Effective Segmentation of Brain Tumors using N-MSFCM and Modified Fuzzy Level Set Algorithm.

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Summary

A brain tumor is a mass of neoplastic cells in the brain which compresses the surrounding tissues and manifests with features of focal neurological deficit or raised intracranial tension or even seizures. Accurate segmentation of brain lesions is an important step in the medical field as it aids in the exact localization of the tumor which helps in determining the prognosis. It also helps to decide the treatment modality. This paper presents a systematic approach to brain tumor segmentation and labeling, which comprises effective pretreatment of denoising with a combination filter, contrast improvement, and a fusion of innovative fuzzy spaces restricted segmentation and improved fuzzy level set segmentation. The effectiveness of this technique is assessed using conventional parameters in comparison to state-of-the-art contemporary segmentation techniques. According to the findings, the new technique surpasses the others and produces better segmentation results.

Keywords:

Clustering, Segmentation, MR images. Fuzzy C Means, Level set.

1. Introduction

The goal of image segmentation is to partition the given image into several meaningful and non-overlapping separate components of interest. Due to low resolution and low contrast, computerized medical picture segmentation is a challenging task. Furthermore, due to instrumental limits, reconstruction methods, and patient movement, the work is frequently made more difficult by the presence of noise and artifacts. There is currently no common algorithm for segmenting medical images. The benefits and snags of an algorithm are frequently dependent on the problem under consideration.

Medical image segmentation is the process of identifying the aberrant tissues i.e., “the Region of Interest (ROI)” from the given image data such as MRI or CT scans and separating it for auxiliary clinical investigation.

A brain tumour is an unusual mass of tissue within the skull that develops and propagates uncontrollably, causing serious consequences. Primary and metastatic brain tumours are the two types of brain tumours. The primary Primary tumours are the initial masses, and metastatic tumours are the widely dispersed masses.

Segmentation of brain tumors attempts to distinguish between healthy and tumorous tissue. This is an important stage in diagnostic and treatment planning to increase the probability of survival of the patient. As manual segmentation is time-consuming and difficult, computer methods that are faster and more accurate are necessary.

Segmenting brain tumors from imaging data is one of the most difficult challenges in medical image processing due to the unpredictable look and structure of the brain.[1]– [3]

Manual segmentation, intensity-based approaches (clustering, thresholding, region growth, and region merging), surface-based approaches (Active contour-based methods), Atlas-based techniques, and hybrid techniques are some of the strategies used in brain MRI segmentation.

The most accurate approach has been proven to be the manual segmentation and labelling by specialist radiologists or experienced physicians. However, the manual process is difficult, inconvenient, and time-consuming. It requires qualified physicians. As a result, automated computer-based methods have been created to circumvent these restrictions.

The intensity of brain tissue is one of the prime criteria for brain MRI segmentation. When intensity values are contaminated by MRI aberrations such as speckle, partial volume effect (PVE), and bias field effect, brightness classification techniques provide incorrect results. As a result, many preparatory procedures are frequently required to prepare MRI data to achieve meaningful and reliable segmentation findings.[2]

Fuzzy C-means clustering is generally used in partitioning medical images[4]. It is an autonomous clustering method to create a fuzzy partition from data. [5]

Manuscript received June 5, 2022
Manuscript revised June 20, 2022
https://doi.org/10.22937/IJCSNS.2022.22.6.69

“Fuzzy C- means clustering:

$$\sum_{j=1}^{k} \sum_{xi \in Cj} U_{i,j}^{m}$$

Where Uij is the degree to which an observation xi belongs to a cluster cj.

µj is the center of the cluster cj.

M is the fuzzifier.

Where,

$$U_{i,j}^{m} = \frac{1}{\sum_{l=1}^{k} \left(\frac{|xi - cj|}{|xi - ck|}\right)^{2/m-1}}$$

And,

$$C_J = \frac{\sum_{x \epsilon c_j} u_{ij}^{m}(x)}{\sum_{x \epsilon c_j} u_{ij}^{m}}$$

Where C_j is the cluster's centroid and u_{ij} is the degree to which an observation x_i belongs to that cluster.

The degree of belonging, u_{ij}, is proportional to the distance between x and the cluster center.

The parameter m is a real number greater than one that defines the level of fuzziness in the cluster. A value of m close to 1 yields a cluster similar to a hard clustering solution such as K-means, whereas a value of m close to infinite yields complete fuzziness.

The fuzzy clustering process is illustrated as follows:

1. Set the number of clusters to k. (by the predictor).
2. Assign coefficients for cluster membership at random to each point.
3. Repeat until the maximum number of iterations (given by "maxit") is reached, or the algorithm has converged (that is, the difference between two iterations of the coefficients is less than the given sensitivity threshold).
4. Using the formula above, calculate the centroid for every cluster.
5. Using the methodology mentioned in steps 1 to 4, compute the coefficients of being in the clusters for every point.” [Source: Fuzzy C-Means Clustering Algorithm - Datanovia]

FCM's benefits include:

- The rapid rate of convergence.
- Flexibility, and,
- No need for supervision.

FCM's drawbacks include:

- Calculation time is long, slowing down the entire procedure.
- Random initial selection's sensitivity.
- In noisy situations, outlier pixels receive extremely low membership values. [6]

2. Review of Related Works

Pham [6], Xu [7] used FCM for MR image segmentat ion, and numerous sophisticated versions have been develo ped by various investigators through ongoing research. [7]–[9].[10]–[13],[1]

Noise, illumination variations, and unclear borders are common in brain scans. As a result, reliable segmentation of brain images remains a research challenge. The work by [13] provides an overview of fuzzy-C-means (FCM) clustering techniques for brain MR image segmentation. The review examines FCM-based algorithms with intensity inhomogeneity correction and noise robustness in depth. Different strategies for updating membership and cluster centroid while modifying a conventional fuzzy objective function are also addressed.

Different FCM algorithms are evaluated based on a variety of characteristics, such as changes to the basic fuzzy objective function and updates to the fuzzy membership function and cluster center. Several key challenges, including algorithmic optimization technique, computational difficulty, and noise endurance, have been highlighted, showing that brightness deformation correction and denoising remain difficult tasks.

Despotovit et al [2] proposed in the article “MRI Segmentation of the Human Brain: Challenges, Methods, and Applications” that by combining 3D neighborhood information and preceding knowledge from atlases, newer segmentation approaches are usually designed to produce more accurate results. As a result of this, segmentation becomes complicated and time-consuming. The authors suggest future research focus on improving the computing speed of segmentation algorithms as well as developing more accurate and noise-resistant systems.

M. S. Yang and H. S. Tsai[15]in their article "A Gaussian kernel-based fuzzy c-means algorithm with a spatial bias correction," proposed that, although Bias-corrected fuzzy c -means (BCFCM) is an effective segmentation technique, it takes a long time to compute and lacks noise stability and outliers. So, some kernel variants of FCM with spatial constraints (KFCM) were proposed to solve those drawbacks.

Q. Song et. Al in "Kernel-based fuzzy local information clustering algorithm self-integrating non-local information," [16]proposed a kernel-based fuzzy local information clustering approach. The technique employs a self-integration method based on the image's local information while also introducing non-local information, addressing some of the current clustering algorithm's issues. The self-integrating method fixes the issue of choosing spatial constraint parameters, and the algorithm remains self-learning and recursively quantifies the parameters; here, the distance measure employs Gaussian kernel influenced distance to improve the robustness against noise and the flexibility of processing data sets; Finally, the local and non-local data are combined at the same instant to provide a segmentation effect that efficiently suppresses the majority of the noise.

T. Ren et al [17] presented Kernel-based FCM(KFCOM) and Weighted fuzzy kernel clustering (WKFCOM) algorithms based on FCM algorithm research. Authors claimed that, by setting a new objective function, the KFCM method dynamically gives weight to each class, allowing the algorithm to obtain good clustering results. It is determined that the WKFCM method not only benefits from the fact that image space information can be used as previous knowledge by the segmentation algorithm. Authors proposed that, although the WKFCM algorithm is a simple of a kind, yet offers quick speed, unsupervised learning, and strengthens resilience. It is a fast and unsupervised technique for reliable brain picture segmentation.

The report by N. Md Norwawi et al [18] provides an understanding of data clustering concepts, with a focus on "image segmentation-based fuzzy clustering algorithms". In addition, the linked study addresses three primary concerns that image segmentation-based fuzzy clustering techniques face: noise sensitivity, cluster center initialization sensitivity, and an uncertain number of real clusters in the image dataset. As a result, these algorithms are encouraging academics to improve their performance to meet the needs of emerging applications.

The authors suggest a combination of the existing FCM algorithms with other metaheuristic algorithms to achieve equilibrium. Authors also suggest enhancing the FCM objective function to be less time demanding and less noise-sensitive by the usage of a multi-objective approach as an objective function to enhance the performance.

C. Li, Gore et.al [19] combined bias field estimation and segmentation of magnetic resonance (MR) images, and offered a novel energy minimization approach, multiplicative intrinsic component optimization (MICO). The suggested technique takes full use of the breakdown of MRI into two multiplicative elements, namely the true image, which represents a physical characteristic of the tissues, and the bias field, which represents intensity inhomogeneity, as well as their respective spatial properties. An energy minimization approach aiming at optimizing the estimations of the "two multiplicative components of an MR image" is used to concurrently accomplish "bias field estimation and segmentation". The authors proposed to extend the MICO to segment even 3D/4D tissues with spatial/Spatio-temporal regularisation. It has been found that MICO outperformed certain popular software in terms of robustness and accuracy, according to quantitative evaluations and assessments.

G. Latif et. Al in their article "Recent Advancements in Fuzzy C-means Based Techniques for Brain MRI Segmentation [6] made a thorough examination of all FCM-based brain tumor segmentation methods like Bias Corrected FCM, Kernelized FCM, Fast Generalized FCM, Improved FCM, Probabilistic FCM, FCM with Spatial Information, Fuzzy Local FCM, and many more. It has been discovered that the most optimal strategy for segmentation based on FCM is still under investigation. Many measures are used to evaluate the performance of various algorithms. Researchers have sought to construct FCM-based segmentation algorithms that partly address the traditional FCM's flaws. However, neither of the presented algorithms has attempted to address all of the flaws in the traditional FCM across all performance metrics.

[20] portray a framework for accurate and resilient brain MRI segmentation, which includes suitable pre-processing phases and uses the efficient basic Support Vector Machine (SVM) method. Even though the proposed technique has several stages such as noise estimation, removal, contrast enhancement, and segmentation, it produces better results, The Authors affirm that the contrast enhancement technique has a positive impact on the automatic image segmentation system's overall performance.

N. Sasirekha and K. R. Kashwan, [20] developed a basic algorithm that employs a combination of image processing techniques and statistical methodologies. Only a dataset of real-degraded low-contrast images is used to evaluate the proposed technique, which is then compared to four existing contrast enhancement algorithms using one unique no-reference measure. The suggested algorithm exhibited encouraging results in the trials because it delivered acceptable-quality results quickly and outperformed the comparative approaches in various crucial features. Even with picture abnormalities including Rician noise, intensity inhomogeneity, and partial volume effect, the proposed segmentation method is a better option for MRI. The method has been evaluated in both synthetic and real-time MRI, and several performance measurements show that it is effective and efficient. When compared to conventional FCM approaches alone, the segmentation is improved by integrating appropriate pre-processing steps.

The Research work by B. N. Li [21] proposes a novel fuzzy level set algorithm to help in medical picture segmentation. Spatial fuzzy clustering allows it to evolve straight from the first segmentation. The findings of fuzzy clustering are also used to determine the governing parameters of level set evolution. Furthermore, locally regularized evolution is used to improve the fuzzy level set technique. The suggested algorithm's performance was assessed using medical pictures from several modalities. The results indicate that it works well for medical image segmentation.

Although numerous upgraded forms of FCM are presently in use, according to the overview of the relevant research, no one algorithm can overcome all of classic FCM's limitations. It suggests that FCM-based MRI segmentation is still a promising field that necessitates more potential research.
Furthermore, this survey recommends adopting effective noise removal methods and contrast enhancement approaches from MR images during the pre-processing step to improve segmentation quality and metrics.

The present research work intends to provide a better tool for brain MRI segmentation that addresses the limitations discussed in the literature review above.
The research work tries to integrate the advantages of "New membership scaled Fuzzy C means clustering" [22] and, "modified level set segmentation" [21]. In addition to that the work adopts a novel and strong denoising scheme, along with the most recent contrast enhancement technique (SMIPC)[22] at the pre-processing stage.

3. Materials and Methods

A new membership scaling FCM (N-MSFCM) proposed by Zhou, et al [23] is implemented in this research for segmentation. This N-MSFCM is based on the finding that the specimens whose nearest cluster center is v assist v's convergence, while the remainder samples impede v's convergence. The triangle inequality is used in the new technique to select many samples whose neighboring cluster centers do not alter in the next round. To raise the effect of in-cluster samples and diminish the effect of out-of-cluster samples in the clustering process, a new strategy for modulating the degree of membership of the selected samples is proposed. The authors verified that this technique not only speeds up the algorithm's convergence but also keeps the excellent clustering quality.

Advantages of N-MSFCM: The algorithm N-MSFCM is tested to be effective on both synthetic and real-world data sets [23]. First, the triangle inequality is used to eliminate samples that do not change their nearest clusters in the following iteration. The fuzzy membership scores are then modified using a new scheme that boosts the effect of in-cluster samples while weakening the effect of out-of-cluster samples. Several exploratory outcomes prove that the new algorithm outperforms or is on par with state-of-the-art fuzzy clustering methods. As a result, it is an excellent complement to fuzzy clustering.

N-MSFCM Algorithm:
"Input: Dataset $X = \{x_1, x_2, \cdot\cdot\cdot, x_n\}$, cluster number c, fuzzy exponent m, and convergence threshold ε;
Step 1: Calculate the cluster center V(1) using the starting membership degree matrix $U(0) \in \mathbb{R}^{c \times n}$; set t:= 1.
Step 2: Compute

$$d_{ij}^{(t)} = \| x_j - v_i^{(t)} \|$$

for $-1 \le i \le c$, $1 \le j \le n$;
Step3: Estimate $U^{(t)}$ with

$$u_{i,j}^{(t)} = \left| \sum_{k=1}^{c} \frac{d_{i,j}^{(t)}}{d_{k,j}^{(t)}}^{2/m-1} \right|^{-1}$$

Step 4: Compute $\tilde{V}$ (t+1) with

$$\tilde{v}i\,(t+1) = \frac{\sum_{j=1}^{n} u_{i,j}^{(t)^m} x_j}{\sum_{j=1}^{n} u_{i,j}^{(t)^m}}$$

Step 5: Calculate

$$\delta_i = \left\| v_i^{t+1} - v_i^t \right\| \forall 1 \le i \le c.$$

Step 6: Remove the X_{Qt}
Step 7: $U_{(t+1)}$ should be updated with the new scheme.
Step 8: Determine $V^{(t+1)}$ using the formula,

$$V_{t+1} = \frac{\sum_{j=1}^{n} u_{i,j}^{(t)^m} x_j}{\sum_{j=1}^{n} u_{i,j}^{(t)^m}}$$

Step 9: If $|X_{Qt}| < n$, and $\| v_i^{t+1} - v_i^t \| \ge \epsilon$ then:
Set t: = t + 1 as the value of t.
Step 10: Otherwise, proceed with $U=U^{(t+1)}$ and $V=V^{(t+1)}$

Output: Membership degree matrix U and cluster center matrix V."

Proposed Model.

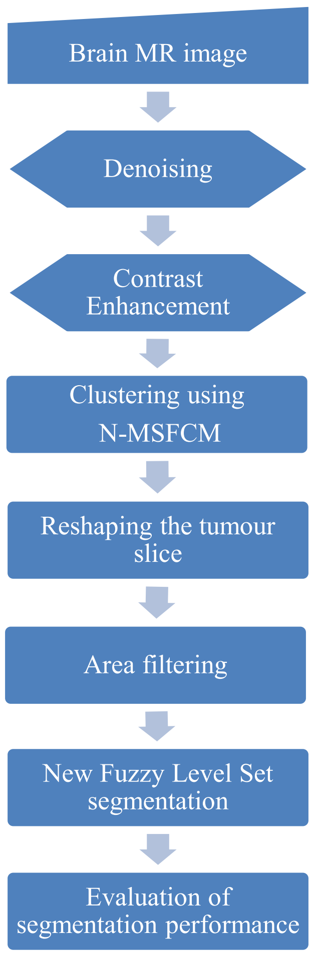


Fig. 1 Flow diagram of the proposed model

Brain MRI Dataset: Here BRATS 2018 Dataset (Axial, coronal and sagittal) is used for experimental purposes.

Denoising: Distinct kinds of noise, such as salt and pepper, Rician, Gaussian, and speckle noise affect the brain MR images significantly. Hence, Computer-based segmentation algorithms demand appropriate filtering at the preprocessing stage. To adaptively reduce noise while keeping image edges, the anisotropic diffusion filter (ADF) was devised. [24] . It was employed in MR imaging (Greig et al. [1992]), and it was automated in a variety of ways, however, continues to yield inadequate outcomes.

In this work, a combination of Adaptive median filter and ADF is employed at the first level in the spatial domain. Following this stage, the residual noise is removed, and this remnant noise (method noise) is subjected to a level 2 wavelet transform. Stein's Unbiased Risk Estimate (SURE) technique is used to threshold detailed coefficients of residual noise in the wavelet domain. The denoised image is created by combining the results of these two stages.

Contrast Enhancement: The technique of Contrast enhancement is applied to the denoised grayscale image. The contrast enhancement algorithm utilized in this study was created by Zohair Al-Ameen [22], and it combines four different statistical methods: "Contrast Stretching Transformation (CST), Standard Logistic Function (SL), Logarithmic Picture Processing (LIP), and Stretching Control Process."

The algorithm's effectiveness is evaluated, and the final outcome is judged to have natural contrast, acceptable brightness, and no obvious flaws.

Clustering: A New Membership Scaling Fuzzy C-Means Clustering Algorithm (shown in Fig. 1) is employed to segment the processed image into 4 clusters[23]

As part of the segmentation postprocessing procedures, the tumor slice is reshaped and an area filter is applied.

New Fuzzy Level Set Segmentation: The new fuzzy level set segmentation developed by [21], presets the initiation and parameter tweaking of the traditional level set segmentation practice by making use of FCM with spatial restrictions to assess the rough contours of interest in a medical image.[21], [25], [26]

The Hamilton-Jacobi function[26] is used to derive the fuzzy level set approach in this work [21]. The formation of the level set will begin at an area near the true borders. the novel approach automatically predicts the governing parameters from fuzzy clustering.

As the level set development approaches the true limits, it stabilizes automatically, which not only prevents boundary leakage but also eliminates the need for manual intervention. All of these enhancements result in a powerful medical picture segmentation method that has decreased the need for human interference.

The present research work incorporates N-MSFCM instead of traditional FCM with spatial constraints in the Modified Fuzzy Level Set Segmentation (MFuzzyLSM) which is primarily based on the Hamilton-Jacobi model of the Partial Differential Equation model and a well-defined, accurate boundary marking has been furnished.

Performance Evaluation: The accuracy, sensitivity, precision, F-measure, Dice, Jaccard, and specificity of the current study were all tested using conventional metrics.

4. Results and Discussions

The method was evaluated on axial, coronal, and sagittal MR images using the Brats 18 brain MRI dataset.

Experiments were carried out on a computer with an Intel(R) Core (TM) i7-6600U processor running at 2.80 GHz and 8 GB of RAM.

The proposed algorithm was created using the MATLAB R2020A platform.

Over 80 MR images were used in the experiments. Dice, Jaccard, Accuracy, Specificity, F-measure, Sensitivity, and other conventional segmentation criteria were used to evaluate the algorithm's performance.

The segmentation performance is validated by comparing the binary images A and B, where A is the ground truth and B is the segmented output.
The confusion matrix is used to analyze the performance of the segmentation output. Here,
True Positive (TP): The model correctly predicted yes, and the result was also correct.
True Negative (TN): The model predicted No, and the real or actual value likewise predicted No.
False Positive (FP): The model predicted Yes, but the value was really No. This is referred to as a Type-I error.
False Negative (FN): The model predicted no, but the actual value was Yes; this is referred to as a Type-II error.
In this research work, the effectiveness of the segmentation is evaluated using the following parameters:

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

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

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

$$\text{Fmeasure} = \frac{2 * \text{TP}}{(2 * \text{TP} + \text{FP} + \text{FN})}$$

F-measure is the harmonic mean(average) of the precision and Sensitivity.

MCC - Matthew's correlation coefficient:

$$\text{MCC} = \frac{(\text{TP} * \text{TN} - \text{FP} * \text{FN})}{\sqrt{(\text{TP} + \text{FP}) * (\text{TP} + \text{FN}) * (\text{TN} + \text{FP}) * (\text{TN} + \text{FN})}}$$

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

Dice co-efficient:
The S$\mathcal{O}$rensen–Dice index is a statistical tool that compares two sets of data. This index has become the most often used tool for validating AI-based picture segmentation algorithms.

$$\text{Dice} = \frac{2 * \text{TP}}{(2 * \text{TP} + \text{FP} + \text{FN})}$$

Jaccard Index:
The Jaccard Index compares two sets of images to see how similar they are.
The index, created by Paul Jaccard, spans from 0 to 1. The closer the two sets of data go to 1, the more similar they are.

$$\text{J}(\text{A}, \text{B}) = \frac{(\text{A} \cap \text{B})}{(\text{A} \cup \text{B})}$$

$$\text{J}(\text{A}, \text{B}) = \frac{\text{Dice}}{2 - \text{Dice}}$$

Results:

The proposed technique is tested using about 80 images from the Brats 2018 dataset. Fig. 2 depicts the outcome of each of the projected work's stages.

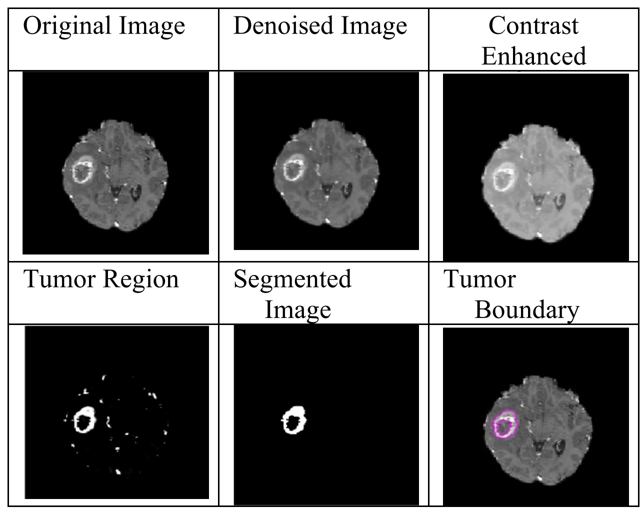


Fig. 2 Different Stages of segmentation.

The outcome of the N-MSFCM clustering algorithm is shown in Fig.3.

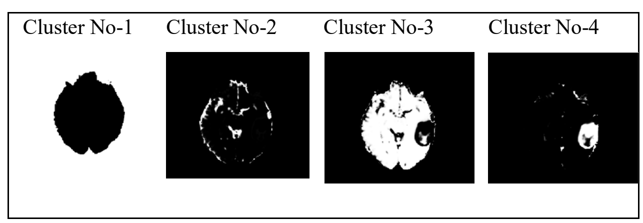


Fig. 3 N-MSFCM clustering with 4 clusters.

The proposed algorithm's outcome is assessed using standard segmentation parameters. It is discovered that the accuracy is consistently high. The average accuracy is roughly 99%. This demonstrates the algorithm's sturdiness. The suggested algorithm was put to the test against several modern and well-known approaches, and it was found to outperform them in terms of accuracy. This is shown in Fig. 4 for one of the images in the dataset.

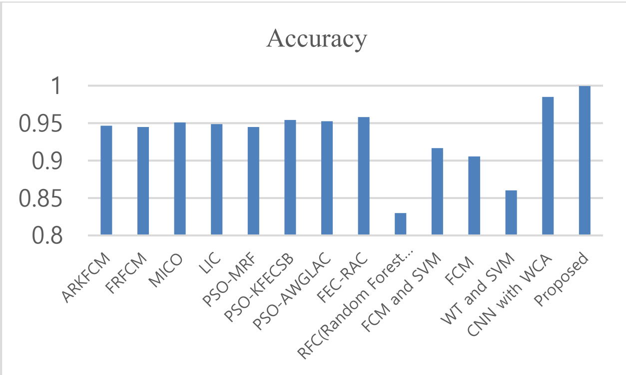


Fig. 4 Accuracy comparison with other contemporary methods

In terms of sensitivity, the proposed algorithm is resilient when compared to other algorithms. [14], [15], [24], [27], [28] [16] Table 1 summarizes the comparative performance outcome.

Table 1 Sensitivity comparison

Method	Sensitivity
ARKFC[29]	0.8932
FRFCM [30]	0.9402
MICO	0.9227
LIC	0.9161
PSO-MRF	0.9346
PSO-KFECSB	0.9344
PSO-AWGLAC	0.8826
FEC-RAC	0.9551
Proposed	**0.9862**

In the present work, Modified Fuzzy Level Set Segmentation (MFuzzyLSM) is used in the final phase. To achieve level set segmentation, N-MSFCM was used instead of a conventional MSFCM. When compared to the existing FCM counterparts, this novel clustering method N-MSFCM has been shown to provide more effective clustering capabilities. The algorithmic superiority of N-MSFCM in terms of Jaccard, Dice, and Sensitivity (Recall) is demonstrated in Fig. 7 and Table 2.

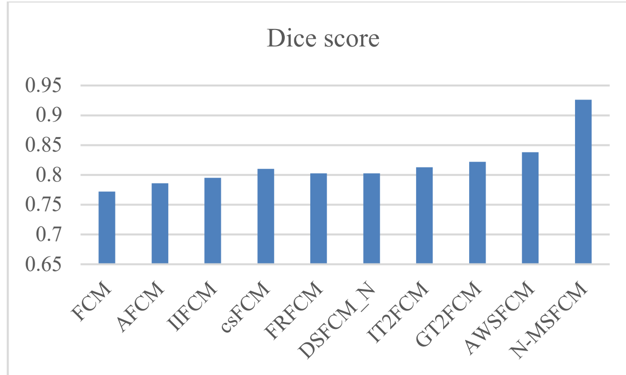


Fig. 7 Comparison of the Dice coefficient with the other methods

Table 2 Performance analysis different FCM techniques

Algorithm	Jaccard	DICE	Accuracy
FCM[5]	0.7234	0.7722	0.8012
AFCM[28]	0.7325	0.7861	0.8112
IIFCM	0.7344	0.7952	0.8322
csFCM[31]	0.7582	0.8102	0.8512
FRFCM	0.7641	0.8025	0.8379
DSFCM_N	0.7324	0.8027	0.8277
IT2FCM	0.7564	0.8129	0.8421
GT2FCM	0.7622	0.8217	0.8499
AWSFCM	0.7741	0.8381	0.8726
N-MSFCM	**0.8749**	**0.9261**	**0.998**

Table 2 Qualitative analysis of the proposed method

	TP	TN	Accuracy	Sensitivity
Image1	1559	96183	0.99457	0.9022
Image2	2322	103964	0.9792	0.9659
Image3	1849	105956	0.9934	0.8809
Image4	2000	104899	0.9849	0.9524
Image5	1453	98223	0.9977	0.9326
Image6	1154	106792	0.9945	0.8703
Image7	2176	105871	0.9955	0.8977
Image8	671	105436	0.99602	0.8841
Image9	2063	105492	0.9903	0.7024
Image10	1374	106478	0.9937	0.6799
Image11	1328	106676	0.9951	0.859
Image12	1783	105797	0.9912	0.8324
Image13	717	107607	0.998	0.9862
Image14	1467	106741	0.997	0.9291
Image15	1260	106837	0.9959	0.9096

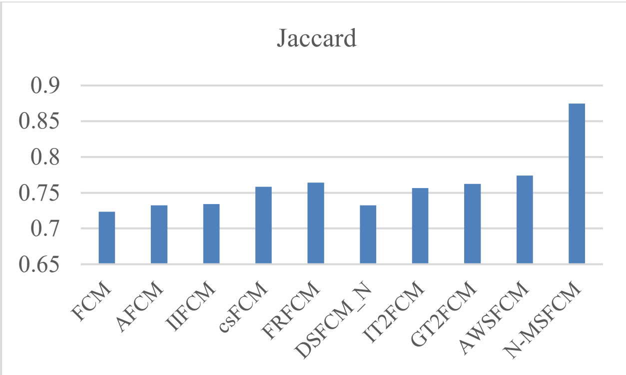


Fig. 8 Comparison of the Jaccard index with the other methods

The proposed technique shows reliable outcome in terms of specificity. In the current study, we acquired an average of 99.56 percent for 17 images. This is presented in Fig. 9.

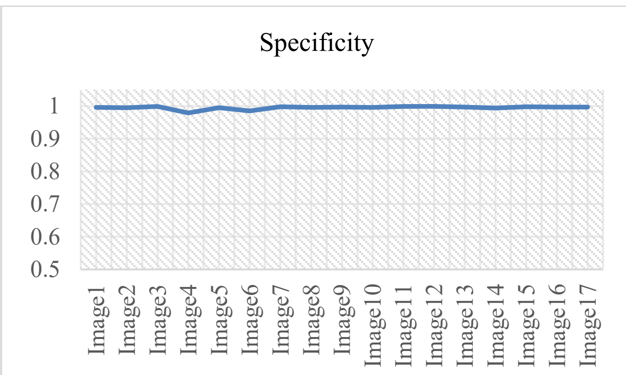


Fig. 9 Consistency in specificity

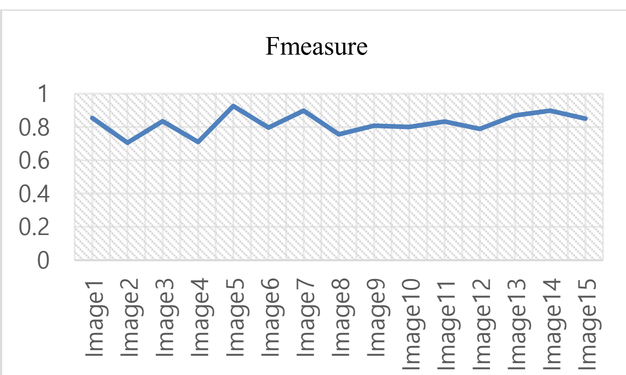


Fig. 10 F-measure graph of the proposed method

The F-measure, a test's accuracy measure, is used to evaluate the quality of binary classification issues as well as problems with multiple binary labels or classes. The present work is more trustworthy and accurate in terms of segmentation, as evidenced by an average output of 82 percent F-measure for a trial of 80 images. This is demonstrated in Fig.10 for a set of 15 images of the dataset.

In analyzing binary classifications, MCC offers a more meaningful and realistic score than accuracy and F-measure. MCC considers all four values in the confusion matrix, (TP, TN, FP, and FN) and a high value indicates that both classes are accurately predicted, even if one is unevenly represented. In the current study, an average of 83 percent MCC maintains the algorithm's trustworthiness as evidenced in Fig. 11.

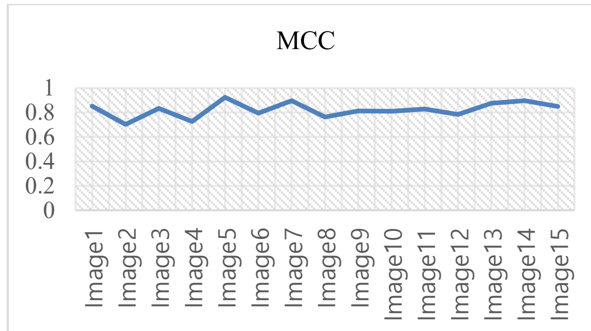


Fig. 11 Homogeneity in Mathew's Correlation Coefficient

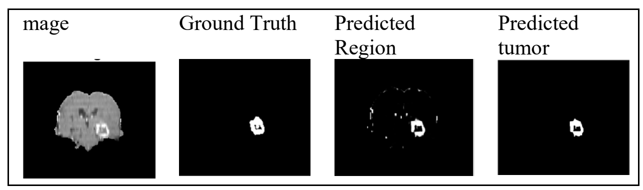
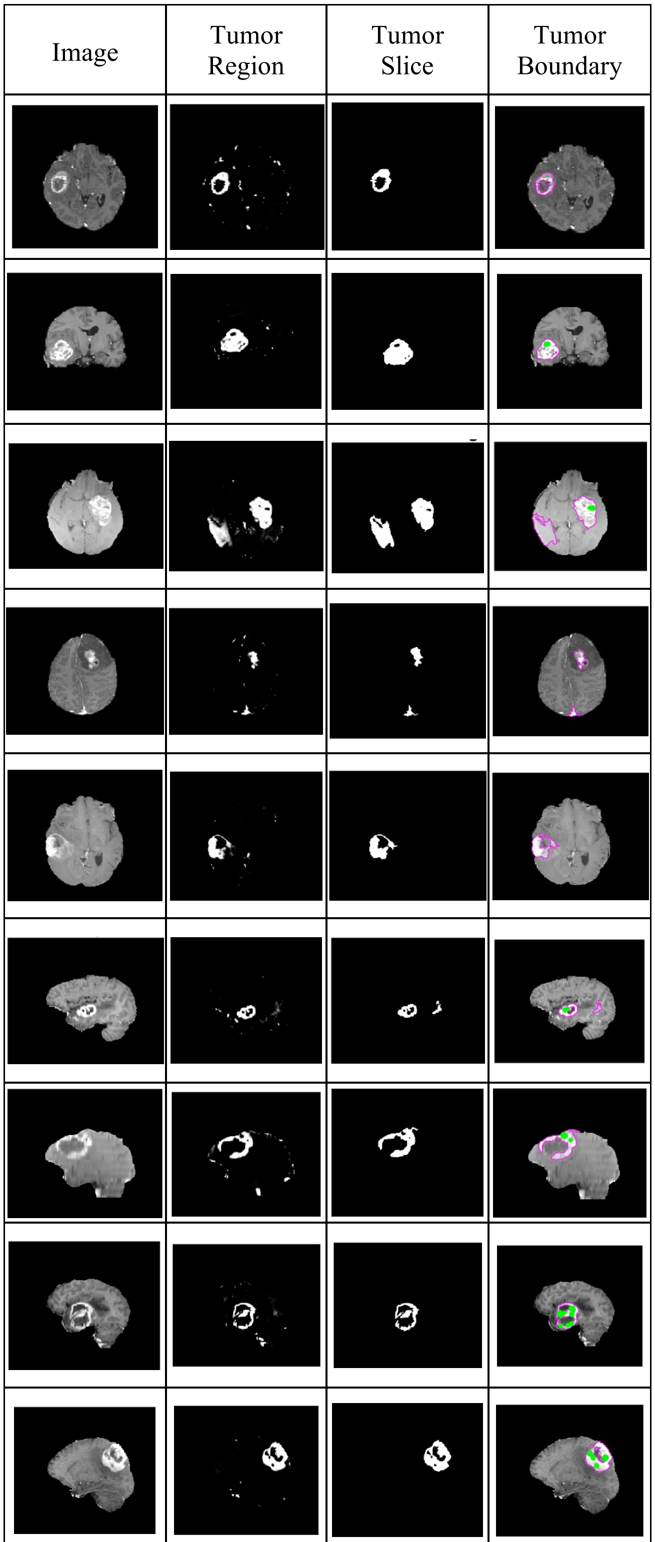


Fig. 12 Segmentation quality outcome of the proposed method



Segmentation outcome of the proposed technique.

5. Conclusion and Future Scope

A stable and reliable approach for segmenting brain MRI has been developed in this study. This novel technique includes unique denoising and contrast enhancement methods in the preprocessing stage. The N-MSFCM membership scaling clustering technique is also included in the innovative fuzzy level set segmentation. By properly detecting the boundaries and labeling, the study yielded encouraging results in terms of segmentation metrics as well as segmentation picture quality. This research could help doctors figure out how to:

- Determine the size of the tumor more precisely.
- The exact location of the tumor.
- This new procedure can help to diagnose easily whether the tumor is benign or malignant as it accurately labels the tumor's boundary and edges,
- This method can identify the number of tumors (single or multi-centric) that can be used to determine the treatment modality.

The future direction of the study suggests pondering the techniques to differentiate between the tumor and the hemorrhage in MR imaging. This might include creating a better clustering algorithm to replace N-MSFCM or incorporating the Mumford- Shaw model of PDEs into the Fuzzy level set technique.

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