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

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. 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 the highest no of pixels are measured at each area for separately gray scale intensity level.

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.](image-url)
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 0 level and 255 represents the white gray level. In the RGB color plane, gamma expression can be expressed as
\[
\gamma_{\text{linear}} = \left\{ \begin{array}{ll}
\frac{y_{\text{rgb}}}{123.12} & \text{if } y_{\text{rgb}} \leq 0.04045 \\
\left( \frac{y_{\text{rgb}} - 0.04045}{0.055} \right)^{2.4} & \text{if } y_{\text{rgb}} > 0.04045
\end{array} \right.
\] (1)

Where y luminance plane is expressed as
\[
Y = 0.2126R + 0.7152G + 0.0722B \tag{2}
\]

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.

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
\[
\bar{x} = \frac{1}{N} \sum_{(x,y)} x, \bar{y} = \frac{1}{N} \sum_{(x,y)} y
\] (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
Histogram Related Threshold Technique for Region based Automatic Brain Tumor Detection

Where Number of gray levels = \( n \)
\( p_k \) is probability of the image gray level

\( H = - \sum_{k=0}^{n-1} p_k \log_2(p_k) \)  

(7)

2.5.3 Proposed Automatic Threshold Selection

Step 1: Calculate avg. std. variation for 4 regions.
Step 2: calculate sum = \( \sum \) 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 are established on just altering an given image with a exact physical element.

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. 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               | If sum < 65                 |
| Threshold = sum             | Threshold = sum×2.5          |
| If Sum <100                | If the sum is between 65 – 90|
| Threshold= sum×0.5          | Threshold = sum×2           |

Table 1. Histogram showing pixel intensity values

| Input Image | brain region | Histogram Graph | Statistics |
|-------------|--------------|----------------|------------|
| Brain Left Region | [Image] | [Graph] | [Statistics] |
| Brain Right Region | [Image] | [Graph] | [Statistics] |
| Brain Upper Region | [Image] | [Graph] | [Statistics] |
| Brain Lower Region | [Image] | [Graph] | [Statistics] |
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).

\[(A \oplus B) = \bigcup_{x \in B} (A_x)\]  
\[(A \ominus B) = \bigcap_{x \in B} (A_x)\]

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 = \[\frac{\sum TP}{\sum (TP+FN)} \times 100\]

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

Specificity = \[\frac{\sum TN}{\sum (TN+FP)} \times 100\]

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 | ![Input Images](image1) | ![Output Images](image2) | 0 | 0 | 0 | 791 |
| PATIENT 2 | ![Input Images](image3) | ![Output Images](image4) | 473 | 154 | 3 | 0 |
| PATIENT 3 | ![Input Images](image5) | ![Output Images](image6) | 0 | 0 | 73 | 14 |
| PATIENT 4 | ![Input Images](image7) | ![Output Images](image8) | 1 | 552 | 0 | 0 |

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

\[
\text{Similarity Index} = \frac{\sum \text{TP}}{2 \cdot \sum \text{TP} + (\text{FN} + \text{FP})} \times 100
\]

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

\[
\text{Accuracy} = \frac{\sum \text{TP+TN}}{\sum \text{TP+TN+FN+FP}} \times 100
\]

Figure 4. Bar graph of tumor index.
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 = \( \frac{\Sigma (TP)}{\Sigma [(TP) + (FP)]} \) *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 03 images 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 Negatives| 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 |
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) |
| ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |
| ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) |
| ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |
5. References

1. Menze B, Reyes M, Van Leemput. The multimodal brain tumor image segmentation. Medical Imaging IEEE Transactions. 2015; 34(10):1993–2024.
2. Prastawa M, Bullitt E, Ho S, Gerig G. A brain tumor segmentation framework based on outlier detection. Medical Image Analysis. Elsevier. 2004; 8(3):275–83.
3. Mustaqeem A, Javed A, Fatima T. An efficient brain tumor detection algorithm using watershed and thresholding based segmentation. IIJGSP. 2012; 4(3):34–9.
4. Yadav, Kowar MK, Sourabh. Brain tumor detection and segmentation using histogram thresholding. IJEAT. 2012; 1(4):16–20.
5. Forbes I, Doyle S, Dojat M, lorenzo DG, Barillot C. Adaptive weighted fusion of multiple mr sequences for brain lesion segmentation. IEEE International Symposium Biomedical Imaging: From Nano to Macro; 2010 Apr. 69–72.
6. Mahalakshmi S, Velmurugan T. Detection of brain tumor by particle swarm optimization using image segmentation. Indian Journal of Science and Technology. 2015 Sep; 8(22). DOI: 10.17485/ijst/2015/v8i22/79092.
7. El-Dahshan E-SA, Hosny T, Salem A-BM. Hybrid intelligent techniques for MRI brain images classification. Digital Signal Processing. Elsevier. 2010; 20(2):433–41.
8. Kinani JMV, Rosales-Silva AJ, Gallegos-Funes FJ, Arellano A. Fuzzy C-means applied to MRI images for an automatic lesion detection using image enhancement and constrained clustering. 4th International Conference on Image Processing Theory, Tools and Applications (IPTA); Paris. 2014 Oct 1-7.
9. Naveen A, Velmurugan T. Identification of calcification in MRI brain images by k-Means algorithm. Indian Journal of Science and Technology. 2015 Nov; 8(29). DOI: 10.17485/ijst/2015/v8i29/83379.
10. Sasirekha N, Kashwan KR. Improved segmentation of MRI brain images by denoising and contrast enhancement. Indian Journal of Science and Technology. 2015 Sep; 8(22). DOI: 10.17485/ijst/2015/v8i22/73050.
11. Kumar EP, Kumar VM, Sumithra MG. Tumour detection in brain mri using improved segmentation algorithm. 4th International IEEE Conference on Computing, Communications and Networking Technology; Tiruchengode. 2013 Jul 1-7.
12. Rajesh T, Malar TSM. Rough set theory and feed forward neural network based brain tumor detection in magnetic resonance images. IEEE International Conference on Advanced Nanomaterials and Emerging Engineering Technologies (ICANMEET); 2013 Jul. p. 240–4.
13. Sachin GN, Khairnar VB Brain tumor detection based on symmetry information. Journal of Engineering Research and Application. 2013; 430–2.
14. Chaudhari AK, Kulkarni JV. Local entropy based brain MR image segmentation. IEEE Advance Computing Conference; Gaziabad. 2013 Feb. p. 1229–33.
15. Iscan Z, Dokur Z, Ölmez T. Tumor detection by using Zernike moments on segmented magnetic resonance brain images. Expert Systems with Applications. Elsevier. 2010; 37(3):2540–9.
16. Shenbagarajan A, Ramalingam V, Balasubramanian C, Palanivel S. Tumor diagnosis in MRI brain image using ACM segmentation and ANN-LM classification techniques. Indian Journal of Science and Technology. 2016 Jan; 9(1). DOI: 10.17485/ijst/2016/v9i1/78766.
17. Prabhu C, Moorthy SN. An improved method to overcome existing problems in brain tumor segmentation. Indian Journal of Science and Technology. 2016 Jan; 9(1). DOI: 10.17485/ijst/2016/v9i1/13734.
18. Baraiya N, Modi H. Comparative study of different methods for brain tumor extraction from MRI images using image processing. Indian Journal of Science and Technology. 2016 Jan; 9(4). DOI: 10.17485/ijst/2016/v9i4/85624.
19. Padmapriya P, Manikanand K, Jeyanthi K, Renuga V, Shivaraman J. Detection and classification of brain tumor using radial basis function. Indian Journal of Science and Technology. 2016 Jan; 9(1). DOI: 10.17485/ijst/2016/v9i1/85758.
20. John N, Wright C, Nabizadeh N. Histogram based gravitational optimization algorithm on single MR modality for automatic brain lesion detection and segmentation. Expert Systems with Applications. Elsevier. 2014; 41(7):7820–36.
21. Saad NM, et al. Segmentation of brain lesions in diffusion-weighted MRI using thresholding technique. IEEE Conference on Signal and Image Processing Applications (ICSIPA); Kaula Lampur. 2011 Nov. p. 249–54.
22. Dahab DA, Ghoniemy SSA, Selim GM. Automated brain tumor detection and identification using image processing and probabilistic neural network techniques. IJIPVC. 2012; 1(2):1–8.
23. Hun Y, Aye K. Fuzzy mathematical morphology approach in image processing. World Academy of Science, Engineering and Technology. 2008; 42.
24. Parameshwarappa V, Nandish S. A segmented morphological approach to detect tumor in brain images. 2014; 4(1).
25. Joseph RP, Singh CS, Manikanand M. Brain tumor MRI image segmentation and detection in image processing. IJRET. 2014 Mar; 3(01). eISSN: 2319-1163, pISSN: 2321-7308.
26. Heijmans H. Mathematical morphology: Basic principles. Proc Summer School Morphological Image Signal Process; Zakopane, Poland. 1995 Sep. p. 1–18.

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