Credit Card Fraud Detection Using Supervised Machine Learning Models

Abstract

Financial fraud is a growing problem with long term consequences in the financial industry and while many techniques have been discovered to solve this problem faced by various companies, data mining has been successfully applied to finance databases to automate analysis of huge volumes of complex data. Data mining has also played a salient role in the detection of credit card fraud in online transactions.

Fraud detection in credit card is a data mining problem. It becomes challenging due to two major reasons – first, the profiles of normal and fraudulent behaviour change frequently and second, the credit card fraud data sets are highly skewed. This paper investigates and checks the performance of Decision Tree, Random Forest, SVC, XGBoost, K-Nearest Neighbors and Logistic Regression on highly skewed credit card fraud data. Dataset of credit card transactions is sourced from European cardholders containing 284,786 transactions. These techniques are applied on the raw and pre-processed data.

The performance of the techniques is evaluated based on accuracy, sensitivity, specificity, precision. The results indicating the optimal accuracy for Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbours, SVC and XGBoost classifiers are 94.4%, 91.9%, 92.9%, 93.9%, 93.4% and 94.95% respectively.

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1. Introduction

1.1 Description

Financial fraud is a growing concern with far reaching consequences in the government, corporate organizations, finance industry. In today's world, high dependency on internet technology has enjoyed increased credit card transactions, but, credit card fraud has also accelerated as online and offline transaction. As credit card transactions become a widespread mode of payment, focus has been given to recent computational methodologies to handle the credit card fraud problem. There are many fraud detection solutions and software which prevent frauds in businesses such as credit card, retail, e-commerce, insurance, and industries.

Data mining technique is one notable and popular methods used in solving credit fraud detection problem. It is impossible to be sheer certain about the true intention and rightfulness behind an application or transaction. In reality, to seek out possible evidences of fraud from the available data, using mathematical algorithms is the best effective option. Fraud detection in credit card is truly the process of identifying those transactions that are fraudulent into two classes of legit class and fraud class transactions. Several techniques are designed and implemented to solve credit card fraud detection such as Genetic Algorithm, Artificial Neural Network, Frequent Itemset Mining, Migrating Birds optimization algorithm, comparative analysis of Logistic Regression, SVC, KNN, XGBoost, Decision Tree and Random Forest is carried out.

Credit card transaction datasets are rarely available, highly imbalanced and skewed. Optimal feature (variables) selection for the models, suitable metric is most important part of data mining to evaluate performance of techniques on skewed credit card fraud data. A number of challenges are associated with credit card detection, namely fraudulent behaviour profile is dynamic, that is fraudulent transactions tend to look like legitimate ones. Credit card fraud detection performance is greatly affected by type of sampling approach used, selection of variables and detection technique used. In the end, conclusions about results of classifier evaluative testing are made and collated.

From the experiments, the result that has been concluded is that Logistic regression has an accuracy of 94.4% while SVC shows accuracy of 93.4%, KNN with 93.9% and Decision tree shows accuracy of 91.9% and Random forest shows accuracy of 92.9% but the best results are obtained by XGBoost with a precise accuracy of 94.95%. However when the learning curves of all the classifiers are evaluated we see that XGBoost overfits along with Random forest and decision tree and only KNN is able to learn whereas others underfit. Hence we conclude that KNN is the best model for our system.

1.2 Problem Formulation

The problem formulation consists of just one sentence and should make it clear to everyone what research problem, you aim to address and to whom and where it is relevant.

Problem Formulation for our project:

Are the existing techniques used for detecting credit card frauds correctly and accurately providing efficient results or can it be improved using Machine Learning?Thus, our project tries to predict credit-card frauds using Machine Learning as it is believed to provide better results as compared to the existing techniques used to detect these frauds.

1.3 Proposed System

These are the proposed techniques 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 suits best and can be adapted by credit card merchants for identifying fraud transactions. The Figure shows the architectural diagram for representing the overall system framework.[5]

Algorithm steps:	
Step 1:	Read the Dataset.
Step 2:	Random Sampling is done on the data set to make it balanced.
Step 3:	Divide the dataset into two parts i.e., Train dataset and Test dataset.
Step 4:	Accuracy and performance metrics has been calculated to know the efficiency for different algorithms.
Step 5:	Then retrieve the best algorithm based on efficiency for the given dataset.

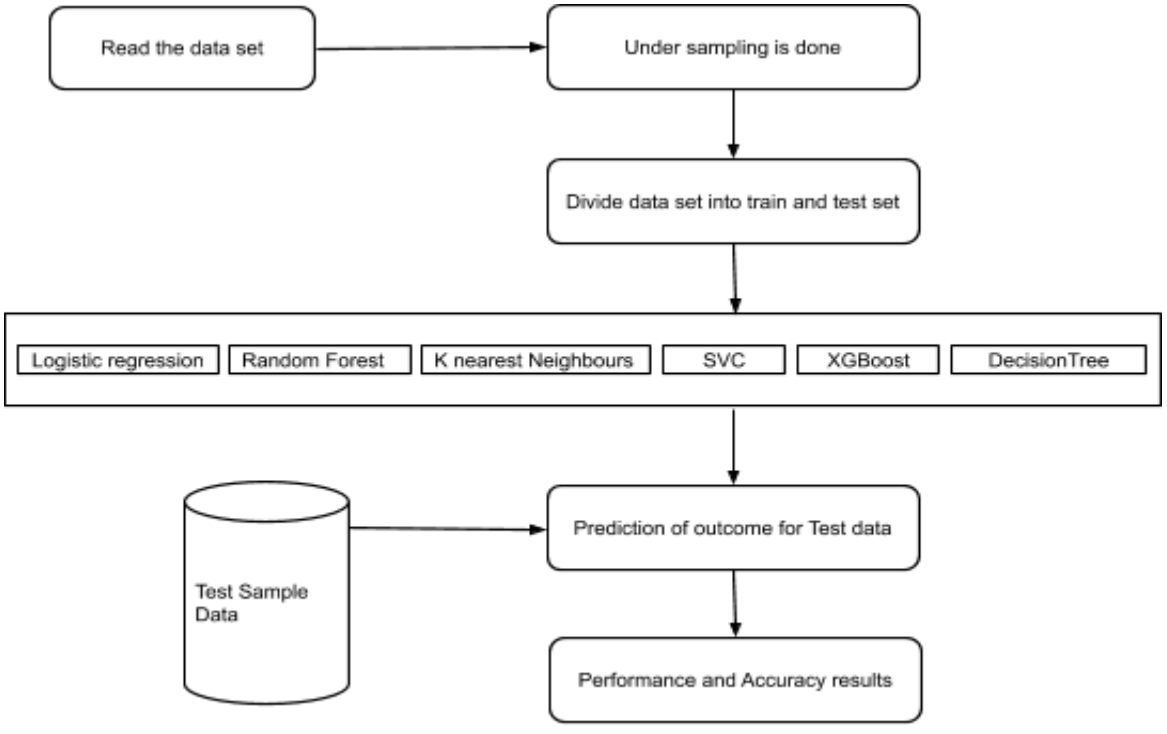


Figure 1: System Architecture

1.4 Scope of the Project

Credit card fraud detection is a very popular but also a difficult problem to solve. Firstly, due to issue of having only a limited amount of data, credit card makes it challenging to match a pattern for dataset. Secondly, there can be many entries in dataset with truncations of fraudsters which also will fit a pattern of legitimate behaviour. Also, the problem has many constraints. Firstly, data sets are not easily accessible for public and the results of researches are often hidden and censored, making the results inaccessible and due to this it is challenging to benchmarking for the models built. Secondly, the improvement of methods is more difficult by the fact that the security concern imposes a limitation to exchange of ideas and methods in fraud detection, and especially in credit card fraud detection. Lastly, the data sets are continuously evolving and changing making the profiles of normal and fraudulent behaviours always different, that is, a legit transaction in the past may be a fraud in present or vice versa. We evaluate six advanced data mining approaches, Logistic Regression, K-Nearest Neighbours, Support Vector Classifiers, Decision Tree and Random Forests and XGBoost and then a collative comparison is made to evaluate which model performed best.

2. Literature Survey

Credit card fraud detection has drawn a lot of research interest and a number of techniques, with special emphasis on neural networks, data mining and distributed data mining have been suggested.

There have been various studies on credit card fraud detection. Machine learning and related methods are most commonly used, which include artificial neural networks, rule-induction techniques, decision trees, logistic regression, and support vector machines[1]

3. System Design

3.1 Functional Requirements

- The model should be able to give accurate and trustworthy predictions.
- The application must show graphical visualization of the predicted results and data in general.
- The user should be able to enter the input values for prediction.

3.2 Non Functional Requirements

Non Functional Requirements will describe how a system should behave and what limits are constrained on its functionality. It generally specifies the system's quality attributes or characteristics.

- Availability: The system should be available to any transaction verification system.
- Correctness: The accuracy of the system should be as maximum as possible for better prediction.
- Maintainability: The system should maintain correct history of records.
- Usability: The system should satisfy a maximum number of banking system needs**.**

3.3 Specific Requirements

Software requirements

1. Languages : Python-3
2. Operating Systems : Windows, Linux, etc.
3. Back End Software : Anaconda, Jupyter notebook.

Hardware Requirements:

1. CPU : Intel Pentium IV 600MHz
2. Hard disk space : 20 GB or more
3. Memory : 4 GB RAM

3.4 Block Diagram, Use Case, class diagram, etc

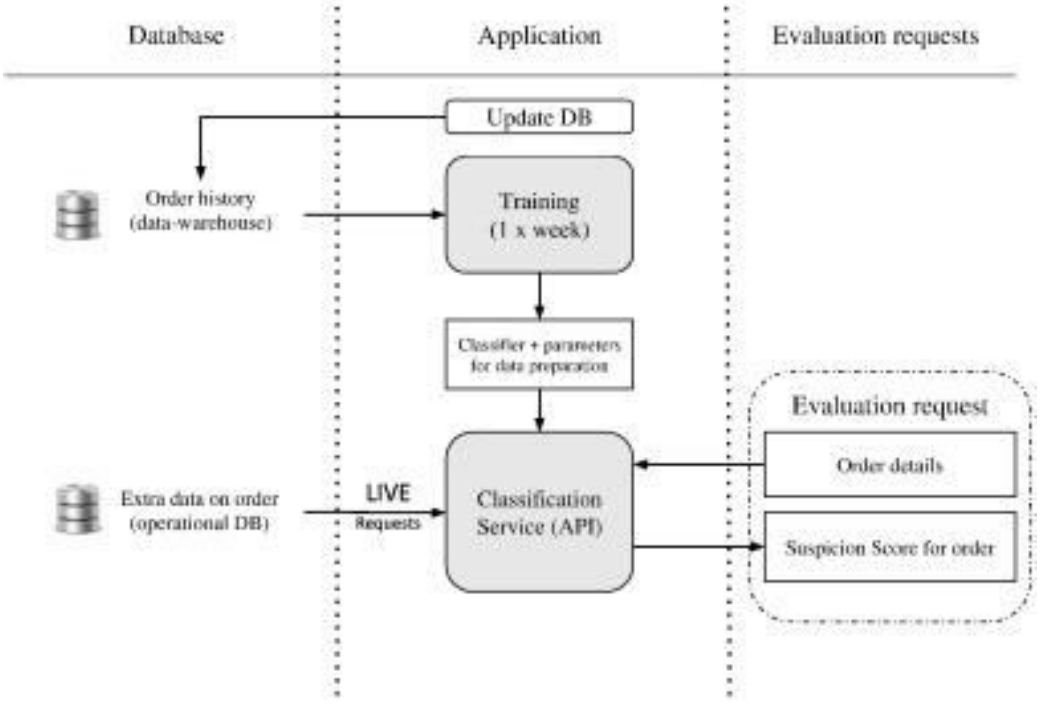


Figure 2: Activity diagram

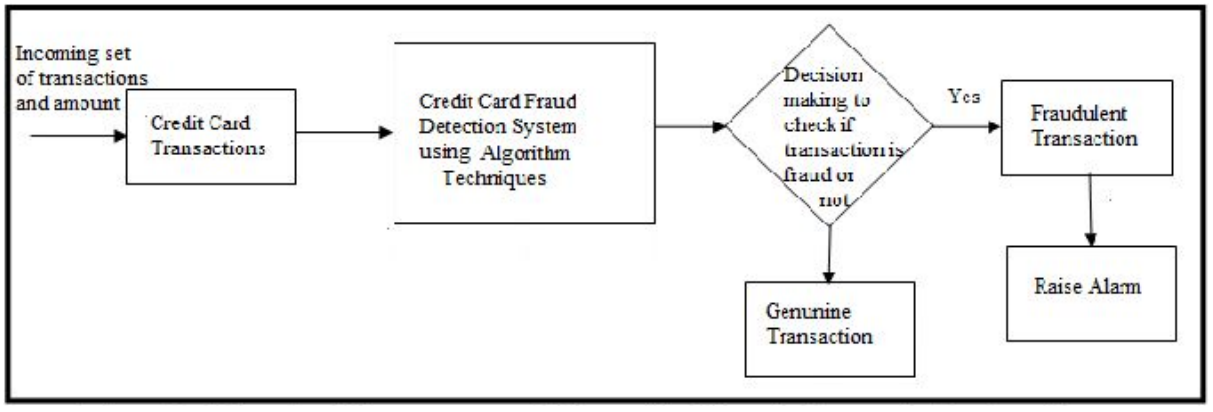


Figure 3: Flow Diagram

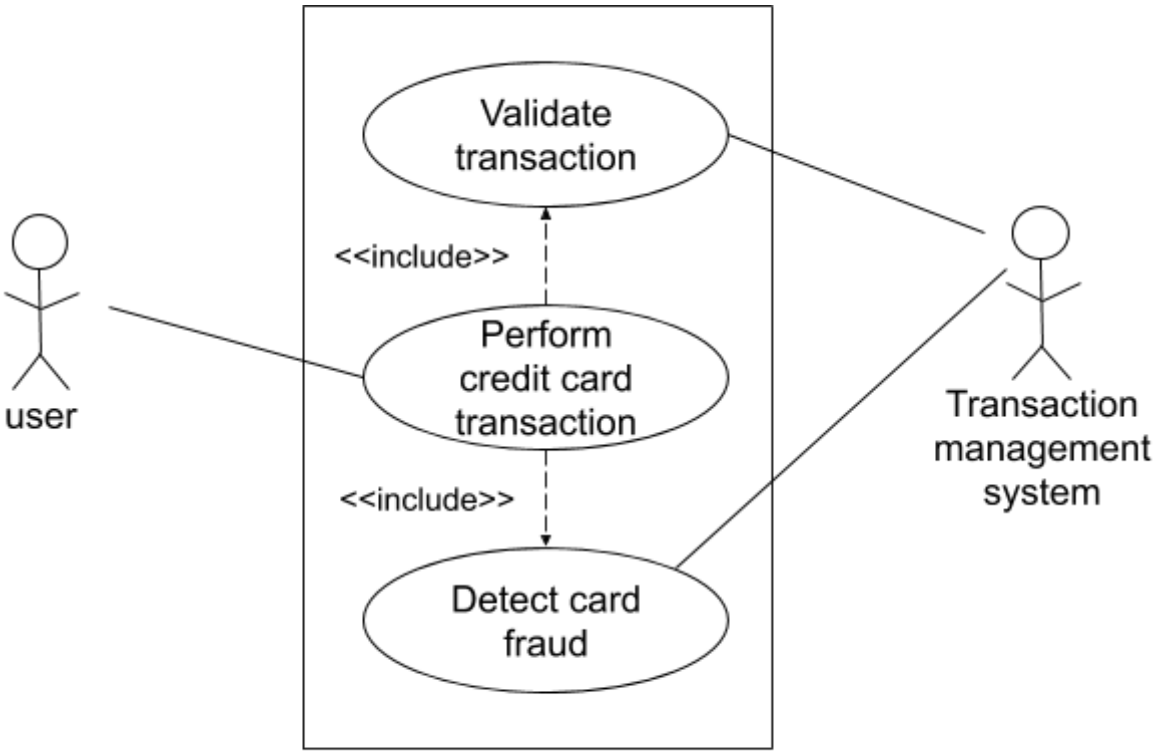


Figure 4: Use Case diagram for fraud detection

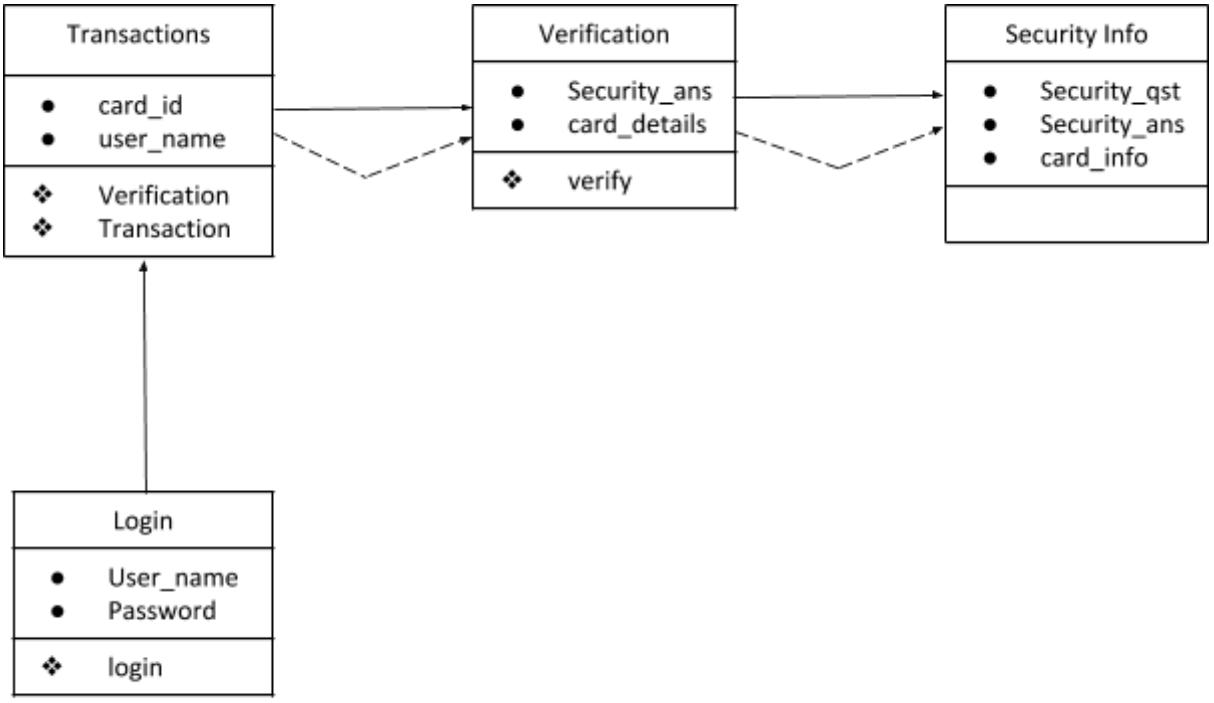


Figure 5: Class Diagram

4. Implementation Details

4.1 Algorithms

Ability of system to automatically learn and improve from experience without being explicitly programmed is called machine learning and it focuses on the development of computer programs that can access data and use it to learn by themselves. And classifier can be stated as an algorithm that is used to implement classification especially in concrete implementation, it also refers to a mathematical function implemented by algorithm that will map input data into category. It is an instance of supervised learning i.e. where training set of correctly identified observations is available.

A. Logistic Regression

Logistic Regression is a supervised classification method that returns the probability of binary dependent variable that is predicted from the independent variable of dataset i.e. logistic regression predicts the probability of an outcome which has two values, either zero or one, no or yes and false or true. Logistic regression has similarities to linear regression, but, in linear regression a straight line is obtained, logistic regression shows a curve. The use of one or several predictors or independent variable is on what prediction is based, logistic regression produces logistic curves which plots the values between zero and one.

Logistic Regression is a regression model where the dependent variable is categorical and analyzes the relationship between multiple independent variables. There are many types of logistic regression model such as binary logistic model, multiple logistic model, binomial logistic models. Binary Logistic Regression model is used to estimate the probability of a binary response based on one or more predictors.

$$p = \frac{e^{\alpha+\beta_n X}}{1 + e^{\alpha+\beta_n X}}$$

Above equation represents the logistic regression in mathematical form.

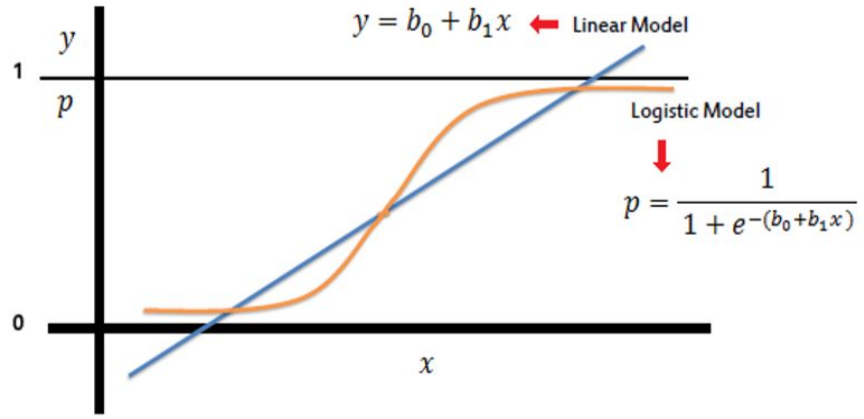


Figure 6: Logistic Curve

This graph shows the difference between linear regression and logistic regression where logistic regression shows a curve but linear regression represents a straight line.

B. **SVM Model (Support Vector Machine)**

SVM is a one of the popular machine learning algorithm for regression, classification. It is a supervised learning algorithm that analyses data used for classification and regression. SVM modeling involves two steps, firstly to train a data set and to obtain a model & then, to use this model to predict information of a testing data set. A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane where SVM model represents the training data points as points in space and then mapping is done so that the points which are of different classes are divided by a gap that is as wide as possible. Mapping is done in to the same space for new data points and then predicted on which side of the gap they fall.

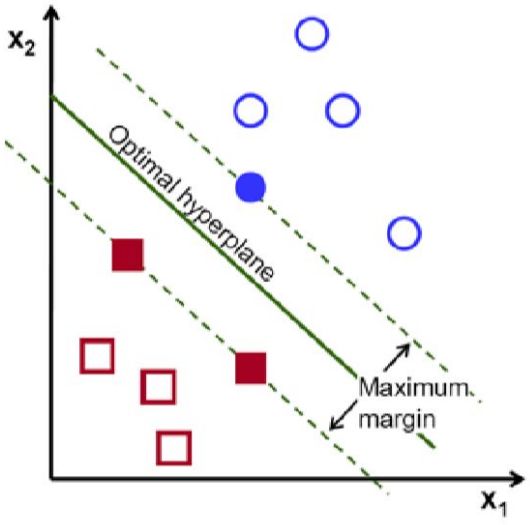


Figure 7: SVM Model Graph

In SVM algorithm, plotting is done as each data item is taken as a point in n-dimensional space where n is number of features, with the value of each feature being the value of a particular coordinate. Then, classification is performed by locating the hyperplane that separates the two classes very well.

C. Decision Tree

Decision tree is an algorithm that uses a tree like graph or model of decisions and their possible outcomes to predict the final decision, this algorithm uses conditional control statement. A Decision tree is an algorithm for approaching discrete-valued target functions, in which decision tree is denoted by a learned function. For inductive learning these types of algorithms are very famous and have been successfully applied to a broad range of tasks.

We give label to a new transaction that is whether it is legit or fraudulent for which class label is unknown and then transaction value is tested against the decision tree, and after that from root node to output/class label for that transaction a path is traced.

$$Entropy(S) = \sum_{i=1} -p_i \log_2 p_i$$

$$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)$$

Decision rules determines the outcome of the content of leaf node. In general rules have the form of 'If condition 1 and condition 2 but not condition 3 then outcome'. Decision tree helps to determine the worst, best and expected values for different scenarios, simplified to understand and interpret and allows addition of new possible scenarios.
Steps for making a decision tree are: to calculate the entropy of every attribute using the dataset in problem, then, dataset is divided into subsets using the attribute for which gain is maximum or entropy is minimum, after that, to make a decision tree node containing that attribute and lastly recursion is performed on subsets using remaining attributes to create a decision tree.

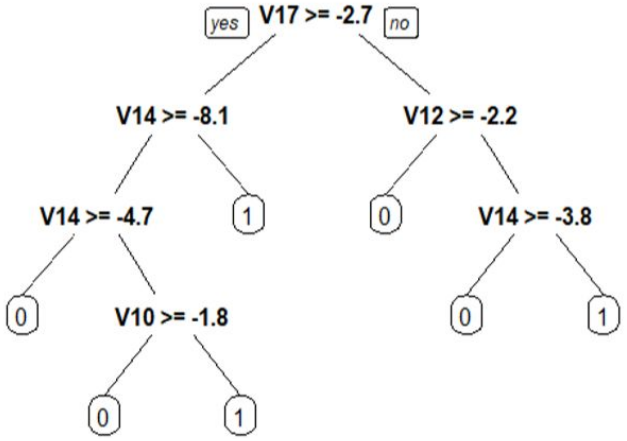


Figure 8: Decision tree

D. <u>Random Forest</u>

Random Forest is an algorithm for classification and regression. Summarily, it is a collection of decision tree classifiers. Random forest has advantage over decision tree as it corrects the habit of overfitting to their training set. A subset of the training set is sampled randomly so that to train each individual tree and then a decision tree is built, each node then splits on a feature selected from a random subset of the full feature set. Even for large data sets with many features and data instances training is extremely fast in random forest and because each tree is trained independently of the others. The Random Forest algorithm has been found to provides a good estimate of the generalization error and to be resistant to overfitting. Random forest ranks the importance of variables in a regression or classification problem in a natural way can be done by Random Forest.

E. K-Nearest Neighbour Classifier

The k-nearest neighbour is an instance based learning which carries out its classification based on a similarity measure, like Euclidean, Manhattan or Minkowski distance functions. The first two distance measures work well with continuous variables while the third suits categorical variables. The Euclidean distance measure is used in this study for the kNN classifier. The Euclidean distance (Dij) between two input vectors (Xi, Xj) is given by:

$$D_{ij} = \sqrt{\sum_{k=1}^{n} \left(X_{ik} - X_{jk}\right)^2} \quad \text{k=1,2,…,n}$$

For every data point in the dataset, the Euclidean distance between an input data point and current point is calculated. These distances are sorted in increasing order and k items with lowest distances to the input data point are selected. The majority class among these items is found and the classifier returns the majority class as the classification for the input point. Parameter tuning for k is carried out for k = 1, 3, 5, 7, 9, 11 and k = 3 showed optimal performance. Thus, value of k = 3 is used in the classifier.

F. XGBoost

XGBoost is a short form for Extreme Gradient Boosting. Boosting is a sequential process. Multiple trees are created and the information of the first tree is fed as input to the second tree so that it improves the prediction in subsequent iterations. Basically it is a additive tree model where it add new trees that complement the already built ones. XGBoost handles missing values and it works only for numeric data.

4.2 Working of the project

It is important that credit card companies are able to recognize fraudulent credit card transactions so that customers are not charged for items that they did not purchase.

Dataset

The datasets contain 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 numeric 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

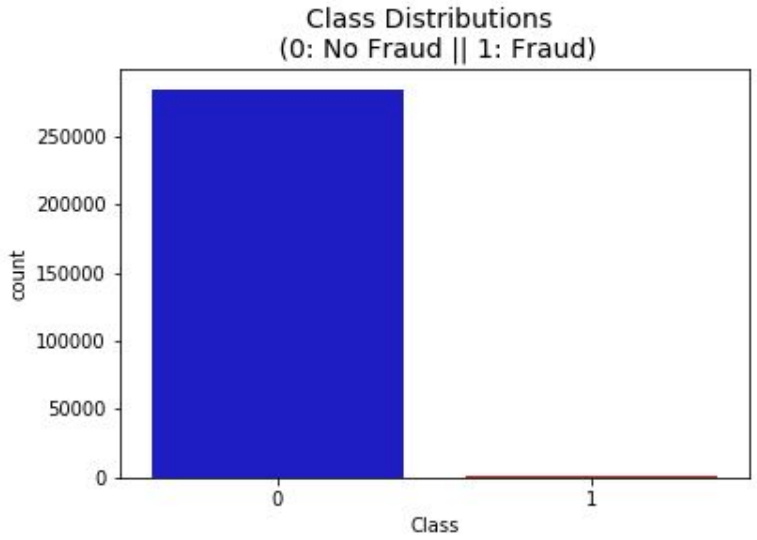
first transaction in the dataset. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-sensitive learning. Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise. There are no "Null" values, so we don't have to work on ways to replace values.

```
   ...: dataset.describe()
Out[1]:
                Time             V1      ...              Amount          Class
count  284807.000000  2.848070e+05      ...       284807.000000  284807.000000
mean    94813.859575  3.919560e-15      ...           88.349619       0.001727
std     47488.145955  1.958696e+00      ...          250.120109       0.041527
min         0.000000 -5.640751e+01      ...            0.000000       0.000000
25%     54201.500000 -9.203734e-01      ...            5.600000       0.000000
50%     84692.000000  1.810880e-02      ...           22.000000       0.000000
75%    139320.500000  1.315642e+00      ...           77.165000       0.000000
max    172792.000000  2.454930e+00      ...        25691.160000       1.000000
```

```
In [2]: dataset.head()
Out[2]:
   Time        V1        V2        V3  ...         V27       V28  Amount  Class
0   0.0 -1.359807 -0.072781  2.536347  ...    0.133558 -0.021053  149.62      0
1   0.0  1.191857  0.266151  0.166480  ...   -0.008983  0.014724    2.69      0
2   1.0 -1.358354 -1.340163  1.773209  ...   -0.055353 -0.059752  378.66      0
3   1.0 -0.966272 -0.185226  1.792993  ...    0.062723  0.061458  123.50      0
4   2.0 -1.158233  0.877737  1.548718  ...    0.219422  0.215153   69.99      0
```

Given the class imbalance ratio, we recommend measuring the accuracy using the Area Under the Precision-Recall Curve (AUPRC). Confusion matrix accuracy is not meaningful for unbalanced classification.

Why directly running prediction on the dataset is not a good idea?



No frauds 99.83% of dataset

Frauds 0.17% of dataset

Notice how imbalanced is our original dataset is! Most of the transactions are non-fraud. If we use this data frame as the base for our predictive models and analysis, we might get a lot of errors and our algorithms will probably overfit since it will "assume" that most transactions are not fraud. But we don't want our model to assume, we want our model to detect patterns that give signs of fraud!

Credit card dataset is highly imbalanced dataset because it carries more legitimate transactions as compared to the fraudulent one. That means prediction will get very high accuracy score without detecting a fraud transaction. When we apply any classification algorithm directly on the dataset we get the following results.

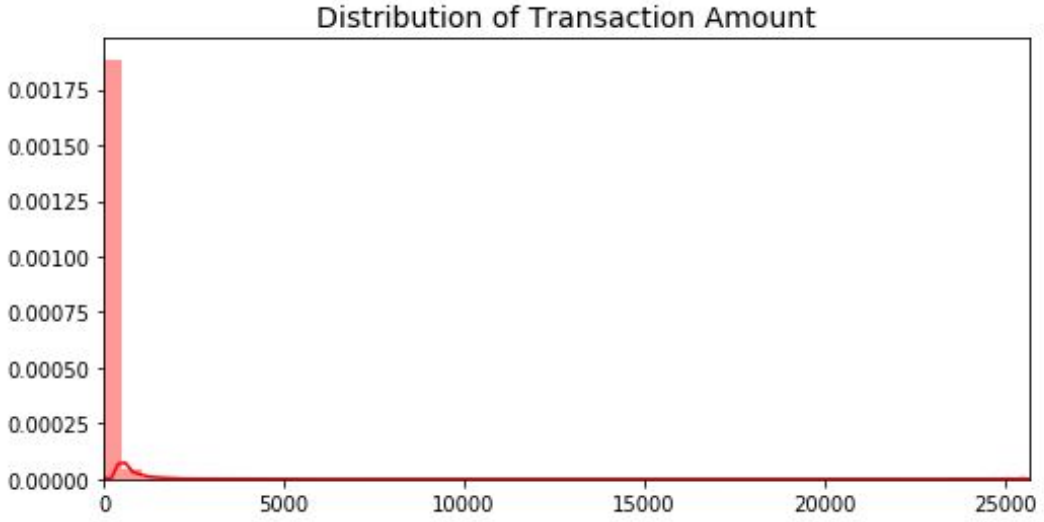
Directly applying the classification:

```
KNearest
[[56864     0]
 [   93     5]]
accuracy_score: 0.9983673326077034
miscalssification: 0.0016326673922966162
Sensitivity :  1.0
Specificity :  0.05102040816326531
precision_score: 1.0
f1_score: 0.09708737864077671

LogisiticRegression
[[56853    11]
 [   46    52]]
accuracy_score: 0.9989993328885924
miscalssification: 0.0010006671114075605
Sensitivity :  0.9998065559932471
Specificity :  0.5306122448979592
precision_score: 0.8253968253968254
f1_score: 0.6459627329192548
```

```
XGBClassifier
[[56858     6]
 [   18    80]]
accuracy_score: 0.9995786664794073
miscalssification: 0.0004213335205927038
Sensitivity :  0.9998944850872257
Specificity :  0.8163265306122449
precision_score: 0.9302325581395349
f1_score: 0.8695652173913043

RandomForestClassifier
[[56862     2]
 [   21    77]]
accuracy_score: 0.9995962220427653
miscalssification: 0.0004037779572346744 7
Sensitivity :  0.9999648283624085
Specificity :  0.7857142857142857
precision_score: 0.9746835443037974
f1_score: 0.8700564971751412
```

The results deal with a problem called accuracy paradox. The ACCURACY PARADOX is the paradoxical finding that accuracy is not a good metric for predictive models when classifying in predictive analytics. This is because a simple model may have a high level of accuracy but be too crude to be useful. For example, if the incidence of category A is dominant, being found in 99% of cases, then predicting that every case is category A will have an accuracy of 99%. Precision and recall are better measures in such cases. The underlying issue is that there is a class imbalance between the positive class and the negative class. Prior probabilities for these classes need to be accounted for in error analysis. Precision and recall help, but precision too can be biased by very unbalanced class priors in the test sets.

Also, by seeing the distributions, we can have an idea how skewed are these features. There are techniques that can help the distributions be less skewed which will be implemented in this report in the future.



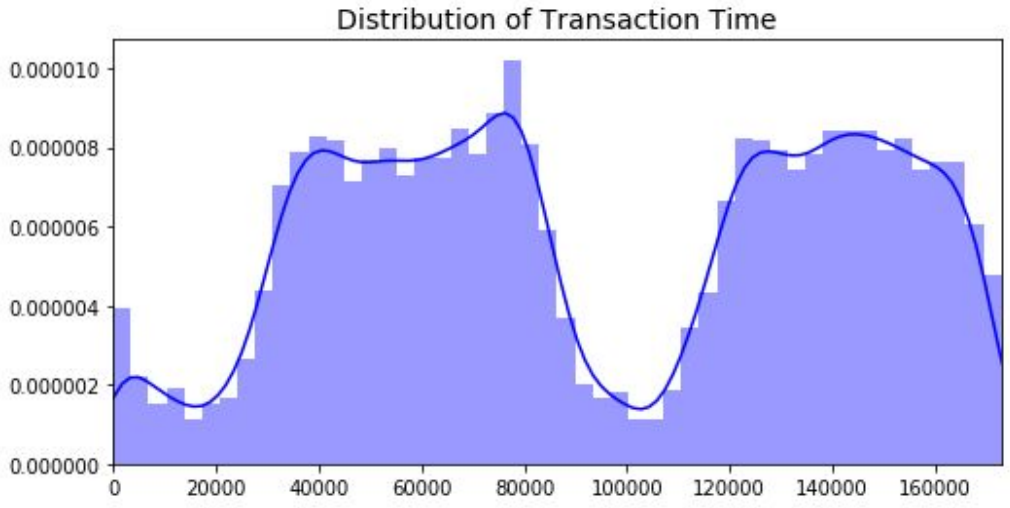


Figure 9: Distribution of Transaction Amount and Time

To handle this kind of problem one better way is to class distribution, i.e., sampling minority classes. In sampling minority, class training example can be increased in proportion to the majority class to raise the chance of correct prediction by the algorithm.

Scaling and Distributing:

In this phase, we will first scale the columns comprise of Time and Amount. Time and amount should be scaled as the other columns. On the other hand, we need to also create a subsample of the data frame in order to have an equal amount of Fraud and Non-Fraud cases, helping our algorithms better understand patterns that determines whether a transaction is a fraud or not.

In this scenario, our subsample will be a data frame with a 50/50 ratio of fraud and non-fraud transactions. Meaning our sub-sample will have the same amount of fraud and non-fraud transactions.

We need to create a sub sample because we saw that the original data frame was heavily imbalanced! Using the original data frame will cause the following issues:

1. Overfitting: Our classification models will assume that in most cases there are no frauds! What we want for our model is to be certain when a fraud occurs.
2. Wrong Correlations: Although we don't know what the "V" features stand for, it will be useful to understand how each of this feature influence the result (Fraud or No Fraud) by having an imbalance data frame we are not able to see the true correlations between the class and features.

We use RobustScalar to scale time and amount, the reason being that they scale features using statistics that are robust to outliers.

This Scaler removes the median and scales the data according to the quantile range (defaults to IQR: Interquartile Range). The IQR is the range between the 1st quartile (25th quantile) and the 3rd quartile (75th quantile).

Cantering and scaling happen independently on each feature by computing the relevant statistics on the samples in the training set. Median and interquartile range are then stored to be used on later data using the transform method.
Standardization of a dataset is a common requirement for many machine learning estimators. Typically, this is done by removing the mean and scaling to unit variance.

However, outliers can often influence the sample mean / variance in a negative way. In such cases, the median and the interquartile range often give better results.

As RobustScaler, QuantileTransformer is robust to outliers in the sense that adding or removing outliers in the training set will yield approximately the same transformation on held out data. But contrary to RobustScaler, QuantileTransformer will also automatically collapse any outlier by setting them to the a priori defined range boundaries (0 and 1).
Splitting the Data (Original DataFrame)

Summary:

- There are 492 cases of fraud in our dataset so we can randomly get 492 cases of non-fraud to create our new sub data frame.
- We concatenate the 492 cases of fraud and non-fraud, creating a new sub-sample.

Scaled amount and scaled time are the columns with scaled values:

```
from sklearn.preprocessing import StandardScaler, RobustScaler
rob_scaler = RobustScaler()
dataset['scaled_amount'] = rob_scaler.fit_transform(dataset['Amount'].values.reshape(-1,1))
dataset['scaled_time'] = rob_scaler.fit_transform(dataset['Time'].values.reshape(-1,1))
dataset.drop(['Time','Amount'], axis=1, inplace=True)
scaled_amount = dataset['scaled_amount']
scaled_time = dataset['scaled_time']
dataset.drop(['scaled_amount', 'scaled_time'], axis=1, inplace=True)
dataset.insert(0, 'scaled_amount', scaled_amount)
dataset.insert(1, 'scaled_time', scaled_time)
# Amount and Time are Scaled!
```

```
In [6]: dataset.head()
Out[6]:
        scaled_amount  scaled_time         V1  ...         V27       V28  Class
42948       -0.167680    -0.509675  -0.256652  ...   -0.547145 -0.380498      0
74625       -0.293579    -0.340923  -0.357039  ...    0.243853  0.085171      0
236178      -0.296793     0.751959  -0.443426  ...   -0.665420 -0.268262      0
192669       0.041920     0.529940   2.334822  ...    0.006936 -0.071813      0
15736        1.089779    -0.675866 -23.914101  ...    1.458076  0.430315      1
```

Before proceeding with the Random Under Sampling technique we have to separate the original data frame for testing purposes, although we are splitting the data when implementing Random Under Sampling or Oversampling techniques, we want to test our models on the original testing set, not on the testing set created by either of these techniques. The main goal is to fit the model either with the data frames that were under sample and oversample (in order for our models to detect the patterns), and test it on the original testing set.

One of the most common and simplest strategies to handle imbalanced data is to under sample the majority class.
Oversampling the minority class can result in overfitting problems if we oversample before cross-validating.

```
In [8]: X = dataset.drop('Class', axis=1)
   ...: y = dataset[['Class']]
   ...: from sklearn.model_selection import StratifiedShuffleSplit
   ...: sss = StratifiedShuffleSplit(n_splits=5, test_size=0.2, random_state=42)
   ...: for train_index, test_index in sss.split(X, y):
   ...:     print("Train:", train_index, "Test:", test_index)
   ...:     original_Xtrain, original_Xtest = X.iloc[train_index], X.iloc[test_index]
   ...:     original_ytrain, original_ytest = y.iloc[train_index], y.iloc[test_index]
   ...:
   ...: original_Xtrain = original_Xtrain.values
   ...: original_Xtest = original_Xtest.values
   ...: original_ytrain = original_ytrain.values
   ...: original_ytest = original_ytest.values
   ...: train_unique_label, train_counts_label = np.unique(original_ytrain,
return_counts=True)
   ...: test_unique_label, test_counts_label = np.unique(original_ytest,
return_counts=True)
   ...: print('-' * 100)
   ...: print('Label Distributions: \n')
   ...: print(train_counts_label/ len(original_ytrain))
   ...: print(test_counts_label/ len(original_ytest))
```

```
Train: [265518 180305  42664 ...  29062  13766  17677] Test: [263020  11378 147283 ... 274532 269819  64170]
Train: [ 72227 114282  16818 ... 264471 191914 284017] Test: [202638  32978 128121 ... 244024 127667  48318]
Train: [ 20895 114622 167683 ... 244502 178972 218506] Test: [284352  82483  90981 ... 171224 168807 271602]
Train: [122248 181660 194400 ... 104631 277586  29432] Test: [225673  63348  68025 ... 279451  77554  76043]
Train: [241684 223467 136928 ...  86495 160550  49633] Test: [157557 204860  83760 ... 251478 178967 216850]
--------------------------------------------------------------------------------------------------------
Label Distributions:

[0.99827075 0.00172925]
[0.99827955 0.00172045]
```

Under Sampling :

In this phase of the project we will implement *"Under Sampling"* which basically consists of removing data in order to have a more balanced dataset and thus avoiding our models to overfitting.[4]

- The first thing we have to do is determine how imbalanced is our class (use "value_counts()" on the class column to determine the amount for each label)
- Once we determine how many instances are considered fraud transactions (Fraud = "1") , we should bring the non-fraud transactions to the same amount as fraud transactions (assuming we want a 50/50 ratio), this will be equivalent to 492 cases of fraud and 492 cases of non-fraud transactions.
- After implementing this technique, we have a sub-sample of our data frame with a 50/50 ratio with regards to our classes. Then the next step we will implement is to shuffle the data to see if our models can maintain a certain accuracy every time, we run this script.

Note: The main issue with "Random Under-Sampling" is that we run the risk that our classification models will not perform as accurate as we would like to since there is a great deal of information loss (bringing 492 non-fraud transaction from 284,315 non-fraud transaction)

```
In [9]: dataset = dataset.sample(frac=1)
   ...: # amount of fraud classes 492 rows.
   ...: fraud_df = dataset.loc[dataset['Class'] == 1]
   ...: non_fraud_df = dataset.loc[dataset['Class'] == 0][:497]
   ...: normal_distributed_df = pd.concat([fraud_df, non_fraud_df])
   ...: # Shuffle dataframe rows
   ...: new_df = normal_distributed_df.sample(frac=1, random_state=42)
   ...: new_df.head()
   ...: new_df.describe()
   ...: print('Distribution of the Classes in the subsample dataset')
   ...: print(new_df['Class'].value_counts()/len(new_df))
Distribution of the Classes in the subsample dataset
0    0.502528
1    0.497472
Name: Class, dtype: float64
```

Now that we have our dataframe correctly balanced, we can go further with our **analysis** and **data preprocessing**.

Now that we have sampled our data set, we apply our supervised learning models.

```
In [26]: classifiers = {
    ...:     "RandomForestClassifier": RandomForestClassifier(n_estimators=300),
    ...:     "LogisiticRegression": LogisticRegression(),
    ...:     "KNearest": KNeighborsClassifier(),
    ...:     "Support Vector Classifier": SVC(),
    ...:     "DecisionTreeClassifier": DecisionTreeClassifier(),
    ...:     "XGBClassifier":XGBClassifier()
    ...: }
```

```
In [30]: for key, classifier in classifiers.items():
    ...:     classifier.fit(X_train, y_train)
    ...:     y_pred = classifier.predict(X_test)
    ...:     #metrics
    ...:     print("Classifiers: ", classifier.__class__.__name__)
    ...:     cm=confusion_matrix(y_test, y_pred)
    ...:     print(cm)
Classifiers:  DecisionTreeClassifier
[[84  7]
 [11 96]]
Classifiers:  RandomForestClassifier
[[90  1]
 [14 93]]
Classifiers:  LogisticRegression
[[88  3]
 [13 94]]
Classifiers:  KNeighborsClassifier
[[90  1]
 [16 91]]
Classifiers:  SVC
[[90  1]
 [14 93]]
Classifiers:  XGBClassifier
[[86  5]
 [12 95]]
```

5. Result Analysis

Learning Curves:

- The wider the gap between the training score and the cross-validation score, the more likely your model is overfitting (high variance).
- If the score is low in both training and cross-validation sets this is an indication that our model is underfitting (high bias)
- K Nearest Neighbour Classifier shows the best score in both training and cross-validating sets.

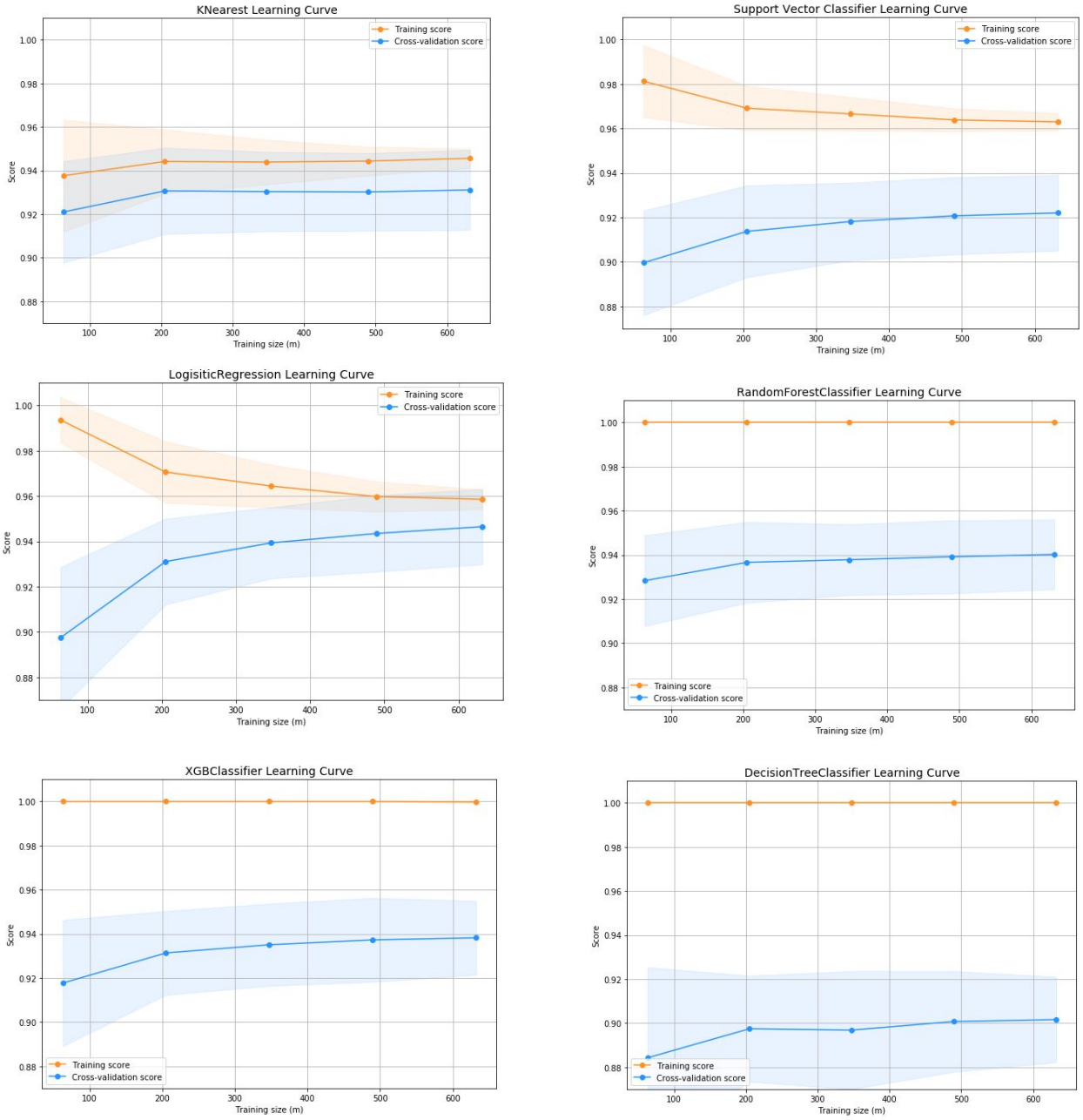


Figure 10: Learning Curves of Models

Metrics:

In order to compare various techniques we calculate the true positive, true negative, false positive and false negative generated by a system or an algorithm and use these in quantitative measurements to evaluate and compare performance of different systems.

True Positive (TP) is number of transactions that were fraudulent and were also classified as fraudulent by the system. True Negative (TN) is number of transactions that were legitimate and were also classified as legitimate. False Positive (FP) is number of transactions that were legitimate but were wrongly classified as fraudulent transactions. False Negative (FN) is number of transactions that were fraudulent but were wrongly classified as legitimate transactions by the system.

Table 1: Basic Metrics for sampled data distribution

Metrics	Classifiers					
	Random Forest	Decision Tree	XGBoost	KNearest	SVC	Logistic Regression
True Positive	90	86	90	91	87	90
False Positive	1	5	1	0	4	1
False Negative	13	11	9	12	9	10
True Negative	94	96	98	95	98	97

Table 2: Accuracy results for sampled data distribution

Metrics	Classifiers					
	Random Forest	Decision Tree	XGBoost	KNearest	SVC	Logistic Regression
Accuracy	0.9293	0.9192	0.9495	0.9394	0.9343	0.9444
Sensitivity	0.8785	0.8972	0.9159	0.8878	0.9159	0.9065
Specificity	0.9890	0.9341	0.98901	1.0	0.9560	0.9890
Precision	0.9895	0.9505	0.9899	1.0	0.9608	0.9898
F1 score	0.93069	0.9231	0.9515	0.9406	0.9378	0.9463

From the above table it is clear that the XGboost gives the highest accuracy followed by Logistic regression, SVC and KNN.

6. Future scope

With increasing number of bank fraudulency and cyber crime cases, need of a secure testing system is on rise. And this is a direct solution to this problem. It can be extended to a duplex verification of not only a customer(debit-ant) but also of the seller(credit-ant). It can be taken and used on a regular basis just like OTP. It can be used to even assess past transaction in database to find whether certain transactions were fraudulent or not and also would be able to produce evidence in such cases. Also optimization techniques on the proposed models and testing on new models can be done.

7. Conclusion

Although there are several fraud detection techniques available today, none is able to detect all frauds completely when they are actually happening, they usually detect it after the fraud has been committed. This happens because a very minuscule number of transactions from the total transactions are actually fraudulent in nature. So we need a technology that can detect the fraudulent transaction when it is taking place so that it can be stopped then and there and that too in a minimum cost. So the major task of today is to build an accurate, precise and fast detecting fraud detection system for credit card frauds that can detect not only frauds happening over the internet like phishing and site cloning but also tampering with the credit card itself i.e. it signals an alarm when the tampered credit card is being used. The major drawback of all the techniques is that they are not guaranteed to give the same results in all environments. They give better results with a particular type of dataset and poor or unsatisfactory results with other type. Thus, the results are purely dependent on the dataset type used.

In our undersample data, our model is unable to detect for a large number of cases, the non fraud transactions correctly and instead, mis-classifies those non fraud transactions as fraud cases. Imagine that people that were making regular purchases got their card blocked due to the reason that our model classified that transaction as a fraud transaction, this will be a huge disadvantage for the financial institution. The number of customer complaints and customer dissatisfaction will increase. The next step of this analysis will be to do an outlier removal on our undersample dataset and see if our accuracy in the test set improves.

In this paper, Machine learning technique like Logistic regression, Decision Tree, Random forest, K-Nearest Neighbours, SVC and XGBoost classifiers were used to detect the fraud in credit card system. Sensitivity, Specificity, accuracy and error rate are used to evaluate the performance for the proposed system. From the experiments, the result that has been concluded is that Logistic regression has an accuracy of 94.4% while SVC shows accuracy of 93.4%, KNN with 93.9% and Decision tree shows accuracy of 91.9% and Random forest shows accuracy of 92.9% but the best results are obtained by XGBoost with a precise accuracy of 94.95%. However when the learning curves of all the classifiers are evaluated we see that XGBoost overfits along with Random forest and decision tree and only KNN is able to learn whereas others underfit. Hence we conclude that KNN is the best model for our system.