AGGRANDIZED KERNEL CLASSIFIER-OPTIMIZATION METHOD TO ENHANCE THE DETECTION OF CREDIT CARD FRAUDS

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Abstract: The most popular mode of payment in the regular purchase and online purchases has increased with credit cards, due to which there is a tremendous rise in credit card frauds.To detect the frauds in credit card transaction is a challenge for the researchers. The availability of real data owing the confidentiality issues and also to handleimbalanced data available. There are different classification methods to detect the frauds in credit card transactions as a single standalone model or as hybrid models. This paper mainly focus on how the details of behavioral patterns of customer in the usage of credit card helps to improve to detect the credit card frauds. The proposed work involves the optimized feature selection by fuzzy particle swarm optimization method followed by the effective aggrandized kernel based support vector machine to amplify the detection of frauds. The metrics used in exploring the proposed work are accuracy, recall, fraud detection rate and concept drift rate. This innovative detection work refreshes the social profile of the customer and performs effectively better than other fraud detection methods. The dataset used from UCI repository and implemented in MATLAB framework.

Keywords: **Credit card, Classification, Fraud detection, Fuzzy particle swarm optimization,Kernel, Support vector machine, Datamining, Clustering.**

1 .INTRODUCTION

Fraud is an intensive criminal activity done by a person or thing intended to deceive others, typically by excessively demanding or being credited with personal gain.There are two mechanism to handle the fraud: fraud prevention and fraud detection. Fraud prevention stops the fraud to occur in the first place where as fraud detection is required when a fraudulent transactions is done by a fraudster.

Credit card transactions[1] can be done physically or digitally. In physical transaction, we use the card placed on scanner reader giving the card information like password. In digitally, we do it via telephone or internet, giving the card number, card verification number and the expiry date of the respective card. The illegal use of the card information in purchases leads to credit card frauds[2]. With the rise in the usage of credit cards has led to an increase in fraudulent transactions.

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To detect a credit card fraud transaction there are various data mining classification methods[3] which works as a single stand alone or as hybrid model. Thus understanding the behavioral patterns of the user by considering the previous transactions can improve the detection of frauds. There are certain optimization techniques like particle swarm optimization algorithm which help in selecting the important features from the dataset thus improving the classification methods to identify the fraudulent transaction effectively.

This paper is presented as follows: Section II gives the related studies,Section III highlights the proposed methodology,Section IVshows the results and discussion, followed byconclusion and references.

2. RELATED STUDIES.

Halvaiee et al [4] addressed detection of fraud using Artificial Immune System in credit cards. They have induced novel prototypical AIS centered fraud detection model (AFDM). In this work, they have used an immune system motivated algorithm (AIRS) which is used to improve detection of fraud. Using this approach, the accuracy is increased to 25%, the budget is reduced to 85%, and compared to the base algorithm decreases response time of the system to 40%.

Zareapoor et al [5] presented the best classification algorithm, bagging classifier constructed on decision tree, for fraud detection. They have highlighted the common classification algorithms like Naïve Bayes (NB), Support Vector Machines (SVM), K-Nearest Neighbor algorithms (KNN) and found that these can be ensemble to construct new model classifier. To validate the advantage of bagging ensemble method, the recital estimation is prepared taking place at real time dataset of the credit card deals.

Şahin et al [6] developed fraud prevention mechanisms, the necessary device and perhaps the finest method to break many such frauds. The work developed various decision tree and support vector machine based classifiers and used to detect frauds in credit cards. The real time dataset is used to relate the presentation of decision tree and SVM models.

Whitrow et al [7] proposed an aggregation framework for transaction-level detection, employing different classification methods. These ways are applied using real dataset in two case studies. The extent of the gathering epoch includes the massive influence on its performance. Transaction aggregation is found to be profitable in numerous circumstances. Also, when random forest classifier is used the aggregation appears significantly active. Meanwhile, random forests are pledge to achieve better results than alternative classifiers, including KNN, SVM and logistic regression. Aggregation do have the benefit to acquire better results from the population drift.

Dal Pozzolo et al [8] developed an efficient fraud detection algorithm that reduces the loss, and further methods depend on the progressive machine learning techniques to support fraud detectors. It gives a solution from the expert's perspective by converging on disputes such as imbalanced, non-stationary assessment. A real time dataset from a business partner were used for investigation.

Jha et al [9] utilized a deal aggregation policy to identify frauds in credit card usage. The aggregate transaction for measuring purchaser ordering deeds for every deal and also used to spot fraudulent transactions. During this work, real time deals of an international company were used to estimate the model and for aggregating the deals.

Bahnsen et al [10] proposedalgorithmic rule with von mises distribution for generating fresh featuressupporting and evaluating the interrupted performance of the transaction time. A European card company real data are used. Related to different

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detection methods, measured the manner they work and produce better results. The results showed a mean increase in savings by including the planned intervallic features into the models.

Van Vlasselaer et al [11] proposed Anomaly preventionusing advanced transaction Exploration (APATE), a unique methodology to spotfraudulentcredit card deals lead in on-line purchasing. This methodology associates crucial options resulting from the inward deals feature, thus arrive to the history of the deals of client by the fundamentals of Regency, Frequency, and Monetary (RFM). Also introduced a network-based sorts with the manipulation of the links of credit card holders and traders thus achieving a time-dependent suspicion mark for every network object. The outcomes displays that each intrinsic and network-based featureistorobustlyintertwined sides of identicalimage. The arrangementof the two classes offeaturesleads tothe simplestexecution prototypes that can give better AUC-scores greater than0.98.

Quah et al [12] focused to construct a real time system by analyzing the behavioral features to interpret the fraud cases. It makes use of self-organization map for detecting the frauds by interpreting, removing and studying the purchaserbehavior. Now a days, it has become easier to commit frauds through net by new mechanisms.

Sahin et al [13] introduced decision tree techniquethat minimizes classification prices by the selection of splitted attribute at each non terminal node. Using the real time dataset, this model performance is related to other classifiers. During this approach, cost of misclassification is the fluctuatingparameter.The developed approach performs efficiently than other strategies.

Srivastava et al [14] introduced hidden Markov model (HMM) and is applied for detecting the fraud. This model is trained initially using usual behavior of an original cardholder. If the HMM does not acknowledge the arriving deal of a credit card by high probability, it is reflected as a fraud. By equivalent time, it should confirm that true deals are not removed. Thus the tentative result shows the efficiency of the method and compared against other strategies.

3. METHODOLOGY OF THE PROPOSED WORK.

The dataset is taken from the UCI repository[3] database representing Taiwan business dataset having 30,000 records with 23 attributesincluding the amount of credit, age, gender, marital status, education, history of the past 6 months of payment , amount of bill payment of 6 months and the amount of the previous bill payment. The work is implemented in the MATLAB framework.

The procedural steps required to build the model as shown in Fig.1:

- Initially, the raw features of the card holders are preprocessed by grouping them into three groups based on their amount criteria i.e, low, medium and high using Kmeans clustering as in Fig.2.
- The fuzzy swarm optimization method is used to select the behavioral patterns by considering their previous transactions,thus selecting the most appropriate features that could enhance the process of detection.
- Classifying the patterns as genuine and fraudulent respectively using aggrandized kernel based support vector machine.
- Finally, the cardholder’s behavioral profile is refreshed by feedback mechanism.

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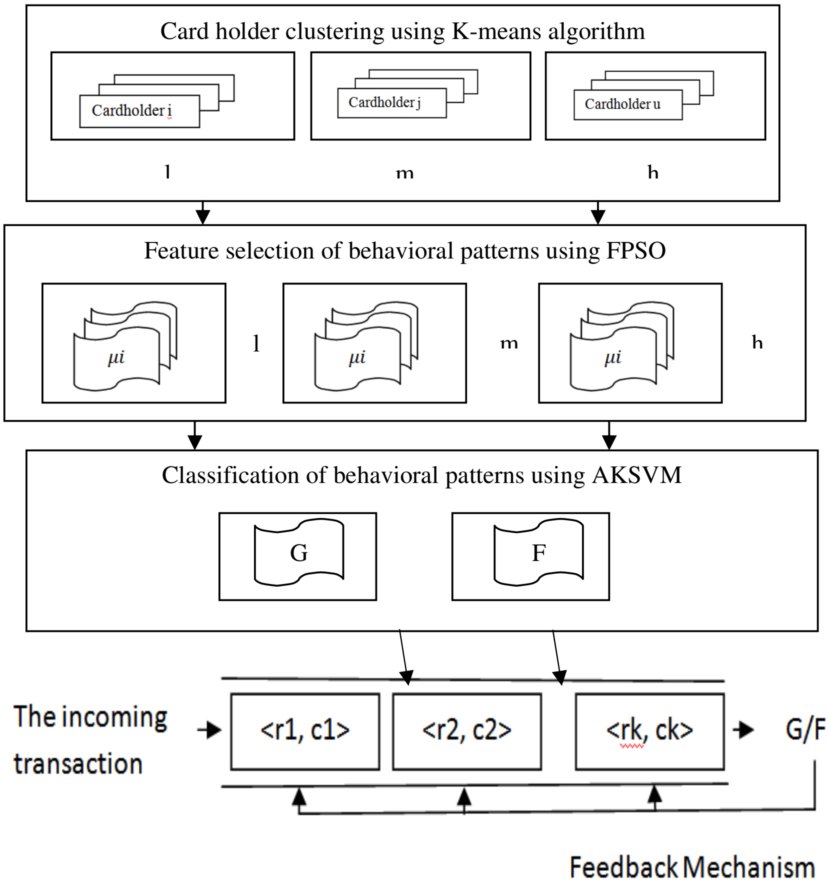

Fig. 1.The generated framework for the detection of credit card fraud [3].

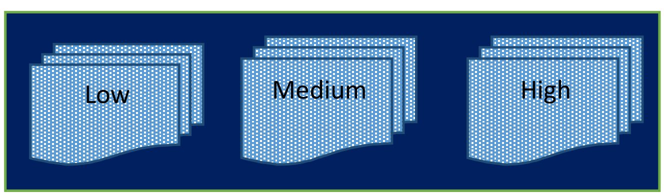

Fig.2: Kmeans Clustering of cardholder.

3.1.KMEANS CLUSTERING OF CARDHOLDER'S.

Three groups of cardholder's are generated on the basis of the amount of transactions low, medium and high respectively as in Fig.1. The sum of squares is minimized by considering x spotting in d coordinates into k clusters.Let us consider three cluster of id's, S={l,m,h} highlighting the each cardholder's identity. The sparse problematic of data is resolved by considering all transactions done by the cardholder's in a set than using a single cardholder deals [15].

3.2.FUZZY PARTICLE SWARM OPTIMIZATION FOR FEATURE SELECTION OF THE INTERACTIVE PATTERNS.

Particle swarm optimization(PSO) optimizes a problem iteratively improving the solution considering the given degree of quality. The algorithm begins with populating particles in a space where the position denotes the possible result for that particular problem and velocity is reset erratically in the search space. The fitness value of all particle position is calculated and the velocity of each particle is reorganized by two points, individual finest position and global finest position. In anticipated FPSO

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technique the position and velocity of particles reconstructed to signify the fuzzy relation among variables. The Fuzzy Particle Swarm Optimization (FPSO) algorithm, denotes the position of the particle X which represents the fuzzy relation from the set of data objects, O={ $o_1,o_2,o_3,\ldots o_n$}, to set of cluster center's,Z={ $z_1,z_2,z_3,\ldots z_c$}. X is given by the "equation (1)".

$$X = \begin{bmatrix} \mu_{11} & \cdots & \mu_{1c} \\ \vdots & \ddots & \vdots \\ \mu_{n1} & \cdots & \mu_{nc} \end{bmatrix} \quad (1)$$

whereu$_{ij}$ represents the membership function of the ith object with jth cluster with constraints.

A fuzzy matrix μ_{mn} is generated with m rows representing the data objects and n columns for the clusters respectively. To overawed the limitations of fuzzy systems, the capabilities of the global search is used in PSO procedure of the derived algorithm. Using the matrix calculations [3], we could arrive at the equation for the position and velocity of the particle,

$$V(t+1) = w \otimes V(t) \oplus (c_1 r_1) \otimes \big(pbest(t) \ominus X(t)\big) \oplus (c_2 r_2) \otimes \big(gbest(t) \ominus X(t)\big) \quad (2)$$

$$X(t+1) = X(t) \oplus V(t+1) \quad (3)$$

Where X and V represents the position and velocity of the particle. The inertia weight is w, c_1 and c_2 are acceleration positive coefficient constants that on the process of search switch the impact of pbest and gbest. The individual or private best position, is the finest position the particle had visited denoted by pbest and gbest denotes the finest position the swarm had visited later the first step time. The random values in the range[0,1] is denoted by r_1 and r_2.

To normalize the position matrix[3], all negative values are assigned to zero. If in a row all the elements are zero we have to recalculate by sequence of arbitrary values in the range[0,1] and without violating the constraints, thus matrix is changed as

$$Xnormal = \begin{bmatrix} \mu_{11}/\sum_{j=1}^{c} \mu_{1j} & \cdots & \mu_{1c}/\sum_{j=1}^{c} \mu_{1j} \\ \vdots & \ddots & \vdots \\ \mu_{n1}/\sum_{j=1}^{c} \mu_{nj} & \cdots & \mu_{nc}/\sum_{j=1}^{c} \mu_{nj} \end{bmatrix} \quad (4)$$

The FPSO algorithm requires a fitness function to generalize the result given by "equation 5".

$$f(X) = \frac{K}{J_m} \quad (5)$$

where K represents a constant and $J_m$is the objective function. As the value of J_m is reduced more effective the individual fitness value. We can generate a set of standard features for each cluster by considering all cardholder's normal feature set as in "equation (6)".

$$G_j = \cup_{id \in j} G^{id}, \forall j \in V \quad (6)$$

The characterization of interactive arrangements may be opaque once resolved by human knowledge. As such it is difficult to classify precise behaviour sets into standard feature sets in the real world. To unify high level abstract knowledge, it is appropriate to use classification methods to solve the supervised learning problems.

*3.1.*AGGRANDIZED KERNEL BASED SUPPORT VECTOR MACHINE CLASSIFICATION METHOD.

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Support vector machine is a machine learning approach which classify the data by using support vectors and signify the data patterns. To given data samples N, two class classification strategy is used to find the discriminant function f(x),such that y_i=f(x_i). Thus, f(X)=sgn (w .x-b) where w .x-b =0 is the splitting hyperplane in space. The hyperplane possessing the maximum splitting margin for the classification is done by the selected discriminant function. [16]. Finally f(x) = sgn(PI i=1 $\alpha_i y_i(x_i \cdot x - b)$ represents the absolute linear discriminant function, where I is the total training records, x_i is the support vectors and $y_i \in \{-1, +1\}$ is the label linked with the training data, $0 \leq \alpha_i \leq C$ (constant C > 0).When the data area space splitted non-linear manner,we get the non-linear discriminant function as in "equation(7)",

$$f(x) = sgn(\sum_{i=1}^{l} \alpha_i y_i K(x_i, x) + b), (7)$$

where K(x_i, x) is the kernel function which is mainly used to change data points. The sigmoid function, polynomial function, radial basis function and linear function are the general kernel functions. The kernel function is not used to differentiate the data features. In the kernel function of SVM,K(x_i, x), all features of the training and test datasets are equally preserved. Considering all features likewise may lead to inefficient process and will upset the accurateness of SVM[16]. The best method to treat different features is by adding weights to the respective kernel function [17]. The importance of every feature is highlighted by the given weights. The proposed kernel function is expressed by K (wx_i,wx), where w is a vector containing feature weights of data set. A non-linear discriminant function with feature weights is developed by "equation (8)",

$$f(x) = sgn(\sum_{i=1}^{l} \alpha_i y_i K(wx_i, wx) + b), (8)$$

This enhanced kernel is independent on any other kernel functions. A Kernel function is derived by different weights assigned to the features. From a training data, we may compute and derive feature weights by using rough set strategy. The main rules used are 1) A weight 0 is assigned, if a feature is not in any reducts; 2) a feature is defined essential, if its occurrence in the reducts is more; 3) if a reducthas less number of features, the most required is considered. The needed feature for a reduct is also represented by the only one feature of a reducts. Algorithm.1 depicts the rank of features by assigning feature weights using rough set strategy. After the completion of ranking, the feature with weight zero is removed.

Algorithm.1: The Feature weight estimation added to Kernel Function.

Input: Derived features.
Output: Weight vector w.
To determine the reducts from D by rough sets.
1.$D_{feature}$= total no: of features in D;
2.$D_{reducts}$= total no: of reducts of D;
// Initialize the weight all the features in D.//
3.fori=0 to $D_{feature}$ do
4.W_i =0;
endfor
//Compute the weights for every feature.//
5.for(i=0 to $D_{feature}$) do
6.for (j=0 to D_{reduct}) do
7. If (featurei in the j^{th}reductR_j) then
8.n=number of features in R_j;
9.w_i=w_i+1.n;
endif
endfor
endfor

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3.4.RESPONSE APPROACH TO IMPART THE CARDHOLDER'S SOCIAL PROFILE.

This projected technique utilizes a criticism component to refresh the profile of every cardholder once a fresh deal comes [3]. Every cardholder u in cluster j has a set $C_j^u = \{c_1, c_2, \ldots\ldots, c_k\}$.

A ranking score is allocated to every group[3], and the summary of cardholder is articulated to as a 2-tuple <>, where:

- c_i is one of the interactive conduct standard in set C_j^u.
- r_i is one of the evaluation score of the group c_i.

In the preceding stage, a Priority Queue is utilized to pick a group with the most noteworthy ranking gain featured by a grey block. When this technique identifies a erroneous guess then the latest transactions will not be conform to the cardholder's profile. The rating score of the classifier is changed by utilizing the true label of the incoming transactions. Subsequently, propose an input system for refreshing the rank. The classifier is rewarded if it predicts correctly (i.e., ri = ri+1) in the event, else it will be rebuffed (i.e., rj = rj-1). By utilizing this criticism component, the following exchange can be estimated by a group c* to such an extent that r* is the most elevated ranking gain in $\{r_1, r_{2\ldots.} r_k\}$[3]. It is described in Algorithm 2.

Algorithm.2: Rate score for a set of classifiers of a cardholder.

Input: Exclusive *id* of a cardholder, a set of 2-tuples
$\{< r_i, c_i > | i = 1, \ldots\ldots, k\}$and an inward
deal with p -1 earlier deals
Output: A fresh set of 2-tuples $\{< r_i', c_i > | i = 1, \ldots\ldots, k\}$
1. Xid: = a vector of inward deal with p - 1
preceding deals gained from Algorithm 1;
2. c* := a group acquired peak rate score
via a Priority Queue ;
3. pred := forecast tag of X^{id} with c* ;
4. label := Accurate tag of the inward deal ;
5. ifpred≠ tag and tag = 0 then
6. for (i := 1; i≤ k; i++) do
7. $pred_i$ = forecast tag of X^{id} using c_i;
8. if$pred_i$≠ tag then
9. $r_i' := r_i - 1;$
10. else
11. $r_i' := r_i + 1;$
12. endif
13. endfor
14. endif

4. RESULTS AND DISCUSSIONS.

The framework developed has increased the performance of the classification method Aggrandized Kernel Support Vector Machine to detect the credit card frauds. The anticipated fuzzy swarm optimization method had increased the detection by selecting the appropriate features that could enhance the output. From the 23 attributes given in the dataset, best 15 attributes is required for detection which has been predicted by the weightage proportion assigned to each feature.The analytical measures used is the Accuracy, Recall, Concept drift detection rate(CDDR) and Fraud feature detection rate (FFDR).The fraud transactions are classified into two ways: Label 1 and Label

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2. Label 1 denotes the fraudulent transaction due to fraud features and label 2 denote the fraudulent transaction due to unexpected concept drift .These two mentioned cases are vectored by FFDR and CDDR respectively.The analytical measures are detected on the basis of the confusion matrix. The summary of the prediction results on classification given by the confusion matrix shown in Fig.3.

	Class 1 Predicted	Class 2 Predicted
Class 1 Actual	TP	FN
Class 2 Actual	FP	TN

Fig.3. Confusion Matrix

Class 1: Positive & Class 2: Negative.
TP-Positive observation, Predicted positive
FN- Positive observation, Predicted negative.
FP- Negative observation, Predicted positive and TN- Negative observation, Predicted positive.

We have compared three methods with the resultant confusion matrix:

- ❖ Support Vector Machine as standalone classifier classifies the training dataset into genuine and fraudulent,the analytical measures accuracy with 78 %., recall is 81.51%, FFDR is 0.9394 and CDDR is 0.4322.
- ❖ After the clustering by K-means,followed by the feature selection by FPSO, upon which our classifier SVM is applied to classify the dataset into genuine and fraudulent. The analytical indication accuracy have 85.59%, Recall is 87.19%, FFDR has a value 0.9589 and CDDR is 0.3168.With this approach, we arrived to a conclusion that if feature selection is done by an optimization method,the classifier's ability in detection too increased.
- ❖ The proposed work thus uses the theme of k-means clustering, followed by the feature selection by FPSO, then applied to an enhanced SVM done by enhancing its kernel function as given by "equation 8" where different weights are assigned to the features. Feature estimation is done according to "Algorithm.1".This enhanced kernel function is named as "Aggrandized Kernel Based SVM".

Table 1. Simulation Results of the Proposed Work.

Metrics	Existing(SVM)	FPSO+SVM	FPSO+AKSVM
Accuracy(%)	78.51	85.59	92.25
Recall (%)	81.15	87.19	93.61
CDDR	0.4322	0.3168	0.1971
FFDR	0.9394	0.9589	0.9860

Fig.4 shows the graphical representation of each analytical metrics considering the existing, FPSO-SVM and the proposed work FPSO-AKSVM. Deriving the conclusion that the proposed work achieved higher accuracy, recall and fraud feature detection rate .The concept drift detection rate is reduced thus genuine transaction highlighted as fraud is reduced.

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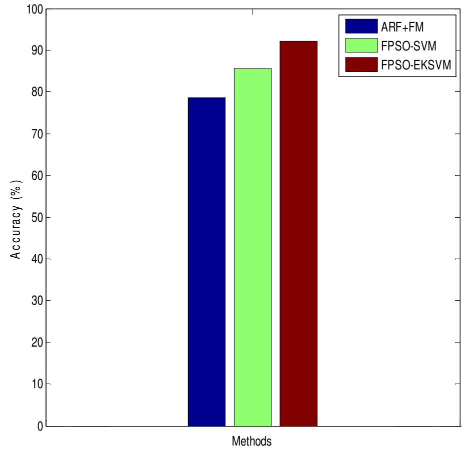
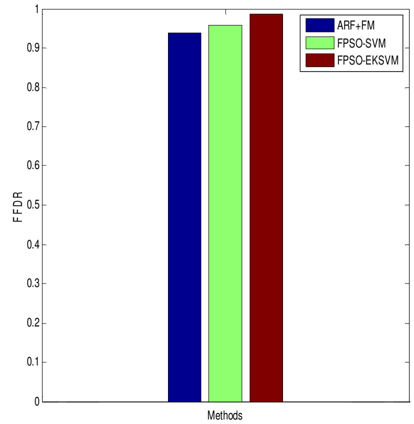
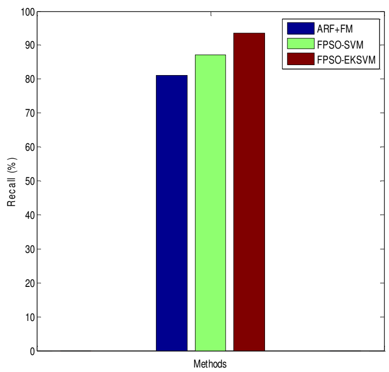


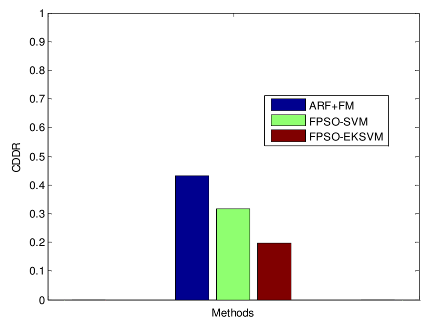
4(a)



4(b)



4(c)



4(d)

Fig.4: Quality metrics of the proposed work.(a) Accuracy(%) (b) FFDR (c) Recall (%) (d) CDDR

5. CONCLUSIONS

In this research approach, an innovative fraud detection method has been developed and evaluated. To construct a fresh collaborative profile of a cardholder, the mode of the collaborative arrangements from the similar cardholders are selected. This technique gives accuracy in finding out fraudulent transactions and minimizing the number of false alerts. Aggrandized Kernel-based Support Vector Machine (AKSVM) algorithm in a credit card fraud detection system results in detecting or predicting fraud probably in a very short period after the transactions have been made. This will ultimately avoid the banks and customers from huge money losses which will decrease risks. The experimental outcome illustrate the recital and success of the anticipated method and achieves good accuracy compared with the other two methods at the detection of transactions. Also, we are going to propose a bank club alarm system like an IPS (Intrusion Prevention System) as a preventive measure against fraud and employ the proposed method in other banking areas.

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REFERENCES

[1]. Dal Pozzolo, A., Boracchi, G., Caelen, O., Alippi, C., &Bontempi, G. (2017). Credit card fraud detection: a realistic modeling and a novel learning strategy. *IEEE transactions on neural networks and learning systems*, *29*(8), 3784-3797.

[2]. Jiang, C., Song, J., Liu, G., Zheng, L., & Luan, W. (2018). Credit card fraud detection: A novel approach using aggregation strategy and feedback mechanism. *IEEE Internet of Things Journal*, *5*(5), 3637-3647.

[3].Jisha.MV, .D.Vimal Kumar, Fuzzy particle swarm optimization feature selection and aggrandized classifier for uncovering frauds in credit card deals, International journal of engineering and advanced technology,ISSN-2249-8958, Vo(9),issue-3,Feb-2020.

[4].Halvaiee, N. S., &Akbari, M. K. (2014). A novel model for credit card fraud detection using Artificial Immune Systems. *Applied soft computing*, *24*, 40-49.

[5].Zareapoor, M., &Shamsolmoali, P. (2015). Application of credit card fraud detection: Based on bagging ensemble classifier. *Procedia computer science*, *48*(2015), 679-685.

[6]Şahin, Y. G., &Duman, E. (2011). Detecting credit card fraud by decision trees and support vector machines.

[7].Whitrow, C., Hand, D. J., Juszczak, P., Weston, D., & Adams, N. M. (2009). Transaction aggregation as a strategy for credit card fraud detection. *Data mining and knowledge discovery*, *18*(1), 30-55.

[8].Dal Pozzolo, A., Caelen, O., Le Borgne, Y. A., Waterschoot, S., &Bontempi, G. (2014). Learned lessons in credit card fraud detection from a practitioner perspective. *Expert systems with applications*, *41*(10), 4915-4928.

[9].Jha, S., Guillen, M., & Westland, J. C. (2012). Employing transaction aggregation strategy to detect credit card fraud. *Expert systems with applications*, *39*(16), 12650-12657.

[10].Bahnsen, A. C., Aouada, D., Stojanovic, A., &Ottersten, B. (2016). Feature engineering strategies for credit card fraud detection. *Expert Systems with Applications*, *51*, 134-142.

[11].Van Vlasselaer, V., Bravo, C., Caelen, O., Eliassi-Rad, T., Akoglu, L., Snoeck, M., &Baesens, B. (2015). APATE: A novel approach for automated credit card transaction fraud detection using network-based extensions. *Decision Support Systems*, *75*, 38-48.

[12].Quah, J. T., &Sriganesh, M. (2008). Real-time credit card fraud detection using computational intelligence. *Expert systems with applications*, *35*(4), 1721-1732.

[13].Sahin, Y., Bulkan, S., &Duman, E. (2013). A cost-sensitive decision tree approach for fraud detection. *Expert Systems with Applications*, *40*(15), 5916-5923.

[14].Srivastava, A., Kundu, A., Sural, S., &Majumdar, A. (2008). Credit card fraud detection using hidden Markov model. *IEEE Transactions on dependable and secure computing*, *5*(1), 37-48

[15]. Jiang, C., Song, J., Liu, G., Zheng, L., & Luan, W. (2018). Credit card fraud detection: A novel approach using aggregation strategy and feedback mechanism. *IEEE Internet of Things Journal*, *5*(5), 3637-3647.

[16]. Kobayashi, K., & Komaki, F. (2006). Information criteria for support vector machines. *IEEE transactions on neural networks*, *17*(3), 571-577.

[17]. Chung, K. M., Kao, W. C., Sun, C. L., Wang, L. L., & Lin, C. J. (2003). Radius margin bounds for support vector machines with the RBF kernel. *Neural computation*, *15*(11), 2643-2681

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