRI image. Intensity mapping is done here to obtain the uniform intensities at each and every pixel thus; the region with abnormal intensities will be highlighted. This will reduce the segmentation complexity. After mapping intensity, the image is subjected to the extraction of a region with outer skull region as shown in figure.9(b).

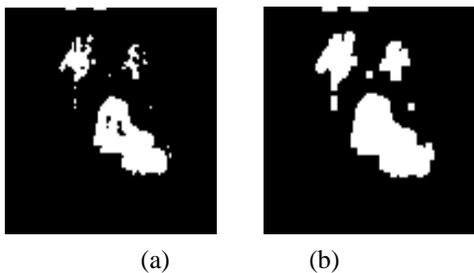


Figure 10. (a) Threshold binarized image (b) Recurrent segmentation image

After obtaining the extracted region with outer skull region, the image is subjected to Thresholding. By Thresholding the image will be binarized and the region with abnormalities will be in gray color and the remaining region is the black color. Figure.10(a) shows the thresholded binarized image and the recurrent segmentation image is shown in figure.10(b).



Figure 11. Region filled image  
Region filling is done to avoid the edge cuttings. By region filling, the edges will be clearly highlighted and the regions will be obtained with exact boundaries. Figure.11 shows the region filled image having regions with clear boundaries.



Figure 12. Segmented Mass regions  
Figure.12 shows the final extracted region in which the tumor is existing. The above figure also shows the region with clear edges.

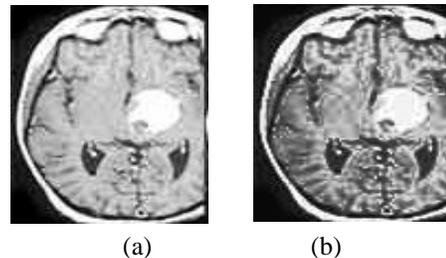


Figure 13. (a) Original Test sample (b) Histogram equalized image

Figure.13 (a) represents the original MRI image used for testing. Initially, to enhance the illumination and to eliminate the noise effect, the histogram equalization is applied and the obtained histogram equalized MRI image is shown in figure.13 (b).

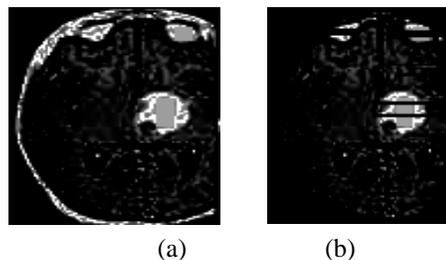


Figure 14. (a) Intensity Mapped Image (b) Boundary region extraction

Figure.14 (a) shows the intensity mapped MRI image. Intensity mapping is done here to obtain the uniform intensities at each and every pixel thus; the region with abnormal intensities will be highlighted. This will reduce the segmentation complexity. After mapping intensity, the image is subjected to the extraction of a region with outer skull region as shown in figure.14(b).

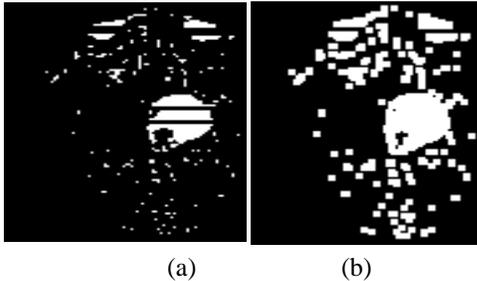


Figure 15. (a) Threshold binarized image  
(b) Recurrent segmentation image  
After obtaining the extracted region with outer skull region, the image is subjected to Thresholding. By Thresholding the image will be binarized and the region with abnormalities will be in gray color and the remaining region is the black color. Figure.15(a) shows the thresholded binarized image and the recurrent segmentation image is shown in figure.15(b).



Figure.16. Region filled image

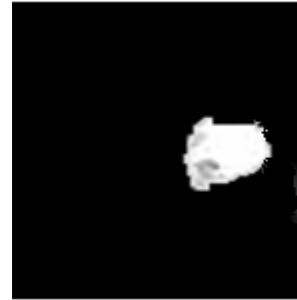


Figure.17. Segmented Region of Mass

Figure.17 shows the final extracted region in which the tumor is existing. The above figure also shows the region with clear edges.

Along with this experimental evaluation, the proposed and conventional approaches are subjected to subjective quality test experiment.

**Evaluation**

For assessing the accuracy of segmentation we have considered three parameters: Dice Similarity Coefficient (DSC), Positive Predictive Value (PPV) and Sensitivity. The DSC [51] measures the overlap between the manual and the automatic segmentation. It is defined as,

$$DSC = \frac{2TP}{FP + 2TP + FN'}$$

Where TP, FP and FN are the numbers of true positive, false positive and false negative detections, respectively. PPV is a measure of the amount of FP and TP, defined as,

$$PPV = \frac{TP}{TP + FP}$$

Lastly, Sensitivity is used to evaluate the total number of TP and FN detections, being represented as

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

Table 1. Comparative Results of Proposed Method and Conventional LS Method

Dataset	Method	Grade	DSC	PPV	Sensitivity
Leader board	Proposed	HGG	0.87	0.92	0.85
		LGG	0.66	0.53	0.88
		Combined	0.83	0.86	0.84
	Conventional LS Method	Combined	0.70	0.65	0.87
Challenge	Proposed (with Preprocessing)	HGG	0.85	0.87	0.85
	Proposed (no rotations)	HGG	0.82	0.77	0.92
	Proposed (with rotations)	HGG	0.86	0.82	0.90
	Conventional LS Method	HGG	0.86	0.80	0.90

Table.1 shows that the proposed approach results in better accuracy comparing to Conventional Level Set Method. By examining the literature one can conclude that no method is yet able to score the first place in all performance metrics for segmentation of brain tumor.

### V. Conclusion

We have presented an improvised brain tumor recognition system for the MR images using the level set coding and dynamic Thresholding binarization logic. It is found that the system proved in better segmentation during the tumor recognition process. The accuracy level and iteration time is found to be improved considerably in tumor recognition compared to the conventional LS segmentation. Since implementation of proposed method is done on single image so no worries of variance in intensity across multiple MR images. This method is suitable for 2-D MRI images; in future we will try to extend it for 3-D MRI images

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