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Research Article

A COMBINATION OF THRESHOLD BASED PARTICLE SWARM OPTIMIZATION AND FUZZY K-MEANS SEGMENTATION TECHNIQUES FOR MRI BRAIN TUMOR DETECTION

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ABSTRACT

Segmenting the tumor from the brain Magnetic Resonance Imaging (MRI) is an important and demanding task in the recent days. Because, it helps for the medical experts during the disease diagnosis process. So, different image processing techniques are developed in the existing works for an efficient brain tumor detection and segmentation. But, it lacks some major issues such as, increased complexity, inaccurate segmentation, increased dimensionality, and over segmentation. Thus, this paper aims to design a new segmentation system based on the combination of Threshold based Particle Swarm Optimization (T-PSO), and Fuzzy K-Means (FKM) for an accurate tumor segmentation from brain MRIs. Initially, the given MRI brain is preprocessed to remove the noise in the image by implementing the Fuzzy Adaptive Median Filtering (FAMF) technique. After that, the features of the filtered image are extracted with the use of eXtented Center Symmetric – Local Derivative Pattern (XCS – LDP) technique. It efficiently extracts the features of the image for the better segmentation. Finally, the T-PSO and FKM techniques are applied to segment the tumor region based on the extracted features. The novelty of this paper is, it identifies the common pixels from the images that are segmented by T-PSO and FKM. So, it improves the accuracy of the proposed segmentation system. During experimentation, the performance results of existing and proposed brain tumor segmentation techniques are analyzed and compared by using various measures.

Keywords: Brain Tumor, Magnetic Resonance Imaging (MRI), Image Segmentation, Fuzzy Adaptive Median Filtering (FAMF), eXtended Center Symmetric – Local Derivative Pattern (XCS-LDP), Threshold based Particle Swarm Optimization (T-PSO), and Fuzzy K-Means (FKM).

INTRODUCTION

BRAIN tumor detection plays an important and essential role in many medical imaging applications (1-3). It is the main organ in the human body that contains the Gray Matter (GM), White Matter (WM), and Cerebrospinal Fluid (CSF) parts. The overall operations of the brain are performed in a controlled manner, because the cells in the human body has the capability to multiply them. When these cells are growth uncontrollably, the abnormality can be occurred, which is known brain tumor. It is a collection of abnormal cells that can be classified (4-6) into two types such as benign (non-cancerous), and malignant (cancerous). In which, the benign tumors grow in a regulated way, and it does not occupy the surrounding brain tissues. But, the malignant grow quickly, which spreads to the other parts of the brain. So, detecting these tumors are highly demanded in the recent days for disease diagnosis. For this purpose, different imaging modalities are used by the medical experts for proper treatment. The Magnetic Resonance Imaging (MRI) (7) is one of the widely used imaging modality for brain tumor segmentation and classification. The main advantages of using MRI are as follows:

- It has the capability to accurately detect the abnormalities in the soft tissue structures.
- It enables the visualization of the active parts in the brain.
- It does not involve any kind of radiations.

Problem description

MRI brain tumor segmentation is a highly critical task, because the size, shape, location and intensity can vary for different image. In manual segmentation, the medical expert is required to identify the tumor part, which leads increased time consumption and misclassification results. So, a semi-automatic automatic segmentation technique is developed in the traditional works. But, it also requires a human experts during the process of segmentation. To solve these issues, a fully automatic segmentation system is developed, which reduces the overall time consumption, avoids misclassification, and improves the efficiency of segmentation. In the existing works, various fully automatic segmentation systems are developed with the use different image processing techniques. But, it lacks with some major issues such as, over segmentation, inaccurate results, and increased computational complexity. Thus, this paper develops a novel segmentation system based on the Computer Aided Diagnosis (CAD) model, which includes the stages of preprocessing, feature extraction, feature selection, and segmentation. The proposed work mainly focuses to develop an efficient model by employing different image processing techniques.

Objectives

Based on the problem identification, this research work has the following objectives:

- To preprocess the image by efficiently eliminating the noise from the given image, a Fuzzy Adaptive Median Filtering (FAMF) technique is developed.
- To extract the meaningful features for an efficient segmentation, an eXtented Center Symmetric – Local Derivative Pattern (XCS-LDP) technique is introduced.
- To accurately segment the tumor region based on the extracted features, two different segmentation techniques such as, thresholding and Fuzzy K-Means (FKM) are proposed.

Organization

The rest of the sections in the paper are organized as follows: In Section II, the image processing techniques that include preprocessing, feature extraction, feature selection, segmentation, and classification are surveyed with its advantages and disadvantages. In Section III, the clear description about the proposed methodology is presented. The performance results of both existing and proposed techniques are evaluated with respect to different parameter measures in Section IV. Finally, the overall summary of the paper and the future enhancement that will be implemented further are stated in Section V.

RELATED WORKS

In this section, the existing techniques and algorithms used for an efficient brain tumor detection and segmentation are surveyed. Also, it investigates the advantages and disadvantages of those works.

Preprocessing

Abdel-Maksoud, et al (8) recommended a hybrid clustering technique, namely, KIFCM by integrating the k-means and Fuzzy C-Means (FCM) algorithms for an efficient tumor segmentation. This work includes the following stages:

- Preprocessing
- Clustering
- Feature extraction and contouring
- Segmentation

Here, the median filtering technique was implemented to eliminate the noise from the image before processing it. The aim of preprocessing was to improve the quality of image and to remove the skull. After that, the KIFCM technique was implemented to cluster the image with reduced number of iteration and execution time. Then, the object was extracted from the background with the use of thresholding segmentation technique. Finally, the active contour level set was applied to segment the tumor region from the given image. However, this paper required to improve the accuracy of segmentation. *Rajeswari and Sharmila* (9) surveyed some of the preprocessing techniques for improving the quality of brain MRIs. The filtering techniques that surveyed in this paper were,

- Average filter
- Median filter
- Weiner filter

Based on the PSNR value, the better filtering technique was identified for improving the quality of image. *Malathi and Nadirabanu* (10) suggested a k-means clustering technique for detecting the tumor region from the brain MRIs. This work involves the processes of image acquisition, preprocessing, segmentation and tumor detection. The benefit of this work was, it has the capability to segment the tumor region from various MRIs. Also, it was studied that the image enhancement and noise removal were the main stages of tumor segmentation.

Feature extraction and feature selection

Kong, et al (11) developed an Information Theoretic Discriminative Segmentation (ITDS) technique for segmenting the tumor from brain MRIs by implementing the clustering based feature selection approach. Here, a Simple Linear Iterative Clustering (SLIC) technique was used to generate the 3D voxels from brain MRI. From that, it was analyzed that the suggested technique required minimum time consumption by efficiently extracting the meaningful features for segmentation. *Bron, et al* (12) recommended different feature selection techniques such as direct approach and iterative approach for an efficient brain tumor segmentation. In this work, the feature selection techniques were categorized into the following types:

- Filter methods
- Wrapper methods
- Embedded methods

Also, the SVM technique was utilized to rank the features based on the weights of a statistical test. *Nabizadeh and Kubat* (13) designed a fully automatic image segmentation system based on the Gabor wavelet and statistical feature extraction techniques. The main aim of this paper was to solve the problems of computational complexity by implementing the fully automated system. Moreover, the single spectral MRIs were considered in this work for improving the computational efficiency of segmentation. *Islam, et al* (14) developed a multifractal feature based segmentation technique for an efficient brain tumor detection. Here, the tumor affected area was differentiated from the non-tumor area by using the Adaboost ensemble classifier. But, the suggested technique was not highly suitable, if the image has complex tumor regions.

Segmentation and classification

Njeh, et al (15) introduced a graph cut distribution matching approach for detecting the type of tumor from the MRIs. Here, the normal regions were characterized by estimating the non-parametric model distribution. The aim of this paper was to evaluate the global similarity between the distributions that avoided the occurrence of small and isolated regions. Also, the distribution matching and data driven algorithms were developed for segmenting an exact tumor region. Moreover, the MICCAI dataset was utilized to evaluate the performance of the suggested brain tumor segmentation technique. From the analysis, it was observed that the suggested technique required to improve the image quality to reduce the artifacts by providing an efficient segmentation. *Moeskops, et al* (16) introduced an automatic segmentation technique for segmenting the WM, GM and CSF from the brain MRIs. Here, the multi-stage classification technique was implemented to split the problem into multiple tasks for classifying the tissue type in an accurate manner. In the first stage, the voxels were labeled to assign the tissue class in the brain mask. In which, each voxel was classified based on the set of features that extracted from the image. However, this paper has the some disadvantages such as inefficiency, and misclassification. *Moreno, et al* (17) suggested a new segmentation methodology for segmenting the tumor from the brain MRIs. The main contributions of this paper was to segment the tumor region using a global convex minimization approach. The advantage of this work was, it obtained a differentiation in GM, WM, and CSF.

Adhikari, et al (18) implemented a conditional spatial Fuzzy C-Means (csFCM) technique for segmenting the MRI brain tumor with increased robustness. This work stated that the traditional FCM technique does not consider the correlation between the neighboring pixels and generated inaccurate clusters. So, the suggested work focused to solve these issues by integrating the local spatial information between the adjacent pixels. The merit of this paper was, it produced the better segmentation results, even if the image has noise and intensity homogeneity. But, it required to integrate the spatial and intensity inhomogeneity by modifying the membership functions of the suggested segmentation technique. *Vishnuvarthanan, et al* (19) identified the tumor and segmented the tissue part by using an unsupervised learning and clustering techniques. Here, a Self-Organizing Map (SOM) was integrated with the Fuzzy K-Means (FKM) technique to provide an accurate segmentation results. The aim of using SOM was to reduce the dimensionality of the features and, FKM was to group the prototypes by segmenting the tissue region. From the paper, it was analyzed that this integrated technique was not highly suitable for handling the large range of data. *Demirhan, et al* (20) suggested a Neural Network (NN) based classification technique to identify the tumor region from the given brain MRIs. This work includes the following stages: preprocessing, skull stripping, feature extraction, feature selection, and classification. Here, the SOM was integrated the Linear Vector Quantization (LVQ) method to analyze the tissue and diagnose the tumor in an efficient manner. This paper failed to improve the accuracy of segmentation by considering the features of knowledge, shape and model.

Kim, et al (21) recommended a mesh to volume registration approach for segmenting the tumor region from the brain MRIs. The main intention of this paper were as follows:

- It attained an increased accuracy and robustness during segmentation.
- It efficiently detects the shape differences between the healthy and disease regions with improved sensitivity.

Moreover, the authors developed a shape based model to encode the shape characteristics of the hippocampus. However, this technique required to reduce the complexity of segmentation. *Roy, et al* (22) introduced a patch based tissue classification model for MRI brain tumor segmentation. Here, a new machine learning framework was developed with the atlas data for segmenting the image based on the patch based features. The relevant features were learned from the atlas by using a subject specific patch dictionary model. The drawback that analyzed from the paper was, it required to manually delineate some atlases from different sequences.

Kumari and Mehra (23) developed a hybrid method by combining the procedures of both Particle Swarm Optimization (PSO) and Support Vector Machine (SVM) for detecting brain neoplasms. Here, the histogram equalization was applied to enhance the quality of the image, then the Discrete Wavelet Transformation (DWT) technique was used to e
xtract the features of the image. Also, the best set of features were selected with the help of PSO, and the SVM was applied to detect the tumor affected region. However, this work failed to prove its superiority by analyzing various performance measures. *Preetha and Suresh* (24) recommended a FCM technique for segmenting the brain tumor in an automated manner. The aim of this technique were, to increase the robustness and efficiency of image segmentation. But, the FCM has an increased computational complexity, due to this drawback, it was not highly suitable for a perfect image segmentation. *Sridhar and Krishna* (25) implemented both the Discrete Cosine Transform (DCT) and Probabilistic Neural Network (PNN) techniques for brain tumor detection and classification. The DCT was mainly used to reduce the dimensionality of the features and the PNN was used to accurately classify the tumor part based on the selected features. The benefits of this paper were, it has a high speed processing capability, and required low computational resources.

From the survey, the existing brain tumor segmentation system has both the advantages and disadvantages. But, it mainly lacks with some major drawbacks:

- Increased computational complexity
- Less efficiency
- Not highly suitable for complex tumor segmentation
- Required to improve the overall efficiency of segmentation
- Not applicable for varying image modalities

In order to solve these issues, this paper aims to develop a new segmentation system for an accurate MRI brain tumor detection and segmentation.

PROPOSED METHOD

In this section, the detailed description about the proposed MRI brain tumor detection and segmentation system is presented. The aim of this paper is to accurately segment the tumor region by implementing various image processing techniques. The overall flow of the proposed system is shown in Figure 1, which includes the following stages:

- Preprocessing
- Feature extraction
- Segmentation

At first, the MRI brain image is given as the input, which contains some artifacts and noise that affects the segmentation results. So, it is highly important to eliminate the noise from the image, for this purpose, a Fuzzy Adaptive Median Filtering (FMAF) technique is implemented in this work. After preprocessing the image, the features of the filtered image are extracted with the use of eXtented Center Symmetric Local Derivative Pattern (XCS – LDP). Then, the threshold of the image is calculated for segmenting the tumor region from the given by using the combination of Particle Swarm Optimization (PSO) and Fuzzy K-Means (FKM) techniques. Here, the newness is implemented in the feature extraction and segmentation stages by implementing an enhanced techniques. The clear description about the proposed techniques are described in the following stages:

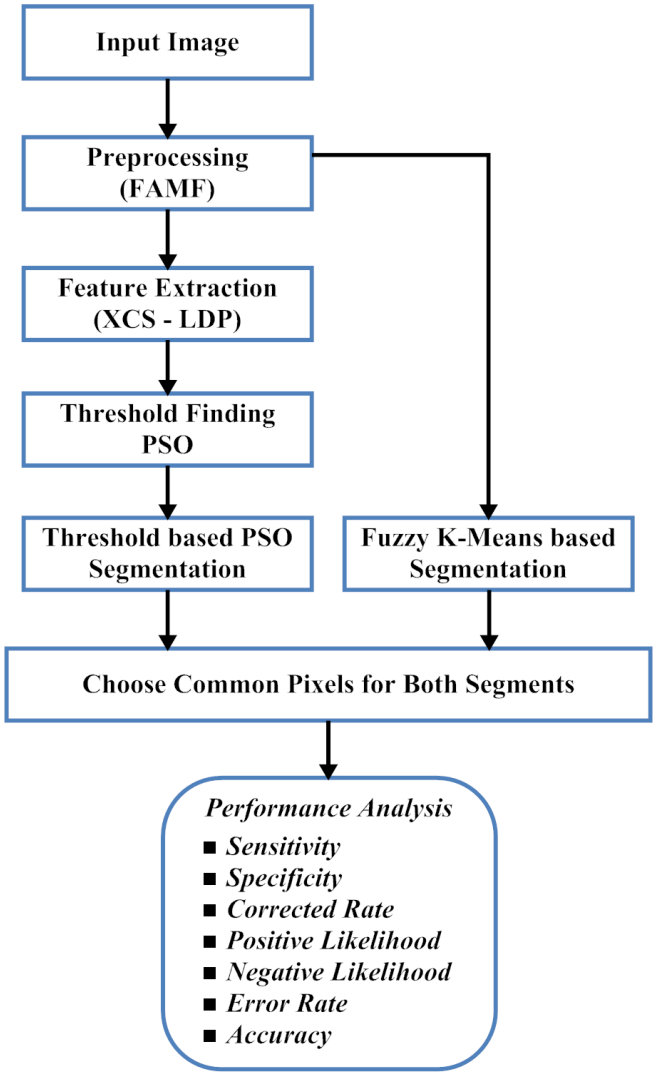


Figure 1. Flow of the proposed system

Preprocessing

The image preprocessing is an essential and demanding task for processing any medical images. Because, the original image contains noise and artifacts, which affects the quality of the image for further processing. Thus, image preprocessing is one of the important process, in which the irrelevant noise are eliminated by using the filtering techniques. In this work, a Fuzzy Adaptive Median Filtering (FAMF) technique is used to preprocess the image, which efficiently reduces the noise. The major objectives of using FAMF are as follows:

- It efficiently removes the level of noise compared than the traditional filtering techniques.
- It enhances the quality of image by increasing the smoothening effect.
- It is highly suitable for processing all kinds of medical images.

Due to these reasons, this paper used a FAMF technique image preprocessing, in which the pixels that is affected by the noise is determined. Then, each pixel in the image is compared with the neighboring pixels for identifying the pixel that is affected by the noise. Consequently, the noisy pixels are replaced with the value of median pixel, which enables the flexibility of the filter to change its size with the intensity of local noise. Here, the local weight operator is modified to design the filter based on the trans-conductance comparator. Furthermore, the intensity difference between the central pixel and the neighboring pixels are estimated in a sliding window. Figure 2 shows the original and preprocessed images.

Algorithm I – Fuzzy Adaptive Median Filtering (FAMF)

Input: *Testing frame – Y;*

Output: *Denoised frame – Y;*

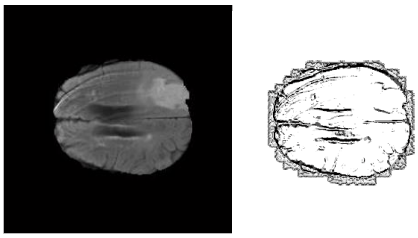
Step 1: *Initialize window size (3 × 3);*

Step 2: *Project window over image matrix,*
W = D (i-1:i+1, j-1:j+1) // Where, i and j represents row and column respectively;

Step 3: *Initializing filtering coefficient,*

$$C = \frac{W_i}{Var(W)} \times \left(W_i + Avg(W)\right)$$

Step 4: *Check neighboring pixel variation;*
Step 5: *S = sort (W);*
Step 6: *If S (1) < S (5) && S (5) < S (9) && 0 < S (5) && S (5) < 255*
Y (i, j) = C;
End if;
Step 7: *If S(1) >= S (5) || S (5) >= S (9) || S(5) == 255 && S(5) == 0*
D (i, j) = D (i, j-1);
End if;



(a) **(b)**

Figure 2 (a). Original image, and (b). Normalized edges

Feature extraction

After preprocessing the image, the features are extracted for accurately spotting the tumor region. Feature extraction is also one of the essential stage in image processing, in which a set of useful features are extracted from the filtered image for making a decision. In this paper, an eXtented Center Symmetric Local Derivative Pattern (XCS – LDP) technique. This technique is enhanced from the base of standard Local Derivative Pattern (LDP) technique. In this algorithm, the filtered result is given as the input, in which the symmetrical diagonal features are extracted in a pixel wise order.

Algorithm II – Extended Center Symmetric Local Diagonal Pattern (XCS-LDP)
Input: ***Filtered result Fitimage***
Output: ***Extracted features Feares***
Step 1: Initialize temporary matrix
$[m, n] = size\ (Filt_{image})$
$Temp_{im1} = zeros\ (m + 2, n + 2)$
Step 2: Assign the original pixels into $Temp_{im1}$
Step 3: $Temp_{im1}(2{:}m + 1, 2{:}n + 1) = Filt_{image}$
Step 4: Initialize window size $win = 3$
Symmetric diagonal features are extracted based on a pixel wise order;
$for\ ii = 1{:}m$
$for\ jj = 1{:}n$
$temp = Temp_{im1}(ii{:}ii + 2, jj{:}jj + 2)$
Convert block into vector form;
$temp\ 1 = temp\ (:)$
$G_{center} = temp1(5);$
$G_0 = temp1(8);$
$G_1 = temp1(9);$
$G_2 = temp1(6);$
$G_3 = temp1(3);$
$G_4 = temp1(2);$
$G_5 = temp1(1);$
$G_6 = temp1(4);$
$G_7 = temp1(7);$
$if\ \big((G_1 - G_5) + G_{center} + (G_1 - G_{center}) * (G_5 - G_{center})\big) \geq 0$
$S_{val1} = 1 * 2^0;$
Else
$S_{val1} = 0 * 2^0;$
End if
$if\big((G_3 - G_7) + G_{center} + (G_7 - G_{center})\big) \geq 0$
$S_{val2} = 1 * 2^1;$
Else
$S_{val2} = 0 * 2^1;$
End if
$if\big((G_5 - G_1) + G_{center} + (G_5 - G_{center}) * (G_1 - G_{center})\big) \geq 0$
$S_{val3} = 1 * 2^2;$
Else
$S_{val3} = 0 * 2^2;$
End if
$if\big((G_7 - G_3) + G_{center} + (G_7 - G_{center}) * (G_3 - G_{center})\big) \geq 0$

$S_{val4} = 1 * 2^3;$
Else
$S_{val4} = 0 * 2^3;$
End if;
$Fea_{res} = S_{val1} + S_{val2} + S_{val3} + S_{val4};$
End for;
End for;

Segmentation

After extracting the features, the image is further segmented by using the combination of two techniques such as, Threshold based Particle Swarm Optimization (T-PSO), and Fuzzy K-Means (FKM). The main reason for using these techniques are, the common pixels that are segmented by the two techniques are considered for an efficient segmentation. Typically, image segmentation is defined as the process of splitting an image into sub-parts for further processing. The accuracy of image processing system is fully depend on the process of segmentation. Thresholding is one of the most widely used segmentation technique that separates the pixels of the image in varying classes based on the level of intensity. But, it cannot be applicable for processing the multichannel image.

Thresholding based particle swarm optimization

Thus, this work integrates the thresholding with the PSO technique, which functions based on the collaborative behavior of the bird flocking. In this technique, each particle represents the candidate solution that is identified based on the specific coordinates in the search space. For each particle, the fitness function is evaluated and compared with the previous value, based on this the best particle in the swarm is identified. After that, the velocity and position with respect to the best particle are updated. The outputs of threshold based PSO and its stretched result are depicted in Figure 3. The major advantages of T-PSO are as follows:

- Increased robustness and efficiency
- Provides the best optimal solution
- Highly flexible
- Simplicity

Algorithm III – Threshold based Segmentation using PSO

Input: ***Feature result 〖Fea〗_res;***

Output: ***Segmented output 〖Seg〗_PSO;***

Step 1: *Initialize population P, particle velocity* P_{vel}, *particle position* $P_{position}$ *and* P_{best}

$P = ones\ (size\ (Fea_{res}, 1), 1) * rand\ (1,1);$

$P_{vel} = rand(1, size(P)), P_{position} = rand(1, P);$

$P_{best} = P_{position};$

Step 2: *Calculate the objective function*

$Objective_{res} = (Fea_{res}(:,1) - 20)^2 + (Fea_{res}(:,2) - 25)^2;$

Step 3: *Compute global best location;*

$If\ Objective_{res} \leq Objective_{prev-res}$

$P_{global-best} = P_{best};$

$Objective_{prev-res} = Objective_{res};$

End if

Step 4: *Iterate the loop for obtaining the global best solution*

$While\ Iter \leq Itermax$

$For\ pp = 1{:}P$

Update velocity;

$Max_{bird} = max(\ Fea_{res})\ ;$

$Max_{velo} = Max_{bird} * Velocity_{clamp};$

Where, $Velocity_{clamp} = 2;$

$Min_{velo} = -Max_{velo};$

$Velocity = Min_{velo}(pp) + (Max_{velo}(pp) - Min_{velo}(pp)) * rand(population, 1);$

Update $P_{position}$ *based on the updated velocity;*

$Objective_{res} = (Fea_{res}(:,1) - 20)^2 + (Fea_{res}(:,2) - 25)^2;$

Compute the global best location

$If\ Objective_{res} \leq Objective_{prev-res}$

$P_{global-best}(i) = P_{best};\ Objective_{prev-res} = Objective_{res};$

$End\ if;$

End for;

End while;

Step 5: *Segment the image with estimated threshold;*

Thresh=$P_{global-best};$

Thresh1=$max(P_{global-best});$

Thresh2=$min(P_{global-best});$

$Final_{thresh} = \frac{Thresh1}{Thresh2};$

$Seg_{PSO} = im2bw(Filt_{image}, Final_{thresh});$

(a) (b)

Figure 3 (a). Thresholding based PSO and (b). Stretched result

Fuzzy k-means segmentation

The FKM segmentation algorithm uses a continuous membership value for estimating the volume of the tumor. Also, it equalizes the population based on the weight and class of the image. It is an extension of traditional k-means algorithm, which identifies the varying number of classes for a given image. The main reasons for using this technique are, it provides an increased accuracy, and it integrates the advantages of both fuzzy and k-means segmentation techniques. The segmented output of FKM technique is shown in Figure 4.

Algorithm IV – Fuzzy K-Means based Segmentation

Input: *Filtered result* $Filt_{image}$;
Output: *Segmented output* Seg_{fuzzyk};
Step 1: *Initialization*
$data = Filt_{image}(:)$;
$row = size\ (data, 1)$;
$N_{class} = 3$; *// Where,* N_{class} *represents the number of clustered class;*
Step 2: *Initialize membership;*
$U = {}^{1}/_{N_{class} * ones(row, N_{class})}$;
$U = U + (sca + rand(row, N_{class}))$; *//Where, sca – scatter representation;*
$U_{initial} = \frac{U}{sum(U)} * ones(N_{class}, 1)$;
Step 3: *Perform morphological operation to cluster the image with initial membership;*
Step 4: *Open the image for performing the morphological operation;*
$Open_{image} = imopen(Filt_{image}, Se)$;
Step 5: *Form the segmented image;*
$for\ xx = 1{:}size(Filt_{image}, 1)$
$for\ yy = 1{:}size(Filt_{image}, 2)$
$If\ Open_{image}(ii, jj) == 255$
$Seg_{fuzzyk}(ii, jj) = 1$;
Else
$Seg_{fuzzyk}(ii, jj) = 0$;
End if;
End for;;

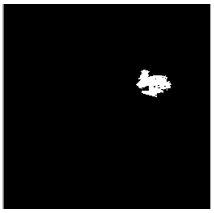


Figure 4. Segmented result using FKM

After segmenting the image using FKM, the segmented outputs of both T-PSO and FKM are compared. Then, the common regions segmented by these techniques are finalized as segmented output, which is shown in Figure 5.

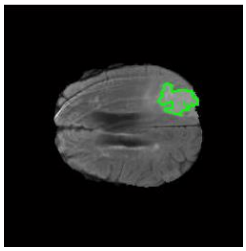


Figure 5. Final segmented result

PERFORMANCE ANALYSIS

In this section, the experimental evaluation of existing and proposed segmentation techniques that are used for MRI brain images are validated. For this purpose, different performance measures are used, which includes sensitivity, specificity, accuracy, jaccard, dice, precision and recall. The dataset that used in this work is, BRATS 2016 obtained from the SICA medical imaging repository (26). In this analysis, varying tumor affected images (i.e. 100 MRIs) are used to evaluate the effectiveness of the proposed segmentation systems.

Sensitivity, specificity, and accuracy

In medical image processing, the sensitivity and specificity measures are widely used for diagnosis purpose. In which, sensitivity is defined as the true positive divided by the sum of true positive and false negative. Also, it is defined as the proportion of true positives that are correctly identified by the proposed T-PSO and FKM technique. Similarly, specificity is defined as the number of true negative results that are divided by the sum of the number of true negatives and false positives. The sensitivity and specificity are calculated as follows:

$$Sensitivity = \frac{TP}{TP+FN} \quad (1)$$

$$Specificity = \frac{TN}{TN+FP} \quad (2)$$

The accuracy of the segmentation technique is measured for identifying the correctness of the segmentation. It is determined based on the values of both sensitivity and specificity values, which is calculated as follows:

$$Accuracy = \frac{TN+TP}{(TN+TP+FN+FP)} \quad (3)$$

Where, TP represents the True Positive, TN represents the True Negative, FP denotes the False Positive and FN indicates the False Negative. The terms that used to determine the sensitivity, specificity, accuracy are illustrated in Table 1.

Table 1. Terms used to define sensitivity, specificity and accuracy

Outcome of the diagnostic test	Condition determined by the standard of truth		
	Positive	**Negative**	**Row Total**
Positive	TP	FP	TP + FP (Total number of subjects with positive result)
Negative	FN	TN	FN + TN (Total number of subjects with negative test)
Column total	TP + FN (Total number of subjects with given condition)	FP + TN (Total number of subjects without given condition)	N = TP + TN +FP + FN (Total number of subjects in study)

Figure 6 shows the sensitivity, specificity, and accuracy of the proposed T-PSO with FKM segmentation techniques. From the results, it is identified that the sensitivity is increased to 86%, the specificity is increased to 100%, and the accuracy is improved to 99%.

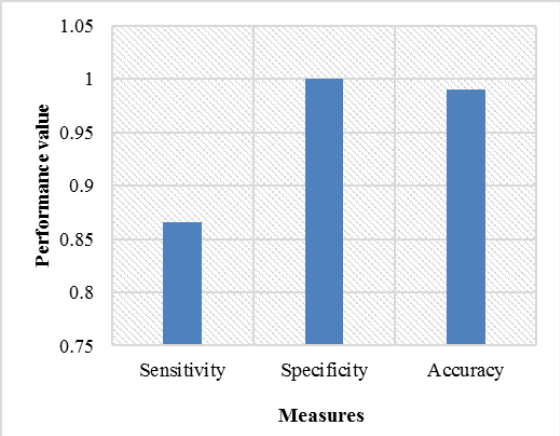


Figure 6. Sensitivity, specificity, and accuracy

Precision and recall

In many medical image processing applications, precision and recall are the mostly used measures for evaluating the effectiveness of image segmentation. Precision is defined as the positive predictive value that provides the results relevant to an accurate segmentation. Then, it is estimated based on the ratio of true positives and true positives plus false positives. Recall is also termed as sensitivity, which provides the most relevant results during tumor segmentation. Based on the values of TP, TN, FP and FN, the precision and recall are estimated as shown in the following equations:

$$Precision = \frac{TP}{(TP+FP)} \quad (4)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (5)$$

Figure 7 shows the precision and recall values of the proposed T-PSO with FKM techniques. From the results, it is observed that the proposed techniques provided an efficient segmentation results by accurately segmenting the regions.

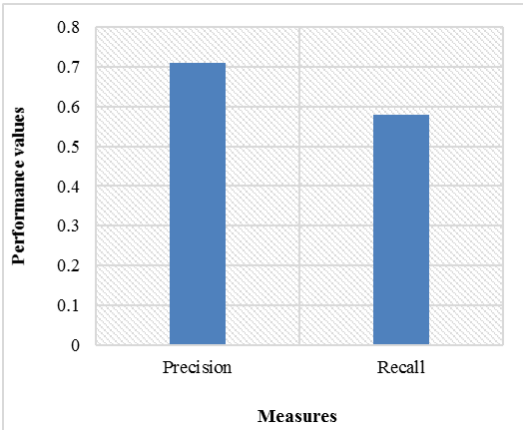


Figure 7. Precision and recall

Jaccard, dice and kappa coefficients

Jaccard, Dice and Kappa are the similarity coefficients that are mainly used for disease diagnosis purpose in medical image processing. In which, Jaccard is defined as the ratio of intersection and union of two objects, which varies from 0 to 1. If the value is 1, the two objects are identical and their sets have no common regions. Moreover, it finds the overlap between two labeled regions *r* in I_1 and I_2 over the union. It is calculated as follows:

$$Jaccard = \frac{|A_{r1} \cap A_{r2}|}{|A_{r1} \cup A_{r2}|} \quad (6)$$

Dice is mainly used to identify the similarity between two different images A_1 and A_2, which is calculated as follows:

$$D_s = \frac{2.|A_{r1} \cap A_{r2}|}{|A_{r1}|+|A_{r2}|} \quad (7)$$

The kappa coefficient measures the difference between the observed agreements of two segmented regions. Moreover, high kappa coefficients provides accurate segmentation results. It is calculated as follows:

$$Kappa\ Coefficient = \frac{(n*sum\ X_{ii}) - sum\ (X_{i+}*X_{+i})}{n^2 - sum\ (X_{i+}*X_{+i})} \quad (8)$$

Where, sum represents the sum across all rows in matrix, X_{i+} indicates the marginal row total X_{+i} indicates the marginal column total and *n* defines the number of observation. Figure 8 shows the

similarity coefficients of the proposed segmentation system, from this, it is evident that the T-PSO with FKM technique provides the better results with increased accuracy.

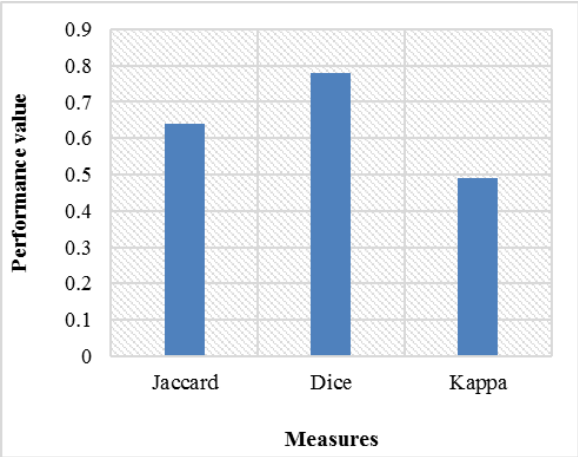


Figure 8. Similarity coefficients

Rand index, global consistency error, and voi

Rand index is defined as the ratio of the computed segmentation and ground truth segmentation. Also, it measures the similarity between two labeled regions, which ranges from 0 to 1. Here, 0 indicates that the two data points are not in the same region, and 1 indicates that the data points are exactly in the same region. It is estimated as follows:

$$R = \frac{x+y}{x+y+z+a} \qquad (9)$$

Where, R indicates the rand index, $x+y$ indicates the number of agreements, and $z+a$ indicates the number of disagreements between two data points. Then, the Global Consistency Error (GCE) estimates the extent of one segment that can be viewed as a refinement of other segmentation. It is calculated as follows:

$$GCE = \frac{1}{n}\{\sum_i (X1, X2, p), \sum_i E(X2.X1.p)\} \quad (10)$$

Where, p indicates the pixel, X1 and X2 indicates the segmentation inputs, which produces the output in the range of [0::1]. The Variation Of Information (VOI) finds the distance between two segmentations based on the average conditional entropy. Table 2 shows the rand index, GCE and VOI of the proposed T-PSO with FKM techniques, from this analysis, it is evaluated that the proposed segmentation technique provides the results in terms of increased rand index, and reduced GCE and VOI.

Table 2. Segmentation results of T-PSO with FKM

Measures	T-PSO with FKM
Rand index	0.98
Global consistency error	0.0128
Variation of Information	0.1019

Comparative analysis

To prove the superiority of the proposed segmentation technique, it is compared with the existing techniques (27) based on the measures of dice, sensitivity, and specificity. During this analysis, the BRATS 2013 dataset is used to evaluate the results of the existing and proposed techniques. From this analysis, it is observed that the proposed technique provides the better results, when compared to the existing technique.

Table 2. Comparison between existing and proposed techniques

Methods	Dice	Specificity	Sensitivity
T-PSO with FKM	0.91	0.9	0.94
Input Cascade CNN	0.88	0.89	0.87
Tustison	0.87	0.85	0.89
MFCascade CNN	0.86	0.92	0.81
Two Path CNN	0.85	0.93	0.8
LocalCascadeCNN	0.88	0.91	0.84
LocalPathCNN	0.85	0.91	0.8
Meier	0.82	0.76	0.92
Reza	0.83	0.82	0.86
Zhao	0.84	0.8	0.89
Cordier	0.84	0.88	0.81
Festa	0.72	0.77	0.72
Doyle	0.71	0.66	0.87

CONCLUSION AND FUTURE WORK

This paper presents a new segmentation system for segmenting the tumor region from the brain MRIs. For this purpose, a T-PSO with FKM techniques are developed in this work, in which the segmented results of both techniques are compared for identifying the common segmented region. Here, the FMAF filtering technique was used to preprocess the image by eliminating the noise and improving the quality. Then, the features of the preprocessed image are extracted by the use of XCS-LDP technique. The novel techniques such as T-PSO and FKM are implemented to segment the tumor portions from the image based on its features. Finally, the common pixels that are detected by these techniques are considered as a tumor portion. During evaluation, the segmentation results of the proposed system is evaluated and compared for improving the effectiveness of T-PSO and FKM techniques. The measures that are used to evaluate the results are accuracy, sensitivity, specificity, similarity coefficients, rand index, GCE, ROI, precision and recall. In this analysis, it is proved that the proposed T-PSO with FKM provides the better results, when compared to the existing segmentation technique.

In future, this work can be enhanced by implementing this segmentation technique for different types of imaging modalities.

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