CREDIT CARD FRAUD DETECTION

TABLE OF CONTENTS

1. Introduction

The project aims to develop a machine learning-based system that analyses transaction data in real-time, effectively detecting credit card fraud while minimizing false positives. This solution will help financial institutions protect against fraudulent transactions, reducing financial losses and ensuring customer trust.

2. Problem Statement

The project aims to develop a machine learning-based system that analyses transaction data in real-time, effectively detecting credit card fraud while minimizing false positives. This solution will help financial institutions protect against fraudulent transactions, reducing financial losses and ensuring customer trust

3. Literature Survey

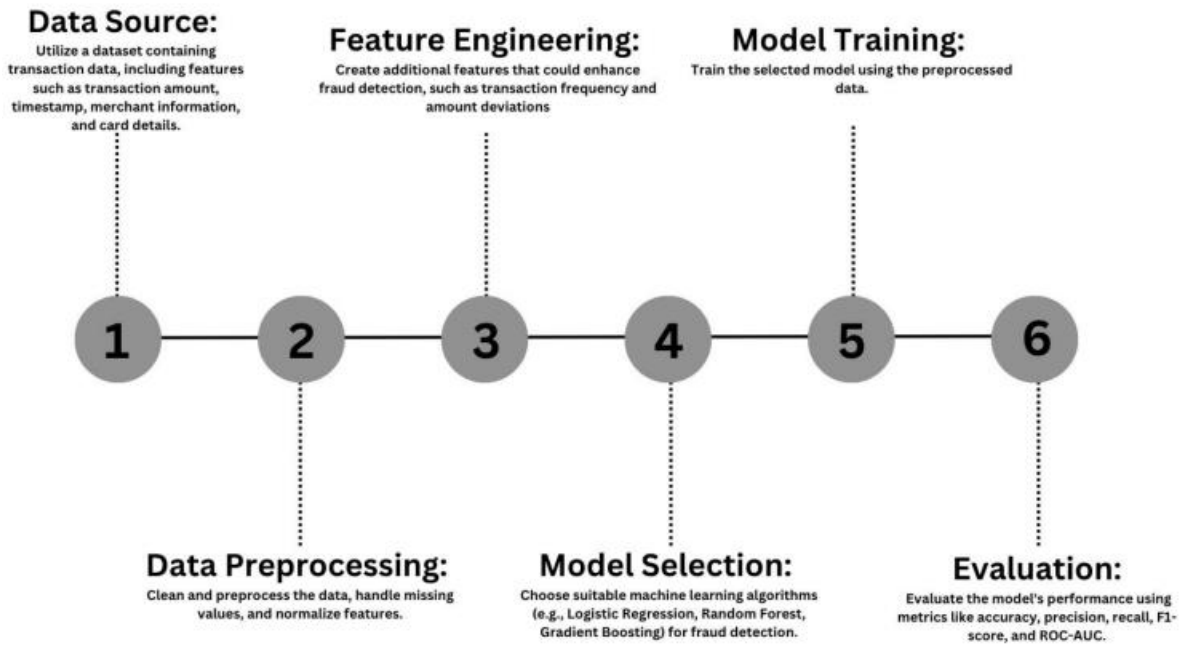
Detection of Credit Card Detection using Machine Learning:

The paper provides a comparative analysis of various techniques such as Logistic Regression, K-Nearest Neighbour, Naïve Bayes, Decision Trees, and Neural Network Algorithms. The study aims to identify the most effective technique for detecting fraudulent transactions and to help financial organizations protect their customers from credit card theft.

Review of Machine Learning Approach:

The paper provides a comparative analysis of various techniques such as Logistic Regression, K-Nearest Neighbour, Naïve Bayes, Decision Trees, and Neural Network Algorithms. The study aims to identify the most effective technique for detecting fraudulent transactions and to help financial organizations protect their customers from credit card theft.

4. Design Thinking Process:



DATASET INFORMATION:

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

MODEL SELECTION AND TRAINING:

Innovation: Ensemble Methods and Classification Methods.

The most powerful model for classification is Logistic Regression and Decision Tree to classify the results, improve the model by changing the various feature selection. Developed the model using ensemble techniques includes Random Forest Classifier and Gradient Boosting Variants etc.

Continuous Learning:

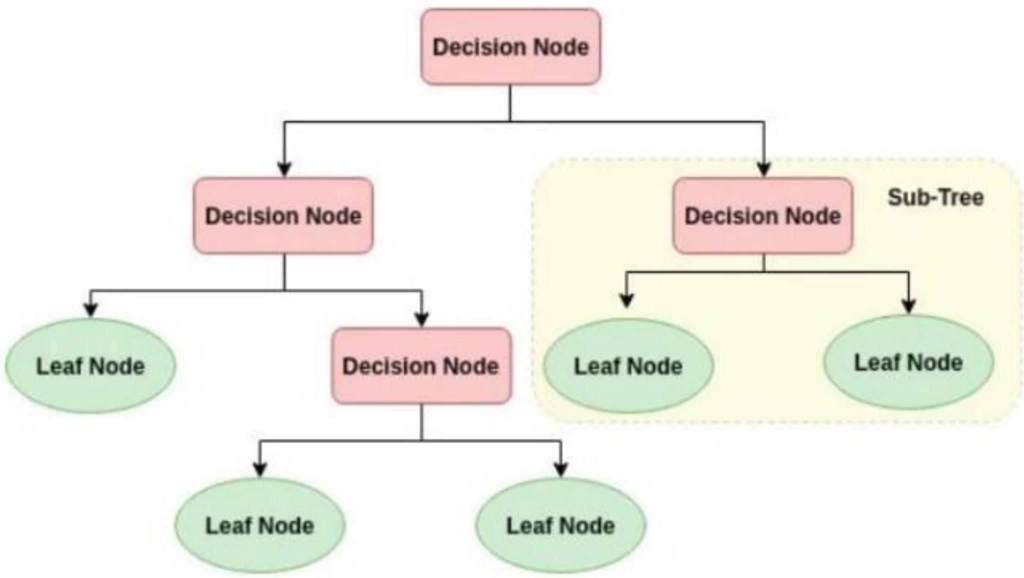
After deploying the model into a production environment, continuous monitoring is essential. It involves real-time tracking of model performance, setting up alerts to detect potential issues or drift in data patterns and regular updates.

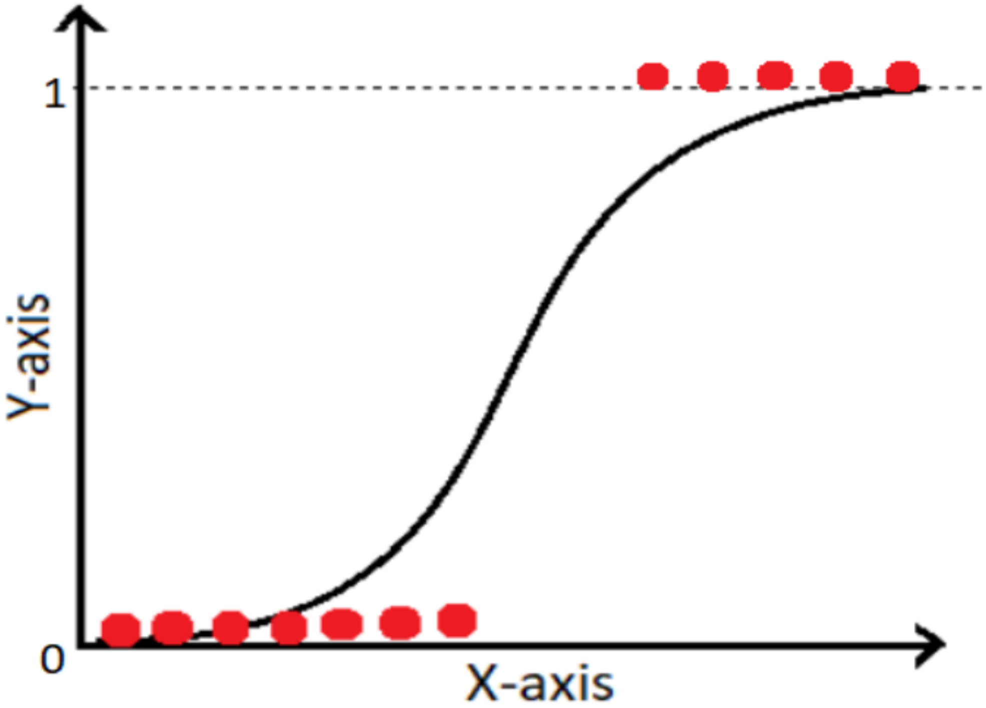
ALGORITHMS USED:

1) RANDOM FOREST

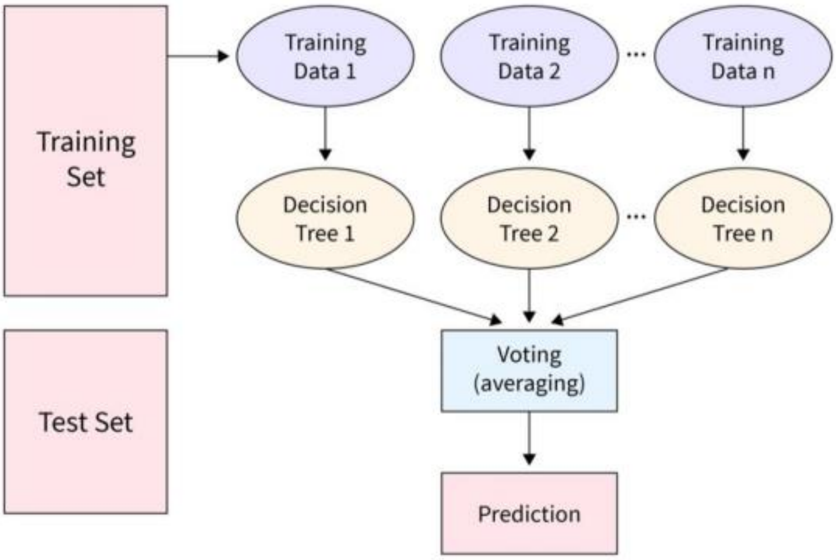
2) DECISION TREE

3)LOGISTICREGRESSION





LOGISTIC REGRESSION



RANDOM FOREST

5.Phases of Development:

5.1 Phase 1: Importing Dependencies

This phase involves importing necessary python libraries and modules. These libraries are required for data processing, visualization and various machine learning tasks.

0.3 Importing required libraries

[5]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
```

5.2 Phase 2: Reading and Viewing Data

In this phase, we are importing the whole dataset into the Jupyter Notebook

0.3.1 Set the jupyter notebook to show maximum number of columns

[6]:
```
pd.options.display.max_columns = None
```

[4]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

0.3.2 Loading the datasets

[21]:
```
ccfd = pd.read_csv('drive/MyDrive/ColabNotebooks/creditcard.csv')
```

0.3.3 Displaying top 5 rows

[22]:
```
ccfd.head()
```

5.3 Phase 3: Data Preprocessing and Exploration

Here data preprocessing and exploration occur, including column selection, column transformation, creating a new feature called Amounts. Since, in given dataset there is no outliers etc.

Scaling the Amount column data

```
from sklearn.preprocessing import StandardScaler
```

```
ss = StandardScaler()
```

```
ccfd['Amounts'] = ss.fit_transform(pd.DataFrame(ccfd['Amount']))
```

```
ccfd.head()
```

V16	V17	V18	V19	V20	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class	Amounts
'0401	0.207971	0.025791	0.403993	0.251412	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021053	149.62	0	0.244964
;3917	-0.114805	-0.183361	-0.145783	-0.069083	-0.225775	-0.638672	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014724	2.69	0	-0.342475
)0083	1.109969	-0.121359	-2.261857	0.524980	0.247998	0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	378.66	0	1.160686
;9647	-0.684093	1.965775	-1.232622	-0.208038	-0.108300	0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458	123.50	0	0.140534
;1449	-0.237033	-0.038195	0.803487	0.408542	-0.009431	0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153	69.99	0	-0.073403

Dropping the duplicate records

```
ccfd.duplicated().any()
```

```
True
```

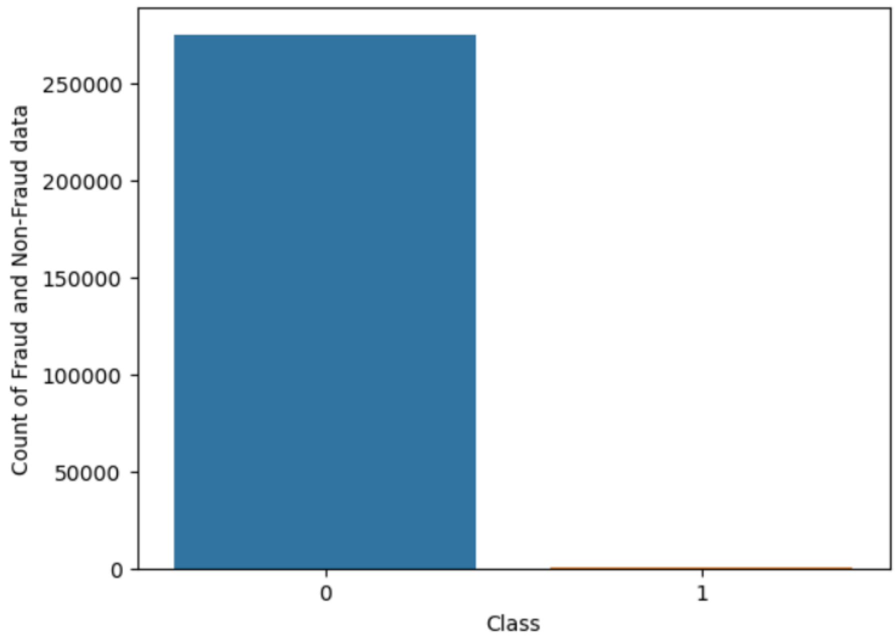
```
ccfd.drop_duplicates(inplace=True)
```

```
ccfd.shape
```

```
(275663, 30)
```

```
284807 - 275663
```

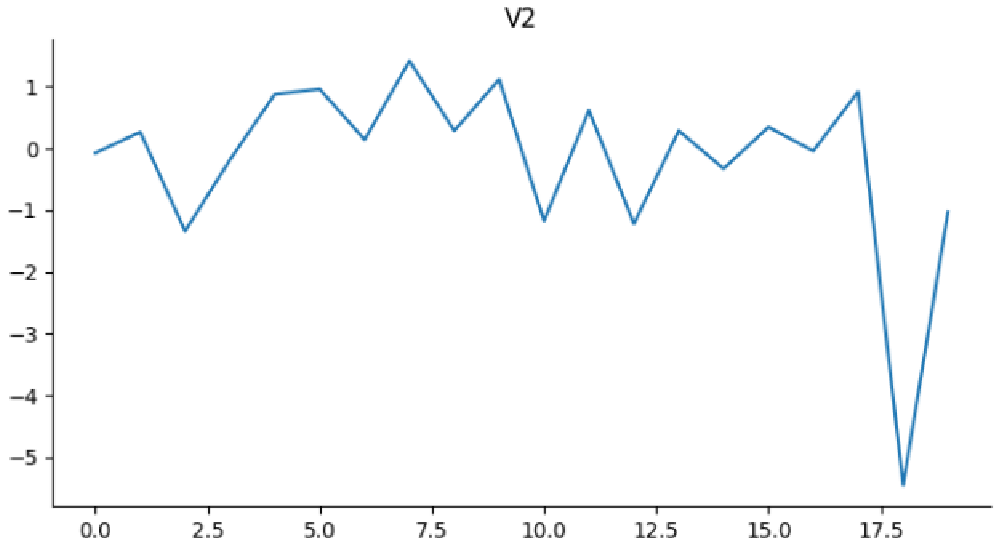
```
9144
```



Getting basis information

```
ccfd.info()
```

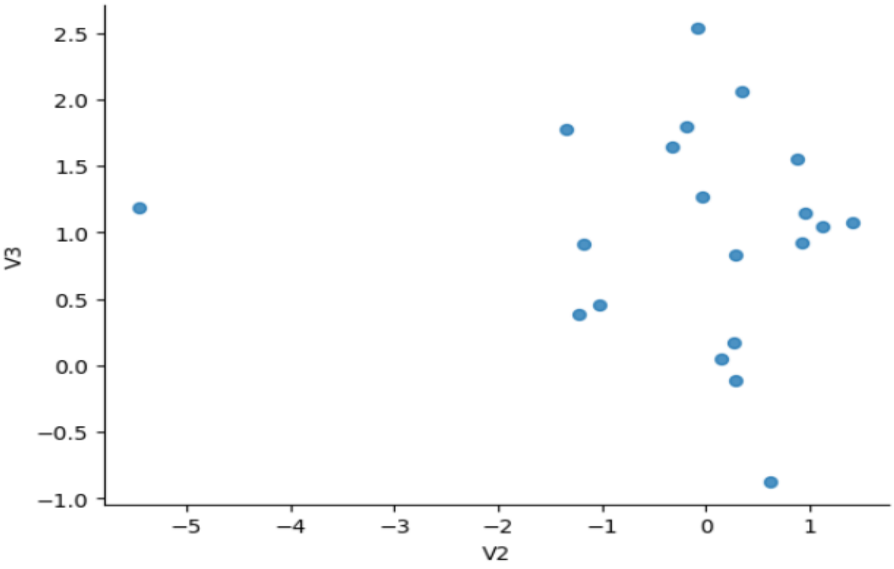
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```



5.4 Phase 4: Model Training

This phase includes splitting the dataset into training and testing sets and preparing the features and target values for machine learning models. Apply under sampling and oversampling technique in this phase.

```
[48]: from matplotlib import pyplot as plt
      _df_6.plot(kind='scatter', x='V2', y='V3', s=32, alpha=.8)
      plt.gca().spines[['top', 'right',]].set_visible(False)
```



Oversampling Technique

```
from imblearn.over_sampling import SMOTE
```

```
x2 = ccfd.drop('Class',axis=1)
```

```
x2.head()
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V1
0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	0.090794	-0.551600	-0.617801	-0.991390	-0.311169	1.46817
1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	-0.166974	1.612727	1.065235	0.489095	-0.143772	0.63555
2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	0.207643	0.624501	0.066084	0.717293	-0.165946	2.34586
3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	-0.054952	-0.226487	0.178228	0.507757	-0.287924	-0.63141
4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	0.753074	-0.822843	0.538196	1.345852	-1.119670	0.17512

```
y2 = ccfd.Class
```

```
y2
```

```
0         0
1         0
2         0
3         0
4         0
         ..
284802    0
284803    0
284804    0
284805    0
284806    0
Name: Class, Length: 275663, dtype: int64
```

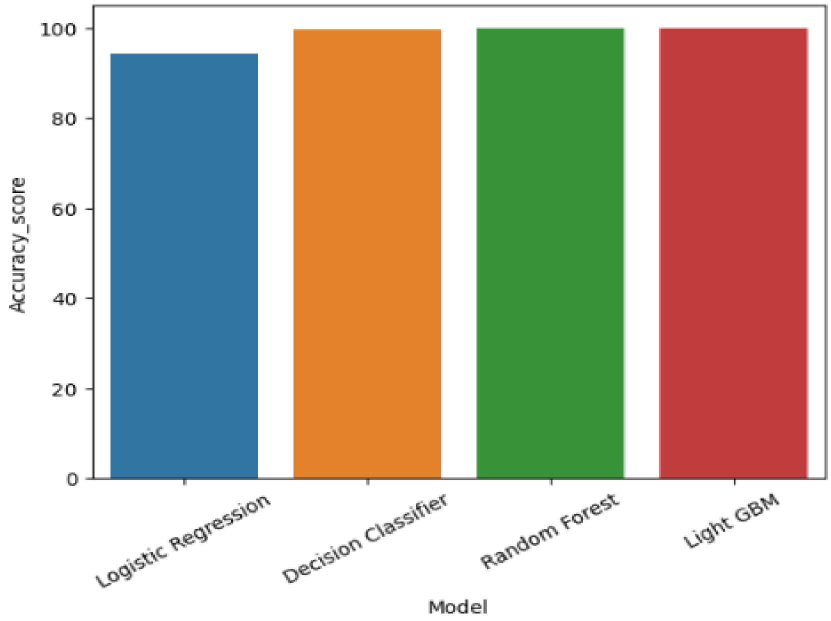
```
X_res,y_res = SMOTE().fit_resample(x2,y2)
```

```
y_res.value_counts()
```

```
Class
0    275190
1    275190
Name: count, dtype: int64
```

	Model	Accuracy_score
0	Logistic Regression	94.438388
1	Decision Classifier	99.824667
2	Random Forest	99.991824
3	Light GBM	99.906428

```
sns.barplot(x = 'Model',y = 'Accuracy_score',data = stats_oversampling)
plt.xticks(rotation=30)
plt.show()
```



6. Conclusion:

Finally, our credit card fraud detection research shows how machine learning may be used to protect financial transactions. We have created a strong model that can detect fraudulent activity by utilizing a variety of classification algorithms and sophisticated data pre-processing techniques. Our novel strategy, which makes use of Light GBM and ensemble approaches, improves the precision and dependability of our forecasts. This research not only shields financial institutions and consumers against fraudulent activity, but it also lays a solid basis for future developments in machine learning-based fraud detection and prevention..