

## **A cost sensitive Random Forest Algorithm for Detecting a credit card Fraud techniques.**

**Dr.M.Rajaiah**, Dean Academics & HOD, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

**Dr.P.Chandrakanth**, Associate Professor, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

**Ms.Sk.Sumaya**, UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

**Ms.Sk.Shabeena**, UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

**Mr.U.Surendra**, UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

**Mr.S.Abhinav**, UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

### **Abstract:**

As technology developed, new business-making mechanisms emerged in the financial sector. One of them is the credit card system. But due to several flaws in this method, numerous issues are raised in this system by credit card frauds. The industry as well as customers who use credit cards is suffering greatly as a result. Lessons on investigating actual credit card figures in relation to privacy concerns are lacking. In the publication, an effort has been made to uncover credit card fraud using algorithms that used machine learning approaches. In this regard, two algorithms are used via Fraud Detection in credit card using Decision Tree and Fraud Detection using Random Forest. Some available online data can be used as a sample to determine the model's efficacy. Then, a financial institution's genuine globe credit card details group is analyzed. Additionally, additional noise is added to the data samples in order to auxiliary assess the systems' durability. The first approach in the study is significant since it builds a tree against the user's behaviors, and by utilizing this tree, frauds will be detected. In the second way, a user activity-based forest will be built, and it will be attempted to identify the suspect using this forest. The findings of the analysis unequivocally demonstrate that the common elective method detects credit card fraud situations with respectable degrees of precision.

**Keywords:** *Gaussian Mixture, Bayesian Network, Clustering, DAG, Credit Card, Tree, Forest, Scam.*

## **1.INTRODUCTION:**

When a firm takes precautions against whipped cash, goods, or amenities obtained through an unlawful credit card operation, credit card scam detection is taking place. Customers and third parties can both be the victims of credit card fraud. There are many techniques developed to prevent such frauds. If such frauds occur, then methods for locating the improper transactions are also devised. Many new and original algorithms have been put out to protect digital data transfers against unwanted access. However, there are certain negative aspects in one way or another. This essay discusses techniques for identifying credit card fraud.

For the purpose of detecting fraud, a variety of supervised and semi-supervised machine learning techniques are used. However, our goal is to address three key issues with the card fraud dataset, namely, the strong class imbalance, the inclusion of labeled and unlabelled samples, and the need to process a large volume of transactions.

Different To identify fraudulent transactions in real-time datasets, supervised machine learning algorithms such as Decision Trees, Naive Bayes's Classification, Least Squares Regression, Logistic Regression, and random forest algorithm are utilized. To train the behavioral characteristics of typical and aberrant transactions, two random forest techniques are utilized. They are CART-based and Random-tree-based random forests. Despite the fact that random forest produces decent results on despite the tiny data set, there are still some issues when the data is unbalanced. The upcoming work will concentrate on resolving the aforementioned issue. The random forest algorithm itself needs to be improved.

Research is being done on investigating meta-classifiers and meta-learning methodologies in managing highly skewed credit card fraud data in order to study the performance of Logistic Regression, K-Nearest Neighbor, and Nave Bayes. Using supervised learning techniques to identify fraud instances may not always be successful. a deep auto-encoder and restricted Boltzmann machine (RBM) model that may create typical transactions to identify abnormalities in typically occurring patterns. Additionally, a hybrid technique that combines the Adaboost and Majority Voting procedures has been devised.

## **2.PROPOSED SYSTEM:**

Machine Learning basically provides the system with the "ability to learn". The machine is able to use previously procured data and analyze it further without being explicitly commanded to. This feature is basically beneficial in detection of credit card frauds. This enables machine learning algorithms to be successfully implemented in the

banking domain to identify the potentially risky transactions. We use various Classification models of Supervised machine learning to predict wrongful transactions with the help of an imbalanced dataset.

### **3.LITERATURE SURVEY:**

Multiple Supervised and Semi-Supervised machine learning techniques are used for fraud detection [8], but we aim is to overcome three main challenges with card frauds related dataset i.e., strong class imbalance, the inclusion of labelled and unlabelled samples, and to increase the ability to process a large number of transactions.

Different Supervised machine learning algorithms [3] like Decision Trees, Naive Bayes Classification, Least Squares Regression, Logistic Regression and SVM are used to detect fraudulent transactions in real-time datasets. Two methods under random forests [6] are used to train the behavioral features of normal and abnormal transactions. They are Random-tree-based random forest and CART-based. Even though random forest obtains good results on small set data, there are still some problems in case of imbalanced data. The future work will focus on solving the above-mentioned problem. The algorithm of the random forest itself should be improved.

Performance of Logistic Regression, K-Nearest Neighbor, and Naïve Bays are analyzed on highly skewed credit card fraud data where Research is carried out on examining meta-classifiers and meta-learning approaches in handling highly imbalanced credit card fraud data.

Through supervised learning methods can be used there may fail at certain cases of detecting the fraud cases. A model of deep Auto-encoder and restricted Boltzmann machine (RBM) [2] that can construct normal transactions to find anomalies from normal patterns. Not only that a hybrid method is developed with a combination of Adaboost and Majority Voting methods [4].

### **4.PROPOSED ANALYSIS**

When contrasted to the customer's prior purchases, card transactions are always foreign. This When they are known as idea drift difficulties, unfamiliarity is a particularly challenging problem in the actual world. It is possible to think off concept drift as a variable that evolves over time and in unexpected ways. These factors significantly unbalance the data. Our research's primary goal is to find a solution to the Concept Drift issue for real-world application.

Attribute name	Description
Transaction id	Identification number of transaction
Cardholder id	Unique identification number given to the cardholder
Amount	Amount transferred or credit in a particular transaction by the customer
Time	Details like time and date, to identify when the transaction was made
Label	To specify whether the transaction is genuine or fraudulent

**Table 1:** Raw features of credit card transactions

Table 1, [1] shows basic features that are captured when any transaction is made.

#### 4.1 Dataset Description

The dataset [11] contains transactions made by a cardholder in duration in 2 days i.e., two days in the month of September 2013. Where there are total 1,00,006 transactions among which there are 492 i.e., 0.172% transactions are fraudulent transactions. This dataset is highly unbalanced. Since providing transaction details of a customer is considered to issue related to confidentiality, therefore most of the features in the dataset are transformed using principal component analysis (PCA). V1, V2, V3,..., V28 are PCA applied features and rest i.e., 'time', 'amount' and 'class' are non-PCA applied features, as shown in table 2

S.no	Feature	Description
1.	Time	Time in seconds to specify the elapses between the current transaction and first transaction.
2.	Amount	Transaction amount
3.	Class	0 – not fraud 1 – fraud

**Table 2:** Attributes of European dataset

According to this matrix, the attribute class is unrelated to the transaction's value and timing. Even from the matrix, it is evident that the qualities used in PCA determine the transaction's class.

**Algorithm:**

Algorithm to derive aggregated transaction details and to extract card holder features using sliding window technique l: length of T

Genuine= [];

Fraud= [];

For i in range 0 to l-w+1:

T: [];

/\* sliding window features\*/

For j in range i+w-1:

/\*Add the transaction to window \*/

T=T+tj id;

End

/\* features extraction related to

amount \*/ ai1=MAX\_AMT(Ti);

ai2=MIN\_AMT(Ti);

ai3=AVG\_AMT(Ti);

ai4=AMT(Ti); For j in range

i+w-1:

/\* Time elapse \*/

xi= Time(tj)-Time(tj-1)

End

Xi= (ai1, ai2,ai3,ai4,ai5,xi);

Y= LABEL(Ti);

/\* classifying a transaction into fraud

or not \*/ if Yi=0 then

Genuine =Genuine U Xi;

Else

Fraud =Fraud

U Xi; End

The old transactions are eliminated when a new one is fed to the window, and step 2 is carried out for each set of transactions. (The Sliding-Window based approach of aggregation algorithm is referred from. After pre-processing, we use the cardholders' behavior patterns in each group to train several classifiers and extract fraud characteristics. Even when we apply classifiers to the dataset, they do not perform well because of the imbalance (shown in fig. 4) in the dataset.

#### 4.2 Proposed Methodology

This section outlines the steps involved in holding a credit card hostage. Credit card companies use a variety of effective techniques to identify and stop frauds, including arrangement orientation, device learning, neural networks, artificial intelligence, and fuzzy logic. In recent years, credit card theft has grown increasingly prevalent. . In Current day, the fraud is one of the key causes of excessive business losses, not only for merchants, distinct clients are also affected. Therefore, there are various ways to spot this form of scam. Initially, the approved and dishonest operations were divided into categories using the clustering approach, which involved data cauterization of areas of factor value.. Additionally, the probability thickness of the credit card operator's previous performance is modeled using a Gaussian mixture model so that the likelihood of current actions may be meant to be perceived. any irregularities from the historical behavior. . Finally, the measurements of a particular user and the indicators of various fraud scenarios are defined using Bayesian networks. Figure 3 below displays an illustration of the suggested model.

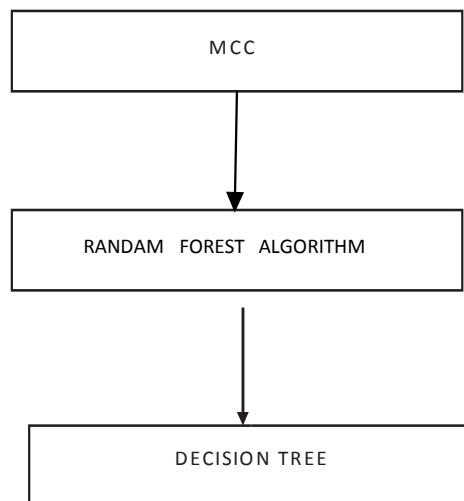


Fig. 4: Proposed Methodology

In our proposed system we use the following formulae to evaluate, accuracy and precision are never good parameters for evaluating a model. But when evaluating any model, accuracy and precision are always thought of as the fundamental factor.

A machine learning metric called the Matthews Correlation Coefficient (MCC) is used to assess the balance of binary (two-class) classifiers. Since it accounts for both true and false values, it is typically seen as a balanced measure that can be applied across all classes.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{MCC} = \frac{\text{TP} * \text{TN} - \text{FP} * \text{FN}}{\sqrt{(\text{TP} + \text{FN})(\text{TP} + \text{FP})(\text{TN} + \text{FN})(\text{TN} + \text{FP})}}$$

MCC =

TP – True Positive

TN- True Negative

FP- False Positive

FN- False Negative

### EXPERIMENTAL RESULTS AND ANALYSIS:

On the original dataset as well as the SMOTE dataset, we have tested a few models. The data are summarized, and the accuracy, precision, and MCC all display significant variations. Even better for decision tree class datasets, we employed the one-class random forest algorithm. Our dataset contains two classes; thus, we can also utilize the one-class random forest algorithm.

Methods	Accuracy	precision	Random forest
Local outlier forest	0.8990	0.0038	0.0172
Isolation forest	0.9011	0.0147	0.1047
Support vector machine	0.9987	0.7681	0.5257

Logistic regression	0.9990	0.875	0.6766
Decision tree	0.9994	0.8854	0.8356
Random forest	0.9994	0.9310	0.8268

**Table 3:** Accuracy, Precision and MCC values before applying SMOTE

Table 3, shows the results on the dataset before applying SMOTE and fig 5, shows the same results graphically.

### One-Class Random Forest

Accuracy: 0.7009 Precision: 0.7015

Methods	Accuracy	Precision	MCC
Local outlier factor	0.4582	0.2941	0.1376
Isolation forest	0.5883	0.9447	0.2961
Logistic regression	0.9718	0.9831	0.9438
Decision tree	0.9708	0.9814	0.9420
Random forest	0.9998	0.9996	0.9996

**Table 4:** Accuracy, Precision and MCC values after applying SMOTE

Table 4, shows the results on the dataset after applying SMOTE and fig 6, shows the same results graphically.

By using our proposed system, we will get below outputs, In the below figure, we are calculating the accuracy levels in the form of pie charts.



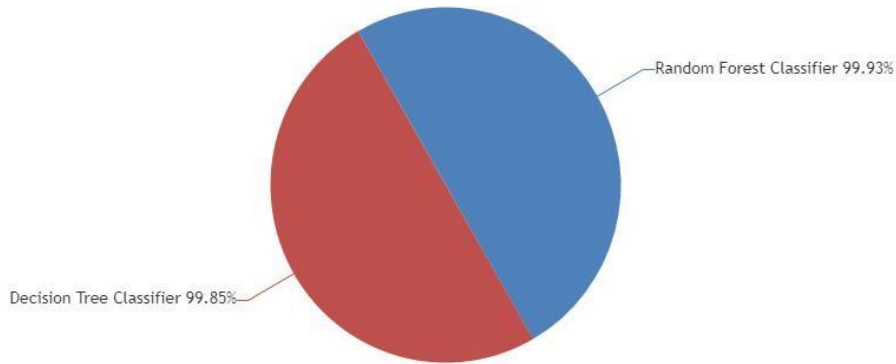


Fig4: accuracy results in the form of pie chart

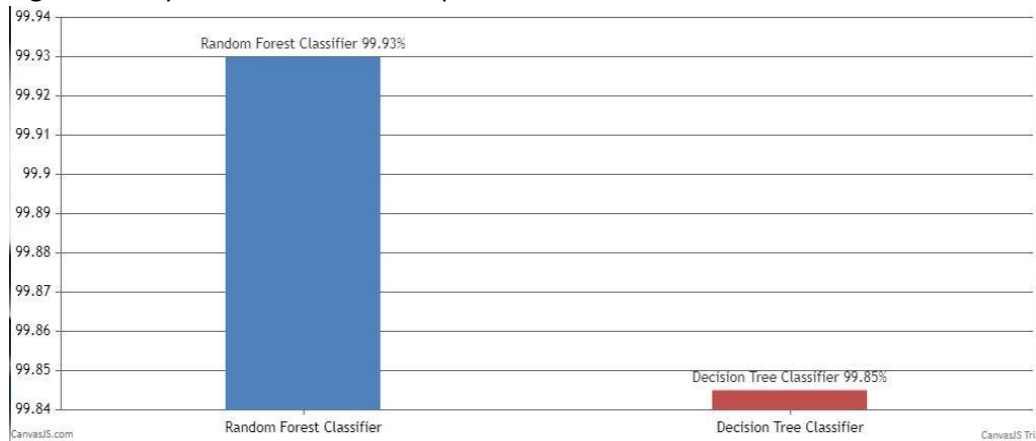


Fig5: Accuracy values in bar charts

In the below figure, Here we are able to see Accuracy values in bar charts

In the below figure, display the output based on the given data set and it displays the credit card fraud cases and valid transactions



Fig. 6: Detected Fraud Data values

## 5.CONCLUSION:

In this study, we created a unique fraud detection technique that groups clients according to their transactions. and analyse behaviour to create a profile for each cardholder. Following the application of various classifiers to three distinct groups, rating scores are produced for each type of classifier. The system adapts as a result of these dynamic changes in the parameters. Prompt response to new cardholder's transactional behaviours. A feedback system is then used to address the issue of notion drift. We The Matthews Correlation Coefficient was shown to be the superior metric for handling imbalance datasets. It wasn't only MCC. solution. We attempted to balance the dataset by using SMOTE and discovered that the classifiers were performing better than before. The use of one-class classifiers, such as one-class SVM, is an alternative method for addressing imbalance datasets. Finally, we found that the algorithms that produced the best outcomes were random forest, decision tree, and logistic regression.

## References:

- [1] Adewumi and A. A. Akinyelu, "A survey of machine learning and nature-inspired based credit card fraud detection techniques," *International Journal of System Assurance Engineering and Management*, vol. 8, pp. 937– 953, 2017J. Clerk Maxwell, *A Treatise on Electricity and Magnetism*, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68-73.
- [2] A. Srivastava, A. Kundu, S. Sural, A. Majumdar, "Credit card fraud detection using hidden Markov model," *IEEE Transactions on Dependable and Secure Computing*, vol. 5, no. 1, pp. 37–48, 2008K. Elissa, "Title of paper if known," unpublished.
- [3] Bansal, J. C., Singh, P. K., Saraswat, M., Verma, A., Jadon, S. S., and Abraham, A. (2011). Inertia weight strategies in particle swarm optimization. In *Nature and Biologically Inspired Computing (NaBIC)*, (Salamanca, Spain, October 19 - 21, 2011).IEEE NaBIC'11,633--640.
- [4] Bello - Orgaz, G., Jung, J. J., & Camacho, D. (2016). Social big data: Recent achievements and new challenges. *Information Fusion*. 28 (Mar.2016), 45--59
- [5] Bharill, N., Tiwari, A., and Malviya, A. (2016). Fuzzy Based Clustering Algorithms to Handle Big Data with Implementation on Apache Spark.In *Proceedings of the IEEE 2nd International Conference on Big Data Computing Service and Applications*, (Oxford, UK, March 29-April 01, 2016). IEEE BigDataService '16, 95--104.
- [6] Y. Sahin, S. Bulkan, and E. Duman, "A cost -sensitive decision tree approach for fraud detection," *Expert Systems with Applications*, vol. 40, no. 15, pp. 5916–5923, 2013.

[7] J. T. Quah, and M. Sriganesh, "Real-time credit card fraud detection using computational intelligence," Expert Systems with Applications, vol. 35, no. 4, pp. 1721–1732, 2008.

[8] S. Bhattacharyya, S. Jha, K. Tharakunnel, and J. C., "Data mining for credit card fraud: A comparative study," Decision Support Systems, vol. 50, no. 3, pp. 602–613, 2011.

[9] S. Panigrahi, A. Kundu, S. Sural, and A. K Majumbar, "Use of Dempster-Shafer theory and Bayesian inferencing for fraud detection in communication networks", Lecture Notes in Computer Science, Springer Berlin/ Heidelberg, Vol. 4586, , 2007, p.446-460

### **Author Profiles**



**Dr.M.Rajaiah**, Currently working as an Dean Academics & HOD in the department of CSE at ASCET (Autonomous), Gudur, Tirupathi(DT).He has published more than 35 papers in Web of Science,Scopus,UGC Journals.



**Dr.P.Chandrakanth**, Currently working as an Assistant professor in the department of CSE at ASCET Autonomous),Gudur, Tirupati(DT).



**Ms.Sk.Sumaya**, B.Tech student in the department of CSE at Audisankara College of Engineering and Technology,Gudur. She has pursuing in compuer science and engineering.



**Ms.Sk.Shabeena**, B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur. She has pursuing in computer science and engineering.



**Mr.U.Surendra**, B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur. he has pursuing in computer science and engineering.



**Mr.S.Abhinav**, B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur. he has pursuing in computer science and engineering.