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Optimal kernel based Neutrosophic Soft sets Clustering for Image Segmentation based on Pareto Optimal Algorithm

B. Prasanthi, N. Nagamalleswararao

Abstract: *In bio-medical image processing, brain image segmentation is an aggressive concept in present days. Disorders of brain mainly requires accurate tissue extraction and classification of magnetic resonance (MR) medical brain images, which is very effective and important to detect different types of tumors, and necrotic tissue classification and segmentation. To handle brain image segmentation, mathematical tools like fuzzy sets, rough sets and soft sets are used to define uncertainty and vagueness of brain images. Accurate and effective segmentation and detection of tumor on brain image is still a challenging task in medical brain images with respect to reduction of noise, smoothness of image and accuracy for segmentation of medical brain images and other parameters. We propose and introduce a Novel Brain Segmentation approach based on neutrosophic soft sets is introduced to explore uncertainties relates to white, grey and cerebro spinal fluid matters for the detection tumor from MR brain image with respect to bias field estimation and co-relation based on decision making. Our proposed approach consist Pareto Optimization algorithm to support neutrosophic soft sets approximations for the optimal kernel parameters (like kernel functions). These approximations are free to define weight parameters and average, median, weight filters and less complexity compared to existing algorithms. Our experimental results show effective performance of proposed approach with respect to segmentation accuracy, time and jacquard parameters compared to existing algorithms.*

Index Terms: *Segmentation of brain image, fuzzy c-means, Intuitionistic neutrosophic soft sets, rough sets, magnetic resonance.*

I. INTRODUCTION

Classification of brain image is thought assignment for image identification and investigation based on image boundary representations, which are effected by noise. It is the crucial step to analyze images with respect to tissue classification, tumor detection, anatomical architecture and computer aided surgery applications [1]. Brain magnetic resonance image mainly divided into three basic matters like white matter (WM), gray matter (GM) and the cerebro spinal fluid (CSF) is essential matters to study different structural modifications and building of tumor growth approaches. Because of noise existence, bias field, brain image segmentation, affect complete volumes and tumor detection of brain image are the main challenging tasks and issues in present days. Still conventional approaches suffer from robustness to outlier image presentation, high communication and computational cost which needs to adjustment of different crucial parameter volumes, tumor detection and less accuracy of segmentation, reduction of noise and image descriptors with loss of image data.

The main promising approach for image segmentation and tumor detection is soft clustering, untrained machine learning, which define similar group of patterns with different clusters which contains soft set boundaries. For brain image, pixel of an image relates to cluster forms based on varying length of image membership functions, this method is applicable to provide accountability to image segmentation. Different clustering has been introduced for brain image tumor detection and segmentation which includes well known Fuzzy C-means clustering (FCM), model mixture methodologies, intuitionistic (FCM) and some hierarchical, hybrid methodologies based on former oriented approaches discussed [8]. Accuracy of these approaches is good without image noise and intensity because they are not applicable to reduction of noise and other features of image.

Recently different types of approaches are developed to improve FCM clustering with reduction of noise to represent different image clusters based on intuitionistic fuzzy set clustering (IFs). Aruna et.al defines modified intuitionistic (FCM) approach accesses the properties from intuitionistic fuzzy sets and Euclidean distance between different pixels in images. Verma et.al represents enhanced intuitionistic FCM (IIFCM) clustering algorithm [14] which defines spatial data based on considerable parameters. Even IIFCM is able to define effective noise tolerance not depends on features training but these approaches depends on Euclidean, Hausdorff and other distance measures performed with image pixel, as a result all these approaches give separable cluster results based on initial selection of centroids. It is well known that some of the optimized kernel parametric functions are to be used to find clusters which are not linearly separable. And also define metrics with respect to performance of these types of methods or algorithms are high sensitive to selection of optimized parametric functions [17, 20, and 21]. Different types [18] [19] have been introduced to eliminate optimal parameters for cluster formation, but they can't perform complete solution for brain image tumor detection and image segmentation in brain images.

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*Correspondence Author(s)
B. Prasanthi, Research Scholar, ANU, Guntur, AP, India and Assistant Professor, Department of IT, R.V.R& J.C College of Engineering, Guntur Andhra Pradesh, India.
Dr N. Nagamalleswararao, Professors, Dept. of IT, R.V.R &J.C College of Engineering, Guntur, Andhra Pradesh, India

We believe that, by applying different optimal and hardware based kernel functional to identify intuisionistic fuzzy set related bunching (clustering) and we want a robust and efficient approach to handle classification/ segmentation of MRI image. Based on these features, image classification problem may convert into optimized problem which is used to find optimal kernel parameters to reduce noise with fuzzy oriented data analysis. For optimization, there are different techniques like Genetic algorithm, porn swarm optimization, DNA genetic algorithms are used to solve classification problem in many areas like clustering analysis, optimization of functional, computation of membrane. Based on this discussion, we propose and introduce a novel Brain Segmentation approach based on Pareto Optimization algorithm to support neutrosophic soft sets approximations to optimize kernel functions, It also defines clustering results with optimization then MRI brain image segmentation and detection of tumor is simple in our approach based on non-dominated region selection in brain images. We empirically study and perform by compare with traditional clustering related approaches based on MRI image database and clinical brain image data sets. Our implemented results show the performance of proposed approach outperforms compare with existing algorithms with respect to efficiency of classification accuracy and other parametric metrics.

Organization of this document as follows: Basic definitions relates to neutrosophic sets, Pareto optimization etc described in section 2. Section 3 describes background work relates to intruitionistic fuzzy c-means clustering approaches. Section 4 defines proposed approach with algorithm implementation. Section 5 presents experimental evaluation performed on UCI related data. Section 6 describes experimental evaluation of proposed approach with comparison to existing methods. Section 7 concludes conclusion of overall work discussed in this paper.

II. BASIC PRELIMINARIES

a.Intuitionistic Neutro Soft sets

Let us consider that A is the sub set of universal set U, with an equivalence relation R, then classification sub sets $U/R=\{A_1,A_2,.......,A_n\}$ (it satisfied different conditions)

$$A_i \subset U, A_i \neq \phi \forall i;$$
$$A_i \bigcap A_j \neq \phi \forall i,j;$$
$$A_1 U A_2,.....,UA_n = U;$$

For each sub set A_i i.e called as category with equivalence relationship R, Single attribute contain in R relation with an object $a_i \in U$ and it is identified by $[a_1]_R$ then internal relation for selected attributes

$$a_1 INT(R) a_2 = \{(a_1,a_2)\in U^2 \mid (a_1,a_2)\in P, P\in U/R\} \quad (1)$$

With equivalence relations with respect to internal relation can be defined as

$$INT(P)=\bigcap_{R\in P} INT(R) \quad (2)$$

Calculate the relation based on intuitionistic neutro soft based rough sets can be defined with lower and upper approximate of relation R with set relation A is

$$\overline{R}A=\cup\{Z\in U/R \mid Z\bigcap A\neq\phi\} \quad (3)$$

b. Neutrosophic sets

An element a relates to U is significantly called universal set relates neutrosophic fuzzy sets X of U, if the falsity user relationship or true user relationship and in determine user membership values i.e. $T_{X(a)}$, $F_{X(a)}$ and $I_{X(a)\leq 0.5}$. If it is not closer to 0.5 then it is insignificant. And also for neutrosophic sets the truth, falsity and in determine membership can't be significant. Based o this, define intuitionistic neutrosophic sets by

$$X=\{<a:T_{X(a)},I_{X(a)},F_{X(a)}>a,a\in U\}$$
(4)
$$\min\{T_{X(a)},F_{X(a)}\}\leq 0.5,$$
$$\min\{T_{X(a)},I_{X(a)}\}\leq 0.5,$$
$$\min\{T_{X(a)},I_{X(a)}\}\leq 0.5, \forall a\in U,$$

With different conditions

$$0\leq T_{X(a)}+I_{X(a)}+F_{X(a)}\leq 2$$

Let us consider the example relates intuitionistic neutrosophic sets, assume that disclosure of universe $U=\{a_1,a_2,a_3\}$ where a_1,a_2,a_3 parameters characterizes the capability, prices of the objects and trustworthiness. Furthermore assume that a_1,a_2,a_3 are in between 0,1 then they can be obtained from different questionnaires from different experts. The experts may concern their opinion in three components such as degree of goodness, indeterminacy with degree and poorness of different characteristics of fuzzy oriented objects. Suppose X be the neutrosophic sets relates U such that $X=\{<a_1,0.3,0.5,0.4>,<a_2,0.4,0.2,0.6>,<x_3,0.7,0.3,0.5>\}$, where the level of benefits of capability is 0.3, level of indeterminacy of ability is 0.5 and level of falsity of ability is 0.4 etc.

c.Fuzzy neutrosophic soft sets

We describe basic preliminary relates to both neutrosophic soft set and neutrosophic set theory. As discussed above U be a preliminary galaxy set and X ⊂ E is a collection of different factors. Let N (U) signifies the collection of total intuitionistic soft sets places of U. The selection (F, A) is known as to be the smooth improved intuitionistic soft set over U, where F is a applying given by F: X → N (U).

A fuzzy neutrosophic set X on disclosure of universe A is defined as

$$X=\left(a,T_X(a),I_X(a),F_X(a)\right),a\in X \quad (5)$$

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Where

$T, I, F, A \rightarrow [0,1]$ & $0 \le T_X(a) + I_X(a) + F_X(a) \le 3$,

U is primary universal set & E be the collection of different attribute relations. X be the non-empty set with total factors, X ⊂ E. P (U) defines a collection of total neutrosophic fuzzy sets [25-27] of U. Set of (F, X) is known as to be the neutrosophic soft based fuzzy set over universal set U, F is given by $F : X \rightarrow P(U)$.

Neutrosophic fuzzy soft set is defined as FNS sets throughout this paper. A neutrosophic fuzzy soft set X is consist over neutrosophic fuzzy set Y i.e $X \subseteq Y$ if

$$\forall a \in A, T_X(a) \le T_Y(a), I_X(a) \le I_Y(a), F_X(a) \ge F_B(a) \quad (6)$$

Like this there are more basic decision making operations present in neutrosophic soft sets, in our implementation, use these relations and make decision on image segmentation and tumor detection from UCI related brain image data sets.

d. Pareto Optimization

Pareto optimality is an effective concept and applied in different domains like economic sciences, computer sciences and social sciences. Here, we give brief review about Pareto optimality and define front based Pareto solution. For multi-variant image segmentation, we have a small set S of achievable arrangements, and relevant criteria T $f_1, f_2, \ldots\ldots, f_T : S \rightarrow R$ for assessing the plausible arrangements. One conceivable objective is to discover x 2 S limiting all criteria at the same time. In many settings, this is an inconceivable errand. Many ways to deal with the multi-target streamlining issue diminish to joining all criteria T into single one. At the point when this is finished with a direct mix, it is typically called linear secularization. Selection of different weights in the straight mix yield distinctive minimizes. Without earlier learning of the relative significance of every foundation, one must utilize a matrix look over every single conceivable weight to distinguish an arrangement of achievable arrangements. To find optimal solution is a robust approach involves finding the optimality. $x \in S$ be the Pareto optimal solution defines ranking for objective selection of query image from different sources. Moreover, we define x strongly related and dominates y if any $f_i(x) \le f_i(y)$ for all i and $f_j(x) \le f_j(y)$ for each i with different objects. A product $x \in S$ is Optimal Pareto method is not dominated with other things present in image. Pareto optimal feasible alternatives are well known solutions to define scalability for straight formation with different front sides like F1 and F2 by eliminating irrelevant medical images based on manifold ranking procedure to arrange different medical images. More usually, the ith Pareto front side is determined by

$$F_i = ParetoOptimalSet / S \setminus \left(\bigcup_{j=1}^{i-1} F_i \right) \quad (7)$$

If $x \in F_k$, x is the depth of Pareto front F_i, then F_i is greater than F_j if $i > j$.

III. RELATED WORK

Original fuzzy c-means (FCM) calculation method [8] based on different objective functions, which are not contain local data information, it is very complex in sensitive with respect to reduction of noise, clustering accuracy and other image artifacts. FCM consists following objective function evaluation

$$J_{FCM\_S}(X,Y) = \sum_{a=1}^{k}\sum_{c=1}^{n}(x_{ac})^m \| x_c - v_i \|^2 + \frac{\beta}{N_R}\sum_{a=1}^{k}\sum_{c=1}^{n}(x_{ac})^m \left(\sum_{r \in N_a} \| x_c - v_i \|^2 \right)$$

(8)

As shown in above equa second option consists spatial details of community around p, where N_i is the collection of each pixel p around with xi, N_R is mean cardinality of N_i, and 0 < b < 1 is a formal argument which controls dimensionality of image details of others who live nearby. Although it assists in managing disturbance, economically it is costly as the area term must be defined in each pixel in image.

Yang and Tsai [19] defines a FCM based Gaussian kernel technique. This technique additionally consist two specific shapes i.e GKFCM1 and GKFCM2 for normal and middle channels, separately. It transfer b parameter with a η_b parameter, which must be ascertained in each cycle for each bunch in [29-32]. Utilizing proper estimation of parameter η_b , this technique could prompt preferable outcomes over FCM_S1 and FCM_S2. Be that as it may, to evaluate a decent incentive for hj, group centroids must be very much isolated, which is hard to ensure. Therefore, the calculation may take numerous emphasess to focalize. In addition, the learning plan requires numerous examples and many group centroids to locate the ideal incentive for η_b . In addition, this procedure doesn't give efficient on small pixel notation in image.

IV. FORMATION OF PROBLEM

We formulate the new objective functions relate to FCM problem in cluster formation, describe derivations to form objective functions. Basic representation of objective function shown in above equation (8), we will modify that to add new features included increasing detection, accuracy of segmentation, and improving different metrics of proposed approach for segmentation and tumor detection of MRI brain images. Each ai is a sequential vector represents in different dimensional way of particular image (grey scale representation of the pixel with image), for easy representation, refer ai, it is pixel value of image i.

Variance relates to Intensity of local image: Change resistance of noise by replacing β with weight measure local information. N_r be the neighborhood of the given size with 6*6 pixel formation, then Intensity of Local variance(LIV) of the each pixel a_k as follows

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$$LIV_k = \frac{\sum_{j \in N_r} \left(a_j - \overline{a_k}\right)^2}{|N_k|} \quad (9)$$

$|N_k|$ denotes pixels present in N_k , and is average image data black and white taken from p in Nk. LIV reports the difference of dimensions in grey scale in the community stabilized by the regional mean grayscale. A huge LIV defines advanced stage with reduction of noise with other image data pixel values. Weight of the brightness for each pixel a_i as follows

$$w_k = \frac{\varsigma_k}{\sum_{j \in N_k} \varsigma_k} \quad (10)$$

Based on weight of each pixel, finally variance of each pixel as follows:

$$\varphi_k \begin{cases} 2 + w_k, \overline{a_k} \prec a_k \\ 2 - w_k, \overline{a_k} \succ a_k \\ 0, \quad \overline{a_k} = a_k \end{cases} \quad (11)$$

After finding variance, rewrite the objective function as follows

$$J_{FCM\_S}(X,Y) = \sum_{a=1}^{k}\sum_{c=1}^{n}(x_{ac})^m \| x_c - v_i \|^2 + \sum_{a=1}^{k}\sum_{c=1}^{n}\phi_c(x_{ac})^m \left(\sum_{r \in N_a} \| \overline{x_c} - v_i \|^2 \right) \quad (12)$$

Since ϕ_c is appropriate grey scale present in specified communication, which is not dependable at any group, it contains to be measured parameters before clustering performed in between images. This is slightly different from consecutive or sequential existing techniques, where each image details should be modified pixel present in image with each group in each version. The above equations give computation cluster formation on MRI segmentation.

b. Optimal Kernel Intuitionistic Neutrosophic Fuzzy Soft Sets

Equation 12 describes Euclidean distance metric to representation of cluster and similar feature representations with similar dimensional shapes, which is not support to real medical image data. It is very complex to support outliers and perturbations. There is only one way to address this problem i.e use optimal image hardware kernel functions to support data into multi-dimensional that data can be easily classified. Main advantage of later approach is to transfer linear calculation functions into non-linear functions with lot of product.

To improve classification accuracy, detection ratio and efficiency based on outlier results, we use optimal hardware related kernel trick replace with distance metrics i.e Mahalanobis and Euclidean distances $\| x_c - v_i \|^2$ with $\| \phi(\overline{x_c}) - \phi(v_i) \|^2$. Based on equa (12), objective kernel functions as follows:

$$J_{OKNFSC}(X,Y) = \sum_{a=1}^{k}\sum_{c=1}^{n}(x_{ac}^*)^m \| \phi(\overline{x_c}) - \phi(v_i) \|^2 + \sum_{a=1}^{k}\sum_{c=1}^{n}\phi_c(x_{ac})^m \left(\sum_{r \in N_a} \| \phi(\overline{x_c}) - \phi(v_i) \|^2 \right) + \sum_{i=1}^{k} \pi_i^* e^{1-\pi_i^*} \quad (13)$$

Where ϕ is the non-linear implicit mapping and $\| \phi(\overline{x_c}) - \phi(v_i) \|^2$ squared distance between mapped pixels x_c and v_i in a image feature dimensions, which are used to calculate optimal hardware related kernel functions present in input image as follows:

$$\| \phi(\overline{x_c}) - \phi(v_i) \|^2 = K(x_k, x_k) + K(v_i, v_i) - 2(x_k, v_i) \quad (14)$$

Where K() is the optimal hardware kernel function, we mainly used kernel related optimal function is Gaussian filter radial bias function [19]

$$K(x_k, v_i) = \exp\left(\frac{-\| x_c - v_i \|^2}{\sigma^2} \right) \quad (15)$$

Then final optimized objective function as follows

$$J_{OKNFSC}(X,Y) = 2\left(\sum_{a=1}^{k}\sum_{c=1}^{n}(x_{ac}^*)^m (1 - K(x_k, v_i)) + \sum_{a=1}^{k}\sum_{c=1}^{n}\phi_c(x_{ac})^m \left(1 - K(x_k, v_i)\right) \right) + \sum_{i=1}^{k} \pi_i^* e^{1-\pi_i^*} \quad (16)$$

Based on required conditions of X and Y and given parameters m, σ and α will minimize the membership functions based on degrees as

$$x_{ic} = \frac{\left((1 - K(x_k, v_i)) + \phi(1 - K(x_k, v_i))\right)^{-1/(m-1)}}{\sum_{j=1}^{c}\left((1 - K(x_k, v_i)) + \phi(1 - K(x_k, v_i))\right)^{-1/(m-1)}} \quad (17)$$

Centroid of the neutrosophic soft sets

$$v_i \frac{\sum_{k=1}^{n}(x_{ik})^m \times (K(x_k, v_i)x_k + \phi K(\overline{x_k}, v_i)\overline{x_k})}{\sum_{k=1}^{n}(x_{ik})^m (K(x_k, v_i) + \phi K(\overline{x_k}, v_i))} \quad (18)$$

This is the basic representation of optimized kernel functional soft set clustering process for the detection of tumor and segmentation of image.

V. PROPOSED ALGORITHM IMPLEMENTATION

We present Pareto Optimal clustering calculation method for hardware kernel related neutrosophic soft sets clustering problem, which will be represented in algorithm 1. This algorithm is generalized version of Pareto Optimal procedure presented in preliminary section. Proposed method consist nested loops, Evaluation procedure defines and controlled specified user constant based on functional iterations, each iteration repeats for each pixel present in image. Inner most loops consists centroids of soft set clusters and distances includes in n-dimensions. The complexity of algorithm is O(cn2d, detailed description of the Pareto Optimal cluster is presented as follows:

Algorithm 1: Pareto Optimal Cluster Algorithm

Input: MRI brain image X, number of cluster k,
t number of iterations, N: size of the image, K: Kernel function
Output: X: membership function, K cluster of Y with different regions.

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Initialize t=0, $X^{(0)}$ & Y
While t=0, $\|U^t - U^{t-1}\| >\in$ do
t=t+1
1: for each pixel j in k clusters do
2: for all Xi in X do
3: if $\|U^{t+1} - U^t\| >\in$ or t<100
4: calculate the initial membership degree $U^t = [u_{ij}]$
5: Determine weight optimized fuzzy rough regions based on neighboring pixels
6: update cluster centroids based on maximum distance in the cluster points
7: compute membership degree $U^{t+1} = [u_{ij}]$
8: Biasing on grouping using β
9: update t=t+1, go to step 4
10: end if, else
12: break
13: end for, end for
15: return X^t and Y

Recall this algorithm implementation for different parameters m, σ and α are given, based on equation (19),(20), we calculate threshold value and clustering values (membership functions and centroid values). Pareto optimal clustering provides optimal values for these parameters are given. Parameter value α and m will be the improvement of intuitionistic fuzzy set clustering, σ will effects the performance with optimal kernel oriented functions. Our proposed approach defines to improve and find resolved and optimal parameters like m, σ and α to retrieve kernel based optimal grouping results for a long way.

In this algorithm potential solution represents three basic variables α , σ and m. Encode, each argument is a string with n number of digits where n is system argument and it describes nucleotide attribute present in data sets. For example, A for 0, G for 1 and C for 3 or 3 for each pixel present in image T. For encoded information to individual digit where number of iterations were increased and represented figure1 (figure 1 to b inserted here) as follows

0	2	3	2	1	3	1	2	0	1	3	2	0	3	1	2	3	0

18 ⟵ v_3 ⟶ 13 | 12 ⟵ v_2 ⟶ 7 | 6 ⟵ v_1 ⟶ 1

Figure1. Encoded individual data example

Each variable y_i mapped with decimal number represents as follows

$$cy_i = \sum_{j=1}^{n} bit(j) \times 4^{j-1} \quad (19)$$

Bit (j) represents j[th] digit from left to current sequence of encoded data for y_i, based on bounded variables and then value of variables can be obtained as follows

$$y_i = \frac{cy_i}{4^n - 1}(h_i - l_i) + l_i \quad (20)$$

Where l_i , h_i are min and maximum of variable y_i and $(h_i - l_i) + 4^n - 1$ is the retrieving of segmentation results decoded with parameter value for y_i. These values are used to generate optimal cluster with encoded and decoded values at 6.45.

VI. EXPERIMENTAL EVALUATION

We present experimental setup of our proposed method with comparison of existing clustering algorithms which includes GKFCM1 [19], GKFCM2 [19], FLICM [25], KWFLICM [22], MICO [23], and RSCFCM [24]. All these clustering approaches mainly tested with three different data sets UCI data sets, synthetic MRI data sets and clinical MRI data sets. These data sets consists Haberman's survival data, breast cancer and SPET image data shown in table 1.

Data sets	No. of instances	No. of attributes	No. of classifications
Survival data	318	4	2
Breast Cancer	1510	11	5
Heart Data set	274	26	3

Table 1. Description of different data sets.

As shown in table 1 synthetic data sets consists weighted scale with pixels and corrupted with 8%,24% noise and grey scale. Clinical brain images consists two collection of data sets, first data set consists 220 sample images has sequences of weighted pixels with 250x250 dimensions. Second data sets consists 587 sample images for each sample consists 150-220 slices, for experiments, we randomly select a sample which is 515x310 pixels. Based on these weight measures we improve the performance of the proposed implementation using following metrics: Jacquard similarity, Mutual information, Segmentation accuracy, time and adjusted rand index for brain tumor detection.

Jacquard co-efficient similarity measure as follows

$$JCS(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} \quad (23)$$

Where S1 is classified volume of image and S2 truly defined image volume of segmented image, based on these parameters mutual information as follows:

$$MI = \frac{MI - E(MI)}{\sqrt{H(S_1).H(S_2)} - E(MI)} \quad (24)$$

$H(S_1)$, $H(S_2)$ are the entropies of segmented volumes respectively, assumed ran index for different clusters as

(25)

P_{11} describes number of pairs present in same cluster, P_{00} denotes different clusters with number of pairs, P_{01} denotes pair of numbers which are present in similar cluster X but different pixels present in image with different clusters in Y and denotes pairs present in dissimilar attributes present in dissimilar clusters in U but same in clusters in V.Based on above metrics we improve the accuracy and other metrics parameters of proposed approach with comparison to existing clustering approaches, for all these metrics, highest value defines improved performance of proposed approach. Experiments are developed in MATLAB;

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these experiments are evaluated with neighborhood of 3x3 pixel rotation. Our application includes high amount of iterations t=100 and threshold convergence $\varepsilon = 0.001$. Based on above discussion, we performed different experiments using simulated database developed in latest image processing software. Our experimental consist realistic magnetic resonance produced by implemented simulator. These data results are come with original values i.e image label pixels are defined for CSF, GM and WM cluster regions. Experiments developed to segment T1 weighted pixel notations corrupted with different noise rations at 3-20%, grey scale uniform into CSF, GM and WM, figure 2 represents weighted segmented results obtained at different brain images.

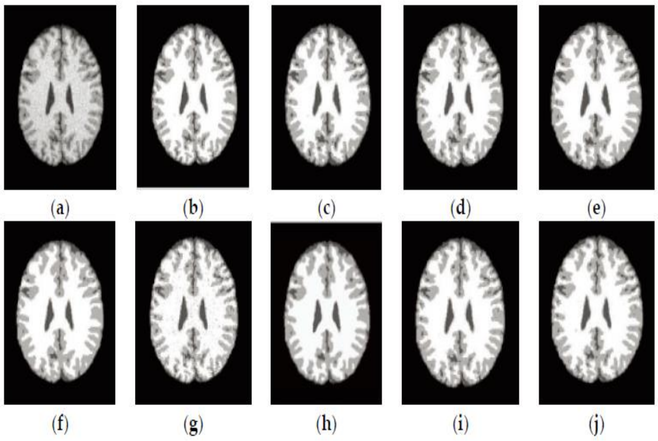

Figure 2. T1 weighted segmented results from simulated results from 0-9 and 9-20% at non-uniform gray scale formations. (a) Original image; (b) Ground truth; (c) GKFCM1; (d) GKFCM2; (e) FLICM; (f) KWFLICM; (g)MICO; (h) RSCFCM; (i) KIFCM1-DNAGA; (j) KIFCM2-DNAGA.

Algorithm	GKFCM1	GKFCM2	FLICM	KWFLICM	MICO	RSCFCM	KIFCM1-DNAGA	**Proposed Approach**
WM	0.932	0.935	0.948	0.938	0.884	0.891	0.939	**0.974**
GM	0.833	0.866	0.856	0.862	0.792	0.851	0.879	**0.899**
CSF	0.791	0.851	0.808	0.815	0.870	0.892	0.875	**0.891**
Average	0.855	0.887	0.885	0.865	0.875	0.885	0.889	**0.912**
Time	0.912	0.584	3.4	85.64	0.64	0.254	0.354	**0.215**

Table 2. Jacquard co-efficient similarity weighted index from 0-7, 9-20 % gray scale un-uniform data results.

As shown table 2, proposed approach gives better results compare to remaining existing algorithms based on results, better results are indicated in bold color. Second experiment with different weighted pixel for 4-20% gray scale with multi dimensional pixel notations. The segmented results are shown in figure 3 and table 3.

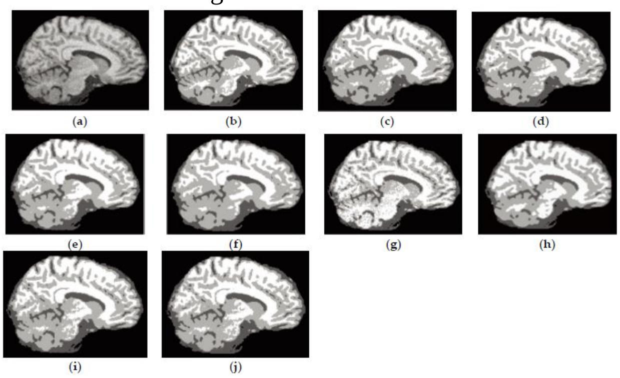

Figure 3.Segmented results presented with different weighted pixels for different approaches.

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Algorithm	GKFCM1	GKFCM2	FLICM	KWFLICM	MICO	RSCFCM	KIFCM1-DNAGA	**Proposed Approach**
WM	0.782	0.795	0.788	0.678	0.802	0.815	0.775	**0.824**
GM	0.816	0.816	0.804	0.794	0.689	0.753	0.825	**0.824**
CSF	0.844	0.862	0.845	0.834	0.870	0.823	0.881	**0.882**
Average	0.825	0.822	0.811	0.833	0.745	0.769	0.824	**0.845**
Time	1.354	1.795	6.214	125.54	0.752	0.785	0.314	**0.324**

Table 3. Segmented results for 7% noise and 20% gray scale data dimensions for different algorithms.

Third experiment is segment to T1 weighted pixel formation with 220 x 191 pixels corrupted at 10% noise, it is commonly effects magnetic resonance images. Segmented results are shown in figure 4 and table 4 describes evaluated values for different brain images.

Algorithm	GKFCM1	GKFCM2	FLICM	KWFLICM	MICO	RSCFCM	KIFCM1-DNAGA	**Proposed Approach**
WM	0.931	0.921	0.929	0.885	0.891	0.926	0.927	**0.934**
GM	0.814	0.837	0.841	0.831	0.841	0.813	0.840	**0.850**
CSF	0.836	0.882	0.871	0.854	0.888	0.885	0.891	**0.901**
Average	0.864	0.882	0.887	0.875	0.875	0.865	0.901	**0.897**
Time	1.954	1.924	3.654	97.54	0.745	0.792	0.210	**0.220**

Table 4. Segmented results for different pixel formation at different noise levels for different algorithms.

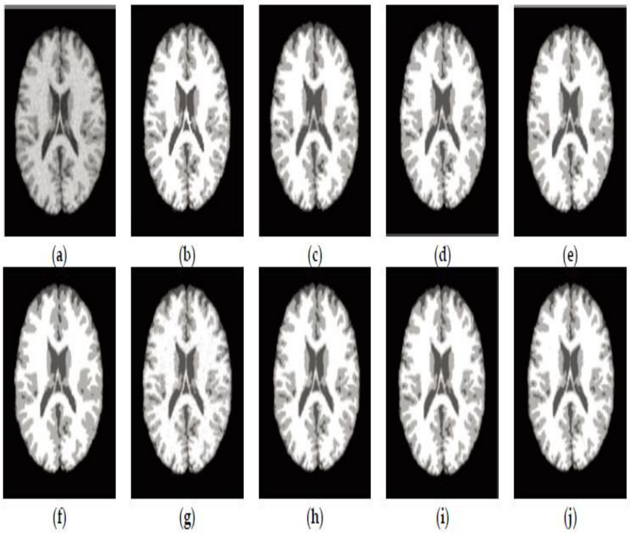

Figure 4.Segmented results from noise 10% with different weight levels for different traditional approaches.

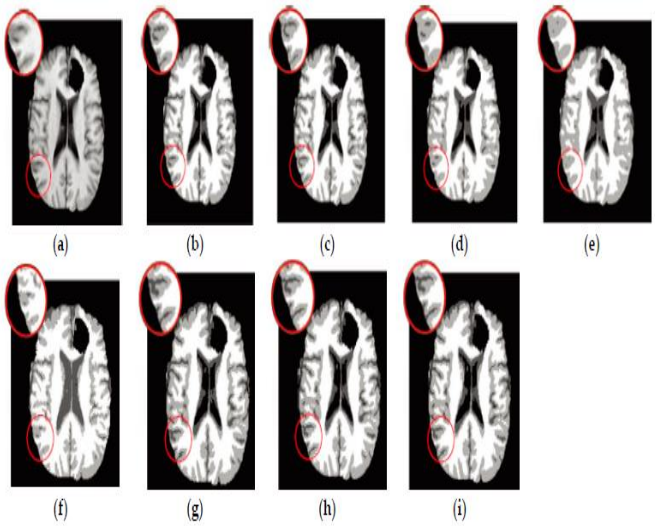

Figure 5. Tumor detection results for different weight measure at different noise (7% -20%) levels at different pixels for brain images.

Figure 5 represents tumor detection results for different weight measures for different image data pixels with maximum data dimensions at different regions.

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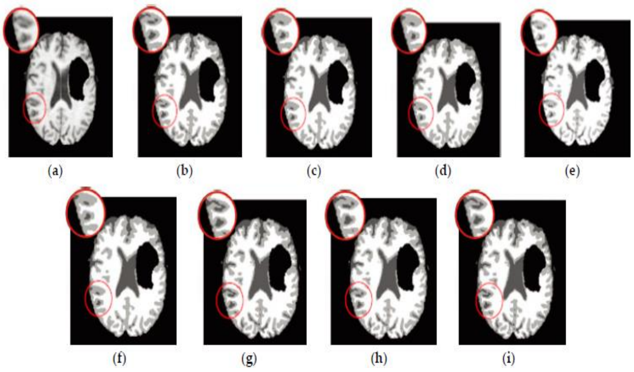

Figure 6. Tumor detection results for different noise ratios like i.e 3%, 9% and 220 x 181 pixel dimensions for different existing algorithms.

Based on above experiments figure 5 and figure 6, the proposed algorithm gives better results when compare to existing algorithms. It defines high Jaccrad similarity results for proposed approach to preserve image noise and dimensionality relates to gray scale homogeneity. Better results are marked with different color and bold them.

7. EXPERIMENTAL RESULTS

We discuss and compare computational complexity of existing algorithms with proposed approach in terms of accuracy of segmentation, jacquard similarity co-efficient and time efficiency for different experimental results. Table 5 and figure 7 shows the segmentation accuracy for proposed approach with existing algorithms.

Noise Ratio	**Type of Tissue**	FCM	FLICM	KWFLICM	MICO	RSCFCM	**Proposed Approach**
0%	GM	0.9565	0.9684	0.9552	0.9539	0.9752	**0.9962**
	CSF	0.9840	0.9843	0.9708	0.9771	0.9864	**0.9941**
	WM	0.9620	0.9705	0.9646	0.9725	0.9872	**0.9949**
3%	GM	0.8543	0.8592	0.8520	0.8510	0.8920	**0.9212**
	CSF	0.8240	0.8692	0.8460	0.8610	0.8964	**0.9149**
	WM	0.8447	0.9151	0.8624	0.9180	0.9190	**0.935**
9%	GM	0.7041	0.7941	0.6748	0.6775	0.7978	**0.8927**
	CSF	0.6629	0.7832	0.7598	0.7606	0.7886	**0.8848**
	WM	0.6266	0.6311	0.7801	0.7898	0.7945	**0.8751**

Table 5. Accuracy results for segmentation of brain image at different noise ratios.

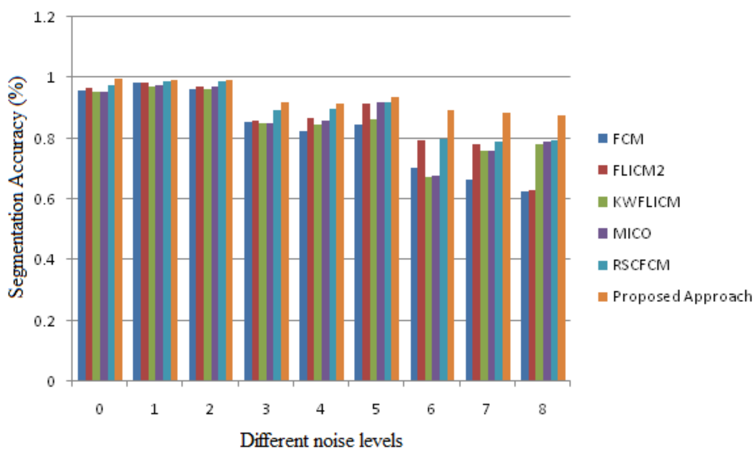

Figure 7.Segmentation accuracy for different noise levels.

Table 6 and figure 8 describes jaccard similarity co-efficient results for different noise states with different approaches based on different weight measures for MRI images.

Noise Ratio Type of TissueFCM FLICM KWFLICM

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Noise Ratio	Type of Tissue	FCM	FLICM	KWFLICM	MICO	RSCFCM	**Proposed Approach**
0%	GM	0.09565	0.09684	0.09552	0.09539	0.09752	**0.0921**
	CSF	0.09840	0.09843	0.09708	00.9771	0.09864	**0.1532**
	WM	0.09620	0.9705	0.09646	0.09725	0.09872	**0.1287**
3%	GM	0.08543	0.08592	0.08520	0.08510	0.08920	**0.3283**
	CSF	0.08240	0.08692	0.08460	0.08610	0.08964	**0.2396**
	WM	0.08447	0.09151	0.08624	0.09180	0.09190	**0.235**
9%	GM	0.07041	0.07941	0.06748	0.06775	0.07978	**0.2463**
	CSF	0.06629	0.07832	0.07598	0.07606	0.07886	**0.3023**
	WM	0.06266	0.06311	0.07801	0.07898	0.07945	**0.2997**

Table 6. Jacquard similarity co-efficient values for different noise levels.

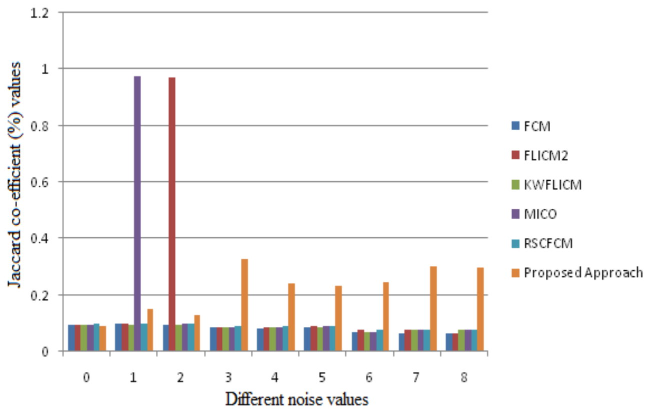

Figure 8. Jacquard co-efficient values at different noise levels for MRI brain images.

Average running time for different approaches with comparison of existing approaches shown in figure 9 with computational cost.

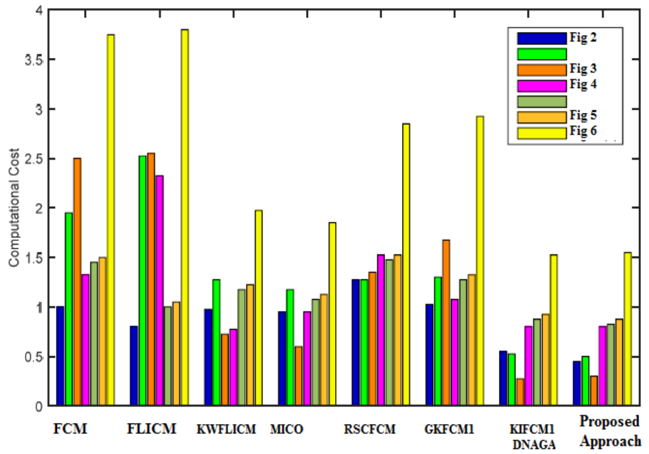

Figure 9. Average running time with different experiments which is defined from sub figures from figure 2-6 at different noise levels for different weight measures.

As shown in above figures and tables, proposed approach gives better results to form optimal cluster for different noise levels based on neutrosophic soft sets for synthetic data sets.

VII. CONCLUSION

We implement and introduce a new and novel Optimization approach to handle MRI segmentation, tumor detection problem as an intuitionistic fuzzy set clustering approach problem and proposed a new neutrosophic soft set based optimized segmentation method to define grouped kernel results. Our proposed defines optimal arguments to obtained optimized group results for classification of image with brain tumor detection. Proposed work performs experimental study by compared with existing clustering approaches using different UCI repository data sets. Our experimental results, proposed method show robustness performance in clustering, segmentation and detection metrics and computational efficiency. Our approach support for minimal MRI data sets, further improvement of our approach is to improve optimal method test in large data sets for UCI data sets.

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