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T1 Weighted MR Brain Image Segmentation with Triangular Intuitionistic Fuzzy Set

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Abstract*: Segmentation of medical image is a very important step in processing of image to help examination of diseases. The early detection of ailments from the normal diseases is essential for the physicist to stop and provide treatment. Increasing Cerebrospinal fluid in brain causes dementia which is an increasing mostly prevalent now days. Segmentation of brain images is a challenge due to the existence of noise and intensity in-homogeneity that creates hesitation in segmenting the tissues. This paper is about a fresh segmentation method that uses triangular membership function to distinguish the early regions of brain tissue with intuitionistic fuzzy set. The triangular membership function helps in identifying the initial clusters and regions and facilitates in the decline of the number of iterations needed for segmentation. The proposed method successfully determines the brain tissues avoiding local minima and need of initial clusters. Hence, outperforms the existing method with increased accuracy and reduced computation time

***Keywords* : Intuitionistic fuzzy sets, segmentation, rough sets, brain image, soft sets.**

I. INTRODUCTION

Although there is a major improvement in medical acquiring devices, still the images obtained are exposed to Noise and strength in homogeneity. These very old rarities are the resultant of inappropriate obtaining devices or procedure of acquiring the images. These improper acquisitions bring about irrelevant data that make the research still work on segmentation. The magnetic resonance (MR) picture of cerebrum is frequently divided into White Matter (WM), Cerebro Spinal Fluid (CSF) and Grey Matter (GM). These segmentations are critical to break down and research the working of cerebrum, treatment organizing and quantitative assessment. Fuzzy C-Mean (FCM) is a successful grouping strategy to cluster MR brain images. Dunn [1] has structured the tactic and later was stretched out by Bezdek [2].

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Fuzzy frameworks cannot take care image pixels present in the limit locale called the indeterminacy set.

Generalized rough C-means presented in [3] used a way to establish the tissues of brain using rough sets. However, the rough sets get rid of the use of upper approximations that does not believe all the pixels in clustering.

Guo et al., [4] utilized Neutrosophic Sets (NS) for clustering down the images degraded with noise and proposed a method to segment with NS based methodology. This methodology utilized α-mean and γ-enhancement activities to represent the image in NS. These NS is applied to bind the indeterminacy present in the image with the part of entropy with indeterminacy set. With the minimization of indeterminacy area, the image consistency of the image rises and makes it outstanding and appropriate for extraction of regions. At long last, the image in the NS area is sectioned utilizing a γ-means technique. NS is applied to MR brain image segmentation with neutrosophic numbers an idea is presented in [5].

In [6] a detailed examination on different set theoretic ways were present to segment brain image segmentation. Also, the work [7] [8] has created interest in working on intuitionistic fuzzy sets (IFS).The IFS is used to decide the region. However, the regions based on IFS additionally experience the ill effects of selecting initial centroids.

In this paper, a novel calculation is given to segment the tissue areas in the brain images. The planned strategy recognizes the underlying regions utilizing triangular fuzzy set. The obtained regions are considered for different membership function for IFS and the centroids are also initialized with the mean values of the regions. The updating of the centroids and the membership functions of IFS are iterated until clusters are constant and exactly identifies the melanoma regions. The algorithm extracts the tissues effectively when compared to other existing algorithms. The computation extricates the tissues viably when contrasted with other existing algorithms.

The Later part of the paper is organized as follows: **Section II** present as background of intuitionistic fuzzy sets Triangular Intuitionistic Sets (TIS). The proposed method, Triangular Intuitionistic Fuzzy C-means (TIFCM) is presented in **Section III**. The experimentation and discussion of the TIFCM algorithm is presented in **Section IV** and finally conclusion is presented in **Section V**.

II. BACKGROUND

A. Fuzzy Set

For any universe X, A fuzzy set for data element x in X is defined with a membership function $\mu(x)$ such that each data element x takes real value in the range of [0, 1]. The membership function $\mu(x)$ specifies the degree of membership of x. The value nearer to 1, the greater the membership.

B. Triangular Fuzzy Set

A triangular fuzzy set is defined with a triplet T = (a, b, c). The triangular membership function $\mu(x)$ for a data element x is given by:

$$\mu_{\bar{a}}(x) = \begin{cases} \frac{x-a}{b-a} & \text{if } a < x \leq b \\ \frac{c-x}{c-b} & \text{if } b < x < c \\ 0 & \text{Otherwise} \end{cases} \quad (1)$$

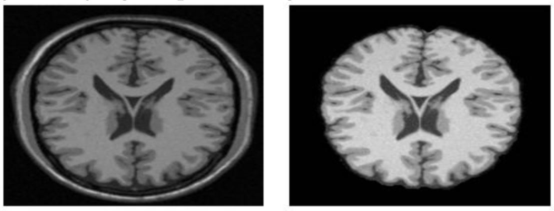
where a, b, c are real values satisfying the condition **a ≤ b ≤ c**. At the position '**b**' the membership function gives the highest degree of $\mu(x)$, i.e., $\mu(x) = 1$; at position **'a'** the value is closer to **0**. The range of values between **[a, c]** specifies the fuzziness of the triangular fuzzy set with lower and upper limit. The narrow the range the less the fuzziness of the triangular fuzzy set.

C. Intuitionistic Fuzzy Set

Atanassov [9] defined IFS as an inclusive version of fuzzy sets for elements that are characterized by a degree of membership $\mu(x)$, vagueness $\gamma(x)$ and non-membership $\pi(x)$. These degrees indicate the positioning of the data element x in a cluster. The membership indicates that the element is designated to the cluster, the non-belonging degree designates the data element as not part of cluster and the vagueness is the dilemma of the pixel belonging to the cluster. This definition of indecision provides extra information to represent imperfect knowledge; has advantage over fuzzy set. The IFS is defined with these three degrees as given below.

$$\mathbf{IFS = \{(x, \mu(x), \pi(x)) \mid x \in X\}} \quad (2)$$

with $\gamma(x) = 1 - (\mu(x) + \pi(x))$. The function $\gamma(x)$ is the intuitionistic fuzzy index that shows the uncertainty degree of element. The IFS must satisfy the condition $0 \leq \mu(x), \gamma(x), \pi(x) \leq 1$ for each element x in X to be an Intuitionistic Fuzzy Sets. Hence, every element x is entitled with three degrees that assist in minimizing the noise, intensity inhomogeneity and exactly conveying the positioning of element x to the cluster.



(a) (b)

Figure-1. (a) Image from Brain web data set with 1mm 90 slice of phantom having 20% INU and 3% noise (b) Image after skull removal.

III. PROPOSED METHODOLOGY

TIFCM based algorithm for segmenting of T1 weighted MR images of the brain is discussed in the section.

A. Triangular membership based fuzzy region determination

The performance of fuzzy based algorithms is highly influenced by the fuzzy functions used for segmentation of images. The performance of the segmentation depends on the functions used to make the fuzzy regions. The proposed technique provides a novel idea by identifying the initial regions with the triangular membership functions which act as the input to the intuitionistic fuzzy C-means. The considered image with size P * Q be represented as X = {$x_i = x_i$ is the intensity of i^{th} pixel of the image} where $1 \leq i \leq P * Q$.

$$\mu_{\bar{a}}(x_i) = \begin{cases} \frac{x_i-a}{b-a} & \text{if } a < x_i \leq b \\ \frac{c-x_i}{c-b} & \text{if } b < x_i < c \\ 0 & \text{Otherwise} \end{cases} \quad (3)$$

The constant a = 70, b = 120 and c = 150 are used for achieving the regions. The values are selected empirically based on experimentation. The regions obtained from the triangular membership function are given as input to the intuitionistic fuzzy C-means. **Figure-2** shows the regions extracted using triangular membership function

B. Triangular Intuitionistic Fuzzy C-means (TIFCM)

The regions obtained from the triangular membership function are used to find the centroids needed to perform intuitionistic fuzzy c-means. The segmentation of image based on intuitionistic fuzzy sets is proposed in [7], [10], [11]. The considered image with size P * Q be represented as X = {$x_i = x_i$ is the intensity of i^{th} pixel of the image} where $1 \leq i \leq P * Q$. The intuitionistic fuzzy set as depiction of X is given as

$$\text{IFS} = \{(x_i, \mu(x_i), \pi(x_i)) \mid x_i \in X\} \quad (4)$$

with $\gamma(x_i) = 1 - (\mu(x_i) + \pi(x_i))$. Here, $\mu(x_i)$ represent membership degree, $\pi(x_i)$ represents non-membership degree and $\gamma(x_i)$ designate the uncertainty value of x_i pixel. In order to get these membership functions, the regions acquire with values $a < x_i \leq b$ of triangular membership function is considered as deterministic region $D(x_i)$ and the values $b < x_i < c$ is considered as hesitancy region $H(x_i)$ and other region as indeterminacy region $I(x_i)$. The membership value $\mu(x_i)$ is calculated using the deterministic region $D(x_i)$ with the given **Equation (5)**.

$$\mu(x_i) = \frac{1}{\sum_{c=1}^{n} \left(\frac{||D(x_i) - C_j||}{||D(x_i) - C_c||} \right)^{\frac{2}{m-1}}} \quad (5)$$

Here, C_j is the cluster centroid j and C_c represents the other clusters centroids excluding j.

Similarly, the non-membership degree $\pi(x_i)$ is calculated using $I(x_i)$ region and the uncertainty value $\gamma(x_i)$ using $H(x_i)$ regions with the **Equations (6) & (7).**

$$\pi(x_i) = \frac{1}{\sum_{c=1}^{n} \left(\frac{||H(x_i)-C_j||}{||H(x_i)-C_c||} \right)^{\frac{2}{m-1}}} \quad (6)$$

$$\gamma(x_i) = \frac{1}{\sum_{c=1}^{n} \left(\frac{||I(x_i)-C_j||}{||I(x_i)-C_c||} \right)^{\frac{2}{m-1}}} \quad (7)$$

The IFS partition matrix $\mu_{IFS}(x_i)$ and cluster centroid C_j are updated using the below equations

$$\mu_{IFS} = \mu(x_i) + \pi(x_i) - \gamma(x_i) \quad (8)$$

$$C_j = \frac{\sum_{x_i \in X} (\mu_{IFS}(x_i))^m (x_i)}{\sum_{x_i \in X} (\mu_{IFS}(x_i))^m} \quad (9)$$

Where m is the fuzziness measure given by the user. m value reaching 1 makes the membership function develop into crisper and more binary, The greater the value of m the greater the fuzziness and blurriness [12]. m satisfying the condition $1.5 < m < 3$ proved to be optimal and the preferred value is 2 in many cases [13], [14].

Mostly the clustering algorithms are iterative and stops when the clusters are stable so, is the case with TIFCM.

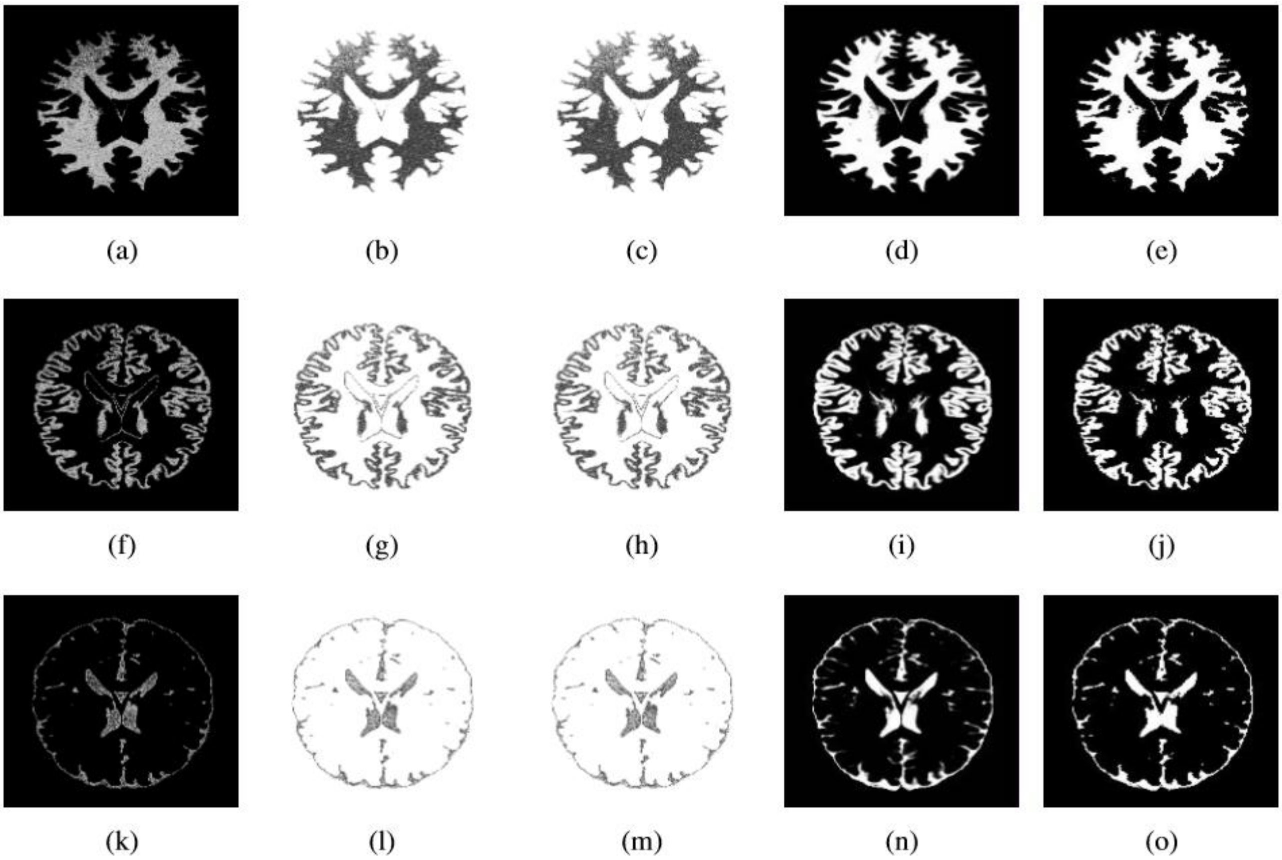


Figure-2. (a)(b)(c)(d)(e) Truth, indeterminacy , false regions Ground truth, TIFCM result of WM.
(f)(g)(h)(i)(j) Truth, indeterminacy , false regions Ground truth, TIFCM result of GM.
(k)(l)(m)(n)(o) Truth, indeterminacy , false regions Ground truth, TIFCM result of CSF.

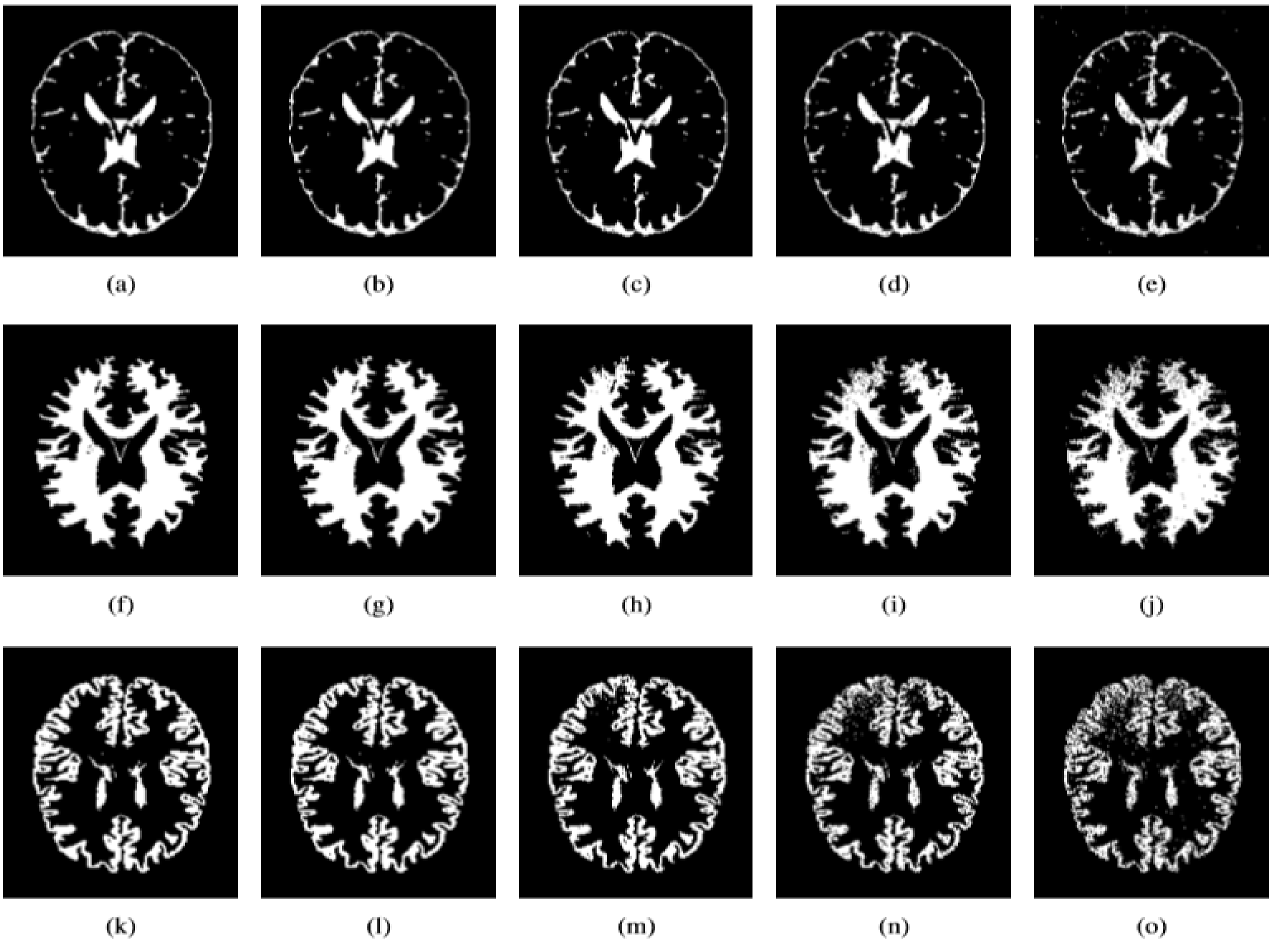


Figure-3. Results of Segmentation of TIFCM- T1 weighted phantom brain image.

(a)(b)(c)(d)(e) CSF tissue in segmented with 0%, 1%, 3%, 5% and 7% noise with 40% INU.
(f)(g)(h)(i)(j) tissue in segmented with 0%, 1%, 3%, 5% and 7% noise with 40% INU.
(k)(l)(m)(n)(o) tissue in segmented with 0%, 1%, 3%, 5%, and 7% noise with 40% INU.

Table – I. Data Sets of Brain Images

Dataset	Dimension	Image Size	Number of Images
Brain Web	2D	181*217	20
IBSR	2D	256*128	20

IV. EXPERIMENTATION AND DISCUSSION

A. Experimental Setup

In order to calculate the proposed TIFCM algorithm, the brain databases used are: (i) Brain Web [15] and (ii) IBSR [16]. The images of Brain Web database images have the format of MINC and IBSR database images are in .hrd and bit8 format. The number of images considered from the databases with specifications are shown in **Table-I** [12].

In the experimental setup for TIFCM for segmenting the images, the fuzzifier value *m* is considered as 2, the figure of clusters is considered as n = 4 (representing GM, WM, CSF and background). The $\mu_{IFS}(x_i)$ is initialized to zeros and the 0.01 is empirically chosen for exit condition for clustering. The experimentation is measured with Dice, Jaccard coefficients and Segmentation accuracy.

The experimentation is performed on 20 images of brain web data set with slice 90 having a thickness of 1 mm and with varied intensity homogeneity (INU = 0, INU = 20 and INU=40) and varied noises 0%, 1%, 3%, 5% , and 7% of brain web and 20 images of IBSR. The results in **Figure-3** shows the results of TIFCM executed with 40% INU and varied noise levels. The visual results proved that the tissue segmented with the proposed algorithm are in accordance to the ground truth.

Table-II shows the segmentation accuracy of the extracted tissues for INU 40% with varied noise levels for phantom image. The results show that segmentation accuracy results give better results in improved accuracy in noise levels. **Table-III** depicts dice coefficient of TIFCM .The dice coefficient value having 80% is considered to produce good accurate results.

As the proposed method uses intuitionistic sets that considered triple membership function for handling the noise effectively, produces 80% at 7% noise. This proves that the proposed method is more efficient even the acquired images are defected by intensity inhomogeneity and noise.

The Jaccard's coefficient is compared with other fuzzy based algorithms referred in [8]. **Figure-4** provides average coefficients of proposed method at various noise and INU levels.

Table-II. Segmentation Accuracy of TIFCM for image in Figure-1

Intensity non-uniformity	Tissue type	0% Noise	1% Noise	3% Noise	5% Noise	7% Noise
40% INU	GM	0.9952	0.9802	0.9730	0.9624	0.9248
	CSF	0.9965	0.9921	0.9862	0.9834	0.9762
	WM	0.9902	0.9886	0.9756	0.9742	0.9644

Table-III. Dice Coefficient of TIFCM for image in Figure-1

Intensity non-uniformity	Tissue type	0% Noise	1% Noise	3% Noise	5% Noise	7% Noise	9% Noise
40% INU	GM	0.9372	0.9346	0.9187	0.9011	0.8834	0.8078
	CSF	0.9362	0.9259	0.9166	0.9121	0.8915	0.8654
	WM	0.9720	0.9698	0.9622	0.9554	0.9326	0.9045

Table-IV. Average Jaccard coefficient of TIFCM for brain images [8]

Intensity non-uniformity	Tissue Type	KM	RKM	FCM	RFCM	GFCM	SFRCM	RIFCM	GRIFCM	TIFCM
40% INU	GM	0.8423	0.8562	0.8540	0.8610	0.8682	0.8902	0.9565	0.9681	0.9718
	CSF	0.8202	0.8572	0.8460	0.8624	0.8484	0.8912	0.9116	0.9281	0.9365
	WM	0.8242	0.8656	0.8426	0.8718	0.8855	0.9164	0.9456	0.9623	0.9712

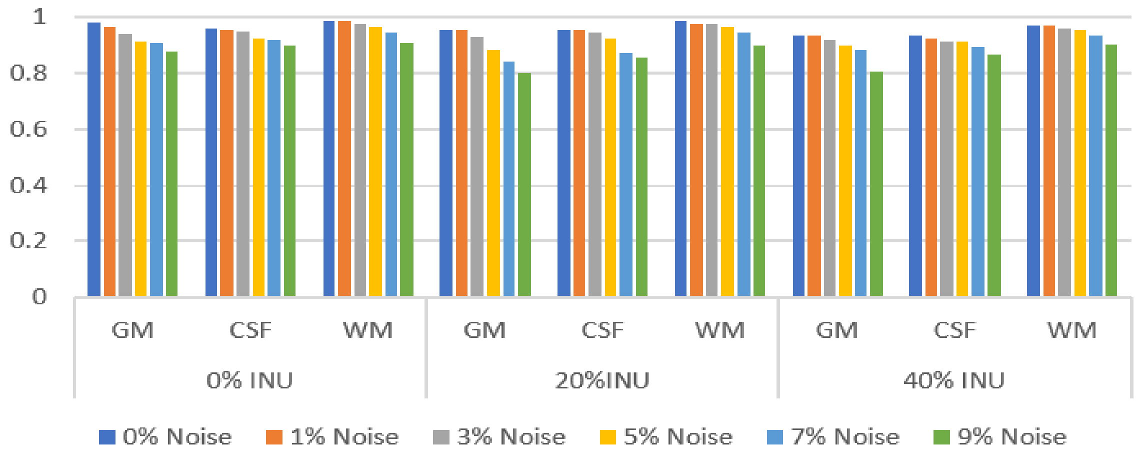


Figure-4 Average Dice coefficient for different noise levels and INU

Table-V Comparison of sets theoretic techniques for clustering MR brain image segmentation [6].

Method	Advantages	Disadvantages
K-Means	• Simple and fast algorithm. Effectively segments round objects. • Clustering is performed using distance measure between pixels and centroids with continuous update of centroids.	• Require initial centroids to perform clustering. • Non deterministic. • Does not allow overlapping of pixels. • Pixel can belong to a single cluster at a time.

Clustering with Fuzzy sets	• C-means makes a pixel to belong to two or more clusters at a time. • C-means define the vagueness of a pixel belonging to a cluster. • Make uses of different membership functions to group the pixels.	• Depends on the membership function. • Sensitive to noise and outliers.
Clustering with Rough sets	• Handles partial volume effect. • Handles the pixels present in the boundary. • Reduces clustering mistakes.	• Negative region pixels are eliminated. • Depends on initial centroids. • Parameter tuning is required.
Clustering with soft sets	• Provides a parameterization tool. • Strong mathematical operators to handle uncertainty.	• Identifying the appropriate mathematical operator for clustering is needed.
Clustering with Intuitionistic sets	• Handles the noise and bias field present in the images. • Uses triple vector to handle the uncertainty.	• Depends on the membership functions. • The triple vector is used to identify the initial cluster regions. • These regions help in reduced clustering mistakes and time.

In **Table-V**, The KM (K-means), FCM (fuzzy based clustering) produces results with less time but cannot handle the uncertainty. Hence, reduces the JC values in presence of noise and bias. RKM, RFCM, GFCM (Rough sets-based clustering) reduces the clustering mistakes with use of lower and upper approximations improving the JC values. However, these include complex instructions and increased time in execution. SFRCM (soft sets-based clustering is less complex with reduced calculation and better results than existing methods but with increased noise and bias the methods fails. Hence, Intuitionistic Fuzzy Sets are preferred to segment brain images as they handle the noise and bias field as well with triple vector. The triple vector is computed based on the image itself and does not lead to local minimum. From **Table-II** and **Table-III**, with increased 7% noise also the method produces high accuracy results. Hence, the proposed method produces accurate results when compared to existing methods in literature.

V. CONCLUSION

The new and automatic segmentation method for brain images has been proposed in this paper with TIFCM. TIFCM is a generalization of FCM that uses TIFS to represent the image and applies them to clustering. TIFS is used to obtain the initial regions with which the centroids are calculated based on the image itself. The proposed method capably handled the uncertainty with indeterminacy region with TIFCM that produced good segmentation results in presence of noise and INU. The methods determine the regions consistently, avoiding the local minima producing improved accuracy and reduced clustering time. The IFS in future can be applied with various membership functions and can be analyzed for best possible function for applying to brain image segmentation

REFERENCES

1. J. C. Dunn, "A fuzzy relative of the isodata process and its use in detecting compact well-separated clusters," Journal of cybernetics, 1973.
2. J. C. Bezdek, Pattern recognition with fuzzy objective function algorithms. Springer Science & Business Media, 2013.
3. X. Li, M. Makkie, B. Lin, M. Sedigh Fazli, I. Davidson, J. Ye, T. Liu, and S. Quinn, "Scalable fast rank-1 dictionary learning for fmri big data analysis," in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, 2016, pp. 511–519.
4. Y. Guo and H. D. Cheng, "New neutrosophic approach to image segmentation," Pattern Recognition, vol. 42, no. 5, pp. 587–595, May 2009.
5. Namburu, A., S. Chakkaravarthy, V. M. Cruz, and H. Seetha. "Single Valued Triangular Neutrosophic Fuzzy c-Means for MR Brain Image Segmentation." In Book of Abstracts, p. 13. 2019.
6. A. Namburu, S. Srinivas Kumar, and E. Srinivasa Reddy, "Review of set theoretic approaches to magnetic resonance brain image segmentation," IETE Journal of Research, pp. 1–18, 2019.
7. Y. K. Dubey, M. M. Mushrif, and K. Mitra, "Segmentation of brain mr images using rough set based intuitionistic fuzzy clustering," Biocybernetics and Biomedical Engineering, vol. 36, no. 2, pp. 413–426, 2016.
8. A. Namburu, S. K. Samayamantula, and S. R. Edara, "Generalised rough intuitionistic fuzzy c-means for magnetic resonance brain image segmentation," IET Image Processing, vol. 11, no. 9, pp. 777–785, 2017.
9. K. T.Atanassov, ""Intuitionistic fuzzy sets"," Fuzzy Sets and Systems, vol. 20, no. 1, pp. 87 – 96, 1986.
10. T. Chaira, "A rank ordered filter for medical image edge enhancement and detection using intuitionistic fuzzy set," Appl. Soft Comput., vol. 12, no. 4, pp. 1259–1266, 2012.
11. H. Verma, R. Agrawal, and A. Sharan, "An improved intuitionistic fuzzy c-means clustering algorithm incorporating local information for brain image segmentation," Appl. Soft Comput., vol. 46, pp. 543—-557, 2015.
12. [D. L. Pham, "Spatial models for fuzzy clustering," Comput. Vis. Image Underst., vol. 84, no. 2, pp. 285–297, 2001.
13. J. C. Bezdek, R. Ehrlich, and W. Full, "Fcm: The fuzzy c-means clustering algorithm," Comput. Geosci., vol. 10, no. 2-3, pp. 191–203, 1984.

14. A. Namburu, S. kumar Samay, and S. R. Edara, "Soft fuzzy rough set-based mr brain image segmentation," Applied Soft Computing, vol. 54, pp. 456–466, 2017.
15. B. Web, "Simulated brain database," McConnell Brain Imaging Centre, Montreal Neurological Institute, McGill, http://brainweb. Bic. Mni. Mcgill. Ca/brainweb, 2004.
16. "Ibsr, the internet brain segmentation repository," http://www.cma.mgh.harvard.edu/ibsr/.

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