Brain Tumor Detection With Tumor Region Analysis Using Adaptive Thresholding And Morphological Operation

Bidhan Biswas
Department of CSE
Sylhet Engineering College
Sylhet, Bangladesh
bidhan536@gmail.com

Hossain Shahid Soroardi
Department of CSE
Sylhet Engineering college
Sylhet, Bangladesh
soroardicse12@gmail.com

Mohammed J. Islam
Department of CSE
Shahjalal University of Science and Technology
Sylhet, Bangladesh
jahir-cse@sust.edu

***Abstract*—Tumor in brain is life threatening but proper detection of tumor at early stage may save many lives. In our research, we have proposed an adaptive threshold value selection technique with morphological operation for the detection of brain tumor which is very much promising. Our proposed method can adapt with different kinds of intensity values of the pixels of MRI FLAIR image and can detect tumor efficiently. Initially we have detected the highest intensity value of the brightest region assuming as tumorous cell and also specify an intensity value which is covering maximum pixels assuming as healthy cells and their difference is also being calculated. If the difference between the maximum intensity value of the brightest region and the intensity value of any random pixel is in the range of the previous difference, then the pixel is detected as a member of tumor cell otherwise not. In this research, we have used BRATS 2013 and 2015 datasets with accuracy 95% and 89.78% respectively. As our datasets have ground truth value, we have examined our detected images with the ground truth images through the parameters centroid and area.**

Keywords—Adaptive thresholding, Area calculation, BRATS, Brain tumor, FLAIR, Image morphology, MRI.

I. INTRODUCTION

In our body, every moment cells are dying and new cells are growing and when this growth becomes uncontrolled it may turn into a tumor. This uncontrolled cells may appear in the brain which can cause brain tumor. Brain tumors can be categorized into two types: benign or non-cancerous and malignant or cancerous. The characteristics of tumor may differ from size, type and age. Tumor may appear in any part of the brain with any size which makes the task more challenging. Magnetic Resonance Imaging (MRI) are used for brain tumor detection and they are of four types T_1 (T_1 weighted image), T_2 (T_2 weighted image), T_{1c} (T_1 weighted MRI after administration of contrast media) and FLAIR (Fluid Attenuated Inversion-Recovery).

There are various types of techniques to detect brain tumor like watershed segmentation, fuzzy C-means technique, convolutional neural network and so on. Aastha Sehgal et al. [1] have developed their method using Fuzzy C-means technique to extract tumor. They have extracted tumor using circularity as a criteria. Sobel filter and histogram equalization are used for image preprocessing and enhancemen. Deepthi Murthy [2] et al. used sobel filter and histogram equalization in their technique for image enhancement and their method was based on thresholding and morphological operation for the segmentation of brain tumor. K.S.Angle Viji [3] et at. Have introduced a method for improving brain tumor shape approximation for two dimensional and three dimensional visualization which may help for accessing tumor. According to their proposed method, watershed segmentation algorithm does not perform better when the difference of the intensity value of the pixels between the cancerous and non-cancerous region is lower. Morphological processing and thresholding (TMP) have been used by Md. Sujan et al. [4] for detecting brain tumor. They have used the database of BRATS and claimed that their proposed method can detect the tumor correctly for 61 patients out of 72. Henna Hooda et al. [5] have measured the performance of K-means, Fuzzy C-means and region growing and according to their evaluation the performance of K-means algorithm is relatively lower than the other methods for brain tumor segmentation. Bjoern H. Menze et al. [6] have presented that no single algorithm do the best for detecting all sub regions of an image. Swe Zin Oo et al. [7] have used watershed segmentation and morphological operation for tumor segmentation. They have classified the images into two groups: brain with and without tumor. If the is not suspected for tumor then the further process need no to be performed. Histogram thresholding has been used by Manoj K Kowar and Sourabh Yadav [8] to detect brain tumor. V. Amsaveni et al. [9] have classified brain tumor using neural network and gabor filter is used by them to extract the features of the detected tumor. M. Kadkhodaei et al. [10] have used three dimensional super voxels based on intensities to segment tumor. Glioma tumors are segmented by them based on classification of super voxels. A connection between fuzzy c-means (FCM) and cellular automated method has been established by Chaiyanan Sompong et al. [11] for brain tumor segmentation. The method is experimented on the dataset of BRATS 2013 to evaluate the effectiveness of the technique. C. C. Benson et al. [12] have introduced an atlas based marker detection method for solving over-segmentation. They have detected a problem with fuzzy c-means clustering for selecting initial centroid which was solved by using histogram. Finally improved version of fuzzy c-means clustering and watershed algorithm was implemented to segment tumor.

In section II of our paper, we have described the methodology of our proposed technique. Initially we have converted the three dimensional image into two dimensional image using look 3D viewer. After two dimensional conversion, we have used an adaptive technique for tumor detection where the difference of gray values between the

tumorous region and non-tumorous region is emphasized. We have detected the centroid of the tumorous region cluster and calculated the approximate area and compared these parameters with ground truth image to optimize the method. This comparison is illustrated in the dataset and accuracy part in section III. This comparison and optimization techniques maximize our accuracy rate and make our technique stronger.

II. METHODOLOGY

In our proposed method, we have used the dataset of BRATS 2013 [13] and 2015 [14] which is an open database with ground truth value for brain tumor detection. In the dataset the images are in three dimensional format and we have used Look 3D Viewer [15] for the conversion of three dimensional to two dimensional format in our technique. In BRATS dataset, MRI images are of four types (T_1, T_{1c}, T_2 and FLAIR) and among them we have performed our technique using FLAIR images because in two dimensional format of FLAIR images, the comparatively brighter region is suspected as tumorous region.

Our proposed method has five major modules: preprocessing, adaptive threshold seed point selection, tumor extraction, morphological operation and tumor blob detection. Selection of fallacious threshold points may affect the proper detection of tumor, so in the proposed technique, we have emphasized in the selection of threshold point to keep pace with different intensity of gray values of an image.

A. Preprocessing

The two dimensional converted FLAIR images of our dataset are in RGB format. Initially, the RGB images are converted to grayscale format. The grayscale images are resized into 250x250 by row and column to maintain a standard dimension. In FLAIR image, the brightest region is suspected as tumor affected region. Our goal is to detect the tumor region and analyze it.

B. Adaptive Threshold Seed Point Selection

A two dimensional grayscale image is nothing but a combination of pixels containing gray values with different intensities bounded by certain dimensions. After the preprocessing step, we have two dimensional image where our suspected region for tumor is comparatively brighter than other regions.

Every pixel of the image is being visited to find the gray value with highest intensity. We have defined a variable named maximum(M_x) and initialized it with 0 for the comparison with the intensity of gray values and update the value of the variable while getting an intensity value larger than the current value of M_x. After getting the final value of M_x, we know that the intensity value of the tumor affected region will not be greater than M_x.

As the gray scale intensity is stored as 8 bit integer, therefore there will be at most 256 shades of gray. Ignoring the background pixels containing the gray value 0 of the MRI of brain image, a distinct intensity value covering maximum non-tumorous region (I_{nmx}) is selected and beyond that intensity value, tumor begins to grow. If the intensity value covers all the pixels of the brain then the brain is detected as healthy (tumor free).

The difference ($D_f = M_x - I_{nmx}$) between maximum intensity value (M_x) and intensity value covering maximum region (I_{nmx}) is calculated for the further operation of tumor extraction. We have used general set theory: Let us assume that,

U= {Set of all pixels of MRI image}

TR = {Tumor affected region}

NTR = {Non-tumorous region}

$TR \subset U$

$NTR \subset U$

According to set theory, the union of TR and NTR ($TR \cup NTR$) will generate the original image where TR and NTR both are subsets of U. For tumor extraction process, while visiting every pixel of the grayscale image, we have subtracted the intensity value of gray level for each pixel from M_x. If the difference lies in the pre-calculated difference D_f then we have denoted it as a member of tumorous region. But our evaluation with BRATS dataset denotes that difference of intensity value with M_x for any pixel may detect some non-tumorous region as tumorous. This result signifies that a gray value that does not cover maximum region may also be non-tumorous. We have examined that with respect to the statistical approach when the value of I_{nmx} (intensity value) is less than or equal to 50 for selecting adaptive threshold point, subtraction of 80 from D_f otherwise subtraction of 25 from D_f will calculate the accurate threshold point. Final threshold seed point,

$T_h = D_f - 80$; ($I_{nmx} <= 50$) otherwise,

$T_h = D_f - 25$; ($I_{nmx} > 50$)

C. Tumor Extraction

The current difference (C_{def} = M_x – intensity of gray value for current pixel) has been compare with threshold point to recognize it as tumorous or non-tumorous. If the C_{def} is equal to or above T_h then it will be identified as tumorous otherwise non-tumorous.

After selecting the non-tumorous region (NTR), we can subtract the set of NTR from U (set of all pixels of MRI image) to get Tumorous region.

$TR = U - NTR$

The intensity value set of gray level for the set of NTR will never be the member of set TR that means the members of NTR will be the elements of the complement set of TR.

$NTR \in TR^c$

For extracting the tumor, we have put 0 for non-tumorous region and 255 for tumorous region as gray value. Finally the tumor region is extracted. Making the tumorous region more understandable in shape and size, morphological operation will be done.

D. Morphological Operation

Morphological operation combines with erosion, dilation, opening and closing. Resulting extracted output will be eroded to lessen some pixels of the image. Then dilation results in some added pixels to form the shape of the tumor for proper visualization.

In our technique, we have performed with structuring element (B) of two neighborhood for visiting all possible locations of the image. Let, MRI binarized image is denoted as A and Euclidian space is E. The erosion [16] of image A by the structuring element B is:

$A\Theta B = \{z \mid (B)_z \subseteq A\}$ where B_z is the translation of B by the vector z. The reflection of structuring element $\hat{B}$ with respect to the origin and shifting this reflection by z, the dilation of image A by B can be denoted as: $A \oplus B$.

$A \oplus B = \{z \mid (\hat{B})_z \cap A \neq \Phi\}$.

The relation between erosion and dilation can be written as:

$(A\Theta B)^c = A^c \oplus \hat{B}$.

E. Tumor Detection

After morphological operation, hole fill technique is used. A detected tumor region may have gap inside boundary of the extracted tumor that will be filled up by using hole fill technique which will be more understandable.

For neglecting the tumor which is not covering above 200 pixels in the image, we have performed big area opening operation. We have assumed that the image of the tumorous region that is not covering 200 pixels is not a tumor at all. Finally after big area opening, the exact tumor region is detected. The detected tumor will be analyzed in result analysis portion to measure our efficiency with respect to ground truth image. The centroid and area of the tumor have been calculated for both output tumorous region and tumorous region of ground truth image. The difference between the centroids and area are the parameters of our accuracy.

F. Algorithm

Adaptive thresholding and morphological operation technique for brain tumor segmentation:

Step1: Load MRI input image.

Step2: RGB to Gray image conversion.

Step3: Resizing image into 250x250.

Step4: Finding maximum intensity value of gray level from the cancerous region.

Step5: Detecting the intensity value which covers the maximum non-cancerous region.

Step6: Applying adaptive thresholding technique.

Step7: Erode the image of step6 with structuring element [1; 1].

Step8: Dilate the image after eroding with structuring element [1; 1].

Step9: Hole fill the image of step8.

Step10: Big area opening of step9.

Step11: Detection of tumor region.

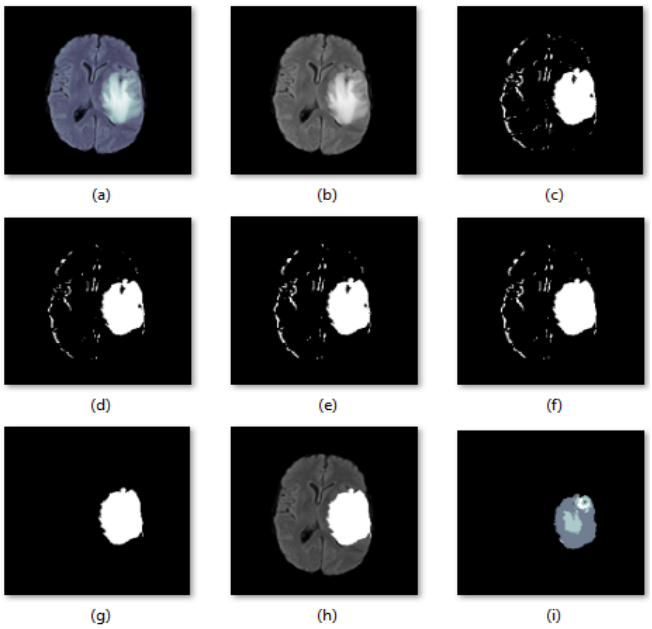

Fig. 1. *Output image for proposed method: (a) MRI input image (b) Grayscale image (c) After adaptive thresholding (d) Erosion (e) Dilation (f) Hole filling (g) Big area opening (h) Detected tumor (i) Ground truth image.*

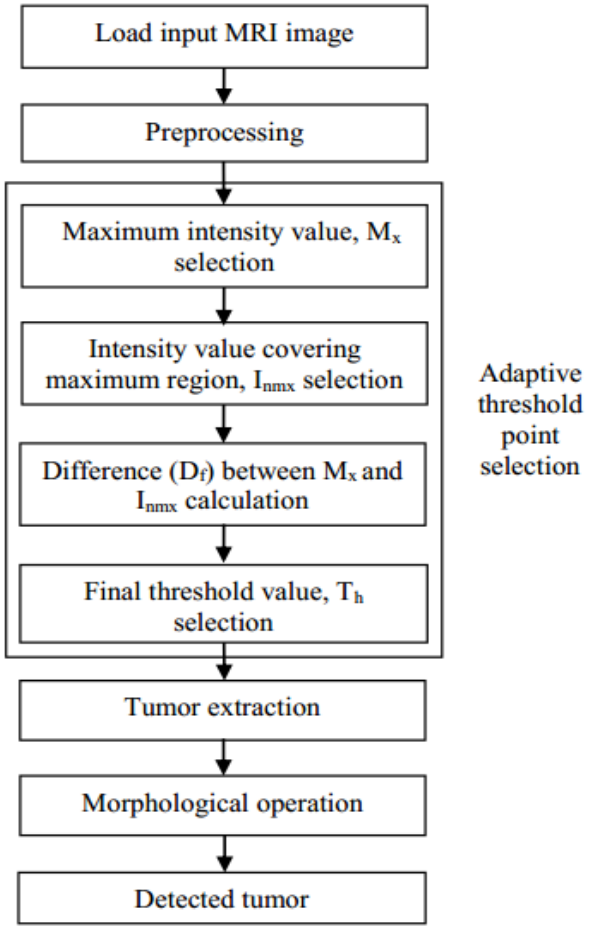

Fig. 2. *Flow chart of adaptive thresholding and morphological operation*

G. Result Analysis

The centroid of detected tumorous region and tumorous region of ground truth image have been identified with x, y coordinate form two dimensional Cartesian coordinate system.

Euclidian distance between this two centroids will determine that how far the centroid of the detected tumor is located from the true position.

$$\text{Centroid Distance}=\sqrt{\{(X_{truth}-X_{output})^2+(Y_{truth}-Y_{output})^2\}}$$

For area calculation, we have calculated the area of a single pixel with the dot per inch (dpi) value. After multiplying the total number of pixels of tumorous region with the area of a single pixel, we have found the area of the detected tumor. Same process is applied to calculate the area of the tumor of ground truth image. The comparison between the output area and truth area denotes the difference between the areas.

Through this two parameters, we have analyzed the difference between the centroids and areas to measure the performance of proposed method.

Area calculation:

Horizontal resolution = 96 dpi

Vertical resolution = 96 dpi

T_{pixels} = Total number of tumorous pixels.

So, 1 pixel area, A = (1/96)*(1/96) (in inch^2)

Total area = T_{pixels} * A (in inch^2)

Area difference (%) = (Tumorous region of ground truth image – Tumorous region of output image) * 100

III. Dataset and Accuracy

BRATS is an open dataset for research. In this paper, we have tested our proposed method with 2D FLAIR images on BRATS 2013 and 2015 datasets. In 2013 database, there are real diagnosed and synthetic images but in 2015 there are only real patient diagnosed images. In BRATS, there are two types of tumor data, one of them is high grade (HG) and another one is low grade (LG). The MRI images in BRATS are of two categories: training and testing data. The training dataset has its' own ground truth value with which we have tested our output images. In the training dataset, there are 80 images in 2013 and 274 images in 2015. Result analysis for BRATS 2015 and 2013 datasets using confusion matrix has been shown in Table. I and II. In BRATS 2013 dataset, there are 50 simulated images and the confusion matrix for synthetic images (Syn.) is shown in Table III.

We have measured our accuracy using confusion matrix. According to confusion matrix, when a tumorous region is detected as tumorous, it is noted as true positive (TP). If a non- tumorous region is detected correctly non-tumorous then it is true negative (TN). When the true image is non-tumorous but detected as tumorous then it is noted as False positive (FP). An incorrect detection of tumorous region as non-tumorous is False Negative (FN).

TABLE I. Confusion Matrix for BRATS 2015 Dataset

Total number of image = 274	**Confusion matrix**		
	Detection of tumor: NO	***Detection of tumor: YES***	***Total***
Presence of tumor in ground truth: NO	TN = 33	FP = 7	40
Presence of tumor in ground truth: YES	FN = 21	TP = 213	234

Finally, the addition of true positive and true negative value and division of the result by total number of samples results in our method accuracy.

Accuracy (%): (TP+ TN)/Total number of image = 89.78%

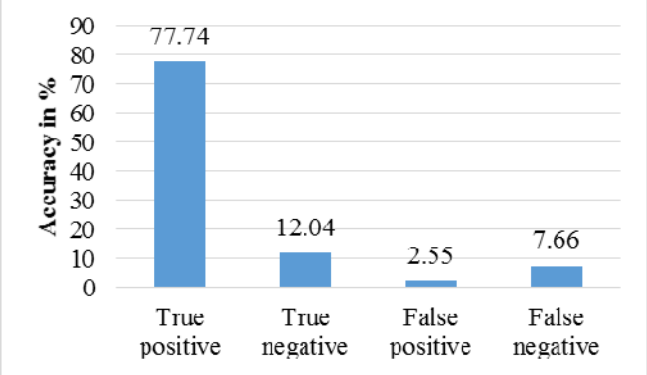

Fig. 3. *Result from confusion matrix for BRATS 2015 dataset*

TABLE II. Confusion Matrix for BRATS 2013 Dataset

Total number of image = 80	**Confusion matrix**		
	Detection of tumor: NO	***Detection of tumor: YES***	***Total***
Presence of tumor in ground truth: NO	TN = 7	FP = 1	8
Presence of tumor in ground truth: YES	FN = 3	TP = 69	72

Accuracy (%): (TP + TN)/Total number of image = 95%

TABLE III. Confusion Matrix for BRATS 2013 Synthetic Dataset

Total number of image = 50	**Confusion matrix**		
	Detection of tumor: NO	***Detection of tumor: YES***	***Total***
Presence of tumor in ground truth: NO	TN = 4	FP = 0	4
Presence of tumor in ground truth: YES	FN = 2	TP = 44	46

In 2016, thresholding and morphological processing (TMP) [4] method was used to detect brain tumor. After noise removal they have used OTSU's global thresholding and an addition of 0.3 was shown with the threshold value

rather it was not proved with mathematical operation that how this addition of 0.3 with threshold value can detect tumor more efficiently. In the paper it was claimed that the introduced technique can detect tumors of 61 patients out of 72 from BRATS 2013 dataset with accuracy 84.72% using confusion matrix. Our proposed adaptive thresholding and morphological operation (ATMO) can detect about 76 patients status of tumor out of 80 patients using the full dataset of BRATS 2013 which gives us the accuracy of 95%. We have shown that how do we compare the intensity value of gray level with the maximum intensity value M_x to detect tumorous cell. After detecting the tumorous region the morphological operation can provide actual size and shape of tumor. Our detected results have also been examined with ground truth results to show the accuracy more transparently. The result analysis of ATMO method and TMP method have been shown in Fig. 4.

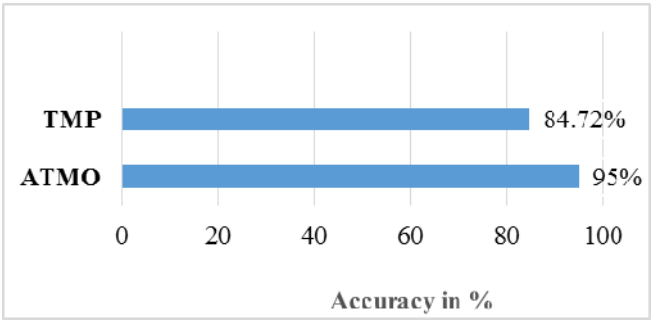

Fig. 4. *Performance analysis of TMP and ATMO method.*

Our proposed method can also detect multiple tumors efficiently. It can detect multiple tumors cause according to our approach, the maximum intensity value (M_x) selection process is true for every tumorous region. While visiting each pixel the difference between the intensity value of current pixel and M_x is being compared with difference D_f to detect tumorous region and this pixel may lying anywhere in the image. The threshold seed point selection process helps enough to determine tumorous region in almost exact location which is shown in the Table. V to prove the reliability of the introduced method. The large dataset of testing images enriches the performance and result analysis process examines our accuracy. Here, the centroid of the tumor and area have been calculated for output and truth images.

TABLE IV. CENTROID LOCALIZATION AND AREA MEASURMENT FOR SAMPLE DATASET

Image serial number	Output Centroid (x, y)	Output Area (inch^2)	Truth Centroid (x, y)	Truth Area (inch^2)
HG_Brats_0001_1 (BRATS 2015)	88.4039 130.5601	0.2592	89.1725 129.5441	0.2680
HG_Brats_217_0001 (BRATS 2015)	93.4286 178.3551	0.3236	93.9754 177.5362	0.3525
HG_Brats_361_0001 (BRATS 2015)	87.8651 167.6606	0.3257	87.2907 167.5904	0.3367
LG_Brats_152_0001 (BRATS 2015)	93.7677 116.3655	0.2037	94.0951 115.6511	0.2258
Brats_LG_0004 (BRATS 2013)	158.1990 151.0213	0.1887	162.4966 146.1300	0.2237
Syn_Brats_HG_0021 (BRATS 2013)	99.2795 80.5813	0.3296	99.6335 80.6174	0.3321
Syn_Brats_LG_0012 (BRATS 2013)	150.2554 74.5618	0.1852	150.5191 75.5686	0.2040

The values of centroid and area of output and ground truth images from Table. IV have been used in Table. V to measure performance of proposed technique.

TABLE V. RESULT ANALYSIS WITH THE PARAMETERS: CENTROID AND AREA

Image serial number	Centroid Distance	Area Difference (%)	Result
HG_Brats_0001_1 (BRATS 2015)	1.2739	0.88	Detected
HG_Brats_217_0001 (BRATS 2015)	0.9847	2.90	Detected
HG_Brats_361_0001 (BRATS 2015)	0.5747	1.10	Detected
LG_Brats_152_0001 (BRATS 2015)	0.7858	2.21	Detected
Brats_LG_0004 (BRATS 2013)	6.5111	3.50	Detected
Syn_Brats_HG_0021(BRATS2013)	0.3558	0.25	Detected
Syn_Brats_LG_0012 (BRATS 2013)	1.0408	1.88	Detected

IV. CONCLUSION

We have presented an adaptive technique for making an automated process to select threshold point in tumor detection. General set theory technique to classify tumorous and non-tumorous region generates a new ideas for brain tumor detection. The result analysis process and comparison between the output result and ground truth value determines the performance of introduced method in an effective way. We want to work with three dimensional images in future. If we can detect tumor in three dimensional format with exact location and area then it will be a milestone in medical science.

REFERENCES

[1] Aastha Sehgal, Shashwat Goel, "Atomatic Brain Tumor Segmentation And Extraction In MR Images," *Conference on Advances in Signal Processing (CASP)* Jun 9-10,2016.

[2] Deepthi Murthy T.S., G. Sadashivappa, "Brain Tumor Segmentation Using Thresholding, Morphological Operations And Extraction Of Features Of Tumor," *International Conference on Advances in Electronics, Computers and Communications (ICAECC)* 2014.

[3] K.S. Angel Viji, Dr J.Jayakumari, "Automatic Detection of Brain Tumor based on Magnetic Resonance Image using CAD System with watershed segmentation," *International Conference on Signal Processing, Communication, Computing and Networking Technologies (ICSCCN)* 2011.

[4] Md.Sujan, Syed Abdullah Noman, "A Segmentation based Automated System for Brain Tumor Detection," *International Journal of Computer Applications* (0975-8887) Volume 153 – No 10 November 2016.

[5] Heena Hooda, Om Prakash Verma and Tripti Singhal, "Brain Tumor Segmentation: A Performance Analysis using K-means, Fuzzy C-means and Region Growing Algorithm," *IEEE International*

Conference on Advanced Communication Control and Computing Technologics (ICACCCT) 2014.

[6] Bjoern H. Menze, Andras Jakab, and Keyvan Farahani, "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," *IEEE TRANSACTIONS ON MEDICAL IMAGING*, VOL. 34, NO. 10, OCTOBER 2015.

[7] Swe Zin Oo, Aung Soe Khaing, "BRAIN TUMOR DETECTION AND SEGMENTATION USING WATERSHED SEGMENTATION AND MORPHOLOGICAL OPERATION," *IJRET: International Journal of Research in Engineering and Technology* eISSN: 2319-1163 | pISSN: 2321-7308.

[8] Manoj K Kowar and Sourabh Yadav, "Brain Tumor Detection and Segmentation Using Histogram Thresholding," *International Journal of Engineering and Advanced Technology (IJEAT)* ISSN: 2249-8958, Volume-1, Issue-4, April 2012.

[9] V. Amsaveni, N. Albert Singh, "Detection of Brain Tumor using Neural Network," *IEEE-31661 4th ICCCNT*-2013, July 4-6,2013.

[10] M. Kadkhodaei, "Automatic Segmentation of Multimodal Brain Tumor Images Based on Classification of Super-Voxels," *IEEE*, 2016.

[11] Chaiyanan Sompong, "Brain Tumor Segmentation Using Cellular Automata-based Fuzzy C-Means," *13th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, 2016.

[12] C. C. Benson, V. Deepa, "Brain tumor segmentation from MR brain images using improved fuzzy c-means clustering and watershed algorithm," *International Conference on Advances in Computing Communications and Informatics (ICACCI)*, 2016.

[13] https://www.smir.ch/BRATS/Start2013.

[14] https://www.smir.ch/BRATS/Start2015.

[15] http://www.mathworks.com/matlabcentral/fileexchange/29067-look3d--a-3-d-image-viewer.

[16] Rafael C. Gonzalez, Richard E. Woods and Steven L. Eddins, "*Digital Image Processing Using MATLAB*," Second Edition, Pearson Prentice Hall, 2009, Chapter 9.