

# A Novel Method for Automatic Detection of Brain Tumor from MR Image

A. Kaur<sup>1\*</sup> and N.Sohi<sup>2</sup>

<sup>1</sup>Department of Computer Engineering, Punjabi University, Patiala, Punjab, India

<sup>2</sup>Department of Computer Engineering, Punjabi University, Patiala, Punjab, India

\*Corresponding Author: amangajebasia344@gmail.com Mob- 94782-81636

Available online at: [www.ijcseonline.org](http://www.ijcseonline.org)

Accepted: 16/Jul/2018, Published: 31/July/2018

**Abstract**— Image processing is an important aspect of medical science to visualize the different anatomical structures of human body. Sometimes it becomes very difficult or impossible to detect or visualize such hidden abnormal structures by using simple imaging. Brain tumor is one of the major causes for mortality among children and adults. Extensive research is being carried out to develop automatic algorithms for detection of Tumor from Brain images captured using MR imaging. Still there are challenges like time requirements, inaccuracy, need of human intervention and complexity of images in detecting region of interest. In this study, an algorithm is proposed for detection of Tumor from MR Brain images, which is based upon thresholding, region growing and genetic algorithm. Performance evaluation of proposed algorithm and studied state-of-the-art algorithms suggests that proposed algorithm gives best results for Tumor detection from MR brain images.

**Keywords**— Brain tumor detection, medical image, segmentation, magnetic resonance imaging (MRI).

## I. INTRODUCTION

Image segmentation is one of the most important tasks in medical image analysis and is often used as the first and the most critical step in many clinical applications. It is the process of partitioning a digital image into multiple segments which consist of sets of pixels. More precisely, image segmentation is the process of assigning a label to each and every pixel in an image such that the pixels with the same label share certain visual characteristics [8]. In brain MRI analysis, it is commonly used for measuring and visualizing the brain's anatomical structures, for analyzing brain changes, for delineating pathological regions, and for surgical planning and image-guided interventions. It is also used to locate objects and boundaries (lines, curves, etc.) in a particular image [7]. The goal of segmentation is to simplify and/or change the representation of an image into something that is easier and more meaningful to analyze. Medical image segmentation aims to:

- Study anatomical structure.
- Identify the Region of Interest (ROI) i.e. locate tumor, lesion and any other abnormalities.
- Measure tissue volume to measure growth of tumor or decrease in size of tumor with treatment.
- Helps in treatment planning prior to radiation, therapy in radiation and dose calculation.

**I.1 Brain Tumor:** Brain tumor is an abnormal growth of tissue inside the brain or central spine that can disrupt proper

brain functioning. Many different types of brain tumors exist. Primary brain tumors originate from the brain cells. Primary brain tumors may spread to other parts of the brain or to the spine, but rarely to other organs. Metastatic or secondary brain tumors begin in another part of the body and then spread to the brain. These tumors are more common than primary brain tumors and are named by the location in which they begin [10].

Tumors can be of the following types:

- **Benign:** It is the least aggressive type of brain tumor as it does not contain cancer cells, grows slowly, and typically have clear borders that do not spread into other tissue. It originates from cells within or surrounding the brain.
- **Malignant:** Malignant brain tumors contain cancer cells and often do not have clear borders. They are considered to be life threatening because they grow rapidly and invade surrounding brain tissue.

People with a brain tumor may experience the following symptoms or signs which may be general or specific. Sometimes, people with a brain tumor do not have any of these changes or the cause of a symptom may be a different medical condition and is not a brain tumor. General symptoms are caused by the pressure of the tumor on the brain or spinal cord whereas specific symptoms are caused when a specific part of the brain is not working well because of the tumor. The signs and symptoms vary greatly and



- Probability of Background pixels,  $w_1$  is  
 $w_1 = \text{No. of Background Pixels} / \text{Size of image}$
- Mean of Foreground pixels,  $u_0$  is  
 $u_0 = \text{Foreground Sum} / \text{No. of Foreground Pixels}$
- Mean of Background pixels,  $u_1$  is defined as  
 $u_1 = \text{Background Sum} / \text{No. of Background Pixels}$

II.I.III Gray level value for which between-class variance maximizes is chosen as threshold,  $T$  to segment image:  
 $T = \text{Max} \{w_0 * w_1 * (u_0 - u_1)^2\}$

**II.II Fuzzy C-Mean:** Firstly the Fuzzy C-Mean algorithm was introduced by Dunn [16] and later on it was extended by Bezdek. It's a kind of soft segmentation clustering method and delivers better results as compared to hard segmentation clustering method for retaining the information from an input image. The Fuzzy C-Mean algorithm is the most widely used clustering algorithm in which each item has the probability of belonging to more than one group hence named "fuzzy". For each item degree of membership is decided by probability distribution of each item over the clusters. FCM performs segmentation by classifying the pixels in such a way that each pixel may belong to multiple clusters with the degree of membership that ranges from 0 to 1. It delivers flexibility and also deals with the uncertainty factor as it allows the fuzzy boundaries to exist between the different clusters [11].

$$\mu_{ij} = 1 / \sum_{k=1}^c (d_{ij} / d_{ik})^{(2/m-1)}$$

$$v_j = \left( \sum_{i=1}^n (\mu_{ij})^m x_i \right) / \left( \sum_{i=1}^n (\mu_{ij})^m \right), \forall j = 1, 2, \dots, c$$

The most striking feature of FCM is that it does not calculate the absolute membership of a data point instead it calculates the likelihood i.e. degree of membership and that's why FCM can be extremely fast as the number of required iterations in order to achieve a specific clustering exercise corresponds to the required accuracy.

**II.III K-Means Clustering:** K-Means is a kind of unsupervised segmentation technique. It is one of the simplest clustering technique that tends to optimize the partitioning decision on the basis of initial sets of cluster which are defined by the user and are updated after each iteration. K-Means uses the hard segmentation approach as it restricts the membership of a pixel exclusively to a single class. Moreover K-Means has low computational complexity and also takes lesser execution time as compared to FCM. As the number of clusters for segmenting the medical images is usually known so KM proves to be a suitable algorithm for segmentation of medical images [8].

$$J = \sum_{j=1}^K \sum_{n \in S_j} |x_n - \mu_j|^2,$$

K-Means aims to find groups or clusters in the data, where the variable  $K$  denotes the number of groups or clusters.

**II.IV Watershed and Edge Detection Method:** It is mostly used for colored MR images of the brain. The advanced watershed technique that uses the markers based approach has proved that the Tumor region detection is better in colored MR images than gray scale pixels [4]. Watershed techniques are mainly used for performing image segmentation and edge detection tasks. It is implemented in conjunction with  $K$  means clustering where  $k$  means technique is used for obtaining a primary segmented image. After that watershed technique processes that image for dividing it into markers and completes the watershed line with the help of these markers. Then the image is stored in the format of region adjacency graph (RAG). The initial segmentation results are obtained by the watershed algorithm and then edge maps are obtained on the basis of two edge strengths and mean gray values merging techniques [9].

### III. PROPOSED ALGORITHM FOR BRAIN TUMOR DETECTION

Detection of Brain tumor at early stage is very difficult task due to complex nature of medical images and many other issues like poor contrast, uneven illumination, obscure contours etc. So it becomes difficult for doctors to identify tumor and their causes [10]. Here we come up with the system, where system will detect brain tumor from MR images. User has to select the image. The selected image will be uploaded into the system and system will process the image by applying image processing steps. We apply filter to image for removing noise, unwanted region and other environmental interference from image. Moreover it helps in removing additional cerebral tissues such as fat, skin, and skull etc. For removing noise from the uploaded image we have used bilateral filter. After removal of noise we apply a unique algorithm to detect tumor from brain image but edges of the image are not sharp so we apply Canny edge detector for detecting the diffused edges and boundaries. Then we apply image segmentation technique for extracting region of interest (ROI) i.e. brain tumor using the benefits of region growing and Genetic algorithm.

**III.I Edge Detection:** Edge detection is a critical element in image processing, since edges contain a major function of image information. The function of edge detection is to identify the boundaries of homogeneous regions in an image based on properties such as intensity and texture [9]. It performs a 2-D spatial gradient measurement on an image and returns edges at those points where the gradient of image is high. Many edge detection algorithms have been developed based on computation of the intensity gradient vector, which is sensitive to noise in the image. To suppress

the noise, some spatial averaging may be combined with differentiation such as the Laplacian of Gaussian operator and the detection of zero crossing. In the proposed algorithm for clarifying the tumor boundaries from image Canny edge detector is used. Figure 2 represents the general processing functions performed by the proposed algorithm for extracting tumor region from MR image of brain.

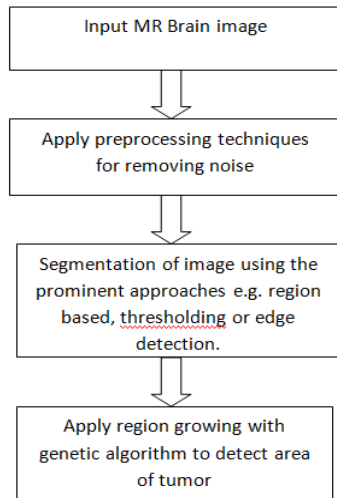


Figure 2 Flowchart of Proposed Algorithm for extracting Tumor from MR brain image

**III.II Region growing technique:** It is a simple image segmentation method based on the region. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points. This approach to segmentation examines the neighboring pixels of initial "seed points" and determines whether the neighbors of the pixel should be added to the region or not, based on certain conditions and is iterated to yield different regions [8]. The region growing technique is carried out for the segmentation of image.

**III.III Genetic Algorithm:** Genetic algorithm proposed by Holland (1975) tends to determine the appropriate value of a criterion by simulating the evolution of a population until survival of best fitted individuals. The survivors are individuals obtained by crossing-over, mutation and selection of individuals from the previous generation [2].

Figure 3 represents the workflow of genetic algorithm. GA is considered as a good candidate for finding out the most appropriate combination of segmentation results due to the following two reasons:

- An evaluation criterion is not very easy to differentiate. GA is an optimization method that does not necessitate to differentiate the fitness function but only to evaluate it.
- If the population is important enough considering the size of the search space we have good guarantees that we will reach the optimal value of fitness [3].

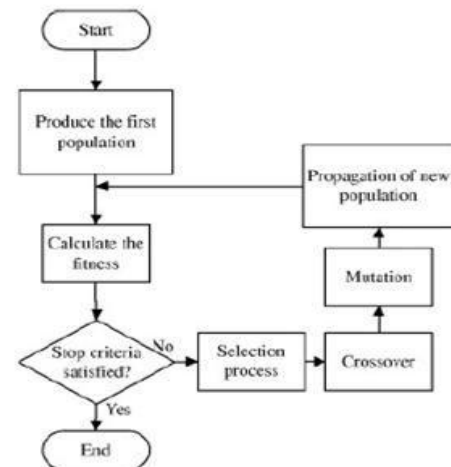


Figure 3 Flowchart of Genetic Algorithm

GA is a special kind of local search which tends to models our own understanding of evolution. In essence a number of simultaneous agents (the population) each having an encoded state (the chromosome) perform a random walk (mutations) around the search space, while forming new solutions from combinations of existing solutions (crossover) and, thus adjusting and refocusing the efforts of the search on exceptionally good areas once located [1]. There are some important pinpoints that should be taken care while applying Genetic algorithm to an application:

- How the population can be encoded (binary, integer, decimal, etc).
- How the population can be mutated (mutate all genes, some genes, etc).
- How the parents should be selected for crossovers (roulette wheel, tournament selection).
- How the crossovers can be performed (uniform, single-point).
- For evaluation what fitness function should be used?

Although these pinpoints appear to be very intricate, but in cases where the energy functional has hundreds or even thousands of dependent parameters or variables, they can yield appropriate values of all these variables or parameters.

#### IV. PERFORMANCE EVALUATION OF PROPOSED ALGORITHM

The proposed system is evaluated using the following performance metrics:

**IV.I Correlation Coefficient:** In 1895, Karl Pearson comes up with the product-moment correlation coefficient. It is used to epitomize the degree of correlation and linear dependence that exists between measured quantities and depicts how strong the relationship is by returning a value that ranges

between -1 and 1, value above 0.5 is considered as a candidate of better performance.

**IV.II Mean Square Error (MSE):** It measures the cumulative means of squares of error between the estimator, i.e., original image and what is estimated. It signifies the squared error loss in computations.

Possible Outcomes of Confusion Matrix are True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN); TN and TP are correctly segmented tumor and brain pixels, FP pixels are incorrectly detected as tumor and FN are falsely detected as brain element [10]. The outcomes of Confusion matrix are used for deriving the values of Precision, Recall, and F-measure.

**IV.III Precision** measures the exactitude of quality, i.e., fragments of fetched pixel elements that are admissible. It is Type 2 Error. Mathematically Precision can be represented as

$$Pr = (TP)/(TP + FP)$$

**IV.IV Recall** measures the completeness of quantity which means fragment of admissible pixel elements that are fetched. It is also known as sensitivity or Type 1 Error. Mathematically Recall can be represented as

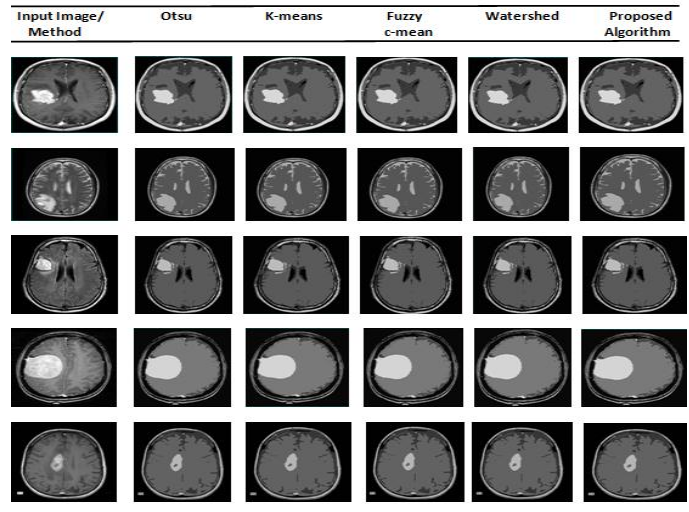
$$Rc = (TP)/(TP+FN)$$

Table 1 Quantitative Results of proposed and other algorithms for various performance metrics

Image	Method	Coorelation Coefficient	Mean Square Error	Precision	Recall
Image 1	Otsu	0.68	4.30	0.77	0.70
	K-means	0.66	2.90	0.59	0.70
	Fuzzy c-mean	0.69	3.32	0.74	0.62
	Watershed	0.68	3.18	0.66	0.56
	<b>Proposed Algorithm</b>	<b>0.80</b>	<b>1.87</b>	<b>0.89</b>	<b>0.99</b>
Image 2	Otsu	0.69	2.84	0.73	0.72
	K-means	0.73	4.67	0.58	0.72
	Fuzzy c-mean	0.69	3.04	0.74	0.69
	Watershed	0.66	3.20	0.60	0.60
	<b>Proposed Algorithm</b>	<b>0.79</b>	<b>2.14</b>	<b>0.91</b>	<b>0.99</b>
Image 3	Otsu	0.70	3.41	0.72	0.65
	K-means	0.72	4.71	0.60	0.66
	Fuzzy c-mean	0.68	3.52	0.76	0.65
	Watershed	0.71	3.20	0.60	0.55
	<b>Proposed Algorithm</b>	<b>0.77</b>	<b>2.45</b>	<b>0.98</b>	<b>0.99</b>
Image 4	Otsu	0.66	3.67	0.77	0.73
	K-means	0.72	2.89	0.55	0.67
	Fuzzy c-mean	0.72	3.22	0.78	0.64
	Watershed	0.65	4.23	0.61	0.53
	<b>Proposed Algorithm</b>	<b>0.86</b>	<b>1.76</b>	<b>0.93</b>	<b>0.99</b>
	Otsu	0.73	3.34	0.70	0.65
	K-means	0.65	4.67	0.64	0.63

Image 5	Fuzzy c-mean	0.73	4.69	0.67	0.67
	Watershed	0.71	3.84	0.63	0.54
	<b>Proposed Algorithm</b>	<b>0.82</b>	<b>2.66</b>	<b>0.95</b>	<b>0.99</b>

Table 2 Outputs of various Segmentation algorithms for Brain Tumor Detection



## V. RESULTS AND DISSUCIONS

For computing the results of performance metrics stated in Section IV experiments are implemented in Java, Jdk 1.8 version, Net beans 8.1on i5 processor. The performance of all the algorithms is evaluated using both Qualitative and Quantitative evaluation trends and results of the stated performance metrics are analyzed and compared. The Quantitative results (numerical values) are represented in Table1 for objective evaluation and Qualitative results (human observation based results) are represented in Table 2 for subjective evaluation.

An algorithm can deliver satisfactory results for one or more parameter but may not be suitable for rest of the parameters. So performance of studied algorithms is analyzed on a tested dataset out of which results of some images are presented in Table1 and Table 2 .Quantitative results in Table 1 depicts that among all the existing methods which are stated in Section II Otsu delivers satisfactory results for all the parameters. K-means provides good results for Correlation Coefficient, MSE and Recall but it delivers comparatively less suitable values for Precision as compared to Otsu. FCM is a tradeoff between K-means and Watershed. It behaves well for all the parameters. Among all the existing algorithms Watershed gives the lowest results when tested for all parameters.

Otsu attains highest performance among all state-of-the-art methods so the performance of proposed algorithm is mainly evaluated with Otsu method. The proposed technique has

increased values of Correlation Coefficient, Precision, Recall and reduced value of Mean square error as compared to Otsu method. Quantitative results in Table 1 depicts that the proposed method has more accurate and satisfactory results for all the performance metrics stated in Section IV as compared to the methods stated in Section II.

## VI. CONCLUSIONS

The proposed algorithm for automatic brain tumor detection from MR brain image is based upon genetic algorithm and region growing methodology. It produces satisfactory results giving appropriate number of regions in segmented output image. It automates the process while taking minimum time and space. The segmented tumor region is clearly visible in the outputs. Proposed algorithm gives best results for various performance metrics. Hence it outperforms other studied state-of-the-art algorithms for brain tumor detection from MR images.

## REFERENCES

- [1] G.R. Chandra, K.R. Rao, "Tumor detection in brain using Genetic Algorithm" In the Proceedings of the 2016 7th International Conference on Communication, Computing and Virtualization, pp.449-457, 2016.
- [2] C. Li , R. Chiao, "Multi-resolution genetic clustering algorithm for texture segmentation", Image and Vision Computing, Vol. 21, pp. 955 – 966, 2003.
- [3] E.Y. Kim, S.H. Park, H.J. Kim, "A genetic algorithm-based segmentation of Markov random field modeled images", IEEE Transaction, Vol. 7, pp. 301- 315, 2000.
- [4] M. Gong, Y.H. Yang, "Genetic-based multi resolution color image segmentation", Vision Interface, pp. 141–148. 2001.
- [5] Abdullah, "Implementation of an improved cellular neural network algorithm for brain tumor detection", In International Conference on Biomedical Engineering , pp.611-615, 2012.
- [6] A. Bianchi, J. V. Miller, A. Montillo, "Brain tumor segmentation with symmetric texture and symmetric intensity-based decision forests", In IEEE 10th International Symposium on Biomedical Imaging, pp.748-751, 2013.
- [7] A. Halder, D.K. Kole, "Automatic Brain Tumor Detection and Isolation of Tumor Cells from MRI Images", International Journal of Computer Applications, Vol.39, No.2, 2012.
- [8] Gajanayake, Randike, Yapa, R. Dharshana, Badra, "Comparison of standard image segmentation methods for segmentation of brain tumors from 2D MR images", In the Proceedings of the 2009 IEEE 4th International Conference on Industrial and Information Systems, pp. 301-305, 2009.
- [9] I. Maiti, M. Chakraborty, "A new method for brain tumor segmentation based on watershed and edge detection algorithms in HSV colour model", In National Conference on Computing and Communication Systems, 2012.
- [10] N. Sohi, L. Kaur, S. Gupta, "Enhanced Thresholding algorithm to Extract Tumor region from MR brain images", In the Proceedings of International Conference on Electrical engineering and Computer Science, 2012.
- [11] S. Albayrak, F. Amasyali, "Fuzzy C-Means Clustering on Medical Diagnosis Systems", International 12th Turkish Symposium on Artificial Intelligence and Neural Networks, 2003.
- [12] K. Thapaliya and G. Kwon, "Extraction of brain tumor based on morphological operations", In the Proceedings of 2012 IEEE-8th international Conference on Computing Technology and Information Management, pp. 515-520, 2012.
- [13] K. J Gorgolewski, P. L Bazin, D. S Margulies, "Fifty Shades of Gray Matter: using bayesian priors to improve the power of whole-brain Voxel and connexe wise inferences", In International Workshop, Pattern Recognition in Neuro-imaging, pp.194-197, 2013.
- [14] F.W. Prior, S. J. Fouke, T. Benzinger, A. Boyd, L.Kim, "Predicting a multi-parametric probability map of active tumor extent using random forests", In Annual International Conference on Engineering in Medicine and Biology Society, pp.6478-6481, 2014.
- [15] A. Q. Syedi, K. Narayanan, "Detection of Tumour in MRI Images Using Artificial Neural Networks", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 3, Issue 9, 2012.
- [16] J.C. Dunn, "A fuzzy relative of the ISODATA process and its use in detecting compact well separated clusters", Journal of Cybernetics, Vol. 3, No.3, pp. 32–57, 1973.