



Research Article

Gaussian mixture model and K-means based spatial interval valued intuitionistic fuzzy C-means clustering incorporating the D_α operator for MRI image segmentation

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ABSTRACT

In medical image analysis, brain magnetic resonance image segmentation is still a difficult task. Therefore, it is crucial to provide an efficient method for identifying neurological illnesses and organising their therapies. In this work, we provide an approach to improve the segmentation of MRI images. To eliminate skull artefacts, morphological operators are first used for preprocessing. The first cluster centroids are then found by combining the Gaussian Mixture Model with K-means clustering. For better segmentation, we further integrate this with our Spatial Interval-Valued Intuitionistic Fuzzy C-Means clustering approach by adding the D_α operator. This method effectively handles geographical information and uncertainty, improving segmentation performance. Existing approaches, including interval-valued intuitionistic fuzzy C-means clustering algorithm is contrasted with the suggested approach. Results from experiments show that our hybrid approach improves segmentation results. The quantitative measures, the dice coefficient and Jaccard similarity, which are displayed in tables, attest to the fact that this method solves segmentation issues. and yields more trustworthy outcomes for clinical applications, making it a useful tool for medical diagnostics.

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INTRODUCTION

Since magnetic resonance imaging (MRI) has great contrast distinction of soft tissues and high resolution, as noted by Mishra PK et al., it is a cornerstone of medical diagnosis, especially for brain imaging Brain MRI image segmentation plays a critical role in the diagnosis and follow-up of neurological diseases, including multiple sclerosis, tumours, and

other brain disorders [1]. According to Verma et al. [2], segmentation of MRI images facilitates reliable diagnosis and treatment planning by identifying and isolating distinct tissue structures and regions affected by abnormalities.

To keep computational costs low, standard algorithms like Gaussian Mixture Models (GMM) and K-means clustering are frequently chosen for data segmentation. According to Lin et al. [3], K-means achieves this

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partitioning by reducing the internal variance of K separate clusters, whereas GMM adopts a more flexible strategy by fitting the dataset across several Gaussian distributions. Nevertheless, when applied to MRI scans, these classical models often fail to yield clean results due to artifact-related issues like image noise and intensity non-uniformity.

To address these challenges, fuzzy clustering techniques have been introduced to provide greater flexibility in data classification by allowing individual data points to belong to more than one cluster to varying degrees. Among these techniques, the Fuzzy C-means (FCM) algorithm provides a flexible approach to image segmentation by assigning a membership value to each data point with respect to each cluster. Building on the FCM framework, Kala R et al. [4] proposed the Spatial Intuitionistic Fuzzy C-means (SIVFCM) algorithm, which incorporates a hesitation degree to represent the uncertainty associated with cluster membership more effectively. This additional consideration is particularly beneficial for medical image segmentation, where the boundaries between different regions are often indistinct.

Conventional FCM can be affected by the choice of initial parameters and may produce unsatisfactory results when the input images contain considerable noise. To address these issues, Kaushal et al. and Wei et al. [5, 6] proposed an Intuitionistic Fuzzy C-Means (IFCM) clustering method incorporating local information. The method adjusts the contribution of local image information during clustering, thereby improving the robustness of the fuzzy partition in the presence of noise. In another study, Dubey et al. [7] employed a rough set-based strategy for selecting the initial cluster centres and relevant parameters. The experimental results indicated that the proposed parameter-selection scheme achieved improved segmentation results compared with other optimization approaches.

Ji et al. and Li et al. [8, 9] introduced a clustering strategy that concurrently maximizes the likelihood function and minimizes the covariance across Gaussian Mixture Model (GMM) components. This method was subsequently integrated into a Particle Filter GMM (PFGMM) framework and benchmarked against standard baselines, including PFGMM paired with Expectation-Maximization (EM) and PFGMM with K-means. Although the proposed approach enhanced particle filter tracking accuracy, its generalizability remains restricted to specific data types, and the authors omitted a detailed computational complexity analysis.

Tiwari et al. [10] have devised a fuzzy c-means clustering algorithm that integrates entropy and is weighted by uncertainty parameters to improve the segmentation of noisy 3D brain MRI data. Ray et al. [7] introduced an approach that effectively captures spatial uncertainty by incorporating Shannon entropy alongside both globally and geographically constrained local membership functions. By directly addressing issues related to noise and intensity inhomogeneity, their technique delivers improved segmentation accuracy over traditional algorithms.

Ji Z et al. and Arora J et al. [11,12] have stated that “by considering the geographic context of each pixel and thus mitigating the effects of noise and enhancing the coherence of segmented regions, the incorporation of spatial information into clustering algorithms further improves segmentation accuracy”. To better manage uncertainties and spatial dependencies in medical pictures, sophisticated techniques have been developed, such as Spatial Interval-Valued Intuitionistic Fuzzy C-Means (SIVIFCM), which integrates interval-valued intuitionistic fuzzy sets.

Ahmed et al. [13] reported that the selection of suitable initial cluster centres can have a significant effect on clustering performance. In conventional approaches, the cluster centres are generally initialized randomly, which can lead to poor segmentation and inconsistent results. Similar approaches for addressing the initialization of cluster centres have also been reported by Patel et al. and Vivoli et al. [14, 15]. Dhal KG et al. [25] stated that “rough set-based clustering was also used to predict the cluster centre of a picture, but noise and intensity inhomogeneity prevented this prediction from being successful”. By employing GMM and K-means for initial cluster centre identification, it gives the clustering process a more dependable and accurate starting point, improving the total segmentation quality. The proposed approach takes advantage of the ability of GMM to model data distributions while utilizing the fast convergence of K-means for determining suitable cluster centres. Owing to its simplicity and computational speed, K-means is widely applied in both academic research and practical applications. However, the use of the distance from Euclid as a similarity measure hinders its inability to understand complex non-linear use structures. A GMM is a potent dynamical and probabilistic clustering method.

Jagatheswari S et al. [16]: The $\Delta\alpha$ operator is an additional novel element incorporated into our approach. By altering the distance measure, this operator improves the ability of fuzzy clustering algorithms to distinguish between similar but different tissue types. With the $\Delta\alpha$ operator included in the SIVIFCM algorithm, our method can effectively handle the intricacies and uncertainties present in MRI pictures.

The intended approach is to greatly improve MRI brain image segmentation by combining GMM, K-means, and SIVIFCM with the $\Delta\alpha$ operator. The objective of this research is to enhance the diagnosis and treatment planning procedures for neurological disorders by offering a more reliable and precise tool for defining various tissue types and diseased locations. A more dependable solution to the segmentation problems in brain MRI images is provided by the combination of these cutting-edge techniques, which solve the shortcomings of conventional approaches.

The article has the following structure. Section 2 presents early notions. The suggested SIVIFCM clustering technique using GMM and K-Means for MRI image segmentation is further described in Section 3. The findings of brain MRI segmentation are shown in section 4, along with

a comparison of the suggested approach with the IVIFCM approach. We finally included the closing thoughts and upcoming work in section 5.

PRELIMINARY CONCEPTS

Gaussian Mixture Model

A continuous probability distribution known as the Gaussian distribution (GD), or normal distribution, is provided

$$R(Y|\mu, \Sigma) = \frac{1}{(2\pi)^{\frac{D}{2}} \sqrt{|\Sigma|}} \exp\left(-\frac{(Y-\mu)^T \Sigma^{-1} (Y-\mu)}{2}\right) \quad (1)$$

where μ is a D-dimensional mean vector, Σ is a D×D covariance matrix, which describes the shape of the Gaussian and $\sqrt{|\Sigma|}$ denotes the determinant of Σ .

The mean as well as the standard deviation together characterise the GD, which is harmonious about the mean. But the unimodal characteristic associated with a single distribution of Gaussian shapes cannot learn the varied resource use behaviour of Cloud workloads because it cannot represent the numerous density zones within a multimodal collection of information encountered in real-world scenarios [3]. A combination of Gaussian distributions can be a suitable model for complex, multimodal phenomena.

An ellipsoidal-shaped cluster is formed via an unsupervised clustering approach called a GMM, which uses the EM to estimate probability densities. The model for each cluster is a Gaussian distribution. GMMs can offer a more accurate numerical evaluation of adaptation per number of clusters since they consider both the mean and the covariance, as opposed to merely the mean as in K-Means (KM) [13].

A GMM may be written as a linear amalgam of the fundamental Gaussian distribution of chances.

$$P(Y) = \sum_{k=1}^K \pi_k R(Y|\mu, \Sigma_k) \quad (2)$$

where π_k , the mixing coefficient, provides a rough indication of the apparent density of each Gaussian portion and K are the total quantity of components in the combination model. The Gaussian density given by $N(X|\mu, \Sigma_k)$, is called a component of the mixture model. Each component k is described by a Gaussian distribution with mean μ_k , covariance Σ_k and the mixing coefficient π_k .

Maximum likelihood (ML) for the GMM

The log likelihood function for a mixture of Gaussian, given a set of R autonomous and equally distributed observations $y_1, y_2, \dots, y_R$, is given by

$$\ln P(Y|\pi, \mu, \Sigma) = \sum_{n=1}^R \ln \left\{ \sum_{k=1}^K \pi_k N(y_n|\mu, \Sigma) \right\} \quad (3)$$

Because the likelihood function is the product of several tiny probabilities, it prevents numerical underflow [14].

Algorithm for expectation-maximization (EM) in GMM

The EM method is used to find the ML predictions of variables in probabilistic formulations of GMM. The chance of maximising the two parameters variance and mean is what determines the GMM. Thus, the EM technique is used to estimate the parameters. The number of means, classes, mixing coefficients, and variance were all initialised at the beginning. Utilising the current parameter values, calculate the posterior probabilities in the expectation step [14, 34],

$$\gamma_k(y_n) = \frac{\pi_k G(y_n|\mu_k, \sigma_k)}{\sum_{l=1}^n \pi_l G(y_n|\mu_l, \sigma_l)} \quad (4)$$

where G is the model of a Gaussian mixture. Using the given inferred probabilities, the following equations are used, accordingly, to determine parameters like mean (μ_m), variance (σ_m), and mixing coefficient (π_m) in the optimisation stage.

$$\mu_k^{new} = \mu_l = \frac{\sum_{j=1}^n \gamma_k(y_j)(y_j)}{\sum_{j=1}^n \gamma_k(y_j)} \quad (5)$$

$$\pi_k^{new} = \pi_l = \frac{1}{n} \sum_{j=1}^n \gamma_k(y_n) \quad (6)$$

$$\sigma_k^{new} = \sigma_l = \frac{\sum_{j=1}^n \gamma_k(y_n)(y_n - y_l)(y_n - y_l)^T}{\sum_{j=1}^n \gamma_k(y_n)} \quad (7)$$

K-means Clustering

K-means clustering divides data into groups known as clusters, which reflect data with related features, based on the attributes of a given collection of data points. A dataset is partitioned using the KM clustering technique into K unique, non-overlapping groups [15]. The objective is to reduce the variance within every cluster, which may be expressed as a reduction of the total squared distances between each cluster centroid and the data points. For continuous data, each cluster is represented by the centroid which is the means of cluster members. Medoid, which is the object that appears the most frequently, is utilised as the grouping pattern for data that is categorical. In the given dataset $X = \{y_1, y_2, \dots, y_n\}$, where a d-dimensional data point y_i belongs to R^d .

The objective function of the K-means algorithm is to decrease the sum of squared distances between each point and its designated centroid [34].

$$J = \sum_{j=1}^K \sum_{i=1}^n r_{ij} \|y_j - c_j\|^2 \quad (8)$$

$$\text{where, } r_{ij} = \begin{cases} 1 & \text{if } j = \arg \min_k \|x_i - c_k\|^2 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

$$c_j = \frac{\sum_{i=1}^n r_{ij} x_i}{\sum_{i=1}^n r_{ij}} \quad (10)$$

D_α Operator

Let $\alpha \in [0,1]$. An operator D_α is a mapping $D_\alpha: S_b([0,1]) \rightarrow [0,1]$ such that satisfies the following conditions [16]:

- (1) If $\underline{y} = \bar{y}$, then $D_\alpha(y) = \underline{y}$
- (2) $D_0(y) = \underline{y}$, $D_1(y) = \bar{y}$ for all $y \in S_b([0,1])$
- (3) If $y_1 \leq y_2$ with $y_1, y_2 \in S_b([0,1])$, then $D_\alpha(y_1) \leq D_\alpha(y_2)$
- (4) $D_\alpha([0,1]) = \alpha$ for any $\alpha \in [0,1]$.

Construction spatial interval valued fuzzy sets using D_α operator

Assume that the familial set of all closed smaller intervals in $[0,1]$ is $S_b([0,1])$. The definition of the mapping $G: [0,1] \times [0,1] \rightarrow S_b([0,1])$ is $G(v, \delta, \gamma) = [\underline{G}(v, \delta, \gamma), \overline{G}(v, \delta, \gamma)]$,

Where, $\underline{G}(v, \delta, \gamma) = v \cdot (1 - \gamma \cdot \delta)$

$$\overline{G}(v, \delta, \gamma) = v \cdot (1 - \gamma \cdot \delta) + \gamma \cdot \delta$$

This implies that, $G(v, \delta, \gamma) = [v \cdot (1 - \gamma \cdot \delta), v \cdot (1 - \gamma \cdot \delta) + \gamma \cdot \delta]$

MATERIALS AND METHODS

This section outlines the overall process of the GMM & K-means based SIVIFCM method used to segment brain MR images.

Hybrid GMM-K-means Strategy for Cluster Centre Initialization

The initialization of cluster centres plays an important role in the convergence and overall performance of clustering algorithms used for image segmentation. In this work, a hybrid initialization strategy based on Gaussian Mixture Models (GMM) and K-means clustering is employed to obtain more appropriate initial cluster centres instead of selecting them randomly [32, 34]. Initially, GMM is applied to represent the image data using multiple Gaussian components, and the means of these components are considered as statistically informed initial centres. These means are subsequently provided to the K-means algorithm as its starting cluster centres. In this way, the probabilistic modelling capability of GMM is combined with the iterative refinement of K-means to improve the initial centres. Compared with conventional random initialization, the proposed strategy provides more stable cluster initialization, leading to improved clustering performance and faster convergence. Consequently, the approach contributes to more consistent and reliable segmentation results, particularly for image clustering applications [32, 38, 39].

Formulation of SIVIFS Image Representation Using the D_α operator

The interval-valued intuitionistic fuzzy generator (IVIFG) is utilized to transform the image into an interval-valued intuitionistic fuzzy representation. Picture

segmentation in [4, 11, 21] makes use of interval valued intuitionistic fuzzy picture representation. The IVIFS representation of with levels of intensity varying from 0 to $L - 1$, a picture with size $S \times T$ pixels is [28, 29]

$$T = \{y_{ij}, [LS_F(y_{ij}), US_F(y_{ij})], [LT_F(y_{ij}), UT_F(y_{ij})]\}, \quad 1 \leq i < S, \quad 1 \leq j < T. \quad (11)$$

The degrees of Lower interval value of membership, Upper interval value of membership, Lower interval value of non-membership, and the variables represent the upper interval value of Lack of membership of the $(i, j)^{th}$ picture element in the picture itself $LS_F(y_{ij})$, $US_F(y_{ij})$, $LT_F(y_{ij})$ and $UT_F(y_{ij})$, respectively.

To determine the membership value, an image is normalized (N_m) using the following techniques:

$$N_m(I(i, j)) = \frac{(i, j)_l - (i, j)_{min}}{(i, j)_{max} - (i, j)_{min}} \quad (12)$$

Whereas $(i, j)_{min}$ and $(i, j)_{max}$ indicate the greatest and lowest intensity values of image I , and $(i, j)_l$ represents the intensity value of $(i, j)^{th}$ pixel. Intensity levels between 0 and 1 are produced via normalization. Subsequently, we constructed membership degree values for a picture using the equivalency function limited as follows.

$$mF(I(i, j)) = 0.582(\exp(1 - |N_m(I(i, j)) - m_l|) - 1) \quad (13)$$

Where m_l denotes the mean intensity value of $N_m(I)$.

The degree of lack of membership function is ascertained using the fuzzy complement function that follows[3]:

$$nmF(I(i, j)) = (I - mF(i, j)(\exp(\frac{-mF}{a\sigma}))^{\frac{1}{a}})^{\frac{1}{a}}, a > 0 \quad (14)$$

where $a = 5$ is used because to the symmetry of the intuitive fuzzy index between membership degree values, and sigma is the standard deviation value of an image with a range of 0.37 to 0.38. because it provides a stronger contrast between the cluster sections [7].

Lastly, the hesitation degree, often known as the fuzzy index, is determined as

$$Pi_F(I(i, j)) = 1 - mF(I(i, j)) - nmF(I(i, j)) \quad (15)$$

There is still some doubt as to whether the selected value is approximative in the intuitionistic fuzzy membership function, even if the value is assigned by decreasing hesitancy in assigning the constant value [22]. Therefore, selecting an assortment of values as opposed to a precise value is an option. IVIFS is used as a result to eliminate the ambiguity present in IFS. By establishing a mapping in the manner described below, IVIFS is built as in [21, 29, 30].

$$LmF = mF \cdot (v \cdot (1 - \gamma_m \cdot \delta_m)) - p \cdot Pi_F$$

$$UmF = mF \cdot (v \cdot (1 - \gamma_m \cdot \delta_m) + \gamma_m \cdot \delta_m) + \alpha \cdot Pi_F$$

$$LnmF = nmF \cdot (v \cdot (1 - \gamma_m \cdot \delta_m)) - q \cdot Pi_F$$

$$UnmF = mF \cdot (v \cdot (1 - \gamma_m \cdot \delta_m) + \gamma_m \cdot \delta_m) + \beta \cdot Pi_F$$

In addition, $0 \leq \alpha + \beta \leq 1$, $0 \leq \alpha + p \leq 1$ & $0 \leq \beta + q \leq 1$,
State $WmF = UmF - LmF = (\alpha + p) \cdot Pi_F$ $WnmF = UnmF - LnmF = (\beta + q) \cdot Pi_F$

where δ_m is the difference between the maximum and minimum values in the membership matrix and γ_m is $(1 - 2 \cdot \sigma)$ (σ are the membership matrix's standard deviation, which ranges between 0.35 and 0.37) [10, 12, 16, 30].

Spatial Interval Valued Intuitionistic Fuzzy C-Means Clustering

A drawback of FCM's objective function for image segmentation is that it ignores any spatial relationships between the pixels in the image. Second, the membership function of FCM is primarily defined by the measure of similarity $d(x_k, v_i)$ between the cluster centre and the pixel intensity. Higher membership is determined by the values of cluster intensity relative to the cluster core. Noise thus has a significant impact on the membership function. Accurate segmentation occurs in MR images when the noise and intensity are not uniform, and FCM approaches perform less well in this regard [6, 18, 19]. We've used Euclidean distance and average distance (AD), as determined by interval valued intuitionistic fuzzy [35, 37], are not the same. The goal of this adjustment is to improve the clustering process's output quality. This is supplied by in order to address these problems [12, 20, 30].

$$d_{SIVIF}(y_k, v_i) = \left\{ \frac{1}{n} \left[(LmF(y_k) - LmF(v_i))^2 + (UmF(y_k) - UmF(v_i))^2 + (LnmF(y_k) - LnmF(v_i))^2 + (UnmF(y_k) - UnmF(v_i))^2 + (WmF(y_k) - WmF(v_i))^2 + (WnmF(y_k) - WnmF(v_i))^2 \right] \right\}^{\frac{1}{2}} \quad (16)$$

$$\min J_m(U, V; Y) = \sum_{i=1}^c \sum_{j=1}^N (u_{ij})^m \|y_j - v_i\|^2 + \alpha \sum_{i=1}^c \sum_{j=1}^N (u_{ij})^m \|y_j - v_i\|^2 + \sum_{i=1}^c W mF * (y_i) \times e^{1-WmF*(y_i)} \quad (17)$$

Subject to $\sum_{i=1}^c u_{ij} = 1$, $1 \leq j \leq N$,
where $wmF \cdot (y_i) = \frac{1}{n} \sum_{j=1}^N wmF(y_i)$.

The optimisation issue (17) may be solved using the Lagrangian multiplier procedure, and its membership and centroids are found as:

$$u_{ik} = \frac{1}{\sum_{j=1}^c \left(\frac{(1 + \alpha) \|y_k - v_i\|^2}{(1 + \alpha) \|y_k - v_j\|^2} \right)^{\frac{2}{m-1}}} \quad (18)$$

$$v_i = \frac{\sum_{k=1}^N (u_{ik})^m y_k}{\sum_{k=1}^N (u_{ik})^m} \quad (19)$$

When updating the membership function, the cluster centroid of the pixel value is considered [23, 24]. This algorithm uses the fuzzifier parameter value $m=2$, which was chosen based on the literature review. As a result, tissue segmentation becomes more precise as the uneven distribution of noise and intensity seen in non-brain magnetic resonance imaging is balanced.

Algorithm 1 Pseudo-code of Proposed method for Gaussian mixture model and k-means based spatial interval valued intuitionistic fuzzy c means clustering with D_α operator.

Require: Input MRI image, Number of cluster= $v_1, v_2, \dots, v_c$, fuzzifier parameter= m , Convergence threshold= ϵ

Ensure: Output image : Segmented tumor region

Step 1: Preprocessing steps like skull stripping using morphological operators and noise removal using median filter.

Step 2: Compute Normalization matrix using min-max method.

$$Nm(I(i, j)) = \frac{(i, j)_l - (i, j)_{\min}}{(i, j)_{\max} - (i, j)_{\min}}$$

Step 3: Compute Membership matrix using the following function.

$$mF(I(i, j)) = 0.582(\exp(-|Nm(I(i, j)) - m_l|) - 1)$$

Step 4: Compute Non-membership matrix using the following function:

$$nmF(I(i, j)) = (1 - mF(i, j)) \left(\exp\left(\frac{-mF}{a\sigma}\right) \right)^{1/a}, a > 0$$

Step 5: Compute Hesitancy matrix:

$$Pi_F(I(i, j)) = 1 - mF(I(i, j)) - NmF(I(i, j))$$

Step 6: Compute interval valued membership and non-membership functions with D_α operator.

Step 7: Initialization of cluster centres using Gaussian mixture model and K-means.

Step 8: Compute Distance between pixels and cluster centres using Average Euclidean distance measure.

Step 9: Update membership matrix and cluster centres using objective function.

Step 10: Convergence check: If the change in membership matrix satisfies

$$\|u_{ik}^{(t+1)} - u_{ik}^{(t)}\| < \epsilon, i = 1, 2, \dots, n \text{ and } k = v_1, v_2, \dots, v_c.$$

then stop, else repeat steps(8-9).

Step 11: Compute final segmented tumor region is taken with the corresponding maximum cluster centre point to extract the most significant tumor region.

RESULTS AND DISCUSSION

Actual Pictures

The dataset used in this experimental study was provided by the KGS Advanced MR and CT Scan Facilities in Madurai, Tamil Nadu, India [30]. Several tumour-containing brain MR

imaging datasets were used in the tests. Following preprocessing [33], centroid values for brain imaging clusters were determined using GMM and K-means clustering [29,36,38]. Better centroid values were thus obtained by the first cluster centres, which lowered the overall time required for the segmentation procedure. This method provides a better centre for cluster centre updates using data points than earlier approaches [11]. Compared to the current approach, the recommended SIVIFCM's method produces superior segmentation results since it uses spatial values with the Da operator. If there isn't a tumour, the cerebrospinal fluid (CSF), grey matter (GM), and white matter (WM) are seen separately. Three cluster cores are seen in this instance, which suggests malignancy. Due to its high intensity, the brain slice tumour area grows into the largest cluster core of the three. After detection, morphological procedures and prolonged maxima transformation are

used to eradicate the cancerous region. The performance of the recommended approach randomly chosen on 3 slices out of 50 slices is shown in Figure 1. As shown in Figure 1, the first row comprises three original images, the second row their corresponding pre-processed images, the third row the segmentation results of the IVIFCM method, the fourth row the GMM and K-means based spatial interval valued intuitionistic fuzzy c means clustering incorporating the Da operator (GK-SIVIFCM) method, and the fifth row the manual segmentation results of the images. Table 1 uses Dice and Jaccard coefficients to compare our proposed method's segmented region (predicted image) to the IVIFCM methods manually segmented tumour region (ground truth picture). Metrics such as sensitivity, specificity, and accuracy are used to assess the way effectively your model sets apart the item of interest (foreground) from the surrounding objects. They give information

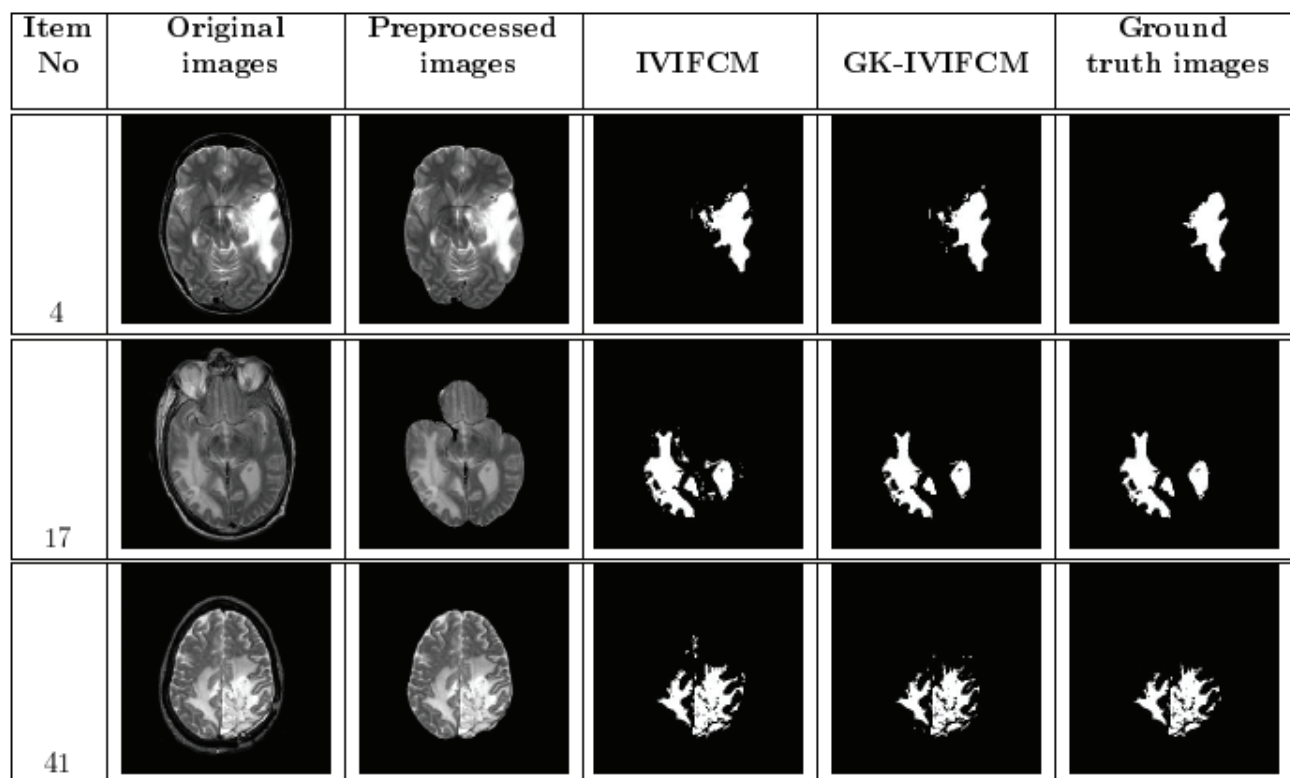


Figure 1. Comparison of Segmentation results.

Table 1. Comparison of Dice coefficient (DC) and Jaccard similarity (JS) obtained using IVIFCM and GK-SIVIFCM of image number 4,17, and 41.

Item	Dice Coefficient		Jaccard Similarity	
	IVIFCM	GK-SIVIFCM	IVIFCM	GK-SIVIFCM
4	0.9197	0.9583	0.8514	0.9202
17	0.9487	0.9783	0.9024	0.9575
41	0.9249	0.9750	0.8603	0.9512

on many elements of the segmentation performance. Table 2 compares the sensitivity, specificity, and accuracy of our proposed approach's segmented region (predicted image) to the IVIFCM method employing a manually segmented tumour region (ground truth). Compared to alternative approaches already in use, our recommended methodology produces superior outcomes.

Synthetic images

The suggested technique utilises virtual brain MRI images from the Brain web database [7]. For segmentation, 2D transverse slices and T1-weighted images with a 1 mm resolution were used. The photographs were evaluated with different degrees of intensity inhomogeneities (0%, and 20%) and noise (3%, 5%, and 7%). Here only provided

Table 2. Comparison of Dice coefficient (DC) and Jaccard similarity (JS) obtained using IVIFCM and GK-SIVIFCM

Item	Sensitivity		Specificity		Precision	
	IVIFCM	GK-SIVIFCM	IVIFCM	GK-SIVIFCM	IVIFCM	GK-SIVIFCM
4	1.0000	1.0000	0.9932	0.9966	0.8514	0.9202
17	0.9997	0.9647	0.9940	0.9996	0.9027	0.9922
41	0.9954	0.9766	0.9918	0.9986	0.8637	0.9734

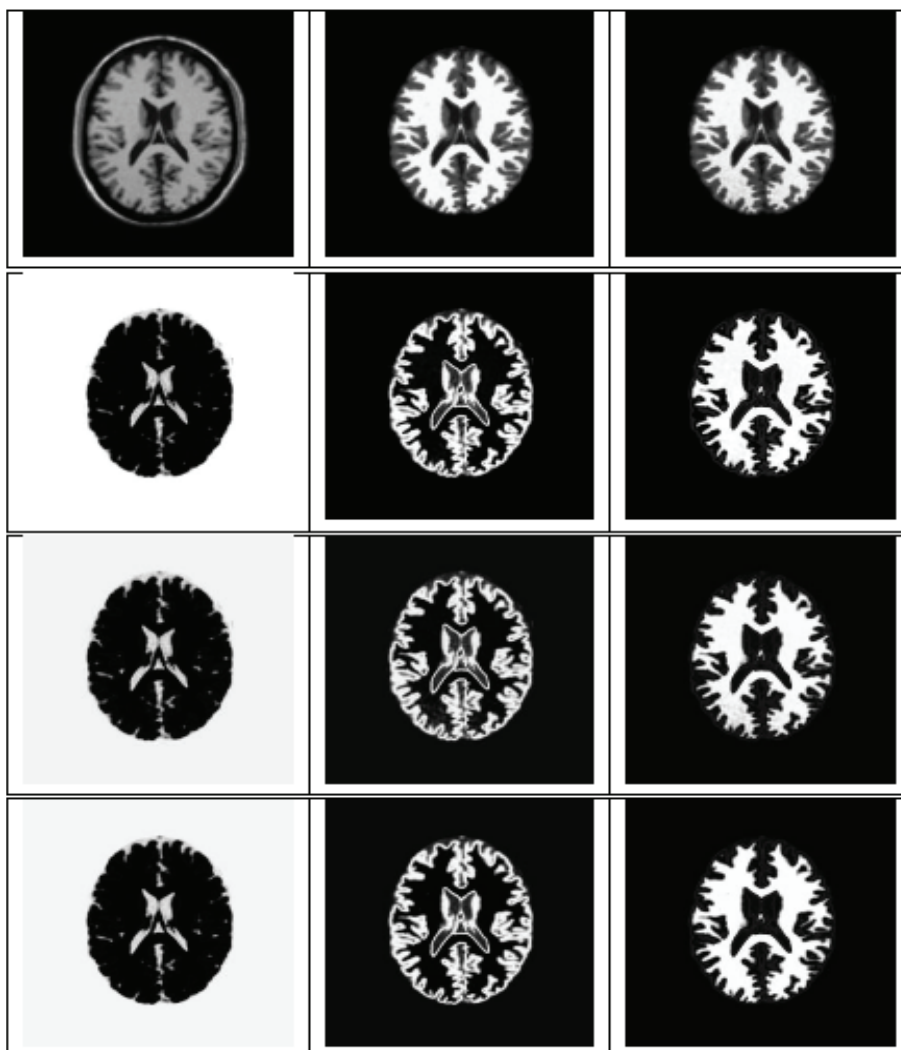


Figure 2. First row: Original image, ground truth, segmentation results using indicated method with 3% noise and 20% intensity inhomogeneity respectively. Second row: CSF, GM, WM of IVIFCM area. Third row: CSF, GM, WM of GK-SIVIFCM area. Fourth row: Region of CSF, GM, WM.

3% noise and 20% intensity inhomogeneity picture. Figure 2 shows effectiveness of spatial interval-valued fuzzy c-means clustering using GMM and KM, using the Da operator approach. The first row of Figure 2 displays the original image, skull removed ground truth, our method skull removed image. The second row depicts CSF, GM, and WM areas calculated using the IVIFCM technique. The third row emphasised the GK-SIVIFCM method's cerebrospinal fluid (CSF), white matter (WM), and grey matter (GM) areas. The fourth row includes ground truth areas for CSF, GM, and WM. The segmentation results for the GM, WM, and CSF areas are provided in the third row, using 0% noise and 0% intensity inhomogeneity as the ground truth. Table 3 displays the DC and JS values for the IVIFCM method and GK-SIVIFCM methodology. Table 4 shows the volume similarity and Kappa coefficients for CSF, GM, and WM using the IVIFCM and GK-SIVIFCM

techniques. Comparing the segmentation results to the ground truth shows that the suggested technique properly localises tissues and has a high degree of consistency with the ground truth. This implies that the GK-SIVIFCM approach for segmenting brain MRI images works well under a variety of noise and intensity inhomogeneity circumstances.

Quantitative Metrics

The suggested algorithm's performance is verified by quantitative assessment utilising the following indices:

1. Dice Coefficient (DC)/ Overlap ratio:

It is the correspondence between the ground truth and the segmentation result. It is described as [5,12]

$$DC(I1, I2) = \frac{2|I1 \cap I2|}{|I1| + |I2|} \text{ (or) } DC = \frac{2TP}{2TP + FP + FN}$$

Table 3. Dice coefficient (DC) and Jaccard similarity (JS) for MR brain images produced with IVIFCM and GK-SIVIFCM with different noise levels of 3%, 5%, and 7% with 20% intensity inhomogeneity are compared.

Noise Level	Tissue Type	Dice Coefficient		Jaccard Similarity	
		IVIFCM	GK-SIVIFCM	IVIFCM	GK-SIVIFCM
3%	CSF	0.9935	0.9978	0.9871	0.9956
	GM	0.8443	0.9328	0.7306	0.8741
	WM	0.9702	0.9511	0.9422	0.9061
5%	CSF	0.9933	0.9974	0.9688	0.9949
	GM	0.8445	0.9348	0.7309	0.8775
	WM	0.9698	0.9315	0.9414	0.8717
7%	CSF	0.9932	0.9973	0.9685	0.9946
	GM	0.8477	0.9200	0.7357	0.8518
	WM	0.9638	0.9493	0.9301	0.9036

Table 4. Volume Similarity and Kappa Coefficient for different noise levels of 3%, 5%, and 7% with 20% intensity inhomogeneity of IVIFCM, Proposed method with Ground truth images.

Noise Level	Tissue Type	Volume Similarity		Kappa Coefficient	
		IVIFCM	GK-SIVIFCM	IVIFCM	GK-SIVIFCM
3%	CSF	0.9936	0.9988	0.9751	0.9914
	GM	0.8701	0.9890	0.8188	0.9197
	WM	0.9867	0.9527	0.9650	0.9428
5%	CSF	0.9934	0.9346	0.9745	0.9202
	GM	0.8749	0.9947	0.8189	0.9222
	WM	0.9840	0.9990	0.9645	0.9899
7%	CSF	0.9934	0.9518	0.9740	0.9408
	GM	0.8762	0.9927	0.8226	0.9044
	WM	0.9827	0.9995	0.9574	0.9895

2. Jaccard similarity (JS): It may be defined as the proportion of two sets' overlap and combination that reflects the segmentation and ground truth pictures that were acquired [5,17].

$$JS(I1, I2) = \frac{2|I1 \cap I2|}{|I1 \cup I2|}$$

DC values provide the relative overlap index between the ground truth image and the segmentation produced by the suggested approach. In highly comparable collections, JS values are more sensitive. $I1$ and $I2$ are the numbers of pixels that, when employing the suggested technique and the ground truth, are categorised into one class, respectively. In both findings, the number of pixels segmented as a single class is expressed as $|I1 \cap I2|$. The number of pixels shared by both outcomes is $|I1 \cup I2|$. These metrics reach a value of 1 in cases where the segmentation outcomes perfectly align with the ground truth, and 0 in cases where there is no alignment.

Confusion Table: This matrix displays the brain cells for a specific class on rows vs the fundamental truth class on sections. [30] as false positives (FP), false negatives (FN), and true positives (TP). Thus, for every class, the true positives (TP) are represented by the diagonal item in this confusion table. Definition of false negative (FN): the proportion of ground truth pixels that were inadvertently segmented as other classes. The fraction of pixels that are mistakenly classified as belonging to a class over those that do not in the ground truth is known as the false positive (FP).

Three more evaluation criteria, which are specified as follows, are also utilised for comparisons based on TN, FP, FN, and TP [2]:

1. Sensitivity (Recall) = $TP / (TP + FN)$.
2. Specificity = $TN / (TN + FP)$
3. Precision = $TP / (TP + FP)$

The results of the proposed technique are compared with IVIFCM based on Dice coefficient (DC) and Jaccard similarity (JS). In addition to the Dice coefficient (DC) and Jaccard similarity (JS), Table 2 shows the segmented regions of cerebrospinal fluid, grey matter, and white matter created for T1 weighted MR brain images with 0% intensity inhomogeneity and variable noise level as 1%, 5%, 9%, and 13%. Table 1 demonstrates that the Jaccard similarity and dice coefficient values for CSF, WM, and GM using the proposed methodology are larger than those obtained using the IVIFCM method [7,26,27,31] for all photos with noise levels of 1%, 5%, 9%, and 13%. The IVIFCM approach is also compared to the GK-SIVIFCM algorithm. Considering the DC value (overlap ratio), The outputs are evaluated in accordance with the overlap ratio (DC value). Correspondence ratios between brain magnetic resonance imaging and noise levels of 5% and 20% intensity inhomogeneity are shown in Figure 2.

CONCLUSION

In this paper, the Da operator is combined with the Spatial Interval-Valued Intuitionistic Fuzzy C-Means (SIVIFCM) clustering algorithm to create a hybrid method for robust picture segmentation. The suggested method initialises the centroids for cluster centres by combining the Gaussian Mixture Model (GMM) with K-means clustering. The outcomes show that, in comparison to current techniques, the proposed method produces superior segmentation. The results show that the SIVIFCM algorithm is very good at segmenting pictures because its fuzzy-based method effectively manages the uncertainties in brain MRI images, which improves segmentation accuracy. Additionally, this approach could improve the detection of diseases and help doctors treat patients more effectively. Other kinds of medical photos can be segmented using this method in the future.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

There are two sources of data that provide credence to the results of this investigation. The KGS Advanced MR and CT scan facilities in Madurai, Tamil Nadu, India, provided the initial dataset. If you would want access to this data, please contact the KGS facility (phone number: +91 452 2524321, 2528929, 97125 59730) and make a legitimate request. The brain web simulation database of normal brain magnetic resonance imaging (MRI) data, which can be accessed by the public at Brain Web website, is the source of the second dataset. If you follow the terms and conditions, you are free to access and use this dataset.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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