Fuzzy Based Association Rule Mining and Classifier for Market Basket Scrutiny to Enhance the Key Security in Organization

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Abstract - Current technical achievements of storing data and database management technologies also provided windows to new productivity techniques for all forms of organization. Market Basket Analysis (often referred to as association rule mining) has become a valuable way of finding company buying trends by collecting associations or co-occurrences in store transaction databases. Since the information gained from the study could be used to shape marketing, sales, service, and operating strategies, it also has generated increased interest in research. Nevertheless, current methods that fail to reveal essential buying patterns in such a multi-store environment, due to an underlying assumption that the items under review are already on shelf throughout all stores most the time. We are implementing a new approach in this paper to address that deficiency. Security is however considered to become an important aspect of individually performed transactions and regular database itemsets that are partitioned horizontally. This research work presents a novel vital protection algorithm which utilizes RSA cryptographic concept based on classifier, in addition to making security for eventually purchased sometimes used item sets of transaction purposes. The classifier uses information of several frequently used itemsets, and presents the actual company with a key value. For example, if there are any reliance users, only the valid users may get that market info. The majority of the reliance organisation's customers may not permitted to pick the main interest of the results. First, with the aid of the Enhanced Fuzzy-based Weighted Association Rule Mining Algorithm (EFWARM), the frequent itemsets are mined to mine the frequency item set. The Fuzzy-based multi-kernel spherical support vector (FMSSVM) classifier then optimizes the key functions of the frequently itemsets mined.

Keywords - Association rules, Customer relationship management, FMSSVM, Frequent item set mining, key values, Market basket analysis.

I. INTRODUCTION

In view of the developments in ICT, companies can easily acquire and maintain transactional and demographical information at affordable rates on individual customers. One problem for companies that have made significant investments in the processing of customer data would be how to obtain vital information from the large customer records to achieve competitive advantage. Market basket analysis (defined as association rule mining) has become a tool by eliminating associations or co-occurrences of transaction bases of stores to identify consumers ' buying habits. Finding, for instance, that supermarket customers can buy milk, bread and cheese with each other or that bank customers can use a range of services collectively can assist manager design stores, websites, product mixes and bundles, and other marketing campaigns.

The methodology has received significant research attention and several extensions were recently launched, including (1) improvements in the algorithm; (2) fuzzy rules; (3) multi-level and generalized rules ; (4) quantitative rules ; (5) spatial rules ; (6) inter-transaction rules ; (7) intriguing rules ; and (8) temporal association rules. Security in individual transactions and in regular itemsets for horizontally divided databases is often known to be such an important element. This research presents a new key security algorithm using RSA's cryptographic methodology wherein the classifier maximizes its key principles in order to guarantee the security of the often used objects that are eventually purchased for the transaction [4,5].

The classification system uses the data on several used items and then gives the individual organization a key value. For example, only valid users will get that market information if there are reliability users. The other users of the reliance organization cannot select the main value of the data First the regular objects are mined using Probabilistic Graphic Model techniques [6] by the Enhanced Fuzzy-based Weighted Association. The Fuzzy-based MSVM classifier would then review the values of the mined frequency items [7]. The classifier is the Fuzzy-based MSVM.

II. LITERATURE SURVEY

Zhixin et al., [8] proposed an enhanced technique of classification based on rules of Predictive Association. Classification Dependent Predictive Association Rules (CPAR) have been one of the forms of association classification system that combines the advantages of associative classification and classification based on traditional rules. CPAR is more effective for rule generation than traditional rule-based classification, as most replicate calculations are neglected and multiple literals could be used to make multiple guidelines around the same time. Since the above-mentioned benefit prevents replicate measurement in rules creation, in class rule propagation ambiguity and the disruption of incorrect class rules the predictive methods have the drawback. However, in situations where no laws are followed, it is unsuccessful. The author suggests Class Weighting Adjustment Center Vector based pre-classification and post-processing of support vector machine (SVM) to prevent these difficulties.

Wang et al. [9] proposed a novel rule calculation method in Classification Association Rule Mining. Classification Association Rule Mining (CARM) seems to be the new classification rule mining method which used Classification Association Rules (CARs) to develop an association rule mining oriented classifier. The particular CARM algorithm that will be used is not considered, a similar set of CARs is generated continuously from either the data, and a classifier is typically provided as a standardized CAR list, based on a selected approach to rule ordering. In the distant past, many approaches to rule ordering have been identified, that could be classified as rule weighting, support-confidence, and hybrid. In every strategy, an alternative rule-weighting method named CISRW (Rule Weighting based on Class-Item Score) and a rule-weighting based rule that sets mechanisms depending on CISRW. Two hybrid strategies are added later and built by combining support-trust and CISRW.

Bartik [10] provided association-based data classification for use in web mining. Classification as per the laws of the mining association is a safer classification system that is accessible to people. The author's aim is to force a change to the simple association-based classification methodology which can be used to collect data from Web pages. Changing the technique and requiring discretization of quantitative features are provided.

Omari et al.,[11] have introduced a new spatial measure for exciting frequent mining of items. Frequent itemset mining allows to search large transaction databases for effectively linked objects and transactions. This metric is due to the fact that some recent transactions usually hide interesting frequently used itemsets. Through decreasing the search time, this minimizes the expense of looking for repeated itemsets. However, this step can be used to improve the Apriori Algorithm search method implemented.

Qiang et al., [12] proposed a method of classification of associations based on the rules compactness. Associative classification combines the high accuracy of classification and a high versatility. At the same time, this associative classification undertakes an overfitting even though the classification rules met the least support and the lowest confidence is restored to the classifier as strong association rules return. An innovative classification technique for associations has been focused onto the introduction of the rules; it expands the Apriori Algorithm that recognizes the interesting, significant and conflicting relation between rules. Observational testing reveals that the proposed method has greater accuracy in the classification compared to CBA and CMAR.

Rui Chang et al. [13] have introduced a new optimisation algorithm named APRIORI-IMPROVE dependent on Apriori's inadequacy. APRIORI-IMPROVE algorithm provides optimization on the generation of 2 items, compression of transactions and many others. To save space and time, APRIORI-IMPROVE utilizes hash patterns to produce L2, using efficient horizontal data interpretation and optimized storage strategy. The efficiency analysis indicates APRIORI-IMPROVE to be much quicker than Apriori

III. PROPOSED METHODOLOGY

This chapter addresses the newly launched secured transactional model dependent market basket analysis for profit and revenue growth. It consists of 2 stages. The main one involves frequent itemset mining using an Enhanced Fuzzy-based Weighted Association Rule Mining (EFWARM) algorithm of effective mining of frequent itemsets according to Probabilistic Graphical Model and the next involves the key generation using RSA cryptographic technique shown in Figure 1.

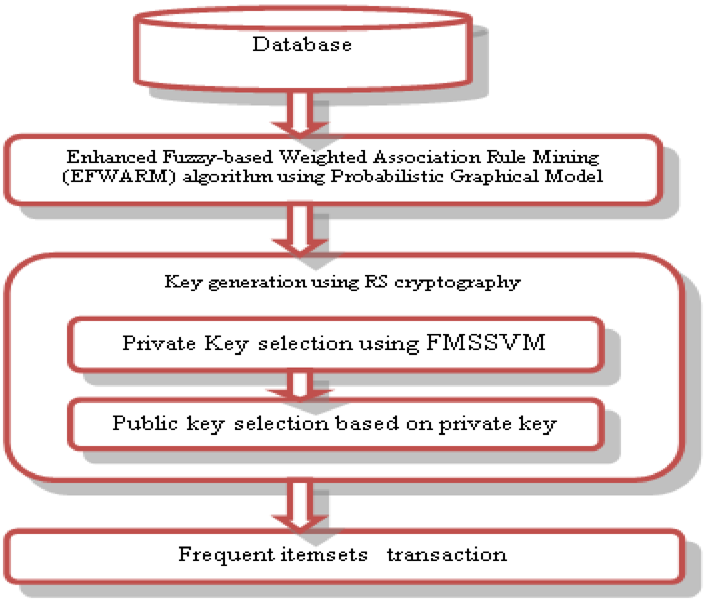

Figure:1. Proposed system

It begins from mining the frequent item set out from the association rule mining database to provide the company with this detail.

A. Enhanced Fuzzy-based Weighted Association Rule Mining (EFWARM) algorithm using Probabilistic Graphical Model

In this article the E-FWARM algorithm can be used for efficient extraction from the database of the regular itemsets. The research work's main aim is to extract the maximum frequency items while needing greater complexity. To exclude the objects with low variance, the pre-filtering approach is extended to the input dataset. Then standardization zero-mean is implemented and the weight as assigned to each item of data. Data discretization has been done, and the E-FWARM algorithm has been implemented to the regular itemsets for mining. Depending on the suggested algorithm the rule is developed. Finally, the analysis of the data is done as part of the rule produced. The emerging E-FWARM algorithm offers maximum frequency items association rules, reliability and minimal execution time as opposed to the current algorithms.

Let set of data 'D' consists of a series of transactions T= t1, t2,..,tn with a set of items I= i1,i2,..,iI. A Fuzzy dataset D' involves fuzzy transactions T'= t1',t2',..,tn' with Fuzzy sets linked with each item in I and identified by a set of linguistic labels L= l1,l2,..,lL. A weight 'w' is allocated to each verbal label in the set. To each attribute ti'[ij]is related with numerous Fuzzy sets. A membership degree offers the degree of association in the range [0-1]. This specifies the correspondence among attribute meaning and collection of linguistic labels.

Definition:
Fuzzy Item Weight (FIW) has become a real non-negative number whose value varies respectively 0 and 1. Every Fuzzy package is correlated with this. The weight of a fuzzy set for an item ij is represented as ij[lkw].

Fuzzy Itemset Transaction Weight (FITW) would be the cumulative weights of all of the fuzzy sets related to the items included in a single transaction in the itemset. The FITW for an array is measured as

$$X=k=1L([ilw]\in X)t'[ijlkw] \qquad (1)$$

Fuzzy Weighted Support (FWS) would be the aggregate FITW amounts of all itemsets in the transactions to a total transaction number.

$$FWSX=i=1nk=1L([ilw]\in X)t'[ijlkw]n \qquad (2)$$

Fuzzy weighted trust is really the proportion of a satisfactory number of votes$X\cup Y$ to the sum of votes satisfying X with $Z=X\cup Y$ It is derived as

FWCXY=i=1nk=1z([zlw]∈z)t'[ijzkw]k=1X([ilw]∈X)t'[ijXkw] (3)

FWARM

The FWARM algorithm is indeed a part of the ARM algorithms' first breadth traversal group. Ck indicates the set of cardinal candidate itemsets 'k' 'w' reflects the weight of a items, 'F' suggests the set of frequent itemsets, 'R' suggests the set of possible rules and R denotes the final set of Fuzzy weighted association rules.

B. E-FWARM Mining Algorithm Based on Probabilistic Graphical Model

The association rule mining algorithm which is determined by the probabilistic graph incorporates both the probabilistic and Apriori graph model. The early phase of the approach discovers all the frequent sets of two-item by applying the Apriori algorithm, and subsequently the frequent sets intend to be denoted with the aid of a probabilistic graph. Compliant with the probabilistic graph, the association rules could also be extracted. Furthermore, the confidence coefficient and the support coefficient relating to all the association rules could also be calculated concurrently. One disadvantage come across by utilizing the probabilistic graph is that during the frequent items searching, we could get around the requirement for cyclic scanning of all the data items.

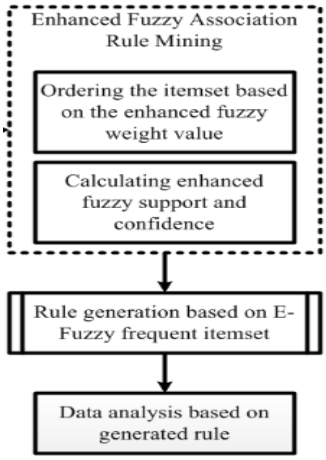

Figure 2: Flow diagram of EFARM

The phases carried out in the mining of association rules for power transformers state parameters based on the probabilistic graphical model are detailed mentioned below.

Step:1 Taking the support of Apriori, receive the entire frequent two-item sets. Apriori utilizes the iterative approach determined by the exploration of layer after layer, generates the frequent item sets out of the candidate item sets and creates the association rules by applying the frequent item sets [14]. Nevertheless, merely one and two-item sets are investigated in this course. Henceforth, the intricacy included in the process of retrieval can be decreased considerably.

C. E-FWARM Algorithm

For the purpose of data clustering and establishing the center of every fuzzy set and maximum and minimum values for every field of the dataset that acts as the input, FCM is employed. The dataset is converted into a fuzzy dataset by the triangular and trapezoid membership functions [15]. The triangular membership function is defined by means of the equation given below:

$$\boldsymbol{f(x;a,b,c)} = \begin{cases} \mathbf{0}, & \boldsymbol{x \le a} \\ \frac{x-a}{b-a} & \boldsymbol{a \le x \le b} \\ \frac{c-x}{c-b} & \boldsymbol{b \le x \le c} \\ \mathbf{0}, & \boldsymbol{c \le x} \end{cases} \tag{3}$$

Where ‘a’, ‘b’ and ‘c’ are the scalar parameters and ‘x’ is a vector. The parameters ‘a’ and ‘c’ signifies the base of the triangle and parameter ‘b’ represents the peak. The trapezoidal membership function is defined as

$$\boldsymbol{\mu}(\boldsymbol{x},\boldsymbol{a},\boldsymbol{b},\boldsymbol{c}) = \begin{cases} \mathbf{0}, & \boldsymbol{x} < \boldsymbol{a}, \boldsymbol{x} > \boldsymbol{d} \\ \frac{x-a}{b-a} & \boldsymbol{a} \leq \boldsymbol{x} \leq \boldsymbol{b} \\ \mathbf{1} & \boldsymbol{b} \leq \boldsymbol{x} \leq \boldsymbol{c} \\ \frac{c-x}{c-b}, & \boldsymbol{c} \leq \boldsymbol{x} \leq \boldsymbol{d} \end{cases} \quad (4)$$

Where 'a' and 'd' denotes the lower limit and upper limit and 'b' and 'c' represents the lower limit and upper limit of the center. Fig.3 depicts the triangular and trapezoid membership functions.

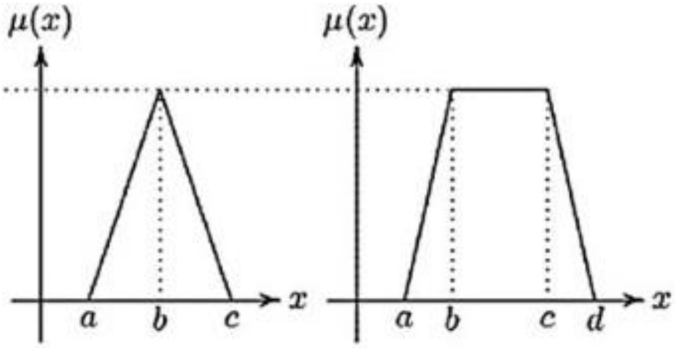

Fig.3 Triangular and trapezoid membership functions

A support value is computed for each item by aggregating the fuzzy membership functions for all data records. This aggregate value is stored in the primary candidate itemset C_1. The items that are greater than or equal to the minimum support min $_sup$are moved to large primary itemsets L_1. The items are joined and combined as $\{\{c[1], c[i]\}, \{c[1], c[i+1]\}, \ldots, \{c[1], c[n]\}\}$. The items for each itemset do not belong to the same field. After every itemset is stored in the secondary candidate itemset C_2, the support value for each itemset is computed using a minimum operator for the fuzzy values of the items. The result of the minimum values in that itemset is added for all records. Finally, the added value is stored in the C_2.

The itemsets whose value is greater than min $_sup$are moved to large secondary itemsets L_2. This combination is based on the every sub-itemset of the candidate itemset C_K. The candidate itemset should be a frequent itemset in the previous large itemset L_{k_1}. The terms in the candidate itemset do not belong to the same field. The items are stored in the tertiary itemset C_3 and the support value is computed for each candidate itemset. The itemsets whose value is greater than or equal to the min $_sup$are moved to the large itemset L_3. The itemsets are combined until the itemset L_n is empty. The itemsets are pruned by selecting the itemsets including the target attribute. The itemsets are expressed as IF-THEN, the confidence value (CV) is computed as

$$CV = \frac{\sum[(IF) \cap (THEN)]}{\sum(min(IF))} \quad (5)$$

The extracted rules are stored in the Knowledge Base (KB). The rules in the LB are inferred to the Fuzzy Inference System (FIS). The frequency of all the items in the database is assumed to be same, if the min $_sup$value is used for a whole database. The database contains high frequency items. Only few frequent itemsets are extracted, if the min $_sup$value is set too high. More number of frequent itemsets can be extracted, if the min $_sup$value is set too low. The FCM-Multiple Support (MS) Apriori model uses the FCM and MSApriori approach for extracting the highly frequent itemsets from the fuzzy datasets. The FCM-MSApriori inherits the benefits of both the FCM and MSApriori approach and provides more flexibility to the real-time applications.

Proposed Algorithm

FCM: {clustering dataset}
Find the fuzzy sets of the quantitative dataset
Calculate the sum of the membership values for each fuzzy term for all records
If $sum \geq$ min $\_sup$ then
Insert the fuzzy term into L_1
For $k = 2; L_{k-1} \neq \emptyset; k++$ do
$C_k = generate\ candidate\ from\ L_{k-1}$
{
Insert into C_k
Select itemset; $p.term_1$; $q.term_2$,... $p.term_{k-1}, q.term_{k-1}$
From p,q
Where $p.term_1$= $q.term_2$,..., $p.term_{k-2} = q.term_{k-2}, p.term_{k-1} \neq q.term_{k-1}$
}
For each itemset $c \in C_k$ do
Check all the sub-itemsets of all itemsets in C_k and it should be a frequent itemset in L_{k-1}
For each $(k-1)$ subset 's' of 'c' do

If $c \in L_{k-1}$ then
Delete c from C_k
End For
End For
For each itemset candidate in C_k do
Calculate the support value
If $sum \geq \min\_\text{sup}$ then
Insert the fuzzy itemset into L_k
End For
End For
Select the frequent itemsets including the target attribute
Form the frequent itemsets that exist in L_2 to L_n under the form "If-Then"
For each rule
Calculate the confidence value for each rule
If $CV \geq \min\_conf$ then
Accept the rule
End For
Check the rules for contradiction
Insert all the accepted rules in KB
Infer the generated rules in KB using FIS

Input: 'D'- Dataset
'IW' - Itemset weight, 'wsup' - Weighted support, 'wconf' - Weighted confidence, 'm' – itemset, C_m- Candidate itemset, F_m- Frequent itemset, c'- Number of candidate itemsets in C_m, Fz - Fuzzy Association rule, fs - Fuzzy itemset in fuzzy association rule, rs - Rules generated from C_m, WAR – Rules, $\min\_wsup$- Minimum weighted support, $\min\_wconf$ - Minimum weighted confidence
Output: WAR'- Set of weighted association rules
$m = 0; C_m = \emptyset; F_m = \emptyset$
$C_m = Set\ of\ 1\ iterations$
$m \to 1$
Begin
If $C_m = \emptyset$ break
$\forall c' \in C_m$
$c'.weighted\ support \to weighted\ support\ count$
If $c'.weighted\ support > \min\_wsup$
$Fz \to Fz \cup c'$
$m \to m + 1$
$C_{mk} = generate\ candidates\ (Fz_{m-1})$
End
If $fs \in Fz_m$
generate set of candidate rules $\{rs_1, \dots, rs_n\}$
$WAR \to WAR \cup rs$
$\forall rs \in WAR$
$rs.weighted\ confidence \to weighted\ confidence\ value$
If $rs.weighted\ confidence > \min\_wconf$

$$WAR' = WAR' \cup rs$$

Here, the frequently bought itemsets are extracted from the store database and this information has to be securely sent to the organization and for this, in the next subsequent step, the encryption of the frequent itemsets is done with the help of RSA cryptography key.

D. Key Generation Using RSA Cryptography

PKC mechanism utilizes a single key for all the authentication process and then another key for all the encryption process. The sophisticated PKC had first been described using a two-key crypto scheme where users and businesses could communicate safely on an unsafe channel of communication without exchanging a secret key. RSA is each of PKC's first and yet most popular implementation that it remained in use for key exchange until recent times. Each of the keys in PKC is known as the public key (p) and can be released as broadly as the owner wishes. The other key shall be the private key (d) and shall never be disclosed to a third party.

Arbitrary values are usually selected for the private keys. Nevertheless, unless their selection is properly done, these can proceed to creation of infinite number of values in the computations that involve public key. In addition, the range of private keys must be designed to produce usable public keys and also in line with other limitations such as size. A spherical SVM classifier based on Fuzzy is used separately as two cases with these objectives in mind.

E. Private Key Selection using Fuzzy-based spherical SVM (FSSVM) classifier

The SVM classifier is usually earlier built for two classifications, and then used to fix the problem once the function consists of small samples, high-dimensional data, nonlinearity, etc. The SVM, nevertheless, contains low tendency to grasp the feature's large data sets, contributing to a loss of output accuracy. So this paper uses the fuzzy-based multi-kernel spherical SVM classifier. Newly created, the kernel function is predicated on the fuzzy membership feature, that is integrated in to the spherical SVM classifier to achieve better precision quality. The design of the kernel function is an important element for the classifier, that implicitly defines the high-dimensional space characteristic data where a maximum hyperplane margin is discovered. After which, the kernel function includes a and b — the two variables that are calculated by the function of the Fuzzy triangular membership. In the fuzzy logic the membership function reflects the kernel of truth as both an expansion of valuation. For classical sets, the membership function is to also include the indicator functions. Therefore, the spherical SVM classifier focused on fuzzy exploits specific kernel function that shows improved performance in object detection.

F. Design a new kernel function using the triangular membership function

The kernel approach has been commonly used for the SVM, and it also relies on the data that is conveyed here between data arguments only through the dot products. The concept under the kernel function would be to give the non-linear, separable data a bridge from the linear data. The kernel function has two benefits: (i) It is inclined to establish non-linear decision limits for the classifier and (ii) The kernel function is used to allow the consumer to submit the data to a classifier without all the help of a fixed-dimensional vector space. Thus, the two kernel functions like exponential and tangential are used to represent the higher-dimensional vector in which the data is effectively recognized by the classifier. The recently developed kernel is thus represented in

$$K=\exp -Vc.*Vd +\tanh(-Vc.*Vd) \quad (6)$$

Where and are the weights determined by the method of the fuzzy triangular membership. The additive kernel function as described just like the function of the Gaussian kernel without the use of the function's square norm. It is part of the function of the radial-basis kernel. The tangential kernel is often recognized as the kernel function of the sigmoid and multilayer perceptrons. According to its origin from the NN theory, this kernel function is very common with SVM classifier. Therefore, weights are calculated using the method of triangular membership.

The sufficient information as to the triangular membership function in the article is already given.

Fuzzy spherical SVM—a new classifier

When the kernel function is defined, then it will be integrated with the classifier for the spherical SVM. Therefore, to use the violating vectors of the function as well as its respective weights, the center of a enclosed ball the sphere radius and the stop criteria, the spherical SVM classifier is obtained. The suggested spherical SVM classificator based on fuzzy is described as following.

The frequent itemsets collected which are defined in the proposed classifier to (ji, ki), where i=1, 2,...,s, ji is the feature vector, ki is the output class, and s is the number of data samples. Then the function of the hyperplane is described

$$kiji*w+h-i \quad (7)$$

With subject to ‖M-pi‖2R2

Initialisation: The random feature vector is selected all through initialization as well as its weight has been initialised to one. The center is then calculated together with its weights by the feature vectors, and the radius is often deliberated to use the ball centre.

M=i=1siji where 0,o1

$$R=+1+1C,\ 12 \quad (8)$$

Where M is the centre, x is the weight, R is the radius and d is constant.

ii. Evaluate the violating vectors : For every iteration, the two violating vectors are generated by the number of draw attempts. At first, we have drawn the random subset of size Sr from the whole dataset. Then, the first violating vector is estimated by the maximal distance between the feature vector and centre of the ball. After the violating vector is defined, the subset is drawn again by the number of draw attempts, Da. Here, the second violating vector is declared by the minimal distance between the centre and feature. The violating vectors are generated by

$$Vc‖M-fi‖>1+R \quad (9)$$

$$Vd‖M-fi‖>1+R \quad (10)$$

Where Vc and Vd are the two violating vectors with respect to the centre of the sphere and feature vector.

iii.Compute , and : By using the two violating vectors, we can upgrade the centre of the ball. This new centre is utilised to estimate the parameter . The new centre of the ball is calculated as

$$M'=M+\eta(Vc-Vd) \quad (11)$$

Here, the new sphere of the centre M' touches the violating vector Vc, then, the radius should be satisfied by the following condition:

$$‖M'-Vc‖=R \quad (12)$$

Then, Eq. (11) can be written with respect to the violating vectors and the centre of the sphere as

$$‖M+\eta Vc-Vd-Vc‖2=R2 \quad (13)$$

Then, the parameter is computed by the two violating vectors and centre:

$$\delta=Vc-Vd\times(Vc-MK2 \quad (14)$$

Where K is the newly developed multi-kernel function which constitutes exponential and tangential kernel function. Here, the kernel function is expressed by the dot products between the two violating vectors Vc and Vd. The kernel function is the most important significant part in SVM classifier and can be used in many applications. The exponential and tangential kernel functions are used to implicit the feature space without a prior knowledge of the data coordinates in that space.

Using η and R2 value, we can estimate the by

$$=\delta-2-K2-R2K2 \quad (15)$$

iv.Updating the violating vector weights: The weights of the two violating vectors are denoted by c and d. Thus, their weights are updated using the η parameter, which is represented by

$$\eta=\min\{,Vd\} \quad (16)$$

Then, the weights are updated by

$$cc+\eta \quad (17)$$

$$cc+\eta \quad (18)$$

$$dd+\eta \quad (19)$$

Where c and d denote the weights of two violating vectors Vc and Vd and is the parameter used to update the vector weights, which then leads to upgrading the centre of the sphere in the proposed classifier. Finally, in the proposed classifier, the updating process is repeated until the stopping criterion is reached.

Therefore, FSSVM chooses a private key for improving the security. In a similar manner, FSSVM can also choose an optimal random number, R.

Before the encryption, both user A and organization B should have the knowledge to assess the RSA parameters and incorporate the text into numeric data as well. On this, numeral ASCII values are being used to translate the text into digits. Instead, by taking steps provided below, A and B can securely send the transaction data.

1. Two users A and B select the RSA parameters.
2. User A selects the Key Generation Point KGP.
3. Private key number P_{rA} is selected by User A with the aid of FSSVM algorithm
4. Key generation point and public key designed from the private key are communicated to B organization.
5. Organization B ciphers the text using the public key P_{uA} of User A.

a. Develop the text message which has to be transmitted
b. Calculate the respective ASCII value
c. Get value R (any random number) employing FSSVM.
d. Estimate the cipher parts using point multiplication
e. Calculate the next cipher part using point addition or point doubling
f. Compute cipher text as assumed in equation to give User A

6. The decryption procedure carried out by A is given as.

a. Get the cipher text CP.
b. Get the left segment C1 and right segment C3 of the CP individually.
c. Multiply with PrA to the left segment and then subtract it from the right segment to obtain MP
d. Translate it back to the list of ASCII values.
e. ASCII values are then mapped onto respective characters

IV. RESULT AND DISCUSSION

The results obtained from the addition of new model tests are discussed in this chapter. The model is applied by means of the NS2 method. The comparison with the Fuzzy-based spherical SVM (FSSVM), the current RSESVM, GRI, AES algorithms and the recently introduced RSA cryptographic being conducted in view of Precision, Accuracy and Error measurements for multi tasks database.

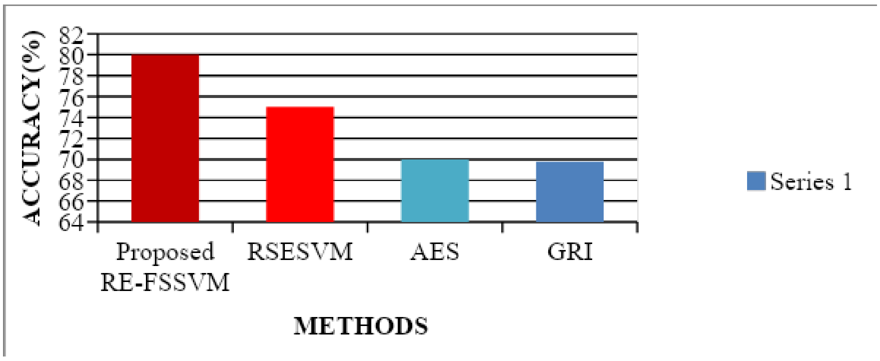

Figure:4. Accuracy results comparison vs. classifiers

Figure 4 shows the results achieved in terms of the accuracy metrics from the performance correlation between three various techniques including GRI, AES, RSESVM and RE-FSSVM. From the analysis, it could be assumed which the proposed RE-FSSVM technique produces far greater accuracy of 80%, whereas other techniques, like RSESVM, AES and GRI techniques produce only 75%, 70.00% and 69.76% respectively.

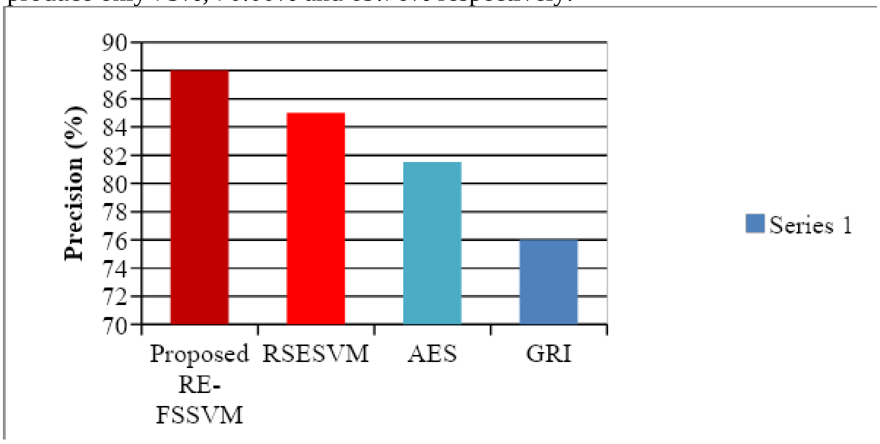

Figure :5. Precision results comparison vs. classifiers

Figure 5 shows the results achieved in terms of the accuracy metrics from the performance correlation between three various techniques including GRI, AES, RSESVM and RE-FSSVM. From the analysis, it could be assumed which the proposed RE-FSSVM technique produces far greater accuracy of 88%, whereas other techniques, like AES, GRI and RSESVM techniques produce only 81.5% ,76% and 85% respectively.

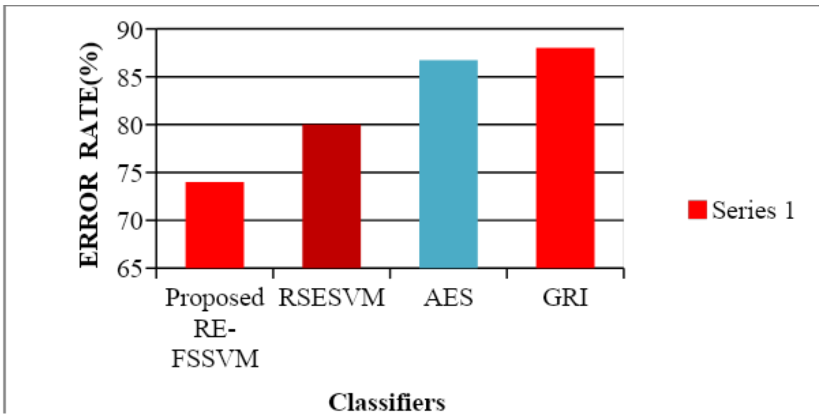

Figure: 6. Error rate results comparison vs. classifiers

Figure 6 shows the results achieved in terms of the Error rate metrics from the performance correlation between three various techniques including GRI, AES, RSESVM and RE-FSSVM. From the analysis, it could be assumed which the proposed RE-FSSVM technique produces far greater accuracy of 74%, whereas other techniques, like RSESVM, AES and GRI techniques produce only 86.75% , 88% and 80% respectively.

V. CONCLUSION AND FUTURE WORK

The application of different web technologies and innovative algorithms in this research seems to be hopeful of making possible solutions concerning the study of customer buying habits. Using the Enhanced Fuzzy-based Weighted Association Rule Mining Algorithm for mining the regular item set using Probabilistic Graphical Model strategies, the mining of regular itemsets is performed initially. Afterwards, the key will also be generated using the RSA algorithm, as well as the Fuzzy-based multi-kernel spherical support vector (FSSVM) classifier will be used for secret key collection. The work planned for all the future would provide the integration of particular features that perhaps the research was unable to explore through the use of a more robust system algorithm, which in effect will make it easier for the system to run efficiently and with greater efficiency. Measures to improve the search strategies could also help to increase market and productivity.

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