credit-card-fraud-detection-infosys-project

December 21, 2024

[1]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
df = pd.read_csv('/kaggle/input/credit-card/creditcard.csv')
df.head()
```

[2]:
```
   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]
```

[3]:
```
df.shape
```

[3]:
```
(284807, 31)
```

[4]:
```
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
```

[5]:
```
df.isnull().sum()
```

[5]:
```
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
```

[6]:
```
df['Class'].value_counts()
```

[6]:
```
Class
0    284315
1       492
Name: count, dtype: int64
```

[7]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Visualize class distribution
sns.countplot(x='Class', data=df)
plt.title('Class Distribution (Fraud vs Non-Fraud)')
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()
```

[8]:
```
legit_df = df[df['Class'] == 0]
fraud_df = df[df['Class'] == 1]

legit_df.shape
```

[8]: (284315, 31)

[9]:
```
fraud_df.shape
```

[9]: (492, 31)

[10]:
```
legit_df.Amount.describe()
```

[10]:
```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
```

```
max       25691.160000
Name: Amount, dtype: float64
```

[11]:
```python
fraud_df.Amount.describe()
```

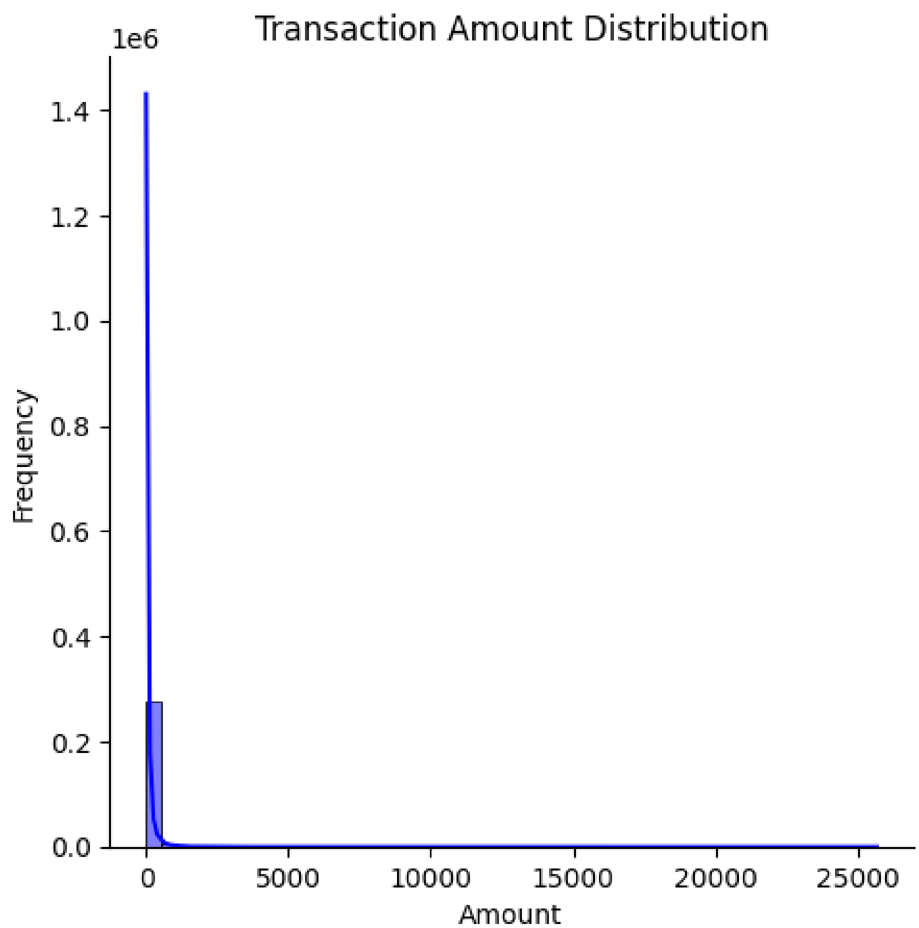
[11]:
```
count      492.000000
mean       122.211321
std        256.683288
min          0.000000
25%          1.000000
50%          9.250000
75%        105.890000
max       2125.870000
Name: Amount, dtype: float64
```

[12]:
```python
df.groupby('Class').mean().T
```

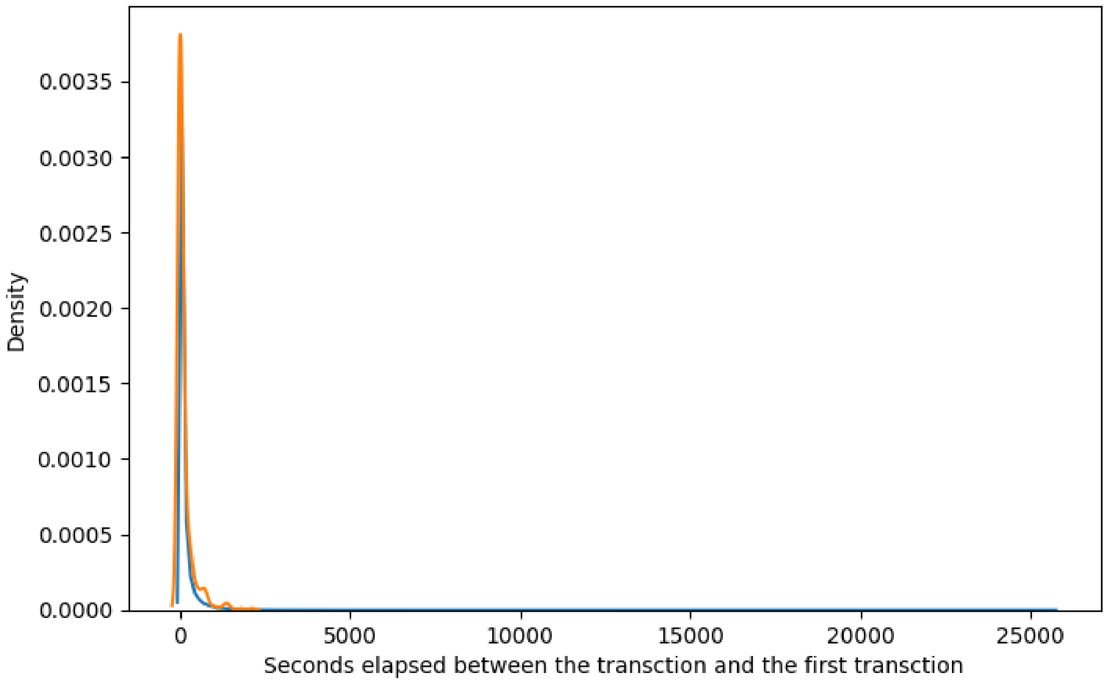
[12]:
```
Class              0             1
Time    94838.202258  80746.806911
V1          0.008258     -4.771948
V2         -0.006271      3.623778
V3          0.012171     -7.033281
V4         -0.007860      4.542029
V5          0.005453     -3.151225
V6          0.002419     -1.397737
V7          0.009637     -5.568731
V8         -0.000987      0.570636
V9          0.004467     -2.581123
V10         0.009824     -5.676883
V11        -0.006576      3.800173
V12         0.010832     -6.259393
V13         0.000189     -0.109334
V14         0.012064     -6.971723
V15         0.000161     -0.092929
V16         0.007164     -4.139946
V17         0.011535     -6.665836
V18         0.003887     -2.246308
V19        -0.001178      0.680659
V20        -0.000644      0.372319
V21        -0.001235      0.713588
V22        -0.000024      0.014049
V23         0.000070     -0.040308
V24         0.000182     -0.105130
V25        -0.000072      0.041449
V26        -0.000089      0.051648
V27        -0.000295      0.170575
V28        -0.000131      0.075667
```

```
Amount      88.291022    122.211321
```

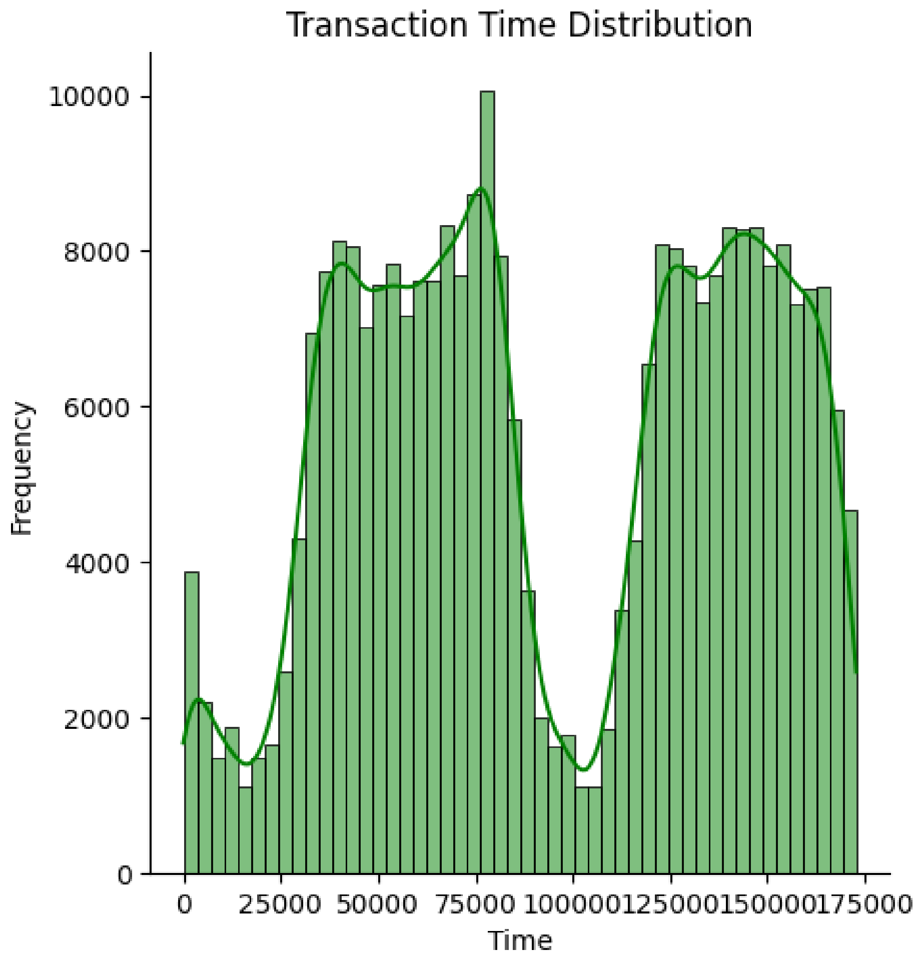
[13]:
```
# Distribution of 'Amount' feature
sns.displot(df['Amount'], bins=50, kde=True, color='blue')
plt.title('Transaction Amount Distribution')
plt.xlabel('Amount')
plt.ylabel('Frequency')
plt.show()
```



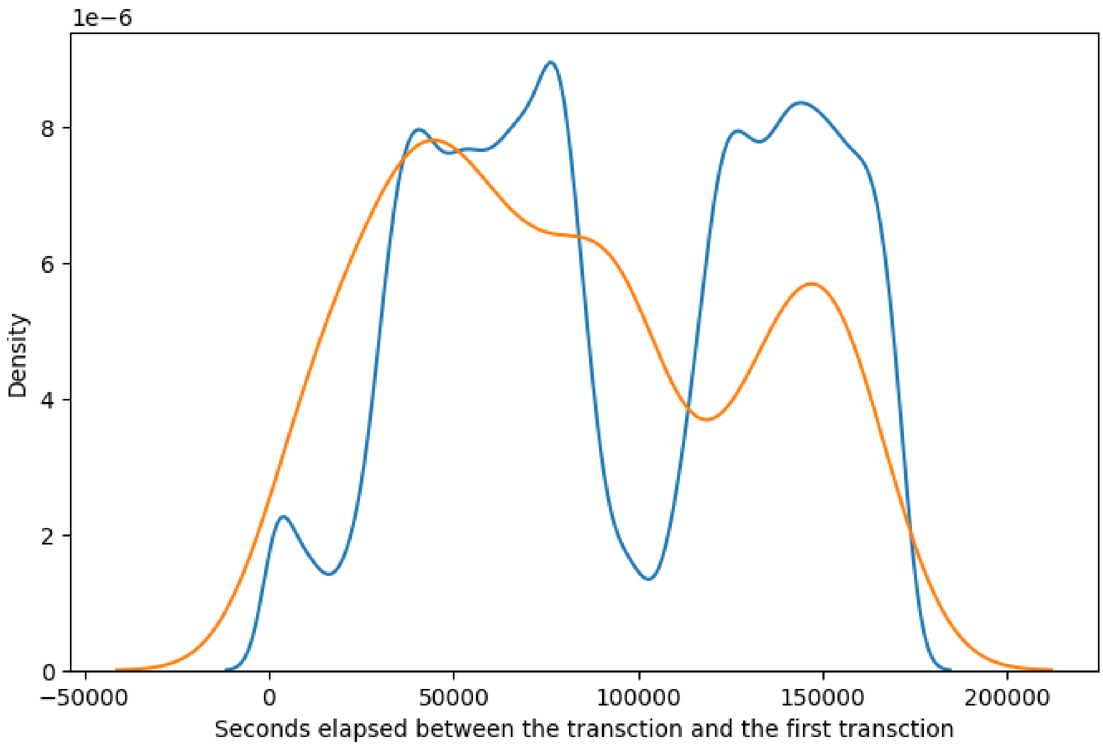
[14]:
```
plt.figure(figsize=(8,5))
ax = sns.distplot(legit_df['Amount'],label='fraudulent',hist=False)
ax = sns.distplot(fraud_df['Amount'],label='non fraudulent',hist=False)
ax.set(xlabel='Seconds elapsed between the transction and the first transction')
plt.show()
```



[15]:
```
# Distribution of 'Time' feature
sns.displot(df['Time'], bins=50, kde=True, color='green')
plt.title('Transaction Time Distribution')
plt.xlabel('Time')
plt.ylabel('Frequency')
plt.show()
```

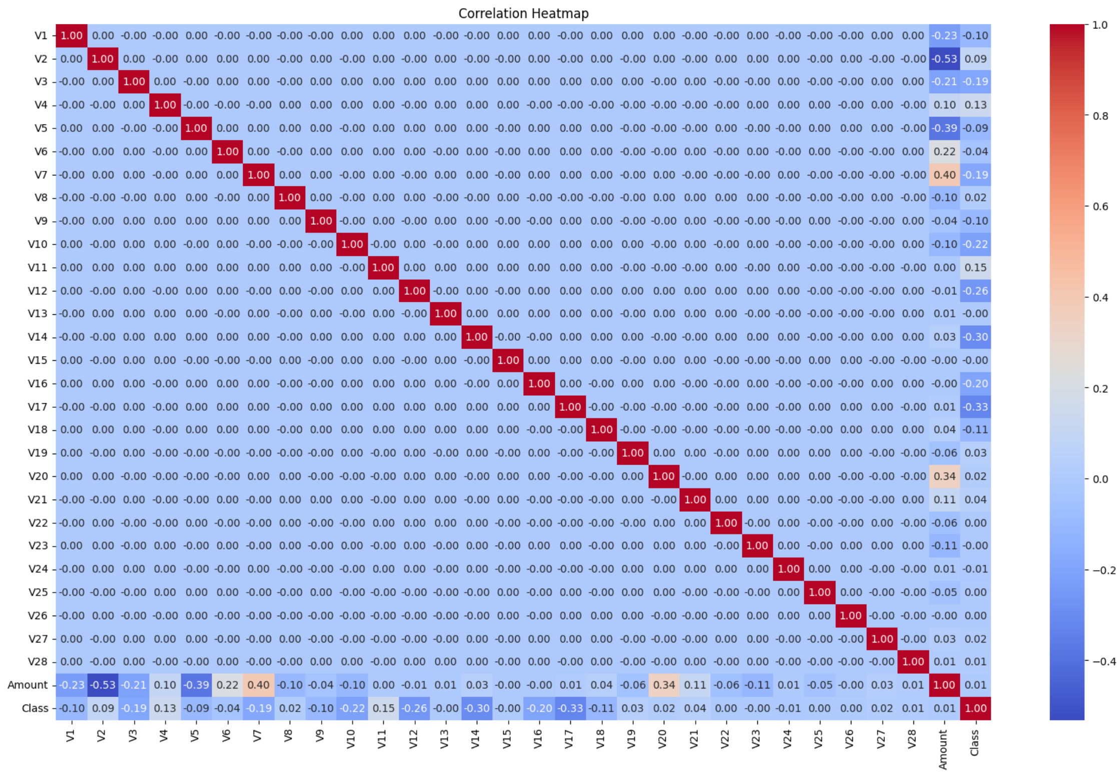


[16]:
```
plt.figure(figsize=(8,5))
ax = sns.distplot(legit_df['Time'],label='fraudulent',hist=False)
ax = sns.distplot(fraud_df['Time'],label='non fraudulent',hist=False)
ax.set(xlabel='Seconds elapsed between the transction and the first transction')
plt.show()
```

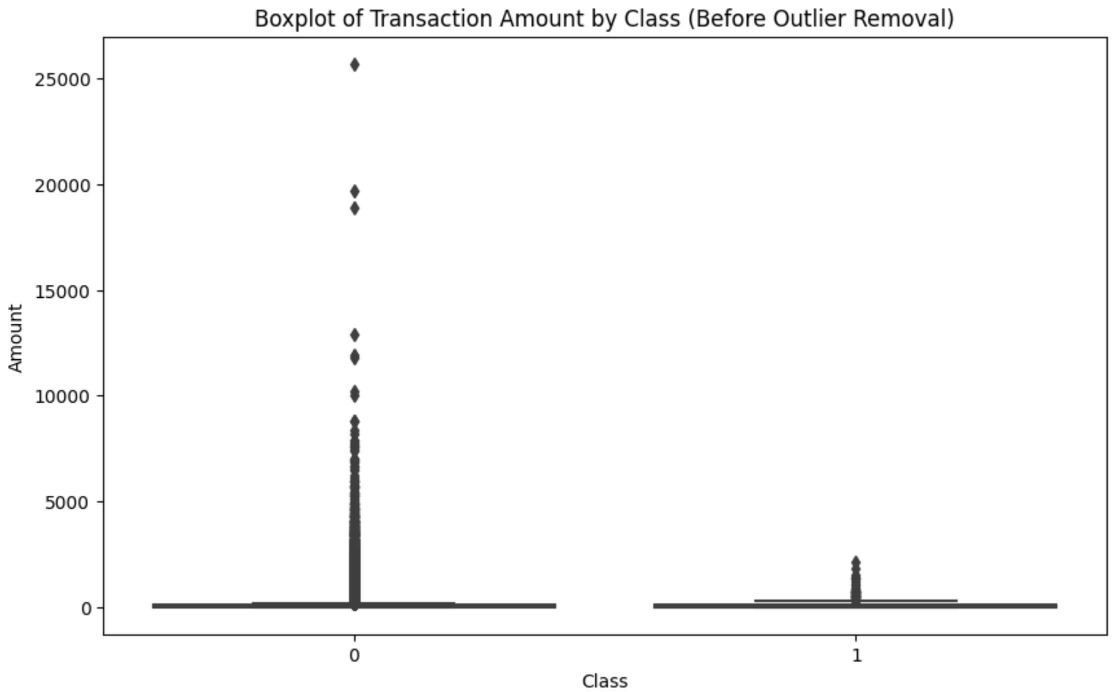


[17]:
```
df.drop('Time', axis=1, inplace=True)
```

[18]:
```
plt.figure(figsize=(20, 12))
sns.heatmap(df.corr(), cmap='coolwarm', annot=True, fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```



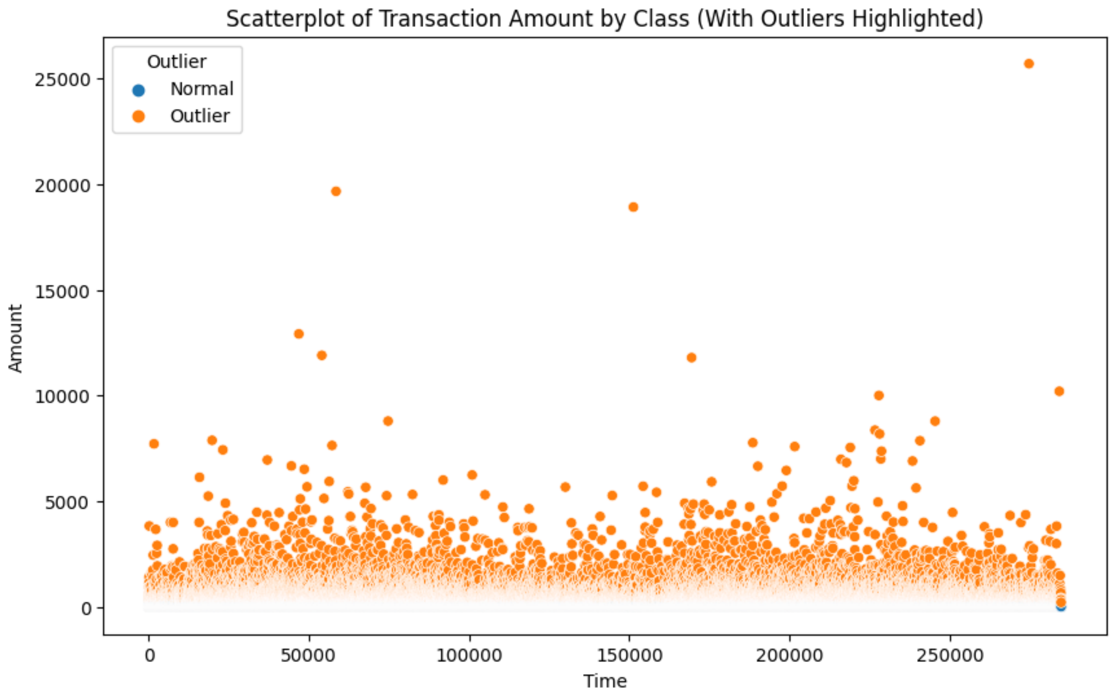
[19]:
```
# Visualize potential outliers
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='Class', y='Amount')
plt.title('Boxplot of Transaction Amount by Class (Before Outlier Removal)')
plt.show()
```



[20]:
```python
# Detecting Outliers using IQR
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1


outliers = ((df['Amount'] < (Q1['Amount'] - 1.5 * IQR['Amount'])) |
                   (df['Amount'] > (Q3['Amount'] + 1.5 * IQR['Amount'])))

outlier_df = df.copy()
outlier_df['Outlier'] = np.where(outliers, 'Outlier', 'Normal')

print(f'Number of Outliers Detected: {outliers.sum()}')
```

```
Number of Outliers Detected: 31904
```

[21]:
```python
# Scatterplot of 'Amount' by 'Class' with outliers highlighted
plt.figure(figsize=(10, 6))
sns.scatterplot(x=outlier_df.index, y='Amount', hue='Outlier', data=outlier_df)
plt.title('Scatterplot of Transaction Amount by Class (With Outliers␣
  ↪Highlighted)')
plt.xlabel('Time')
plt.ylabel('Amount')
plt.show()
```



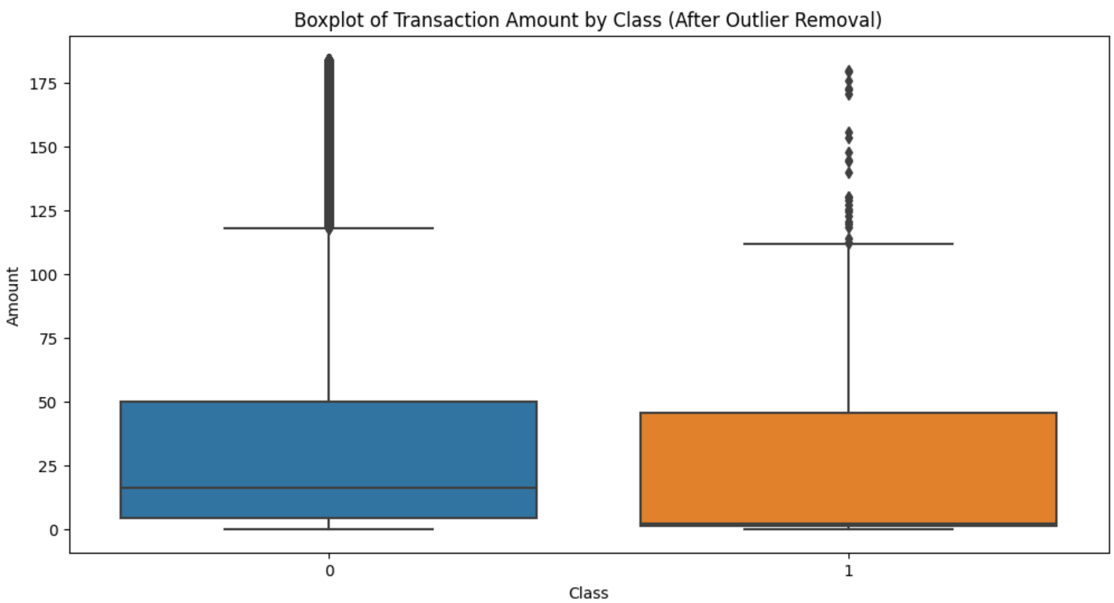
[22]:
```
# Check how many outliers are being detected
print(f"Number of outliers detected: {outliers.sum()}")
print(f"Number of normal points: {len(outliers) - outliers.sum()}")

# Print a few rows to verify the 'Outlier' column
outlier_df[['Amount', 'Outlier']].head()
```

```
Number of outliers detected: 31904
Number of normal points: 252903
```

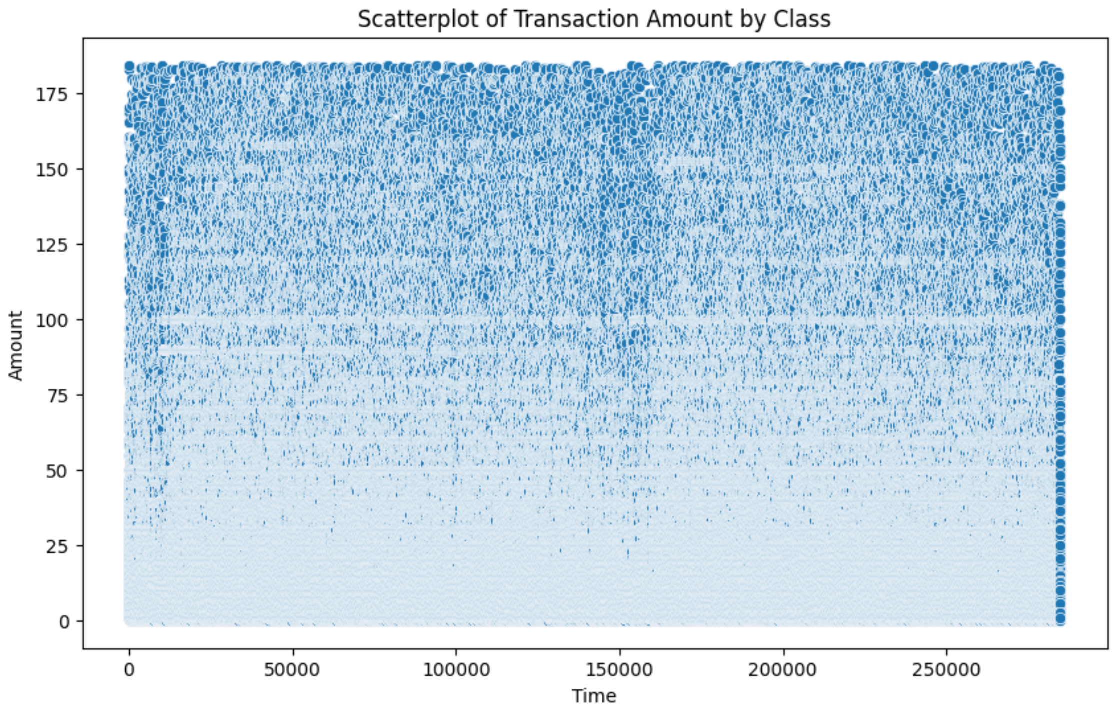
[22]:

	Amount	Outlier
0	149.62	Normal
1	2.69	Normal
2	378.66	Outlier
3	123.50	Normal
4	69.99	Normal

[23]:
```
cleaned_df = df[~outliers]

# Boxplot after removing outliers
plt.figure(figsize=(12, 6))
sns.boxplot(data=cleaned_df, x='Class', y='Amount')
plt.title('Boxplot of Transaction Amount by Class (After Outlier Removal)')
plt.show()
```



[24]:
```
# Scatterplot of 'Amount' by 'Class' with outliers highlighted
plt.figure(figsize=(10, 6))
sns.scatterplot(x=cleaned_df.index, y='Amount', data=cleaned_df)
plt.title('Scatterplot of Transaction Amount by Class')
plt.xlabel('Time')
plt.ylabel('Amount')
plt.show()
```



[25]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
cleaned_df['Amount'] = scaler.fit_transform(cleaned_df[['Amount']])
cleaned_df['Amount'].head()
```

[25]:
```
0    2.718502
1   -0.765550
3    2.099136
4    0.830290
5   -0.742312
Name: Amount, dtype: float64
```

[26]:
```
X = cleaned_df.drop('Class', axis=1)
y = cleaned_df['Class']
```

[27]:
```
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_state=42)
```

[28]:
```
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42)
```

```
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)


print("\nClass Distribution After Resampling:")
print(pd.Series(y_resampled).value_counts())
```

```
Class Distribution After Resampling:
Class
0    202012
1    202012
Name: count, dtype: int64
```

[29]:
```
from collections import Counter

print("Original Class Distribution:", Counter(y_train))
print("Resampled Class Distribution:", Counter(y_resampled))
```

```
Original Class Distribution: Counter({0: 202012, 1: 310})
Resampled Class Distribution: Counter({0: 202012, 1: 202012})
```

[30]:
```
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪roc_auc_score, roc_curve, precision_recall_curve, auc
import joblib

def evaluate_model(model, X_train, y_train, X_test, y_test, model_name):
    print(f"\n{model_name}:")

    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_pred_proba = model.predict_proba(X_test)[:, 1]

    # Confusion Matrix
    print("\nConfusion Matrix:")
    print(confusion_matrix(y_test, y_pred))

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

    # ROC-AUC
    roc_auc = roc_auc_score(y_test, y_pred_proba)
    print(f"\nROC-AUC Score: {roc_auc:.4f}")

    # Precision-Recall Curve
    precision, recall, _ = precision_recall_curve(y_test, y_pred_proba)
    pr_auc = auc(recall, precision)
    print(f"Precision-Recall AUC: {pr_auc:.4f}")
```

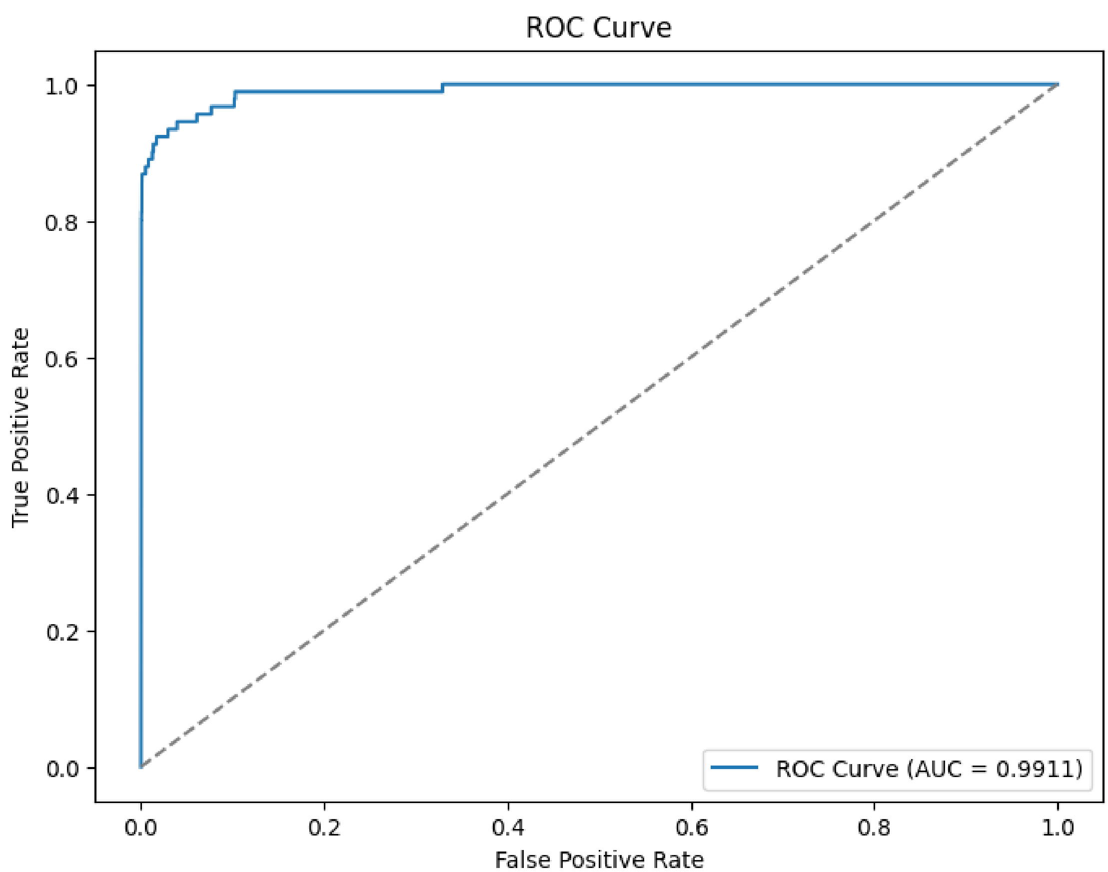
```
    # Plot ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, label=f'ROC Curve (AUC = {roc_auc:.4f})')
    plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend()
    plt.show()

    # Plot Precision-Recall Curve
    plt.figure(figsize=(8, 6))
    plt.plot(recall, precision, label=f'Precision-Recall Curve (AUC = {pr_auc:.
↪4f})')
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.title('Precision-Recall Curve')
    plt.legend()
    plt.show()

    # Save the model
    model_path = f'{model_name.lower().replace(" ", "_")}_model.pkl'
    joblib.dump(model, model_path)
    print(f"Model saved at: {model_path}")
```

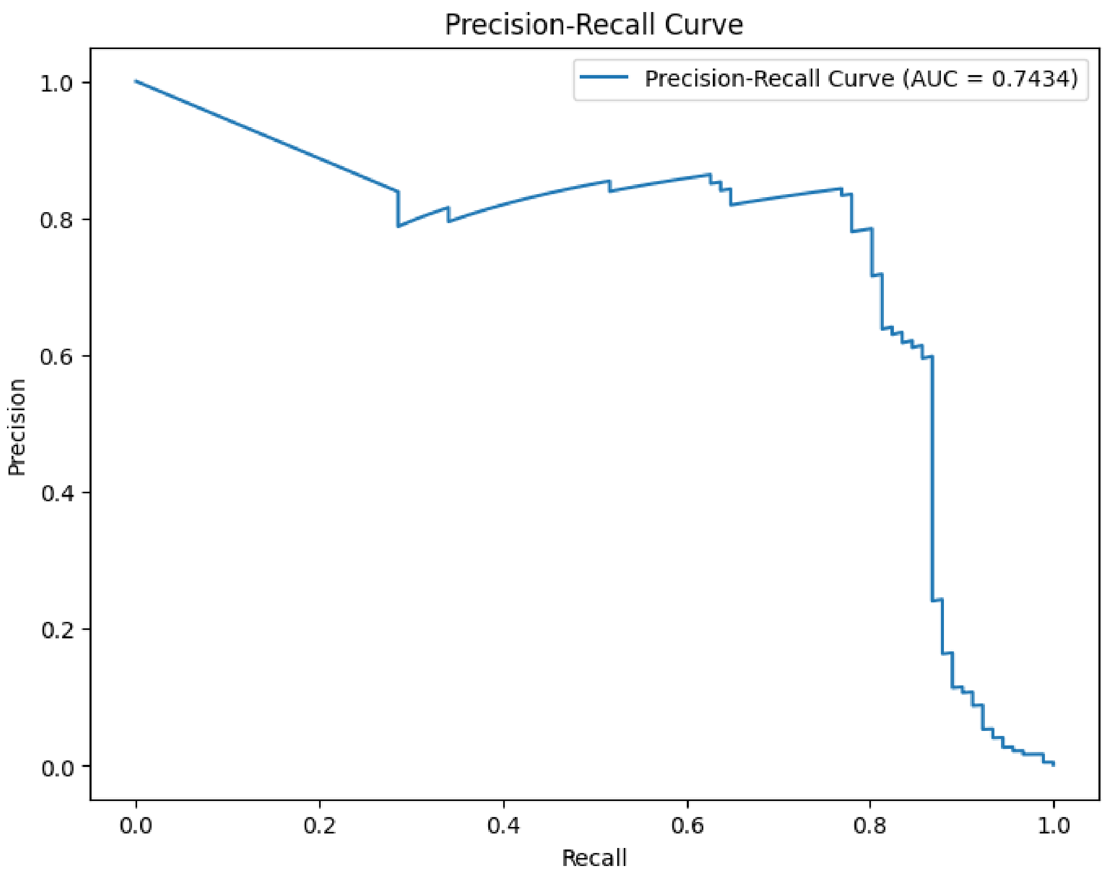
[31]:
```
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from lightgbm import LGBMClassifier
from catboost import CatBoostClassifier
```

[32]:
```
# Logistic Regression
logistic_model = LogisticRegression(max_iter=1000, random_state=42)
evaluate_model(logistic_model, X_resampled, y_resampled, X_test, y_test,␣
↪"Logistic Regression")
```

```
Logistic Regression:

Confusion Matrix:
[[49566   924]
 [    7    84]]

Classification Report:
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     50490
           1       0.08      0.92      0.15        91

    accuracy                           0.98     50581
   macro avg       0.54      0.95      0.57     50581
weighted avg       1.00      0.98      0.99     50581


ROC-AUC Score: 0.9911
Precision-Recall AUC: 0.7434
```





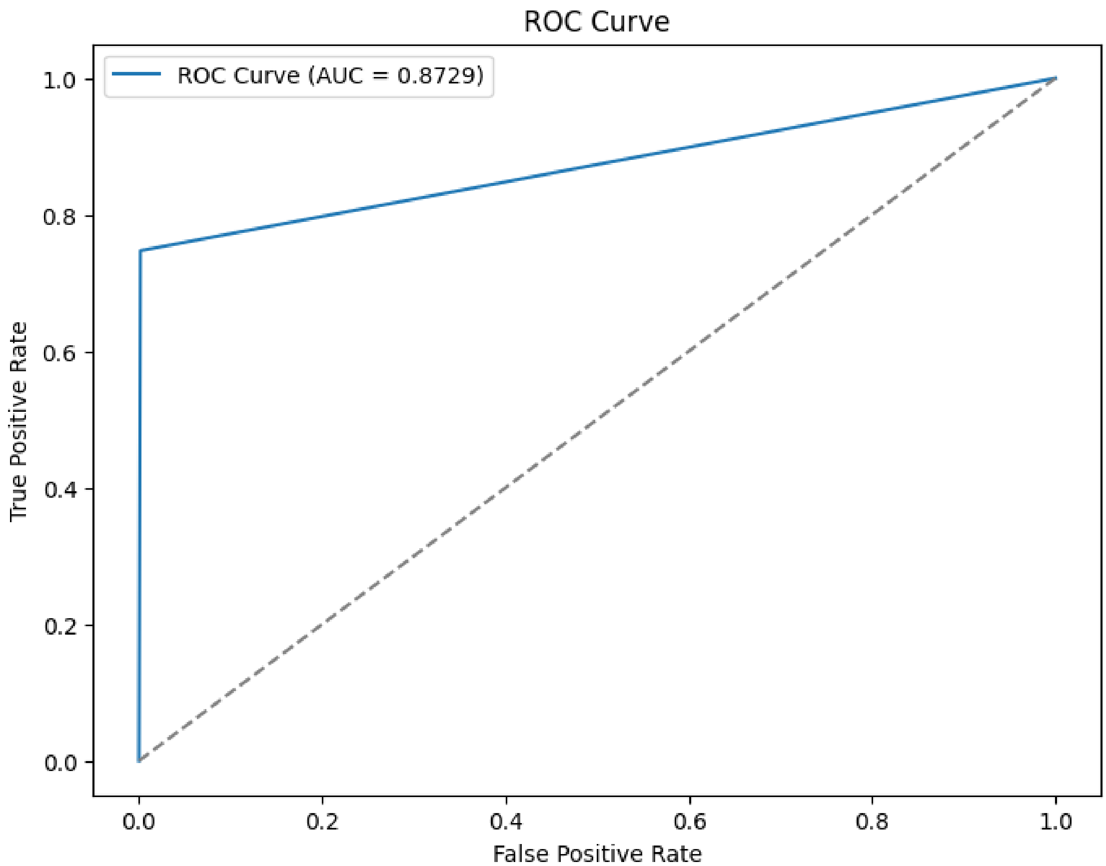

```
Model saved at: logistic_regression_model.pkl
```

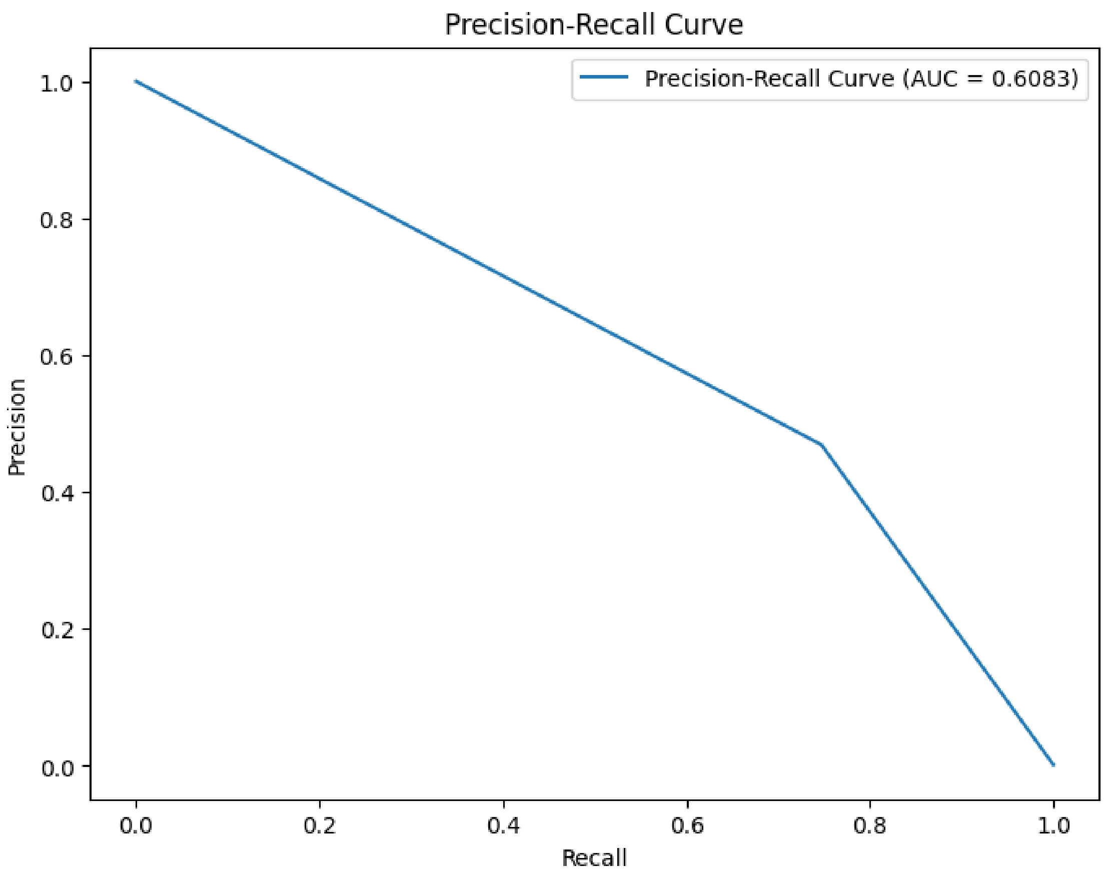
[33]:

```
# Decision Tree
dt_model = DecisionTreeClassifier(random_state=42)
evaluate_model(dt_model, X_resampled, y_resampled, X_test, y_test, "Decision␣
↪Tree")
```

```
Decision Tree:

Confusion Matrix:
[[50413    77]
 [   23    68]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     50490
           1       0.47      0.75      0.58        91
```

```
    accuracy                           1.00     50581
   macro avg       0.73      0.87      0.79     50581
weighted avg       1.00      1.00      1.00     50581


ROC-AUC Score: 0.8729
Precision-Recall AUC: 0.6083
```





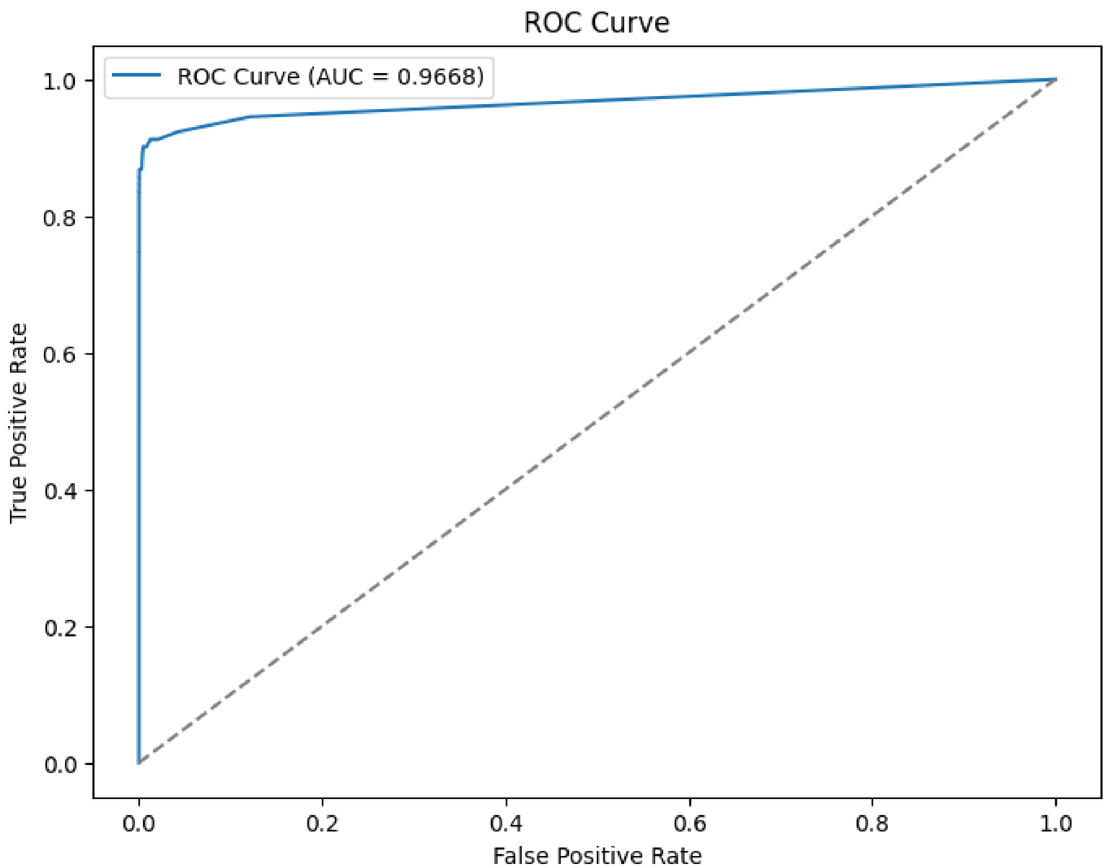

```
Model saved at: decision_tree_model.pkl
```

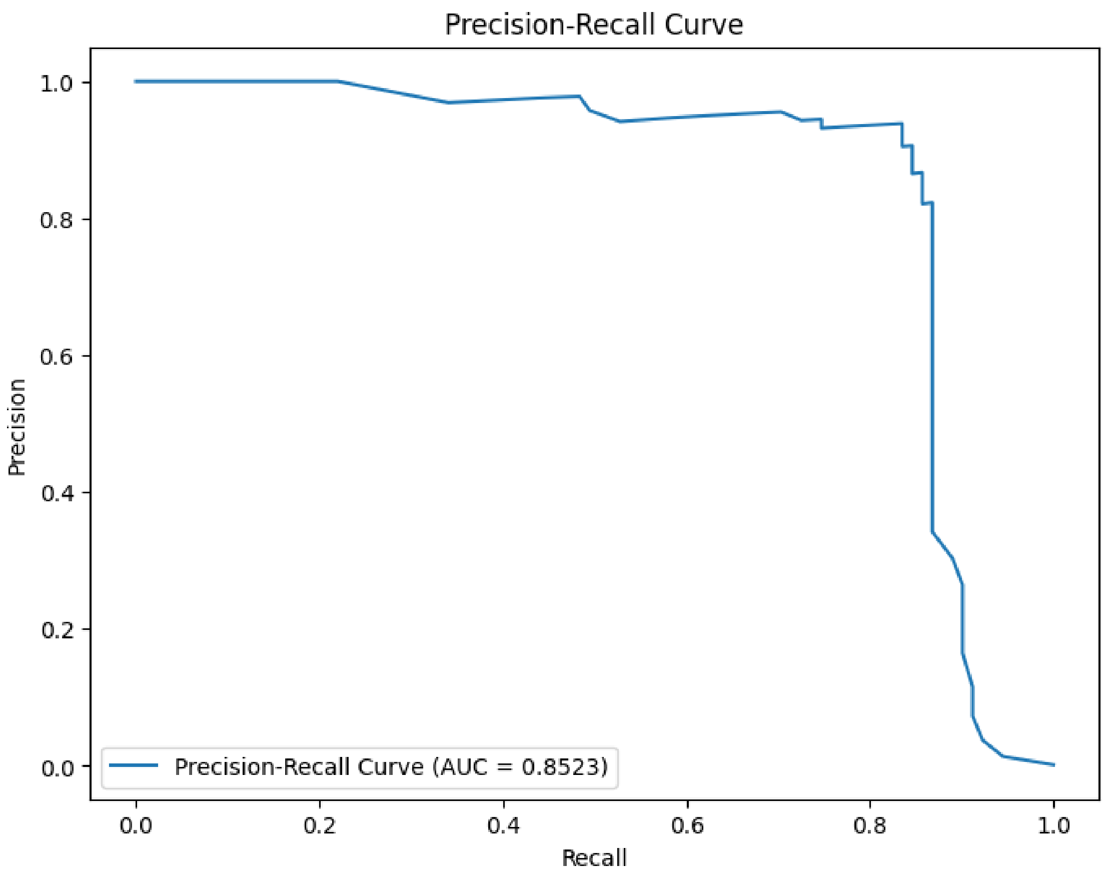
[34]:
```
# Random Forest
rf_model = RandomForestClassifier(random_state=42)
evaluate_model(rf_model, X_resampled, y_resampled, X_test, y_test, "Random␣
↪Forest")
```

```
Random Forest:

Confusion Matrix:
[[50481     9]
 [   14    77]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     50490
           1       0.90      0.85      0.87        91
```

accuracy			1.00	50581
macro avg	0.95	0.92	0.93	50581
weighted avg	1.00	1.00	1.00	50581

```
ROC-AUC Score: 0.9668
Precision-Recall AUC: 0.8523
```





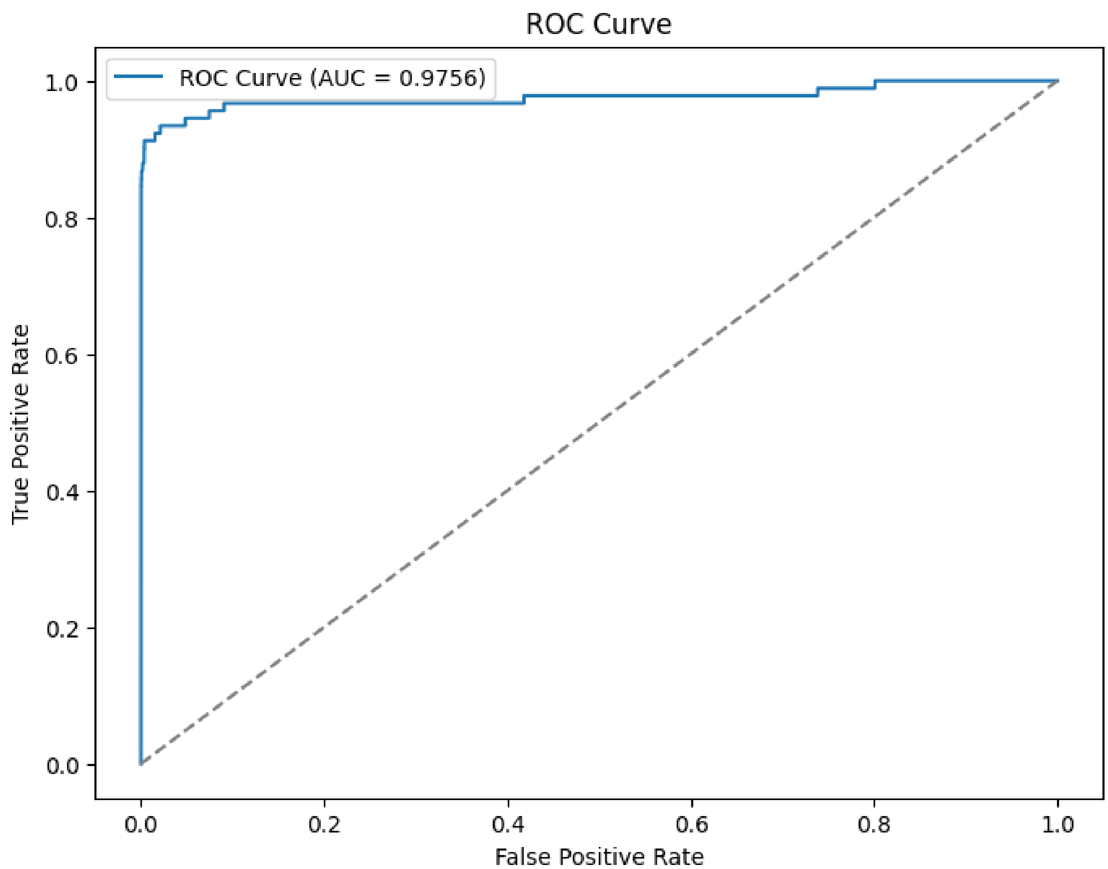

```
Model saved at: random_forest_model.pkl
```

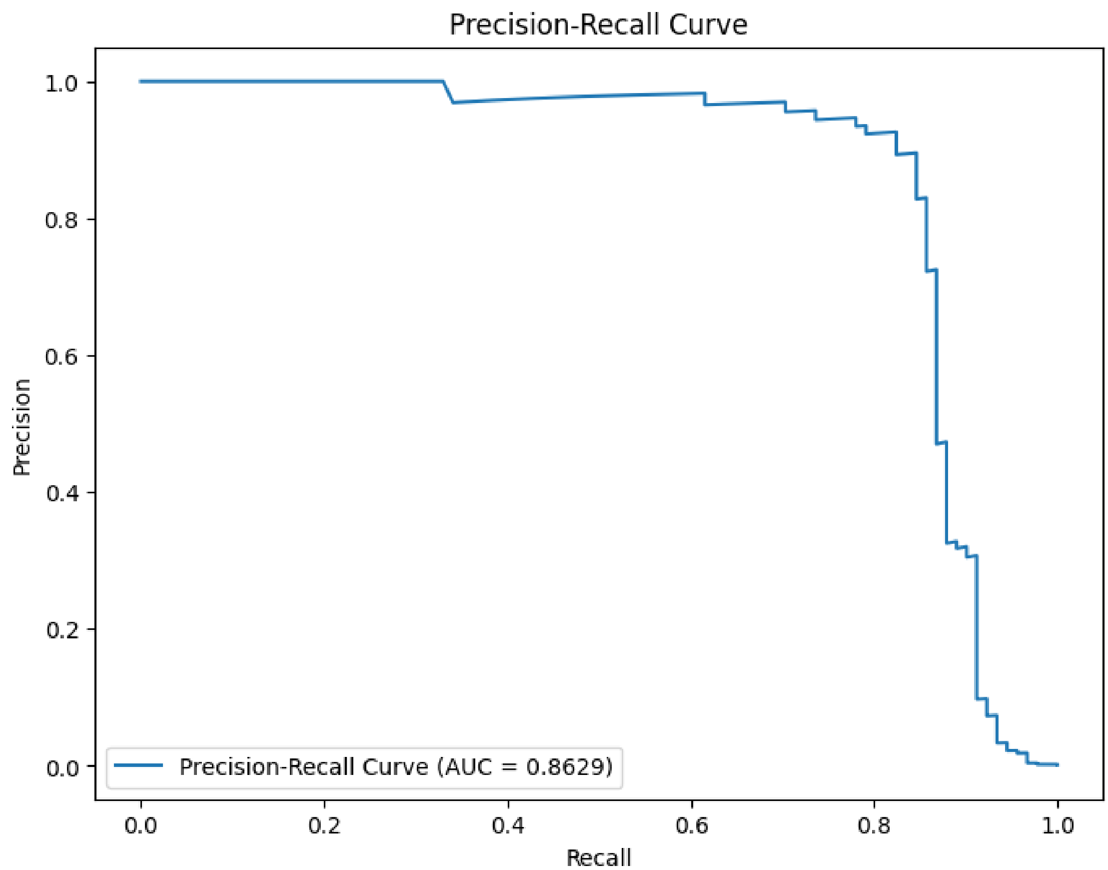
[35]:

```python
# XGBoost
xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='logloss',␣
 ↪random_state=42)
evaluate_model(xgb_model, X_resampled, y_resampled, X_test, y_test, "XGBoost")
```

```
XGBoost:

Confusion Matrix:
[[50474    16]
 [   13    78]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     50490
           1       0.83      0.86      0.84        91
```

```
    accuracy                           1.00     50581
   macro avg       0.91      0.93      0.92     50581
weighted avg       1.00      1.00      1.00     50581


ROC-AUC Score: 0.9756
Precision-Recall AUC: 0.8629
```



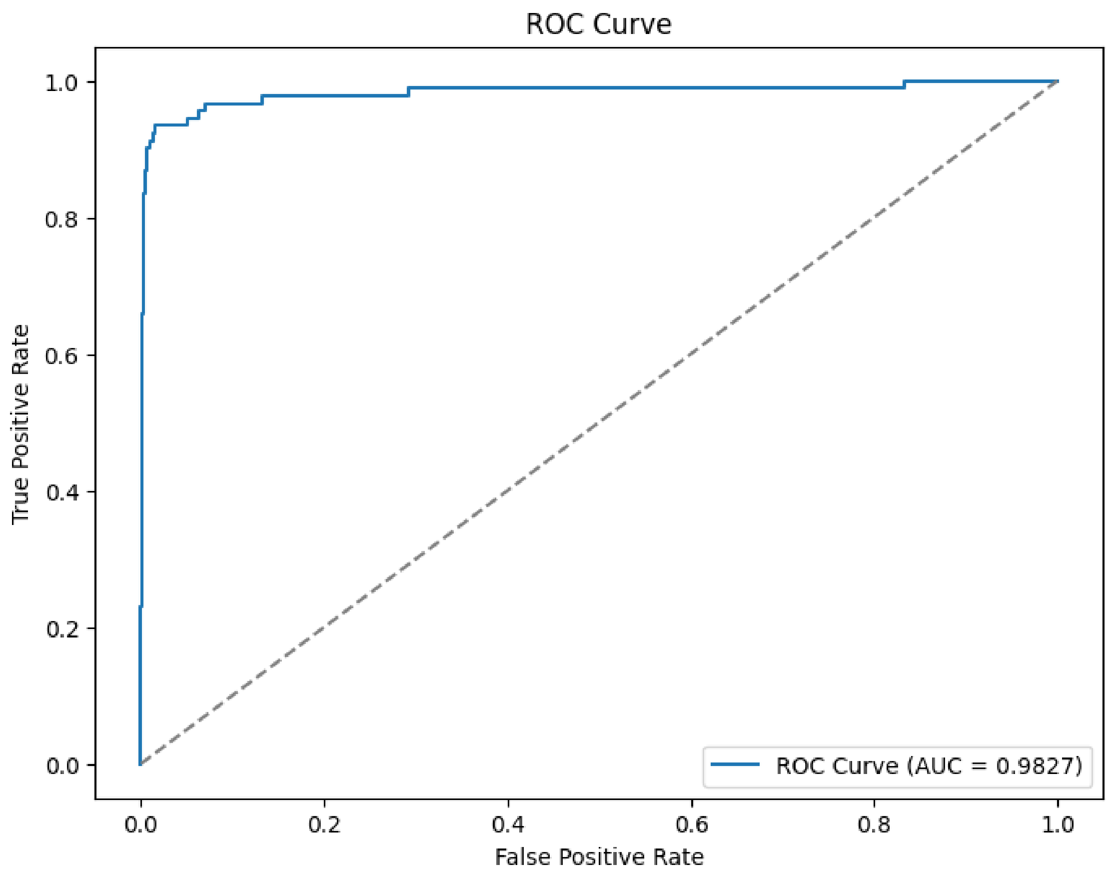


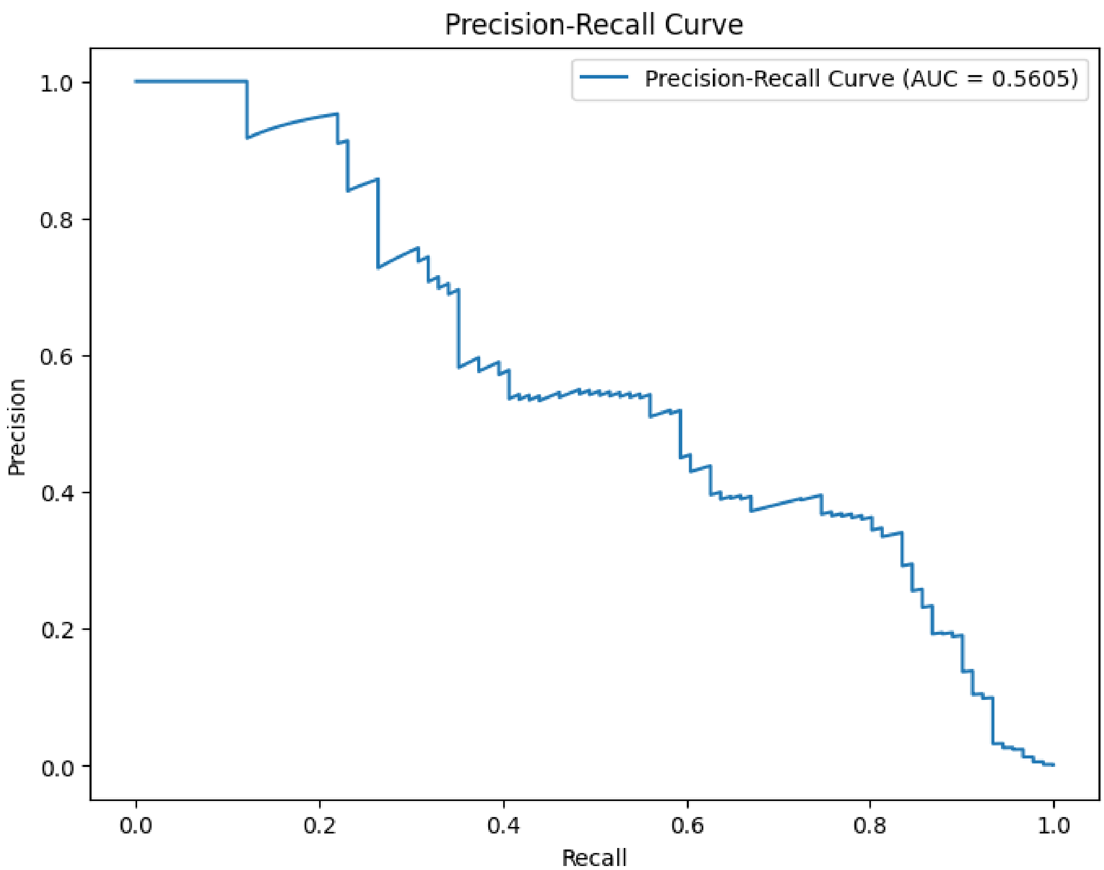

```
Model saved at: xgboost_model.pkl
```

[36]:
```
# Support Vector Machine
svm_model = SVC(probability=True, random_state=42)
evaluate_model(svm_model, X_resampled, y_resampled, X_test, y_test, "Support␣
↪Vector Machine")
```

```
Support Vector Machine:

Confusion Matrix:
[[49940   550]
 [    8    83]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99     50490
           1       0.13      0.91      0.23        91
```

```
    accuracy                           0.99     50581
   macro avg       0.57      0.95      0.61     50581
weighted avg       1.00      0.99      0.99     50581


ROC-AUC Score: 0.9827
Precision-Recall AUC: 0.5605
```





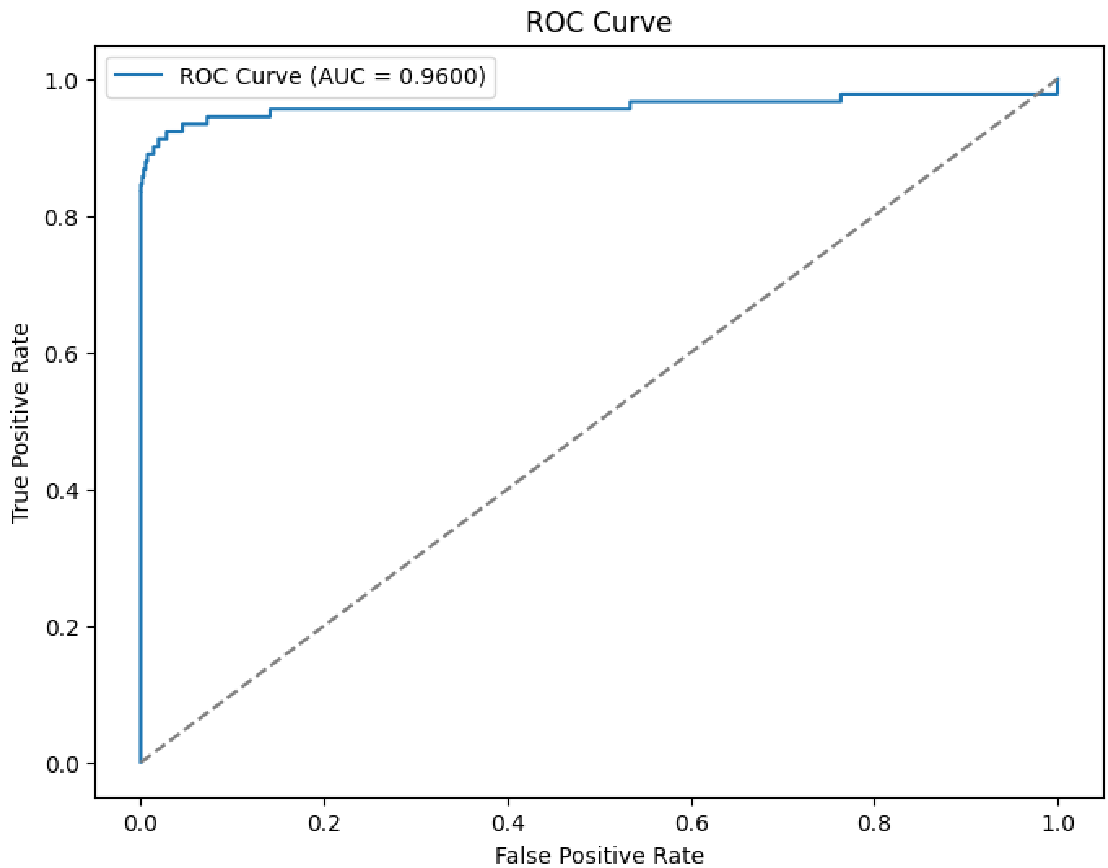
Model saved at: support_vector_machine_model.pkl

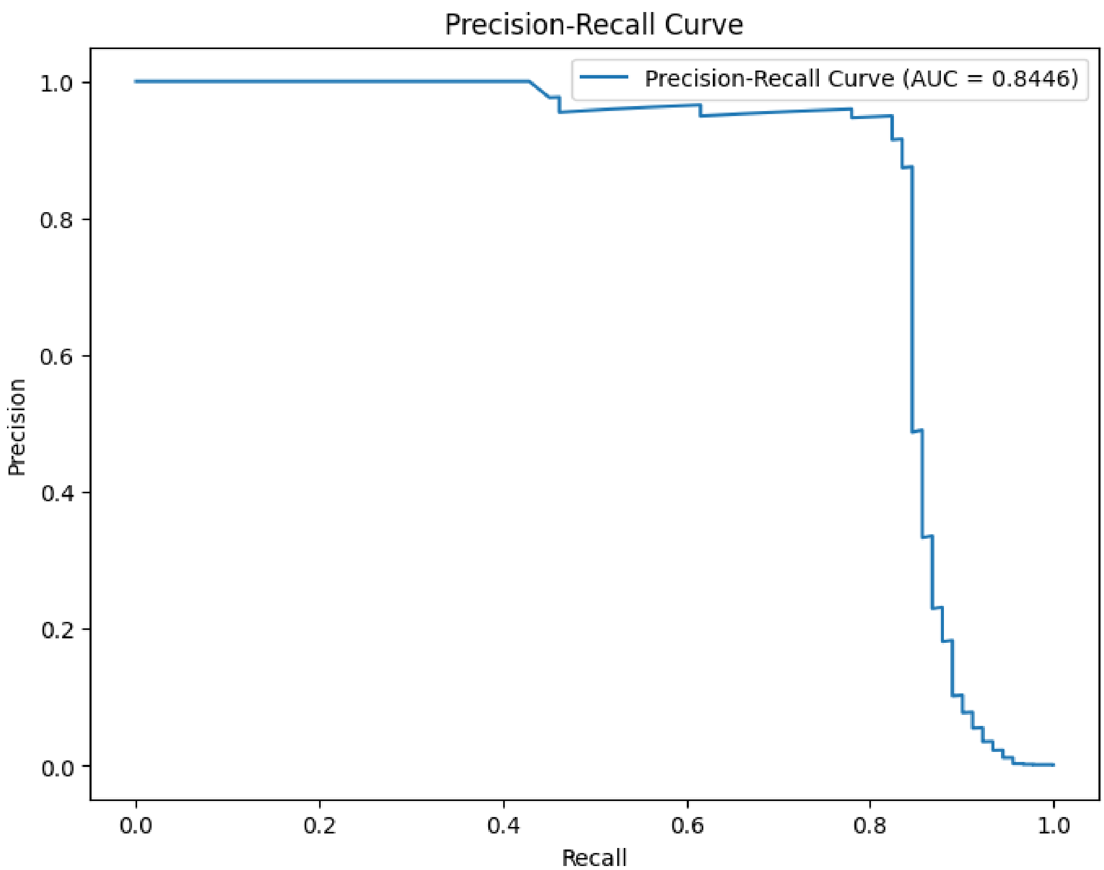
[37]:

```
# LightGBM
lgbm_model = LGBMClassifier(random_state=42)
evaluate_model(lgbm_model, X_resampled, y_resampled, X_test, y_test, "LightGBM")
```

```
LightGBM:
[LightGBM] [Info] Number of positive: 202012, number of negative: 202012
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.066005 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 7395
[LightGBM] [Info] Number of data points in the train set: 404024, number of used
features: 29
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000

Confusion Matrix:
[[50454    36]
 [   14    77]]
```

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

           0       1.00      1.00      1.00     50490
           1       0.68      0.85      0.75        91

    accuracy                           1.00     50581
   macro avg       0.84      0.92      0.88     50581
weighted avg       1.00      1.00      1.00     50581


ROC-AUC Score: 0.9600
Precision-Recall AUC: 0.8446
```



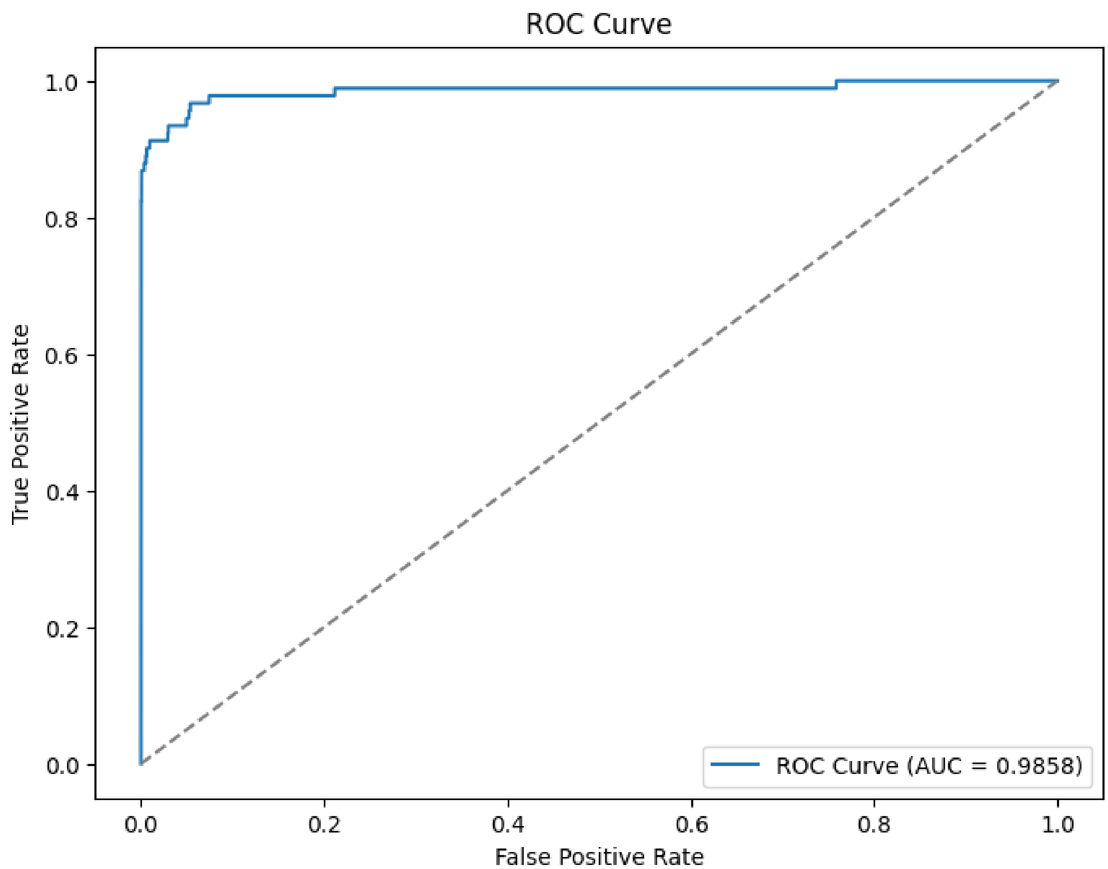


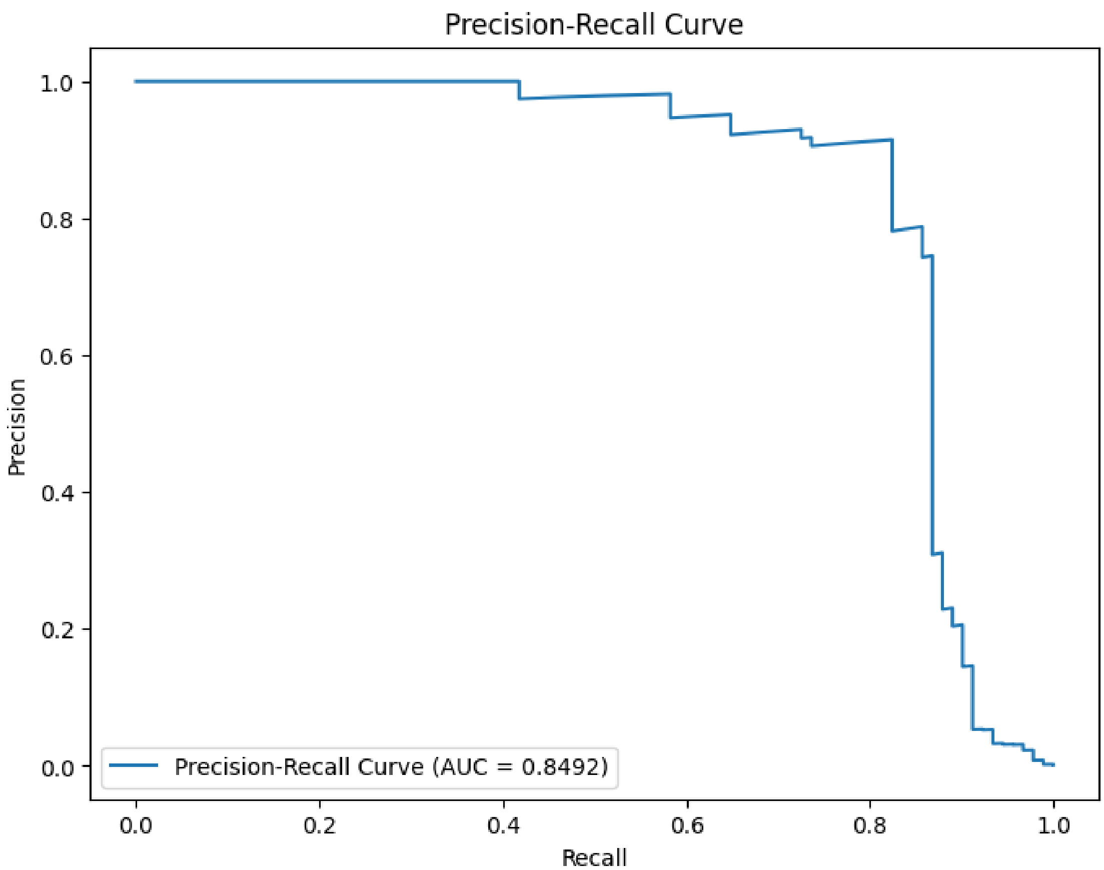

```
Model saved at: lightgbm_model.pkl
```

[38]:
```
# CatBoost
catboost_model = CatBoostClassifier(verbose=0, random_state=42)
evaluate_model(catboost_model, X_resampled, y_resampled, X_test, y_test,
    ↪"CatBoost")
```

```
CatBoost:

Confusion Matrix:
[[50430    60]
 [   12    79]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     50490
           1       0.57      0.87      0.69        91
```

```
    accuracy                           1.00     50581
   macro avg       0.78      0.93      0.84     50581
weighted avg       1.00      1.00      1.00     50581


ROC-AUC Score: 0.9858
Precision-Recall AUC: 0.8492
```

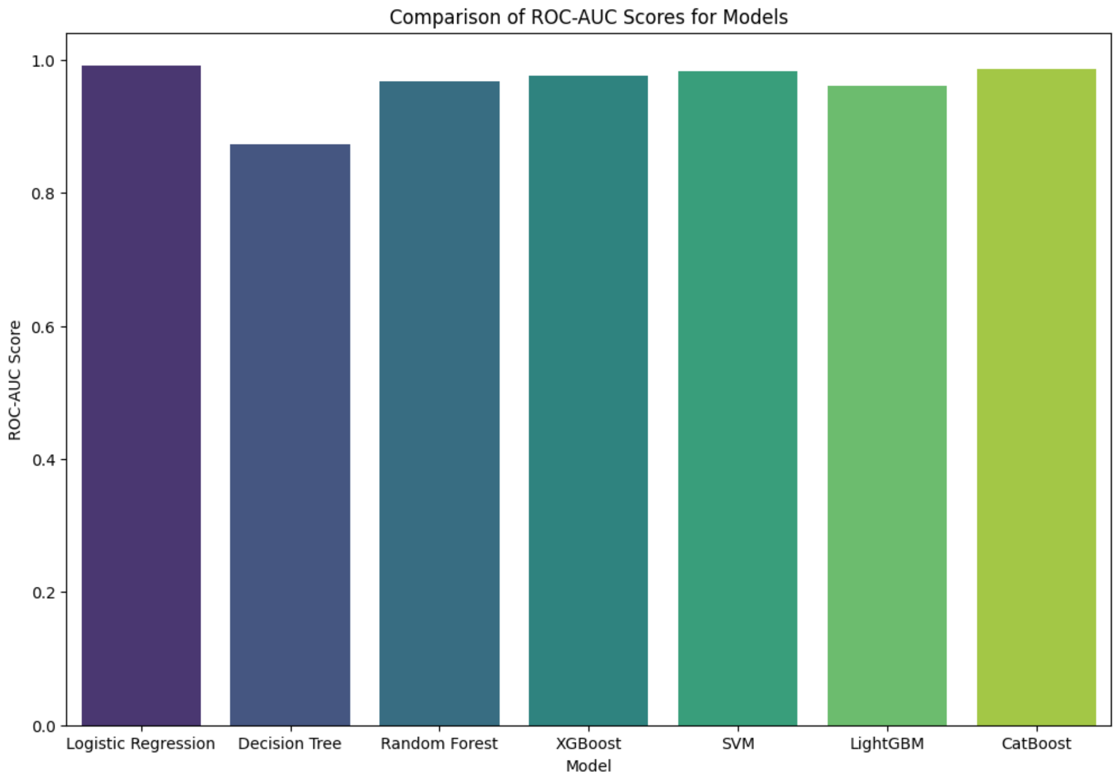





```
Model saved at: catboost_model.pkl
```

[39]:
```
models = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'XGBoost',
 ↪'SVM', 'LightGBM', 'CatBoost']
roc_auc_scores = [
    roc_auc_score(y_test, logistic_model.predict_proba(X_test)[:, 1]),
    roc_auc_score(y_test, dt_model.predict_proba(X_test)[:, 1]),
    roc_auc_score(y_test, rf_model.predict_proba(X_test)[:, 1]),
    roc_auc_score(y_test, xgb_model.predict_proba(X_test)[:, 1]),
    roc_auc_score(y_test, svm_model.predict_proba(X_test)[:, 1]),
    roc_auc_score(y_test, lgbm_model.predict_proba(X_test)[:, 1]),
    roc_auc_score(y_test, catboost_model.predict_proba(X_test)[:, 1])
]
```

[40]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x=models, y=roc_auc_scores, palette='viridis')
plt.title('Comparison of ROC-AUC Scores for Models')
plt.ylabel('ROC-AUC Score')
plt.xlabel('Model')
plt.show()
```



Comparison of ROC-AUC Scores for Models
ROC-AUC Score
1.0
0.8
0.6
0.4
0.2
0.0
Logistic Regression
Decision Tree
Random Forest
XGBoost
SVM
LightGBM
CatBoost
Model