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Fuzzy C-Means Clustering with Ant Colony Optimization Algorithm (Fcm-Aco) For Brain Tumor Segmentation

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Abstract

The Brain tumor is one of the most common executioner diseases for human being. At present researchers are building up a best optimization algorithm to detect presence of brain tumor based on image segmentation technique.Brain tumor segmentation in multimodal Magnetic Resonance Imaging (MRI) is broadly utilized as a crucial cycle for careful planning and simulation, treatment planning preceding radiation therapy, therapy assessment and intra-employable neuro route and image neurosurgery. In the wake of enhancing the brain MR image, this research, proposed technique is to segment the brain tumor MR image. In this paper we proposed fuzzy c-means clustering with Ant Colony Optimization Algorithm (FCM-ACO) for segmentation. The experimental result shows that the proposed FCM-ACO provides better result.

Keywords:*Brain tumor, image segmentation, Magnetic Resonance Imaging, fuzzy c-means clustering, Ant Colony Optimization Algorithm.*

1. INTRODUCTION

An uncontrolled, unnatural growth and division of the cells in the body is supposed to be cancer. While brain tumor is an Occurrence of a mass or unnatural cell growth and division in the brain tissue, yet rarely all in all, they are considered as the most lethal cancers. In upgrading the treatment prospects, early investigation of the gliomas has a critical impact. Figured Tomography (CT), Single-Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS) and Magnetic Resonance Imaging (MRI) are the Medical Imaging techniques, which give the huge insights about the shape, size, location and metabolism of brain tumors aiding finding. Mix of these methodologies gives the greatest insights regarding the brain tumors, due to its great delicate tissue contrast and generally accessibility MRI is considered as the standard procedure. The fields like medical sciences, microscopy, astronomy, computer vision, geology, and numerous different fields are the multidisciplinary region of Digital image processing.

The brain tumor is recognized by utilizing Magnetic Resonance Images (MRI). The expanded information on strange and ordinary anatomy for medical exploration was offered by the MR image.

Brain tumor will happen in the sensory system, despite spinal tumors and periphery nerve tumors. This is a fundamental metastasis, yet its clinical issue isn't like different tumors and is a limited remedial confinement. In the event that the brain tissue gets influences, it makes incapacity to the focal sensory system, as motor unsettling influences, tangible, faculties, and even psychological limit. Besides, brain tumors sway makes a dull issue in the cranial hole which in grown-ups is a closed space with settled size.

Brain tumor segmentation in multimodal Magnetic Resonance Imaging (MRI) is broadly utilized as a crucial cycle for careful planning and simulation, treatment planning preceding radiation therapy, therapy assessment and intra-employable neuro route and image neurosurgery. Nonetheless, dividing brain tumor physically isn't just a difficult undertaking, yet additionally a time-consuming one, preferring thusly, the rise of computerized approaches. All in all, image segmentation techniques can be grouped in:

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a. Threshold-based techniques: are commonly utilized for gray level images. A threshold value T is characterized to split the image in two sections: closer view and background based on pixel value
b. Histogram-based techniques: the histogram of the apparent multitude of pixels is calculated, and according to peaks and valleys various clusters are framed
c. Edge detection techniques: first and second request subsidiaries are utilized for detection of edges. Edges are separated in two categories: intensity edges and texture edges
d. Region-based techniques: utilizes region developing and region splitting-merging procedures. Region developing procedure groups pixels or sub regions into huge regions based on predefined criteria. Region split-merge isolates image into disjoint regions and afterward either merge or potentially split to fulfil essential constraints
e. Watershed Transformation techniques: considered to be more steady than the past techniques, it considers the gradient magnitude of an image (GMI) as a topographic surface. Pixels having the most elevated GMI correspond to watershed lines, which speak to region boundaries.
Clustering is the most mainstream strategy for medical image segmentation, with fuzzy c-means clustering with Ant Optimization Algorithm being the typical techniques. FCM is a sort of straightforward mechanical clustering technique based on investigating least value of the objective function. In this chapter is located in this context of optimization techniques. This research presents another technique to tackle clustering and image segmentation issues by Ant Colony optimization. In this phase proposed fuzzy c-means clustering with Ant Colony Optimization Algorithm (FCM-ACO) for segmentation.

2. EXISTING METHODOLOGY

2.1 Watershed Method

The watershed based methods utilizes the concept of topological interpretation. In this the intensity speaks to the bowls having hole in its minima from where the water spills. At the point when water reaches the fringe of bowl the adjacent bowls are merged together. To keep up detachment between bowls dams are required and are the fringes of region of segmentation. These dams are constructed utilizing dilation. The watershed methods consider the gradient of image as topographic surface. The pixels having more gradient are spoken to as boundaries which are continuous.

2.2 Threshold Method

Thresholding methods are the least complex methods for image segmentation. These methods partition the image pixels with respect to their intensity level. These methods are utilized over images having lighter objects than background. The selection of these methods can be manual or automatic for example can be based on earlier knowledge or data of image features. There are basically three kinds of thresholding:

2.2.1 Global Thresholding:

This is finished by utilizing any fitting threshold value/T. This value of T will be constant for whole image. Based on T the yield image q(x,y) can be acquired from unique image p(x, y) as:

$$Q(x, y) = \begin{Bmatrix} 1, if p(x,y) > T \\ 0, if p(x,y) \leq T \end{Bmatrix} \quad (1)$$

2.2.2 Variable Thresholding:

In this sort of thresholding, the value of T can fluctuate over the image. This can additionally be of two sorts:
Local Threshold: In this the value of T relies on the neighbourhood of x and y.
Adaptive Threshold: The value of T is a function of x and y.

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2.2.3 Multiple Thresholding:

Multiple Thresholding: In this kind of thresholding, there are different threshold values like T0 and T1. By utilizing these yield image can be computed as:

$$Q(x, y) = \begin{Bmatrix} m, if p(x,y) > T1 \\ n, if p(x,y) \leq T1 \\ 0, if p(x,y) \leq T0 \end{Bmatrix} \quad (2)$$

The values of thresholds can be computed with the assistance of the peaks of the image histograms. Straightforward algorithms can likewise be produced to compute these

2.3 DWT method

The Discrete Wavelet Transform (DWT) is based on sub-band coding, it is found to yield a quick computation of Wavelet Transform. Discrete Wavelet Transform is anything but difficult to execute and reduces the computation time. The establishments of DWT were in 1976 when it uses to decompose discrete time signals. At the point when comparative work was done in speech signal coding which was named as sub-band coding? At 1983, and another technique like sub-band coding was created it is known as pyramidal coding, and later numerous enhancements were made to these coding schemes which is utilized in efficient multi-goal investigation schemes of image. The initial step is to choose a wavelet type, and a level N of decomposition. In this case biorthogonal 3.5 wavelets were chosen with a level N of 10. Biorthogonal wavelets are commonly utilized in image processing to detect and channel white Gaussian commotion, because of their high contrast of neighbouring pixel intensity values. Utilizing these wavelets a wavelet transformation is performed on the two dimensional image.

3. PROPOSED METHODOLOGY

Clustering is the best method for segmentation and could be applied to assortment of circumstances. Yet, it represents a complex optimization issue and the reasons could be the enormous search space of the optimization and the non-convex nature of clustering objective function. This may prompt an enormous number of local minima. In this approach an image is seen as a bunch of multi-dimensional data which can be classified into various parts based on certain predefined criterion. Upgrades in clustering techniques could be acquired by coordinating it with fuzzy theory, and transformative technique like ACO. Along these lines, this chapter utilized clustering segmentation techniques for conclusion of tumor and calculating tumor territory in MRI images.

Here, a clustering based Fuzzy C-Means with ACO (FCM-ACO) method will be considered for image segmentation and the relating segmentation process is uncovered in Figure 1.

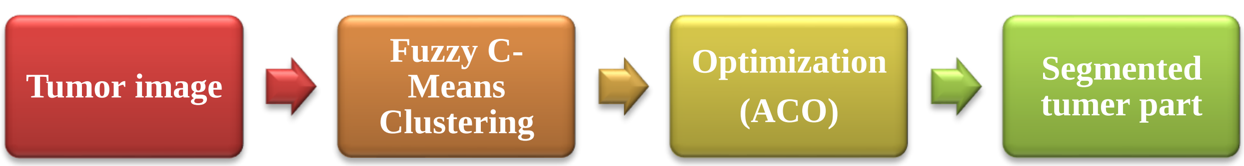

Figure 1: Segmentation Process

3.1 Fuzzy C Means Segmentation

Fuzzy C Means (FCM) is one of the well-known methods in fuzzy clustering and has applied to medical issues. The standard FCM method is start from k-means clustering algorithm. The FCM algorithm was created by Dunn in 1973 and it was improved by Bezdek, 1981.

Advantages of FCM:

Provinces extra homogeneous

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Diminishes fake spots
Eliminates noisy spots
Fewer complexes to commotion than different techniques.
For a bunch of N MRI image is characterized as X = {x1, x2, … ,xN} then FCM algorithm partitions the arrangement of image based on center v calculation and participation network U. Limited the objective function of FCM algorithm Ffcm based on the acquired centers and participation degrees is given as Follows:

$$F_{fcm} = \sum_{i=1}^{c} \sum_{k=1}^{N} \mu_{ik}^{r} ||X_k - V_i||^2 \qquad (3)$$

In the above condition N characterizes the quantity of examples; C speaks to the quantity of clusters in the given MRI image, r relates the genuine number which is under 1 it controls the parcel of image, μik is the level of fuzzy participation of pixel xk in the ith cluster and likeness measures in the function is given by boundary ‖. ‖.
Typically Euclid: ean distances measures are utilized for comparability measure its functions are expressed in two different ways are:
Its function to limit the data when enormous participation values are given to include examples and it close to the nearest cluster centers.
The low participation functions are far away from their cluster center.
Minimize the objective function of FCM F_{fcm} is given as follows:

$$\sum_{i=1}^{c} \mu_{ik} = 1 \qquad (4)$$

We have

$$\frac{\partial F_{fcm}}{\partial \mu_{ik}} = 0 \; and \; \frac{\partial F_{fcm}}{\partial v_i} = 0 \qquad (5)$$

These gives the following constrains:

$$\mu_{ik} = \frac{1}{||X_k - V_i||^{\frac{2}{m-1}} / \sum_{c=1}^{c} ||X_k - V_c||^{\frac{2}{m-1}}} \qquad (6)$$

and

$$v_i = \frac{\sum_{k=1}^{N} \mu_{ik}^{r} X_k}{\sum_{k=1}^{N} \mu_{ik}^{r}} \qquad (7)$$

FCM algorithm
Step 1: Let x = $\{x_1, x_2, \dots\dots x_n\}$ be the set of data points along with c=$\{c_1, c_2, \dots\dots c_n\}$
Be the set of centres.
Step 2: For opt for the optimized cluster centre or centroid in the segmentation procedure incorporating GWO technique.
Step 3: Calculate the objective function of the Fuzzy techniques by means of beneath function

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{m} ||x_i - c_j||^2 \, 3.28$$

Step 4: Calculate the fuzzy membership function u_{ij} using

$$u_{ij} = \frac{1}{\sum (d_{ij}/d_{ik})^{(2(m-1))}} \, 3.29$$

Step 5: Compute the fuzzy centres c_j

$$c_j = \left(\frac{(\sum_{i=1}^{n} (u_{ij})^m x_i)}{(\sum_{i=1}^{n} (u_{ij})^m)} \right) \forall_j = 1,2, \dots\dots c \qquad 3.30$$

Step 6: Replicate step 4 as well as 5 until the maximum of J_m value is realized
or$||U^{(k+1)} - U^k|| < \beta$

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Parameter Description

J	Objective Function
m	Fuzziness Index m$\in [1,\infty]$
u_{ij}	Membership of i^{th} data to j^{th} cluster center.
c	Number of cluster center.
d_{ij}	Equation distance between i^{th} data and j^{th} cluster center.
c_j	j^{th} cluster center
k	Iteration Step
β	Termination criterion between [0, 1].
U	$(u_{ij})_{n*c}$Is the fuzzy membership matrix.

Table 1 Fuzzy Parameter Description

The parameter m controls the fuzziness of the following segment, with 2□m is utilized as a piece of this audit. The objective capacity is reduced when pixels close to the concentrations of their clusters are consigned high enrolment regards, and low participation characteristics are assigned to pixels with far from the concentrations of their clusters. The enrolment function converses to the likelihood that a pixel finds a place with a specific cluster.

3.2 OPTIMIZATION ALGORITHM

Optimization implies the route toward choosing the best game plan from the course of action of each and every conceivable response for boosts or limits the cost of the issue. This procedure is conceded to accomplish the segmented image, and to accomplish the centroid optimization of the tumor image with most extraordinary precision. The proposed optimization is Ant Colony Optimization.

Ant Colony Optimization

Ant colony optimization (ACO) is a nature-enlivened optimization algorithm propelled by the normal phenomenon that ants store pheromone on the ground to stamp some ideal way that ought to be trailed by different individuals from the colony. The principal ACO algorithm, called the ant system, was proposed by Dorigo. ACO has been generally applied in different problems. In this proposition, ACO is introduced to embrace the image segmentation problem, where the point is to extract the edge data introduced in the image, since it is crucial to comprehend the image's content. The proposed approach abuses various ants, which proceed onward the image driven by the local variety of the image's intensity values, to build up a pheromone network, which speaks to the edge data at each pixel location of the image. Ant colony optimization is applied for the image processing which are on the premise continuous optimization. This paper proposes an ant colony optimization (ACO) based algorithm for continuous optimization problems on images like image edge detection, image compression, image segmentation, structural damage monitoring etc in image processing.

Algorithm for ACO
Initialization of Pheromone, K, maximum iteration, ρ, For each ant
Movement of kth ant from pixel i to pixel j according to the probability equation for K number of steps
First update of the pheromone matrix locally (local pheromone update)
Find out binary mask
Second update of the pheromone matrix globally
End for

The below figure 2 represented flowchart for the proposed segmentation process.

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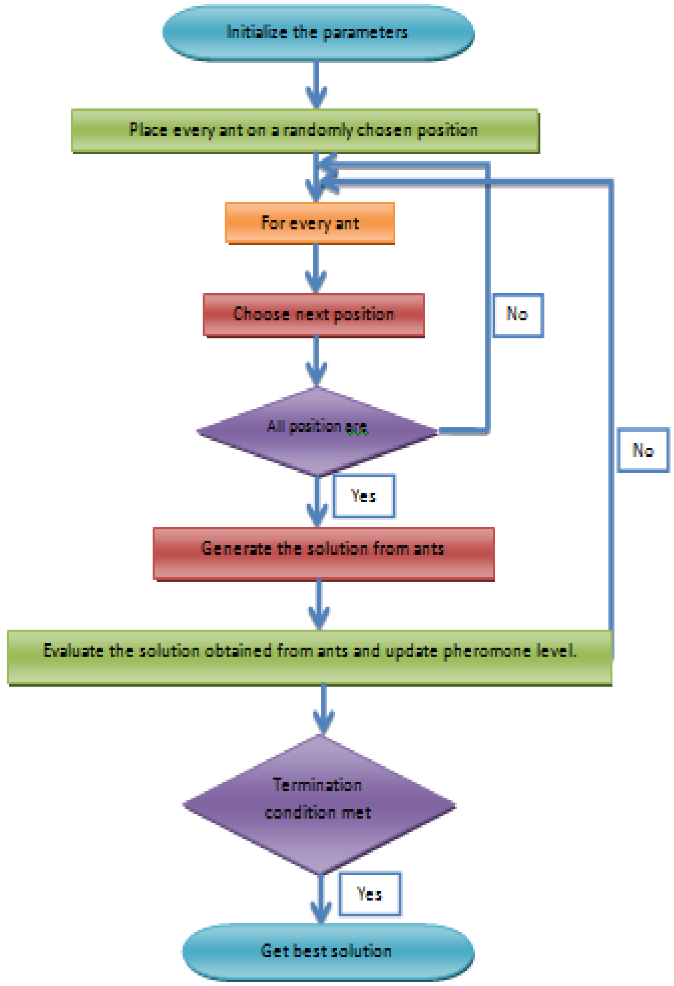
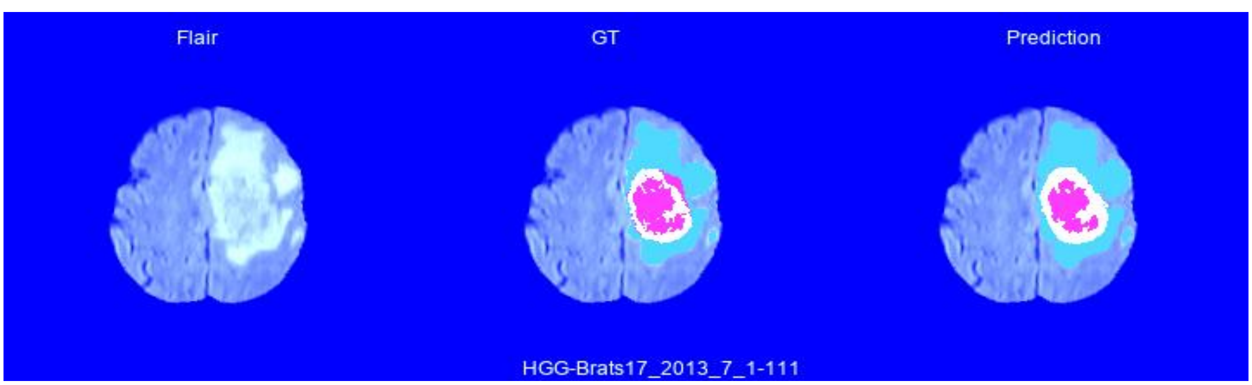


Figure 2: Flowchart for the Proposed Method



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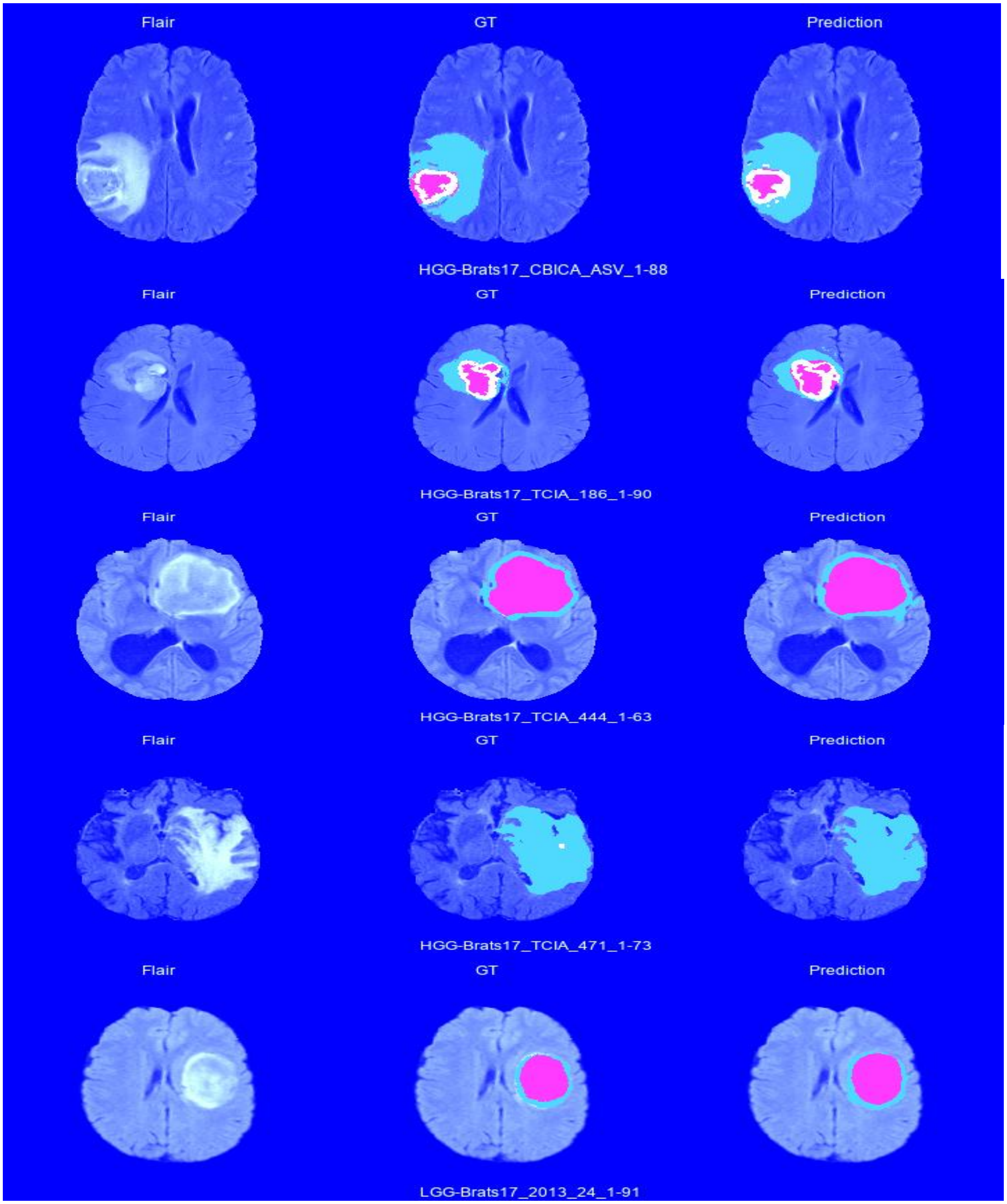

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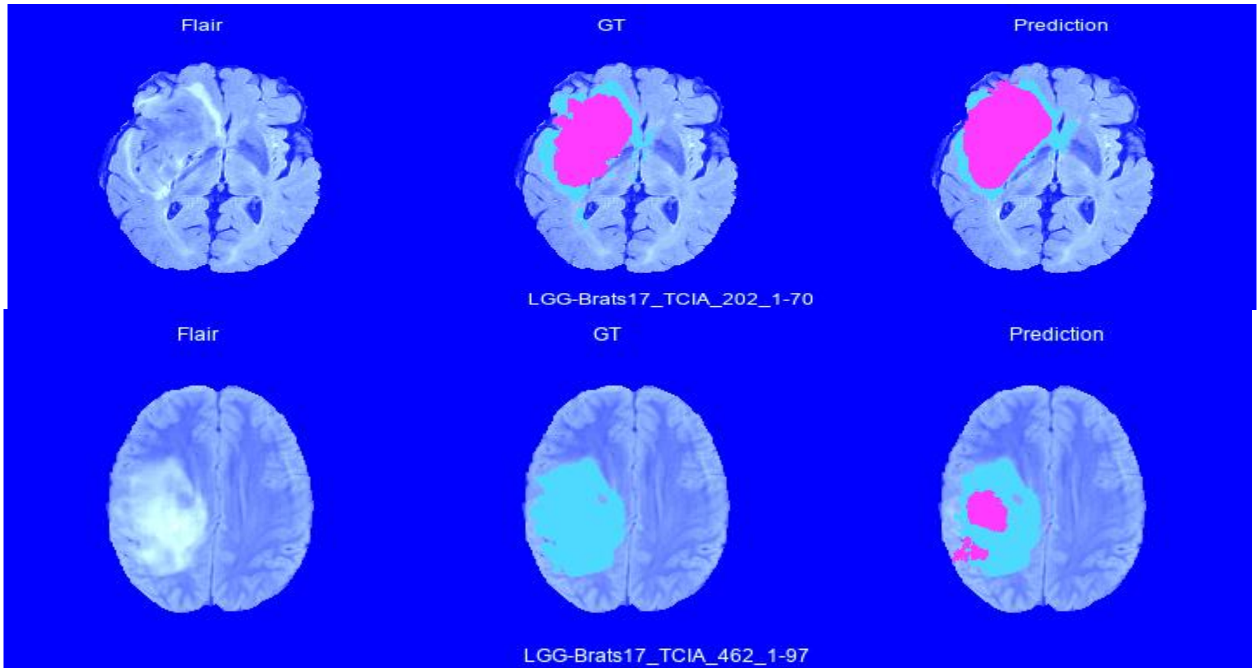

4. EXPERIMENTAL RESULT

This section will describe the comparison between different segmentation techniques as far as accuracy, sensitivity and specificity value. The techniques utilized for the comparisons are watershed segmentation, threshold segmentation and DWT. Here FCM-ACO is the proposed method utilized for segmentation of this work.

4.1. Comparison of Various Segmentation Techniques with Accuracy

Images	Watershed	Threshold	DWT	Proposed FCM-ACO
Image 1	81.22	82.45	83.48	86.87
Image 2	83.52	83.84	84.74	88.74
Image 3	84.01	85.15	88.21	90.55
Image 4	87.35	89.67	90.48	92.46
Image 5	90.65	92.23	93.66	96.91

Table 2: Comparison table of Various Segmentation Techniques with Accuracy

Table 2 shows that Comparison table of Various Segmentation Techniques with Accuracy, comparison between existing watershed, threshold, DWT and proposed FCM-ACO method regarding accuracy. In Image 1 the accuracy value of FCM-ACO segmentation has 86.87% and the accuracy of existing watershed, threshold, DWT has 81.22%, 82.45% and 83.48% respectively. What's more, in Image 5 the accuracy value of FCM-ACO segmentation has 96.91% and the accuracy of existing watershed, threshold, DWT has 90.65%, 92.23% and 93.66% respectively which is lower than the proposed FCM-ACO segmentation method. The performance of the proposed FCM-ACO method is better compared with other existing methods regarding accuracy.

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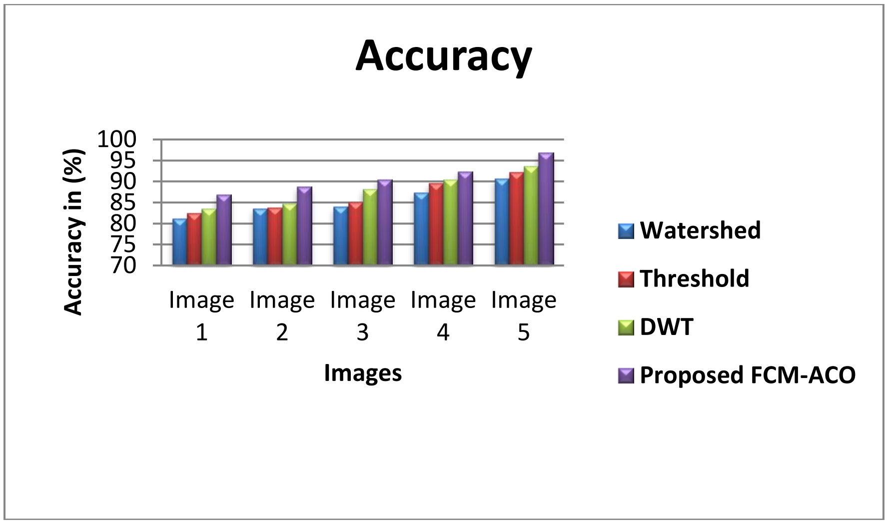

Figure 3: Comparison Chart of Various Segmentation Techniques with Accuracy

Figure 3 shows that Comparison Chart of Various Segmentation Techniques with Accuracy, comparison between existing watershed, threshold, DWT and proposed FCM-ACO method regarding accuracy. In Image 5 the accuracy value of FCM-ACO segmentation has 96.91% and the accuracy of existing watershed, threshold, DWT has 90.65%, 92.23% and 93.66% respectively which is lower than the proposed FCM-ACO segmentation method. The performance of the proposed FCM-ACO method is better compared with other existing methods regarding accuracy.

4.2.Comparison of Various Segmentation Techniques with Specificity

Images	Watershed	Threshold	DWT	Proposed FCM-ACO
Image 1	85.021	85.425	85.302	86.452
Image 2	86.224	86.649	86.714	86.999
Image 3	83.121	83.154	84.231	84.745
Image 4	90.135	90.267	90.498	91.406
Image 5	92.365	92.623	93.606	93.910

Table 3: Comparison table of Various Segmentation Techniques with Specificity

Table 3 shows that Comparison table of Various Segmentation Techniques with Accuracy, comparison between existing watershed, threshold, DWT and proposed FCM-ACO method regarding accuracy. In Image 1 the accuracy value of FCM-ACO segmentation has 86.452% and the accuracy of existing watershed, threshold, DWT has 85.021%, 85.425% and 85.302% respectively. Also, in Image 5 the accuracy value of FCM-ACO segmentation has 93.910% and the accuracy of existing watershed, threshold, DWT has 92.365%, 92.623% and 93.606% respectively which is lower than the proposed FCM-ACO segmentation method. The performance of the proposed FCM-ACO method is better compared with other existing methods as far as accuracy.

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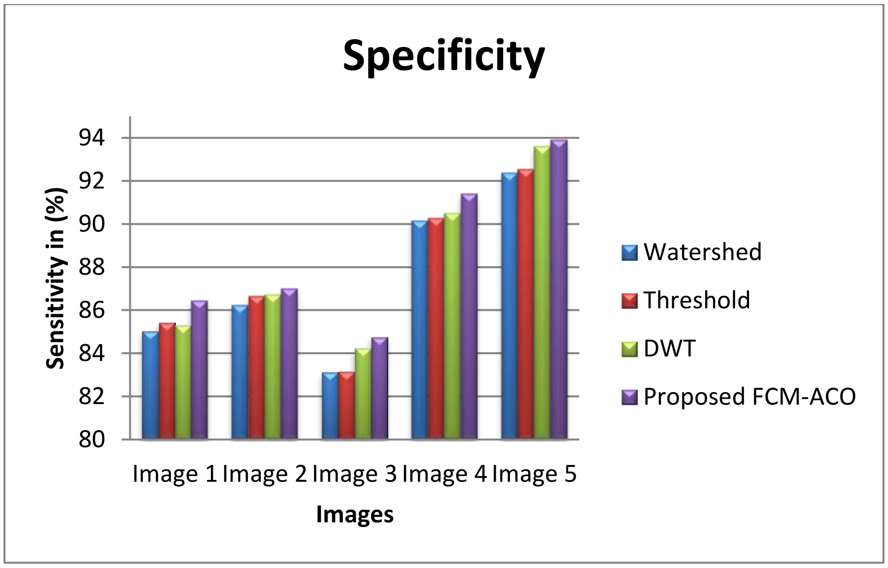

Figure 4: Comparison Chart of Various Segmentation Techniques with Specificity

Figure 4 shows that Comparison Chart of Various Segmentation Techniques with Accuracy, comparison between existing watershed, threshold, DWT and proposed FCM-ACO method regarding accuracy. In Image 5 the accuracy value of FCM-ACO segmentation has 93.910% and the accuracy of existing watershed, threshold, DWT has 92.365%, 92.623% and 93.606% respectively which is lower than the proposed FCM-ACO segmentation method. The performance of the proposed FCM-ACO method is better compared with other existing methods as far as accuracy.

4.3.Comparison of Various Segmentation Techniques with Sensitivity

Images	Watershed	Threshold	DWT	Proposed FCM-ACO
Image 1	68.02	69.35	70.74	71.26
Image 2	70.26	72.57	73.09	74.23
Image 3	71.18	72.19	72.89	75.08
Image 4	72.11	73.36	75.04	76.14
Image 5	74.22	75.67	76.85	77.99

Table 4: Comparison table of Various Segmentation Techniques with Sensitivity

Table 4 shows that Comparison table of Various Segmentation Techniques with Accuracy, comparison between existing watershed, threshold, DWT and proposed FCM-ACO method as far as accuracy. In Image 1 the accuracy value of FCM-ACO segmentation has 71.26% and the accuracy of existing watershed, threshold, DWT has 68.02%, 69.35% and 70.74% respectively. Furthermore, in Image 5 the accuracy value of FCM-ACO segmentation has 77.99% and the accuracy of existing watershed, threshold, DWT has 74.22%, 75.67% and 76.85% respectively which is lower than the proposed FCM-ACO segmentation method. The performance of the proposed FCM-ACO method is better compared with other existing methods regarding accuracy.

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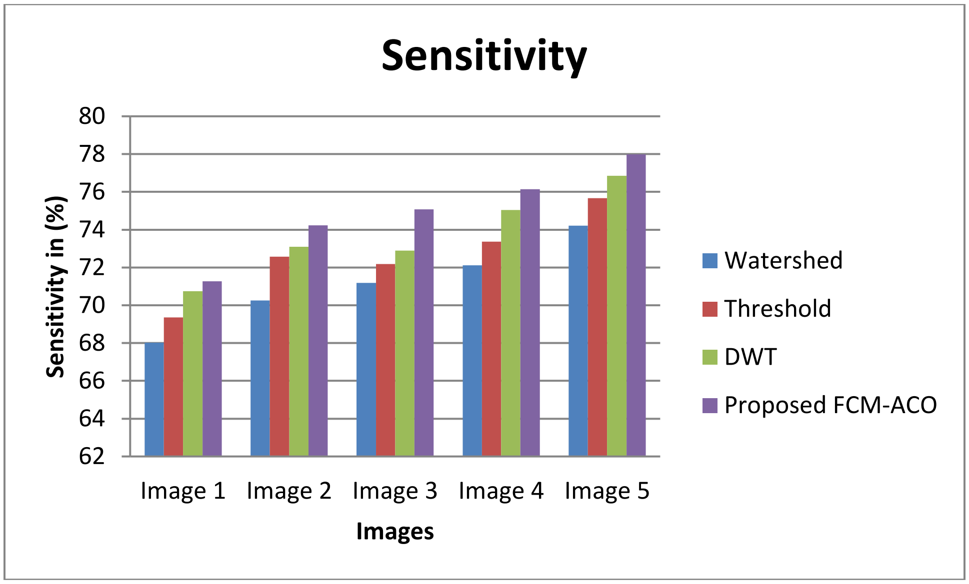

Figure 5: Comparison Chart of Various Segmentation Techniques with Specificity

Figure 5 shows that Comparison Chart of Various Segmentation Techniques with Accuracy, comparison between existing watershed, threshold, DWT and proposed FCM-ACO method as far as accuracy. In Image 5 the accuracy value of FCM-ACO segmentation has 77.99% and the accuracy of existing watershed, threshold, DWT has 74.22%, 75.67% and 76.85% respectively which is lower than the proposed FCM-ACO segmentation method. The performance of the proposed FCM-ACO method is better compared with other existing methods as far as accuracy.

CONCLUSION

The denoising MRI brain image decreases the difficulty in segmentation. The improvement of any abnormal tissue will increase the intracranial weight in the brain and it prompts harm in central nervous system hence the patient lives are in peril condition. The detection or segmentation is required for medical conclusion and spare the patient life through early detection. In medical field surgical and therapy is utilized to detect or segmentation of tumor from MRI image yet this method is time consuming. However there is no such best optimization algorithm accessible. So there is an incredible breadth for growing such an algorithm. To manage this work in this research work, FCM-ACO has been proposed to detect presence of brain tumor based on image segmentation technique. The proposed method is reducing the complexity and improving the performance. The exploratory outcome demonstrated that the proposed Fuzzy c-means clustering with Ant Optimization Algorithm (FCM-ACO) method gives better performance.

REFERENCE

[1]. S. K. Adhikari, J. K. Sing, D. K. Basu and M. Nasipuri, "A spatial fuzzy C-means algorithm with application to MRI image segmentation," 2015 Eighth International Conference on Advances in Pattern Recognition (ICAPR), Kolkata, 2015, pp. 1-6.

[2]. B. Devkota, AbeerAlsadoon, P.W.C. Prasad, A. K. Singh, A. Elchouemi, "Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction," 6th International Conference on Smart Computing and Communications, ICSCC 2017, 7-8 December 2017, Kurukshetra, India.

[3]. K. Rajesh Babu, P.V. Naganjaneyulu and K. Satya Prasad, "Performance Analysis for Efficient Brain Tumor Segmentation by using Clustering Algorithm," Indian Journal of Science and Technology, Vol 10(11), March 2017.

ISSN: 2233 -7857 IJFGCN

[4].Umit Ilhan, Ahmet Ilhan, “Brain tumor segmentation based on a new threshold approach,” Procedia Computer Science, ISSN: 1877- 0509, Vol: 120, Page: 580-587, Publication Year: 2017.
[5].S.R.Telrandhe, A.Pimpalkar, A.Kendhe, “Detection of Brain Tumor from MRI Images by Using Segmentation and SVM”, World Conference on Futuristic Trends in Research and Innovation for Social Welfare, 2016.
[6].NooshinNabizadeh, Miroslav Kubat, “Automatic tumor segmentation in single-spectral MRI using a texture-based and contour-based algorithm”, Expert Systems with Applications, 77, pp. 1-10, 2017. [27] Song, Yantao& Ji, Zexuan& Sun, Quansen&Yuhui, Zheng. (2016). A Novel Brain Tumor Segmentation from Multi-Modality MRI via A Level-Set-Based Model. Journal of Signal Processing Systems. 87. 10.1007/s11265-016-1188-4.
[7]. Pei L, Reza SMS, Li W, Davatzikos C, Iftekharuddin KM. Improved brain tumor segmentation by utilizing tumor growth model in longitudinal brain MRI. Proc SPIE Int Soc Opt Eng. 2017.
[8]. C. H. Rao, P. V. Naganjaneyulu and K. S. Prasad, "Brain Tumor Detection and Segmentation Using Conditional Random Field," 2017 IEEE 7th International Advance Computing Conference (IACC), Hyderabad, 2017, pp. 807-810.
[9] P.Patil, S.Pawar, S.Patil, A.Nichal, “A Review Paper on Brain Tumor Segmentation and Detection”, International Journal for Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, Volume 5, January 2017.
[10].J.Thripathi, A.Chaudhary, “Brain Tumor Detection and Segmentation”, International Journal of Advanced Research in Computer Science, Volume 9, May – June 2018.
[11]. S. R. Telrandhe, A. Pimpalkar and A. Kendhe, "Detection of brain tumor from MRI images by using segmentation & SVM," 2016 World Conference on Futuristic Trends in Research and Innovation for Social Welfare (Startup Conclave), Coimbatore, 2016, pp. 1-6.
[12].J.M.Lojzim, M.Fries, “Brain Tumor Segmentation Using Morphological Processing and the Discrete Wavelet Transform”, Journal of Young Investigators, August 2017.
[13].Eman Abdel-Maksoud, Mohammed Elmogy, Rashid Al-Awadi, “Brain tumor segmentation based on a hybrid clustering technique”, Elsevier. Volume 16, Issue 1, March 2015.
[14].Q.N.Rehman, I.Ahmed, G.Masood, N.U.Saquib, M.Khan, A.Adnan, “Segmentation of Brain Tumor in Multimodal MRI Using Histogram Differencing & KNN”, International Journal of Advanced Computer Science and Applications, Volume 8, 2017.
[15].B.Devkota, A.Alsadoon, P.W.C.Prasad, A.K.Singh, A.Elchoucmi, “Image Segmentation for Early Stage Brain Tumor Detection Using Mathematical Morphological Reconstruction”, 6th International Conference on Smart Computing and Communications, 7 – 8 December 2017.
[16].K.Bhima, A.Jagan, “Analysis of MRI Based Brain Tumor Identification Using Segmentation Technique”, International Conference on Communication and Signal Processing, 6 – April 2016.
[17]. A.Sehgal, S.Goel, “Automatic Brain Segmentation and Extraction in MR Images”, Conference on Advances in Signal Processing, 2016.

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