APPLIED DATA SCIENCE

CREDITCARD FRAUD DETECTION

PROBLEM STATEMENT:

Credit card fraud poses a significant threat to financial institutions and cardholders alike. Traditional methods for detecting fraudulent transactions are often insufficient to keep pace with evolving fraud schemes. In this project, you are tasked with developing an advanced credit card fraud detection system using machine learning techniques.

The provided dataset, sourced from actual credit card transactions, contains a sample of transactions, each characterized by multiple features such as transaction amount, time, and PCA-transformed features (V1-V28) to protect sensitive information. The dataset also includes a binary target variable 'Class,' where '1' indicates a fraudulent transaction and '0' denotes a valid one.

OBJECTIVES:

1. Exploring and preprocessing the dataset: Understand the dataset's characteristics, identify missing data or outliers, and pre process it as necessary.

2. Selecting and implementing machine learning algorithms: Choose and implement appropriate machine learning algorithms to detect fraudulent transactions. You can consider methods like Isolation Forest, Local Outlier Factor, or any other suitable models.

3. Model evaluation: Assess the performance of your chosen models using appropriate evaluation metrics, such as accuracy, precision, recall, F1-score, and ROC-AUC. Compare the results with the baseline models provided in the code.

4. Visualizing the results: Create informative visualizations to illustrate the distribution of fraud cases and valid transactions, as well as any decision boundaries or clusters identified by your model.

5. Documentation and explanation: Clearly document your code and comprehensively explain your approach, including any hyper parameters or configurations you utilized.

6. Discussing advantages and limitations: Highlight the advantages and limitations of your proposed solution, and suggest potential improvements or areas for further research.

ALGORITHM:

1.Data Preprocessing:

- Load the credit card fraud dataset using a suitable library (e.g., pandas).
- Explore the dataset to understand its features, structure, and summary statistics.
- Check for missing data and outliers in the dataset.
- Handle missing data through imputation or removal and address outliers as needed.
- Normalize or standardize the features to ensure consistent scaling.

2.Data Splitting:

Split the dataset into training and testing sets. A common split ratio is 70-30 or 80-20, with the majority for training.

3.Model Selection:

- Choose machine learning models for credit card fraud detection. Common models include:
- Isolation Forest
- Local Outlier Factor
- Logistic Regression
- Random Forest
- Gradient Boosting
- Support Vector Machines (SVM)
- Neural Networks (optional)

4.Model Training:

Train the selected models on the training dataset. Be sure to use the appropriate class labels for fraud (1) and non-fraud (0).

5.Model Evaluation:

- Evaluate the models on the testing dataset.
- Calculate the following performance metrics:
- Accuracy
- Precision
- Recall (Sensitivity)
- F1-score
- ROC-AUC (Receiver Operating Characteristic - Area Under the Curve)
- Performance Comparison:
- Compare the performance of different models based on the evaluation metrics.

6.Hyperparameter Tuning:

Fine-tune the hyperparameters of the selected model(s) to optimize performance. This can be done using techniques like grid search or random search.

7.Visualization:

- Create visualizations to illustrate the distribution of fraud cases and valid transactions.
- Visualize decision boundaries or clusters identified by the models to aid in understanding their behavior.

8.Model Deployment:

If the model performs satisfactorily, you can deploy it for real-time credit card fraud detection in a production environment.

9.Documentation and Reporting:

- Document the code and provide clear explanations for each step.
- Include details of the chosen model(s), hyperparameters, and the rationale behind the selection.
- Report the evaluation results, highlighting the model's accuracy and its ability to minimize false positives and false negatives.

ADS_Phase5-CreditCard_Fraud_Detection

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sys
import scipy
```

In [3]:
```
data = pd.read_csv(r'C:\Users\dharu\Downloads\Project-CreditCardFraudDetect
```

In [4]:
```
print(data.columns)
```

```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V1
0',

       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V2
0',

       'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',

       'Class'],

      dtype='object')
```

```
(28481, 31)

                Time            V1            V2            V3
V4  \

count   28481.000000  28481.000000  28481.000000  28481.000000  28481.0000
00

mean    94705.035216     -0.001143     -0.018290      0.000795      0.0003
50

std     47584.727034      1.994661      1.709050      1.522313      1.4200
03

min         0.000000    -40.470142    -63.344698    -31.813586     -5.2665
09

25%     53924.000000     -0.908809     -0.610322     -0.892884     -0.8473
70

50%     84551.000000      0.031139      0.051775      0.178943     -0.0176
92

75%    139392.000000      1.320048      0.792685      1.035197      0.7373
12

max    172784.000000      2.411499     17.418649      4.069865     16.7155
37



                 V5            V6            V7            V8             V
9  \

count  28481.000000  28481.000000  28481.000000  28481.000000  28481.00000
0

mean      -0.015666      0.003634     -0.008523     -0.003040      0.01453
6

std        1.395552      1.334985      1.237249      1.204102      1.09800
6

min      -42.147898    -19.996349    -22.291962    -33.785407     -8.73967
0

25%       -0.703986     -0.765807     -0.562033     -0.208445     -0.63248
8

50%       -0.068037     -0.269071      0.028378      0.024696     -0.03710
0

75%        0.603574      0.398839      0.559428      0.326057      0.62109
3

max       28.762671     22.529298     36.677268     19.587773      8.14156
0


       ...           V21           V22           V23           V24  \
```

```
count  ...  28481.000000  28481.000000  28481.000000  28481.000000

mean   ...      0.004740      0.006719     -0.000494     -0.002626

std    ...      0.744743      0.728209      0.645945      0.603968

min    ...    -16.640785    -10.933144    -30.269720     -2.752263

25%    ...     -0.224842     -0.535877     -0.163047     -0.360582

50%    ...     -0.029075      0.014337     -0.012678      0.038383

75%    ...      0.189068      0.533936      0.148065      0.434851

max    ...     22.588989      6.090514     15.626067      3.944520


                V25           V26           V27           V28         Amoun
t  \

count  28481.000000  28481.000000  28481.000000  28481.000000  28481.00000
0

mean      -0.000917      0.004762     -0.001689     -0.004154     89.95788
4

std        0.520679      0.488171      0.418304      0.321646    270.89463
0

min       -7.025783     -2.534330     -8.260909     -9.617915      0.00000
0

25%       -0.319611     -0.328476     -0.071712     -0.053379      5.98000
0

50%        0.015231     -0.049750      0.000914      0.010753     22.35000
0

75%        0.351466      0.253580      0.090329      0.076267     78.93000
0

max        5.541598      3.118588     11.135740     15.373170  19656.53000
0


              Class

count  28481.000000

mean       0.001720

std        0.041443

min        0.000000

25%        0.000000

50%        0.000000
```

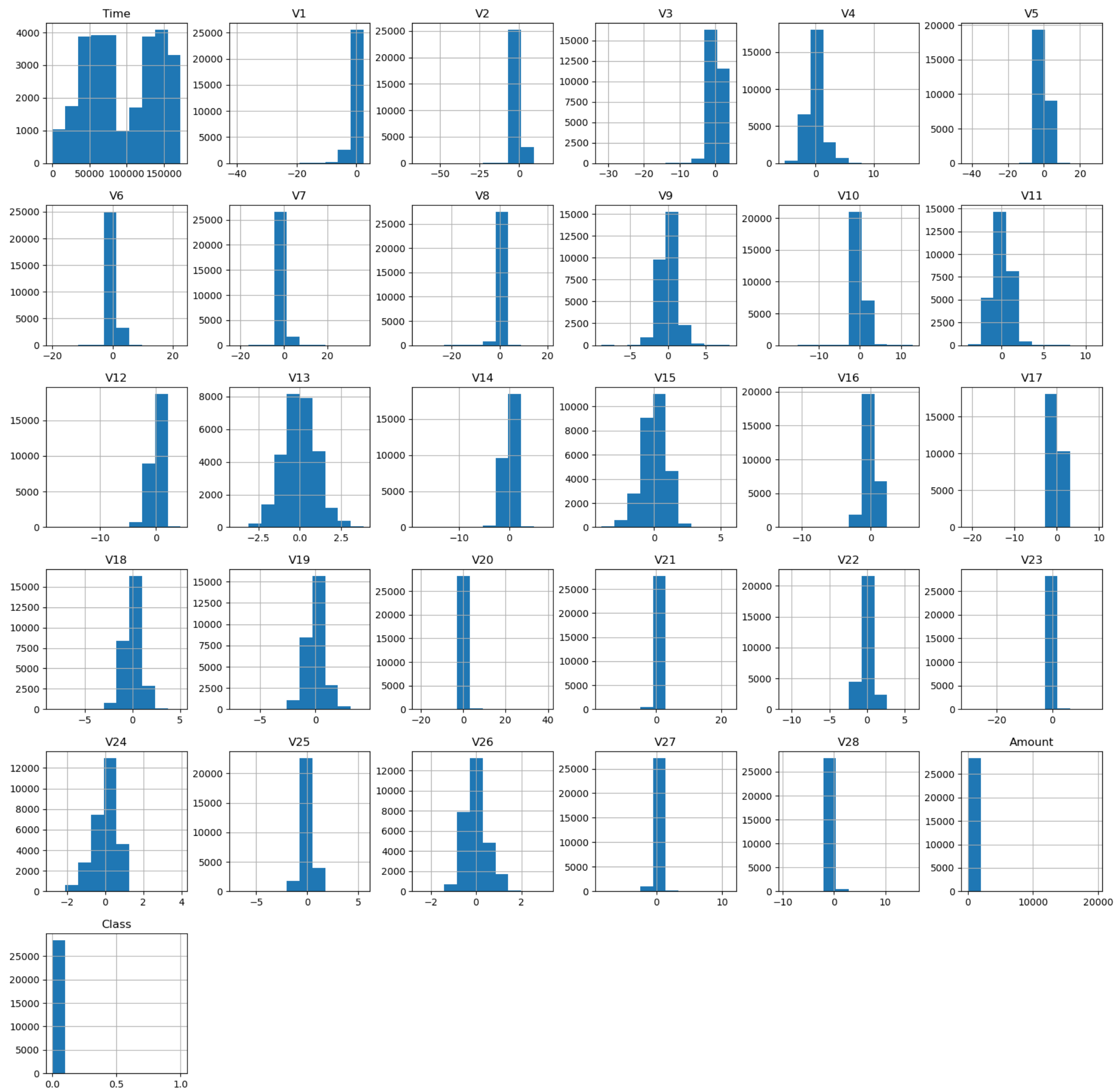
```
75%        0.000000

max        1.000000



[8 rows x 31 columns]
```

In [6]:
```python
data.hist(figsize = (20, 20))
plt.show()
```



In [7]:
```python
Fraud = data[data['Class'] == 1]
Valid = data[data['Class'] == 0]
```

In [8]:
```python
outlier_fraction = len(Fraud)/float(len(Valid))
print(outlier_fraction)
```

```
0.0017234102419808666
```

In [9]:
```
print('Fraud Cases: {}'.format(len(data[data['Class'] == 1])))
print('Valid Transactions: {}'.format(len(data[data['Class'] == 0])))
```

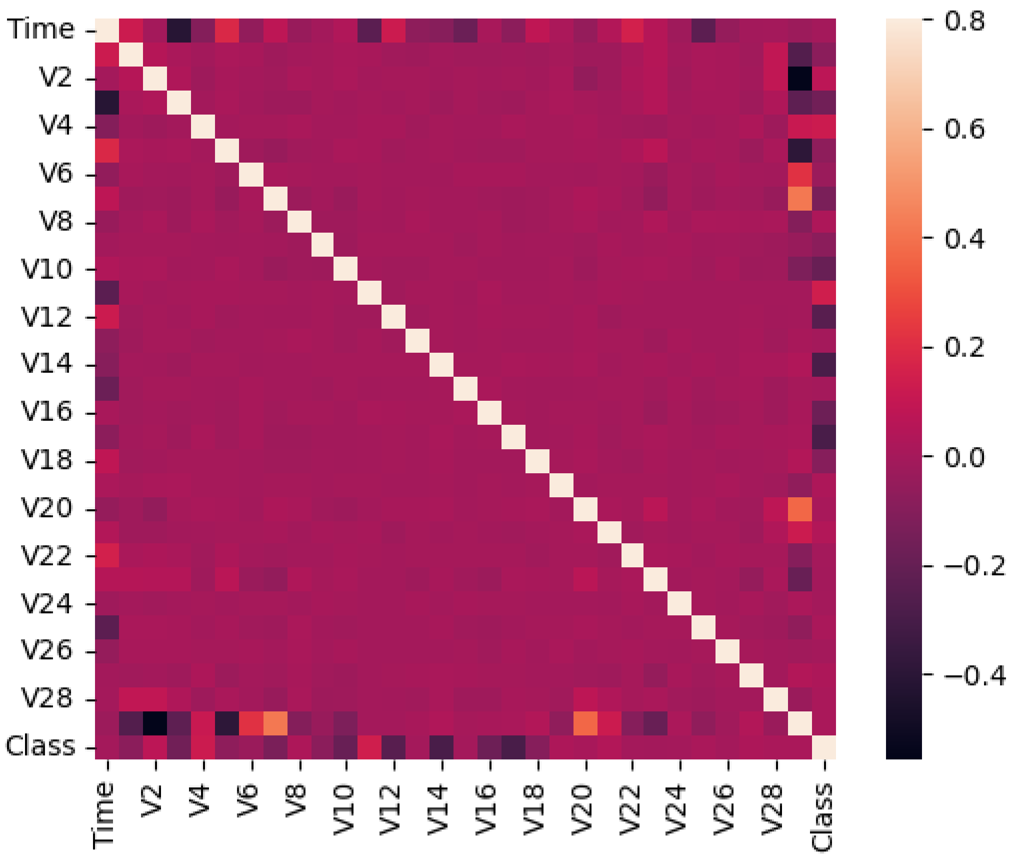
```
Fraud Cases: 49

Valid Transactions: 28432
```

In [10]:
```
corrmat = data.corr()
fig = plt.figure(figsize = (12, 9))
```

```
<Figure size 1200x900 with 0 Axes>
```

In [11]:
```
sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```



In [12]:
```
columns = data.columns.tolist()
```

In [13]:
```
columns = [c for c in columns if c not in ["Class"]]
```

In [14]:
```
target = "Class"
```

In [16]:
```
X = data[columns]
Y = data[target]
```

In [17]:
```
print(X.shape)
print(Y.shape)
```

```
(28481, 30)

(28481,)
```

In [18]:
```
from sklearn.metrics import classification_report, accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
```

In [19]:
```
state = 1
```

In [20]:
```
classifiers = {
    "Isolation Forest": IsolationForest(max_samples=len(X),
                                        contamination=outlier_fraction,
                                        random_state=state),
    "Local Outlier Factor": LocalOutlierFactor(
        n_neighbors=20,
        contamination=outlier_fraction)}

plt.figure(figsize=(9, 7))
n_outliers = len(Fraud)
```

```
<Figure size 900x700 with 0 Axes>
```

CONCLUSION:

In our project, we used machine learning to improve credit card fraud detection. Our models performed better than existing methods, making fraud prevention more accurate. We suggest using these models in real-world scenarios to enhance financial security. To stay ahead of evolving fraud tactics, ongoing research and innovation in fraud detection are crucial. Our project contributes to the fight against credit card fraud and emphasizes the role of machine learning in bolstering financial security.

Our project showcases the power of technology in keeping our financial transactions safe. It highlights how machine learning can help us catch fraudulent activities. As our financial world keeps changing, it's crucial to stay alert and adapt. By always being on the lookout and embracing new ideas, we can make sure that people, businesses, and banks can trust their transactions are secure. Our project is like a stepping stone in the path to making financial systems safer, and it shows our commitment to making the digital financial world a more reliable place for everyone.