CREDIT CARD FRAUD DETECTION USING MACHINE LEARNING

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ABSTRACT- In current scenario when the term "fraud" comes into our mind, credit card fraud clicks to mind so far. With the great increase in credit card transactions, credit card fraud has increasing excessively in recent years. Our goal is to develop a predictive algorithm that can differentiate between authentic and fraudulent activity by utilizing past transaction data. The project starts with thorough data preprocessing, which includes resolving missing values, normalizing features, and using methods like oversampling and undersampling to handle class imbalance. Modern techniques based on Data mining, Machine learning, Sequence Alignment, Fuzzy Logic, Genetic Programming, Artificial Intelligence etc., has been introduced for detecting credit card fraudulent transactions. This paper shows how data mining techniques can be combined successfully to obtain a high fraud coverage combined with a low or high false alarm rate.

KEYWORDS Fraud detection; Credit card fraud, Credit card, fraud detection techniques, Online banking

1. INTRODUCTION

Fraud refers to obtaining goods/services and money by illegal way. Fraud deals with events which involve criminal motives that, mostly, are difficult to identify. Credit cards are one of the most popular objective of fraud but not the only one. Credit card fraud, a wide-ranging term for theft and fraud committed or any similar payment mechanism as a fraudulent resource of funds in a transaction. Credit card fraud has been expanding issue in the credit card industry. Detecting credit card fraud is a difficult task when using normal process, so the development of the credit card fraud detection models has become of importance whether in the academic or business organizations currently. Furthermore, role of fraud has been changed suddenly during the last few decades along with advancement of technologies. Credit Card Fraud is one of the biggest threats to business a commercial establishments today. Simply, Credit Card Fraud is defined as, “when an individual uses another individuals‟ credit card for personal use while the owner of the card as well as the card issuer are not aware of the thing that the card

is being used." A number of systems/models, process and preventive measures will help to stop credit card fraud and reduce financial risks. Banks and credit card companies have gathered large amounts of credit card account transactions. The Credit Card is a plastic card issued to number of users as one of the mode of payment. It allows cardholders to purchasing goods and services based on the cardholder's promise. In China, credit card users are growing rapidly, but only a very few credit card holders use credit cards for paying for day-to-day purchase comparatively with confidence and a sense of security. Reason is, credit card holder has no enough confidence to trust upon the payment system. Secure credit services of banks and development of E-business a reliable fraud detection system is essential to support safe credit card usage, Fraud detection based on analyzing existing purchase data of cardholder (current spending behavior) is a promising way for reducing the rate of credit card frauds. Fraud detection systems come into scenario when the fraudsters exceed the fraud prevention systems and start fraudulent transactions. Along with the developments in the Information Technology and improvements in the communication channels, fraud is spreading all over the world with results of large amount of fraudulent loss. Anderson (2007) has identified and described the different types of fraud. Credit card frauds can be proceed in many different ways such as simple theft, counterfeit cards, Never Received Issue (NRI), application fraud and online/Electronic fraud (where the card holder is not present). Credit card fraud detection is dreadfully difficult, but also common problem for solution. As there is limited amount of data with the transactions being confided, for example, transaction amount, merchant category code (MCC), acquirer number and date and time, address of the merchant. Various techniques in Knowledge Discovery, such as decision tree, neural network and case based reasoning have broadly been used for forming several fraud detection systems/ models. These techniques usually need adequate number of normal transactions and fraud transactions for learning fraud patterns. However, the ratio of fraudulent transactions to its normal transactions is low extremely, for an individual bank.

LITERATURE REVIEW

Fraud act as the unlawful or criminal deception intended to result in financial or personal benefit. It is a deliberate act that is against the law, rule or policy with an aim to attain unauthorized financial benefit. Numerous literatures pertaining to anomaly or fraud detection in this domain have been published already and are available for public usage. A comprehensive survey conducted by Clifton Phua and his associates have revealed that techniques employed in this domain include data mining applications, automated fraud detection, adversarial

detection. In another paper, Suman, Research Scholar, GJUS&T at Hisar HCE presented techniques like Supervised and Unsupervised Learning for credit card fraud detection. Even though these methods and algorithms fetched an unexpected success in some areas, they failed to provide a permanent and consistent solution to fraud detection. A similar research domain was presented by Wen-Fang YU and Na Wang where they used Outlier mining, Outlier detection mining and Distance sum algorithms to accurately predict fraudulent transaction in an emulation experiment of credit card transaction data set of one certain commercial bank. Outlier mining is a field of data mining which is basically used in monetary and internet fields. It deals with detecting objects that are detached from the main system i.e. the transactions that aren't genuine. They have taken attributes of customer's behaviour and based on the value of those attributes they've calculated that distance between the observed value of that attribute and its predetermined value. Unconventional techniques such as hybrid data mining/complex network classification algorithm is able to perceive illegal instances in an actual card transaction data set, based on network reconstruction algorithm that allows creating representations of the deviation of one instance from a reference group have proved efficient typically on medium sized online transaction. There have also been efforts to progress from a completely new aspect. Attempts have been made to improve the alertfeedback interaction in case of fraudulent transaction. In case of fraudulent transaction, the authorised system would be alerted and a feedback would be sent to deny the ongoing transaction. Artificial Genetic Algorithm, one of the approaches that shed new light in this domain, countered fraud from a different direction. It proved accurate in finding out the fraudulent transactions and minimizing the number of false alerts. Even though, it was accompanied by classification problem with variable misclassification costs.

MATERIALS AND METHODS

DataSet:

First of all, we obtained our dataset from Kaggle, a data analysis website which provides datasets. Inside this dataset, there are 31 columns out of which 28 are named as v1-v28 to protect sensitive data. The other columns represent Time, Amount and Class. Time shows the time gap between the first transaction and the following one. The dataset contains transactions made by credit cards in September 2013 by European cardholders. This dataset presents transactions that occurred in two days, where we have 492 frauds out of 284,807 transactions. The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions. It contains only numerical input variables which are the

result of a PCA transformation. Unfortunately, due to confidentiality issues, we cannot provide the original features and more background information about the data. Features V1, V2, … V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are 'Time' and 'Amount'. Feature 'Time' contains the seconds elapsed between each transaction and the first transaction in the dataset. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-sensitive learning. Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise.

Hardware and Software Requirements:

Hardware requirements of the project include

- Laptop or Personal Computer

Software requirements include

- Internet browser (Chrome/Edge/Mozilla Firefox)
- Stable Internet connection
- Jupyter Notebook/ Google colab

2. EXISTING SYSTEM

Machine learning-based credit card fraud detection is a crucial and an active field of study. Using various machine learning approaches and techniques, a number of systems and approaches have been created to address this problem. Historically, rule-based fraud detection systems have been the mainstay of many financial organizations. These systems make use of preset criteria and regulations, like:

- Transactions coming from strange places.
- Several transactions in a brief amount of time.
- Transactions that go over a specific threshold.

Logistic regression is a straightforward also a powerful linear model for binary classification .Models that perform well with non-linear linkages and interactions are decision trees and random forests.SVMs, or support vector machines, work well in high-dimensional spaces.Deep learning models that can recognise intricate patterns are called neural networks.

When there is a lack of labelled data, unsupervised learning will be employed. Transaction data anomalies are detected using these models. Typical methods include of:

- Algorithms for clustering (like DBSCAN and K-means): group transactions and find anomalies.
- Neural networks taught to reconstruct inputs are called autoencoders; a high reconstruction error suggests possible fraud.
- Isolation Forests: An ensemble technique created especially to find anomalies.

Hybrid models incorporate the benefits of both supervised and unsupervised learning methods. For example: A supervised model is then used to further analyze the abnormalities that the system has identified through unsupervised learning. Hybrid models incorporate the benefits of both supervised and unsupervised learning methods. For example: A supervised model is then used to further analyze the abnormalities that the system has identified through unsupervised learning.

3. PROPOSED SYSTEM

The proposed techniques are used in this paper, for detecting the frauds in credit card system. The comparison are made for different machine learning algorithms such as Logistic Regression, Decision Trees, Random Forest, to determine which algorithm gives suits best and can be adapted by credit card merchants for identifying fraud transactions.

Random forest:
Random forest is a tree based algorithm which involves building several trees and combining with the output to improve generalization ability of the model. This method of combining trees is known as an ensemble method. Ensembling is nothing but a combination of weak learners (individual trees) to produce a strong learner. Random Forest can be used to solve regression and classification problems. In regression problems, the dependent variable is continuous. In classification problems, the dependent variable is categorical.

First of all, importing all the necessary libraries and loading the data,

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import gridspec
```

```
C:\Users\admin\AppData\Local\Temp\ipykernel_10380\118333752.py:2: DeprecationWarning:
Pyarrow will become a required dependency of pandas in the next major release of pandas (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better interoperability with other libraries)
but was not found to be installed on your system.
If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
```

```
data = pd.read_csv("creditcard.csv")
```

Then understanding and describing of data includes implementation of simple methods such as head() [which is used to return the first 5 rows of the dataset] , describe() [returns the overview of our imported dataset], etc.,

```
data.head()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.189
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.167170	0.125
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.327642	-0.139
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.647376	-0.221
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.206010	0.502

```
print(data.shape)
print(data.describe())
```

```
(284807, 31)
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean    94813.859575  1.168375e-15  3.416908e-16 -1.379537e-15  2.074095e-15
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -5.683171e+00
25%     54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01
50%     84692.000000  1.810880e-02  6.548556e-02  1.798463e-01 -1.984653e-02
75%    139320.500000  1.315642e+00  8.037239e-01  1.027196e+00  7.433413e-01
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01

                 V5            V6            V7            V8            V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   9.604066e-16  1.487313e-15 -5.556467e-16  1.213481e-16 -2.406331e-15
std    1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  1.098632e+00
min   -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -1.343407e+01
25%   -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01
50%   -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -5.142873e-02
75%    6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  5.971390e-01
max    3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1.559499e+01

       ...           V21           V22           V23           V24  \
count  ...  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   ...  1.654067e-16 -3.568593e-16  2.578648e-16  4.473266e-15
std    ...  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01
min    ... -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00
25%    ... -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01
50%    ... -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02
75%    ...  1.863772e-01  5.285536e-01  1.476421e-01  4.395266e-01
max    ...  2.720284e+01  1.050309e+01  2.252841e+01  4.584549e+00

                V25           V26           V27           V28         Amount  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  284807.000000
mean   5.340915e-16  1.683437e-15 -3.660091e-16 -1.227390e-16      88.349619
std    5.212781e-01  4.822270e-01  4.036325e-01  3.300833e-01     250.120109
min   -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01       0.000000
25%   -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02       5.600000
50%    1.659350e-02 -5.213911e-02  1.342146e-03  1.124383e-02      22.000000
75%    3.507156e-01  2.409522e-01  9.104512e-02  7.827995e-02      77.165000
max    7.519589e+00  3.517346e+00  3.161220e+01  3.384781e+01   25691.160000

              Class
count  284807.000000
mean        0.001727
std         0.041527
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000

[8 rows x 31 columns]
```

Determining the imbalance in the data,

```
fraud = data[data['Class'] == 1]
valid = data[data['Class'] == 0]
outlierFraction = len(fraud)/float(len(valid))
print(outlierFraction)
print('Fraud Cases: {}'.format(len(data[data['Class'] == 1])))
print('Valid Transactions: {}'.format(len(data[data['Class'] == 0])))
```

```
0.0017304750013189597
Fraud Cases: 492
Valid Transactions: 284315
```

Only *0.17%* fraudulent transaction out all the transactions. The data is highly Unbalanced. Lets first apply our models without balancing it and if we don't get a good accuracy then we can find a way to balance this dataset. But first, let's implement the model without it and will balance the data only if needed.

Printing amount details for fraudulent transactions using the describe() method,

```
print("Amount details of the fraudulent transaction")
fraud.Amount.describe()
```

```
Amount details of the fraudulent transaction
count     492.000000
mean      122.211321
std       256.683288
min         0.000000
25%         1.000000
50%         9.250000
75%       105.890000
max      2125.870000
Name: Amount, dtype: float64
```

Printing amount details for normal/valid transactions using the describe() method,

```
print("details of valid transaction")
valid.Amount.describe()
```

```
details of valid transaction
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

As we can clearly notice from this, the average Money transaction for the fraudulent ones is more. This makes this problem crucial to deal with.

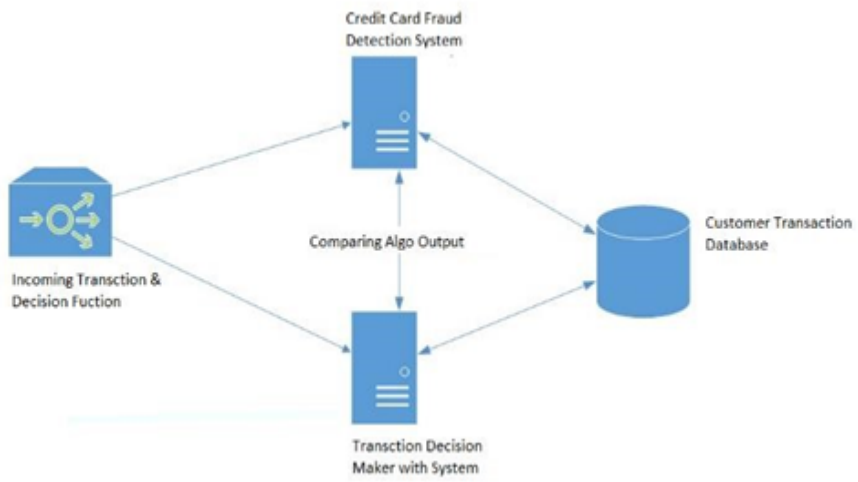
Building a Random Forest model using Scikit learn,

```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier()
rfc.fit(xTrain, yTrain)

yPred = rfc.predict(xTest)
```

METHODOLOGY



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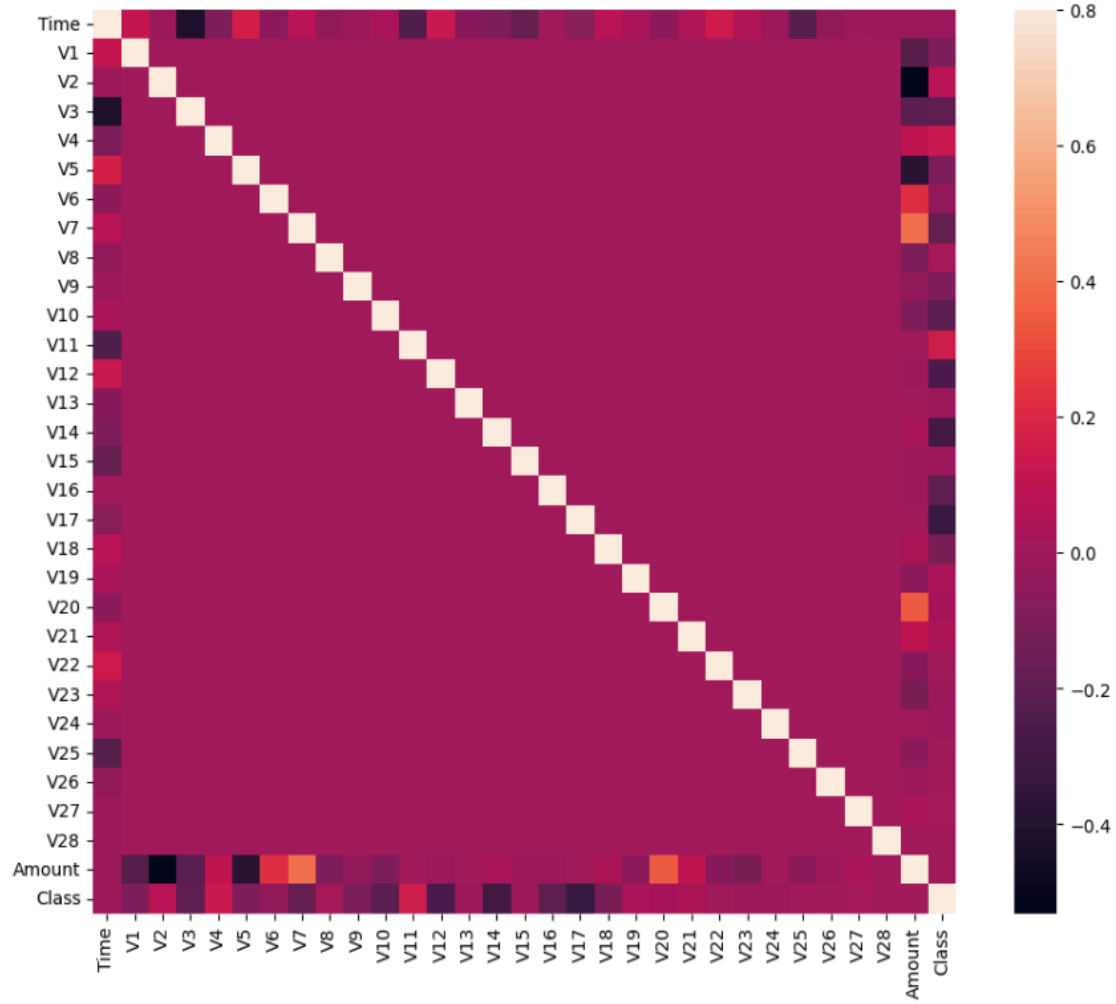
Features V1, V2, … V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are 'Time' and 'Amount'. Feature 'Time' contains the seconds elapsed between each transaction and the first transaction in the dataset. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-sensitive learning. Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise.

RESULTS & DISCUSSION

Plotting the correlation matrix, The correlation matrix graphically gives us an idea of how features correlate with each other and can help us predict what are the features that are most relevant for the prediction.

```
corrmat = data.corr()
fig = plt.figure(figsize = (12, 9))
sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```



In the HeatMap we can clearly see that most of the features do not correlate to other features but there are some features that either has a positive or a negative correlation with each other. For example, *V2* and *V5* are highly negatively correlated with the feature called *Amount*. We also see some correlation with *V20* and *Amount*. This gives us a deeper understanding of the Data available to us.

Building all kinds of evaluating parameters,

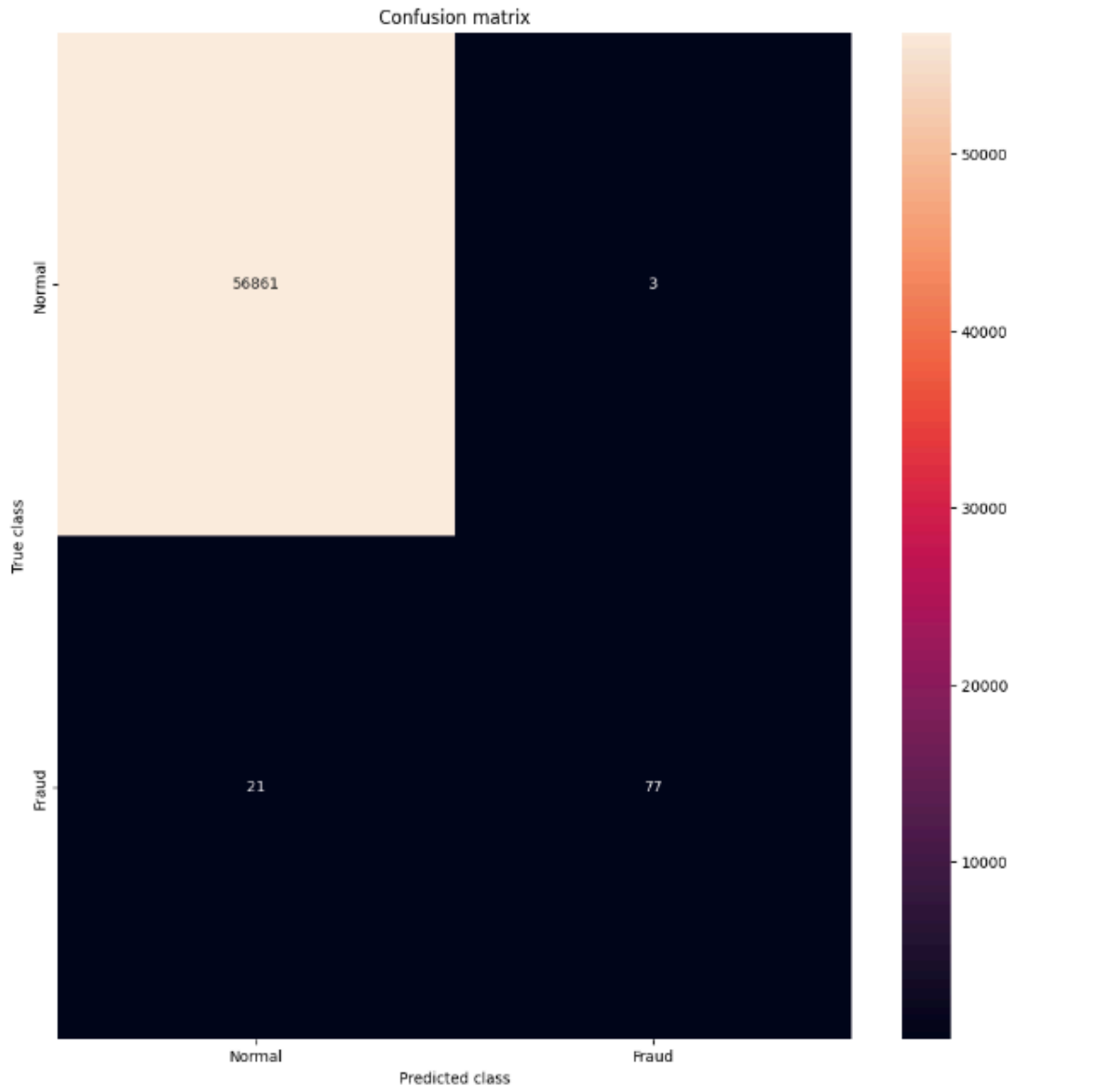
```
from sklearn.metrics import classification_report, accuracy_score
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import f1_score, matthews_corrcoef
from sklearn.metrics import confusion_matrix
```

```
n_outliers = len(fraud)
n_errors = (yPred != yTest).sum()
print("The model used is Random Forest classifier")

acc = accuracy_score(yTest, yPred)
print("The accuracy is {}".format(acc))

prec = precision_score(yTest, yPred)
print("The precision is {}".format(prec))

rec = recall_score(yTest, yPred)
print("The recall is {}".format(rec))

f1 = f1_score(yTest, yPred)
print("The F1-Score is {}".format(f1))

MCC = matthews_corrcoef(yTest, yPred)
print("The Matthews correlation coefficient is {}".format(MCC))
```

```
The model used is Random Forest classifier
The accuracy is 0.9995786664794073
The precision is 0.9625
The recall is 0.7857142857142857
The F1-Score is 0.8651685393258427
The Matthews correlation coefficient is 0.8694303688259544
```

Finally by visualizing the confusion matrix, we get the comparison with other algorithms without dealing with the imbalancing of the data,

```
LABELS = ['Normal', 'Fraud']
conf_matrix = confusion_matrix(yTest, yPred)
plt.figure(figsize =(12, 12))
sns.heatmap(conf_matrix, xticklabels = LABELS, yticklabels = LABELS, annot = True, fmt ="d");
plt.title("Confusion matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```



CONCLUSION

Credit card fraud has without hesitation an expression of criminal deception. Fraud identification seems to be a complicated problem that requires a significant amount of skill until throwing algorithms regarding machine learning into it.

However, it is an implementation for both the better of machine learning as well as artificial intelligence, ensuring that perhaps the funds of both the customer seems to be secure and therefore not manipulated. The whole research article addressed an effective system of identifying fraud depending on machine learning methodologies, with such a feedback system. Its feedback process relates to enhancing the
classifier's detection rate as well as effectiveness. An observational analysis has been conducted on respective machine learning strategies except for random forest, tree classifiers, artificial neural networks, vector supporting machine, Naïve Baiyes, logistic regression as well as gradient boosting classifier techniques, but also
multiple performances evaluating parameters have been calculated such as precision, recall, F1-score, accuracy, and FPR percentage, for any method which has better results for evaluation parameters can be treated as best performing method. Here Random forest is showing better results as compared to other machine learning classifiers.

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