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Research Article

Incorporation of Modified Region Growing into FCM Clustering for Extraction of Tumors in MR Images

Lovepreet Singh Brar[1], Jaget Singh[1], Bhawana Agrawal[2], Sunil Agrawal[1] and Ayush Dogra[3]

[1]*Department of Electronics and Communication Engineering, University Institute of Engineering and Technology, Panjab University, Chandigarh 160014, India*
[2]*University Institute of Chemical Engineering and Technology, Panjab University, Chandigarh 160014, India*
[3]*Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, 140401, India*

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Corresponding Author:
Sunil Agrawal
Department of Electronics and Communication Engineering, University Institute of Engineering and Technology, Panjab University, Chandigarh 160014, India
Email: s.agrawal@pu.ac.in

Abstract: Due to the tremendous growth of medical Magnetic Resonance (MR) images, it becomes an essential requirement for an automated extraction of diagnostically salient parts of the images to refine the transmission and storage process. Research method: This paper proposes an automated unsupervised machine learning segmentation technique named fuzzy c-means clustering based on modified region growing algorithm (RG-FCM) for the extraction of tumors from MR brain images. The average intensity value of the foreground region extracted by the Otsu thresholding technique is selected as seed point of the region growing algorithm, and spatial constraints extracted from modified region growing technique are then incorporated into the objective function of Fuzzy C-Means clustering to improve cluster separation and refine centroid selection, particularly in images with uneven illumination. Results and Discussion: The empirical evaluation exhibits the superior performance of the presented technique, and performs better than Possibilistic Fuzzy C-Means (PFCM) and conventional FCM. The mathematical results evaluated on a dataset of 60 MR images indicate the improvement in Jaccard and dice indices by (3-5) and (6-8) % from PFCM and conventional FCM respectively. Therefore, this incorporation of the modified region growing technique into FCM can be employed for real time processing due to its less execution time and can be expanded for the computer-assisted identification of abnormal tissue proliferation in MRI brain images.

Keywords: Image Segmentation, Tumor Extraction, Otsu's Threshold, Region Growing Technique, FCM Clustering, Jaccard and Dice Indices

Introduction

In the field of biomedical images, the development of new techniques for transmission and storage of images has led to advancements in fields like medical image processing, where extraction of the informative parts from medical images is a core capability. In medical imaging, extracting and preserving high-quality informative parts or object of interest is critical for accurate diagnosis and patient care. The techniques that focus on efficiently identifying, isolating, and preserving these key areas of an image are essential because they enhance the reduction of data that needs to be processed and transmitted while maintaining the integrity of important diagnostic information. The soft computing techniques have made significant strides in extracting the tumorous regions from Magnetic Resonance (MR) images. The tumor is formed by abnormal growth of the cells, which can be benign or malignant. The benign tumors grow slowly and are mainly confined to a particular area of that organ, but malignant tumors are cancerous, which grow rapidly and can metastasize to different parts of the body. The malignant tumors are also often more difficult to treat and may require a combination of surgery, radiation, and chemotherapy. Therefore, the early detection of these tumors can improve the patient outcomes and daily functioning, but tumor extraction from noisy MR images is a difficult task. Therefore, preprocessing steps are required to improve the extraction of noisy MR images (Sran *et al*., 2020a).

In recent years, a lot of segmentation methods for MR brain images have been published. The different

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techniques for segmentation of MR images are categorized as thresholding method, region growing method, active contours method, clustering method, neural networks, and fuzzy logic methods (Kaewkamnerd *et al.,* 2019) The various thresholding techniques are commonly employed for image segmentation, with threshold values either manually defined or adaptively determined to accurately classify pixels into desired categories. However, these thresholding methods fail to extract informative parts in multichannel images (Abd *et al*., 2023). In region-based segmentation, similarity is measured by the difference between a pixel's intensity and the region's mean intensity, and the pixel with the smallest difference is assigned to the region. But, sometimes it produces undesired results when the intensity difference is quite large compared to a certain threshold, and picking an incorrect initial point or seed point in the region-growing algorithm also leads to different segmentation results (Despotović *et al.,* 2015).

Active contour methods are works on the concept of energy minimization to delineate object boundaries within an image, starting from manually initialized points (Brar *et al*., 2025a). These methods are able to handle complex topological structures, but these methods lead to undesired convergence of the contour in the presence of cluttering in the image (Costea *et al*., 2021). It has been observed that in order to detect the tumorous region, completely automated algorithms currently in use need to be trained or supervised beforehand. The deep learning models are shown to be effective for medical image segmentation and achieve high accuracy than unsupervised machine learning techniques, but large training time leads to slow convergence and increases the execution time compared to proposed model (RG-FCM) and may lead to overlifting by reducing the training dataset and these deep learning models have a higher computational cost than the proposed model (Hesamian *et al*., 2019).

Fuzzy C-Means (FCM) clustering is among the most widely adopted techniques in the field of segmentation, but it results in different segmentation results in noisy images due to biased initialization of cluster centroids, and therefore spatial constraints are integrated into the objective function of fuzzy c-means clustering to improve the extraction of diagnostic parts in noisy images. This extraction of the spatial information can remove the biased initialization by selecting cluster centers from the desired information enables to avoid multiple runs of the algorithm (Brar *et al*., 2025b). Therefore, numerous approaches have been presented to extract the accurate informative parts from medical images by incorporating different techniques to FCM clustering (Hu, 2015).

Literature Review

Pal *et al*. (2005) presented a hybrid model using Possibilistic Fuzzy C-Means (PFCM), by combining Possibilistic C-Means (PCM) and FCM clustering. This integration of both techniques overcomes the problem of coinciding clusters in uneven illumination images. The mathematical evaluation of the presented work demonstrated superior performance compared to state-of-the-art methods.

Al-Faris *et al*. (2014) presented an automated method for extracting the informative parts from medical images by modifying the initialization of seed point in the region growing algorithm. This segmentation work employed morphological thinning after the active contours method, and this technique was evaluated on a dataset of 40 images, and ANOVA test demonstrated that the presented model is significant in terms of misclassification rate ($p = 0.002$) and relative overlap ($p = 0.045$).

Nithila and Kumar (2016) presented a hybrid technique by integrating region-based active contours into fuzzy c-means clustering to extract the informative parts or lung lesions from Computed Tomography (CT) scans. The success of this technique was demonstrated by the experimental results, which reveal a reduced run time from 440 s to 18 s and reduce the error rate by 12% compared to LBF.

Wei *et al*. (2018) reported an ensemble fuzzy clustering based on the KL divergence method to overcome the low accuracy of fuzzy clustering in noisy images. First, different fuzzy clustering techniques are used to classify the data, and then KL divergence is integrated into objective function of fuzzy clustering, which aggregates the soft clustering findings. The experimental findings demonstrated that the presented technique outperforms traditional methods in synthetic and real-time image processing.

Sreenivasulu and Varadarajan (2019) reported an enhanced region-growing method for segmenting and extracting target structures from MR images, and segmented parts of the image are subjected to non-uniform compression. The experimental results demonstrate that the modified region-growing algorithm achieves superior sensitivity and accuracy compared to the PFCM clustering method. This modified segmentation technique results in the improvement in various compression metrics like CR increases by 0.3 and PSNR increases by 8 dB compared to PFCM.

Sran *et al*. (2020b) presented the segmentation-based compression technique in which the object of interest is extracted from MR brain images by incorporating a saliency model to fuzzy c-means clustering, and further segmented parts are subjected to non-uniform compression using the SPIHT algorithm at different bit rates. The mathematical outcomes showed the improvement in Jaccard and dice indices and different compression metrics.

Fang *et al*. (2021) presented an edge-based active contour model guided by region-based fuzzy energy to address incorrect energy convergence in noisy images. This energy formulation integrates both hybrid and local fuzzy information to effectively steer the contour toward the boundaries of objects of interest, and empirical evaluation of the experiments reveals that the presented work performs better than state-of-the-art methods in terms of the dice coefficient.

Sran *et al.* (2021a) described various visual saliency algorithms to extract the objects of interest from MR images of the brain. The different saliency models that include the fuzzy threshold-based saliency model, spectral residency, saliency by induction, and image signature were evaluated using the BRATS dataset of MR brain images. These models showed superior findings in natural images but were unable to extract tumorous regions from MR images except for the fuzzy threshold-based saliency model.

Sran *et al.* (2021b) presented an automated technique to extract the diagnostic information from MR brain images. This technique is implemented by incorporating a saliency model into the objective function of the fuzzy thresholding technique, which enables the detection of diagnostic areas in MR images. The empirical evaluation demonstrated that the presented work outperforms kernel-based fuzzy c-means clustering and mean shift fuzzy c-means in terms of Jaccard index (0.84 ± 0.04), Dice index (0.91 ± 0.02), and F-measure (0.88 ± 0.10).

Wei *et al.* (2023) presented an improvement in the interval type-2 probabilistic FCM algorithm (IT2PFCM) by incorporating its objective function into adaptive spatial constraints to overcome the inaccuracy of the algorithm in uneven illumination images. The series of experiments were performed on real and synthetic images, and its empirical evaluation endorses superior results compared to conventional methods.

Thomas and Kumar (2024) presented the hybrid technique by incorporating the firefly optimization algorithm with FCM clustering to improve the convergence speed of the algorithm. The firefly optimization algorithm aimed to find the optimum global threshold, which results in the improvement of the convergence speed of FCM clustering. The mathematical findings demonstrated that the presented technique exhibits better results when compared with K-means and Otsu threshold.

Kujur *et al.* (2022) conducted a comparative analysis of various CNN models on brain tumor and Alzheimer's disease datasets, both with and without the application of Principal Component Analysis (PCA). Their findings indicate that the Alzheimer's dataset exhibits greater data complexity than the brain tumor dataset. The highest achieved accuracies were 98.02% for the Alzheimer's dataset and 99.27% for the brain tumor dataset, highlighting the significant impact of data complexity on CNN model performance.

It has been observed that most of the algorithms result in inaccurate extraction of the diagnostic parts from MR images. The region-growing algorithms suffers due to automatic initialization of seed points because manual selection of the seed point may lead to wrong initialization, and most of the presented fuzzy c-means techniques lack spatial information, and incorrect selection of initial centroid results in undesired segmentation in noisy images. Therefore, it is crucial to develop an appropriate segmentation technique to achieve desired segmentation results in MR images.

The presented work's contribution can be summed up as follows:

- The modified region growing algorithm is used to extract the spatial constraints of the MR images
- The seed point is chosen using an automated global thresholding technique known as Otsu's threshold technique, and the mean intensity pixel value of the region of interest obtained by the thresholding technique is chosen as the seed point
- The spatial constraints extracted from the modified region growing algorithm is incorporated into the objective function of fuzzy c-means clustering to improve the working of the FCM algorithm in uneven illumination images
- The empirical evaluation of the proposed segmentation technique endorses superior performance when compared with traditional methods in terms of various segmentation metrics

Methods

The modified region growing-based FCM (RG-FCM) is applied to the magnetic resonance images of the brain for accurate demarcation of the informative parts. The region growing algorithm operates based on pixel similarity, initiating the process from a seed point selected within an informative region and expanding by incorporating neighboring pixels with similar characteristics and terminates the process if further growing is not possible, but wrong or manual selection of the seed point may lead to inaccurate segmentation. Therefore, the Otsu threshold is integrated to the region growing algorithm to automate the initialization of the seed point.

Otsu's threshold is global thresholding technique used to determine the optimum threshold of an image based on interclass maximization and segments the image into foreground (informative part) and background regions, and the average intensity value of the foreground part is chosen as the seed point to automate its initialization in the region growing algorithm. The spatial features extracted from the modified region growing algorithm are integrated into the objective function of FCM clustering.

Fuzzy c-means clustering is an effective distance-based unsupervised machine learning algorithm for classification of data by calculating the Euclidean distance of each point from the centroid, and membership values are updated till the difference is less than the tolerance value, but selection of the centroid gets affected in noisy images, resulting in undesired segmentation. Therefore, for refining cluster formation and centroid selection, spatial constraints derived from the modified region growing algorithm are integrated into the objective function of the fuzzy c-means clustering method.

The proposed framework of segmentation technique is demonstrated in Figure 1 and tested on 60 MR images to prove its effectiveness. Firstly, the input image is subjected to an automated thresholding technique using Otsu's threshold to segment the image into foreground and background regions, and the average pixel value of the foreground region is selected as the seed point for the region growing technique to obtain the spatial information, and this information is incorporated into the FCM clustering technique for splitting the data into clusters and refining the selection of the centroids in noisy images, and the membership table is updated on the basis of Euclidean distance until constant values are obtained. This incorporation of spatial constraints into FCM clustering results in the improvement in various segmentation metrics for different MR images.

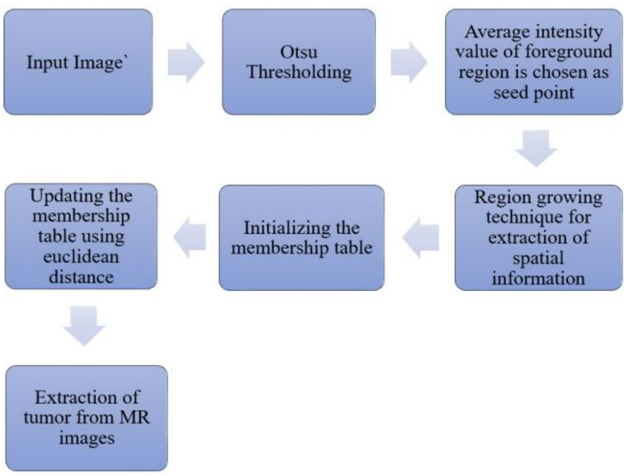

Fig. 1: Proposed Framework of Segmentation Technique

Automated Threshold Using Otsu's Thresholding Technique

Otsu's thresholding method is an automated and non-parametric technique used to determine the optimum threshold based on interclass maximization. This method is based on the maximum variance of various classes as a criterion to segment the image into foreground and background regions (Huang *et al*., 2021). Otsu's thresholding method is widely used in the detection of abnormalities in medical images for large-scale datasets due to its low computational complexity. The average intensity value of the foreground region obtained using the thresholding technique is considered as the seed point for the region growing algorithm.

Spatial Constraints Extracted by Region Growing Algorithm

Region growing algorithm is process of grouping the pixels or subregions to get bigger region present in an image. The automated seed point is selected through Otsu's thresholding technique to avoid any biased selection of the seed point which may spike the error rate of segmenting algorithm, and after this initial seed starts growing by adding neighbors of homogeneous intensity which are sharing similar characteristics. If pixels of adjacent regions meet the similarity criterion or share similar spatial properties, then these pixels are grouped into the region of interest. This process continues till it achieves intensity difference between region mean and adjacent pixel becomes larger than certain threshold (Melouah and Layachi, 2018). This threshold acts as a similarity criterion between the mean region pixel and the adjacent pixel, and the pixel is added to the mean region only if their intensity difference is within the threshold.

The adaptive thresholding is implied to region-growing algorithm for making the termination process more robust. In the adaptive thresholding technique, thresholds are adjusted on the basis of statistical properties of the region. Therefore, pixel intensity is compared to various thresholds instead of a fixed threshold, and this algorithm provides the spatial information of the object of interest. These spatial constraints are further incorporated into fuzzy c-means clustering resulting in accurate extraction of tumorous regions from MR images (Brar *et al*., 2025a).

Extraction of Tumor by Incorporating Spatial Information into Fuzzy C-Means Clustering

The spatial information extracted from the modified region growing technique is integrated into the objective function of FCM clustering. FCM clustering is a distance-based unsupervised machine learning technique in which each data point belongs to a particular cluster with a certain probability known as membership value. This membership table is initialized with random values, and centroids of different clusters are computed. Then after this, membership values start updating by calculating Euclidean distance between each point from centroids, and this process continues until constant values are obtained for membership values (Christ *et al*., 2011).

The spatial constraints extracted from the modified region growing technique enable the correct location of centroids in uneven illumination images. Therefore, the proposed work performs well even in noisy images and reduces the computational complexity of the algorithm as compared to other conventional methods.

PSUEDO CODE OF PROPOSED SEGMENTATION TECHNIQUE

 # I → Input Image

 # Automated Threshold using Otsu's Thresholding technique

Step 1: Determining the histogram and probabilities of every pixel value.

$$P_i = \frac{N_i}{N_k};\ \sum_{i=0}^{L-1} P_i = 1 \quad (1)$$

where L →intensity levels, N_i → no. of levels having intensity i and N_k→ no. of pixels

Step 2: Choosing random threshold (T) and probability distributions of both classes are given by Equation 2:

$$w_1(T) = \sum_{i=1}^{T} P_i \text{ and } w_2(T) = \sum_{i=T+1}^{L} P_i \quad (2)$$

Step 3: Computing the mean levels μ_1 and μ_2 using Equation 3:

$$\mu_1 = \sum_{i=1}^{T} \frac{i\,P_i}{w_1(T)} \text{ and } \mu_2 = \sum_{i=T+1}^{L} \frac{i\,P_i}{w_2(T)} \quad (3)$$

Step 4: Computing weighted variance σ_I^2 using variance of both regions σ_1^2 and σ_2^2.

$$\sigma_I^2 = W_1\sigma_1^2 + W_2\sigma_2^2 \quad (4)$$

Step 5: Otsu's threshold corresponds to region having minimum class variance and that particular region is considered as foreground region.

 # F represents the foreground region obtained by thresholding technique.

 # Spatial information extracted by region growing Algorithm

Step 6: Average intensity value of foreground region F is selected as starting point or seed point for automated initialization of Region Growing technique.

Step 7: Initial seed grows by adding neighbors sharing similar characteristics.

Step 8: Foreground region F is divided into different sub regions $F_1, F_2 \ldots\ldots\ldots F_N$ such that a) $\bigcup_j^n F_j = F$ b) $F_i \cap F_j = null$, c) P (S_i) =True and d) $P(F_i \cup F_j)$=False for any adjacent regions F_i and F_j.

 # P(F) is logical predicate defined over points in F

Step 9: This process of region growing stops when intensity difference between region's mean μ and new pixel becomes larger than a particular threshold.

$$t < \|\mu_i - p_i\|$$

 # Spatial constraints (S) extracted from modified region growing algorithm are incorporated into objective function of FCM clustering.

 # Extraction of tumor by integrating spatial constraints into Fuzzy c-means clustering

Step 10: FCM tries to minimize the objective function given by Equation 5:

$$J\,(P,V) = \sum_{i=1}^{k} \sum_S (u_{c_i}(S_k))^m \,\|S_k - v_i\|^2 \quad (5)$$

Where v_i is center of cluster i, P is fuzzy partition of spatial constraints S, m is weight exponent (u_{c_i}) is degree of membership and $\|S_k - v_i\|^2$ is the Euclidean distance from center of cluster.

Step 11: Updating the membership matrix using Equation 6:

$$U_{ij} = \frac{1}{\sum_{k=1}^{c}\left[\frac{\|s_j - c_i\|}{s_j - c_k}\right]^{\frac{2}{m-1}}} \quad (6)$$

Step 12: Computing clustering centers using equation

$$C = \frac{\sum_{j=1}^{n} U_{ij} * R_j}{\sum_{j=1}^{n} U_{ij}^{p}} \quad (7)$$

Step 13: Terminate if it satisfies Equation 8, else go to step 11.

$$C^{k-1} - C^k < \varepsilon \quad (8)$$

 # Automated detection of tumors from magnetic resonance images of the brain using proposed method.

Segmentation Metrics

The accuracy of the tumorous regions extracted from MR brain images is evaluated using various segmentation metrics like Jaccard and dice indices, Percentage of extracted region, Precision, Recall, and F-measure.

- Jaccard Index (*J*) is used to measure homogeneity and diversity between extracted parts (€) and ground truth (Ø) images and is empirically evaluated by the ratio of intersection and union of € and Ø and given by Eq. 9 (Alqarafi *et al*., 2024):

- $$J = \frac{|€ \cap Ø|}{|€ \cup Ø|} \quad (9)$$

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- Dice Index (D) is also known as the spatial overlap index, used to gauge the degree of overlap between extracted region images *(€*) and ground truth images from the dataset (*Ø*), and empirically evaluated using Equation 10 (Alqarafi *et al*., 2024):

$$D = 2\frac{|€ \cap Ø|}{|€| + |Ø|} \quad (10)$$

- Percentage of extracted region is evaluated by obtaining binary masks from the extracted regions and comparing them with the area of their respective ground truth binary masks for a measure of similarity. This percentage of extracted regions is evaluated using Equation 11 (Brar *et al*., 2025b):

$$Extracted\ Area = \frac{\theta_{white}}{\theta_{white} + \theta_{black}} \times 100\% \quad (11)$$

- Where θ_{white} and θ_{black} are white and black pixels of binary mask Respectively
- Precision, Recall and F-measure are segmentation metrics used to evaluate boundaries of extracted parts empirically. Precision is based on true positive pixels evaluated using Equation 12, and Recall is used to calculate the percentage of true positive pixels evaluated using Equation 13, and F-measure is evaluated using values of precision and recall to gauge the accuracy of the proposed algorithm, and it is given by Equation 14 (Kujur *et al*., 2022):

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

$$Recall = \frac{TP}{TP+FN} \quad (13)$$

$$F - measure = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (14)$$

- Where TP is true positive, FP is false positive, and FN is false negative

Dataset

60 Brain MRI images taken from dataset used by Chakrabarty (2019*)* were tested to validate the effectiveness of the proposed segmentation method. The database comprised different tumorous images of MR brain of size 256×256 pixels, and proposed segmentation technique was implemented in MATLAB R2017b.

Results and Discussion

The proposed segmentation technique by incorporating a modified region growing algorithm into FCM clustering (RG-FCM) is applied to the MR images in the Kaggle database and compared with conventional Fuzzy C-Means (FCM) clustering and Possibilistic Fuzzy C-Means (PFCM) to validate its effectiveness in terms of various segmentation metrics. The conventional FCM and PFCM proved to be inefficient in noisy images due to coinciding clusters leading to undesired segmentation results. The comparative analysis of the proposed technique with state-of-the-art methods in terms of Jaccard and dice indices, and % of the extracted area is demonstrated in Table 1.

Table 1: Empirical analysis of RG-FCM with FCM & PFCM in terms of Jaccard and Dice indices, and % of Extracted Area

Methods	JACCARD INDEX			DICE INDEX			% of Extracted Area			
Parameters Patients ↓	FCM	PFCM	RG-FCM	FCM	PFCM	RG-FCM	FCM	PFCM	RG-FCM	% of GT Area
Patient 1	0.9421	0.9556	0.9949	0.9489	0.9605	0.9978	4.16	3.42	2.80	2.86
Patient 2	0.8954	0.9192	0.9433	0.9504	0.9602	0.9631	7.63	5.12	3.45	3.13
Patient 6	0.9572	0.9632	0.9820	0.9631	0.9723	0.9901	7.12	6.60	5.73	5.50
Patient 12	0.9217	0.9345	0.9514	0.9555	0.9678	0.9679	10.11	9.09	8.63	8.71
Patient 13	0.9091	0.9101	0.9299	0.9456	0.9534	0.9577	5.17	4.20	3.91	3.89

The mathematical evaluation demonstrated in Table 1 exhibits superior performance of the modified region growing-based FCM clustering technique when compared with FCM and PFCM. The data shown in Table 1 exhibits improvement in Jaccard and dice indices, and the percentage of extracted area obtained from RG-FCM has nearer values to the area of Ground Truth (GT) images. The pictorial delineation of empirical analysis of Jaccard and dice indices of different patients is demonstrated in Figs. 1 and 3 for the better visualization of comparative performance of the proposed technique with conventional methods.

The empirical analysis of various segmentation techniques depicted in Figs. 2 and 3 validates the efficacy of the proposed segmentation technique over state-of-the-art methods. Therefore, extraction of spatial information using a modified region growing algorithm and its integration into fuzzy c-means clustering leads to accurate demarcation of tumorous regions in MR images.

Statistical Analysis of Various Segmentation Metrics

The comparative analysis of the proposed segmentation technique with conventional FCM and PFCM is extended to other segmentation metrics like precision, recall, and F-measure to justify the efficacy of the proposed algorithm. Therefore, statistical analysis of various segmentation metrics for 12 different MR slices of the brain is demonstrated in Fig. 4 to validate the effectiveness of the proposed algorithm.

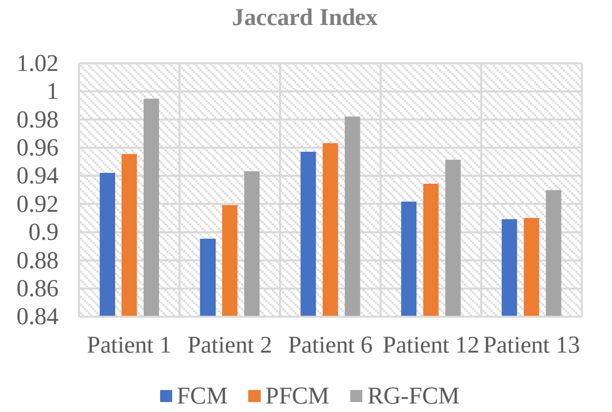

Fig. 2: Pictorial delineation of Jaccard index of different patients

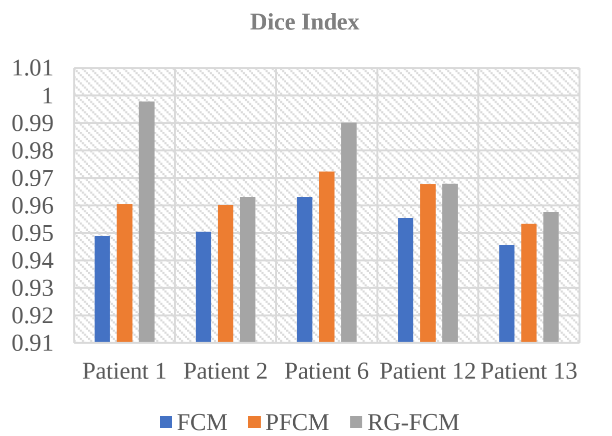

Fig. 3: Pictorial delineation of dice index of different patients

The statistical analysis depicted in Fig. 4 validates the efficacy of the proposed technique, RG-FCM in the demarcation of tumorous regions in MR brain images, and data obtained by evaluating various segmentation metrics exhibits the higher values of RG-FCM as compared to conventional FCM and PFCM.

Statistical Analysis Using ANOVA Test

The analysis of variance (ANOVA) test for statistical analysis of various parameters has been conducted to prove the efficacy of the proposed model. The statistical analysis depicted that RG-FCM is significantly superior to PFCM and conventional FCM ($p < 0.01$) in terms of Jaccard Index differences, while differences between PFCM and conventional FCM are insignificant ($p > 0.05$). The statistical analysis also demonstrates that RG-FCM is significantly better than PFCM and conventional FCM ($p < 0.01$) in terms of F-measure, and the difference between PFCM and conventional FCM is also significant ($p < 0.05$) in terms of F-measure.

The spatial characteristics of MR images used for testing the efficacy of the proposed model vary due to different sizes of tumors and different noise levels of images, but ANOVA test results reveal that the proposed model is significant in terms of various segmentation metrics and therefore justifies the proposed model to be less sensitive to variation in characteristics of images and results in less variation of segmentation parameters in different images. Therefore, the proposed segmentation model can be efficiently employed to different medical imaging modalities due to its less sensitivity, and further, this model can be expanded to clinical use for computer-aided detection of diagnostic parts.

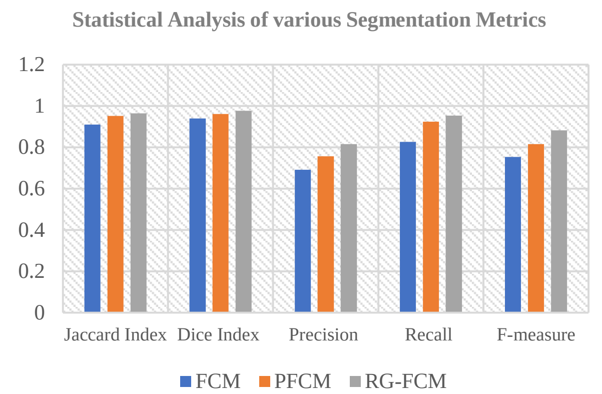

Fig. 4: Statistical Analysis of various Segmentation Metrics

Execution Time of the Proposed Algorithm

Various segmentation metrics justify the efficacy of the proposed technique in extracting the tumorous regions in MR images, and it also yields less execution time, which reduces the computational complexity of the algorithm to deal with copious MR images produced in real life. The integration of spatial information extracted using a modified region growing algorithm eases finding the cluster centers, which helps in reducing the run time of the algorithm as compared to FCM and PFCM. The statistical analysis of execution time of 12 MRI slices obtained using RG-FCM, FCM, and PFCM is demonstrated in Table 2.

Table 2: Statistical Analysis of Execution Time

Execution Time (s)	RG-FCM	PFCM	FCM
Mean	3.12	6.5	5.21
Standard Deviation	0.28	1.22	1.13

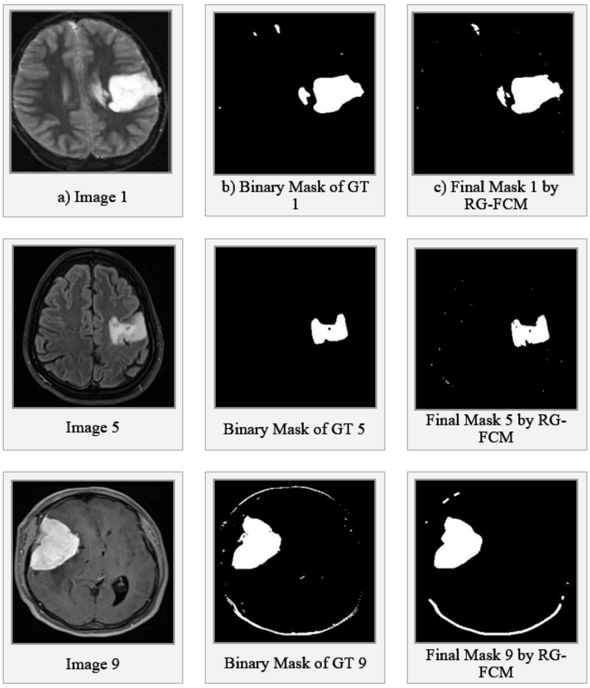

Fig. 1: (a) MR Images of patients 1, 5 & 9 (b) Binary masks of Ground Truth Images (c) Mask of regions extracted by RG-FCM

Qualitative Analysis

The tumorous regions extracted from different MR images are manifested in Fig. ***1*** for qualitative analysis and better visualization of segmented regions of different patients. The visual inspection of these images demonstrates that extracted region binary masks are almost similar to the binary masks of ground truth images, which validates the efficacy of the proposed segmentation technique.

Conclusion

The rate of increase in the production of medical images like MR images is due to advancements in medical technology, and therefore it creates an essential requirement of preserving the diagnostic parts of MR images to smoothen the storage and transmission process. In this paper, an incorporation model of modified region growing and FCM clustering is presented to enhance the extraction of tumorous regions from MR images of the brain. The proposed method requires no preprocessing of noisy images and justifies its efficacy in unevenly illuminated images as compared to conventional FCM and PFCM. The empirical evaluation validates the effectiveness of RG-FCM in terms of similarity parameters (Jaccard and dice indices) and boundary-based parameters (Precision and Recall). The proposed technique can be employed in real-time processing due to its low computational complexity, and it can be expanded to clinical use for automated detection of the object of interest, but proposed model may face challenges in the medical images having heterogeneous objects of interest and ambiguous boundaries with limited contrast. Therefore, some preprocessing steps are required that can define the boundaries of objects of interest clearly to avoid convergence error. The proposed model may not be able to differentiate the type of tumor, whether it is a high grade or low-grade glioma, which may affect the diagnostic process.

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Authors Contributions

Lovepreet Singh Brar: Data Analysis; Experiment; writing Manuscript.

Jaget Singh: Data Analysis and reviewing the manuscript.

Bhawana Agrawal: Final proof reading of the manuscript.

Sunil Agrawal: Data Analysis and Research Plan

Ayush Dogra: reviewing and editing the final manuscript.

Ethics

The authors have no acknowledgements to declare.

Conflict of Interest

The authors declare that dthere is no conflict of interest regarding the publication of this paper.

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