CSCI5502_Project_Sharma_Tapas_Xia

April 23, 2024

[ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from imblearn.over_sampling import SMOTE
from google.colab import drive
drive.mount('/content/drive')
data_path =  r'./drive/My Drive/creditcard.csv'
df = pd.read_csv(data_path)
```

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

[ ]:
```
creditcard_df = pd.read_csv(data_path)
```

[ ]:
```
unprocessed_df = creditcard_df
```

#**Dataset Description Details**:- The dataset comprises credit card transactions conducted by European cardholders in September 2013. This dataset comprises transactions that took place during a span of two days, with a total of 492 instances of fraud out of a total of 284,807 transactions.

The dataset comprises numerical input variables that have undergone a Principal Component Analysis (PCA) transformation. Some of the original characteristics are distance_from_home, distance_from_last_transaction, ratio_to_median_purchase_price, repeat_retailer, used_chip, used_pin_number, and online_order, which are transformed into variables using PCA. The principle components derived with PCA are denoted as V1, V2,… V28. The only characteristics that have not undergone PCA transformation are 'Time' and 'Amount'. Characteristic In the dataset, the variable 'Time' represents the duration in seconds between each transaction and the initial transaction. The 'Amount' feature represents the transaction amount and can be utilized for example-dependent cost-sensitive learning. Characteristic The response variable, denoted as 'Class', assumes a value of 1 when fraud is present and 0 when it is not.

The dataset exhibits a significant imbalance, with the positive class (defined as frauds) representing a mere 0.172% of the total transactions. There are total 284,807 records and 31 fields.

To solve this Imbalanced issue we will implement **SMOTE** algorithm to make the transaction baised. Dataset contains numerical input variables which are the result of a PCA transformation. In the original dataset we

Source - https://data.world/raghu543/credit-card-fraud-data

Solving method:- The given problem statement is comes under binary classification We have to solve problem using different machine learning algorithm as well as deep learning algorithms

Limitations - Due to confidentiality issues, the initial characteristics and additional contextual details of the data are converted into major components features V1, V2,... V28 using PCA.

[ ]:
```
creditcard_df.describe()
```

[ ]:
```
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean    94813.859575  1.759061e-12 -8.251130e-13 -9.654937e-13  8.321385e-13
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -5.683171e+00
25%     54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01
50%     84692.000000  1.810880e-02  6.548556e-02  1.798463e-01 -1.984653e-02
75%    139320.500000  1.315642e+00  8.037239e-01  1.027196e+00  7.433413e-01
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01

                 V5            V6            V7            V8            V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   1.649999e-13  4.248366e-13 -3.054600e-13  8.777971e-14 -1.179749e-12
std    1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  1.098632e+00
min   -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -1.343407e+01
25%   -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01
50%   -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -5.142873e-02
75%    6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  5.971390e-01
max    3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1.559499e+01

       …           V21           V22           V23           V24  \
count  …  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   … -3.405756e-13 -5.723197e-13 -9.725856e-13  1.464150e-12
std    …  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01
min    … -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00
25%    … -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01
50%    … -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02
75%    …  1.863772e-01  5.285536e-01  1.476421e-01  4.395266e-01
max    …  2.720284e+01  1.050309e+01  2.252841e+01  4.584549e+00

                V25           V26           V27           V28         Amount  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  284807.000000
mean  -6.987102e-13 -5.617874e-13  3.332082e-12 -3.518874e-12      88.349619
std    5.212781e-01  4.822270e-01  4.036325e-01  3.300833e-01     250.120109
min   -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01       0.000000
25%   -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02       5.600000
50%    1.659350e-02 -5.213911e-02  1.342146e-03  1.124383e-02      22.000000
75%    3.507156e-01  2.409522e-01  9.104512e-02  7.827995e-02      77.165000
max    7.519589e+00  3.517346e+00  3.161220e+01  3.384781e+01   25691.160000
```

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

[8 rows x 31 columns]
```

[ ]:
```
creditcard_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
```

All columns have either float or integer datatypes, indicating the absence of noise values such as **?** or **.**. If such values were present, the datatype would have been **object**.

Removing all the null values from the dataset and replacing those values with mean value of the column.

[ ]:
```
for column in creditcard_df.columns:
    if creditcard_df[column].isna().sum() > 0:
        mean_value = creditcard_df[column].mean()
        creditcard_df[column].fillna(mean_value, inplace=True)
```

[ ]:
```
creditcard_df.isna().sum()
```

[ ]:
```
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
```

#Multicollinearity check with VIF

Multicollinearity occurs when there are two or more independent variables in a multiple regression model, which have a high correlation among themselves. When some features are highly correlated, we might have difficulty in distinguishing between their individual effects on the dependent variable. Multicollinearity can be detected using various techniques, one such technique being the Variance Inflation Factor(VIF).

[ ]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

[ ]:
```
X =␣
 ↪creditcard_df[['Time','V1','V2','V3','V4','V5','V6','V7','V8','V9','V10','V11','V12','V13',


vif_data = pd.DataFrame()
vif_data["feature"] = X.columns

vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                          for i in range(len(X.columns))]
```

[ ]:
```
print(vif_data)
```

```
   feature       VIF
0     Time  2.339084
1       V1  1.621694
2       V2  3.869377
3       V3  1.255585
4       V4  1.137944
5       V5  2.753075
6       V6  1.522122
7       V7  2.510165
8       V8  1.097151
9       V9  1.018831
10     V10  1.115668
11     V11  1.028861
12     V12  1.011961
13     V13  1.003434
14     V14  1.026832
15     V15  1.014135
16     V16  1.000371
17     V17  1.004772
18     V18  1.006568
19     V19  1.037809
20     V20  2.233934
21     V21  1.100720
```

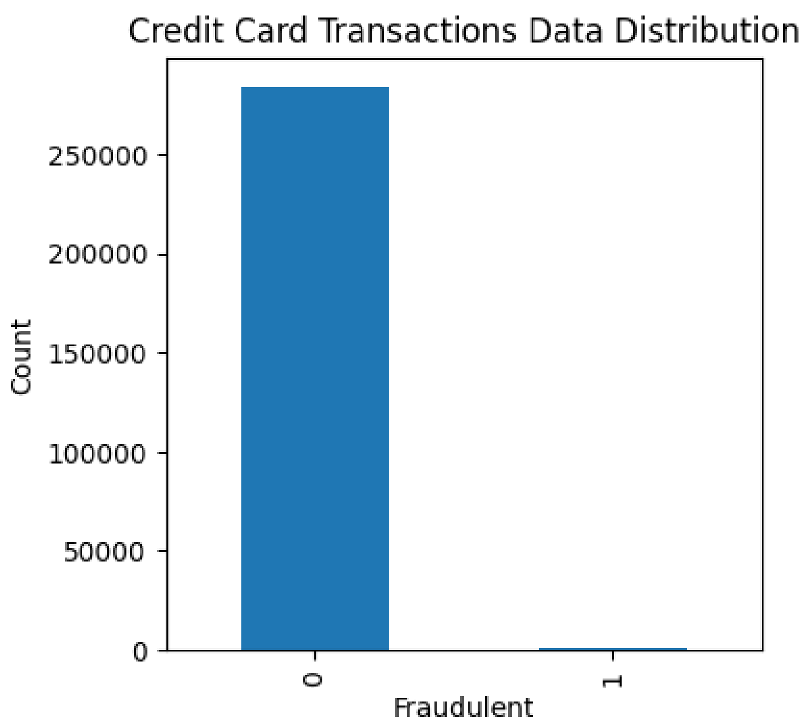
```
22      V22   1.082384
23      V23   1.149268
24      V24   1.000659
25      V25   1.013388
26      V26   1.000487
27      V27   1.008979
28      V28   1.001425
29  Amount  11.499791
```

[ ]:
```python
def plot_heatmap_of_correlation(df):
    corr = df.corr()
    plt.figure(figsize=(18, 10))
    heat = sns.heatmap(data=corr, annot=True)
    plt.title('Heatmap of Correlation')
    plt.show()

def plot_fraud_transaction_histogram(df):
    fraud = df[df['class'] == 1]
    plt.figure(figsize=(8, 6))
    sns.histplot(data=fraud, x='Amount', bins=65, kde=True)
    plt.title("Distribution of Fraud Transactions")
    plt.xlabel('Amount')
    plt.ylabel('Frequency')
    plt.show()

def plot_real_transaction_histogram(df):
    real = df[df['class'] == 0]
    plt.figure(figsize=(8, 6))
    sns.histplot(data=real, x='Amount', bins=65, kde=True)
    plt.title("Distribution of Real Transactions")
    plt.xlabel('Amount')
    plt.ylabel('Frequency')
    plt.show()

def plot_amount_distribution_for_transactions(df):
    plt.figure(figsize=(6, 4))
    sns.boxplot(x='class', y='Amount', data=df)
    plt.title('Amount Distribution for Fraud and Real Transactions')
    plt.show()

def plot_transaction_time_distribution(df):
    plt.figure(figsize=(6, 4))
    plt.title('Distribution of Transactions with Respect to Time', fontsize=14)
    sns.distplot(df['Time'], bins=120)
    plt.show()

def plot_transaction_counts_by_hour(df):
```

```python
    plt.figure(figsize=(10, 6))
    df['Hour'] = df['Time'] // 3600
    plt.title('Transaction Counts by Hour', fontsize=14)
    sns.countplot(x='Hour', hue='class', data=df)
    plt.xlabel('Hour of the Day')
    plt.ylabel('Transaction Count')
    plt.xticks(rotation=45)
    plt.show()

def plot_transaction_counts_by_day(df):
    plt.figure(figsize=(10, 6))
    df['Day'] = 1
    df.loc[df['Time'] >= 25*3600, 'Day'] = 2
    plt.title('Transaction Counts by Day', fontsize=14)
    sns.countplot(x='Day', hue='class', data=df)
    plt.xlabel('Day')
    plt.ylabel('Transaction Count')
    plt.show()

def plot_transaction_amount_vs_time(df):
    plt.figure(figsize=(10, 6))
    plt.scatter(df[df['class'] == 0]['Time'], df[df['class'] == 0]['Amount'],␣
 ↪label='Real', alpha=0.5, marker='o')
    plt.scatter(df[df['class'] == 1]['Time'], df[df['class'] == 1]['Amount'],␣
 ↪label='Fraud', alpha=0.5, marker='x')
    plt.title('Transaction Amount vs Time')
    plt.xlabel('Time')
    plt.ylabel('Amount')
    plt.legend()
    plt.show()

def plot_transaction_amount_vs_features(df):
    features = ['V1', 'V2', 'V3', 'V4', 'V5']
    plt.figure(figsize=(14, 10))
    for i, feature in enumerate(features, start=1):
        plt.subplot(2, 3, i)
        sns.scatterplot(x=feature, y='Amount', hue='class', data=df, alpha=0.5)
        plt.title(f'Transaction Amount vs {feature}')
        plt.xlabel(feature)
        plt.ylabel('Amount')
    plt.tight_layout()
    plt.show()

def plot_class_distribution(df):
    class_counts = df['class'].value_counts()
    plt.figure(figsize=(8, 6))
```

```
    plt.pie(class_counts, labels=class_counts.index, autopct='%1.1f%%',␣
 ↪startangle=140)
    plt.title('Transaction Class Distribution')
    plt.axis('equal')
    plt.show()
```

[ ]:
```
# See distribution of target class
creditcard_df['class'].value_counts().plot.bar(figsize=(4,4),␣
 ↪xlabel='Fraudulent', ylabel='Count', title='Credit Card Transactions Data␣
 ↪Distribution')
plt.show()
```



[ ]:
```
def dataset_analysis(df):
    fraud = df[df['class'] == 1]
    real = df[df['class'] == 0]

    percent_real = (len(real) / (len(real) + len(fraud))) * 100
    percent_fraud = (len(fraud) / (len(real) + len(fraud))) * 100

    print(f'Number of Real Transactions = {len(real)} and the Percentage of␣
 ↪Real Transactions = {percent_real:.3f}%')
    print(f'Number of Fraud Transactions = {len(fraud)} and the Percentage of␣
 ↪Fraud Transactions = {percent_fraud:.3f}%')
```

```
dataset_analysis(creditcard_df)
```

```
Number of Real Transactions = 284315 and the Percentage of Real Transactions =
99.827%
Number of Fraud Transactions = 492 and the Percentage of Fraud Transactions =
0.173%
```

In the below pie chart we are visually representing the distribution of transaction classes (real vs. fraud) in the dataset.

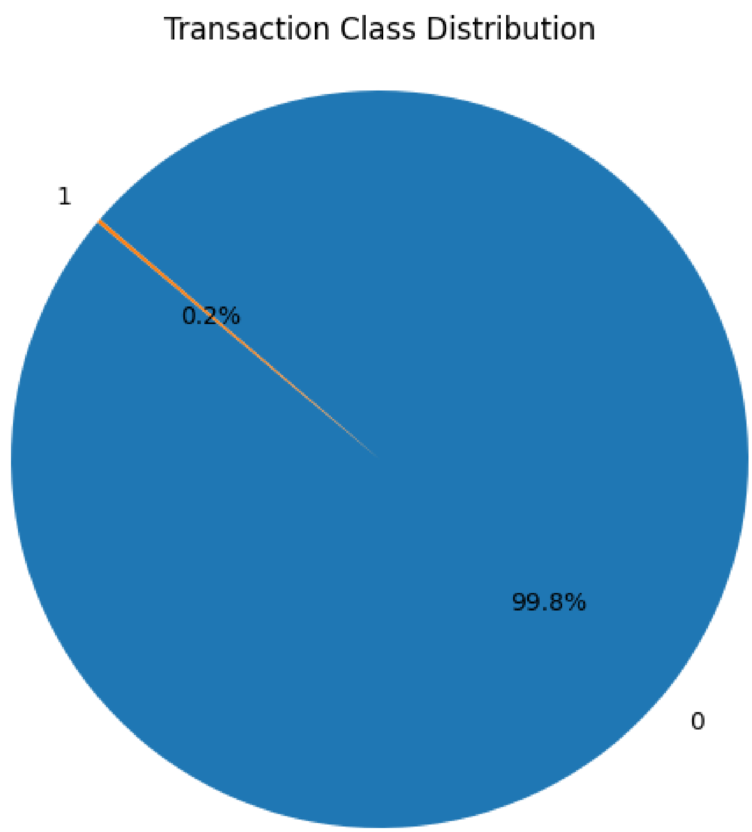
Pie chart Analysis -

1. The pie chart visually shows the proportion of real transactions compared to fraudulent transactions in the dataset.
2. The larger portion of the pie represents real transactions, while the smaller portion represents fraudulent transactions.
3. Each slice of the pie is labeled with the corresponding class (real or fraud) and its percentage of the total number of transactions.

There are 284,315 real transactions, accounting for approximately 99.827% of the total.

There are 492 fraudulent transactions, accounting for approximately 0.173% of the total.

```
[ ]: plot_class_distribution(creditcard_df)
```

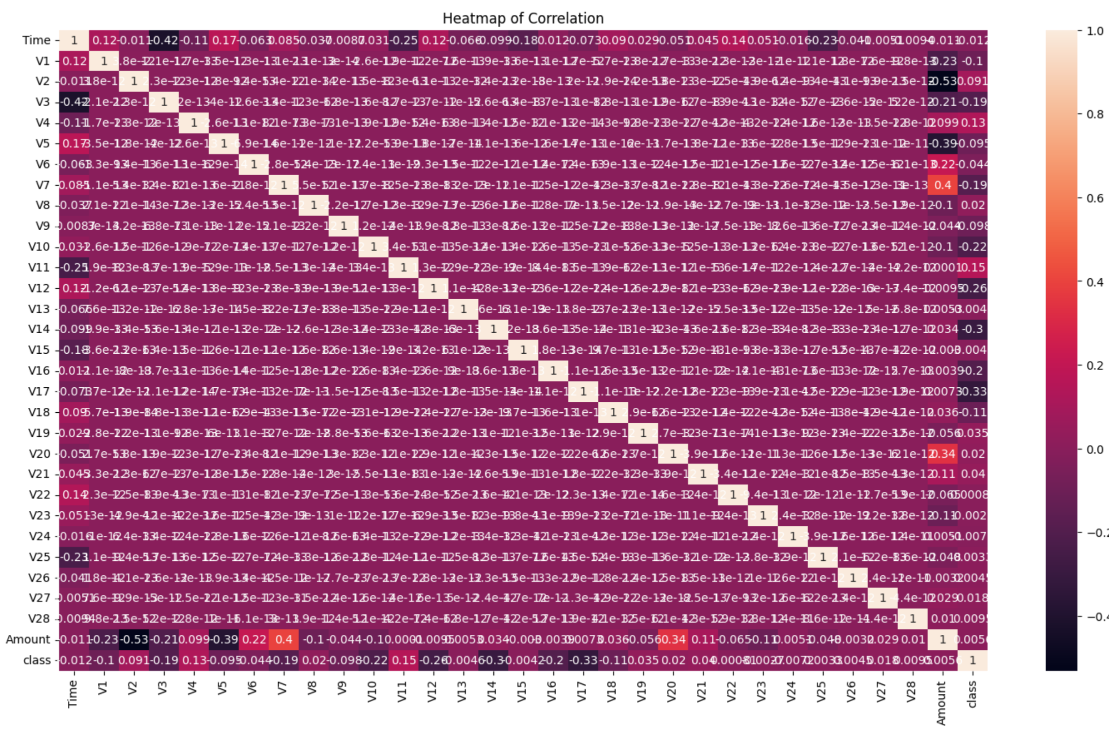


The below correlation matrix shows how each feature in the dataset correlates with every other feature.

1. It is useful for understanding the relationships between different features in a dataset.
2. A high positive correlation (close to 1) between two features indicates that they tend to increase or decrease together.
3. A high negative correlation (close to -1) indicates that as one feature increases, the other tends to decrease, and vice versa.
4. A correlation close to 0 suggests that there is little to no linear relationship between the features.
5. By analyzing the heatmap, you can identify patterns and dependencies between features, which can be helpful in feature selection, dimensionality reduction, and understanding the underlying structure of the data.

From below plot, we can conclude that the features are not correlated.

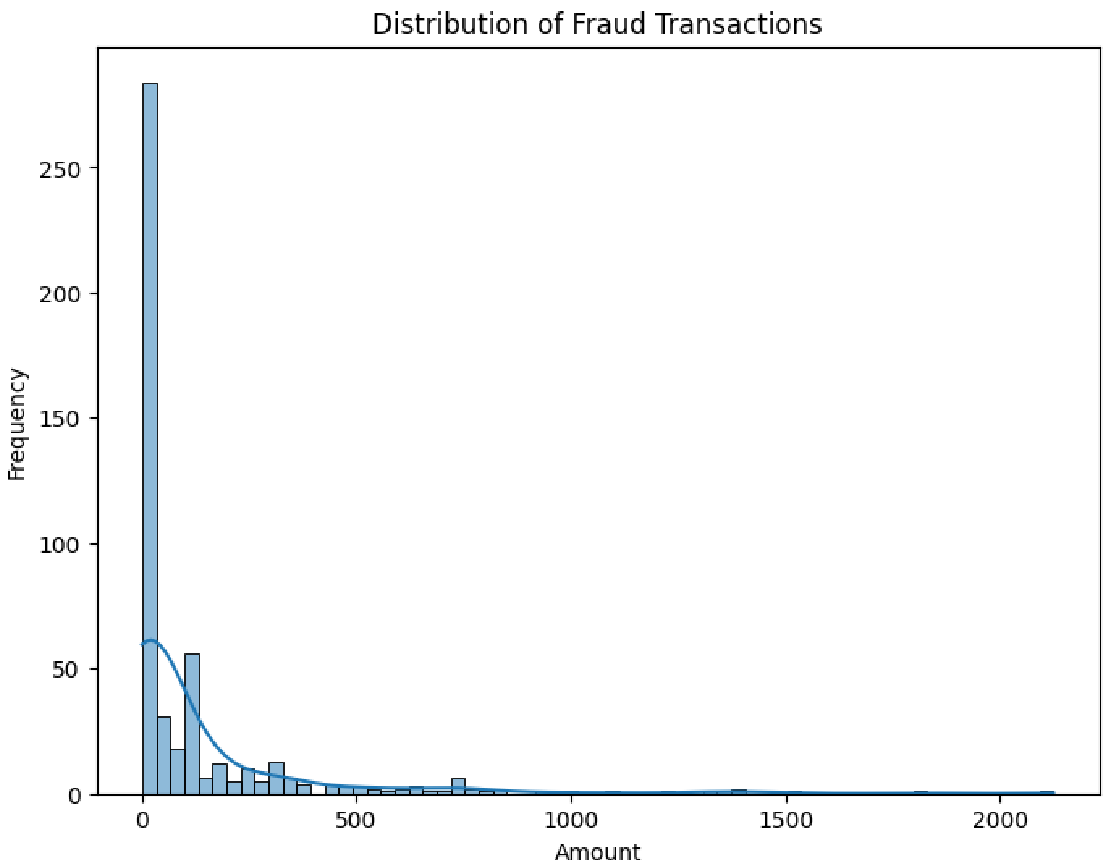
[ ]:
```
# Plot heatmap of correlations
plot_heatmap_of_correlation(creditcard_df)
```



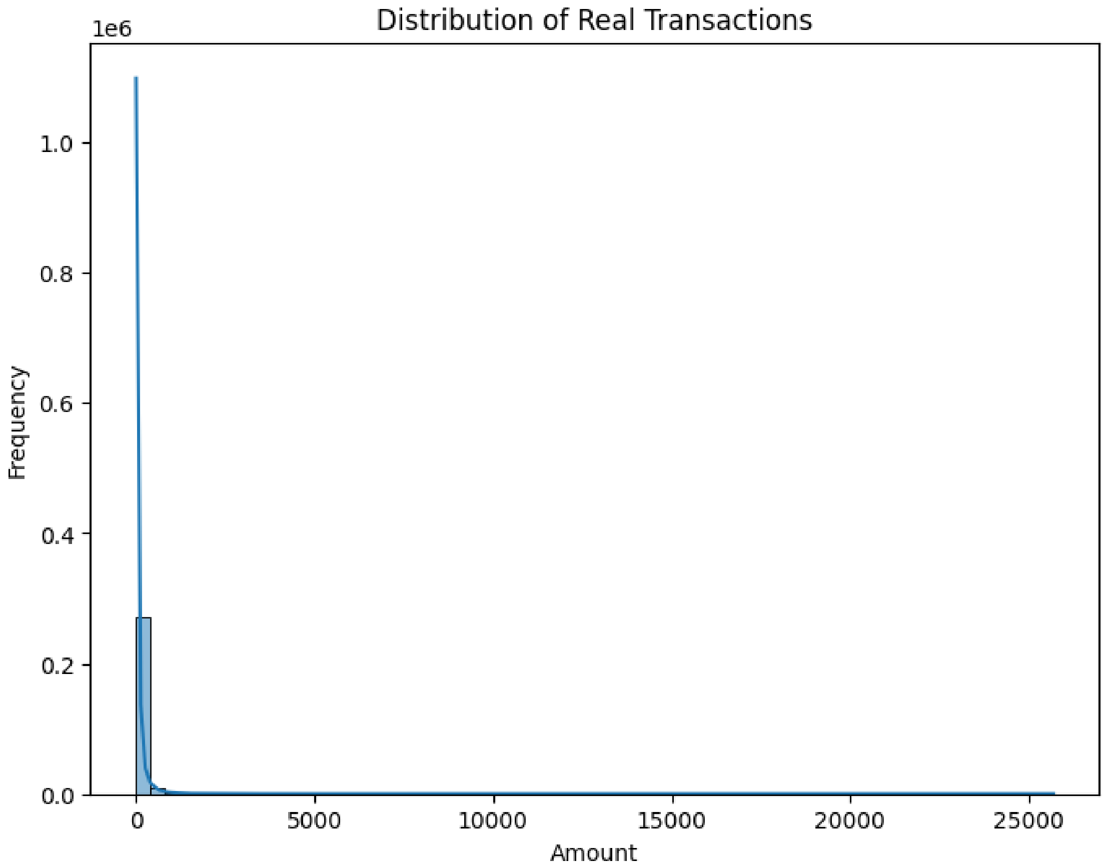
Below histograms provide a visual representation of the distribution of transaction amounts for both fraud and real transactions.

1. By comparing the two histograms, you can visually assess whether there are any noticeable differences in the distribution of transaction amounts between fraud and real transactions.
2. Understanding these differences can help in identifying potential patterns or anomalies associated with fraudulent transactions, such as unusually high or low transaction amounts.
3. This analysis can be valuable for developing fraud detection algorithms or understanding the characteristics of fraudulent transactions in the dataset.

[ ]:
```
plot_fraud_transaction_histogram(creditcard_df)
```



[ ]:
```
plot_real_transaction_histogram(creditcard_df)
```



Above Histogram plot result analysis

[ ]:
```
print("Fraud Transaction distribution:")
print(creditcard_df[creditcard_df['class'] == 1]['Amount'].value_counts().
  ↪head())
print("\n")
print("Maximum amount of fraud transaction:",␣
  ↪creditcard_df[creditcard_df['class'] == 1]['Amount'].max())
print("Minimum amount of fraud transaction:",␣
  ↪creditcard_df[creditcard_df['class'] == 1]['Amount'].min())
```

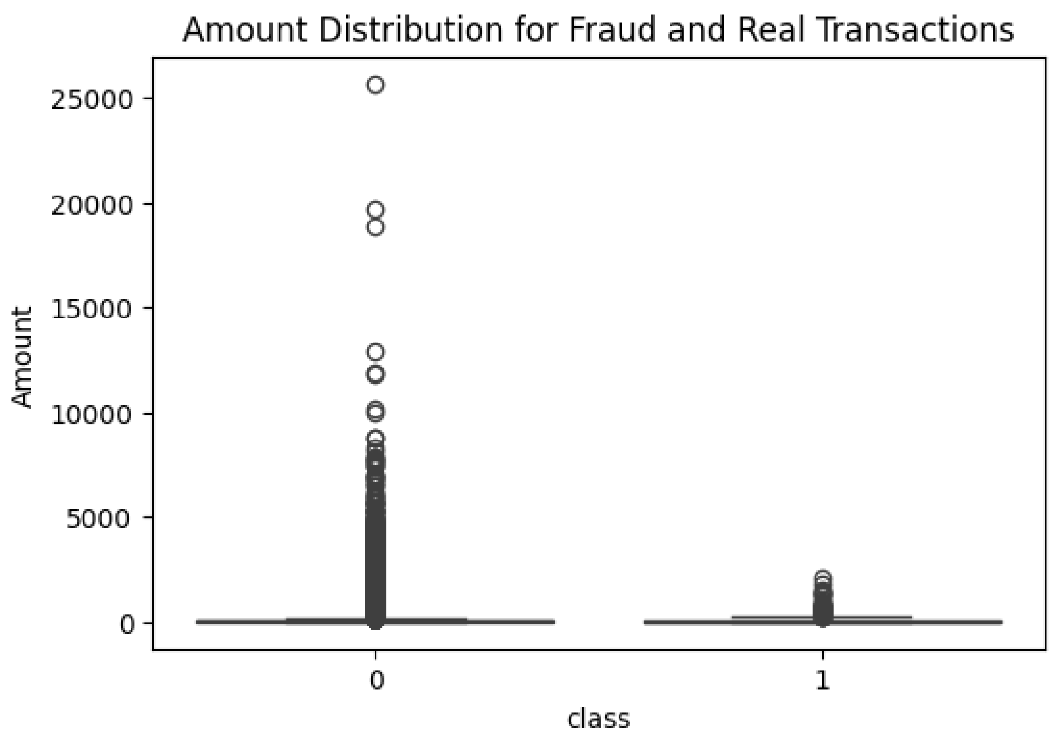
```
Fraud Transaction distribution:
1.00     113
0.00      27
99.99     27
0.76      17
0.77      10
Name: Amount, dtype: int64
```

```
Maximum amount of fraud transaction: 2125.87
Minimum amount of fraud transaction: 0.0
```

The purpose of the below plot is to visualize and compare the distribution of transaction amounts between fraud and real transactions using a boxplot.

1. This plot helps in identifying any significant differences or patterns in the transaction amounts associated with fraudulent activities compared to legitimate transactions.
2. Moreover, Understanding these differences can aid in developing effective fraud detection strategies and models.

[ ]:
```
plot_amount_distribution_for_transactions(creditcard_df)
```



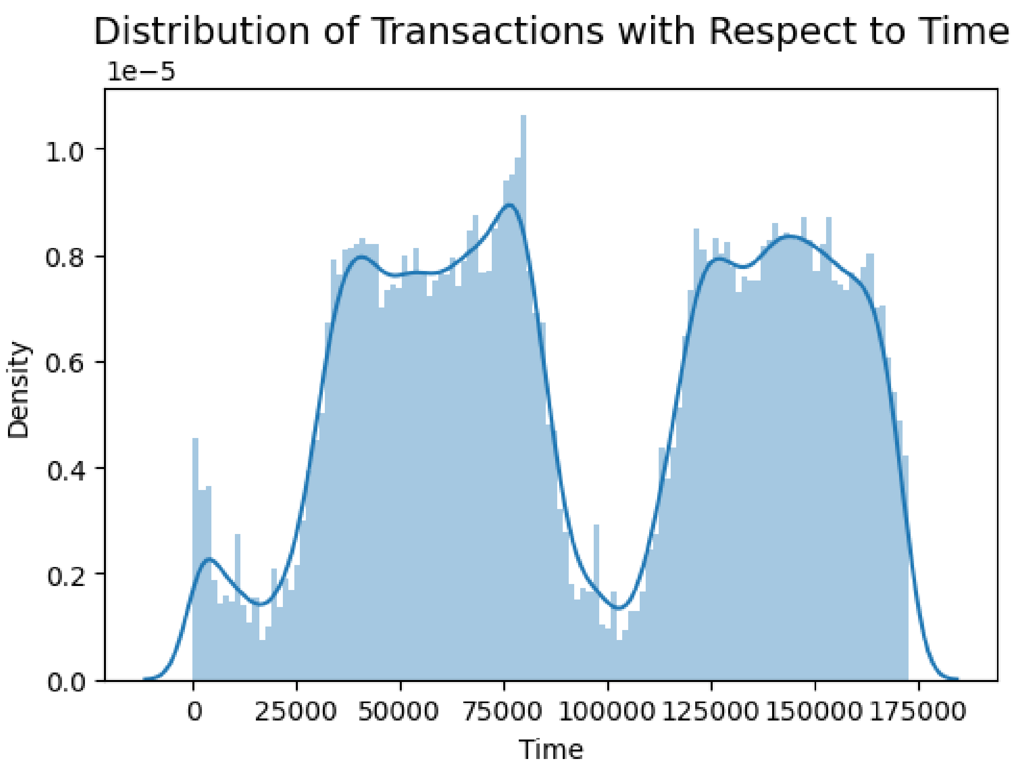
Below plot is to visualize the distribution of transactions over time.

1. The histogram provides insights into the frequency or density of transactions occurring at different points in time.
2. Peaks in the histogram indicate periods of higher transaction activity, while valleys represent periods of lower activity.
3. By examining the shape and pattern of the histogram, you can identify any temporal trends or patterns in transaction activity.

Overall, plot helps in understanding the overall pattern of transaction activity, such as peak hours or periods of increased transaction volume.

[ ]:
```
plot_transaction_time_distribution(creditcard_df)
```

```
<ipython-input-40-ad04cba562f0>:35: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Time'], bins=120)
```



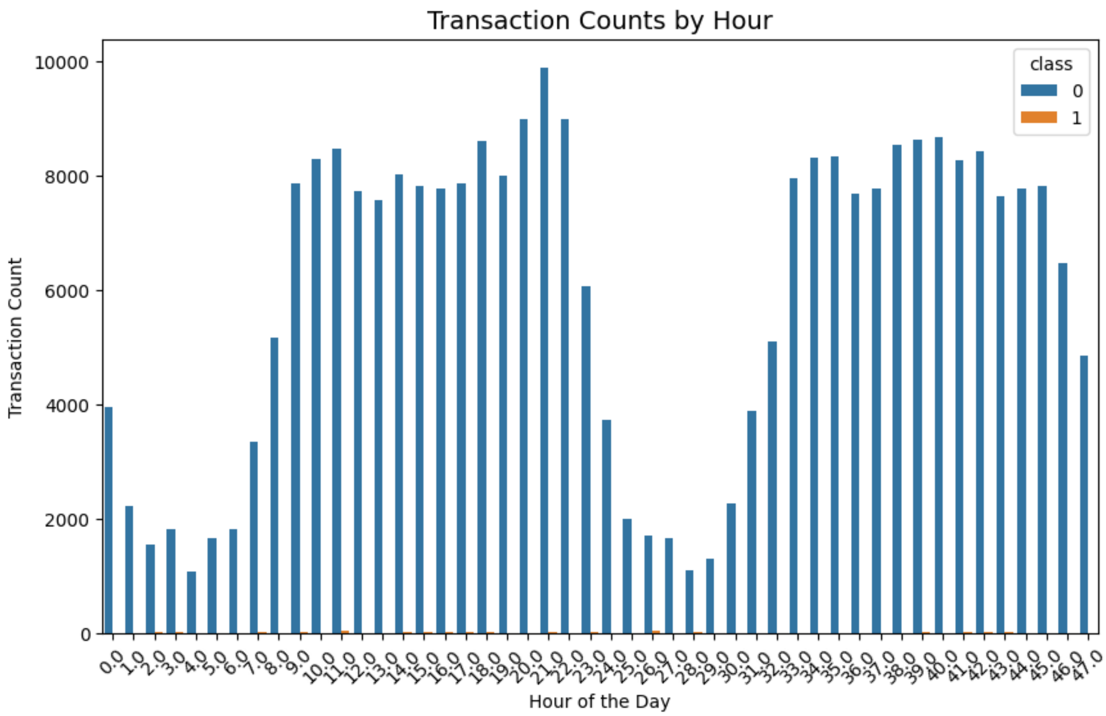
Below plot to visualize the distribution of transaction counts by hour of the day, categorized by transaction class (fraudulent vs. non-fraudulent).

1. The x-axis represents the hours of the day, while the y-axis represents the count of transactions.
2. The bars are color-coded based on the transaction class (fraudulent vs. non-fraudulent), allowing for easy comparison between the two classes.
3. By examining the plot, you can identify any patterns or trends in transaction counts through-

out the day and observe if there are specific hours with higher or lower transaction activity.

Overall, plot helps in understanding the temporal patterns of transaction activity and identifying any anomalies or trends associated with specific hours.

[ ]:
```
plot_transaction_counts_by_hour(creditcard_df)
```

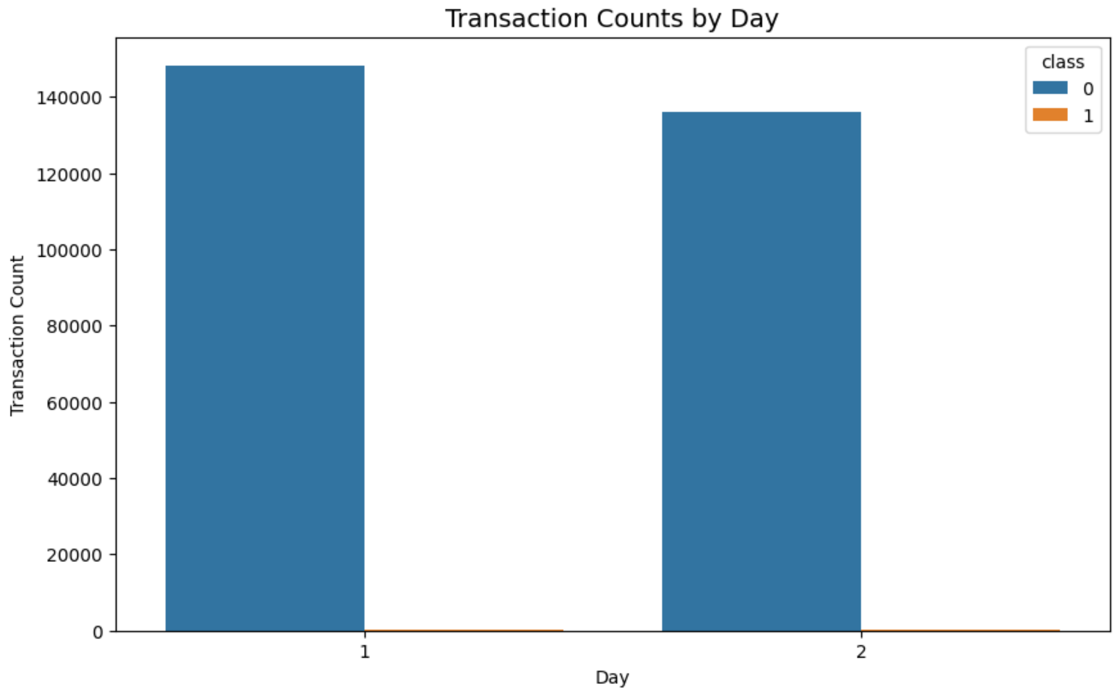


Below plot to visualize the distribution of transaction counts by day, categorized by transaction class (fraudulent vs. non-fraudulent)

1. The x-axis represents the days, while the y-axis represents the count of transactions.
2. The bars are color-coded based on the transaction class (fraudulent vs. non-fraudulent), allowing for easy comparison between the two classes.
3. By examining the plot, you can identify any patterns or trends in transaction counts throughout the days and observe if there are specific days with higher or lower transaction activity.

Overall, plot helps in understanding the temporal patterns of transaction activity and identifying any anomalies or trends associated with specific days.

[ ]:
```
plot_transaction_counts_by_day(creditcard_df)
```

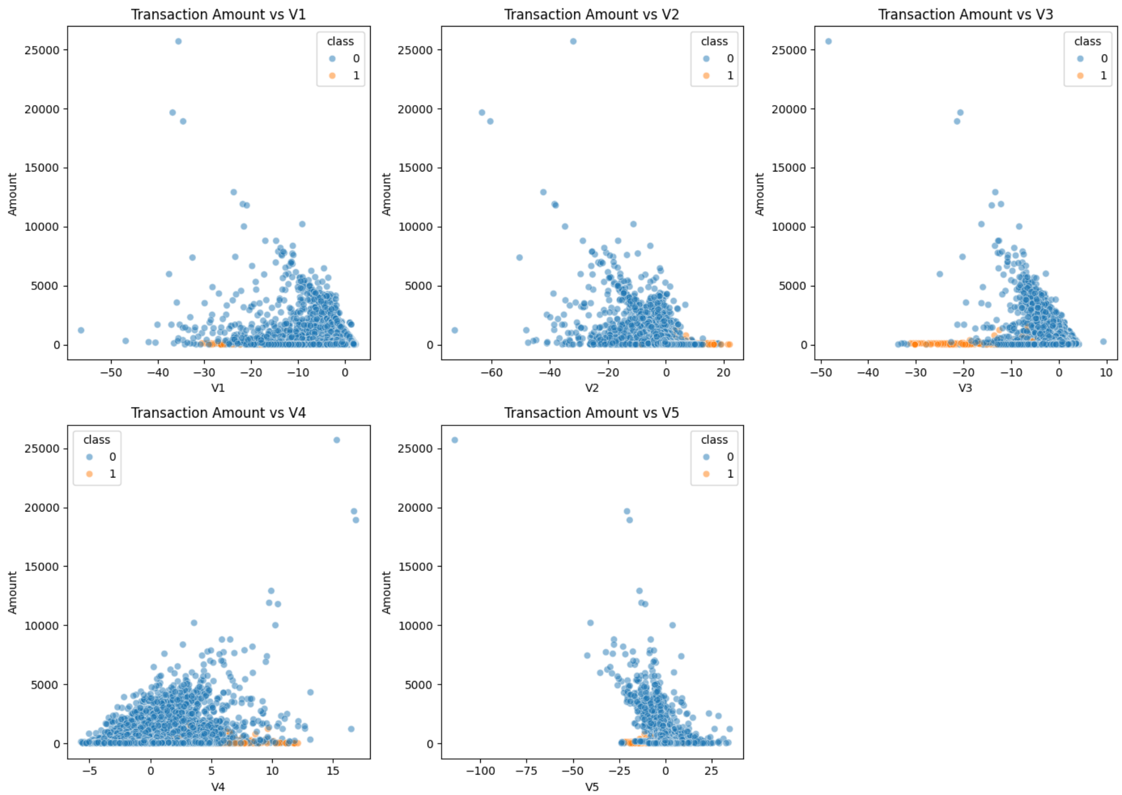


Below code generates multiple scatter plots to visualize the relationship between transaction amounts and selected features (V1 to V5), categorized by transaction class (fraudulent vs. non-fraudulent).

1. Each scatter plot shows the relationship between transaction amounts ('Amount') and a specific feature (V1 to V5).
2. The x-axis represents the feature values, while the y-axis represents the transaction amounts.Points in the scatter plot represent individual transactions.
3. Each subplot is color-coded based on the transaction class (fraudulent vs. non-fraudulent), with different colors representing different classes.
4. By examining the scatter plots, you can observe how transaction amounts vary concerning different feature values for both fraud and non-fraud transactions. The scatter plots allow you to identify any clusters, outliers, or correlations between transaction amounts and the selected features.

Overall, the plot generated provides valuable insights into the relationship between transaction amounts and selected features, aiding in the analysis and detection of fraudulent transactions.

[ ]:
```
plot_transaction_amount_vs_features(creditcard_df)
```



Class Imbalance

Whenever there is an issue with a classification problem and the classes are not represented equally, we say that the data is imbalanced. Applying classifiers to the dataset would most likely result in inaccurate predictions for every category. This was seen as a hurdle when attempting to learn from extremely Imbalanced data sets.

SMOTE stands for "Synthetic Minority OverSampling Method." In this method, synthesis new data from the minority class rather than replicating existing data.

SMOTE creates synthetic samples of the minority class by selecting similar instances and creating new synthetic examples along the line segments joining those instances in the feature space.

[ ]:
```
X = creditcard_df.drop('class', axis=1)
y = creditcard_df['class']

smote = SMOTE(random_state=42)
```

[ ]:
```
X_resampled, y_resampled = smote.fit_resample(X, y)

balanced_df = X_resampled.copy()
balanced_df['class'] = y_resampled
```

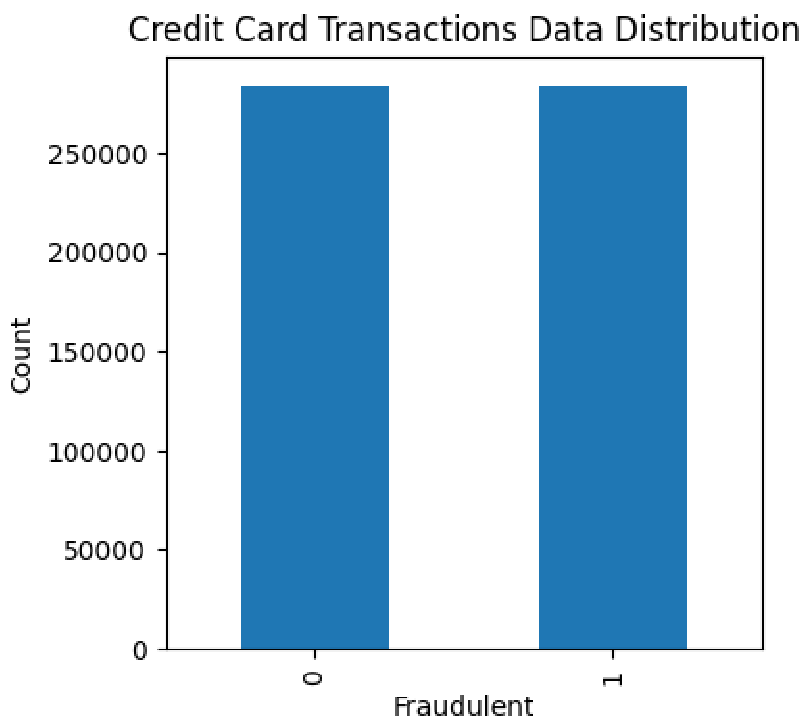
Balanced dataframe after SMOTE

[ ]:
```
balanced_df.head()
```

[ ]:
```
   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
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9  …       V21       V22       V23       V24       V25  \
0  0.098698  0.363787  … -0.018307  0.277838 -0.110474  0.066928  0.128539
1  0.085102 -0.255425  … -0.225775 -0.638672  0.101288 -0.339846  0.167170
2  0.247676 -1.514654  …  0.247998  0.771679  0.909412 -0.689281 -0.327642
3  0.377436 -1.387024  … -0.108300  0.005274 -0.190321 -1.175575  0.647376
4 -0.270533  0.817739  … -0.009431  0.798278 -0.137458  0.141267 -0.206010

        V26       V27       V28  Amount  class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
2 -0.139097 -0.055353 -0.059752  378.66      0
3 -0.221929  0.062723  0.061458  123.50      0
4  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
```

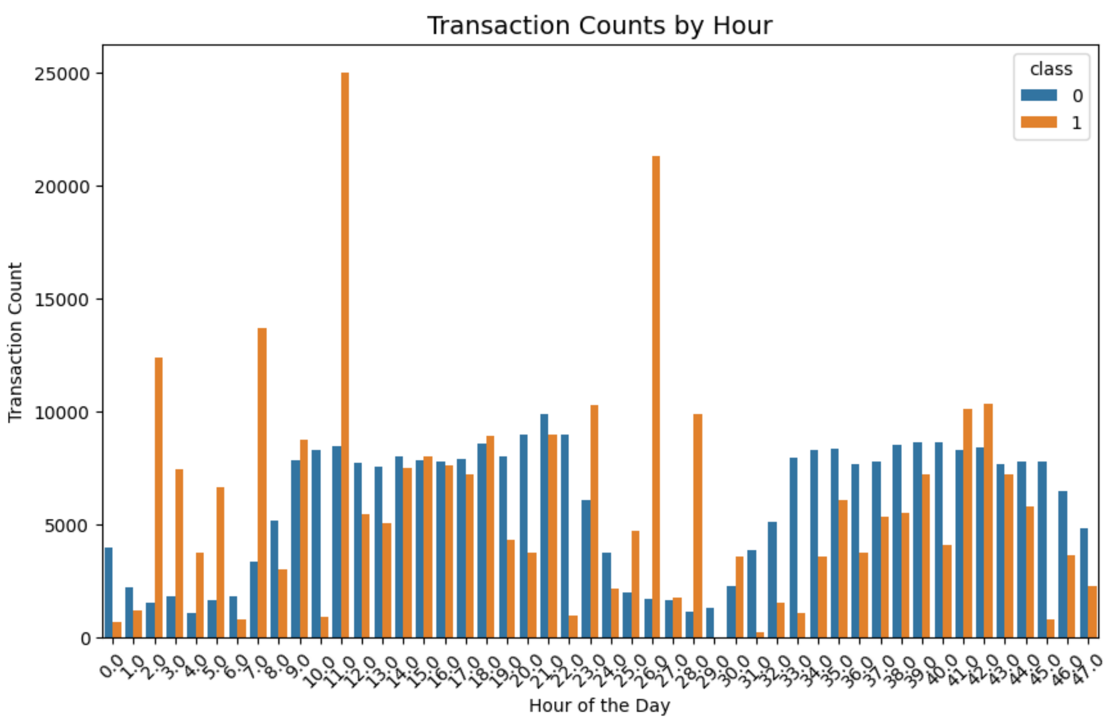
#Dataset After Processing

[ ]:
```
# See distribution of target class
balanced_df['class'].value_counts().plot.bar(figsize=(4,4),␣
 ↪xlabel='Fraudulent', ylabel='Count', title='Credit Card Transactions Data␣
 ↪Distribution')
plt.show()
```

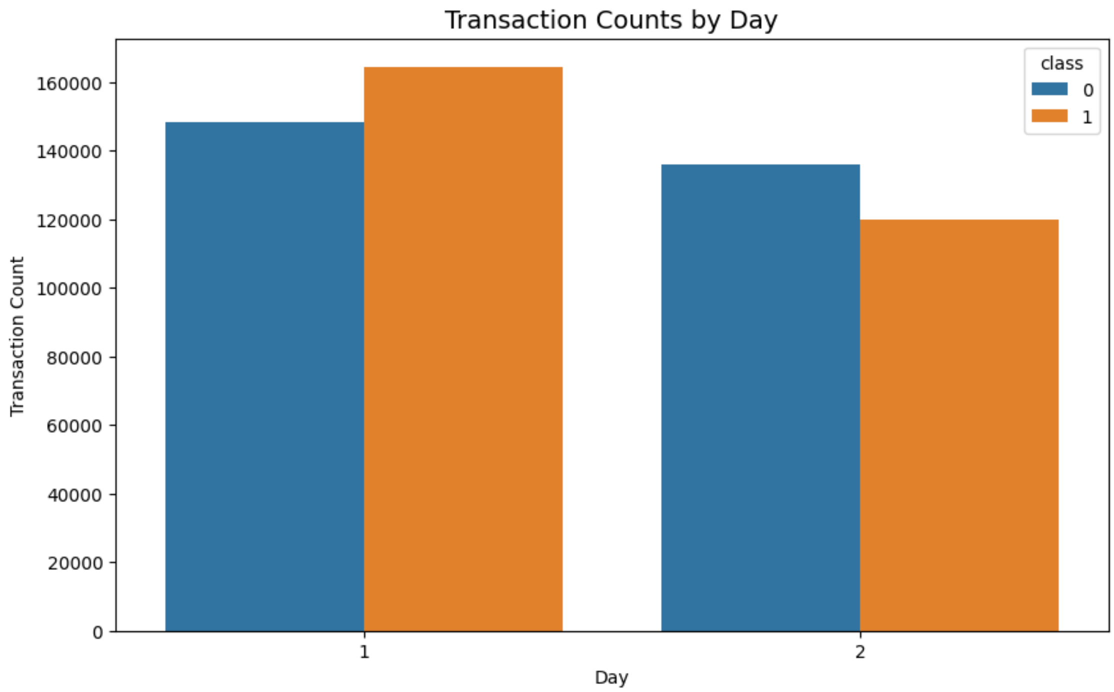


Plots after balancing the datasets

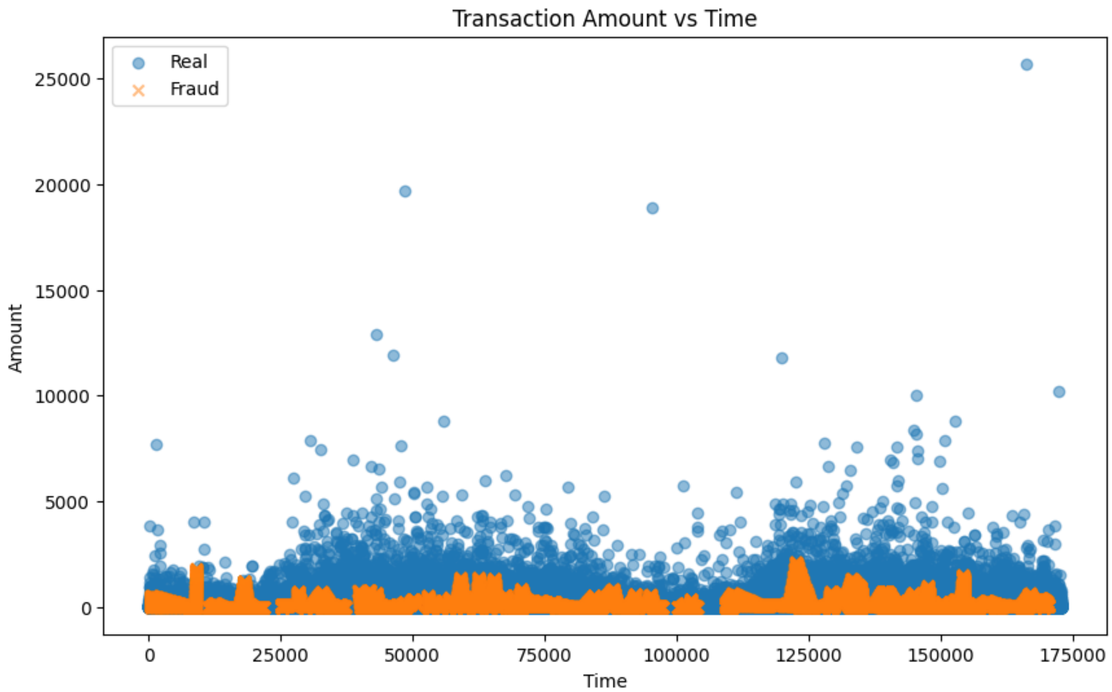
[ ]:
```
plot_transaction_counts_by_hour(balanced_df)
```



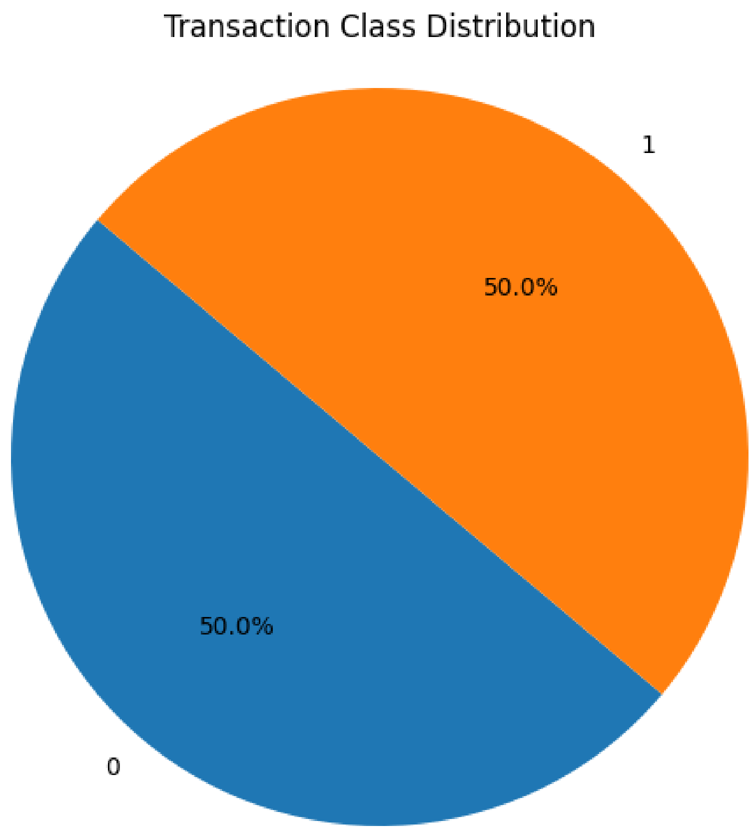
```
[ ]: plot_transaction_counts_by_day(balanced_df)
```



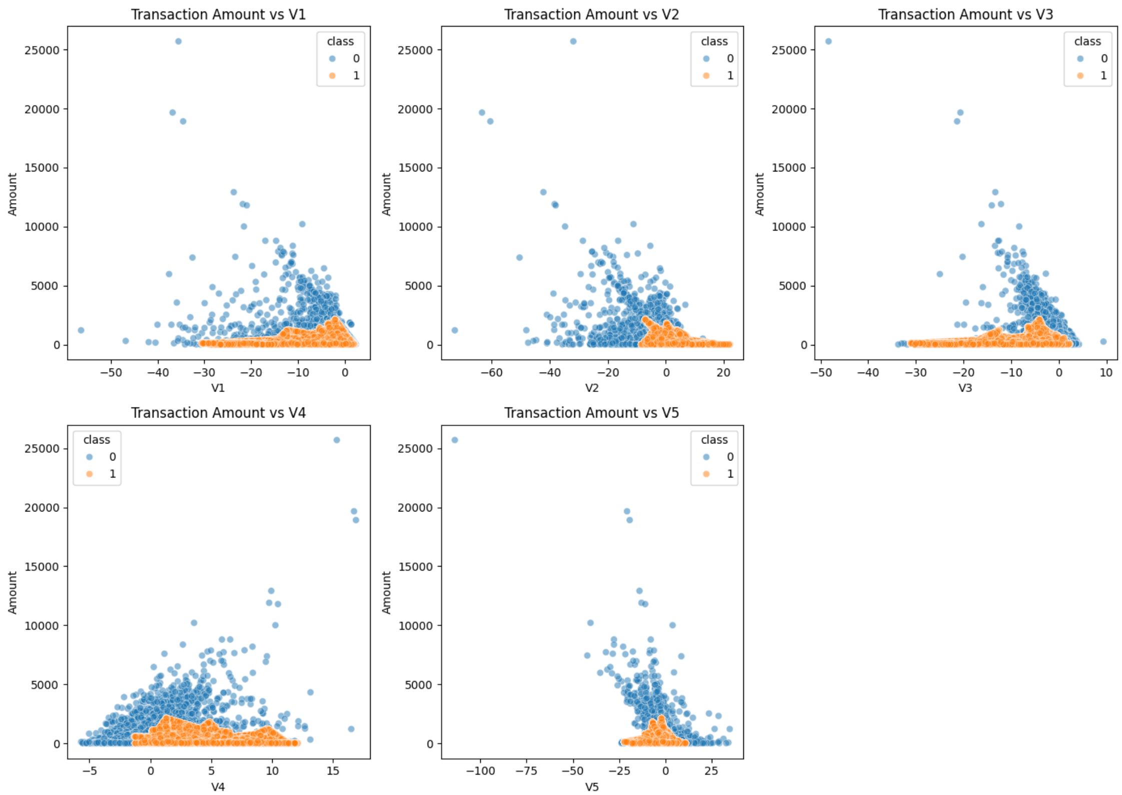

```
[ ]: plot_transaction_amount_vs_time(balanced_df)
```



[ ]:
```
plot_class_distribution(balanced_df)
```



[ ]:
```
plot_transaction_amount_vs_features(balanced_df)
```



#**Dataset before processing**

[ ]:
```
creditcard_df
```

[ ]:
```
            Time         V1         V2        V3        V4        V5  \
0            0.0  -1.359807  -0.072781  2.536347  1.378155 -0.338321
1            0.0   1.191857   0.266151  0.166480  0.448154  0.060018
2            1.0  -1.358354  -1.340163  1.773209  0.379780 -0.503198
3            1.0  -0.966272  -0.185226  1.792993 -0.863291 -0.010309
4            2.0  -1.158233   0.877737  1.548718  0.403034 -0.407193
…            …          …          …         …         …         …
284802  172786.0 -11.881118  10.071785 -9.834783 -2.066656 -5.364473
284803  172787.0  -0.732789  -0.055080  2.035030 -0.738589  0.868229
284804  172788.0   1.919565  -0.301254 -3.249640 -0.557828  2.630515
284805  172788.0  -0.240440   0.530483  0.702510  0.689799 -0.377961
284806  172792.0  -0.533413  -0.189733  0.703337 -0.506271 -0.012546

              V6        V7        V8        V9  …       V21       V22  \
0       0.462388  0.239599  0.098698  0.363787  … -0.018307  0.277838
1      -0.082361 -0.078803  0.085102 -0.255425  … -0.225775 -0.638672
2       1.800499  0.791461  0.247676 -1.514654  …  0.247998  0.771679
3       1.247203  0.237609  0.377436 -1.387024  … -0.108300  0.005274
```

```
4       0.095921  0.592941 -0.270533  0.817739  … -0.009431  0.798278
…            …         …         …         …   …        …         …
284802 -2.606837 -4.918215  7.305334  1.914428  …  0.213454  0.111864
284803  1.058415  0.024330  0.294869  0.584800  …  0.214205  0.924384
284804  3.031260 -0.296827  0.708417  0.432454  …  0.232045  0.578229
284805  0.623708 -0.686180  0.679145  0.392087  …  0.265245  0.800049
284806 -0.649617  1.577006 -0.414650  0.486180  …  0.261057  0.643078

             V23       V24       V25       V26       V27       V28  Amount  \
0      -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053  149.62
1       0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724    2.69
2       0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66
3      -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458  123.50
4      -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153   69.99
…            …         …         …         …         …         …       …
284802  1.014480 -0.509348  1.436807  0.250034  0.943651  0.823731    0.77
284803  0.012463 -1.016226 -0.606624 -0.395255  0.068472 -0.053527   24.79
284804 -0.037501  0.640134  0.265745 -0.087371  0.004455 -0.026561   67.88
284805 -0.163298  0.123205 -0.569159  0.546668  0.108821  0.104533   10.00
284806  0.376777  0.008797 -0.473649 -0.818267 -0.002415  0.013649  217.00

        class
0           0
1           0
2           0
3           0
4           0
…         …
284802      0
284803      0
284804      0
284805      0
284806      0

[284807 rows x 31 columns]
```

#Dataset after processing

[ ]:
```
balanced_df
```

[ ]:
```
                    Time        V1        V2        V3        V4        V5  \
0               0.000000 -1.359807 -0.072781  2.536347  1.378155 -0.338321
1               0.000000  1.191857  0.266151  0.166480  0.448154  0.060018
2               1.000000 -1.358354 -1.340163  1.773209  0.379780 -0.503198
3               1.000000 -0.966272 -0.185226  1.792993 -0.863291 -0.010309
4               2.000000 -1.158233  0.877737  1.548718  0.403034 -0.407193
…                    …         …         …         …         …         …
```

```
568625  144838.659385 -6.379157  1.672637 -5.885670  2.068340 -0.668576
568626   65965.011763 -2.479028  0.958932 -1.782249  1.541783 -1.191990
568627   34592.129093 -1.799894  2.368957 -2.673997  1.705968 -1.355923
568628  129683.002907  0.255234  2.432041 -5.388252  3.793925 -0.230814
568629   91471.277869 -4.453646  3.210469 -5.294410  1.449911 -1.264653

              V6        V7        V8        V9  …       V21       V22  \
0       0.462388  0.239599  0.098698  0.363787  … -0.018307  0.277838
1      -0.082361 -0.078803  0.085102 -0.255425  … -0.225775 -0.638672
2       1.800499  0.791461  0.247676 -1.514654  …  0.247998  0.771679
3       1.247203  0.237609  0.377436 -1.387024  … -0.108300  0.005274
4       0.095921  0.592941 -0.270533  0.817739  … -0.009431  0.798278
…            …         …         …         …  …         …         …
568625 -3.336450 -4.995823  2.632847 -2.275158  …  0.641337 -0.249308
568626 -0.466794 -1.957161  0.312580 -0.433956  …  0.351983  0.208869
568627 -1.121788 -2.057832 -1.677459 -0.659287  …  1.473371 -0.581778
568628 -1.382725 -1.572929  0.748305 -1.600633  …  0.316760 -0.036858
568629 -0.493626 -3.130644 -4.165957  0.998760  …  4.414468 -1.065864

             V23       V24       V25       V26       V27       V28  \
0      -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
1       0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724
2       0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
3      -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458
4      -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153
…            …         …         …         …         …         …
568625 -2.311290 -0.159402  1.190079 -0.258067  0.777265 -0.728919
568626 -0.235986 -0.404446  0.220454  0.685263 -0.890346  0.598736
568627 -0.013899 -0.144597  0.120315  0.242272 -0.121166 -0.534238
568628  0.182968  0.190701 -0.339250 -0.272824  0.315507 -0.091005
568629  0.798149  0.299668  0.064660 -0.446730 -0.363233  1.018147

            Amount  class
0       149.620000      0
1         2.690000      0
2       378.660000      0
3       123.500000      0
4        69.990000      0
…              …    …
568625    7.334751      1
568626   74.507571      1
568627  102.486823      1
568628   58.346854      1
568629  143.872749      1

[568630 rows x 31 columns]
```

#Model Implmentation

Implmented following 7 models on imbalanced data and balanced data achieved with the help of SMOTE algorithm.

1. Naive Bayes
2. Logistic Regression
3. Decision Tree
4. Random Forest
5. Long short-term memory (LSTM)
6. k-nearest neighbors (KNN)
7. Feedforward neural Network (FNN)

#Imbalanced dataset

[ ]:
```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import confusion_matrix, accuracy_score,␣
↪f1_score,classification_report, precision_score, recall_score, roc_curve, auc
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout
from keras.optimizers import Adam
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
```

[ ]:
```
X = creditcard_df.drop(columns=['class'])
y = creditcard_df['class']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

#Naive Bayes

[ ]:
```
params = {'var_smoothing': np.logspace(0, -9, num=100)}
nb_classifier = GaussianNB()
grid_search = GridSearchCV(nb_classifier, params, cv=5, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)

best_nb_classifier = grid_search.best_estimator_

y_pred = best_nb_classifier.predict(X_test)
```

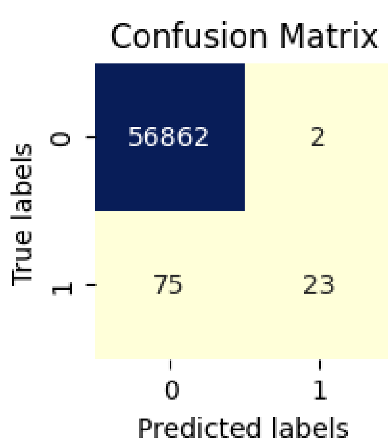
```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

```
/usr/local/lib/python3.10/dist-
packages/joblib/externals/loky/backend/fork_exec.py:38: RuntimeWarning:
os.fork() was called. os.fork() is incompatible with multithreaded code, and JAX
```

```
is multithreaded, so this will likely lead to a deadlock.
  pid = os.fork()
```

[ ]:
```python
accuracy_NB = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_NB)

conf_matrix_NB = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_NB, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_NB = f1_score(y_test, y_pred)
print("F1 Score:", f1_NB)

precision_NB = precision_score(y_test, y_pred)
print("Precision:", precision_NB)

recall_NB = recall_score(y_test, y_pred)
print("Recall:", recall_NB)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9986482216214319
```

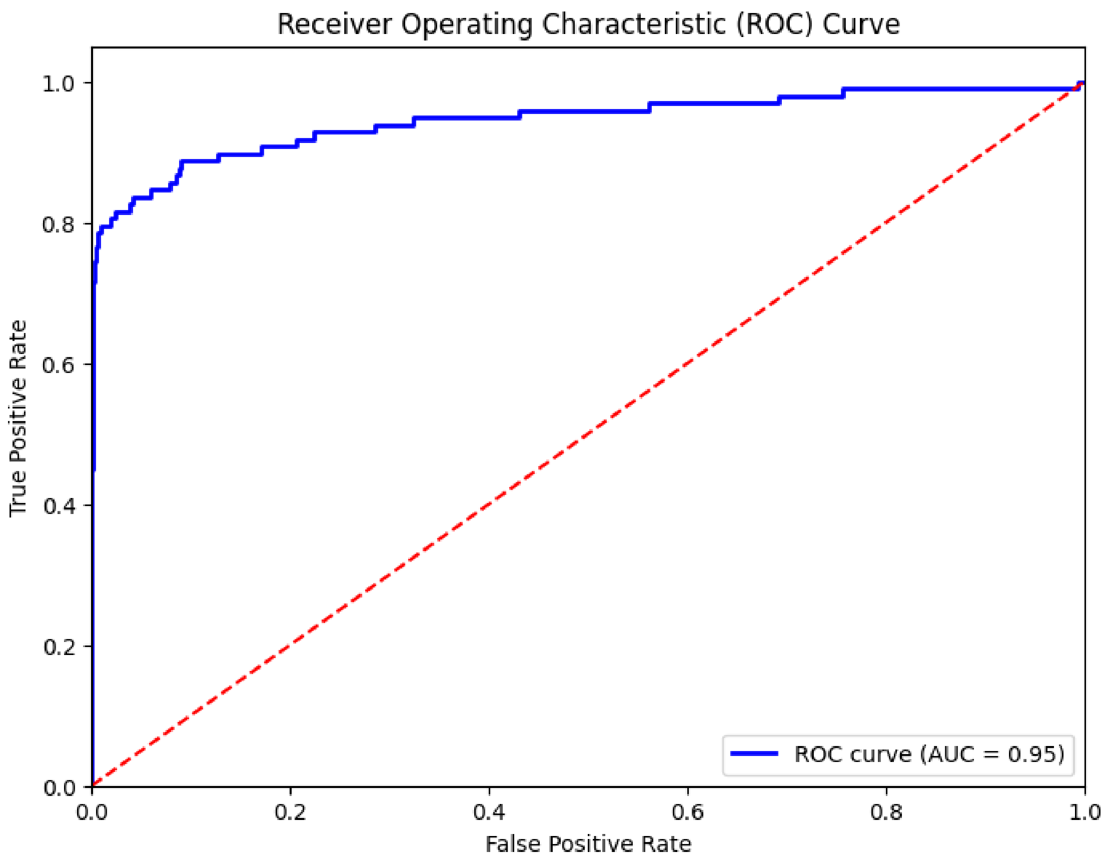



```
F1 Score: 0.37398373983739835
Precision: 0.92
Recall: 0.23469387755102042
```

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.92      0.23      0.37        98

    accuracy                           1.00     56962
   macro avg       0.96      0.62      0.69     56962
weighted avg       1.00      1.00      1.00     56962
```

[ ]:
```
y_prob = best_nb_classifier.predict_proba(X_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc_NB = auc(fpr, tpr)

print("ROC_AUC:", roc_auc_NB)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
↪roc_auc_NB)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
ROC_AUC: 0.9453806001860509
```



#**Logistic Regression**

[ ]:
```
param_grid = {
    'penalty': ['l1', 'l2'],
    'C': [0.001, 0.01, 0.1, 1, 10, 100]
}

logreg = LogisticRegression()

grid_search = GridSearchCV(estimator=logreg, param_grid=param_grid, cv=5,␣
 ↪scoring='accuracy', verbose=1, n_jobs=-1)

grid_search.fit(X_train, y_train)

best_logreg = grid_search.best_estimator_

y_pred = best_logreg.predict(X_test)

print("\nBest Hyperparameters:", grid_search.best_params_)
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
```

```
/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py:378: FitFailedWarning:
30 fits failed out of a total of 60.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
30 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py", line 686, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_logistic.py", line 1162, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_logistic.py", line 54, in _check_solver
    raise ValueError(
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penalty.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:952:
UserWarning: One or more of the test scores are non-finite: [        nan
0.99877987        nan 0.99891593        nan 0.9990476
        nan 0.99898615        nan 0.99895543        nan 0.99893349]
  warnings.warn(
```

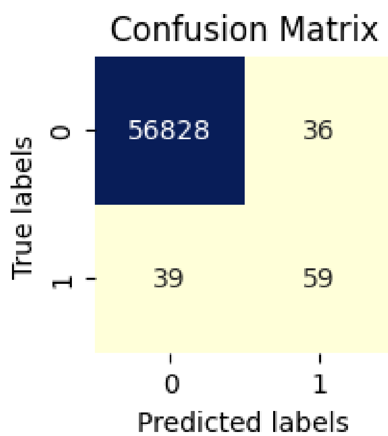
```
Best Hyperparameters: {'C': 0.1, 'penalty': 'l2'}
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[ ]:
```
accuracy_LR = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_LR)
```

```
conf_matrix_LR = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_LR, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_LR = f1_score(y_test, y_pred)
print("F1 Score:", f1_LR)

precision_LR = precision_score(y_test, y_pred)
print("Precision:", precision_LR)

recall_LR = recall_score(y_test, y_pred)
print("Recall:", recall_LR)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9986833327481479
```

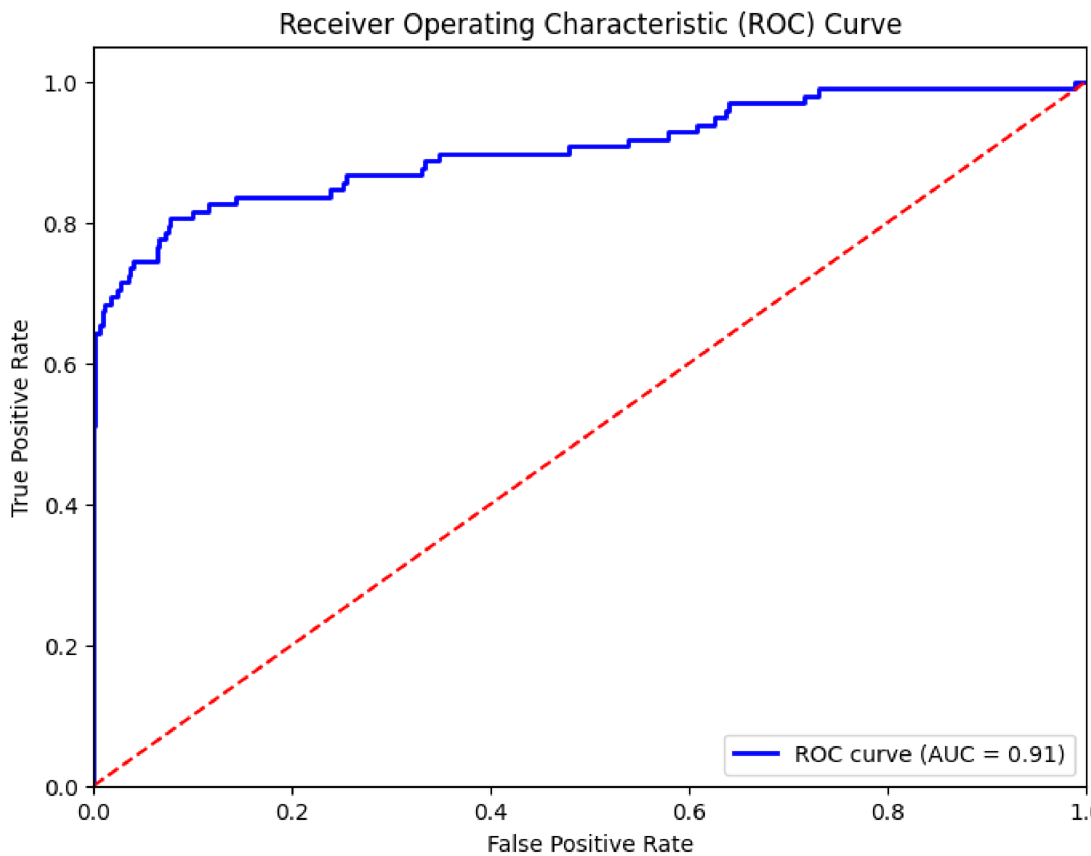



```
F1 Score: 0.6113989637305699
Precision: 0.6210526315789474
Recall: 0.6020408163265306

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.62      0.60      0.61        98
```

```
    accuracy                           1.00     56962
   macro avg       0.81      0.80      0.81     56962
weighted avg       1.00      1.00      1.00     56962
```

[ ]:
```python
y_prob = best_logreg.predict_proba(X_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc_LR = auc(fpr, tpr)

print("ROC_AUC:", roc_auc_LR)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc_LR)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
ROC_AUC: 0.9050803636029539
```



#Decision Tree

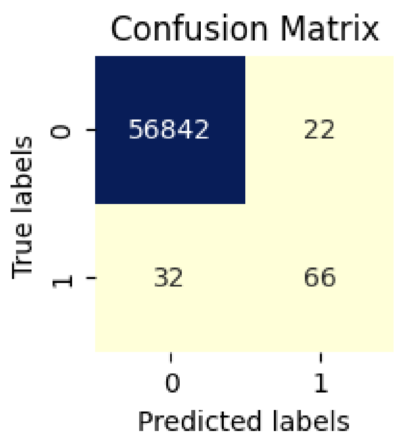
```
[ ]: clf = DecisionTreeClassifier(max_depth=15, max_features='auto',␣
      ↪criterion='entropy', random_state=42)

     clf.fit(X_train, y_train)

     y_pred = clf.predict(X_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/tree/_classes.py:269:
FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be
removed in 1.3. To keep the past behaviour, explicitly set
`max_features='sqrt'`.
  warnings.warn(
```

```
[ ]: accuracy_DT = accuracy_score(y_test, y_pred)
     print("Accuracy:", accuracy_DT)

     conf_matrix_DT = confusion_matrix(y_test, y_pred)
     plt.figure(figsize=(2, 2))
```

```
sns.heatmap(conf_matrix_DT, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_DT = f1_score(y_test, y_pred)
print("F1 Score:", f1_DT)

precision_DT = precision_score(y_test, y_pred)
print("Precision:", precision_DT)

recall_DT = recall_score(y_test, y_pred)
print("Recall:", recall_DT)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9990519995786665
```

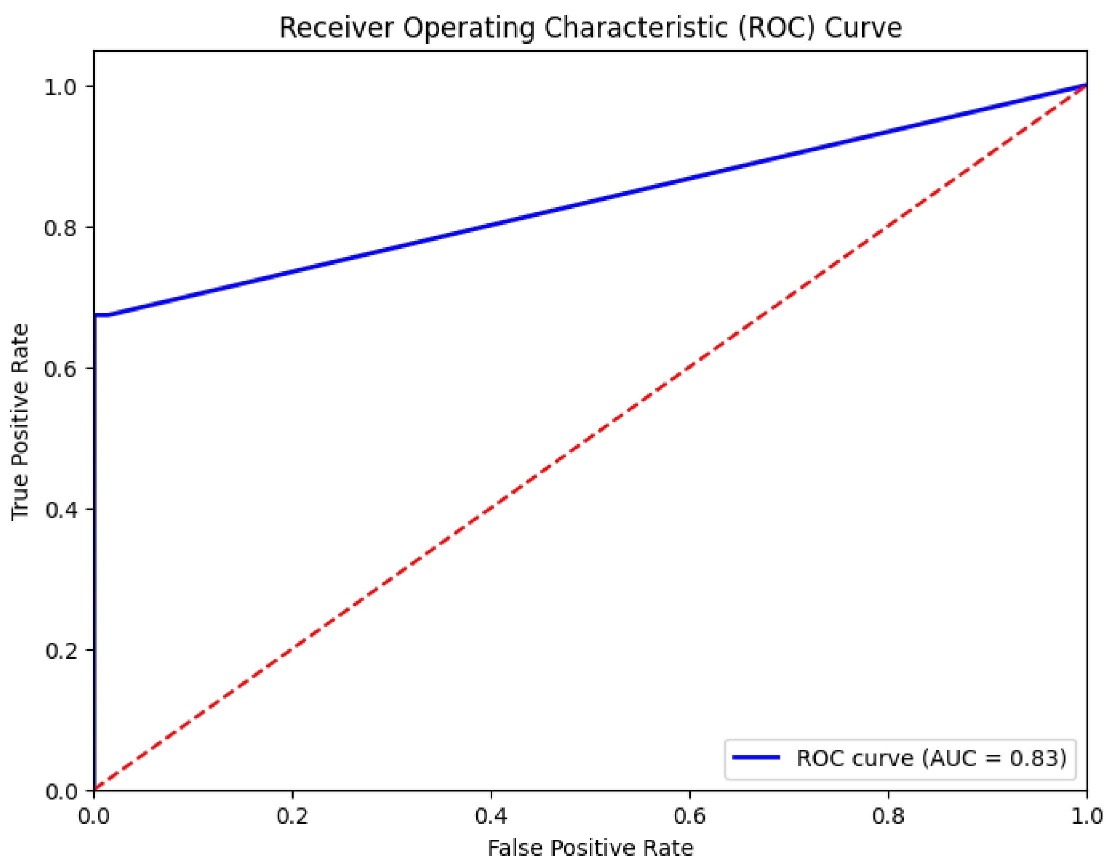



```
F1 Score: 0.7096774193548386
Precision: 0.75
Recall: 0.673469387755102

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.75      0.67      0.71        98

    accuracy                           1.00     56962
   macro avg       0.87      0.84      0.85     56962
```

```
weighted avg       1.00      1.00      1.00     56962
```

[ ]:
```python
y_prob = clf.predict_proba(X_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc_DT = auc(fpr, tpr)

print("ROC_AUC:", roc_auc_DT)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %
  roc_auc_DT)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
ROC_AUC: 0.8342387637384723
```

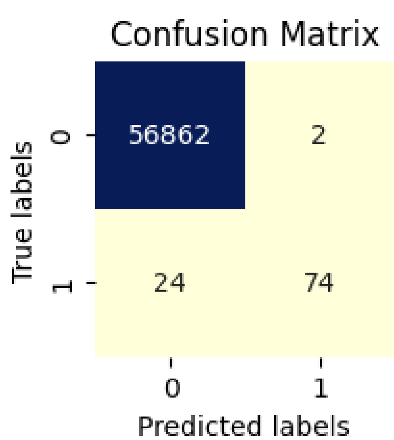


#Random Forest

[ ]:
```
clf = RandomForestClassifier(n_estimators=50, random_state=42)

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
```

[ ]:
```
accuracy_RF = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_RF)

conf_matrix_RF = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_RF, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_RF = f1_score(y_test, y_pred)
print("F1 Score:", f1_RF)

precision_RF = precision_score(y_test, y_pred)
print("Precision:", precision_RF)

recall_RF = recall_score(y_test, y_pred)
print("Recall:", recall_RF)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

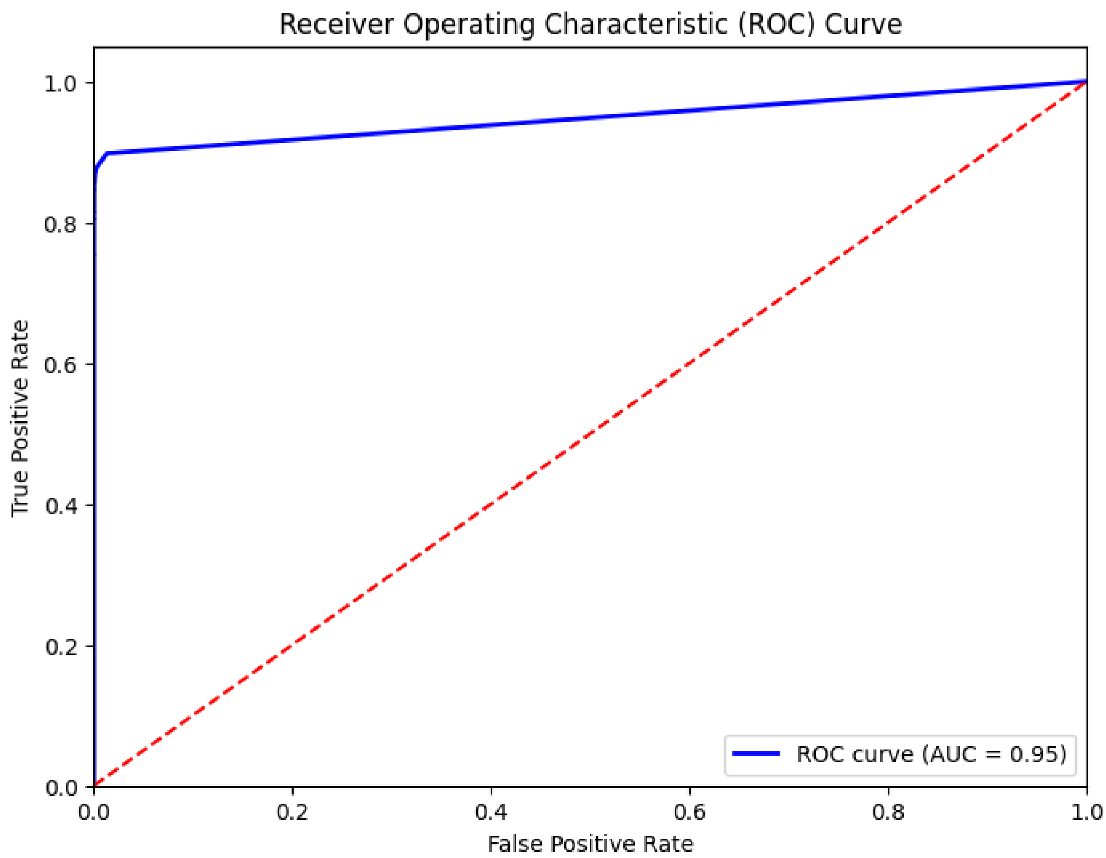
```
Accuracy: 0.9995435553526912
```



```
F1 Score: 0.8505747126436782
Precision: 0.9736842105263158
Recall: 0.7551020408163265

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.97      0.76      0.85        98

    accuracy                           1.00     56962
   macro avg       0.99      0.88      0.93     56962
weighted avg       1.00      1.00      1.00     56962
```

[ ]:
```
y_prob = clf.predict_proba(X_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc_RF = auc(fpr, tpr)

print("ROC_AUC:", roc_auc_RF)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %
 ↪roc_auc_RF)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
ROC_AUC: 0.9480902518576366
```



#**Long Short-Term Memory Networks (LSTM)**

[ ]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

timesteps = 1
X_train_reshaped = X_train_scaled.reshape(X_train_scaled.shape[0], timesteps,␣
↪X_train_scaled.shape[1])
X_test_reshaped = X_test_scaled.reshape(X_test_scaled.shape[0], timesteps,␣
↪X_test_scaled.shape[1])

model = Sequential()
model.add(LSTM(units=64, input_shape=(X_train_reshaped.shape[1],␣
↪X_train_reshaped.shape[2])))
model.add(Dropout(0.2))
model.add(Dense(units=1, activation='sigmoid'))

optimizer = Adam(lr=0.001)
```

```
model.compile(optimizer=optimizer, loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])

model.fit(X_train_reshaped, y_train, epochs=10, batch_size=64,␣
 ↪validation_split=0.2)


y_pred_proba = model.predict(X_test_reshaped)
y_pred = (y_pred_proba > 0.5).astype(int)
```

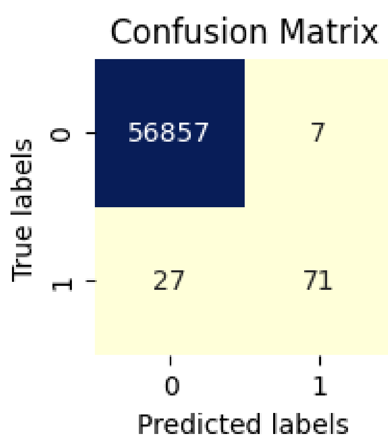
```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate`
or use the legacy optimizer, e.g.,tf.keras.optimizers.legacy.Adam.
```

```
Epoch 1/10
2849/2849 [==============================] - 15s 4ms/step - loss: 0.0317 -
accuracy: 0.9966 - val_loss: 0.0028 - val_accuracy: 0.9994
Epoch 2/10
2849/2849 [==============================] - 12s 4ms/step - loss: 0.0030 -
accuracy: 0.9994 - val_loss: 0.0025 - val_accuracy: 0.9994
Epoch 3/10
2849/2849 [==============================] - 12s 4ms/step - loss: 0.0027 -
accuracy: 0.9995 - val_loss: 0.0024 - val_accuracy: 0.9995
Epoch 4/10
2849/2849 [==============================] - 11s 4ms/step - loss: 0.0024 -
accuracy: 0.9995 - val_loss: 0.0024 - val_accuracy: 0.9994
Epoch 5/10
2849/2849 [==============================] - 12s 4ms/step - loss: 0.0022 -
accuracy: 0.9995 - val_loss: 0.0026 - val_accuracy: 0.9994
Epoch 6/10
2849/2849 [==============================] - 12s 4ms/step - loss: 0.0021 -
accuracy: 0.9995 - val_loss: 0.0026 - val_accuracy: 0.9995
Epoch 7/10
2849/2849 [==============================] - 12s 4ms/step - loss: 0.0020 -
accuracy: 0.9995 - val_loss: 0.0025 - val_accuracy: 0.9994
Epoch 8/10
2849/2849 [==============================] - 12s 4ms/step - loss: 0.0019 -
accuracy: 0.9996 - val_loss: 0.0024 - val_accuracy: 0.9994
Epoch 9/10
2849/2849 [==============================] - 13s 4ms/step - loss: 0.0018 -
accuracy: 0.9996 - val_loss: 0.0025 - val_accuracy: 0.9994
Epoch 10/10
2849/2849 [==============================] - 12s 4ms/step - loss: 0.0016 -
accuracy: 0.9996 - val_loss: 0.0027 - val_accuracy: 0.9995
1781/1781 [==============================] - 4s 2ms/step
```

[ ]:
```
accuracy_LSTM = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_LSTM)
```

```
conf_matrix_LSTM = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_LSTM, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_LSTM = f1_score(y_test, y_pred)
print("F1 Score:", f1_LSTM)

precision_LSTM = precision_score(y_test, y_pred)
print("Precision:", precision_LSTM)

recall_LSTM = recall_score(y_test, y_pred)
print("Recall:", recall_LSTM)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.999403110845827
```



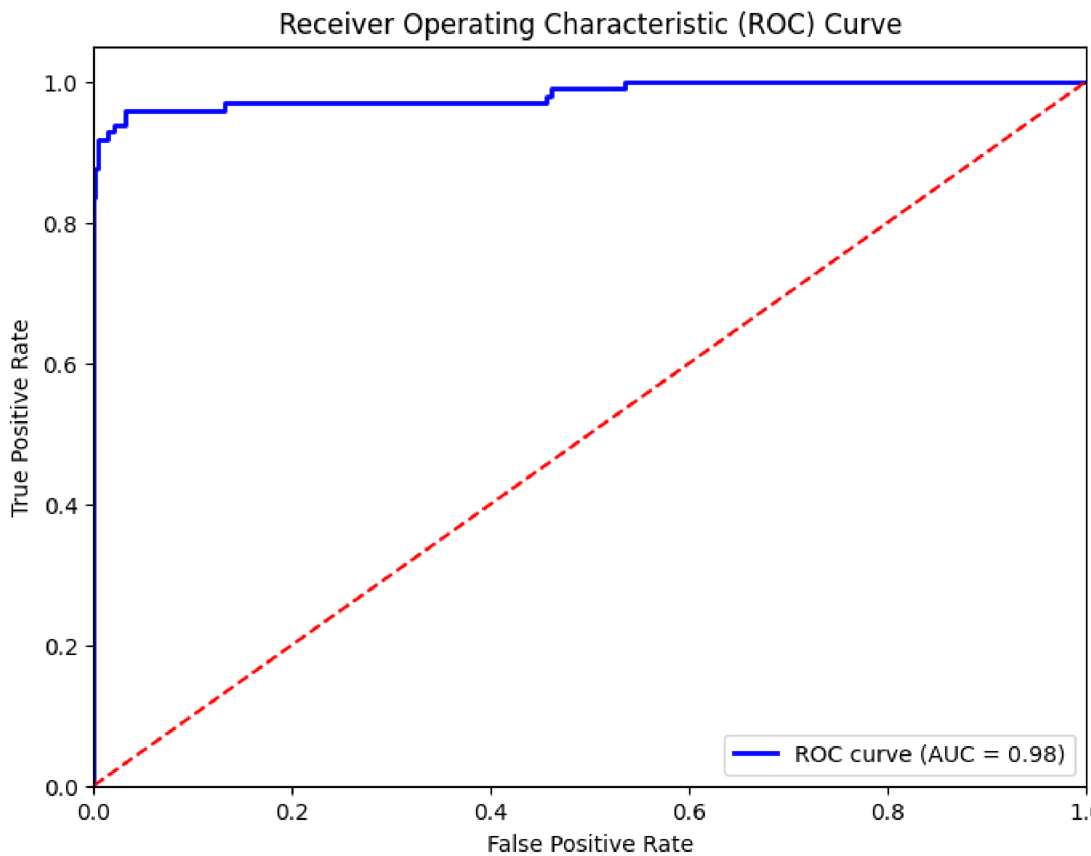

```
F1 Score: 0.8068181818181819
Precision: 0.9102564102564102
Recall: 0.7244897959183674

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.91      0.72      0.81        98
```

```
    accuracy                           1.00     56962
   macro avg       0.95      0.86      0.90     56962
weighted avg       1.00      1.00      1.00     56962
```

[ ]:

```
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

# Calculating AUC-ROC
roc_auc_LSTM = auc(fpr, tpr)
print("AUC-ROC:", roc_auc_LSTM)

# Plotting ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc_LSTM)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
AUC-ROC: 0.9826097785765967
```



#**KNN**

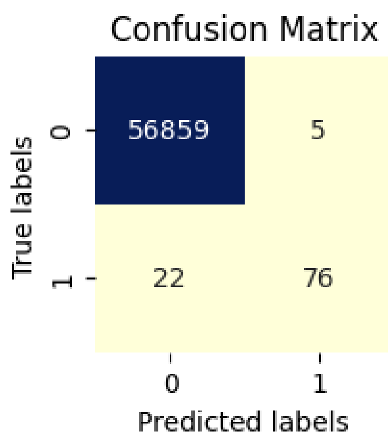
[ ]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

knn = KNeighborsClassifier(n_neighbors=5)

knn.fit(X_train_scaled, y_train)

y_pred = knn.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9995259997893332
```

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.94      0.78      0.85        98

    accuracy                           1.00     56962
   macro avg       0.97      0.89      0.92     56962
weighted avg       1.00      1.00      1.00     56962
```

[ ]:
```python
accuracy_KNN = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_KNN)

conf_matrix_KNN = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_KNN, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_KNN = f1_score(y_test, y_pred)
print("F1 Score:", f1_KNN)

precision_KNN = precision_score(y_test, y_pred)
print("Precision:", precision_KNN)

recall_KNN = recall_score(y_test, y_pred)
print("Recall:", recall_KNN)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9995259997893332
```

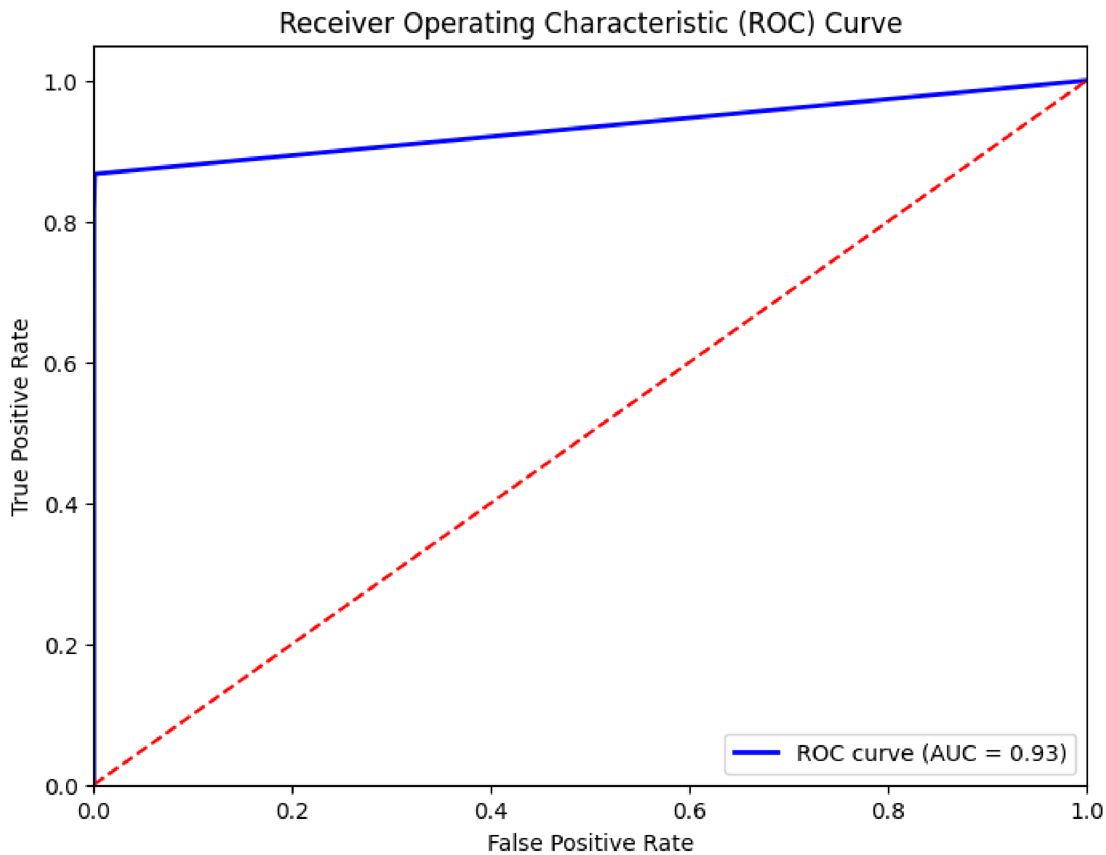



```
F1 Score: 0.8491620111731844
Precision: 0.9382716049382716
Recall: 0.7755102040816326

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.94      0.78      0.85        98

    accuracy                           1.00     56962
   macro avg       0.97      0.89      0.92     56962
weighted avg       1.00      1.00      1.00     56962
```

[ ]:
```
y_pred_proba = knn.predict_proba(X_test_scaled)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

roc_auc_KNN = auc(fpr, tpr)
print("AUC-ROC:", roc_auc_KNN)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
  ↪roc_auc_KNN)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
```

```
plt.legend(loc="lower right")
plt.show()
```

```
AUC-ROC: 0.9335599690776705
```



#FNN

```
[ ]: scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Defining the FNN model
model = Sequential()
model.add(Dense(units=64, activation='relu', input_shape=(X_train_scaled.
  ↪shape[1],)))
model.add(Dense(units=32, activation='relu'))
model.add(Dense(units=1, activation='sigmoid'))

# Compiling the model
```

```
model.compile(optimizer='adam', loss='binary_crossentropy',␣
↪metrics=['accuracy'])

# Training the model
model.fit(X_train_scaled, y_train, epochs=10, batch_size=64, validation_split=0.
↪2)

# Evaluating the model
y_pred_proba = model.predict(X_test_scaled)
y_pred = (y_pred_proba > 0.5).astype(int)
```

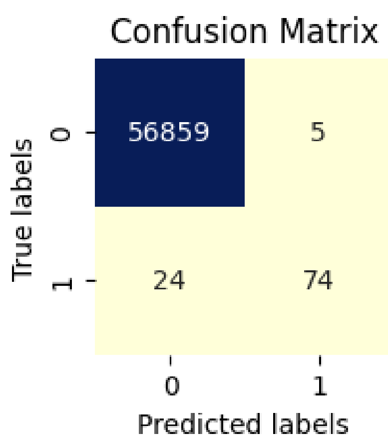
```
Epoch 1/10
2849/2849 [==============================] - 9s 3ms/step - loss: 0.0110 -
accuracy: 0.9976 - val_loss: 0.0032 - val_accuracy: 0.9994
Epoch 2/10
2849/2849 [==============================] - 8s 3ms/step - loss: 0.0033 -
accuracy: 0.9994 - val_loss: 0.0030 - val_accuracy: 0.9993
Epoch 3/10
2849/2849 [==============================] - 6s 2ms/step - loss: 0.0029 -
accuracy: 0.9994 - val_loss: 0.0026 - val_accuracy: 0.9994
Epoch 4/10
2849/2849 [==============================] - 8s 3ms/step - loss: 0.0025 -
accuracy: 0.9995 - val_loss: 0.0027 - val_accuracy: 0.9993
Epoch 5/10
2849/2849 [==============================] - 6s 2ms/step - loss: 0.0023 -
accuracy: 0.9995 - val_loss: 0.0029 - val_accuracy: 0.9993
Epoch 6/10
2849/2849 [==============================] - 7s 3ms/step - loss: 0.0021 -
accuracy: 0.9995 - val_loss: 0.0031 - val_accuracy: 0.9994
Epoch 7/10
2849/2849 [==============================] - 7s 2ms/step - loss: 0.0021 -
accuracy: 0.9995 - val_loss: 0.0026 - val_accuracy: 0.9995
Epoch 8/10
2849/2849 [==============================] - 8s 3ms/step - loss: 0.0018 -
accuracy: 0.9996 - val_loss: 0.0026 - val_accuracy: 0.9995
Epoch 9/10
2849/2849 [==============================] - 7s 2ms/step - loss: 0.0018 -
accuracy: 0.9996 - val_loss: 0.0033 - val_accuracy: 0.9993
Epoch 10/10
2849/2849 [==============================] - 8s 3ms/step - loss: 0.0016 -
accuracy: 0.9996 - val_loss: 0.0029 - val_accuracy: 0.9996
1781/1781 [==============================] - 3s 2ms/step
```

[ ]:

```
accuracy_FNN = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_FNN)

conf_matrix_FNN = confusion_matrix(y_test, y_pred)
```

```
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_FNN, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_FNN = f1_score(y_test, y_pred)
print("F1 Score:", f1_FNN)

precision_FNN = precision_score(y_test, y_pred)
print("Precision:", precision_FNN)

recall_FNN = recall_score(y_test, y_pred)
print("Recall:", recall_FNN)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9994908886626171
```



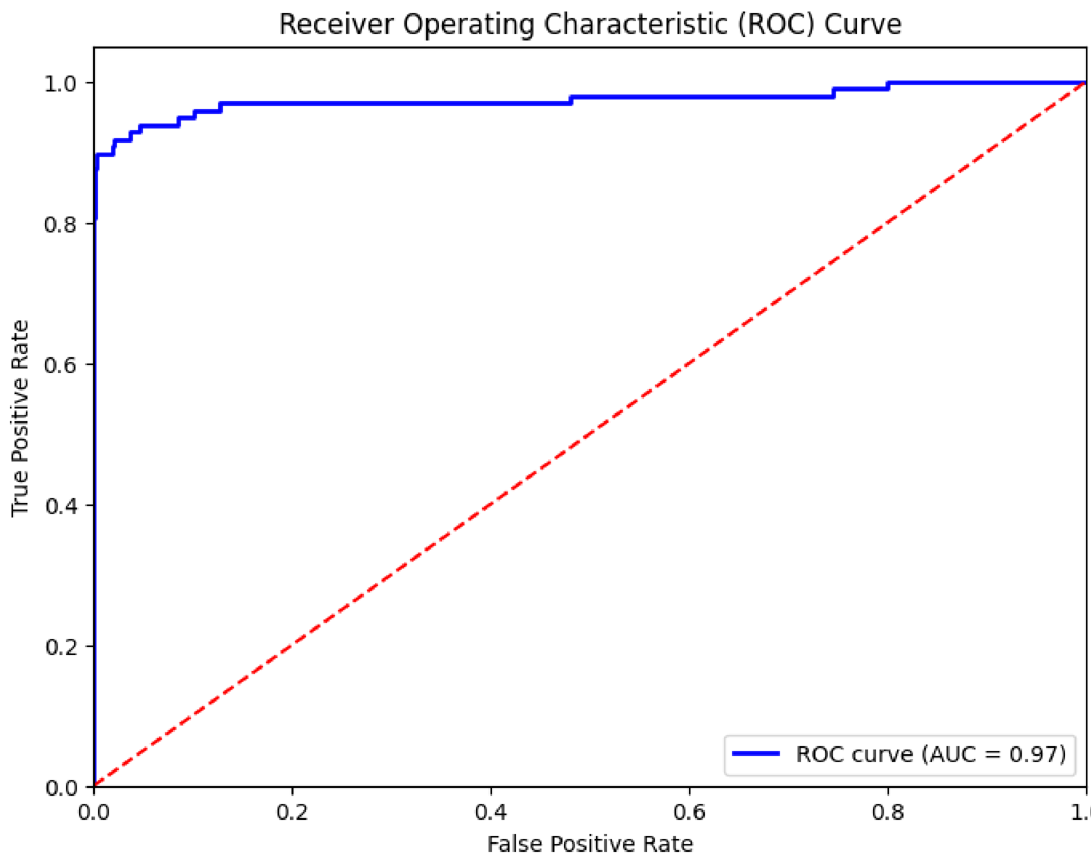

```
F1 Score: 0.8361581920903955
Precision: 0.9367088607594937
Recall: 0.7551020408163265

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.94      0.76      0.84        98

    accuracy                           1.00     56962
```

```
   macro avg       0.97      0.88      0.92     56962
weighted avg       1.00      1.00      1.00     56962
```

[ ]:

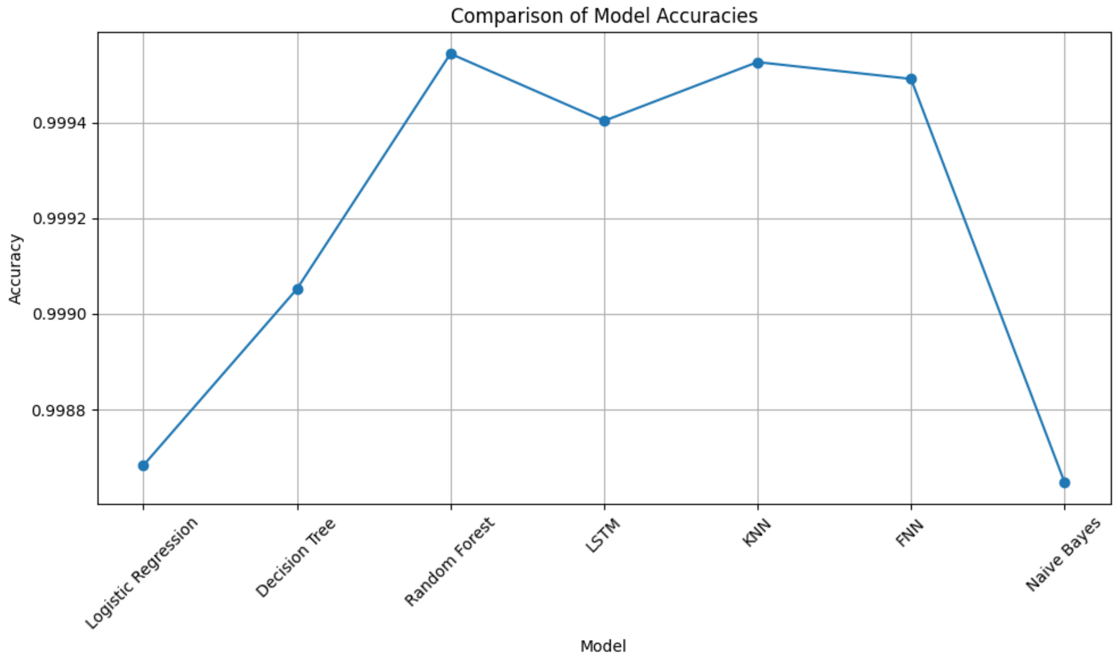
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

# Calculating AUC-ROC
roc_auc_FNN = auc(fpr, tpr)
print("AUC-ROC:", roc_auc_FNN)

# Plotting ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc_FNN)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
AUC-ROC: 0.9747706306777072
```



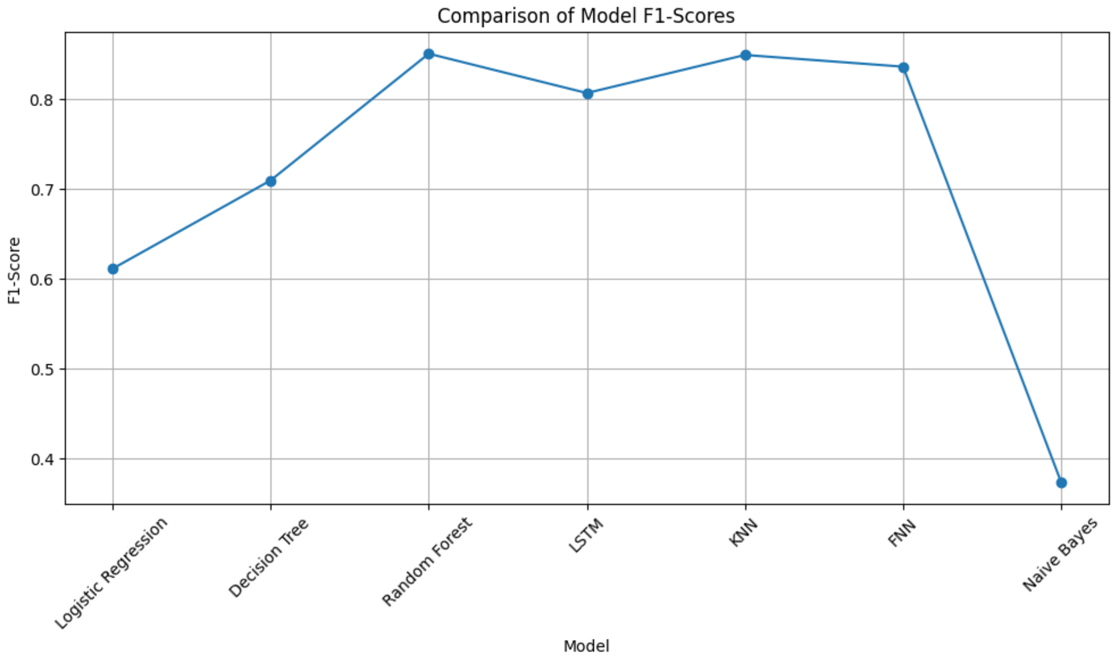
#Comparing Accuracy for all implemented models on Imbalanced dataset

[ ]:
```python
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
 ↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [accuracy_LR, accuracy_DT, accuracy_RF, accuracy_LSTM,␣
 ↪accuracy_KNN, accuracy_FNN, accuracy_NB]

plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model Accuracies')
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



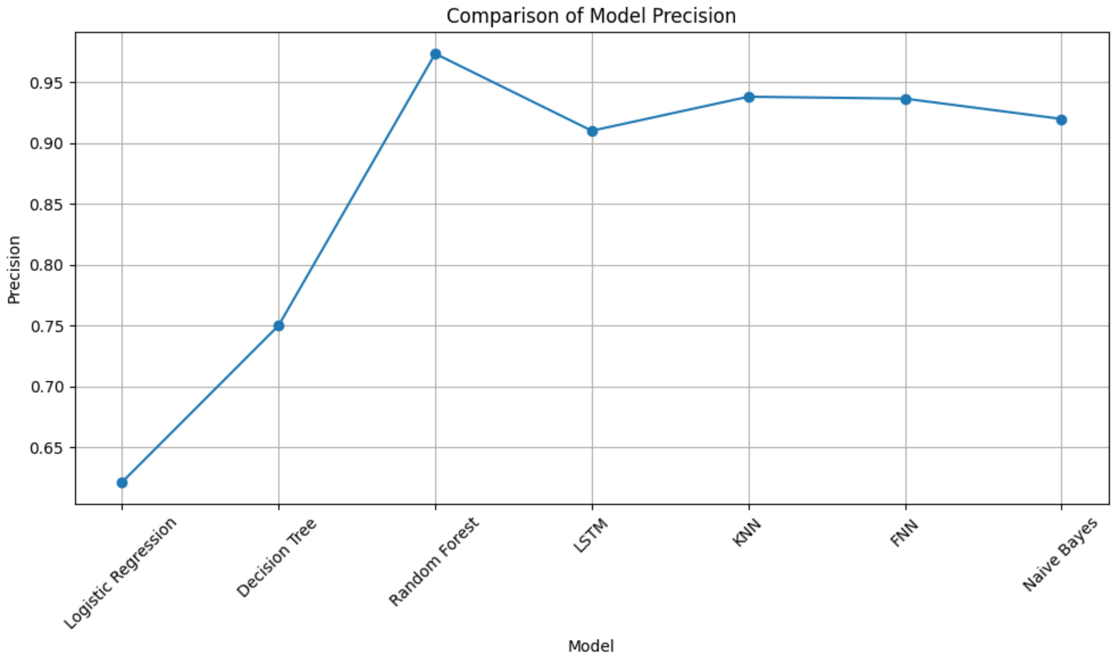
#Comparing F1 - Score for all implemented models on Imbalanced dataset

[ ]:
```
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [f1_LR, f1_DT, f1_RF, f1_LSTM, f1_KNN, f1_FNN, f1_NB]

plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model F1-Scores')
plt.xlabel('Model')
plt.ylabel('F1-Score')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



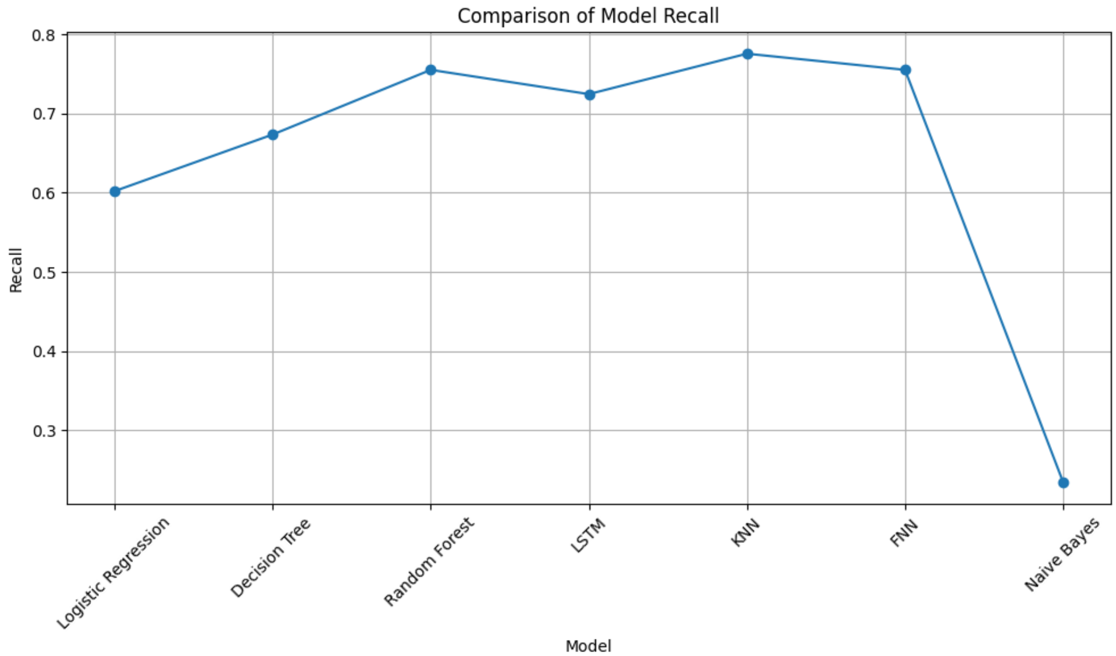
#Comparing Precision for all implemented models on Imbalanced dataset

[ ]:
```python
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [precision_LR, precision_DT, precision_RF, precision_LSTM,␣
↪precision_KNN, precision_FNN, precision_NB]

plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model Precision')
plt.xlabel('Model')
plt.ylabel('Precision')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



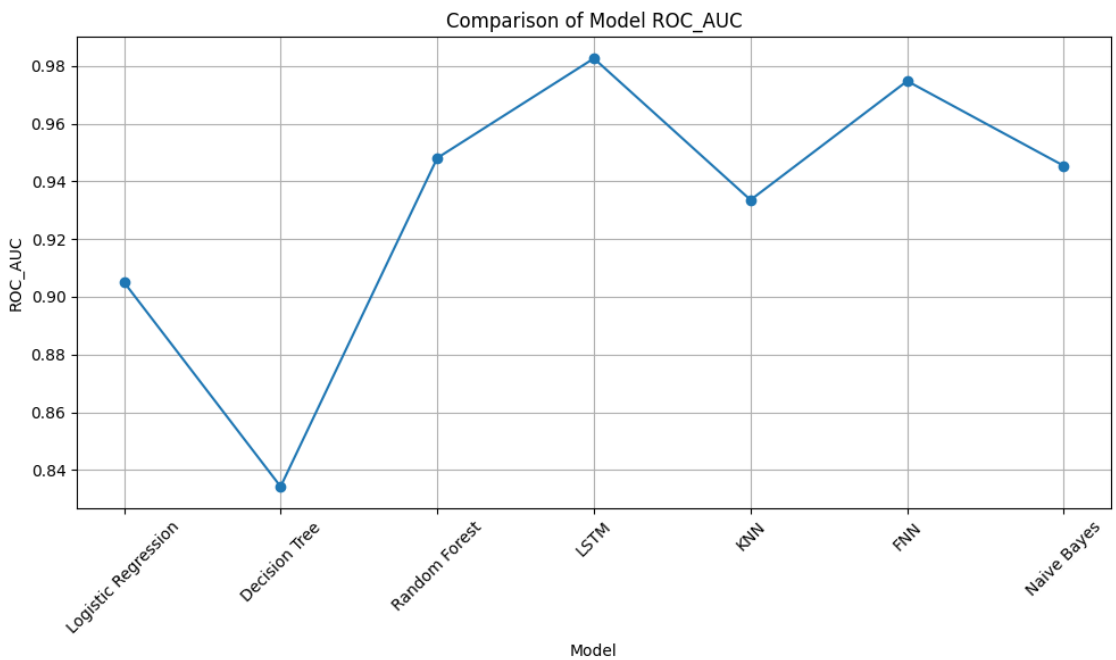
#Comparing Recall for all implemented models on Imbalanced dataset

[ ]:
```
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [recall_LR, recall_DT, recall_RF, recall_LSTM, recall_KNN,␣
↪recall_FNN, recall_NB]

plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model Recall')
plt.xlabel('Model')
plt.ylabel('Recall')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



#Comparing Area under Receiver Operating Characteristic (ROC) Curve for all implemented models on Imbalanced dataset

[ ]:
```
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [roc_auc_LR, roc_auc_DT, roc_auc_RF, roc_auc_LSTM, roc_auc_KNN,␣
↪roc_auc_FNN, roc_auc_NB]

plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model ROC_AUC')
plt.xlabel('Model')
plt.ylabel('ROC_AUC')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



[ ]:

[ ]:

[ ]:

#Balanced Dataset

[ ]:
```
X = balanced_df.drop(columns=['class'])
y = balanced_df['class']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

#Naive Bayes

[ ]:
```
params = {'var_smoothing': np.logspace(0, -9, num=100)}
nb_classifier = GaussianNB()
grid_search = GridSearchCV(nb_classifier, params, cv=5, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)

best_nb_classifier = grid_search.best_estimator_
```

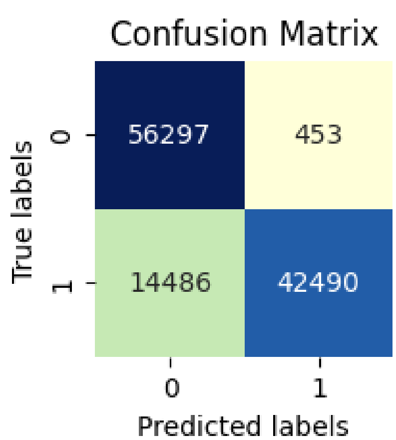
```
y_pred = best_nb_classifier.predict(X_test)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

```
/usr/local/lib/python3.10/dist-
packages/joblib/externals/loky/backend/fork_exec.py:38: RuntimeWarning:
os.fork() was called. os.fork() is incompatible with multithreaded code, and JAX
is multithreaded, so this will likely lead to a deadlock.
  pid = os.fork()
```

[ ]:
```
accuracy_NB = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_NB)

conf_matrix_NB = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_NB, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_NB = f1_score(y_test, y_pred)
print("F1 Score:", f1_NB)

precision_NB = precision_score(y_test, y_pred)
print("Precision:", precision_NB)

recall_NB = recall_score(y_test, y_pred)
print("Recall:", recall_NB)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

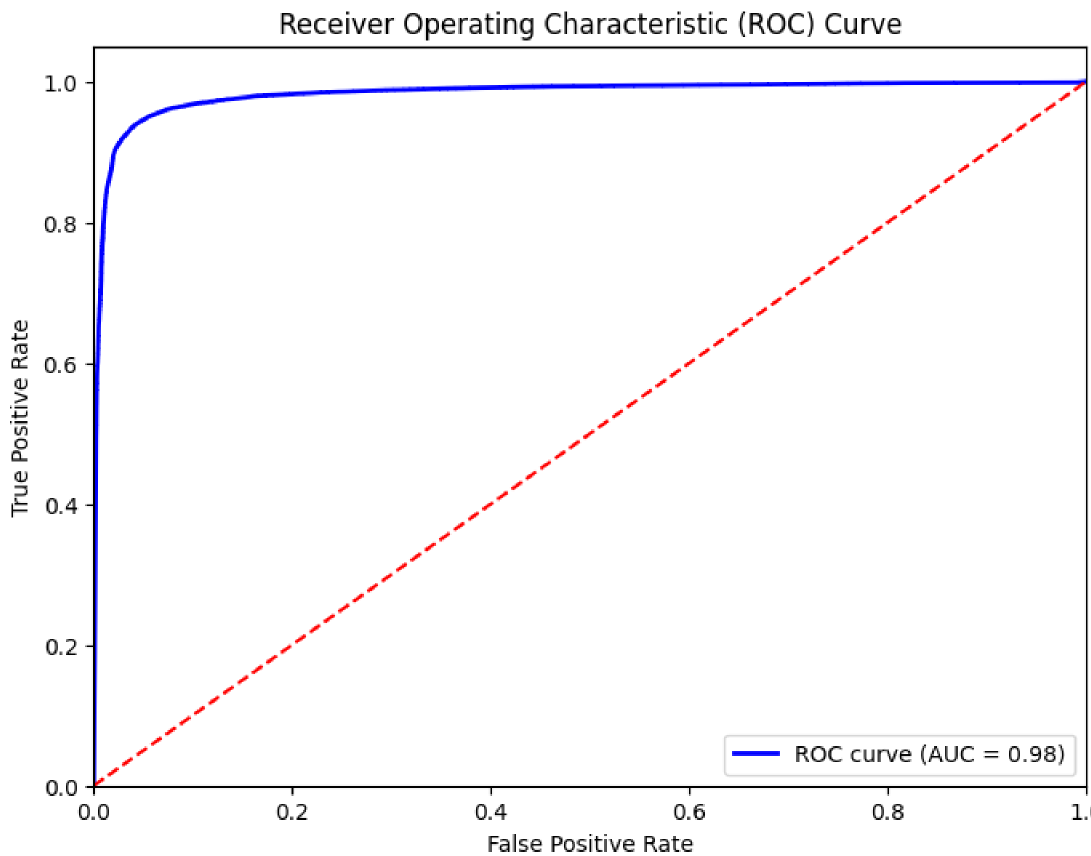
```
Accuracy: 0.8686404164395125
```



```
F1 Score: 0.8504888960057647
Precision: 0.9894511328970962
Recall: 0.745752597584948

Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.99      0.88     56750
           1       0.99      0.75      0.85     56976

    accuracy                           0.87    113726
   macro avg       0.89      0.87      0.87    113726
weighted avg       0.89      0.87      0.87    113726
```

[ ]:
```
y_prob = best_nb_classifier.predict_proba(X_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc_NB = auc(fpr, tpr)

print("ROC_AUC:", roc_auc_NB)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc_NB)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
ROC_AUC: 0.982717349727283
```



#Logistic Regression

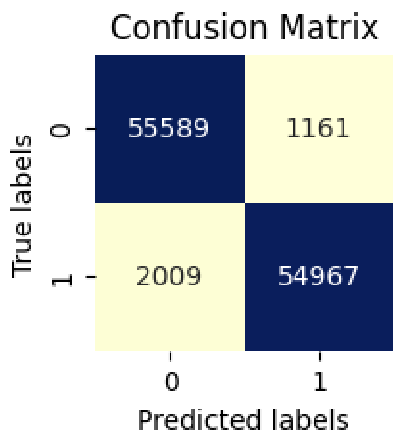
[ ]:
```
param_grid = {
    'penalty': ['l1', 'l2'],
    'C': [0.001, 0.01, 0.1, 1, 10, 100]
}

logreg = LogisticRegression()

grid_search = GridSearchCV(estimator=logreg, param_grid=param_grid, cv=5,␣
 ↪scoring='accuracy', verbose=1, n_jobs=-1)

grid_search.fit(X_train, y_train)

best_logreg = grid_search.best_estimator_

y_pred = best_logreg.predict(X_test)

print("\nBest Hyperparameters:", grid_search.best_params_)
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits

/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py:378: FitFailedWarning:
30 fits failed out of a total of 60.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
30 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py", line 686, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_logistic.py", line 1162, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_logistic.py", line 54, in _check_solver
    raise ValueError(
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penalty.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:952:
UserWarning: One or more of the test scores are non-finite: [        nan
0.97104884        nan 0.97263818        nan 0.97235461
        nan 0.97026626        nan 0.9697101         nan 0.96974747]
  warnings.warn(

Best Hyperparameters: {'C': 0.01, 'penalty': 'l2'}
```

[ ]:
```python
accuracy_LR = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_LR)

conf_matrix_LR = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_LR, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_LR = f1_score(y_test, y_pred)
print("F1 Score:", f1_LR)
```

```python
precision_LR = precision_score(y_test, y_pred)
print("Precision:", precision_LR)

recall_LR = recall_score(y_test, y_pred)
print("Recall:", recall_LR)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9721259870214375
```

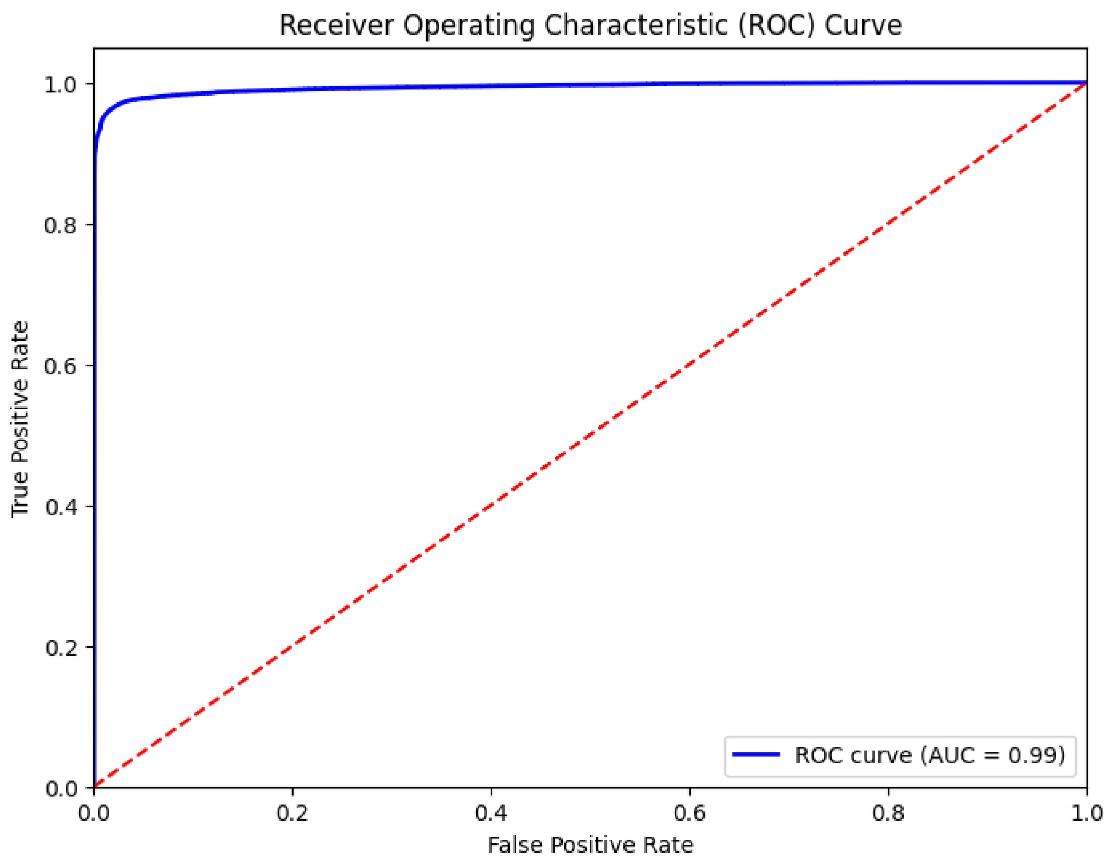



```
F1 Score: 0.9719726976941576
Precision: 0.9793151368301026
Recall: 0.9647395394552092

Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.98      0.97     56750
           1       0.98      0.96      0.97     56976

    accuracy                           0.97    113726
   macro avg       0.97      0.97      0.97    113726
weighted avg       0.97      0.97      0.97    113726
```

[ ]:
```python
y_prob = best_logreg.predict_proba(X_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc_LR = auc(fpr, tpr)
```

```
print("ROC_AUC:", roc_auc_LR)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc_LR)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
ROC_AUC: 0.9934243790104991
```



#Decision Tree

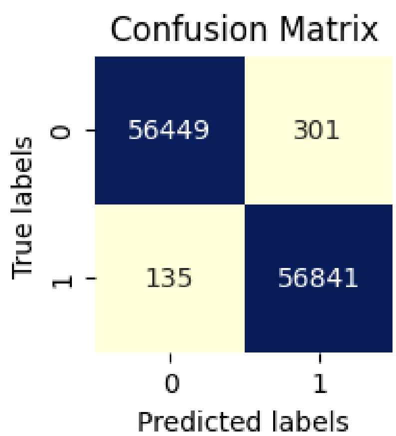
```
[ ]: clf = DecisionTreeClassifier(max_depth=15, max_features='auto',␣
 ↪criterion='entropy', random_state=42)
```

```
clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/tree/_classes.py:269:
FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be
removed in 1.3. To keep the past behaviour, explicitly set
`max_features='sqrt'`.
  warnings.warn(
```

[ ]:
```
accuracy_DT = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_DT)

conf_matrix_DT = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_DT, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_DT = f1_score(y_test, y_pred)
print("F1 Score:", f1_DT)

precision_DT = precision_score(y_test, y_pred)
print("Precision:", precision_DT)

recall_DT = recall_score(y_test, y_pred)
print("Recall:", recall_DT)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9961662240824438
```

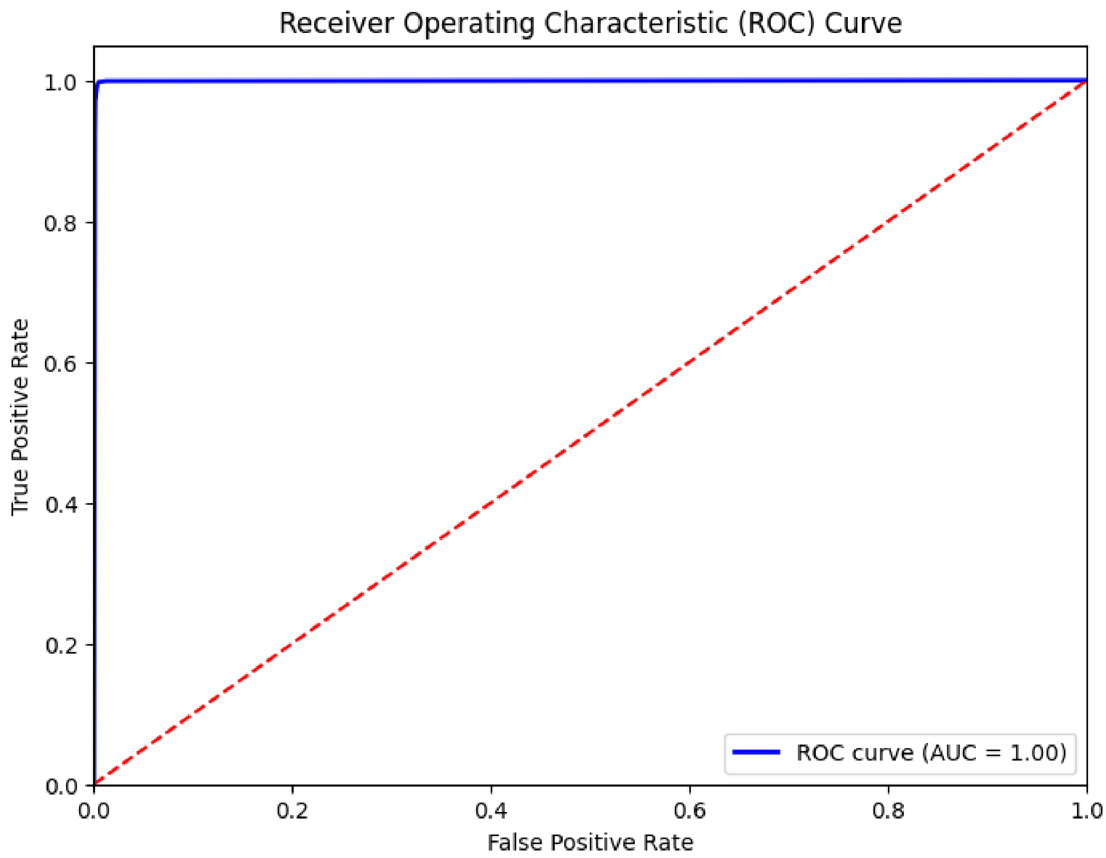



```
F1 Score: 0.9961793932596085
Precision: 0.9947324209863148
Recall: 0.9976305812973884

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00     56750
           1       0.99      1.00      1.00     56976

    accuracy                           1.00    113726
   macro avg       1.00      1.00      1.00    113726
weighted avg       1.00      1.00      1.00    113726
```

[ ]:
```
y_prob = clf.predict_proba(X_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc_DT = auc(fpr, tpr)

print("ROC_AUC:", roc_auc_DT)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc_DT)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
```

```
plt.legend(loc="lower right")
plt.show()
```

ROC_AUC: 0.9988852839498382



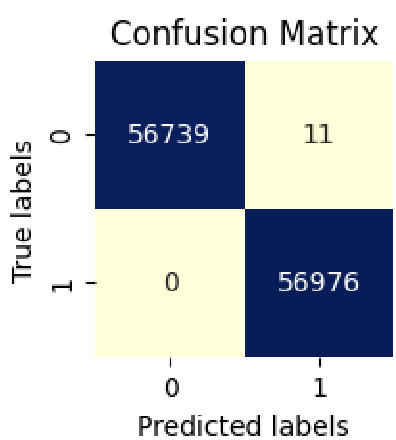
#Random Forest

[ ]:
```
clf = RandomForestClassifier(n_estimators=50, random_state=42)

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
```

[ ]:
```
accuracy_RF = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_RF)

conf_matrix_RF = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_RF, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
```

```
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_RF = f1_score(y_test, y_pred)
print("F1 Score:", f1_RF)

precision_RF = precision_score(y_test, y_pred)
print("Precision:", precision_RF)

recall_RF = recall_score(y_test, y_pred)
print("Recall:", recall_RF)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

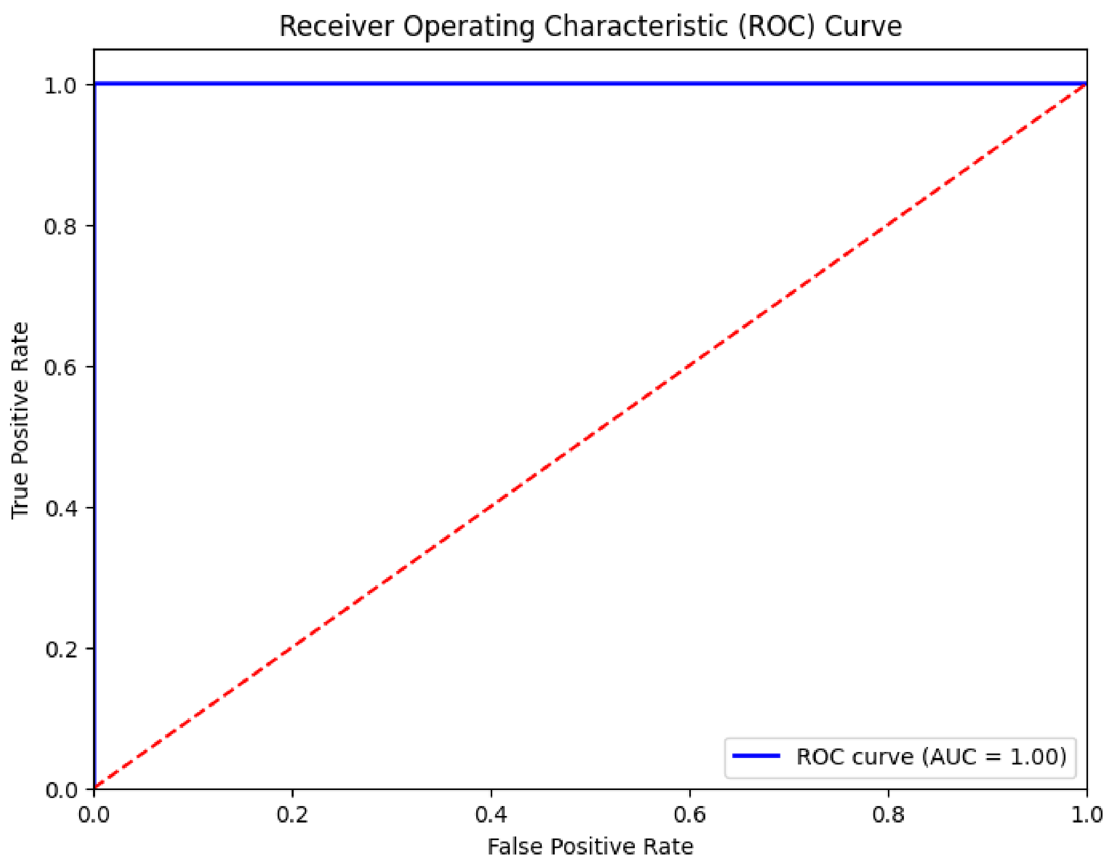
```
Accuracy: 0.999903276295658
```




```
F1 Score: 0.9999034774444338
Precision: 0.9998069735202766
Recall: 1.0

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56750
           1       1.00      1.00      1.00     56976

    accuracy                           1.00    113726
   macro avg       1.00      1.00      1.00    113726
weighted avg       1.00      1.00      1.00    113726
```

[ ]:
```
y_prob = clf.predict_proba(X_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc_RF = auc(fpr, tpr)

print("ROC_AUC:", roc_auc_RF)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc_RF)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
ROC_AUC: 0.9999902006811431
```



#Long Short-Term Memory Networks (LSTM)

[ ]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

timesteps = 1
X_train_reshaped = X_train_scaled.reshape(X_train_scaled.shape[0], timesteps,␣
↪X_train_scaled.shape[1])
X_test_reshaped = X_test_scaled.reshape(X_test_scaled.shape[0], timesteps,␣
↪X_test_scaled.shape[1])

model = Sequential()
model.add(LSTM(units=64, input_shape=(X_train_reshaped.shape[1],␣
↪X_train_reshaped.shape[2])))
model.add(Dropout(0.2))
model.add(Dense(units=1, activation='sigmoid'))

optimizer = Adam(lr=0.001)
model.compile(optimizer=optimizer, loss='binary_crossentropy',␣
↪metrics=['accuracy'])

model.fit(X_train_reshaped, y_train, epochs=10, batch_size=64,␣
↪validation_split=0.2)


y_pred_proba = model.predict(X_test_reshaped)
y_pred = (y_pred_proba > 0.5).astype(int)
```

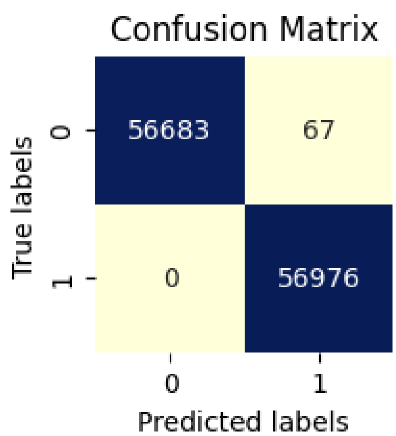
```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate`
or use the legacy optimizer, e.g.,tf.keras.optimizers.legacy.Adam.
```

```
Epoch 1/10
5687/5687 [==============================] - 36s 6ms/step - loss: 0.0614 -
accuracy: 0.9778 - val_loss: 0.0285 - val_accuracy: 0.9887
Epoch 2/10
5687/5687 [==============================] - 37s 6ms/step - loss: 0.0237 -
accuracy: 0.9917 - val_loss: 0.0154 - val_accuracy: 0.9947
Epoch 3/10
5687/5687 [==============================] - 24s 4ms/step - loss: 0.0157 -
accuracy: 0.9948 - val_loss: 0.0102 - val_accuracy: 0.9968
Epoch 4/10
5687/5687 [==============================] - 22s 4ms/step - loss: 0.0116 -
accuracy: 0.9961 - val_loss: 0.0070 - val_accuracy: 0.9983
Epoch 5/10
5687/5687 [==============================] - 29s 5ms/step - loss: 0.0089 -
accuracy: 0.9972 - val_loss: 0.0054 - val_accuracy: 0.9986
Epoch 6/10
```

```
5687/5687 [==============================] - 24s 4ms/step - loss: 0.0073 -
accuracy: 0.9978 - val_loss: 0.0040 - val_accuracy: 0.9990
Epoch 7/10
5687/5687 [==============================] - 26s 5ms/step - loss: 0.0060 -
accuracy: 0.9981 - val_loss: 0.0033 - val_accuracy: 0.9993
Epoch 8/10
5687/5687 [==============================] - 32s 6ms/step - loss: 0.0052 -
accuracy: 0.9984 - val_loss: 0.0029 - val_accuracy: 0.9992
Epoch 9/10
5687/5687 [==============================] - 25s 4ms/step - loss: 0.0045 -
accuracy: 0.9986 - val_loss: 0.0023 - val_accuracy: 0.9995
Epoch 10/10
5687/5687 [==============================] - 22s 4ms/step - loss: 0.0040 -
accuracy: 0.9988 - val_loss: 0.0021 - val_accuracy: 0.9995
3554/3554 [==============================] - 7s 2ms/step
```

[ ]:
```
accuracy_LSTM = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_LSTM)

conf_matrix_LSTM = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_LSTM, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_LSTM = f1_score(y_test, y_pred)
print("F1 Score:", f1_LSTM)

precision_LSTM = precision_score(y_test, y_pred)
print("Precision:", precision_LSTM)

recall_LSTM = recall_score(y_test, y_pred)
print("Recall:", recall_LSTM)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9994108647099168
```

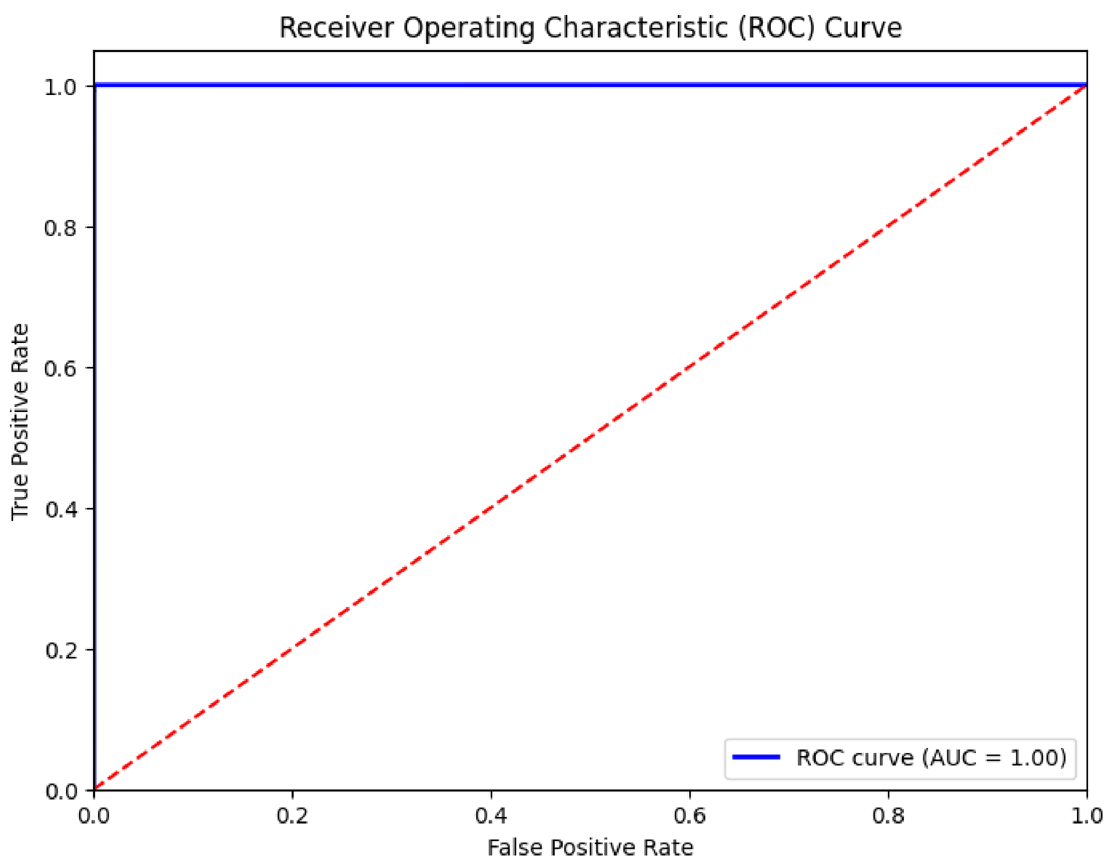



```
F1 Score: 0.999412378638648
Precision: 0.9988254474694529
Recall: 1.0

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56750
           1       1.00      1.00      1.00     56976

    accuracy                           1.00    113726
   macro avg       1.00      1.00      1.00    113726
weighted avg       1.00      1.00      1.00    113726
```

[ ]:
```python
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

# Calculating AUC-ROC
roc_auc_LSTM = auc(fpr, tpr)
print("AUC-ROC:", roc_auc_LSTM)

# Plotting ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc_LSTM)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
```

```
plt.legend(loc="lower right")
plt.show()
```

AUC-ROC: 0.999976808536433



#KNN

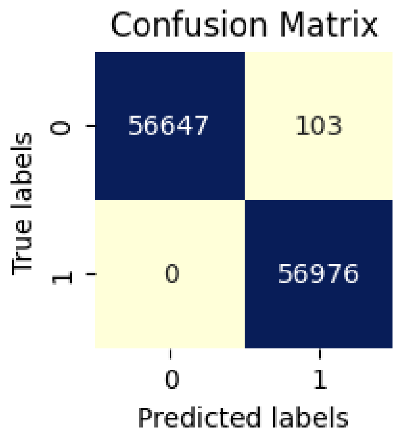
[ ]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

knn = KNeighborsClassifier(n_neighbors=5)

knn.fit(X_train_scaled, y_train)

y_pred = knn.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9990943144047975

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56750
           1       1.00      1.00      1.00     56976

    accuracy                           1.00    113726
   macro avg       1.00      1.00      1.00    113726
weighted avg       1.00      1.00      1.00    113726
```

[ ]:
```
accuracy_KNN = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_KNN)

conf_matrix_KNN = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_KNN, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_KNN = f1_score(y_test, y_pred)
print("F1 Score:", f1_KNN)

precision_KNN = precision_score(y_test, y_pred)
print("Precision:", precision_KNN)

recall_KNN = recall_score(y_test, y_pred)
print("Recall:", recall_KNN)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9990943144047975
```

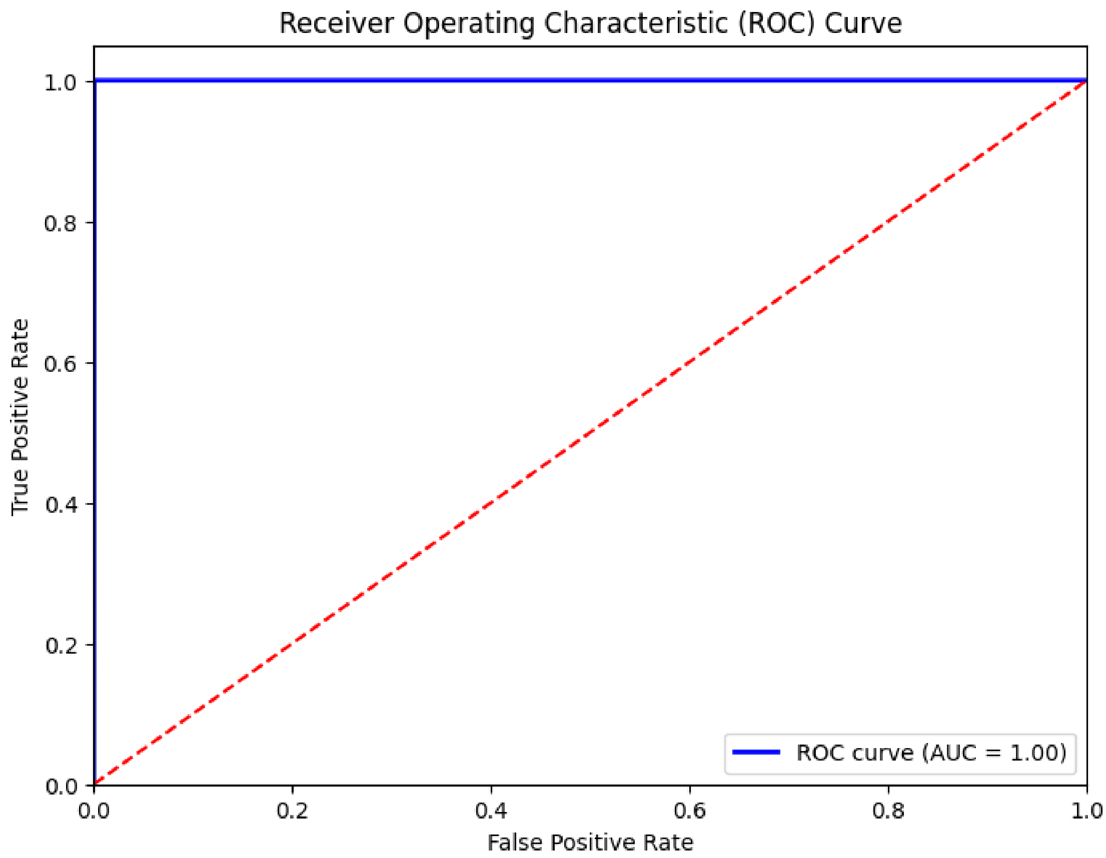



```
F1 Score: 0.9990969269212222
Precision: 0.9981954834527584
Recall: 1.0

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56750
           1       1.00      1.00      1.00     56976

    accuracy                           1.00    113726
   macro avg       1.00      1.00      1.00    113726
weighted avg       1.00      1.00      1.00    113726
```

[ ]:
```
y_pred_proba = knn.predict_proba(X_test_scaled)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

roc_auc_KNN = auc(fpr, tpr)
print("AUC-ROC:", roc_auc_KNN)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
↪roc_auc_KNN)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
```

```
plt.legend(loc="lower right")
plt.show()
```

```
AUC-ROC: 0.9997092511013216
```

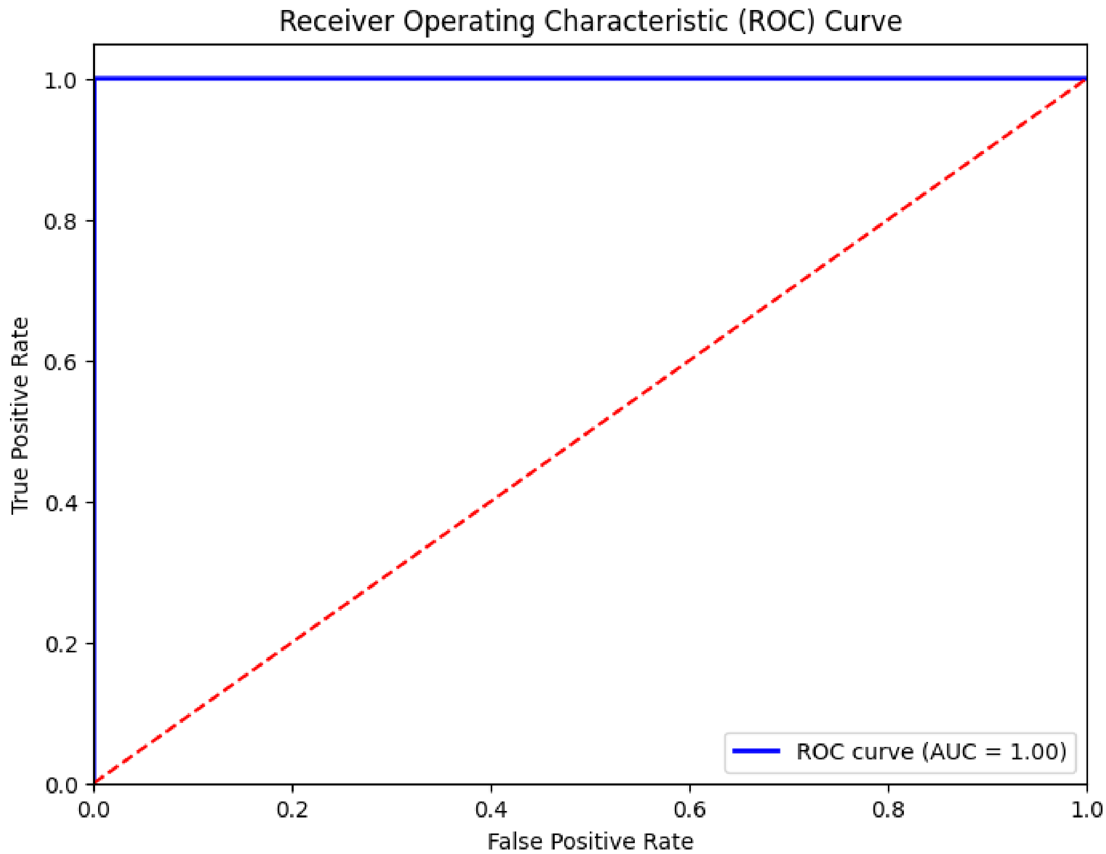


#FNN

```
[ ]: fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

# Calculating AUC-ROC
roc_auc_FNN = auc(fpr, tpr)
print("AUC-ROC:", roc_auc_FNN)

# Plotting ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc_FNN)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

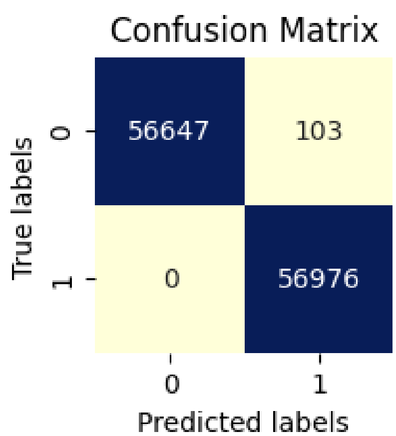
```
AUC-ROC: 0.9997092511013216
```



[ ]:
```
accuracy_FNN = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_FNN)

conf_matrix_FNN = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(2, 2))
sns.heatmap(conf_matrix_FNN, annot=True, cmap="YlGnBu", fmt='g', cbar=False)
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

f1_FNN = f1_score(y_test, y_pred)
```

```
print("F1 Score:", f1_FNN)

precision_FNN = precision_score(y_test, y_pred)
print("Precision:", precision_FNN)

recall_FNN = recall_score(y_test, y_pred)
print("Recall:", recall_FNN)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9990943144047975
```

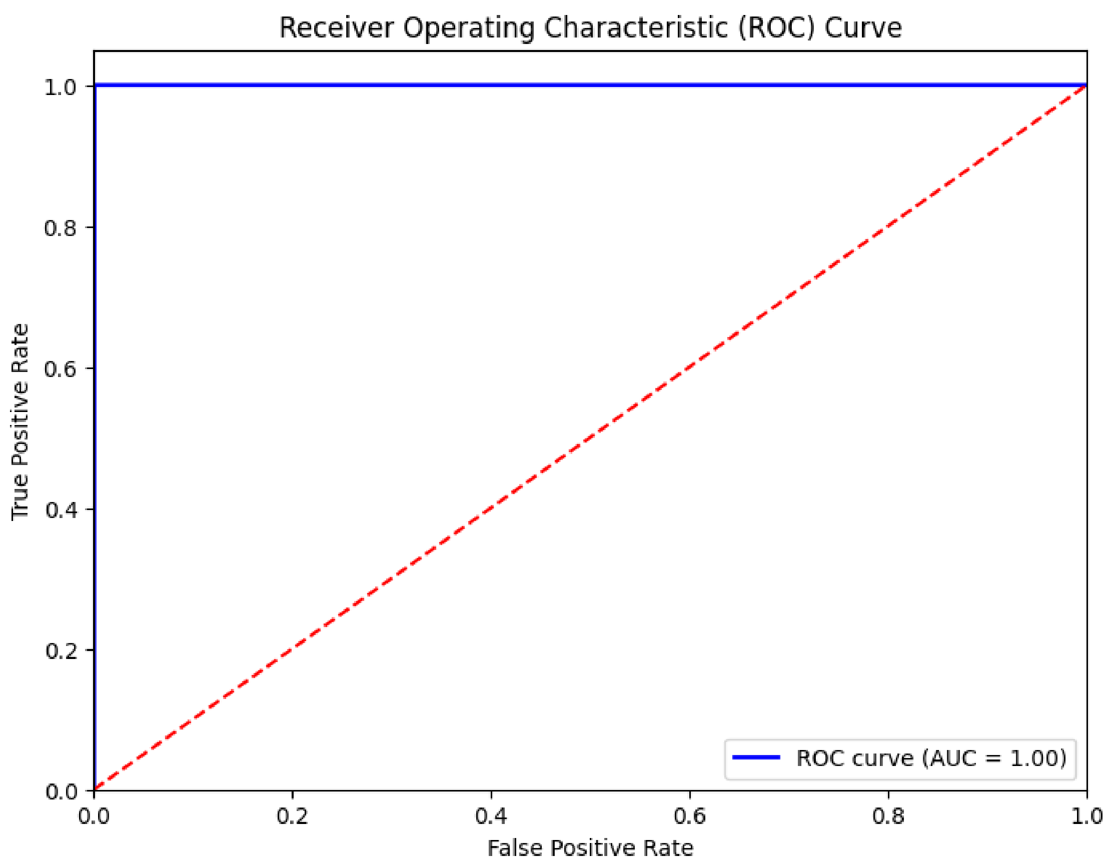



```
F1 Score: 0.9990969269212222
Precision: 0.9981954834527584
Recall: 1.0

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56750
           1       1.00      1.00      1.00     56976

    accuracy                           1.00    113726
   macro avg       1.00      1.00      1.00    113726
weighted avg       1.00      1.00      1.00    113726
```

[ ]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

# Calculating AUC-ROC
roc_auc_FNN = auc(fpr, tpr)
```

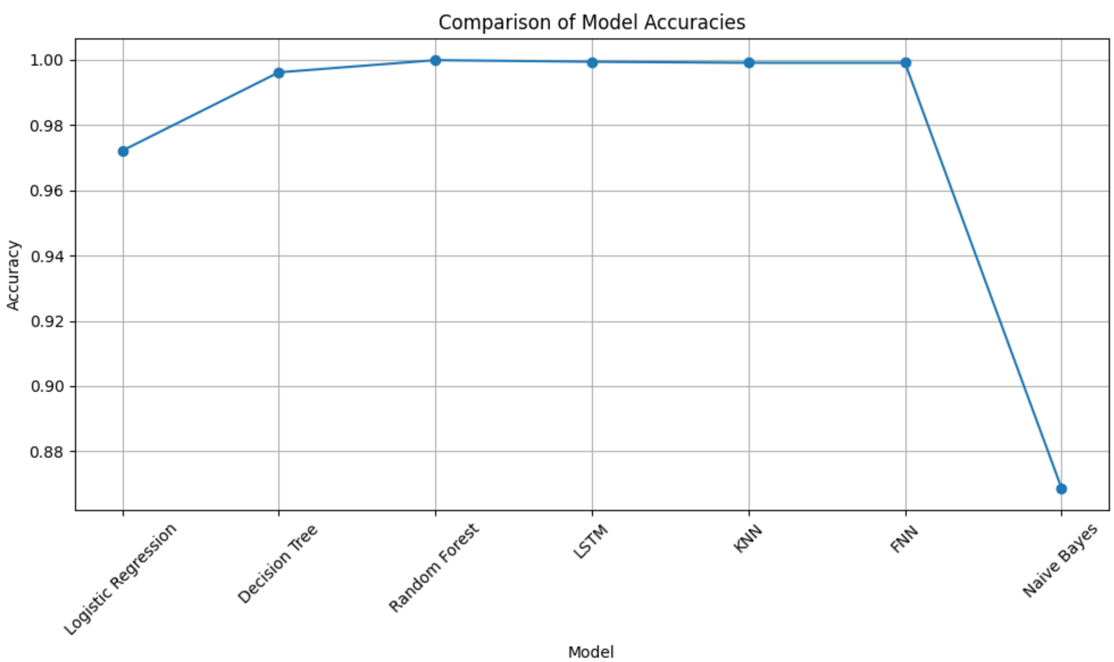
```
print("AUC-ROC:", roc_auc_FNN)

# Plotting ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' %␣
↪roc_auc_FNN)
plt.plot([0, 1], [0, 1], color='red', 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('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
AUC-ROC: 0.9997092511013216
```



#Comparing Accuracy for all implemented models on balanced dataset

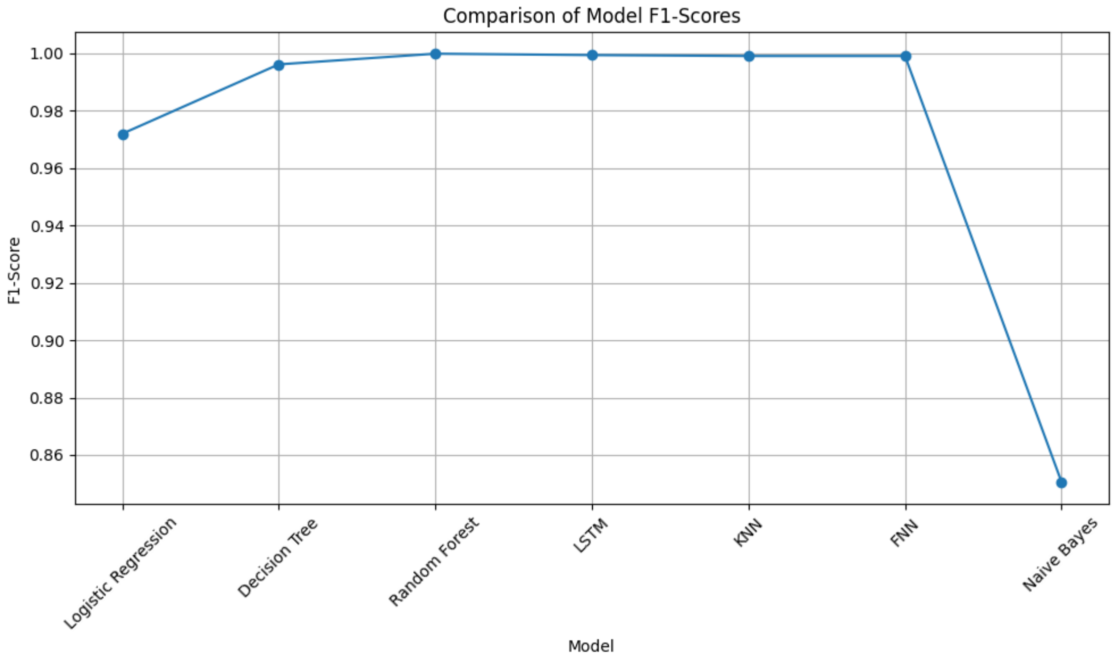
```
[ ]: import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
 ↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [accuracy_LR, accuracy_DT, accuracy_RF, accuracy_LSTM,␣
 ↪accuracy_KNN, accuracy_FNN, accuracy_NB]

plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model Accuracies')
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



#Comparing F1 - Score for all implemented models on balanced dataset

```
[ ]: import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
 ↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [f1_LR, f1_DT, f1_RF, f1_LSTM, f1_KNN, f1_FNN, f1_NB]
```

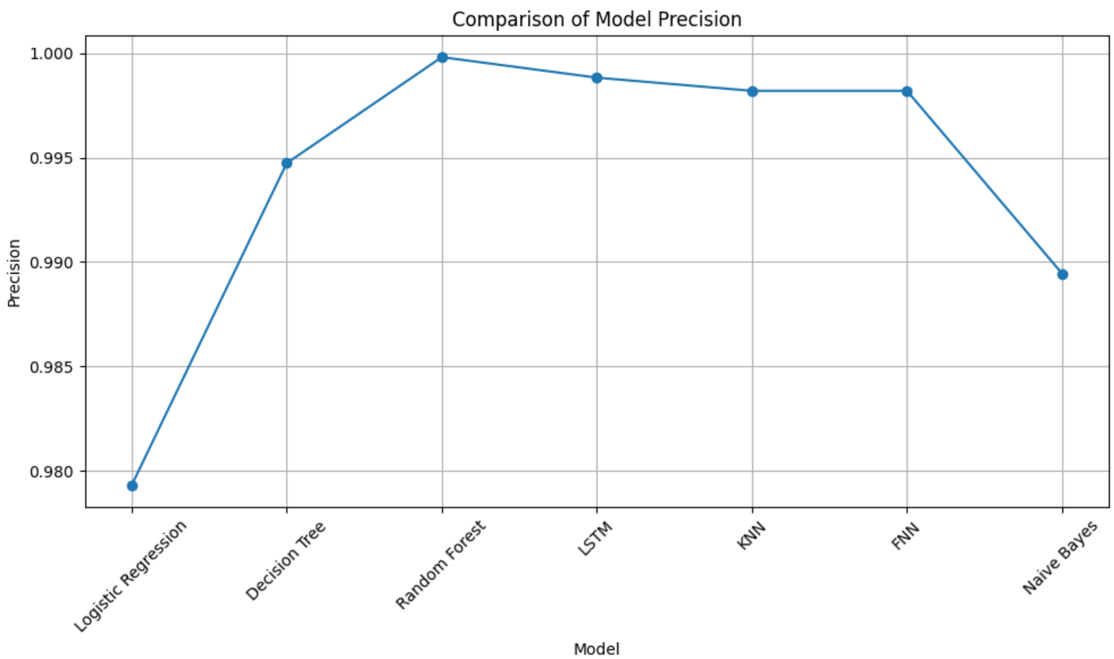
```
plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model F1-Scores')
plt.xlabel('Model')
plt.ylabel('F1-Score')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



#Comparing Precision for all implemented models on balanced dataset

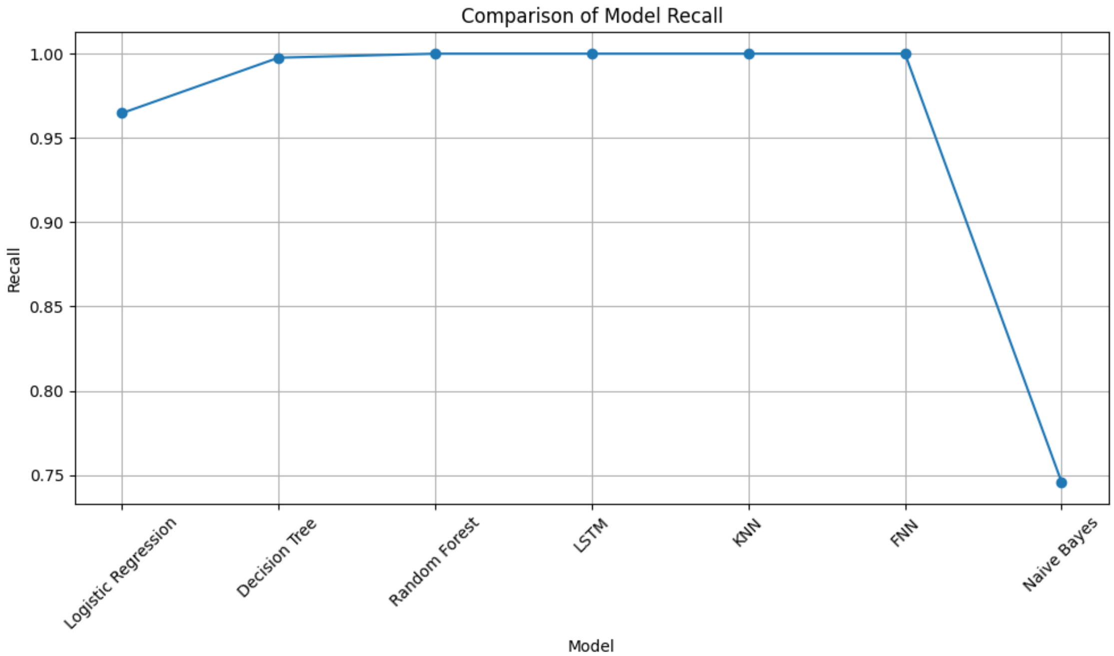
[ ]:
```
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [precision_LR, precision_DT, precision_RF, precision_LSTM,␣
↪precision_KNN, precision_FNN, precision_NB]

plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model Precision')
plt.xlabel('Model')
plt.ylabel('Precision')
plt.xticks(rotation=45)
```

```
plt.grid(True)
plt.tight_layout()
plt.show()
```



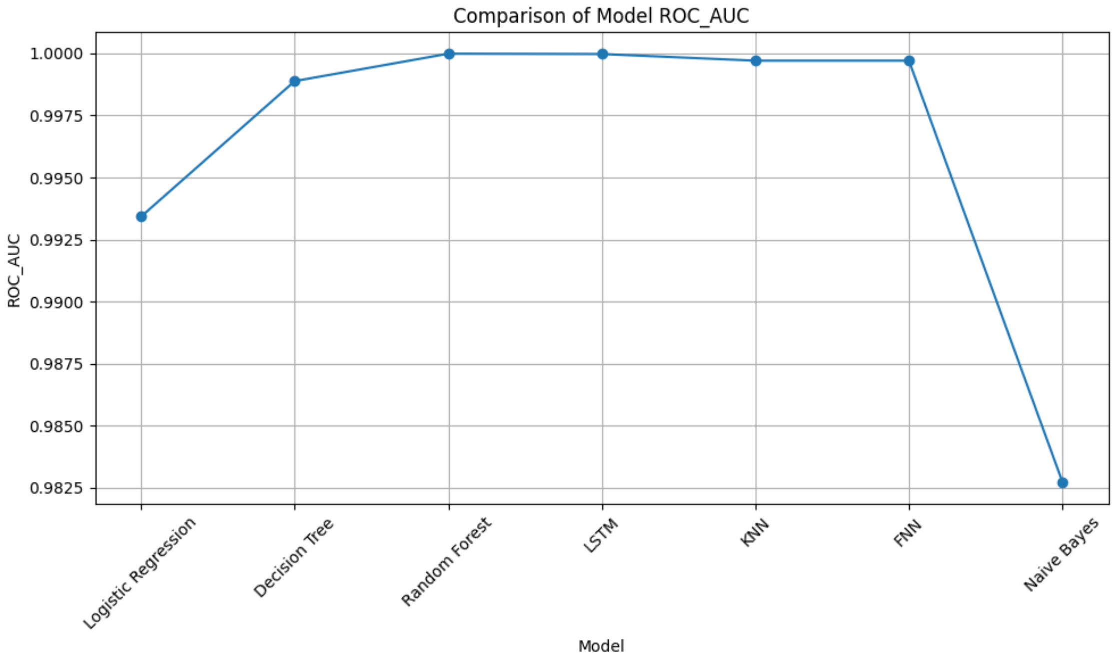
#Comparing Recall for all implemented models on balanced dataset

[ ]:
```
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [recall_LR, recall_DT, recall_RF, recall_LSTM, recall_KNN,␣
↪recall_FNN, recall_NB]

plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model Recall')
plt.xlabel('Model')
plt.ylabel('Recall')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



#Comparing Area under Receiver Operating Characteristic (ROC) Curve for all implemented models on balanced dataset

[ ]:
```
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'LSTM',␣
↪'KNN', 'FNN', 'Naive Bayes']
accuracies = [roc_auc_LR, roc_auc_DT, roc_auc_RF, roc_auc_LSTM, roc_auc_KNN,␣
↪roc_auc_FNN, roc_auc_NB]

plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Comparison of Model ROC_AUC')
plt.xlabel('Model')
plt.ylabel('ROC_AUC')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```


Comparison of Model ROC_AUC
ROC_AUC
1.0000
0.9975
0.9950
0.9925
0.9900
0.9875
0.9850
0.9825
Logistic Regression
Decision Tree
Random Forest
LSTM
KNN
FNN
Naive Bayes
Model