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Histogram Related Threshold Technique for Region based Automatic Brain Tumor Detection

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Abstract

Background: A tumor is a gathering of tissues that grows in a disordered manner that normalizes growth. Brain tumor detection in MRI, CT, PET scan is most interesting area in the medical image field. The main objective is developing a novel technique i.e., histogram based region related detection of brain tumor. **Method:** An automatic algorithm for detection of brain tumor and its tumor segmentation using MRI T1 weighted, MRI flair images is presented. The proposed algorithm divides the brain into four regions Top half, bottom half, right-side half and left side half. It utilizes pixel intensity levels obtained from the each region histogram of an image for the segmentation as the result is more useful to analyze the raw image. The mathematical descriptions like statistical parameters of the proposed approach are presented in detail. The proposed algorithm reduces misclassification errors where the minimal dissimilarity within each object by its own cannot guarantee the desirable result and a comparison is made with the existing techniques like entropy and moments thresholding. **Findings:** Brain tumor is effectively detected and located in the brain by dividing the whole brain image into four regions. After dividing the brain into four halves histogram is applied individual part of the divided region. The histogram is the no of the amount of the pixel intensity. A performance evaluation is also done by checked the results by reference/ground truth MRI images through which sensitivity and accuracy of the proposed algorithm can be determined. The performance measures Sensitivity, Specificity, Accuracy and Similarity index obtained from the proposed method are 91.429%, 86.667%, 90%, 92.754%, respectively. The statistical parameters reveal the algorithm stability and reliability. The results obtained by this algorithm are included in the study and found comparatively better than the results obtained with Entropy and Moments Thresholding techniques. **Applications:** The proposed histogram based brain tumor detection and analysis efficiently dealt with detection of brain tumor and image classification procedure. Doctors practice the information obtained from the algorithm results to verify the most suitable course of treatment.

Keywords: Entropy, Histogram, Morphology, Moments, Segmentation

1. Introduction

One of the important steps in most of the medical imaging analysis is to extract the boundary of an area of our interest i.e. in this study a tumor region. Detection of Brain tumor and its tumor segmentation is occur also semi manually/fully automatically[1]. On the other hand, automatic detection overcomes most of the disadvantages of manual detection by using image segmentation and other meticulous approaches. Automated segmentation approaches developed earlier, such as segmentation based on outlier detection[2]. This method consists of three major stages. First, the algorithm identifies abnormal areas, where the intensity levels of the normal brain is deviated from the abnormal tumor area. The second step, the abnormal area yet again composed of both tumor and edema. Lastly, approximations for abnormal areas of the given appearance of intensity parameters are achieved, these properties are very useful in the region growing segmentation[3], histogram based detection and segmentation[4,5] used adaptive technique. Recent works have comprised the association detection of tumor is likely possible with K-Nearest Neighbor, Nearest Neighbor, Minimum Mean Distance method, ANN and (SVM),

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particle swarm optimization[6] all these are supervised classifiers .Clustering methods, fuzzy c-means and k-Means algorithms are come under the unsupervised methods[7–9]. Different algorithms were developed to detect brain tumors from MR Images based on contrast enhancement[10] and segmentation, feed forward neural network and based on symmetry analysis are presented in[11–13] respectively.

In MRI Brain images, typically comprise noise, non-uniform intensity levels and occasionally deviation. The MRI segmentation is completed by means of textural features. Entropy method is an amount statistical of randomness that can be useful to describe the surface texture of the given input image. For a given image, its entropy can be secure roughly with the histogram of the image[14]. Initially, geometric moments were applied. Though, the usage with geometric moments takes the subsequent difficulties. They are delicate to error of digitization and slight shape deformations and Equation (2).

Author in[16] suggested an procedure distributed with classification & segmentation procedure for tumour examination with practice for extraction of feature approaches. Author in[17] presented an algorithm to eliminate the stumbling blocks associated with the segmentation techniques. Author in[18] found out the accuracy by comparing the different methods like region based, thresholding and watershed. In the current study other statistical parameters are also calculated along with accuracy. Author in[19] executed a methodology to detect and classify brain tumor utilizing information from EEG signals. RBF is used to extract the acquired information from EEG signals.

Histogram related thresholding technique for region based automatic segmentation of tumor is suggested in this work, is based on intensity of pixel shades acquired with the image histogram. The procedure is executed for detection brain tumor and segmentation of MRI T2, Flair and T1 weighted images. It is significant to reflect that in preceding research, the selection of threshold methods was achieved physically for the detection and segmentation, but in this proposed work, a novel method is established for the threshold value selection for automatic segmentation for each image separately. The proposed algorithm performs three steps, segmented brain tumor is highlighted. First, preprocessing of an image is done in order to convert an image into a default size and format. Second, the histograms of four regions of the image are considered independently. Once this is done, the currently designed automatic technique for threshold selection is applied in order to transform the grayscale picture into a binary image by means of a histogram thresholding method. Finally, morphological operations are performed for removing unwanted areas existing in an image. Depending on the objects detected in the image its area and other statistical parameters are calculated.

The automatic thresholding technique is based on the accurate selection of threshold value so that only the objects of interest are highlighted. It is interested by the impression similarities of intensity among brain abnormal areas and normal areas[21], the highest no of pixels are measured at each area for separately gray scale intensity level[22].

2. Methodology

The algorithm presented in this section is performed by an automatic thresholding technique in its place of physically changing the threshold for each image. The threshold selection is done automatically based upon the mean and standard deviation of each region among four sub-regions. The algorithm is divided primarily into three stages.

- Pre-processing of the MRI brain scan images.
- Image segmentation.
- Morphology.

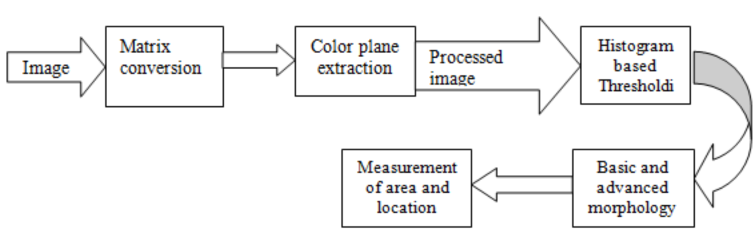


Figure 1. Proposed methodology.

2.1 Acquisition of MRI Images

MRI gray-scale is loaded to the algorithm and displays them with a default size of 200×200. A Gray-scale transformed image is well-defined by means of a huge matrix, its levels are numerical values between 0 and 255, black color represents the o level and 255 represents the white gray level[22].

In the RGB color plane, gamma expression can be expressed as

$$c_{linear} = \begin{cases} \frac{c_{argb}}{12.92} & c_{srgb} \leq 0.04045 \\ \left(\frac{c_{srgb}+0.055}{1.055}\right)^{2.4} & c_{srgb} > 0.04045 \end{cases} \quad (1)$$

Where y luminance plane is expressed as

$$Y = .2126R + .7152G + .0722B \quad (2)$$

For detection of tumor, 50 MRI images were tested with this algorithm.

2.2 Color Plane Extraction

In a 32-bit color image is coded in memory as moreover an RGB or an HSL image. RGB images quantity color data by means of 8 bits each for the red plane, green plane, and blue plane of color. In the HSL, color data is represented as 8 bits respectively for hue, saturation, and luminance, the alpha plane is used in both cases.

2.3 Color Model Transformation from RGB to HSI

The RGB model is a simple and primary color model However, this model not precise for digital image processing applications in the meantime its R, G and B plane values are extremely interrelated, So, R, G, and B elements are frequently changed into further color models.

For clear perceptual systems the HSI color model is the most demonstrative attractive model, and it is extensively useful in any image processing applications.

HSI model benefits other than RGB Model:

- In HIS model, the intensity plane is greater at bright color pixels and less intensity at dark pixels.
- Hue and Saturation planes have very excellent correlation with respect to human visualization perception.
- Comparing RGB mode to HIS model, segmenting the regions is generally attractive and effective.
- The hue plane specifies the dominant wavelength.
- Saturation axis specifies the how much amount the color is mixed with white color.
- The intensity axis specifies the illumination of a color.

2.4 Histogram Analysis

Histogram of digital image can be defined by frequency occurrence of pixels in a given image. In an 8 bit gray scale image 256 gray intensity shades are presented. For color images, three different histograms of Red, Green, Blue can also developed.

It is evident from the statistics of four histograms that the mean value in the right half and lower half are greater than 50 where maximum values are 255. The average standard deviation from the mean value is also high in these regions. By this it is assumed that the tumor lies in the regions as there are more high intensity pixels. (Refer Table 1).

2.5 Thresholding

Threshold segmentation is done to covert a grayscale image to a binary. In this thresholding technique key point is, choosing a threshold value for exact segmentation of the region.

2.5.1 Moments Thresholding

For the input image of gray level moments are calculated before applying the thresholding. The moments of that thresholded image are retained unaffected with the selection of thresholds. The image pixel intensities of definite specific weighted average (moment) is called a moments.

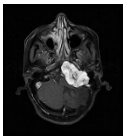
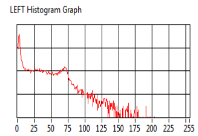
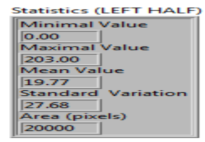
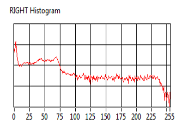
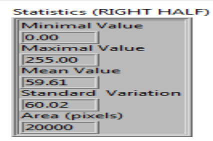
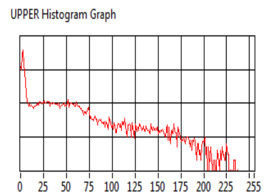
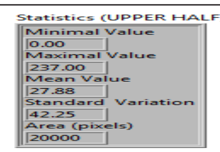
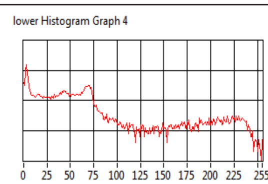
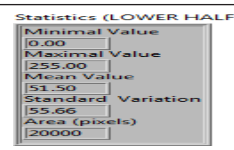
The segmented head for center of mass is expressed as

$$\bar{x} = \frac{1}{N}\sum_{(x,y)}\sum_{\in T} x \bar{y} = \frac{1}{N}\sum_{(x,y)}\sum_{\in T} y \quad (5)$$

2.5.2 Entropy

Entropy is explained as statistical amount of changeability, usage of describe the image texture also depends on the random variable, but only depends on the distribution. The conditions relate to the gray shades, where the separate pixels can accept. For instance, in an 8-bit image there are 256 gray states, suppose all gray levels are equally adjusted, like histogram equalized, the extent of gray levels are extreme The equation for entropy H can be expressed as

Table 1. Histogram showing pixel intensity values

<table>
<tr><th>Input Image</th><th>brain region</th><th>Histogram Graph</th><th>Statistics</th></tr>
<tr><td rowspan="4"></td><td>Brain Left Region</td><td>
</td><td>
</td></tr>
<tr><td>Brain Right Region</td><td>
</td><td>
</td></tr>
<tr><td>Brain Upper Region</td><td>
</td><td>
</td></tr>
<tr><td>Brain Lower Region</td><td>
</td><td>
</td></tr>
</table>

$$H = -\sum_{x=0}^{n-1} pk \ \log2(pk) \qquad (7)$$

Where Number of gray levels = n
pk is probability of the image gray level

2.5.3 Proposed Automatic Threshold Selection

Step 1: Calculate avg. std. variation for 4 regions.
Step 2: calculate sum= Σ mean of no mask regions.

In the proposed thresholding technique, a predefined value is compared to the standard deviation of each region. Based on this result image masking is performed. After the masking operation is completed threshold value is selected by adding the means of all the regions. (Refer Table 2).

2.6 Morphology

Morphological operations of an image[23] are established on just altering an given image with a exact physical element[24,25].

In this procedure, detection of the tumors in the brain the using Morphological segmentation is applied, the basic actions comprises opening, closing, erosion and dilation processes[26]. The expressions for dilation and erosion are specified by Relations (8) and (9).

Table 2. Novel thresholding technique

If avg. std. variation < 40	If Avg. std. variation >= 40
A. No masking	A. Masking enabled Max pixel <249 The region is masked.
B .Threshold Selection	B. Threshold Selection
If sum ≥ 100 Threshold = sum	If sum < 65 Threshold = sum×2.5
If Sum <100 Threshold= sum×0.5	If the sum is between 65 – 90 Threshold = sum×2 If the sum is between 90 – 120 Threshold = sum×1.5 If the sum is between 120 - 175 Threshold = sum If the sum is between 175 - 250 Threshold = sum÷1.5 If the sum is between 250 - 360 Threshold = sum÷2 If the sum >360 Threshold = sum÷2.5 If sum >45 Threshold = sum÷3

$$(A \oplus B) = \left[x: (\hat{B})_x \cap A \neq \emptyset\right] = \cup_{x \geq B}(A_x) \quad (8)$$

$$(A \ominus B) = \left[x: (\hat{B})_x \subseteq\right] = \cap_{x \leq B}(A_x) \quad (9)$$

The expression for Opening and closing operations of gray scale images are identical to binary images and are represented by the Relations (10) and (11).

$$(AoB) = (A \ominus B) \oplus B \quad (10)$$

$$(A.B) = (A \oplus B) \ominus B \quad (11)$$

3. Simulation Results

The following Table gives the details of the tumor area present along with the location of it in the brain according the hemispheres of the brain. This technique is verified with the ground truth images and reports are taken from the hospitals. On this ground truth images this technique is applied and segmented images are obtained .And also tumor in each quadrant of the brain in pixels are achieved. Refer Table 3.

The below Table gives the details of simulation output for estimation of statistical parameters. (Refer Table 4. and Figure 4).

3.1 Performance Evaluation

True Positive (TP) = Patients / images histologically confirmed to have Tumors are correctly detected to contain Tumors.

True Negative (TN) = Patient / Images Histologically confirmed to have No Tumor are correctly detected to contain No Tumors.

False Negative (FN) =Patient / Images Histologically confirmed to have tumors are in-correctly detected to contain No Tumors.

False Positive (FP) = Patients / Images histologically confirmed to have No tumors are in-correctly detected to contain Tumors.

Sensitivity: (True Positive Rate) processes the portion (%) of Positives which imperfectly recognized as having the illness.

Sensitivity = [Σ TP / Σ (TP+FN)] *100

Specificity: (True Negative Rate), processes the portion (%) of Negatives which are properly recognized as NOT having the illness.

Specificity = [Σ TN / Σ (TN+FP)] *100

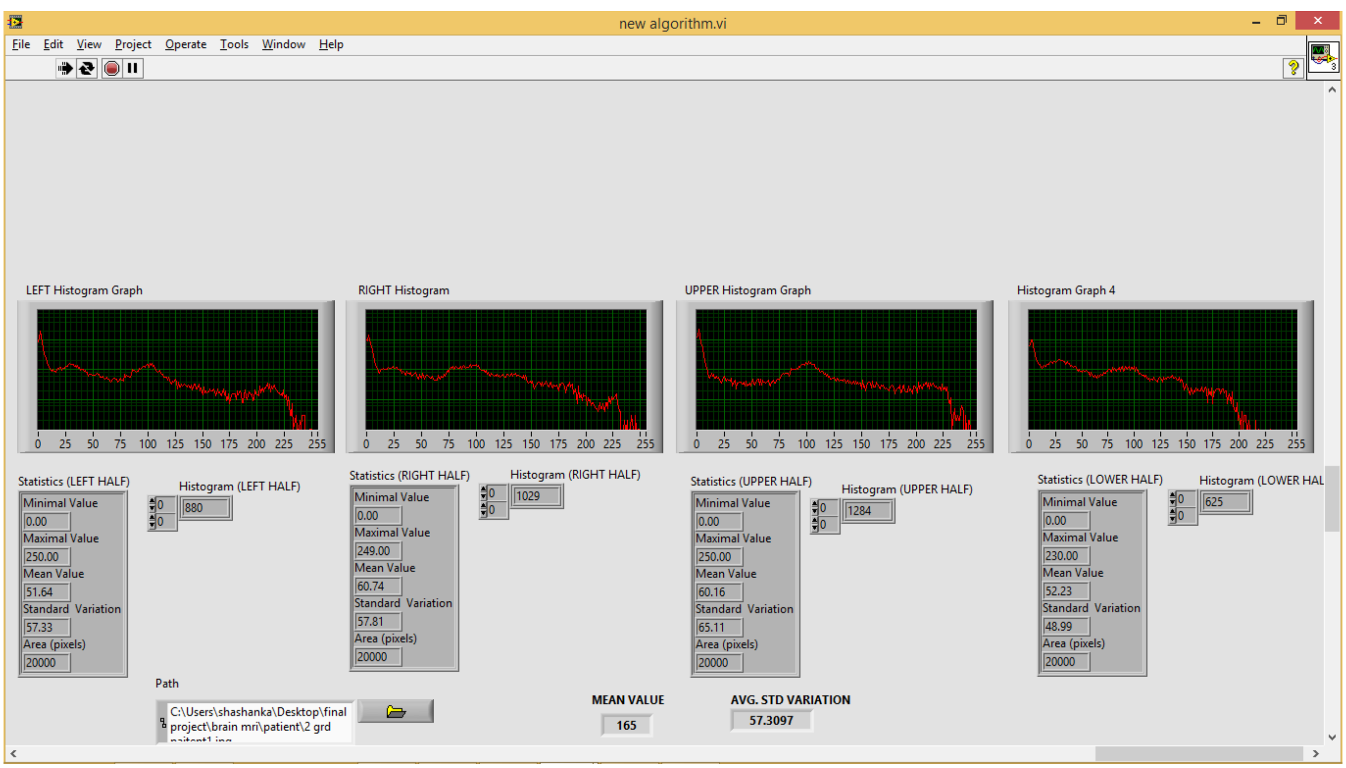


Figure 2. Simulation results. Patient 2. Histogram analysis.

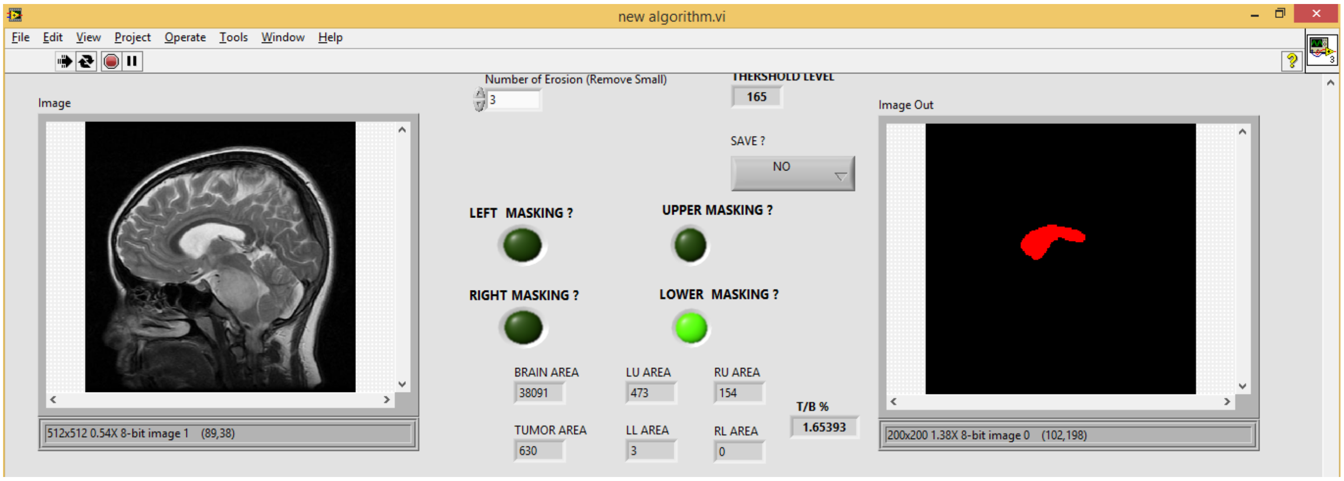
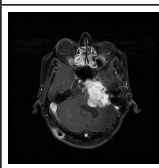
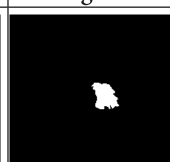
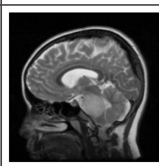
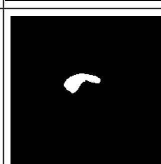
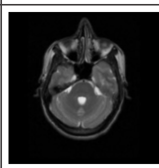
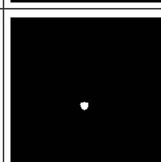
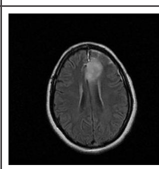
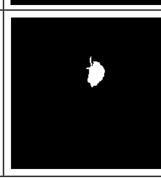


Figure 3. Patient-2 tumor segmentation.

Table 3. Tumor segmentation and its location for ground truth images

Sl. No,	Input images	Output images	Tumor area region wise(in pixels)			
			Left upper	Right upper	Left lower	Right Lower
PATIENT 1			0	0	0	791
PAITENT 2			473	154	3	0
PAITENT 3			0	0	73	14
PAITENT 4			1	552	0	0

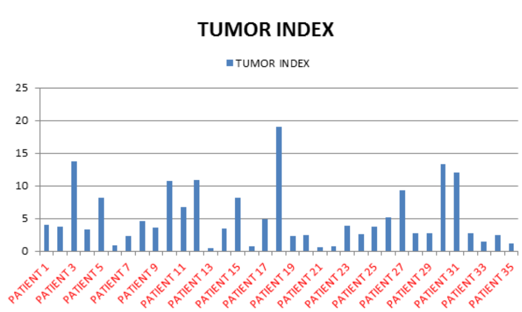


Figure 4. Bar graph of tumor index.

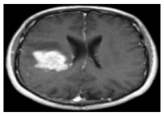
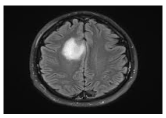
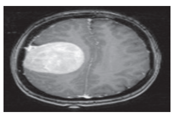
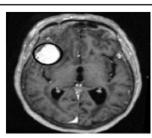
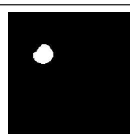
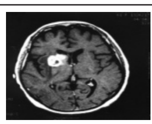
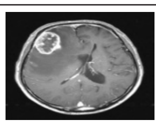
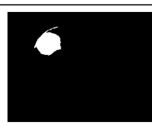
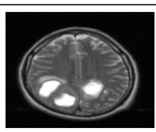
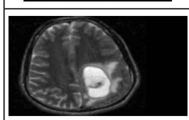
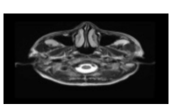
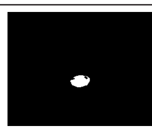
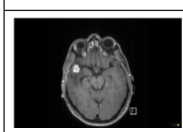
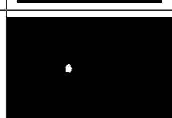
Similarity Index: It is a measure of the similarity between the un-distorted reference Image and the distorted image (Image containing the tumor).

Similarity Index= 2 ∑ (TP) / [2 ∑ (TP) + (FN+FP)] *100

Accuracy: It is a measure of the closeness of the measurements (Detections) to true Value.

Accuracy = [∑ TP+TN / ∑ TP+TN+FN+FP)] *100

Table 4. Tumor segmentation and its location for other patients

Input images	Output images	Brain area (b) (In pixels)	Tumor area (t) (In pixels)	Ratio (B/t) %	Tumor area region wise (In pixels)			
					Left upper	Right upper	Left lower	Right Lower
		30817	1231	3.995	448	0	783	0
		20467	773	3.777	771	0	2	0
		26793	3367	13.686	1955	1	1711	0
		28385	768	2.706	768	0	0	0
		32970	484	1.468	474	0	10	0
		24283	1108	4.563	1108	0	0	0
		21058	1431	6.796	0	0	948	483
		21596	1767	8.182	0	0	841	926
		15323	405	2.643	0	0	191	214
		12046	96	0.797	96	0	0	0

Precision: It is definite as the accuracy as the combination of both actuality and exactness.

Precision = ∑ (TP) / ∑ [(TP) + (FP)] *100

The algorithm is tested on 50 patients MRI images, Brain tumor effected images are 35 and 15 are unaffected images with a brain tumor. In proposed Region based brain tumor detection technique 32 images are found as true positives, 13 as true negatives, 02 as false positives and 03images are detected as false negatives. But in the case of Entropy and moments thresholding, no tumor is detected as tumor so the true positives are less 20, 25 respectively. The algorithm is tested with normal images, true negatives are 13 proposed technique and 12, 11 for the Moments and Entropy Technique. False positive are 07, 14 which are high in the moments, Entropy and less in proposed technique. (Refer Table 5. and Table 6).

Table 5. Comparison with different threshold techniques

Method	Total Brain Images	Moments	Entropy	Proposed method
True Positives	50	25	20	32
True Negatives	50	12	11	13
False Positives	50	07	14	02
False negitives	50	06	05	03

Table 6. Statistical parameters

Parameter	Entropy Method (%)	Moments Method (%)	Proposed Method (%)
Sensitivity	80	80.64	91.42
Specificity	44	63.15	86.66
Accuracy	62	74	90
Similarity index	66.66	67.79	92.75

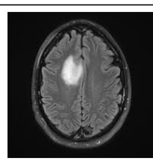
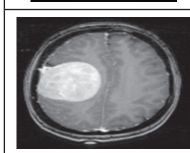
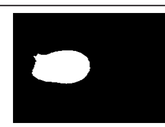
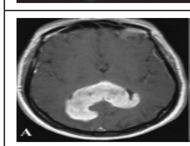
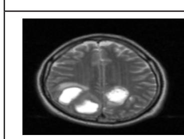
In this comparative study, it is concluded that, the proposed technique is efficient compared to the entropy and moments. The quantitative and qualitative parameters of the proposed technique are greater when compared to these two techniques. In proposed algorithm Sensitivity, Specificity, Accuracy, Similarity index are 91.42, 86.66, 90, 92.75 etc and are more high than the moments and Entropy technique and comparative study is shown in the Table 7.

3.2 Comparison of Proposed Technique with Entropy and Moments Techniques

4. Conclusion

An algorithm is proposed using LabVIEW 2012. The performance analysis this technique, calculated qualitatively & quantitatively by means of the standard images. It decreases misclassification errors where the minimal dissimilarity within each object by its own cannot guarantee the desirable result. The benefit of this proposed technique is developed with the graphical programming language LabVIEW that, it offers a robust and competent environment and tool for making fast, slight complex and valuable algorithm.

Table 7. Comparison with entropy and moments techniques

Input image	Different threshold technique		
	Entropy	Moments	Novel technique
			
			
			
			

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