ONLINE PAYMENTS FRAUD DETECTION USING MACHINE LEARNING

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Abstract

Fraudulent online transactions have caused significant damage and loss to individuals and companies over a period of time. There has been an increase in online fraud with the progression of state-of-the-art technologies and worldwide communication. The design of efficient fraud detection algorithms is critical for reducing these losses. Machine learning and statistical techniques play a vital role in the detection of fraudulent transactions. Fraud detection model implementation is particularly challenging due to the lack of data, sensitive nature of data, and the unbalanced class distributions. It is tough to draw inferences and build better models due to the confidentiality of the records. In this paper we aim to focus on the problems: i) the role of sampling in the presence of class imbalance (i.e., nonfraudulent transactions are more in the percentage of the total transactions), ii) building and analyzing various machine learning models, iii) to assess and validate the performances of different fraud detection techniques. This paper has research directions toward applying machine learning for data analysis. We have designed and assessed a prototype of a fraudulent transactions detection system that will be able to meet real-world demands and increase the security of transactions for the customers.

Highlights

The primary objectives of this paper are drafted as follows

To address the above-mentioned challenges, this research has employed various techniques to handle the problems in online fraud detection. The following are the major contributions.

- The main objective of this research is to build statistical machine learning models to detect fraudulent transactions in real-time with great accuracy.
- To come up with various statistical techniques to deal with the imbalanced nature of the data. Like synthetic scaling of the data, which can decrease the skew without affecting the data integrity. This can help to improve the accuracy of the models.

To build an application that can detect the legitimacy of the transaction in real-time and increase the security to prevent fraud.

1.INTRODUCTION

Online transactions have become inevitable due to the ease of online purchases. To balance their busy schedules, people stick to online shopping. It enables us to trade any things available in different geographic regions. Due to advancements in e-commerce, people benefit from offers because they are attracted to online shopping. Though online shopping has enabled easy transactions, fraudulent transactions are also possible [1]. Fraudulent online transactions have caused significant damage and loss to individuals and companies over a period. There has been an increase in online fraud with the progression of state-of-the-art technologies and worldwide communication. The development of new technologies paves new ways for criminals to commit fraud like credit card frauds, ecommerce frauds, online transaction frauds, etc. Figure 1 presents the estimated fraudulent transaction loss by 2024[1]. According to the Associate of Certified Fraud Examiners estimates, the fraud costs the organization nearly $3.7trillion a year, i.e., a company typically loses five percent of its revenue due to fraud. As shown in Fig. 1 it is estimated that online payment fraud is growing annually and may amount to $50 billion by 2024 which was $26 billion in 2019 [1]. It has become the need of the hour to address the issue of online transaction fraud.

Online fraud is a term used for referring to theft and fraud committed using any kind of payment method like cards, online transactions, etc. Different types of online fraud are as follows (shown in Fig. 2):

1. Clean: It is a type of fraud where the fraudulent can pass through the merchant's checks as he pretends to be a legitimate user.
2. Account Takeover: A fraudulent connects his credit card to an account of a legitimate user.
3. Friendly: A Legitimate user denies the transaction made and the merchant has chargeback. It is also called Chargeback fraud.
4. Identity: Acquisition of personal sensitive details like passport or account number by impersonation is called Identity fraud.
5. Affiliate: The use of company details for individual purposes online is called Affiliate Fraud.

. Re-shipping: Use of recruited person or mule for re-shipping products purchased using stolen credit cards.

7. Botnets: A machine or Robot impersonates the geographical location of a legitimate credit card and performs transactions online. Due to the same geographical location, the transaction seems to be legitimate.

. Phishing: The fraudulent gathers sensitive information from authenticated users by sending seemingly official emails.

9. Whaling: Similar to phishing except that the target is a fixed set of consumers belonging to a profitable online firm.
10. Pharming: When performing online shopping customers are redirected to unauthorized websites where the user’s sensitive information may be gathered.
11. Triangulation: Credit card information is gathered from authenticated users through third-party online auctions or ticketing sites.

Credit card fraud is a type of Identity fraud. The mechanism used in identity fraud or Identity theft is impersonation. An authenticated user tries to impersonate an existing or non-existing user in Identity theft. Credit card frauds are considered to contribute a major part in frauds as they are easy due to transactions online and physical absence online. [1]. Fraudsters have their mechanisms for obtaining credit card details and the transactions are as though they are legitimate transactions. Transactions are classified into Card present Transactions (CP) and Card Not Present (CNP). A transaction is of the former type if the transaction is done in person at the time of sales. A transaction is of a later type when neither the card nor the cardholder is physically available during the transaction. The most common scenario of CNP transactions are:

1. Online Transactions: Cardholder and Card is in the same location and the merchant is elsewhere. Based on authentication verification, the purchase is sanctioned.
2. Purchase using Telephonic conversations: Similar to the previous method, merchants and cards are at different locations. The telephone number from which the call is made enables security checks.
3. Mail Orders: As with earlier types of the purchase order is accepted through the mail. A digital signature enables hassle-free transactions.
4. Subscription Payments: A customer pays for Mobile or TV etc. subscriptions. In the earlier method, similar orders were placed. It differs from the earlier case where the customer interaction does not occur at all during purchase.
5. Cloud Wallet Payment: This is an option that is widely used in the present era. In this type of transaction, mobile phone applications may act as a proxy for cards. The transaction is between the user and the cloud server. Security is the main concern in this type of transaction.

The proposed system works to identify credit card fraud. Researchers have been working in detecting credit card fraud, which accounts for the majority of online frauds. Detection of fraudulent transactions using the traditional condition-based system is inefficient and viable for hackers. Hence it is essential to deduce a process that is capable of analyzing tremendous amounts of data which should be adaptive to the tactics used by the fraudsters. When addressing the problem of fraud detection, the first challenge anyone faces is the imbalance in the dataset. Only 0.01% of transactions that take place around the world are fraudulent, and the rest are legitimate. [1] The dominance of the non-fraudulent class causes a major challenge. It causes an imbalance in detecting the characteristics of fraudulent transactions. In this project, we observe and analyze the various sampling techniques like random under-sampling, random oversampling, and Synthetic Minority Over-sampling Technique (SMOTe). This helps to tackle the imbalanced data problem.

The second part of this paper mainly focuses on building and training various machine learning models, which will help in the classification. Some of the models built in this project are logistic regression, decision tree, naïve Bayes, random forest, XGboost, KNN, and artificial neural networks (ANN). All these models are built, trained, tested, and validated based on various statistical parameters like precision, recall, and F1 score. Once the model is built and analyzed, the best-performing model is selected to be incorporated into the web application, which can predict the nature of the transaction in real-time. The idea is that the web application acquires the data from the ongoing and runs it through the model to determine the nature of the transaction.

2 Related Works

Credit card fraud detection is one of the hottest topics in the field of banking and computer science. Lots of time and money are being spent on the research to come up with a better prediction system. Researchers have done lots of work in the field of machine learning and have come up with various techniques that incorporate machine learning to detect online frauds [2]. The thesis [1] by Dal Pozzolo Andrea,” Adaptive Machine learning for credit card fraud detection”, gives an overall ideology of how the credit card fraud detection system works. The first part of this section explains the prediction and classification using machine learning. The second part justifies the use of various sampling techniques to improve the performance. The third part focuses on the analysis and performance evaluation of the various ML models. Finally, it shows the implementation of the Fraud Detection System (FDS) in the realtime scenario using web API

2 1 CREDIT CARD FROUD DETECTION

[3–9] discusses the working of various ML techniques. [5] [6] [8] shows the use of simple and primitive machine learning techniques for the binary classifier. [9] Is a comparative study between various machine learning algorithms and neural networks. The main challenge faced in all the mentioned papers is the availability of the dataset. Since the banking information is sensitive, they are hidden and protected which makes it difficult to derive inference from the data. Lots of processing capacity and time are spent on building the models. In [4] the problem with this approach is that random forest always leads to an overfitting problem. [14–25] are about the implementation of the best-performing models in the real-time scenario. According to these papers, most the real-time implementation is in the beginning stage. A web application or an API can be used to check the legitimacy of the transaction when it is taking place. It requires additional computational requirements. Also, the dataset is dynamic, so the model must adapt on its own. The main challenge is that the system must be capable of handling millions of transactions taking place every minute. It requires a powerful computing system to handle this process. [26–27] provide online information about credit card fraud and the issues that online transactions face if the problem becomes undetected.

2 2 IMMBALENCED CLASSIFIER

The imbalanced nature of the dataset and how it can be handled is the next part of the research. [12] [13] discusses in detail various sampling techniques and how the skewed data set affects the results of the model. The large distribution of non-fraudulent transactions, when compared to fraudulent transactions, is known as skewed distribution. The oversampling method generates or recreates the existing samples to overcome the problem of skewed distribution in data samples. Synthetic cost-based data set overcomes the problem of skewed distribution [12]. [17] Mainly covers the different analysis techniques that can be used to evaluate the models. In [6], various cross-validation techniques are used to validate the models. K-fold CV and leave one out CV are some of the commonly used techniques. Also, this paper covers statistical evaluation tools like the ROC curve, Area under Precision-Recall Curve (AUPRC), and F1 score. These evaluate the classification ability of the models. Paper [17] explains the feature extraction used to find the importance of each variable. Given the imbalanced nature of the data, the results of the model are always skewed towards the major class. So, the AUC score cannot be used to evaluate the models. Other statistical parameters like precision and recall are used.

3. Research Contribution

To address the above-mentioned challenges, this research has employed various techniques to handle the problems in online fraud detection. The following are the major contributions.

- The main objective of this research is to build statistical machine learning models to detect fraudulent transactions in real-time with great accuracy.
- To come up with various statistical techniques to deal with the imbalanced nature of the data. Like synthetic scaling of the data, which can decrease the skew without affecting the data integrity. This can help to improve the accuracy of the models.
- To build an application that can detect the legitimacy of the transaction in real-time and increase the security to prevent fraud.

3.1 Challenge and motivation

Enormous Data: A large amount of data is processed on a daily basis and the models built must be suitable and fast to detect fraudulent transactions.

Imbalanced Data i.e., the fraudulent transaction in the dataset is very low this makes it difficult to identify the frauds.

Data availability: The banking data is confidential and hence difficult to obtain.

Misclassified Data: hard to catch and report every fraudulent transaction. This causes misclassification of the models.

Adaptive techniques are found and used against the model by the hackers.

4. Dataset Used

[Dataset][1] https://www.kaggle.com/aherparesh/credit-card-fraud-detection/data

The above dataset has nearly 3500 records of transactions. It has around 400 records of fraudulent transactions. The dataset has 10 predictors and one target. The dataset is cleaned and pre-processed before implementing any machine learning algorithms. Data attributes in the dataset are Average Amount per transaction, Transaction amount, Is declined, Total Number of declines/day, is Foreign Transaction, is High-Risk Country, Daily_charge back_avg_amt, 6_month_avg_chbk_amt,6-month_chbk_freq and Is Fraud

5. Pre-processing Of Data

The dataset which was imported has to be cleaned before it is fit for building models. The abovementioned credit card data has empty columns and unnecessary fields and missing values which have to be cleaned.

Figure 3 depicts a data set before preprocessing. In Fig. 3 the transaction date is empty, and the fraudulent column has Y and N which cannot be observed by the model. It has to be formatted as 0 and 1.
In Fig. 4 the data is preprocessed. The unnecessary columns which are not helpful in the model building were dropped, the empty columns were removed, and the rows missing values are dropped.

5.1 Standardaization

The dataset has to be brought to s normal form for the models to be built properly. This helps in improving the data exploration and data modeling part. Figure 5 presents the Normalized dataset.

6.Proposed work

This research proposes a novel technique that focuses on the task of detecting online transaction frauds in realtime. The objective of this work is to design a computationally inexpensive and accurate machine learning model for fraud detection. Various machine learning models are deployed. Three different techniques are deployed to handle the imbalanced data. They are random oversampling, random undersampling, and SMOTe technique. Figure 6 shows the Steps in Credit Card Processing

6.1.Model Bulding

Various models have been used to detect fraudulent transactions online. These models are briefly discussed in this section. Since fraud detection is a classification problem, our focus is mainly on classification models. Also, as we are planning to deal with the imbalanced nature of the data, we intend to build models that handle the minority class.

6.1.1 Logistic Regression

Logistic regression is one of the powerful classification tools borrowed by machine learning from the field of statistics. It is a simple yet powerful way to model binomial outcomes with one or more predicting variables. It measures the relationship between the predictor and the target variables by calculating probabilities using a logistic function, which is the cumulative logistic distribution. The vector β = (β1, β2, β3,…, βn) represents the coefficients and X = (X1, X2, X3,…, Xn) represents the multiple predictors in the dataset, and ϵ is the model's error.

$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots + \beta_n X_n + \epsilon$ (Equ. 1)

Equ. 1 represents the primary logistic function. The probability of the classes can be determined by the logarithmic function given below in Equ. 2

$$l = \log_b \left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \text{ (Equ.2)}$$

By simple algebraic manipulation to Equ. 2, we get p, which is the probability of the minority class.

6.1.2 K Nearest Neighbors(KNN)

Based on nearest neighbors for a given query point, a non-parametric method KNN is devised. For a given data set, the Euclidean distance is computed between the data set and the available data set. Among the data set, the data points with minimal Euclidian

$$\sqrt{\sum_{i=1}^{n}(xi - yi)^2} \text{ (Equ. 3)}$$

Equ. 3 shows the Euclidean distance function.

6.1.3 Navie Bayes

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$$P(Y/X_1, X2,...,X_n) = \frac{P(X1,X2, . . . ,Xn/Y)P(Y)}{P(X1,X2, . . . ,Xn)} \quad \text{(Equ. 4)}$$

Equ. 5 shows the Bayesian conditional probabilities of each class with respect to the predictors X_1, $X_{2, ...,}$ X_n.

6.1.4 Decision tree

A decision tree is a tree data structure that helps to arrive at inference derivation based on conditions to predict the outputs. A class attribute is represented by a leaf node and each intermediate node is split into sub-nodes based on the attribute. The path obtained from Root to leaf is used for forming the classification rule. Data are classified by using the attributes of each node. It is used for further classification and regression models.

6.1.5 Random Forest

Just like the Decision tree, the random forest can also be used for both classification and regression problems. It is mainly used for classification problems. Just like a real forest is made up of many trees, a random forest is nothing but a combination of multiple decision-making trees. Nodes of the random forest are composed of decision trees, each one deriving the prediction from the dataset. It is an ensemble technique consisting of multiple trees. The only problem is the overfitting of the model.

Figure 7 presents the working of the Random Forest model.

6.1.6 SVM

Support Vector Machine (SVM) is a supervised machine learning algorithm. It can be used to handle both classification and regression problems. Just like random forest SVM is mainly used as a classifier. In SVM, the data points are plotted in a dimensional space, where the coordinate is the value of the variables. Now the classification can be performed by finding the hyper-plane. Fig explains the splitting of the data points in a ndimensional space.

6.1.7 XGBoost

XGBoost is an example of the ensemble learning technique. Using just a single model to handle realworld problems is not usually enough. Ensemble learning techniques are collections of models and it is suitable in many scenarios. The resultant output is achieved by the aggregation of several models.

The models above which other models are built are called the base learners. Different algorithms can be integrated with the base model. The commonly used base learners are bagging and boosting. This technique can be used with any model, but it is most commonly used with decision trees.

6.2 Imbalenced classifier

Two different approaches are taken to tackle the imbalanced class problem. The first approach is a data preprocessing technique to handle the classes, like oversampling and under-sampling. The second approach is based on generating new data

- **Under-sampling** is sampling class is points from the major class so that both the classes will be balanced.
- **Oversampling** is adding more data points to the minor class in order to increase their numbers.
- **SMOTE** synthetically generates new data points in the minor class within a bounded region to increase its number.

6.2.1 Random under sampling

The Random Under sampling technique balances class distribution by randomly eliminating the majority of class data points. This is done until the major and the minor class data points are balanced. Random under sampling involves randomly selecting data points from the majority class to delete from the training dataset. This has the effect of reducing the number of data points in the major class in the sampled version of the training dataset.

6.2.2 Random Oversampling

In this method, the minority class is replicated or new observations are created. Using the new minority class the imbalance may be reduced. This method of replication and re-creation enables the increase in minority data. But the drawback of the method is that it may encounter an over-fitting problem as the data are replicated.

6.2.3 SMOTe

SMOTe is an oversampling technique that artificially generates data points in the minority class to increase the number and balance the dataset. This technique works by choosing a random point from the minority class and making a bounded region inside the minority class now the data points are generated within this region. In this way, we can be sure that the integrity of the dataset is not compromised by these additional instances.

In this research, we primarily relied on SMOTe technique to handle the imbalanced nature of the data. All the models are subjected to SMOTe to see the improvement in their performance.

7.Results

The results and accuracies of models are compiled together to perform the evaluation of different models under different conditions. We also analyze the other statistical performance of the models to see how well the models perform the classification. Because of the skewed nature of the data, it is important to check the Area under the Precision-Recall Curve (AUPRC) because the accuracy parameter is not reliable

7.1 Accuracy,Precision,Recall,and F1 score

To measure Accuracy, Precision, Recall, and F1 score, the following parameters are needed.

TP = True Positive. Fraudulent transactions. The model is predicted as fraudulent.

TN = True Negative. Legitimate transactions. The model is predicted as Legitimate.

FP = False Positive. Legitimate transactions. The model is predicted as fraudulent.

FN = False Negative. Fraudulent transactions. The model is predicted as Legitimate.

Accuracy

Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$ (Equ. 5)

Equ 5 gives the accuracy of the model which depicts how many data points are correctly classified. Precision

Precision

TP Recall = T

———P+FP (Equ. 6)

Equ 6 gives the precision of the model. It answers the question “out of all transactions that are predicted to be fraudulent, what percent are actually fraudulent”.

Recall

$$Recall = \frac{TP}{TP+FN} \quad \text{(Equ. 7)}$$

Equ 7 gives the recall of the model. It basically answers the question “out of all the fraudulent transactions how many are correctly classified by the model”.

F1 Score

$$F1Score = 2 * \frac{Recall*Precision}{Recall+Precision} \quad \text{(Equ. 8)}$$

Equ. 8 gives the F1 score of the model. F1 score is the harmonic mean of the recall and precision. F1 score takes both false positives and false negatives into account. In an imbalanced data F1 score is more effective than the accuracy

7.2. Model Performance

The Confusion Matrix of the applied methods is given in Fig. 8. The F1 score, precision, recall, and AUC of each model are calculated to analyze the performance of the models. All these data are tabulated below. The bestperforming model is used to build the fraud predicting Application. The below table gives the final performance of the model after the SMOTe technique is deployed.

Table 1
Model Performance for a small sample data set

Models	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.985	0.970	0.923	0.946
KNN	0.977	0.948	0.885	0.916
Naive Bayes	0.951	0.840	0.800	0.819
Decision tree	0.924	0.960	0.466	0.628
SVM	0.992	0.990	0.952	0.970
Random forest	0.985	0.960	0.933	0.947
XGBoost	0.984	0.951	0.933	0.942

According to Table 1, the highest F1 score is provided by the SVM model and closely followed by the random forest. This signifies that the best classification is provided by the SVM with a F1 score of 97%.

So, the SVM model is used in the application to detect frauds.

Figure 9 shows the ROC curve is plotted for all the models built to analyze the performance of the models. From the curves, we can infer that the SVM classifier has the maximum AUC (Area under the Curve). The AUC score of the SVM is 0.975.

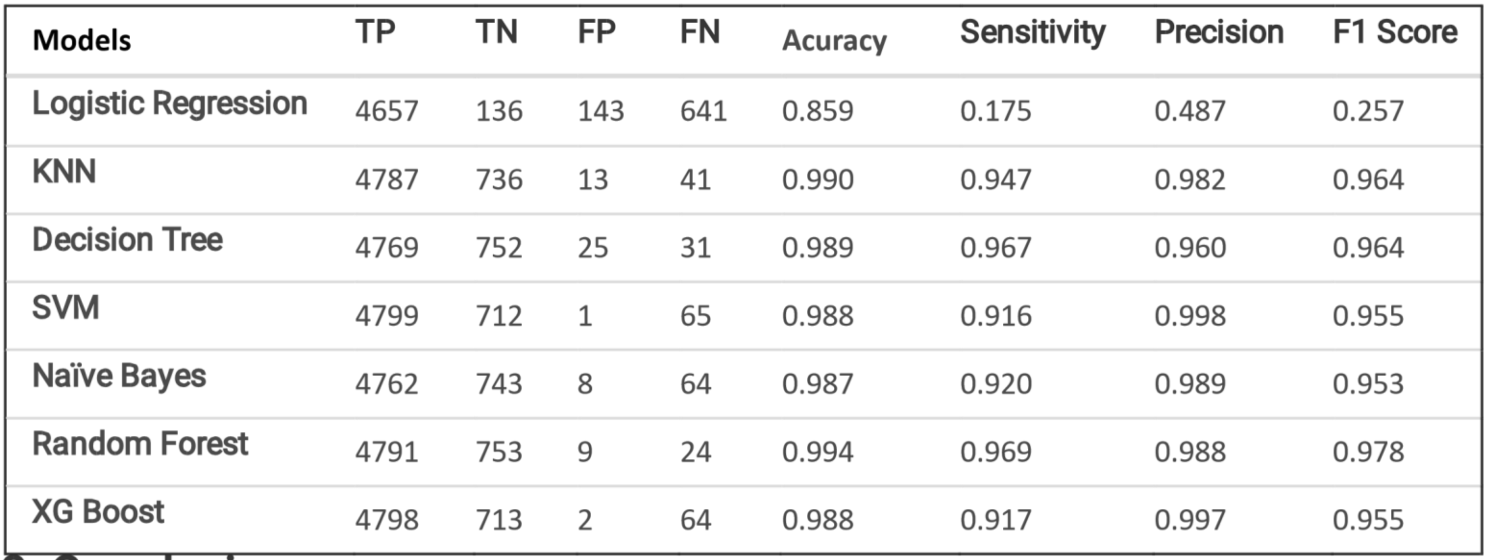
In order to run some more comparative analyses on the model, the model has been trained using a larger dataset with nearly 22500 records. This will give an insight into how the model performs once the transaction is increased and the dataset skewed. The dataset is extended to 22500 transactions. The model's new metrics are observed so as to compare them with the previous results of the model. A sample screenshot for the Random Forest model is available in Fig. 10. It was observed that when data sets are increased, Logistic regression fails to achieve F1 score when compared to the other models. It is because the Random Forest Model exhibits a high F1 score of 0.978. The ROC curve is plotted for the models and is available in Fig. 12.

Although Logistic regression is a relatively simple model and will underperform against more complex models, Logistic regression works under the assumption that there is no multicollinearity. Multicollinearity occurs when there are two or more independent variables in a multiple regression model, which have a high correlation among themselves. One way to find multicollinearity in a dataset is to check the Variance Inflation Factor (VIF) of the features. The VIF values during the algorithm performance is given in Fig. 11.

We can see that VIF values of ‘Is declined’, ‘isHighRiskCountry’, ‘Daily_chargeback_avg_amt’ and ‘6_month_avg_chbk_amt’ are high, which indicates that there is a multicollinearity in the dataset 2. This issue can be resolved by dropping the columns. But because of the lack of availability of data we cannot rely on the performance of logistic regression.

Table 2

Model Performance for large Data set



Models	TP	TN	FP	FN	Acuracy	Sensitivity	Precision	F1 Score
Logistic Regression	4657	136	143	641	0.859	0.175	0.487	0.257
KNN	4787	736	13	41	0.990	0.947	0.982	0.964
Decision Tree	4769	752	25	31	0.989	0.967	0.960	0.964
SVM	4799	712	1	65	0.988	0.916	0.998	0.955
Naïve Bayes	4762	743	8	64	0.987	0.920	0.989	0.953
Random Forest	4791	753	9	24	0.994	0.969	0.988	0.978
XG Boost	4798	713	2	64	0.988	0.917	0.997	0.955

8. Conclusion

Finding fraudulent online transactions is one of the major problems faced in banking and online societies today. In this paper, we have built various machine learning models and analyzed their performances against different datasets based on the capacity and the volume of the data.

Declarations

Ethical Approval

Testing the models against a different dataset with considerable volume helps us to understand the model performance in real-time. By applying the SMOTE, we handled the imbalanced nature of the dataset. The other way of handling an imbalanced dataset is to use oneclass classifiers like one-class SVM, random under sampling and random oversampling. After analyzing the models with large data sets, Random Forest gives the maximum F1 score of 97% and it is used as a primary model to build the web application. We finally observed that random forest and XGBoost are the algorithms that gave better results. The work can be extended to develop adaptive machine learning fraudulent detection methods for complex real-world data which is characterized by imbalance data set.

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Not applicable

Consent to Publish

Not applicable

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Free available data used

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Online Payments Fraud Detection using Python

I will start this task by importing the necessary Python libraries and the **data set** we need for this task:

```
import pandas as pd import numpy

as np data = pd.read_csv("credit

card.csv") print(data.head())
```

```
   step   type        amount     nameOrig      oldbalanceOrg    newbalanceOrig  \
0   1   PAYMENT     9839.64    C1231006815    170136.0          160296.36
1   1   PAYMENT     1864.28    C1666544295     21249.0           19384.72
2   1   TRANSFER     181.00    C1305486145       181.0               0.00
3   1   CASH_OUT     181.00    C840083671        181.0               0.00
4   1   PAYMENT    11668.14    C2048537720     41554.0           29885.86
```

```
     nameDest          oldbalanceDest     newbalanceDest       isFraud    isFlaggedFraud
0    M1979787155          0.0                0.0                  0           0
1    M2044282225          0.0                0.0                  0           0
2    C553264065           0.0                0.0                  1           0
3    C38997010         21182.0               0.0                  1           0
4    M1230701703          0.0                0.0                  0           0
```

Now, let’s have a look at whether this dataset has any null values or not:

```
print(data.isnull().sum())
step                    0
type                    0
amount                  0
nameOrig                0 oldbalanceOrg
0 newbalanceOrig    0
nameDest                0 oldbalanceDest
0 newbalanceDest    0
isFraud                 0
isFlaggedFraud      0 dtype:
int64
```

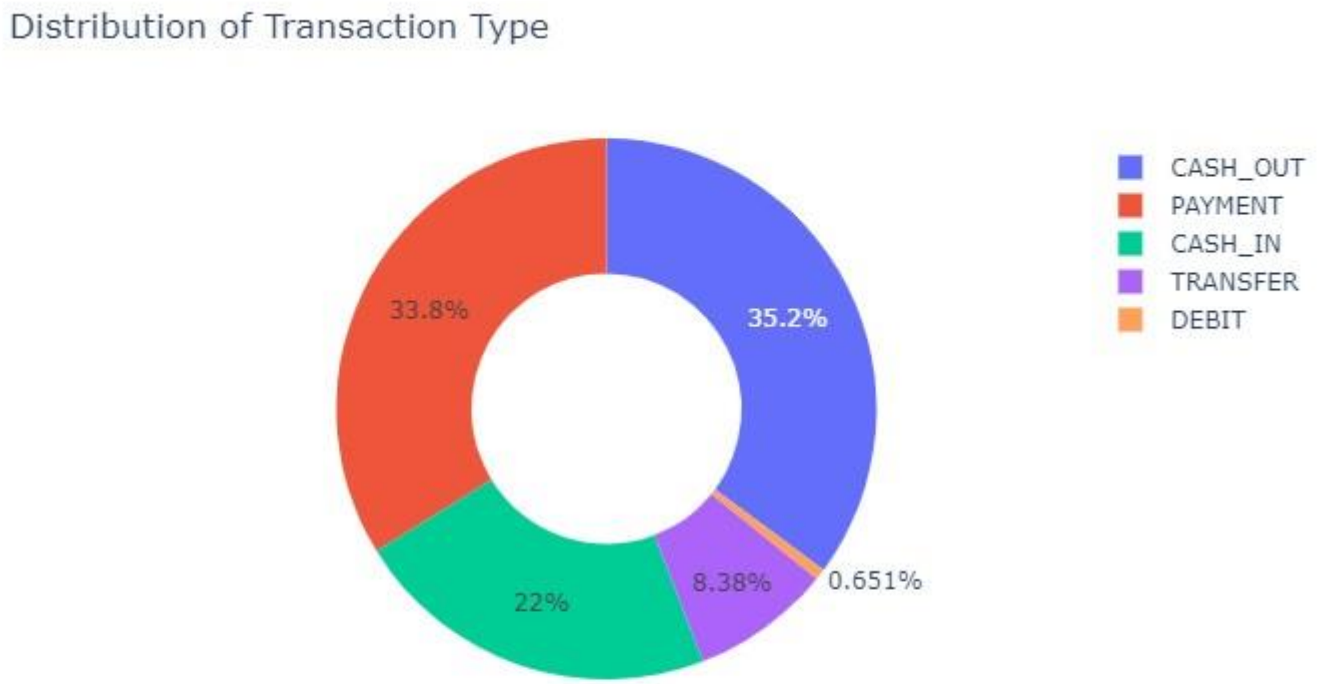
So this dataset does not have any null values. Before moving forward, now, let’s have a look at the type of transaction mentioned in the dataset:

```
    # Exploring transaction type
    print(data.type.value_counts())
```

```
CASH_OUT        2237500
PAYMENT         2151495
CASH_IN         1399284
TRANSFER        532909
DEBIT           41432
Name: type, dtype: int64
```

```
    type = data["type"].value_counts()

    transactions = type.index
                                                        quantity = type.values
```

```
import plotly.express as px

figure = px.pie(data,

         values=quantity,

         names=transactions,hole = 0.5,

         title="Distribution of Transaction Type")

figure.show()
```



Now let’s have a look at the correlation between the features of the data with the **isFraud** column:

```
# Checking correlation    correlation
= data.corr()
print(correlation["isFraud"].sort_values(ascending=False))
```

```
isFraud                    1.000000 amount
0.076688 isFlaggedFraud
0.044109
```

```
step                    0.031578 oldbalanceOrg
0.010154 newbalanceDest       0.000535
oldbalanceDest       -0.005885
newbalanceOrig       -0.008148
Name: isFraud, dtype: float64
```

Now let’s transform the categorical features into numerical. Here I will also transform the values of the **isFraud** column into No Fraud and Fraud labels to have a better understanding of the output:

```
data["type"] = data["type"].map({"CASH_OUT": 1, "PAYMENT": 2,
                                 "CASH_IN": 3, "TRANSFER": 4,
                                 "DEBIT": 5})
data["isFraud"] = data["isFraud"].map({0: "No Fraud", 1: "Fraud"})
print(data.head())
```

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Figures

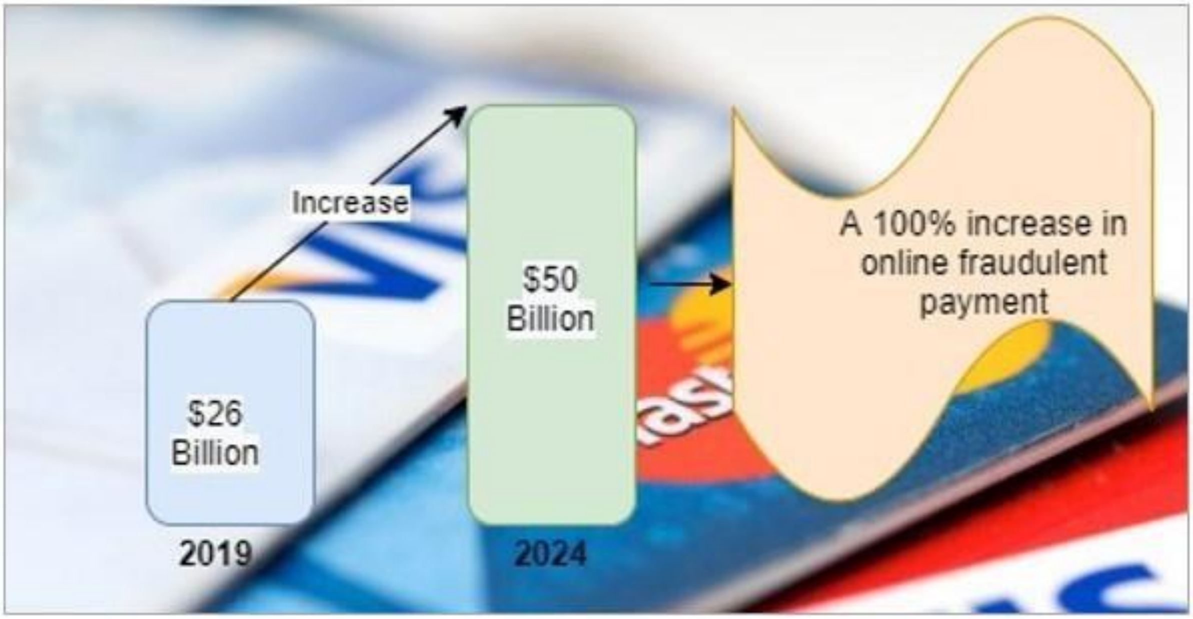


Figure 1

Increase in Online fraudulent payment.

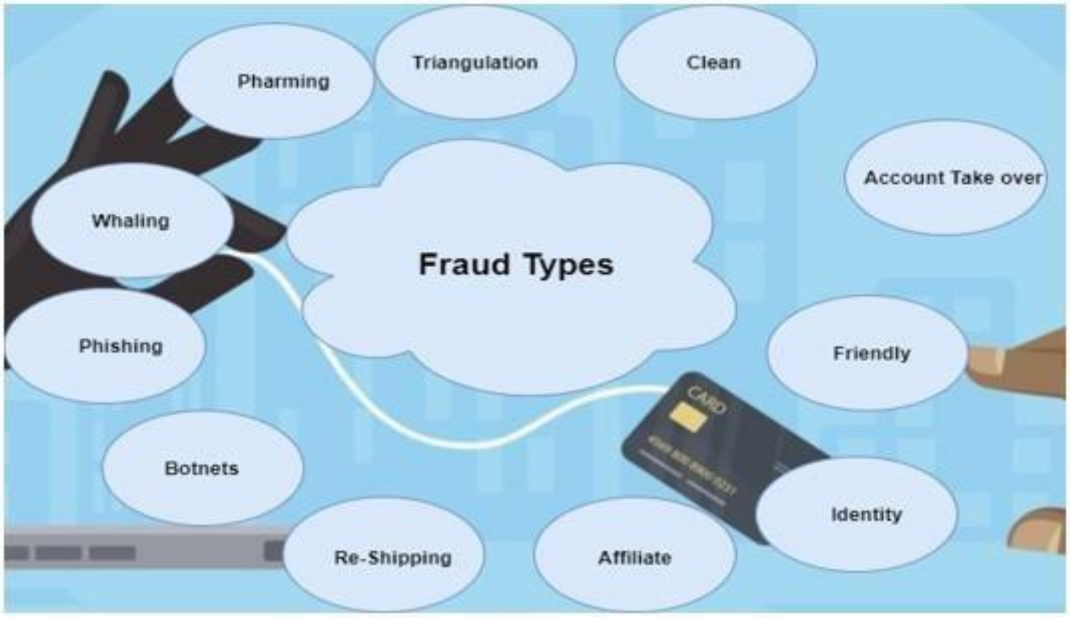
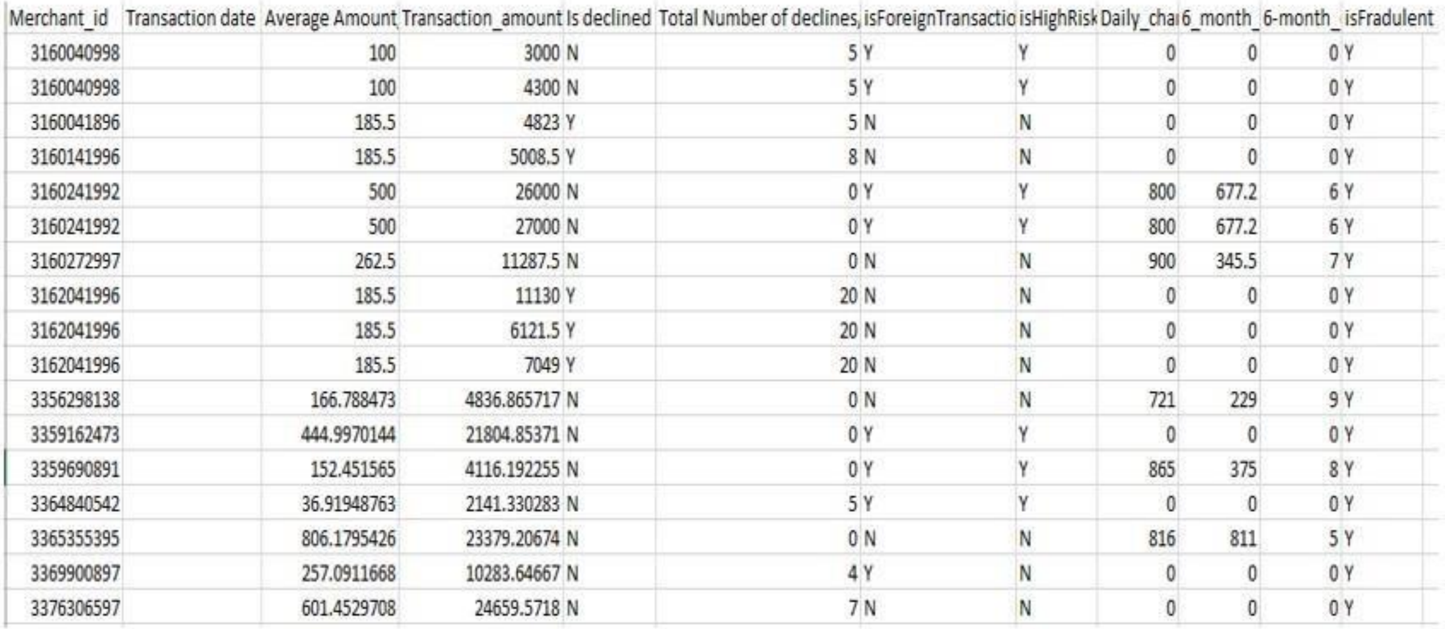


Figure 2

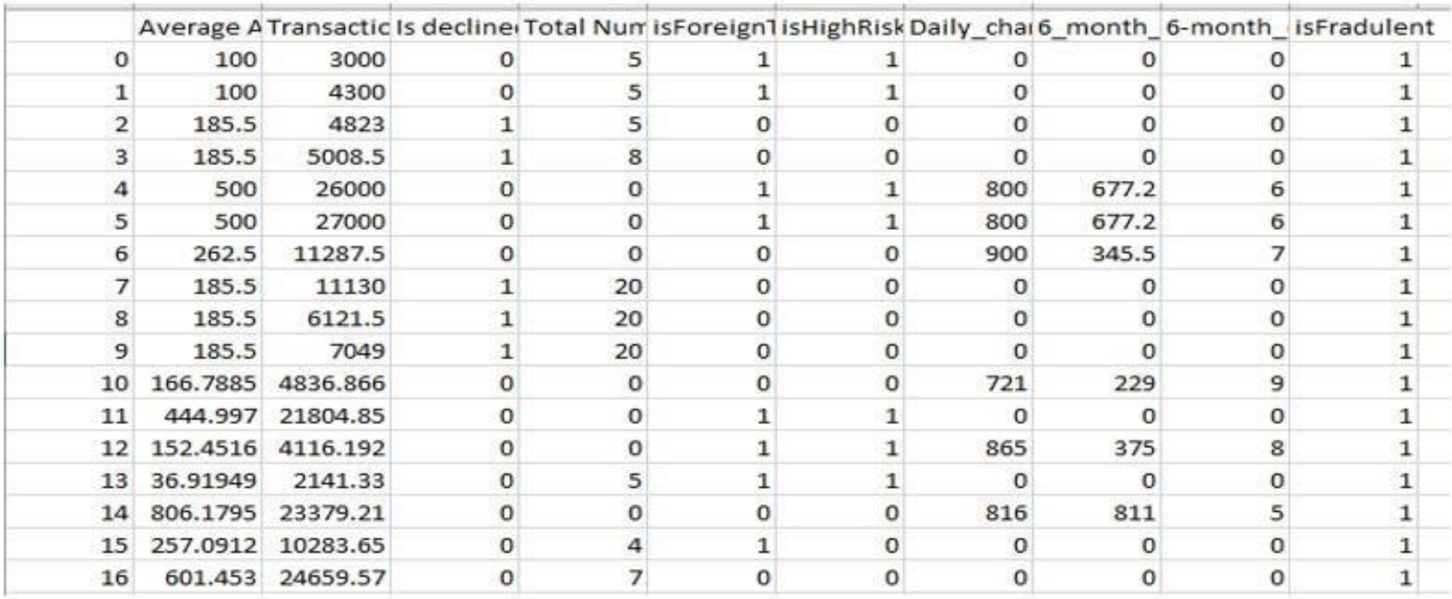
Types of Online Frauds



Merchant_id	Transaction date	Average Amount	Transaction_amount	Is declined	Total Number of declines,	isForeignTransactio	isHighRisk	Daily_cha	6_month_	6-month_	isFradulent
3160040998		100	3000	N	5	Y	Y	0	0	0	Y
3160040998		100	4300	N	5	Y	Y	0	0	0	Y
3160041896		185.5	4823	Y	5	N	N	0	0	0	Y
3160141996		185.5	5008.5	Y	8	N	N	0	0	0	Y
3160241992		500	26000	N	0	Y	Y	800	677.2	6	Y
3160241992		500	27000	N	0	Y	Y	800	677.2	6	Y
3160272997		262.5	11287.5	N	0	N	N	900	345.5	7	Y
3162041996		185.5	11130	Y	20	N	N	0	0	0	Y
3162041996		185.5	6121.5	Y	20	N	N	0	0	0	Y
3162041996		185.5	7049	Y	20	N	N	0	0	0	Y
3356298138		166.788473	4836.865717	N	0	N	N	721	229	9	Y
3359162473		444.9970144	21804.85371	N	0	Y	Y	0	0	0	Y
3359690891		152.451565	4116.192255	N	0	Y	Y	865	375	8	Y
3364840542		36.91948763	2141.330283	N	5	Y	Y	0	0	0	Y
3365355395		806.1795426	23379.20674	N	0	N	N	816	811	5	Y
3369900897		257.0911668	10283.64667	N	4	Y	N	0	0	0	Y
3376306597		601.4529708	24659.5718	N	7	N	N	0	0	0	Y

Figure 3

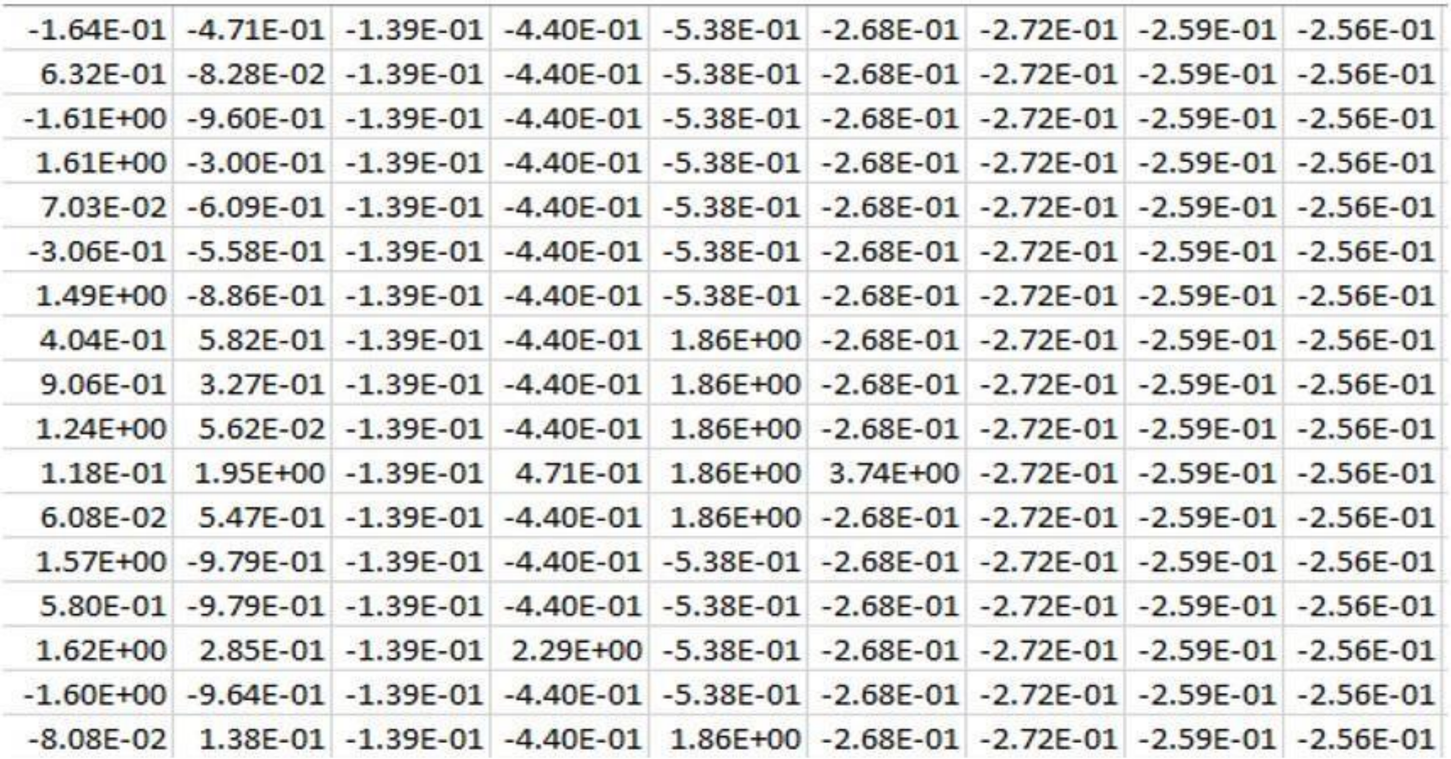
Dataset before preprocessing



	Average A	Transactic	Is decline	Total Num	isForeignT	isHighRisk	Daily_cha	6_month_	6-month_	isFradulent
0	100	3000	0	5	1	1	0	0	0	1
1	100	4300	0	5	1	1	0	0	0	1
2	185.5	4823	1	5	0	0	0	0	0	1
3	185.5	5008.5	1	8	0	0	0	0	0	1
4	500	26000	0	0	1	1	800	677.2	6	1
5	500	27000	0	0	1	1	800	677.2	6	1
6	262.5	11287.5	0	0	0	0	900	345.5	7	1
7	185.5	11130	1	20	0	0	0	0	0	1
8	185.5	6121.5	1	20	0	0	0	0	0	1
9	185.5	7049	1	20	0	0	0	0	0	1
10	166.7885	4836.866	0	0	0	0	721	229	9	1
11	444.997	21804.85	0	0	1	1	0	0	0	1
12	152.4516	4116.192	0	0	1	1	865	375	8	1
13	36.91949	2141.33	0	5	1	1	0	0	0	1
14	806.1795	23379.21	0	0	0	0	816	811	5	1
15	257.0912	10283.65	0	4	1	0	0	0	0	1
16	601.453	24659.57	0	7	0	0	0	0	0	1

Figure 4

Dataset after preprocessing and formatting



-1.64E-01	-4.71E-01	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
6.32E-01	-8.28E-02	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
-1.61E+00	-9.60E-01	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
1.61E+00	-3.00E-01	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
7.03E-02	-6.09E-01	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
-3.06E-01	-5.58E-01	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
1.49E+00	-8.86E-01	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
4.04E-01	5.82E-01	-1.39E-01	-4.40E-01	1.86E+00	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
9.06E-01	3.27E-01	-1.39E-01	-4.40E-01	1.86E+00	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
1.24E+00	5.62E-02	-1.39E-01	-4.40E-01	1.86E+00	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
1.18E-01	1.95E+00	-1.39E-01	4.71E-01	1.86E+00	3.74E+00	-2.72E-01	-2.59E-01	-2.56E-01
6.08E-02	5.47E-01	-1.39E-01	-4.40E-01	1.86E+00	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
1.57E+00	-9.79E-01	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
5.80E-01	-9.79E-01	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
1.62E+00	2.85E-01	-1.39E-01	2.29E+00	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
-1.60E+00	-9.64E-01	-1.39E-01	-4.40E-01	-5.38E-01	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01
-8.08E-02	1.38E-01	-1.39E-01	-4.40E-01	1.86E+00	-2.68E-01	-2.72E-01	-2.59E-01	-2.56E-01

Figure 5

Normalized dataset

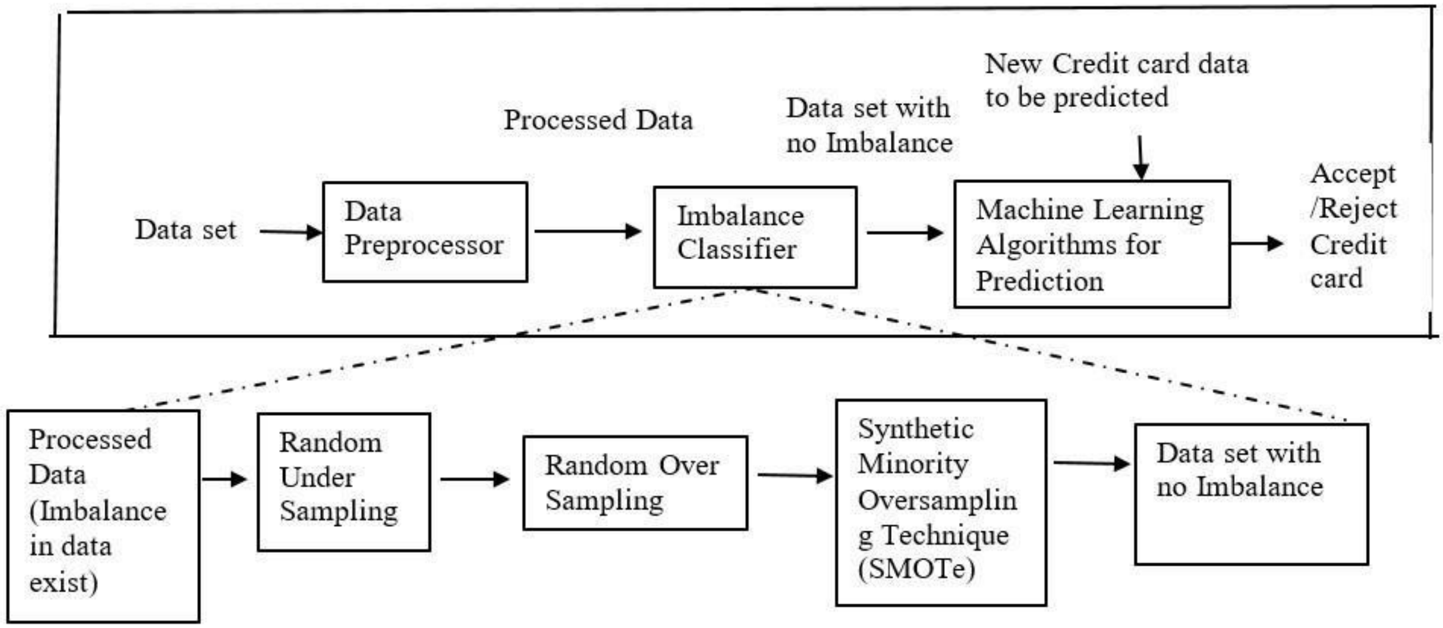

New Credit card data to be predicted
Processed Data
Data set with no Imbalance
Data set
Data Preprocessor
Imbalance Classifier
Machine Learning Algorithms for Prediction
Accept /Reject Credit card
Processed Data (Imbalance in data exist)
Random Under Sampling
Random Over Sampling
Synthetic Minority Oversamplin g Technique (SMOTe)
Data set with no Imbalance

Figure 6

Steps in Credit Card Processing

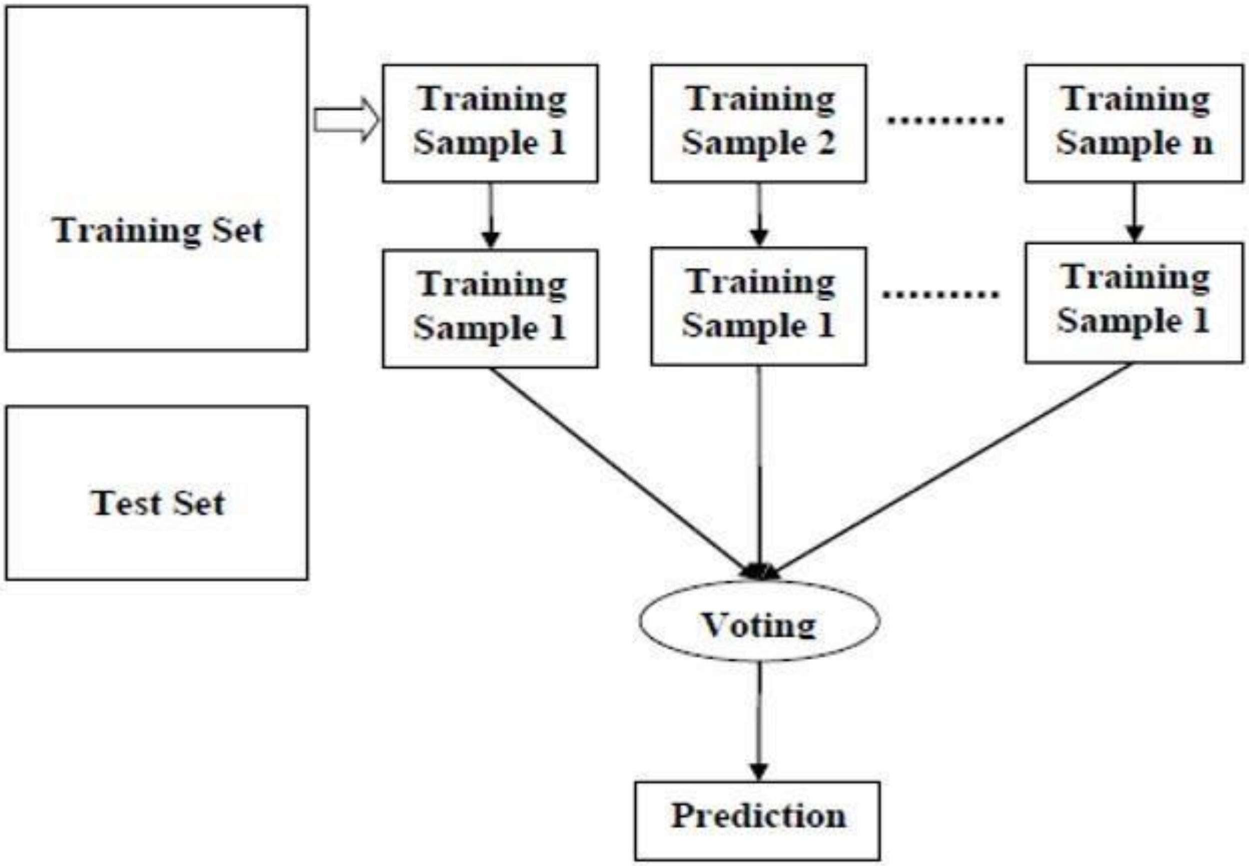
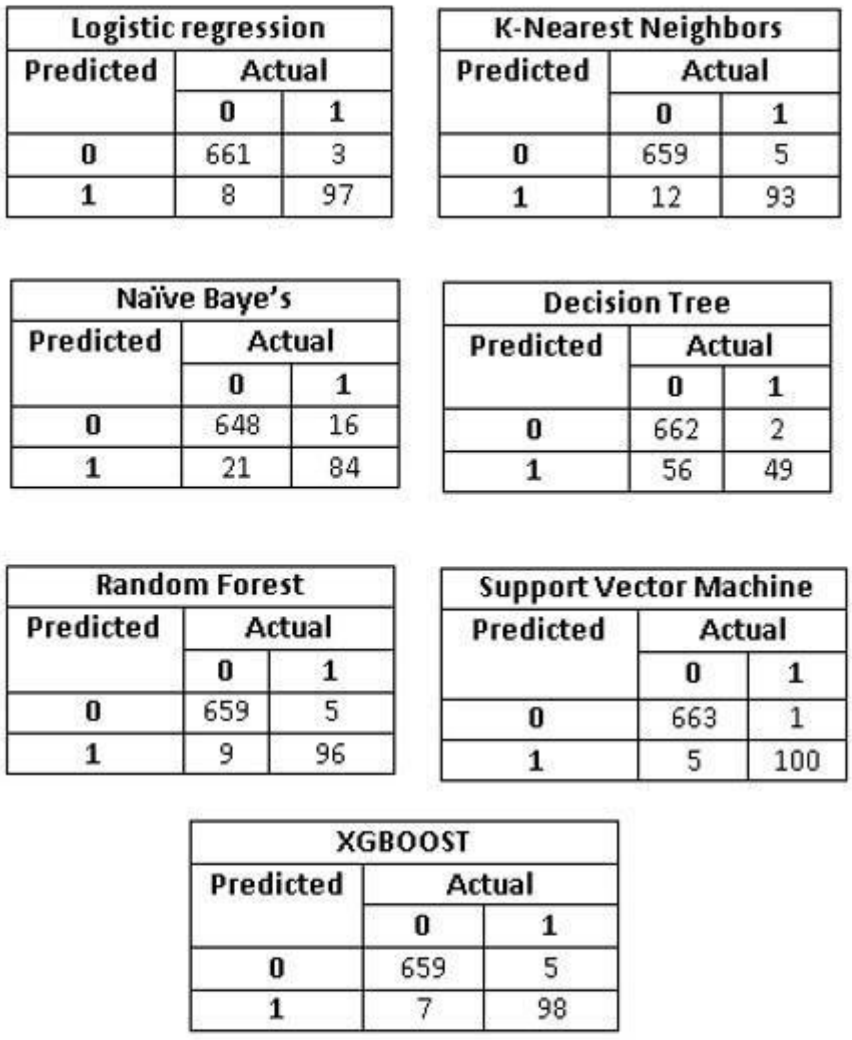


Figure 7

Working of Random Forest Model



Logistic regression		
Predicted	Actual	
	0	1
0	661	3
1	8	97

K-Nearest Neighbors		
Predicted	Actual	
	0	1
0	659	5
1	12	93

Naïve Baye's		
Predicted	Actual	
	0	1
0	648	16
1	21	84

Decision Tree		
Predicted	Actual	
	0	1
0	662	2
1	56	49

Random Forest		
Predicted	Actual	
	0	1
0	659	5
1	9	96

Support Vector Machine		
Predicted	Actual	
	0	1
0	663	1
1	5	100

XGBOOST		
Predicted	Actual	
	0	1
0	659	5
1	7	98

Figure 8

Confusion matrix for the algorithms

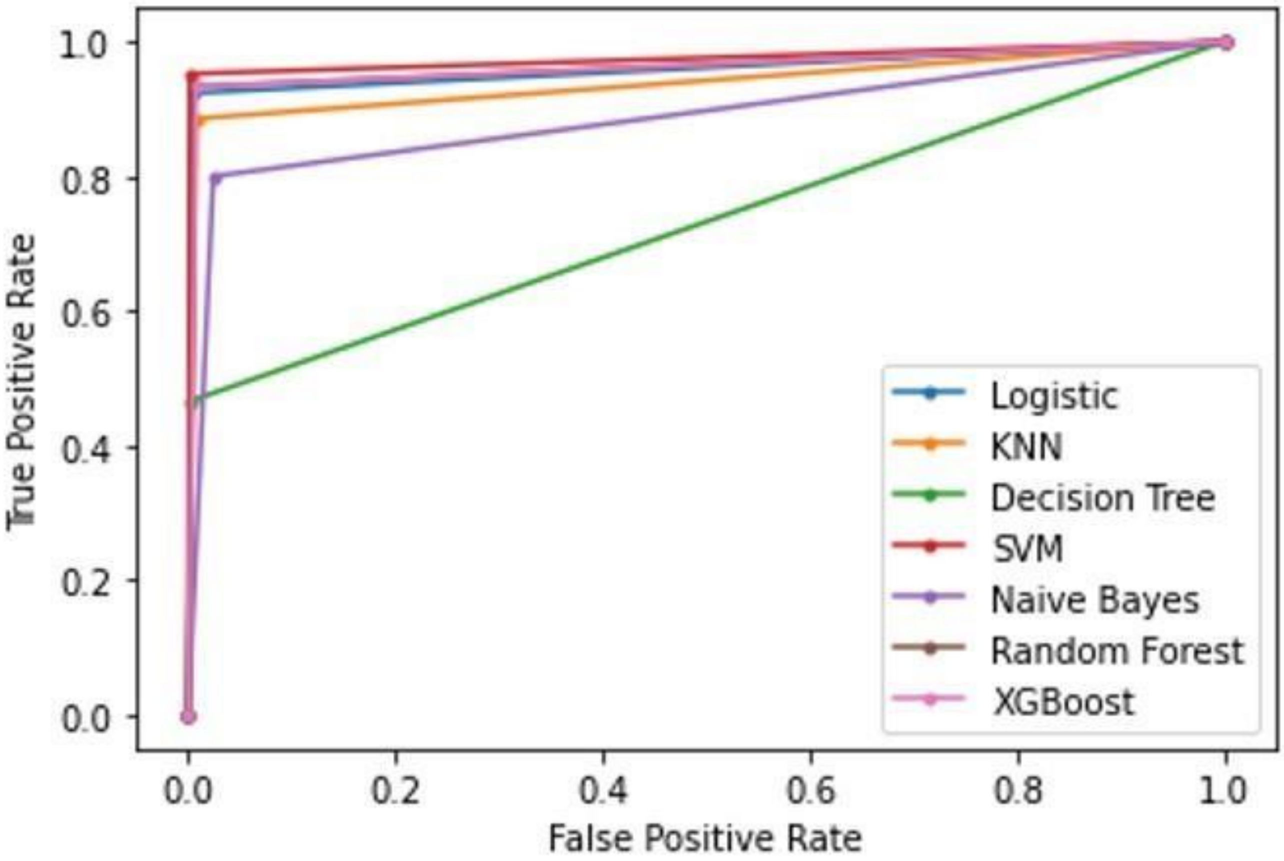
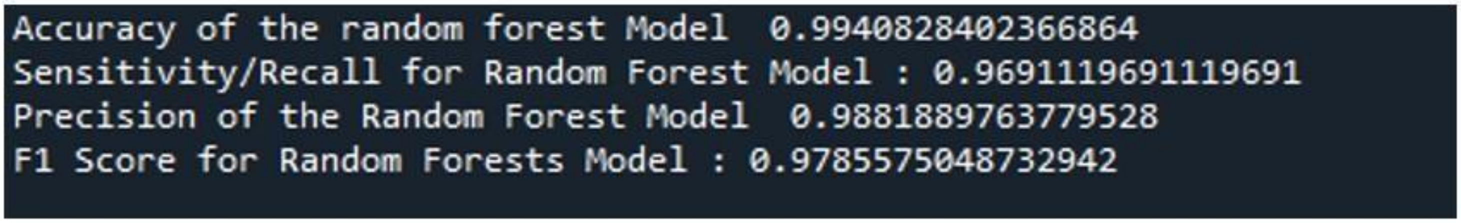


Figure 9

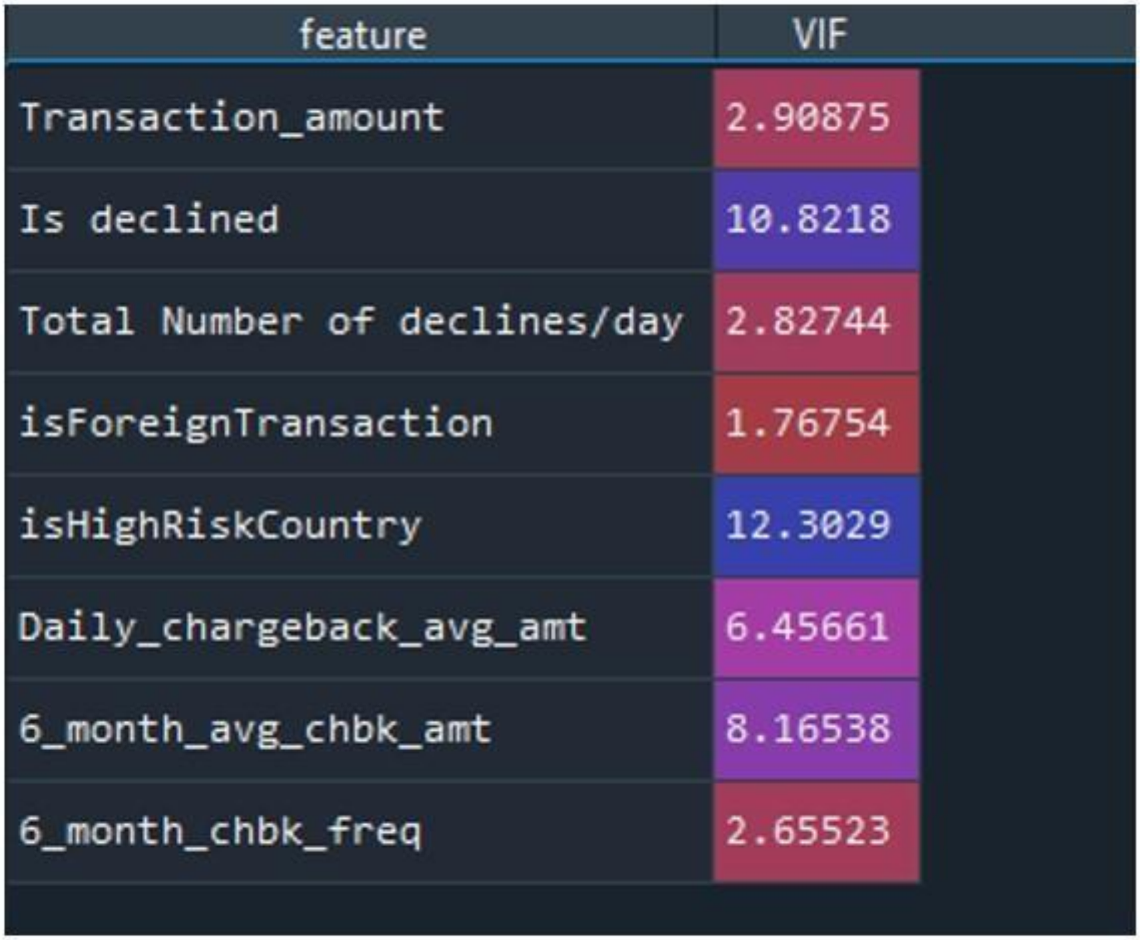
ROC curve 1



```
Accuracy of the random forest Model  0.9940828402366864
Sensitivity/Recall for Random Forest Model : 0.9691119691119691
Precision of the Random Forest Model  0.9881889763779528
F1 Score for Random Forests Model : 0.9785575048732942
```

Figure 10

Output for Random Forest Model



feature	VIF
Transaction_amount	2.90875
Is declined	10.8218
Total Number of declines/day	2.82744
isForeignTransaction	1.76754
isHighRiskCountry	12.3029
Daily_chargeback_avg_amt	6.45661
6_month_avg_chbk_amt	8.16538
6_month_chbk_freq	2.65523

Figure 11

VIF of Logistic Regression

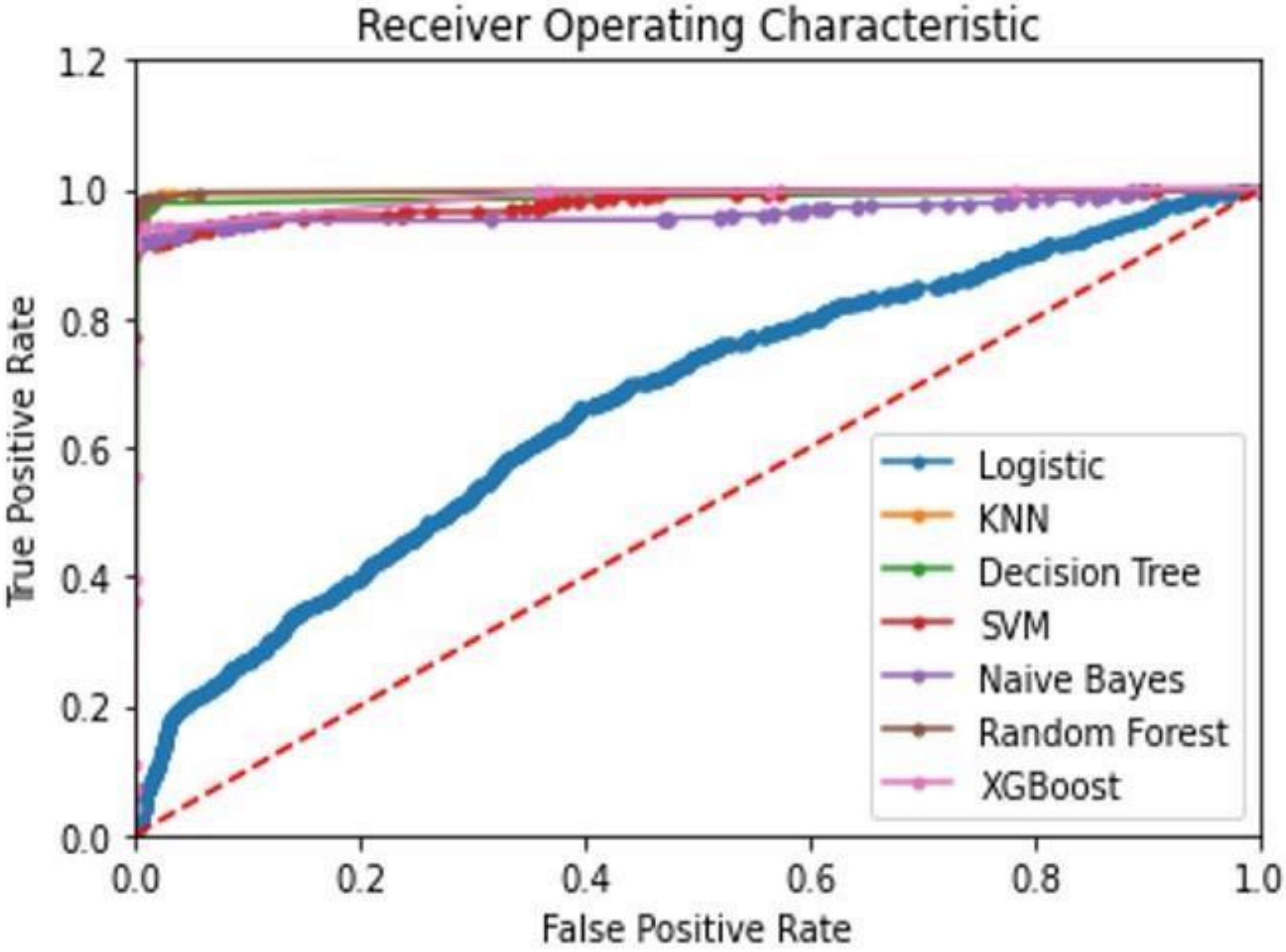


Figure 12

ROC Curve 2