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AUTOMATIC IDENTIFICATION OF TUMOR BASED ON IMPROVED CLUSTER ENSEMBLE SEGMENTATION FROM MRI BRAIN MEDICAL IMAGES

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ABSTRACT

Classification of Magnetic Resonance Imaging (MRI) is an aggressive concept to handle mathematical relations like Fuzzy, Rough Soft sets evaluation from bio-medical brain images. Processing of Soft, Rough, and Fuzzy mathematical theories are of scientific importance in the field of Bio-medical applications. Some of the authors have introduced Rough, Soft, and Fuzzy sets with connected and mathematical relations associated with each other. In this paper, we propose an Improved Intuitionistic Cluster Ensemble Segmentation Approach (IICESA) for the identification of brain tumor based on weight of image pixel with associative noise reduction in image selection. This technique also reduces Magnetic Resonance (MR) of brain from selected region based on threshold, which is explored from pixel weight to produce segmentation of brain tumor tissue from bio-medical images. All selected regions created intutionistic fuzzy, rough sets to enable and predict brain tumor tissue from medical brain images. This results of the simulated proposed approach gives efficient accuracy when compared to traditional approaches like Fuzzy C-Means (FCM), Generalized FCM (GFCM), and Soft Rough based FCM (SRFCM), Intutionistic Rough FCM (IRFCM) based on analysis of results.

Keywords: *Brain Image Segmentation, Magnetic Resonance Imaging, Bio-Medical Images, Mathematical Relations, Cluster Ensemble Process, Fuzzy C-Means Clustering.*

1. INTRODUCTION

Presently in the area of medical imaging and analysis, segmentation plays a vital role in the areas of clinical applications like tissue volume suggestions in light of measurement, decision-making, and coordinated pixel concentrations for medical procedure improvement applications. Segmentation of medical images has a vital role in handling the MR medical imaging examinations having various deformities and the potential of expecting the treatment, identification of the right area to be examined and treated. These MR images comprises of three major tissues viz., White Matter (WM), Grey Matter (GM), and Cerebro Spinal Fluid (CSF). Investigation of these tissues is of primary importance in order to estimate and assess the deformity inside the image region and thereby applying effective segmentation procedures to have a precise understanding about the region of damage. In the area of Bio-medical imaging, the investigation of MR images help out to give a deeper insight about the region of damage and figure out the areas of damage, compared to manual segmentation procedures based on MR segmentation, help to have a high significant degree of accuracy in particular pertaining to neuropathic deformities. Therefore, applying appropriate MR procedures help to identify more clearly the damaged cells, in particular related to cancerous activities.

In general, every MRI image consists of speckles that have the phenomenal importance leading to misclassification rate. Therefore, it is necessary to handle this speckle noise more appropriately so that the misclassification rate

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associated with the MRI images minimizes and consequently the effective segmentation of the damaged tissues can be made more visible.

Many techniques based on clustering approaches, Fuzzy C-Means approaches have been considered to identify this speckle noise. However, these methods have certain disadvantages like the K-Means clustering is a semi supervised in nature which needs initial estimates to be given manually and which may not yield better results. In relative, in Fuzzy C-Means algorithm, the associatedness of intra - cluster similarities are to be considered in order to overcome misclassification rates.

To overcome these limitations, Rough set based classifications have been considered which overcome the deformities with respect to above said methods. In this procedure while segmenting the MR images, the related pixels, which are having a predefined label, are grouped together and thereby ensures a noteworthy boundary allocation, which indirectly helps to identify the deformity inside the image regions. However, it has its own limitation while identifying and characterizing the cluster regions.

The results of Cerebro Spinal Fluid (CSF) are given below to have precise understanding. To underline the limitations of Rough sets in this approach, we propose Intuitionistic Cluster Ensemble Segmentation Approach (IICESA).

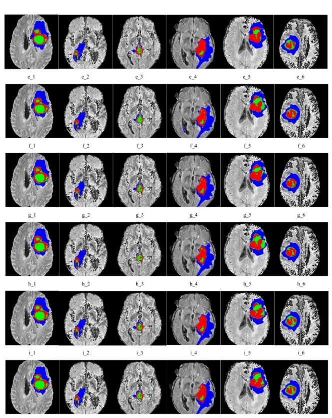

Figure 1: Ground Truth and Segmented Image Description

A portion of the fuzzy related to intuitionistic sets or soft sets presented in the writing. Some methodologies have fundamental limits in line with the group with edge values. These grouping of pixels help in extracting the boundary pixels within the CSF region. Unpleasant sets and rough sets were explored w.r.t MR picture classification to deal with the determination of the exact region within the medical image associated with efficient results in classification of tumor. These procedures lead towards over segmentation or under segmentation results. To overcome this limitation, Soft based fuzzy related rough sets are involved to separate and group portioned outcomes for clinical brain images. Feng et al. (2011), proposed the idea of evaluating the techniques based on soft set based rough fuzzy sets in medical image segmentation with direction. Due to heterogeneous nature of CSF, different selection of weights are to be assigned in order to classify the segmented tissues of the brain tumor more accurately.

In this document, we proposed Improved Intuitionistic Cluster Ensemble Segmentation Approach (IICESA) for the identification of brain tumor based on weight of image pixel with associative noise reduction in image selection. This technique also reduces Magnetic Resonance (MR) of brain from selected region based on threshold which is explored from pixel weight to produce segmentation of brain tumor issue from Bio-medical images.

Main contribution of proposed approach is described as follows -

a) Identification of brain tumor in medical image based on improved automatic region selection based on membership functions
b) Evaluate centroid based on threshold pixel formation based on histogram pixel intensity value
c) Proposed calculation describes realistic and synthetic brain image divided into different filtered functions i.e., GM, WM and CSF

2. LITERATURE REVIEW

In 1993, Pawlak [1982; 1982A] published a book titled Hard Sets and Soft Sets that traces the origins of soft set theories [Pawlak, 1994]. His concept of soft sets is an amalgamation of conventional, disagreeable, and fuzzy sets. The fundamental ideas of the theories of soft sets and some of its probable applications were presented

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in this work, which was sparked by Molodtsov and published in 1999 under the title 'soft set theories: first outcome'.

In order to softly register and portray the tied together perspective of fuzzy sets through neighborhoods, Lin et. al. 1996, established set theories and suggested that soft sets, also known as fuzzy sets, should dynamically be characterised by such structures (soft sets). W-soft set, F-soft set, P-soft set, B-soft set, C-soft set, N-soft set, FP-soft set, and FF-soft sets have been separated in light of such structures.

In the study, Maji et. al. (2001), mixed fuzzy and soft set hypotheses; the fuzzy soft set theories is a broader soft set model that makes descriptions of the target world more generally acceptable, pragmatic, and occasionally exact of fundamental leadership. Again, in 2003, some users' work included soft set theories. In a basic leadership issue, Roy and Maji (2007) presented a revolutionary strategy for protest acknowledgement from ambiguous multi spectator information. Pei and Miao (2005) discussed how soft sets and data frameworks are related. Soft sets are shown to belong to a class of unusual data frameworks. The more general results also show that segment sort soft sets and data frameworks have comparable formal structures and that fuzzy soft sets and fuzzy data frameworks are equal once soft sets are extended to a few classes of general situations. According to Xiao et. al. (2005), a proper definition and method are intended for recognizing soft data designs by constructing the data table in accordance with soft set theories while at the same time, arrangements are suggested in relation to various acknowledgment vectors. Mushrif et. al. (2006) investigated the surface grouping using a Classification Algorithm and Soft Set Theory. The fundamental characteristics of soft sets are discussed in Aktas and Cagman's (2007) article, which also contrasts soft sets with the related concepts of fuzzy sets and rough sets. Kovkov et. al. (2007) have demonstrated the strength of sets provided by imperatives is taken into account within the context of the theories of soft sets around the same time..

The fundamental ideas of soft rings, which are actually a parameterized collection of subrings of a ring, are presented by Acar et. al. (2010). Babitha and Sunil (2010) established the concept of soft set relations as a subsoft arrangement of the Cartesian outcome of the soft sets, along with several related concepts as proportionate soft set connection, segment, structure, work, and so forth. In order to build a soft max-min basic leadership technique that can be effectively connected to the problems that contain vulnerabilities and furthermore improving a few new outcomes, results of soft sets, and uni-int choice capacity, Cagman and Enginoglu (2010) characterized soft lattices and their operations that are more practical to influence hypothetical investigations in the soft set hypothesis. The purpose of this study, according to Feng et al. (2011), is to provide a method for combining fuzzy sets, unpleasant sets, and soft sets in general. This system gives rise to a few exciting new concepts, such as harsh soft sets, soft unpleasant sets, and soft-unpleasant fuzzy sets. The purpose of this study, according to Feng et al. (2011), is to provide further understanding about fundamental leadership, such as interim esteemed fuzzy soft sets - a cross breed display that combines soft with interim esteemed fuzzy settings. Numerous authors have produced work in a variety of fields, such as soft cross sections [Fu Li et. al. 2010], bijective soft sets [Gong et. al. 2010], and soft mappings [Majumdar and Samanta, 2010]. In addition, Majumdar and Samanta (2010) summarized the concept of fuzzy soft sets as it was introduced by Maji et. al. (2003). In their 2010 study, Qin and Hong handle the mathematical construction of soft sets and create grid architectures. Soft correspondence is shown to be a connection between harmony and a few operations, and soft remainder variable-based math is established. The concept of select disjunctive soft sets is putforth by Xiao et. al. (2010) in their study, which also concentrates several of its operations, such as restricted /loose.

Additionally, operations, dependencies between bijective soft sets and restricted disjunctive soft sets, and so on were discussed. In addition to discussing the fundamental characteristics of ambiguous soft sets, Xu et. al. (2010) offer the concept of obscure soft sets as an extension of the soft set. Some crucial characteristics associated with these new operations were explored by Ali et al. (2011). Four idempotent monoids are offered as ascent by a collection of all soft sets regarding fresh operations. Alkhazaleh et. al. (2011) gave the definitions of a soft multiset and its key

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operations, such as supplement, union, and convergence, in their study as an interpretation of Molodtsov's soft set. In their presentation of soft subfields of a field and soft sub-modules of a left R-module from 2011, Atagun and Sezgin studied the related properties of soft substructures of rings, fields, and modules. Babitha and Sunil (2011) gave an anti-symmetric connection and transitive conclusion of a soft set connection and suggested Warshall's computation in their article. A few examples are shown along with the idea of a soft ring and soft perfect over a ring that was suggested by Celik et. al. (2011). Likewise, we learned some new characteristics of soft standards and soft rings.

Semi-group theory and intuitionistic fuzzy soft sets were related by Zhou et. al. (2011). A soft cross section, soft sub-lattice, finish soft grid, specific soft cross section, distributive soft grid, soft chain, and concentrate their relevant qualities were described by Karaaslan et. al.,(2016). The similitude between soft sets hypothesis, which is an extension of the balance for the soft set hypothesis, had been thought about by Min (2012). Singh and Onyeozili (2013) outlined the fundamental goal, clarified certain calculated fallacies in the fundamentals of the soft set hypothesis, and looked at the distributive and assimilation aspects of soft set operations [Singh and Onyeozili, 2013]. The results Singh and Onyeozili (2013) developed in this study include restricted union limited crossing point, expanded convergence, and confined distinction on soft sets, all of which are associated with distributive features of AND (as well as) operations. In light of trapezoidal fuzzy numbers, Xiao et. al. (2012) research aims to expand existing soft sets to trapezoidal fuzzy soft sets. An integrated FCM and fuzzy soft set for provider choice issue in view of hazard assessment was developed by Xiao et. al. in 2012. To address the provider determination issue, this analysis first coordinates the fuzzy soft set model and Fuzzy Cognitive Map (FCM).

3. PRELIMINARIES

This section describes the basic preliminaries used for the identification of brain tumor tissue based on Fuzzy C-Means mathematical evaluation described as follows.

Let us consider segmentation of image with different mapping notations i.e., $\{a_1, a_1, a_3, \ldots\ldots a_n\}$ & $\{k_1, k_1, k_3, \ldots\ldots k_n\}$ are the selected region formations with objective based on Fuzzy C-Means is described as

$$H_{RCM}\begin{cases} A_1 \; if\,(R(D_j) \neq \phi, J(D_j) = \phi \\ B_1 \; if\,(R(D_j) = \phi, J(D_j) \neq \phi \\ X_1 \qquad X_1 * A_1 + X_h * B_1; \\ if \quad (R(D_j) \neq \phi, J(D_j) \neq \phi \end{cases} \quad \text{---(1)}$$

Based on above condition we form selected pixel values from bio-medical images is described as

$$\begin{cases} A_1 = \sum_{j=1}^{k} \sum_{a_i \in R(B_j)} \| a_i - B_j \|^2 \\ B_1 = \sum_{j=1}^{k} \sum_{a_i \in R(B_j) - R(B_j)} \| a_i - B_j \|^2 * (u_{ij})^m \\ J(D_j) = R(C_j) - \underline{R}(C_j) \end{cases} \quad \text{---(2)}$$

Threshold calculation based on selected pixel region is described as

$$T = \left(\frac{u_{ij}}{\arg\max(u_{ij})} \right) <= threshold \quad \text{---(3)}$$

u_{ij} be weighted value of pixel i^{th} which is identified with j^{th} present in selected region of medical image, above equation describes the evaluation of threshold parameter sequence with different associated parameters based on weight of pixel formation from different medical images.

Mathematical relations i.e. Fuzzy, Soft, Rough set describes overall process of selection of dynamic pixel notation from image values.

Define the relation G be the basic set and E be the factor related set, for selection of rough and soft set based relation using R over G*E, here G*E be the approximate rough set selection based on smoothing factor present in selected medical image. Then we define the relation between extensive parameter sequences as follows:

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$$\ddot{R}(A) = \{\left(\mu, \mu_{R(A)}(v), \lambda_{R(A)}(\mu)\right) \mu \in G\}$$

Where

$$\mu_{R(A)}(v) = \underset{a \in R_s(v)}{\nabla} [\mu_A(a,x) \wedge \mu_A(a)]$$

$$\lambda_{R(A)}(v) = \underset{a \in E}{\nabla} [1-(\lambda_A(v,a) \wedge \lambda_A(a))]$$

---(4)

This relation describes intutionistic fuzzy based rough set based on G, E, R values, here $(A) \in$ IF(U) be the explored mathematical relation $(A) \in$ IF (G), Based on these parameters, evaluate approximately matching data relations.

4. PROPOSED METHODOLOGY

This section describes the procedure of proposed methodology i.e., Improved Intuitionistic Cluster Ensemble Segmentation Approach (IICESA) for the identification of brain tumor with efficient extraction of tumor part from medical images.

Let us consider the multi objective parameters with specific function K(X, Y, α) to reduce the representation of tumor classification in medical images. Based on derived parameter a_{ij} with similarity matrix B, matrix relates to membership function A performed centroid u_i and biased field α_I with conditions check 0 and 1; 0 describes tumor classification conditions. Calculation of tumor tissue classification function is described as

(A, B,α)=i=1ck=1$naikm$||gk−$\omega k\alpha k$−bi ||2+a˜1+i=1$caikm$

---(5)

Here a˜=$kgkn$ for the identification tumor classification

A. Extraction of Field Estimation from the Image:

Derivative function K (A, B, α) associated with assigned parameter α_k then it is described as 0 then it is classified as tumor, parameter is 1 then it is non tumor

∂(A, B,α)∂α_k=i=1c∂∂αkk=1$nxaikm$(gk− $\omega k\alpha k$−bi)^2

---(6)

For second estimation function ith parameter on α_k with described function

$$\left[-\sum_{i=1}^{c} a_{ik}^m g_k + \sum_{i=1}^{c} a_{ik}^m \omega_k g_k + \sum_{i=1}^{c} a_{ik}^m v_k\right]_{x=x_k^*} = 0$$

---(7)

Then differential function from above equations is described as

$$\left[-g_k \sum_{i=1}^{c} a_{ik}^m + \omega_k g_k \sum_{i=1}^{c} a_{ik}^m + \sum_{i=1}^{c} a x_{ik}^m v_k\right] = 0$$

$$\omega^* a_k g_k \sum_{i=1}^{c} a_{ik}^m = g_k \sum_{i=1}^{c} a_{ik}^m - \sum_{i=1}^{c} a_{ik}^m v_k$$

---(8)

Based on this distance function with gradient parameters based on bias function is described as

$$\alpha_k = \frac{1}{\omega_k}\left(b_k - \frac{\sum_{i=1}^{c} a_{ik}^m v_k}{\sum_{i=1}^{c} a_{ik}^m}\right)$$

---(9)

B. Procedure to evaluate brain tumor classification is described in algorithm 1:

Input: medical image, sample binary mask image, ($\hat{u}_1(h)$)($\hat{u}2(h)$).

Output: Classified image with tumor detection

S1: Based on above equations evaluate multi scale feature instance from image

S2: identify the feature distance of each pixel present in medical image and define classify the region is

$$R = \left\{h \,|\, \left(\hat{u}(h) > \hat{u}(h-1)\right) \& \left(\hat{u}(h) > \hat{u}(h+1)\right)\right\}$$

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Where R be the Region of all the pixels present in tumor of brain images

S3: Identify the threshold of all images with pixel locations from classified region is

$$K = \left\{ h \mid \left(\widehat{u}(h) > \widehat{u}(h-1) \right) \& \& \left(\widehat{u}(h) > \widehat{u}(h+1) \right) \right\}$$

Where K be the all the pixel threshold of image based on height and weight of image

S4: Remove all the background pixels

$$\widehat{u}(h+1) \neq \widehat{u}(h-1)$$

S5: Check each foreground and background pixels values

If (h is high) &

Where R=R-h;

If (h is low) &

$$\widehat{u}(h+1) \neq \widehat{u}(h-1)$$

then K=K-;

S6: Based on interaction values of all the pixels in image evaluated and represented as

$$\{[1,i_1],[2,i_2],[3,i_3],\ldots,[n,i_n]\};$$

S7: Segmented water body images like $S_1, S_2, S_3, \ldots, S_{|n|}$

Figure 2 &Algorithm 1: Step by step procedure to classify brain tumor from medical images

If $w \in (1,0)$ be the function relates to membership based on biased parameter value $\omega = 0.007$ which is increased to 0.09 to $w_1, w_2, \ldots\ldots, w_n$

Based on above derivative functions, updated cluster centroid is described as

$$\left[\sum_{k=1}^{n} a_{ik}^{m} (g_k - \omega_k \alpha_k - b_i) \right]_{b_i = b_i^*} = 0 \quad \text{---(10)}$$

After updating cluster, it is represented as

$$y_1^{k*} = \frac{\sum_{k=1}^{n} x_{ik}^{m} (g_k - \omega_k \alpha_k)}{\sum_{k=1}^{n} x_{ik}^{m}} \quad \text{---(11)}$$

Based on above equations, update the cluster with identification of tumor from brain medical images. Based on membership functions, if MF is present in between 0 and 1 then if it is 1 then it is classified as brain tumor and 0 then it is described as non-tumor from medical brain images.

5. EXPERIMENTAL SETUP

This section describes about implemented methodology i.e., IICESA. Here, we describe the processing of brain medical images which are collected from internet sources https://www.nitrc.org/frs/?group_id=48&release_id=3124 and http://brainweb.bic.mni.mcgill.ca/brainweb/, these data is publicly available and it is outsourced data. We simulated the results on MATLAB using downloaded medical images. After downloading images, convert them into required format, which is readable to machine using some pre-processing approaches. By using scale invariant feature transform, extract the feature from brain medical images and implemented with rough based image data analysis. We compared our implemented approach with different traditional approaches like i.e., K-Means Clustering (K-MC), Fuzzy C-Means (FCM), Extended FCM (EFCM), Gaussian Kernel based FCM (GKFCM) and Rough Set based FCM (RSFCM) with respect to accuracy of segmentation in identifying tumor of medical image and co-efficient relates to Jacquard in segmented images. All the experimental results of proposed implemented approach described in following figures with different notations.

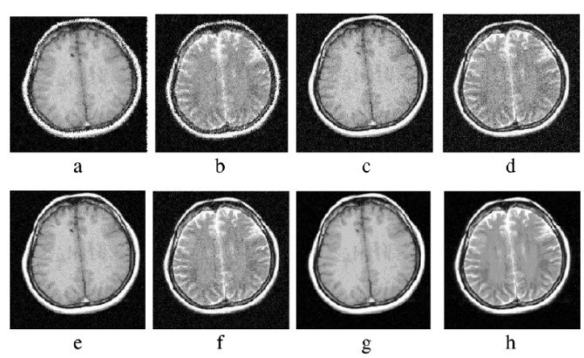

Figure 3 Filtering noise with different notations based on weighs of brain images.

Figure 3 shows the noise filtering ratios at different pixel levels i.e. matter relates to white (WM), Matter relates to Grey (GM), Spinal fluid relates to Cerebro (CSF), these levels described at different filter conditions like

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median, average and weight to explore robust segmentation results in processing of MRI brain medical images.

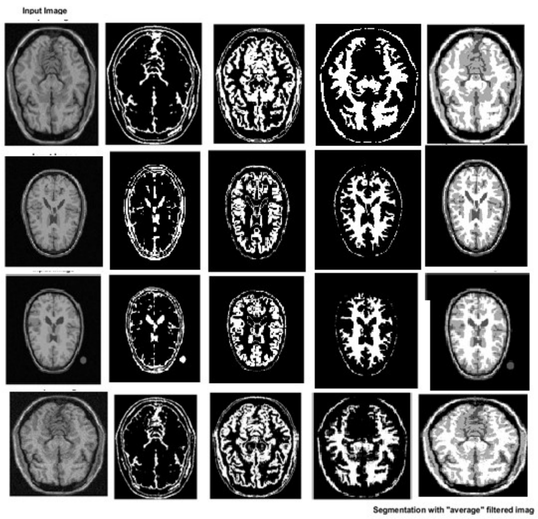

Figure 4. Average pixel format values with different formations

Figure 4 describes the segmented brain images at average filter level with weighted pixels for identification of tumor from input images. It also shows the medical brain image segmentation with noise reduction at different formations of pixels identification. Some of pixels are represented with high resolution in representation of medical image with associated normal formations.

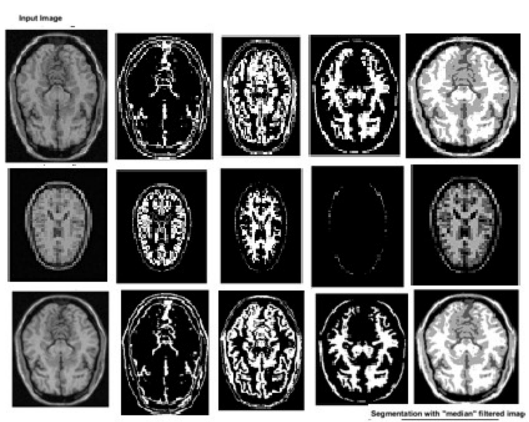

Figure 5. Representation of images with median level pixel representation

Results of proposed implementation with different median pixel values at filter conditions like WM, GM, CSF formations in reading of brain medical images. In this, we upload input brain image and then it is converted into different binary notations and then converted into image pixel formations at pixel levels. Weight filter based segmented images at different GM, WM and CSF filtering conditions described in figure 6

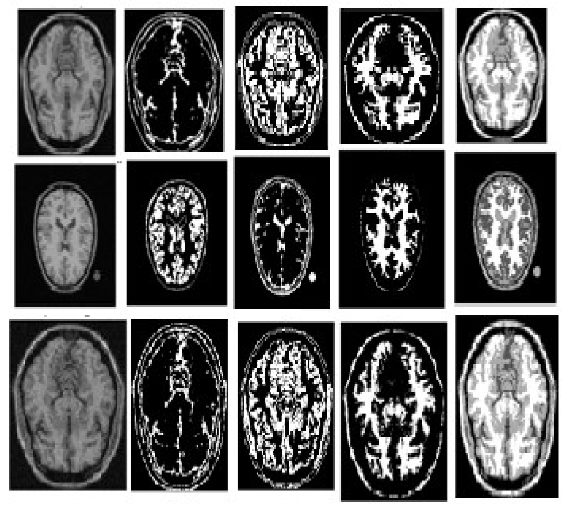

Figure 6. Weight based pixel resultant images with different formations.

As shown in figure 6, weight based brain segmented images with weight segmented filter sequence results that are taken from different regions, evaluate region extraction uploaded images based on max-distance and then converted into required image pixel format. Above figure shows different approaches i.e. K-Means (KM), Fuzzy C-Means (FCM), Generalized Fuzzy C-means (GFCM, Gaussian Kernel based Fuzzy C-Means algorithm (GKFCM) and Soft, Fuzzy Rough sets C-means (SFRCM) and proposed approach. When compared to all traditional approaches, IICESA gives better dimensionality with respect extraction of features from brain medical images. IICESA gives robust and superior results with respect to classification of tumor with mathematical relations like intutionistic fuzzy based rough related soft sets.

6. ANALYSIS OF QUANTITATIVE MATHEMATICAL PARAMETERS

Based on the above results of proposed approach and other traditional approaches describe quantitative analysis of image retrieval with respect to evaluation of accuracy and Jacquard Coefficient (JC). Evaluation of

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Jacquard Coefficient based on dimensionality reduction in brain tumor classification is described as follows

$$CJ = \frac{A \cap B}{A \cup B} \qquad \text{---(12)}$$

A be the segmented image & B be the truth analysis of image ground analysis. If CJ >75% then resultant accuracy of segmentation is described as truth or not truth.

Accuracy of segmentation gives better performance in terms of analysis of ground truth in image and pixel dimensionality at different pixel notations. Evaluation of segmentation of accuracy mainly depends on following sequence of parameters

Positive based on true values: Evaluation of ground truth pixels values are distinguished with number of accurate pixel dimensions for segmentation of accuracy

Negative based on true values: Evaluation of distinguished ground truth pixel values with false pixel dimension values in evaluation of jacquard co-efficient

Positive based on false values: Mean of real image pixel evaluation with false ground truth pixel dimensions which are extracted in local histogram accessed image

Negative based on false values: Evaluation of ground truth false pixel analysis with false dimensionality reduction values in extracted region.

Proposed approach evaluates efficient noise reduction segmentation values with comparison to traditional approaches.

7. RESULTS AND DISCUSSION

This section describes the overall performance of traditional methodologies with proposed approach from segmentation of brain related medical images. Comparison was made with different cluster approaches in identification of cluster, which contain similarity of pixel dimensionality based on max-distance metric performed on real time image processing applications. Below Table 1 represents accuracy and Jacquard Coefficient values of different approaches.

Table 1 - Different segmentation of accuracy values with respect to tissue pixel values

Ratio of Noise	Tissue classification	KMC	FCM	GFCM	GKFCM	SFRCM	IICESA
3%	GM	0.9675	0.9892	0.9678	0.9756	0.9864	0.9992
	CSF	0.9750	0.9753	0.9675	0.9753	0.9735	0.9851
	WM	0.8534	0.9635	0.9545	0.9852	0.9752	0.9957
6%	GM	0.8945	0.9693	0.8753	0.8612	0.8920	0.9426
	CSF	0.8653	0.7945	0.8924	0.8745	0.8964	0.9452
	WM	0.8756	0.9356	0.8712	0.9254	0.9190	0.9642
9%	GM	0.8051	0.8051	0.7848	0.7885	0.7978	0.8927
	CSF	0.7639	0.7962	0.8574	0.8607	0.7886	0.8848
	WM	0.7326	0.7422	0.8854	0.8878	0.7945	0.8751

Table 2 - Different Jacquard co-efficient simulated values at different filtered functions

Ratio to noise	Tissue classification	KMC	FCM	GFCM	GKFCM	SFRCM	IICESA
3%	GM	0.0956	0.0968	0.0955	0.0953	0.0975	0.0921
	CSF	0.0984	0.0984	0.0970	0.0977	0.0986	0.1532
	WM	0.0962	0.9705	0.0964	0.0972	0.0987	0.1287
6%	GM	0.0854	0.0859	0.0852	0.0851	0.0892	0.3283
	CSF	0.0824	0.0869	0.0846	0.0861	0.0896	0.2396
	WM	0.0844	0.0915	0.0862	0.0918	0.0919	0.235
9%	GM	0.0704	0.0794	0.0674	0.0677	0.0797	0.2463
	CSF	0.0662	0.0783	0.0759	0.0760	0.0788	0.3023
	WM	0.0626	0.0631	0.0780	0.0789	0.0794	0.2997

As shown in Table 1, at different filtered pixel functions of proposed implementation and other traditional approaches, whenever percentage of region extraction increases, then automatically proposed approach gave better efficient and robust classification results, which means it reaches high resolutions in extraction of segmented part of brain medical images.

Similarly, Accuracy of segmentation (SA) is described in Table 1, co-efficient of jacquard variable described in Table 2. Table 1 & 2 evaluates combination values with respect to identification of tumor in segmentation of brain image. Experiments performed based on soft based fuzzy related soft sets using proposed approach are compared to traditional approaches i.e., SFRCM, KMC, FCM, and Generalized FCM. All these traditional approaches does not evaluate and meet efficient pixel extraction and not build combine calculation in pixel region extraction for accuracy that relates to segmentation and coefficient that relates jacquard based on features relates to false positive, false negative, true positive and true negative values at different cases is presented.

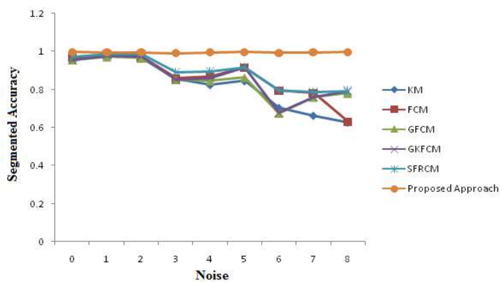

Figure 7 : Performance evaluation of accuracy with respect to segmentation of tumor classification of brain image.

As shown in figure, proposed model shows highest accuracy of IICESA with comparison to traditional approaches, KMC, FCM, GFCM, SRFCM; gives less performance in selection of region from segmented images in classification of tumor from medical image sources.

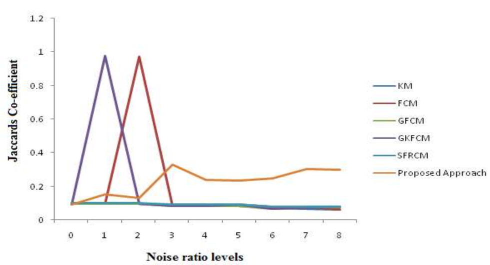

Figure 8 Performance evaluation of jacquard co-efficient with respect to different approaches

Based on above results, clearly showcase the efficient performance of proposed approach in comparison to different traditional approaches. It gives better accuracy segmented ratio and jacquard co-efficient from extracted region of explored image, performance with comparison to different techniques decreases the accuracy and co-efficient; whenever different image filter labels increased then IICESA gives better accuracy because of reduction in dimensionality in segmented histogram image with different notations. Fuzzy based soft related rough set mathematical relations give better accuracy with classification of image features accurately.

8. SUMMARY

In this paper, we proposed Improved Intuitionistic Cluster Ensemble Segmentation Approach (IICESA) for segmentation of medical MR brain images have been presented. The extensive fuzzy based soft and rough mathematical relations are used to enable intutionistic fuzzy based brain tumor segmentation based on proposed approach. This proposed approach performs noise reduction using intutionistic fuzzy relations and histogram pixel region evaluation based on weight factor of each image. Proposed algorithm depends on fuzzy membership function and explore the cancroids based on method of histogram which is perform efficient; Practical experimental result give better outcome - Synthetic and clinical with accurate brain segmentation results when compared with traditional approaches. Further improvement of implemented methodology is to explore notation between different pixels pattern with respect to extraction of pattern from selected region. Also, improve the dimensionality of segmented image and compute noise reduction in generation of histogram.

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