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# Dear Readers,

It is my utmost pleasure to extend a heartfelt welcome to each of you as we embark on a thrilling journey into the realm of our scientific journal dedicated to the diverse applications of soft computational approaches in bioinformatics.

As the Editor of this IIOAB Journal issue, under the topic of Embracing the Boundless Horizons of Soft Computational Approaches in Bioinformatics, I am thrilled to witness the convergence of innovative methodologies and cutting-edge technologies in the realm of bioinformatics. Our journal serves as a conduit for the dissemination of pioneering research, transformative algorithms, and novel applications that harness the power of soft computational techniques in unraveling the mysteries of biological systems.

Your expertise, dedication, and scholarly contributions play an integral role in shaping the future landscape of bioinformatics. Through your research, you illuminate the path toward understanding complex biological phenomena, deciphering genetic codes, and exploring the intricate networks of biomolecular interactions.

The interdisciplinary nature of this field not only drives innovation but also holds immense promise for revolutionizing healthcare, agriculture, pharmaceuticals, and beyond. Your endeavors in this field are invaluable, propelling us towards groundbreaking discoveries and applications with profound implications for society.

I encourage each of you to share your groundbreaking insights, submit your pioneering research, and engage in vibrant discussions within our journal's pages. Let us collaboratively nurture an environment where ideas flourish, collaborations thrive, and knowledge propels us forward.

Thank you for your unwavering commitment to advancing the frontiers of bioinformatics through the integration of soft computational approaches. I eagerly anticipate the wealth of knowledge and transformative insights that will emanate from your contributions.



Warm regards, Guest Editor: Prof. S. Arun Kumar and Prof. T. Arun Kumar EDITORIAL

# OPEN ACCESS APPLICATIONS OF SOFT COMPUTIONAL APPROACHES IN BIOINFORMATICS

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In today's world, the use of soft computational approaches has been increased to a variety of bioinformatics application. Bioinformatics approaches - from soft computational methods such as fuzzy system, neural networks, evolutionary algorithms, statistical model algorithms are currently attractive topic in wide variety of bioinformatics research areas. Usually, biological systems and its objects have intrinsically fuzzy as their features and behaviors consist of randomness or uncertainty in nature. Subsequently, only limited computational intelligence approaches are available to handle bio-informatics problems. In order to address the research gap, this special issue identifies the novel work that focuses on the recent advances in bioinformatics, bio-inspired methods, and contribution of computational intelligence approaches to solve biological problems. In the following section, we start by providing the readers of this special issue a brief overview of these research papers.

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KEY WORDS

Bio informatics: Soft Computing, Optimization Methodology

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#### EDITORIAL: APPLICATIONS OF SOFT COMPUTATIONAL APPROACHES IN BIOINFORMATICS (ASCB)

The first paper in this special issue, "Diagnosis of diabetic retinopathy from fundus image using fuzzy c-means clustering algorithm", Mohan Jagannath and Kanagasabai Adalarasu presents novel spatially weighted Fuzzy C-Means clustering algorithm for vessel detection in ocular fundus images.

The second paper by Pradeep Reedy et al. intend presenting a novel on-demand multicast routing protocol generally known as Cross-Layered Ant Colony Optimization Multicast Routing Protocol (CLAMR). The result of this selected protocol has been improved and enhanced version of the already existing on-demand multicast routing protocol (ODMRP).

The next paper by Sasi Kumar and Tripathy describes the improvement in automated analysis for human brain signal processing to finding alzheimer's disease using intelligent techniques. Also they presented an improved fuzzy firefly algorithm, which would enhance the classification of the brain signal efficiently with minimum iteration.

The predictive analytical approach towards improving the crop growth yield using fuzzy cognitive maps is the focus of the next paper. Gunasundari Anantharaj et al. describe an important case study to multiple rethegorical factors from the basis of improved crop yield. Moreover, this paper proposes Fuzzy Cognitive Map approach to help in decisive making and suggesting an optimized solution of improving crop yield as well compared with existing approaches such as Genetic Algorithm and Artificial Neural Networks (ANN).

The subsequent two papers deal with a recent wireless sensor network research issues. The paper by Roselin Jones et al. focuses an novel redeployment strategies for balanced coverage in Wireless Sensor Network (WSN). Moreover, the proposed redeployment strategies significantly result in balanced point coverage, which in turn, improves the overall lifetime of the network. Likewise, next paper by Rajesh et al. proposing Chaos Theory based Data Aggregation (CTAg) based approach to reduce redundant information and number of packet transmission between aggregator and sink node in WSN.

The next paper by Maheswari Arumugam and Arun Kumar Sangaiah gives a brief review on various methods applicable for feature extraction and classification of bio signals for cardiac arrhythmia. Similarly, the paper





complemented by Challa Anusha et al. determines the evaluation criteria of social network usage from the perspective of student academic performance, authors have integrated multi-criteria decision making (MCDM) approaches: (a) Quality Function Deployment (QFD), (b) Decision Making Trial and Evaluation Laboratory (DEMATEL) and (c) Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) under fuzzy environment is proposed.

The next paper by Suresh Thangakrishnan and Kadarkaraiyandi Ramar presents biometrics for identifying a person in the world by the physiological features in the human body. Various biometric techniques include features in the human body like the facial, iris, gestures, fingerprint, gene, key stroke biometrics, etc. Subsequently, next paper by Prabhavathy Paneer, BalakrishnaTripathy tunes the existing rough c-means and fuzzy c-means and integrates them into a tuned hybrid soft clustering algorithm termed as the tuned rough-fuzzy c-means algorithm. In addition, the proposed algorithm performance is compared with the existing rough c means, fuzzy c-means, and rough fuzzy c –means approaches.

Dynamic fuzzy clustering algorithm on cancer data and identify the changes in cluster structures for every incoming new data set with respect to previous data is the focus of a next paper. Chatti Subbalakshmi et al. elaborates fuzzy c-means clustering or soft clustering algorithm on cancer data to get initial clustering solution, after that for each cycle added into the new cases for apply conditions to identify the changes.

The next paper by Ramsingh, and Bhuvaneswari presents hybridized approach for biomarker discovery using Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The proposed approach is found to be better for identifying optimal gene is verified based on biological validation. Further, next paper by Nagaraju and Tripathy presents the rough equality and rough equivalence in the context of covering based optimistic multi-granular rough sets and establish their properties in the general form as well as in the replacement form.

Final paper by Suja et al. sums up the Extreme Learning Machine (ELM) has been simple and effective algorithm for single-hidden layer feed forward neural networks (SLFN) which automatically classifies the EMG signal into healthy, myopathic or neuropathic.

# EDITORS' BACKGROUND



Arun Kumar Sangaiah obtained his Doctor of Philosophy (Ph.D.) in Computer Science and Engineering from VIT University, Vellore, Tamil Nadu, India. He is presently working as a Associate Professor in School of Computing Science and Engineering, VIT University, India. His experience and areas of interest focus on Software Engineering, Soft Computing, Wireless Networks, Bio-Informatics, and Embedded Systems. He has author of more than 100 publications in different journals and conference of National and International repute. Dr.Arun Kumar is member of international advisory board of IJIIT (IGI publisher) and editorial board member of IJIES, Japan. Also, he has served a special guest editor of various international journals (Inderscience, Hindawi, IGI publishers). He is active member for Compute Society of India. He has guided many research students and post-graduate students in the field of software engineering, communication networks, ad hoc networks, database, and soft computing techniques.



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# DIAGNOSIS OF DIABETIC RETINOPATHY FROM FUNDUS IMAGE USING FUZZY C-MEANS CLUSTERING ALGORITHM

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# ABSTRACT

Diabetic retinopathy is a chronic disorder which is considered as a major source of vision loss in patients suffering from diabetes. It is characterized by the destructive of blood vessels that nourish the retina. However, early detection of such disorder through regular diagnosis, vision loss can be avoided. In order to reduce the diagnosis cost and enhance the automated analysis, modern image processing tools are used to detect the existence of disorders in the retinal images acquired during the initial process of screenings. This paper presents a methodology for the extraction of exudates within blood vessels from fundus images using Fuzzy c-Means (FCM) clustering algorithm. Matched filter was applied for vessel extraction with the help of adaptive histogram equalization, thresholding method and segmenting method, which incorporates spatial neighborhood information into the FCM clustering algorithm. A standard diabetic retinopathy database was used in this study to test the proposed algorithm. This methodology showed improved sensitivity and accuracy of the segmented result. The proposed method seems to be promising as it can also detect the very small areas of exudates. Such an image processing technique can reduce the work of ophthalmologists and help in patient screening, treatment and clinical studies.

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**KEY WORDS** 

Diabetic retinopathy; Fuzzy c-Means; digital fundus image; exudates

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# INTRODUCTION

Diabetic retinopathy is an emerging cause of vision loss in both developed and developing countries. The World Health Organization (WHO) has projected the number of adults with diabetes in the world would increase exceptionally: from 135million in 1995 to 300 million in 2025. In India, this condition is expected to be the greater; (i.e.) nearly 195% from 18 million in 1995 to 54 million in 2025 [1-3].

Diabetic retinopathy is a chronic disorder which is considered as a major source in patients suffering from diabetes [4]. It is characterized by the destructive of blood vessels that nourish the retina. It is of two categories: category 1 primarily initiated by autoimmune pancreatic b-cell damage and described by absolute insulin deficiency, and category 2 described by insulin conflict and relative insulin deficiency [5]. For example, in the USA; it was estimated that nearly 7% of the US population achieved the diagnostic criteria for diabetes [6]. In Saudi Arabia the occurrence of diabetes mellitus was estimated at around 31% and it grows with age [7]. It is the general cause of vision loss between the age-group of 20 and 65 years. Recently an extensive study had been performed in various aspects of diabetic retinopathy.

The most effective treatment is detecting the condition in premature stage through regular screenings [8, 9]. During the screenings, color fundus images are obtained using fundus camera. However, as a result large number of fundus images are produced which requires physical investigation and diagnosis. Moreover, medical experts like ophthalmologists need to spend their time and energy to analysis these images. It would be more affordable if the initial process of analyzing the images can be done automatic so that merely the abnormal fundus images need to be diagnosed by the ophthalmologists [8, 10].

On the other hand, diabetic retinopathy which consequences from long-term diabetes mellitus, it is a common disease that clues to choroidal neo-vascularization [2]. The choroidal neo-vascularization is a significant stage that leads to vision loss. It decreases the amount of blood supplied to the retina. One of the treatment strategies is that

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the affected areas of the retina are photocoagulated with the help of lasers. To achieve satisfactory results, the expert has to identify the choroidal neo-vascularization and cauterize it completely. Optic disc and blood vessels should be carefully avoided while radiating the area of acute vision.

Retina is a thin clear structure including of several layers. The cells within the retina includes three major components: (1) neuronal component which contribute the retina its visual function by converting light to electrical signals; (2) Glial components are the supporting column of the retina; and (3) Vascular components which delivers the inner retina while the outer retinal is being delivered by diffusion from choroidal circulation [5]. Diabetes will produce its result on both neuronal and vascular components of the retina.

Several issues were found to influence diabetic retinopathy including chronic characteristics of the disease, age, pregnancy, blood pressure, hyper-viscosity, kidney failure and anemia. Hyper-viscosity of the blood [11] influences the diabetic retinopathy.

More accurate and reliable solution through image processing and artificial intelligence tools included Genetic Algorithm (GA) and Artificial Neural Network (ANN) [12, 13]. Currently numerous clustering algorithms have been developed for image segmentation. Artificial intelligence and fuzzy based method such as Adaptive Neuro-Fuzzy Inference System (ANFIS), K-Means, Fuzzy c-Means (FCM) [14-17] are considered to be effective in image segmentation. Khalida et al. [18] suggested FCM as a clustering technique for segmentation of color image based on the elementary region developing method and used membership grades of pixels to categorize pixels into suitable segments.

The research framework of this paper is to perform FCM algorithm on fundus image to extract the exudates within blood vessels. The organization of the rest of this paper is as follows: Section 2 presents our methods, including the overview of the methodology, detection, filtering, template matching and descriptions of clustering algorithm's structure. Section 3 discusses the results and discussions. Finally, the paper ends with a short summary in Section 4.

# MATERIALS AND METHODS

The proposed research framework starts with pre-processing which is mainly to enhance the image quality for the stages that follows. The image pixel values were permanently altered and enhanced data was used for further analysis. Pre-processing suppressed the undesired information and enhances the desired features. Pre-processing involved brightness correction, detection of edges, histogram equalization and so on.

### Detection

Diabetic patients require routine eye examinations so that interrelated eye problems can be identified and treated efficiently. Most diabetic patients are normally observed by an endocrinologist who works closely with the ophthalmologist.

### Filtering

A fundus camera delivers fundus image in digital form which can be effectually used for the computer based automated detection of diabetic retinopathy. The performance on one of the normal fundus image is shown in Figure – 1.

One of the most important components of our system is the filters, which extracts the ideal data for the diagnosis. Matched filter was used for vessel segmentation that acquires more computational time than other edge detector for the same purpose [1, 19].

Unfortunately due to uneven illumination it may appear darker because macula centered fundus images are often captured on both right and left eye [9]. To rectify this problem we have to use illumination equalization to normalize the luminosity across the image. Adaptive histogram equalization enhances the blood vessels in vessel segmentation [21]. Since blood vessels usually have lower reflectance when compared with the background, these types of contrast enhancement improve the vessel segmentation.

### Template matching

The normal and healthy fundus images were taken and kept as standard to separate the abnormalities in the test image. This standard image acted as the template. Both the standard image and test images were transformed from RGB to gray levels and later by point processing (pixel by pixel) both the images were assessed.

During assessment, the further objects present in the test image got separated and made clearly visible in the result. While comparing, if the test image matches with a normal one, then it gets cancelled as there is no difference in pixel values between



the two images. The basic requirement of the proposed method is that, the references of the normal fundus image and the test images must be taken in the same orientation with same lighting, background and so on [21, 22].

# Proposed methodology

The proposed methodology is composed of four steps. Since blood vessels usually have lower reflectance compared with the background, a green component of fundus image will be separated. It was preprocessed to reduce the noise. Then we applied the matched filter to enhance blood vessels. The spatially weighted Fuzzy c-Means (FCM) clustering algorithm is used to distinguish between vessel segments and the background of the matched filter response (MFR) image [3]. A label filtering technique is used to remove the misclassified pixels.



#### Fig: 1. Vessel segmentation of original fundus image.

In order to extract the enhanced segments in the matched filter response images, an effective thresholding scheme is necessary to avoid complicated relationships or overlap between foreground and background. Hence thresholding based on spatially weighted FCM clustering algorithm was implemented.

The spatially weighted FCM clustering algorithm was formulated by combining the information of spatial neighboring into the FCM algorithm [3]. The weight in the algorithm was modified by bearing in mind the neighborhood influence on the central pixel to improve the performance of image thresholding.

The computation time of the proposed method is very fast as compared to the conventional techniques since the gray level histogram of image was used as an alternative of the whole data of image to compute the parameter for the FCM algorithm [22]. Due to the concern of the neighborhood information, the proposed method seemed to be noise resistant.

# **Clustering algorithm**

In this paper, a prior knowledge about spectral information for certain land cover classes is preferred, in order to classify image in fuzzy logic manner. Steps to implement the algorithm are given below.

- Step 1: Assign the number of clusters.
- Step 2: Randomly allocate input vector to the cluster. Create partition.

Step 3: Compute a cluster as center, the mean of each vector component of all vectors assigned to that cluster. Repeat for all clusters.

- Step 4: Estimate the distance between each and every center and input vector.
- Step 5: Update partition by assigning each input vector to its nearest cluster center.
- Step 6: Stop if center do not move any more otherwise loop to Step 4.

The proposed method uses an iterative clustering method that yields a best c partition, Since FCM algorithm is iterative and time consuming, the gray level histogram of image was used to the algorithm [23].



# **RESULTS AND DISCUSSIONS**

In order to evaluate the performance, we compare our simulation results with the state-of-the-art results obtained from piecewise threshold probing, local entropy thresholding, well known Otsu thresholding and hand-labeled ground truth segmentations [1, 24]. The vessel detection from Otsu thresholding is depicted in Figure - 2.

In this section, the results obtained from our proposed algorithm are presented. Results are compared with the well-known Otsu thresholding. Moreover, since the algorithm behavior should be image size independent, a statistical study of the measures variation was performed out. The study was based on the processing of 20 normal retinal images of each class and on three sets of measurements: one for the original images, one associated to halved area versions of the original images, and another for doubled area versions of the original images. The results of the present study revealed that the proposed algorithm is robust to differences in resolution of the image.



Fig: 2. Vessel detection from Otsu thresholding.

The proposed method preserves the computational ease and also can achieve accurate segmentation results in the case of normal fundus images and abnormal images with obscure blood vessel appearance. Blood vessel width is deliberated by interpolation technique and award elevated disparity among normal and abnormal images.

The algorithm was implemented in MATLAB version 2009b and is run on a 1.7GHz Core 2 Duo personal computer with a memory of 8 GB. Test fundus images are taken from the stare database. Normal retinal images and affected images are used for the experiment. The computational time for the complete procedure of the proposed algorithm just takes about one minute for each fundus image. Among the 30 images of standard diabetic retinopathy Database, 20 normal images with no pathology (normal) and 10 abnormal images including pathology that obscures or even confuses the blood vessel appearance in varying positions of the image (abnormal) are taken for analysis.

Detection of vessel in fundus images produces unconnected parallel edges to let extraction of blood vessels using spatial weighted FCM [Figure-3]. The edge detection techniques produce better results only when the edges are distinct and sharp. The proposed methodology performs better by segmenting even the smaller blood vessels. The proposed methodology segments the blood vessels very well from the background and extracts the exudates to classify fundus images. The proposed method has achieved 94.5% accuracy in identifying all the retinal images with exudates, and 86% accuracy in classifying normal retinal images as normal. But it shows that the major obstacle of this approach is the presence of lesions in the abnormal Images. From the above experimentation it is found that Global Otsu thresholding algorithm for vessels segmentation is best suited because it is compatible with template matching algorithm.



Early diagnosis of diabetic retinopathy was suggested based on decision support system by Kahai et al. [25]. Normal and prolific diabetic retinopathy phases were automatically classified with the help of dimensions of the RGB components of the blood vessels coupled with a neural network technique. Nayak et al. [26] have investigated exudates and blood vessel area along with texture parameters together with neural network to classify fundus images into normal and diabetic retinopathy. Recently, Acharya et al. [27] used support vector machine (SVM) classifier to categorize the fundus image into normal and prolific diabetic retinopathy phases. They have established an average accuracy of 82%. Larsen et al. [28] have developed an automated system, which identified around 90% of patients with diabetic retinopathy and around 82% of patients without diabetic retinopathy, when implemented in a screening population involving of patients with untreated diabetic retinopathy.



Fig: 3. Vessel detection from spatial weighted Fuzzy c-Means clustering algorithm.

With the proposed method, automatic detection of exudates due to diabetic retinopathy is achieved within short computational period. The accuracy is seemed to be increased using Fuzzy c-Means compared to the results from existing literatures. In order to support the sophisticated operations imposed in the automated image diagnosis by sophisticated embedded systems can be used. These automated systems can be attached with an ophthalmoscope from which the fundus image is entered and a separate visual device can be used to display the output in terms of the normal and abnormal conditions of the disease. Further the above algorithms can be enhanced to produce results including the grade and severity of the disease.

# **CONCLUSION AND FUTURE WORK**

In the present study, a spatially weighted Fuzzy c-Means clustering algorithm for vessel detection in ocular fundus images is proposed. The proposed method not only considered the advantage of the fuzzy system, but also deliberates the spatial neighborhood relation among pixels. The way the weight in the algorithm used plays a key role in improving the performance of the clustering algorithm. The proposed method maintains the computational simplicity and also achieves accurate segmentation results in the case of normal fundus images and images with obscure blood vessel appearance. The proposed method can be further amended by considering the optic disc region, vessel curving and crossings of the retinal image. However, obtained results of proposed method show that the method is able to perform the optic cup and disc detection, but it involves further improvement and parameter tuning to be incorporated to this specific purpose. The future work also aims at applying the shape analysis and classification strategies to the segmented vessels produced by method described in this study. Because of its simplicity and general nature the proposed algorithm seems to be applicable to a variety of other applications. An automated process for the early diagnoses and intervention can hence be of great aid to the patient and ophthalmologist alike in the appropriate supervision of this widespread disease.



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#### CONFLICT OF INTERESTS

We declare that we have no conflict of interest with any of the suggested reviewers and that the paper has not been supported by any grant to declare and have no personal relationships with other people or organizations that could inappropriately influence (bias) their work.

#### FINANCIAL DISCLOSURE

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# CLAMR-AN ENHANCED BIO-INSPIRED ROUTING PROTOCOL FOR WIRELESS ADHOC NETWORKS

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# ABSTRACT

Establishing communication through portable devices without the dependence on or constraints of any central infrastructure is possible in Ad hoc networks. But this very feature of the absence of a central infrastructure and the random mobility of the devices also give rise to multiple problems involving security and routing. The challenge encountered by multicast routing protocols in this ambience is to envisage creating a multi-hop routing within the constraints of the mobility of the host and the bandwidth. The role of multicast routing in wireless ad hoc networks is very significant and pivotal. We intend presenting in this paper a novel on-demand multicast routing protocol known as Cross-Layered Ant Colony Optimization Multicast Routing Protocol (CLAMR). This selected protocol is an improved and enhanced version of the already existing on-demand multicast routing protocol (ODMRP) with the enhancement of Bio-inspired Ant Colony mechanism. The fundamental mechanism of ODMRP is utilized in the proposed method along with the enhanced features of cross layer, applying ant colony optimization. This CLAMR is a robust and efficient protocol with minimal overhead. The scalability and improved performance levels of the proposed algorithm at higher traffic load in comparison to the existing algorithms are evident from the simulations performed using network simulator 2.

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**KEY WORDS** 

Cross layered, Ant Colony, ODMRP, Wireless Networks

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# INTRODUCTION

Several routing schemes have been projected for the purpose of providing adequate and efficient performance of ad hoc networks. Basing on time based determination of routes; ad hoc routing is classified as proactive [1-4] or reactive routing [1-6]. Routing decisions are continuously made in proactive routing in such a way that the routes are instantly available when transmission of packets is required. Some existing proactive protocols are DBF, DSDV [1] and WRP. Routes in reactive routing protocols [2] are determined on the basis of as-needed i.e., the node requests for a route when there is a need to transmit a packet. TORA, DSR [3], AODV [1], ABR and RDMAR are a few reactive routing protocols. Exchange of routing information in proactive routing consumes a large amount of radio resources. In addition, the validity of the pre-determined routes in an ad hoc network may rapidly be lost corresponding to its rapidly changing topology. Prior studies prove that the reactive protocols are effective in performance when compared with the proactive protocols. In recent years several multicast [6-8] routing protocols along with the existing unicast routing protocols have been proposed for ad hoc networks. Some of the proposed multicast routing protocols are capable of supporting unicast routing also, which itself is a special form of multicast. The two-fold classification of the proposed multicast routing is as tree-based and mesh-based. Tree-based protocols [7, 8, 10] create a tree connecting all its multicast members. Generally, tree-based protocols are considered more efficient in comparison to the mesh-based protocols. But, the absence of an alternate path between the source and destination conditions it as less robust in the contexts of changing topologies. Consequently, failure of every link in a multicast tree may trigger a series of exchanges of control messages for tree re-build. In contrast to the tree-based protocols having only on existing path between any two nodes, meshbased protocols permit existence of redundant paths between the nodes with their built-in mechanism of provision for alternate paths and as a result failure of a link need not require or initiate a re-computation of a mesh. Meshbased protocols are proved to be robust as per the previous studies.

ODMRP [6] is a multicast mesh-based ad hoc routing protocol. The source node in ODMRP protocol periodically broadcasts Join Request whenever it has data to be sent in order to discover and maintain the multicast routes. Rest of the nodes, when they receive non-duplicate packet, re-broadcast it. On receiving Join Request, the



multicast group member node replies with a Join Reply. A route is established through all the subsequent replies by the nodes in the reverse path. Use of soft states in ODMRP marks leaving a group in an automatic timeout. As illustrated, reliance of ODMRP on frequent network-wide flooding may result into a problem of scalability particularly when the source nodes are more. More prominent control packet overhead can be perceived in the context of small multicast group in comparison to the total network.

# **RELATED WORKS**

In recent studies, there is an extensive focus on the discovery of multipath and extension of QoS of the on-demand routing protocol in such a way as to address the issues pertaining to the single path routing protocols such as AODV [1, 2, and 9] and DSR [1-6]. Ant colony-based multi-path QoS-aware routing (AMQR) [11, 13, 14, and 15] integrates link-disjoint multipath routing and swarm intelligence to choose multiple paths for providing QoS services [16, 17, 18, 19]. The nature of the ad hoc routing protocols whether proactive or reactive depends on the factor of when the routes are determined. With the process of a continuous exchange of routing information among [20] nodes, the routes to destination are pre-determined in proactive routing protocols. When packets need to be transmitted, immediate availability of routes is ensured. Wireless Routing Protocol (WRP) [1-6] and the Destination Sequenced Distance Vector (DSDV) [2] routing protocol are a few instances of proactive routing protocols [1-6]. In contrast, routes are determined on-demand only in reactive routing protocols. A node sends a guery for a route to the network when required to transmit a packet. TORA, DSR and AODV [9] are some much known reactive ad hoc routing protocols. But exclusively proactive or reactive routing protocols do not suit the requirements of MANETs. More frequent changes in network topology than the routing requests are possible in MANETs. In such circumstances, the information of routing generated by the proactive routing protocols stays stale. On the other hand, the reactive routing protocols [1-6] conduct a global search for on-demand route discovery process requiring considerable traffic control. This can easily result in saturation in the bandwidth constrained MANETs in a very short interval of time. So, the literature proposes a number of ad hoc multicast routing protocols which are much more than being just extensions of the unicast routing protocols under reference. This is exactly the opposite of what is experienced in wired networks with the several multicast routing protocols acting just as multicast extension counterparts of their corresponding unicast routing protocols. An ad hoc routing protocol to be robust and efficient, must not depend or rely on any implied unicast routing protocol for determining the route or updates. Extensive work has been done for evaluating the performance of the protocols of routing in ad hoc networks.

# PROPOSED MODEL

CLAMR can be interpreted as a QoS enabled multipath routing protocol developed on the basis of the foraging behavior of ant colony [15, 21]. The source generates both the ant agents (called reactive FW\_ANT) to find multiple paths to the destination and BW ANT to set up return paths [18]. The respective qualities of the paths are indicated in the form of pheromone table. NHA is considered as metric during the route discovery phase to assess the goodness of the highly available links and nodes. The NHA is considered for finding the path. The metrics used for the computation of NHA [15, 19] are the availability of nodes and links. The NHA can be explained as the probability to discover the next hops [19], which is the node and link availability for routing on a path.

Next hop availability = Link probability × node probability ------(1)

At the phase of route discovery, a source node desirous of transmitting information to the destination node first verifies the trusted neighbors. Then such nodes with greater NHA [21] than threshold are selected. Next, the source node initiates broadcasting FANT to all its neighboring trusted nodes having the NHA in order to control the routing overhead.

Any intermediate node receiving the FW ANT, first verifies if its own address figures in the path field. If the address is present, it discards the FW\_ANT at that stage itself to eliminate further loops. Or else it attaches its address to FW\_ANT and then initiates broadcasts by its NHA values to all its trusted and stable neighbors. In the process of searching for the destination, the FW ANT collects delay of transmission of each link, delay of processing at each node, each link's available capacity and visited number of hops. On FW\_ANT arriving at the destination node d, the destination node first computes the path preference value, by employing end-to-end delay parameter for only such paths meeting the threshold values prescribed by the user and thus generate BW ANT.

Visiting nodes in the path are stacked in the FW\_ANT. By popping up such nodes present in the stack, the BW\_ANT is unicasted to the source node

The pheromone value [21] gets updated when the backward ant reaches any middle node other than the destination node. The pheromone value gets updated in the routing pheromone table of node i as  $T_{\it i,n}$  [15] and it is updated as

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$$T_{i,n} = (1 + T_{i,n}) P(K)_d$$
 ------(2)

Where  $P(K)_d$  [15] is the path preference value of the kth path that satisfied the QoS requirements for the destination d.

# Ant colony optimization for ODMRP

In the mesh based ODMRP multicast, packets are transmitted to the destination by employing the concept of a forwarding group. It can be termed a 'reactive protocol' as it makes use of 'on-demand' procedures for dynamically building up routes and maintaining multicast group membership. The drawbacks inherently present in tree protocols, such as intermittent connectivity, configurations of tree and computations of shortest paths can be avoided through the use of mesh topology. For the maintenance of multicast group members, ODMRP makes use of a soft-state approach. Explicit control information is not required to desert the group. We intend to provide an elaborate explanation of the functioning the process of mesh creation of enhanced ODMRP duly considering the ant colony optimization. The network is flooded with FW-ANT message whenever the source node has data to transmit. The intermediate node, after receiving a (non-duplicate) FW-ANT packet, stores and updates the information regarding the upstream node. The Intermediate nodes continue to flood the FW-ANT packet. After receiving the FW-ANT packet, the receiver builds the PHEROMONE TABLE and transmits the BW-ANT to its neighbors. Then, all the nodes receiving the BW-ANT packets verify their individual IDs against the ID contained in the BW-ANT packet. If a matching is found, the node becomes the forwarding member of the group by setting the FG\_Flag (Forward Group Flag). Further propagation of FW-ANT packet continues, till it arrives at the source. Through the broadcasting of FN-ANT [15, 21] packets at regular intervals, the senders maintain an update of the multicast group. The following data structures are required to be maintained by each host that runs ODMRP:

•Routing table – Each node reactively creates a route table and maintains it. When a non-duplicate FW-ANT containing high pheromone value is received, corresponding entry is inserted or updated. The node stores the information regarding the destination and the subsequent hops to the destination. Next hop information during the transmission of BW-ANT is provided by the route table.

•Forwarding group table – The multicast group information is stored in the forwarding group table by the node acting as a forwarding group node of a multicast. It records the group ID of the multicast and the time stamp.

• **Trust Pheromone table** – It is a table that contains the trust value of the neighbors depending on the threshold value from end-to-end delay.

•Neighboring Information table – This table contains the required information about all the set of neighbors in any specific network.

This table contains the required information about all the set of neighbors in any specific network.

### Cross layer model

MAC and NETWORK layers are fused in the proposed cross layered model in order to achieve a cross layer factor. The load of the node and the bandwidth available for a specific node are calculated. We derive a cross layer factor *clfact* [16] on the basis of these calculations. This cross layer factor can be used as a metric for determining the path from source to destination. Use of the enhanced ODMRP mechanism with Ant Colony Optimization [20, 21] can find all the source- to- destination corresponding routes in network layer. We compute the length of the node and the available bandwidth in each node of the specific routes.

Let B(s) be the available bandwidth at source node s. and B(r) is the available bandwidth at receiver node r, then

B(s,r) = Min(B(s), B(int1), B(int2), B(r)) -----(3)

Where B(s,r) is the available bandwidth for the entire link between source node and receiver node.

Then, apply this mechanism of cross layer to the paths provided by the network layer and select such route having effective *clfac* for the given data rates. In comparison to the original ODMRP mechanism, we get more efficiency and reduced overhead.

1. Calculate the node load for a node i in the network.

$$nodeload_i = \frac{queue\_len_i}{queue\_len\_nodes}$$
 -----(4)

2. Calculate the available bandwidth for a node i

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Where  $Bdw_i$  is the bandwidth of node i,  $Bdw_{ch}$  is the channel bandwidth and 0.8 is the weight factor.

3. Apply cross layer design over network and Mac layer parameters.

 $clfactor = (Max(Bdw_i, nodeload_i))^{-----(6)}$ 

#### Recovery of intermediate node failure

On identification of any route-disruption resulting out of the mobility of the subsequent node along that specific route, the network layer at an intermediate node (referred from now on as FP or failure point) dispatches a packet, indicating Path Failure Notification (PFN) to the source. When the PFN packet is received, every intermediate node invalidates a particular route and blocks further traffic of packets through that route to that specific destination. However, the PFN can be discarded, if the intermediate node has knowledge of any alternate route, which can be utilized for further support in communication. Or else, the node just disseminates the RFN towards the source. The source shifts into snoze mode after the receipt of PFN and carries out subsequent recovery mechanism. The source continues to be in the snoze mode till it receives the restoration notification of the route through the packet of a Route Re-establishment Notification (RRN).

Use of Path Failure Timer checks the source from remaining in the snooze mode indefinitely expecting the arrival of an RRN that could either have been delayed or lost. This timer starts on the source receiving the first PFN. On expiry of the Path Failure Timer, the frozen timers start (as if they received an RRN) and permit the congestion control mechanism of the TCP to take care of the failure.

# **RESULTS AND DISCUSSION**

Radiographic For the purpose of simulation, we utilized NS-2 [22] network simulator. A network model of 50 randomly placed nodes covering an area of 1000m x 1000m figure in our simulation. The simulator functions with a range of 250 meters radio propagation with channel capacity of 2 Mbits/Sec. The size of the multicast group varies with one source in each group sending at the rate of 20 Packets/Sec. 300 seconds of simulation is executed in each simulation. We collected data and averaged over the results arrived at by changing the send numbers in different multiple runs for each changing scenario.

The proposed model utilized the following metrics in order to estimate the performance of the proposed CLAMR mechanism:

•**Packet Delivery Throughput**: This can be described as a corresponding quantification of data packets received at the destination and the dispatched data packets by the CBR sources.

•End-to-End Delay of Data Packets: It is the delay in time between the times of packet origin at the source and packet reaching at the destination. We do not consider the enrooted lost data packets here. But the delay metric certainly considers the delays cropping up due to route discovery, queuing and transmission. Performance of our approach is evaluated by a comparison against the approaches of ODMRP and CL-ODMRP. The performance of the proposed system in comparison to the methods already in existence explicitly appears to be much enhanced as can be perceived from Figure-1 and Figure-2.

The performance of the protocol is further evaluated in varying network scenarios such as the speed of node moving, size of the multicast group and multicast group number.

Node moving speed: 20 multicast destinations are set in this simulation with only 1 source sending the data packets. The rate of traffic generation is 10 packets per second.

**Figure-1** illustrates the performance of packet delivery ratio of CLAMR with CL-ODMRP and ODMRP, respectively, in varying moving speeds. A similarity in performance can be perceived with CL-ODMRP and ODMRP while the speed of the node moving is low. High mobility of the node, generating high dynamics in a built forwarding structure is the reason for this.





Fig: 1. Packet delivery rate vs speed



Fig: 2. Comparison of Average delay with CLAMR

Figure-2 displays a comparison of the average delay of CLAMR against CL-ODMRP and ODMRP, respectively in the context of different moving speeds. A reduction of delay upto 15% as against ODMRP can be achieved through the introduction of cross layer- based ant colony optimization strategy CLAMR.

# CONCLUTION

In this paper, the proposed model Cross-Layered Ant Colony Optimization Multicast Routing Protocol (CLAMR) utilizes the nature inspired ant colony optimization algorithm to find multiple paths during the route discovery phase. A QoS factor has been included to find goodness of the path. The QoS factor is obtained from the cross layer technique. The proposed model yields effective throughput and less delay with the optimizations.

# CONFLICT OF INTEREST

Authors declare no conflict of interest.

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ARTICLE



# DATA AGGREGATION IN NOISY WIRELESS SENSOR NETWORKS USING CHAOS THEORY

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# ABSTRACT

In environmental monitoring applications, the data periodically sensed by Wireless sensor networks (WSNs) have a strong redundancy. The Network consumes more power to transmit the redundant data packets to sink through intermediate nodes which reduces network lifetime. To overcome the redundant data transmission, Chaos Theory based Data Aggregation (CTAg) prediction method is proposed here. The proposed method minimizes the number of packets forwarded to sink node by eliminating redundant packets by using chaos theory based prediction technique. The proposed approach is evaluated using temperature monitoring application dataset collected from Intel Berkley Lab. The CTAg method significantly reduces communication redundancy, data redundancy, and mean square deviation error and also increase prediction accuracy, in turn evidently proved that the lifetime of the network is improved.

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Wireless sensor network; Redundancy; Data aggregation; Time series prediction; Chaos theory;

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# INTRODUCTION

Wireless sensor networks (WSNs) are groups of sensor nodes that are tiny with low power and low cost. Each node consists of a sensing unit, processing unit and communication subsystem [1]. These sensor nodes collect real-time data from the physical environment and transfer the collected data to base station. They are widely used in military, health science, and commercial applications. For example, in health science, a doctor can monitor the physiological information about the patients remotely. In the commercial application, it is used for managing inventory and monitoring product quality [2].

The energy consumption in a wireless sensor network is due to sensing, computing, communication and mobility of nodes. The energy for communication is more expensive, which affects the energy of intermediate nodes during multi hop transmissions of data packets compared to sensing and computation. Energy dissipation during communication that is caused by transmitter or receiver is considered as  $E_{elec}$  and the power dissipation of the transmitter amplifier is taken as  $\varepsilon_{amp}$ . The power consumed by the transmitter for k-bit packet transmission [3, 6] to a distance'd' and assume d<sup>m</sup> as path loss.

$$E_{Tx}(k,d) = E_{elec} * k + \varepsilon_{amp} * d^{m} * k$$
(1)

Let  $E_{elec} = E_T(k, d) = E_R(k) = 50 nJ/bit$ ,  $\varepsilon_{amp} = 100 pJ/bit/m^2$  and m = 2.

$$E_{Rx}(k) = E_{elec} * k \qquad (2)$$

Where  $\mathbb{E}_{Rx}(\mathbf{k})$  is the k-bit message in receiving of energy.

In an environmental monitoring application, information collected by sensor nodes tends to exhibit strong temporal correlation. This redundancy leads to communication overhead, consumes node energy and reduces network efficiency. To overcome this issue, the data aggregation techniques [5] were introduced. Wireless sensor networks are partitioned into source node, intermediate node



(aggregator node) and sink node. The aggregator node performs the data aggregation [4]. It collects data from multiple sensor nodes, which are fused and transferred to the base station. Thus the data aggregation technique eliminates redundancy and minimizes numerous transmissions and thus preserves the network energy.

Chaos theory is the study of complex, nonlinear, dynamic systems [16]. It is a branch of mathematics that deals with systems that appear to be orderly (deterministic) but, in fact, harbor chaotic behaviors. It also deals with systems that appear to be chaotic, but, in fact, have underlying order. Chaos theory studies the behavior of dynamical systems that are highly sensitive to initial conditions, an effect which is popularly referred to as the butterfly effect. The deterministic nature of these systems does not make them predictable. This behavior is known as deterministic chaos, or simply chaos.

The proposed Chaos Theory based Data Aggregation (CTAg) approach predicts the next period data based on the earlier sensed data. The data are collected from ordinary sensor nodes. The aggregator node made a decision between prediction error and prediction threshold, in order to make a conclusion whether to transmit current data to sink node. This technique eliminates the redundancy and minimizes the communication density. The proposed method can also provide better prediction accuracy and prolong sensor node lifetime when compared to other traditional prediction based data fusion techniques. This paper is organized as follows: Section II discusses the prediction base data aggregation and chaos theory based data aggregation (CTAg). Moreover, implementation details and results are given in Section III. Finally, conclude and define our future work in Section IV.

## MATERIALS AND METHODS

#### Prediction based data aggregation- a survey

The energy management is one of the major issues in wireless sensor networks. A sensor utilizes high energy for communication rather than sensing and processing. The redundant communication in noisy channels causes the depletion of network energy. The prediction based data aggregation approach reduced unnecessary data transmission and so energy expenditure in communication subsystem was minimized. Hyuntea Kim et al., [8] exploited linear data prediction method to improve communication efficiency and to minimize energy consumption with data correlation. As the model is designed considering some factors such as the selective transmission, it reduced data accuracy and adjustments in aggregation period caused the network to meet the additional delay. Guiyi Wei et al., [7] proposed a method that saves network energy and eliminates redundant communication by exploiting prediction based data aggregation protocol. However, in this method synchronization time increased due to synchronization has to be done prior to each transmission. Guorui Li et al., [9] proposed an Auto Regressive Integrated Moving Average Model (ARIMA) that predicts the next time value based on the previous observed values. When the prediction error is less than the preconfigured threshold value the aggregator would not transmit the data sensed by the source node. Otherwise, it transmits the data to sink node. Therefore ARIMA model reduced the amount of data transmitted between the ordinary sensor node and aggregator node. Since this method performed aggregation on the ordinary sensor node and aggregator node it increased the computational complexity and reduced accuracy. Rajesh G et al., [10] proposed the data fusion method using Simpson's 3/8 rule to forecast next time data based on the early sensed information. When prediction error is greater than the prediction threshold the cluster head transmits the actual sensed value to the base station. Otherwise, it would not transmit data to the base station. This method reduced unnecessary transmission between cluster head and base station. However, this method provides less prediction accuracy since the deviation error is increased between subsequent values. There are several data fusion techniques in Wireless sensor networks. The main features of the proposed work are that it, Improves the performance of the forecast and Performs less computation to obtain the forecasted data.

#### Chaos theory based data aggregation (CTAg) technique

The typical features of chaos include: 1) Nonlinearity. If it is linear, it cannot be chaotic. 2) Determinism. It has deterministic underlying rules every future state of the system must follow. 3) Sensitivity to initial conditions. Small changes in its initial state can lead to radically different behavior in its final state. Long-term prediction is mostly impossible due to sensitivity to initial conditions. A dynamic system is a simplified model for the time-varying behavior of an actual system [17]. These systems are described using differential equations specifying the rates of change for each variable. A dynamical system of dimension N system first-order differential equations for N variables  $x_1(t) \dots x_N(t)$  evolve with time t according to,

$$\begin{split} \hat{x}_1 &= f_1(x_1, x_2, ..., x_N, t) \quad (3) \\ \hat{x}_2 &= f_2(x_1, x_2, ..., x_N, t) \quad (4) \\ \hat{x}_N &= f_N(x_1, x_2, ..., x_N, t) \quad (5) \end{split}$$

Where  $f_1$ ,  $f_2$  are assigned functions and a dot is a derivative with respect to time.



The system following Characteristics of a Chaotic System:

- Sensitivity to initial conditions
- Non-linear
- Dynamic and mixed topology system and Continuous or periodic time.

So that the Chaos is the aperiodic long-term behavior in a deterministic system that exhibits sensitive dependence on the initial condition. These characteristics enables chaos theory based data aggregation (CTAg) prediction method is suitable for eliminating data redundancy in WSNs.

Considered a hierarchical wireless sensor network G (SN, E) where, SN represents the sensor nodes and E represents links connecting the nodes. These sensor nodes collect weather monitoring data (Temperature, Humidity) periodically. Each node transmits data to sink node through the intermediate node or aggregator node (A). The aggregator (A) will perform data fusion by eliminating redundant data using chaos theory before transmitting the gathered data towards the base station. This will minimize the amount of data transmitted between aggregator node and sink node.



Fig: 1. Architecture for chaos theory based aggregation.

Figure-1 illustrates, the CTAg architecture that consist of two distinct phases, chaos based forecasting and decision phase. The chaos based forecasting phase uses previous time series measurements representing (6) to compute next time period data using (7) and (8). The decision phase will accomplish the comparison between forecast errors  $\mathbf{e}_{t}$  and prediction threshold  $\varepsilon$  to make a decision whether to send actual sensed data to the sink or not. The prediction error was calculated using (10). The prediction error is greater than the prediction threshold the aggregator node transmits sensed data to base station. The aggregator does not send sensed data to sink node when forecast error is less than the prediction threshold.

$$x_t = (x(t_n), x(t_{n+\tau}), x(t_{n+2\tau}), ..., x(t_{n+l(m-1)\tau}))$$
 (6)

Where  $\mathbf{x}_t$  is the chaotic time series, m is the embedding dimension and  $\mathbf{\tau}$  is the delay time.

$$\mathbf{x'}_{t+n} = \mathbf{f}(\mathbf{x}) \tag{7}$$

Where  $\mathbf{x}_{t+n}^{t}$  the prediction data of next time and n is step length of time series forecast.

$$f(x) = x_t + (\tau - (\tau - n)) * FE$$
 (8)



Where,  $\tau = \frac{x - x_{n-t}}{h}$  x is the recent data,  $x_{n-t}$  is the previous time data and  $h = t-t_n$ . Let be t is the time for recent data sensed and  $t_n$  is the time for earlier sensed data value.

The Forward Error (FE)  $\triangle$  is the product of Minimum Forward Error Value (MFEV) with current sensed data and divide to embedded dimension is the order of MFEV.

$$FE(\Delta) = \frac{\Delta^m \mathbf{x}_t}{m!}$$
(9)  
$$\mathbf{e}_t = \mathbf{x}_{t+1} - \mathbf{x}_{t+1}^t$$
(10)

Where  $\mathbf{e}_{t}$  is the prediction error at period  $\mathbf{t}$ .





**Figure-2** illustrates, when an intermediate node performs chaotic time series forecasting is evaluated future value  $\mathbf{x}_{t+1}^{\prime}$  based on the Sensor Nodes (SN) gathered previous time temperature data such as  $\mathbf{x}_{t-2}\mathbf{x}_{t-2}\mathbf{x}_{t-2}\mathbf{x}_{t-1}\mathbf{x}_{t}$ ... after computing predicted value, to measure the forecast error  $\mathbf{x}_{t+1} - \mathbf{x}_{t+1}^{\prime}$  mean that the deviation between actual sensed value and prediction value, then it is compared with prediction threshold value  $\mathbf{z}$ . If the prediction error is higher than the threshold, the actual sensed data transmitted to sink node. Otherwise, the aggregator is not forwarding the packet to the Base Station (BS). Here the aggregator node, predicted threshold based will perform filtering the redundant data. The predicted threshold set as the mean value of the prediction error. The predicted threshold is adaptive. The less deviated data is discarded from gathered continuous time series data set. The more relevant data or non-redundant data is towards base station (BS). But the major and most significant limitation of



chaos theory is the feature that defines it, sensitive dependence on initial conditions that may affect prediction accuracy.

Algorithm 2, illustrates the aggregator node receives predicted data at the point of time t+1. The aggregator decides to transmit data towards the sink or not by doing a comparison with predicted error and prediction threshold.

Algorithm	1:	Chaos	Forecasting	Phase
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Input:		
xt	$\rightarrow$	Time series sensor data
<b>Output:</b>		
$\mathbf{x}'_{t+1}$	$\rightarrow$	Forecasted Data
<b>Process:</b>		
	1.	Get earlier time ser
	x <sub>t</sub> =	x(0), x(1) = (x(3),, x(1))
2. If H	listory	size > 0
	2	$1.  Compute \Delta \mathbf{x}_t = \mathbf{x}_t - \mathbf{x}_{t-1}$
	2	.2. Compute the next time
	series	of the data
	x	$\mathbf{x}_{t+1} = \mathbf{x}_t + \frac{(\tau - (\tau - n))}{n!} \Delta^n \mathbf{x}_t$
	2.3.	Return x <sup>r</sup> t+1
	3.	End if



Input:			
x' <sub>t+1</sub>	Forecasted Data		
x <sub>t+1</sub>	Ac	ctual Sensed Data	
Output:			
Returned A	ctual Sense	d Data	
<b>Process:</b>			
1.	At the p	eriod t aggregator node	
compute	s x' <sub>t+1</sub>		
2.	At period t+1, aggregator node		
receivin	g actual dat	a x <sub>t+1</sub>	
3.	If (x <sub>t+1</sub>	$-x'_{t+1} < \varepsilon$ )	
	3.1.	Redundant Data	
	3.2.	[History] = Sensed data	
4.	Else		
	4.1.	Transmit Non-Redundant	
Dat	a		
	4.2.	[History] = Forecast data	
5.	End If		

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If the prediction error variation is less than a threshold value the aggregator assumes that the sensed data is redundant data. So it does not forward to sink node. Otherwise, assume that the non-redundant data and it conveyed to sink node.

# RESULTS

The CTAg algorithm simulated using OMNET++ simulator with MIXIM package. The actual time series data are collected from wireless sensor networks. Here N=100 nodes are uniformly used to collect data from a sensing area of  $A = 500 \times 500 \text{ m}^2$ . The data are traversed using AODV protocol. In this network, the sensor node spends  $E_{Tx}$  energy to carry the data 'd' distance to next node and utilizes energy  $E_{Tr}$  for receiving data. The total communication energy is  $e_{i}$ . The CTAg is intended to reduce redundant communication and conserve the network energy  $e_{i}$ . In this section, the CTAg algorithm is applied to the temperature monitoring application. The dataset is collected from Intel Berkley Lab [17].

**Table-1** represents the table contains date, time, and node id of the sensed data. The Epoch is a monotonically increasing sequence number from each node. In this dataset we consider the Time (t), Mote id (MID), Epoch (E) and Temperature (T) for evaluation. The CTAg algorithm performance is compared with conventional method of Kalman Filter [KF] prediction based data aggregation [15]. It is observed that the proposed algorithm is better among the data aggregation technique.

Date	Time	Epoch	Mote id	Temperature
03/03/04	09:45	22	1	20.145
03/03/04	10:22	23	1	20.165
03/03/04	10:46	24	1	20.165
03/03/04	11:16	25	1	20.169
03/03/04	11:20	26	1	20.244

#### Table: 1. Example temperature application dataset

#### Performance analysis

**Table-2** represents the comparison of quantitative performance of proposed CTAg algorithm and KF. This table contains the actual data, predicted data, prediction error, and data transmission status and prediction threshold. Here, the prediction threshold as 0.28 is used to evaluate the performance of prediction. In Data Transmission Status, 0 indicates that the data is similar to the previously sent data and 1 indicates that the data is different from previous data. The aggregator will transmit to the sink node data marked as 1 and discard data marked as 0. Hence the communication overhead is reduced. The communication overhead is the ratio of the sensor node actual power consumes the number of packet forwarded to base station (BS) to power consumes after aggregated packet transmitted to base station (BS). Thus the CTAg aggregation method reduces the redundant packet transmission and power consumption.

**Figure–3** represents comparison of actual sensed temperature with Kalman Filter [KF] and CTAg method forecasted the temperature (T) in different time interval. The temperature predicted using CTAg method is close to actual sensed value due to small prediction error and KF method has high variability with sensed data and CTAg due to high deviation error between the sensed and predicted values. It can also be seen that the predicted value of CTAg varies consistently with the observed value and forms a steady growth curve with almost constant prediction error. This stable prediction error rate eliminates the need for the fixing prediction threshold using soft computing technique.

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Figure-4 shows the amount of deviating data that has been transferred. The CTAg method performs better for the forecast threshold up to 0.28 when compared to KF. The CTAg restricts redundant packet transmission from aggregator to sink node compared to the Kalman filter.

Method	Actual Data	Predicted Data	Prediction Error (%)	Data Transmission Status
	20.51	20.77	0.26	0
CTAg	20.54	20.79	0.25	0
	20.61	20.92	0.32	1
	20.86	21.04	0.18	0
	20.51	20.81	0.30	1
KF	20.54	20.78	0.24	0
	20.61	20.92	0.31	1
	20.86	21.13	0.27	0

#### Table: 2. Sample resultant data

Figure-5 based on the forecast threshold 0.03, 0.08, 0.13, 0.18, 0.23, and 0.28. When the predicted threshold is 0.28 the difference between the observed and forecasted value is minimum. Hence it can be inferred that considerable accuracy is achieved at prediction threshold 0.28.





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In **[Figure-6]**, based on the forecast threshold, the number of data aggregation is larger when compared to the Kalman filter. Due to this data aggregation is reduced redundant transmission and communication consumption power.

## CONCLUTION

The energy efficiency is the important key Wireless sensor networks. With data transmission is the major part of energy consumption, chaos theory based time series prediction method to enhance energy efficiency. The proposed Chaos Theory based Data Aggregation (CTAg) based approach reduces redundant data, communication overhead and number of packet transmission between aggregator and sink node by using adaptive thresholds. The time series prediction using CTAg method was energy efficient and performed less computation to obtain the forecasted data. The experiments also show CTAg achieves better performance compared to other prediction approaches like Kalman Filter [KF] based prediction.

#### CONFLICT OF INTEREST

Authors declare no conflict of interest.

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ARTICLE

# DETECTION OF CARDIAC ARRHYTHMIA FROM ECG SIGNALS

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# ABSTRACT

The first and foremost step in the analysis of ECG for various cardiac disease is the extraction of ECG and classification of ECG based on feature extraction. The prediction of any cardiac disease will come correctly if the feature extraction and classification of ECG are correct. It is very difficult for any expert physicians to predict exactly the cardiac arrhythmia as the volume of data is huge. The monitoring of ECG signals for a long period of time is needed as the changes in ECG may occur at any fraction of time. The computer aided approach helps significantly for monitoring ECG signals for long period of time. Many methods like wavelet transform, Independent Component analysis (ICA), Permanent Component analysis (PCA), Time Domain, Wavelet Transform, Power Spectral Density and Fuzzy logic with Neural network techniques are used either separately or in combination by the Researchers for extracting features from ECG signal. It is found from this survey that among many classifiers, most of the research works uses SVM classifier as it gives high classification accuracy. It is also found from this survey that most of research work uses the ECG data from MIT-BIH database or from Physionet. The parameters which determines the suitable technique for feature extraction and classification are found to be classification accuracy, sensitivity and specificity. This paper presents a survey of various approaches

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**KEY WORDS** 

Feature Extraction; Classification; cardiac arrhythmia; classification accuracy; testing data; training data

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### INTRODUCTION

The main tool used in clinical practice to record the electrical activities of heart is ECG. The amplitude and interval features of ECG contains useful information for analysis. The exact identification of the heart disease depends on choosing the correct approach for extracting the features in ECG signals. ECG recording contains volumes of data which is very difficult for manual analysis by the physician. The computer aided analysis of ECG data has drawn the attention of everyone. Many researches are focused in this direction. Hanlin et.al [1] used wavelet transformation for feature extraction from 12 lead ECG signal. They used semi- supervised approach for clustering unlabeled data. Finally the SVM classifier was involved for ECG classification. Ge Dingfei [2] concentrates on the feature extraction of a cardiac abnormal condition called premature ventricular contraction (PVC) and normal sinus rhythm (NSR) and discusses in detail the discrimination between them by conducting data analysis on the data selected from MIT-BIH database. A new method known as Random Projection [7] is used for feature extraction on multi lead ECG signal which mainly concentrates on dimensionality reduction. This method is energy efficient and it is feasible to implement in portable systems for health monitoring. The structure of this paper is as follows: Section 2 discusses the preprocessing methods used to make ECG signal ready for feature extraction along with the techniques for feature extraction by various authors. Section 3 is a discussion on performance of several methods used by the researchers to achieve their goal. Section 4 reflects the research gaps in each of these research works after making a comparon of these techniques with respect to classification accuracy and data size graphically.

#### Data preprocessing methods

The ECG data contains unwanted data which is due to muscle contractions, power line interference and baseline drift. The unwanted signal must be removed to get the original ECG data.



In paper [1], the preprocessing phase comprises of elimination of noise, detection of R peaks and the segmentation of heartbeats. Here Pan Tompkins algorithm is used to find the R peaks. The research work [2] uses the data from MIT-BIH database. The baseline drift and power line interference are removed from ECG signals by a band pass filter with lower frequency pass band of 1Hz and upper frequency pass band of 35 Hz. The ECG data [3] is preprocessed to remove baseline wander and filtered with a band pass filter to remove high and low frequency artifacts. The images for five cardiac conditions namely Normal, Ventricular Flutter, Ventricular Tachycardia, Nodal and Left Bundle Branch Block were collected from physionet database in the work [4]. Totally 100 images were collected from the database. The preprocessing of ECG includes binarization, 1D signal extraction and base line drift removal with median filter. Two kinds of data is used for feature extraction and classification of ECG signals in paper [5]. In this paper the feature points positioning is also done in the preprocessing stage. The data [6] is very large and it is taken from Physiobank archive. Nearly 1200 feature vectors for each class of disease is taken. Here three sets of features are taken for time domain, wavelet transform and for power spectral density. In the preprocessing stage [7] every record consists of 15 simultaneously measured signals. Each of the signals are digitized at 1000 samples / sec and has a 16 bit resolution. The database taken from 60 subjects includes 20 records for normal sinus rhythm, another 20 records for myocardial infarction and 20 cases of cardiomyopathy. Among these 30 subjects are used for training sets and the remaining as testing sets. At any time the selected beat has 700 samples. The analysis in [8] is conducted on ECG signals from MIT-BIH Arrhythmia Database on three kinds of signals namely, the normal ECG, Premature Ventricular Contraction (PVC) and Left Bundle Branch Block (LBBB). The preprocessing phase [9] is applied to whole of the chosen database and the principle characteristics are extracted using Principal Component Analysis (PCA) technique. The tests are conducted on 4 databases randomly generated which comes around 4002 samples. Out of this, 2802 samples of each database is used for training set and the remaining 1200 samples are used as testing set. The raw ECG signal [10] is filtered in frequency domain to remove dc offset. Then fast Fourier transform (FFT) is applied to get low frequency offset removed and baseline drift at zero reference line. Again inverse FFT is applied to get preprocessed signal.

## Methods of feature extraction

In paper [1], a most popular time-frequency transformation called discrete wavelet transform technique is used to map the 12 lead ECG segments into the WT space. The new method introduced in this paper called Semi-supervised discriminant analysis distinctly distinguishes the features for various diseases in the ECG segment. A new beat detection algorithm which does not affect beat shape is used in the research work [2]. This algorithm uses two feature sets of data. The first feature set includes energy of wavelet coefficients and RR ratio for the consecutive beats. The second feature set are selected by pre-selection of the coefficients and further by forward selection process. Further a 6-level discrete wavelet transform decomposition is performed on each beat using a 10th order Daubechies. The morphological features are extracted using wavelet transform and independent component analysis together [3]. The dynamic features are obtained from RR interval information. The wavelet analysis is performed with Daubechies wavelet to forder 8. FastICA algorithm is used here to extract 18 ICA coefficients for every heartbeat. The dimensionality of feature is reduced to 26 by principal component analysis and this results in 9932% variance. The statistical and morphological feature extraction is done in paper [4] through Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) techniques.

The technique employed for extracting the features from ECG in the work [5] is Independent Component analysis (ICA). The authors' claim that by taking 10 independent components for each segment of multi lead data more effective results can be obtained. The feature extraction [6] uses the combination of time domain, wavelet domain and power spectral density features. Finally three divergent feature sets consisting of 8 time domain, 32 wavelet transform and 11 power spectral density features are obtained. Another important point here is that all these features are extracted without using QRS detection. The Random Projection [7] technique is used for generating feature vector for all records in the database. This technique reduces the dimensionality of a data set but preserves the geometrical structure. Accordingly Random Projection has reduced the dimensionality of beat from to 50 samples from 700.

In [8] Kernel Principal Component Analysis (KPCA) is used for extracting the non-linearly related structures to the input space through the solution of an eigenvalue problem in a feature space of higher dimension. Two approaches are used here. The first one uses the combination of Principal Component Analysis (PCA) and modified fuzzy one-against-one (MFOAO) for categorizing multiclass signals. The second approach uses PCA, unbalanced clustering (UC) and fuzzy one-against-one (FOAO) algorithms. The UC algorithm is used for discarding the outliers. The feature extraction [9] is done with Principal Component Analysis (PCA) technique and it is combined with unbalanced clustering algorithm (UC) to reduce the complexity in feature extraction. In [10] Subband analysis is used to divide the signal into various frequency band components. Every beat in every kind of ECG consists of 250 data points after employing a 6 level decomposition on ECG signal. Three kinds of sub band energy calculations namely normal, mean and Relative mean are performed on the extracted energy coefficients of ECG.

# ECG classification methods

In paper [1], the data in the semi supervised discriminant analysis feature space are classifies using support vector machine (SVM). Here the dataset is split into two halves randomly for training and testing. The training set includes 14301 heartbeats and the testing set has 14300 heartbeats. The dataset includes data for six diseases such as Normal, Sinus bradycardia, Left bundle branch beat, Electrical axis left side, Right bundle branch block and Left ventricular hypertrophy.

The ECG classification technique used in paper [2] is Support Vector Machine [SVM]. Here SVM separates all the samples into 2 classes by an optimal hyperplane. The total data in this work are divided into 10 equal size folds. Among these, 9 folds are used for training data. The last fold is trained with 10 classifiers. Finally the ultimate classification performance is determined by averaging the results from all the 10 test sets. The classification tool used in paper [3] is SVM classifier with a Gaussian radial basis function kernel. Based on the training data the SVM classifier is trained. The trained SVM classifier is used to evaluate the data. The implementation of SVM algorithms is through LIBSVM package. The classification of ECG in paper [4] is done using Euclidian and Manhalanobis classifiers. Here 100 segments are taken for training and 50 segments for test samples. These 50 segments are obtained from the extracted 198 segments.



The classification of beats through experiments based on multi-lead data in [5] shows that 11 types of arrhythmia beats can be classified. This work also includes the classification of experimental data from 500 persons. Here the total number of beats collected is 6366 and the abnormal beats in this is 2611. The classification accuracy here is 90.47%, sensitivity is 0.9001 and specificity is 0.9074. The authors indicate that this method can be applied to practical environment. This work also indicates that the training data proportion also affect the result.

The classification algorithms [6] used are decision tree and neural network. In this paper a fivefold cross validation technique is used for the evaluation of the entire ECG database. The experiments also indicate that the classification with decision tree algorithm is better than with neural networks. The classification performance success score, called F- score [6] with entire 51-dimensional features of time domain, wavelet transform and power spectral density feature extractions is 0.947 and it is the highest.

A Neuro-Fuzzy classifier [7] is used for feature classification in ECG signals. This method of classification results in 100% recognition rate for 25 Random Projection coefficient. The method used for classification in [8] is Multi SVM classification on 10 normal signals, 10 Premature Ventricular Contraction (PVC) signals and 14 Left Bundle Branch Block (LBBB) signals. The accuracy of separation of normal beats to abnormal beats is 100% while it is 70% in PVC and 55.71% in LBBB with building of separate SVMs for each pair of classes. In [9] a study is conducted to differentiate five types of heart beat namely normal beat, left bundle branch beat, right bundle branch beat, premature ventricular contraction beat and atrial premature contraction beat. The fuzzy support vector machine (FSVM) is used here for the binary classification of ECG signals. The principal component analysis (PCA), unbalanced clustering (UC) and Fuzzy one-against-one (FOAO) combination is used here for the classification of long term ECG records. The classification of the extracted features [10] is done by using Artificial Neural Network (ANN). The feed forward network uses 1 input layer, 1 hidden layer and 1 output layer. The Multilayer Perceptron (MLP) uses backpropagation algorithm to find the error signal.

# **RESULTS AND DISCUSSIONS**

#### **Discussion on performance**

In paper [1], the semi-supervised discriminant analysis performance accuracy rate is 97.64%. When compared with other algorithms. The SVM classifier used for Multi-category classification here uses the cross validation of optimal parameter of SVM for better classification performance. The classification accuracy depends on the features and classifier used. In paper [2] for 770 ECG records, the overall accuracy of first feature set is 88.07% and the overall accuracy for the second feature set is 77.13%. The overall classification accuracy with both feature sets combined is 93.17%. This work shows that ECG features with lower dimensions can be extracted which improves the classification results.

The feature extraction method used in paper [3] separates 15 types of heartbeats depending on ICA features, features in wavelet and RR interval. The average classification accuracy here is 99.66%. The authors in paper [4] claim that the best classifier found for their work is Manhalanobis Distance Classifier which has a sensitivity (Se) of 96% and specificity (Sp) of 92%. In multi-lead ECG classification system based on improved ICA and SVM [5], 10 independent components from each segment are used for extracting ECG features and this is found to give more effective results. The classifier used here is SVM classifier and it classified 11 types of arrhythmia beats. The accuracy of the technique in comparison to other works is 98.18%. The feature sets [6] of time domain, wavelet transform and power spectral density are compared for processing time on a computer with Intel core i7 processor, 2.8 GHZ processor with 4 GB RAM and it is found that time domain features has less processing time with medium classification performance. In ECG analysis the preprocessing step which is critical is QRS detection. The ECG signals are classified successfully without QRS detection.

The computational complexity of Random Projection based feature extraction [7] technique is low. This helps to implement this technique in real time on a wireless wearable sensor platform. The combined accuracy of KPCA and SVM in normal beats [8] is 100% for normal beats while the accuracy is 70% in Premature Ventricular Contraction (PVC) and 85.71% in Left Bundle Branch Block (LBBB). The analysis shows that Kernel Principal Component Analysis (KPCA) with One against all (OAA) is superior to deal with Multi SVM classification.

When used with a large database, the Modified Fuzzy One –Against-One [9] consumes more time but gives good result. In the research work [10] 5 types of arrhythmias are taken for feature extraction and classification. They are normal beat (N), premature ventricular contraction (PVC), paced beat, right bundle branch block (RBBB) and left bundle branch block (LBBB). A total of 25 heartbeats are used for testing which includes 20 samples for each type of arrhythmia. Nearly 100 heartbeats are taken for training. The classification result shows that Normal subband energy (NSE) gives a high classification accuracy of 100% for normal beats, Mean subband energy (MSE) gives the highest classification accuracy of 91.6% for PVC and Relative mean subband energy (RMSE) gives a higher classification accuracy of 95.8% for normal beats, LBBB and RBBB.



#### Evaluation of various feature extraction and classification methods

Feature

This section of the paper gives an assessment of various methods used for feature abstraction and classification of bio signals. A clear view of several techniques used by various authors for the assessment of bio signals is depicted in **Table-1**. The data from MIT-BIH database is used most commonly by many researchers. The comparison table also indicates that SVM classifier is popularly used. The review study also shows that the size of the data set has a definite relation with the method used for feature extraction and classification of bio signals.

The metrics used for comparison of works of various researchers are classification accuracy, sensitivity and specificity. In certain [6] works the processing time for feature extraction and classification of bio signals are also considered. The study indicates that as the size of the data set increases, the complexity also increases and the process becomes tedious. Therefore an intelligent combination of different extraction methods and classifiers is the solution in this scenario.

Author and year	ECG data collection	extraction method	Classification method	Efficient features	Performance metrics
Hanlin Zhang, 2013	12 lead ECG data	Wavelet transform	SVM classifier	High classification accuracy, good generalization ability	Total classification accuracy = 97.64%
Ge Dingfei, 2012	MIT-BIH database	Wavelet transform	SVM classifier	possible and feasible to extract ECG features with lower dimensions from wavelet coefficients improvement in the classification results	193 ECG records considered and heartbeat classification accuracy is 88.07%
Can Ye, 2010	MIT-BIH Arrhythmias database	Wavelet Transform (WT) Independent Component Analysis (ICA)	SVM classifier	Single-lead performance is superior than any other previous works carried so far	Heartbeat classification accuracy is 99.91% with 84630 records out of 84707 ECG records correctly classified, 15 classes of heartbeats are classified final arrhythmias detection accuracy is 99.93%
Rizwan R. Sheikh, 2009	Physionet	PCA LDA	Two classifiers namely, Euclidean and Manhalanobis used	Classification of cardiac segments based on statistical and morphological features extracted from ECG	Best classifier found is Manhalanobis Distance Classifier with sensitivity Se=96% and specificity Sp=92%
Mi Shen, 2010	MIT-BIH Arrhythmia Database and 2500 practical data gathered from 500 persons	An improved Independent Component Analysis (ICA)	SVM classifier used for multi classification	Classification accuracy compared to other works is 98.18%	For multi classification average accuracy of testing data is 98.18% and the average Sensitivity is 98.68% For practical data 2-classification Experiment accuracy of testing data is 90.47% and the Sensitivity is 90.01%
Serkan Gunal, 2013	Physiobank archive	Time domain (TD), Wavelet transform (WT) and power spectral density (PSD)	Decision tree, Neural network	High classification performance if TD, WT and PSD combined in a large database Less processing time for TD with medium classification performance	For combined TD+WT+PSD features F-score = 94.7% for decision tree F-score = 90.7% for Neural network

#### Table: I. Comparison of various feature extraction and classification methods

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Iva Bogdanova, 2012	Physikalisch- Technische Bundesanstalt (PTB) Diagnostic ECG database	Random Projection	Neuro-Fuzzy classifier	Feasible and energy efficient Can be implemented wireless sensor platforms due to its low complexity	30 subjects ECG data constitutes training set and 30 subjects ECG data constitutes testing set Jaccard index is 90% for 20 coefficients
Maya Kallas, 2012	MIT-BIH Arrhythmia Database	Kernel Principal Component Analysis (KPCA)	Two multi-SVM classification schemes used are 1.One-Against-One (OAO) 2. One-Against-All (OAA)	Higher average classification accuracy	Very high average classification accuracy of 97.39% for OAA with KPCA
Mohamed cherif Nait-Hamoud, 2010	Real database from MIT-BIH arrhythmia database of ECG arrhythmias	Principal Component Analysis (PCA)	Fuzzy Support Vector Machine (FSVM)	The complexity of classification is reduced with Unbalanced Clustering algorithm	The average classification accuracy when PCA+UC+FOAO algorithms used and R=2 is 97.895%
Pratiksha Sarma, 2014	MIT-BIH arrhythmia database	Wavelet subband energy based	Multilayer Perceptron Neural network	Performance optimization of classifier by using statistical properties of subband energy features	Normal subband energy classification accuracy = 90.78% Mean subband energy classification accuracy = 84.12% Relative mean subband energy classification accuracy = 91.62%

The relation between the size of the dataset in terms of heartbeats and the classification accuracy is shown separately in **Table-2**. This table indicates that as the total number of samples increases, the complexity increases for feature extraction and classification. A suitable method has to be carefully selected in this case. The comparison also shows that wavelet transform for feature extraction and SVM classifier for classification gives better results.

#### Table: 2. Relation between data size and classification accuracy

Ref. No.	Size of dataset	Classification accuracy
[1]	Training set data size – 14301 Testing set data size – 14300	97.54%
[2]	770 classes	88.07%
[3]	85300 beats	99.25%
[4]	Training – 100 segments Testing – 50 segments	Se=96% and specificity Sp=92%
[5]	Training data – 7016 heartbeats Testing data – 91.509 heartbeats	90.74% Se=90.019%, Sp=90.74%
[6]	1200 features per class	F-score = 94.7% for decision tree F-score = 90.7% for Neural network
[7]	Training data – 30 real subjects ECG Testing data – 30 real subjects ECG	Jaccard index is 90% for 20 coefficients
[9]	Training data – 2802 samples Testing data – 1200 samples	97.895%
[10]	Training data – 25 heartbeats Testing data – 100 heartbeats	Average classification accuracy = 88.84%

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# DISCUSSION

The graph in **figure-1** gives an idea of which technique to use when the data size is small and big. It is found that good results can be obtained by choosing Independent Component Analysis technique for feature extraction from ECG signals and SVM classifier method for classification of ECG signals.



#### Fig: 1. Dependency between data size and techniques used

The success of the selected method for classification of ECG signals depends on the classification accuracy. This is depicted graphically in **figure-2**. It is found that among many classifiers, SVM classifier in combination with Fuzzy network gives good results.



### Fig: 2. Classification techniques and Classification accuracy

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The technique of semi supervised learning ability [1] gives good result only for small training set and when the labeled data is insufficient. Experiment and analysis have shown that better classification results can be obtained for lower dimension features that that of features with higher dimensions. The study on feature extraction [2] includes only wavelet coefficients with reduced dimension of 34 only. The work in paper [4] is useful only for off-line ECG signal analysis. The authors indicate that their work is helpful for medical students for learning ECG off-line analysis. The research gap in this work is that this is not suitable for online ECG analysis on real time bio signals. The results in [5] shows that the structure of the training data should be in proportion to the overall data to get better results. When the amount of data increases, the computational complexity also increases. Efficient methods of feature selection is mandatory here to get effective results. Focus on fusion of classifiers is necessary as there exists a relationship between the classifiers and the diseases they classify. The evaluation of feature sets [6] and classification is done on four types of heart conditions namely, normal, congestive heart failure, ventricular tachyarrhythmia and atrial fibrillation. No mention is made about the application of this method to other kinds of heart diseases. Also, this technique is applicable for off-line ECG analysis only. For a bigger data set [7] it is necessary to examine the average recognition rate for several executions of the proposed hypothesis. Here it is concluded that due to low computational complexity the Random projection concept is applicable for wireless sensor platforms. But how exactly this technique can be implemented is not highlighted. The research experiments [8] are conducted on MIT-BIH arrhythmia database on only three kinds of cardiac diseases. There is no mention about the application of this technique in real time ECG signal analysis. The results [10] shows that for a particular kind of cardiac disease only a particular type of wavelet subband method must be applied to get high classification accuracy. The decision on which type of wavelet subband energy method is applicable for what kind of cardiac disease comes out after conducting many experiments on trial and error basis.

# **CONCLUSION**

This paper gives a brief review on various methods applicable for feature extraction and classification of bio signals used by different researchers. The research works of various researchers are studied and compared on the basis of techniques used for feature extraction and classification and the resulting accuracy. It is noted that many research works uses wavelet transform for feature extraction and SVM classifier for classification of bio signals. Another interesting feature noted is that the selection of data size has a great impact on the selection of technique to be used for feature extraction and classification of bio signals. Further the study indicates that many research works are being carried out in this area as a feasible solution suitable for clinical application is not achieved so far.

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#### CONFLICT OF INTERESTS

The authors Maheswari Arumugam and Dr. Arun Kumar Sangaiah of The IIOAB Journal are the Research Scholar and Research Supervisor of VIT University, Vellore. The terms of this research work is reviewed and approved by the VIT University in accordance with its policy on objectivity in research.

#### FINANCIAL DISCLOSURE

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# A NEW MCDM APPROACH INTEGRATING QFD, DEMATEL WITH TOPSIS FOR EXPLORING THE EFFECT OF SOCIAL NETWORK USAGE ON ACADEMIC PERFORMANCE

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### ABSTRACT

The rapid advances in internet applications Social Networking Sites (SNS) have become worldwide used internet applications and play a prominent role in student academic performance. In order to determine the evaluation criteria of SNS usage from the perspective of student academic performance, we have integrated multi-criteria decision making (MCDM) approaches: (a) Quality Function Deployment (QFD), (b) Decision Making Trial and Evaluation Laboratory (DEMATEL) and (c) Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) under fuzzy environment is proposed. In this method, the personality, cultural and technology criteria for determining SNS usage on academic performance is established. These three kinds of criteria are assessed from the student and the faculty perspective respectively. Students give their subjective responses about the importance of SNS usage and rating the alternatives with respective to academic performance. Similarly, faculty members give their subjective preferences about the relationship between personality, cultural and technology criteria and the correlation between SNS usage on academic performance of students. Further, the hybridization of QFD, DEMATEL, and TOPSIS has not been available in the literature. Based on this context, we have combined QFD, DEMATEL, and TOPSIS approach for evaluating SNS usage on academic performance from the perspective of university students in India. The proposed approach has been tested in a real case study among VIT university students in India. A numerical illustration for SNS usage on academic performance is also given to demonstrate the application of hybrid MCDM approach.

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**KEY WORDS** 

Social Networking Sites (SNS); Academic Performance Criteria (AC); Fuzzy Multi-Criteria Decision Making (FMCDM); Quality Function Deployment (QFD); Decision Making Trial and Evaluation Laboratory (DEMATEL); Technique for Order Performance by Similarity to Ideal Solution (TOPSIS

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### INTRODUCTION

Social Networking Sites (SNS) includes Facebook and Twitter is gaining popularity and widely used applications among Asian university students. In India, SNS sites are currently utilized by 120.5 million of users on (2014) the demand is estimated at 224.2 million of social network users in 2018, up from 63.1 million in 2012 [19]. Moreover, an earlier study revealed that more than 80% of university students have used Facebook, which is a vital element in university social culture [10]. The earlier studies [1, 3, 4, 6-8, 11-13, 16-18, 20, 21] have addressed the relationship between academic performance and SNS usage through various contexts such as personality (big-five personality factors), technology context (ICT tools) and cultural context (personal importance of SNS and motives of SNS usage). Consistent with the earlier research works, this study has integrated the SNS usage and student academic performance relationship in three contexts: personality context (big-five personality factors), technology context (ICT tools), and cultural context (personal importance of SNS and motives of SNS usage). However, a comprehensive approach for measuring personality, technology, and cultural factors for evaluating SNS usage with relate to student academic performance under fuzzy environment has not been adequately available in the literature. Subsequently, fuzzy multi-criteria decision making for integrating QFD, DEMATEL, and TOPSIS for validating SNS usage on academic performance was not reported in the literature. Thus, to address this research gaps motivated us to develop a combined approach based on QFD-DEMATEL-TOPSIS under fuzzy environment is presented in this study.



To address these research gaps, an empirical study has been carried out in VIT University, India to evaluate SNS usage effectiveness from the perspective of student academic performance. The rest of this paper is organized as follows: Section 2 presents the literature reviews on SNS criteria and it measurements have been used in this study. Sections 3 present the QFD-DEMATEL-TOPSIS approach and assessment framework used in this research. Section 4 and 5 presents the empirical study results and a discussion of the study respectively. A conclusion of the study is presented finally to address the significance of QFD-DEMATEL-TOPSIS to address the SNS effectiveness.

# LITERATURE OF PAST RESEARCH WORKS

This section presents the earlier researches and constructs an assessment methodology that is used in this study.

#### Personality, cultural, and technology context for SNS usage on academic performance

Earlier research studies have addressed the personality context through big-five personality factors (extraversion, neuroticism, agreeableness, openness to experience, and conscientiousness) to measuring SNS usage on academic performance [7, 11-13,16-18]. Consistent with previous research works, this study has addressed personal characteristics from the perspective of SNS effectiveness on student academic performance through big-five indictors. In technology context, earlier studies [4, 14, 15] have investigated the use of ICT in SNS and its positive outcome in educational settings. Further, the research relating SNS and integrate the use of ICT tools that support for SNS has been addressed by few studies. Besides, in technology context, many of the researchers [6, 8, 15, 17, 20] have addressed the cultural difference and the motivations behind the usage of SNS towards the academic performance. Based on this context, the cultural aspects have been evaluated for SNS effectiveness on student academics for SNS usage. The source of measurements and possible evaluation criteria's of SNS effectiveness on academic performance are collectively determined through earlier literature [1, 3, 4, 6-8, 11-18, 20, 21, 27] as follows:

# Table: 1. Summary of source of measurements and possible evaluation criteria's of SNS effectiveness on academic performance

Personality Context(Extraversion, Neuroticism, Agreeableness, Openness to new Experience, Conscientiousness)
Does extraversion motivate you to form new connection that improves your academic performance through SNS?
Do you think extraverts perform better in academics than introverts?
Does being an extrovert help you in gaining more knowledge through SNS?
An extrovert joins more online groups to gain knowledge?
Does Neurotic people find SNS environment to be less anxiety provoking than everyday classroom studies?
Does SNS helps introvert and neurotics students to reach their full potential regarding interaction with their peers and
professors?
Does SNS helps neurotic student to share their idea more freely on SNS?(Yes/No)
Does SNS helps in collecting more people who agrees for same ideology in studies?
To what extent you have found users which engage and endorse interpersonal cooperation easily in studies?
Do you find agreeable individual more cooperative, trusting, and helpful?
Do you think SNS to be innovative in field of education?
Do you think SNS to be better means of education than others?
Are you willing to accept SNS as an educational tool?
Does less conscientiousness student spent more time using SNS and achieve better results in education?
Does conscientious individuals are likely to be high achievers as they have a strong work ethic?
Cultural Context (Personal Importance of SNS and motives for SNS use)
Do you find any information regarding your career or academic interests on social networking sites?
Do you think social networking sites can be an effective tool for e-learning?
Do you think social networking sites are more effective in communicating with your teachers than in actual class?
Do you think social media sites improve your academic performance?
Do you prefer to express your ideas and feelings on social networking sites?
Technology Context <i>(ICT tools)</i>
Does student feel more comfortable in adapting new ICT technology?
Do you find ICT tools helpful for easily access to SNS?
Academic Performance
Are Reflective learning styles include synthesis-analysis and elaborative processing more effective than agented
learning styles include methodical study and fact retention?
Do reflective learning styles (synthesis-analysis and elaborative processing) facilitate deeper understanding?
Do you think openness is most beneficial to learning when students adopt reflective learning styles?
Do you think both personality traits and learning styles are influencing with academic achievement?



Table: 2. Linguistic Terms

The panel of experts has validated the questionnaires and finalized these factors as evaluation criteria to validate SNS usage effectiveness on student academic performance under this study as shown in Table-1.

		-
Linguistic Variable	Corresponding TFN Multiplicative/Fuzzy	Crisp Value
Strongly agree	(3,4,5)/(0.9,1.0,1.0)	5/1.0
Agree	(2,3,4)/(0.7,0.9,1.0)	4/0.9
Neither Disagree Nor Agree	(1,2,3)/(0.3,0.5,0.7)	3/0.7
Disagree	(0,1,2)/(0.0,0.1,0.3)	2/0.3
Strongly Disagree	(0,0,1)/(0.0,0.0,0.1)	1/0.1

## QFD, DEMATEL and TOPSIS

Currently, there is an interest to use fuzzy QFD or House of Quality (HOQ) in multi-criteria decision making approaches. In this paper SNS usage on student academic performance has been categorized in to QFD matrixes (often HOQ) has been applied to determine the importance of parameters. Similarly, the earlier studies [5, 9] have been given a combined methodology of group decision making based on fuzzy linguistic variables for QFD applications. Based on this context, this study has employed QFD and MCDM approaches for measuring SNS usage on academic performance of university students.

Recently, fuzzy DEMATEL approach has been used for evaluation of attributes, interrelationship among the criteria and especially dealing with human uncertainty and subjective vagueness within the decision making process by the use of fuzzy set theory. In the recent studies [22, 24, 25] DEMATEL approach has been investigated in different areas of application in the context of MCDM problems. Likewise this research focuses on DEMATEL approach on designing hybrid methodology for the real data set obtained from VIT University for evaluating SNS usage effectiveness on student academic performance is presented.

TOPSIS, one of the conventional MCDM methods, has been widely used to compute the relative importance of alternatives and solving practical decision making problems with its high computational efficiency and comprehensibility. Moreover, current studies have adopted TOPSIS to solve MCDM problems [2, 24, 26]. Similarly, the basic idea of using TOPSIS in this paper is to compute the ideal solution (best values realistic of criteria) and negative ideal solution (worst values realistic of criteria) for ranking the SNS usage on academic performance factors perceived by university students.

To the best of our knowledge, up to date research on evaluation of SNS usage on academic performance case study under fuzzy environment is very limited. Moreover, assessment framework for the integration of personality, cultural and technology factors for the effectiveness of SNS usage on academic performance has not been adequately presented in the available literature. Further, the hybridization of QFD, fuzzy DEMATEL, and TOPSIS has addressed only in very few studies. Based on this context we have integrated QFD-DEMATEL-TOPSIS approach for evaluating SNS usage on academic performance from the perspective of university students in India.

# FRAMEWORK FOR EVALUATING SNS USAGE ON ACADEMIC PERFORMANCE IN FUZZY ENVIRONMENT

In this study, the QFD approach has been integrated with the fuzzy DEMATEL and TOPSIS approach for the evaluation of SNS usage effectiveness on students' academic performance from the perspective of personality, cultural and technology contexts under a fuzzy environment is proposed.

The proposed QFD-DEMATEL-TOPSIS methodologies for SNS usage on academic performance evaluation framework consists of three parts. First, we have used QFD approach for determine the importance of parameters in the respective contexts. Second, we have applied the DEMATEL approach for determining the weights of the SNS criteria. Finally, we have used fuzzy TOPSIS to identify the rank and significance of the SNS attributes from the perspective of student academic performance.

The construction of proposed framework and computation procedure of hybridization of QFD-DEMATEL-TOPSIS approach under a fuzzy environment is depicted in Figure -1.




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# EMPIRICAL CASE STUDY FOR EVALUATING THE SNS EFFECTIVENESS ON ACADEMIC PERFORMANCE

The main focus of this study is to determine the SNS usage effectiveness at individual, cultural and technology levels in academic performance research phenomenon of university students. To achieve this goal, an empirical study has been carried out in VIT University students located in India. The demographic details of the respondents of this study were undergraduate science, engineering students, and faculty members of VIT University. Two groups of student, S1 and S2, and two groups' faculty, F1 and F2 were approached for representation of their fuzzy preferences. Consequently, the empirical study has been tested among 40 DMs' (20 students and 20 faculties) of this organization to validate the effectiveness of SNS usage on academic performance. According to earlier study [2], we have followed fuzzy preference and multiplicative preference relations for DM's judgments over set of alternatives/criteria. The hybrid fuzzy QFD-DEMATEL-TOPSIS approaches were applied in this case study, as illustrated in the following sections.

#### Quality function deployment application

The basic steps of QFD approach used in this study are as follows:

Step 1: Identify the alternatives, student personality criteria, and academic performance criteria. The identified criteria are as follows:

Ouitouio	Oada	Description
Criteria	Code	Description
		Personality criteria
Extraversion	SC1	Effectiveness of extraversion on SNS usage on academic performance
Neuroticism	SC2	Effectiveness of neuroticism on SNS usage on academic performance
Conscientiousness	SC3	Direct and positive effect of conscientiousness on SNS usage on academic performance
Agreeableness	SC4	Positive effect and agreeableness on SNS usage on academic performance
Openness to experience	SC5	Previous and openness to experience on SNS usage on academic performance
Academic Performance criteria		
ICT Tools	AC1	Effectiveness of ICT tools usage of SNS on academic performance
Personal Importance of SNS	AC2	Effectiveness of personal importance on SNS usage on academic performance
Motives of SNS Usage	AC3	Direct positive effect and motives of SNS usage on academic performance

#### Table: 1. Criteria for evaluation of SNS usage effectiveness

Step 2: Construct the relational matrices and linguistic weight matrices based on the DM's ratings. The matrices, after converting to crisp values have been represented [Table-4 and -5]

Step 3: The rating matrices are aggregated to determine corresponding weights.

#### **Fuzzy DEMATEL application**

Step1: The initial direct-relation matrices are obtained from the QFD application and are represented [Table-6 and -7]. Step2: The initial direct relation matrices D1 and D2 are normalized by equations (1)-(2) to form normalized matrices N1 and N2.

$$m = \max_{1 \le i \le n} \sum_{j=1}^{n} d_{ij}$$
(1)  
$$N = \frac{1}{m} D$$
(2)



Step3: The total relation matrices R1 and R2 are computed by the following equation.

$$R = N(I - N)^{-1}$$
(3)

Step4: Weights of customer criteria and system criteria are computed using the equations (4)-(6)

$$r_i = \sum_{1 \le j \le n} R_{ij} \tag{4}$$

$$c_j = \sum_{1 \le i \le n} R_{ij} \tag{5}$$

$$W_{j} = \sum_{j=1}^{n} (r_{i} + c_{j}) / \sum_{i=1}^{n} \sum_{j=1}^{n} (r_{i} + c_{i})$$
(6)

The priority weights for student criteria (SC) and academic performance criteria (AC) are tabulated in Table-8 and Table-9 respectively.

#### **Fuzzy TOPSIS Application**

The basic steps of Fuzzy-TOPSIS approach used in this study are as follows: *Step 1:* Construct fuzzy assessment decision matrix, determine the alternatives, and normalize the scores in order to find the best alternative [Table-10].

Step 2: Input the weights which is obtained from the DEMATEL method to calculate the weighted normalized decision matrix as given in Table-11.

Step 3: The best evaluation and worst evaluation value with respect to each criterion is determined through FPIS and FNIS.

Step 4: Obtain relative closeness coefficient to the ideal solution and rank the alternatives [Table-12].

# RESULTS

The numerical results of the empirical study have been illustrated as follows:

#### Table: 2(a). Relation between student criteria rated by Student S1

Criteria	SC1	SC2	SC3	SC4	SC5
SC1	0.5	0.65	0.6	0.4	0.65
SC2	0.35	0.5	0.65	0.9	0.65
SC3	0.4	0.35	0.5	0.15	0.15
SC4	0.6	0.1	0.85	0.5	0.65
SC5	0.35	0.65	0.85	0.35	0.5

Table: 3(b). Relation between student criteria rated by student S2

Criteria	SC1	SC2	SC3	SC4	SC5
SC1	0.5	0.55	0.3	0.4	0.65
SC2	0.45	0.5	0.3	0.9	0.35
SC3	0.7	0.7	0.5	0.15	0.65
SC4	0.6	0.1	0.85	0.5	0.65
SC5	0.35	0.65	0.35	0.35	0.5



#### Table: 4 (c). Relation between student criteria rated by faculty F1

Criteria	SC1	SC2	SC3	SC4	SC5
SC1	0.5	0.4	0.2	0.9	0.7
SC2	0.2	0.5	0.6	0.9	0.7
SC3	0.3	0.1	0.5	0.8	0.5
SC4	0.8	0.2	0.7	0.5	0.3
SC5	0.2	0.1	0.2	0.6	0.5

#### Table: 4 (d). Relation between student criteria rated by faculty F2

Criteria	SC1	SC2	SC3	SC4	SC5
SC1	0.5	0.8	0.4	0.1	0.7
SC2	0.2	0.5	0.6	0.9	0.7
SC3	0.7	0.8	0.5	0.9	0.5
SC4	0.8	0.2	0.7	0.5	0.6
SC5	0.2	0.2	0.2	0.6	0.5

#### Table: 4(a). Relationship between academic performance criteria rated by student S1

Criteria	AC1	AC2	AC3
AC1	0.5	0.3	0.6
AC2	0.7	0.5	0.35
AC3	0.4	0.65	0.5

#### Table: 5(b). Relationship between academic performance criteria rated by student S2

Criteria	AC1	AC2	AC3
AC1	0.5	0.3	0.6
AC2	0.7	0.5	0.35
AC3	0.4	0.65	0.5

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#### Table: 5(c). Relationship between academic performance criteria rated by faculty F1

Criteria	AC1	AC2	AC3
AC1	0.5	0.5	0.3
AC2	0.3	0.5	0.4
AC3	0.4	0.5	0.5

#### Table: 5(d): Relationship between academic performance criteria rated by faculty F1

Criteria	AC1	AC2	AC3
AC1	0.5	0.5	0.3
AC2	0.3	0.5	0.4
AC3	0.4	0.5	0.5

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#### Table: 6. Aggregated relationship between student criteria

Criteria	SC1	SC2	SC3	SC4	SC5
SC1	0.5	0.6	0.375	0.45	0.675
SC2	0.3125	0.4625	0.5375	0.9	0.6
SC3	0.525	0.5	0.5	0.5	0.45
SC4	0.7	0.65	0.775	0.5	0.55
SC5	0.275	0.4	0.4	0.475	0.5

#### Table: 7. Aggregated relationship between academic performance criteria

Criteria	AC1	AC2	AC3
AC1	0.5	0.4	0.45
AC2	0.5	0.5	0.375
AC3	0.4	0.575	0.5

# Table: 8. Priority weights of student criteria

Weight
0.3780
0.4219
0.3774
0.4451
0.3775

Table: 9. Priority weights of academic performance criteria

Criteria	Weight
AC1	0.667
AC2	0.661
AC3	0.673

#### Table: 10. Fuzzy rating of alternative with respect to criteria

	SC1	SC2	SC3	SC4	SC5	AC1	AC2	AC3
<b>A</b> 1	(0.2,0.3,0.7,0.8)	(0.1,0.4,0.7,0.8)	(0.3,0.7,0.8,.9)	(0.1,0.3,0.7,0.5)	(0.5,0.6,0.8,1)	(0.4,0.5,0.8,1)	(0.3,0.7,0.8,1)	(0.2,0.5,0.8,1)
A2	(0.1,0.4,0.7,0.9)	(0.3,0.7,0.8,.9)	(0.2,0.5,0.8,1)	(0.1,0.5,0.8,0.9)	(0.2,0.5,0.8,1)	(0.2,0.3,0.7,0.8)	(0.5,0.6,0.8,1)	(0.2,0.3,0.7,0.9)
<b>A</b> 3	(0.3,0.5,0.7,0.8)	(0.2,0.5,0.8,1)	(0.5,0.6,0.8,1)	(0.3,0.7,0.8,.9)	(0.2,0.3,0.7,0.8)	(0.1,0.5,0.8,0.9)	(0.2,0.3,0.5,0.9)	(0.5,0.6,0.8,1)
<b>A</b> 4	(0.4,0.7,0.8,.9)	(0.5,0.6,0.8,1)	(0.2,0.6,0.7,0.8)	(0.2,0.6,0.7,0.8)	(0.5,0.6,0.8,1)	(0.3,0.6,0.8,1)	(0.2,0.5,0.8,1)	(0.5,0.6,0.8,1)
<b>A</b> 5	(0.1,0.5,0.8,0.9)	(0.3,0.8,0.7,1)	(0.1,0.4,0.7,0.9)	(0.1,0.5,0.8,0.9)	(0.3,0.8,0.7,1)	(0.2,0.5,0.8,1)	(0.5,0.6,0.8,1)	(0.3,0.8,0.7,1)



## Table: 11. Weighted normalized matrix

		Be	nefit crite	С	ost criter	ia		
	SC1	SC2	SC3	SC4	SC5	AC1	AC2	AC3
<b>A</b> 1	0.1465	0.1455	0.1807	0.1402	0.1849	0.3286	0.3148	0.3070
A2	0.1538	0.1964	0.1673	0.2015	0.1594	0.2434	0.3260	0.2579
<b>A3</b>	0.1685	0.1819	0.1941	0.2366	0.1275	0.2799	0.2136	0.3561
<b>A</b> 4	0.2051	0.2110	0.1539	0.2015	0.1849	0.3286	0.2810	0.3561
<b>A</b> 5	0.1685	0.2037	0.1405	0.2015	0.1785	0.3043	0.3260	0.1965

Table: 12. Ranking of alternatives

Alternative	Relative closeness to ideal solution	Rank
A1	0.72	1
A2	0.48	4
A3	0.51	3
A4	0.61	2
A5	0.44	5

# DISCUSSION

The integrated QFD-DEMATEL-TOPSIS methodology has been used for investigation of SNS usage on the academic performance of students from Asian countries and especially in VIT University, India. The data used in this study were collected from faculty and students of VIT University to explore the SNS usage on academic performance through survey questionnaires. The faculty and students have given their subjective judgments based on multiplicative preference/fuzzy preference relations as shown **Table- 3**. Totally 4 (5 alternatives) DMs' samples are represented in this study to explore the SNS effectiveness criteria using linguistic assessments on fuzzy preference/multiplicative preference relation. In addition, **Tables 6 and 7** depicts the aggregation of DMs ranking of each alternative with respect to criteria on Table-3 using fuzzy linguistic items as shown in **Table-2**. Subsequently, the relative importance of the criteria and output of QFD modeling has been represented in **Tables-8 and 9**. The weights of DEMATEL results address that Agreeableness (SC4) and Motives of SNS usage (AC3) are more significant that those other evaluation factors. Consequently, the QFD-DEMATEL modeling results have been applied in the TOPSIS method and their results are given in **Tables- 10-12**. From the above results, it can be concluded that alternative A1 is closest to the ideal solution while alternative A5 is farthest from it. Thereby, SNS usage on university students can facilitate the effectiveness of student learning performance in academic organizations.

# CONCLUSION

The main objective of this paper is to provide an approach to evaluate SNS effectiveness on from the student academic performance perspective. In order to do that, a new MCDM approach combining QFD-DEMATEL-TOPSIS has been proposed in the fuzzy environment. Moreover, this proposed approach has been investigated among VIT University students to explore the influence of SNS effectiveness in academic performance. Furthermore, to demonstrate the applicability and creditability of QFD-DEMATEL-TOPSIS approach, the framework has been validated based on the data collected from the VIT university students. Consequently, this study has presents two valuable contributions: (i) a comprehensive overview of the factors influencing SNS usage on academic performance (ii) QFD-DEMATEL-TOPSIS approach to find the relative importance of the criteria and to rank the criteria. In this study, we have suggested a research framework based on QFD-DEMATEL-TOPSIS which can effectively validate and rate the SNS evaluation criteria in the context of students' academic performance. Subsequently, the case study results address that personality, technology, and cultural context factors have a significant impact on the evaluation of the SNS effectiveness of student academic performance in the academic environment. The prototype of proposed approach (QFD-DEMATEL-TOPSIS) can be developed in the future it can be enhanced into an efficient tool to handle MCDM in a real time settings.



Through MCDM approach we have revealed that SNS and its influential factors are the main contributors to enhance student learning performance in an academic setting.

#### **CONFLICT OF INTEREST**

Authors declare no conflict of interest.

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# PERFORAMNCE ENHANCEMENT FOR AUTOMATED ANALYSIS IN HUMAN BRAIN SIGNAL PROCESSING TO FINDING ALZHEIMER'S SYNDROME USING INTELLIGENT TECHNIQUES

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# ABSTRACT

Today efficient brain signal recognition is limited to find different brain diseases; using hardware like Electroencephalogram (EEG), Magnetoencephalograms (MEG), and Functional MRI (fMRI). Alternatively, abnormal brain waves have shown to be associated with particular brain disorders (e.g., Alzheimer's disease and epilepsy). But the problem with this approach is that there are not many algorithms that could efficiently extract signals from a brain to find Alzheimer's disease. In this research paper, we suggest the design of new algorithm which could do this job of translating brain signals to digital text data for Alzheimer's disease. We propose a new approach using which the problem of recognizing brain signals for Alzheimer's disease can be solved. We also provide the implementation details of this software. For the implementation of our idea, we propose a new intelligent technique Architecture. The technique adopted by the EEG signals used in brain for Alzheimer's disease, guided and stimulated us to design this research work. Details regarding the automatic preprocessing and decoding interpretation that would be essential and the shortcomings are also included in the research work. Received on: 10<sup>th</sup>-March-2015 Revised on: 18<sup>th</sup>-May-2015 Accepted on: 26<sup>th</sup>-May-2015 Published on: 8<sup>th</sup> -Aug-2015

**KEY WORDS** 

Electroencephalograph (EEG); Alzheimer; Back Propagation Network (BPN); Independent Component analysis (ICA; Non-Linear Energy Operator (NLEO); Discrete Wavelet Transform (DWT).

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#### INTRODUCTION

In this paper we propose a novel method for the classification of memory disorders and Alzheimer. Memory disorders now a days gain much more attention in the research area because it is the basic symptoms of some major diseases such as cancer and psychiatric problems [1]. After pain, memory disorder is the second most indicator of illness. Memory loss is the basic symptoms of some major diseases such as cancer and Psychiatry. So memory disorder should be detected earlier and thereby give better treatments for the patients. Alzheimer is the abnormal activity of the brain. It is noticed that one in hundreds of the populations are the victims of this diseases. Sometimes Convolutions and unconscious are the symptoms of Alzheimer. All the above two diseases are diagnosed by the encephalograph (EEG).

The electrical fauna of the human nervous classification has been predictable for more than a period. It remains well recognized that the difference of the external potential circulation on the scalp replicates functional happenings emerging from the essential brain. This external potential difference can be verified by sticking a group of electrodes toward the scalp, and computing the electrical energy among couple of these electrodes, which remain before clarified, amplified, and verified. The resultant information is titled the EEG [13]. The EEG needs the lesser signal generosity in the range of microvolts ( $\mu$ V). EEG frequency band are normally classified into five categories. The meaning of these different frequencies is not completely known. They are alpha, beta, theta, delta and gamma. Alpha waves are rhythmic waves occurring at a frequency between 8 and 13 hertz. These waves are found in the normal persons when they are awake in a quiet, resting state [1]. When the subject is in memory loss, the alpha waves disappear completely. Beta waves normally occur in the frequency range of 14 to 30 hertz. These waves can be divided into two type's beta 1 waves and beta 2 waves. Beta 1 is elicited by the mental activity and the other is inhibited by it. Theta waves have frequencies between 4 and 7 hertz. These waves occur during emotional stress, particularly during periods of disappointment and frustration. Delta waves occurs only once every 2 or 3 seconds.

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They occur in deep Alzheimer, in infants and in serious organic brain diseases. Gamma waves consist of lowamplitude, high-frequency waves resulting from attention or sensory stimulation. Architecture for implicated processes is shown in **Figure-1**.

All these waves have their own particular shapes in the signals and if any kind of diseases occur then the normal wave's shapes have changed. Theta and delta waves are normally used to diagnosis the memory disorders. Sometimes the signal shape of Alzheimer and one kind of memory loss disorder say narcolepsy may overlap. Visual inspection of EEG signals is very time consuming and very laborious work. So the EEG signal parameters extracted and analyzed using computers, are highly useful in diagnostics [11]. The information can be as several for example 128 channels then usually 20 channels remain used and copies characteristically last used for 30 to 60 minutes of time domain data, through a bandwidth among 0.1 to 150Hz, which remains demonstrated digitally arranged on a computer screen [15].



#### Fig: 1. Architecture for implicated processes

# **TECHNIQUES AND RESOURCES**

The brain analysis and classification follows a specific method custom designed for the identification of brain diseases. Figure –2 shows the block diagram of the proposed neural network [2] based automated brain signal analysis system.



#### Fig: 2. Automated System design of the proposed system.

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#### Signal attainment and EEG database

EEG acquisition collects these underlying electrical patterns from the scalp, and digitalizes them for computer storage. In our experiments, we have used the10-20 Classification of Electrode Location, which is constructed on the association among the position of an electrode besides the original part of cerebral cortex ["10" and "20" mention to the 10% or 20% interelectrode distance]. These signals include normal and abnormal signals of EEG. Divide them and name them as set A and set B. Set A contain normal signals. B contains abnormal signals such as memory disorders and Alzheimer signals. In the present study we classify them as two datasets.

#### Preprocessing

This Once the signals are acquired, it is necessary to clean them. Usually EEG signals are contaminated [5]. These contaminations may leads to misdiagnosis of diseases. So before analyzing the signals, it should be artifact free [6]. To remove the artifacts there are various methods. However, environments with large, low-frequency electromagnetic fields can cause a significant interference to EEG recordings. The second limitation is the activity of muscles in the head region (e.g. chewing, speaking, etc). The electrical activities of these muscles have, usually, much large amplitude then the EEG. With some effort in quality control and artifact processing the disadvantages can be compensated [14]. The best method for EEG signal preprocessing is Independent Component Analysis (ICA) [10]. ICA is a method for finding underlying factors or components from multivariate statistical data.

ICA outperforms the traditional principal component analysis (PCA) in numerous applications; in specific, it has been suitable in the place of removal of optical artifacts after the EEG, wherever principal PCA could not distinct eye artifacts from brain signals, specifically when they must comparable amplitudes [13]. Principal component analysis (PCA) is alternative technique that remains accessible, when associated with ICA for the selected application went short of effectiveness and efficiency [16].

Let s (t) is the signals generated. These signals are linearly combined through a memory less channel, mathematically described by the mixing matrix A. A has M rows, N columns, and xi (t) (I = 1 ... M) are the signals observed at the channel output.

The mixing model is described by the following equation

X (t) = A.S (t)....(1)

Where s (t) and x (t) are the source and mixture signal vectors, respectively.

After mixing, the preprocessing of ICA involves the following steps. Centering, whitening and rotation. Centering make the signals centered in zero.

The main purpose of centering is to make the zero mean. Centering is achieved by simply subtracting the mean of signal from each reading of that signal.

X = x-E (x).....(2)

The next step is to whiten or sphere the data. This means that remove any correlations in the data [7]. Whitening is achieved by the eigen-value decomposition of the covariance matrix. Taking the covariance between every pair of signals can form a covariance matrix.

This matrix will be square and symmetric.

COV(X) = E(XXT)

Perform eigen-value decomposition on the covariance matrix and then transform the data so the covariance matrix of the transformed data is equal to the identity.

This procedure is called sphereing or whitening.

 $V = ED^{-1/2}E^{T}$ .....(3)

(Eigen value decomposition of covariance matrix E {XX  $^{T}$ } = EDE  $^{T}$  and D-1/2 = diag (d1-1/2, d2-1/2 ... dn-1/2)]

Now rotation can be done by the inverse of whitening operation on the mixing matrix A.

 $S = \tilde{A}^{-1}Z$ .....(4)

Where Z = VX.

The disadvantages of EEG are that the signal to noise ratio is poor; and it is necessary to deal with large subject-specific, inter- and intra-trial variability; hence, sophisticated data analysis has to be completed.





#### Fig: 3. ICA separation of a four sec EEG sample.

#### Segmentation

Novel way to examine non-stationary signals, it remains occasionally calmer to fragment signals hooked on pseudo-stationary sections. By means of adaptive segmentation algorithms [4], the non-stationary signals can be broken down into segments that are pseudo-stationary, and analyzed or processed separately. Signal segmentation is based on energy and frequency of signal and the signal has to be divided according to its characteristics. The main purpose segmentation is to find the edge and the energy of the signal. Among the various segmentation algorithm's NLEO is the best one.

A segmentation algorithm involving a non-linear energy operator (NLEO) is defined as follows.

Where x (n) is the input EEG signal at current time n and  $\Psi$  [ (x (n) ] = x (n -1) x (n-2) -x (n) - x (n-3) is the nonlinear energy operator. Using NLEO, we can calculate the localized energy, and segment boundary. To detect a sudden change in the NLEO, a variable used for segmentation criteria is defined as follows.

Where 2N is the window size. Gnleo (n) reaches a peak when the  $\Psi$  (m) is discontinuous. The boundaries can be detected by the peaks of Gnleo (n). According to the windowing and thresholding equation the significant level can be obtained. The threshold equation can be defined as

T (n) = max [ Gnleo (n – L/2 : n+L/2 ) ], L window length)|).....(7)

Where Gnleo (n) is the energy change in the window obtained by using a moving window with length 2N at center n, and T (n) is the threshold value obtained by using another moving window with length L. G (n) represents the significant energy change after thresholding.

#### Feature extraction

After segmentation features should be extracted. Different features are suited for different diseases. The proposed system uses discrete wavelet transform (DWT) for memory disorders and spectral entropy for Alzheimer [8]. Spectral entropy quantifies the spectral complexity of the time series. Power spectral density is defined as

 $P(\omega) = I / N(|X(\omega)|)....(8)$ 

Where X ( $\omega$ ) represents fast Fourier transform of the signal. The normalization of equation (8) gives the spectral entropy and is defined as

H ( $\omega$ ) = -  $\Sigma$  p $\omega$  log p $\omega$ .....(9)



Discrete wavelet transform (DWT) is suited to non-stationary signals and performs a multiresolution analysis of a signal. It builds on the concept of scales. The following features were found to be suitable for Alzheimer detection [3]. Zero crossing Extrema.

#### Neural network classifier

Artificial Neural Networks (ANN) is considered to be good classifier due to their inherent features such as adaptive learning, robustness, self-organization, and generalization capability [12]. ANN's are particularly useful for complex pattern recognition and classification tasks where enough data are available for training and where the simpler classification algorithms fail. In neural network [9], designing the architecture and network training are the main issues. If training is insufficient, then network will not learn properly. If excessive training of network is unable to generalize the training database. For each type of EEG signals, a corresponding output class is associated. In order to make neural network training [2] more efficient, the input features were normalized so that they fall in the range [0, 1]. Since the number of output class is 2, the ANN with one output is sufficient to produce a code for each class. Figure-4 shows the co-efficient analysis.

The output are represented by





# Fig: 4. Co-efficient analysis

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The proposed system makes use of BPN. It is a multilayer, feed forward and supervised learning model. Back propagation remains the preeminent recognized training algorithm aimed at neural networks besides still one of the maximum suitable. It requires lesser memory necessities than utmost algorithms then frequently influences a suitable error level quite rapidly, even though it can be very slow to converge suitably on an error least possible. Figure-5 shows the BP network.



Fig: 5. Architecture of Back Propagation Network

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#### Validation

The performance of BPN are evaluated by using the two parameters namely sensitivity (SE) and specificity (SP) which are defined as follows.

SE =  $TNcp/TNcp \times 100...$  (10)

Where TNCP signifies the entire quantity of properly identified positive patterns and TNAP signifies the entire amount of actual positive patterns.

A positive pattern specifies a perceived seizure.

 $SP = TN_{CN} / TN_{CN} \times 100....(11)$ 

Where TN<sub>CN</sub> signifies the entire quantity of properly identified negative patterns and TN<sub>AN</sub> signifies the entire quantity of real negative patterns.

A negative pattern specifies an identified non seizure. Figure-6 shows the output screen shot of the final output.



Fig: 6. Screen shot of the Final yield

#### CONCLUSION

The Work proposes an algorithm which will prove useful in biomedical signal processing where a specific underlying signal requires to be extracted from the possibly noisy multi-channel recordings. It is clear that the method is suitable for the extraction of independent components from the measured EEG. The algorithm worked efficiently in extracting memory spindle as well as Alzheimer seizures which were distributed throughout the measurement channels. We expect that this system will be valuable in the department of neurology and will help mankind. Current developments in computer hardware in addition to signal processing have made conceivable the consumption of EEG signals or "brain waves" for communication among humans and computers [13] and the same work can further be extended towards the domain also.

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#### CONFLICT OF INTEREST

No conflict of interest

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EVEN

ARTICLE

# A SURVEY ON FORENSIC SKETCH MATCHING

**OPEN ACCESS** 

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# ABSTRACT

Biometrics is one of the unique ways of identifying a person by the physiological features in the human body. Various biometric techniques includes features in the human body like the facial, iris, gestures, fingerprint, gene, key stroke biometrics, etc. In the facial recognition many algorithms are explored highly with various different orientations. The facial matching framework accepts the input as faces and the outputs the recognized faces from the image database. The objective of forensic sketch matching is the mapping between the image databases with the sketches. Since the information obtained from the victims is almost inadequate the mapping is very complicated. The selection of the features and modeling them for matching without any human intervention is still a challenging task. This paper gives a survey on the various sketch matching techniques that are used in the face matching and recognition. The complexity in forensic sketch matching is analyzed and a new model based on the neural network is proposed to automate the forensic sketch matching system. Received on: 18<sup>th</sup>-March-2015 Revised on: 20<sup>th</sup>-May-2015 Accepted on: 26<sup>th</sup>- June-2015 Published on: 16<sup>th</sup> -Aug-2015

**KEY WORDS** 

Biometrics; Forensic sketch; Sketch matching; Viewed sketches; Face recognition

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# INTRODUCTION

Biometrics is a technique for identifying a person based on the physiological features of the human body. Some of the biometric techniques include fingerprint recognition, facial recognition, iris recognition, key stroke biometrics, signature, voice recognition, hand geometry, DNA. Numerous algorithms are available for face recognition and matching the faces. Various faces are identified automatically by the algorithms. The finger print is also an important feature to uniquely identify the persons. The advantage of finger print biometrics is in the case of twins the face resembles but the finger print of the twins cannot be same. In the forensics finger print plays a major role to identify the suspect easily. But in the forensic images it is impossible to depict the finger print by the artist from a victim. This also applies to the iris recognition where the iris pattern of the human is identified and recognized. In the case of the forensic matching the mapping is to be performed with the facial image and a sketch. So it leads to the development of various face matching algorithms with the forensic sketch and original image. Even the suspect can be identified by the voices, but sometimes it can be duplicated by the hackers. In the DNA a gene matching is done for identifying the suspect. In the key stroke biometrics the key press events of the users are identified and matched. It is useful in detecting uneven access by the fraudulent in the login pages. In forensics the Key stroke and gene plays a lesser role. But the finger print and facial features plays a vital role in identifying the suspect in a crime scene. The major motivation behind this paper is in all the existing models a manual inspection is needed to confirm the criminals. So it is very much necessary for an automated system without human intervention to identify and arrest the criminals before they commit the next assassination.

# OUTLINE OF FACE MATCHING AND SKETCH MATCHING

#### Categories of face matching

Many face matching algorithms are proposed to uniquely identify and recognize the faces. The facial point's distances are collected from the face image and they are mapped with the input image for identifying the faces. Also researchers have explored various face detection algorithms with different categories. Figure-1 shows the various categories given below. It includes face recognition with multiple orientations like straight pose, side pose, with and without spectacles, under various face expressions (mouth open, mouth closed, mouth opened with teeth) and photos



under various illuminations. Also varieties of researches are going with the images under age variations which become a massive challenge.



#### Fig: 1. Various ways for face detection

#### Overview of forensics and sketches

Face matching is a difficult process as it is taken from various sources under various conditions. The sources of image are from surveillance cameras, social networks, and mobile cameras etc which are captured under different conditions. There must be a source to capture the images for the further process. But difficulties arise if there are no image capture sources. It becomes a big challenge for the police to find out the suspect without an image. So to identify the suspect the police identify the people in the crime environment and ask for the information about the person for the further investigation.

Forensic is a logical technique for collecting and analyzing the information about the crime in the earlier period. The aim is to detect the crime and identify the suspect based in the information collected. After collecting the information a sketch is drawn named forensic sketches. Sketches can be categorized into two types one is viewed sketches and another is forensic sketches. As for as viewed sketches in considered the sketch is drawn by viewing the photos of the particular person. So a qualified artist is needed to draw the face of the person. Also the task is not much complex as the photo of the person is available [13].

In the next case of the forensic sketches the information about the person is not available with the artist. All the information are to be collected by the people in the surrounding area where the incident has turn out. So the artist sits along with the people who were on the spot and analyses about the various facial features and draw the sketches. This seems to be complex problems where the image of suspect drawn will not be exactly matching. Many forensic artists are specialized in drawing the forensic sketches [3].

In the case of the forensic sketches certain methodology are to be followed strictly like more preprocessing techniques cannot be applied. The reason behind this is the people in the spot can remember more of the external features of the face than the internal features. External features include hair style, race, color, age factor, gender etc. Internal features are rarely identified. A high preprocessing may leave most of the external features. So a novel preprocessing method is always necessary during the process of forensic sketches. Figure- 2 shows the steps in the forensic sketch matching for face matching [13].

# OVERVIEW OF SKETCH MATCHING TECHNIQUES

There are various techniques available with face sketch recognition. The various images of a single person are combined into a single image and a model is created based on the combination to enhance the matching of the forensic sketches. Even though this method provides an acceptable result a human analysis is needed to pin point the final suspect [1]. The meaningful information from the facial attributes are obtained and cross modeled architecture was created, it works with caricature sketches but still it out performs with forensic sketches [2]. Availability of image data base to for the matching is very less so researchers started to create test set databases with sketches for the matching [4]. The face is converted into a sketch and the matching is performed over the image with the sketches. The comparison with the geometry and the Eigen face methods shows a better performance [5].



Also face photo match retrieval through the sketches are performed by an invariant descriptor called Gabor shape [6]. The features extracted from the viewed face sketches must be spotted in varying illumination, noise and scaling. So researchers has even developed detection using SIFT (Scale Invariant Feature Transform). As for the above said methods the complexity of the problem was not further explored with large set of images [7]. The methodology of converting image into a sketch and vice versa is also performed for the matching of the image. Multi scale markov random fields are used in synthesis and recognition. So a new combined sketch photo model is learned in this method [8].



Fig: 2. Steps in forensic sketch matching

The external features of the suspect can easily identify and explained by the people in the spot. Researchers have developed methods to retrieve images using the tattoo. To eliminate the duplicates various metadata were used by the researchers. The system developed is based on unsupervised method. So further extensions can be done in the semi supervised methods and unsupervised methods [9].

In some methodologies a pseudo sketch based on the local linear safeguard of geometry between the photo and sketch images are generated and non discriminate analysis were used in the recognition of the probe sketch. The external feature hair is omitted in this methodology. Also the above said method will not work with different pose, illumination and photos with different conditions [10]. Certain features in the face can be remembered by the humans easily which includes marks in the faces. In order to identify the facial marks researchers have developed various methods using morphological operators. But still the accuracy can be improved with an automatic mark deduction system [11].

The above said methods were performed only for the viewed sketches. Only two large scale experiments were performed till date with the forensic sketches. The first large scale was done by Brendon klare et al for the



forensic sketches. The sketches and photos are distinguished by SIFT and Multi scale local binary patterns image descriptors. Filtering was done by race and gender also the results were compared which shows improvement in the accuracy [13]. The second large scale was performed by Kotha *et al* where the methodology based on Speeded Up Robust Features (SURF). Also an improved preprocessing method was proposed in order to preserve the external features. But the filters were not used for the improvement of the results [14]. At one point of time a human suggestion is needed to identify the images based on the comparison of top N rankings of the images. A fully automated forensic sketch matching is yet to be developed.

# **PROPOSED ARCHITECTURE**

A proposed architecture that using fuzzy and neural network to reduce manual intervention is given in Figure-3



Fig: 3. Using fuzzy and neural network to reduce manual intervention

# CONCLUSION

This paper gives a clear picture of all the existing methods and the research gaps in the existing methods. So the new framework will take in account of all the facial attributes with the balance of the neural network an automated forensic sketch facial recognition will give an accurate output. The systems complexities are to be analyzed. But due to the insufficient availability of the database the complexity analysis were not performed at all the cases. The



forensic sketches were not performed over various poses with a higher efficiency. So in future an efficient multi pose forensic sketch recognition must be performed without any human intervention.

#### CONFLICT OF INTEREST

Authors declare no conflict of interest.

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# TUNED HYBRID SOFT CLUSTERING ALGORITHM FOR UNCERTAIN INFORMATION SYSTEM

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# ABSTRACT

Clustering is an important mission in the field of machine learning, pattern recognition and web mining. Handling uncertain data in the information system is one of the key research topics in the vicinity of knowledge representation. Number of clustering algorithms are available [23][6][12]27]; but many of those algorithms are challenging when dealing with uncertain data. The aim of the paper is to tune two existing rough c-means and fuzzy c-means and integrate them into a tuned hybrid soft clustering algorithm termed as the tuned rough-fuzzy c-means algorithm. Rough c-means is extremely sensitive to the initial placement of the cluster centers. The proposed algorithm is enhanced by introducing dynamic centroid computation. The proposed algorithm performance is compared with the existing rough c means, fuzzy c-means, and rough fuzzy c –means approaches. The effectiveness of the algorithm is verified on real and synthetic datasets.

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Clustering; Uncertain; RoughSet; Fuzzy; C-means

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#### INTRODUCTION

Cluster analysis [1] is a technique for finding natural groups present in the data. It divides a given data set into a set of clusters in such a way that two objects from the same cluster are as similar as possible and the objects from different clusters are as dissimilar as possible. Clustering techniques have been effectively applied to a wide range of engineering and scientific disciplines such as pattern recognition, machine learning, psychology, biology, medicine, computer vision, communications, and remote sensing. A number of clustering algorithms have been proposed to suit different requirements. Clustering is categorized as hard or soft in nature .Soft clusters may have fuzzy or rough boundaries. In hard clusters, the elements which are similar to each other are placed in the same cluster. The elements whose natures differ with each other drastically are placed in different clusters. Soft clustering [12] helps researchers to discover overlapping clusters in many applications such as web mining and text mining. Hence soft clusters may have two types of boundaries 1) Fuzzy boundary 2) Rough boundary. Fuzzy clusters need an association degree to distinguish each element present in the cluster. The elements in the rough clusters are distinguished with the help of boundary region. The relations between rough sets and fuzzy sets were compared [2, 4]. On the whole, both theories deal with the difficulty of information granulation: the theory of fuzzy sets is centered upon fuzzy information granulation, where as rough set theory is paying attention on crisp information granulation.

Data generation methods create uncertain, incompleteness, and granularity in information system which provides inaccurate result in data analysis. Rough set theory is a valuable tool for data mining. In the past few years the concept of basic rough sets has been extended in many different directions. The original rough set theory proposed by Pawlak [18-20] is based upon equivalence relations defined over a universe. It is the simplest formalization of indiscernibility. However, it cannot deal with a number of uncertain problems in real information systems. This has direct to numerous significant and motivating extensions of the original concept. Bezdek's fuzzy c-means [10, 11] is the another most popular soft clustering algorithm for many real life applications in a very diverse range of domains. K-means is one of the cluster centers. Numerous initialization methods have been proposed [15] to deal with this problem. Efficient hybrid evolutionary data clustering algorithm K-MCI [9] has been presented to handle high dimensional data and large cluster. Fuzzy clustering is suitable to classify ordered sequences in human activity pattern analysis [22]. However, the majority of the present fuzzy clustering modules [3, 4, 16] packaged in both open source and commercial products



have lack of enabling users to explore fuzzy clusters extremely and visually in terms of examination of different relations among clusters.

Attribute weighted fuzzy clustering has became a very active area of research and interval number has been introduced for attribute weighting in the weighted fuzzy c-means (WFCM) clustering approach [13, 25]. The existing fuzzy and rough clustering approaches have been refined based on the concept of shadowed sets. Shadowed clustering [26] has been presented which serves as a conceptual and algorithmic bridge between the FCM and RCM. Much work has been carried out using rough c-means, fuzzy c-means and rough fuzzy c-means in data clustering. The extensive survey of the significant extensions and derivatives of soft clustering approaches have been studied [5, 7]. In this paper, tuned rough fuzzy c-means clustering approach is proposed to resolve the uncertainty of information system.

This paper focuses on traditional rough fuzzy c-means and tuned rough fuzzy c-means approaches for handling uncertainty presents in the information system. The remainder of this paper is organized as follows. The introduction about the work is discussed in section 1. In Section 2, traditional soft clustering algorithms are discussed under materials and methods. Section 3 investigates experimental analysis of tuned soft clustering algorithm for uncertain data. Section 5 discusses performances of the proposed algorithm and this paper concludes in section 6.

# MATERIALS AND METHODS

#### Traditional soft clustering

Fuzzy sets and roughsets [27-31] were incorporated in the c-means framework to develop the fuzzy c-means (FCM) [10], rough cmeans [6, 8, 12, 23, 24] and rough-fuzzy c-means (RFCM) [21, 23] algorithms, respectively. While membership in FCM enables efficient handling of overlapping partitions, the roughest [17, 19] deal with uncertainty, vagueness and incompleteness of data in terms of upper and lower approximations.

#### Rough C-means

Rough c-means algorithm was introduced by Lingras, which describes a cluster by its centroid and its lower and upper approximations. In rough c- means, an object can belong completely in one cluster or can be in the uncertainty region or boundary of two clusters. The lower and upper approximations are weighted differently. In each iteration step of the algorithm, the distance of objects from the cluster centroids are computed and if the difference between the two lowest distances is less than a specified threshold value the element is placed in the boundary of the two clusters. Otherwise, the element is placed in the cluster for which the distance is the minimum.

#### Fuzzy C-means

Developed by Bezdek, the fuzzy C-means algorithm is a powerful method to classify fuzzy data by using the concept of objective function. This approach which minimizes the objective function is expressed in the form of an iterative algorithm makes it possible to reach at an optimal solution, where the solution space is of infinite cardinality. In fuzzy c-means data may belong to one or more than one clusters. It brings in the concept of having membership values. Each object will have a membership in every cluster; which represents the degree to which the element belongs to the cluster. So, here also the clusters are not disjoint. The multiple membership of data models uncertainty of elements belonging to clusters.

#### Rough-Fuzzy C-Means

It combines the concepts of rough set theory and fuzzy set theory. It has been established that the rough membership function is more general than the fuzzy membership function. However, this generalized membership function has some costs to pay as it does not provide a formula to find the membership values for union and intersection of rough sets. However, in fuzzy set theory we have definite formulae for the computation of the membership values. Thus the hybrid algorithms takes care of both the features by providing membership values to elements as well as modeling vagueness in data through the boundary concept. The concepts of lower and upper approximations in rough set deals with uncertainty and, vagueness whereas the concept of membership function in fuzzy set helps in enhancing and evaluating overlapping clusters.

According to rough set theory if  $x_i \in \underline{B}Ui$  then object  $x_i$  is contained completely in cluster  $U_i$  and if then object  $x_i$  belongs to cluster  $U_i$ and also belongs to another cluster. Hence according to fuzzy set theory the objects in boundary approximation should have different degree of membership on the clusters. So in RFCM the membership values of objects in lower approximation are  $\mu_{ii}$  = 1 while for those in boundary region are determined by the membership values.



- 1. Assign initial means v<sub>i</sub>, i=1, 2, 3,..., c. Choose values for fuzzifier  $m_1$  and threshold  $\epsilon$  and  $\delta$ . Set iteration counter t=1.
- Compute membership µ<sub>ii</sub> by equation (1) for c clusters and n objects.
- 3. If  $\mu_{ij}$  and  $\mu_{ik}$  be the two highest membership value of  $x_i$  and  $(\mu_{ii} \mu_{ki}) \le \delta$ , then  $x_i \in A(\beta_i)$  and  $x_i \in \overline{A(\beta_{k'})}$ . Furthermore,  $x_i$  is not part of any lower bound.
- 4. Otherwise,  $x_i \in \underline{A}(\beta_i)$ . In addition, by properties of rough sets,  $x_i \in \overline{A}(\beta_i)$ .
- Modify µ<sub>ii</sub> considering lower and boundary regions for c clusters and n objects.
- Compute new centroid as per equation (1). 6.
- 7. Repeat steps 2 to 7, by incrementing t, until  $|\mu_{ii}(t-1) \mu_{ii}(t)| > \varepsilon$

 $f \Lambda(\rho_{\tau}) \neq \rho D(\rho_{\tau}) \neq \rho$ 

$$v_{i} = \begin{cases} v \times C_{1} + w \times D_{1} \\ C_{1} & \text{if } \underline{A}(\beta_{I}) \neq \varphi, B(\beta_{i}) = \varphi \\ D_{1} & \text{if } \underline{A}(\beta_{I}) = \varphi, B(\beta_{i}) \neq \varphi \end{cases}$$

$$C_{1} = \frac{1}{|\underline{A}(\beta_{i})|} \sum_{x_{j} \in \underline{A}(\beta_{i})} x_{j} \quad D_{1} = \frac{1}{n_{i}} \sum_{x_{j} \in B(\beta_{i})} (\mu_{ij})^{m_{1}} x_{j} \text{ where } n_{i} = \sum_{x_{j} \in B(\beta_{i})} (\mu_{ij})^{m_{1}} x_{j}$$

 $|A(\beta_i)|$  represents the cardinality of  $A(\beta_i)$ . 0 < w < w < 1

## Tuned soft clustering

In particular the recent promising developments in the fusion of soft cluster algorithms show the need for approaches that holistically address uncertainty. Hence, soft clustering will continue in the attention of researchers and most likely attract yet more practitioners in the ground of data mining in support of their real life applications. The objective of this paper is to analyze Georg Peters [6] cluster algorithm rigorously and point out potential for further development. Based on the analyze we have presented a tuned rough fuzzy cluster algorithm and apply it to synthetic and real time market data.

#### Tuned rough C-means [6]

Lingras et.a[12] discussed rough clustering algorithm. Georg Peters evaluated Lingras et al. rough cluster algorithm and recommended some alternative solutions. This led to the new refined rough k-means algorithm.

Georg Peters cluster rough cluster algorithm goes as follows:

- (a) Initialization: Randomly assign each data object to exactly one lower approximation. Hence, the data object will also belong to the upper approximation of the same cluster.
- (b) Calculation of the new means. The means are calculated as follows:

$$\overline{m}_{k} = \omega_{l} \sum_{\overline{X}_{n} \in \underline{C_{k}}} \frac{\overrightarrow{X}_{n}}{|\underline{C_{k}}|} + \omega_{u} \sum_{\overline{X}_{n} \in \overline{C_{k}}} \frac{\overrightarrow{X}_{n}}{|\overline{C_{k}}|}$$

With  $\omega_l + \omega_u = 1$ 

Now, the lower approximation of each cluster always has at least one member. Therefore  $|C_k| \neq \varphi, \forall k$  and by definition

 $\overline{C_k} \neq \varphi, \forall k$ 

- (c) (i) Assign the data objects to the approximations. Assign the data object that represents a cluster to its lower and upper approximation.
  - 1. Find the minimal distance between cluster k and all data objects n and assign data object I to lower and upper



approximation of cluster h:

$$d(\overrightarrow{X_l, m_h}) = \min_{n, k} d(\overrightarrow{X_n, m_k}) \Rightarrow \overrightarrow{X_l} \in \underline{C_k} \land \overrightarrow{X_l} \in \overline{C_k}$$

2. Exclude  $\overrightarrow{X_l}$  and  $\overrightarrow{m_h}$ . If clusters are left – so far, in the above step (a) no data object has been assigned to them – ao

 - go back to Step (a). Otherwise continue with Step (ii).

(ii) For each remaining data point  $X_m$  (m=1, 2, ...., M, with M=N-K) determine its closest mean  $m_h$ :

$$d_{m,h}^{\min} = d(X_m, m_h) = \min_{\substack{k=1 \ K}} d(X_m, m_k)$$

Assign  $X'_m$  to the upper approximation of cluster h.

(iii) Determine the mean  $m_t$  that are also close to  $X_m$ . Take the relative distance as defined above where  $\zeta$  is a given relative threshold

$$T' = \left\{ t : \frac{\overrightarrow{d(X'_m, m_k)}}{\overrightarrow{\rightarrow} \rightarrow} \leq \zeta \land h \neq k \\ d(X'_m, m_h) \right\}$$

If  $T' \neq \phi$  ( $x'_m$  is also close to at least one other mean  $m_t$  besides  $m_h$ ).

Then  $\overrightarrow{X_m} \in \overline{C_t}, \forall t \in T'.$  $\overrightarrow{X_m} \in C_h$ 

(d) Check convergence for the algorithm. If the algorithm has not converged continue with step 2 else stop.

George peters refined rough c-means algorithm by replacing boundary into upper approximation in mean computation

#### Tuned rough fuzzy C-means

The algorithm as presented by Lingas et al. is numerical instable since there are data constellations where lower approximation is empty in some cases. The clusters will be weak if there is no representative the proposed algorithm ensures that each lower approximation has at least one member. It is implemented by assigning the data point that is closest to a mean to the lower approximation of the cluster. Otherwise the cluster seems to be weak since it has no sure representative. We have used relative distance represented by George peters instead of Lingras' et al. absolute distance measure to determine the set T. Rough C-means is one of the most extensively used partitioned based clustering algorithms and it is extremely sensitive to the initial placement of the cluster centers. Numerous initialization methods have been proposed [15] to deal with this problem. Here, we also addressed the solution for selection of cluster centers.

The tuned rough fuzzy c-means as follows:

Algorithm: Tuned Rough Fuzzy C-means

- 1 Assign initial means vi, i=1, 2, 3,..., c. Choose values for fuzzifier  $m_1$  and threshold  $\varepsilon$  and  $\delta$ . Set iteration counter
- 2 Compute membership µij by equation (2) for c clusters and n objects.



- 4 Otherwise, xj  $\in \underline{A}(\beta_i)$ . In addition, by properties of rough sets, xj  $\in \overline{A}(\beta_i)$ .
- 5 Modify µij considering lower and boundary regions for c clusters and n objects.
- 6 Compute new centroid as per equation (2).
- 7 Repeat steps 2 to 7, by incrementing t, until  $|\mu_{ij}(t-1) \mu_{ij}(t)| > \epsilon$

$$v_{i} = \begin{cases} \sim & \text{if } \underline{A}(\beta_{I}) \neq \varphi, \mathbf{B}(\beta_{i}) \neq \varphi \\ w \times C_{1} + w \times D_{1} \\ C_{1} & \text{if } \underline{A}(\beta_{I}) \neq \varphi, \mathbf{B}(\beta_{i}) = \varphi \\ D_{1} & \text{if } \underline{A}(\beta_{I}) = \varphi, \mathbf{B}(\beta_{i}) \neq \varphi \end{cases}$$

$$C_{1} = \frac{1}{|\underline{\Delta}(\beta_{i})|} \sum_{x_{j} \in \underline{\Delta}(\beta_{i})} x_{j} \quad D_{1} = \frac{\sum_{x_{j} \in \underline{\Lambda}(\beta_{i})} x_{j} + \sum_{x_{j} \in \underline{B}(\beta_{i})} (\mu_{ij})^{m_{1}} x_{j}}{n_{i} + \sum_{x_{j} \in \underline{B}(\beta_{i})} (\mu_{ij})^{m_{1}}} \in where \quad n_{i} = \sum_{x_{j} \in \underline{B}(\beta_{i})} (\mu_{ij})^{m_{1}}$$

 $|A(\beta_i)|$  represents the cardinality of  $A(\beta_i)$ . 0 < W < w < 1

#### Selection of initial centroid for rough fuzzy C-means algorithm

Step 1: From n objects calculate a point whose attribute values are average of n objects attribute values. Hence, first initial centroid is average on n- objects.

Step 2: Select next initial centroids from n-objects in such a way that the Euclidean distance of that object is maximum from other selected initial centroids.

Step 3: Repeat step 2 until we get k initial centroids.

From these steps the initial centroids are derived and tuned rough fuzzy c-means algorithm is tested for the dynamic centroids and random centroids.

# RESULTS

#### **Experimental analysis**

The traditional soft clustering algorithms such as rough c-means(RCM), Fuzzy C-means (FCM), Rough-Fuzzy Cmeans(RFCM), Rough-Intuitionistic-fuzzy C-means (RIFCM) and proposed tuned rough fuzzy c-means (TRFCM) algorithms are implemented using Java.UCI Machine Learning Repository, Wholesale customers Data Set [29] is used to evaluate the performance of the above said algorithms. The data set refers to clients of a wholesale distributor. It includes the annual spending in monetary units on diverse product categories. The centroid formulae for the algorithms are given in the Table 1. The traditional and tuned soft clustering algorithms are tested with random centroid selection and proposed centroid computation method and it's shown in Figure -1.



#### Table: 1. Comparisons of Centroid formulae of the various soft clustering algorithms

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 $v_i = \frac{1}{n_i} \sum_{j=1}^{n} (\mu_{ij})^{m_1} x_j; \text{ where } : n_i \cdot = \sum_{j=1}^{n} (\mu_{ij})^{m_1}$ FCM  $v_{i} = \begin{cases} \sim & if \underline{\mathbf{A}}(\beta_{I}) \neq \varphi, \mathbf{B}(\beta_{i}) \neq \varphi \\ w \times C_{1} + w \times D_{1} \\ C_{1} & if \underline{\mathbf{A}}(\beta_{I}) \neq \varphi, \mathbf{B}(\beta_{i}) = \varphi \\ D_{1} & if \underline{\mathbf{A}}(\beta_{I}) = \varphi, \mathbf{B}(\beta_{i}) \neq \varphi \end{cases}$ RFCM where  $C_1 = \frac{1}{|\underline{\Delta}(\beta_i)|} \sum_{x_j \in \underline{\Delta}(\beta_i)} x_j \quad D_l = \frac{1}{n_i} \sum_{x_j \in B(\beta_i)} (\mu_{ij})^{m_l} x_j \quad n_i = \sum_{x_j \in B(\beta_i)} (\mu_{ij})^{m_l} x_j$  $V_{i} = \begin{cases} \sum_{\substack{w_{low} \frac{x_{k} \in \underline{B}U_{i}}{|\underline{B}U_{i}|} + w_{up} \frac{x_{k} \in BN(U_{i})}{\frac{\sum}{|\underline{K}|} (\mu_{ik})^{m}} & \text{if } |\underline{B}U_{i}| \neq \varphi \quad \text{and } |BN(U_{i})| \neq \varphi \\ \frac{\sum_{\substack{x_{k} \in BN(U_{i})}}{\frac{\sum}{|\underline{K}|} (\mu_{ik})^{m}} & \text{if } |\underline{B}U_{i}| = \varphi \quad \text{and } |BN(U_{i})| \neq \varphi \\ \frac{\sum_{\substack{x_{k} \in BN(U_{i})}}{\frac{\sum}{|\underline{K}|} (\mu_{ik})^{m}} & \text{if } |\underline{B}U_{i}| = \varphi \quad \text{and } |BN(U_{i})| \neq \varphi \end{cases}$ RIFCM  $\frac{\sum\limits_{x_k \in \underline{B}U_i} x_k}{|\underline{B}U_i|}$ ELSE  $\overline{m}_{k} = \omega_{l} \sum_{\overline{X}_{n} \in \underline{C}_{k}} \frac{\overrightarrow{X}_{n}}{|\underline{C}_{k}|} + \omega_{u} \sum_{\overline{X}_{n} \in \overline{C}_{k}} \frac{\overrightarrow{X}_{n}}{|\overline{C}_{k}|}, \omega_{l} + \omega_{u} = 1$ **Tuned RCM**  $\begin{pmatrix} \sim & \text{if } \underline{\mathbf{A}}(\beta_I) \neq \varphi, \mathbf{B}(\beta_i) \neq \varphi \\ w \times C_1 + w \times D_1 \end{pmatrix}$  $\begin{array}{ccc} v_i = & C_l & \quad if \ \underline{\mathbf{A}}(\beta_I) \neq \varphi, \\ B(\beta_i) = \varphi \\ D_l & \quad if \ \underline{\mathbf{A}}(\beta_I) = \varphi, \\ B(\beta_i) \neq \varphi \end{array}$ **Tuned RFCM** where  $C_1 = \frac{1}{|\underline{A}(\beta_i)|} \sum_{x_j \in \underline{A}(\beta_i)} x_j$   $D_1 = \frac{\sum\limits_{x_j \in \underline{A}(\beta_i)} x_j + \sum\limits_{x_j \in \underline{B}(\beta_i)} (\mu_{ij})^{m_1} x_j}{n_i + \sum\limits_{x_j \in \underline{B}(\beta_i)} (\mu_{ij})^{m_1}} n_i = \sum\limits_{x_j \in \underline{B}(\beta_i)} (\mu_{ij})^{m_1}$ 



	Cluster	Low	Upper	Total	
	1	0	105	105	
	2	18	19	37	
	3	59	29	88	
3	4	210	29	239	
1	5	0	124	124	
CM.	- Random Cent	roids			
.CM - Dutp	Random Cent	roids M (run)	22		
Outp	Random Cent	M (run)	Herer	Terel	
CM-	Random Cent out - modRC	Low	H Upper	Total	
CM- Dutp	Cluster	Low 112	W Upper 180	Total 292	
CM- Dutp	-Random Cent out - modRCl Cluster 1 2	Low 112 105	W Upper 180 19	Total 292 124	
	Random Cent out - modRCl Cluster 1 2 3	Low 112 105	W Upper 180 19 0	Total 292 124 1	
	Cluster 1 2 3 4	Low 112 105 1 18	W Upper 180 19 0 78	Total 292 124 1 96	
	Random Cent out - modRC Cluster 1 2 3 4 5	Low 112 105 1 18 5	W Upper 180 19 0 78 121	Total 292 124 1 96 126	
Outp	Cluster 1 2 3 4 5 DB Index	Low 112 105 1 18 5 x: 2.9	W Upper 180 19 0 78 121 12782	Total 292 124 1 96 126	

#### Fig: 1. a

outh		
	run:	
1	Cluster 1 : 2.1041768% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]	1.1359986% of [2.0, 3.0, 7057.0, 9810.0,
2	Cluster 2 : 95.25728% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]	97.47512% of [2.0, 3.0, 7057.0, 9810.0,
0	Cluster 3 : 0.93450713% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]	0.4919163% of [2.0, 3.0, 7057.0, 9810.0,
2	Cluster 4 : 1.129488% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]	0.59406514 of [2.0, 3.0, 7057.0, 9810.0,
24	Cluster 5 : 0.57454324% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]	0.3028948% of [2.0, 3.0, 7057.0, 9810.0,
	DD T-days 9 5(2)(2)	
	DB INGEX: 3.36/1623	
	BUILD SUCCESSFUL (total time: 1 second) FCM-Random Centroids	
	BUILD SUCCESSFUL (total time: 1 second) FCM-Random Centroids	
)utpu	BUILD SUCCESSFUL (total time: 1 second) FCM-Random Centroids	
)utpu	BUILD SUCCESSFUL (total time: 1 second) FCM-Random Centroids At-modFCM (run) # Cluster 1 : 1.1615362% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]	0.61746657% of [2.0, 3.0, 7057.0, 9810.0
utpu	BUILD SUCCESSFUL (total time: 1 second) FCM-Random Centroids At-modFCM (run) % Cluster 1 : 1.1615362% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] Cluster 2 : 95.55289% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]	0.61746657% of [2.0, 3.0, 7057.0, 9810.0 97.61406% of [2.0, 3.0, 7057.0, 9810.0,
utpu	BUILD SUCCESSFUL (total time: 1 second) FCM-Random Centroids At-modFCM (run) % Cluster 1 : 1.1615362% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] Cluster 2 : 95.55289% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] Cluster 3 : 0.59041566% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]	0.61746657% of [2.0, 3.0, 7057.0, 9810.0 97.61406% of [2.0, 3.0, 7057.0, 9810.0, 0.31455353% of [2.0, 3.0, 7057.0, 9810.0
utpu	BUILD SUCCESSFUL (total time: 1 second) FCM-Random Centroids At-modFCM (run) % Cluster 1 : 1.1615362% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] Cluster 2 : 95.55289% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] Cluster 3 : 0.59041566% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] Cluster 4 : 1.7260928% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]	0.61746657% of [2.0, 3.0, 7057.0, 9810.0 97.61406% of [2.0, 3.0, 7057.0, 9810.0, 0.31455353% of [2.0, 3.0, 7057.0, 9810.0 0.93852794% of [2.0, 3.0, 7057.0, 9810.0
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# Fig: 1. b



Cluster Centrolds: ().05556307, 0.11107462, 0.11107462, 0.12059854, 0.12695515, 0.039260767, 0.27681215, 0.00046054573] (0.7575662, 0.5771664, 0.11107462, 0.1205976, 0.111767664, 0.039260767, 0.27681215, 0.0007184461) (0.676362, 0.5771667, 0.6022167, 0.000218976, 0.111767664, 0.0471776, 0.02621677, 0.27681215, 0.0005120217) ().0476362, 0.047702, 0.0221877, 0.0483466, 0.4047176, 0.0471776, 0.02621677, 0.02180877, 0.0005120217) ().0476362, 0.047702, 0.0221877, 0.0483464, 0.047176, 0.0447176, 0.0421677, 0.11107647, 0.00512027) Cluster Cutrons: ().0476362, 0.0497167, 0.04921897, 0.0483162, 0.22019, 0.01162769, 0.0482167, 0.00512027) Cluster 1 : 40.889395 of [2.0, 3.0, 24073, 0, 3463, 0, 22019, 0, 5154, 0, 4397, 0, 14523, 0, 120587, 0, 1413, 0, 2004 Cluster 2 : 100.04 of [2.0, 3.0, 12467, 0, 34643, 0, 22019, 0, 5154, 0, 4397, 0, 14523, 0, 1263, 0, 2707, 0, 9810, 0, Cluster 1 : 100.04 of [2.0, 3.0, 1245, 0, 1194, 0, 421, 0, 464, 0, 507, 0, 1788, 0] 10.054 of [2.0, 3.0, 9843, 0, 3463, 0, 22019, 0, 5154, 0, 4397, 0] 10.054 of [2.0, 3.0, 9843, 0, 3463, 0, 22019, 0, 5164, 0, 4397, 0] 10.054 of [2.0, 3.0, 9843, 0, 3464, 0, Cluster 1 : 10.04 of [2.0, 3.0, 1245, 0, 1194, 0, 421, 0, 464, 0, 507, 0, 1788, 0] 10.054 of [2.0, 3.0, 9843, 0, 3463, 0, 2005, 0, 5164, 0, 4397, 0, 14523, 0] 2.64812954 of [2.0, 3.0, 9843, 0, 3464, 0, 11.0 0 135 128 10.1055 128 10.1055 128 10.1055 128 10.1055 128 10.1055 128 10.005530054, 0.3055555, 0.039905472, 0.039459052, 0.056695155, 0.021778452, 0.021778452 10.05456023, 0.7566344, 0.88564545, 0.12056734, 0.43934507, 0.1668230, 0.021778452 10.05456023, 0.75663454, 0.88564545, 0.12056734, 0.43934507, 0.105657055, 0.0356566381 10.00545 of [1.0, 3.0, 12464, 0, 1277407, 0, 116075, 0.036459052, 0.055676653, 0.03576654, 0.02177452 10.00545 of [1.0, 3.0, 12465, 0, 112776, 1456, 0, 110076, 110670, 110670, 11060, 0, 113670, 1137550, 0, 113755546453 10.00545 of [1.0, 3.0, 12465, 0, 11007, 0, 1460, 0, 2146, 0, 2146, 0, 2146, 0, 2146, 0, 2146, 0, 2146, 0, 2146, 0, 2146, 0, 2146, 0, 1	1000	ar - while our frank -
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<pre>[0.54019924, 0.15939446, 0.00928904, 0.11269447, 0.1299202, 0.049924602, 0.1242996, 0.005122097] Cluster Output: : Cluster Output: : Cluster Cutruer: 2 : 100.04 of [2.0, 3.0, 12463.0, 9664.0, 7561.0, 22019.0, 5154.0, 4337.0, 16523.0] 42.859264 of [2.0, 3.0, 4113.0, 2004 Cluster 2 : 100.04 of [2.0, 3.0, 12463.0, 9664.0, 7561.0, 22019.0, 5154.0, 4337.0, 16523.0] 42.859264 of [2.0, 3.0, 4113.0, 2004 Cluster 1 : 100.04 of [2.0, 3.0, 12465.0, 1104.0, 4221.0, 4201.0, 421.0, 4207.0, 1552.0] 42.859264 of [2.0, 3.0, 4113.0, 2004 Cluster 1 : 100.04 of [2.0, 3.0, 24973.0, 36423.0, 22019.0, 5154.0, 4337.0, 16523.0] 42.859264 of [2.0, 3.0, 4113.0, 2004 Cluster Corr Upper Total 1 0 126 126 2 0 126 126 3 0 126 126 3 0 126 128 WILLD SUCCESSFUL (total time: 1 second)  NUTUT MODIFICM (run) # Cluster Controlds: 1 0.004 of [2.0, 3.0, 12717.0] 0.03900472, 0.039439052, 0.046488818, 0.020278862, 0.02177525] 1 0.03548105, 0.8448645, 0.08326515, 0.1375260, 0.10695705, 0.046488818, 0.020278862, 0.02177525] 1 0.03548105, 0.8448645, 0.08326515, 0.1375260, 0.10695705, 0.046488818, 0.020278862, 0.02177525] 1 0.03548105, 0.84486454, 0.08326515, 0.1375260, 0.10695705, 0.046488818, 0.020278862, 0.02177525] 1 0.03548105, 0.84486454, 0.08326515, 0.1375260, 0.10695705, 0.046488818, 0.020278862, 0.00177525] 1 0.03548105, 0.84486454, 0.08326515, 0.1375260, 0.10695705, 0.046488818, 0.020278862, 0.00177525] 1 0.03548105, 0.384486454, 0.08326515, 0.13775200, 0.10695705, 0.046488818, 0.030278862, 0.00177525] 1 0.03548105, 0.394682454, 0.08326515, 0.13775200, 0.10695705, 0.039439052, 0.046484483] 1 0.00416212632, 0.09061054, 0.03326515, 0.13775200, 0.10695705, 0.039439052, 0.04648483] 1 0.0041621623, 0.09061054, 0.037946224, 0.032083004, 0.093439052, 0.018839354, 0.09063983] 1 0.004 of [1.0, 3.0, 13265, 0, 1196, 0, 4221.0, 5604, 0, 507.0, 1788.0] 1 00.04 of [1.0, 3.0, 13265, 0, 1196, 0, 7654, 0, 1384, 0] 1 00.04 of [1.0, 3.0, 13265, 0, 13965, 0, 1396, 0, 2401, 0, 2394, 0, 23963, 0] 1 00.04 of [1.0, 3.0, 13965, 0, 1496, 0, 2402, 0, 3401, 0] 1 00.04</pre>		[0.005750687, 0.6802331, 0.12331778, 0.048334666, 0.04471679, 0.06212637, 0.02186173, 0.029163156]
Cluster Output :         Cluster Output :           Cluster 1 : 00.000 of (2.0, 3.0, 26073.0, 36423.0, 22013.0, 5154.0, 4337.0, 16623.0) (2.0, 50.000 of (2.0, 3.0, 7057.0, 9810.0, 2010.000 of (2.0, 3.0, 7057.0, 9810.0, 22015.0, 5154.0, 4337.0, 16623.0) (2.0, 2202000 of (2.0, 3.0, 4113.0, 2040)           Cluster 1 : 00.000 of (1.0, 3.0, 1285.0, 11326.0, 1130.0, 22015.0, 5154.0, 4337.0, 16623.0) (2.0, 21012500 of (2.0, 3.0, 4113.0, 2040)           Cluster 1 : 00.000 of (1.0, 3.0, 28073.0, 36423.0, 22015.0, 5154.0, 4337.0, 18623.0) (2.0, 21012500 of (2.0, 3.0, 4113.0, 2040)           Cluster 1 : 00.000 of (1.0, 3.0, 1285.0, 1326.0, 1326.0, 22015.0, 5154.0, 4337.0, 18623.0) (2.0, 21012500 of (2.0, 3.0, 4113.0, 2040)           Cluster Controlls           Cluster Controlls           (0.00000000000000000000000000000000000		[0.56818926, 0.15919456, 0.08925904, 0.11259487, 0.1298202, 0.049526602, 0.1262969, 0.035122097]
Cluster 1 : 0.08803% of (2.0, 3.0, 26373.0, 36423.0, 22019.0, 8154.0, 4337.0, 16623.0) 42.853264% of (2.0, 3.0, 7057.0, 9810.0, 2010.0%         Cluster 2 : 100.0% of (2.0, 3.0, 12665.0, 1965.0, 7561.0, 224.0, 2674.0, 1338.0) 100.0% of (2.0, 3.0, 7057.0, 9810.0, 2010.0%         Cluster 5 : 8.2630436 of (2.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0) 12.6263865 of (2.0, 3.0, 4113.0, 2041         Cluster 5 : 8.2630436 of (2.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0) 100.0% of (1.0, 3.0, 5563.0, 36483.0, 22019.0, 5154.0, 4337.0, 16523.0) 2.26181295% of (2.0, 3.0, 4113.0, 2041         Cluster Low Upper Total       0 126 126         1 0 126 128       126         VILD PROCESSFUL (total time: 1 second)       RFCM-Random Centorids         * 0 128 128       128         * 0 128 128       100.0000000000000000000000000000000000		Cluster Output :
Cluster 1 : 40.88234 of (2.0, 3.0, 24373.0, 3423.0, 22015.0, 8184.0, 4337.0, 1463.0) 42, 853264 of (2.0, 3.0, 413.0, 1041) Cluster 2 : 100.04 of (2.0, 3.0, 12450.0, 1046.0, 221.0, 2410.0, 2474.0, 1338.0) Cluster 4 : 100.04 of (1.0, 3.0, 13265.0, 1196.0, 221.0, 5010.0, 5154.0, 4337.0, 16523.0) 2.462845 of (2.0, 3.0, 4113.0, 2048) Cluster 5 : 8.2590434 of (2.0, 3.0, 24373.0, 34423.0, 22019.0, 5154.0, 4337.0, 16523.0) 2.462845 of (2.0, 3.0, 4113.0, 2048) Cluster 5 : 8.2590434 of (2.0, 3.0, 24573.0, 34423.0, 22019.0, 5154.0, 4337.0, 16523.0) 2.461812954 of (2.0, 3.0, 4113.0, 2048) Cluster 5 : 8.2590434 of (2.0, 3.0, 24573.0, 34423.0, 22019.0, 5154.0, 4337.0, 16523.0) 2.461812954 of (2.0, 3.0, 4113.0, 2048) Cluster 5 : 8.2590434 of (2.0, 3.0, 24573.0, 34423.0, 22019.0, 5154.0, 4337.0, 16523.0) 2.461812954 of (2.0, 3.0, 4113.0, 2048) Cluster Low Typer Total 2 80 125 125 3 0 125 125 4 236 125 125 4 236 125 125 4 236 125 125 5 0 126 120 4 of (1.0, 3.0, 13265.0, 1396.0, 4221.0, 6404.0, 507.0, 1788.0) 100.04 of (1.0, 3.0, 5843.0, 3646.0, 100.01107.0, 1146.0, 2344.0, 2363.0, 0.01833951, 0.4563853) 5 0.041502523, 0.9018314, 0.27524973, 0.063754624, 0.05208304, 0.03543953, 0.01833951, 0.04563853) 5 0.041502523, 0.9018314, 0.27524973, 0.05375662, 0.764.0, 1377.0, 1386.0, 1307.0, 1386.0, 1307.0, 1386.0, 1307.0, 1386.0, 1300.0, 1307.0, 1386.0, 1300.0, 100.04 of (1.0, 3.0, 5843.0, 3646.0, 1 5 0.904502523, 0.9018314, 0.27524973, 0.053754624, 0.05208304, 0.03843903) 100.04 of (1.0, 3.0, 2453.0, 3646.0, 1 5 0.904502523, 0.9018314, 0.27524973, 0.053754624, 0.052083004, 0.03843903) 100.04 of (1.0, 3.0, 5845.0, 3646.0, 1 5 0.904502523, 0.9018314, 0.27524973, 0.053754624, 0.3540, 0.3440, 0.2453.0, 0.31375554, 0		
Cluster 2 : 100.04 of [1.0, 3.0, 12489.0, 988.0, 788.0, 244.0, 2494.0, 1398.0] 100.04 of [1.0, 3.0, 100.0, 1100.0, 100.0,		Cluster 1 : 40.8839% of [2.0, 3.0, 26373.0, 36423.0, 22019.0, 5154.0, 4337.0, 16523.0] 42.853256% of [2.0, 3.0, 4113.0, 2048
Cluster 3 : 100.04 of [1.0, 3.0, 12645.0, 1396.0, 4221.0, 6404.0, 607.0, 1788.0] 100.04 of [1.0, 3.0, 5463.0, 2448.0, Cluster 5 : 2000434 of [2.0, 3.0, 24373.0, 34423.0, 22019.0, 5154.0, 4337.0, 14523.0] 2.61812954 of [2.0, 3.0, 4113.0, 2041 1 0 125 125 2 80 125 125 3 0 125 125 B Index: 13.024282 WILD SUCCESSFUL (total time: 1 second)		Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [2.0, 3.0, 7087.0, 9810.0,
Cluster Low Upper Total 1 0 125 125 2 0 125 125 3 0 125 125 3 0 125 125 5 0 125 125 WILD SUCCESSFUL (total time: 1 second) Cluster Centroids: (0.0027953004; 0.9004208; 0.078218155; 0.039805472; 0.039439022; 0.0464888118; 0.020278862; 0.02177352] (0.027953004; 0.9004208; 0.078218155; 0.039805472; 0.039439022; 0.0646488818; 0.020278862; 0.02177352] (0.027953004; 0.9004208; 0.078218155; 0.039805472; 0.039439022; 0.0646488818; 0.020278862; 0.02177352] (0.027953004; 0.9004208; 0.078218155; 0.039805472; 0.039439022; 0.036489818; 0.020278862; 0.02177352] (0.027953004; 0.9004208; 0.0002085; 0.017521804; 0.12025912; 0.45927042; 0.022678055; 0.7129398] (0.02476502; 0.7646534; 0.22156415; 0.4538412; 0.12205912; 0.45927042; 0.022678055; 0.7129398] (0.02476502; 0.7646534; 0.22156415; 0.4538412; 0.12205912; 0.45927042; 0.023878055; 0.7129398] (0.0041502522; 0.0005208; 0.0627764; 0.12777407; 0.16660753; 0.043881277; 0.16666233; 0.035048638] (0.0041502522; 0.00050208; 0.0627764; 0.12777407; 0.16660733; 0.043881277; 0.16666233; 0.035048638] (0.0041502522; 0.0018814; 0.27924973; 0.055795224; 0.052083004; 0.09363903; 0.018833992; 0.04053865; 0.04053865; 0.018833992; 0.04053865; 0.018833992; 0.04053865; 0.018833992; 0.04053865; 0.018833992; 0.04053865; 0.01883399; 0.04079; 0.12665, 0.9666; 0.7561, 0.214, 0.279, 0.1285992; 0.02182127; 0.1285892; 0.04053863; 0.018833992; 0.04053863; 0.018833992; 0.04053865; 0.018833992; 0.04053865; 0.018833992; 0.04053865; 0.01882, 0.018034; 0.27924973; 0.055796224; 0.052083004; 0.09363903; 0.018833992; 0.04053865; 0.018024; 0.0100; 0.0180227; 0.0100; 0.0180227; 0.0100; 0.0180227; 0.0100; 0.01802224; 0.0100; 0.0100; 0.01107; 0.1148; 0.2134; 0.2340; 0.2360; 0.238127; 0.0140; 0.30; 0.21462; 0.30; 0.213827; 0.0140; 0.30; 0.2160; 0.2381; 0.2381; 0.2380; 0.2381; 0.2380; 0.2100; 0.200; 0.200; 0.200; 0.200; 0.200; 0.2381; 0.2381; 0.2381; 0.2380; 0.2381; 0.2381; 0.2380; 0.2100; 0.200; 0.2100; 0.2100; 0.2100; 0.2100; 0.2100; 0.2100; 0.2381; 0.2381; 0.2381; 0.2381; 0.2381; 0.2380; 0.2100; 0.2		Cluster 3 : 7.3725934 OF (2.0, 3.0, 2573.0, 3642.0, 2203.0, 2104.0, 4357.0, 16523.0) 2.622654 OF (2.0, 3.0, 413.0, 20654
Cluster Low Opper Total 2 00 125 125 3 0 125 125 5 0 125 125       RFCM-Random Centorids         Sub Index: 13.0.74287       BUILD SUCCESSFUL (total time: 1 second)         Cluster Centroids:       Cluster Centroids:         [0.0027953044; 0.9006208; 0.078118155, 0.039805472, 0.039439082, 0.046488818, 0.020278662, 0.02177252)       [0.0277953044; 0.9006208; 0.078118155, 0.039805472, 0.039439082, 0.046488818, 0.020278662, 0.02177252)         [0.0027953044; 0.9006208; 0.078218155, 0.13762504, 0.16085708, 0.026401552, 0.1425405, 0.044524433]       [0.024769021, 0.7666534, 0.281544; 0.137727407, 0.16680738, 0.026401552, 0.1425405, 0.044524433]         [0.024769021, 0.7666534, 0.281544; 0.12777407, 0.16680738, 0.026401552, 0.1425405, 0.044524433]       [0.024769021, 0.7666534, 0.281544; 0.12777407, 0.16680738, 0.043381177, 0.14664238, 0.030546680]         [0.00415028228, 0.050052088, 0.06227684, 0.12777407, 0.16680738, 0.043381177, 0.14664238, 0.030546680]       [0.00415028223, 0.05083630, 0.06227684, 0.27764, 0.12777407, 0.16680738, 0.043381374, 0.18833951, 0.04053865]         [0.00415028228, 0.05082088, 0.06227684, 0.13277407, 0.16680738, 0.042038030, 0.018833951, 0.04053865]       [0.00415028223, 0.050846462, 0.062083004, 0.09363903, 0.018833951, 0.04053865]         [0.00415028228, 0.05082088, 0.06227684, 0.1396, 0.11960, 0.11807, 0.1148, 0.2134, 0.2968, 0.113835954 of 11.0, 3.0, 18626, 0.11670, 0.1148, 0.2134, 0.2968, 0.13827574 of 11.0, 3.0, 18626, 0.11670, 0.1148, 0.2134, 0.2968, 0.13832574 of 11.0, 3.0, 216320, 1311         Cluster 1 : 100.04 of [1.0, 3.0, 18815, 3610, 0.11167, 0.1148, 0.2134, 0.2968, 0.13832574 of 11.0, 3.0, 216320, 1311                  [		Cluster 5 : 8.2690434 of [2.0, 3.0, 26373.0, 36423.0, 22019.0, 5154.0, 4337.0, 16523.0] 2.61812954 of [2.0, 3.0, 4113.0, 2048
2       0       125       205         3       0       125       125         3       0       125       125         3       0       125       125         B       0       125       125         B       0       125       125         B       0       125       125         B       0       126       125         B       0       126       125         B       0       126       125         B       0       126       126         B       0       126       0         Cluster Centroids:       [0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.028439082, 0.0246488518, 0.0202788622, 0.02177252]         [0.05456021, 0.7666543, 0.218448624, 0.08326513, 0.13752504, 0.026059104, 0.028570622, 0.7228590]       (0.7833558, 0.060052088, 0.0627764, 0.1277407, 0.16480793, 0.043981177, 0.16466293, 0.038648638]         [0.041502222, 0.9018314, 0.27924973, 0.058796224, 0.0502083004, 0.09363903, 0.018833931, 0.04063863]       (0.041502222, 0.3018344, 0.27924973, 0.05879622, 0.7561, 0, 1383.0]         [0.uster 1: 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 4604.0, 507.0, 1788.0]       100.04 of [1.0, 3.0, 5965.0, 3648.0, 4.0]         [0.uster 2: 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 2474.0, 2374.0, 1338.0]       100.04 of [1.0, 3.0,		Cluster Low Upper Total
3       0       125       125       340         9       0       125       125       340         9       0       125       125       340         9       0       125       125       340         9       0       125       125       340         9       0       125       125       340         9       0       125       340       340         9       0       125       340       340         9       0       125       340       340         9       0       125       340       0.039805472, 0.046488918, 0.020278862, 0.021772523         10.024765021, 0.7646834, 0.281564, 0.13752504, 0.16085708, 0.0426401952, 0.12625405, 0.0345244333       10.0445244333         10.024765021, 0.7646834, 0.27924973, 0.053796224, 0.052083004, 0.03586303, 0.018833991, 0.040538633         10.044552523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.040538633         10.04456021, 0.76463204       110, 0.0, 1107, 0, 1140, 0, 2134, 0, 294.01       100.04 of [1.0, 3.0, 1885.0, 364.0, 0, 1107, 0, 1140, 0, 2134, 0, 294.01       100.04 of [1.0, 3.0, 21632, 0, 1317         101uster 1 : 100.04 of [1.0, 3.0, 1885.0, 3610, 0, 1107, 0, 1480, 2134, 0, 294.01       100.04 of [1.0, 3.0, 21632, 0, 1317         101uster 5 : 100		2 80 125 205
4       236       125       340       RFCM-Random Centorids         5       0       125       125       125         DB Index: 13.024282       BUILD SUCCESSFUL (total time: 1 second)         Xupot -modRFCM (run) H       Cluster Centroids:         (0.0027959044, 0.9006208, 0.078218155, 0.038605472, 0.039439082, 0.046488818, 0.020278862, 0.02177262]       (0.35544105, 0.8444824, 0.0822513, 0.13752504, 0.16055708, 0.024401552, 0.16285704, 0.03887062, 0.038870652, 0.038874633]         (0.002799021, 0.7666354, 0.2016415, 0.13752504, 0.162055702, 0.45527042, 0.025870652, 0.038870652, 0.038544833]       (0.35544105, 0.36448243, 0.06227544, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.0385044638]         (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.039363903, 0.018833991, 0.04053863]       (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.039363903, 0.018833991, 0.04053863]         Cluster Output :       Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.0% of [1.0, 3.0, 5963.0, 3648.0, 9         Cluster 3 : 1.7177984% of [1.0, 3.0, 13265.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.33751538 of [1.0, 3.0, 21692.0, 1317         Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0]       100.0% of [1.0, 3.0, 43088.0, 2100.0,         Cluster Low Upper Total       1       138       149       150         1       138       149       150       RFCM-Computed Centorids       <		3 0 125 125
\$ 0       125       125         B Index: 13.024282       SUID SUCCESSFUE (total time: 1 second)         Durpt-modRFCM (run) N         Cluster Centroids:         [0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252]         [0.55440105, 0.8444824, 0.0832551, 0.13762804, 0.14005708, 0.024401552, 0.1424405, 0.034524433]         [0.02769021, 0.7666534, 0.2816615, 0.45383418, 0.18205512, 0.4538217042, 0.02878055, 0.7122598]         [0.024769021, 0.7666534, 0.2816455, 0.45383418, 0.18205512, 0.4538217042, 0.02878055, 0.7122598]         [0.024769021, 0.7666534, 0.2816455, 0.41397647, 0.1660735, 0.4338170, 0.168839393, 0.018833991, 0.04053863]         [0.024769021, 0.7666534, 0.2816455, 0.41397607, 0.1660735, 0.4338170, 0.168833991, 0.040553863]         [0.0241502523, 0.9018914, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.040553863]         Cluster Output :         Cluster 1 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.04 of [1.0, 3.0, 5963.0, 36648.0, 9665.0, 7561.0, 214.0, 2794.0, 1383.0]         Cluster 2 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.04 of [1.0, 3.0, 21632.0, 361.0, 1107.0, 1148.0, 2134.0, 2963.0]         Cluster 4 : 0.946422044 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       100.04 of [1.0, 3.0, 21632.0, 311         Cluster Low Upper Total       1       138       149       160         1       138		4 235 125 360 RFCM-Random Centorids
DB Index: 13.024282 BUILD SUCCESSFUL (total time: 1 second) Patpot-modRFCM (run) M Cluster Centrolds: [0.0027999044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252] [0.95548105, 0.84448624, 0.08325515, 0.13752504, 0.140085708, 0.026401582, 0.1425405, 0.034524433] [0.902769021, 0.7666534, 0.28156415, 0.45383614, 0.18205708, 0.026401582, 0.14254055, 0.7123980] [0.7833558, 0.060052088, 0.0627764, 0.12777407, 0.16660793, 0.043881177, 0.16666293, 0.035048638] [0.7033558, 0.050052088, 0.0627764, 0.12777407, 0.16660793, 0.043381177, 0.16666293, 0.035048638] [0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863] Cluster Output : Cluster Output : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, 4 Cluster 3 : 1.7117984% of [1.0, 3.0, 18015.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21692.0, 1311 Cluster 4 : 0.94462204% of [1.0, 3.0, 18015.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21692.0, 1311 Cluster 5 : 100.0% of [1.0, 3.0, 13276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster 1 = 138 149 287 2 101 149 280 3 1 1 149 150 4 18 149 157 5 133 149 132 DB Index: 5.273012		5 0 125 125
BUILD SUCCESSFUL (total time: 1 second)           Dutput-modRFCM (run) #           Cluster Centroids:           (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252]           (0.95548105, 0.8444624, 0.08326518, 0.13752504, 0.16058708, 0.026401552, 0.1625405, 0.034524433]           (0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.034524433]           (0.024769021, 0.7666534, 0.28156415, 0.4520533, 0.04338177, 0.16660793, 0.04338197, 0.1666939, 0.018833991, 0.04053863)           (0.041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863)           Cluster Output :           Cluster 1 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]         100.04 of [1.0, 3.0, 5963.0, 36486.0, 4221.0, 6404.0, 2014.0, 2674.0, 138.0]           Cluster 2 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]         100.04 of [1.0, 3.0, 5963.0, 36482.0, 13162.0, 1107.0, 1148.0, 2134.0, 2963.0]           Cluster 3 : 1.71179844 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]         1.31751534 of [1.0, 3.0, 21632.0, 1310           Cluster 4 : 0.944622044 of [1.0, 3.0, 13276.0, 1917.0, 4465.0, 9408.0, 2381.0, 4334.0]         100.04 of [1.0, 3.0, 43088.0, 2100.0, 100.0, 1107.0, 1148.0, 2134.0, 2963.0]           Cluster Low Upper Total         1         138         149         287           2         101         149         180         180           <		DB Index: 13.024282
Dutput - modRFCM (run) #         Cluster Centroids:         (0.0027953044, 0.5006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252]         (0.5558105, 0.050448624, 0.08325519, 0.13752504, 0.16055708, 0.026401552, 0.1625405, 0.034524433]         (0.024765021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025978055, 0.7123398]         (0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638]         (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833931, 0.04053863)         Cluster Output :         Cluster 1 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.04 of [1.0, 3.0, 5963.0, 3648.0, 0         Cluster 2 : 100.04 of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]       100.04 of [1.0, 3.0, 7057.0, 9810.0, 1         Cluster 3 : 1.71179844 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.31751534 of [1.0, 3.0, 21632.0, 131         Cluster 4 : 0.944622044 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.00.04 of [1.0, 3.0, 21632.0, 131         Cluster 5 : 100.04 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.00.04 of [1.0, 3.0, 21632.0, 131         Cluster Low Upper Total       1       138       149       267       2       100.04 of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0]       100.04 of [1.0, 3.0, 43088.0, 2100.0, 0.0]       100.04 of [1.0, 3.0, 43088.0, 2100.0, 0]       100.0		BUILD SUCCESSFUL (total time: 1 second)
Cluster Centroids: (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252] (0.95548105, 0.84448624, 0.08325515, 0.13752504, 0.16085708, 0.026401552, 0.1625405, 0.034524433] (0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7123398] (0.7833558, 0.050052088, 0.0427764, 0.12777407, 0.16660793, 0.043381177, 0.14666293, 0.035048638] (0.7833558, 0.050052088, 0.0427764, 0.12777407, 0.16660793, 0.043381177, 0.14666293, 0.035048638] (0.0041502523, 0.5018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863] Cluster Output : Cluster 1 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.04 of [1.0, 3.0, 5963.0, 3648.0, 0 Cluster 2 : 100.04 of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.04 of [2.0, 3.0, 7057.0, 9810.0, 1 Cluster 4 : 0.94462204 ef [1.0, 3.0, 18815.0, 3610.0, 1107.0, 1148.0, 2184.0, 2963.0] 1.31751534 of [1.0, 3.0, 21632.0, 131 Cluster 4 : 1.094462204 ef [1.0, 3.0, 18815.0, 3610.0, 1107.0, 1148.0, 2184.0, 2963.0] 1.31751534 of [1.0, 3.0, 21632.0, 131 Cluster 5 : 100.04 of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.04 of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 280 3 1 149 150 RFCM-Computed Centorids 5 13 149 150 4 18 149 167 5 13 149 122 DB Index: 5.279362	Outpu	
(0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.0464888818, 0.020278862, 0.02177252] (0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1425405, 0.034524433] (0.920769021, 0.7666534, 0.2815415, 0.45338348, 0.16205912, 0.445927042, 0.025879655, 0.712399] (0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863) Cluster Output : Cluster 1 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.04 of [1.0, 3.0, 5963.0, 3648.0, 4000, 1000, 1107.0, 1148.0, 2134.0, 2963.0] 100.04 of [1.0, 3.0, 5963.0, 3648.0, 4000, 1107.0, 1148.0, 2134.0, 2963.0] 1.03751534 of [1.0, 3.0, 21632.0, 1310] Cluster 2 : 100.04 of [1.0, 3.0, 13815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.81882574 of [1.0, 3.0, 21632.0, 1310] Cluster 5 : 100.04 of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.04 of [1.0, 3.0, 43088.0, 2100.0, 100		at - modRFCM (run) #
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(0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433] (0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7123939] (0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863) Cluster Output : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, 9 Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, 9 Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310 Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.8138257% of [1.0, 3.0, 21632.0, 1310 Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 280 3 1 149 150 4 18 149 167 5 3 3 149 182 DB Index: 5.277832	A	Cluster Centroids:
(0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7129398] (0.7833555, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863) Cluster Output : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, 4000 columns of the state		ut-modRFCM (run) # Cluster Centroids: (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252)
<pre>(0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863] Cluster Cutput : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, 4 Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [2.0, 3.0, 7057.0, 9810.0, 5 Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310 Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.8138257% of [1.0, 3.0, 21632.0, 1310 Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 250 3 1 149 150 RFCM-Computed Centorids 5 3 149 182 DB Index: 5.278852</pre>		<pre>xt-modRFCM (run) # Cluster Centroids:</pre>
<pre>[0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863] Cluster Output : Cluster 1 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.04 of [1.0, 3.0, 5963.0, 3648.0, e Cluster 2 : 100.04 of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.04 of [2.0, 3.0, 7057.0, 9810.0, 2 Cluster 3 : 1.71179844 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.31751534 of [1.0, 3.0, 21632.0, 131 Cluster 4 : 0.944622044 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.31382574 of [1.0, 3.0, 21632.0, 131 Cluster 5 : 100.04 of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.04 of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1</pre>		<pre>xt-modRFCM (run) # Cluster Centroids:</pre>
Cluster Output : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, of Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [2.0, 3.0, 7057.0, 9810.0, 5 Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310 Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.8138257% of [1.0, 3.0, 21632.0, 1310 Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 250 3 1 149 150 RFCM-Computed Centorids 5 33 149 182 DE Index: 5.278352		<pre>xt-modRFCM (run) # Cluster Centroids:</pre>
Cluster Output : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, of Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [2.0, 3.0, 7057.0, 9810.0, 507.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310 Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310 Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.8138257% of [1.0, 3.0, 21632.0, 1310 Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1		<pre>xt-modRFCM (run) # Cluster Centroids:</pre>
Cluster Output : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, 4 Cluster 2 : 100.0% of [2.0, 3.0, 1269.0, 9666.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [1.0, 3.0, 7057.0, 9810.0, 5 Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310 Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.8138257% of [1.0, 3.0, 21632.0, 1310 Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 250 3 1 149 150 RFCM-Computed Centorids 5 33 149 182 DE Index: 5.278352		Cluster Centroids: (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252] (0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433] (0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7129398] (0.783558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863]
Cluster Output : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, or Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [2.0, 3.0, 7057.0, 9810.0, cr Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310 Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.8138257% of [1.0, 3.0, 21632.0, 1310 Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 250 3 1 149 150 RFCM-Computed Centorids 4 18 149 167 5 33 149 182 D8 Index: 5,278352		<pre>ut-modRFCM (run) W Cluster Centroids: (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252) (0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433) (0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7129398) (0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638) (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.093633903, 0.018833991, 0.04053863)</pre>
Cluster 1: 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, Cluster 2: 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [2.0, 3.0, 7057.0, 9810.0, 500.0] Cluster 3: 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310] Cluster 4: 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.8138257% of [1.0, 3.0, 21632.0, 1310] Cluster 5: 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 250 3 1 149 150 RFCM-Computed Centorids 5 33 149 182 DB Index: 5.278352		<pre>ut-modRFCM (run) W Cluster Centroids: (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252) (0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433) (0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7129398) (0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638) (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863)</pre>
Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [2.0, 3.0, 7057.0, 9810.0, 1 Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310 Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.8138257% of [1.0, 3.0, 21632.0, 1310 Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 250 3 1 149 150 RFCM-Computed Centorids 5 33 149 182 DE Index: 5.278352		Cluster Centroids: (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252] (0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433] (0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7129398] (0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863] Cluster Output :
Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1310 Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.8138257% of [1.0, 3.0, 21632.0, 1310 Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 250 3 1 149 150 4 18 149 167 5 33 149 182 D8 Index: 5.278352		Cluster Centroids: (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252] (0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433] (0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7129398] (0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863) Cluster Cutput : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, 4000.0000]
Cluster 4 : 0.944622044 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.81382574 of [1.0, 3.0, 21632.0, 1310 Cluster 5 : 100.04 of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.04 of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 250 3 1 149 150 RFCM-Computed Centorids 4 18 149 167 5 33 149 182 DB Index: 5.278352		Cluster Centroids: (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252] (0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433] (0.024769021, 0.7666534, 0.28156415, 0.45389418, 0.18205912, 0.45927042, 0.025878055, 0.7129398] (0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863) Cluster Output : Cluster Output : Cluster 1 : 100.04 of (1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0) Cluster 2 : 100.04 of (2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0) 100.04 of (2.0, 3.0, 7057.0, 9810.0, 1
Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0] 100.0% of [1.0, 3.0, 43088.0, 2100.0, Cluster Low Upper Total 1 138 149 287 2 101 149 250 3 1 149 150 RFCM-Computed Centorids 4 18 149 167 5 33 149 182 DB Index: 5,278352		Cluster Centroids: (0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252] (0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433] (0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7123398] (0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] (0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.093633903, 0.018833991, 0.04053863] Cluster Output : Cluster Output : Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] 100.0% of [1.0, 3.0, 5963.0, 3648.0, 4 Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] 100.0% of [2.0, 3.0, 7057.0, 9810.0, 5 Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 1.3175153% of [1.0, 3.0, 21632.0, 1318
Cluster         Low         Upper         Total           1         138         149         287           2         101         149         250           3         1         149         150           4         18         149         167           5         33         149         182           DB         Index:         5,278352		Cluster Centroids: [0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252] [0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433] [0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7129398] [0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638] [0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863] Cluster Cutput : Cluster Cutput : Cluster 1 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0] Cluster 2 : 100.04 of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0] Cluster 3 : 1.71179844 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.81382574 of [1.0, 3.0, 21632.0, 1316 Cluster 4 : 0.944622044 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0] 0.81382574 of [1.0, 3.0, 21632.0, 1316
2 101 149 250 3 1 149 150 4 18 149 167 5 33 149 182 D8 Index: 5.278352		at-modRFCM (run) #         Cluster Centroids:         [0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252]         [0.95548105, 0.84448624, 0.08325519, 0.13762504, 0.16085708, 0.026401952, 0.1625405, 0.034524433]         [0.024769021, 0.7666534, 0.28156415, 0.4538418, 0.18205912, 0.45927042, 0.025878055, 0.7123398]         [0.07833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638]         [0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863]         Cluster Output :         Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.0% of [1.0, 3.0, 5963.0, 3648.0, 4         Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]       100.0% of [1.0, 3.0, 7057.0, 9810.0, 5         Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.3175153% of [1.0, 3.0, 21632.0, 1316         Cluster 4 : 0.94462204% of [1.0, 3.0, 12815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.00.0% of [1.0, 3.0, 21632.0, 1316         Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0]       100.0% of [1.0, 3.0, 43088.0, 2100.0, 13107.0, 1348.0, 2381.0, 2963.0]
3         1         149         150         RFCM-Computed Centorids           4         18         149         167         S         33         149         182           D8         Index:         5,278352         182         182         182		at - modRFCM (run) #         Cluster Centroids:         [0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252]         [0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.034524433]         [0.02795901, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.46927042, 0.025878055, 0.7123398]         [0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.14666293, 0.035048638]         [0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863]         Cluster Output :         Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.0% of [1.0, 3.0, 5963.0, 3648.0, 400.0, 1007.0, 1788.0]         Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]       100.0% of [2.0, 3.0, 7057.0, 9810.0, 1007.0, 1148.0, 2134.0, 2963.0]         Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.3175153% of [1.0, 3.0, 21632.0, 1316         Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       0.8138257% of [1.0, 3.0, 21632.0, 1316         Cluster Low Upper Total       1.00.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0]       100.0% of [1.0, 3.0, 43088.0, 2100.0, 1007.0]         Cluster Low Upper Total       1.0139       1.0107.0, 1148.0, 2381.0, 4334.0]       100.0% of [1.0, 3.0, 43088.0, 2100.0, 2100.0, 2100.0, 40088.0, 2100.0, 40088.0, 2100.0, 40088.0, 2100.0, 40088.0, 2000.0] </td
4 18 149 167 5 33 149 182 D8 Index: 5.278352		at - modRFCM (run) #         Cluster Centroids:         [0.00279933044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177262]         [0.95548105, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401952, 0.1625405, 0.03452433]         [0.0247959214, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.465927042, 0.025878055, 0.7123959]         [0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.16666293, 0.035048638]         [0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.040553863]         Cluster Output :         Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.0% of [1.0, 3.0, 5963.0, 3648.0, 4         Cluster 2 : 100.0% of [2.0, 3.0, 12659.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]       100.0% of [1.0, 3.0, 21632.0, 1310         Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.3175153% of [1.0, 3.0, 21632.0, 1310         Cluster 1 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.01.0% of [1.0, 3.0, 21632.0, 1310         Cluster Low Upper Total       1       138       149       287         1       138       149       287       100       148       281.0, 4334.0]       100.0% of [1.0, 3.0, 43088.0, 2100.0,
5 33 149 182 DB Index: 5.278352		at - modRFCM (run) #         Cluster Centroids:         [0.0027933044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252]         [0.55548105, 0.84448624, 0.08325513, 0.13752504, 0.16085708, 0.026401552, 0.1625405, 0.034524433]         [0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.025878055, 0.7129398]         [0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.04338117, 0.16666293, 0.050046638]         [0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.09363903, 0.018833991, 0.04053863]         Cluster Output :         Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.0% of [1.0, 3.0, 5963.0, 3648.0, 4         Cluster 2 : 100.0% of [1.0, 3.0, 12865.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.0% of [1.0, 3.0, 5963.0, 3648.0, 4         Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       13375134 of [1.0, 3.0, 21632.0, 131         Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       0.8138257* of [1.0, 3.0, 21632.0, 131         Cluster Low Upper Total       1       138       149       287         2       201       149       250       201       149       250         3       1       149       250       201       149       250
D8 Index: 5,278352		at -modRFCM (run) #         Cluster Centroids:         [0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252]         [0.95548205, 0.84448624, 0.08325519, 0.13752504, 0.16085708, 0.026401852, 0.1628405, 0.034524433]         [0.024769021, 0.7666534, 0.28156415, 0.45383418, 0.18205912, 0.45927042, 0.02878055, 0.7123398]         [0.733355, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.14666293, 0.035046638]         [0.0041502523, 0.5018314, 0.27924973, 0.053796224, 0.052083004, 0.09363503, 0.018833991, 0.04053863]         Cluster 1 : 100.04 of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.04 of [1.0, 3.0, 5963.0, 3648.0, 4         Cluster 2 : 100.04 of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1388.0]       100.04 of [1.0, 3.0, 5963.0, 3648.0, 4         Cluster 3 : 1.71179644 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.31751554 of [1.0, 3.0, 21632.0, 1316         Cluster 5 : 100.04 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.00.04 of [1.0, 3.0, 21632.0, 1316         Cluster 5 : 100.04 of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.00.04 of [1.0, 3.0, 21632.0, 1316         Cluster 1 in 38       149       287       1.01       1.03       1.49       250       1.149       150       RFCM-Computed Centorids       1.00.04 of [1.0, 3.0, 43088.0, 2100.0, 0.00       1.00.04 of [1.0, 3.0, 43088.0, 2100.0, 0.00       1.01.03       0.43088.0, 2100.0, 0.00
		at -modRFCM (run) #         Cluster Centroids:         [0.0027993044, 0.9006208, 0.078218155, 0.039805472, 0.039439082, 0.046488818, 0.020278862, 0.02177252]         [0.95548105, 0.84448624, 0.08325515, 0.13752504, 0.16055708, 0.026401552, 0.1625405, 0.034524433]         [0.024769021, 0.7666534, 0.28156415, 0.45883418, 0.18205912, 0.45927042, 0.025878055, 0.7123398]         [0.7833558, 0.050052088, 0.0627764, 0.12777407, 0.16680793, 0.043381177, 0.14666293, 0.035048638]         [0.0041502523, 0.9018314, 0.27924973, 0.053796224, 0.052083004, 0.093633903, 0.018833991, 0.04053863]         Cluster Cutput :         Cluster 1 : 100.0% of [1.0, 3.0, 13265.0, 1196.0, 4221.0, 6404.0, 507.0, 1788.0]       100.0% of [1.0, 3.0, 5963.0, 3648.0, 9         Cluster 2 : 100.0% of [2.0, 3.0, 12669.0, 9656.0, 7561.0, 214.0, 2674.0, 1338.0]       100.0% of [1.0, 3.0, 7057.0, 9810.0, 1317         Cluster 3 : 1.7117984% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       1.3175153% of [1.0, 3.0, 21632.0, 131         Cluster 4 : 0.94462204% of [1.0, 3.0, 18815.0, 3610.0, 11107.0, 1148.0, 2134.0, 2963.0]       0.8138257% of [1.0, 3.0, 21632.0, 131         Cluster 5 : 100.0% of [1.0, 3.0, 31276.0, 1917.0, 4469.0, 9408.0, 2381.0, 4334.0]       100.0% of [1.0, 3.0, 43088.0, 2100.0, 131         Cluster 1 bw       Upper       Total       1         1 1 138       149       260       3       1       149       150         3 1 149       150       RFCM-Computed Centorids

# Fig: 1. c



Cluste					
A CONTRACTOR	er Centroi	ds:			
10222375EX15	202223-1-12-22		·		
10.944	61553, 0.9	1477374	6, 0.05729276,	0.16125685, 0.20586348, 0.027063306, 0.20942558, 0.037975084]	
(0.832	269525, 0.	7491524	6, 0.17170061,	0.4253329, 0.48295036, 0.04889895, 0.53585386, 0.05701775)	
(0.744	4497, 0.02	706799,	0.06619416, 0	123268284, 0.15772663, 0.046937305, 0.15439841, 0.03698495]	
[0.005	57543186,	0.67200	0667, 0.1200068	9, 0.047530804, 0.04332394, 0.06101714, 0.020439416, 0.029276028]	
(0.943	37978, 0.9	129667,	, 0.10131788, 0	0.09374552, 0.10495123, 0.028530672, 0.09351887, 0.036122866]	
Cluste	er Output	:			
Cluste	er 1 : 100	.01 of	(1.0. 1.0. 0.0	5352748 0.15025342 0.20347716 0.018637829 0.18180482 0.043700461	67.791875 of [1
Cluste	er 2 : 6.7	9263834	of [1.0, 1.0.	0.02998716. 0.072818376. 0.13980836. 0.0719052. 0.14633548. 0.0363162271	15.2479231 of (
Cluste	er 3 : 3.4	5711114	of [1.0, 1.0,	0.02998716, 0.072818376, 0.13980836, 0.0719052, 0.14633548, 0.036316227]	7.452865% of [1
Cluste	er 4 : 100	1.01 01	[0.0, 1.0, 0.1	1825445, 0.0155358575, 0.045463853, 0.10484189, 0.012345679, 0.03723404]	100.0% of [0.0,
Cluste	er 5 : 100	1.0% of	[1.0, 1.0, 0.1	1294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309]	100.0% of [1.0,
Cluste	er Low	Dener	Total		
1	26	107	133		
2	6	107	113		
3	10	107	125	RIFCM-Random Centorids	
4	236	107	343	ALL OF ALLOUNDED OUT OF THE	
5	47	107	154		
D8 Ind	dex: 6.178	9246			
DVLW	DVVVLDBI V		a bane. a seco		
utput - mor	dRIFCM (run)	) 26			
Clust	ter Centro	ids:			
Clust	ter Centro	ids:			
Clust to.or	ter Centro 02541245,	ids: 0.87991	37, 0.07940321,	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865)	
Clust t0.00 t0.72	ter Centro 02541245, 284082, 0.	ids: 0.87991 7091971	37, 0.07940321, , 0.0954261, 0	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865) .12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)	
Clust [0.00 [0.72 [0.03	ter Centro 02541245, 284082, 0. 15254817,	1d#: 0.87991 7091971 0.76358	137, 0.07940321, 0.0954261, 0. 106, 0.27822503,	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865) .12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599) , 0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.7119461)	
Clust 10.00 10.72 10.72 10.72	ter Centro 02541245, 284082, 0. 15254817, 091294, 0.	1ds: 0.87991 7091971 0.76358 0180209	137, 0.07940321, 0.0954261, 0 106, 0.27822503, 135, 0.0663487,	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865) .12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599) , 0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.71194611 0.12177028, 0.15885676, 0.045969225, 0.15550959, 0.0349503]	
Clust 10.00 10.72 10.03 10.70 10.70	ter Centro 02541245, 284082, 0. 15254817, 091294, 0. 028963638,	0.87991 7091971 0.76358 0180209 0.8755	137, 0.07940321, 0.0954261, 0. 06, 0.27822503, 035, 0.0663487, 424, 0.2766255	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865) 12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599) , 0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.7119461] 0.12177028, 0.15885676, 0.045969225, 0.15850595, 0.0349503] 7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973]	
Clust t0.00 t0.71 t0.01 t0.70 t0.70	ter Centro 02541245, 284082, 0. 15254817, 091294, 0. 028963638,	1d#: 0.87991 7091971 0.76358 0180209 0.8755	137, 0.07940321, 1, 0.0954261, 0 106, 0.27822503, 135, 0.0663487, 1424, 0.2766255	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865) 12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599) . 0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.7119461] 0.12177028, 0.15885676, 0.045969225, 0.15550955, 0.0349503] 7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973]	
Clust [0.00 [0.73 [0.01 [0.76	ter Centro 02541245, 284092, 0. 15254817, 091294, 0. 028963638,	1ds: 0.87991 7091971 0.76358 0180209 0.8765	.37, 0.07940321, 0.0954261, 0. 06, 0.27822503, 35, 0.0663487, 424, 0.27662551	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865) 12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599) , 0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.71194613 0.12177028, 0.15885676, 0.045969225, 0.15550959, 0.03495033 7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.0403969733	
Clust 1 t0.01 1 t0.02 10.02 10.02 10.00 Clust	ter Centro 02541245, 284082, 0. 15254817, 091294, 0. 028963638, ter Output	1ds: 0.87991 7091971 0.76358 0180209 0.8755	137, 0.07940321, 0.0954261, 0. 106, 0.27822503, 135, 0.0663487, 1424, 0.27662557	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865) 12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599] , 0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.71194611 0.12177028, 0.15885676, 0.045969225, 0.15550959, 0.0349503] 7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973]	
Clust (0.00 (0.72 (0.02) (0.02 (0.02) (0	ter Centro 02541245, 284092, 0. 15254817, 091294, 0. 028963638, ter Output ter 1 : 10	1de: 0.87991 7091971 0.76358 0180209 0.8765	137, 0.07940321, 0.0954261, 0. 06, 0.27822503, 035, 0.0663487, 424, 0.2766255 10.0, 1.0, 0.1	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865) 12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599) , 0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.71194611 0.12177028, 0.15885676, 0.045969225, 0.15550959, 0.03495031 7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.0403969733	100.0 <b>%</b> of (0.0,
Clust (0.00 (0.73 (0.03) (0.74 (0.03) (0.74) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.05)	ter Centro 02541245, 284092, 0. 15254817, 051254, 0. 028963638, ter Output ter 1 : 10 ter 2 : 10	1de: 0.87991 0.7691971 0.76958 0180209 0.8759 0.8759	<pre>137, 0.07940321, 0.0954261, 0. 106, 0.27822503, 135, 0.0663487, 1424, 0.2766255 1424, 0.2766255 1424, 0.2766255</pre>	, 0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865) 12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599) , 0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.71194613 0.12177028, 0.15885676, 0.045969225, 0.15550959, 0.03495033 7, 0.05626553, 0.052428953, 0.03731744, 0.01896793, 0.0403969733 11825445, 0.01553588575, 0.045463853, 0.10484189, 0.012345679, 0.037234043	100.0% of (0.0, 100.0% of (1.0,
Clust Clust (0.01 (0.02 (0.01 (0.02 (0.01 Clust Clust Clust Clust	ter Centro 02541245, 284092, 0. 15254917, 091294, 0. 028963638, ter Output ter 1 : 10 ter 1 : 10 ter 2 : 10 ter 3 : 5.	1.ds: 0.87991 7091971 0.76358 0180209 0.8755 .: 0.8755 .: 0.04 of 0.04 of 6903167	137, 0.07940321, . 0.954261, 0. 006, 0.27822503, 355, 0.0663487, 424, 0.27662557 1424, 0.27662557 1 [0.0, 1.0, 0.1] 1 [1.0, 1.0, 0.1] • of [0.0, 1.0, 0.1]	<ul> <li>0.040500537, 0.0401455976, 0.04624528, 0.021077733, 0.022052865)</li> <li>12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)</li> <li>0.4493896, 0.17915569, 0.455467848, 0.023461858, 0.0119461]</li> <li>0.12177028, 0.15885676, 0.045969225, 0.15550559, 0.0349503]</li> <li>7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973]</li> <li>11825445, 0.0155358575, 0.045463853, 0.10484189, 0.012345679, 0.03723404]</li> <li>11294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309]</li> <li>0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> </ul>	100.04 of (0.0, 100.04 of (1.0, 1 4.554252
Clust Clust Clust Clust Clust Clust Clust	ter Centro 02541245, 284082, 0. 15254817, 091294, 0. 028963638, ter Output ter 1 : 10 ter 2 : 10 ter 2 : 5. ter 4 : 3.	1.ds: 0.87991 7091971 0.76358 0180209 0.8755 : 0.00 of 6903167 2728243	<pre>137, 0.07940321, 0.0954261, 0 106, 0.27822503, 135, 0.0663487, 1424, 0.2766255 1 (0.0, 1.0, 0.1 1 (1.0, 1.0, 0.1) 1 (1.0, 1.0, 0.1) 1 of [0.0, 1.0]</pre>	<ul> <li>0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865)</li> <li>12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)</li> <li>0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.7119461]</li> <li>0.12177028, 0.15885676, 0.045969225, 0.15550559, 0.0349503]</li> <li>7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973]</li> <li>11825445, 0.0155358575, 0.045463853, 0.10484189, 0.012345679, 0.03723404]</li> <li>11294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309]</li> <li>0.16774262, 0.048046884, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> <li>0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> </ul>	100.0% of (0.0, 100.0% of (1.0, 1 4.554252 2.919476
Clust (0.00 (0.72 (0.02) (0.02) (0.02) (0.02) Clust Clust Clust Clust Clust	ter Centro 02541245, 284092, 0. 15254817, 091294, 0. 028963438, ter Output ter 1 : 10 ter 2 : 10 ter 2 : 10 ter 3 : 5, ter 4 : 3, ter 5 : 10	1.ds: 0.87591 7091971 0.76580 0180209 0.8765 : : 0.04 of 0.04 of 2728243 0.04 of	<pre>137, 0.07940321, 0.0954261, 0. 066, 0.27822503, 035, 0.0663487, 424, 0.2766255 1 (0.0, 1.0, 0.1 1 (1.0, 1.0, 0.1 1 (1.0, 1.0, 0.1 0 of (0.0, 1.0, 0.1 0 of (0.0, 1.0, 0.1)</pre>	<ul> <li>0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865)</li> <li>12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)</li> <li>0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.7119461]</li> <li>0.12177028, 0.15885676, 0.045969225, 0.15550955, 0.0349503]</li> <li>7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973]</li> <li>11825445, 0.0155358575, 0.045463853, 0.10484189, 0.012345679, 0.03723404]</li> <li>11294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309]</li> <li>0.16774262, 0.048040884, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> <li>27885473, 0.025352994, 0.04815693, 0.15421405, 0.058250047, 0.0903421]</li> </ul>	100.04 of (0.0, 100.04 of (1.0, ) 4.554252 ) 2.919476 100.04 of (0.0,
Clust Clust Clust Clust Clust Clust Clust	ter Centro 02541245, 284082, 0. 15254817, 091294, 0. 028963638, ter Output ter 1 : 10 ter 2 : 10 ter 2 : 10 ter 3 : 5. ter 5 : 10 ter 5 : 10	1.ds: 0.87591 7091971 0.76358 0180209 0.8765 : 0.06 of 0.06 of 2728243 0.06 of 2728243 0.06 of Upper	<pre>137, 0.07940321, 1, 0.0954261, 0 106, 0.27822503, 135, 0.0663487, 1424, 0.2766255 1 (0.0, 1.0, 0.1 1 (1.0, 1.0, 0.1) 1 (1.0, 1.0, 0.1) 1 of (0.0, 1.0, 0.1) 1 of (0.0, 1.0, 0.1) 1 (0.0, 1.0, 0.1)</pre>	<ul> <li>0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865)</li> <li>12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)</li> <li>0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.7119461]</li> <li>0.12177028, 0.15885676, 0.045969225, 0.15550559, 0.034503]</li> <li>7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973]</li> <li>11825445, 0.0155358575, 0.0455463853, 0.10484189, 0.012345679, 0.03723404]</li> <li>11294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309]</li> <li>0.16774262, 0.048040894, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> <li>27885473, 0.025352994, 0.04815693, 0.15421405, 0.058250047, 0.0903421]</li> </ul>	100.04 of [0.0, 100.04 of [1.0, 1 4.554252 2.919476 100.04 of [0.0,
Clust (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) Clust Clust Clust Clust Clust Clust Clust 1	ter Centro 02541245, 284082, 0. 15254817, 091294, 0. 028963638, ter Output ter 1 : 10 ter 2 : 10 ter 3 : 5, ter 5 : 10 ter Low 139	1ds: 0.87591 7091971 0.76580 0180209 0.8765 : 0.04 of 0.04 of 2728243 0.04 of 2728243 0.04 of 2728243	<pre>137, 0.07940321, 0.0954261, 0. 106, 0.27922603, 135, 0.0663487, 1424, 0.2766255 1 (0.0, 1.0, 0.1) 1 (1.0, 1.0, 0.1) 1 of (0.0, 1.0, 0.1) 1 of (0.0, 1.0, 0.1) 1 of (0.0, 1.0, 0.1) 1 of (0.0, 1.0, 0.1) 1 otal 267</pre>	<ul> <li>0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865)</li> <li>12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)</li> <li>0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.71194613</li> <li>0.12177028, 0.15885676, 0.045969225, 0.15550959, 0.03495033</li> <li>7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.0403969733</li> <li>11825445, 0.0155358575, 0.045463853, 0.10484189, 0.012345679, 0.037234043</li> <li>11294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.0278473093</li> <li>0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.0617438483</li> <li>27885473, 0.025352994, 0.04813693, 0.15421405, 0.058250047, 0.09034213</li> </ul>	100.04 of (0.0, 100.04 of (1.0, 1 4.554252 2.919476 100.04 of (0.0,
Clust (0.00) (0.72) (0.02) (0.02) (0.02) (0.02) (0.02) (0.02) (0.02) (10.02) (	ter Centro 02541245, 284092, 0. 15254817, 091294, 0. 028963638, ter Cutput ter 1 : 10 ter 2 : 10 ter 2 : 10 ter 4 : 3. ter 5 : 10 ter Low 139 121	1.ds: 0.87991 7091971 0.76580 0180209 0.8765 0.0% of 6903167 2728243 0.0% of 6903167 2728243 0.0% of 2728243 0.0% of 2728243 0.0% of 2728243 0.0% of 2728243	<pre>137, 0.07940321, 0.0954261, 0. 106, 0.27822503, 135, 0.0663487, 1424, 0.2766255 1 (0.0, 1.0, 0.1 1 (1.0, 1.0, 0.1 1 (1.0, 1.0, 0.1 1 (0.0, 1.0, 0.1 2 (0.0, 1.0, 0.1 1 (0.0, 1.0, 0.1 2 (0.0, 1.0, 0.1 1 (0.0, 0.1) 1 (0.</pre>	<ul> <li>0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865)</li> <li>12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)</li> <li>0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.71194611</li> <li>0.12177028, 0.15885676, 0.045969225, 0.15550959, 0.03495031</li> <li>7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.0403969731</li> <li>11825445, 0.0155358575, 0.045463853, 0.10484189, 0.012345679, 0.03723404]</li> <li>11825445, 0.0155358575, 0.045463853, 0.10484189, 0.012345679, 0.03723404]</li> <li>11825445, 0.0155358575, 0.0454643853, 0.10484189, 0.012345679, 0.03723404]</li> <li>11926404, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309]</li> <li>0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> <li>0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> <li>27885473, 0.025352994, 0.04813693, 0.15421405, 0.058250047, 0.0903421]</li> </ul>	100.0% of (0.0, 100.0% of (1.0, 4.554252 2.91947( 100.0% of (0.0,
Clust (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7)(	ter Centro 02541245, 284092, 0. 15254817, 091294, 0. 028963638, ter Output ter 1 : 10 ter 2 : 10 ter 3 : 5. ter 4 : 3. ter 5 : 10 ter 5 : 10 ter 10w 139 121 1	1ds: 0.87991 7091971 0.76358 0180209 0.8755 0.8755 : 0.0% of 6903167 2728243 0.0% of Upper 128 128 128	<pre>137, 0.07940321, ., 0.0954261, 0 106, 0.27822503, 135, 0.0663487, 1424, 0.2766255 1424, 0.2766255 1 (0.0, 1.0, 0.1 1 (1.0, 1.0, 0.1) 1 of (0.0, 1.0, 0.1) 1 of (0.0, 1.0, 0.1) 1 of (0.0, 1.0, 0.1) 1 Total 267 249 129</pre>	. 0.040500537, 0.040145976, 0.04624528, 0.021077733, 0.022052865) 12495413, 0.14386265, 0.03721334, 0.13998213, 0.03397599] . 0.4493896, 0.17915569, 0.455467848, 0.023461858, 0.7119461] 0.12177028, 0.15885676, 0.045969225, 0.15550555, 0.0349503] 7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973] 11825445, 0.0155358575, 0.045463853, 0.10484189, 0.012345679, 0.03723404] 11294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309] . 0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.061743848] . 0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.061743848] 27885473, 0.025352994, 0.04813693, 0.15421405, 0.058250047, 0.0903421]	100.04 of [0.0, 100.04 of [1.0, 4.554252 2.919476 100.04 of [0.0,
Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust 2 3 4	ter Centro 02541245, 284092, 0. 15254817, 091294, 0. 028963638, ter Output ter 1 : 10 ter 2 : 10 ter 2 : 10 ter 3 : 5. ter 4 : 3. ter 5 : 10 ter Low 139 121 18	Lds: 0.87991 7091971 0.76358 0180209 0.8765 : 0.00 of 6903167 2728243 0.06 of 6903167 2728243 0.06 of 5903167 2728243 0.06 of 228 128 128 128	<pre>137, 0.07940321, 1, 0.0954261, 0 106, 0.27822503, 135, 0.0663487, 1424, 0.2766255 1 (0.0, 1.0, 0.1 1 (1.0, 1.0, 0.1) 1 of (0.0, 0.1) 1 of (0</pre>	<ul> <li>0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865)</li> <li>12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)</li> <li>0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.7119461]</li> <li>0.12177028, 0.1585576, 0.045969225, 0.15550559, 0.034503]</li> <li>7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973]</li> <li>11825445, 0.0155358575, 0.0455463853, 0.10484189, 0.012345679, 0.03723404]</li> <li>11294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309]</li> <li>0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> <li>0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> <li>27885473, 0.025352994, 0.04813693, 0.15421405, 0.058250047, 0.0903421]</li> </ul>	100.04 of [0.0, 100.04 of [1.0, 4.554252 2.919476 100.04 of [0.0,
Clust (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (10.7) (0.0) (10.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) (0.0) (0.7) (0.0) (0.7) (0.0)	ter Centro 02541245, 284092, 0. 15254817, 091294, 0. 028963638, ter Output ter 1 : 10 ter 2 : 10 ter 3 : 5. ter 5 : 10 ter Low 139 121 1 18 33	1ds: 0.87591 7091971 0.76358 0180209 0.8765 : 0.04 of 0.04 of 0.04 of 2728243 0.04 of 128 128 128 128 128	<pre>137, 0.07940321, 1, 0.0954261, 0. 106, 0.27822503, 135, 0.0663487, 1424, 0.2766255; 1 (0.0, 1.0, 0.; 1 (1.0, 1.0, 0.; 1 (1.0, 1.0, 0.; 1 (0.0, 0.; 1 (0.0,</pre>	<ul> <li>0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865)</li> <li>12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)</li> <li>0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.7119461]</li> <li>0.12177028, 0.15885676, 0.045969225, 0.15550955, 0.0349503]</li> <li>7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973]</li> <li>11825445, 0.0155358575, 0.0459643853, 0.10484189, 0.012345679, 0.03723404]</li> <li>11294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309]</li> <li>0.16774262, 0.048040884, 0.11968484, 0.018457038, 0.052199688, 0.061743848]</li> <li>27885473, 0.025352994, 0.04813693, 0.15421405, 0.058250047, 0.0903421]</li> </ul>	100.0% of (0.0, 100.0% of (1.0, 4.554252 2.919476 100.0% of (0.0,
Clust (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust Clust	ter Centro 02541245, 284082, 0. 15254817, 091294, 0. 028963638, ter Output ter 1 : 10 ter 2 : 10 ter 2 : 10 ter 5 : 10 ter 5 : 10 ter Low 139 121 1 1 8 33 ndex: 5.50	1ds: 0.87591 7091971 0.76588 0180209 0.8765 2000 of 0.04 of 6903167 2728243 0.04 of 2728243 0.04 of 128 128 128 128 128 128 128	<pre>137, 0.07940321, 0.0954261, 0. 106, 0.27922803, 135, 0.0663487, 1424, 0.2766255 1424, 0.2766255 15 [1.0, 1.0, 0.1] 15 [1.0, 1.0, 0.1] 16 of [0.0, 1.0, 0.1] 16 of [0.0, 1.0, 0.1] 16 of [0.0, 1.0, 0.1] 16 1 16 1</pre>	<ul> <li>0.040500537, 0.040165976, 0.04624528, 0.021077733, 0.022052865)</li> <li>12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599)</li> <li>0.4493896, 0.17915569, 0.45467848, 0.023461858, 0.71194613</li> <li>0.12177028, 0.15885676, 0.045969225, 0.15550959, 0.03495033</li> <li>7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.0403969733</li> </ul>	100.04 of (0.0, 100.04 of (1.0, 1 4.554252 2.919476 100.04 of (0.0,
Clust (0.0) (0.7) (0.0) (0.7) (0.0) (0.7) (0.0) Clust Clust Clust Clust Clust Clust Clust S DB Ir BUIL	ter Centro 02541245, 284092, 0. 15254817, 091294, 0. 028963638, ter Output ter 1 : 10 ter 2 : 10 ter 2 : 10 ter 3 : 5. ter 5 : 10 ter Low 139 121 1 1 1 33 ndex: 5.50 D SUCCESSE	Lds: 0.87991 7091971 0.7658 0180209 0.8765 0.04 of 903167 2722243 0.04 of 903167 128 128 128 128 128 128 128 128	<pre>137, 0.07940321, 0.0954261, 0. 106, 0.27822503, 135, 0.0663487, 1424, 0.2766255 1424, 0.2766255 15 (0.0, 1.0, 0.1) 15 of (0.0, 1.0, 0.1) 16 of (0.0, 1.0, 0.1) 16 of (0.0, 1.0, 0.1) 17 otal 267 249 129 146 161 181 time: 3 second 18 otal</pre>	(0.040500537, 0.040145976, 0.04624528, 0.021077733, 0.022052865) 12496413, 0.14386265, 0.03721334, 0.13998213, 0.03397599) (0.44938956, 0.17915569, 0.45467848, 0.023461859, 0.7119461] 0.12177028, 0.15885676, 0.045969225, 0.15550959, 0.0349503] 7, 0.05626553, 0.052428953, 0.09731744, 0.01896793, 0.040396973] 11825445, 0.0155358575, 0.045463853, 0.10484189, 0.012345679, 0.03723404] 11294004, 0.13072723, 0.08146416, 0.0031063047, 0.0654272, 0.027847309] (0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.0617438468] 0.16774262, 0.048404884, 0.11968484, 0.018457038, 0.052199688, 0.0617438468] 27885473, 0.025352994, 0.04813693, 0.15421405, 0.058250047, 0.0903421]	100.04 of (0.0, 100.04 of (1.0, 4.554252 2.919476 100.04 of (0.0,





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Output - newRRCM (run) #
D
     Cluster Centroids:
     [0.9974359, 0.9769231, 0.11337482, 0.09593226, 0.11595102, 0.022663072, 0.10985477, 0.026645975]
     [1.0, 0.98333335, 0.21442425, 0.58236705, 0.60338833, 0.043145586, 0.658173, 0.054620706]
     [0.99670327, 0.97032964, 0.05956939, 0.12616834, 0.10715535, 0.03671412, 0.10877894, 0.1298938]
82
     [0.0, 0.8868824, 0.11733575, 0.041977037, 0.041183162, 0.05794213, 0.018293133, 0.026716366]
     [0.775. 0.0037500001, C.06107472, 0.12455726, 0.16507179, 0.045793295, 0.16185482, 0.03559783]
     Cluster Output :
     Cluste: Low
                   Upper Total
            30
                    87
                            117
     1
     2
             6
                    3
                            9
     3
             2
                    89
                            91
             237
                    62
                            299
     4
     5
            19
                    61
                            80
                                                            Tuned RCM-Random Centroids
     DB Index: 7.8387375
     RUTID SUCCESSIUL (FARA) Fima-
Output - modRRCM (run) 34
D
      Cluster Centroids:
      [0.0, 0.8818501, 0.08951014, 0.0390229, 0.0386027, 0.049406096, 0.018120985, 0.022295
      (1.0, 0.97720003, 0.08355733, 0.1346251, 0.16255602, 0.023785736, 0.15979835, 0.03672
      [0.0, 1.0, 0.32853016, 0.59767437, 0.21737069, 0.60004276, 0.0057809134, 1.0]
26
      [0.823, 0.0375, 0.059909344, 0.1333718, 0.17293385, 0.041111365, 0.17237191, 0.035530
      [0.0, 0.9875, 0.52219987, 0.08869543, 0.087274864, 0.17645161, 0.030959219, 0.0564551
      Cluster Output :
      Cluster Low
                      Upper
                               Total
               204
                        87
                                291
      1
                                125
               103
                        22
      2
      3
               2
                        0
                                2
                                                        Tuned RCM-Computed Centroids
               19
                        81
                                100
      4
      s
               8
                        28
                                36
      DB Index : 2.8790536
      BUILD SUCCESSFUL (total time: 0 seconds)
```



Fig: 1. e

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r - reikr	CM (run)	R				
Cluste	er 1 : 3:	2.691067	of [2.0,	3.0, 26373.0, 36423.0, 22019.	0, 5154.0, 4337.0, 16523	.0] 100.0% of (2.0, 3.0, 44466.0,
Cluste	er 2 : 1	00.0% of	(2.0, 3.0	12669.0, 9656.0, 7561.0, 214	1.0, 2674.0, 1338.0]	100.0% of [2.0, 3.0, 7057.0, 9810.0, 9
Cluste	er 3 : 7	5190835	f of [2.0,	3.0, 26373.0, 36423.0, 22019.	0, 5154.0, 4337.0, 16523	.0] 3.599629% of [2.0, 3.0, 4967.0
Cluste	er 4 : 1	10.05 of	[1.0, 3.0	13265.0, 1196.0, 4221.0, 640	04.0, 507.0, 1788.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 6
Cluste	er 5 : 1	4.649023	of [2.0,	3.0, 26373.0, 36423.0, 22019.	0, 5154.0, 4337.0, 16523	.0] 8.088775% of [2.0, 3.0, 4967.0
Cluste	er Low	Upper	Total			
1	7	78	85			
2	91	78	169			
3	14	78	92			
4	236	78	314			
5	14	78	92	Tur	ed RFCM-Random Cen	troids
DB Ind	dex: 3.9	501686				
	_					
- refRF	CM (run)	22				
t-refRF	CM (run) er 1 : 10	N 0.0% of	(1.0, 3.0,	13265.0, 1196.0, 4221.0, 640	4.0, 507.0, 1788.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61
t-refRF Cluste Cluste	CM (run) er 1 : 10 er 2 : 10	N 0.0% of 0.0% of	(1.0, 3.0, (2.0, 3.0,	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 95
t-refRF Cluste Cluste Cluste	CM (run) er 1 : 10 er 2 : 10 er 3 : 3.	N 0.0% of 0.0% of 2128692	(1.0, 3.0, [2.0, 3.0, of [1.0,	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 95 2.7234871% of [1.0, 3.0, 29729.0, 4786.
t - refRF Cluste Cluste Cluste Cluste	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1.	N 0.0% of 0.0% of 2128692 446947%	(1.0, 3.0, (2.0, 3.0, of (1.0, of (1.0, 3	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 98 2.7234871% of [1.0, 3.0, 29729.0, 4786. 1.3817345% of [1.0, 3.0, 29729.0, 4786.
t-refRF Cluste Cluste Cluste Cluste Cluste	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1. er 5 : 59	N 0.0% of 0.0% of 2128692 446947% 0.043015	(1.0, 3.0, (2.0, 3.0, of (1.0, of (1.0, 3 of (1.0, 3 of (1.0, 3	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0, 3.0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 98 2.7234871% of [1.0, 3.0, 29729.0, 4786. 1.3817345% of [1.0, 3.0, 29729.0, 4786. 100.0% of [1.0, 3.0, 43088.0, 2100.0, 2
t - refRF Cluste Cluste Cluste Cluste Cluste Cluste	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1. er 5 : 59 er Low	N 0.0% of 0.0% of 2128692' 446947% 0.043015' Upper	(1.0, 3.0, [2.0, 3.0, of [1.0, of [1.0, 3 of [1.0, 3 of [1.0, Total	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0, 3.0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 98 2.7234871% of [1.0, 3.0, 29729.0, 4786. 1.3817345% of [1.0, 3.0, 29729.0, 4786. 100.0% of [1.0, 3.0, 43088.0, 2100.0, 2
t - refRF Cluste Cluste Cluste Cluste Cluste Luste	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1. er 5 : 59 er Low 194	<pre>8 0.0% of 0.0% of 2128692' 446947% 0.043015' Upper 120</pre>	(1.0, 3.0, [2.0, 3.0, s of [1.0, of [1.0, 3 s of [1.0, Total 314	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0, 3.0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 95 2.7234871% of [1.0, 3.0, 29729.0, 4786. 1.3817345% of [1.0, 3.0, 29729.0, 4786. 100.0% of [1.0, 3.0, 43088.0, 2100.0, 2
t-refRF Cluste Cluste Cluste Cluste Cluste 1 2	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1. er 5 : 59 er Low 194 101	N 0.0% of 0.0% of 2128692 446947% 0.043015 Upper 120 120	(1.0, 3.0, (2.0, 3.0, of (1.0, 3 of (1.0, 3 of (1.0, 3 of (1.0, 3 Total 314 221	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0, 3.0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 95 2.7234871% of [1.0, 3.0, 29729.0, 4786. 1.3817345% of [1.0, 3.0, 29729.0, 4786. 100.0% of [1.0, 3.0, 43088.0, 2100.0, 2
t-refRF Cluste Cluste Cluste Cluste Cluste 1 2 3	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1. er 5 : 59 er Low 194 101 1	N 10.0% of 2128692' 446947% 0.043015' Upper 120 120 120	<pre>[1.0, 3.0, [2.0, 3.0, of [1.0, 3] of [1.0, 3] of [1.0, 3] of [1.0, 3] 10 Total 314 221 121</pre>	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0, 3.0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 95 2.7234871% of [1.0, 3.0, 29729.0, 4786. 1.3817345% of [1.0, 3.0, 29729.0, 4786. 100.0% of [1.0, 3.0, 43088.0, 2100.0, 2
t-refRF Cluste Cluste Cluste Cluste Cluste 1 2 3 4	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1. er 5 : 59 er Low 194 101 1 1	N 0.0% of 0.0% of 2128692' 446947% 0.043015' Upper 120 120 120 120	<pre>[1.0, 3.0, [2.0, 3.0, of [1.0, 3] of [1.0, 3.0] of [1.0, 3.0] of [1.0, 3.0] of [1.0, 3.0] of [1.0, 3.0] of [1.0, 3.0] of [1.0, 3] of [1.0, 3] of</pre>	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0, 3.0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0]	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 95 2.7234871% of [1.0, 3.0, 29729.0, 4786. 1.3817345% of [1.0, 3.0, 29729.0, 4786. 100.0% of [1.0, 3.0, 43088.0, 2100.0, 2
t-refRF Cluste Cluste Cluste Cluste Cluste 1 2 3 4 5	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1. er 5 : 59 er Low 194 101 1 1 18 6	<pre>x x 0.0% of 0.0% of 2128692' 446947% 0.043015' Upper 120 120 120 120 120 120</pre>	(1.0, 3.0, [2.0, 3.0, of [1.0, 3 of [1.0, 3 of [1.0, 3 of [1.0, 3 Total 314 221 121 138 126	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0, 3.0, 31276.0, 1917.0, 4469.0,	<ul> <li>4.0, 507.0, 1788.0]</li> <li>.0, 2674.0, 1338.0]</li> <li>9408.0, 2381.0, 4334.0]</li> <li>9408.0, 2381.0, 4334.0]</li> <li>9408.0, 2381.0, 4334.0]</li> <li>9408.0, 2381.0, 4334.0]</li> </ul>	100.0% of [1.0, 3.0, 5963.0, 3648.0, 61 100.0% of [2.0, 3.0, 7057.0, 9810.0, 95 2.7234871% of [1.0, 3.0, 29729.0, 4786. 1.3817345% of [1.0, 3.0, 29729.0, 4786. 100.0% of [1.0, 3.0, 43088.0, 2100.0, 2
t-refRF Cluste Cluste Cluste Cluste Cluste 1 2 3 4 5	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1. er 5 : 59 er Low 194 101 1 18 6	<pre>8 0.0% of 0.0% of 2128692' 446947% 0.043015' Upper 120 120 120 120 120 120 120 120 120 120</pre>	(1.0, 3.0, [2.0, 3.0, of [1.0, 3 of [1.0, 3 of [1.0, 3 of [1.0, 3 14 221 121 138 126	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0, 3.0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0]	100.04 of [1.0, 3.0, 5963.0, 3648.0, 61 100.04 of [2.0, 3.0, 7057.0, 9810.0, 98 2.72348714 of [1.0, 3.0, 29729.0, 4786. 1.38173454 of [1.0, 3.0, 29729.0, 4786. 100.04 of [1.0, 3.0, 43088.0, 2100.0, 2
t-refRF Cluste Cluste Cluste Cluste Cluste 1 2 3 4 5 DB Ind	CM (run) er 1 : 10 er 2 : 10 er 3 : 3. er 4 : 1. er 5 : 59 er Low 194 101 1 1 18 6 5 ex: 3.65	<pre>8 10.0% of 10.0% of 2128692' 446947% 0.043015' Upper 120 120 120 120 120 120 120 120 120 120</pre>	(1.0, 3.0, [2.0, 3.0, of [1.0, 3 of [1.0, 3 of [1.0, 3 of [1.0, 3 14 221 121 138 126	13265.0, 1196.0, 4221.0, 640 12669.0, 9656.0, 7561.0, 214 3.0, 31276.0, 1917.0, 4469.0, .0, 31276.0, 1917.0, 4469.0, 3.0, 31276.0, 1917.0, 4469.0,	4.0, 507.0, 1788.0] .0, 2674.0, 1338.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0] 9408.0, 2381.0, 4334.0]	100.04 of [1.0, 3.0, 5963.0, 3648.0, 6 100.04 of [2.0, 3.0, 7057.0, 9810.0, 9 2.72348714 of [1.0, 3.0, 29729.0, 4786 1.38173454 of [1.0, 3.0, 29729.0, 4786 100.04 of [1.0, 3.0, 43088.0, 2100.0, 3 100.04 of [1.0, 3.0, 43088.0, 2100.0, 3

#### Fig: 1. f

Fig: 1. a-f. The Cluster formation comparisons using random centroid with proposed computation centroid for traditional soft clustering algorithms (RCM,FCM,RFCM,RIFCM) and Tuned hybrid soft clustering algorithms (TRFCM).

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The clustering algorithms described are partitive, requiring pre-specification of the number of clusters. The results are dependent on the choice of c.

# DISCUSSION

There exist validity indexes to evaluate the goodness of clustering, corresponding to a given value of c. In this paper, we compute the optimal number of clusters c0 in terms of the DB and D cluster validity indexes. The DB is a function of the ratio of the sum of within-cluster distance to between-cluster separation.

Let  $\{\mathbf{x}_1, \ldots, \mathbf{x}_{|ck|}\}$  be a set of patterns lying in a cluster  $U_k$ . Then, the average distance between objects within the cluster  $U_k$  is expressed as:

$$S(U_k) = \frac{\sum_{i,i} ||\mathbf{x}_i - \mathbf{x}_i||}{|c_k|(|c_k|-1)} \quad \text{where } \mathbf{x}_i, \, \mathbf{x}_i \in U_k, \, \text{and } i \neq i'$$

The between-cluster separation is defined as:

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$$d(U_k, U_l) = \frac{\sum_{i,j} ||x_i - x_j||}{|c_k||c_l|}$$

Where  $\mathbf{x}_i \in U_k$ ,  $\mathbf{x}_j \in U_l$ , such that k = l. The optimal clustering, for  $c = c_0$ , minimizes

$$DB = \frac{1}{c} \sum \max_{j \neq i} \left\{ \frac{S(U_i) + S(U_j)}{d(U_i, U_j)} \right\}$$

for  $1 \le i, j \le c$ . Thereby, the within-cluster distance  $S(U_i)$  is minimized while the between-cluster separation  $d(U_i, U_j)$  gets maximized. Like DB index, the *D* index is designed to identify sets of clusters that are compact and separated. Here, we maximize for  $1 \le i, j \le c$ . The inter-cluster separation is maximized, while minimizing intracluster distances. Note that the denominator of DB is analogous to the numerator of *D*.

$$D = \min_{j} \left\{ \min_{\substack{i \neq j \\ k}} \left\{ \frac{d(U_i, U_j)}{\max_k S(U_k)} \right\} \right\}$$

The computation of the initial centroids of each cluster instead of random allocation generates a lower DB index resulting in clusters with greater accuracy. The traditional and tuned soft clustering algorithms are compared using DB index with default initial centroids and computed initial centroids. The results are shown in Table- 2 for 5 cluster and Table- 3 for Table-4 clusters.

Table: 2. Comparisons of	f Clustering Algorithms	s using DB index with	different centroids fo	r 5 cluster
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Algorithm	No. of Clusters	Del	Epsilon	DB index with default initial centroids	DB index with computed initial centroids
RCM	5	0.3	-	12.046244	2.912782
FCM	5	-	0.05	3.5671623	3.4679413
RFCM	5	0.2	0.05	6.4094977	5.577581
RIFCM	5	0.2	0.05	6.1789246	5.5049195
Tuned RCM	5	1.5	0.05	14.211797	2.0191371
Tuned RFCM	5	1.4	0.05	4.375386	2.335935

Table: 3. Comparisons of Clustering	g Algorithms using DB index with different centroids for 4 clusters
-------------------------------------	---

Algorithm	No. of Clusters	Del	Epsilon	DB index with default initial centroids	DB index with computed initial centroids
RCM	4	0.2	-	14.110096	2.1260233
FCM	4	-	0.05	2.4907343	2.3366437
RFCM	4	0.2	0.05	3.1227834	2.5758417

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RIFCM	4	0.2	0.05	4.22623	2.7078934
Tuned RCM	4	1.4	0.05	13.310548	1.8863555
Tuned RFCM	4	1.4	0.05	2.4247031	2.2060814

Upon analyzing the output produced by each algorithm in terms of DB index, it can be concluded that the efficiency of the algorithm is greatly affected by the parameters that are used for conclusion.



#### رها) Fig: 2. Performance of Clustering Algorithms using DB index with different centroids (a) for 5 cluster (b) for 4 Cluster

The performances of the various soft clustering algorithms are represented in Figure- 2 (a) and (b) respectively. The various soft clustering approaches are validated with number of cluster 4 and 5. All the approaches are tested for random centriod and dynamic centriod computation. The Result shows that, the proposed tuned RFCM algorithm performs very well than other soft clustering approaches with respect to number of cluster and dynamic centriod computation.

# CONCLUSION

Data Clustering is one of the vital research domains with a number of issues. Much of the work done in hard clustering algorithms and a few work carried out in traditional soft clustering algorithms such as rough c-means and fuzzy c-means. In this paper, a tuned hybrid soft clustering algorithm termed as tuned rough fuzzy c-means algorithm is presented. The selection of initial centroid is one of the issues in c-means algorithm, which is resolved by dynamic computation in the proposed algorithm. UCI Machine Learning Repository, Wholesale customers Data Set has been used to compare and validate the performance of the proposed algorithm with traditional soft clustering approaches.

# CONFLICT OF INTEREST

Authors declare no conflict of interest.

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#### FINANCIAL DISCLOSURE

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**OPEN ACCESS** ARTICLE

# TRACKING OF CHNGES IN CANCER DATA USING SOFTCLUSTERING

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# ABSTRACT

Data mining is process of extracting the knowledge from large amount of data and its methods are being used efficiently in biological and biomedical applications. Soft computing is for intelligent management systems and its components are fuzzy logic, evaluation computing and genetic algorithms. In recent years, combinations of data mining with soft computing approaches are more suitable for bio-informatics. Clustering is a process of unsupervised learning algorithm in data mining which can be implemented using soft computing approaches. Fuzzy Clustering or soft clustering is based on fuzzy set theory. It groups the data based on partial membership function and it assigns data point more than one cluster. It is used in many biomedical databases, like gene expression, protein sequences; image processing and image segmentation is main step for detection of cancer. In this paper, we proposed dynamic fuzzy clustering algorithm to identify changes in cluster structure. We applied on Wisconsin breast cancer data is collected periodically grouped into eight with class (benign / malignant). We executed fuzzy c-means clustering in individual groups and also executed dynamic fuzzy clustering by incrementally adding instances of groups. We presented our observation of results in both cases which can be support the analysis of cancer state between the instances of class.

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Data mining; soft computing; breast cancer data; dynamic fuzzy clustering;

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#### INTRODUCTION

In Data analysis, data mining plays major role in many application databases like business intelligence, science and engineering, bio-informatics, medical analytics. Data mining is part of "Knowledge Discovery in Databases" (KDD) [1] and it is computational process of finding patterns in large databases. It is set of methods with association of artificial intelligence, machine learning, statistics and database systems to handle different types of data. The main data mining tasks are supervised and unsupervised learning methods and the most frequently used unsupervised learning method is cluster analysis [2]; process of grouping most similar objects into clusters depend on similarity measures.

There are many clustering models are present in literature, connectivity models, centroid models, density models, graph-based models. All these algorithms are called hard clustering or exclusive clustering, as they assign data point to only one cluster as it uses conventional crisp set theory. The many complex applications in biology, medicine, the humanities, management sciences require mathematics and analytical methods with uncertain and unpredictable. But these algorithms do not handles application databases with uncertainty, imprecision, partial truth and approximation characteristics, hence soft computing approaches are introduced in cluster analysis to support these databases. The components of soft computing are Fuzzy logic, Neural networks [3], Evolutionary computation [4] and Support Vector Machines [5] and has been most frequently applied successfully in Bioinformatics and Biomedicine in recent years [6].

Fuzzy logic deals with approximate and value ranges in between 0 and 1 and it was introduced with the 1965 proposal of fuzzy set theory by Lotfi A. Zadeh [7, 8]. It had been applied to several areas, from control areas to intelligence systems. The fuzzy clustering or soft clustering uses fuzzy set theory for grouping data objects and it assigns partial membership value for each data objects to each cluster. Fuzzy c-means is centroid based fuzzy clustering algorithm and it uses degree of membership value to cluster data point [9, 10].


In this paper, we have used soft clustering method, i.e. Fuzzy c-means is to group the cancer data. Fuzz c-means takes number of clusters in prior to execution and it has to update as data change. The objective of this paper is, we consider the problem of clustering on cancer data set and identifying the changes in the data as data is added periodically. For that, we selected Wisconsin breast cancer database is collected from UCI repository which was obtained from University of Wisconsin hospitals, Madison from Dr. William H Walberg. They collected breast cancer instances continuous eight months and grouped into eight. Each instance defined by nine features and one class (benign / malignant). We implemented fuzzy c-means clustering on individual groups of instances and then applied dynamic fuzzy c-means algorithm by incrementally adding instances of groups in R data mining software.

The paper is organized as, related work is given in section 2, dynamic fuzzy clustering in section 3, results are given in section 3 and conclusion is mentioned in section 4.

### **RELATED WORK**

#### Fuzzy clustering

The fuzzy clustering defined by the fuzzy set theory and it is a process of grouping the objects by allowing the concept of partial membership, in which each object can belong to multiple clusters. For all data object, it assigns the membership values between 0 to 1 represents fit in for each cluster and the sum of the membership values of each data objects to all clusters must be 1. The high membership value shows more likely that data object belongs to that cluster. The most widely used fuzzy clustering algorithm is Fuzzy C-Means (FCM) [11].

Given a set of n data objects,  $p_k = p_1$ ,  $p_2$ ,  $p_3$ ,  $p_n$  the algorithm minimizes a weighted within group of sum of squared error an objective function shown in equation (1).

$$J = \sum_{i=1}^{n} \sum_{k=1}^{n} \mu_{ik}^{m} \| p_{i} - v_{k} \|^{2}$$
(1)

Where *J* is objective function, *n* is number of data objects, *c* is cluster number,  $\mu_{ik}$  membership value,  $p_i$  is data object,  $v_k$  is center of cluster *k*, *m* is fuzziness factor value always greater than one. The center of  $k^{th}$  cluster can be calculated using equation (2) as,

(2)

$$v_k = \frac{\sum_{i=1}^{n} \mu_{ik}^{i} p_i}{\sum_{i=1}^{n} \mu_{ik}^{i}}$$

The fuzzy membership value can calculated using equation (3) as,

$$\mu_{ik} = \frac{1}{\sum_{i=1}^{n} (|p_i - v_k|| |p_i - v_i|)^{\frac{2}{m-1}}}$$
(3)

The fuzzy c-means is objective function-based clustering method, which takes cluster number determined before the execution of algorithm. The deficiency of algorithm is, it does not identify noise and outliers as it uses sum of square error objective function. The second deficiency FCM, defined by Krishnapuram and Keller is that due to the constraint on membership shows as degree of sharing, but not as degree of possibility of a point belonging to a class. Mainly it deals with similarity between perfectly described objects, i.e. all feature values are exactly known and it does not deal with the uncertainty included by missing or incorrect data.

### Cluster validity

The internal cluster validity can be done by using Silhouette cluster validity index is defined as [12, 13]:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

Where a (i) is average dissimilarity between data point (i) and all other data within the similar cluster and b(i) is the minimum average dissimilarity of i to all other cluster. The positive value of s(i) indicates the correct clustering and negative value shows the incorrect clustering.

(4)



## DYNAMIC FUZZY CLUSTERING

The main objective of dynamic fuzzy clustering is to revise the initial parameters of the algorithm when new data is added. Fuzzy c-means clustering algorithm requires number of clusters as an input value and this value is defined by data size. When data size changes number of clusters might be changes. Therefore, for each new incoming data cycle of dynamic fuzzy clustering as illustrate in Figure-1.



#### Fig: 1. Cycle of dynamic fuzzy clustering algorithm.

The general steps of algorithm are given as:

Initial clustering:

Step1: find the size of data set *n* for D<sub>initial</sub>;
Step 2: for n= 1 to n-1/2 Calculate cluster average silhouette width S for each cluster;
Step 3: find c with maximum cluster average silhouette width;
Step 4: execute fuzzy c-means clustering algorithm;

For each new incoming data D<sub>new</sub>

Step 5: add new data with old data as,  $D = D_{inital} + D_{new}$ Repeat step1 to step4 In this algorithm, we are adding the data incrementally and finding the cluster changes in data.

## RESULTS

We have used Wisconsin breast cancer database is collected from UCI repository which was obtained from University of Wisconsin hospitals, Madison from Dr. William H Walberg. They collected samples periodically and made into eight groups as:

Each instance consists of 9 attributes and one class (benign/malignant) with range of values as: # Attribute Domain

1. Clump Thickness 1 - 10 2. Uniformity of Cell Size 1 - 10 3. Uniformity of Cell Shape 1 - 10 4. Marginal Adhesion 1 - 10 5. Single Epithelial Cell Size 1 - 10 6. Bare Nuclei 1 - 107. Bland Chromatin 1 - 101 - 10 8. Normal Nucleoli 9. Mitoses 1 - 102 for benign and 4 for malignant 10. Class



## Results of fuzzy c-means on individual groups of cancer data

For each group of data, we executed fuzzy c-means clustering after finding right number of clusters using silhouette cluster validity index. Our observations are for all individual eight groups of data resulting only two right clusters which indicate only two class values (benign/malignant) exits. From the results of fuzzy c-means on group1 data, some of the instance's membership values partially belongs to benign and malignant. But in next seven groups, the Dunn's partition coefficient indicates, there is no overlapping instance which shows instance belongs to any one class. From the result of eight groups, we have identified that silhouette width gradually increasing, i.e. instances are very close to each other with same characteristic. The comparative results between each group are given in Table-1, the centers of eight group clusters are given Table-2 and for each group fuzzy c-means cluster centers are shown in Figure -2.

	Group 1 with 367 instances	Group 2 with 70 instances	Group 3 with 31 instances	Group 4 with 17 instances	Group 5 With 48 Instances	Group 6 With 49 instances	Group 7 With 31 Instances	Group 8 With 86 instances
Clus Avg Sil width	0.69340811	0.87437541	0.8765545	0.9372129	0.8434955	0.8871365	0.7294244	0.8878145
Right c value	2	2	2	2	2	2	2	2
Dunn_coeff	0.8041438	0.9035008	0.904723	0.9583406	0.897402	0.9212774	0.8312131	0.9178934
Belgian	207	14	8	3	11	09	19	74
Malignant	160	56	23	14	37	40	12	12

#### Table: 1. Results of fuzzy c-means clustering algorithm for eight groups of cancer data

#### Table: 2. Fuzzy c-means cluster centers of eight groups of cancer instances

	Cluster center s	Clump thicknes s	Uniformit y cell size	Uniformit y cell shape	Marginal adhesio n	Single Epithelia I Cell Size	Bare nuclei	Bland chromati n	Normal nucleoli	Mitose s
Group	Cluster1	2.160705	2.838931	1.428396	1.54586	1.368898	2.23415	1.551031	2.635899	1.45633 7
1	Cluster 2	3.898318	7.367233	6.570298	6.643348	5.579655	5.68044 5	8.065509	5.63092	6.32049 5
Group	Cluster1	2.015703	2.707998	1.578677	1.718243	1.390675	2.16455 1	1.185944	1.909195	1.31573 2
2	Cluster 2	3.831131	8.082565	8.120871	7.860144	5.168349	5.77297 5	8.372444	6.79263	5.38635 4
Group	Cluster1	3.9925	7.772094	6.34029	6.367802	6.603301	5.10001 2	8.420575	8.448891	7.17303 2
3	Cluster 2	2.061884	3.835446	1.178616	1.313346	1.882224	2.00856 5	1.580559	1.127177	1.06911 9
Group	Cluster1	3.997523	7.093996	8.31591	8.357888	8.232472	6.37437 6	8.301134	8.709004	8.44112 2
4	Cluster 2	2.003191	4.294436	1.218299	1.290711	1.355207	1.79121 3	1.012295	1.150615	1.00959 1
Group	Cluster1	3.947392	6.252951	7.346187	7.155194	7.63559	4.29317 7	8.736356	6.53448	4.95016
5	Cluster 2	2.063439	3.20521	1.211239	1.190368	1.313407	1.83781 3	1.287205	1.704877	1.04445 8
Group	Cluster1	2.017287	3.464124	1.237472	1.303173	1.165077	1.95613 6	1.217999	2.229199	1.19853 6
6	Cluster 2	3.977982	7.076954	7.993649	7.721948	6.686502	4.84257	8.063018	7.784607	6.93336 1
Group	Cluster1	2.088273	3.903984	1.265267	1.599191	1.55003	2.04042 9	1.259187	1.774887	1.15655 5
7	Cluster 2	3.99606	6.438842	7.514016	7.442704	7.437029	5.10665 4	7.721833	7.746245	5.17270 1
Group 8	Cluster1	2.013597	2.863381	1.216343	1.392772	1.305293	2.08517 6	1.162901	1.657168	1.11491 8

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## Fig: 2. Fuzzy c-means cluster centers.



Fig: 3. The outputs of fuzzy c-means cluster points.

## Results of dynamic fuzzy clustering algorithm

We have executed initial clustering on group1 data with 316 instances and incrementally we added remaining group of data in the next cycles. The results are given Table-3 and clustering points

### Table: 3. Results of dynamic fuzzy c-means clustering algorithm

	Cycle-1	Cycle-2	Cycle-3	Cycle-4	Cycle-5	Cycle-6	Cycle-7	Cycle-8
Data size	367	437	468	485	533	582	613	697
Clus Avg Sil width	0.69340811	0.7204372	0.72818879	0.73489439	0.7443762	0.7564407	0.7547007	0.7687378
Right c value	2	2	2	2	2	2	2	2
Dunn_coeff	0.8041438	0.8187395	0.8222193	0.825793	0.8315249	0.838496	0.8375065	0.8455845
Belgian	207	263	286	301	338	378	396	469
Malignant	160	174	182	184	195	204	217	228

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ny(x = g1, k = 2, metric = "SqEuclidean"))



"SoFucidean" maxit = 150



## Fig: 4. For each cycle of dynamic fuzzy c-means cluster points.

	Cluster	Clump	Uniformity	Uniformity	Marginal	Single	Bare	Bland	Normal	Mitoses
	centers	thickness	cell size	cell shape	adhesion	Epithelial	nuclei	chromatin	nucleoli	
						Cell Size				
Group1	Cluster1	2.160703	2.838925	1.428393	1.545856	1.368896	2.234148	1.551025	2.635896	1.456334
	Cluster 2	3.898317	7.367231	6.570284	6.643336	5.579643	5.680435	8.065507	5.630912	6.320481
Group 2	Cluster1	2.129815	2.810183	1.459899	1.582505	1.373803	2.219787	1.473415	2.4792	1.425762
	Cluster 2	3.892513	7.433734	6.707197	6.747639	5.537787	5.68313	8.089441	5.734023	6.247491
Group 3	Cluster1	3.897594	7.450822	6.688592	6.727644	5.597415	5.651275	8.105787	5.878557	6.303923
	Cluster 2	2.12504	2.890006	1.44051	1.563888	1.413542	2.205181	1.483058	2.374672	1.399523
Group 4	Cluster1	3.899821	7.438435	6.727208	6.764603	5.658186	5.668592	8.114747	5.939162	6.355033
	Cluster 2	2.120565	2.96046	1.431706	1.553691	1.411136	2.187144	1.464081	2.318261	1.382631
Group 5	Cluster1	2.114216	2.987723	1.408163	1.513945	1.40153	2.148456	1.443685	2.249238	1.344811
	Cluster 2	3.902375	7.367682	6.754794	6.778681	5.773704	5.585881	8.15409	5.975062	6.275716
Group 6	Cluster1	2.104058	3.040041	1.3894	1.492056	1.376849	2.127336	1.41911	2.247866	1.3284
	Cluster 2	3.906056	7.353648	6.818226	6.82056	5.813291	5.557155	8.14977	6.058938	6.309007
Group 7	Cluster1	2.104699	3.08218	1.387464	1.500128	1.386206	2.125459	1.414027	2.229006	1.322869
	Cluster 2	3.911752	7.302867	6.859551	6.859199	5.917126	5.529439	8.137364	6.16135	6.248692
Group 8	Cluster1	2.091352	3.049704	1.365231	1.486661	1.37489	2.12169	1.375652	2.142978	1.290061
	Cluster 2	3.912348	7.235365	6.968129	6.930414	5.972788	5.531019	8.01619	6.215421	6.08946

## Table: 4. Dynamic fuzzy c-means cluster centers of eight groups of cancer instances

xit = 1000

clusplotifanny/x = g1234, k = 2,

## DISCUSSIONS

In The Wisconsin breast cancer database consists of eight groups of cancer instances with one class. These instances are already classified into benign or malignant. In our experiment, initially we have done fuzzy c-means on individual groups. For that, we removed the class filed and we applied fuzzy c-means clustering on nine features. From the results it shows that all groups of instance are clustered into only two groups and it was similar to classification according database. We identified that in group1 instances having overlapping, i.e. some instances partially belongs both groups. But in next groups does not have overlapping instances and they almost belong to one group. The cancer instances in overlapping portion between classes, it is difficult to find state of

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patient. In next step, we executed dynamic fuzzy c-means where we added gradually groups of instances and every time we checked the number of clusters. In all cycles, instances are grouped into two and overlapping between them. We identified the changes in class centers and silhouette widths. With these results, one can identify the similarity between the breast cancer patients within the same group and other group patients.

## CONCLUSION

We consider the problem of tracking of changes in cancer data using soft clustering algorithm. The clustering can be performed using hard computing or soft computing approaches. Hard clustering is not efficient to handle impression, uncertainty, partial truth and approximation data set. Soft computing approaches successful in handling this type of data and it supports many complex applications. We apply the fuzzy c-means clustering or soft clustering on Wisconsin breast cancer data on individual groups, after that for each cycle incrementally added group cases and apply dynamic fuzzy c-means clustering algorithm. We projected results in each case which can be useful for finding the comparison between group instances. This method can be implemented using any other soft clustering methods to improve the results.

#### CONFLICT OF INTEREST

Authors declare no conflict of interest.

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#### FINANCIAL DISCLOSURE

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ARTICLE



## APPROXIMATE EQUALITIES FOR COVERING BASED OPTIMISTIC MULTI GRANULAR ROUGH SETS AND THEIR PROPERTIES

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## ABSTRACT

Imprecision in modern day data has become a common feature and in order to efficiently handle them many uncertainty based models have been put forth in the literature. Rough set model introduced by Pawlak has established itself to be an efficient model in many real life situations. But the basic rough set model of Pawlak has limited applications because of the constraint of it being dependent on equivalence relations. The equivalent mathematical concept to equivalence relation is that of a partition. A cover is a generalization of the notion of partition and this led to the development of covering based rough sets, which has better modeling power than basic rough sets. Following the concepts of granular computing rough set introduced by Pawlak is single granulation. So, in order to handle multi-granularity, two types of multi-granularities called optimistic multi-granulation and pessimistic multi-granulation were introduced in 2006 and 2010 respectively. Recently these two concepts of multi-granulation and covering based rough sets were combined to define covering based multi-granular rough sets. The equality of sets in mathematics is too redundant to have any fruitful real life application as it does not include user knowledge into it, which is normally done in practice. In order to handle this rough equalities were defined by Pawlak et al, which was extended by Tripathy in2008 to define rough equivalence. In this paper we introduce and study covering based optimistic multi-granular approximate equalities and study their properties. We study two types of properties called general properties and replacement properties. A real life example is used for illustration of the concepts and also to aid in the construction of counter examples in the proofs of the properties.

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## INTRODUCTION

Data in real life are mostly imprecise in nature and so the conventional tools for formal modeling, reasoning and computing, which are crisp, deterministic and precise in characteristics, are inadequate to handle them. This gives rise to the development of several imprecise models, of which rough sets introduced by Pawlak [5, 6] is one of the most efficient one. It has been proved to be very efficient to capture impreciseness in data. According to Pawlak, the knowledge of human beings depends upon their capability to classify objects of universes. Equivalence relations on any universe induce classifications through the equivalence classes associated with them. So, Pawlak had taken equivalence relations to define rough sets and related notions.

A pair of crisp sets called the lower and upper approximations are associated with every rough set. Lower approximation comprising of elements certainly belong to it and upper approximation comprising of elements certainly or possibly belong to it, with respect to the available information.

This basic rough set has been extended further in many directions. These extensions are actually either based on tolerance relations or any such relations that do not require the stringent restrictions of an equivalence relation.

From the point of view of granular computing, basic rough set theory deals with a single granulation [17]. However, in some application areas we need to handle more than one granulation at a time and this necessitated the development of multi-granular rough sets (MGRS)[7], where at least two equivalence relations are taken for granulation of a universe. This concept is further extended by considering covers and this lead to the development of covering based multi granular rough sets(CBMGRS). They are of two types namely, optimistic and pessimistic. In this paper optimistic one is considered. Four types of CBOMGRS are defined and their properties, general and replacement, are established.

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Equality of sets in mathematics is a very stringent notion and its application is also limited. In real life situations we use our own knowledge about the universe of discourse to determine the equality of sets. However, such interception of user in deciding the equality of sets is very much expected. In order to make a place for user knowledge in deciding the equality of sets fully or partially, three kinds of rough equalities were introduced by Novotny and Pawlak [5,6]. In fact three notions were introduced, called the top rough equality, the bottom rough equality and the rough equality. Now the sets can be equal or not from the user point of view. They had established several properties of these notions. They tried to interchange the concepts of top rough equality and bottom rough equality in the properties to find their validity and commented that these properties do not hold true under such circumstances.

This paper is organized into four sections. First section provides the over view and related literatures. Section two presents various definitions and notions required. Section three introduces multi granular rough equalities and its general and replacement properties. In this section real life examples are considered to prove few properties as sample. In section four conclusion to the work are presented.

## **DEFINITIONS AND NOTATIONS**

#### Rough set

The notion of rough set was introduced by Z.Pawlak in the year 1982 ([5]). We extract the definition and present below.

Let *U* be a universe of discourse and *R* be an equivalence relation over *U*. By *U/R* we denote the family of all equivalence classes of *R*, referred to as categories or concepts of *R* and the equivalence class of an element  $x \in U$  is denoted by  $[x]_R$ . By a knowledge base, we understand a relational system K = (U, P), where *U* is as above and *P* is a family of equivalence relations over *U*. For any subset  $Q (\neq \phi) \subseteq P$ , the intersection of all equivalence relations in Q is denoted by IND(Q) and is called the indiscernibility relation over Q. Given any  $A \subseteq U$  and  $R \in IND(K)$ , we associate two subsets,  $\underline{R}A = \bigcup \{B \in U / R : B \subseteq A\}$  and  $\overline{R}A = \bigcup \{B \in U / R : B \cap A \neq \phi\}$ , called the R-lower and R-upper approximations of 'A' respectively. The R-boundary of 'A' is denoted by  $BN_R(A)$  and is given by  $BN_R(A) = \overline{R}A - \underline{R}A$ . The elements of  $\underline{R}$  A are those elements of U, which can certainly be classified as elements of A, and the elements of  $\overline{R}$  A are those elements of U, which can possibly be classified as elements of *R*. We say that A is rough with respect to R if and only if  $\underline{R}A \neq \overline{R}A$ , equivalently  $BN_R(A) \neq \phi$ . 'A' is said to be R-definable if and only if  $\underline{R}A = \overline{R}A$ , or  $BN_R(A) = \phi$ .

## Covering based rough sets

Basic rough sets introduced by Pawlak have been extended in many ways. One such extension is the notion of covering based rough sets, where the notion of partitions is replaced by the general notion of covers [16]. In this section we introduce the basics of these sets.

**Definition 2.2.1:** ([23, 25]) Let U be a universe and C = {C<sub>1</sub>,C<sub>2</sub>,...., C<sub>n</sub>} be a family of non-empty subsets of U that may be overlapping in nature. If  $\bigcup C$  = U, then C is called a covering of U. The pair (U, C) is called covering approximation space. For any A  $\subseteq$  U, the covering lower and upper approximations of 'A' with respect to C can be defined as follows

- (2.2.1)  $\underline{C}(A) = \bigcup \{C_i \subset A, i \in \{1, 2, \dots, n\}\}$
- (2.2.2)  $\overline{C}(A) = \bigcup \{C_i \cap A \neq \phi, i \in \{1, 2, \dots, n\}\}$

The pair  $(\underline{C}(A), \overline{C}(A))$  is called covering based rough set associated with X with respect to cover C if  $\underline{C}(A) \neq \overline{C}(A)$ , i.e., A is said to be roughly definable with respect to C. Otherwise A is said to be C-definable.

**Definition 2.2.2:** ([23,25]) Given a covering approximation space (U, C) for any  $x \in U$ , sets  $Md_c(x)$  and  $MD_c(x)$  are respectively called minimal and maximal descriptors of x with respect to C,

(2.2.3)  $md_c(x) = \{S \in C \mid x \in S \text{ and } (\forall T \in C \text{ if } (x \in T \text{ and } T \subseteq S) \text{ then } S = T)\}$ 

It is a set of all minimal covers containing x where a minimal cover containing x be one for which no proper sub cover containing x exists.

(2.2.4) 
$$MD_c(x) = \{S \in C \mid x \in S \text{ and } (\forall T \in C \text{ if } (x \in T \text{ and } T \supseteq S) \text{ then } S = T)\}$$



It is a set of all maximal covers containing x where a maximal cover containing x be one for which no proper super cover containing x exists.

#### Multi granular rough sets

In the view of granular computing (proposed by L. A. Zadeh), an equivalence relation on the universe can be regarded as a granulation, and a partition on the universe can be regarded as a granulation space [5, 6]. For an incomplete information system, similarly, a tolerance relation on the universe can be one regard as a granulation, and a cover induced by the relation can be regarded as a granulation space. Several measures in knowledge base closely associated with granular computing, such as knowledge granulation, granulation measure, information entropy and rough entropy. On research of rough set method based on multi-granulations, Y. H. Qian and J. Y. Liang introduced a rough set model based on multi-granulations [7], which is established by using multi equivalence relations.

**Definition 2.3.1 ([23, 25])** Let K= (U, **R**) be a knowledge base, **R** be a family of equivalence relations, T,  $S \in \mathbf{R}$ . We define the optimistic multi-granular lower approximation and upper approximation of X in U as

(2.3.1) 
$$\frac{T+S(A)}{\overline{T+S}(A)} = \bigcup \{x / [x]_T \subseteq A \text{ or } [x]_s \subseteq A\} \text{ and}$$
  
(2.3.2) 
$$\overline{T+S}(A) = (T+S(A^C))^C$$

#### Covering based optimistic multi granular rough sets

The notion of Multi-granular rough sets have been extended to covering approximation spaces. They can be of two types; namely, optimistic and pessimistic. By employing minimal and maximal descriptors four types of CBOMGRS are possible. The definitions of four types of CBOMGRS are as follows [4].

Let (U, C) be a covering approximation space,  $C_1$  and  $C_2$  be two covers in C and A be any subset of U. The four types of optimistic covering based optimistic multi granular rough sets, are defined as follows.

**Definition 2.4.1([16]):** The first type CBOMGRS lower and upper approximations with respect to C<sub>1</sub> and C<sub>2</sub> are defined as (2.4.1)  $O_{C_1+C_2}(A) = \{x \in U / \cap md_{C_1}(x) \subseteq A \text{ or } \cap md_{C_2}(x) \subseteq A\}$  and (2.4.2)  $O_{C_1+C_2}(A) = \{x \in U / (\cap md_{C_1}(x)) \cap A \neq \phi \text{ and } (\cap md_{C_2}(x)) \cap A \neq \phi\}$ 

**Definition 2.4.2([16])**: The second type CBOMGRS lower and upper approximations with respect to C<sub>1</sub> and C<sub>2</sub> are defined as (2.4.3)  $S_{C_1+C_2}(A) = \{x \in U \mid \bigcup md_{C_1}(x) \subseteq A \text{ or } \bigcup md_{C_2}(x) \subseteq A\}$  and

(2.4. 4) 
$$\overline{S_{C_1+C_2}}(A) = \{x \in U / (\bigcup md_{C_1}(x)) \cap A \neq \phi \text{ and } (\bigcup md_{C_2}(x)) \cap A \neq \phi\}$$

**Definition 2.4.3([16])**: The third type CBOMGRS lower and upper approximations with respect to C<sub>1</sub> and C<sub>2</sub> are defined as (2.4.5)  $T_{C_1+C_2}(A) = \{x \in U / \cap MD_{C_1}(x) \subseteq A \text{ or } \cap MD_{C_2}(x) \subseteq A\}$  and

(2.4. 6) 
$$\overline{T_{C_1+C_2}}(A) = \{x \in U / (\bigcap MD_{C_1}(x)) \cap A \neq \phi \text{ and } (\bigcap MD_{C_2}(x)) \cap A \neq \phi\}$$

**Definition 2.4.4([16]):** The fourth type CBOMGRS lower and upper approximations with respect to C<sub>1</sub> and C<sub>2</sub> are defined as (2.4.7)  $L_{C_1+C_2}(A) = \{x \in U / \bigcup MD_{C_1}(x) \subseteq A \text{ or } \bigcup MD_{C_2}(x) \subseteq A\}$  and (2.4.8)  $\overline{L_{C_1+C_2}(A)} = \{x \in U / (\bigcup MD_{C_1}(x)) \cap A \neq \phi \text{ and } (\bigcup MD_{C_2}(x)) \cap A \neq \phi\}$ 

## Properties of covering based optimistic multi granular rough sets

The following are the properties of covering based optimistic multi granular rough sets. Here 'w' denotes any of the four types first, second, third or fourth of optimistic multigranulation. Let A and B be any two subsets of U. We omit the proofs of these properties as these are more or less trivial. The proofs can also be found in [15,16].

(2.5.1) 
$$A \subseteq B \Longrightarrow W_{C_1 + C_2}(A) \subseteq W_{C_1 + C_2}(B)$$

$$(2.5.2) A \subseteq B \Longrightarrow \overline{W_{C_1+C_2}}(A) \subseteq \overline{W_{C_1+C_2}}(B)$$

(2.5.3) 
$$W_{C_1+C_2}(\sim A) = \sim \overline{W_{C_1+C_2}}(A)$$

(2.5.4) 
$$\overline{W_{C_1+C_2}}(\sim A) = \sim \underline{W_{C_1+C_2}}(A)$$

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$$(2.5.5) \quad W_{C_1+C_2}(A \bigcup B) \supseteq W_{C_1+C_2}(A) \bigcup W_{C_1+C_2}(B)$$

(2.5.6) 
$$\overline{W_{C_1+C_2}}(A \cup B) \supseteq \overline{W_{C_1+C_2}}(A) \cup \overline{W_{C_1+C_2}}(B)$$

$$(2.5.7) \quad W_{C_1+C_2}(A \cap B) \subseteq W_{C_1+C_2}(A) \cap W_{C_1+C_2}(B)$$

(2.5.8) 
$$\overline{W_{C_1+C_2}}(A \cap B) \subseteq \overline{W_{C_1+C_2}}(A) \cap \overline{W_{C_1+C_2}}(B)$$

#### RESULTS

#### Approximate equalities

The equality of sets or domains used in mathematics is too stringent. In most of the real life situations we often consider equality of sets or domains, as approximately equal under the existing circumstances. These existing circumstances serve as user knowledge about the set or domain. So, they play a significant role in approximate reasoning. Also, one can state that it mostly depends upon the knowledge the assessors have about the set of domains under consideration as a whole but not on the knowledge about individuals of the sets or domains.

As a step to include user knowledge in considering likely equality of sets, Novotny and Pawlak [5,6] introduced the following rough equalities of two sets A and B which are subsets of U.

Let K = (U, R) be a knowledge base,  $A, B \subseteq U$  and  $R \in IND(K)$ . **Definition 3.1:** We say that,

(3.1.1) A and B are bottom rough equal (A  $\overline{R}$  B) if and if only RA = RB.

(3.1.2)A and B are top rough equal (A R B) if and if only  $\overline{RA} = \overline{RB}$ .

(3.1.3) A and B are rough equal (A R eq B) if and if only RA = RB and  $\overline{RA} = \overline{RB}$  i.e., (A  $\overline{R}$  B) and (A R B).

There are several properties of these approximate equalities established by Novotny and Pawlak in the form of general and replacement properties. The replacement properties are those properties obtained from the general properties by interchanging the top and bottom equalities. As noted by them, all these approximate equalities of sets are relative in character; that is, sets are equal or not equal from our point of view depending on what we know about them. So, in a sense the definition of rough equality incorporates user knowledge about the universe in arriving at equality of sets or domains. However, these notions of approximate equalities of sets boil down to equality of sets again. So, in order to make the equalities more general, a notion called rough equivalences was introduced by Tripathy in 2008 [16]. These notions are more general and more applicable in real life situations. An example of cattle in a society is taken by him to explain the drawbacks in the earlier notion and also to establish the superiority of the new notions in the real life scenario. These two different forms of approximate equalities have been generalized to the context of multi-granulation by Tripathy along with coauthors in a series of papers [14-17, 24-26].

In this paper we shall introduce the concepts of approximate equalities and rough equivalence to the context of covering based optimistic multi granulations and prove their properties (both general and replacement). We establish both the direct as well as the replacement properties for both these notions. In fact two types of covering based multi granular rough equalities and equivalences are possible, namely, optimistic and pessimistic. In this paper optimistic ones are considered. First type covering based optimistic multi granular rough set is considered and its rough equalities and equivalences are studied. The direct properties of such sets are stated and proved first. Later its replacement properties are also studied and proved. To substantiate better understanding of these concepts few of these properties are studied and interpreted in terms of one real life example.

## Covering based optimistic multi granular approximate equalities

We introduce in the following the different covering based optimistic multi granular rough equalities for first type, CBOMGRS, and study their properties. For the other types of multi granulations similar definitions hold good.

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Let C<sub>1</sub> and C<sub>2</sub> be two covers on U and let O denotes first type of CBOMGRS.

#### **Definition 3.2**: We say that,

A and B are bottom  $C_1+C_2$  rough equal to each other (A  $= C_1+C_2$ (3.2.1)B) iff  $O_{C_1+C_2}(A) = O_{C_1+C_2}(B)$ .

(3.2.2) A and B are top C<sub>1</sub>+C<sub>2</sub> rough equal to each other (A<sup>C<sub>1</sub>+C<sub>2</sub></sup> B) iff  $\overrightarrow{O_{C_1+C_2}}(A) = \overrightarrow{O_{C_1+C_2}}(B)$ 

(3.2.3) A and B are optimistic total rough equal to each other with respect to C<sub>1</sub> and C<sub>2</sub> (A r C<sub>1</sub>+C<sub>2</sub> eq B) iff  $O_{C_1+C_2}(A) = O_{C_1+C_2}(B)$  and  $\overrightarrow{O_{C_1+C_2}}(A) = \overrightarrow{O_{C_1+C_2}}(B)$ .

#### Properties for first type of covering based optimistic multi granular approximate equalities

The general properties of first type of covering based rough equalities are stated, proved and substantiated with few proofs and examples wherever necessary.

Let  $C_1$  and  $C_2$  be two covers on U and  $C_1, C_2 \in C$  and  $A, B \subseteq U$ . Let F denotes first type CBOMGRS. Then

(3.3.1) A  $\stackrel{=}{}_{C_1+C_2}$  B if  $A \cap B \stackrel{=}{}_{C_1+C_2}$  A and B both. But the converse may not be true in general.

**Proof:** Given  $A \cap B \stackrel{=}{_{C_1+C_2}} A \implies O_{C_1+C_2}(A \cap B) = O_{C_1+C_2}(A)$  and Given  $A \cap B \stackrel{=}{_{C_1+C_2}} B \implies O_{C_1+C_2}(A \cap B) = O_{C_1+C_2}(B)$ 

From the above two expressions we have

$$\underline{O_{C_1+C_2}}(A) = \underline{O_{C_1+C_2}}(B) \implies A_{C_1+C_2}B.$$

For the converse part logical equivalence of the statements  $(a \wedge b) \vee (c \wedge d)$  and  $(a \vee c) \wedge (b \vee d)$ , where a, b, c and d are any four logical statements. However, from their truth values we find that these two statements are not equivalent to each other in the following case.

a	В	с	d
True	False	False	True
False	True	True	False

So, examples can be provided which satisfy any of the above cases to show that the converse is not true.

(3.3.2) A  $\stackrel{C_1+C_2}{=}$  B if  $A \bigcup B \stackrel{C_1+C_2}{=}$  A and B both. The converse may not be true in general. Proof: Given  $A UB \stackrel{C_1+C_2}{=} A \Longrightarrow \overline{O_{C_1+C_2}}(AUB) = \overline{O_{C_1+C_2}}(A)$  and Given  $A UB \stackrel{C_1+C_2}{=} B \Longrightarrow \overline{O_{C_1+C_2}}(AUB) = \overline{O_{C_1+C_2}}(B)$ From the above two expressions we have  $\overline{O_{C_1+C_2}}(A) = \overline{O_{C_1+C_2}}(B) \Longrightarrow A_{=}^{C_1+C_2} B.$ 

The converse part is not true as in property 1. We note that the truth of the converse depends upon the logical equivalence of the two statements,  $(a \lor b) \land (c \lor d)$  and  $(a \land c) \lor (b \land d)$ . However, we find the statements quoted are not true in the following cases.



a	b	С	d
True	False	False	True
False	True	True	False

So, examples can be constructed such that the above two cases occur to show that the converse part does not hold.

(3.3.3)  $A_{=}^{C_1+C_2} A'$  and  $B_{=}^{C_1+C_2} B'$  may not imply that  $A \bigcup B_{=}^{C_1+C_2} A' \bigcup B'$ 

**Proof:** The converse part is not true as in property 1. We note that the truth of the converse depends upon the logical equivalence of the two statements,  $(a \lor b) \land (c \lor d)$  and  $(a \land c) \lor (b \land d)$ . However, we find the statements quoted are not true in the following cases.

a	В	С	d
True	False	False	True
False	True	True	False

So, examples can be constructed such that the above two cases occur to show that the converse part does not hold.

(3.3.4) A  $\stackrel{=}{}_{C_1+C_2} A'$  and B  $\stackrel{=}{}_{C_1+C_2} B'$  may not imply that  $A \bigcap B \stackrel{=}{}_{C_1+C_2} A' \bigcap B'$ **Proof:** Let us consider the following real life example to prove the above property.

**Example 1:** Consider the following data table. Let us consider 3 columns of it, such as, Faculty name, Roles and Project Numbers. Roles column specifies different roles each faculty play in the school, such as, Program chair-1, Division chair-2, and Year co-ordinator-3. Project Numbers column specifies number of the project on which faculty works on.

S.No.	Faculty Name	Division	Collection. Experience (yrs)	Distribution Experience (yrs)	Sex	Roles	Project Numbers
1	Alia –x <sub>1</sub>	1	2	0	Female	1	1
2	Brinda-x <sub>2</sub>	2	1	0	Female	3	2
3	Cris-x <sub>3</sub>	1	3	3	Male	2	2
4	Danya-x <sub>4</sub>	2	1	1	Male	2	3
5	Esha-x <sub>5</sub>	1	3	3	Female	1, 2	2
6	Feroz-x <sub>6</sub>	2	3	0	Male	2	1, 3
7	Gokul-x <sub>7</sub>	1	1	4	Male	3	4
8	Harsha-x <sub>8</sub>	2	2	4	Male	3	4

### **Table:1. Faculty Information**



Based on roles and project number columns two sets of covers are obtained as given below. Let U = Set of faculties =  $\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$  and the following two covers  $C_1$  and  $C_2$ , are generated as given below.

 $U/C_1$  = Covers obtained based on roles of faculties = { { $x_1, x_5$  }, { $x_3, x_4, x_5, x_6$  }, { $x_2, x_7, x_8$  } }

 $U/C_2 = \text{Covers obtained based on project numbers they work on} = \{\{x_1, x_6\}, \{x_2, x_3, x_5\}, \{x_4, x_6\}, \{x_7, x_8\}\}, \{x_7, x_8\}\}, \{x_8, x_8\}, \{$ 

#### Interpretation of approximate equalities

Consider subsets  $A, B \subseteq U$ . Then the lower approximation of any set can be interpreted as a group of people who are certainly part of the committee and the upper approximation of any set can be interpreted as a group of people who are either certainly or possibly be part of the committee.

Two sets A and B are said to be optimistic bottom equivalent to each other with respect to  $C_1$  and  $C_2$  if their lower approximations with respect to  $C_1+C_2$  are the same. That is the set of faculties who are certainly in A with respect to  $C_1$  or with respect to  $C_2$  is same as the set of faculties who are certainly in B with respect to  $C_1$  or with respect to  $C_2$ .

Two sets A and B are said to be optimistic top equivalent to each other with respect to  $C_1$  and  $C_2$  if their upper approximations with respect to  $C_1+C_2$  are the same. That is the set of faculties who are certainly or possibly be in A with respect to  $C_1$  and with respect to  $C_2$  is same as the set of faculties who are certainly or possibly be in B with respect to  $C_1$  and with respect to  $C_2$ .

#### Elements $\mathbf{X}_1$ **X**2 **X**3 $X_4$ **X**5 X<sub>6</sub> $X_7$ **X**8 Minimal Descriptors ${x_3, x_4, x_5, x_6}$ ${x_{3}, x_{4}, x_{5}, x}$ $^{md}C_{1}(x)$ $\{X_1, X_5\}$ ${x_{2}, x_{7},$ ${x_3, x_4, x_5, x_6}$ {X<sub>5</sub>} $\{x_2, x_7, x_8\}$ $\{x_2, x_7, x_8\}$ $X_8$ 6,**}** $\{X_4, X_6\}$ $\{X_1, X_6\}$ $\{x_2, x_3,$ $\{x_2, x_3, x_5\}$ $\{x_2, x_3,$ ${X_6}$ $\{x_7, x_8\}$ $\{x_7, x_8\}$ $md_{C_{1}}(x)$

#### Table: 2. Table of minimal descriptors generated for C1 and C2

Let A = { $x_3, x_4, x_5, x_6$ }, A' = { $x_1, x_3, x_4, x_5, x_6$ }, B = { $x_5, x_6, x_7, x_8$ }, and B' = { $x_1, x_5, x_6, x_7, x_8$ }  $O_{C_1+C_2}(A) = \{x_3, x_4, x_5, x_6\}$  and  $O_{C_1+C_2}(A') = \{x_3, x_4, x_5, x_6\}$  $O_{C_1+C_2}(B) = \{x_5, x_6, x_7, x_8\}$  and  $O_{C_1+C_2}(B') = \{x_5, x_6, x_7, x_8\}$ 

 $O_{C_1+C_2}(A \cap B) = \{x_5, x_6\} and O_{C_1+C_2}(A' \cap B') = \{x_1, x_5, x_6\}$  $O_{C_1+C_2}(A \cap B) \neq O_{C_1+C_2}(A' \cap B')$ . Thus  $A \cap B \stackrel{\neq}{}_{C_1+C_2} A' \cap B'$ 

(3.3.5)  $A_{-}^{C_1+C_2} B \implies A \bigcup B^{C_1+C_2} U$ **Proof:** Given A  $\stackrel{C_1+C_2}{=}$  B  $\Rightarrow \overline{O_{C_1+C_2}}(A) = \overline{O_{C_1+C_2}}(B)$ . But by (2.5.6)  $\overline{O_{C_1+C_2}}(A \cup B) \supseteq \overline{O_{C_1+C_2}}(A) \cup \overline{O_{C_1+C_2}}(B)$ . Thus we have  $\overline{O_{C_1+C_2}}(A \cup B^c) \supseteq \overline{O_{C_1+C_2}}(A) \cup \overline{O_{C_1+C_2}}(B^c)$ 

 $\overline{A \cap B} = \{x_5, x_6\}$  and  $A' \cap B' = \{x_1, x_5, x_6\}$ 

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$$= \overline{O_{C_1+C_2}}(B) \cup ((O_{C_1+C_2}(B))^C) = \overline{O_{C_1+C_2}}(B) \cup ((\overline{O_{C_1+C_2}}B \setminus BN_{C_1+C_2}B)^C)$$
$$= \overline{O_{C_1+C_2}}(B) \cup (\overline{O_{C_1+C_2}}(B))^C = U \implies A \cup B^{C C_1+C_2}U$$

This completes the proof.

(3.3.6) A  $\stackrel{=}{C_1+C_2}$  B =>  $A \bigcap B^{C_1+C_2} \phi$ **Proof:** Given A  $\stackrel{=}{_{C_1+C_2}}$  B =>  $O_{C_1+C_2}(A) = O_{C_1+C_2}(B)$ . But by (2.5.7)  $O_{C_1+C_2}(A\cap B) \subseteq O_{C_1+C_2}(A) \cap O_{C_1+C_2}(B)$  . Thus we have  $\underline{O_{C_1+C_2}}(A \cap B^c) \subseteq \underline{O_{C_1+C_2}}(A) \cap \underline{O_{C_1+C_2}}(B^c) = \underline{O_{C_1+C_2}}(A) \cap \left(\overline{O_{C_1+C_2}}(B)\right)^c$  $= O_{C_1+C_2}(A) \cap (U - O_{C_1+C_2}(B) - BN_{C_1+C_2}(B)) \subseteq O_{C_1+C_2}(A) \cap (U - O_{C_1+C_2}(B)) = \phi.$  $\Rightarrow A \cap B^{C C_1 + C_2} \phi$ 

(3.3.7) If  $A \subseteq B$  and  $B \stackrel{C_1+C_2}{=} \phi$  then  $A \stackrel{C_1+C_2}{=} \phi$ **Proof:** Given  $A \subseteq B$  and  $B_{=}^{C_1+C_2} \phi$ . So we have  $\overline{O_{C_1+C_2}}(B) = \phi$ . As  $A \subseteq B \Longrightarrow$  $\Rightarrow \overline{O_{C_1+C_2}}(A) \subseteq \overline{O_{C_1+C_2}}(B) = \phi \Rightarrow A \stackrel{C_1+C_2}{=} \phi.$ 

(3.3.8) If  $A \subseteq B$  and  $A \stackrel{C_1+C_2}{=} U$  then  $B \stackrel{C_1+C_2}{=} U$ **Proof:** Given  $A \subseteq B$  and  $A \stackrel{C_1+C_2}{=} U$ . So we have  $\overline{O_{C_1+C_2}}(A) = U$ . As  $B \supseteq A \Longrightarrow$  $\Rightarrow \overline{O_{C_1+C_2}}(B) \supseteq \overline{O_{C_1+C_2}}(A) = U \Rightarrow B \stackrel{C_1+C_2}{=} U.$ 

(3.3.9) A 
$$_{=}^{C_{1}+C_{2}}$$
 B iff  $A^{C} _{C_{1}+C_{2}}^{=} B^{C}$   
**Proof:** Given A  $_{=}^{C_{1}+C_{2}}$  B  $\overline{O_{C_{1}+C_{2}}}(A) = \overline{O_{C_{1}+C_{2}}}(B)$   
*But we know that*  
 $\overline{O_{C_{1}+C_{2}}}(A) = (\underline{O_{C_{1}+C_{2}}}(A^{C}))^{C} \Leftrightarrow (\underline{O_{C_{1}+C_{2}}}(A^{C}))^{C} = (\underline{O_{C_{1}+C_{2}}}(B^{C}))^{C} \Leftrightarrow \underline{O_{C_{1}+C_{2}}}(A^{C}) = \underline{O_{C_{1}+C_{2}}}(B^{C})$   
 $\iff A^{C} _{C_{1}+C_{2}}^{=} B^{C}$ 

(3.3.10) If A  $_{C_1+C_2} \phi$  or B  $_{C_1+C_2} \phi$  then A[]B  $_{C_1+C_2} \phi$ Proof: Given A  $\stackrel{=}{_{C_1+C_2}} \phi$  or B  $\stackrel{=}{_{C_1+C_2}} \phi \Rightarrow O_{C_1+C_2}(A) = \phi$  or  $O_{C_1+C_2}(B) = \phi$  $\Rightarrow O_{C_1+C_2}(A) \cap O_{C_1+C_2}(B) = \phi$ . But by (2.5.7)  $\underline{O_{C_1+C_2}}(A \cap B) \subseteq \underline{O_{C_1+C_2}}(A) \cap \underline{O_{C_1+C_2}}(B) \implies O_{C_1+C_2}(A \cap B) = \phi \implies A \cap B \stackrel{=}{\underset{C_1+C_2}{=}} \phi.$ (3.3.11) If A  $\stackrel{C_1+C_2}{-}$  U or B  $\stackrel{C_1+C_2}{-}$  U then  $A \bigcup B \stackrel{C_1+C_2}{-}$  U

**Proof:** Given A  $\stackrel{C_1+C_2}{=}$  U or B  $\stackrel{C_1+C_2}{=}$  U  $\Rightarrow \overline{O_{C_1+C_2}}(A) = U$  or  $\overline{O_{C_1+C_2}}(B) = U$ 

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# Replacement properties for first type of covering based optimistic multi granular approximate equalities

These properties are also called as interchange properties. We have stated above the observation of Novotny and Pawlak in connection with holding of the properties for rough equalities when the bottom and top equalities are interchanged. They categorically told that the properties do not hold under this change. However, it is shown by Tripathy et al [16] that some of these properties hold under the interchange where as some other hold with some additional conditions which are sufficient but not necessary. They are stated as below along with their proofs. We use a real life example as detailed below, which shall be used to illustrate the properties as well as provide counter examples whenever necessary.

**Example 2:** Let us consider **Table-1**. Assume that an exam committee for the school of computing science and engineering (SCSE) is to be constituted to carry out activities such as collecting the question paper bundles and distributing the answer sheet bundles. Assume that there are 8 faculties available for the purpose. Their collection and distribution experiences in years along with their sex and division they belong to are considered for forming two sets of covers as given below.

 $C_1$ =Cover obtained by defining similarity relation between two faculties such that they are related to each other iff they belong to different divisions with their average collection experience as exactly 2 years and at most one them be a female faculty

 $U/C_1 = \{ \{x_1, x_8\}, \{x_2, x_3\}, \{x_3, x_4\}, \{x_4, x_5\}, \{x_6, x_7\} \}$ 

 $C_2$ = Cover obtained by defining similarity relation between two faculties such that they are related to each other iff they belong to different divisions with their average distribution experience as exactly 2 years and at most one of them be a female faculty

 $U/C_2 = \{ \{x_1, x_8\}, \{x_2, x_7\}, \{x_3, x_4\}, \{x_4, x_5\}, \{x_6, x_7\} \}$ 

### Interpretation of approximate equalities

Consider subsets  $A, B \subseteq U$ . Then the lower approximation of any set can be interpreted as a group of people who are certainly part of the committee and the upper approximation of any set can be interpreted as a group of people who are either certainly or possibly be part of the committee.

Two sets A and B are said to be optimistic bottom equivalent to each other with respect to  $C_1$  and  $C_2$  if their lower approximations with respect to  $C_1+C_2$  are the same. That is the set of faculties who are certainly in A with respect to  $C_1$  or with respect to  $C_2$  is same as the set of faculties who are certainly in B with respect to  $C_1$  or with respect to  $C_2$ .

Two sets A and B are said to be optimistic top equivalent to each other with respect to  $C_1$  and  $C_2$  if their upper approximations with respect to  $C_1+C_2$  are the same. That is the set of faculties who are certainly or possibly be in A with respect to  $C_1$  and with respect to  $C_2$  is same as the set of faculties who are certainly or possibly be in B with respect to  $C_1$  and with respect to  $C_2$ .

Let us consider first type of CBOMGRS. Its lower and upper approximations are determined based on minimal descriptors.



The minimal descriptor table for the two covers for the above example is as shown below.

Table: 3. Table of minimal descriptors for C<sub>1</sub> and C<sub>2</sub>

Elements Minimum Descriptors	<b>X</b> 1	<b>X</b> <sub>2</sub>	<b>X</b> 3	<b>X</b> 4	<b>X</b> 5	<b>X</b> 6	<b>X</b> <sub>7</sub>	<b>X</b> 8
$md_{C_1}(x)$	$\{x_1, x_8\}$	{x <sub>2</sub> ,x <sub>3</sub> }	{X <sub>3</sub> }	{X <sub>4</sub> }	$\{x_4, x_5\}$	{x <sub>6</sub> ,x <sub>7</sub> }	{x <sub>6</sub> ,x <sub>7</sub> }	{x <sub>1</sub> ,x <sub>8</sub> }
$md_{C_2}(x)$	${x_1, x_8}$	{x <sub>2</sub> ,x <sub>7</sub> }	{x <sub>3</sub> ,x <sub>4</sub> }	{X <sub>4</sub> }	${x_4, x_5}$	{x <sub>6</sub> ,x <sub>7</sub> }	{x <sub>6</sub> ,x <sub>7</sub> }	{x <sub>1</sub> ,x <sub>8</sub> }

(3.4.1) A  $\stackrel{C_1+C_2}{=}$  B if  $A \cap B \stackrel{C_1+C_2}{=}$  A and B both. The converse need not be true.

**Proof:** Given  $A \bigcap B \stackrel{C_1+C_2}{=} A \Longrightarrow \overline{O_{C_1+C_2}}(A \cap B) = \overline{O_{C_1+C_2}}(A)$ Given  $A \bigcap B \stackrel{C_1+C_2}{=} B \Longrightarrow \overline{O_{C_1+C_2}}(A \cap B) = \overline{O_{C_1+C_2}}(B)$ From the above two expressions we have,  $\overline{O_{C_1+C_2}}(A) = \overline{O_{C_1+C_2}}(B) \Longrightarrow A \stackrel{C_1+C_2}{=} B.$ 

This part can be interpreted as, if the set of faculty certainly or possibly be in committee for  $A \cap B$  with respect to  $C_1+C_2$  is the same as that of A and B, then the set of faculty certainly or possibly be in committee for A with respect to  $C_1+C_2$  will be same as that of B. It means that a committee obtained through common people from sets A and B having same group of people who are either certainly or possibly be in the committee is the same as the committees obtained from A and B having same group of people who are either certainly or possibly be in the committee, then those committees obtained from A and B that way will be equal.

The following example shows that converse need not be true.

Let 
$$A = \{x_3, x_6\}$$
,  $B = \{x_3, x_7\}$  and  
 $\overline{O_{C_1+C_2}}(A) = \{x_3, x_6, x_7\}$ ,  $\overline{O_{C_1+C_2}}(B) = \{x_3, x_6, x_7\}$  and  $\overline{O_{C_1+C_2}}(A \cap B) = \{x_3\}$   
Thus  $\overline{O_{C_1+C_2}}(A \cap B) \neq \overline{O_{C_1+C_2}}(A)$  and  $\overline{O_{C_1+C_2}}(A \cap B) \neq \overline{O_{C_1+C_2}}(B)$   
though  $\overline{O_{C_1+C_2}}(A) = \overline{O_{C_1+C_2}}(B)$ 

The converse part can be interpreted as, though the sets of faculty certainly or possibly be in committee with respect to  $C_1+C_2$  are the same for A and B but the set of faculty certainly or possibly be in committee for  $A \cap B$  with respect to  $C_1+C_2$  is not same as that of A and B. It means that a committee obtained through common people from sets A and B having same group of people who are either certainly or possibly be in the committee obtained from A and B having same group of people who are either certainly or possibly be in the committee. Then the committees obtained from A and B that way need not be equal.

 $(3.4.2)A \stackrel{=}{}_{C_{1}+C_{2}} B \text{ if } A \bigcup B \stackrel{=}{}_{C_{1}+C_{2}} A \text{ and } B \text{ both. The converse need not be true}$  **Proof:** Given  $A \bigcup B \stackrel{=}{}_{C_{1}+C_{2}} A \Longrightarrow O_{C_{1}+C_{2}}(A \bigcup B) = O_{C_{1}+C_{2}}(A) \text{ and}$ Given  $A \bigcup B \stackrel{=}{}_{C_{1}+C_{2}} B \Longrightarrow O_{C_{1}+C_{2}}(A \bigcup B) = O_{C_{1}+C_{2}}(B)$ From the above two expressions we have  $O_{C_{1}+C_{2}}(A) = O_{C_{1}+C_{2}}(B) \text{ and so } A \stackrel{=}{}_{C_{1}+C_{2}}B.$ 

This part can be interpreted as, if the set of faculty certainly be in committee for  $A \bigcup B$  with respect to  $C_1+C_2$  is the same as that of A and B, then the set of faculty certainly be in committee for A with respect to  $C_1+C_2$  will be same as that of B. It means that a committee obtained through the people from sets A and B having same group of people who are certainly be in the committee is the same as the committees obtained from A and B having same



group of people who are certainly be in the committee, then the committees obtained from A and B that way will be equal.

The following example shows that the converse need not be true.  
Let A = {
$$x_4, x_6$$
}, B = { $x_4, x_7$ } and A  $\cup$  B = { $x_4, x_6, x_7$ }  
 $\frac{O_{C_1+C_2}(A) = {x_4}$  and  $O_{C_1+C_2}(B) = {x_4}$   $O_{C_1+C_2}(A \cup B) = {x_4, x_6, x_7}$   
Thus  $O_{C_1+C_2}(A \cup B) \neq O_{C_1+C_2}(A)$  and  $O_{C_1+C_2}(A \cup B) \neq O_{C_1+C_2}(B)$   
though  $O_{C_1+C_2}(A) = O_{C_1+C_2}(B)$ 

The converse part can be interpreted as, though the sets of faculty certainly in committee with respect to C1+C2 are the same for A and B, but the set of faculty certainly in committee for  $A \bigcup B$  with respect to  $C_1+C_2$  is not the same as that of A and B It means that a committee obtained through common people from sets A and B having same group of people who are certainly in the committee, may not be the same as the committee obtained from A and B having same group of people who are certainly in the committee. Then the committees obtained from A and B that way need not be equal.

$$(3.4.3)A_{C_{1}+C_{2}} A' and B_{C_{1}+C_{2}} B' may not imply that A \bigcup B_{C_{1}+C_{2}} A' \bigcup B'$$
**Proof:** The following example establishes the above proof.  
Let A = {x<sub>3</sub>, x<sub>6</sub>}, A' = {x<sub>1</sub>, x<sub>3</sub>}, B = {x<sub>6</sub>, x<sub>8</sub>} and B' = {x<sub>7</sub>, x<sub>8</sub>}. Then  

$$\frac{O_{C_{1}+C_{2}}(A) = {x_{3}} and O_{C_{1}+C_{2}}(A') = {x_{3}}$$

$$\frac{O_{C_{1}+C_{2}}(B) = \phi and O_{C_{1}+C_{2}}(B') = \phi}{(A') and O_{C_{1}+C_{2}}(B)} = O_{C_{1}+C_{2}}(B')$$
Thus A  $\stackrel{=}{_{C_{1}+C_{2}}} A' and B \stackrel{=}{_{C_{1}+C_{2}}} B'.$   
Now,  $A \bigcup B = {x_{3}, x_{6}, x_{8}}, \text{ so } O_{C_{1}+C_{2}}(A' \bigcup B') = {x_{1}}$   
Also,  $A' \bigcup B' = {x_{1}, x_{3}, x_{7}, x_{8}}, \text{ so } O_{C_{1}+C_{2}}(A' \bigcup B') = {x_{1}, x_{8}}$   
Thus  $O_{C_{1}+C_{2}}(A \bigcup B) \neq O_{C_{1}+C_{2}}(A' \bigcup B') = {x_{1}, x_{8}}$ 

$$(3.4.4)A \stackrel{C_{1}+C_{2}}{=} A' \text{ and } B \stackrel{C_{1}+C_{2}}{=} B' \text{ may not imply that } A \cap B \stackrel{C_{1}+C_{2}}{=} A' \cap B'$$
**Proof:** The following example establishes the proof.  
Let A = {x\_{3}, x\_{4}}, A' = {x\_{3}, x\_{5}}, B = {x\_{4}, x\_{6}} and B' = {x\_{4}, x\_{7}}. Then  
 $\overline{O_{C_{1}+C_{2}}}(A) = {x_{3}, x_{4}, x_{5}} and \overline{O_{C_{1}+C_{2}}}(A') = {x_{3}, x_{4}, x_{5}};$   
 $\overline{O_{C_{1}+C_{2}}}(B) = {x_{4}, x_{6}, x_{7}} and \overline{O_{C_{1}+C_{2}}}(B') = {x_{4}, x_{6}, x_{7}}.$   
So,  $\overline{O_{C_{1}+C_{2}}}(A) = \overline{O_{C_{1}+C_{2}}}(A') and \overline{O_{C_{1}+C_{2}}}(B) = \overline{O_{C_{1}+C_{2}}}(B')$   
But  $A \cap B = {x_{4}} = \overline{O_{C_{1}+C_{2}}}(A \cap B) = {x_{4}}.$   
and  $A' \cap B' = \phi = \overline{O_{C_{1}+C_{2}}}(A' \cap B') = \phi.$   
Thus,  $\overline{O_{C_{1}+C_{2}}}(A \cap B) \neq \overline{O_{C_{1}+C_{2}}}(A' \cap B') = > A \cap B \stackrel{C_{1}+C_{2}}{\neq} A' \cap B'.$ 

(3.4.5) A  $_{C_1+C_2}^{=}$  B =>  $A \bigcup B^{C} _{C_1+C_2}^{=}$  U

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**Proof:** Given A  $\stackrel{=}{}_{C_1+C_2} B \Rightarrow \underline{O_{C_1+C_2}}(A) = \underline{O_{C_1+C_2}}(B)$ . But from (2.5.5)  $\underline{O_{C_1+C_2}}(A \cup B) \supseteq \underline{O_{C_1+C_2}}(A) \cup \underline{O_{C_1+C_2}}(B)$ . Thus, we have  $\underline{O_{C_1+C_2}}(A \cup B) \supseteq \underline{O_{C_1+C_2}}(A) \cup \underline{O_{C_1+C_2}}(B) = \underline{O_{C_1+C_2}}(B) \cup (\overline{O_{C_1+C_2}}(B))^c$  $= \underline{O_{C_1+C_2}}(B) \bigcup (U - (\underline{O_{C_1+C_2}}(B) - BN_{C_1+C_2}B))$  $\subseteq \underline{O_{C_1+C_2}}(B) \bigcup (U - \underline{O_{C_1+C_2}}(B)) = U \implies A \bigcup B' \stackrel{=}{\underset{C_1+C_2}{=}} U$ 

$$(3.4.6) \quad A \stackrel{C_{1}+C_{2}}{=} B \Rightarrow A \cap B^{c} \stackrel{=}{_{C_{1}+C_{2}}} \phi$$

$$Proof: \text{ Given } A \stackrel{C_{1}+C_{2}}{=} B \Rightarrow \overline{O_{C_{1}+C_{2}}}(A) = \overline{O_{C_{1}+C_{2}}}(B) \text{ . But from } (2.5.8)$$

$$\overline{O_{C_{1}+C_{2}}}(A \cap B) \subseteq \overline{O_{C_{1}+C_{2}}}(A) \cap \overline{O_{C_{1}+C_{2}}}(B) \text{ . Thus, we have}$$

$$\overline{O_{C_{1}+C_{2}}}(A \cap B^{c}) \subseteq \overline{O_{C_{1}+C_{2}}}(A) \cap \overline{O_{C_{1}+C_{2}}}(B^{c}) = \overline{O_{C_{1}+C_{2}}}(A) \cap (\underline{O_{C_{1}+C_{2}}}(B))^{c} = \overline{O_{C_{1}+C_{2}}}(A) \cap (U - \underline{O_{C_{1}+C_{2}}}(B))$$

$$\subseteq BN_{C_{1}+C_{2}}(B)$$

$$\Rightarrow A \cap B' \stackrel{C_{1}+C_{2}}{\neq} \phi.$$

(3.4.7) If 
$$A \subseteq B$$
 and  $B \stackrel{=}{\underset{C_1+C_2}{=}} \phi$  then  $A \stackrel{=}{\underset{C_1+C_2}{=}} \phi$   
**Proof:** Given  $A \subseteq B$  and  $B \stackrel{=}{\underset{C_1+C_2}{=}} \phi$ . So, we have  $\underbrace{O_{C_1+C_2}}(B) = \phi$ . As  $A \subseteq B \Longrightarrow A = \phi \Longrightarrow \underbrace{O_{C_1+C_2}}(A) = \phi$   
 $\Longrightarrow A \stackrel{=}{\underset{C_1+C_2}{=}} \phi$ 

(3.4.8) If 
$$A \subseteq B$$
 and  $A \stackrel{=}{_{C_1+C_2}} U$  then  $B \stackrel{=}{_{C_1+C_2}} U$   
**Proof:** Given  $A \subseteq B$  and  $B \stackrel{=}{_{C_1+C_2}} U$ . So  $\underbrace{O_{C_1+C_2}}(A) = U$ . As  $A \subseteq B \Longrightarrow O_{C_1+C_2}(A) \subseteq O_{C_1+C_2}(B)$ , we have  
 $\underbrace{O_{C_1+C_2}}(B) = U$   
 $\Longrightarrow B \stackrel{=}{_{C_1+C_2}} U$ .

(3.4.9) A 
$$_{C_1+C_2}^{=}$$
 B iff  $A^{c} C_1+C_2 = B^{c}$   
**Proof:** Given A  $_{C_1+C_2}^{=}$  B  
But we know that  $O_{C_1+C_2}(A) = (\overline{O_{C_1+C_2}}(A^c))^c$   
 $=> (\overline{O_{C_1+C_2}}(A^c))^c = (\overline{O_{C_1+C_2}}(B^c))^c => \overline{O_{C_1+C_2}}(A^c) = \overline{O_{C_1+C_2}}(A^c)$   
 $O_{C_1+C_2}(A) = O_{C_1+C_2}(B) => A^c C_1+C_2 = B^c$   
In a similar way converse will also be proved.  
(3.4.10) If A  $_{=}^{C_1+C_2} \phi$  or B  $_{=}^{C_1+C_2} \phi$  then  $A \cap B _{=}^{C_1+C_2} \phi$ 

(3.4.10) If A 
$$\stackrel{C_1+C_2}{=} \phi$$
 or B  $\stackrel{C_1+C_2}{=} \phi$  then  $A \cap B \stackrel{C_1+C_2}{=} \phi$   
**Proof:** Given A  $\stackrel{C_1+C_2}{=} \phi$  or B  $\stackrel{C_1+C_2}{=} \phi$ . So,  $\overline{O_{C_1+C_2}}(A) = \phi$  or  $\overline{O_{C_1+C_2}}(B) = \phi$   $\Longrightarrow \overline{O_{C_1+C_2}}(A) \cap \overline{O_{C_1+C_2}}(B) = \phi$ .  
But from (2.5.8)  $\overline{O_{C_1+C_2}}(A \cap B) \subseteq \overline{O_{C_1+C_2}}(A) \cap \overline{O_{C_1+C_2}}(B) \Longrightarrow \overline{O_{C_1+C_2}}(A \cap B) = \phi$   $\Longrightarrow A \cap B \stackrel{C_1+C_2}{=} \phi$ 

(3.4.11) If A 
$$\stackrel{=}{}_{C_1+C_2}$$
 U or B  $\stackrel{=}{}_{C_1+C_2}$  U then  $A \bigcup B \stackrel{=}{}_{C_1+C_2}$  U



**Proof:** Given A  $\stackrel{C_1+C_2}{=}$  U or B  $\stackrel{C_1+C_2}{=}$  U. So,  $\underbrace{O_{C_1+C_2}(A) = U \text{ or } O_{C_1+C_2}(B) = U}_{=} = \underbrace{O_{C_1+C_2}(A) \cup O_{C_1+C_2}(B) =$ 

#### Approximate rough equivalence for covering based optimistic multi granulation

We now introduce the different rough equivalences for the first type of covering based optimistic multi granular rough set (CBOMGRS). These definitions will be the same for other types. Then we study, prove and provide counter examples for its direct and replacement properties as per requirement.

Let  $C_1$  and  $C_2$  be two covers on U and  $C_1, C_2 \in C$  and  $A, B \subseteq U$ . Let F denotes first type CBOMGRS.

**Definition 3.5**: We say that,

(3.5.1) A and B are bottom rough  $C_1 + C_2$  equivalent to each other (A  $_{C_1+C_2}^{\approx}$  B) iff  $O_{C_1+C_2}(A)$  and  $O_{C_1+C_2}(B)$  are  $\phi$  or not  $\phi$  together. (3.5.2) A and B are top rough  $C_1 + C_2$  equivalent to each other (A  $_{\approx}^{C_1+C_2}$  B) iff  $\overline{O_{C_1+C_2}}(A)$  and  $\overline{O_{C_1+C_2}}(B)$  are U or not U together. (3.5.3) A and B are total rough  $C_1 + C_2$  equivalent to each other (A  $r_{-}C_1+C_2$  eqv B) iff  $O_{C_1+C_2}(A)$  and  $O_{C_1+C_2}(B)$  are  $\phi$  or not  $\phi$  together and  $\overline{O_{C_1+C_2}}(A)$  and  $\overline{O_{C_1+C_2}}(B)$ are U or not U together.

Following are the generalization of the approximate rough inclusions introduced by Pawlak [5,6] and approximate rough comparisons introduced by Tripathy et al[16]. We define these concepts in the context of first type of covering based

optimistic multi granulation as below.

#### **Definition 3.6:**

Let K=(U,R) be a knowledge base and  $A, B \subseteq U$  and  $C_1, C_2 \in C$ . Then

(i) We say A is bottom  $C_1 + C_2$  rough included in B  $(A \underset{C_1+C_2}{\subseteq} B)$  iff  $O_{C_1+C_2}(A) \subseteq O_{C_1+C_2}(B)$ .

(ii) We say A is bottom  $C_1 + C_2$  rough included in B  $(A \subseteq^{C_1+C_2} B)$  iff  $\overline{O_{C_1+C_2}}(A) \subseteq \overline{O_{C_1+C_2}}(B)$ . (iii) We say A is rough  $C_1 + C_2$  included in B iff  $\underline{O_{C_1+C_2}}(A) \subseteq \underline{O_{C_1+C_2}}(B)$  and  $\overline{O_{C_1+C_2}}(B) \subseteq \overline{O_{C_1+C_2}}(A)$ .

#### Definition3.7:

Let K=(U,R) be a knowledge base and  $A, B \subseteq U$  and  $C_1, C_2 \in C$ . Then

(i) We say that  $A, B \subseteq U$  are bottom  $C_1 + C_2$  comparable iff  $A \subseteq_{C_1+C_2} B$  or  $B \subseteq_{C_1+C_2} A$ .

(ii) We say that  $A, B \subseteq U$  are top  $C_1 + C_2$  comparable iff  $A \subset C_1 + C_2 B$  or  $B \subset C_1 + C_2 A$ .

(iii) We say that  $A, B \subseteq U$  are  $C_1 + C_2$  comparable iff A and B are both bottom  $C_1 + C_2$  and top  $C_1 + C_2$  comparable.



#### Properties for covering based optimistic multi granular approximate equivalence

(3.6.1)(i) If  $A \bigcap B \underset{C_1+C_2}{\approx} A$  and  $A \bigcap B \underset{C_1+C_2}{\approx} B$  then  $A \underset{C_1+C_2}{\approx} B$ . (ii) The converse of (i) is not necessarily true. (iii) The converse is true in (iii) if A and B is bottom  $C_1 + C_2$  comparable. (iv) the condition in (iii) is not necessary **Proof:** (i)  $O_{C_1+C_2}(A \cap B)$  and  $O_{C_1+C_2}(A)$  are either  $\phi$  or not  $\phi$  together (given).  $O_{C_1+C_2}(A \cap B)$  and  $O_{C_1+C_2}(B)$  are either  $\phi$  or not  $\phi$  together (given). Then  $O_{C_1+C_2}(A)$  and  $O_{C_1+C_2}(B)$  are either  $\phi$  or not  $\phi$  together (derived). Thus  $A \stackrel{\approx}{_{C_1+C_2}} B$ . (ii) Continuing with example 2 by taking  $A = \{x_3\}$  and  $B = \{x_6, x_7\}$ , we have  $O_{c_1+c_2}(A) = \{x_3\} \neq \phi \text{ and } O_{c_1+c_2}(B) = \{x_6, x_7\} \neq \phi => A_{C_1+C_2}^{\approx} B.$  But  $A \cap B = \phi$ . Then  $O_{C_1+C_2}(A \cap B) = \phi \Longrightarrow A \cap B \text{ not } \underset{C_1+C_2}{\sim} A \text{ and } B \text{ both.}$ (iii) Even if A and B is bottom  $C_1 + C_2$  comparable, we have  $O_{C_1+C_2}(A \cap B) \subseteq O_{C_1+C_2}(A)$  or  $O_{C_1+C_2}(B)$  as the case may be. So, if both  $O_{C_1+C_2}(A)$  and  $O_{C_1+C_2}(B)$  are  $\phi$ , we have  $O_{C_1+C_2}(A \cap B) = \phi$ . But when both are not  $\phi$ , we cannot say the same for  $O_{C_1+C_2}(A\cap B)$ (iv) Continuing with example 2 by taking  $A = \{x_4, x_5, x_6, x_7\}$  and  $B = \{x_1, x_4, x_8\}$ , we have  $\underline{O_{c_1+c_2}}(A) = \{x_3, x_5, x_6, x_7\} \neq \phi, O_{c_1+c_2}(B) = \{x_1, x_4, x_8\} \neq \phi \Longrightarrow A_{C_1+C_2}^{\sim}B.$ Also A and B are not bottom  $C_1 + C_2$  comparable. But  $A \cap B = \{x_4\}$ . Then  $O_{C_1+C_2}(A \cap B) \neq \phi \implies A \cap B \underset{C_1+C_2}{\approx} A$  and  $A \cap B \underset{C_1+C_2}{\approx} B$ though A and B are not bottom  $C_1 + C_2$  comparable. (3.6.2)(i) If  $A \cup B \overset{C_1+C_2}{\underset{\approx}{\sim}} A$  and  $A \cup B \overset{C_1+C_2}{\underset{\approx}{\sim}} B$  then  $A \overset{C_1+C_2}{\underset{\approx}{\sim}} B$ . (ii)The converse of (i) is not necessarily true. (iii) The converse cannot be true even if A and B are top  $C_1 + C_2$  comparable. (iv) The conditions in (iii) is not necessary. **Proof:** 

(i)  $\overline{O_{C_1+C_2}}(A \bigcup B)$  and  $O_{C_1+C_2}(A)$  are either U or not U together (given).  $\overline{O_{C_1+C_2}}(A \bigcup B)$  and  $O_{C_1+C_2}(B)$  are either U or not U together (given). Then  $O_{C_1+C_2}(A)$  and  $O_{C_1+C_2}(B)$  are either U or not U together (derived). Thus  $A \stackrel{C_1+C_2}{\longrightarrow} B$ . (ii) Continuing with example 2 by taking  $A = \{x_1, x_2, x_3, x_4\}$  and  $B = \{x_5, x_6, x_7\}$ , we have  $\overline{O_{C_1+C_2}}(A) = \{x_1, x_2, x_3, x_4, x_8\} \neq U \text{ and } \overline{O_{C_1+C_2}}(B) = \{x_5, x_6, x_7\} \neq U \Longrightarrow A_{\approx}^{C_1+C_2}B.$  But  $A \bigcup B = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}. Then \ \overline{O_{C_1 + C_2}}(A \bigcup B) = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\} = U$  $=> A \bigcup B \text{ not } \bigcap_{a=1}^{C_1+C_2} A \text{ and } B \text{ both.}$ 

(iii) Even if A and B is bottom  $C_1 + C_2$  comparable, we have  $O_{C_1+C_2}(A \cup B) \subseteq O_{C_1+C_2}(A)$  or  $O_{C_1+C_2}(B)$  as the

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case may be. So, if both  $O_{C_1+C_2}(A)$  and  $O_{C_1+C_2}(B)$  are U, we have  $O_{C_1+C_2}(A \cup B) = U$ . But when both are not U,

we cannot say the same for  $O_{C_1+C_2}(A \cup B)$ .

(iv) Continuing with example 2 by taking  $A = \{x_1, x_2, x_3, x_4\}$  and  $B = \{x_5, x_6\}$  we have

 $\overline{O_{C_1+C_2}}(A) = \{x_1, x_2, x_3, x_4, x_8\} \neq U \text{ and } \overline{O_{C_1+C_2}}(B) = \{x_5, x_6\} \neq U$  $\Longrightarrow \overline{O_{C_1+C_2}}(A) \not\subset \overline{O_{C_1+C_2}}(B) \text{ or } \overline{O_{C_1+C_2}}(B) \not\subset \overline{O_{C_1+C_2}}(A)$ 

 $\Rightarrow$  A and B are not top  $C_1 + C_2$  comparable.

And  $A \cup B = \{x_1, x_2, x_3, x_4\}$ . Then  $\overline{O_{C+C}}(A \cup B) = \{x_1, x_2, x_3, x_4, x_5, x_6, x_8\} \neq U$  $=> A \bigcup B \overset{C_1+C_2}{\approx} A \text{ and } B \text{ both though } A \text{ and } B \text{ are not top } C_1 + C_2 \text{ comparable.}$ 

(3.6.3)(i) If A  $\overset{C_1+C_2}{\approx}$  A' and B  $\overset{C_1+C_2}{\approx}$  B' then it may or may not be true that  $A \cup B \overset{C_1+C_2}{\approx} A' \cup B'$ .

(ii) A sufficient condition for the result in (i) to be true is that A and B are top  $C_1 + C_2$  comparable and

A' and B' are top  $C_1 + C_2$  comparable.

(iii) The conditions in (ii) are not necessary for result in (i) to be true.

**Proof:** (i) The result fails to be true when all  $\overline{O_{G_1+C_2}}(A)$ ,  $\overline{O_{G_1+C_2}}(A')$ ,  $\overline{O_{G_1+C_2}}(B)$ , and  $\overline{O_{G_1+C_2}}(B')$  are not Uand exactly one of  $A \cup B$  and  $A' \cup B'$  is U, then result will fail. The following example shows that. Continuing with example 2 by taking  $A = \{x_1, x_2, x_3, x_4\}$ ,  $A' = \{x_5, x_6, x_7\}$ ,  $B = \{x_1, x_5, x_6, x_7\}$ , and  $B' = \{x_3, x_4, x_5\}$ , we have This implies that  $\Delta C_1 + C_2 \Lambda$ ,

$$\begin{array}{l}
O_{C_{1}+C_{2}}(A) = \{x_{1}, x_{2}, x_{3}, x_{4}, x_{8}\} \neq U \quad and \quad O_{C_{1}+C_{2}}(A') = \{x_{5}, x_{6}, x_{7}\} \neq U \text{ Inis implies that } A \xrightarrow{\sim} A \text{ .} \\
\overline{O_{C_{1}+C_{2}}}(B) = \{x_{1}, x_{5}, x_{6}, x_{7}\} \neq U \quad and \quad \overline{O_{C_{1}+C_{2}}}(B') = \{x_{3}, x_{4}, x_{5}\} \neq U \text{ . This implies that } B \xrightarrow{C_{1}+C_{2}} B'. \\
But \quad A \bigcup B = \{x_{1}, x_{2}, x_{3}, x_{4}, x_{5}, x_{6}, x_{7}\} \quad and \quad A' \bigcup B' = \{x_{1}, x_{3}, x_{4}, x_{5}, x_{6}, x_{7}\} \\
\overline{O_{C_{1}+C_{2}}}(A \bigcup B) = \{x_{1}, x_{2}, x_{3}, x_{4}, x_{5}, x_{6}, x_{7}, x_{8}\} = U \quad and \quad \overline{O_{C_{1}+C_{2}}}(A' \bigcup B') = \{x_{1}, x_{3}, x_{4}, x_{5}, x_{6}, x_{7}, x_{8}\} \neq U \\
=> A \bigcup B \quad not \quad \overset{C_{1}+C_{2}}{\approx} A' \bigcup B'.
\end{array}$$

(ii) We have  $\overline{O_{G_1+C_2}}(A) \neq U, \overline{O_{G_1+C_2}}(A') \neq U, \overline{O_{G_1+C_2}}(B) \neq U$ , and  $\overline{O_{G_1+C_2}}(B') \neq U$ . So, under the hypothesis,

$$\overline{O_{C_1+C_2}}(A \cup B) \supseteq \overline{O_{C_1+C_2}}(A) \cup \overline{O_{C_1+C_2}}(B) = \overline{O_{C_1+C_2}}(A) \text{ or } \overline{O_{C_1+C_2}}(B) \text{ , which is not equal to } U \text{ . Similarly,}$$
$$\overline{O_{C_1+C_2}}(A \cup B') \neq U \text{ .Hence } A \cup B \overset{C_1+C_2}{\approx} A' \cup B'.$$

(iii) Continuing with example 2 by taking  $A = \{x_1, x_2, x_3, x_4\}$ ,  $A' = \{x_5, x_6, x_7\}$ ,  $B = \{x_1, x_5, x_6, x_7\}$  and  $B' = \{x_2, x_3, x_4\}$ ,  $x_5$ , we have

 $\overline{O_{C_1+C_2}}(A) = \{x_1, x_2, x_3, x_4, x_8\} \neq U$  and  $\overline{O_{C_1+C_2}}(A') = \{x_5, x_6, x_7\} \neq U$ . This implies that A and A' are not top rough comparable.

 $\overline{O_{C_1+C_2}}(B) = \{x_1, x_5, x_6, x_7\} \neq U \text{ and } \overline{O_{C_1+C_2}}(B') = \{x_3, x_4, x_5\} \neq U$ . This implies that B and B' are not top rough comparable.

But 
$$A \cup B = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$$
 and  $A' \cup B' = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$   
 $\overline{O_{C_1+C_2}}(A \cup B) = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\} = U$  and  $\overline{O_{C_1+C_2}}(A' \cup B') = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\} = U$   
 $=> A \cup B \stackrel{C_1+C_2}{=} A' \cup B'.$ 

(3.6.4)(i) If A  $\stackrel{\approx}{}_{C_1+C_2}$  A' and B  $\stackrel{\approx}{}_{C_1+C_2}$  B' then it may or may not be true that  $A \cap B \stackrel{\approx}{}_{C_1+C_2} A' \cap B'$ .

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- (ii) A sufficient condition for the result in (i) to be true is that A and Bare bottom  $C_1 + C_2$  comparable and A' and B'
- are bottom  $C_1 + C_2$  comparable.

(iii) The conditions in (ii) are not necessary for result in (i) to be true.

**Proof:** (i) The result fails to be true when all  $O_{C_1+C_2}(A)$ ,  $O_{C_1+C_2}(A')$ ,  $O_{C_1+C_2}(B)$ , and  $O_{C_1+C_2}(B')$  are not  $\phi$  and exactly

one of  $A \cap B$  and  $A' \cap B'$  is  $\phi$ , then result will fail. The following example shows that. Continuing with example 2 by taking A={x<sub>3</sub>}, A'= {x<sub>6</sub>, x<sub>7</sub>}, B={x<sub>4</sub>}, and B'={x<sub>4</sub>, x<sub>6</sub>, x<sub>7</sub>}, we have  $O_{C_1+C_2}(A) = {x_3} \neq \phi$  and  $O_{C_1+C_2}(A') = {x_6, x_7} \neq \phi$ . This implies that A  $\stackrel{\approx}{C_1+C_2} A'$ .

 $\underbrace{O_{C_1+C_2}(B) = \{x_4\} \neq \phi \text{ and } O_{C_1+C_2}(B') = \{x_6, x_7\} \neq \phi \cdot \text{This implies that } B_{C_1+C_2}^{\approx} B'.}_{But \ A \cap B = \phi \text{ and } A' \cap B' = \{x_6, x_7\} \cdot O_{C_1+C_2}(A \cap B) = \phi \text{ and } O_{C_1+C_2}(A' \cap B') = \{x_6, x_7\} \neq \phi.}$  $=> A \cap B \text{ not } \sum_{C_1+C_2}^{\infty} A' \cap B'.$ 

(ii) We have  $\underline{O_{C_1+C_2}}(A) \neq \phi, \underline{O_{C_1+C_2}}(A') \neq \phi, \underline{O_{C_1+C_2}}(B) \neq \phi, and \underline{O_{C_1+C_2}}(B') \neq \phi$ . So, under the hypothesis,

$$\underline{O_{C_1+C_2}}(A \cap B) \subseteq \underline{O_{C_1+C_2}}(A) \cap \underline{O_{C_1+C_2}}(B) = \underline{O_{C_1+C_2}}(A) \text{ or } \underline{O_{C_1+C_2}}(B) \neq \phi \cdot$$
  

$$\underline{O_{C_1+C_2}}(A' \cap B') \neq \phi \cdot$$
  
Similarly,

Hence,  $A \cap B \stackrel{\approx}{\underset{C_1+C_2}{\sim}} A' \cap B'$ .

(iii) Continuing with example 2 by taking A={ $x_6, x_7$ }, A'= { $x_1, x_8$ }, B={ $x_2, x_6, x_7$ }, and B'={ $x_1, x_2, x_8$ }, we have  $\underbrace{O_{C_1+C_2}}_{C_1+C_2}(A) = {x_6, x_7} \neq \phi \quad and \quad \underbrace{O_{C_1+C_2}}_{C_1+C_2}(A') = {x_1, x_8} \neq \phi. \text{ This implies that A and A' are not bottom}$ 

comparable.

 $\underbrace{O_{C_1+C_2}(B) = \{x_2, x_6, x_7\} \neq \phi \text{ and } \underbrace{O_{C_1+C_2}(B') = \{x_1, x_6\} \neq \phi}_{C_1+C_2}$ . This implies that B and B' are not bottom comparable. But  $A \cap B = \{x_6, x_7\}$  and  $A' \cap B' = \{x_1, x_8\}$   $O_{C_1+C_2}(A \cap B) = \{x_6, x_7\} \neq \phi$  and  $O_{C_1+C_2}(A' \cap B') = \{x_1, x_8\} \neq \phi$ .

 $\Rightarrow A \cap B \stackrel{\approx}{}_{C_1+C_2} A' \cap B'.$ 

(3.6.5) (i) A  ${}^{C_1+C_2}_{\approx}$  B may or may not imply that  $(A \cup \sim B) {}^{C_1+C_2}_{\approx}$  U.

(ii) A sufficient condition for the result in (i) to hold is that A and B are bottom  $C_1 + C_2$  equal.

(iii) The conditions in (ii) are not necessary for the result in (i) to hold.

**Proof:** (i) The result fails to hold true when  $\overline{O_{C_1+C_2}}(A) \neq U$ ,  $\overline{O_{C_1+C_2}}(B) \neq U$  and still  $\overline{O_{C_1+C_2}}(A \cup \sim B) = U$ . (ii) The condition in (ii) is not sufficient as we have  $\overline{O_{C_1+C_2}}(A \cup \sim B) \supseteq \overline{O_{C_1+C_2}}(A) \cup \overline{O_{C_1+C_2}}(\sim B) = \overline{O_{C_1+C_2}}(A) \cup \overline{O_{C_1+C_2}}(\sim A) \supseteq \overline{O_{C_1+C_2}}(A \cup \sim A) = U$ (iii) Continuing with example 2 by taking A={x<sub>1</sub>, x<sub>3</sub>, x<sub>4</sub>, x<sub>7</sub>} and B={x<sub>1</sub>, x<sub>8</sub>}, we have  $\underline{O_{C_1+C_2}}(A) = {x_2, x_3, x_4}$  and  $\underline{O_{C_1+C_2}}(B) = {x_1, x_8} => A$  and B is not bottom rough equal.  $\sim B={x_2, x_3, x_4, x_5, x_6, x_7}$  and  $\overline{A} \cup \sim B = {x_1, x_2, x_3, x_4, x_5, x_6, x_7}$  $\overline{O_{C_1+C_2}}(A \cup \sim B) = {x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8} = U => A \cup \sim B \overset{C_1+C_2}{\approx} U$ .



(3.6.6) (i) A  $\stackrel{\sim}{}_{C_1+C_2}$  B may or may not imply that  $(A \cup \sim B) \stackrel{\sim}{}_{C_1+C_2}$  U.

(ii) A sufficient condition for the result in (i) to hold is that A and B are top  $C_1 + C_2$  equal.

(iii) The conditions in (ii) are not necessary for the result in (i) to hold.

**Proof:** (i) The result fails to hold true when  $O_{C_1+C_1}(A) \neq \phi$ ,  $O_{C_1+C_1}(B) \neq \phi$  and still  $O_{C_1+C_1}(A \cap B) = \phi$ . (ii) The condition in (ii) is not sufficient as we have  $O_{C_1+C_2}(A \cap \sim B) \subseteq O_{C_1+C_2}(A) \cap O_{C_1+C_2}(\sim B) = O_{C_1+C_2}(A) \cup O_{C_1+C_2}(\sim A) \subseteq O_{C_1+C_2}(A \cap \sim A) = \phi$ (iii) Continuing with example 2 by taking  $A=\{x_1, x_2, x_5\}$  and  $B=\{x_2, x_3, x_4\}$ , we have  $O_{C_1+C_2}(A) = \{x_1, x_2, x_5\}$  and  $\overline{O_{C_1+C_2}}(B) = \{x_2, x_3, x_5\} \Longrightarrow A$  and B is not top rough equal.  $\sim B = \{x_1, x_5, x_6, x_7, x_8\}$  and  $A \cap \sim B = \{x_1, x_5\}$  $O_{C_1+C_2}(A \cap \sim b) = \phi \Longrightarrow A \cap \sim B \underset{C_1+C_2}{\approx} \phi$ 

(3.6.7) If  $A \subseteq B$  and  $B \underset{C_1+C_2}{\sim} \phi$  then  $A \underset{C_1+C_2}{\sim} \phi$ . Proof: As  $B_{C_1+C_2}^{\approx} \phi$ , we have  $O_{C_1+C_2}(B) = \phi$ . So, if  $A \subseteq B$ ,  $O_{C_1+C_2}(A) \subseteq O_{C_1+C_2}(B) = \phi$ . Thus  $A_{C_1+C_2}^{\approx} \phi$ .

(3.6.8) If  $A \subset B$  and A  $C_1+C_2 U$  then B  $C_1+C_2 U$ . Proof: As A  $\overset{C_1+C_2}{\approx} U$ , we have  $\overline{O_{C_1+C_2}}(A) = U$ . So, if  $A \subseteq B$ ,  $\overline{O_{C_1+C_2}}(B) \supseteq \overline{O_{C_1+C_2}}(A) = U$ . Thus B  $\overset{C_1+C_2}{\sim} U$ .

(3.6.9) A  $\stackrel{C_1+C_2}{\approx}$  B iff ~A  $\stackrel{\approx}{\underset{C_1+C_2}{\approx}}$  ~B. Proof: The proof follows from the property,  $O_{C_1+C_2}(\sim A) = \sim \overline{O_{C_1+C_2}(A)}$ .

(3.6.10) A  $\underset{C_1+C_2}{\approx} \phi$ , B  $\underset{C_1+C_2}{\approx} \phi$  implies that  $A \bigcap B \underset{C_1+C_2}{\approx} \phi$ . Proof: The proof follows directly from the fact that under the hypothesis the only possibility <sup>1S</sup>  $O_{C_1+C_2}(A) = O_{C_1+C_2}(B) = \phi$ 

(3.6.11)  $A_{\approx}^{C_1+C_2} U$ ,  $B_{\approx}^{C_1+C_2} U$  implies that  $A \cup B_{\approx}^{C_1+C_2} U$ .

Proof: The proof follows directly from the fact that under the hypothesis the only possibility is  $\overline{O_{C_1+C_2}}(A) = \overline{O_{C_1+C_2}}(B) = U$ 

### Replacement properties for covering based optimistic multi granular approximate equivalence

(3.7.1) (i) if  $A \cap B \stackrel{C_1+C_2}{\approx} A$  and  $A \cap B \stackrel{C_1+C_2}{\approx} B$  then  $A \stackrel{C_1+C_2}{\approx} B$ . (ii) The converse of (i) is not necessarily true.

**Proof:** (i) Here  $\overline{O_{C_1+C_2}}(A)$  and  $\overline{O_{C_1+C_2}}(A \cap B)$  are U or not U together and  $\overline{O_{C_1+C_2}}(B)$ and  $O_{C_1+C_2}(A \cap B)$  are

U or not U together. Being common, we get  $\overline{O_{G+C_2}}(A)$  and  $\overline{O_{G+C_2}}(B)$  are U or not U together. So, A  $\overset{C_1+C_2}{\approx}$  B.

(ii) Continuing with example 2 by taking  $A = \{x_1, x_2, x_3, x_4, x_6, x_7\}$  and  $B = \{x_2, x_3, x_4, x_6, x_7, x_8\}$ , we have



But 
$$A \cap B = \{x_2, x_3, x_4, x_6, x_7\}$$
. Then  $\overline{O_{C_1+C_2}}(A \cap B) = \{x_2, x_3, x_4, x_5, x_6, x_7\} \neq U$   
=>  $A \cap B$  not  $\overset{C_1+C_2}{\approx} A$  and  $B$  both.

(3.7.2) (i) if  $A \cup B \stackrel{\approx}{}_{C_1+C_2} A$  and  $A \cap B \stackrel{\approx}{}_{C_1+C_2} B$  then  $A \stackrel{\approx}{}_{C_1+C_2} B$ . (ii) The converse of (i) is not necessarily true.

 $\underline{O}_{C_1+C_2}(A)$  and  $\underline{O}_{C_1+C_2}(A \cup B)$  are  $\phi$  or not  $\phi$  together and **Proof:** (i) Here and  $O_{C_1+C_2}(B)$ 

 $\underline{O_{C_1+C_2}}(A \cup B)^{\operatorname{are}}$ 

 $\phi$  or not  $\phi$  together. Being common, we get and  $O_{C_1+C_2}(B)$  are  $\phi$  or not  $\phi$  together. So,  $A_{\approx}^{C_1+C_2} B$ . (ii) Continuing with example 2 by taking  $A = \{x_6\}$  and  $B = \{x_7\}$  we have

$$\underbrace{O_{c_1+c_2}}_{C_1+c_2}(A) = \phi \quad and \quad \underbrace{O_{c_1+c_2}}_{C_1+c_2}(B) = \phi \Longrightarrow A_{C_1+C_2}^{\ast}B. \text{ But } A \cup B = \{x_6, x_7\}. \text{ Then} \\
\underbrace{O_{c_1+c_2}}_{C_1+c_2}(A \cup B) = \{x_6, x_7\} \neq \phi \Longrightarrow A \cup B \quad not \quad \underset{C_1+C_2}{\overset{\ast}{}}A \text{ and } B \text{ both.}$$

(3.7.3) A  $\underset{C_1+C_2}{\sim}$  A' and B  $\underset{C_1+C_2}{\sim}$  B' may not necessarily imply that  $A \bigcup B \underset{C_1+C_2}{\sim} A' \bigcup B'$ .

**Proof:** When 
$$\underline{O_{C_1+C_2}}(A), \underline{O_{C_1+C_2}}(B), \underline{O_{C_1+C_2}}(A'), \underline{O_{C_1+C_2}}(B')$$
 are all  $\phi$ , one of  $O_{C_1+C_2}(A \cup B)$  and  $O_{C_1+C_2}(A' \cup B')$  is

 $\phi$  but the other one is not  $\phi$  the result fails to be true. Continuing example 2 by taking A={x<sub>6</sub>}, A'=  $\{x_8\}, B=\{x_2\} \text{ and } B'=\{x_1\},\$ 

$$\underbrace{O_{C_1+C_2}}_{But}(A) = \phi, \underbrace{O_{C_1+C_2}}_{A}(A') = \phi, \underbrace{O_{C_1+C_2}}_{B}(B) = \phi, and \underbrace{O_{C_1+C_2}}_{C_1+C_2}(B') = \phi \cdots$$

$$\underbrace{But}_{A} \bigcup B = \{\mathbf{x}_2, \mathbf{x}_6\} and A' \bigcup B' = \{\mathbf{x}_1, \mathbf{x}_8\}$$

$$\overline{O_{C_1+C_2}}(A \bigcup B) = \phi and \overline{O_{C_1+C_2}}(A' \bigcup B') = \{\mathbf{x}_1, \mathbf{x}_8\} \neq \phi.$$

$$=> A \bigcup B not \stackrel{C_1+C_2}{\approx} A' \bigcup B'.$$

(3.7.4) A  $\stackrel{C_1+C_2}{\simeq}$  A' and B  $\stackrel{C_1+C_2}{\simeq}$  B' may not necessarily imply that  $A \cap B \stackrel{C_1+C_2}{\simeq} A' \cap B'$ .

**Proof:** When 
$$\overline{O_{C_1+C_2}}(A), \overline{O_{C_1+C_2}}(B), \overline{O_{C_1+C_2}}(A'), \overline{O_{C_1+C_2}}(B')$$
 are all  $U$ , one of  $\overline{O_{C_1+C_2}}(A \cap B)$  and  $\overline{O_{C_1+C_2}}(A' \cap B')$ 

is U but the other one is not U the result fails to be true.

Continuing with example 2 by taking  $A = \{x_1, x_2, x_3, x_4, x_5, x_7\}$ ,  $A' = \{x_1, x_2, x_3, x_4, x_6, x_7, x_8\}$ ,  $B = \{x_2, x_3, x_4, x_5, x_7\}$ ,  $A' = \{x_1, x_2, x_3, x_4, x_6, x_7, x_8\}$ ,  $B = \{x_2, x_3, x_4, x_5, x_7\}$ ,  $A' = \{x_1, x_2, x_3, x$  $x_4, x_5, x_7, x_8\},\$ and B'={ $x_2$   $x_3$   $x_4$   $x_6$   $x_7$   $x_9$ } we have

$$\underline{O_{C_1+C_2}}(A) = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\} = U, \underline{O_{C_1+C_2}}(A') = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\} = U,$$

 $O_{C_1+C_2}(B) = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\} = U, and O_{C_1+C_2}(B') = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\} = U.$ But  $A \cap B = \{x_2, x_3, x_4, x_5, x_7\}$  and  $A' \cap B' = \{x_2, x_3, x_4, x_6, x_7, x_8\}$   $O_{C_1+C_2}(A \cap B) = \{x_2, x_3, x_4, x_5, x_8\}$ and  $O_{C_1+C_2}(A'\cap B') = \{x_1, x_2, x_3, x_4, x_5, x_7, x_8\} = U \Longrightarrow A \cap B \text{ not } \underset{C_1+C_2}{\approx} A'\cap B'.$ 

(3.7.5) A  $\underset{C_1+C_2}{\approx}$  B may or may not imply that  $A \bigcup \sim B \underset{C_1+C_2}{\approx} U$ . **Proof:** Continuing with example 2 by taking  $A = \{x_1, x_3, x_4, x_7, x_8\}$  and  $B = \{x_1\}$ , we have  $\overline{O_{C_1+C_2}}(A) = \{x_1, x_3, x_4, x_7, x_8\} \text{ and } \overline{O_{C_1+C_2}}(B) = \{x_1, x_8\}.$  $\sim B = \{x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$  and  $A \cup \sim B = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_7\} = U$ 

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$$O_{C_1+C_2}(A \cup \sim B) = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\} = U \Longrightarrow A \cup \sim B \overset{C_1+C_2}{\approx} U.$$

(3.7.6) A  ${}^{C_1+C_2}_{\approx}$  B may or may not imply that  $A \cap \sim B {}^{C_1+C_2}_{\approx} \cdot \phi$ .

**Proof:** Continuing with example 2 by taking  $A=\{x_5\}$  and  $B=\{x_5, x_6, x_7\}$ , we have

 $O_{C_1+C_2}(A) = \phi$  and  $O_{C_1+C_2}(B) = \{\mathbf{x}_6, \mathbf{x}_7\} \Longrightarrow A$  and B is not top rough equal.

 $\sim B = \{x_1, x_2, x_3, x_4, x_8\}$  and  $A \cap \sim B = \phi$ 

 $O_{C_1+C_2}(A \cap \sim B) = \phi \Longrightarrow A \cap \sim B \underset{C_1+C_2}{\sim} \phi$ 

We would like to make the following comments in connection with the following properties from (3.7.7) to (3.7.11).

(i) We know that  $\underline{O_{C_1+C_2}}(U) = U$ . So, bottom  $C_1 + C_2$  -equivalent to U can be considered under the case that

 $O_{C_1+C_2}(U) \neq \phi$ 

(ii) We know that  $\overline{O_{C_1+C_2}}(\phi) = \phi$ . So, bottom  $C_1 + C_2$  -equivalent to U can be considered under the case that

```
\overline{O_{C_1+C_2}}(\phi) \neq U.
```

The proofs of the properties from (3.7.7) to (3.7.11) are trivial and we omit them.

(3.7.7) If  $A \subseteq B$  and  $B \overset{C_1+C_2}{\approx} \phi$  then  $A \overset{C_1+C_2}{\approx} \phi$ .

(3.7.8) If  $A \subseteq B$  and B  $\underset{C_1+C_2}{\overset{\approx}{\leftarrow}} U$  then A  $\underset{C_1+C_2}{\overset{\approx}{\leftarrow}} U$ . (3.7.9) A  $\underset{C_1+C_2}{\overset{\approx}{\leftarrow}}$  B iff  $\sim A \underset{C_1+C_2}{\overset{\approx}{\leftarrow}} \sim B$ . (3.7.10) A  $\underset{\approx}{\overset{c_1+C_2}{\leftarrow}} \phi$ , B  $\underset{\approx}{\overset{c_1+C_2}{\leftarrow}} \phi \Longrightarrow A \cap B \underset{\approx}{\overset{c_1+C_2}{\leftarrow}} \phi$ . (3.7.11) A  $\underset{C_1+C_2}{\overset{c_2}{\leftarrow}} U$ , B  $\underset{C_1+C_2}{\overset{c_2}{\leftarrow}} U \Longrightarrow A \cup B \underset{\approx}{\overset{c_1+C_2}{\leftarrow}} U$ .

## CONCLUSION

The equality of sets in mathematics is too stringent and is mostly not applicable in real life situations. The problem in this definition is that although in real life situations we use our knowledge about the universe to decide about the equality of sets, which is mostly approximate in nature, we do not do so for set equality. As an attempt to incorporate user knowledge in equality, Novotny and Pawlak introduced the concept of rough equality and Tripathy et al introduced the concept of rough equivalence. The unigranular rough set concept introduced by Pawlak has been extended to define multigranular rough sets by Qian et al. Also, instead of using partitions, covers have been used to define covering based rough sets recently. In this paper we define and study the rough equality and rough equivalence in the context of covering based optimistic multigranular rough sets and to establish their properties in the general form as well as in the replacement form. We take the help of a real life example to illustrate the concepts and also to provide counter examples is establishing the properties.

### CONFLICT OF INTEREST

Authors declare no conflict of interest.

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## A HYBRID ELM-WAVELET TECHNIQUE FOR THE CLASSIFICATION AND DIAGNOSIS OF NEUROMUSCULAR DISORDER USING EMG SIGNAL

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## ABSTRACT

Electromyogram (EMG) signal classification plays a major role in the diagnosis of neuromuscular disorder. The Motor Unit Action Potentials (MUAPs) in an electromyographic signal is one, which offers a significant source of information to evaluate the neuromuscular disorders. Neuromuscular diseases are the one that affect the control of muscular and nervous system. The proposed method employs a technique called Extreme Learning Machine (ELM) for the classification of EMG signal into healthy, myopathy or neuropathy. Discrete Wavelet Transform (DWT) / Wavelet Packet Transform (WPT) are the methods used for feature extraction individually. The performance of ELM together with DWT (ELM-DWT) and ELM with WPT (ELM-WPT) are compared with each other and it is found that the time complexity and number of feature vectors in ELM-WPT is reduced. The number of features is minimal in ELM-WPT compared with the ELM-DWT. The performance of ELM is evaluated using the confusion matrix and in terms of specificity, sensitivity, computational time and classification accuracy. The learning phase of ELM is completed in less than a second. The classification accuracy of ELM-WPT is 100%. The obtained result indicates that proposed ELM is very effective in the diagnosis of neuromuscular disorders

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**KEY WORDS** 

Electromyogram (EMG); Motor Unit Action Potentials (MUAPs); Extreme Learning Machine (ELM); Discrete Wavelet Transform (DWT): Wavelet Packet Transform (WPT).

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## INTRODUCTION

The human skeletal muscular system consists of the nervous system and the muscular system, which together form the neuromuscular system. The disorders which originate in the nervous system, in the neuromuscular junctions, and in the muscle fibers are known as neuromuscular disorders. It has different degrees of severity ranging from minor loss of strength to amputation due to neuron or muscle death [1]. Proper diagnosis of the disorder is of vital importance so that more focused treatment can be administered in the early stage [2]. Electromyography (EMG) signal is used for diagnosing patients with neuromuscular disorders. Pathological changes in the structure of motor units cause neuromuscular disorders, which can be classified into muscular (myopathy) and neuronal disorders (neuropathy) [3]. In myopathic disorders, the duration and the area to amplitude ratio of the action potential is reduced whereas in case of neuropathic disorder the duration and the area to amplitude ratio of the action potential is increased. In order to compensate low amplitude in myopathic disorder, a larger number of motor units are hired at lower than the normal levels of muscular contraction. In neurogenic disorder, the excited motor neurons are decreased in number and in order to keep a certain force of contraction, the available motor neuron must fire at higher rate than normal to balance the motor neuron loss. For an effective computerized EMG signal classification, an efficient treatment of EMG signals must be carried out [4]. The principle of this diagnostic system involves extraction of features from the acquired raw EMG signal which in turn helps in the diagnosis of neuromuscular disorder [1]. In this study, statistical features of Discrete Wavelet Transform (DWT) and Wavelet Packet Transform (WPT) have been used as a comparative study to characterize the EMG signal pattern in the diagnosis of neuromuscular disorder. These statistical features give major differences between healthy, myopathic and neurogenic signals and are useful for disease classification. The extracted statistical features are used as inputs to the ELM classifier. ELM is an efficient learning algorithm which performs well in classification application. This algorithm provides excellent performance at extremely fast learning speed [5]. ELM is an extensively used learning method that is capable of directly approximating nonlinear mappings by input data and provides models for a number of natural and artificial problems [6].



Englehart et al. [7] used the feature sets based on Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Wavelet Packet Transform (WPT) as an effective representation for EMG classification. The best performance is exhibited when using a combination of WPT, Principal Component Analysis (PCA), Linear Discrimminant Analysis (LDA), yielding an average classification error of 6.25%. Christodoulou and Pattichis [8] applied two different pattern recognition techniques for the classification of MUAPs. They compared the performance of two algorithms namely i) Artificial Neural Network (ANN) technique based on unsupervised learning, by means of a revised version of the Self-Organizing Feature Maps (SOFM) algorithm and Learning Vector Quantization (LVQ) ii) a statistical pattern recognition technique based on the Euclidean distance. It was found that the performance of ANN technique was better with the success rate of 97.6%. The advantage of this technique is that the learning is achieved in one epoch for both SOFM and LVQ algorithms. A key issue in LVQ is the choice of an appropriate measure of distance or similarity for training and classification. Subasi et al. [9] described the use of Autoregressive (AR) model with Wavelet Neural Network (WNN) to classify the EMG signals. They compared the performance of Feed forward Error Back Propagation Artificial Neural Network (FEBANN) and WNN based classifiers. The WNN performs better than FEBANN with a classification accuracy of 90.7%. The computational speed of WNN is faster when compared with Back Propagation Neural Network (BPNN). But the issue in this method is due to the unavailability of structured method to determine the optimum level of WNN factors, it is set by trial and error [10]. Katsis et al [11] proposed a novel method for the classification of MUAP's from the intramuscular EMG signals and obtained MUAPs classification accuracy of 86%. Abdulhmit Subasi [4] introduced the fuzzy based technique, ANFIS (Adaptive Neuro Fuzzy Inference System) for EMG signal classification and compared its performance with Multi Layer Perceptron Neural Network (MLPNN) and Dynamic Fuzzy Neural Network (DFNN). Among the three methods, it was reported that ANFIS performed better with an accuracy of 95%. In [1] Abdulhamit Subasi introduced PSO-SVM to improve the EMG signal classification and succeeded with the classification accuracy of 97.41%. Huang et al. [5] illustrated a new learning algorithm called Extreme Learning Machine (ELM) for Single-hidden Layer Feed forward Neural networks (SLFNs) which randomly chooses hidden nodes and analytically determines the output weights of SLFNs. Zong et al. [12] used ELM classifier to recognize the face and compared the result with that of SVM. It was reported that the recognition accuracy and training time of ELM was better than SVM with less optimization constraint. Liang et al. [13] used ELM to classify five mental tasks from different subjects using electroencephalogram (EEG) signals and compared the results with BPNN and SVM. It was found that ELM performed better than the other two techniques.

Neuromuscular disorders are those that affect the brain, spinal cord, nerves and muscles causing muscular weakness or muscle tissue wasting. During initial stages of the disease, pathological changes in the EMG signals are not much predominant which causes difficulty in the diagnosis of neuromuscular disorder. In such cases wavelet transforms can be used to characterize the localized frequency content of each MUP [4, 14, 15].

## MATERIALS AND METHODS

## Feature extraction methods

In the proposed method, ELM is used to classify the EMG signals as shown in Fig.1 and consists of three steps:

- The EMG signal is decomposed either using Discrete Wavelet Transform (DWT) or Wavelet Packet Transform (WPT) into different frequency bands.
- Statistical features are extracted from these sub-bands to represent each EMG signal.
- An unknown EMG signal is classified as Healthy or Myopathic or Neurogenic using the soft computing technique (ELM).



#### Fig: 1. Block diagram of the proposed method



This research work makes use of 30 EMG data collected from various subjects for analysis. Fig. 2 shows a sample of healthy, neuropathy EMG data.



#### Fig: 2. Healthy, neuropathy and myopathy EMG data.

The choice of features of raw signals is very important for the accomplishment of any signal classification system. WT is one of the most capable methods to extract features from the EMG signals [4]. In this research work, WPT and DWT are used for feature extraction individually, from the EMG signal and their performances are compared with each other.

#### A) Feature extraction using discrete wavelet transform

The Wavelet transform (WT) is the one which provides both the time and frequency information at the same time. The wavelet transform decomposes a signal into a set of basic functions called wavelets that are obtained by dilations, contractions and shifts of an exclusive function called wavelet prototype translations [16, 17, 18, 19]. The wavelet transform in which the wavelets are sampled at discrete intervals is known as DWT [20]. As the time domain signal is passed through various high pass and low pass filters, the output of either is taken and the process is repeated. This process is known as decomposition. This continues until the signal decomposed to a pre-defined level. Thus, cluster of signals correspond to the same signal, but all related to different frequency bands. Lower and higher frequencies are better resolved in frequency and time respectively [4].

Repeated low-pass and high-pass filtering of the time domain signal results in the decomposition of the signal into different frequency bands. The down-sampled outputs of first high-pass and low-pass filters provide the detail, D1 and the approximation, A1 information respectively. The outputs of the high-pass and low-pass filters, are sub-sampled by 2. As the result of decomposition, the time resolution is halved and the frequency resolution is doubled, because the frequency band of the signal now spans only half the previous frequency band, successfully reducing the uncertainty in the frequency by half. The above procedure is also known as the sub-band coding which can be repeated for further decomposition. At each level, the filtering and sub-sampling results in half the number of samples and half the frequency band spanned. The first approximation A1 is further decomposed and this process is continued. In this research work, Daubechies 4 (DB4) wavelet filter is used for decomposition and reconstruction [4].

To represent the time-frequency distribution of the EMG signals, the following statistical features are used:

Mean values of the coefficients in each sub-band: The mean indicates the average value of a signal and is given by Equation (1)



(1)

where x<sub>i</sub> represents the corresponding coefficient; N denotes the total number of coefficients.

Variance of the wavelet coefficients in each sub-band: Variance indicates how far/close the data points are to the mean value of the coefficients and is computed as in Equation(2)

 $Var(x_i) = E[x_i^x] - [E[x_i]]^2$ 

(2)

Skewness of the coefficients in each sub-band: Skewness is a measure of extent to which the probability distribution of a real valued random variable leans to one side of the mean. The skewness value may be positive or negative and is given in Equation (3).

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where  $\mu_{a}$  is third moment about mean;  $\sigma$  is the standard deviation.

Entropy of the coefficients in each sub-band. Entropy is a numerical measure of the randomness of a signal. Then entropy is given by Equation (4)

$$\mathbf{H}(\mathbf{X}) = \sum_{i=1}^{n} \mathbf{p}(\mathbf{x}_i) \log_{\mathbf{x}_i} \mathbf{p}(\mathbf{x}_i) \tag{4}$$

(3)

where X is the random variable with n outcomes  $\{X_{2}, X_{2}, X_{3}, \dots, X_{n}\}$ .

Standard Deviation of the coefficients in each sub-band: The standard deviation (a) shows how much variation or dispersion from

the average exists. A large value of *a* indicates that the data points are far from the mean and a small value of *a* indicates that they

are clustered closely around the mean. c is calculated using the Equation (5)

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\mathbf{x}_i - \boldsymbol{\mu})^2}$$
 (5)

where  $\mu$  is the mean,  $x_i$  denotes the corresponding coefficient.

Ratio of absolute mean values of adjacent sub-band: It denotes the ratio of the mean values of the adjacent sub-bands which is given by the Equation (6)

where  $\mu_{a}$  represents the absolute mean of a coefficient,  $\mu_{a+1}$  is the absolute mean value of its adjacent coefficient.

Two sets of features, feature set 1(F1) and feature set 2 (F2) are used as input to ELM-DWT individually. F1 is the one, which is used in the existing method [1]. To compare the performance of the proposed method with the existing method; F1 is included in the present work. F1 comprises of features such as mean of absolute values of coefficient in each sub-band, standard deviation of the wavelet coefficient in each sub-band, ratio of absolute mean values of adjacent sub-bands and F2 comprises mean, variance, skewness and entropy of the wavelet coefficient in each sub-band.

Thus by extracting 6 different values for mean and standard deviation, 5 different values for ratio of absolute mean values of adjacent sub-band, a total of 17 features are extracted for F1. Similarly, by extracting 6 different values for mean, variance, skewness and entropy of the coefficients in each sub-band, a sum of 24 features are extracted in case of F2. These features are calculated from the frequency bands D1, D2, D3, D4, D5 and A5 of DWT and then used as input to ELM classifier.

#### B) Feature extraction using wavelet packet transform (WPT)

In DWT decomposition, a signal is decomposed into two frequency bands such as lower frequency band (approximation coefficients) and higher frequency band (detail coefficients) and the low frequency band is used for further decomposition, thus it gives a left recursive binary tree structure. In case of Wavelet packet Transform (WPT), a balanced binary tree structure is generated since both lower and higher frequency bands are decomposed into two sub-bands. It helps to divide the high frequency side into smaller bands which cannot be achieved by using DWT [21]. In our analysis, Daubechies 2 (db2) family of wavelet packets is implemented as the mother wavelet. As a result of 3 level decompositions, 8(2<sup>3</sup>) feature vectors are extracted from each signal frame and are used as input to ELM classifier for the classification of the EMG signals. The feature extracted from the wavelet packet is energy feature and it is given by Equation (7)

$$E = \sum_{i=1}^{n} x_i |^2$$

(7)

where xi denotes the wavelet packet coefficient.

#### Classifier- extreme learning machine

Guang-Bin Huang introduced ELM which is a Single-hidden Layer Feed forward Neural network (SLFN) with at most L hidden nodes and with almost any nonlinear activation function can exactly learn L distinct observations. SLFNs can be considered as a linear system after the input weights and the hidden layer biases are chosen randomly. The output weights (linking the hidden layer to the output layer) of SLFNs can be analytically determined through simple generalized inverse operation of the hidden layer output matrices. ELM can approximate any target continuous function and classify any disjoint regions [5]

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#### Fig: 3. ELM Architecture.

Fig: 3 shows the ELM architecture which consists of single hidden layer. The number of input neuron corresponds to the number of input features. The number of hidden neurons is equal to or greater than the input neurons. The number of output neuron is equal to the number of classes. For N arbitrary distinct samples  $(x_i, t_i)$  where  $x_i = [x_{ij}, x_{ij}, \dots, x_{in}]^T$  and  $t_1 = [t_{i_1}, t_{i_2}, \dots, t_{i_m}]^T$ , standard SLFNs with L hidden nodes and activation function g(x) are mathematically modeled as in Equation (8)

$$\sum_{j=1}^{L} \beta_j g_j(\mathbf{x}_i) = \sum_{j=1}^{L} \beta_j g_j(\mathbf{w}_j \, \mathbf{x}_i + \mathbf{b}_j) = \mathbf{a}_j \text{ where } i=1,2, \dots, N$$
(8)

Where  $w_j = \begin{bmatrix} w_{j_1}, w_{j_2}, \dots, w_{j_L} \end{bmatrix}^{T}$  is the weight vector connecting the  $j^{th}$  hidden node and the input nodes,  $\beta_j = \begin{bmatrix} \beta_{j_1}, \beta_{j_2}, \dots, \beta_{j_m} \end{bmatrix}^{T}$  is the weight vector connecting the  $j^{th}$  hidden node and the output nodes, and  $b_j$  is the threshold of the  $j^{th}$  hidden node.  $w_{j,x_i}$ denotes the inner product of w and X. That standard SLFNs with L hidden nodes with activation function g(x) can approximate these N samples with zero error means

(9)

i.e.,  $\sum_{j=1}^{t} \mathbf{e}_{j} - \mathbf{r}_{j} = \mathbf{0}$  and there exist  $w_{j}$  and  $\beta_{j}$  such that

 $T = \beta H$ 

$$\sum_{i=1}^{L} \beta_{i}g(w_{i} x_{i} + b_{j}) = t_{j} j = 1, 2, 3, \dots L$$

(10)

The Equation (9) can be written compactly as shown in Equation (10)

Where  $H, \beta, T$  are given in Equation(11), Equation (15) and Equation (16)

$$H(w_{\nu},\ldots,w_{\nu},b_{\nu},\ldots,b_{\nu},x_{\nu},\ldots,x_{n}) = \begin{bmatrix} g(w_{\nu},x_{1}+b_{1}) & \cdots & g(w_{\nu},x_{1}+b_{\ell}) \\ \vdots & \ddots & \vdots \\ g(w_{\nu},x_{n}+b_{1}) & \cdots & g(w_{\nu},x_{n}+b_{\ell}) \end{bmatrix}$$
(11)

g(w<sub>p</sub>x<sub>k</sub>b<sub>p</sub>) is the activation function and it may be Unipolar sigmoid, Bipolar sigmoid or Gaussian . H is called the hidden layer output matrix of the neural network; the  $j^{\pm}$  column of H is the  $j^{\pm}$  hidden node output with respect to inputs  $x_{2}, x_{2}, \dots, x_{N}$  [5].

Unipolar sigmoid activation function is calculated using the formula as given in Equation (12)

$$g(w_{j} x_{i} b_{j}) = \frac{1}{1 + e^{(-((w_{j} - x_{i}) + b_{j}) - k)}}$$
(12)

Bipolar sigmoid activation function is represented as in Equation (13)

$$g(w_j, x_{i_j} b_j) = \frac{1 - e^{\left(-\left[(w_j - u_j\right] + b_j\right] - i\right)}}{1 - e^{\left(-\left[(w_j - u_j\right] + b_j\right] - i\right)}}$$
(13)

Gaussian function is calculated using the Equation (14)

$$g(\mathbf{w}_{j} \mathbf{x}_{i}, \mathbf{b}_{j}) = o^{(-\mathbf{b}_{j} \cdot \|\mathbf{x}_{i} - \mathbf{w}_{j}\|)}$$
(14)

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where  $\AA$  is the learning rate whose range is 0-1.



## **RESULT AND DISCUSSION**

#### Data acquisition

EMG data are collected from 15 healthy subjects (fourteen females and one male) with ages ranging from 22 to 42 years, 1 myopathy subject (male) with age 75 and 11 neuropathy subjects (seven males and four females) with ages ranging from 55 to 65. The signal was acquired by placing 3 electrodes on the biceps using Labview software and DAQ with a sampling rate of 1 KHz and 16 bit resolution. In addition, 1 healthy, 1 myopathy and 1 neuropathy EMG data are obtained from physionet [22].

Selection of Wavelet and level of decomposition plays a very important role in the extraction of features. In the existing method mentioned [1], four statistical features namely Mean of the absolute values of the coefficients, Average power of the wavelet coefficients in each sub-band, Standard deviation of the coefficients from each sub-band and Ratio of the absolute mean values of adjacent sub-bands were the features extracted for classification using PSO-SVM classifier and it resulted in a classification accuracy of 97.41%.

In the proposed method, ELM uses the features extracted through DWT and WPT separately for the classification of EMG signal. The performance of the methods ELM-DWT and ELM-WPT are compared with each other.

### **ELM-DWT**

The performance of ELM-DWT is evaluated for two sets of features F1 and F2 as mentioned in section 2.1. In order to compare the proposed method with the existing method, the first feature set F1(17 features) is classified using ELM which yielded a classification accuracy of 100%. The number of feature vectors used in the proposed method is 17, whereas 23 feature vectors were used in the work mentioned in [1]. As the number of features used for classification reduces, the computational time reduces. Hence classification with limited number of features is advantageous. The performance of the proposed method is also evaluated with second feature set F2 (24 features), which again yielded a classification rate of 100%.

#### ELM-WPT

In this method, EMG signal is decomposed into 3 levels using Wavelet Packet Transform (WPT) with Daubechies order 2 (db2) wavelet. Thus  $2^3 = 8$  numbers of packets are obtained. Wavelet packet energy feature is computed for each packet. Thus a total of 8 feature vectors have been extracted using WPT and classified using ELM which again yielded a classification accuracy of 100%. Though both methods ELM-DWT and ELM-WPT yielded a result of 100%, the latter method is computationally efficient because of its ability to classify with a limited number of features.

Theoretically the number of nodes in the hidden layer of the classifier is equal to or greater than the number of input nodes. If the number is too small, ELM may not reflect the relationship between input data and output value. On the contrary, a large number may create such a complex network that might lead to a very large output error caused by

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over-fitting of the training sample. The parameters used for ELM-DWT and ELM-WPT are shown in **Table-1**. The activation function used in the classifier may be Unipolar sigmoid or Bipolar sigmoid or Gaussian. The activation function for which ELM yielded 100% classification accuracy is shown in **Table-2**. From the collected EMG data, 5 data (2 healthy, 1 myopathic and 2 neurogenic) are used for training and 25 data (14 healthy, 1 myopathic and 10 neurogenic) are used for testing.

#### Table: 1. Parameters used in ELM

Parameter	ELM-	ELM-DWT		
	WPT	Feature set 1	Feature Set 2	
Number of Input node	8	17	24	
Number of Hidden node	8	20	30	
Number of Output node	3	3	3	
Learning Rate	0.001	0.001	0.001	

#### Table: 2. Various activation functions used in ELM

Method		Unipolar Sigmoid	Bipolar Sigmoid	Gaussian function
	ELM-WPT	×	×	×
ELM-	Feature Set1			×
DWT	Feature Set2	×		

The classification accuracy of the ELM classifier is 100 % each. Irrespective of the number of training data sets, ELM performs well and guarantees an accuracy of 100%. Classification results of the ELM are visualized using confusion matrix [23]. The confusion matrix showing the classification results of ELM is shown in Table-3.

#### Table: 3. Confusion matrix of ELM classifier

Output/desired	Result (Healthy)	Result (Myopathy)	Result (Neuropathy)
Result (Healthy)	14	0	0
Result (Myopathy)	0	1	0
Result (Neuropathy)	0	0	10

## DISCUSSION

The computation of the following parameters showed the test performance of ELM:

Specificity: Number of correctly classified healthy subjects/ number of total healthy subjects

Sensitivity (myopathy): Number of correctly classified subjects suffering from myopathy/number of total subjects suffering from myopathy.

**Sensitivity (neuropathy):** Number of correctly classified subjects suffering from neuropathy disorder/number of total subjects suffering from neuropathy disorder.

Classification accuracy: number of correctly classified subjects/ number of total subjects.

Classification accuracy =  $\sum_{n=1}^{n} \frac{D_{c}}{N}$ 

(17)

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where, Dc is the diagonal elements of the confusion matrix, N is the total number of training/testing samples. The values of these parameters are tabulated in **Table-4**. The ELM classified healthy subjects, myopathy subjects and subjects suffering from neuropathy with the accuracy of 100%. Table .4 shows the classification success rate obtained for 30 EMG recordings.

Statistical Parameters	ELM- WPT	ELM-DWT	
		Feature set 1	Feature Set 2
Computational Time (sec)	12.678	14.522	17.427
Specificity	1	1	1
Sensitivity (neuropathy)	1	1	1
Sensitivity (myopathy)	1	1	1
Classification Accuracy (%)	100	100	100

### Table: 4. Comparison of ELM-WPT and ELM-DWT models for EMG signal classification

## CONCLUSION

Electromyography plays an important role in clinical neurological diagnosis, to indicate the location and type of abnormality or expose disorders that are clinically uncertain. The classification of neuromuscular disorders is essential for correct diagnosis. The proposed method, Extreme Learning Machine (ELM) is a simple and effective algorithm for single-hidden layer feed forward neural networks (SLFN) which automatically classifies the EMG signal into healthy, myopathic or neuropathic. For any classification application, feature extraction is necessary and in this research work DWT, WPT are the two used individually. The proposed techniques ELM-DWT and ELM-WPT are found to be best when compared with the existing techniques in terms of classification accuracy and number of feature vectors. Among the proposed techniques, ELM-WPT excels ELM-DWT in terms of computational time and number of features. The learning speed of ELM is extremely fast. From the simulation result, it can be seen that the learning phase of ELM is completed in less than a second. The ELM appears to be suitable in applications which require fast prediction and response capability. For any type of activation function, the classification accuracy of ELM-WPT is 100%.

## CONFLICT OF INTEREST

Authors declare no conflict of interest.

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# A HYBRID PSO-GA APPROACH FOR BIOMARKER DISCOVERY

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## ABSTRACT

The advancement in genomic and proteomic has paved way for identifying methodologies to identify gene involved in life threatening diseases. Biomarker refers to specific gene and products with biochemical features to measure the progress of the diseases. Various soft computing techniques are applied to identify biomarkers from large micro array chips. In this paper a hybridized approach for biomarker discovery using Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) is proposed. The proposed approach is tested with microarray lymphoma dataset. Based on the experimental run twelve gene were identified as significant gene and 3 gene were found in the disease pathway which can be verified with experts to name as biomarkers using the methodology proposed. The experimental results are validated using panther tool for biological significance and verified with related literature papers. From the results it is found the performance of the algorithm is good for identifying significant gene for bio marker discovery.

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**KEY WORDS** 

Biomarker, PSO, GA, Gene Pathway, Significant gene Gene Ontology (GO)

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### INTRODUCTION

DNA microarray is a rapid growing technology used for the study of gene expression profiles and it is a classic probe hybridization method which provides access to thousands of gene at once. Generally, microarray data are images, which are transformed into gene expression matrixes in which rows represent gene and columns represent the expression values of gene under various experimental conditions. Microarray technologies enable the simultaneous interrogation of the expression level of thousands of gene to obtain a quantitative assessment of their differential activity in a given tissue or cell [1]. Recently the microarray technology has a gained interest of their use in clinical trials and disease diagnosis for identifying genomic factors that are prognostic for prediction or identification of Biomarker.

Biomarkers (short for biological markers) are biological measures of a biological state. By definition, a biomarker is "a characteristic that is objectively measured and evaluated as an indicator of normal biological processes, pathogenic processes or pharmacological responses to a therapeutic intervention [2]. Biomarkers are the measures used to perform a clinical assessment such as blood pressure or cholesterol level and are used to monitor and predict health states in individuals or across populations so that appropriate therapeutic intervention can be planned [3-5]. Biomarker discovery is proved as one of the most broadly applicable and successful means of translating molecular and genomic data into clinical practice [6]. Evolutionary algorithm and soft computing techniques are applied in large for analysis of gene profiles for Biomarker prediction and identification. Genetic algorithms are hybridized with bio-inspired algorithms for microarray analysis to identify the significant gene. Identification of significant gene from large gene set becomes essential to identify the biomarkers of specific diseases [7]. The authors Zhang F [8], Hui-Huang Hsu [9] used data mining to identify biological markers for the diagnostic classification and prognostic assessment in the context of microarray and proteomic data A hybridized Particle Swarm Optimization and Genetic Algorithm PSO-GA is proposed in this paper to identify significant gene from DNA microarray for biomarker discovery. The proposed work is implemented using Rlanguage for Lymphoma cancer dataset. The paper is organized as follows. Section II discusses the literature related to the work. Section III describes the hybridized approach for identifying biomarker using PSO with Genetic algorithm. In Section IV the experimental results are discussed followed by Conclusion in section V,



followed by Limitations and Future scope in section VI.

### LITERATURE STUDY

This section discusses the literature related to the work. The literature are discussed in three sub sections namely Preprocessing techniques of microarray data for significant gene analysis, literature related to evolutionary algorithm and hybridized approaches.

#### Statistical techniques for microarray data

Statistical measures are widely used to identify the most and least selected attributes from large samples using various statistical tests as F-Test, T-Test, Chi-Square and Annova. In microarray dataset the gene are viewed as random samples and rank based statistical measures are widely used to identify the best expressed gene profiles from microarray data. The literature for ranking gene as part of pre-processing of microarray data is discussed in this section.

Statistical approaches like k Nearest Neighbor, Iterative regression imputation, Mean Squared Error, F-Test, Ttest, chi-square, ANOVA and F-Test are used to pre-process the microarray dataset to impute missing values and rank gene. The authors Miguel Rocha and Isabel Rocha [4] suggested substituting of missing values with mean, median and mode using imputation method k nearest neighbor for microarray dataset. M. Templ et al., [10] used KNN methods for estimating missing values in compositional data. The authors also have discussed about T-test and ANOVA for identifying differentially expressed gene in microarray data. Matt Blackwell [11] analyzed Multiple Hypothesis Testing F-test in microarray data and S. N. Mukherjee, S. J. Roberts et al., [12] proposed a gene-ranking algorithm whose main novelty is the use of bootstrapped P-value for microarray datasets. The authors Guoqiang Yu, et.al, [13] used MSE (Mean Squared Error) to select candidate gene for classification. MSE is minimized to achieve the desired output (class target).Yoko Omura and Jun Sese [14], used Mean Square Error to select significant gene and generates pClusters from the selected gene. Mohd Sazli Saad [15], used MSE as objective function to calculate fitness value of each chromosome represented as gene in Genetic algorithm to pass the best chromosome for the consecutive generations.

#### PSO - GA

Particle swarm optimization is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality [16]. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity [17]. Each particle's movement is influenced by its local best known position but, is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles [18]. This is expected to move the swarm toward the best solutions. The algorithm is very simple but powerful.

The genetic algorithm is a model of machine learning which derives its behavior from a metaphor of the processes of evolution in nature Genetic algorithm are found to be widely used microarray data to improve the classification accuracy [19]. Algorithm is started with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population [20]. This is motivated by a hope, that the new population will be better than the old one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chances they have to reproduce [21]. This is repeated until some condition (for example number of populations or improvement of the best solution) is satisfied. Laetitia Jourdan et. al.[4] they have proposed a 2-phase approach using a specific genetic algorithm for the feature selection problem, they used a genetic algorithm (GA). Linyu Yang [19] and C.H. Ooi and Patrick Tan (2003) [22] used Genetic algorithm to design a gene-selection scheme predict the disease. J. Yu, et. al.,[23] and Edmundo Bonilla Huerta [6] applied Genetic Algorithm to find the gene subsets that produce high prognostic classification accuracy.

The authors Barnali Sahua et.al. [16] and Keisuke Kameyama [18] used Particle swarm Optimization (PSO) as a optimization technique for the classification of high dimensional cancer microarray data. Qinghai Bai [21],



concluded that performance of PSO is fast, easy and effective for optimization problem compared to other approaches and author strongly suggested that, PSO provides better result when combined with other techniques. Yuji Zhang et.al, [24] proposed a method of hybrid of genetic algorithm and particle swarm optimization (GA-PSO) to train the NN (Neural Network) models. The authors C.H. Ooi and Patrick Tan [8], Linyu Yang ,et.al., [19] applied genetic algorithm for multi-class prediction problem. The authors stated that the parallelized searching capability of GA helps to design a gene-selection scheme that determines the optimal set of gene in a multiclass dataset which classifies the samples within the dataset with minimal error and accurate prediction. Shital C. Shah [25] described that, GA based approach uniquely identified some gene/SNPs that could not be identified by the approaches like Information Gain and REG Regression approaches. Laetitia Jourdan et. al. [26] Proposed a 2-phase approach using a specific genetic algorithm with clustering algorithm for multi factorial disease prediction. The authors Ramsingh et.al. [27] Proposed genetic algorithm with K-Means clustering to identify significant gene from microarray dataset. The authors Vanitha et.al, [28] used evolutionary approaches such as optimization methods to generate best gene combinations to achieve higher level classification accuracy.

The biomarker gene are some specific gene which is highly significant causing gene mutation resulting in specific diseases. Indentifying biomarker gene can be viewed as an optimization problem to identify minimum number of gene which are highly significant bases on their gene expression profiles. From the literature study it is found that PSO, GA and other approaches are applied as standalone approaches for identifying significant gene from microarray dataset. These approaches when applied and iterated for more number of runs identify the best gene expression profiles which are highly significant. Biomarker identification requires accurate validation of the gene expression profiles to identify the gene in specific diseases. In this paper a novel methodology is proposed to filter the optimal gene using a two level optimization process using the hybrid PSO-GA approach to identify the significant gene to discover biomarkers for diseases.

### **BIOMARKER DISCOVERY USING PSO-GA**

This section discusses the proposed methodology and framework to identify genomic biomarker for microarray dataset. The framework for Biomarker discovery using PSO-GA given in **Figure-1** is consists of three phases Pre Processing phase, phase II as PSO-GA hybrid approach and verification and validation phase as the third phase.

### Phase I

Pre-processing phase is the first phase used for analyzing Gene expression features of microarray dataset using statistical techniques. Microarray data contains of noisy and inconsistent data. The Pre-processing techniques are used to reduce noisy and inconsistent data using imputation methods. k Nearest Neighbor (kNN) is a data mining technique to impute missing expression data in microarray in the proposed work to fill in the missing values. For each gene with missing values, it finds the k Nearest Neighbor using a distance metric, confined to the columns for which those gene are not missing. The microarray data is normalized using the statistical techniques.

Based on the detailed study and analysis of various statistical methods for microarray data through experimental result and comparison MSE is found to identify highly significant gene which are semantically relevant compared to other approaches from the literature study. MSE is used as fitness function to rank significant gene. The mean squared error is arguably the most important criterion used to evaluate the performance of a predictor or an estimator. (The subtle distinction between predictors and estimators is that random variables are predicted and constants are estimated.) The mean squared error is also useful to relay the concepts of bias, precision, and accuracy in statistical estimation.

 $\sum_{i=1}^{n} (x_i \bar{x})^2$ 

n = size (number of individuals) **x** = mean value of individuals **X** = value of individual ----Eq 1





#### Fig: 1. Biomarker discovery using PSO-GA

# Phase II: PSO - GA hybrid approach

The second phase of the framework is presented with the methodology to identify significant gene for biomarker discovery using hybridized PSO - GA algorithm. In this methodology the PSO algorithm is applied initially on the dataset and best populated gene are passed as input to GA process to identifying the best significant gene, as a two level optimization process the detailed methodology is presented in the below section.

### **PSO algorithm - parameters**

In PSO algorithm the particles are initialized at random positions, to explore the search space to find better solutions. In each iteration each particle adjusts its velocity to follow two best solutions. The first is the cognitive part, where the particle follows its own best solution found so far. This is the solution that produces the lowest cost (has the highest fitness). This value is called pBest (particle best). The other best value is the current best solution of the swarm, i.e., the best solution by any particle in the swarm. This value is called gBest (global best).

In the proposed PSO algorithm gene expression values in microarray dataset are encoded as a particle. The fitness value of the particle is calculated using MSE given in Eq 1 gBest and pBest are calculated in each iteration based on the fitness value of gene, where gBest is the best fitness value of all gene in the entire population and pBest is the fitness value of gene in each population, the velocity and position of the particles are calculated using Eq 2 and Eq 3. The best ranked gene are passed to the GA process. The best ranked gene are removed from the PSO population for next iteration. This cycle is iterated until there is minimum number of gene in the population. The parameters of PSO algorithm is given in Table-1

New velocity $v' = v + c1.r1$ . (pBest - x) + c2.r2. (gBest - x)	Eq 2
New position $x' = x + v'$	Eq 3
New position $x' = x + y'$	-



- v = current velocity
- c = current position
- c = coefficient
- r = random values, 0 >=  $r1 \ll 1$  and 0 >=  $r2 \ll 1, 0 \ll c1 \ll 2, and 0 \ll c2 \ll 2$

The parameters for Hybridized PSO - GA algorithm for PSO Approach is given in Table-1.

#### Table: 1. Parameters of PSO

No. of particles	4026
Fitness function	MSE
Total no. of iterations	100

The below section describes the Genetic Algorithm parameters modeled for the work.

#### Genetic algorithm - parameters

Genetic Algorithms are efficient search methods based on the principles of natural selection and population genetics [29]. GA can search the solution space to find an optimal or near optimal solution by using evaluation and genetic operator functions to maintain the useful schemata of chromosomes in the population, in which chromosomes are evaluated using a fitness function to determine their fitness. According to the principle of survival of the fittest, Chromosome with a higher fitness will have higher probability of survival in each generation and thereby offspring with higher probability are generated. The genetic algorithm parameters modeled for identifying significant gene are given in Table- 2.

#### Table: 2. Parameters of GA

Chromosome - Size		33	
Generations		100	
Populations –Size		100	
Selection		Random Selection	
Fitness		MSE	
	Crossover	Single point crossover	
GA operators	Mutation	Substitution	
	Mutation rate	0.8	

The GA cycle stops the process if the genetic algorithm reaches local optimum or after the maximum number of solutions that already defined. The pseudo code for proposed work is given below:

Proposed pseudo code : Hybridized PSO and GA
Pop // input , population for PSO
// gene is a particle
Repeat
For each gene
Initialize gene
End
do
For each gene
Calculate fitness value
If the fitness value is better than the best fitness value (pBest) in history Update pBest = current best value
End
Choose the gene with the best fitness value of all the particles as the gBest
For each gene
Calculate gene velocity
Equation7 // equation to calculate velocity
Update gene position
Equation 8 //equation to calculate position
End
If (maximum iterations ==TRUE)

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Population p=best 1000 gene from PSO
pop=(pop-best 1000 gene)
if(size(pop) < sufficient)
break(PSO)
end if
//Genetic algorithm
Initialize population p
do
For i in 1:100 \\ Crossover
Randomly select two parents $X_A$ and $X_B$ from p
Generate $X_C$ and $X_D$ by one-point crossover to $X_A$ and $X_B$
End for
For j in 1.size(p1) \\ Fitness
Fitness value = $\sum_{j=1}^{n} (x_j - \bar{x})^2$
End for
Select 100 chromosomes with minimum MSE value
//Best chromosome selection
while there is no recurrence of chromosome in generation
In recurrence of chromosome = TRUE
For (K In 1:100) //Mutation
Select duplicate chromosome XK from pr
If Yk is unfoosible
I AK IS UITEdSIDE Replace with best gone
End if
End for
End if
Else
Stop // reaches local optimum or maximum no. of generation
Update p // Update
p = best 100 fittest chromosomes
Returning best solution p //Return
PSO(pop)

## Phase II: Verification and validation

The proposed work is validated biologically using PANTHER tool. PANTHER is an online biological tool used to analyze the biological significance of proteins and gene. PANTHER produces the output of list of gene which are involved in Gene Ontology functionalities such as Molecular function, biological process, cellular component and disease pathway. In this proposed work GO functionalities and pathway are analyzed to find out biological relevance and biological significance of 12 extracted gene from phase II. The experimental results of these approaches are discussed in result and discussion section. The results are also verified and compared with literature result.

# Significant gene

The gene from the microarray dataset is identified as significant based on the biological validation using Gene Ontology. The gene is available in GO only when the gene has functionalities in Biological Process, Molecular Function and Cellular Component. The gene identified using the proposed approaches are termed as significant when the gene is available under GO taking part in all the three functionalities.

# RESULTS AND DISCUSSION

### Experimental results

The experimental results of proposed work are discussed in this section. Lymphoma microarray dataset is used for the proposed work. The dataset is downloaded from [http:/llmpp.nih.gov/lymphoma/data.shtml]. The microarray dataset consists of 4026 gene and 96 samples. In this section the experimental analysis of PSO-GA approaches are presented in detail. The experiments were conducted on the data set by executing the algorithms PSO and GA individually. The experimental analysis are presented below.

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## Normal PSO

The PSO algorithm is applied on the lymphoma dataset for identification of significant gene for biomarker discovery. On experimental run 33 gene are identified from 4026 gene using PSO approach in which 12 gene are found as significant based on the biological validation taking part in all the functionalities in this approach. The **Figure-1** presents the best significant gene based on fitness value using PSO approach. The fitness plot of the normal PSO approach for the dataset is given in **Figure-2**.



### Genetic algorithm

The experimental result of Genetic Algorithm is presented below. The chromosome for GA approach is modeled with 33 gene of microarray data. The GA is run with the with a population size of 100 for 50 and 100 generations. 424 gene are identified using GA is given in **Table-3** with fitness score. **Figure-3** represents the significant gene for 50 and 100 generations. From the graph it is observed that the no of gene get optimum after 15 generations. 12 gene were found to be significant in GA approach based on the biological validation of GO.

Table: 3. Experimental Result - GA

Total No of Genes	4026
Significant Gene	424
Best Chromosome Fitness For first 10 generation	1230.21, 1046.75, 1009.72, 1140.30, 975.18, 975.72, 926.19, 911.82, 898.91, 911.82
Best Fit chromosome	688.31

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Fig: 3. Significant gene of 50, 100 generations

# Hybrid PSO- GA

The experimental result of the proposed approach hybrid PSO- GA with comparison of Normal PSO and GA approach are discussed below. To identify the biomarker the proposed approach PSO-GA identifies the significant gene with a two level optimization process filtering the best gene in every population of the iterations.



Fig: 4. Best Chromosomes from Hybrid PSO - GA

The **Figure-4** represents the value of 62 best chromosomes derived from hybrid PSO - GA approach. The comparison of gene for the proposed approach PSO-GA with PSO and GA is given in **Table-3** and **Figure-5**. On analysis of gene it is found that 12 common gene found in all the three approaches is termed as highly significant gene. 12 Gene identified from the dataset are:



GENE722X, GENE1634X, GENE699X, GENE3836X, GENE2485X, GENE707X, GENE1432X, GENE1806X, GENE185X, GENE2029X and GENE2551X.

#### Table: 4. Gene counts of PSO, GA & PSO-GA

	No. of iteration	No. of significant gene
Normal PSO	100	33
GA	100	424
Hybrid PSO - GA	100	62



#### Fig: 5 Comparison of PSO approaches

# **Biological validation**

The extracted gene using PSO-GA approaches are verified using PANTHER tool for validating biological significance. The biological validations of the gene are done using Gene Ontology (GO) functionalities and pathway.

# GO functionalities

The identified gene are verified in Gene Ontology functionalities Biological Process, Molecular Function and Cellular Component. A biological process is a process of a living organism. Biological processes are made up of any number of chemical reactions or other events that result in a transformation. Molecular function describes activities, such as catalytic or binding activities, that occur at the molecular level. GO molecular function terms represent activities rather than the entities (molecules or complexes) that perform the actions, and do not specify where or when, or in what context, the action takes place. Cellular component refers to the unique, highly organized substances of which cells, and thus living organisms, are composed. Cells are the structural and functional units of life. The gene ontology found to be for the extracted twelve gene for BP,MF,CC is significant in Figure– 6(a),6(b),6(c).



#### Fig: 6 (a) Biological processes

It can be inferred from **Figure-6(a)** identified 12 gene are involved in 9 biological process like biological regulation, biogeneis, cellular process, development process, immune system process, localisation, metabolic process, multi cellular organism process, response to stimulates and all the 12 gene are active in more than one process





From **Figure-6** (b) it can be inferred that identified 12 gene are involved in 5 molecular function like binding, catalytic activity, nucleic acid binding, respirator activity, structural molecular activity and are active in more than one process. Each colour represent the molecular activity of the gene.



#### Fig: 6 (c). Cellular components

**Figure–6 (c)** It can be inferred that identified 12 gene are involved in 2 cellular components like cell part and macromolecular complex. Hence based on the result it is found that the gene are involved in the BP and there are chances to be marked as biomarker. where the five gene GENE1432X, GENE1806X, GENE185X, GENE2029X and GENE2551X identified in this work are also found in literatures [30][31][32].

# Pathway validation

The experimental results are also verified with pathway database. The **Figure-7** shows gene involved in the diseases pathways using panther tool for the biological validation of the proposed approach. The 12 gene identified from PSO-GA approach are found in more than 1 pathway. Out of 12 gene five gene GENE1432X, GENE1806X, GENE185X, GENE2029X and GENE2551X identified in this work is found already in literatures [30][31][32].

From the experimental analysis the three gene GENE1432X [30], GENE1806X [31], GENE185X [32] are found in the diseases pathway. The three gene are identified in the proposed approach found in the diseases pathway which has to be further verified for biological significance by experts to mark as biomarkers.

In **[Figure-6]**, based on the forecast threshold, the number of data aggregation is larger when compared to the Kalman filter. Due to this data aggregation is reduced redundant transmission and communication consumption power.

# CONCLUSION

Biomarker discovery has become important in many aspects of drug discovery and development. Biomarkers predict toxicity and help to save hundreds of millions of dollars with the early termination of costly clinical trials. Many biomarkers play important roles in diagnostic and prognostic applications, where they help to detect or predict diseases. In this work, a hybridized approach of Particle Swarm Optimization and Genetic Algorithm for retrieving highly significant gene is done as a two level optimization process. From the experimental results out of 4026 gene of Lymphoma microarray dataset 12 gene were found to be significant in all the three approaches PSO, GA, PSO-GA. Out of 12 gene 3 gene were found in the diseases pathway and GO functionalities using the biological validation approach of this work. 3 gene when verified with domain experts can be marked as biomarker.

The proposed approach is found to be better for identifying optimal gene using the two level process PSO-GA is verified based on biological validation. The proposed algorithm compared with the other approaches is found to be significant in performance.





#### Fig: 7. Pathway of 12 Gene using PSO-GA

# LIMITATION AND FUTURE SCOPE

The limitation of the proposed work is, that it is iterated only for little iteration due to the hardware constraints. The work is tested only on one dataset the proposed approach can be verified with other microarray dataset in future. The experimental run can be further extended by implementing using map reduce framework with the existing hardware. The approach will be further tried with other algorithmic approaches in future.

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#### CONFLICT OF INTERESTS

Authors declare no conflict of interest.

#### FINANCIAL DISCLOSURE

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# A PREDICTIVE ANALYTICAL APPROACH TOWARDS IMPROVING THE CROP GROWTH YIELD USING FUZZY COGNITIVE MAPS - CROYAN

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# ABSTRACT

Improving the crop yield is always a major challenge for farming community as well for agricultural scientists. Though various computational approaches have been followed traditionally in practice, still a persistent decision making method to improve crop yield is not predicted and lies as a misnomer. Multiple rethegorical factors / parameters form the basis of improved crop yield. This paper proposes Fuzzy Cognitive Map approach to help in decisive making and suggesting an optimized solution of improving crop yield as well as compared with existing approaches such as Genetic Algorithm (GA) and Artificial Neural Network (ANN). The research work considers two major crops namely Sugarcane and Red Chilli for analysis. The results show that FCM provides a higher accuracy in supporting crop growth yield with higher similarity ratio of expected growth and actual growth.

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**KEY WORDS** 

CROYAN, Fuzzy Cognitive Map, Crop Growth, Crop Yield, Yield Accuracy

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# INTRODUCTION

Wireless Consistent monitor and control over crop growth [11] is the major variant of precision agriculture with support of greenhouses [22], which are considered as biophysical systems with inputs, outputs and control process mechanisms which adds to cost and complexity in maintenance. Hence designing a natural crop growth and yield system with support over understanding the growth variables and formulating the decision making is the primary objective of this work.

Decision making on improved crop yield helps to:

[a] Understand and identify the supportive metrics related to improving crop growth and yield.

[b] Support with deterministic decision making with consistent monitoring and control over crop yield at each growth phase

[c] Support crop growth by understanding and analyzing the environmental and demographic control parameters to estimate crop yield.

Understanding crop yield management [13] and its behavior in agricultural domain carries much importance since it relationally influences climate, region aspects or farming demographic factors. Computational approaches can be considered which support in predictive analysis of crop growth and yield. Approaches such as genetic algorithms [4][6], Artificial Neural Networks (ANN) [7], Bayesian Approach [12], fuzzy models [20] are well applicable, though such models can be adopted in complex situations, it does not achieve an optimal solution for highly dynamic and multi-variable solutions. Hence the need for an efficient knowledge-based system approach utilizing the Fuzzy Cognitive Maps (FCMs) [8] [10] approach for characterizing crop yield of behavior is discussed in this paper.

FCM is a modeling approach based on exploiting knowledge and experience. The novelty of the method is based on the use of the soft computing method of fuzzy cognitive maps to handle experts' knowledge and on the unsupervised learning algorithm for FCMs to assess measurement data and update initial knowledge. The advent



of precision farming generates data which, because of their type and complexity, are not efficiently analyzed by traditional methods. The FCM technique has been proved for its accuracy and efficiency from the literature survey as well flexible to handle experts' knowledge and through the appropriate learning algorithms can update the initial knowledge.

Two major crops are being considered for analysis such as Sugarcane (botanical name : Saccharum Officinarum), Chilli (botanical name : Capsicum annuum L.; Capsicum frutescene L.). These crops are considered for analysis and survey since all the three crops are well grown in India and commonly in most of the tropical regions.

The FCM model developed consists of nodes linked by directed edges, where the nodes represent the main factors in crop growth production such as soil texture, water composition as well organic matter of soil such as pH, K, P, Mg, N, Ca, Na. The directed edges show the cause-effect (weighted) relationships between the soil properties and crop grown field. The proposed method was evaluated for 300 cases measured for subsequent years such as 2007, 2008, 2009, 2010, and 2011 based upon data obtained from International Council of Agricultural Research (ICAR) and related agricultural datasets.

The proposed FCM model enhanced by the unsupervised nonlinear Bee Hive learning algorithm<sup>[23]</sup>, can support a success rate on an average of greater than 75%, for years 2009, 2010 and 2011 dataset referred as estimating/predicting the yield between fuzzy categories ("worst", "low", "average", "high", "best"). The main advantage of this approach is the sufficient interpretability and transparency of the proposed FCM model, which make it a convenient consulting tool in describing crop yield behavior for Chilli and Sugarcane crops. The work describes crop yield analysis being obtained from an uncontrolled farm field and not from a precision or data not obtained from temperature and hygrometric conditions in greenhouses. Hence this work carries much importance in an uncontrolled, stochastic farm field procedure.

CROYAN method works on an association based mining algorithm which is binded to the moderated patterns obtained from FCM. Fuzzy Cognitive approach observes the variable metrics and factors contributing the improved yield of crop while predictive pattern mining model determines the accuracy of selecting the crop based on variable metrics. The paper is organized as follows, Section-2 focuses on detailed survey and analysis on mechanisms to improve crop yield and need for such methods, while Section-3 elaborates on FCM and its methods, dataset and algorithm. Section-4 discusses on CROYAN with its implementation and Section-5 summarizes the work with future works to be carried out.

## SURVEY AND ANALYSIS

This section presents a detailed survey and analysis of existing works which support decisive making approaches [10, 15] for crop yield are discussed. Applying soft computational and statistical approaches for crop yield analysis is not much considered under major research challenges [20]. In order to derive an accurate crop yield, predictive mining approach on fuzzy cognitive method could prove elusive. Crop yield attributes to some common basic factors which are related to crop growth parameters and disorders parameters such as high rainfall, irrigation procedures [4], moderate sunlight intensity, rocky soil type which may not attribute to growth of crops in general. Such change in unexpected frequency may affect severity of crop yield as unexpected by farming community. Though this paper supports on decisive making and mechanisms to achieve crop yield [1,4], the detailed and indepth analysis of the factors attributing to destruction of crop growth [2] is primarily not within the scope of this work.

Asefa Taa et al [2] discussed multiple factors which attribute to consistent crop growth needs to be automated which impose high accuracy and complexity [2]. The phenomenon of crop growth cannot be completed automated or sensed upon due to the need for supporting precise and periodical evaluation of biotic status of crops and their natural growth. This paper discusses on the underlying factors behind design and implementation of a crop yield decision making system which adopts growth and yield sensitive metrics on control and monitoring growth process of crops. This approach is compared and analyzed over similar crop growth trends which are achieved over similar climatic and regional factors phenomena.

# NEED FOR FUZZY COGNITIVE MAPS

As artificial intelligence and heuristic approaches are not often sufficient to obtain high quality prediction, the proposal can be extended to supplement using knowledge base and adaptive soft computational approaches. Predicting crop yields at an early stage in the growing season can be of great importance. The correlation of the corn yield [7, 16] helped to permit the early yield prediction and the appropriate management of the farm land.

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Crop growth models were developed in agriculture by using mean values of input and outputs [17]. Several crop growth models have been developed by Xirogiannis [19]. Papageorgiou [13] presents the soft computing technique of Fuzzy Cognitive Maps (FCM) to connect yield defining parameters with yield in cotton crop production in India as the basis for a decision support system for precision agriculture application. FCM was chosen because of the nature of the application as it is a complex process and FCMs have been proved suitable for this kind of problem. Due to consistent change in temperature and hygrometric conditions, rapid decisions are highly essential to predict and control yield of crop or manage diseases to avoid dissemination and permanent infestation of crop growth [4] [12] hence soft computational approaches would suffice.

## **METHODS**

The methods and procedures being followed can be summarized.

#### (a) Data Set

The dataset collected over 300 record sets consisting of weather, soil, water, regional and crop growth data over the year 2007, 2009, 2010, 2011 catering to the region of Dharwad in Karnataka and Cuddalore in Tamilnadu for Sugarcane crop and Guntur in Andhra Pradesh and Madurai in Tamilnadu for Redchilli crop. The results are compared with bench marking genetic algorithm and ANN systems

#### (b) Metrics adopted

Few of the major metrics adopted in this research work are (i) Average yield achieved over per year (tons/hga), (ii)Average crop production per year each ha, (iii) Mean Crop Yield

#### (c) Soil - Water

Total Soil-Water Potential (SWP) can be used to determine the capacity of water available for crop transpiration from each soil layer. The capacity of the soil to hold enough water supports the growth of crop. Hence type of soil and water has a potential role in crop growth as well vield

#### (d) Role of NDVI

NDVI (Normalized Difference Vegetation Index) along with variable crop growth metrics suggests a useful way for crop yield assessment models whose approaches vary from simple integration to more complicated transformation. NDVI [9] has proved to improve vegetation greenness, which indicates the level of healthiness in the crop growth

#### (e) Selection of crop and growth region

Major Chilli growing states in India are Andhra Pradesh, Tamil Nadu, Maharashstra, and Karnataka which together constitute nearly 75 per cent of the total area. Hence dataset has been collected for Guntur (16.3008° N, 80.4428° E), and near by regions such as Khamman and Cuddappa in State of Andhra Pradesh. In Tamilnadu, Sugarcane dataset in Karur district (10.9338334 N, 78.0883645E) and near by Erode are collected for analysis. In both the regions Chilli variety K-1 and CO-1 are used for analysis while CO-265 variety for Sugarcane crop.

### FUZZY COGNITIVE MAP

Fuzzy cognitive maps (FCM) [3] [8] along with SVM (Support Vector machines) [5] helps in understanding and modeling crop yield and representing crop expert knowledge, since fuzzy cognitive theory [6] supports on theory of fuzzy logic and cognitive map, which are capable of dealing with uncertainty issues.

#### Modeling approach using Fuzzy Cognitive Maps

Fuzzy Cognitive Map (FCM) methodology [14, 17] is a symbolic representation for the description and modeling of complex system. Fuzzy Cognitive Maps describe different aspects in the behavior of a complex system in terms of concepts. FCMs illustrate the whole system by a graph showing the cause and effect along concepts, and are a simple way to describe the system's model and behavior in a symbolic manner, exploiting the accumulated knowledge of the system. A Fuzzy Cognitive Map integrates the accumulated experience and knowledge on the operation of the system.

Fuzzy Cognitive Maps (FCM), Tsadiras [18], defines it as a gualitative alternative approach to formulate dynamic systems. This approach can be considered to represent formal method to represent predictions and taking decisions. This work investigates the crop yield and variability crop yield prediction in chilli and sugarcane crops.



Crop management in these crops are highly complex with interacting parameters such as water, climate, soil factors which play major role in improving the yield of crop.

The FCM model possess nodes which show the variable factors affecting crop yield using a directed graph G(V,E). The cause effect relationship between the factors and crop yield can be depicted and analyzed. As shown in Fig-1 each components or elements contributing to growth of crop can be considered as Node, 'Na', through 'Ne' while all linkages which may be related between multiple nodes can be termed as Edges as 'E1' through 'E6', generally as Ei.



#### Fig:1. FCM representation using graph theory G (V,E)

FCM assigns a weight as 'Ei' for each edge, and each node 'Ni' binds the value to its weight. The causal relationship between two concepts Nj and Ni in fuzzy is explained with weights Ei, which considers the value in the range –1 to 1. Three possible types of causal relationships between concepts are followed:

(a) Ei > 0 which indicates positive causality between concepts Nj and Ni, which indicates that an increase or decrease in the value of Nj leads to an increase (decrease) in the value of Ni.

(b) Ei < 0 which indicates negative causality between concepts Nj and Ni, which indicates that an increase (decrease) in the value of Nj leads to a decrease (increase) in the value of Ni.

(c) Ei = 0 which indicates no relationship between Nj and Ni.

The FCM process can be inferred from the following mathematical formulation in equation 1.



Here, gi denotes the value of Ni node, while simulation is carried out over 'k', Ei is the linkage value between two nodes 'Ni' and 'f' is a sigmoid threshold function, which is  $1/(1+e-\Box x)$ .  $\Box$  lies between a value [0,1]. The fuzzy metric for crop yield lies between the ranges {low influence, moderate influence, acceptable influence, strong influence, best influence} over crop growth and production.

The fuzzy IF-THEN rules that experts use to describe the relationship among concepts assume the following form, where A and Bare linguistic variables: IF value of concept INFLUENCE Ni is "Low", AND

value of concept INFLUENCE Nj is "Average" THEN linguistic weight INFLUENCE Ei is "Acceptable"

where Low, Average, Acceptable are linguistic INFLUENCE variables taking values in the range [0, 1].

Each interconnection described by a fuzzy linguistic variable from the determined set, associates the relationship between the two concepts and establishes the grade of causality between the two concepts.

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#### Mapping the component values between the edges and variable nodes

The dataset collected over 300 cases consists of weather, soil, water and crop data during the years 2007, 2008, 2009, 2010 and 2011 for the region of Guntur in Andhra Pradesh. The Sugarcane data obtained for 250 record sets are obtained from Karur in Tamilnadu. The data is validated with base line data and maintained as repository. The results are compared with bench marking fuzzy and Artificial Neural Networks (ANN) systems.

# RESULTS AND DISCUSSION

# **CROYAN:** Crop yield analysis using FCM approach



#### Fig: 2. CROYAN architecture and functionality

Figure-2 explains CROYAN architecture which extracts the features of crop growth from data set and determines the crop yield efficiently. The baseline dataset is validated based on historical datasets and verified. FCM is being generated on crop growth parameters using metrics [Table-1]. Polygon clusters are generated for variable growth parameters.

The coefficients of empirical equation have been obtained using a analytical breakpoint (m) based on optimization of a mean of three years of Sugarcane and Chilli crop yield. [Table -2] shows the breakpoint achieved when the actual maximum yield achieved is equivalent to the expected yield. CROYAN methodology uses polygonal analysis to mine related datasets, which formulates the following steps:

- 1. Collect/Generate polygonal clusters for multiple related datasets
- 2. Meta cluster polygonal clusters
- 3. Extract interesting patterns / create summaries from polygonal clusters

CROYAN methodology adopts a multi clustered polygon based architecture, which defines variable multiple clusters required to identify the fitness of crop yield. Polygonal clusters [14] defined using Hausdroff metric suggests each clusters based on crop type, region associated with crop growth and production as shown in Figure-3. Each polygonal clusters originating from different datasets typically overlap, which provide an option to restrict cluster overlap in final clustering. Each clusters usually assumes that inter dependent polygons do not overlap and most uses the Hausdroff distance [11] to assess polygon similarity for crop yield. Figure-3 shows the set of polygonal clusters which depends on crop sow values and its relational yield values. This measure is vital in its definition due to its need for identifying the crop growth measure which is required for identifying the crop yield.

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#### Fig: 3. Cluster sets generated as polygonal clusters

#### **CROYAN** inputs and definition

A clustering set S={X1, ..., Xn} —at most one metric is selected from each meta cluster Xi, (i=1,...n).

1. The crop growth provides individual cluster crop yield function FitU whose values are  $[0, \infty)$ .

2. A fitness threshold value defined with  $\theta U$ 

U being set of lower unfit clusters are occupy not included in the final clustering.

3. A cluster distance threshold θcroyan\_dist which determines the cluster overlap/coverage can be tolerated. 4. A cluster distance function Z is defined between clusters of croyan dist,

For Xi  $\subset$  S, where i = 1...n

Begin

 $\begin{array}{l} \mbox{Find } Z \subseteq X1 \ \cup \hdots \ \cup \ Xn \ that \ maximizes: \ q \ (Z) > \mbox{FitU } (Xi) \\ \mbox{subject to:} \\ \mbox{a)} \quad \forall \ X \in Z \ \forall \ X' \in Z \ ( \ X \neq X' \ \Rightarrow \ croyan\_dist(X,X') > \mbox{$\theta$croyan\_dist } ) \\ \mbox{b)} \quad \forall \ X \in Z \ ( \ FitU \ (X) > \mbox{$\theta$U } ) \\ \mbox{c)} \quad \forall \ X \in Z \ \forall \ X' \in Z \ ( \ X' \in \ Xi \in S \land X \neq X' \ ) \Rightarrow i \neq n ) \end{array}$ 

End

The goal is to maximize the number of fitness measures of crop yield among clusters which have been selected from polygon clusters. The constraint 'a' prevents any two clusters that are too close to each other but are both included in the final clustering. Constraint 'c' makes sure that at most one cluster from each cluster being selected. Constraint 'b' determines the policy for fitness measure where the fitness can satisfy step (2). Here, Z is the cluster distance function defined based on CROYAN distance threshold level, FitU is the fitness measure obtained to understand the optimal crop yield.

#### Model

The FCM model possess nodes which show the variable factors affecting crop yield using a directed graph G(V,E) shown in **Figure-1**. The cause effect relationship between the factors controlling the crop yield and aspects which support in crop yield can be analyzed.





#### Fig: 4. Crop Yield analysis based on FCM variant metrics

vield.

**Figure-4** shows the analysis of metrics required for crop growth, over variable FCM nodal components such as climatic variants, growth micro-variants, regional demographic variants, water and soil variants. Each variant possess multiple crop growth dependent elements which plays a vital role in crop production and detecting the

## Analysis and predictions

Early detection of crop yield growth symptoms or initial analysis of NDVI parameters related to the key-point in the crop yield index (CYI) Support in gathering the climatic data through meteorological stations, data on crop growth rendered by agricultural stations were the primary means of data collection procedure. This work adopts the following crop growth metrics such as temperature condition index (TCI) for mapping and monitoring of crop growth metric which also indicates the assessment of vegetation health and productivity. Variable parameters such as TCI, soil moisture, surface temperature and average rainfall as shown in Fig-5 are the valuable sources of information for the estimation and prediction of crop growth conditions.



#### Fig: 5. FCM mapping of Chilli crop growth parameters and its corresponding outcome 'O'

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**Figure-5** shows components 'Fi' as metrics responsible for Chilli crop growth, which are interdependent on one other and hence map to 'FSi' components as primary variables that plays vital role in crop growth. 'Oi' depicts the final outcome of crop growth outcome, which may be "High in Yield" or "Normal Yield" or "Less Yield". Similar sugarcane crop growth can be obtained using FCM approach. 'Wi' indicates the weight assigned for components on priority, which gets updated based on crop yield based metrics. For any change in weight, the component required for yield also gets varied.

The actual crop yield achieved over Chilli and Sugarcane compared with higher predicted yield for crops were compared as shown in **[Table-2]**. The Residual crop yield becomes equal to expected change in crop yield, based on condition of growth issues which primarily depends on breakpoint applied. The model empirical equation for Sugarcane and Chilli crops, thus obtained with coefficients **[Table-2]** is given as:

#### Table: 1. FCM nodal components adopted for CROYAN

А	Precipitation Value/ day
В	Maximum Cloud Cover/ day
С	Radiation Sunshine/ day
D	Vapour Pressure/ day
E	Wind Pressure/ day
F	Snow Depth/ day
G	Average Humidity/ day
Н	Average Temperature/ day
	Monthly Average Rainfall
J	Soil Ph concentration
К	Soil nutrient value
L	Water Ph value
Μ	Air Pollution Level
Ν	Climatic Metrics
0	Nutrient Manure metric
Р	Water nutrient metric
A1	Soil Type
B1	Soil composition
C1	Soil Manure
D1	Percentage of Anti-oxidants
E1	Soil Humidity
A2	Water type
B2	Water Composition
C2	Oxidation Ratio
D2	Water mineral and pollutant ratio
A3	Soil Plough methods
B3	Crop watering interval
C3	Weed removal methods
D3	Manure laying methods
E3	Pesticides application methods
	A B C D E F G H I J K L M N O P A 1 B 1 C 1 D 1 E 1 A 2 B 2 C 2 D A 3 B 3 C 3 D 3 E 3

 Table: 2. Achieving crop yield using FCM. Predicted and observed crop yield of Sugarcane for Karur, Tamilnadu and Chilli crop for Guntur, Andhra Pradesh using Fuzzy Cognitive Maps

	Sugar cane crop yield			Chilli crop yield		
Year	Predicted	Actual / Observed	Residual	Predicted	Actual /Observed	Residual
2007-J	120.8	119.5419	1.2581	36.5	34.9126	1.5874
2007–A	87.112	83.7547	3.3573	32.0	31.2125	1.7875
2008-J	126.13	120.6428	5.4872	31.5	32.8647	-1.3647
2008-A	139.130	138.4765	0.6535	38.0	36.8840	1.1160
2009-J	134.118	133.1821	0.9359	41.5	41.9016	-0.4016
2009-A	126 117	125.7217	1.3953	43.5	43.3660	0.1340
2010-J	99.462	98.5832	0.8788	35.0	34.2990	1.2990
2010-A	124.138	123.8340	0.3040	39.0	37.7836	1.2164
2011-J	138.145	137.5609	0.5841	41.9	41.5585	0.4585

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The SSToolbox 3.61 [21] software supports methodology to store, represent, filter and analyze the acquired field data. All the collected data were interpolated in order to produce a map on a 10m x 10m grid size that corresponds to a reliable field management unit. The years are indicated in two formats as 'J' for January yield, 'M' for may yield, 'A' for august yield and 'O' for October yield. It can be observed from [Table-2] that the residual crop yield is 87.42% predicted similar both for sugarcane and Chilli crop.

### Performance analysis

The performance of CROYAN is analyzed over crops Chilli and Sugarcane which are well grown in humid temperature climatic regions. Crop growth parameters required for crop growth, to improve the yield and improve production, are considered for analysis.



#### Fig: 6 Sugarcane Crop yield obtained for actual yield, expected yield using CROYAN

Figure-6 discusses on Sugarcane crop yield achieved using CROYAN analytical approach during the years 2010 to 2012 for the months Jan, May and October respectively. It is understood that the yield analysis using actual and expected is averaging over 5.93% to 7.27%. The accuracy of actual yield over the predicted yield confirms the performance of CROYAN for Sugarcane crop.



Fig: 7. Crop Yield analyzed over CROYAN and other approaches



Figure-7 compares the performance of crop yield analysis over CROYAN, CRY approach which uses Bee Hive computational approach and ANN approach which shows that the vield prediction ratio achieved over CROYAN is higher than other approaches. ANN approach show a lower performance for the dataset used with 250 records primarily due to memory occupation during runtime and achieve local optima.



#### Fig: 8 Chilli Crop Yield achieved for Actual and Observed Yield

Figure-8 explains the performance of CROYAN over Chilli crop, where the observed yield and predicted yield are analyzed for variable 'H' [Table-1] for temperature as metric. The obtained yield is identified to be relative to temperature which aids in growth of Chilli crop for Guntur region. As Chilli crop is highly grown under humid climates as well in regions which require high sunlight, the field 'H' is considered for analysis.

# CONCLUSION

This work investigates the crop yield and variability crop yield prediction in Chilli, Sugarcane. Fuzzy Cognitive Map is adopted in this research work to suggest and identify the yield among crops. The analysis had been carried out using NDVI parameters and its CYI metrics which determine the vield estimate and reference metrics. FCM approach is compared with other traditional approaches, such as CRY and ANN approaches, it can be noticed that CROYAN approach converges to every local optimum, hence the observed yield and actual yield datasets has much similarities. Further the work can be improved to find the suitability of variable climatic situations and challengeable crop growth analysis.

### CONFLICT OF INTEREST

Authors declare no conflict of interest.

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