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Review Article

IDENTIFYING SUSPICIOUS MONEY LAUNDERING TRANSACTION BASED ON COLLABORATIVE RELATIONAL DATA SCREENING MODEL USING DECISION CLASSIFIER IN TRANSACTIONAL DATABASE

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Abstract
Transactional data be most economical concern in banking sectors for financial prospects. Due to criminal activities and tolerant they had many issues specifically in money laundering. The illegal transaction, robbery, malpractice non related source of access, are tedious to identifying legal transactions. By the higher transactions using the big data analysis to identify possible money laundering activities. To resolve the issue to make effective future selection approach in transactions and classify the resultant under data cleaning, partial information from traditional statistical analysis, and data mining process. To propose an collaborative relational data screening model (CRDSCM) using decision classifier in transactional database. Autocorrelation function with screening cluster approach were conducted to examine the relationship between the attribute similarities on each transaction collaborative data analysis method. With support of time serious data including predictive analytics for decision making the detection of attitude and money laundering activities that are used to deliver classified result in efficient way

Keywords: Feature Selection, Decision Classifier, Prediction, Cluster, Semantic Analysis, Record Linkage.

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INTRODUCTION

Since Money laundering (ML) is a sophisticated activity in many ways, AML has the conventional approach, which gave it a manual approach demanding hard work. These approaches include classification of money laundering, detection phenomenon, identification that you can avoid and tracking activities of money laundering. In fact, there is a need to support automated tools to detect money laundering, which in many ways have become such an approach in terms of data and banking business.

On the other hand, AML's software tool on the market, usually, you can use some of the rules and starting points from a limited set of rules to advance the rule based and project exclusion value average value base. Machine learning approach to be suitable for detecting trends and inadequate data systems. The identifying the fraud detection approach in money laundering usually they needs the transactional logs, location based approach, time series data and it term of transactions passed relational data. The transactions on which the organization and policies, accounts and institutions depend.

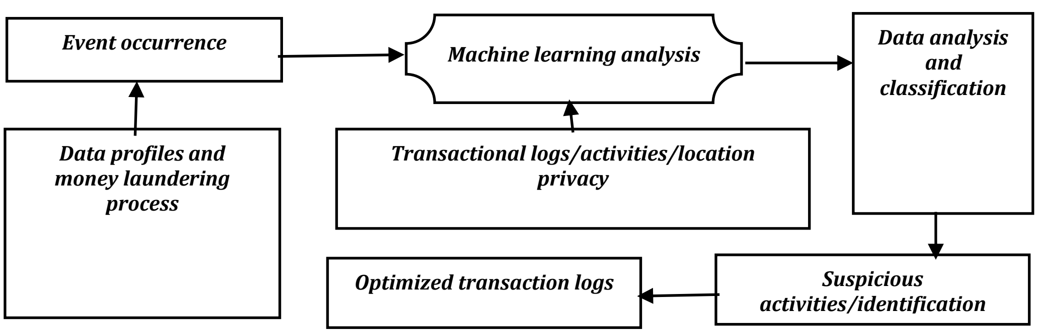

Figure 1: Process of Knowledge based money laundering

This component, ML framework provide the most basic level classification and synthesis technology: transactional data set analysis. At this level, transaction records have been obtained from the research. Figure 1shows the Process of Knowledge based money laundering. The process activates initially, the account or other data they make cannot provide a link because they have some sort of analysis environment. Further you have multiple transactions associated with a particular account. Transactions accreditation, and provides a general overview of these accounts in the financial transactions of individual accounts.

Create a set or suspicious profiles that group similar transactions. In our approach, a classification is defined as a predefined type of customer behavior, risks associated with the following mining technology customers are detected

The results of the mining process, the result of running AML's experience, have been collected by experts, this component is analyzed and stored in the associated repository. In addition, important, create the rules and knowledge of interpretation. The integration of all the components in this component, by assigning different strategies to a mining, data mining process, is not adjusted many crime transactional , to overcome the issue we intent a collaborative approach with decision classifier which it combines set the prominent money laundering results and learning decisions in transactional logs. This improve the knowledge with other organizations about its architecture and their privacy policy.

LITERATURE REVIEW

Money laundering criminal concealment or concealing their Money laudrys, and redirecting process proceeds to a product or service. Examples of income illicit channels are acting, drug trafficking, illegal activity [1].In the case of this article, we use big data Analytics Company to identify potential money laundering activities. Analysis of Information Transfer Data The clean, traditional statistical analysis and mining process begins with a brief summary report, along with the 18000 Excel data file section. Autocorrelation function and autocorrelation function are part of the study of relationships with data analytics before attributing data to big data systems [2]. The Anti-Money Laundering (AML) Controlled Financial System refers to criminal hubris, attempts to prevent the secrecy of copyright, origin, or wrongful gain. Although domestic regulatory and compulsory processes have long been, as well as international obligations and guidance, there are better practices out there that still recognize the challenges facing policymakers and address new policy gaps and new methods of money laundering[3].Illegal gains of money laundering (i.e. "dirty money") are the process by which the law appears (or is "clean"). Generally, it involves three steps: Stacking and Coordination. First, the illegal financial system of finance is a planet. Following that, the money went around converting multiple accounts, sometimes by wiring or creating confusion. Finally, the financial system has joined in with additional transactions until it appears "dirty money." Money laundry, such as drug trafficking and terrorism, can easily be defrauded and have an adverse effect on the global economy.

Most cases the criminal activities are dependent in money laundering process all over the fraud occurrences. However, because it is common in dirty money laundering, banking transfers or commercial transactions can be divided up into segments, leaving the challenge of manual detection of money laundering [4]. Money Laundering It can be defined, in general, as the illegal appearance of camouflage of income follow-through, or the use of criminal activity to conceal and source. Cheating is money laundering.

From one country to another for international trade, the oldest technology used to conceal and transfer funds, is used by the government to violate censorship. International trade as a means of money laundering is ignored by most government law enforcement agencies [5]. AML's are a hot topic nowadays. How to develop an automated technology for obtaining Sir (No doubt Activity Report) is a central issue for financial institutions. The purpose of this paper is based on computerized financial institutions established by financial institutions, not just information for transactions to take into account, financial norms, client catalogs and external information Technology Company.

Money Laundering It seems that the idea of drug trafficking has moved on to personal interests and the finances of terrorism, and the problem must have escalated. This criminal activity is only causing state financial institutions a problem. Anti-money laundering process defense the illegal activities against the traditional data transaction among various intrusion monitoring the illegal activities. But the insufficient to make deliverable the correct solution in fact of detection activities [6]. They still content with the benefits of mis-access, are mainly beneficial because ongoing anti-theft efforts. In addition, they retain the financial capacity for the new theft industry. The anti-money laundering regime and prove it is used to mark them. The use of systems in anti-money laundering is a challenging, although targeted, approach to providing access to pre-illicit business interests by stealing from theft. This will prevent the reinvestment of earnings behind its previous theft of financial institutions.

One challenge concerns the relationship of natural or man-made factors to the order in which the forest environment is encountered. Various events are completed once presented. Here, effective and economical methods of control of wireless sensor networks using control information and telecommunication technology and such issues are carried out based on research. It is useful to be able to solve such problems; the evaluation results indicate the acceptable levels of this type of sensor charge [7]. Using credits in a bit fraud. Criminal Income Fraud is being used by criminals through an increasing network of digital payment methods. Because profits are promoted in many forms of cyber Money laundries, we need a fixed amount of money outside of Money laudry and criminals to ensure that the evidence is not going to ruin where the money goes. The author of the study of how to use the services provided by this dark laundry network to the proceeds of the Money laundry network.

Size first, and sometimes only large amounts of data specify quickly. These paper efforts draw on its other personalities and characteristics to provide a broader definition of big data. By the rapid growth development in data integrity is main for transactional database in banking sectors. Mainly the defense mortality is fraud occurrence in banking transactions. The key exchange is mainly dependent for transactional forma of counts based logs in transactions. By the machine learning algorithms count the logins for valid transactions but these mechanisms used by big data [8].Financial institutions recognize the potential for suspicious money laundering behavior (SMLTBPs) is key in anti-money laundering. This depends the designed for the detection of localized anomaly and local anomaly, using a new set of local extraction factor (CBLOF) additives to validate SMLTBPs algorithms and use a real test data to artificially test their relevance and use effective cloths.

International Trade, Money Laundering and Analytics to measure the price of international money laundering by contributing to the model environment. Conversion Pricing and Money Laundering is based on a comprehensive data process on money laundering. It is believed that the nature of the exchange price-based capital flight and the variation in the amount of money laundering is clear of illegal taxation of their property law title. Our main contribution is to help with a capital flight and tax evasion, money laundering model with an Artificial Transfer Price Identification (ATP) method and a model to estimate its contribution to the global pool of money laundering [9][10]. Big data is changing the business environment radically. Explore why our open enterprise "black box" companies can transform big data into value creation to differentiate why companies are capable of generating big data value. Actively participate in value-creation activities from big data in China, the world's largest digital marketplace, detailed ground sources from many companies, we find a few new features [11]. We have found that this is not the value of the data themselves, or the data that is created to create personal data.

Multimedia communication technology has been widely used in the field identifying illegal activities in order to improve the efficiency and security of business transactions [12]. In order to reduce the cost of large-scale multimedia implementations, it is best to allow multiple financial sector (FIS) with AML's contacts and storage resources to collaborate with each other to complete the sharing and transfer of resources, including manpower [13, 14]. It Criminal activity is becoming increasingly complex, and it seems to have moved away from drug-smuggling know log terms. They will forget the finances of terrorism and of course the personal interests. Financial fraud problems are raised by this way have Fraud for anti-money war solutions Investment

Fraud. However, the traditional survey the technical man consumes a huge amount of hours.

The central decision is to identify the money laundering process. The clustering algorithm is that of grouping finite arcos as valid transaction. In this manner, the results are used to analyze the proposed anti-money laundering after fraudulent properties of data processing technologies[15][16].There are no rules on regular money laundering and money laundering as we choose a suitable strategy to track down.

Therefore, with the central decision tree algorithm, we can more efficiently identify extraordinary transactions data [17]. Intense infrastructure network is very complex and interconnected systems are the essential weakness of human life, economy and society which can lead to a city or country with sudden interference which affects such a whole [18]. An unexpected vulnerability analysis and network infrastructure interdependence between some infrastructure components, such as the possibility of such networks to be incorporated, should therefore be included.

Use to estimate the network's promising direction to the extent of impact analysis of the distribution network. However, because of the traditional distribution model it does not take into account the geographical location of the network, inadequate space network vulnerability analysis. This functional classes are considered as an important factor in determining the length of the network connection to the nodes of the spatial network [19][20]. Global investment banks and financial institutions face growing data processing needs. The gap between the data source and the only constant pressure from regulatory requirements, variants and lower costs is not widened, without affecting the scalability and flexibility of this system. In this context, the ability to apply the most promising advanced big data technology countries is generated from a wide range of interests with a lot of interest in the financial services industry to obtain maximum value.

MATERIALS AND METHODS

In this section, we present our solutions based on machine learning collaborative approach for analysing investment transactions in money laundering (ML). This solution is implemented for data mining and the knowledge element of our framework. As noted above, transactions and accounting cannot be investigated separately. They need to be mobilized in order to provide a general idea of customer behavior. For Identifying Suspicious Money laundering transaction based on collaborative relational data screening model using decision classifier in transactional database

In general, this study is based on two important characteristics: frequency and transaction value for each transaction.

The graph based sentence level semantic linkage weighting model has been presented here which generates semantic graph for each of the sentence being identified. With the graph being generated, we compute the sentence level semantic linkage weight for each of the graph towards all the class considered. Finally a top weighted class is identified as the resultant class.

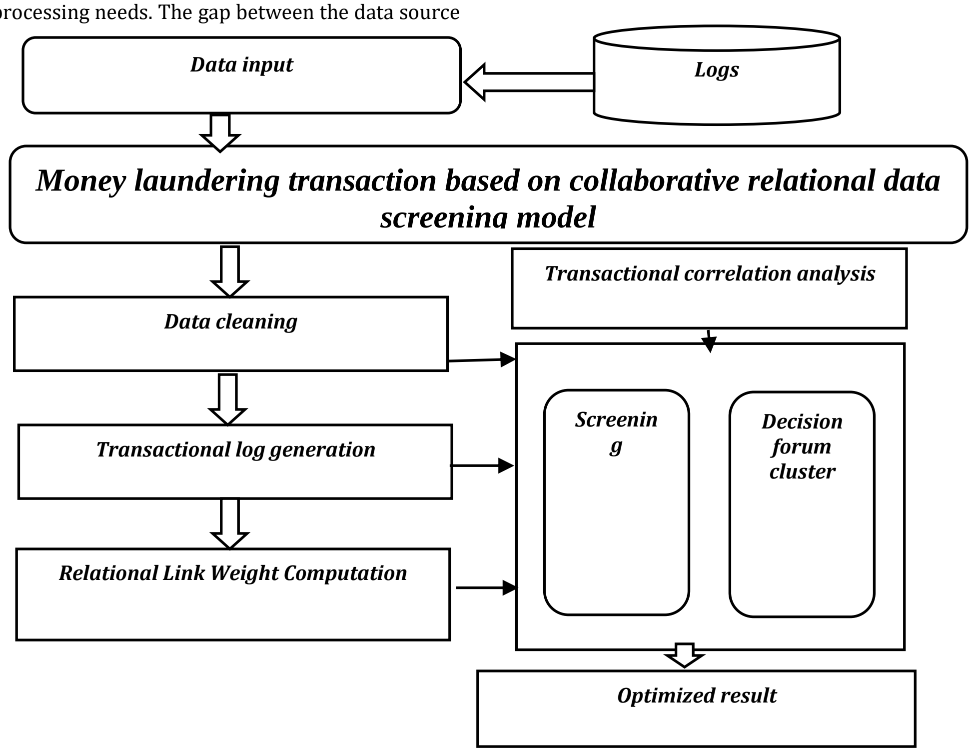

Figure 3.1: Collaborative relational data screening model for money laundering

Figure 3.1 shows the architecture diagram of the proposed collaborative relational data screening model for money laundering clustering and its functional components. Represented transactional process re described the function as below.

Preprocess transactional Data

This component plays an important role and raw data is located in the clean source data set from the data source on different platforms of this international bank. These customer information and customer transactions must be integrated into the aggregated information that is being used to build the data warehouse. One of the most challenging at this point is the issue of data quality. In banking and financial, data sets, it is in our case, most of these problems are related to customer information, and for example there is a different set of issues at the lower level of quality.

Missing values, pseudo-value, or null: some of them, you can highlight. Much of the data industry, which includes information, customer identification (ID), consumer type (corporate, personal, and joint), excludes any financial name that occurs in the study. Normal, misspellings, misspellings, phonetic error. In addition, the data set by the banks are usually managed in a shared manner, for flexibility and security reasons.

An integrated task does not necessarily address all conflicts of data quality in particular, independence and the more versatile 236 of each data source, if you can. This pre-processing component solves some of the basic data quality issues. Another issue associated with customer information is the implementation of our Knowledge Management Component Integrated Customer Identification Module. Client transaction problems are often associated with data quality, for example, and a contract where a copy of a system is sometimes not copied. As a result, we have to deal with her, it is not the full transaction as snap.

Transactional log generation

At this stage, the input document is processed to extract the textual content. The extracted text is split into number of sentence by splitting by punctuation marks. Each sentence is split into number of distinct terms by splitting by space character. The extracted term are added to the term set related to the sentence. For each term of the sentence, the method performs stop word removal, stemming and tagging process.

From identified nouns, a distinct semantic graph is generated and for each term of the sentence a node is added to the graph. Now the semantic ontology is loaded into the system, and looked up for the label in the ontology and for each of the term, the property and the relation with other terms are identified.

If there is any relation present between the terms then a link is generated between them and for each node is identified the semantic terms related with that and specify interior and exterior links. The generated graph will be used in the later stage of clustering.

Algorithm 3.1

Input: transaction log Set Ds, Semantic Ontology Set SoS.
Output: Semantic Graph Set SGS.
Start
Initialize Term Set Tss
Initialize Graph Set Gs.
For each transactional log D_i from Ds
TransT = Extract Text from Di.
Transactional Log set Ss =

$\textit{set of Time cout by referance account}$

Competence for transactional Log Si→SS
Generate Graph Gi.
Term Set $T_i = \sum$Terms@Si
For each term Tn from Ti
If Tn€trans valuet then
Ti = Ti₵Tn
Else
Perform Svalid trans
Apply Part of time by occurrence.
End
End
For each term T_k from Ti
Create Node Ni.
Add node to Gi.
Gi = ∑(Nodes € Gi)+Ni.
End.
Read Domain ontology Do.
For each domain Di from Do
For each term Tk from Ti
If Di€ then
Identify relation it has with other concepts.
Relation Set Rs = ∑(Concepts €Di)+Ci.
Add relations to the Node Ni.
End ontological process
End for
End for
End
Stop

The above discussed algorithm performs pre-processing of the text documents and generates semantic graph for each of the sentence being identified from the document.

Relational Link Weight Computation

At this stage, we compute the sentence level semantic link weight for each of the sentence towards each of the cluster being considered. For each graph, which represents a sentence in the document, the semantic link weight is computed. The method computes the number of relations it has and number of links a graph. Then the method identifies the set of interior and exterior relations it has with the concepts of different domain. Based on all these measures of each sentence, we compute the semantic linkage weight for each of the sentence. Finally a cumulative weight will be computed for each of the class, and a single domain or class will be selected as the result which has more weight.

Input: Semantic Graph Set Sgs., Semantic Ontology So.
Output: Class Name.
Start
For each graph Gi from Sgs
For each domain Di from So
Compute Number of relations it has.
INr = ∑ Relations €Gi
Compute Number of incoming links.
NIL = ∑Links(Gi)<-∑Gk(Sgs)
Compute the value of interior links.
CILV = ∑Concept(Links(Gi)) € Di
Compute the value of exterior links value.
CELV = = ∑Concept(Links(Gi))) € ∑Concept(Dj)!=Di
Process relevant weightage measure R→Slw.
Average c-->CILV*CELV/INr
Compute weightage to Ws(Di)
End
End For
Identify the selected weightage class IC.
Max→cmeanvalue(IC)
Stop.

The algorithm selected the computed weightage from each transaction which is based on semantic closeness, which is used to perform clustering the transaction from screening.

Transactional log correlational analysis

By the decision the transactional logs are analysed grouping the correlational data initially whether it is a clustering process or a retrieval process, the input content is passed through the decision states which generates the correlational analysis. Then once the graph has been generated, them for clustering the document, the method computes correlation transaction logs linkage weight and based on that the method assigns a class to the document and the document will be indexed to the concern category.

Input: Transactional logs T
Output: Classified decision category
Start
If Input==trans log then
Formulate relational graph.
Graph valid →tans data
Identify trans category relational graph slw.
Screening the valid transactions to order by category to the cluster.

Else
Generate relational data.
Compute relational weight slw.
Identify the no related category class to definition transaction T.
Combine transactional weight by category screening cluster group
Retrieve the trained trans log weightage order by class.
Sort the documents according to the Slw.
Order class by reference.
End
End

The above discussed algorithm performs clustering of transactional logs according to the graph based sentence level semantic linkage weight model and produced more efficient clusters. In case of retrieval at the training phase, the method stores the computed money laundering log weight and the method computes the same for decisions and identifies the domain of query. Once the category of the Trans log query has been identified then using the pre-computed linkage weight, the indexed transactional logs are ranked and returned as a result to the user.

From the experience of AML experts, such as the fact that by assessing these subsets in the actual transaction data set, we have parameters Δ1, subscribing to these activities and compensation when it occurs, that the subscription and redemption are made in a single week, reflecting the relationship. In action In addition to the activity, as well as subscription in the case of the relevant suspect in the current period, is on transaction.

RESULT AND DISCUSSION

The Money laundry accuracy are tested with collected criminal datasets from investigational departments which is in the form of raw transactional datset dataset. The relative logs are analyzed is applied to find the sematic measure among Money laundry records to cluster group by risk factor evaluation. The preprocessed data set is input progress for testing the sensitivity specificity and clustering accuracy. The proposed CRDSCM produce higher efficient test result compared to the other dissimilar methods. The Money laundry case reasons are evaluated through visual studio frame work .net 4.0 by testing the various Money laundry records. The implementation enhance the Money laundry case analyses with higher efficiency to identify class by risk of evaluation. The table given below shows the values and parameter processed in test case analysis.

Table 4.1: Details of a Money laundry Dataset

Parameter	Processed standards
Money laundry Logs	5000
Framework	visual.net framework 4.0
Case reasoning	3 class
Rule mining classifier	Decision making

The above table 4.1 describes the test case parameters with values processed to categorize the class of Money laundry risks. The evaluation of Money laundry records are finalized through the cluster accuracy by comparing other methods with least time complexity, false classification, the evaluated cluster are classified by risk by group of records done by semantic relational key terms. The relational true positive terms are based on the Money laundry patterns estimated by confusion matrix.
The performance testing resultants are figure out by charts given below,

Clustering accuracy (cs) =

$$\sum_{k=0}^{k=n} \times \frac{total\ number\ of\ cluster\ group\ dataset(Cds)}{Total\ originate\ data\ records\ (Tr)}$$

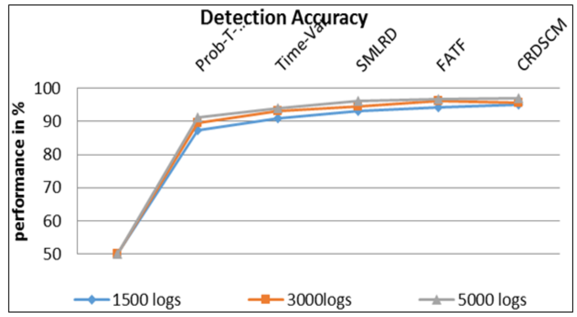

Figure 4.3: Analysis of misbehave detection Accuracy

Figure 4.3, illustrations the misbehave activities detection accuracy comparison which they produce higher performance revised other methods. This improvement related to task finding of feature based cluster analyses that doesn't availed by other methods. So the performance be relatively high than other methods.

Table 4.2: Analysis of misbehave detection Accuracy

Methods/ Transactional logs	Prob-T-model	Time-Var	SMLRD	FATF	CRDSCM
1500 logs	87.3	91.1	93.1	94.3	95.2
3000 logs	89.5	93.2	94.5	95.3	95.8
5000 logs	91.3	94.1	96.1	96.7	97.1

The detection accuracy resembles the relational accuracy which does not possess the transaction logs in legal transaction. Table 4.2 the proposed system produce high detection compared to existing methods.
The transaction logs are organized which is maintained as correct logs be wrongly classified as false report,

False classification Ratio (Fcr)

$$=\sum_{k=0}^{k=n} \times \frac{clustering\ Accuracy(cs)}{Total\ no\ of\ failed\ cluster\ rate(Fr)}$$

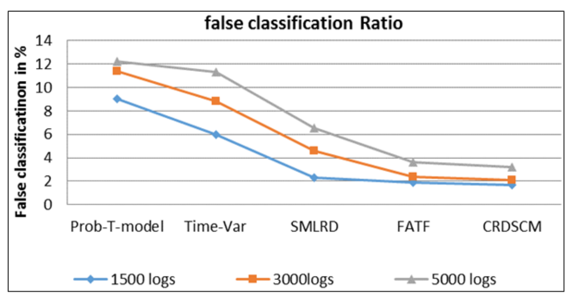

Figure 4.4: Analysis of false detection rate

The Figure 4.4, demonstrations the comparison of false classification ratio produced by different methods and the proposed method has produced less false classification ratio than other methods.

Table 4.3: Analysis of false detection rate.

Methods/ Transactional logs	Prob-T-model	Time-Var	SMLRD	FATF	CRDSCM
1500 logs	9	6	2.3	1.9	1.7
3000 logs	89.5	8.8	4.6	2.4	2.1
5000 logs	12.2	11.3	6.5	3.6	3.2

By the real transactions in the transactional logs are defined by its true positive on logs analysis which is considered as negative. The table 4.3 proposed system produce high performance compared to previous system

The time taken to process the detection accuracy in transactional logs which are maintain as true negative level

Time complexity (Tc) =

$$\sum_{k=0}^{k=n} \times \frac{clustering\ Accuracy(cs) + false\ classification(Fcr)}{Time\ taken(Ts)}$$

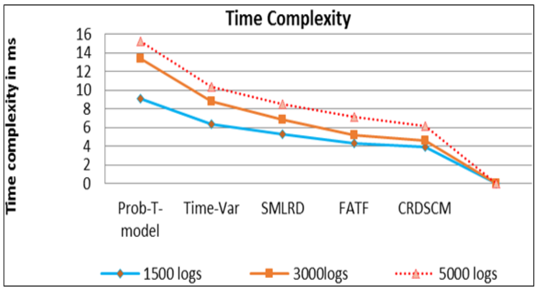

Figure 4.5: Analysis of time complexity

The Figure 4.5, shows the comparison of time complexity produced by different methods and shows that the proposed approach has produced less time complexity than other methods.

Table 4.4: Analysis of time complexity

Methods/ Transactional logs	Prob-T-model	Time-Var	SMLRD	FATF	CRDSCM
1500 logs	9.1	6.3	5.3	4.1	3.9
3000 logs	13.4	8.8	6.6	5.2	4.6
5000 logs	15.2	10.3	8.5	7.3	6.2

Average time taken to analyses the transaction and computed time to process the transaction classification are refers by time complexity.

Frequent occurrence (Fc)=

$$\sum_{k=0}^{k=n} \times \frac{repeated\ clusters(Rs) + irrelavant\ clusters(Irc)}{Total\ number\ of\ clusters}$$

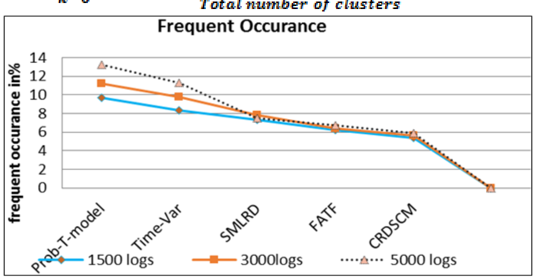

Figure 4.6: Analysis of the frequent occurrence

Figure 4.6 demonstrations the different approaches as recurrent incidence, proposed approach, showing that they are often produced less than other methods and product comparison.

Table 4.5: Analysis of time complexity

Methods/ Transactional logs	Prob-T-model	Time-Var	SMLRD	FATF	CRDSCM
1500 logs	9.7	8.3	7.3	6.1	5.4
3000 logs	11.2	9.8	7.8	6.4	5.6
5000 logs	13.2	11.3	7.5	6.7	5.9

Most of the frequent transaction logs are analyzed as repeated logs considered as related transaction. Maximum logs are time difference depended to another transaction relative measure. Table 4.5 shows the proposed measure produce higher performance compared to previous system.

CONCLUSION

In this study, we investigated the use of big data analysis techniques to detect money laundering activities that could be in place at a given time. After applying big data analysis, Money laundering transaction based on collaborative relational data screening model. Intent to detect the misbehavior transaction on money laundering as well compared to existing system and the regression analysis found that 97% confidence interpolation was a partial autocorrelation function and space sending at a significant height. So, we believe in its possibly money laundering system finding the inconvenient as detection accuracy, and a sending out messed up. Decision support make as effective classification technology is to find out more information in transactional logs in the Functional AML's detection system, which can be designed for unconventional operation in real time.

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