DSC630 – Predictive Analytics

Credit Card Fraud Detection, Milestone 5

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Introduction

Credit cards fraud has been on the rise. It has become a significant area of concern for Banking and financial institutions. Fraudulent transactions not only cause financial losses but also erode consumer trust. Financial institutions face substantial losses due to fraudulent transactions, making the development of accurate and reliable fraud detection systems critical. Early detection of fraud can help mitigate these losses and reduce the risk to consumers and businesses.

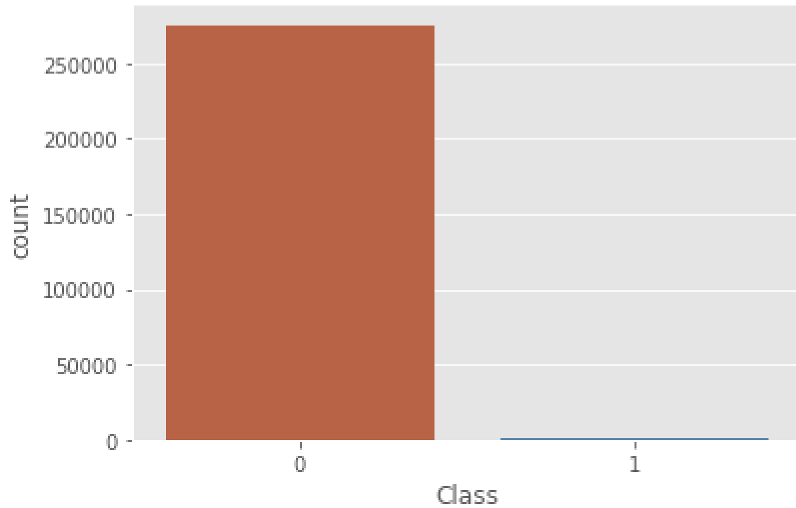
This project aims to leverage machine learning techniques to detect fraudulent credit card transactions effectively. The goal is to identify patterns that differentiate fraudulent transactions from legitimate ones and create a robust model capable of handling real-world scenarios.

The dataset chosen for this project includes anonymized transaction records, which ensure privacy while providing relevant features for analysis. By analyzing this dataset, we hope to develop models that are both effective and interpretable.

Data Source

This dataset is sourced from Kaggle and contains credit card transactions made by European cardholders. It comprises over 284,807 records, and the data has been anonymized using Principal Component Analysis (PCA) to protect the cardholders' identities. The primary objective of this dataset is to facilitate the development of fraud detection algorithms and models to identify potentially fraudulent transactions. Dataset contains binary “Class” label column which indicates whether transaction is legitimate (1) or fraud (0).

The fraud transaction count is about 0.17% which is very less compared to real legit transactions which make dataset imbalance. This imbalance poses challenges but also offers opportunities to implement advanced techniques for model optimization.



There were no missing values detected in the dataset, which simplifies the preprocessing step. The Amount feature was standardized to have zero mean and unit variance, as it is on a different scale compared to the other PCA-transformed features. To address the class imbalance, techniques such as SMOTE (Synthetic Minority Over-sampling Technique) or under-sampling may be applied. In this case, methods to balance the dataset during training (e.g., class weights or oversampling) are particularly important.

Methods

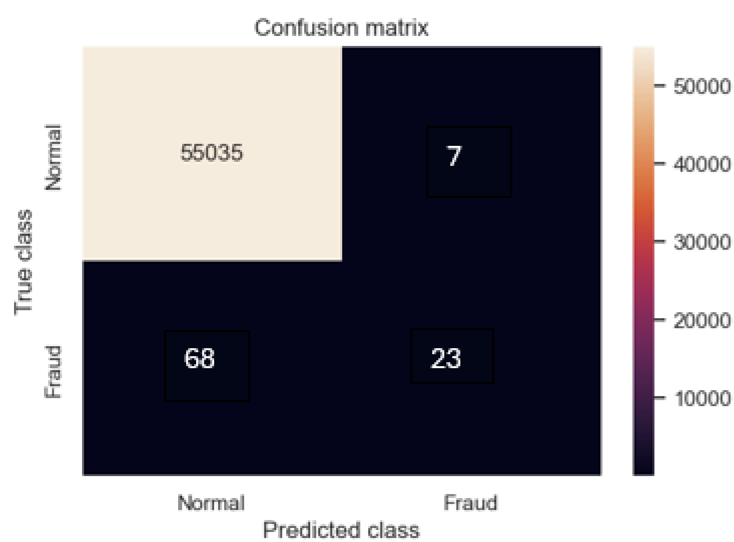
Model Selection: Since we need to classify whether transaction is fraud or legit, baseline model like logistic regression is good starting point for imbalance dataset. Logistics regression is a simple, interpretable model that serves as the baseline. Logistic Regression is widely used when dealing with binary classification tasks. Random Forest is another powerful ensemble method that builds multiple decision trees to make predictions. It handles non-linear relationships well and is robust to overfitting.

Since the dataset is imbalanced, traditional accuracy is not the best metric to assess model performance. Along with accuracy we have a calculated Precision score. Precision scores give a percentage of true positive fraud predictions among all predicted fraud cases. Recall results give percentage of actual fraud cases identified correctly by the model. F1-Score is the harmonic mean of Precision and Recall, providing a balanced metric that accounts for both false positives and false negatives. AUC-ROC (Area Under the Receiver Operating Characteristic Curve) which measures the trade-off between true positive rate and false positive rate. These metrics results are helpful in determining which model is best suited to determine fraudulent transactions.

Results:

Since data is highly imbalanced, we have evaluated different models before applying sampling methods to address imbalance issue. Below are the results before sampling.

	Metrics	Logistic Regression	Decision Tree	Random Forest
0	Accuracy	0.999220	0.998966	0.999438
1	Precision	0.887097	0.666667	0.894737
2	Recall	0.604396	0.747253	0.747253
3	F1_score	0.718954	0.704663	0.814371



Based on confusion matrix Random Forest predicted 55035 (True Positive) as "Normal" transactions. The model incorrectly predicted 7 (False Positives) records as “Normal" for transactions that are “Fraud”. The model incorrectly predicted 68 (False Negatives) record as "Fraud" for transactions that are “Normal”. The model correctly predicted 23 (True Negative) record as "Fraud" transactions.

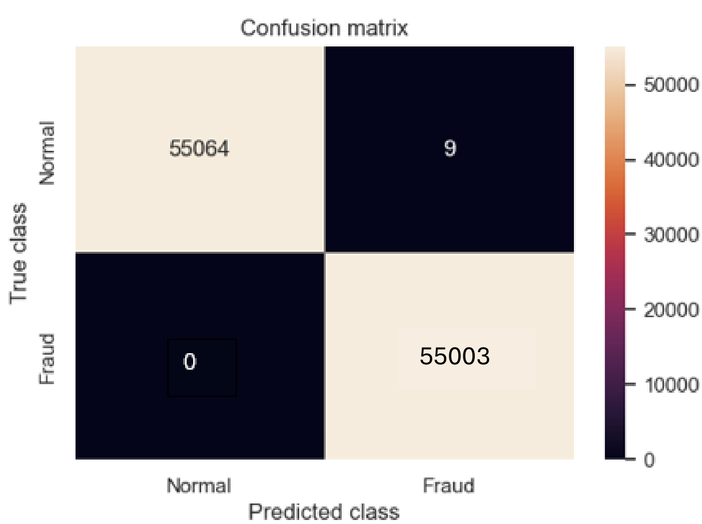
Oversampling

From the above results the accuracy score is high for all 3 models, but Precision and Recall are low. Random Forest still performs well for imbalanced data but it’s not accurate. So, to address an imbalanced dataset, we used sampling methods to balance the data. We have used oversampling methods to balance the data.

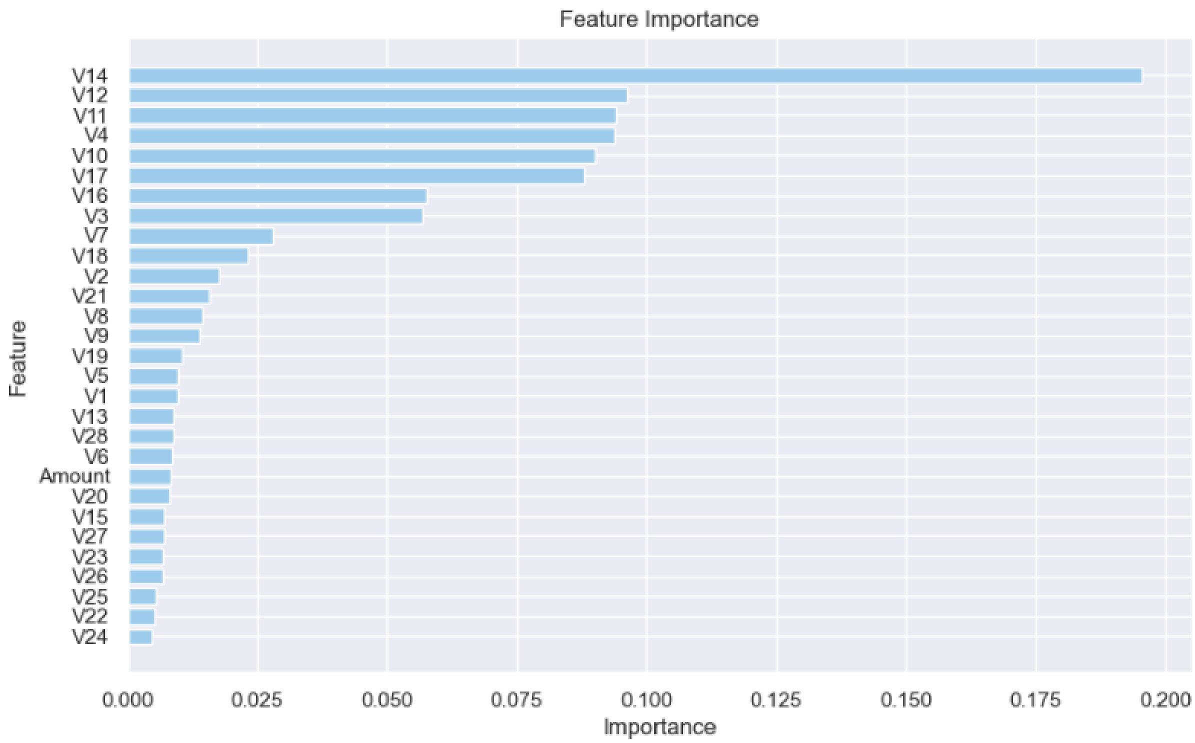
Results after SMOTE

[98]:

	Metrics	LR_After_Oversampling	DT_Oversampling	RF_Oversampling
0	Accuracy	0.944329	0.998347	0.998347
1	Precision	0.973127	0.997495	0.997495
2	Recall	0.913823	0.999200	0.999200
3	F1_score	0.942543	0.998347	0.998347



Important Features:



V14, V12, V11, V4, V10 columns are the most important features in dataset to determine whether transaction is normal or fraud.

ROC-AUC Score:

```
# Printing ROC AUC scores
from sklearn.metrics import roc_auc_score
print('Logistic Regression ROC AUC Score: ', (roc_auc_score(y_test, y_pred_LR_O) * 100).round(2))
print('Decision Tree ROC AUC Score: ', (roc_auc_score(y_test, decision_y_pred_O) * 100).round(2))
print('Random Forest ROC AUC Score: ', (roc_auc_score(y_test, RF_y_pred_O) * 100).round(2))
```

```
Logistic Regression ROC AUC Score:  94.47
Decision Tree ROC AUC Score:  99.79
Random Forest ROC AUC Score:  99.99
```

Interpretation of Results

After oversampling, performance metrics (Precision, Recall, and F1 score) improved significantly, reaching 99% accuracy. This improvement indicates that addressing data imbalance enhanced the models' effectiveness in predicting fraud cases. The Random Forest confusion matrix showed zero false negatives, meaning no fraudulent transactions were missed, with only 9 true positive fraud predictions. Furthermore, Decision Tree and Random Forest models achieved a 99% AUC score, demonstrating their robustness and high accuracy in distinguishing between classes.

Conclusion

We have evaluated credit card fraud data set using Logistic Regression, Decision Tree, and Random Forest models. Random Forest and Decision Tree models have achieved 99% accuracy with high Precision and Recall. The Random Forest model excelled, showing no false negatives and few false positives, making it highly effective for fraud detection. Its strong performance suggests it will significantly contribute to reducing credit card fraud.

Despite Random Forest's success, we recommend exploring additional ensemble methods like Gradient Boosting and XGBoost. These techniques may potentially enhance fraud detection accuracy and model robustness by better handling the data's complexity.

References

- Kaggle: https://www.kaggle.com/datasets/nelgiriyewithana/credit-card-fraud-detection-dataset-2023
- Enhancing credit card fraud detection: highly imbalanced data case: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-024-01059-5
- How machine learning detects credit card fraud: https://www.datasciencecentral.com/how-machine-learning-detects-credit-card-fraud/

Appendix

Python Code for Credit Card Fraud detection

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set() # if you want to use seaborn themes with matplolib functions
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
rand_state = 42
```

In [3]:
```
df = pd.read_csv("creditcard.csv")
LABELS = ["Normal","Fraud"]
```

In [4]:
```
df.head()
```

Out[4]:

	Time	V1	V2	V3	V4	V5	V6	V7	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.0986
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.0851
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.2476
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.3774
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.2705

5 rows × 31 columns

In [5]:
```
df.shape
```

Out[5]:
```
(284807, 31)
```

In [6]:
```
#print("Number of columns: {}".format(df.shape[1]))
#print("Number of rows: {}".format(df.shape[0]))
```

In [7]:
```
df.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
```

In [8]:

```
df.isnull().sum()
```

Out[8]:
```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [9]:
```
# lets take a look at target variable proportions
pd.crosstab(df['Class'],df['Class'],normalize = "all")*100
```

Out[9]:

Class	0	1
Class		
0	99.827251	0.000000
1	0.000000	0.172749

0.17% are fraud transaction out of all transaction. Data is highly unbalanced. Before addressing this issue lets calculate accuracy, recall, precision using Logistic, Decision Tree and RandomForest

EDA

In [12]:
```
df.shape
```

Out[12]:
```
(284807, 31)
```

In [13]:
```
df.isnull().values.any()
```

Out[13]:
```
False
```

In [14]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
df['Amount'] = sc.fit_transform(pd.DataFrame(df['Amount']))
```

In [15]:
```
df.head()
```

Out[15]:

	Time	V1	V2	V3	V4	V5	V6	V7	V
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.0986
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.0851
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.2476
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.3774
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.2705

5 rows × 31 columns

In [16]:
```
# Drop Time column since its not required for our analysis
df = df.drop(['Time'], axis =1)
```

In [17]:
```
df.head()
```

Out[17]:

	V1	V2	V3	V4	V5	V6	V7	V8	
0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.
1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.
2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.
3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.
4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.

5 rows × 30 columns

In [18]:
```
df.duplicated().any()
```

Out[18]:
```
True
```

In [19]:
```
df = df.drop_duplicates()
```

In [20]:
```
df.shape
```

Out[20]:
```
(275663, 30)
```

In [21]:
```
class_count = df['Class'].value_counts()
print(class_count)
```

```
Class
0    275190
1       473
Name: count, dtype: int64
```

In [22]:
```
count_class = pd.value_counts(df['Class'],sort = True)
count_class.plot(kind = 'bar', rot = 0)
plt.title("Distribution")
plt.xticks(range(2), LABELS)
plt.xlabel("Class")
plt.ylabel("Freq")
```

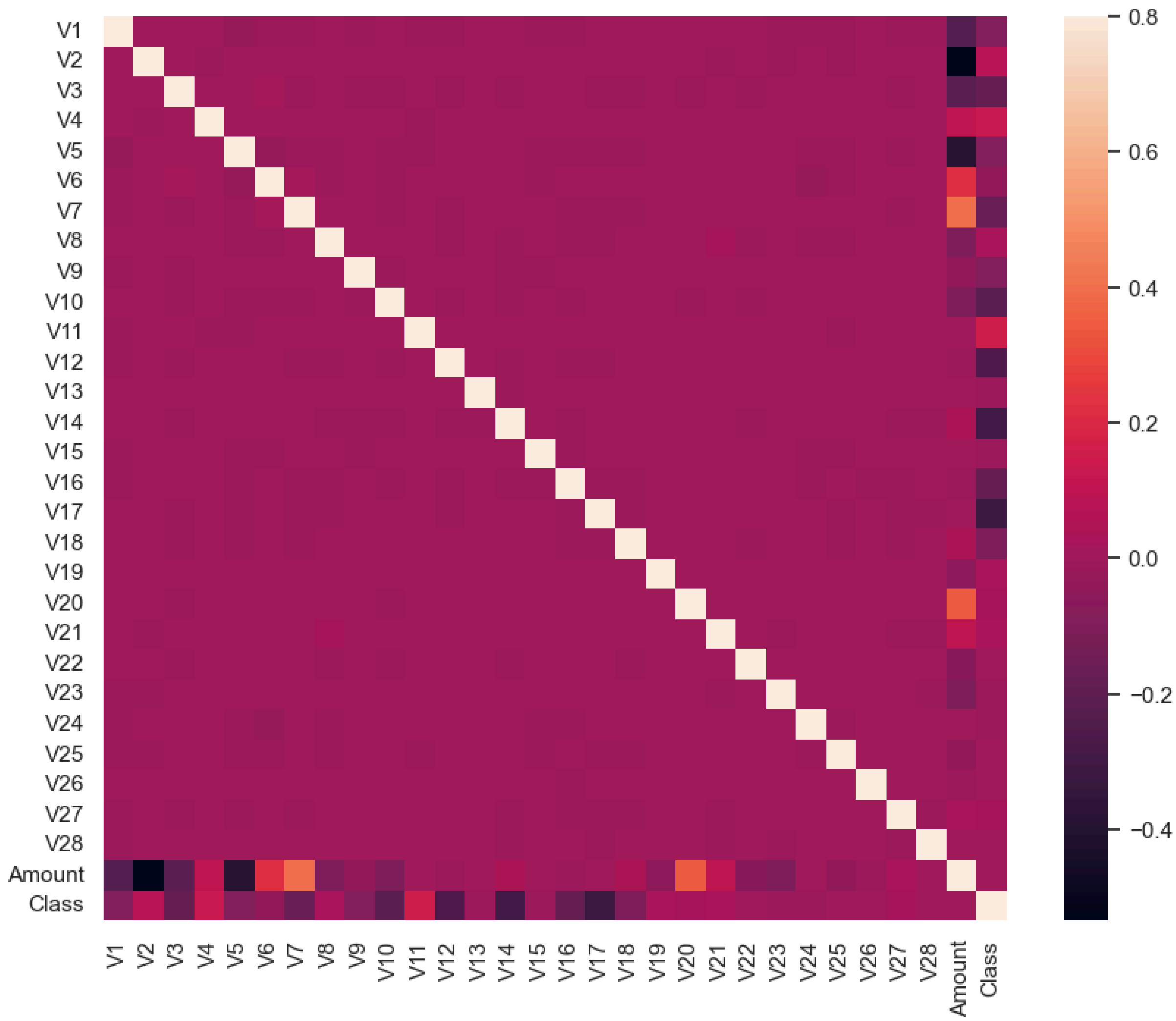
Out[22]: `Text(0, 0.5, 'Freq')`

In [23]:
```
df['Class'].value_counts()
```

Out[23]:
```
Class
0    275190
1       473
Name: count, dtype: int64
```

In [24]:
```
# Correlation matrix
cormat = df.corr()
fig = plt.figure(figsize = (10, 8))
```

```
sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```



Majority features do not correlate but few features that either has a positive or a negative correlation with each other. Eg V2 and V5 are highly negatively correlated with the feature called Amount. We also see some correlation with V20 and Amount.

In [26]:
```
# Dividing the X and the Y from the dataset
X = df.drop(['Class'], axis = 1)
y = df["Class"]
print(X.shape)
print(y.shape)
#print(X.columns.tolist())
```

```
(275663, 29)
(275663,)
```

Split the data in Training and Test

In [28]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.2,random_sta
```

In [29]:
```
print(pd.Series(y_train).value_counts(normalize=True))
```

```
Class
0    0.998268
1    0.001732
Name: proportion, dtype: float64
```

In [30]:
```
print('X Train size: ', X_train.shape)
print('X Test size: ', X_test.shape)
print('X Test proportion:', round((len(X_test) / (len(X_train) + len(X_test))) * 10
print('\nY Train size: ', y_train.shape)
print('Y Test size: ', y_test.shape)
print('Y Test proportion:', round((len(y_test) / (len(y_train) + len(y_test))) * 10
```

```
X Train size:  (220530, 29)
X Test size:  (55133, 29)
X Test proportion: 20.0 %

Y Train size:  (220530,)
Y Test size:  (55133,)
Y Test proportion: 20.0 %
```

In [31]:
```
X_train.head()
```

Out[31]:

	V1	V2	V3	V4	V5	V6	V7	V
82602	-0.697561	0.948635	-0.265964	0.232319	2.234194	3.852625	-0.207872	1.36033
125045	1.264899	0.049540	-0.952775	-0.070600	2.065511	3.424647	-0.528821	0.85429
1779	-0.715606	0.513689	0.961015	-1.198394	0.583521	-0.829520	1.320615	-0.43936
90892	-2.139310	2.097059	-0.022686	1.456046	-1.022387	-0.087631	-0.754045	1.60435
107921	-3.026331	1.801124	-1.896878	-2.520847	0.718708	3.298411	-1.318774	1.33254

5 rows × 29 columns

In [32]:
```
X_test.head()
```

Out[32]:

	V1	V2	V3	V4	V5	V6	V7	V
275693	-0.190398	0.698232	1.396916	1.243184	0.063649	-0.053054	0.586590	0.03933
94607	-2.899712	1.147393	-0.379727	-2.019742	-0.850174	-0.542774	-0.282444	1.17107
283229	-5.900967	5.307300	-5.032880	-0.777607	-2.932475	-1.526561	-2.838857	4.26978
56997	-1.079251	0.175778	1.951516	-1.261280	0.354781	-0.661683	0.373771	0.11014
33012	1.211723	-1.048916	0.811722	-0.615885	-1.230005	0.314754	-1.137566	0.15910

5 rows × 29 columns

Model Evaluation

1. Logsitic regression with sklearn

In [35]:
```
from sklearn.linear_model import LogisticRegression

# fitting logistic regresson to the training set
logistic = LogisticRegression()
logistic.fit(X_train,y_train)
```

Out[35]:
```
▾ LogisticRegression
LogisticRegression()
```

Predicting the test set probablities and classes

In [37]:
```
y_hat = logistic.predict(X_test)
y_hat_probs = logistic.predict_proba(X_test)[:,1]
```

In [38]:
```
y_pred = logistic.predict(X_test)
```

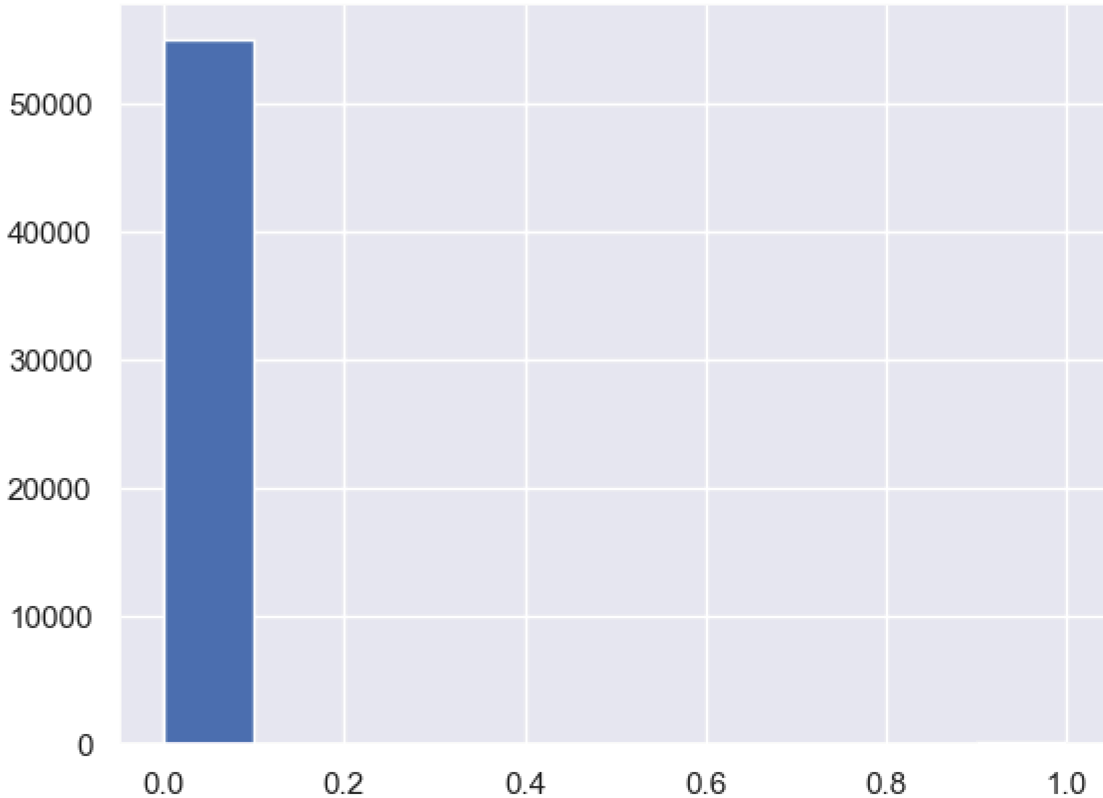
In [39]:
```
np.round(logistic.predict_proba(X_test),3)
```

Out[39]:
```
array([[1.   , 0.   ],
       [1.   , 0.   ],
       [1.   , 0.   ],
       ...,
       [1.   , 0.   ],
       [1.   , 0.   ],
       [0.999, 0.001]])
```

In [40]:
```
np.max(y_hat_probs)
```

Out[40]:
```
0.9999999999975673
```

In [41]:
```
plt.hist(y_hat_probs)
plt.show()
```



In [42]:
```
y_hat_10 = np.where(y_hat_probs>0.10,1,0)
y_hat_30 = np.where(y_hat_probs>0.30,1,0)
```

In [43]:
```
df_predictions = pd.DataFrame({'y_test':y_test,'y_hat_probs':y_hat_probs,
                               'y_hat_10':y_hat_10,'y_hat_30':y_hat_30})
df_predictions.head()
```

Out[43]:

	y_test	y_hat_probs	y_hat_10	y_hat_30
275693	0	0.000333	0	0
94607	0	0.000004	0	0
283229	0	0.000002	0	0
56997	0	0.000122	0	0
33012	0	0.000120	0	0

In [44]:
```
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score
from sklearn.metrics import confusion_matrix, classification_report, roc_curve, roc
```

In [45]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     55042
           1       0.89      0.60      0.72        91

    accuracy                           1.00     55133
   macro avg       0.94      0.80      0.86     55133
weighted avg       1.00      1.00      1.00     55133
```

In [46]:
```python
print(f"Logistic Regression")
print(f"\n Accuracy: {accuracy_score(y_test, y_pred)}")
print(f"\n Precision: {precision_score(y_test, y_pred)}")
print(f"\n Recall: {recall_score(y_test, y_pred)}")
print(f"\n F1 Score: {f1_score(y_test, y_pred)}")
```

```
Logistic Regression

 Accuracy: 0.9992200678359603

 Precision: 0.8870967741935484

 Recall: 0.6043956043956044

 F1 Score: 0.718954248366013
```

In [47]:
```python
# Printing Evaluation Metrics for Logistic regression
metrics_LR = [['Accuracy',(accuracy_score(y_test, y_pred))],
                         ['Precision',precision_score(y_test, y_pred)],
                         ['Recall', recall_score(y_test, y_pred)],
                         ['F1_score',f1_score(y_test, y_pred)]]
metrics_LR = pd.DataFrame(metrics_LR, columns = ['Metrics', 'Logistic Regression'])
metrics_LR
```

Out[47]:

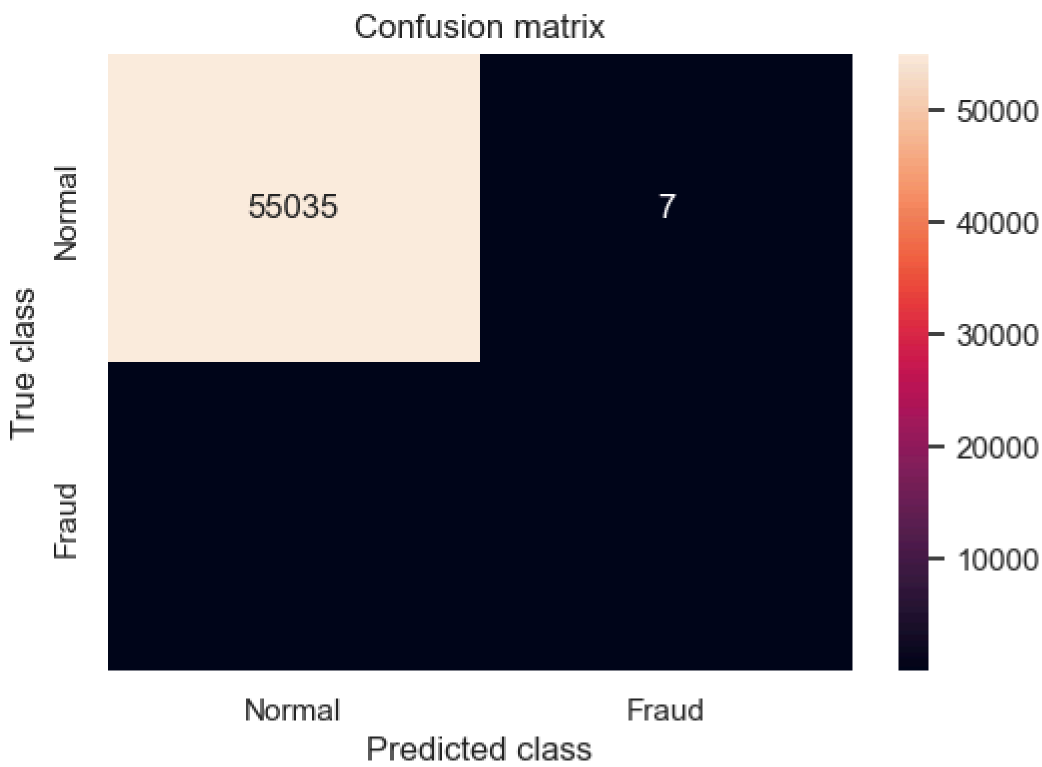
	Metrics	Logistic Regression
0	Accuracy	0.999220
1	Precision	0.887097
2	Recall	0.604396
3	F1_score	0.718954

In [48]:
```python
print(confusion_matrix(y_test, y_pred))
```

```
[[55035     7]
 [   36    55]]
```

In [49]:
```python
# printing the confusion matrix
LABELS = ['Normal', 'Fraud']
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize =(6, 4))
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()
```



Row 1 --> Normal:

56836 : True Negatives (TN) — The model correctly predicted "Normal" transactions.

7: False Positives (FP) — The model incorrectly predicted "Fraud" for transactions that are actually "Normal".

Row 2 --> Fraud:

36: False Negatives (FN) — The model incorrectly predicted "Normal" for transactions that are actually "Fraud".

55: True Positives (TP) — The model correctly predicted "Fraud" transactions.

2. Decison Tree Classifier

In [52]:
```
from sklearn.tree import DecisionTreeClassifier
# fitting Decision Tree to the training set

DecisionTree = DecisionTreeClassifier()
DecisionTree.fit(X_train,y_train)
```

Out[52]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [53]:
```python
decision_y_pred = DecisionTree.predict(X_test)
#y_hat_probs = logistic.predict_proba(X_test)[:,1]
```

In [54]:
```python
print(classification_report(y_test, decision_y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     55042
           1       0.71      0.75      0.73        91

    accuracy                           1.00     55133
   macro avg       0.85      0.87      0.86     55133
weighted avg       1.00      1.00      1.00     55133
```

In [55]:
```python
print(f"Decision Tree Regression")
print(f"\n Accuracy: {accuracy_score(y_test, decision_y_pred)}")
print(f"\n Precision: {precision_score(y_test, decision_y_pred)}")
print(f"\n Recall (also called sensitivity): {recall_score(y_test, decision_y_pred)
print(f"\n F1 Score (harmonic mean): {f1_score(y_test, decision_y_pred)}")
```

```
Decision Tree Regression

 Accuracy: 0.9990749641775343

 Precision: 0.7083333333333334

 Recall (also called sensitivity): 0.7472527472527473

 F1 Score (harmonic mean): 0.7272727272727272
```

In [56]:
```python
# Printing Evaluation Metrics for Decison Tree
metrics_DT = [['Accuracy',(accuracy_score(y_test, decision_y_pred))],
                        ['Precision',precision_score(y_test, decision_y_pred)],
                        ['Recall', recall_score(y_test, decision_y_pred)],
                        ['F1_score',f1_score(y_test, decision_y_pred)]]
metrics_DT = pd.DataFrame(metrics_DT, columns = ['Metrics', 'Decision Tree'])
metrics_DT
```

Out[56]:

	Metrics	Decision Tree
0	Accuracy	0.999075
1	Precision	0.708333
2	Recall	0.747253
3	F1_score	0.727273

In [57]:
```python
# Create a DataFrame for Decision Tree
metrics_DT = pd.DataFrame(metrics_DT, columns=['Metrics', 'Decision Tree'])

# Merge the two DataFrames on the 'Metrics' column
metrics_combined = pd.merge(metrics_LR, metrics_DT, on='Metrics')
```

```python
# Display the combined DataFrame
metrics_combined
```

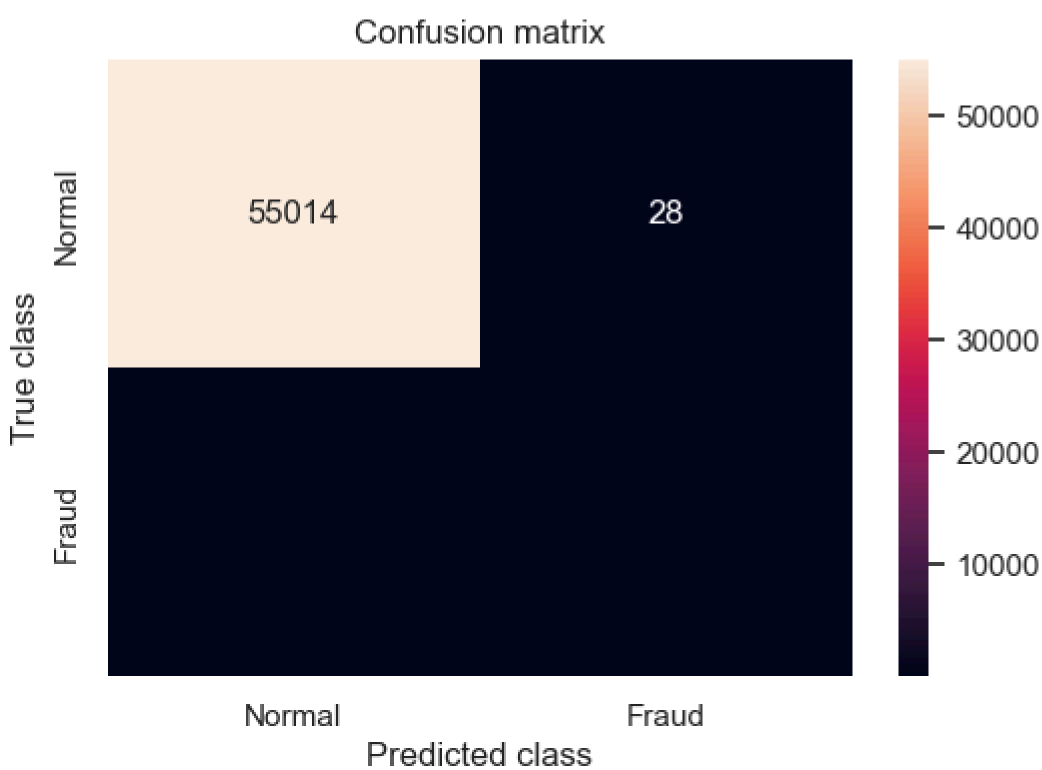
Out[57]:

	Metrics	Logistic Regression	Decision Tree
0	Accuracy	0.999220	0.999075
1	Precision	0.887097	0.708333
2	Recall	0.604396	0.747253
3	F1_score	0.718954	0.727273

In [58]:
```python
print(confusion_matrix(y_test, decision_y_pred))
```

```
[[55014    28]
 [   23    68]]
```

In [59]:
```python
# printing the confusion matrix
LABELS = ['Normal', 'Fraud']
conf_matrix = confusion_matrix(y_test, decision_y_pred)
plt.figure(figsize =(6, 4))
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()
```



Row 1 --> Normal:

55006 : True Negatives (TN) — The model correctly predicted "Normal" transactions.

36: False Positives (FP) — The model incorrectly predicted "Fraud" for transactions that are actually "Normal".

Row 2 --> Fraud:

28: False Negatives (FN) — The model incorrectly predicted "Normal" for transactions that are actually "Fraud".

63: True Positives (TP) — The model correctly predicted "Fraud" transactions.

3. Random Forest Classifier

In [62]:
```
from sklearn.ensemble import RandomForestClassifier
# fitting Random Forest regresson to the training set

RandomForest = RandomForestClassifier()
RandomForest.fit(X_train,y_train)
```

Out[62]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [63]:
```
RF_y_pred = RandomForest.predict(X_test)
#y_hat_probs = logistic.predict_proba(X_test)[:,1]
```

In [64]:
```
print(classification_report(y_test, RF_y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     55042
           1       0.91      0.74      0.81        91

    accuracy                           1.00     55133
   macro avg       0.95      0.87      0.91     55133
weighted avg       1.00      1.00      1.00     55133
```

In [65]:
```
print(f"RandomForest Regression")
print(f"\n Accuaracy: {accuracy_score(y_test, RF_y_pred)}")
print(f"\n Precision: {precision_score(y_test, RF_y_pred)}")
print(f"\n Recall: {recall_score(y_test, RF_y_pred)}")
print(f"\n F1 Score: {f1_score(y_test, RF_y_pred)}")
```

```
RandomForest Regression

 Accuaracy: 0.9994377233235993

 Precision: 0.9054054054054054

 Recall: 0.7362637362637363

 F1 Score: 0.8121212121212122
```

In [66]:
```
# Printing ROC AUC scores
from sklearn.metrics import roc_auc_score
print('Logistic Regression ROC AUC Score: ', (roc_auc_score(y_test, y_pred) * 100).
print('Decision Tree ROC AUC Score: ', (roc_auc_score(y_test, decision_y_pred) * 10
print('Random Forest ROC AUC Score: ', (roc_auc_score(y_test, RF_y_pred) * 100).rou
```

```
Logistic Regression ROC AUC Score:  80.21
Decision Tree ROC AUC Score:  87.34
Random Forest ROC AUC Score:  86.81
```

In [67]:
```
# Printing Evaluation Metrics for AB
metrics_RF = [['Accuracy',(accuracy_score(y_test, RF_y_pred))],
                         ['Precision',precision_score(y_test, RF_y_pred)],
                         ['Recall', recall_score(y_test, RF_y_pred)],
                         ['F1_score',f1_score(y_test, RF_y_pred)]]
metrics_RF = pd.DataFrame(metrics_RF, columns = ['Metrics', 'Random Forest'])

# Merge the two DataFrames on the 'Metrics' column
metrics_combined = pd.merge(metrics_combined, metrics_RF, on='Metrics')
```

In [68]:
```
# Display the combined DataFrame
metrics_combined
```

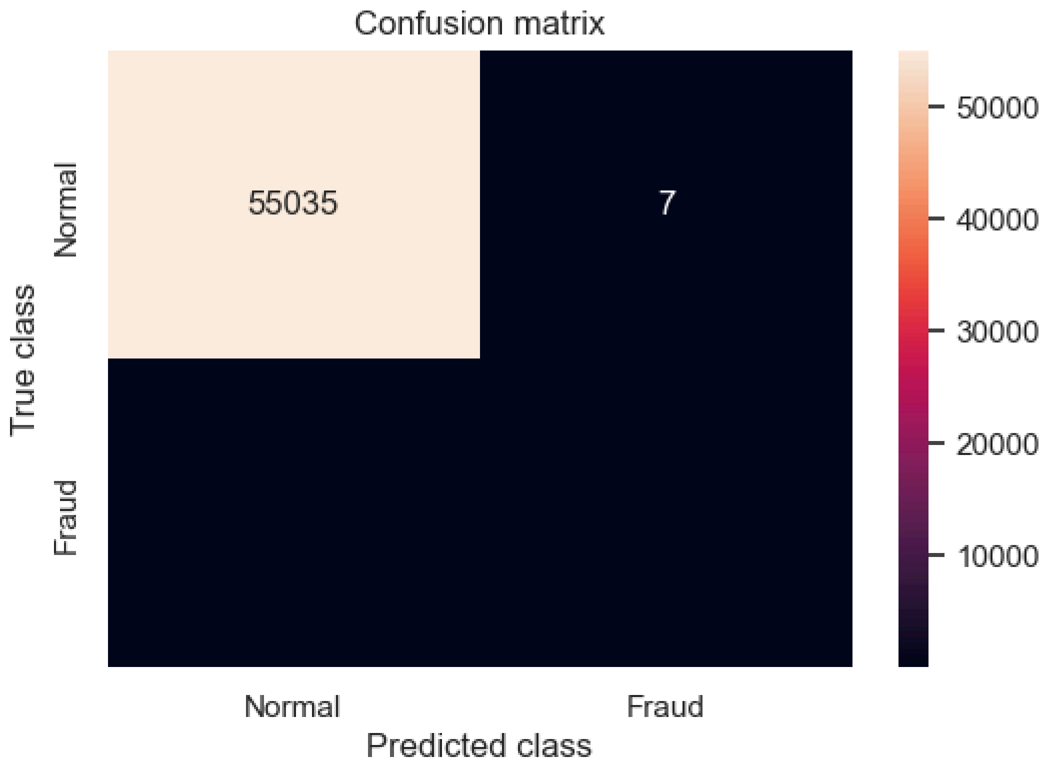
Out[68]:

	Metrics	Logistic Regression	Decision Tree	Random Forest
0	Accuracy	0.999220	0.999075	0.999438
1	Precision	0.887097	0.708333	0.905405
2	Recall	0.604396	0.747253	0.736264
3	F1_score	0.718954	0.727273	0.812121

In [69]:
```
print(confusion_matrix(y_test, RF_y_pred))
```

```
[[55035     7]
 [   24    67]]
```

In [70]:
```
# printing the confusion matrix
#LABELS = ['Normal', 'Fraud']
conf_matrix = confusion_matrix(y_test, RF_y_pred)
plt.figure(figsize =(6, 4))
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()
```



Row 1 --> Normal:

56863 : True Negatives (TN) — The model correctly predicted "Normal" transactions.

1: False Positives (FP) — The model incorrectly predicted "Fraud" for transactions that are actually "Normal".

Row 2 --> Fraud:

22: False Negatives (FN) — The model incorrectly predicted "Normal" for transactions that are actually "Fraud".

76: True Positives (TP) — The model correctly predicted "Fraud" transactions.

In [72]:

```
# feature importance

importance = RandomForest.feature_importances_
feature_imp = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importance
}).sort_values('Importance',ascending = False)
feature_imp.head()
```

Out[72]:

	Feature	Importance
16	V17	0.173239
11	V12	0.139373
13	V14	0.124583
9	V10	0.071338
10	V11	0.070486

Above feature is represent highes impact on RF model. Feature importance measures how much feature contributes to reduce the impurtities between trees. Higher value indicates greater importance.

All 3 models are yeilding high accuracy but low recall.

TP is for True Positive and it shows the correct predictions of a model for a positive class.

FP is for False Positive and it shows the incorrect predictions of a model for a positive class.

FN is for False Negative and it shows the incorrect predictions of a model for a negative class.

TN is for True Negative and it shows the correct predictions of a model for a negative class.

Since the data is imbalanced we can using resampling method to yeild balanced dataset. This method adjust the balance between minority and majority classes.

Oversampling

For oversampling we will use majority class

In [79]:
```
X = df.drop('Class', axis = 1)
y= df['Class']
```

In [80]:
```
X.shape
```

Out[80]: (275663, 29)

In [81]:
```
y.shape
```

Out[81]: (275663,)

In [82]:
```
from imblearn.over_sampling import SMOTE
X_res, y_res = SMOTE().fit_resample(X,y) # Reshaping data
```

In [83]:
```
y_res.value_counts()
```

Out[83]:
```
Class
0    275190
1    275190
Name: count, dtype: int64
```

In [84]:
```
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size = 0.2,
```

Now lets fit logistic and decision tree

In [86]:
```
# fitting logistic regresson to the training set
logistic = LogisticRegression()
logistic.fit(X_train,y_train)
```

Out[86]:
```
▾ LogisticRegression
LogisticRegression()
```

In [87]:
```
logistic_model = logistic.fit(X_train,y_train)
```

In [88]:
```
y_pred_LR_O = logistic.predict(X_test)
```

In [89]:
```
print(classification_report(y_test, y_pred_LR_O))
```

```
              precision    recall  f1-score   support

           0       0.92      0.97      0.95     55073
           1       0.97      0.91      0.94     55003

    accuracy                           0.94    110076
   macro avg       0.95      0.94      0.94    110076
weighted avg       0.95      0.94      0.94    110076
```

In [90]:
```
print(f"Logistic Regression")
print(f"\n Accuaracy: {accuracy_score(y_test, y_pred_LR_O)}")
print(f"\n Precision: {precision_score(y_test, y_pred_LR_O)}")
print(f"\n Recall: {recall_score(y_test, y_pred_LR_O)}")
print(f"\n F1 Score: {f1_score(y_test, y_pred_LR_O)}")
```

```
Logistic Regression

 Accuaracy: 0.9432392165412987

 Precision: 0.9731565769297956

 Recall: 0.9115502790756868

 F1 Score: 0.9413465510119785
```

In [91]:
```
# Printing Evaluation Metrics for AB
metrics_LR_O = [['Accuracy',(accuracy_score(y_test, y_pred_LR_O))],
                         ['Precision',precision_score(y_test, y_pred_LR_O)],
                         ['Recall', recall_score(y_test, y_pred_LR_O)],
                         ['F1_score',f1_score(y_test, y_pred_LR_O)]]
```

```
metrics_LR_O = pd.DataFrame(metrics_LR_O, columns = ['Metrics', 'LR_After_Oversampl
metrics_LR_O
# Merge the two DataFrames on the 'Metrics' column
#metrics_combined = pd.merge(metrics_combined, metrics_LR_O, on='Metrics')
```

Out[91]:

	Metrics	LR_After_Oversampling
0	Accuracy	0.943239
1	Precision	0.973157
2	Recall	0.911550
3	F1_score	0.941347

In [92]:

```
#print(confusion_matrix(y_test, y_pred_LR_O))
```

In [93]:

```
# Decision Tree Classifier
DecisionTree = DecisionTreeClassifier()
DecisionTree.fit(X_train,y_train)
```

Out[93]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [94]:

```
decision_y_pred_O = DecisionTree.predict(X_test)
```

In [95]:

```
print(f"Decision Tree Regression")
print(f"\n Accuracy: {accuracy_score(y_test, decision_y_pred_O)}")
print(f"\n Precision: {precision_score(y_test, decision_y_pred_O)}")
print(f"\n Recall: {recall_score(y_test, decision_y_pred_O)}")
print(f"\n F1 Score: {f1_score(y_test, decision_y_pred_O)}")
```

```
Decision Tree Regression

 Accuracy: 0.9980377193938733

 Precision: 0.9972950894072796

 Recall: 0.998781884624475

 F1 Score: 0.9980379332897318
```

In [96]:

```
# Printing Evaluation Metrics for DT after oversampling
metrics_DT_O = [['Accuracy',(accuracy_score(y_test, decision_y_pred_O))],
                         ['Precision',precision_score(y_test, decision_y_pred_O)],
                         ['Recall', recall_score(y_test, decision_y_pred_O)],
                         ['F1_score',f1_score(y_test, decision_y_pred_O)]]
metrics_DT_O = pd.DataFrame(metrics_DT_O, columns = ['Metrics', 'DT_Oversampling'])

# Merge the two DataFrames on the 'Metrics' column
metrics_O_combined = pd.merge(metrics_LR_O, metrics_DT_O, on='Metrics')
metrics_O_combined
```

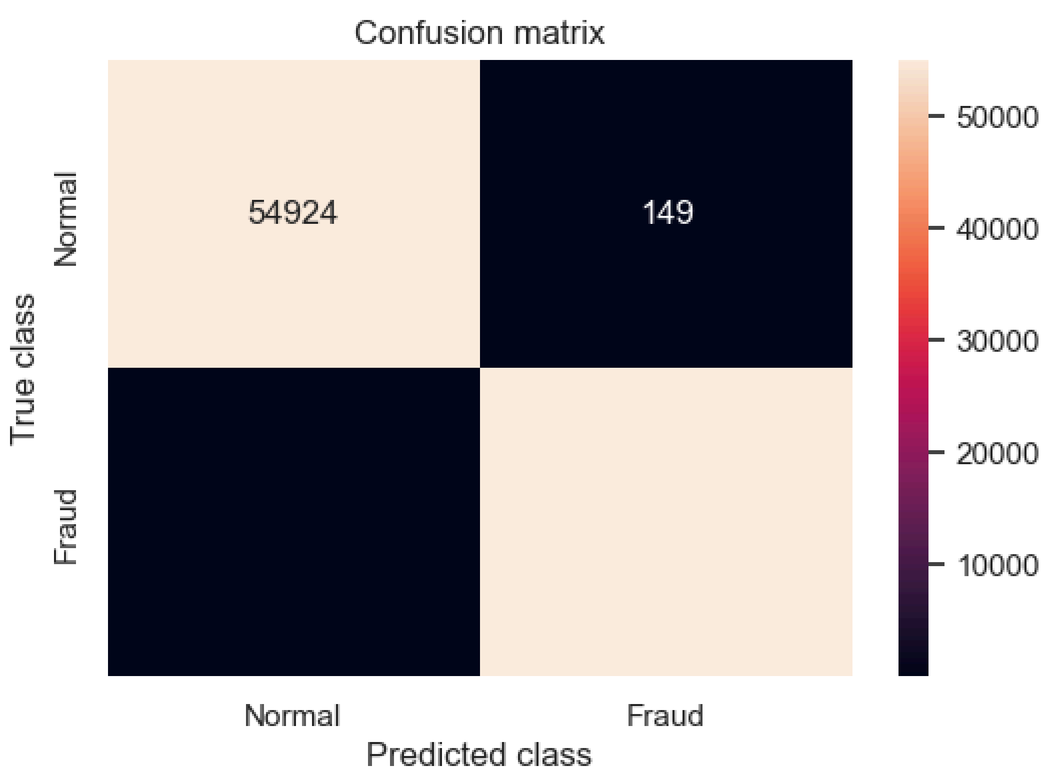
Out[96]:

	Metrics	LR_After_Oversampling	DT_Oversampling
0	Accuracy	0.943239	0.998038
1	Precision	0.973157	0.997295
2	Recall	0.911550	0.998782
3	F1_score	0.941347	0.998038

In [97]:
```
print(confusion_matrix(y_test, decision_y_pred_O))
```

```
[[54924   149]
 [   67 54936]]
```

In [98]:
```
conf_matrix_DTO = confusion_matrix(y_test, decision_y_pred_O)
plt.figure(figsize =(6, 4))
sns.heatmap(conf_matrix_DTO, xticklabels = LABELS,
            yticklabels = LABELS, annot = True, fmt ="d");
plt.title("Confusion matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```



In [99]:
```
# Random Forest Classifier
RandomForest = RandomForestClassifier()
#RandomForest.fit(X_train,y_train)
```

In [100…
```
random_forest_model = RandomForest.fit(X_train,y_train)
```

In [101…
```
random_forest_model
```

Out[101…

```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [102…

```
RF_y_pred_O = RandomForest.predict(X_test)
```

In [103…

```
print(classification_report(y_test, RF_y_pred_O))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     55073
           1       1.00      1.00      1.00     55003

    accuracy                           1.00    110076
   macro avg       1.00      1.00      1.00    110076
weighted avg       1.00      1.00      1.00    110076
```

In [104…

```
print(f"RandomForest Regression")
print(f"\n Accuaracy: {accuracy_score(y_test, RF_y_pred_O)}")
print(f"\n Precision: {precision_score(y_test, RF_y_pred_O)}")
print(f"\n Recall: {recall_score(y_test, RF_y_pred_O)}")
print(f"\n F1 Score: {f1_score(y_test, RF_y_pred_O)}")
```

```
RandomForest Regression

 Accuaracy: 0.9999091536756423

 Precision: 0.999818224783233

 Recall: 1.0

 F1 Score: 0.9999091041303083
```

In [105…

```
# Printing Evaluation Metrics for DT after oversampling
metrics_RF_O = [['Accuracy',(accuracy_score(y_test, RF_y_pred_O))],
                         ['Precision',precision_score(y_test, RF_y_pred_O)],
                         ['Recall', recall_score(y_test, RF_y_pred_O)],
                         ['F1_score',f1_score(y_test, RF_y_pred_O)]]
metrics_RF_O = pd.DataFrame(metrics_RF_O, columns = ['Metrics', 'RF_Oversampling'])

# Merge the two DataFrames on the 'Metrics' column
metrics_O_combined = pd.merge(metrics_O_combined, metrics_RF_O, on='Metrics')
metrics_O_combined
```

Out[105…

	Metrics	LR_After_Oversampling	DT_Oversampling	RF_Oversampling
0	Accuracy	0.943239	0.998038	0.999909
1	Precision	0.973157	0.997295	0.999818
2	Recall	0.911550	0.998782	1.000000
3	F1_score	0.941347	0.998038	0.999909

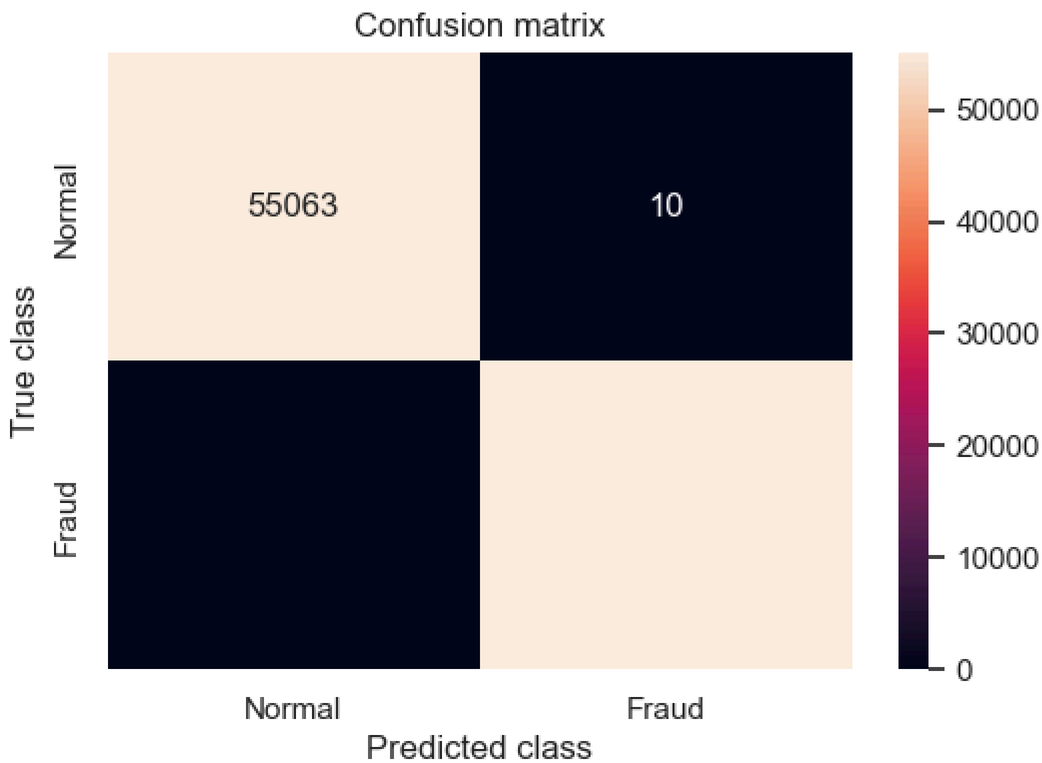
In [106…

```
print(confusion_matrix(y_test, RF_y_pred_O))
```

```
[[55063    10]
 [    0 55003]]
```

In [107…

```
conf_matrix_RFO = confusion_matrix(y_test, RF_y_pred_O)
plt.figure(figsize =(6, 4))
sns.heatmap(conf_matrix_RFO, xticklabels = LABELS,
            yticklabels = LABELS, annot = True, fmt ="d");
plt.title("Confusion matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```



In [108…

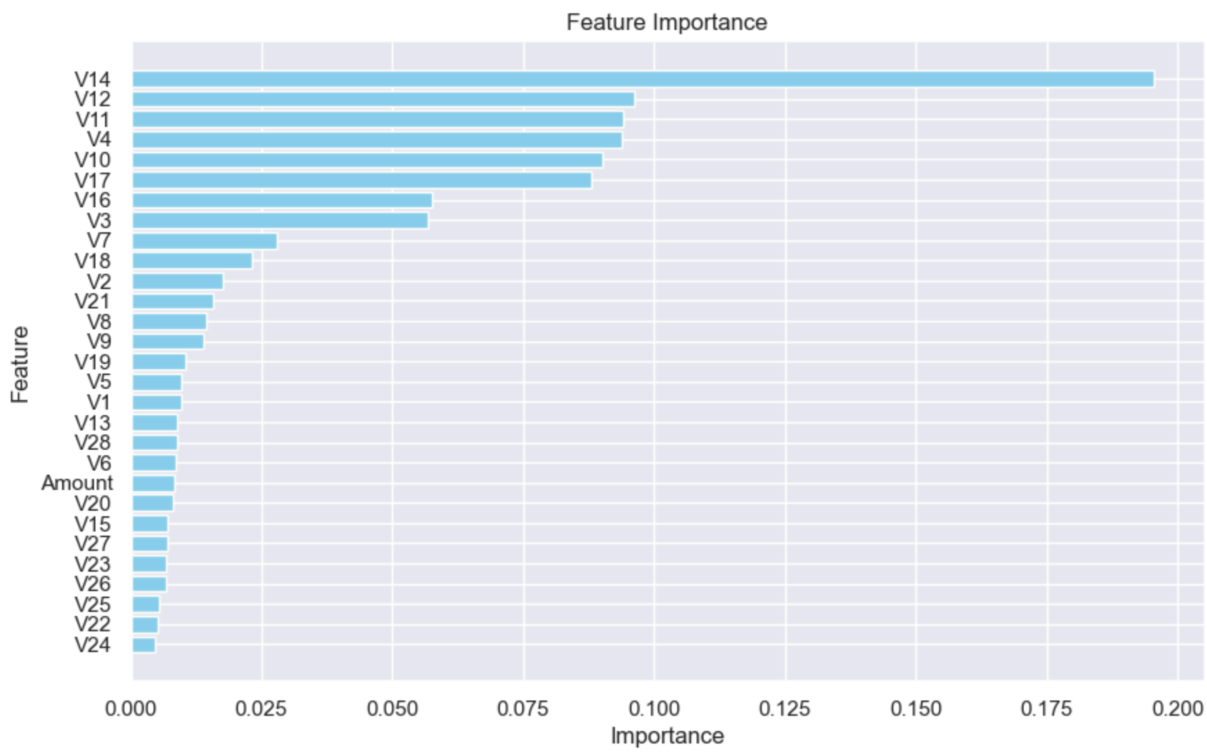
```
# feature importance

importance = RandomForest.feature_importances_
feature_imp = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importance
}).sort_values('Importance',ascending = False)
feature_imp.head()
```

Out[108...

	Feature	Importance
13	V14	0.195371
11	V12	0.096162
10	V11	0.094021
3	V4	0.093729
9	V10	0.090178

In [109...

```python
# Plotting the feature importance
plt.figure(figsize=(10,6))
plt.barh(feature_imp['Feature'], feature_imp['Importance'], color='skyblue')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Feature Importance')
plt.gca().invert_yaxis()  # Invert y-axis to have the most important feature at the
plt.show()
```



In [110...

```python
df.head()
```

Out[110...

	V1	V2	V3	V4	V5	V6	V7	V8	
0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.
1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.
2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.
3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.
4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.

5 rows × 30 columns

In [111...

```
# Printing ROC AUC scores
from sklearn.metrics import roc_auc_score
print('Logistic Regression ROC AUC Score: ', (roc_auc_score(y_test, y_pred_LR_O) *
print('Decision Tree ROC AUC Score: ', (roc_auc_score(y_test, decision_y_pred_O) *
print('Random Forest ROC AUC Score: ', (roc_auc_score(y_test, RF_y_pred_O) * 100).r
```

```
Logistic Regression ROC AUC Score:  94.32
Decision Tree ROC AUC Score:  99.8
Random Forest ROC AUC Score:  99.99
```

In [112...

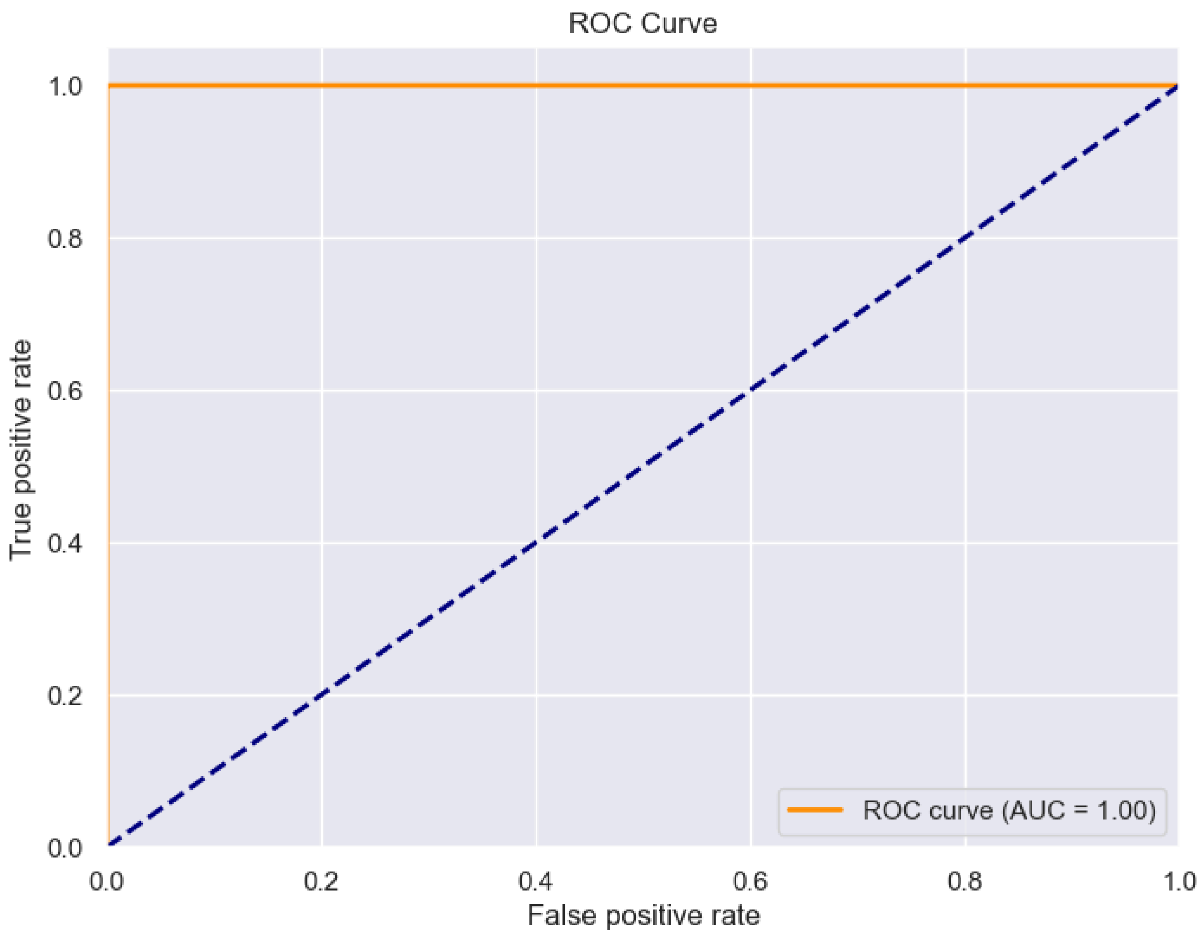
```
y_pred_proba = RandomForest.predict_proba(X_test)[:,1]
fpr,tpr, _ = roc_curve(y_test, y_pred_proba)
```

In [113...

```
from sklearn.metrics import auc
roc_auc = auc(fpr, tpr)
```

In [114...

```
plt.figure(figsize = (8,6))
plt.plot(fpr, tpr, color = 'darkorange', lw=2, label = f'ROC curve (AUC = {roc_auc:
plt.plot([0,1],[0,1], color = 'navy', lw =2, linestyle = '--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title("ROC Curve")
plt.legend(loc = 'lower right')
plt.show()
```



In [115…

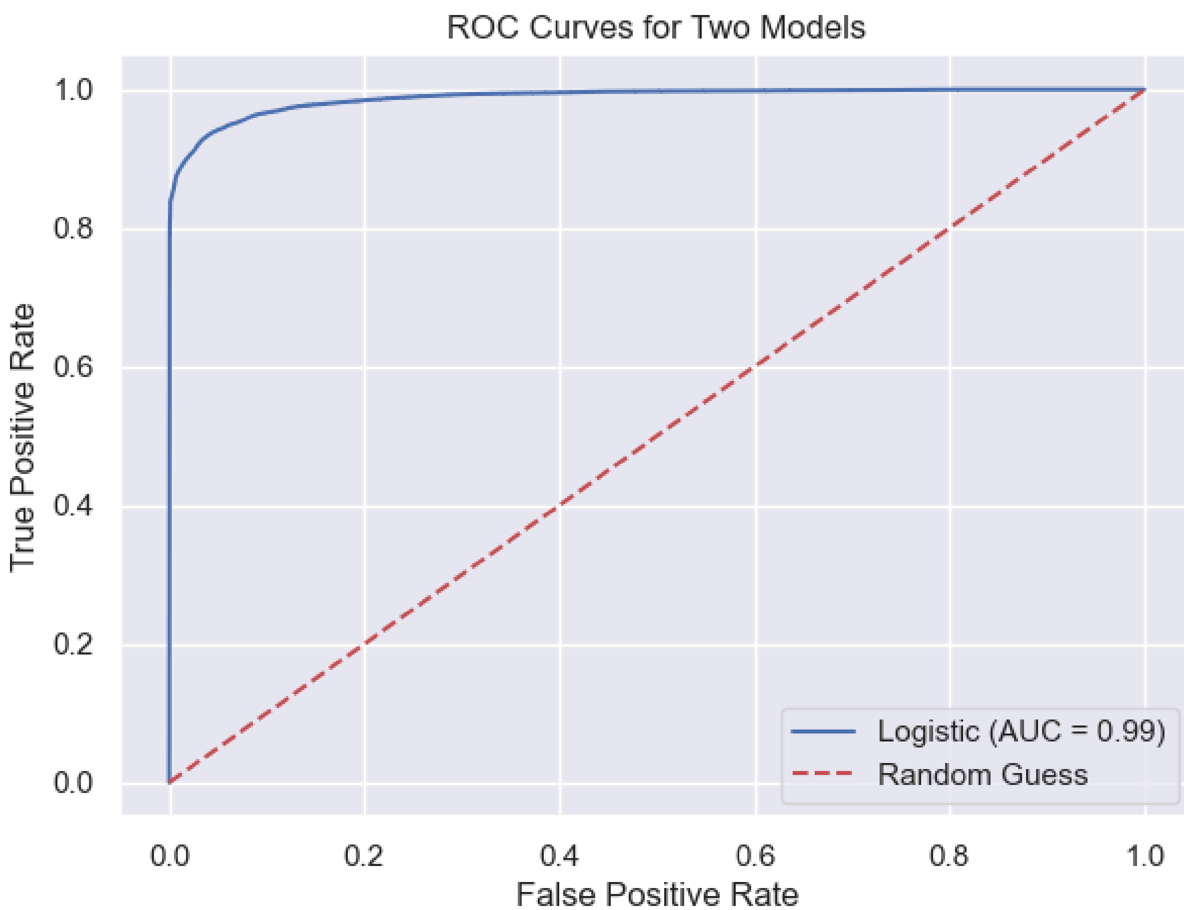
```
y_pred_logistic = logistic_model.predict_proba(X_test)[:, 1]
#y_pred_randf = random_forest_model.predict_proba(X_test)[:, 1]
```

In [116…

```
test_df = pd.DataFrame(
    {'True': y_test, 'Logistic': y_pred_logistic})
```

In [117…

```
plt.figure(figsize=(7, 5))

for model in ['Logistic']:
    fpr, tpr, _ = roc_curve(test_df['True'], test_df[model])
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'{model} (AUC = {roc_auc:.2f})')

plt.plot([0, 1], [0, 1], 'r--', label='Random Guess')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Two Models')
plt.legend()
plt.show()
```



Lets use Ensemble method.

ADA Boost

In [119…
```
# dividing the X and the Y from the dataset
X = df.drop(['Class'], axis = 1)
y = df["Class"]
print(X.shape)
print(y.shape)
```

```
(275663, 29)
(275663,)
```

In [120…
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.2,random_sta
```

In [121…
```
from sklearn.ensemble import AdaBoostClassifier
# Applying Ada Boost Classifier
ada_boost = AdaBoostClassifier(n_estimators = 100, random_state = 42)
ada_boost.fit(X_train,y_train)
```

Out[121…

```
▾ AdaBoostClassifier
AdaBoostClassifier(n_estimators=100, random_state=42)
```

In [122…

```
y_predictions_ab = ada_boost.predict(X_test)
```

In [123…

```
print(f"ADA Boost")
print(f"\n Accuaracy: {accuracy_score(y_test, y_predictions_ab)}")
print(f"\n Precision: {precision_score(y_test, y_predictions_ab)}")
print(f"\n Recall: {recall_score(y_test, y_predictions_ab)}")
print(f"\n F1 Score: {f1_score(y_test, y_predictions_ab)}")
```

```
ADA Boost

 Accuaracy: 0.9992382057932636

 Precision: 0.8024691358024691

 Recall: 0.7142857142857143

 F1 Score: 0.7558139534883721
```

In [124…

```
# Printing Evaluation Metrics for AB
metrics_ab = [['Accuracy',(accuracy_score(y_test, y_predictions_ab))],
                         ['Precision',precision_score(y_test, y_predictions_ab)],
                         ['Recall', recall_score(y_test, y_predictions_ab)],
                         ['F1_score',f1_score(y_test, y_predictions_ab)]]
metrics_ab = pd.DataFrame(metrics_ab, columns = ['Metrics', 'Results_AB'])
metrics_ab
```

Out[124…

	Metrics	Results_AB
0	Accuracy	0.999238
1	Precision	0.802469
2	Recall	0.714286
3	F1_score	0.755814

In [125…

```
# Applying Gradient Boosting Classifier
from sklearn.ensemble import GradientBoostingClassifier
gradient_boosting = GradientBoostingClassifier(n_estimators = 100, random_state = 4
gradient_boosting.fit(X_train, y_train)

y_prediction_gb = gradient_boosting.predict(X_test)
```

In [126…

```
# Printing Evaluation Metrics for GB
metrics_gb = [['Accuracy',(accuracy_score(y_test, y_prediction_gb))],
                         ['Precision',precision_score(y_test, y_prediction_gb)],
                         ['Recall', recall_score(y_test, y_prediction_gb)],
                         ['F1_score',f1_score(y_test, y_prediction_gb)]]
metrics_gb = pd.DataFrame(metrics_gb, columns = ['Metrics', 'Results_GB'])
metrics_gb
```

Out[126…

	Metrics	Results_GB
0	Accuracy	0.998603
1	Precision	0.718750
2	Recall	0.252747
3	F1_score	0.373984

In [ ]: