training

January 3, 2025

[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]:
```
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
```

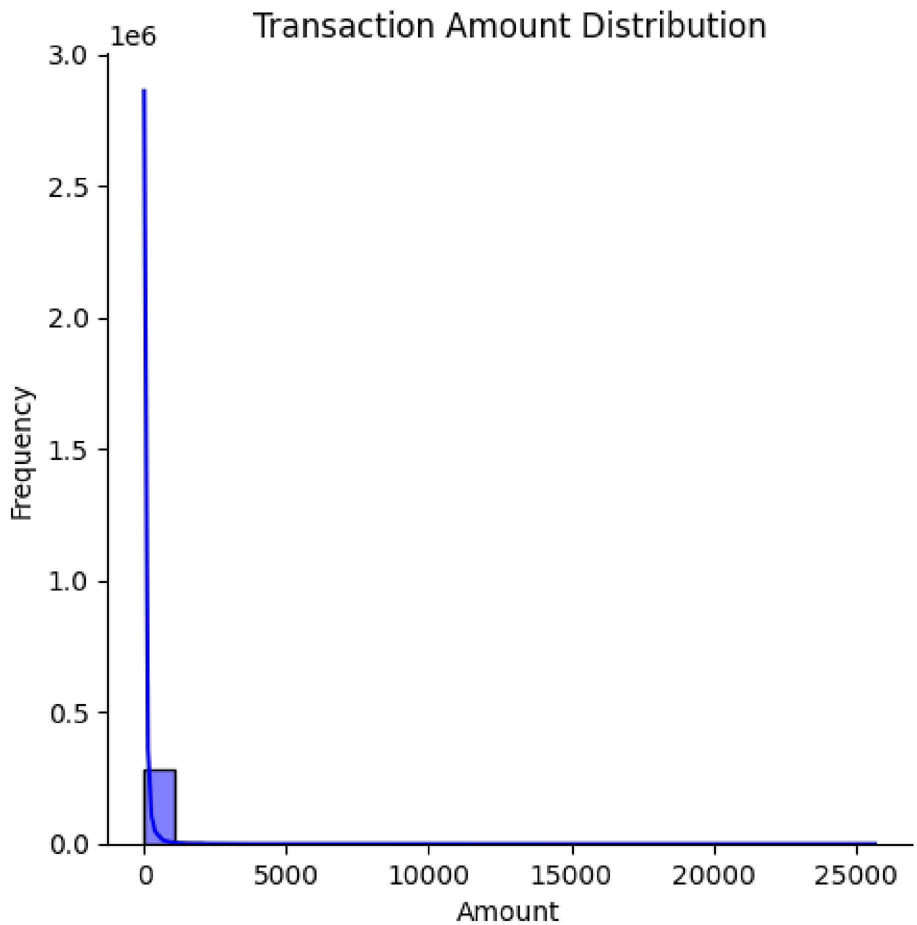
[12]:
```
df.groupby('Class').mean().T
```

[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
```

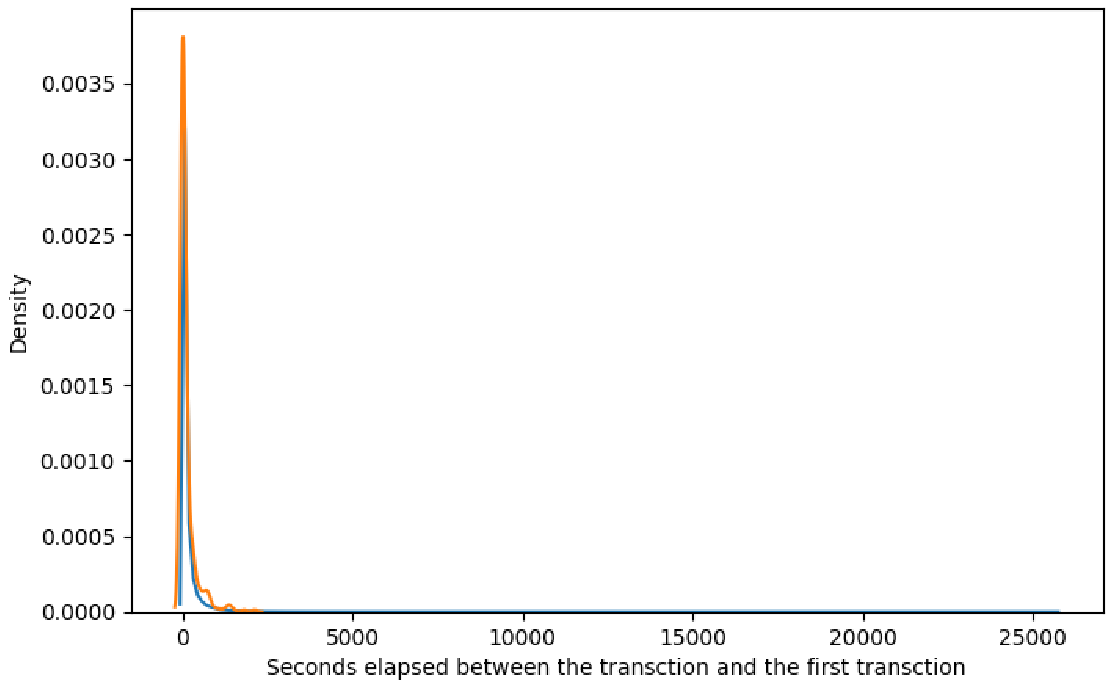
[13]:

```
# Distribution of 'Amount' feature
sns.displot(df['Amount'], bins=25, kde=True, color='blue')
plt.title('Transaction Amount Distribution')
plt.xlabel('Amount')
plt.ylabel('Frequency')
plt.show()
```

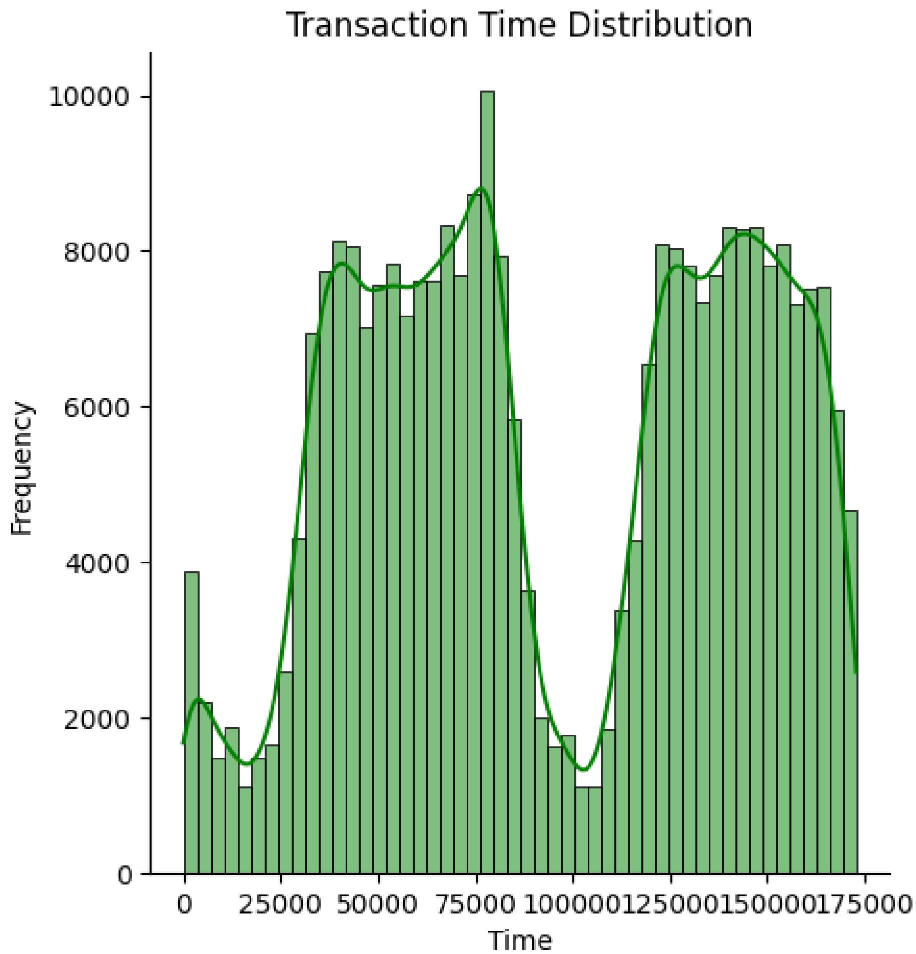


[14]:

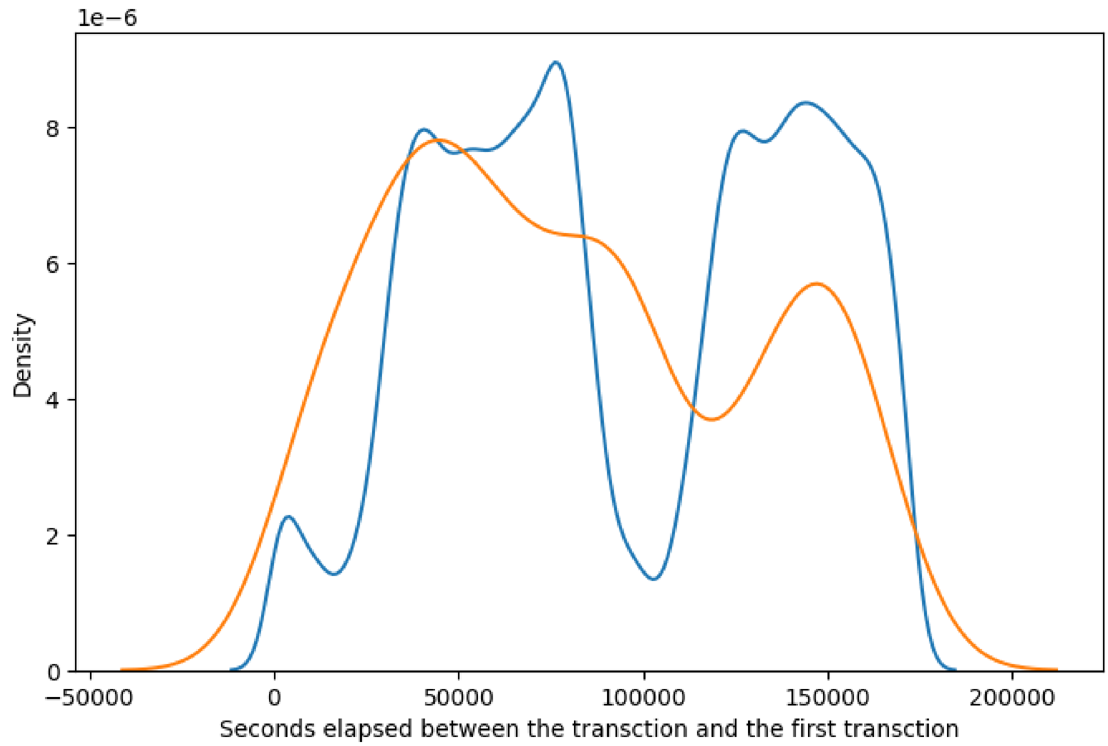
```
plt.figure(figsize=(8,5))
ax = sns.distplot(legit_df['Amount'],label='fraudulent',hist=False)
ax = sns.distplot(fraud_df['Amount'],label='non fraudulent',hist=False)
ax.set(xlabel='Seconds elapsed between the transction and the first transction')
plt.show()
```



[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()
```

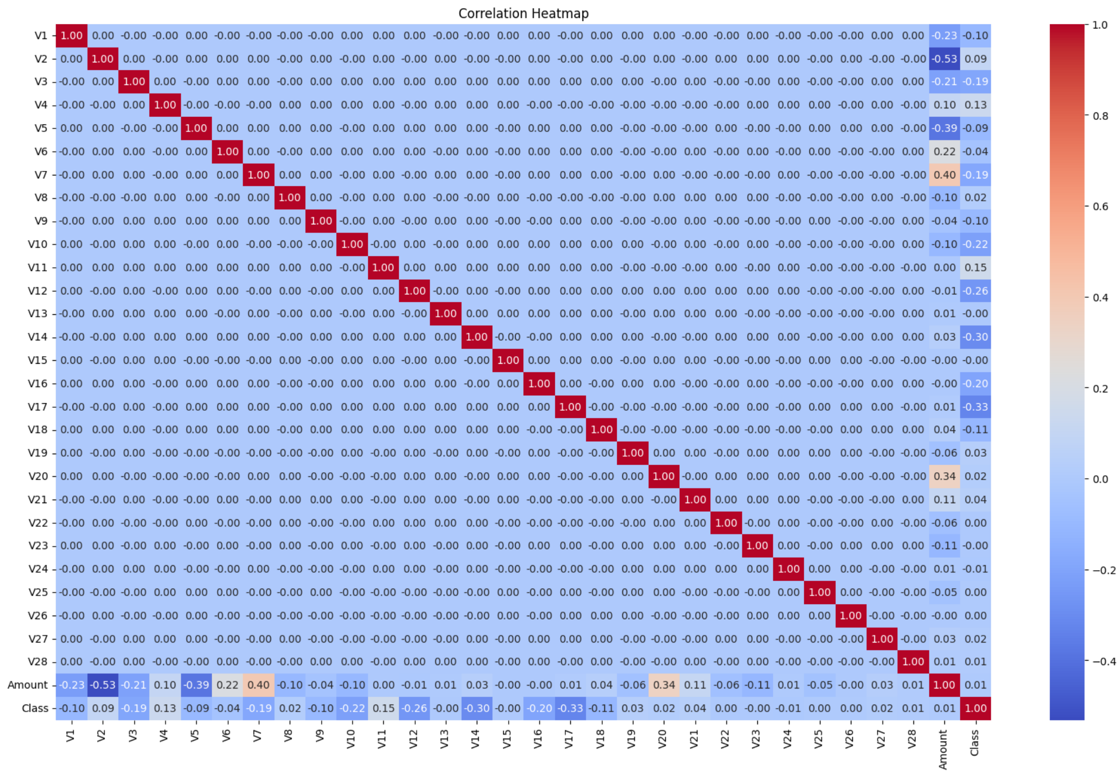


[16]:
```
plt.figure(figsize=(8,5))
ax = sns.distplot(legit_df['Time'],label='fraudulent',hist=False)
ax = sns.distplot(fraud_df['Time'],label='non fraudulent',hist=False)
ax.set(xlabel='Seconds elapsed between the transction and the first transction')
plt.show()
```



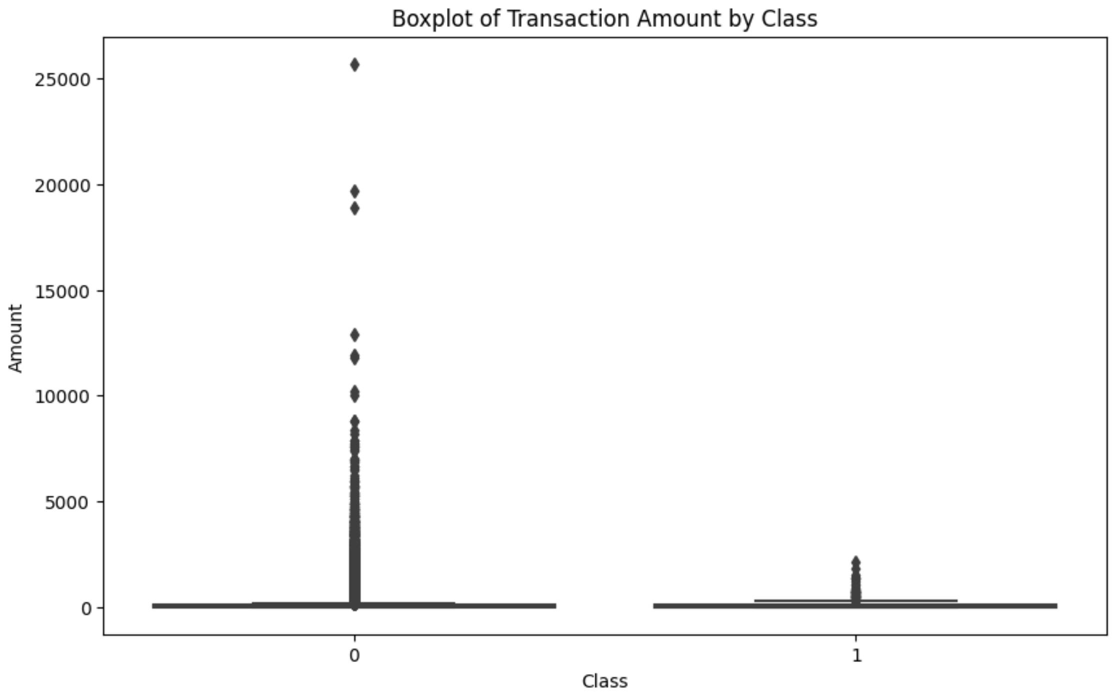
[17]:
```
df.drop('Time', axis=1, inplace=True)
```

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



[19]:

```python
# Visualize potential outliers
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='Class', y='Amount')
plt.title('Boxplot of Transaction Amount by Class')
plt.show()
```

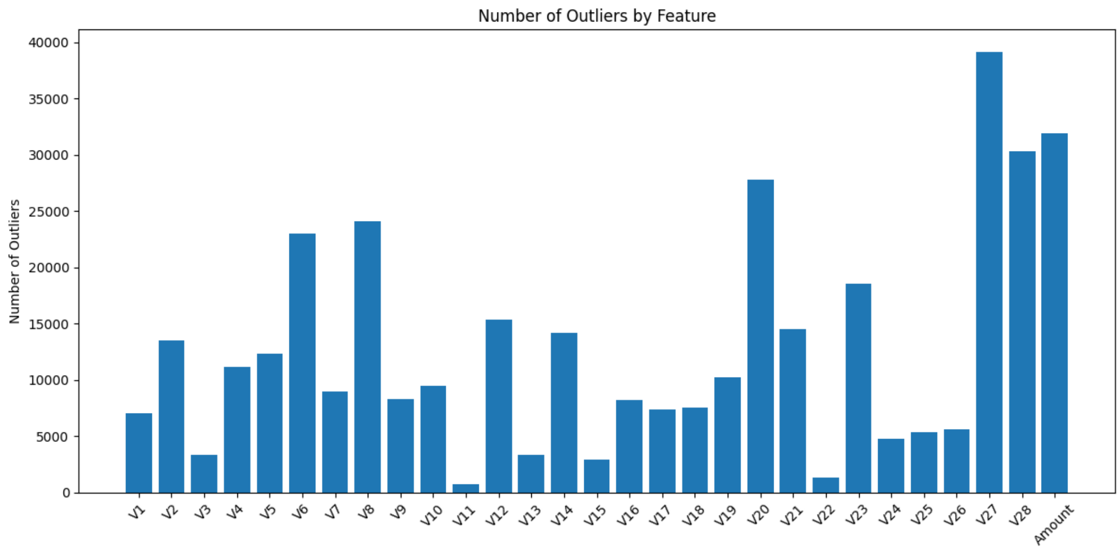


[20]:
```python
# Calculate outliers for each numeric feature
numeric_cols = df.select_dtypes(include=['float64', 'int64']).columns
numeric_cols = numeric_cols.drop('Class')

outliers_by_feature = {}
for col in numeric_cols:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1

    outliers = ((df[col] < (Q1 - 1.5 * IQR)) | (df[col] > (Q3 + 1.5 * IQR)))
    outliers_by_feature[col] = outliers.sum()

    print(f'Outliers in {col}: {outliers.sum()}')
```

```
Outliers in V1: 7062
Outliers in V2: 13526
Outliers in V3: 3363
Outliers in V4: 11148
Outliers in V5: 12295
Outliers in V6: 22965
Outliers in V7: 8948
Outliers in V8: 24134
Outliers in V9: 8283
Outliers in V10: 9496
```

```
Outliers in V11: 780
Outliers in V12: 15348
Outliers in V13: 3368
Outliers in V14: 14149
Outliers in V15: 2894
Outliers in V16: 8184
Outliers in V17: 7420
Outliers in V18: 7533
Outliers in V19: 10205
Outliers in V20: 27770
Outliers in V21: 14497
Outliers in V22: 1317
Outliers in V23: 18541
Outliers in V24: 4774
Outliers in V25: 5367
Outliers in V26: 5596
Outliers in V27: 39163
Outliers in V28: 30342
Outliers in Amount: 31904
```

[21]:
```python
# Visualize outliers
plt.figure(figsize=(12,6))
plt.bar(outliers_by_feature.keys(), outliers_by_feature.values())
plt.xticks(rotation=45)
plt.title('Number of Outliers by Feature')
plt.ylabel('Number of Outliers')
plt.tight_layout()
plt.show()
```



[22]:
```
from sklearn.preprocessing import RobustScaler

scaler = RobustScaler()
df[numeric_cols] = scaler.fit_transform(df[numeric_cols])
df.head()
```

[22]:
```
         V1        V2        V3        V4        V5        V6        V7  \
0 -0.616237 -0.098602  1.228905  0.878152 -0.217859  0.631245  0.177406
1  0.524929  0.143100 -0.006970  0.293974  0.087726  0.164395 -0.105740
2 -0.615587 -1.002407  0.830932  0.251024 -0.344345  1.778007  0.668164
3 -0.440239 -0.178789  0.841250 -0.529808  0.033775  1.303832  0.175637
4 -0.526089  0.579239  0.713861  0.265632 -0.270695  0.317183  0.491625

         V8        V9       V10  …       V21       V22       V23       V24  \
0  0.142432  0.334787  0.185689  …  0.026866  0.253109 -0.320791  0.032681
1  0.117064 -0.164482 -0.074854  … -0.473332 -0.602719  0.363442 -0.479557
2  0.420388 -1.179796  0.303796  …  0.668917  0.714254  2.974603 -0.919589
3  0.662489 -1.076888  0.038374  … -0.190105 -0.001408 -0.578786 -1.531963
4 -0.546463  0.700808  0.855099  …  0.048266  0.739092 -0.407980  0.126293

        V25       V26       V27       V28    Amount  Class
0  0.167619 -0.241182  0.816731 -0.246091  1.783274      0
1  0.225462  0.313475 -0.063781  0.026519 -0.269825      0
2 -0.515430 -0.153111 -0.350218 -0.540962  4.983721      0
3  0.944482 -0.298959  0.379163  0.382611  1.418291      0
4 -0.333308  0.976221  1.347133  1.553716  0.670579      0

[5 rows x 30 columns]
```

[23]:
```
# Random State
random_state = 1
```

[24]:
```
X = df.drop('Class', axis=1)
y = df['Class']
```

[25]:
```
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=random_state, stratify=y)

# Split Data Shape
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[25]:
```
((227845, 29), (56962, 29), (227845,), (56962,))
```

[26]:
```
print("\nClass Distribution Before Resampling:")
print(pd.Series(y_train).value_counts())
```

```
Class Distribution Before Resampling:
Class
0    227451
1       394
Name: count, dtype: int64
```

[27]:
```
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=random_state)
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    227451
1    227451
Name: count, dtype: int64
```

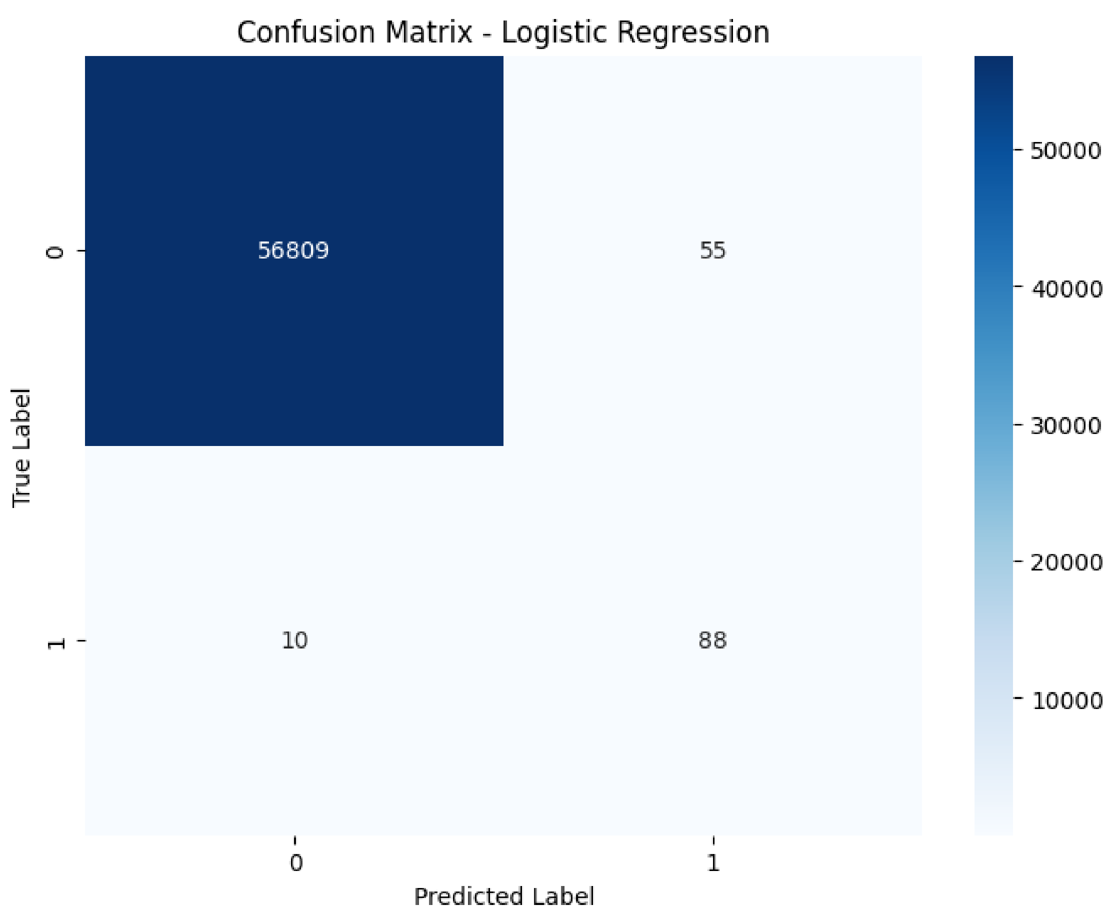
[28]:
```
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import LinearSVC
from lightgbm import LGBMClassifier
from catboost import CatBoostClassifier
from sklearn.calibration import CalibratedClassifierCV
```

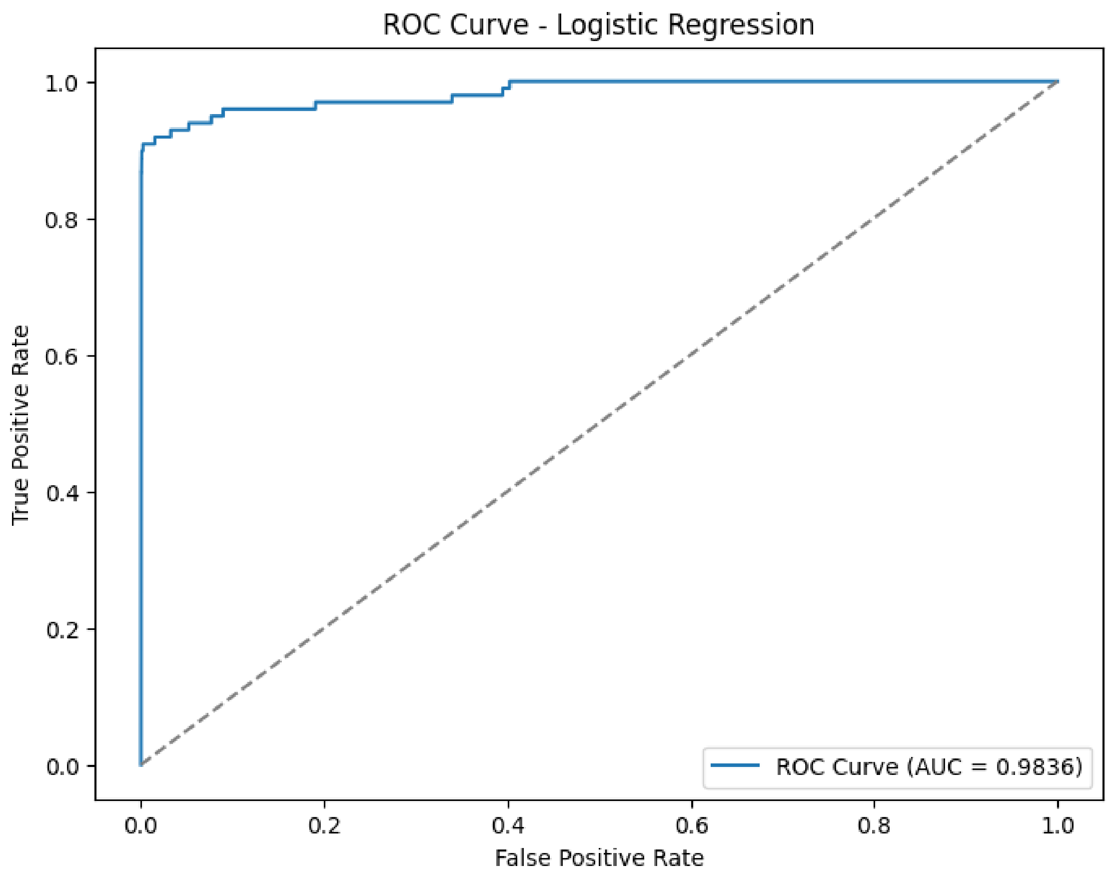
[29]:
```
from sklearn.metrics import *
import pickle

all_metrics = {}

def evaluate_model(model, X_train, y_train, X_test, y_test, model_name,␣
 ↪threshold=0.99):
    model.fit(X_train, y_train)
    y_pred_proba = model.predict_proba(X_test)[:, 1]
    y_pred = (y_pred_proba >= threshold).astype(int)

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_pred_proba)

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
```

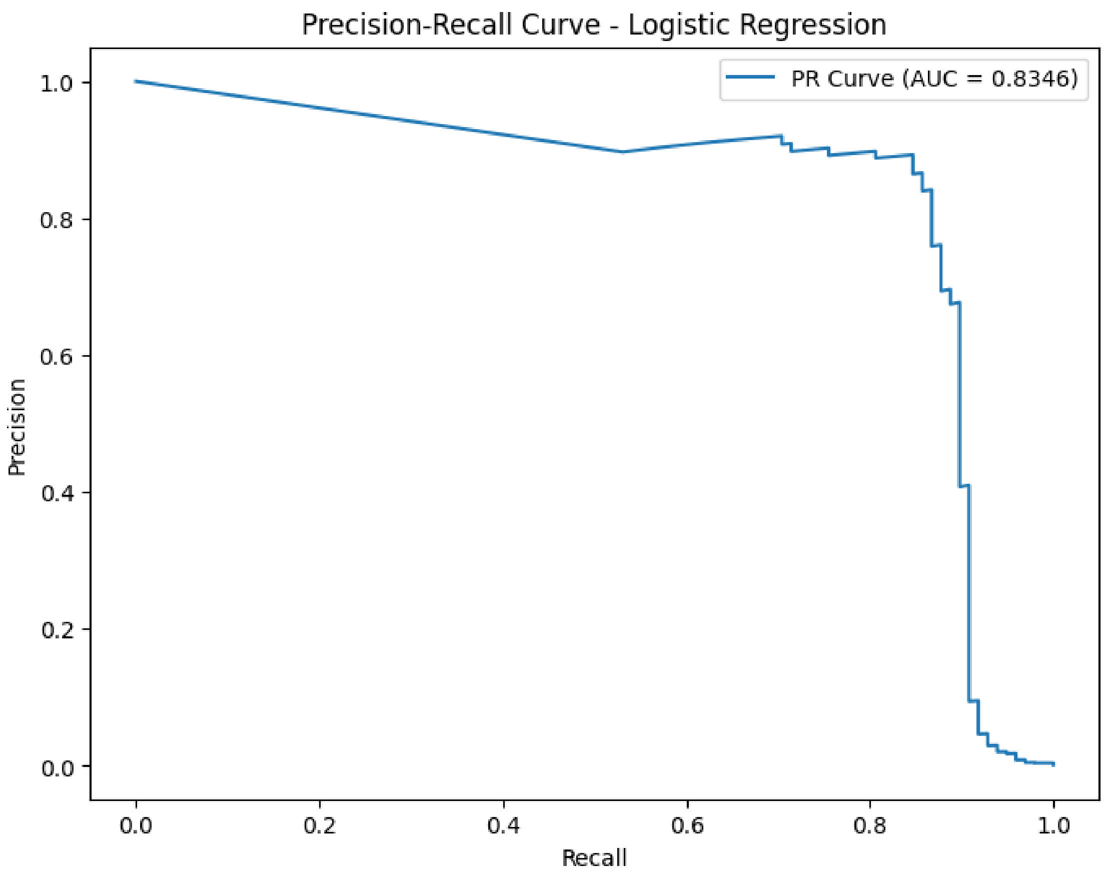
```
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title(f'Confusion Matrix - {model_name}')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()

# 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(f'ROC Curve - {model_name}')
plt.legend()
plt.show()

# Precision-Recall Curve
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_proba)
pr_auc = auc(recall, precision)
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, label=f'PR Curve (AUC = {pr_auc:.4f})')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title(f'Precision-Recall Curve - {model_name}')
plt.legend()
plt.show()

# Optimal threshold (e.g., maximizing F1-Score)
f1_scores = 2 * (precision * recall) / (precision + recall + 1e-10)
optimal_idx = np.argmax(f1_scores)
optimal_threshold = thresholds[optimal_idx]
print(f"Optimal Threshold (Max F1-Score): {optimal_threshold:.4f}")

metrics = {
    'Accuracy': accuracy,
    'ROC-AUC': roc_auc,
    'Precision': precision_score(y_test, y_pred),
    'Recall': recall_score(y_test, y_pred),
    'F1-Score': f1_score(y_test, y_pred),
    'Optimal Threshold': optimal_threshold,
    'True Negatives': cm[0][0],
    'False Positives': cm[0][1],
    'False Negatives': cm[1][0],
    'True Positives': cm[1][1]
}
```

```
    all_metrics[model_name] = metrics

    print(f"\n{model_name} Classification Report:")
    print(classification_report(y_test, y_pred))
    metrics_df = pd.DataFrame([metrics], index=[model_name])

    # Save the model
    model_path = f'{model_name.lower().replace(" ", "_")}_model.pkl'
    with open(model_path, 'wb') as file:
        pickle.dump(model, file)
    print(f"Model saved at: {model_path}")

    return metrics_df.T
```

[30]:
```
# Logistic Regression
logistic_model = LogisticRegression(random_state=random_state)
evaluate_model(logistic_model, X_resampled, y_resampled, X_test, y_test,␣
↪"Logistic Regression")
```




ROC Curve - Logistic Regression
True Positive Rate
False Positive Rate
ROC Curve (AUC = 0.9836)
0.0
0.2
0.4
0.6
0.8
1.0




```
Optimal Threshold (Max F1-Score): 1.0000

Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.62      0.90      0.73        98

    accuracy                           1.00     56962
   macro avg       0.81      0.95      0.86     56962
weighted avg       1.00      1.00      1.00     56962

Model saved at: logistic_regression_model.pkl
```

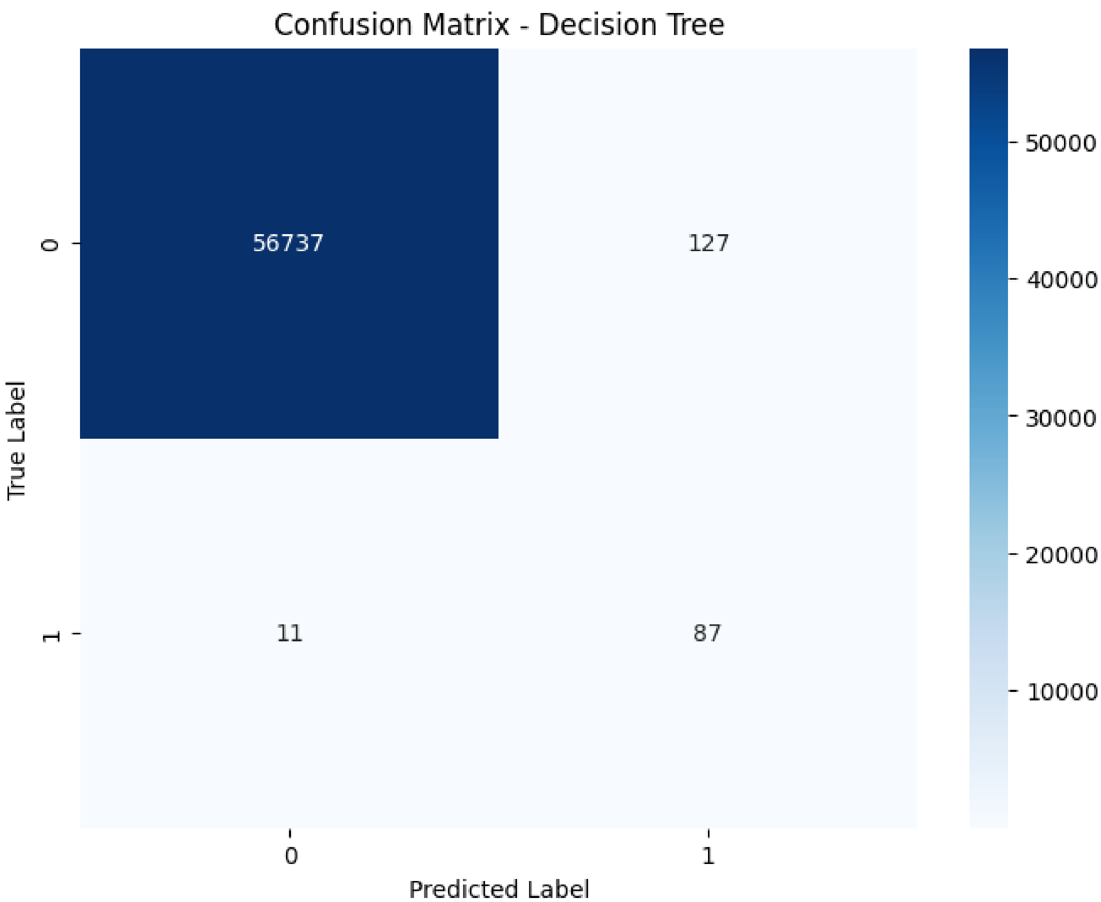
[30]:

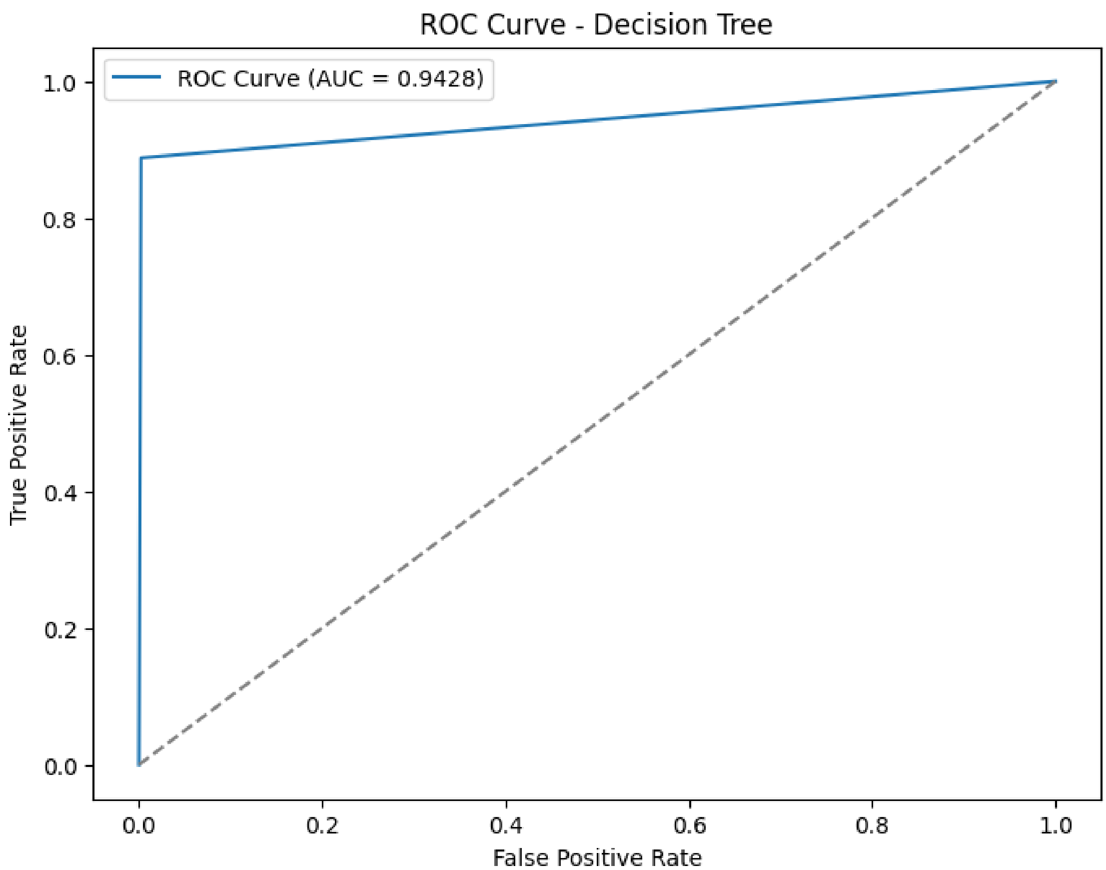
	Logistic Regression
Accuracy	0.998859
ROC-AUC	0.983626
Precision	0.615385
Recall	0.897959
F1-Score	0.730290

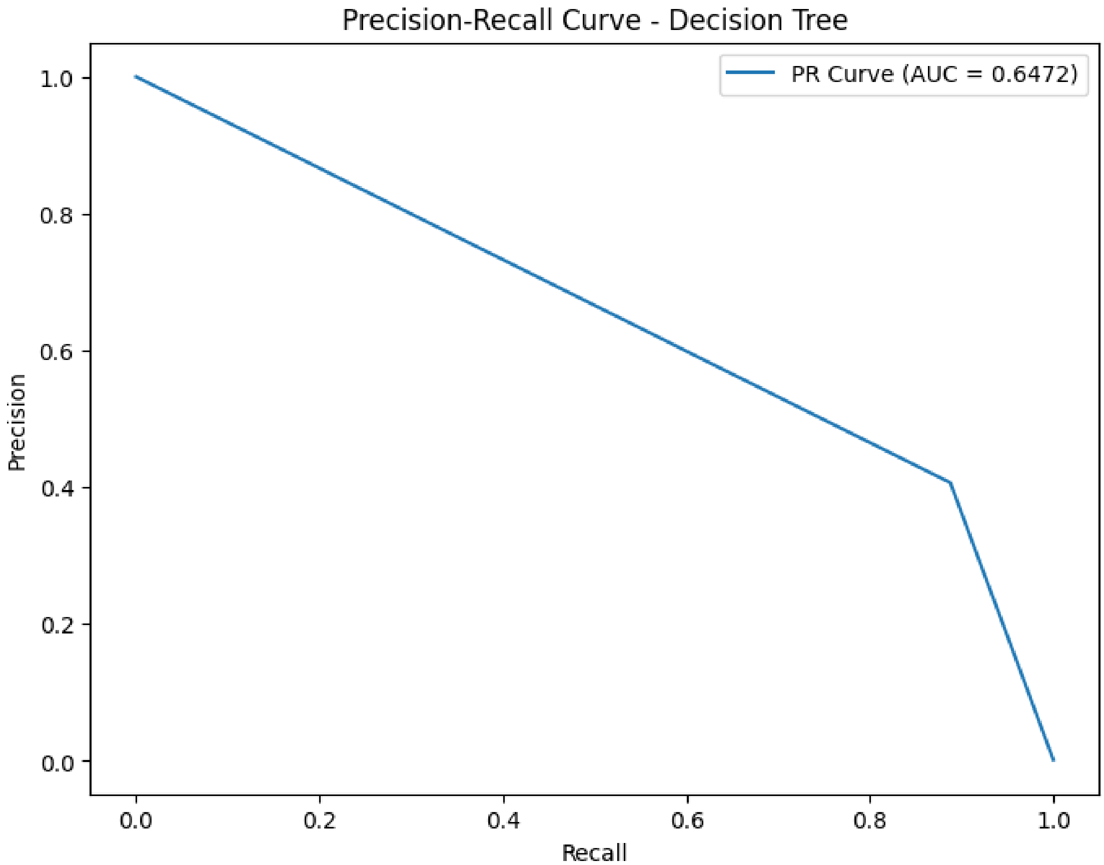
```
Optimal Threshold             1.000000
True Negatives            56809.000000
False Positives              55.000000
False Negatives              10.000000
True Positives               88.000000
```

[31]:

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




ROC Curve - Decision Tree
ROC Curve (AUC = 0.9428)
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate



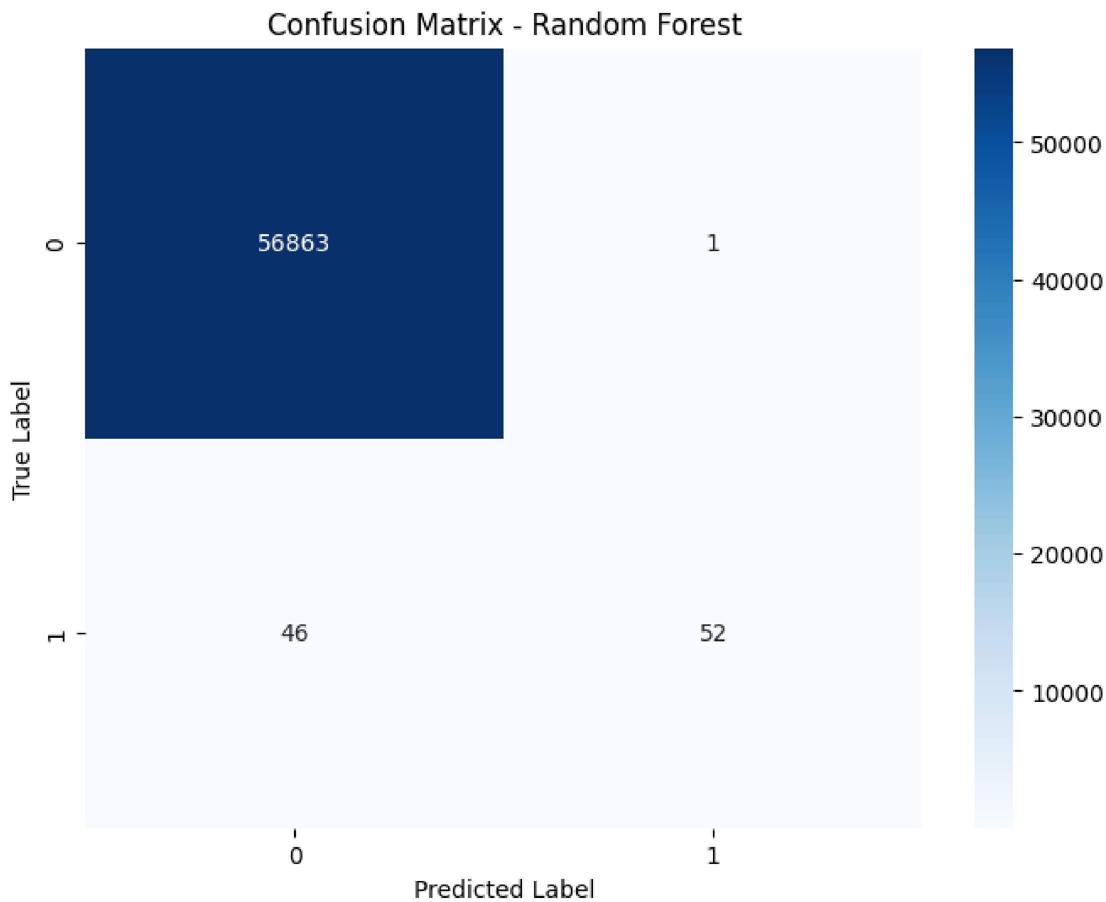

```
Optimal Threshold (Max F1-Score): 1.0000

Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.41      0.89      0.56        98

    accuracy                           1.00     56962
   macro avg       0.70      0.94      0.78     56962
weighted avg       1.00      1.00      1.00     56962

Model saved at: decision_tree_model.pkl
```

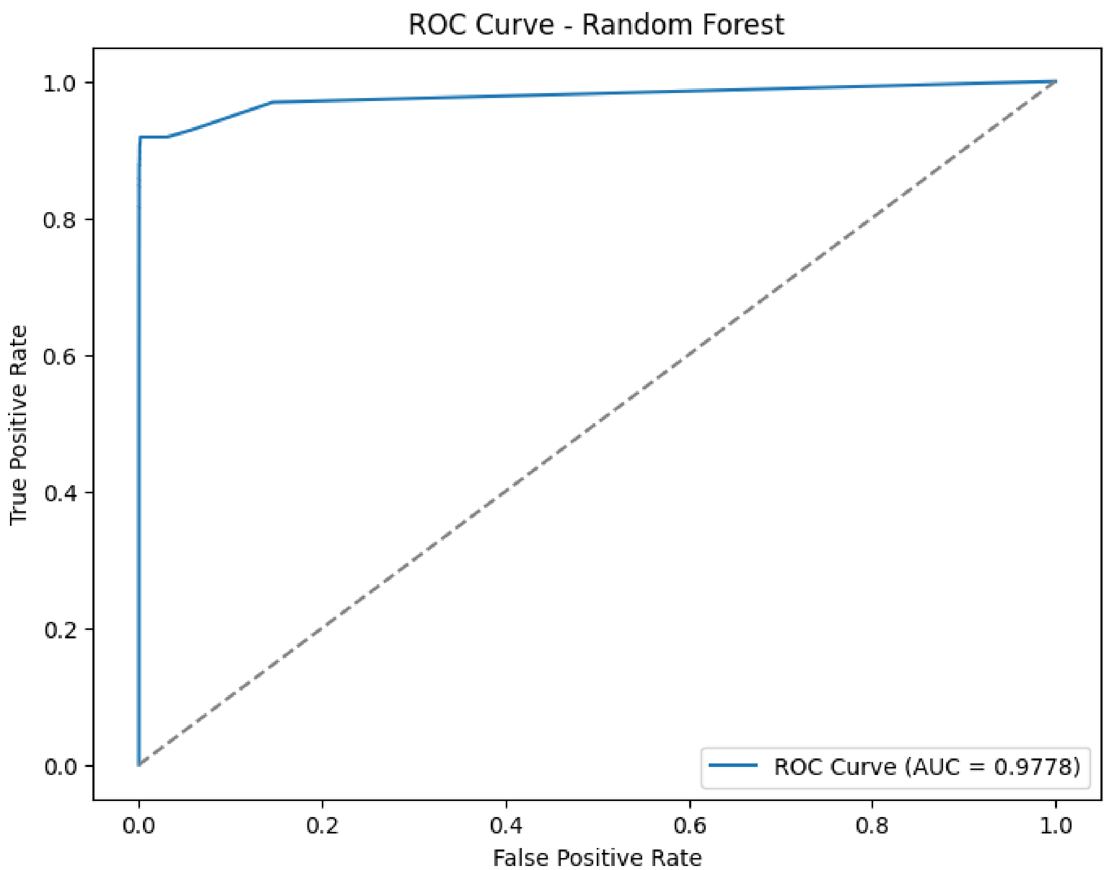
[31]:

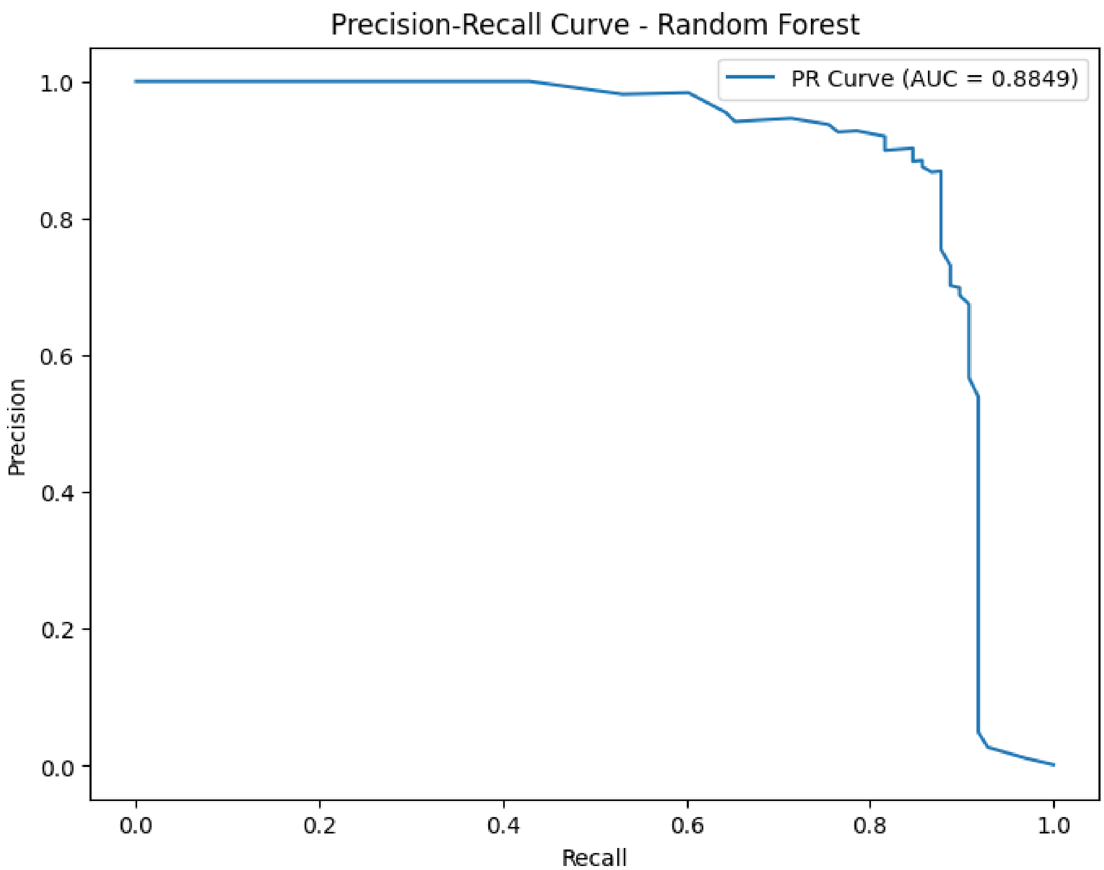
	Decision Tree
Accuracy	0.997577
ROC-AUC	0.942761
Precision	0.406542
Recall	0.887755
F1-Score	0.557692

```
Optimal Threshold        1.000000
True Negatives       56737.000000
False Positives        127.000000
False Negatives         11.000000
True Positives          87.000000
```

[32]:
```
# Random Forest
rf_model = RandomForestClassifier(random_state=random_state)
evaluate_model(rf_model, X_resampled, y_resampled, X_test, y_test, "Random␣
↪Forest")
```




ROC Curve - Random Forest
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC Curve (AUC = 0.9778)




```
Optimal Threshold (Max F1-Score): 0.7500

Random Forest Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.98      0.53      0.69        98

    accuracy                           1.00     56962
   macro avg       0.99      0.77      0.84     56962
weighted avg       1.00      1.00      1.00     56962

Model saved at: random_forest_model.pkl
```

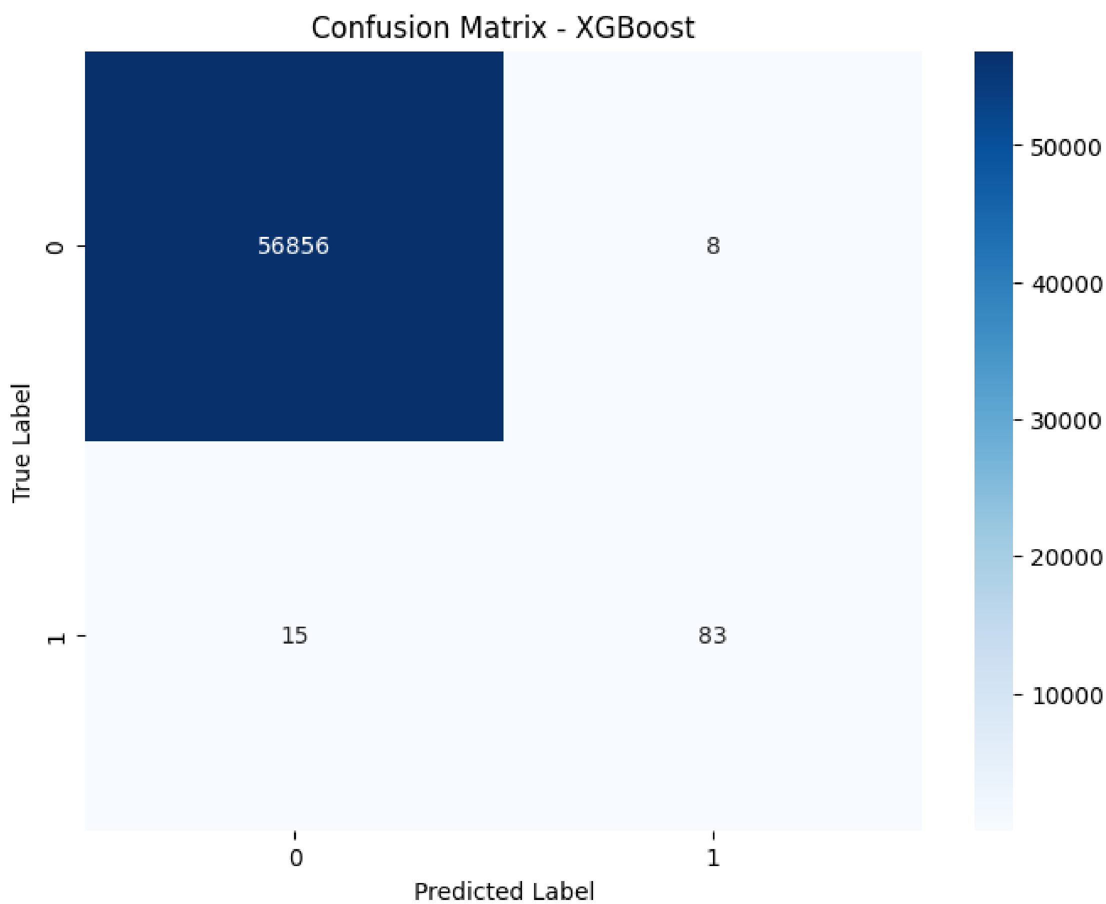
[32]:

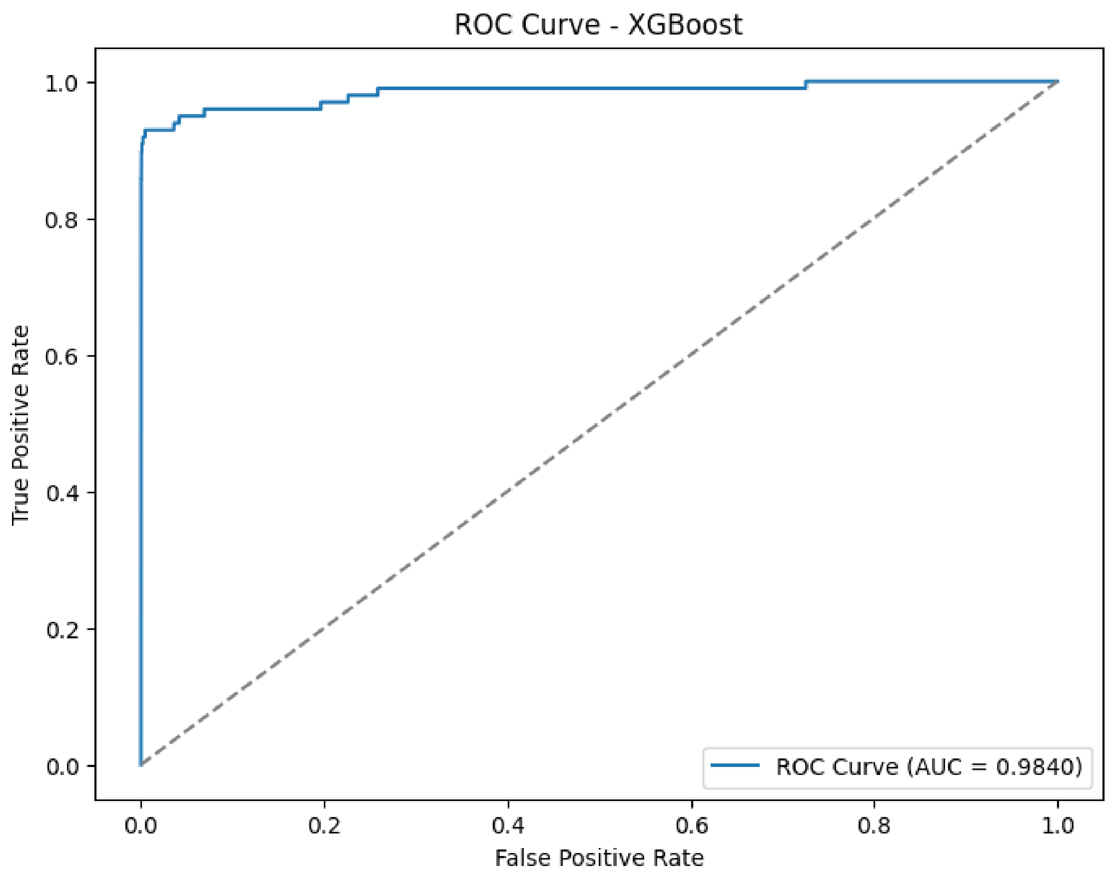
	Random Forest
Accuracy	0.999175
ROC-AUC	0.977802
Precision	0.981132
Recall	0.530612
F1-Score	0.688742

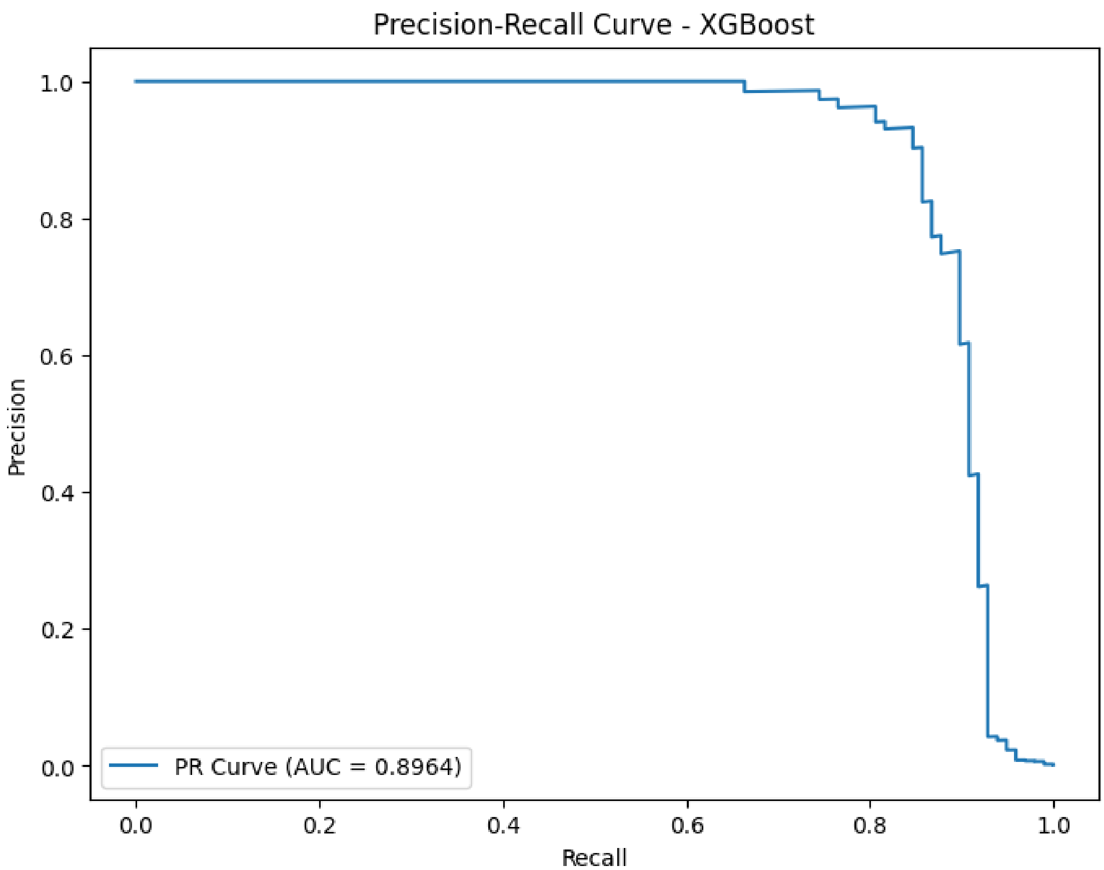
```
Optimal Threshold        0.750000
True Negatives       56863.000000
False Positives          1.000000
False Negatives         46.000000
True Positives          52.000000
```

[33]:

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




ROC Curve - XGBoost
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC Curve (AUC = 0.9840)



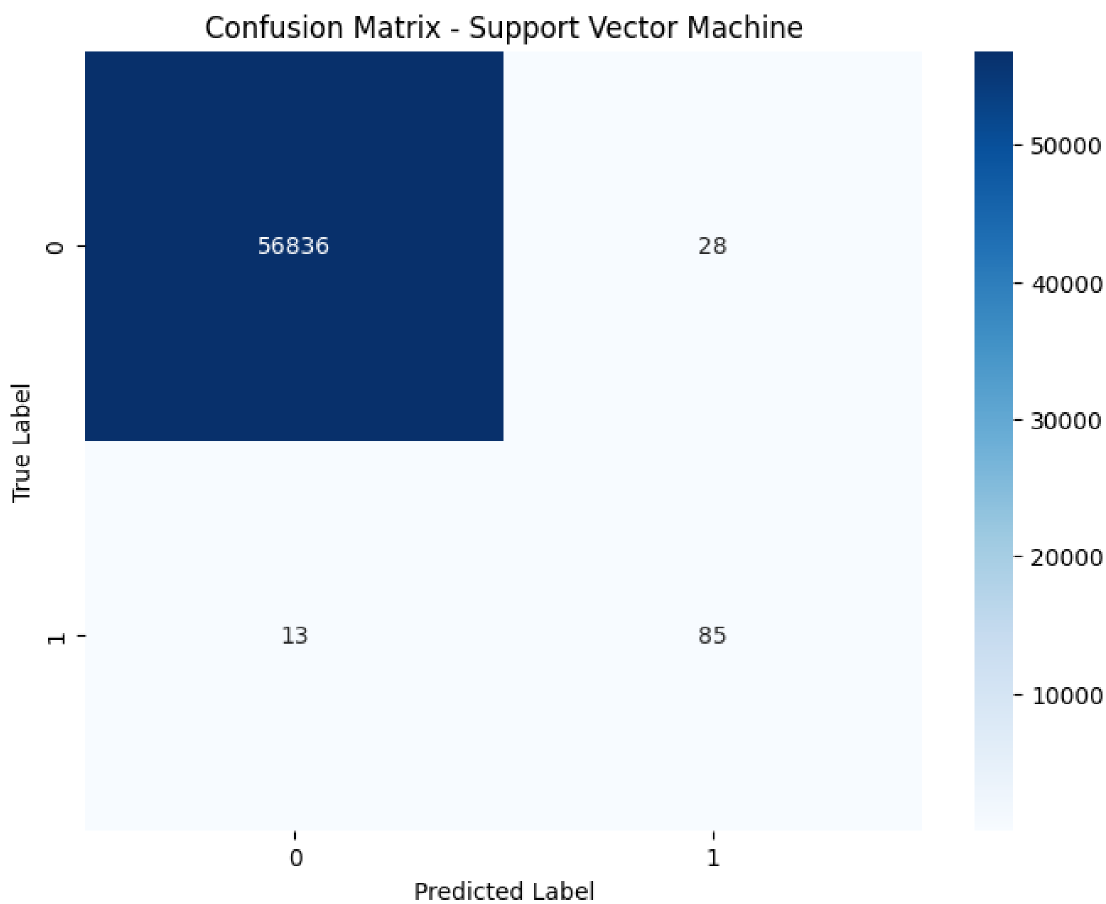

```
Optimal Threshold (Max F1-Score): 0.9976

XGBoost Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.91      0.85      0.88        98

    accuracy                           1.00     56962
   macro avg       0.96      0.92      0.94     56962
weighted avg       1.00      1.00      1.00     56962

Model saved at: xgboost_model.pkl
```

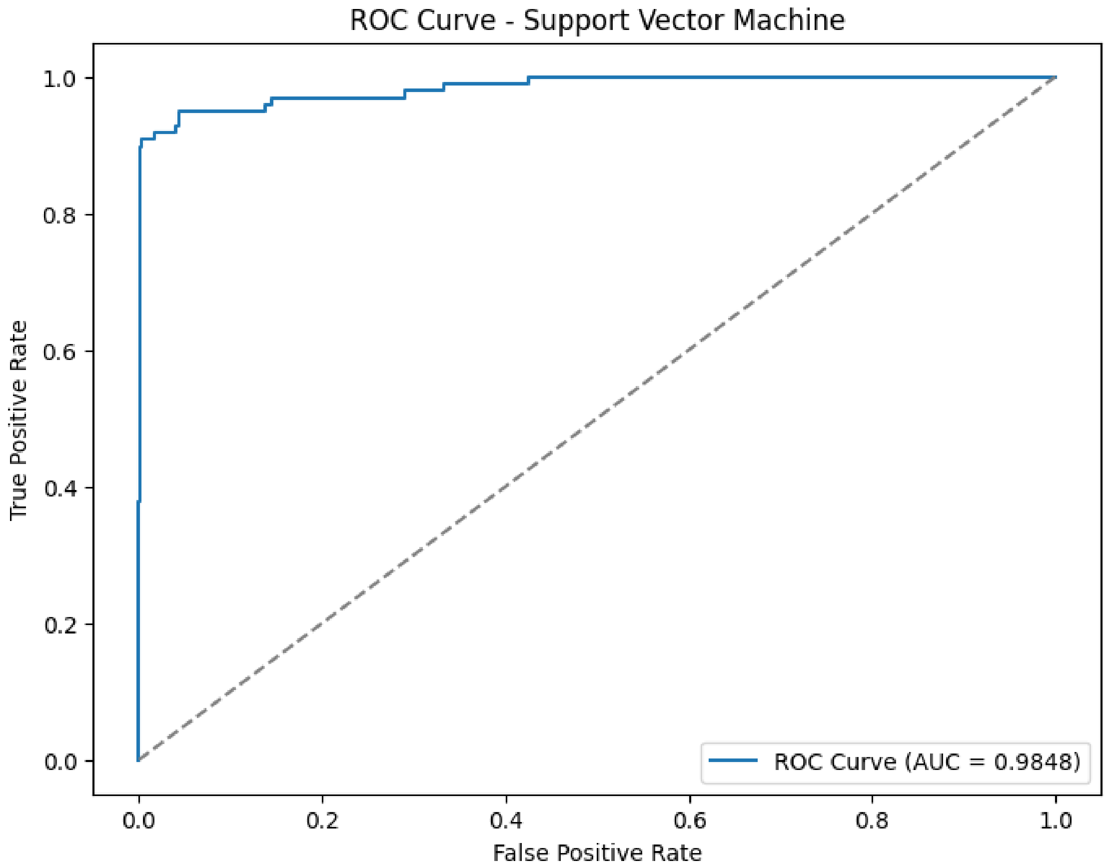
[33]:

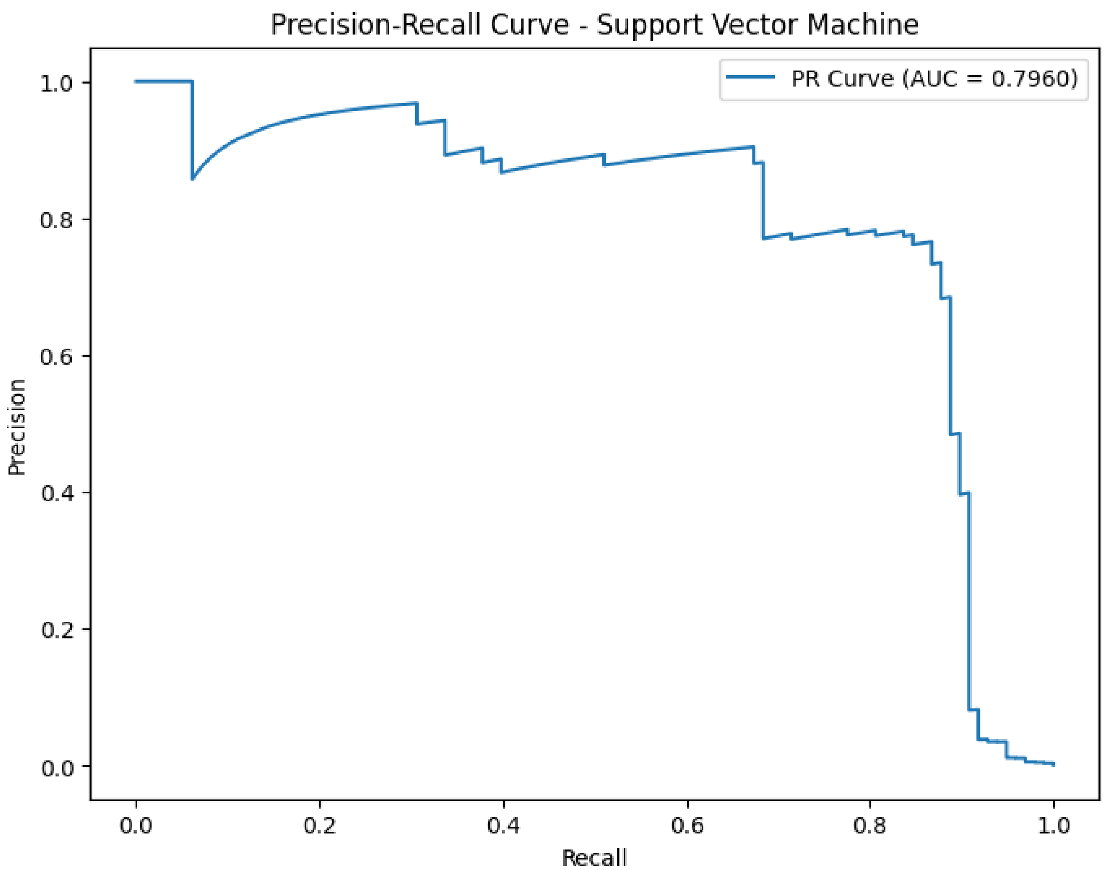
	XGBoost
Accuracy	0.999596
ROC-AUC	0.984043
Precision	0.912088
Recall	0.846939
F1-Score	0.878307

```
Optimal Threshold       0.997589
True Negatives      56856.000000
False Positives         8.000000
False Negatives        15.000000
True Positives         83.000000
```

[34]:
```python
# Support Vector Machine
linear_svc = LinearSVC(max_iter=10000)
svm_model = CalibratedClassifierCV(base_estimator=linear_svc, cv=5)
evaluate_model(svm_model, X_resampled, y_resampled, X_test, y_test, "Support␣
↪Vector Machine")
```




ROC Curve - Support Vector Machine
True Positive Rate
False Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
ROC Curve (AUC = 0.9848)




```
Optimal Threshold (Max F1-Score): 0.9945

Support Vector Machine Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.75      0.87      0.81        98

    accuracy                           1.00     56962
   macro avg       0.88      0.93      0.90     56962
weighted avg       1.00      1.00      1.00     56962

Model saved at: support_vector_machine_model.pkl
```

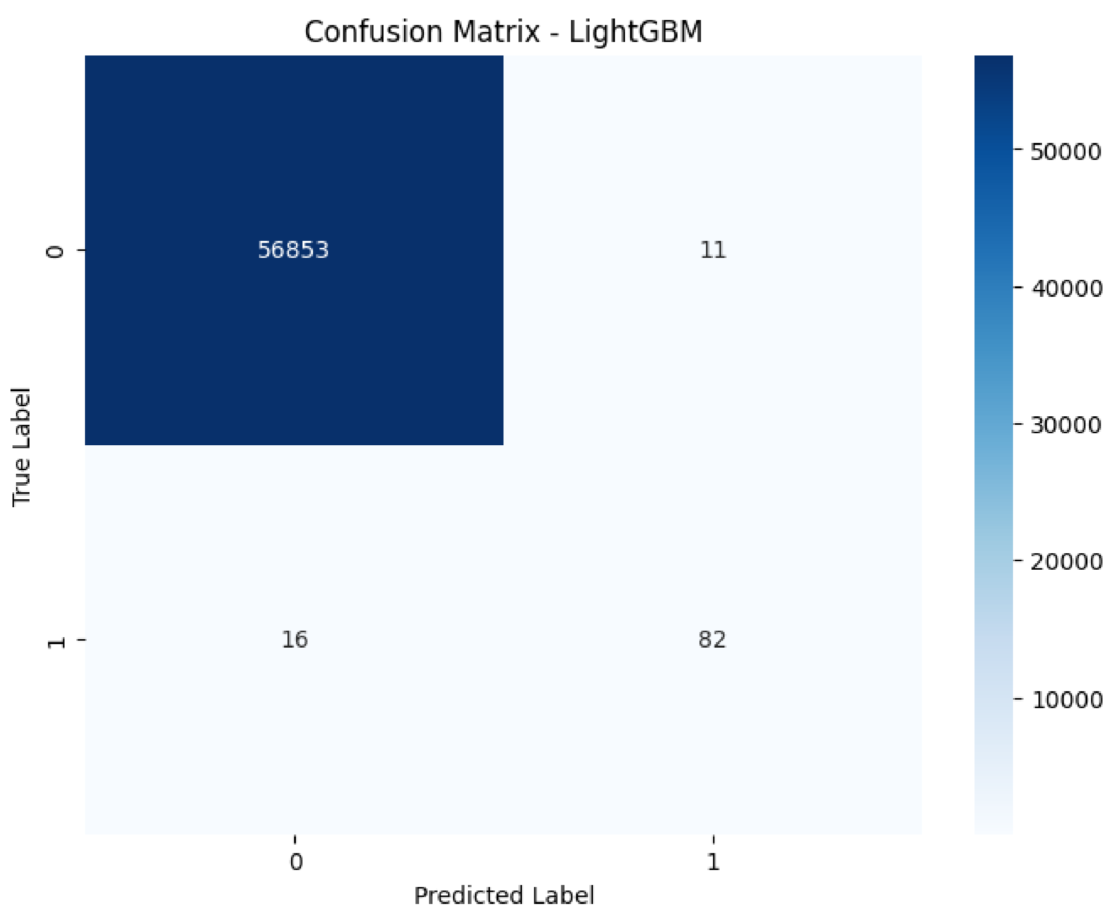
[34]:

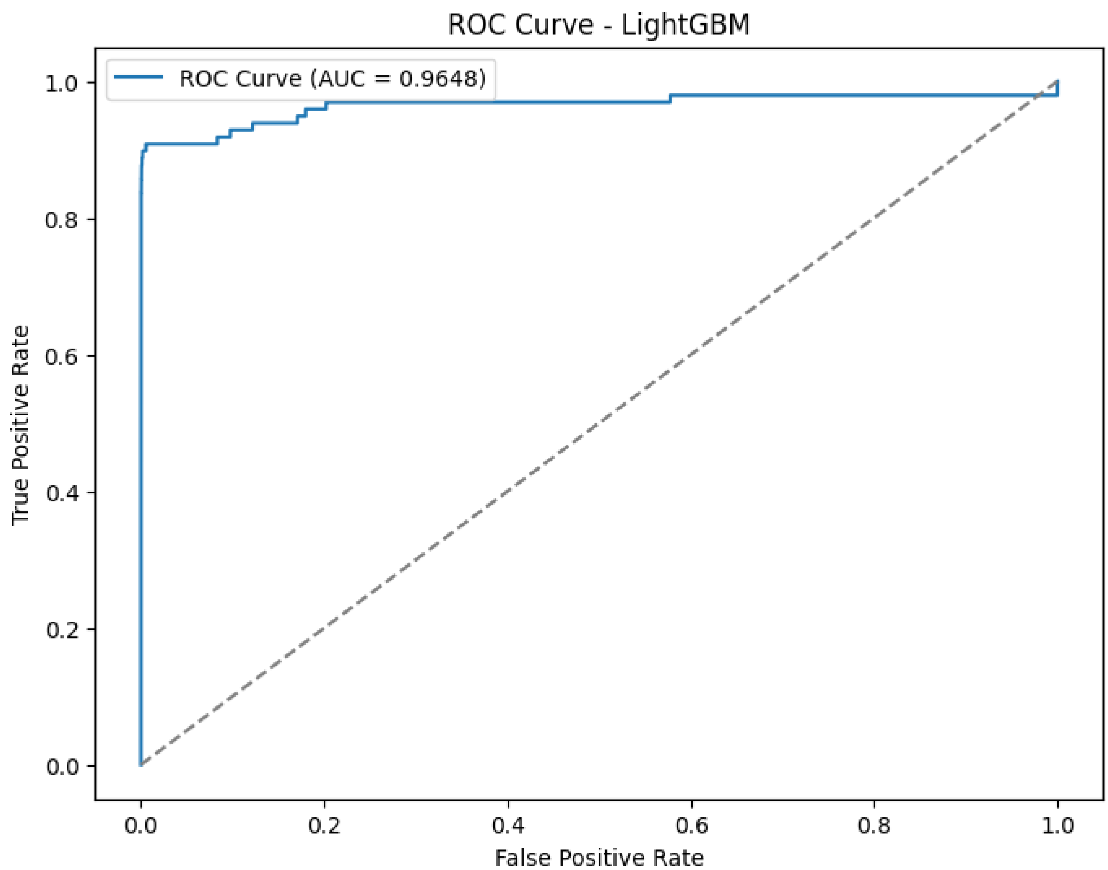
	Support Vector Machine
Accuracy	0.999280
ROC-AUC	0.984772
Precision	0.752212
Recall	0.867347
F1-Score	0.805687

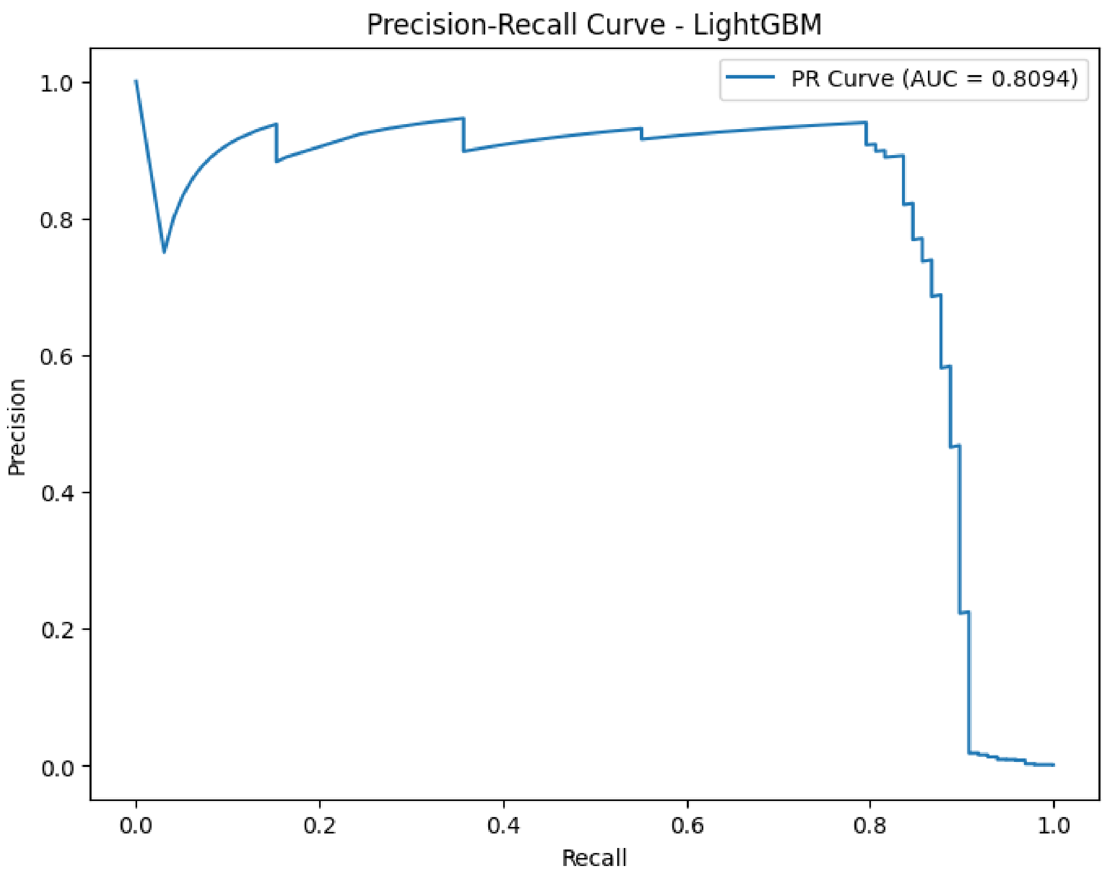
```
Optimal Threshold               0.994470
True Negatives              56836.000000
False Positives                28.000000
False Negatives                13.000000
True Positives                 85.000000
```

[35]:
```python
# LightGBM
lgbm_model = LGBMClassifier(random_state=random_state)
evaluate_model(lgbm_model, X_resampled, y_resampled, X_test, y_test, "LightGBM")
```

```
[LightGBM] [Info] Number of positive: 227451, number of negative: 227451
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.076268 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: 454902, number of used
features: 29
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```




ROC Curve - LightGBM
ROC Curve (AUC = 0.9648)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0



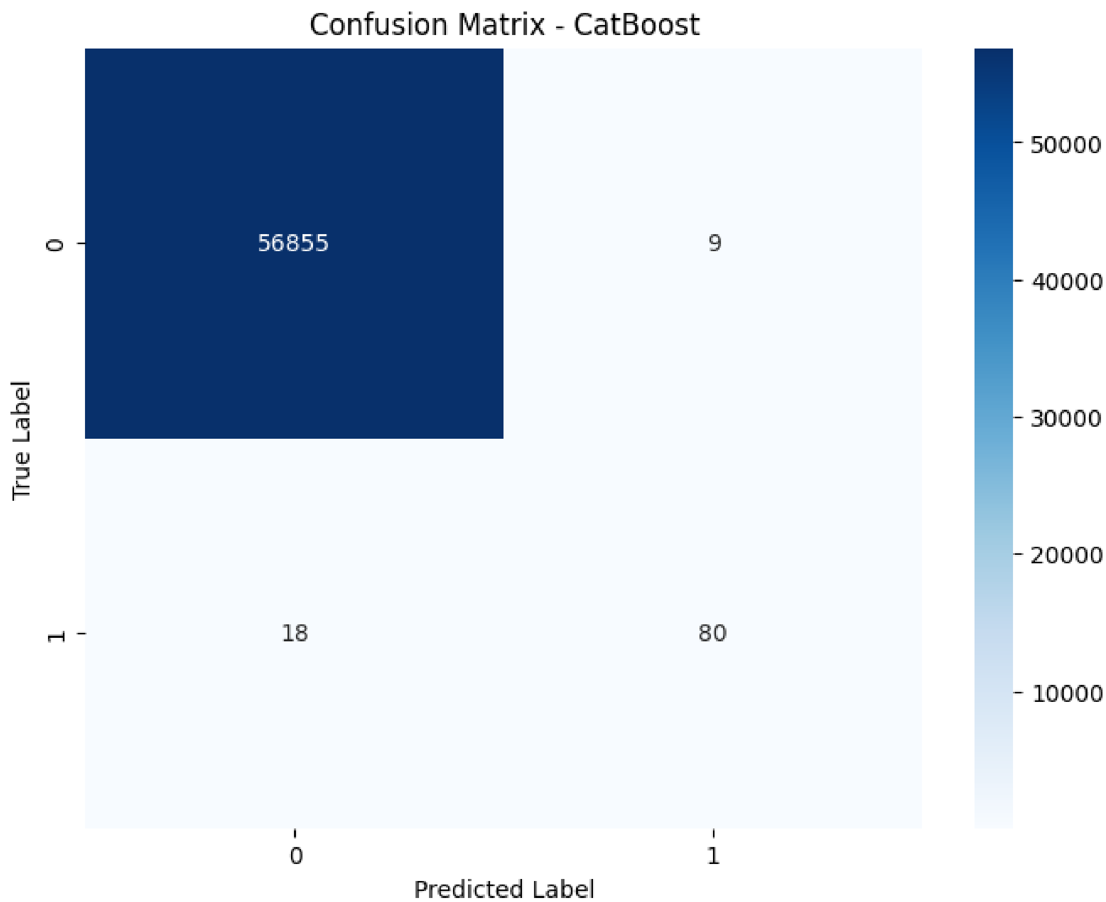

```
Optimal Threshold (Max F1-Score): 0.9935

LightGBM Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.88      0.84      0.86        98

    accuracy                           1.00     56962
   macro avg       0.94      0.92      0.93     56962
weighted avg       1.00      1.00      1.00     56962

Model saved at: lightgbm_model.pkl
```

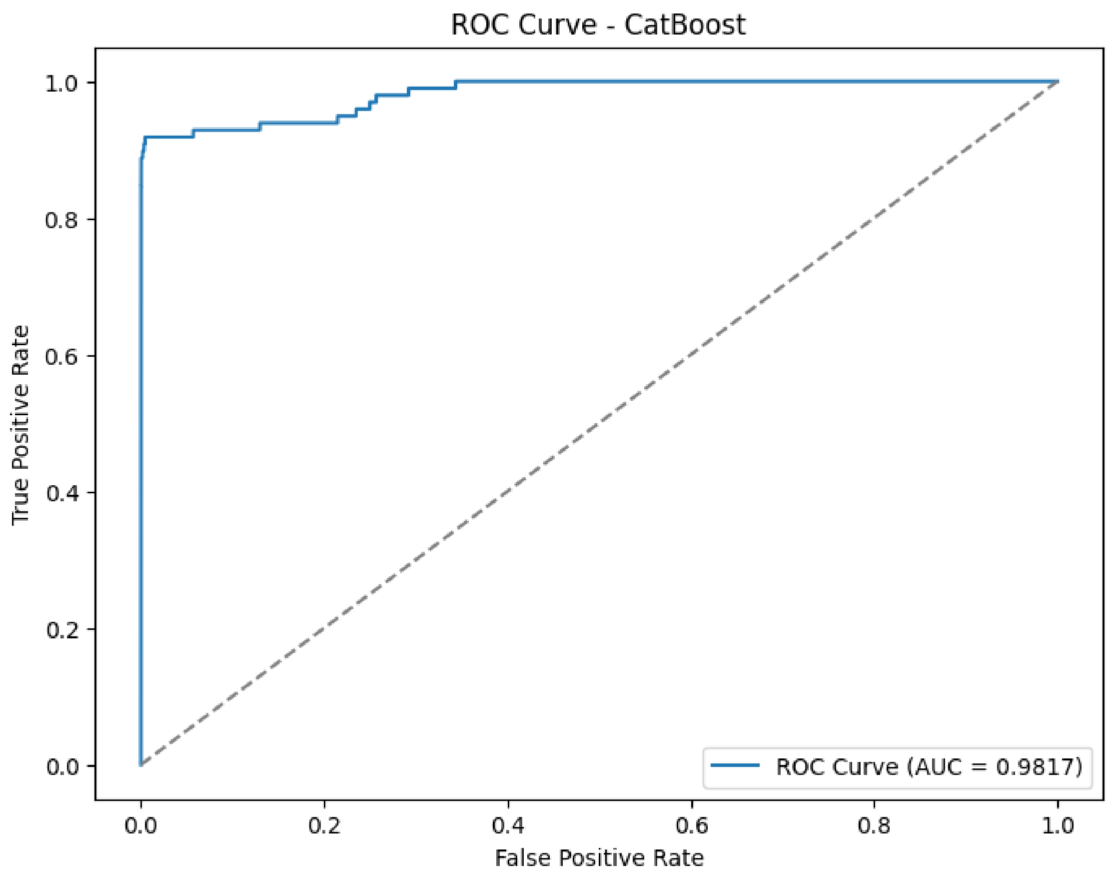
[35]:

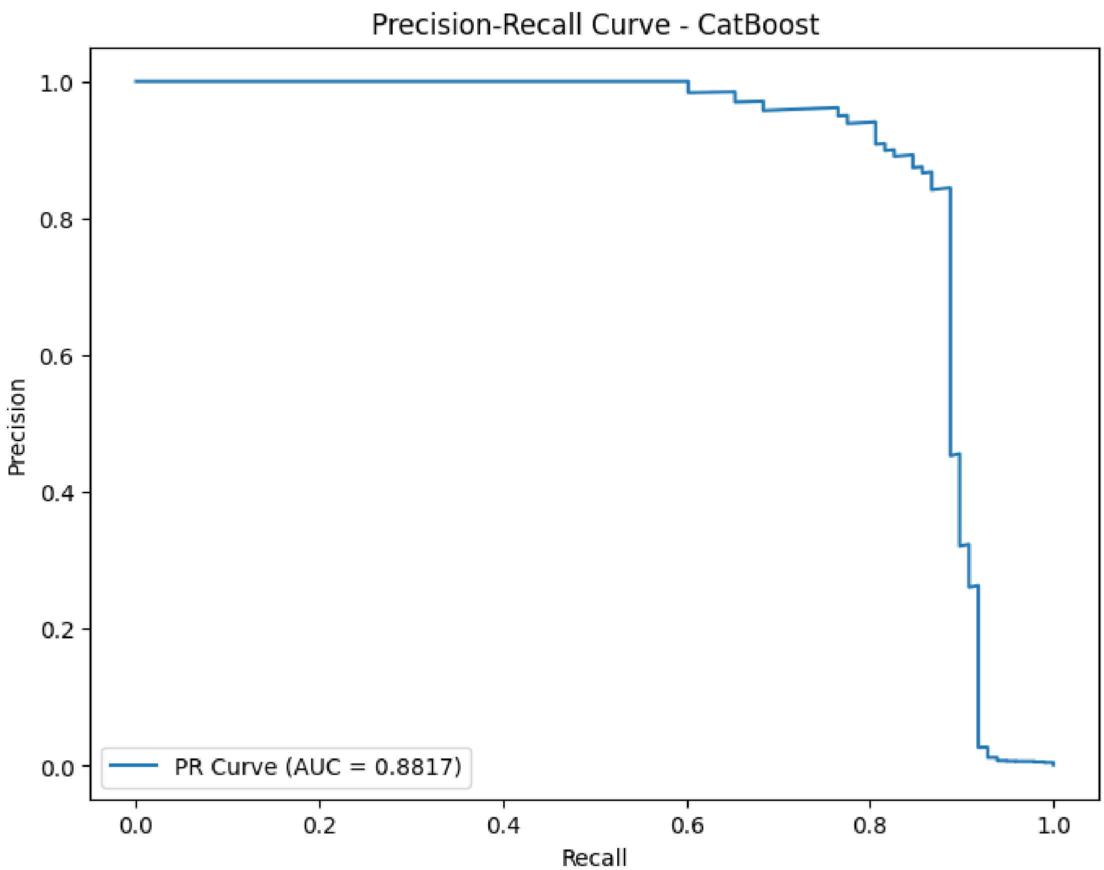
	LightGBM
Accuracy	0.999526
ROC-AUC	0.964819
Precision	0.881720
Recall	0.836735
F1-Score	0.858639

```
Optimal Threshold       0.993473
True Negatives      56853.000000
False Positives        11.000000
False Negatives        16.000000
True Positives         82.000000
```

[36]:
```python
# CatBoost
catboost_model = CatBoostClassifier(verbose=0, random_state=random_state)
evaluate_model(catboost_model, X_resampled, y_resampled, X_test, y_test,␣
 ↪"CatBoost")
```




ROC Curve - CatBoost
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC Curve (AUC = 0.9817)




```
Optimal Threshold (Max F1-Score): 0.9572

CatBoost Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.90      0.82      0.86        98

    accuracy                           1.00     56962
   macro avg       0.95      0.91      0.93     56962
weighted avg       1.00      1.00      1.00     56962

Model saved at: catboost_model.pkl
```

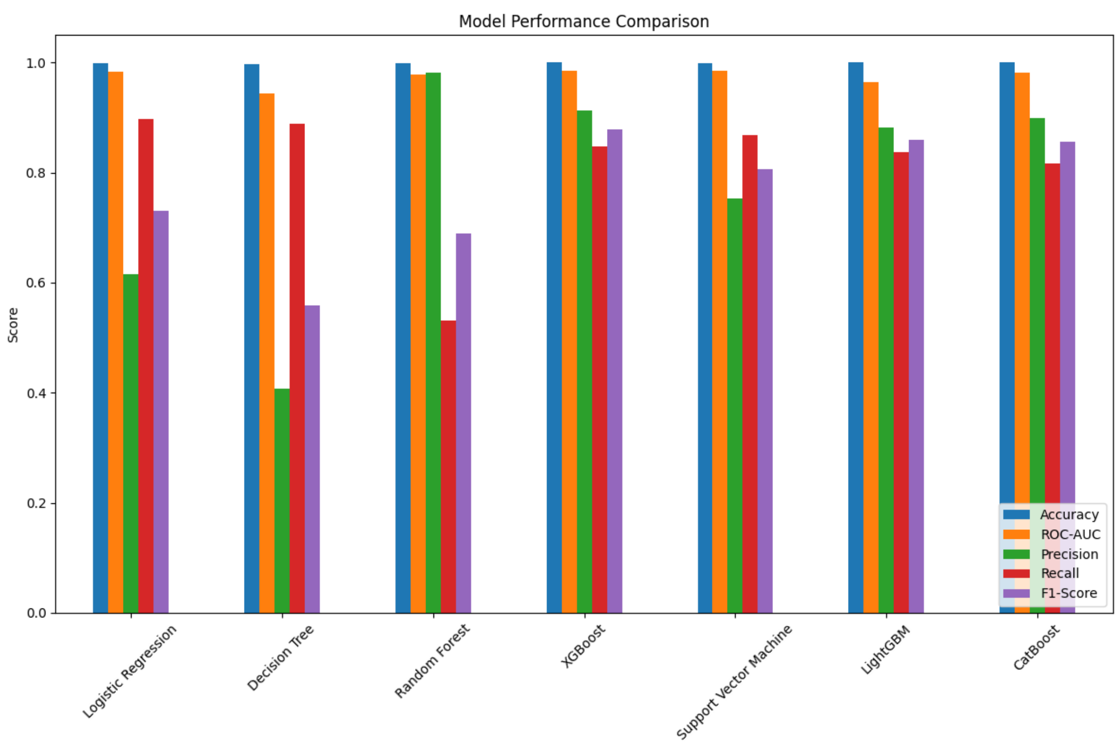
[36]:

	CatBoost
Accuracy	0.999526
ROC-AUC	0.981731
Precision	0.898876
Recall	0.816327
F1-Score	0.855615

```
Optimal Threshold        0.957154
True Negatives       56855.000000
False Positives          9.000000
False Negatives         18.000000
True Positives          80.000000
```

[37]:
```python
def compare_models(metrics_list):
    # Convert metrics to DataFrame
    metrics_df = pd.DataFrame(metrics_list)

    # Plot metrics comparison
    metrics_to_plot = ['Accuracy', 'ROC-AUC', 'Precision', 'Recall', 'F1-Score']
    metrics_df.T[metrics_to_plot].plot(kind='bar', figsize=(12, 8))
    plt.title('Model Performance Comparison')
    plt.ylabel('Score')
    plt.xticks(rotation=45)
    plt.legend(loc='lower right')
    plt.tight_layout()
    plt.show()

    return metrics_df
```

[38]:
```python
result_df = compare_models(all_metrics)
result_df
```



[38]:

```
                     Logistic Regression  Decision Tree  Random Forest  \
Accuracy                        0.998859       0.997577       0.999175
ROC-AUC                         0.983626       0.942761       0.977802
Precision                       0.615385       0.406542       0.981132
Recall                          0.897959       0.887755       0.530612
F1-Score                        0.730290       0.557692       0.688742
Optimal Threshold               1.000000       1.000000       0.750000
True Negatives              56809.000000   56737.000000   56863.000000
False Positives                55.000000     127.000000       1.000000
False Negatives                10.000000      11.000000      46.000000
True Positives                 88.000000      87.000000      52.000000

                        XGBoost  Support Vector Machine       LightGBM  \
Accuracy               0.999596                0.999280       0.999526
ROC-AUC                0.984043                0.984772       0.964819
Precision              0.912088                0.752212       0.881720
Recall                 0.846939                0.867347       0.836735
F1-Score               0.878307                0.805687       0.858639
Optimal Threshold      0.997589                0.994470       0.993473
True Negatives     56856.000000            56836.000000   56853.000000
False Positives        8.000000               28.000000      11.000000
False Negatives       15.000000               13.000000      16.000000
True Positives        83.000000               85.000000      82.000000

                       CatBoost
Accuracy               0.999526
ROC-AUC                0.981731
Precision              0.898876
Recall                 0.816327
F1-Score               0.855615
Optimal Threshold      0.957154
True Negatives     56855.000000
False Positives        9.000000
False Negatives       18.000000
True Positives        80.000000
```

[39]:

```python
# Find the best model based on Accuracy
metrics_df = result_df.T
best_model = metrics_df.loc[metrics_df['Accuracy'].idxmax()]
print("\nBest Model:")
print(best_model)
```

```
Best Model:
Accuracy                  0.999596
ROC-AUC                   0.984043
```

```
Precision                 0.912088
Recall                    0.846939
F1-Score                  0.878307
Optimal Threshold         0.997589
True Negatives        56856.000000
False Positives           8.000000
False Negatives          15.000000
True Positives           83.000000
Name: XGBoost, dtype: float64
```