Research paper on An improved credit card fraud detection using machine Learning models

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Abstract-The usage of credit cards for online and regular purchases is exponentially increasing and so is the fraud related with it. A large number of fraud transactions are made every day. Various modern techniques like Data Mining, Genetic Programming, etc. are used in detecting fraudulent transactions. This paper uses genetic algorithm which comprises of techniques for finding optimal solution for the problem and implicitly generating the result of the fraudulent transaction. The main aim is to detect the fraudulent transaction and to develop a method of generating test data. This algorithm is a heuristic approach used to solve high complexity computational problems. It is an optimization technique and evolutionary search based on the genetic and natural selection. The implementation of an efficient fraud detection system is imperative for all credit card issuing companies and their clients to minimize their losses.

The speedy participation in online primarily based transactional activities raises the fallacious cases everywhere and causes tremendous losses to the personal and financial business. [1] Although several criminal activities are occurring in commercial business, fraudulent e-card activities are among the foremost prevailing and disturbed regarding by online customers. Data processing techniques were used to check the patterns and characteristics of suspicious and non-suspicious transactions supported normalized and anomalies knowledge. On the opposite hand, machine learning (ML) techniques were used to predict the suspicious and non-suspicious transactions mechanically by victimization classifiers [2][5]. This paper discusses the supervised based mostly classification. When preprocessing the dataset using normalization and Principal element Analysis, all the classifiers achieved over 95.0% accuracy compared to results reached before preprocessing the dataset.

Keywords—*ML; Classification; Data processing; supervised; learning.*

I. INTRODUCTION

As businesses still move into the online community which currency is transacted dynamically in cash-less banking finance, adequate anomalies detection stay an important factor for bank systems. Not for the reason to stop the explicit cost obtained with counterfeit activities although verify that automated and manual reviews don't adversely wedge legitimate customers [3]. In deposit or withdraw trade, illegal transactions on card happens once someone abducts information from the card to undertake to purchases while no permission given from the holder and conjointly the detection of these dishonourable transactions has become a significant activity for payment processors.

A typical fraud detection systems encompass associate academic degree automatic tool and a manual technique. The automatic tool depends on fraud detection rules. It analyses all the new incoming transactions and assigns a fallacious score.

Fraud investigators produce the manual technique [6]. They concentrate on transactions with a high fallacious score and turn back binary feedback (fraud or legal) on all analysed activity. The fraud detection systems are supported professionally driven rules, knowledge-driven rules or a combination of every style of rules [4].

The created rules try to verify specific things of fraud discovered by the fraud investigators. A state of affairs of fraud is "a cardholder can avoid dealing throughout a given country and, among the 2 next weeks, he can another dealing for a given amount in another given country. If this example is detected among transactions, then the anomaly detection system will manufacture an academic degree alert. Machine learning algorithms rules. They learn the fallacious patterns and check out to find them during a data-stream of new incoming transactions. The usually used machine learning algorithms embody supply regression, SVM Fraud detection may be a problematic machine learning for many reasons.

Fraud can be defined as wrongful or criminal deception intended to result in financial or personal gain [1], or to damage another individual without necessarily leading to direct legal consequences. The two main mechanisms to avoid frauds and losses due to fraudulent activities are fraud prevention and fraud detection systems. Fraud prevention is the proactive mechanism with the goal of disabling the occurrence of fraud.

Fraud detection systems come into play when the fraudsters surpass the fraud prevention systems and start a fraudulent transaction. Nobody can understand whether a fraudulent transaction has passed the prevention mechanisms.

Accordingly, the goal of the fraud detection systems is to check every transaction for the possibility of being fraudulent regardless of the prevention mechanisms, and to identify fraudulent ones as quickly as possible after the fraudster has begun to perpetrate a fraudulent transaction. A review of the fraud detection systems can be found in [2-5].

With the developments in the information technology and improvements in the communication channels, fraud is spreading all over the world with results of huge financial losses. Though fraud can be perpetrated through many types of media, including mail, wire, phone and the Internet, online media such as Internet are the most popular ones. Because of the international availability of the web and ease with which users can hide their location and identity over Internet transactions, there is a rapid growth of committing fraudulent actions over this medium. Furthermore, with the improvements in the bandwidth of internetworking channels, fraudsters have the chance to form fraud networks among themselves through information change and collaboration all over the world. As a result, frauds committed over internet such as online credit card frauds become the most popular ones because of their nature.

Credit card frauds can be made in many ways such as simple theft, application fraud, counterfeit cards, never received issue (NRI) and online fraud (where the card holder is not present). In online fraud, the transaction is made remotely and only the card's details are needed. A manual signature, a

PIN or a card imprint are not required at the time of purchase. Though prevention mechanisms like CHIP&PIN decrease the fraudulent activities through simple theft, counterfeit cards and NRI; online frauds (internet and mail order frauds) are still increasing in both amount and number of transactions. There has been a growing amount of financial losses due to credit card frauds as the usage of the credit cards become more and more common. Many papers reported huge amounts of losses in different countries [2, 6-7]. According to Visa reports about European countries, about 50% of the whole credit card fraud losses in 2008 are due to online frauds.

II. STRUCTURE OF THE CREDIT CARD DATA

The credit card data used in this study are taken from a national bank's credit card data warehouses with the required permissions. The past data in the credit card data warehouses are used to form a data mart representing the card usage profiles of the customers. Though some of the customers may have more than one credit card, each card is taken as a unique profile because customers with more than one card generally use each card for a different purpose. Every card profile consists of variables each of which discloses a behavioral characteristic of the card usage. These variables may show the spending habits of the customers with respect to geographical locations, days of the month, hours of the day or merchant category codes (MCC) which show the type of the merchant where the transaction takes place. Later on, these variables are used to build a model to be used in the fraud detection systems to distinguish fraudulent activities which show significant deviations from the card usage profile stored in the data-mart.

The number of transactions for each card differs from one to other; however, each transaction record is of the same fixed length and includes the same fields. Hand and Blunt gave a detailed description of the characteristics of credit card data [11]. These fields range from the date and hour of the transaction to the amount, transaction type, MCC code, address of the merchant where the transaction is done and etc. The date and hour of the transaction record shows when the transaction is made. Transaction type shows whether this transaction is a purchase or a cash-advance transaction. MCC code shows the type of the merchant store where the transaction takes place.

These are fixed codes given by the members of the VISA International Service Association. However; however, many of these codes form natural groups. So, instead of working with hundreds of codes, we grouped them into 25 groups according to their nature and the risk of availability to commit a fraud. The goods or services bought from merchant stores in some MCC codes can be easily converted to cash. As a result, transactions belonging to these MCC codes are more open to fraud and more risky from the transactions belonging to others.

The grouping of the MCC codes are done according to both the number of the fraudulent transactions made belonging to each MCC code and the interviews done with the personnel of the data supplier bank with domain expertise about the subject.

The distribution of our credit card data with respect to being normal or fraudulent is highly imbalanced with a ratio of about 20000 normal transaction records to one fraudulent transaction record. So, to enable the models to learn both types of profiles, some under sampling or oversampling techniques should be used. Instead of oversampling the fraudulent records by making multiple copies or etc., we use stratified sampling to under sample the legitimate records to a meaningful number.

Firstly, we identify the variables which show the most different distributions w.r.t. being fraudulent or normal. Then, we use these variables as the key variables in stratified sampling so that the characteristics of their distributions w.r.t. being fraudulent or not remains same.

A. Advantages-

1) The detection of the fraud is found much faster than the existing system.

2) In case of the existing system even the original card holder is also checked for fraud detection. But in this system no need to check the original user as we maintain a log.

3) We can find the most accurate detection using this technique.

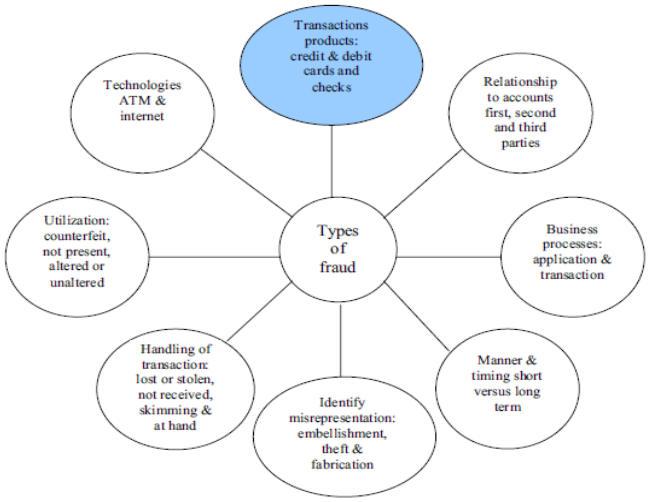

Fig.1: Types of fraud

4) This reduces the tedious work of an employee in the

B. Application-

1) Provide easy and well security to Online Shopping.
2) Detect Frauds and trace the location from where the transaction has been made.

C. Problems With Credit Card Fraud Detection-

There are lots of issues that makethis procedure tough to implement and one of the biggest problems associated with fraud detection is the lack of both the literature providing experimental results and of real world data for academic researchers to perform experiments on. The reasonbehind this is the sensitive financial data associated with the fraud that has to be kept confidential for the purpose of customer's privacy. Now, here we enumerate different properties a fraud detection system should have in order to generate proper results:

1) The system should be able to handle skewed distributions, since only a very small percentage of all credit card transactions is fraudulent.
2) There should be a proper means to handle the noise. Noise is the errors that is present in the data, for example, incorrect dates. This noise in actual data limits the accuracy of generalization that can be achieved, irrespective of how extensive the training set is.
3) Another problem related to this field is overlapping data. Many transactions may resemble fraudulent transactions when actually they are genuine transactions. The opposite also happens, when a fraudulent transactions appears to be genuine.
4) The systems should be able to adapt themselves to new kinds of fraud. Since after a while,successful fraud techniques decreases in efficiency due to the fact that they become well known becausean efficient fraudster always find a new and inventive ways of performing his job.
5) There is a need for good metrics to evaluate the classifier system. For example, the overall accuracy is not suited for evaluation on a skewed distribution, since even with a very high accuracy; almost all fraudulent transactions can be misclassified.
6) The system should take care of the amount of money that is being lost due to fraud and the amount of money that will be required to detect that fraud. For example, no profit is made by stopping a fraudulent transaction that is way lesser than the amount of money that will be required to detect it.
7) These points directus to the most important necessity of the fraud detection system, which is, a decision layer. The decision layer decides what action to take when fraudulent behavior is observed taking into account factors like, the frequency and amount of the transaction.

D. Credit Card Fraud Detection Methods-

The Credit Card Fraud Detection Problem includes modeling past credit card transactions with the knowledge of the ones that turned out to be fraud. This model is then used to identify whether a new transaction is fraudulent or not. Our aim here is to detect 100% of the fraudulent transactions while minimizing the incorrect fraud classifications.

Credit card fraud detection methods On doing the literature survey of various methods for fraud detection we come to the conclusion that to detect credit card fraud there are multiple approaches like:

1) Logistic regression
2) AdaBoost
3) Gradient Boosting
4) Bagging
5) Random forest
6) Neural network

E. Logistic Regression-

Logistic Regression Logistic Regression is a supervised classification method that returnsthe probability of binary dependent variable that is predicted from the independent variableof dataset that is logistic regression predict the probability of an outcome which has two values either zero or one, yes or no and false or true. Logistic regression has similarities to linear regressionbut as in linear regression a straight line is obtained, logistic regression showsa curve. The use of one or several predictorsor independent variableis on what prediction is based, logistic regression produces logistic curves which plots the values between zero and one.

III. LITERATURE REVIEW

Table 1. A summary of studies investigating different statistical techniques in credit card fraud

Study	Country	Method	Details
Aleskerov et al. (1997)	Germany	Neural networks	Card-watch
Bently et al. (2000)	UK	Genetic programming	Logic rules and scoring process
Bolton & Hand (2002)	UK	Clustering techniques	Peer group analysis and break point analysis
Brause et al. (1999a)	Germany	Data mining techniques & neural networks	Data mining application combined probabilistic and neuro-adaptive approach
Chan et al. (1999)	USA	Algorithms	Suspect behavioral prediction
Dorronsoro et al. (1997)	Spain	Neural networks	Neural classifier
Ezawa & Norton (1996)	USA	Bayesian networks	Telecommunication industry
Fan et al. (2001)	USA	Decision tree	Inductive decision tree
Ghosh & Reilly (1994)	USA	Neural networks	FDS (fraud detection system)
Kim & Kim (2002)	Korea	Neural classifier	Improving detection efficiency and focusing on bias of training sample as in skewed distribution. To reduce "mis-detections".
Kokkinaki (1997)	Cyprus	Decision tree	Similarity tree based on decision tree logic
Leonard (1995)	Canada	Expert system	Rule-based Expert system for fraud detection (fraud modelling)
Maes et al. (2002)	USA	Bayesian networks & neural networks	Credit card industry, back-propagation of error signals
Kim & Kim (2002)	Korea	Neural classifier	Improving detection efficiency and focusing on bias of training sample as in skewed distribution. To reduce "mis-detections".
Kokkinaki (1997)	Cyprus	Decision tree	Similarity tree based on decision tree logic
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Maes et al. (2002)	USA	Bayesian networks & neural networks	Credit card industry, back-propagation of error signals
Quah & Sriganesh (2007)	Singapore	Neural networks	Self-Organizing Map (SOM) through real-time fraud detection system
Wheeler & Aitken (2000)	UK	Combining algorithms	Diagnostic algorithms; diagnostic resolution strategies; probabilistic curve algorithm; best match algorithm; negative selection algorithms; density selection algorithms and approaches
Zaslavsky & Strizkak (2006)	Ukraine	Neural networks	SOM, algorithm for detection of fraudulent operations in payment system

IV. RESULTS

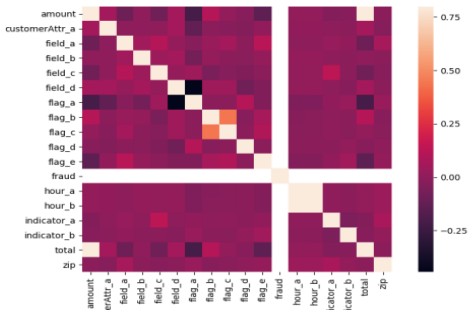
This detection process constitutes of four steps. These steps are mentioned below-

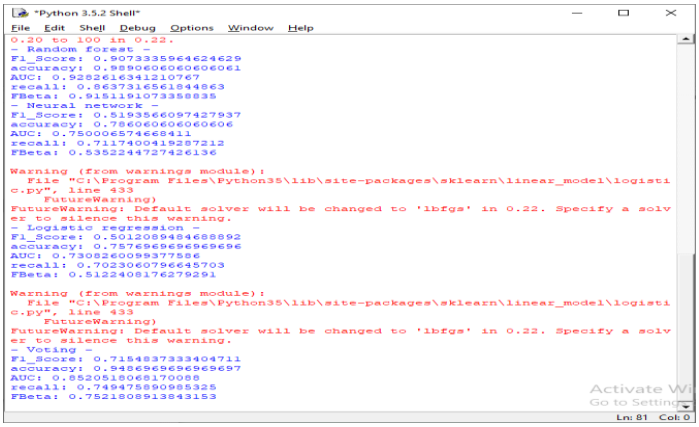
A. Input all the transactions record and standardize the data. Finally get the sample which includes the confidential information about the card holder in the data set with their consent.

B. In this step the CCusage frequency count, CC location, CC overdraft, Current bank balance and average daily spending is computed.

C. Generating critical values after finding out the limited number of generations for critical fraud detected, monitorable fraud detected, ordinary fraud detected, etc. using Genetic Algorithm.

D. Generate fraud transactions detected in the final step. It is done by applying detection mining on critical values obtained in the process of fraud detection.





V. CONCLUSION

The importance of Machine Learning and Data Science cannot be overstated. If you are interested in studying past trends and training machines to learn with time how to define scenarios, identify and label events, or predict a value in the present or future, data science is of the essence. It is essential to study the underlying data and model it by selecting an appropriate algorithm to approach any such use case. The various control parameters of the algorithm need to be tweaked to fit the data set. As a result, the developed application improves and becomes more efficient in solving the problem.

Credit card fraud has been deeply rooted in the ecommerce industry. In this scenario more of the financial losses are associated with the e-commerce merchants. To save merchant from these losses we have proposed the Credit Card fraud risk assessment model. In order to improve fraud risk assessment we have used combination of two presented methods. In proposed model, genetic algorithm is applied on the clusters generated by Logistic regression algorithm. Genetic algorithm will optimize the output generated by Logistic regression.

The rule engine is used so that system is scalable in terms of rules. In future this model can be extended by adding various rules in rule engine to improve accuracy of the system.

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