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An Enriched Intuitionistic Kernel Based K-Medoids Clustering for Indeterminacy Handling in ADHD Prediction

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***Abstract:** In recent year it is revealed that prevalence of attention-deficit/hyperactivity disorder (ADHD) among primary school children's is widespread. ADHD is considered as one of the most common childhood disorders and can endure through adolescence and adulthood. Addressing and accurate diagnosis of ADHD in earlier stages will be very effective for proper and timely treatment. But it is very complex to differentiate behaviour that reflect ADHD victim from the normal growth. Though there are several existing works are available for detecting ADHD using machine learning handling indeterminacy is a toughest challenge among researchers. This paper aims at developing an unsupervised learning model-based feature subset selection to eradicate the problem of indeterminacy in handling ADHD prediction. This work adapted introduced the concept of intuitionistic kernel-based k-medoids clustering (IKKMC) for grouping similar type of ADHD patients through the knowledge of degree of membership and degree of hesitation. In this work the outliers are easily handled with intuitionistic fuzzy logic. After performing clustering, the potential feature subset involved in ADHD prediction is identified by applying Recursive Feature elimination model. The simulation results provide the evidence for IKKMC with RFE selected feature subset increases the prediction process of ADHD more accurately than other state of art.*

***Keywords** : Attention-deficit/hyperactivity disorder, Intuitionistic fuzzy, Recursive feature elimination, Kernel, K-Medoids and Indeterminacy.*

I. INTRODUCTION

In recent survey [1] it is reported that nearly 5% of school-age children and 2 to 4% of the adults are spotted with Attention Deficit Hyperactivity Disorder(ADHD) or its associated symptoms. ADHD is naturally considered as inattention, impulsivity, hyperactivity and reduced administrative function and its verdict is usually made on the source of these interactive indications. ADHD begins in childhood and mostly continues into adulthood. Among children neurological disorder is increasing around the world and it is discovered that one in five persons in the world will be pretentious by neurological illness.

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ADHD diagnosis comprises of many steps and it is not a conventional frontward process. Truly, it starts with specially designed questionnaire regarding the symptoms and medical history and sometimes physical examination is also done. Different psychological tests are also steered to make sure the symptoms are casual only by mental health and not by any other issues. Discovering presence of ADHD at earlier stages may help to assist the victims in right treatment. The ADHD patients often exhibits challenging behaviors like impulsivity, inattention, failure in academics, dysfunction in social activities, etc., Thus it is important to produce accurate diagnosis of ADHD among children's which will be beneficial to the concern individual, as well as the society and their family. Diagnostic models based clinical dataset uses behavioral scales which was subjective to determine the presence of ADHD symptoms.
The machine learning in one of the emerging fields involved in behaviour learning, which greatly improves the prediction accuracy in medical field. Researchers started focusing on predicting ADHD using machine learning paradigm, but most of the work fails to handle the inconsistencies in discovering the ADHD more accurately.

II. LITERATURE SURVEY

This section discusses about few existing works on ADHD disease detection using machine learning algorithms in detail. Peng et al [2] developed an extreme learning machine which uses support vector machine which collects the clinical ADHD dataset diagnosis. They assess the efficiency of computation for a sample size of ADHD dataset. They developed an ADHD classification model which acquires 340 cortical attributes which are automatically extracted from the brain segments with five basic cortical attributes. To select the optimal features for ADHD classification they used F-score and SFS methods. Using leave one out cross validation, ELM and SVM performance are analyzed. Polanczyk et al [3] reported a survey on ADHD prevalence by two most complete systematic reviews. They performed study on both methodological features like diagnostic criteria, impairment criterion, source of information, etc., and geographical locations under consideration of studies.
Flavio Luizet al. [4] designed a Bayesian network model for subsidiary detection of dementia, this process is used to classify mild cognitive impairment and AD. This method uses the diagnostic condition and suggestions from experts in this domain. The parameters used in Bayesian network is computed using supervised learning models.

Gomułae et al [5] used the feature extension method to enhance the accuracy of classification for discretized data.Basavappa S.R. et al. [6] in their work used depth first along with backward searching method to detect dementia. By analyzing the behavior of the experts, with their cognitive, emotional characteristics their neuropsychological outcomes are evaluated. Chattopadhyay et al[7] introduced a fuzzy controller-based hybrid approach in feed forward neural network for diagnosing the grades of accuracy. The model is represented in the form of fuzzy values and the dataset is fed into the feed forward neural network. It uses back propagation to correct the error of the network by adjusting their weights on trail and error basis.

Dabek, Filip and Jesus J. Canban[8] devised a neural network model which analysis nearly of 89,840 patients. The neural network model uses this dataset for both training and testing. They worked on several psychological conditions to predict abnormalities among patients.Tawseef et al [9] developed prediction model using three different classification models like artificial neural network, decision tree and naïve bayes. They predicted two different diseases Parkinson and tumour. The results show that naïve bayes produce more accuracy than other two algorithms. Masri and Jani [10] introduced an expert system using fuzzy rule based reasoning and fuzzy genetic algorithm for diagnosing mental health problems. It is helpful for psychologists as an assisting tool to treat their patients and also provides suggestion for treatment plans.

Chattopadhyay et al. [11] in their work used fuzzy neural network for categorizing depression among adults. In this work two supervised learning models and one unsupervised technique is utilized. Adaptive neural network based fuzzy system and neural network with back propagation are used as supervised models. Self-organizing map with ANN is used as unsupervised model. From the result it is stated that hybrid system performed better than the traditional ANN. Rahman et al. [12] in their work compared several classification models like Bayesian network, single conjunctive rule-based learning, multilayer perceptron, neuro fuzzy, decision tree and fuzzy rule generation system to diagnose diabetes at earlier stages.

Khemphila and Veera [13]used back propagation with multilayer ANN for discovering presence of Parkinson disease with feature subset selection using Information gain. Pirooznia Mehdi et al. [14] used mining approaches to discover mood disorders. They used six different classifiers like logistic regression, support vector machine, radial basis function, random forest and scoring method. From the analysis it is stated that polygenic score classifier produces better result while comparing other methods. Kipli et al. [15] discovered mental depression using MRI scans. They used four various feature selection models namely information gain, SVM, relief and one R to generate feature subset. They reported that SVM with expectation maximization and information gain with random tree achieves highest accuracy in diagnosing metal depression.

Dabek et al. [16] constructed a neural network to forecast about likeness of developing psychological constraints such as behavioral disorders, depression disorders, anxiety and post-traumatic stress. They used sixty attributes for diagnosing these diseases. Among them only 25 were considered as significant to diagnose the disorder. They used multiclass classifier to classify the presence or absence of disorder.

Aleksandar et al [17] in their work anticipated multiple classifiers to categorize adult ADHD using power spectra of EEG measurements. They used nearly 117 samples of adult's information to determine the presence or absence of ADHD. They used four different criteria such as two resting conditions and two neuropsychological tasks as measurement of ADHD. They used variants of support vector machine with Karnaugh map to discover the discrimination between ADHD and control groups.

III. BACKGROUND STUDY

A. Intuitionistic Fuzzy Set

The generalization of fuzzy logic is known as intuitionistic fuzzy, developed by Atanassov [19], its aims to represent each element in terms of membership degree μ and non-membership degree ϑ. Let us assume that B is an intuitionistic fuzzy set in Y, then it is signified as follows:

$B=\{y, \mu_B(y), \vartheta_B(y)| y\in Y\}$ (1)

The value of both $\mu_B(y)$, $\vartheta_B(y)$ lie between 0 to 1 with the following criteria

$0\leq\mu_B(y) + \vartheta_B(y) \leq 1$ (2)

The intuitionistic fuzzy logic becomes fuzzy when the value of non-membership degree $\vartheta_B(y) = 1 - \mu_B(y)$. The main essential factor involved in intuitionistic fuzzy sets is considering the hesitation degree $\pi_B(y)$, where real time factors consist of certain degree of uncertainty which is clearly defined by this parameter ad it is signified as

$\pi_B(y) = 1- \mu_B(y) -\vartheta_B(y);\ 0\leq\pi_B(y)\leq 1$ (3)

B. Intuitionistic Fuzzy K-medoids

The Intuitionistic fuzzy K-Medoids clusters the dataset of n objects by representing their degree of membership and the hesitation to each cluster used. The number of cluster's to be used for clustering is analyzed using silhouette method which interprets and validates the consistency within the clusters of datasets. Intuitionistic Fuzzy K-medoids clustering algorithms it consists of two major processing phases. First, revealing a suitable function to discover every instances membership degree of all clusters [20, 21]. Second, attain a method that computes the cluster centers. Naturally the subsequent objective function is used as the membership degree calculating function.

$P(Z,X) = \sum_{i=1}^{k} \sum_{j=1}^{n} \mu_{ij}^{m} r(x_j, z_i)$ (4)

The cluster center is updated as

$\mu_{ij}^{*}=\mu_{ij} + \pi_{ij}$ (5)

$$\pi_{ij} = 1 - \mu_{ij} - (1 - (\mu_{ij})^{\alpha})^{1/\alpha} \quad (6)$$

Where μ_{ij} represents the degree associated with membership of the j[th] object x_j to the i[th] cluster z_i, where Z contains the cluster center as medoid, and $r(x_i z_j)$ is a difference measure between the i[th] cluster centre(medoid) and the j[th] object. Euclidean distance is used for dissimilarity measure between x_i and z_j and π_{ij} is the hesitation degree of j[th] object with i[th] cluster.

IV. METHODOLOGY

In this proposed work the dataset is collected from ADHD 200 dataset [18].This work used 50 participants information to diagnose ADHD. This dataset is comprised of personal characteristic data such as site of data collection, age, gender, handedness, performance IQ, verbal IQ, and full-scale IQ and the fMRI diagnostic data. The collected raw dataset under goes data preprocessing such as data cleaning, normalization and irrelevant attributes elimination. The rows and columns whose entire content consist of null values are removed as the initial stage of preprocessing. Next, the dataset is in different range of values, so, to treat all the features with equal consideration while performing clustering task, the dataset is normalized using Z-Score Normalization.

$$Z = \frac{x-\mu}{\sigma} \quad (7)$$

Where, x is the value to be normalized and μ is the mean value of the particular feature and σ is the standard deviation of the concern feature. Once the normalization is applied the value of dataset lies between the range of 0 to 1.

The dataset with irrelevant values of features which consist of same value for the entire records are removed for further processing. The intuitionistic kernel-based k-medoids is used for clustering the ADHD dataset into normal, medium and high ADHD by handling the inconsistencies prevail in the dataset. After clustering the dataset, the potential features which greatly involved in clustering of dataset into type of ADHD is discovered by applying recursive feature elimination which sorts the attributes on the basis of score produced by the selected feature subset and it selects the attributes which have high score value. Finally, simulation analysis is done by comparing the existing models k-means and Dbscan with the proposed model is done. Figure [1] depicts detailed architecture of the proposed IKKMC for ADHD detection.

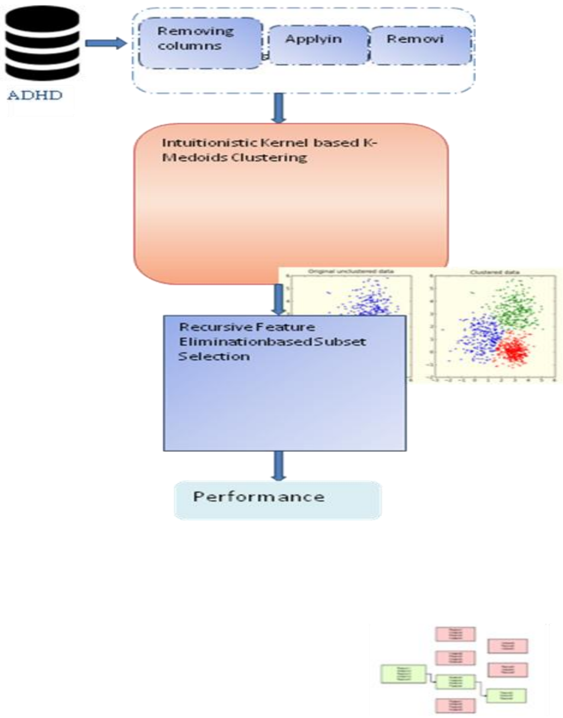

Figure: 1 Overall Architecture of IKKMC for ADHD detection.

A. Intuitionistic Kernel based K-Medoids Clustering (IKKMC)

The instances of ADHD are clustered using Intuitionistic Kernel based K-Medoids Clustering. The primary steps involved in this IKKMC is listed as follows:

- Representing each instances of the ADHD dataset to intuitionistic fuzzy representation so that it handles the uncertainty of clustering more precisely
- Altering the objective function of IKKMC
- Updating the cluster center (i.e) closest medoid, using membership, hesitation degree and set of cluster centers (closest medoid)
- Using intuitionistic kernel for measuring distance among instances and their corresponding medoids.

The process of clustering begins as follows:

Let O = $\{o_1, o_2, o_3, .. o_n\}$ denotes a set of n objects in a dataset O. The distance between the two objects o_i and o_j is signified by $ds(o_1, o_2)$. The medoids are initialized among the cluster centers in an random order and the set of medoids are denotes as $\nu = \{\nu_1, \nu_2, \ldots, \nu_k\}, \nu_i \in O$, where ν is the subset of O. The O_k is the c valued vectors where c > 1. In Intuitionistic based Fuzzy K medoids, each instance is assigned to c fuzzy clusters, so that entire intra-cluster distance is termed by the minimizing the object function which is represented as follows:

$$J_{IKKM}(U,\nu) = \sum_{i=1}^{k} \sum_{j=1}^{n} (\mu_{ij})^m \left\| o_j - \nu_i \right\|^2 \quad (8)$$

Here the distance between ADHD instance and the Medoid instance which is used as the cluster center is computed using Euclidean distance measure as shown in the formula (), which is applicable only for the same shape of cluster, and it is under the assumption that the clusters are uncorrelated. But it is not true in case of handling real time datasets like ADHD. Hence, in this paper kernel based distance function is adapted to project the dataset into a higher feature space which leads to optimally separate the data to different clusters. The objective function used for intuitionistic k medoids is as follow:

$$J_{IKM}(U,\nu) = \left(\sum_{i=1}^{k} \sum_{j=1}^{n} (\mu_{ij}{}^{*})^m \left\| \varphi(o_j) - \varphi(\nu_i) \right\|^2 + \sum_{i=1}^{k} \pi_i^{*} e^{1-\pi_i^{*}} \right) \quad (9)$$

Where φ is an implied nonlinear map which in applied on each data instance to map the original non-linear feature space ν_i to higher feature space so that it becomesseparable to from clusters. $\left\| \varphi(\bar{o}_j) - \varphi(\nu_i) \right\|^2$ is the square distance between the data instance of ADHD and the Data instance $\varphi(o_j)$ which is selected as the Centre or Medoid $\varphi(\nu_i)$.

The feature space difference (i.e.) dissimilarity among the attributes of two different instances are computing using the kernel as follows:

$$\left\| \varphi(\bar{o}_j) - \varphi(\nu_i) \right\|^2 = kd(o_j, o_j) + kd(\nu_i, \nu_i) - 2(o_j, \nu_i) \quad (10)$$

The intuitionistic kernel function used the Laplace radial basis function [20] as represented in the below function so that the linear classification model can separate the non-linear dataset by defining kernel boundaries.

$$\mathrm{Kd}(o_j, \nu_i) = \exp\left(-\frac{\|o_j - \nu_i\|}{\sigma^2}\right) \quad (11)$$

Where σ determines the kernel spread and $\|o_j - \nu_i\|$ is the euclidean distance between the Data instance o_j which is selected as the Centre or Medoid ν_i. Using the Laplace radial basis kernel function the objective function mention in the equation () can be rewritten as follows

$$J_{IKKM}(U, \nu) = \left(2 \sum_{i=1}^{k} \sum_{j=1}^{n} (\mu_{ij}{}^{*})^{m} (1 - kd(o_j - \nu_i) + \sum_{i=1}^{k} \pi_i^{*} e^{1-\pi_j^{*}}\right) \quad (12)$$

At each iteration the cluster medoid and the membership matrix has to be updated and the process of clustering stops in two criteria such as either a maximum number of iterationsis reached, or the value of the objective function increasescompared to the previous iteration

$$U_{ij}^{*} = \frac{(1-kd(o_j, \nu_i))^{-1/(m-1)}}{\sum_{i=1}^{c} (1-kd(o_j, \nu_i))^{-1/(m-1)}} \quad (13)$$

$$\nu_i = \min_{o \in \xi} \sum_{j=1}^{n} U_{ij}^{m} * kd_{ij}(o_j, o) * o_j \quad (14)$$

For a cluster c, the medoidis defined as the point that minimizes its distance withall points in the datasets depending on their membershipto cluster c. As this determination has a quadratic costO(n2) with the number n of objects in the dataset, this work uses a linearization algorithm as proposed by [21].

B. Feature Subset Selection Using Recursive Feature Elimination

After performing clustering to discover similar instances of ADHD dataset, the features which contribute more on clustering is determined by applying Recursive Feature Elimination method. It is used to discover the weakest attributes and removes it from the feature list until quantified number of attributes reached. In this model each feature is ranked based on their influence in detection of instances belongingness to a specific clustering, it preserves the attributes which have independent nature and eliminates the dependent ones. While using RFE it needs the information of predefined number of attributes to keep, but in real time database it is not possible to know in advance. To overcome this problem and to determine the optimal number of attributes, cross-validation is and it computes the overall score for each combination of different feature subset. Then finally, it selects the feature subset attributes with best score as potential feature subsets by removing other attributes which are not member of this subset. To determine the score of the attributes the chi-square is used to determine the association among the selected feature set.

$$X^2 = \frac{(OF - EF)^2}{EF} \quad (15)$$

Where the chisquare is a measure square of difference among observed frequency(OF) and expected frequency (EF)divided by exepected frequency.

Algorithm: IFKKM based ADHD detection
Input:ADHD 200 Dataset
Output: Potential Feature Subset Selection
Begin
Stage 1:

a) Initialize the cluster medoids in an arbitrary fashion $\nu = \{\nu_1, \nu_2, \ldots, \nu_k\}$
b) Initialize the membership value of U_{ij}^{*} for all i,j as shown between 0 to 1 whose sum should be equal to 1
c) Compute the objective function according to the equation (12) to stop either if its value is below a certain tolerance value
d) Compute a new U_{ij}^{*} using the equation (13) and update the cluster medoid using the equation (14)
e) Go to step c

Stage 2: Input: clustered instances

a) Gain the importance of each attribute in the instance using chi-square as given in the formula (15)
b) Remove the least importance feature
c) Apply the IFFKMC to determine the accuracy
d) If feature subset is not empty then go to b) else stop

V. SIMULATION RESULT

The simulation of IFKKM is done using Matlab Software. The dataset ADHD 200 is preprocessed and 50 instances with 11 attributes are used in this work. The performance of IFKKM is compared with other two unsupervised learning models k-means and DBSCAN. The evaluation metrics used in this process are probability distribution, Accuracy and Mean Square Error of these models.

A. Dataset Description

This research work collects the data from ADHD-200 dataset organized by ADHD-200 Global Competition [18]. It consists of participant's data which includes resting state functional magnetic resonance imaging (fMRI) scan along with personal characteristics and diagnostic data (site of data collection, age, gender, handedness, performance IQ, verbal IQ, and full scale IQ). This work used 50 participants information to diagnose ADHD.

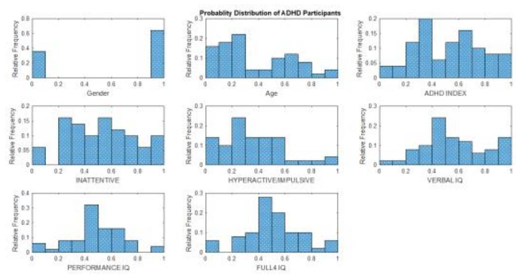

Figure: 2 Probability distribution of each attributes in ADHD 200

The Figure [2] displays the probability distribution of instances based on attributes like gender, age, ADHD index, inattentive score, hyperactive/impulsive score, verbal IQ, Performance IQ and Full4IQ which are used of determining the presence or absence of AHDD among children. The distribution of the values is shown in the graph which lies between the values 0 to 1. While using Recursive Feature Elimination based subset Selection among 24 attributes only 6 attributes are selected as potential feature subset to diagnose the type of ADHD. The attributes used are ADHD Index, Inattentive, Hyper/Impulsive, IQ Measure, Verbal IQ and Performance IQ.

Based on the score obtained by each feature subset the Recursive Feature elimination model chooses this six attributes as the most promising and independent features for discovering the type of ADHD among children's.

Table:1 Performance Analysis based on Correctly Clustered and Incorrectly Clustered Instances.

Clustering Methods	Correctly Clustered	Incorrectly Clustered
IKKMC _+ RFE	0.96	0.04
IKKMC	0.88	0.12
DBSCAN	0.82	0.18
K-Means	0.64	0.36

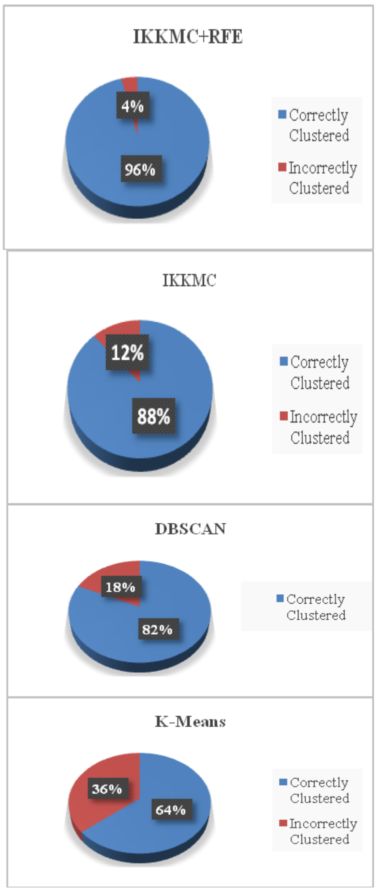

Figure: 3 Performance Comparison Of Four Different Clustering Mechanisms

From the Table[1] and the Figure[3], it is observed that the performance of four different clustering models has been done. The results show that before applying feature selection method the correctly clustered instance of IKKMC is 0.88 and after applying feature subset selection using Recursive feature elimination method, with the reduced feature subset, the IKKMC is clustered based on obtained significant feature subset which produces higher clustering rate of 0.96 as correctly clustered instances. The remaining algorithms K-means and DBSCAN produces 0.64 and 0.82 as the correctly clustered instances, this is due to the inability of handling inconsistencies and influence of more correlated variables presence leads to the worst performance in clustering ADHD patients. It is also noted that IKKM as positively increased its clustering accuracy after it is clustered using the feature subset selected by the Recursive Feature Elimination. The irrelevant attributes for detection of ADHD presence or absence are removed by this algorithm and only the most independent attributes which score high values are considered as potential attributes for this process. Hence, the performance of IKKMC+ RFE produces better result than IKKMC, K-Means and DBSCAN Methods.

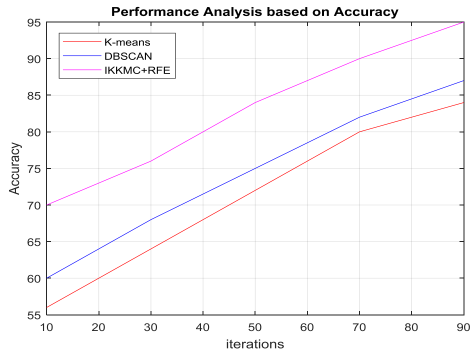

Figure: 4 Performance Comparison based on Accuracy

The Figure[4] illustrates the performance of the proposed model IFKKMC with Recursive Feature Elimination (RFE) with other two existing models DBSCAN and K-means. The existing models cluster the dataset either with density or distance. They fail to handle the instances which lie in the borders of the clusters or the instance which doesn't belongs to any of the clusters.

This situation is known as inconsistencies which are often not considered as much important and they are ignored in standard clustering. But this proposed work focuses on dealing such inconsistencies by developing an intuitionistic fuzzy representation of each instances towards degree of membership, non-membership and hesitation values on each cluster. Depending on the highest degree obtained by each instances they are treated accordingly. The result proved the accuracy produced by IFKKMC with RFE is highest while comparing other clustering models in AHDH detection.

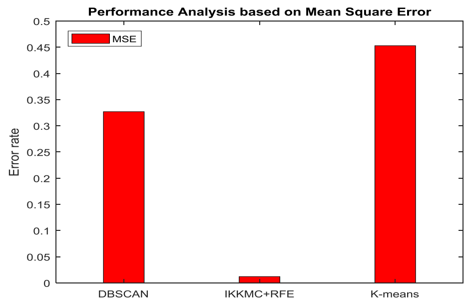

Figure: 5 Performance Comparison based on Error Rate

The MSE metric is used to evaluate the model's quality. It computes average squared difference among the expected values and observed values on n number of instances in ADHD dataset

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Expected_i - Observed_i)^2$$

The Figure[5] shows the error rate produced by each clustering models for ADHD detection. The error rate of k-means is high because it clusters the instances only based on the similarity alone and fails to handle the outliers.

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The DBSCAN is next to that, it selects the centre point based on their density information the instances which are farthest are considered as noise or outliers and it avoids those instances from clustering process. But IKKMC+RFE uses the hesitation degree as an important factor while clustering instance's and thus it produces less error rate while comparing the other models.

VI. CONCLUSION

This work predicts the presence of ADHD among children's by devising an indeterminacy handling system known as intuitionistic kernel-based k-medoids clustering. Predicting the type of ADHD at the beginning stage will improve the life style of the victim with proper treatment by experts. This work used ADHD 200 dataset for analyzing the characteristic of three type of ADHD victims such as normal, medium and high. This work used kernel-based k-medoids clustering for non-linear partitioning of the ADHD instance using unsupervised learning model. From the clustered instance the important attributes which contribute more in detection of ADHD is identified by using recursive feature elimination model which generates potential features which involves in prediction process. The problem of indeterminacy is well handled by representing each instance belonginess to each cluster in terms of degree of membership and hesitation degree.

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