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Classification of MR medical images Based Rough-Fuzzy K-Means

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Abstract : *Image classification is very significant for many vision of computer and it has acquired significant solicitude from industry and research over last years. We, explore an algorithm via the approximation of Fuzzy -Rough- K-means (FRKM), to bring to light data reliance, data decreasing, estimated of the classification (partition) of the set, and induction of rule from databases of the image. Rough theory provide a successful approach of carrying on precariousness and furthermore applied for image classification feature similarity dimensionality reduction and style categorization. The suggested algorithm is derived from a k means classifier using rough theory for segmentation (or processing) of the image which is moreover split into two portions. Exploratory conclusion output that, suggested method execute well and get better the classification outputs in the fuzzy areas of the image. The results explain that the FRKM execute well than purely using rough set, it can get 94.4% accuracy figure of image classification that, is over 88.25% by using only rough set.*
Keywords: *Rough theory; fuzzy theory; K-means; Image classifications; Uncertain Images; RGB images.*

I. Introduction

Image segmentation still challenging tasks in image analysis (processing). And it has more benefits in pattern recognition field. Image processing search with the extrication of defect information [13, 27, 28]. Image division is begin to be more important for medicinal diagnosis process. Currently, expansion of an active computer assisted diagnosis suit which, assist the radiologist thus became very interested. The aim changed from replacing the radiologist into over a second opinion. [25, 26]. Consequently, efficient research on lineaments extracted and their function to classification processes make researchers select features arbitrarily as involvement to their regulations. In that process the image is divided into diverse regions, even though, they have the same features. Numerous approaches of image segmentation are occurred. Edge-based method, zone-by mechanisms and threshold-build on mechanisms and so on. Images are separated regarding to their overall feature division by grouping and image segmentation manners. We could present a segmentation method based on K-means using rough theory jointly with fuzzy set.

Since the nineties of the previous century, there exist a rapid evolution in size, uncertainty and intricacy of electronic data being collected and stocked, For model great number of different of medicinal mechanism are occur, which produce thousands of medical images per a day.The high volume of MR medical images is so difficult to be read by physicians, the precision rate resort to decrease, and automatic reading of digital MR medical are turn to very attractive Images. That is why the computer evaluated diagnosis methods are vital to advocate the medical tools to get best performance and advantages [1]. Based on this increase of huge data, the task of extracting significate information in the sort of patterns, relationships and applied in implementation as decision support, appreciation and classification has become hard and essential. Furthermore the necessity to explore implicit data structures in disordered attribute data calls for effective data analysis with minimal human interference. We call that, the arithmetic theories are master tools for perform these goals. We consider that, the master problem in image classification and collaboration with the huge magnitude of information is the high overlapping between Image classes and uncertainty.Many attempts achieved to investigate into and study this problem. In [1] a techniques of information is utilized in detection to discover and assort oddity in breast cancer. They use neural system of networks and series rules as the data mining algorithms. Classification (partition) results were of 81.25% with neural system and 69.11% with grouping principles.The noticeable advantage on the neural framework is the high quality of classification, but it require more time for training contrasted to different methods. Accordingly, it is significant to diminish the neural framework practice period and modulate the classifying accuracy simultaneously. In [2]) A Bayes theory is utilized to search and distinguish interesting regions. In [3] a manner for merit definition of disadvantage in breast using a border based classification algorithm has presented. In [4], authors find an evaluation of different manners that enable to get textile attributes from zones of attention extracted from mammogram images. In [5], catch sight of ripple transformation, utilized discover micro-groups of calcifications in medicinal images. In [6] a cooperative method of neural system, deploy to distinguish medicinal image. This classifier technique is constructed on the backpropagation neural algorithm jointly rough theory. In addendum, some other techniques were offered using fuzzy theory [7] and Markov models [8].Even though this effort, still not exceedingly used mechanism to distinguish medicinal images.For the reason that, this medical section requires high classifying accuracy and low training time. In this project, a new mechanism have made within medicinal images classification using the backpropagation K-Means jointly the rough reduction theory which we indicate fuzzy Rough K-Means ( ). It is tested on real datasets MIAS [9], interpret the images of mammographic and integrate 92.4% accuracy of classifying which is better than 85.25% using back-propagation neural network algorithm purely in [9]. Simultaneously, the time of practice is decreased distinctively.

Image classification [10] and [11] is very importing function within image operating together with a quite necessary preprocessing stage in problems on the zone of image operating, computer visualization, and model assessment. Medical image classification [10, 11 and [12] is an intricate and defiance job, in order that, the essential ease of the imagesThe brain has especially more rough explication and partition is very significant for detecting fibroid necrosis and edema tissues so as to prescribe appropriate therapy [10] and [13]. Most papers medicinal image classification relates to its application for MR images, particularly in brain imaging. Because of its merit to integrate variance from a size of tissue parameters, more different pulse sequences occur for gaining MR images [14], [15] and [16]. Detecting the optimal pulse sequence for integrating precise classification (12) is therefore an engrossing problem that needs information of the fundamental problem features (properties or attributes) of anatomy to be classified [10], and [11]. MR images is a significant characteristic of a particular species imaging technicality for the sake of early discovering of abnormal variance in tissues and organs. Many techniques almost done for medicinal image classification [10], [15], [11], [14], [13], and [17]. Rough Theory offered by [18] is a tool to analyze fuzzy and incertitude steady in integrating decision [19], and [20]. It does not rely on as sessional knowing out of data set, and it test and detect certain relation among data just from the point of view of data's disgraceful attribute [14], just using the denotation of maximal and minimal approaches of a class, as quite as approximation space and forms of sets [18]. [21] Presented a manner which constructs on this view, but uses a rough classifier only. The rough classifier feels back probabilities that an assured pixel (element) belongs to a assured class. The likelihood knowledge could be benefit by uncertainty categorization. By employing the analyses aforementioned, we could concerned with rough theory in to brain image classification. Experiential results explain the Highness of rough method of brain classification.

We established a classification manner that let us to assessment unbelief in the data. The classification method is locate on rough theory. That segmentation bring into play to approach the minimum and maximize classes as probabilities. With the data, by which, we could envisage the classified images as the uncertainty for any class. The main conception underlying the rough approximation to data classification is to discover, what range sub-group of given objects (in our context: subdivision of the pixels) appreciates another class of items of concern. Objects are equated by considering their characterizations. An object features redacted as a multidimensional of function values representing the object's features or attributes [22]. This property used while we apply rough approximation to multichannel imaging data.

II. Preliminaries

2.1 Rough Set

Rough theory is stratified for former time to diminish the original feature sets and get classifications rules. In the 2nd stage the back-propagation k-mean used beside rough set to obtain classifications of medicinal image.

2.1.1 Rough Theory

Rough theory is belt on the idea of approximation domain and approximation models for sets and concepts [18], [19], and [20]. Let that the data is tabulated form, called the decision data table. The (row lines) of a data table represented to the objects (in our situation: pixels) and the vertical line (columns) represented to the features (in our situation: pixel attributes). For information of data training, we take sub-set as a sample of objects. We consider that each samples object has a section tag assigned to it to indicate to which class it belongs. We name the attribute label a decision attribute, the residue of features (attribute) are called conditional attributes. Suppose U indicate the group of all sample space (objects) and A the group of all properties of that objects (conditional features).

2.1.2 Information system

An information or data system of a phenomena, is an order pair (U, A), where U is the group of objects and *A* is the group of properties of that objects [23]. Each $a \in A$ implies a function $a: U \rightarrow V_a$ where V_a is the group of values that property *a* may have.

In applications, we permanently discern between conditional C, and decision features D, where $C \cap D = 0$. Often, we define decision systems (U, C, D). let $x \in U$ and $B \subset F$.Furthermore, let $[x]_B$ denote the equivalent class defined as

$$[x]_B = \{y : x \sim_B y\} \tag{1}$$

The relationship ~B is nominated similarity relation. It constructs the base of rough theory. So, *~B* is a subdivision of all classes that have matching detailing.

2.1.3 Similarity relation

Each subcategory of features $B \subseteq A$ put together a similarity relation (or same) $\sim B = \{(x, y) \in U \times U : \forall a \in B a(x) = a(y)\}$ for every $x \in U$, there exist equivalence class $[x]_B$ in division of *U* is generated by *~B*.

2.1.4 Rough Approximation

Suggest an informative data system $S = (U, A)$, $X \subseteq U$, and $B \subseteq A$. Suppose we interpret two processes setting to each $X \subseteq U$, two sets $B_*(X)$ and $B^*(X)$, denoted the *B*- minimize and the *B*- maximize approximation of *X*, respectively, and interpreted within next relations:

$$B^*(x) = \bigcup_{X \in U} \{B(x) \mid B(x) \cap X \neq \phi\} \tag{2}$$

$$B_*(x) = \bigcup_{X \in U} \{B(x) \mid B(x) \subseteq X\} \tag{3}$$

Hence, the B-upper set approximation is the coalition of all B- equivalent classes that joint the set, whereas the B-lower set approximation is the combination of every B-equivalent classes that are involved in the set [24]. The set

$$BN_B(X) = B^*(X) - B_*(X) \tag{4}$$

Will be indicated to as the B-border region of *X*. If the border region of *X* has no element, i.e., $BN_B(X) = \varnothing$, then X is friable (precise) with regarding to B; in the inverse state, i.e., if $BN_B(X) \neq \varnothing$, then X is indicated to as rough (imprecise) with regarding to *B*. Thus, the group of objects is rough (imprecise) if we can't decide it by the denotation of data or information, i.e. it has some objects that could be set to either as member of the sub-set or its completeness in vision of given information.

2.2 K-means

When applying the rough classification to medical image, we get involves domains of ambiguity. If we desire to get a decision for elements in the ambiguous area or if we desire to figure a probability for those elements closeness to an assured class (or segment), we desire to couple our rough classification with k-means segmentations. Consequently, to do this, we compute the means into every feature in each rule. For those elements x that are in the ambiguous regions, we measure the dimensions

$$d(x,\ k_l) = \sqrt{\sum_{j=1}^{m} (x_j - k_{lj})} \tag{5}$$

While x_j indicates the j^{th} property value of object *x* and k_{ij} denotes the intermediate amount of the j^{th} property for the l^{th} class. Then, object *x* could be set to the nearest suitable rule or code with regarding to the defined distance. That procedure itself would be bring to bear in case of inconsistencies, i.e., when there exist moreover matching rule for an object. The defined distances represent probabilities. Every matching rule contributes probabilities to its conclusion weight. The probabilities would combined class with powerful magnitude of probabilities is chosen. Quality assessment similar to support, strength, accuracy, and coverage (20), attached with the decision rules can be bring to bear for reducing subgroup of decision rules.

2.2.1 The Algorithm of Rough theory and K-means (RKM)

The algorithm of rough theory and *K*-means (*RKM*) is composed with two steps. The first is the attributes decrease using rough information gain theory. The second is back- promulgation algorithm. Imagine which all numeric attributes have gotten discrete.

Algorithm 1: Rule generation

Input: the Information data system $(U, C \cup D)$ and reduct $R = \{a_1, a_2, \ldots, a_m\} \subseteq C$

Output: decision ruling (*R*)

for $u \in U$ do
for $a_i \in R$ do
$v_i = a_i(u)$;
end for
$v_d = d(u)$;
$RULES(R) = RULES(R) \cup a_1 = v_1, \ldots, a_1 = v_1 \Rightarrow d = v_d$.
end for
Regain RULES (*R*)

2.2.2 K-means algorithm

K-Means basic algorithm be created of next proceedings:

- Initialize
- loop till ending stipulation is met:

1. For every element in that image, stat that cell to a class which, the dimension from this cell to center or class mean, that, is minimized.
2. The center or class mean of every class Recomputed, derive from pixels which, be owned by it.

- End loop;

2.3 Rough classification

Given an informative system, we can apply rough theory to compute minimize and maximize approximations as fully as possible, negative and positive regions and boundaries. The calculation stage which be in need have achieved for a rough segmentation is to formulate the rules which do just as an exact classifier. That rules are utilized as a base of notation of best cuts.

2.3.1. The Best cuts

- Features selection

Let $IS = (U, A \cup \{d\})$ be an informative system with conditional features A and attributes of decision d. To inform an informative system from an image, first we get samples out of image which we aspire to classify (to the smallest extent or degree sample for each class, then we add more channels to RGB (red green blue) color like $Cie*$ Lab colors, mean for rgb within the 8-neighborhood, variance, standard deviation, etc. then we could compute all probable cuts as following:

Where $\{v_1^a < v_2^a < .... < v_n^a\} = \{a(x) : x \in U\}$ and $n_a \leq n$

Subsequently the group of whole possible cuts on A is denoted by:

$$C_a = \{(a, \frac{v_1^a + v_2^a}{2}), (a, \frac{v_2^a + v_3^a}{2}), \ldots, (a, \frac{v_{n-1}^a + v_n^a}{2})\} \tag{6}$$

Class respecting to all probable cuts on all features is denoted by: $C_A = \bigcup_{a \in A} c_a$

1) 2.3.2. Find Best cuts

Concept for searching best cut is to seek for a cut $c \in A$ which recognizes largest amount of pairs of elements. Let $L = \{Xi \in U\}$ where Xi is partitioning U, thereafter we compute for all $(a, c) \in CA$ the size of pairs of elements $W^X(a, c)$ which discerns by each cut of C_A as following,

$$WX(a,c) = LX(a,c) \cdot RX(a,c) - \sum lX(a,c) \cdot rXi\ (a,c) \tag{7}$$

are numbers of elements out of X be suited to the j^{th} decision class and being on the left and right-handed- side of the cut (a, c) (correspondingly). Choose cut $cmax \in CA$ that, differentiate the major size of pairs of elements in L. let in C_{max} inside BCA, then eject it out of CA. Eject all pairs of elements out of L recognized by C_{max}.

2.4 Algorithm for classify MRI medical image

Input: The consistent decision table A.

Output: The semi minimum subset of cuts P consistent with A

Data Construction: ***D:*** the semi minimum subset of cuts;

***L* = *PART* (*D*):** the partitioning of U nominated by D;

CA: group of all probable cuts on A.

Method: D = f; $L = U$; CA = *group of all probable cuts on A Compute the value WD*(a, c) *for all cuts from CA* and seek for a cut $(a*, c*)$ which *maximize the function WD*$(\bullet)$, i.e.

$(a*, c*) = \arg (a, c)\ max\ WD(a, c)$ set $D = D \cup (a*, c*)$; $CA = CA-(a*, c*)$ (8)

To whole $X \in L$ do;

If X be formed of elements from one decision class therefore eject X out of L;

If $(a*, c*)$ divides the set X to X_1, & $X2$

Thereafter eliminate X away from L

Join the two sets X_1, & X_2 to L

If L is become empty thereafter

Stop.

Else Go to 2.

End.

2.5 Fuzzy-Rough Sets

In real enforcement, knowledge is either rough (fuzzy) or exact-valued, for that reason, traditional rough theory enter a problem. It wasn't available in the traditional theory to say which two attribute values are comparable and the how much comparable percent; i.e.; two relative values may only disparity as an outcome of ambiguity, but RST deems them as distinct as two values of a various volume. So that, there exist a demand to develop mechanisms that, produce a process for knowledge formation of fuzzy and exact-value attribute data which use the size to which values are indistinguishable. That could be done over use fuzzy jointly rough theory. Fuzzy jointly rough sets contain the concerning but distinguished concept of vagueness (for fuzzy theory) and the similarity (for rough theory), together take place with reason of distrust data. A *T*-function fuzzy likeness relationship is utilized for approach fuzzy *X* low and up approach are:

$$\mu_{\underline{R_P X}}(x) = \inf\ I_{y\in U}\left(\mu_{R_P}(x,y), \mu_x(y)\right) \tag{9}$$

$$\mu_{\overline{R_P X}}(x) = \sup\ I_{y\in U}\left(\mu_{R_P}(x,y), \mu_x(y)\right) \tag{10}$$

Where, *I* is an ambiguous (fuzzy) and *T* is a norm. R_P is the fuzzy likeness relationship produced by the group of attributes *P*:

$$\mu_{R_P}(x,y) = T_{a\in P}\left\{\mu_{R_a}(x,y)\right\} \tag{11}$$

$\mu_{R_a}(x,y)$ is the account to that, elements *x* & *y* are likeness for attribute a, and might be determined in numerous ways. In an alike way to the main ambiguity rough approach, the fuzzy assured region would be indicated as:

$$\mu POS_{R_P(D)}(x) = \sup_{X\in U/D}\ \mu_{R_P X}(x) \tag{12}$$

A substantial matter in knowledge dissection is the detection of independencies among features. The rough-fuzzy dependency grade *D* to subset of attribute *P* would be appointed as:

$$\dot{\gamma}_P(D) = \frac{\sum_{X\in U}\mu_{R_P(D)}(X)}{|U|} \tag{13}$$

A fuzzy-rough reduct R would be indicated as a least number of attributes that, save the dependency grade with whole knowledge

$$\dot{\gamma}_R(D) = \dot{\gamma}_C(D) \tag{14}$$

2.5.1 Algorithm of fuzzy and K-Means

Classification algorithm of Fuzzy & *K*-means partitions data points into *k* classes $S_l\ (l = 1, 2, \dots k)$ and classes S_l are associated with representatives (class center) C_j. The connection among the information point and class representative is fuzzy. That is, a membership $u_{i,j} \in [0,1]$ is applied to state the membership grade of information point X_i into class center C_j. Indicate the group of information points *as* $S = \{X_i\}$. The algorithm of Fuzzy & K--mean is belt on decreasing the next deformation:

$$J = \sum_{j=1}^{k}\sum_{i=1}^{N} u_{i,j}^{m} d_{ij} \tag{15}$$

With regard to the representative class C_j and memberships $u_{i,j}$, where *N* is the stage of information points; m is the fuzzy variable; *k* is the stage of class; and d_{ij} is dimension between information point X_i and class representative C_j . It is renowned that $u_{i,j}$ $u_{i,j}$ would be content with the next restriction:

$$\sum_{j=1}^{k} u_{i,j} = 1,\ \text{for } i = 1 \text{ to } N$$

The main procedure of FKM is transitive a given group of model vectors into an amended one via partitioning information points.. It starts with a combination of primary class means and repeats this procedure till ending contented standard, i.e.; every two classes haven't the same representative class; if there occur two class means coincide, a class mean should concerned to cancel seashell in the repeated procedure. If $d_{ij} < \eta$, then $u_{i,j} = 1$ and $u_{i,l} = 0$ for $l \neq j$, where η is a teeny positive number. Now, the fuzzy *k*-means classification algorithm is given as follows:-

1. Enter a collection of initial class centers $SC_0 = \{C_j(0)\}$ and the amount of ε. Set *p=1.*
2. Specified collection of class centers SC_p, compute d_{ij} for $i = 1, \dots, N$ and $j = 1, \dots, k$. Update memberships $u_{i,j}$ using the following equation:

$$u_{i,j} = \left(\left(d_{i,j}\right)^{1/(m-1)} \sum_{l=1}^{k}\left(\frac{1}{d_{i,j}}\right)^{1/(m-1)}\right)^{-1} \tag{16}$$

If $d_{ij} < \eta$, set $u_{i,j} = 1$, where η is a teeny positive number.

3. Compute the mean to any class employing the posterior equation below to get a new combination of class representatives SC_{p+1},

$$C_j(p) = \frac{\sum_{i=1}^{N} u_{ij}^m X_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{17}$$

If $\|C_j(p) - C_j(p-1)\| < \epsilon$ for $j = 1$ to k, then stop, where $\varepsilon > 0$ is a teeny number greater than zero. Otherwise set $p+1 \rightarrow p$ and move to stage 2. The main complication of Fuzzy *K*-mean is from stage 2 & stage 3.

Anywise, the complication computational of step 3 is much less than that of step 2. Thence, the complication computational, in terms of the figure of distance computation, of ***FKM*** is $O(Nkt)$, where t, is the figure of iterations is.

III. Proposed Technique

Fuzzy & k-means is one of the classical algorithms available for the classification. Even though this algorithm is brittle as it permits an element to be happen perfectly in one group. To beat the impediments of brittle classification fuzzy based classification was introduced. The distribution of element is fuzzy based manners can be refined by rough classification. Upon on the min and max approximates of rough group, the rough fuzzy k-means classification algorithm upgrade the compilation of membership function become more reasonable

3.1 Rough Set Based Fuzzy and K-Means Algorithm

Certain procedure of $RFKM$ classification algorithm are defined as:

1. Locate the class figure k $(2 <= k <= n)$, parameter m, initial matrix of member function, the upper approximate limit A_i of class, an appropriate number $\varepsilon > 0$ and $s = 0$.
2. We can figure centroids by:

$$C_i = \frac{\sum_{j=1}^{N} U_{ij}^m X_j}{\sum_{j=1}^{N} U_{ij}^m} \tag{18}$$

3. If $X_j \notin$ the max approximate, then $U_{ij} = 0$. Otherwise, update U_{ij} as shown below

$$U_{ij} = \frac{1}{\sum_{l=1, X_j \in Rwi}^{k} \left(\frac{d_{ij}^2}{d_{ij}^2}\right)^{\frac{1}{m-1}}} \tag{19}$$

4. If $\|U^{(s)} - U^{(s+1)}\| < \varepsilon$.

3.1.1 Membership of features value

First, initial class centers $\{P_1, P_2, \dots, P_c\}$ were produced by randomly selecting c points from an image point set. Where $c \in [c_{min}, c_{max}]$, $c_{min} = 2$, $c_{max} = (n$ is the pixels number), for each class centers P_i is defined by n numeric attribute $\{F_i, i = 1, 2, \dots n\}$. Then every attribute F_i is given by its membership figure conformable to three degree fuzzy, defined as, low(L), medium (M), and high (H), which characterized respectively by a π - membership function

$$\mu(F_i) = \begin{cases} 2\left(1 - \frac{|F_i - c|}{\lambda}\right)^2 & \text{for } \frac{\lambda}{2} \le |F_i - c| \le \lambda \\ 1 - 2\left(\frac{|F_i - c|}{\lambda}\right)^2 & \text{for } 0 \le |F_i - c| \le \lambda \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

Where λ is the radius of the π -membership function with c as the central point. To pick out the center c and radius λ.Thus, we obtain an initial classification set center wherever each class center is explained by a combination of fuzzy set.

3.1.2 Decision Table for the Initial class Centers Set

Def. 1: figure of likeness among two distinct categories centers is given as: $\alpha = \frac{\sum_{i=1}^{n} \mu(F_i)}{n}$

Maximize the value of the likeness, the closer the two classification center is.

Def. 2: In a same class centers set, if a class center has a same similarity value to another one, subsequently they are defined as redundant class mean of each other.
Proposition 1: If A and B are redundant class center each other, B and C are redundant class center each other, then A, B and C be owned by to a redundant the selfsame of class center, i.e.
$A \leftrightarrow B, B \leftrightarrow C \Rightarrow A \leftrightarrow B \leftrightarrow C$
Based on what mentioned above, taking initial class centers as objects, taking class centers features F_i, the middle degree *c* and the radius λ as conditional attributes, taking grade of likeness between two different class centers as decision attribute by computing the π -membership value, thus a decision system for the first category of class centers can be assigned as:
$T = < U, P \cup R, C, D >$
Where $U = \{x_i, i = 1, 2 \ldots m\}$, it indicates an elementary class centers set; $P \cup R$ is a finite category of the elementary class center of attributes (where P is a collection of condition attributes, R is a collection of the decision attributes); $C = \{p_i, i = 1, 2 \ldots n\}$ (where p_i is a range of the elementary class center of attribute); $D: U \times P \cup R \rightarrow C$ is the redundant data, which defines a likeness relation on U.

3.1.3 Eliminating redundant class centers from the initial class centers set
Assuming $D(x)$ denotes a decision rule, $D(x)|P$ (condition) and $D(x)|R$(decision) denote the restriction that $D(x)$ to P and R respectively, i and j denotes two distinct class centers respectively, and other assumptions are as what above-mentioned selfsame. Based on what described above, the initial class means could be optimized by reduction theory correspond to the following steps:

1. Deducing the compatibility of each rule of an elementary class center set decision table z if $D(i)|P(\text{condition}) = D(j)|P(\text{condition})$ and $D(i)|R(\text{decision}) = D(j)|R(\text{decision})$, then rules of an elementary class center set decision table are compatible; if $D(i)|P(\text{condition}) = D(j)|P(\text{condition})$, but $D(i)|R(\text{decision}) \neq D(j)|R(\text{decision})$, then rules of an elementary class center set decision table are not compatible.
2. Ascertaining redundant conditional attributes of an elementary class center set decision table; if an initial class center set decision table are compatible, then when $p \in P$ and $Ind(P) = Ind(P - p)$, p*a redundant attribute is* and it can be leaved out, otherwise p can't be leaved out. If an initial class center set decision table are not compatible, then computing its positive region $POS(P, R)$. if $p \in P$, when $POS(P, R) = POS(P - p, D)$, then p can be leaved out, otherwise p can't be leaved out.
3. Eliminating redundant decision items from an initial class center decision table. For each condition attribute p carries out the aforementioned procedure till condition attribute set does not change. As soon as redundant initial class centers in the initial class set is eliminated, a reduced class center set is used as the FCM initial input variance for image segmentation. To figure quality of classes, the $Xie - Beni$ index was used:

$$XB = \frac{\sum_{j=1}^{c} \sum_{i=1}^{n} \mu_{ij}^2 \|x_i - v_i\|^2 / n}{min_{ij} \|v_i - v_j\|} \quad (21)$$

A smaller XB reflects that, the classes have greater separation with each other and are more compact.
Based on what descript above, now the procedure for Rough Sets based FKM segmentation manner can be summered as follows:

1. Initiate the figure of classes to c randomly, where $2 \leq c \leq \sqrt{n}$ and n is amount of picture points.
2. Randomly select c pixels from raw data to be class means.
3. Optimize the elementary class means category by Rough.
4. Put variable $t = 0$, and a tiny figure greater than zero ε.
5. Calculate (at $t = 0$) or update (at $t > 0$) the matrix of membership $U = \{u_{k,x}\}$ using equation (18).
6. Update the class centers by equation (19).
7. Compute the corresponding $Xie - Beni$ index using equation (21).
8. Repeat step 5-8 until $\|XB^{t+1} - XB^{t}\| < \varepsilon$
9. Return the best XB and best center positions**.**

3 2. **Quality Measures**
In request to adjudicate the accuracy and fineness of our segmentations, we should first define the quality measures. When using synthetic data, the land verity is known and we can figure the segmentation accuracy

$$S_A = \frac{M_P}{T_{NP}},$$

Where, M_P is the amount of misclassified pixels and T_{NP} is the overall amount of pixels. For actual data, we can use other measurements for example compactness and isolation.

3.3 Classification Multichannel Medical Image

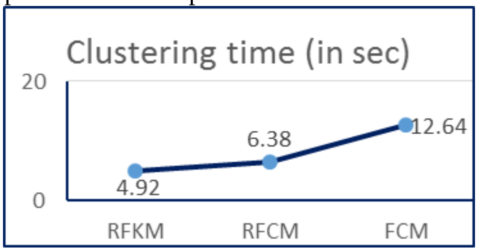
We applied our semi-automatic system to assort or classify Multichannel image from the medical section partition. The data set we used are obtained of a human brain of resolution 336 × 411 × 1004 We have chosen the 2D slice depicted are be obvious in the Figure. No. 1, for assembling the training set. A small sample from that slide was selected to choose six different classes interactively. The chosen regions are be obvious in the Figure. No. 1. We initiated the 21- features and used our classification regarding on rough classification. We deduce also a fineness (quality) term Q (I) for the classification by integrating the precision (accuracy) figures for the 6 classes. We use rough set and k-means to assort or classify brain medical MRI into 6 classes.

IV. Experimental Results

User-led classification using brushing in case space and using machine learning style to classify all data from the brushed selection: (a) Specifying the practice set by interactively Specifying image Areas and respective classes (or clusters). (b) Medical color imaging data segmentation based on *RKM* classification, where blue color is used to view an area of imperfect between the two neighboring classes. (Data set courtesy of Art Toga, university of California, L.A., USA.) Experimental results on real images are described in detail. In these experiences, the figure of numerous kinds of elements in the image from manual analyses was treated as the figure of classes to be indicated. They were also used as the parameter for $\boldsymbol{FKM}$. The $\boldsymbol{Xie - Beni}$ index value has been utilized throughout to evaluate the quality of the classification for all algorithms. All experiments were implemented on PC with 3.2 GHz i5 processor using MATLAB (version9.0). Proposed algorithm applied on all images. This *RFKM* image classification method partitions into different regions exactly. Visually as well as theoretically our method gives better results other than state of the art methods like, *FCM*, *RFCM*. We present a classification time of experiment for 2 experiments and shows that *RFKM* performs better than *FCM* and *RFCM*

Table 1: clustering time of experiment for 2 experiments

	Average of the XB index values	**Clustering time (in sec)**
FCM	0.033024	12.64
RFCM	0.030578	5.48
RFKM	0.028197	4.92



V. Conclusion

A cooperative fuzzy, rough and-*K*-means classifying method applied to medical image classification has presented. This classifier used the algorithm of K-means backpropagation and rough theory. In this work rough set information gain reduction theory is applied to decrease the redundancy attributes firstly to lessen time and computational burden. Moreover, we demonstrated how important the image pre-segmenting phase is in building a classifier. The evaluation of the fuzzy rough –k-means (*FRKM*) was carried out on MIAS dataset and empirical outcomes show that the quality of *FRKM* reaches 94.4% than 88.43% which execute back-propagation algorithm itself. Also, to assess the clarity of classes, the $\boldsymbol{Xie - Beni}$ index was utilized as class validity index. Experimental results indicate the superiority of the proposed method in image segmentation.

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