# Credit Card Fraud Detection Report 📊 💳

## 1. Introduction

### 1.1 Background

Credit card fraud is a major challenge in the financial industry, causing substantial financial losses to institutions and customers. With the growing reliance on online transactions, detecting fraudulent activities accurately and in real-time has become a necessity. This report outlines the development of a machine learning-based fraud detection system leveraging historical transaction data.

### 1.2 Objective

The objectives of this project are:

- 🔍 **Detect fraudulent transactions**: Build a predictive model that can accurately identify fraudulent activities.
- 🔧 **Reduce false positives**: Ensure minimal disruptions to legitimate customers by improving prediction precision.
- 📈 **Enhance trust and security**: Provide a reliable solution to bolster financial transaction safety.

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## 2. Data Analysis

### 2.1 Data Overview

- **Dataset**: The Kaggle Credit Card Fraud Detection dataset, containing 284,807 transactions.
- **Features**:
  - `Time` : Seconds elapsed since the first transaction.
  - `V1-V28` : Principal components derived from PCA transformation.
  - `Amount` : Transaction amount.
  - `Class` : Target variable (1 = Fraudulent, 0 = Legitimate).
- **Class Imbalance**: Fraudulent transactions constitute only **0.17%** of the dataset, presenting a significant class imbalance challenge.

### 2.2 Data Preprocessing

- **Handling Missing Values**: Verified no missing data in the dataset.

- **Duplicate Removal**: Identified and removed **1,081 duplicate records**.
- **Feature Scaling**: Normalized numerical features using `StandardScaler` to ensure uniform feature contribution.
- **Class Imbalance Mitigation**: Applied **SMOTE** (Synthetic Minority Oversampling Technique) to balance the dataset.

### 2.3 Exploratory Data Analysis (EDA)

- **Class Distribution**: Visualized the significant imbalance between legitimate and fraudulent transactions.
- **Correlation Analysis**: Features exhibited weak correlations due to PCA transformations.
- **Transaction Amount**: Explored differences in transaction amounts between fraudulent and legitimate classes.

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## 3. Machine Learning Model Development

### 3.1 Models Considered

Three machine learning models were evaluated:

1. 🌲 **Random Forest Classifier**: A robust ensemble method effective for classification tasks.
2. 🧮 **Logistic Regression**: A simple and interpretable model for binary classification.
3. 🚀 **XGBoost Classifier**: A gradient boosting framework known for its efficiency and accuracy.

### 3.2 Model Training

- **Data Splitting**: Dataset was split into **80% training** and **20% testing** subsets.
- **Dimensionality Reduction**: Reduced features to 10 principal components using PCA, capturing 95% of the variance.
- **Cross-Validation**: Employed 5-fold cross-validation to ensure generalization and mitigate overfitting.

### 3.3 Hyperparameter Tuning

- **GridSearchCV**: Tuned Random Forest hyperparameters for optimal performance.
- **RandomizedSearchCV**: Conducted hyperparameter optimization for XGBoost to enhance results.

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## 4. Model Evaluation and Results

## 4.1 Evaluation Metrics

The models were assessed based on the following metrics:

- **Accuracy**: Proportion of correct predictions among all predictions.
- **Precision**: Percentage of correct positive predictions.
- **Recall**: Ability to identify all fraudulent transactions (sensitivity).
- **F1 Score**: Balances precision and recall.
- **ROC-AUC**: Measures model discrimination ability.

## 4.2 Model Performance

| Model | Accuracy | Precision | Recall | F1 Score | ROC-AUC |
|---|---|---|---|---|---|
| 🌲 **Random Forest** | 0.9994 | 0.83 | 0.82 | 0.82 | 0.91 |
| 🧮 **Logistic Regression** | 0.9800 | 0.07 | 0.90 | 0.12 | 0.53 |
| 🚀 **XGBoost** | 0.9900 | 0.13 | 0.84 | 0.22 | 0.56 |

## 4.3 Key Insights

- **Random Forest**: Achieved the best balance between accuracy, precision, and recall, making it the most effective model.
- **XGBoost**: High recall but limited precision due to false positives.
- **Logistic Regression**: Struggled with fraud detection due to the dataset's severe class imbalance.

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# 5. Conclusion

## 5.1 Summary

This project successfully developed a machine learning-based framework for credit card fraud detection. Key accomplishments include:

- Comprehensive data preprocessing and exploratory analysis.
- Effective handling of class imbalance using SMOTE.
- Identification of **Random Forest** as the best-performing model with an accuracy of **99.94%** and a ROC-AUC score of **0.91**.

## 5.2 Recommendations and Future Work

- **Model Refinement**: Explore advanced ensemble methods like LightGBM or deep learning approaches for further improvements.

- **Real-Time Deployment**: Integrate the model into live transaction monitoring systems to detect fraud as it occurs.
- **Feature Engineering**: Investigate additional domain-specific features or feature interactions to enhance model performance.

## 5.3 Final Remarks

The findings of this project underscore the potential of machine learning in enhancing fraud detection systems. A robust and scalable solution like this can help financial institutions mitigate risks, reduce losses, and ensure a secure digital payment environment.

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In [117…

```
# Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
from sklearn.utils.class_weight import compute_class_weight
from imblearn.over_sampling import SMOTE
from sklearn.decomposition import PCA

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
# Load Data
df = pd.read_csv('Dataset/creditcard.csv')
```

In [3]:

```
df.head()
```

Out[3]:

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

5 rows × 31 columns

In [4]:

```
df.shape
```

Out[4]:

```
(284807, 31)
```

In [5]:
```python
# Basic Data Overview
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

In [6]:
```python
df.describe()
```

Out[6]:

| | Time | V1 | V2 | V3 | V4 | |
|---|---|---|---|---|---|---|
| **count** | 284807.000000 | 2.848070e+05 | 2.848070e+05 | 2.848070e+05 | 2.848070e+05 | 2.8480 |
| **mean** | 94813.859575 | 1.168375e-15 | 3.416908e-16 | -1.379537e-15 | 2.074095e-15 | 9.6040 |
| **std** | 47488.145955 | 1.958696e+00 | 1.651309e+00 | 1.516255e+00 | 1.415869e+00 | 1.3802 |
| **min** | 0.000000 | -5.640751e+01 | -7.271573e+01 | -4.832559e+01 | -5.683171e+00 | -1.1374 |
| **25%** | 54201.500000 | -9.203734e-01 | -5.985499e-01 | -8.903648e-01 | -8.486401e-01 | -6.9159 |
| **50%** | 84692.000000 | 1.810880e-02 | 6.548556e-02 | 1.798463e-01 | -1.984653e-02 | -5.4335 |
| **75%** | 139320.500000 | 1.315642e+00 | 8.037239e-01 | 1.027196e+00 | 7.433413e-01 | 6.1192 |
| **max** | 172792.000000 | 2.454930e+00 | 2.205773e+01 | 9.382558e+00 | 1.687534e+01 | 3.4801 |

8 rows × 31 columns

In [7]:

```
# Check for Missing Values
df.isnull().sum()
```

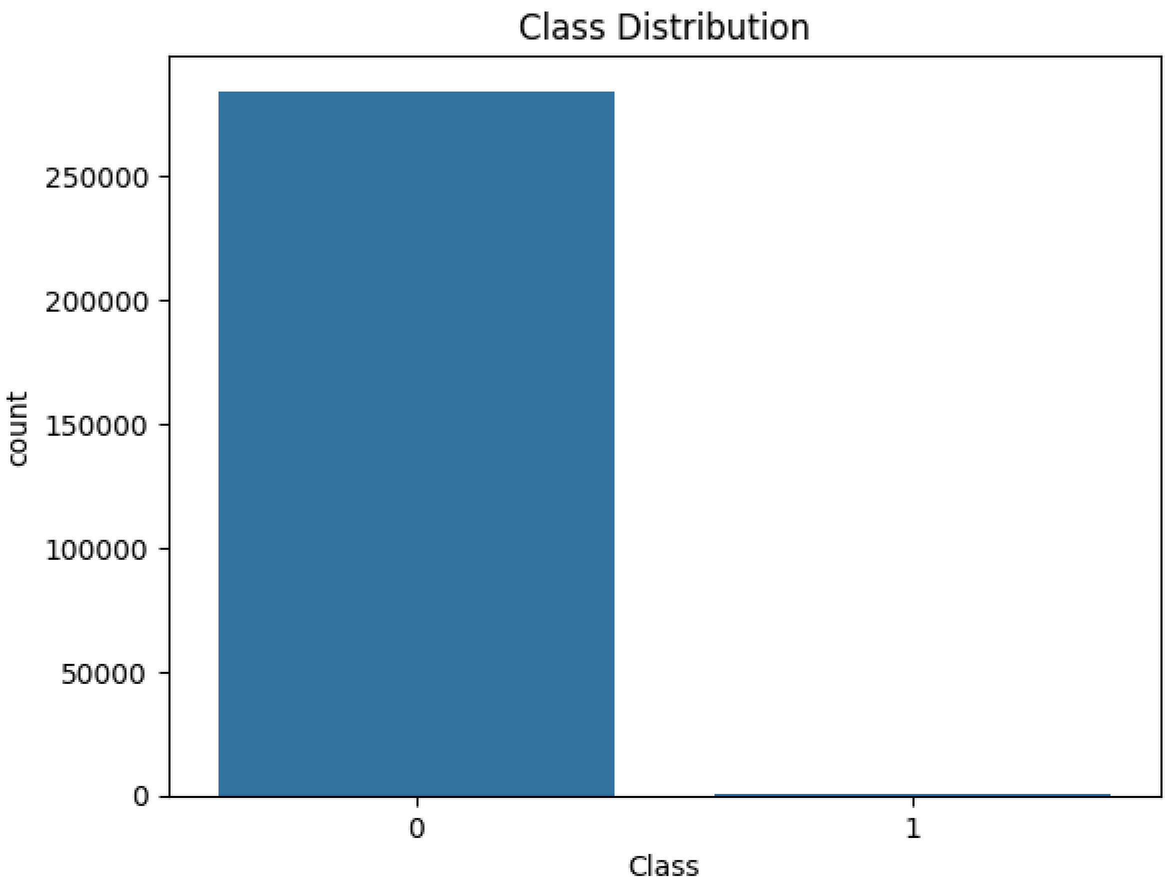
Out[7]:

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

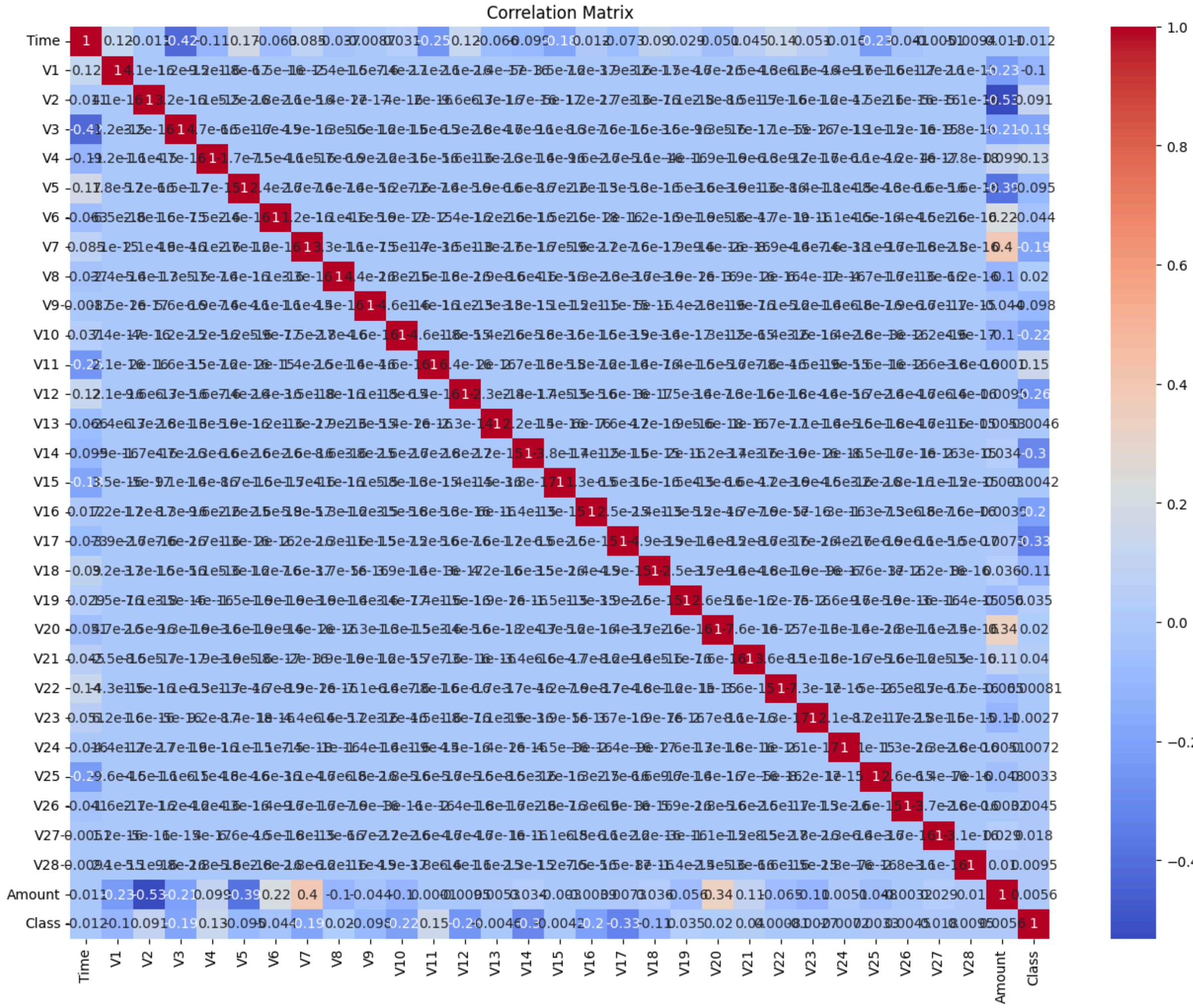
In [8]:
```
# Check for Duplicates
df.duplicated().sum()
```

Out[8]: 1081

In [9]:
```
# Data Distribution (Target Variable)
sns.countplot(x='Class', data=df)
plt.title('Class Distribution')
plt.show()
```



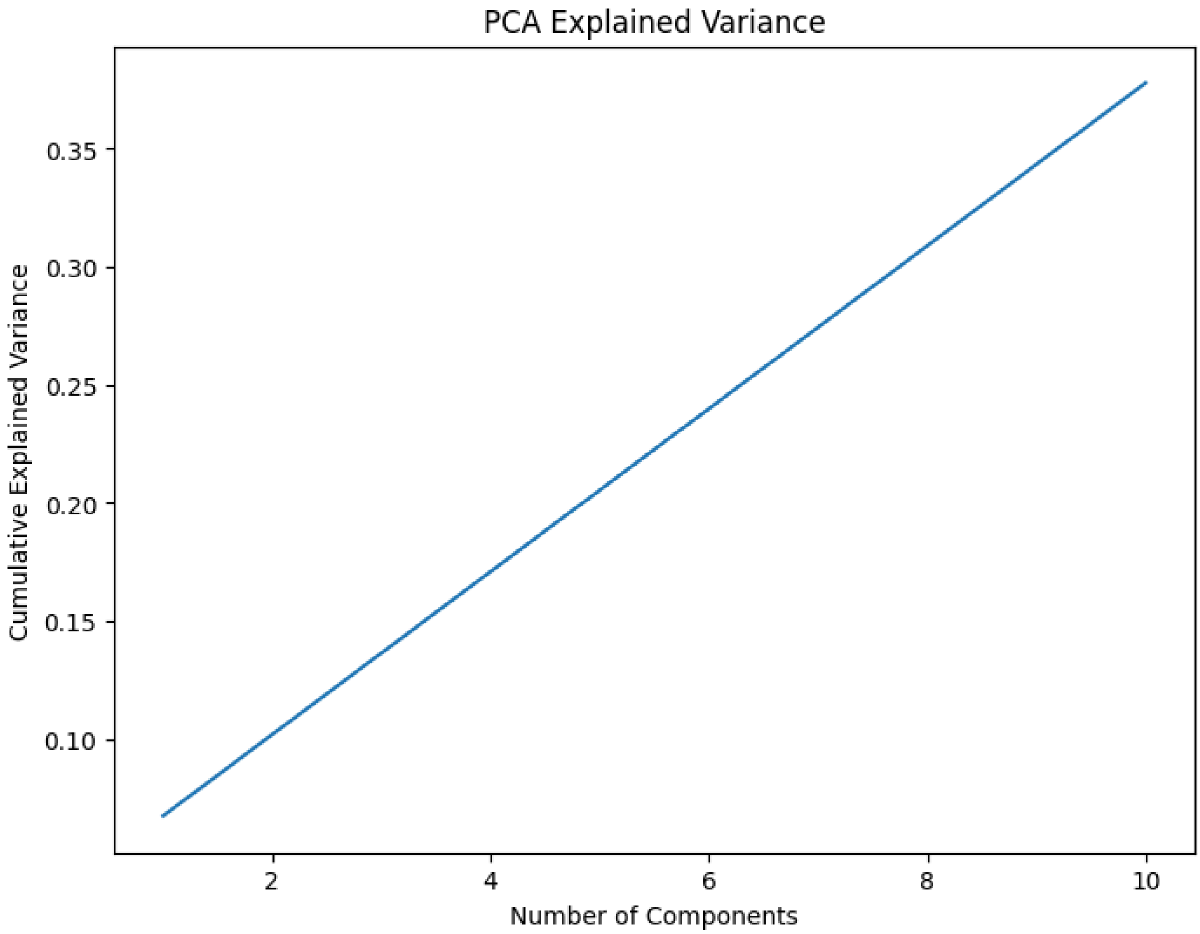

In [10]:
```
# Correlation Matrix (for feature exploration)
corr_matrix = df.corr()
plt.figure(figsize=(16, 12))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



In [11]:
```
# Standardizing the Data (for PCA & Models)
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df.drop(columns=['Time', 'Class']))
```

In [12]:
```
# PCA (Principal Component Analysis)
pca = PCA(n_components=10)
pca_result = pca.fit_transform(scaled_data)
```

In [13]:
```
# Explained Variance Ratio
plt.figure(figsize=(8, 6))
sns.lineplot(x=np.arange(1, 11), y=np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('PCA Explained Variance')
plt.show()
```




In [14]:
```
# Using PCA-Transformed Data for Model
X = pca_result
y = df['Class']
```

In [15]:
```
# Splitting the Data into Train and Test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [16]:
```
# Handling Class Imbalance using SMOTE
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
```

In [17]:
```
# Model Initialization (Random Forest Classifier)
rf = RandomForestClassifier(n_estimators=100, random_state=42, class_weight='balanc
```

In [18]:
```
# Training the Model
rf.fit(X_train_res, y_train_res)
```

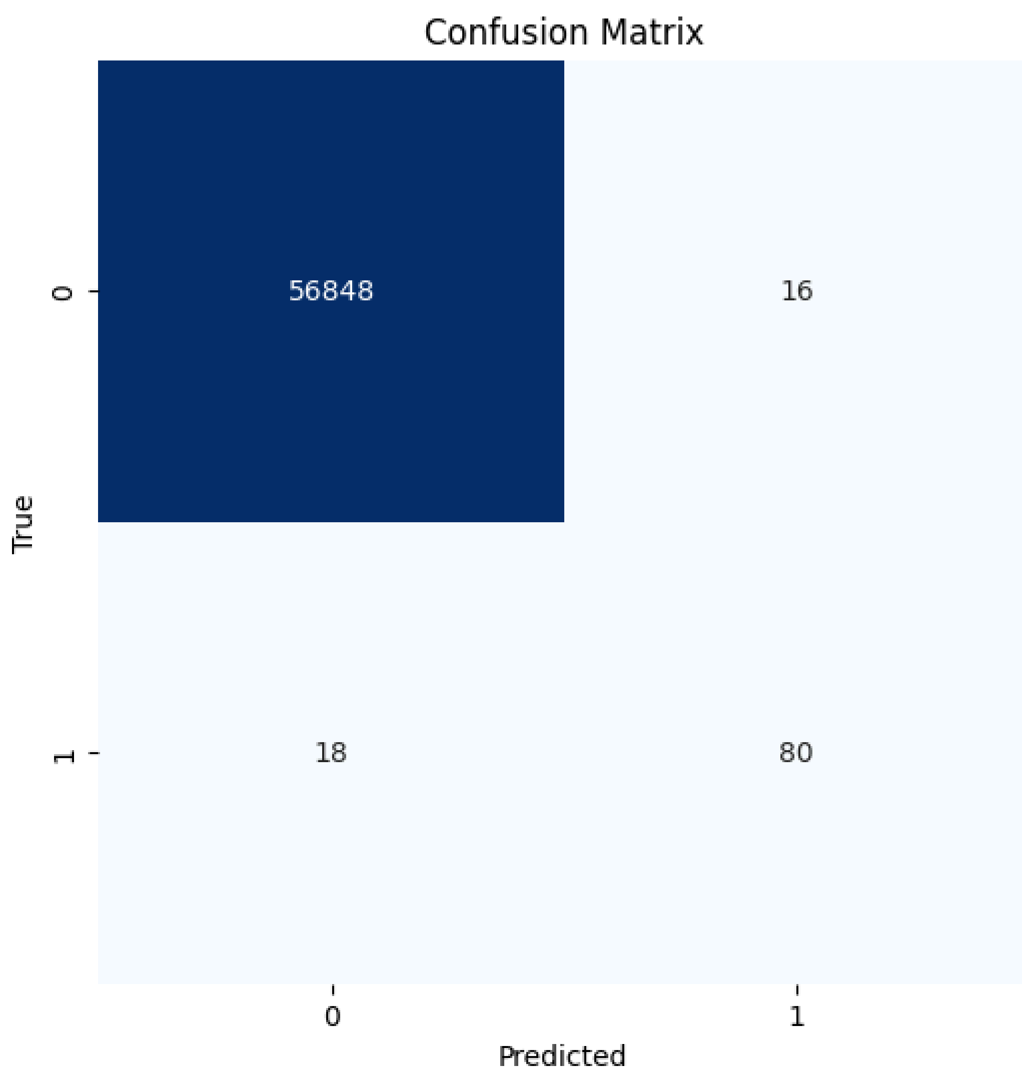
Out[18]:
```
RandomForestClassifier
RandomForestClassifier(class_weight='balanced', random_state=42)
```

In [19]:
```
# Model Prediction
y_pred = rf.predict(X_test)
```

In [20]:
```
# Classification Report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.83      0.82      0.82        98

    accuracy                           1.00     56962
   macro avg       0.92      0.91      0.91     56962
weighted avg       1.00      1.00      1.00     56962
```

In [21]:
```
# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

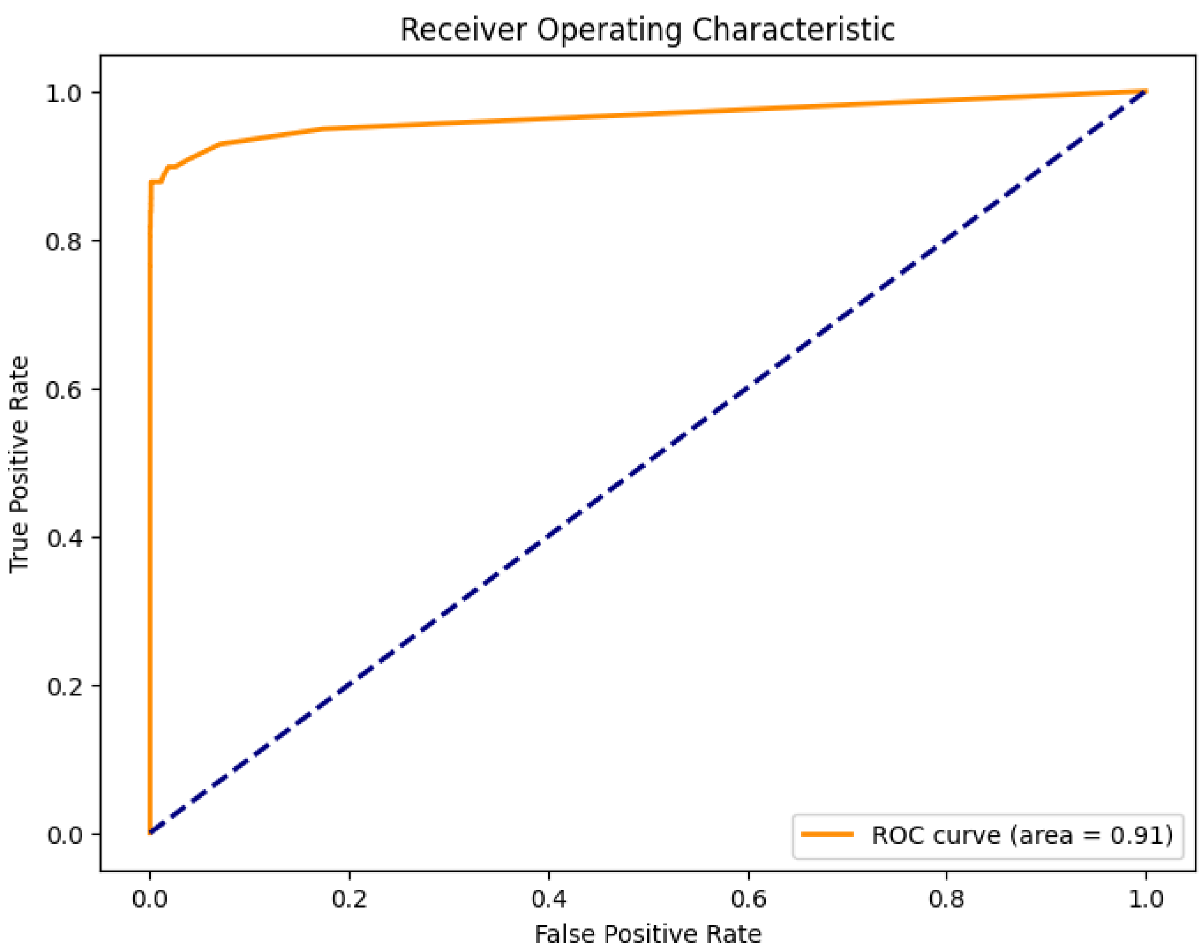


In [22]:

```
# ROC Curve & AUC Score
from sklearn.metrics import roc_curve
fpr, tpr, thresholds = roc_curve(y_test, rf.predict_proba(X_test)[:, 1])
roc_auc = roc_auc_score(y_test, y_pred)
```

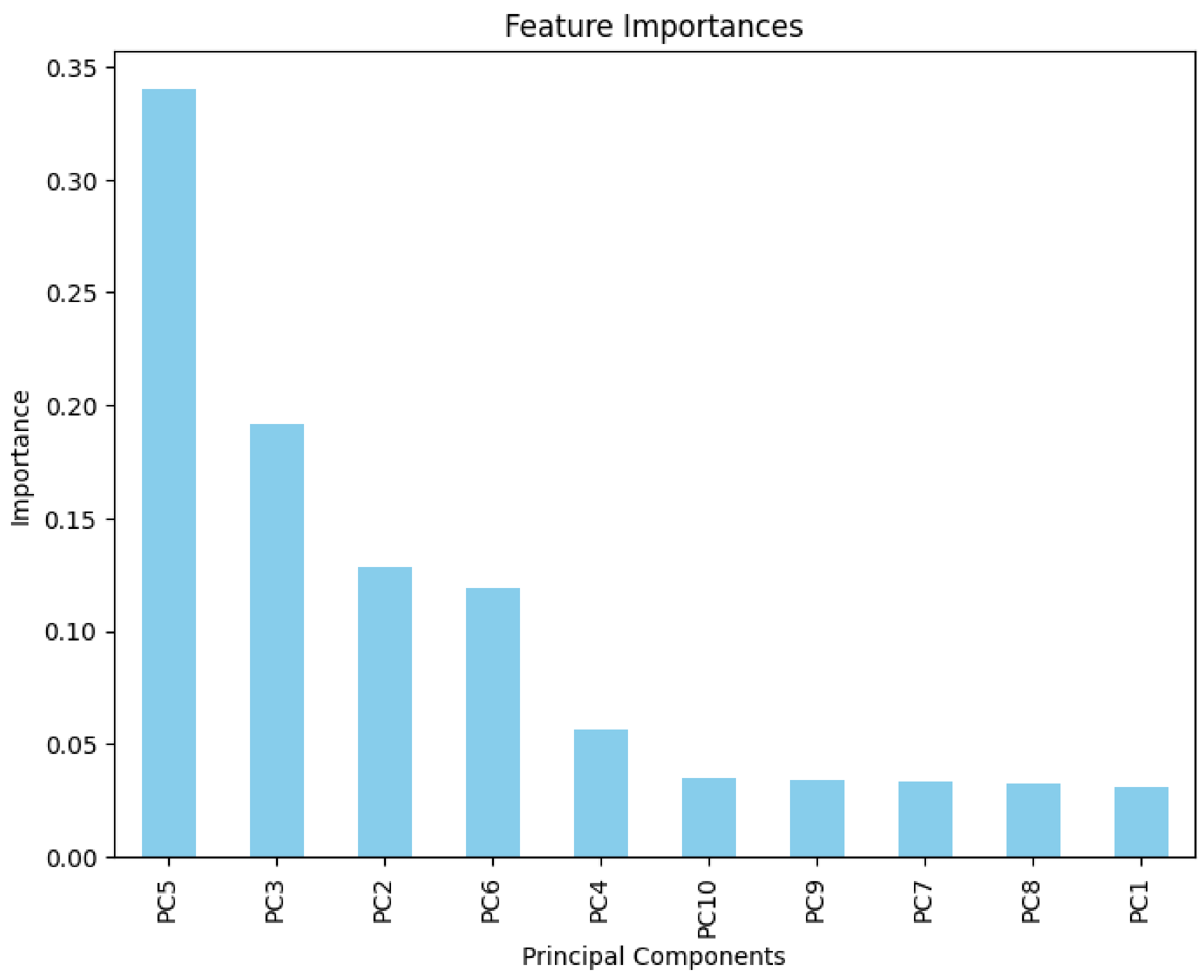
In [23]:

```
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.2f
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc='lower right')
plt.show()
```




In [24]:

```
# Feature Importances
feature_importances = pd.Series(rf.feature_importances_, index=[f'PC{i+1}' for i in
plt.figure(figsize=(8, 6))
feature_importances.sort_values(ascending=False).plot(kind='bar', color='skyblue')
plt.title('Feature Importances')
plt.xlabel('Principal Components')
plt.ylabel('Importance')
plt.show()
```




In [25]:
```
# Model Evaluation Metrics
accuracy = rf.score(X_test, y_test)
print(f"Accuracy: {accuracy:.4f}")
```

```
Accuracy: 0.9994
```

In [26]:
```
# Hyperparameter Tuning using GridSearchCV
from sklearn.model_selection import GridSearchCV
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10]
}
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=3, n_jobs=-1, ve
grid_search.fit(X_train_res, y_train_res)
```

```
Fitting 3 folds for each of 18 candidates, totalling 54 fits
```

Out[26]:

▸ **GridSearchCV**

▸ **best_estimator_: RandomForestClassifier**

▸ RandomForestClassifier

In [27]:
```python
# Best Parameters from GridSearchCV
print("Best Parameters:", grid_search.best_params_)
```

```
Best Parameters: {'max_depth': 30, 'min_samples_split': 2, 'n_estimators': 200}
```

In [28]:
```python
# Re-training Model with Best Parameters
best_rf = grid_search.best_estimator_
best_rf.fit(X_train_res, y_train_res)
```

Out[28]:

RandomForestClassifier

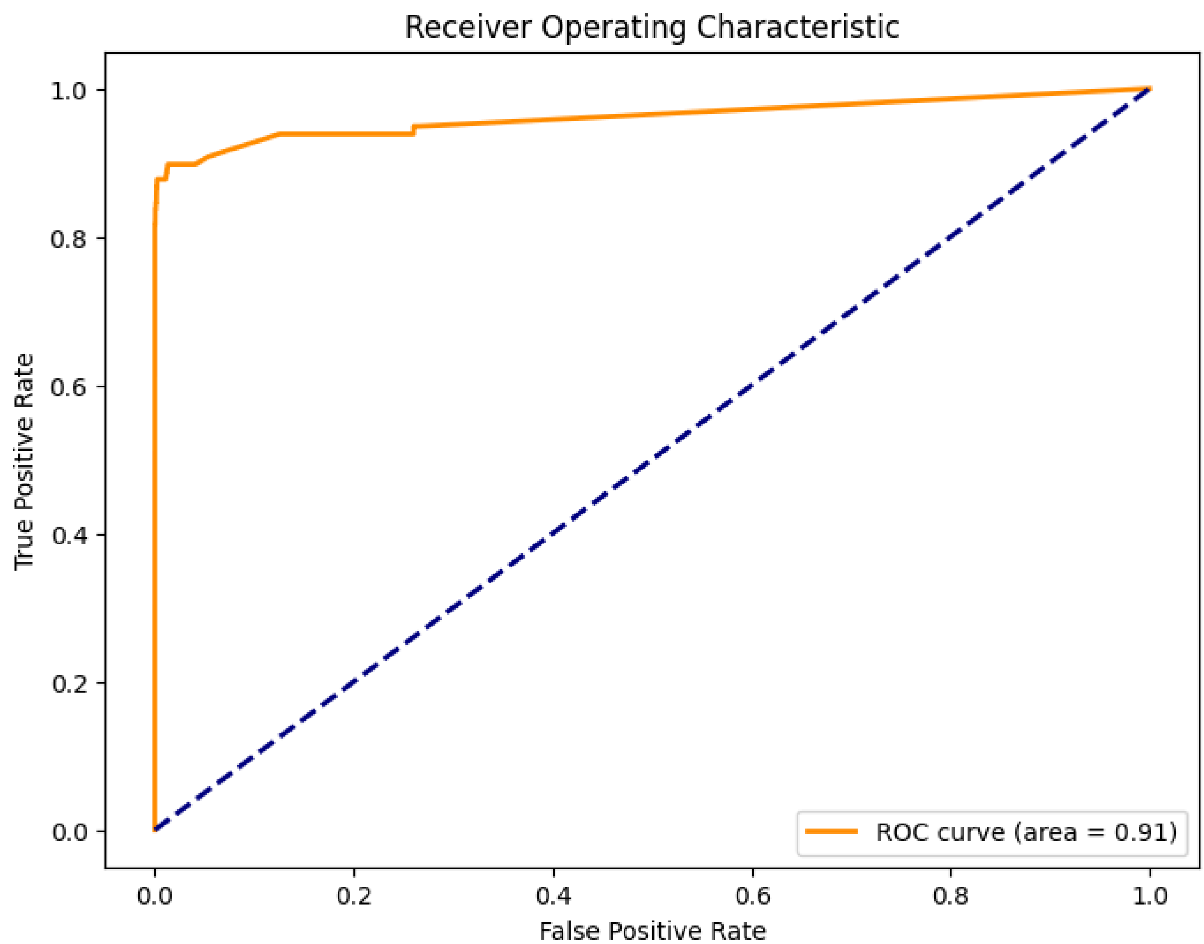
```
RandomForestClassifier(class_weight='balanced', max_depth=30, n_estimators
=200,
                       random_state=42)
```

In [29]:
```python
# Evaluation of Best Model
y_pred_best = best_rf.predict(X_test)
print(classification_report(y_test, y_pred_best))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.84      0.82      0.83        98

    accuracy                           1.00     56962
   macro avg       0.92      0.91      0.91     56962
weighted avg       1.00      1.00      1.00     56962
```

In [30]:
```python
# ROC Curve & AUC for Best Model
fpr_best, tpr_best, thresholds_best = roc_curve(y_test, best_rf.predict_proba(X_tes
roc_auc_best = roc_auc_score(y_test, y_pred_best)
```

In [31]:
```python
plt.figure(figsize=(8, 6))
plt.plot(fpr_best, tpr_best, color='darkorange', lw=2, label=f'ROC curve (area = {r
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc='lower right')
plt.show()
```




In [41]:
```
# Tuning Random Forest with RandomizedSearchCV
from sklearn.model_selection import RandomizedSearchCV
rf = RandomForestClassifier()
param_dist = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'max_features': [None, 'sqrt', 'log2']
}
random_search = RandomizedSearchCV(estimator=rf, param_distributions=param_dist, n_
random_search.fit(X_train_res, y_train_res)
```

Out[41]:
```
▸ RandomizedSearchCV
▸ best_estimator_:
  RandomForestClassifier
  ▸ RandomForestClassifier
```

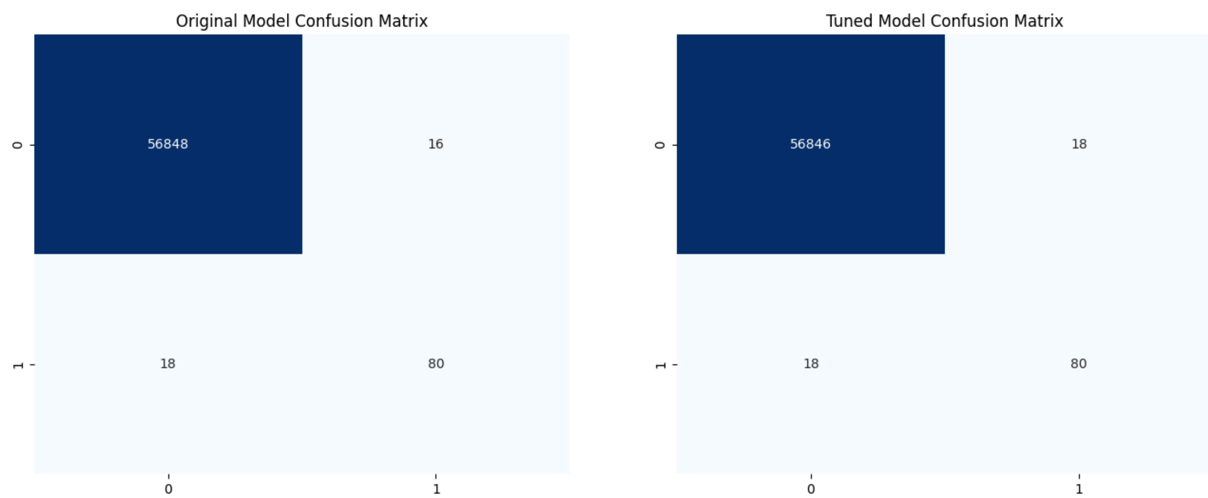
In [42]:
```
# Best Parameters from RandomizedSearchCV
print("Best Parameters (RandomizedSearch):", random_search.best_params_)
```

```
Best Parameters (RandomizedSearch): {'n_estimators': 200, 'min_samples_split': 10,
'max_features': 'sqrt', 'max_depth': 30}
```

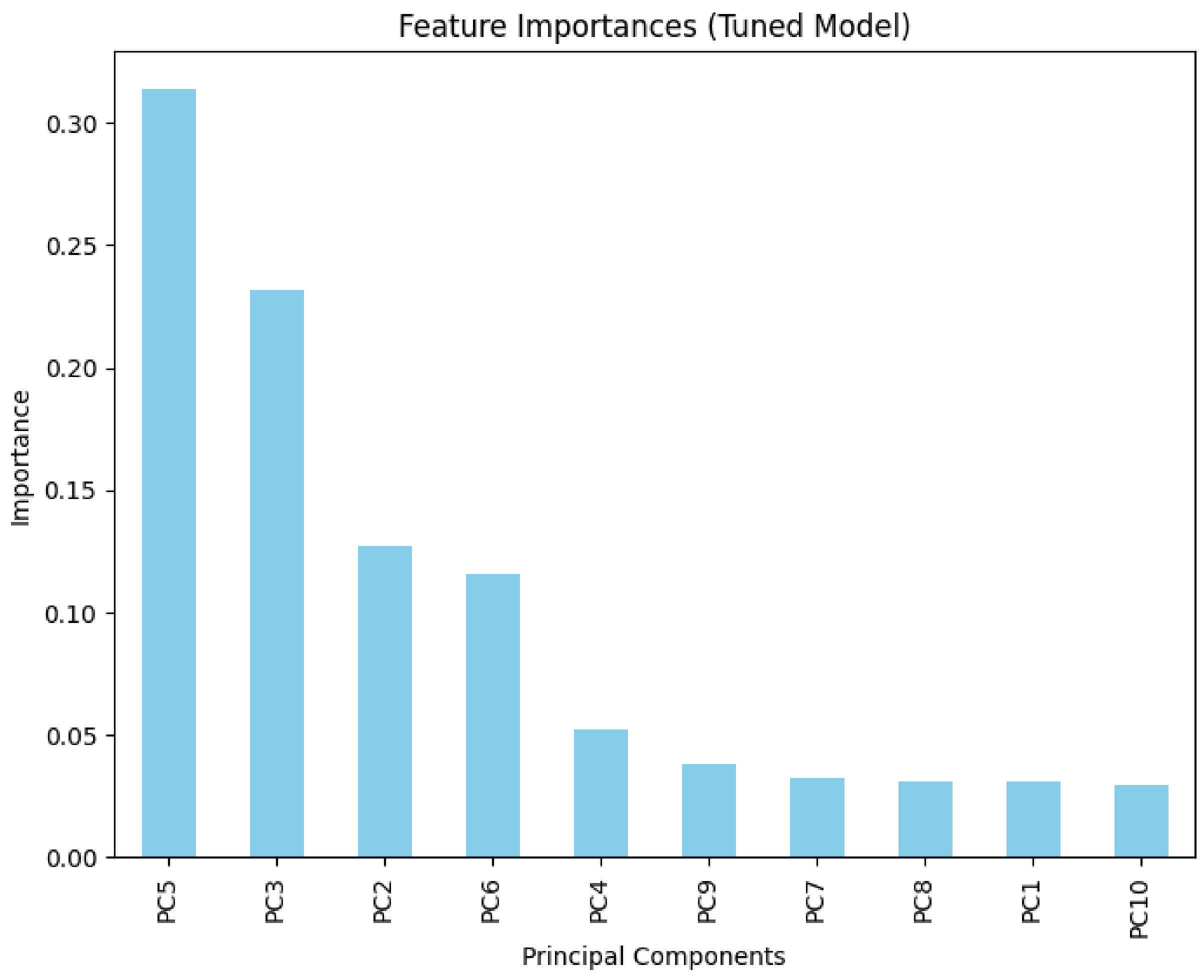
In [43]:
```python
# Evaluating RandomizedSearchCV Model
best_rf_random = random_search.best_estimator_
best_rf_random.fit(X_train_res, y_train_res)
y_pred_random = best_rf_random.predict(X_test)

print(classification_report(y_test, y_pred_random))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.82      0.82      0.82        98

    accuracy                           1.00     56962
   macro avg       0.91      0.91      0.91     56962
weighted avg       1.00      1.00      1.00     56962
```

In [44]:
```python
# Model Comparison: Original vs Tuned
fig, axes = plt.subplots(1, 2, figsize=(16, 6))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cb
axes[0].set_title('Original Model Confusion Matrix')
sns.heatmap(confusion_matrix(y_test, y_pred_random), annot=True, fmt='d', cmap='Blu
axes[1].set_title('Tuned Model Confusion Matrix')
plt.show()
```




In [45]:
```python
# Feature Importance from Tuned Model
feature_importances_random = pd.Series(best_rf_random.feature_importances_, index=[
plt.figure(figsize=(8, 6))
feature_importances_random.sort_values(ascending=False).plot(kind='bar', color='sky
plt.title('Feature Importances (Tuned Model)')
plt.xlabel('Principal Components')
plt.ylabel('Importance')
plt.show()
```




In [76]:
```
# Model Calibration
from sklearn.calibration import CalibratedClassifierCV
calibrated_rf = CalibratedClassifierCV(best_rf_random, method='sigmoid', cv='prefit
calibrated_rf.fit(X_test, y_test)
```

Out[76]:

```
▸ CalibratedClassifierCV

▸ estimator:
RandomForestClassifier

▸ RandomForestClassifier
```

In [47]:
```
# Calibrated Model Evaluation
y_pred_calibrated = calibrated_rf.predict(X_test)
print(classification_report(y_test, y_pred_calibrated))
```

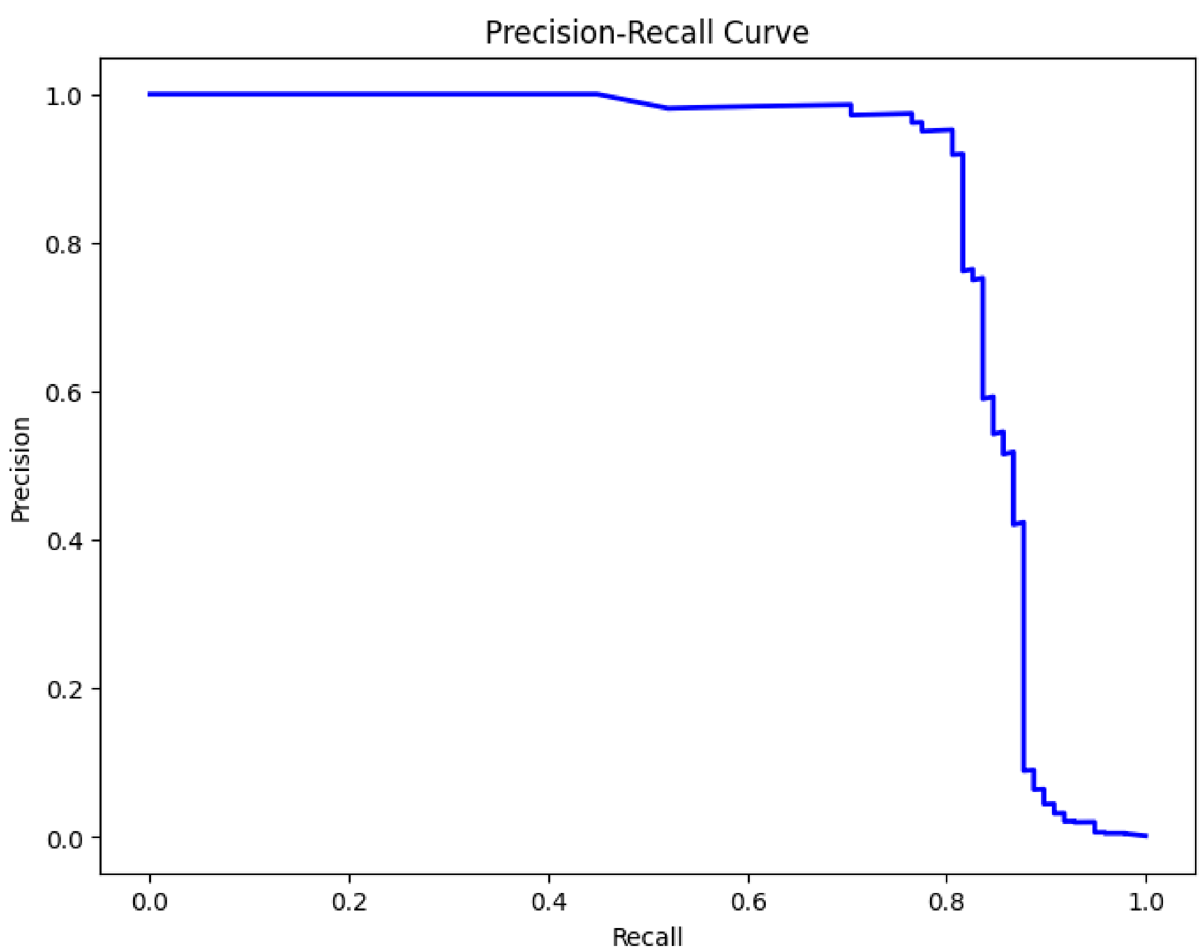
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.95      0.81      0.87        98

    accuracy                           1.00     56962
   macro avg       0.98      0.90      0.94     56962
weighted avg       1.00      1.00      1.00     56962
```

In [48]:

```python
# Precision-Recall Curve
from sklearn.metrics import precision_recall_curve
precision, recall, thresholds_pr = precision_recall_curve(y_test, best_rf_random.pr
```

In [49]:

```python
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, color='b', lw=2)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.show()
```




In [50]:

```python
# Evaluate on an Imbalanced Dataset
X_train_imbalanced, X_test_imbalanced, y_train_imbalanced, y_test_imbalanced = trai
    X, y, test_size=0.2, random_state=42, stratify=y)
```

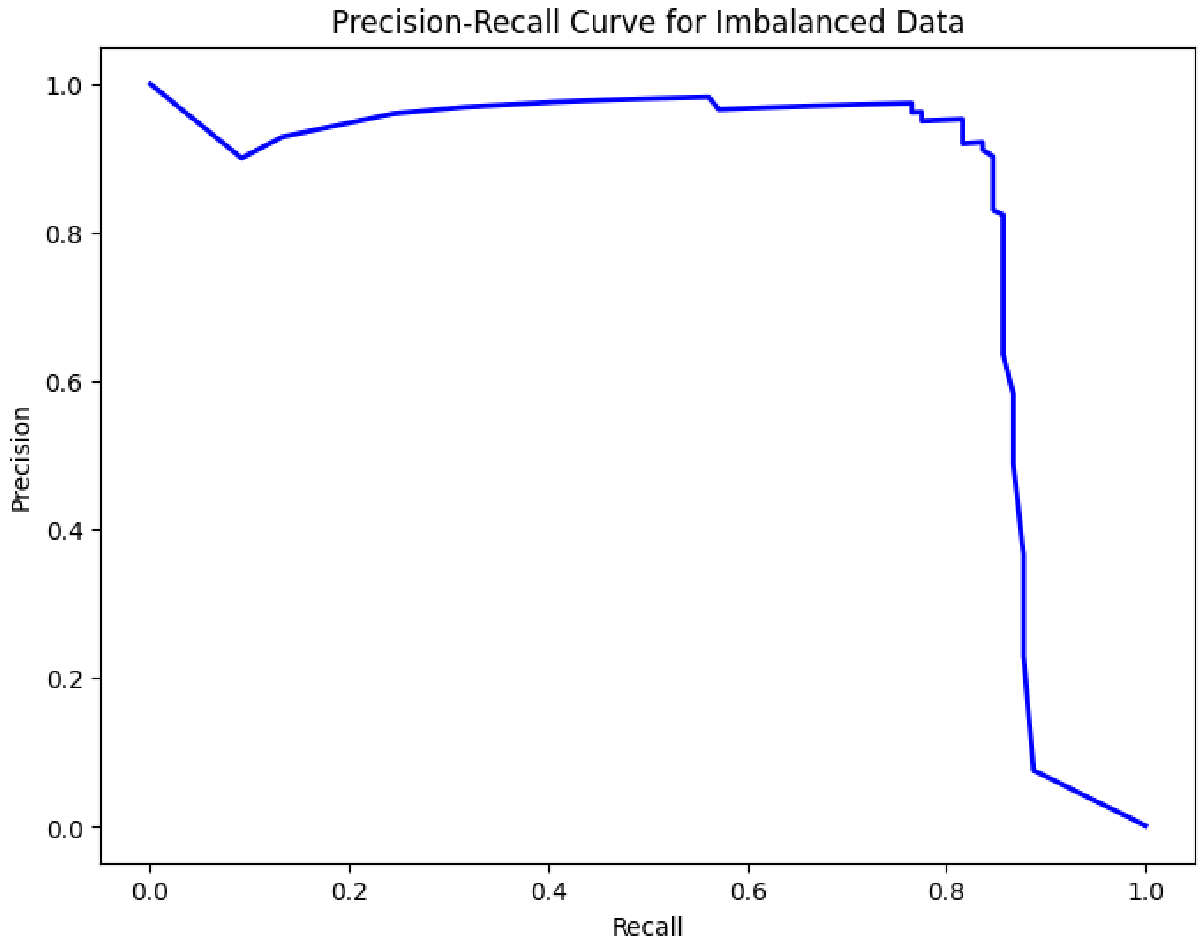
In [51]:
```
# Model Evaluation for Imbalanced Data
rf_imbalanced = RandomForestClassifier(n_estimators=100, random_state=42, class_wei
rf_imbalanced.fit(X_train_imbalanced, y_train_imbalanced)
y_pred_imbalanced = rf_imbalanced.predict(X_test_imbalanced)

print("Classification Report for Imbalanced Data (Random Forest):")
print(classification_report(y_test_imbalanced, y_pred_imbalanced))
```

```
Classification Report for Imbalanced Data (Random Forest):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.96      0.78      0.86        98

    accuracy                           1.00     56962
   macro avg       0.98      0.89      0.93     56962
weighted avg       1.00      1.00      1.00     56962
```

In [52]:
```
# F1 Score Evaluation
from sklearn.metrics import f1_score

# Calculate F1 Score
f1 = f1_score(y_test_imbalanced, y_pred_imbalanced)
print(f"F1 Score for Random Forest on Imbalanced Data: {f1:.4f}")
```

```
F1 Score for Random Forest on Imbalanced Data: 0.8588
```

In [53]:
```
# Visualize Precision-Recall Curve to understand F1 score's behavior
from sklearn.metrics import precision_recall_curve
precision, recall, _ = precision_recall_curve(y_test_imbalanced, rf_imbalanced.pred

plt.figure(figsize=(8, 6))
plt.plot(recall, precision, color='b', lw=2)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve for Imbalanced Data')
plt.show()
```




In [55]:

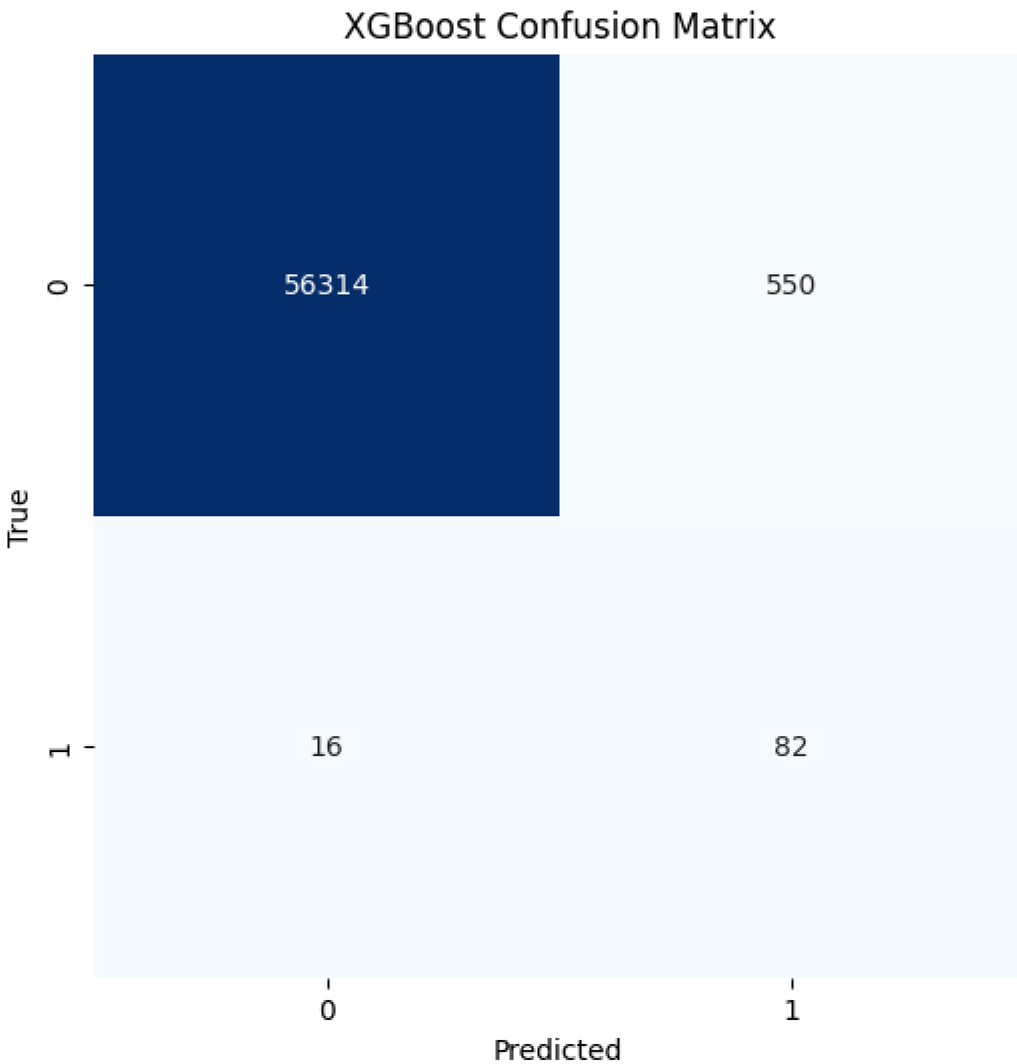
```
# Alternative Model (e.g., XGBoost)
import xgboost as xgb
# Calculate scale_pos_weight
class_weights = compute_class_weight(
    class_weight='balanced',
    classes=np.unique(y_train),
    y=y_train
)
scale_pos_weight = class_weights[1]
xgb_model = xgb.XGBClassifier(scale_pos_weight=scale_pos_weight)
xgb_model.fit(X_train_res, y_train_res)
y_pred_xgb = xgb_model.predict(X_test)
```

In [56]:

```
# Evaluation of XGBoost Model
print(classification_report(y_test, y_pred_xgb))
```

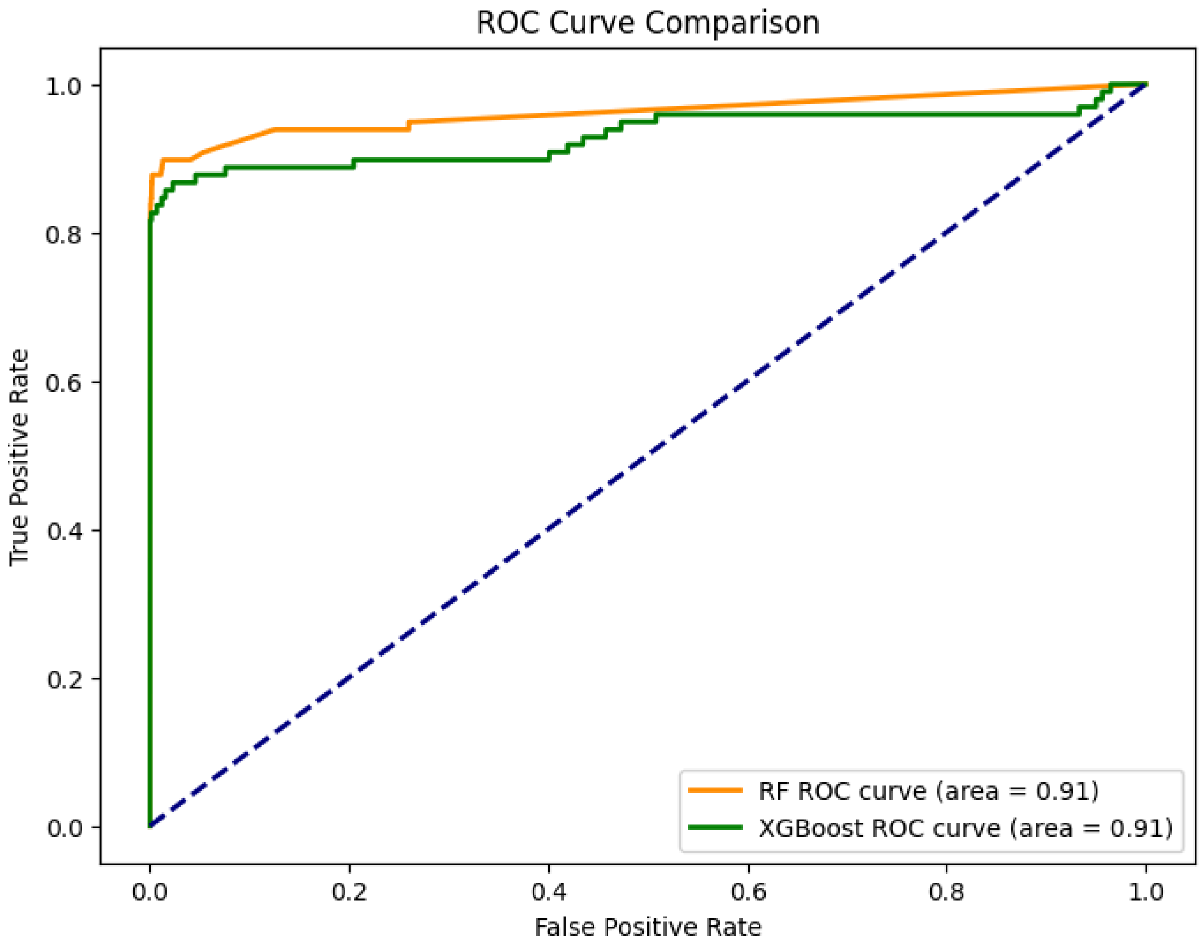
```
              precision    recall  f1-score   support

           0       1.00      0.99      0.99     56864
           1       0.13      0.84      0.22        98

    accuracy                           0.99     56962
   macro avg       0.56      0.91      0.61     56962
weighted avg       1.00      0.99      0.99     56962
```

In [57]:
```python
# XGBoost Model Evaluation (Confusion Matrix)
conf_matrix_xgb = confusion_matrix(y_test, y_pred_xgb)
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix_xgb, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('XGBoost Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```




In [58]:
```python
# Compare XGBoost vs Random Forest (ROC)
fpr_xgb, tpr_xgb, thresholds_xgb = roc_curve(y_test, xgb_model.predict_proba(X_test
roc_auc_xgb = roc_auc_score(y_test, y_pred_xgb)
```

In [59]:
```python
plt.figure(figsize=(8, 6))
plt.plot(fpr_best, tpr_best, color='darkorange', lw=2, label=f'RF ROC curve (area =
plt.plot(fpr_xgb, tpr_xgb, color='green', lw=2, label=f'XGBoost ROC curve (area = {
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend(loc='lower right')
plt.show()
```



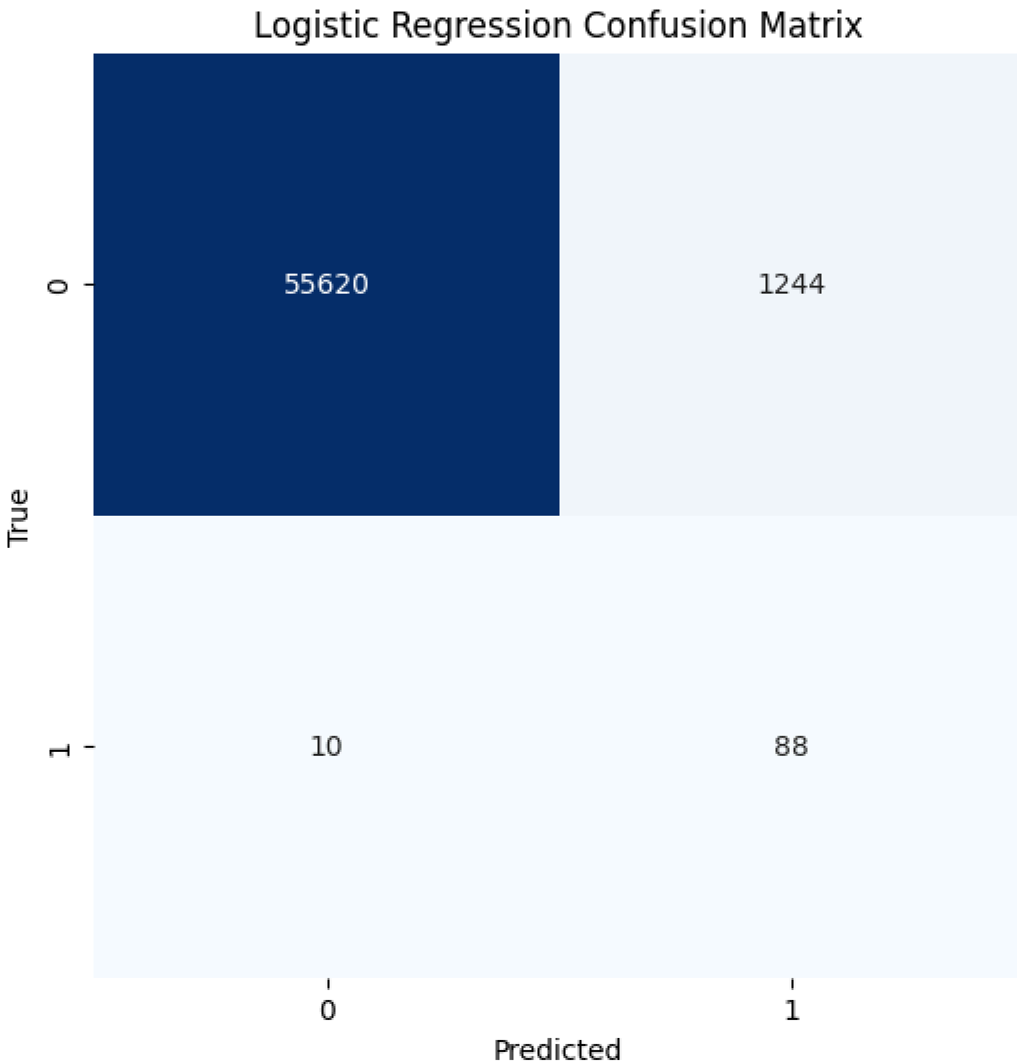

In [60]:
```
# Alternative Model - Logistic Regression
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression(max_iter=1000, class_weight='balanced', random_state=4
log_reg.fit(X_train_res, y_train_res)
y_pred_lr = log_reg.predict(X_test)
```

In [61]:
```
# Logistic Regression Model Evaluation
print(classification_report(y_test, y_pred_lr))
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     56864
           1       0.07      0.90      0.12        98

    accuracy                           0.98     56962
   macro avg       0.53      0.94      0.56     56962
weighted avg       1.00      0.98      0.99     56962
```

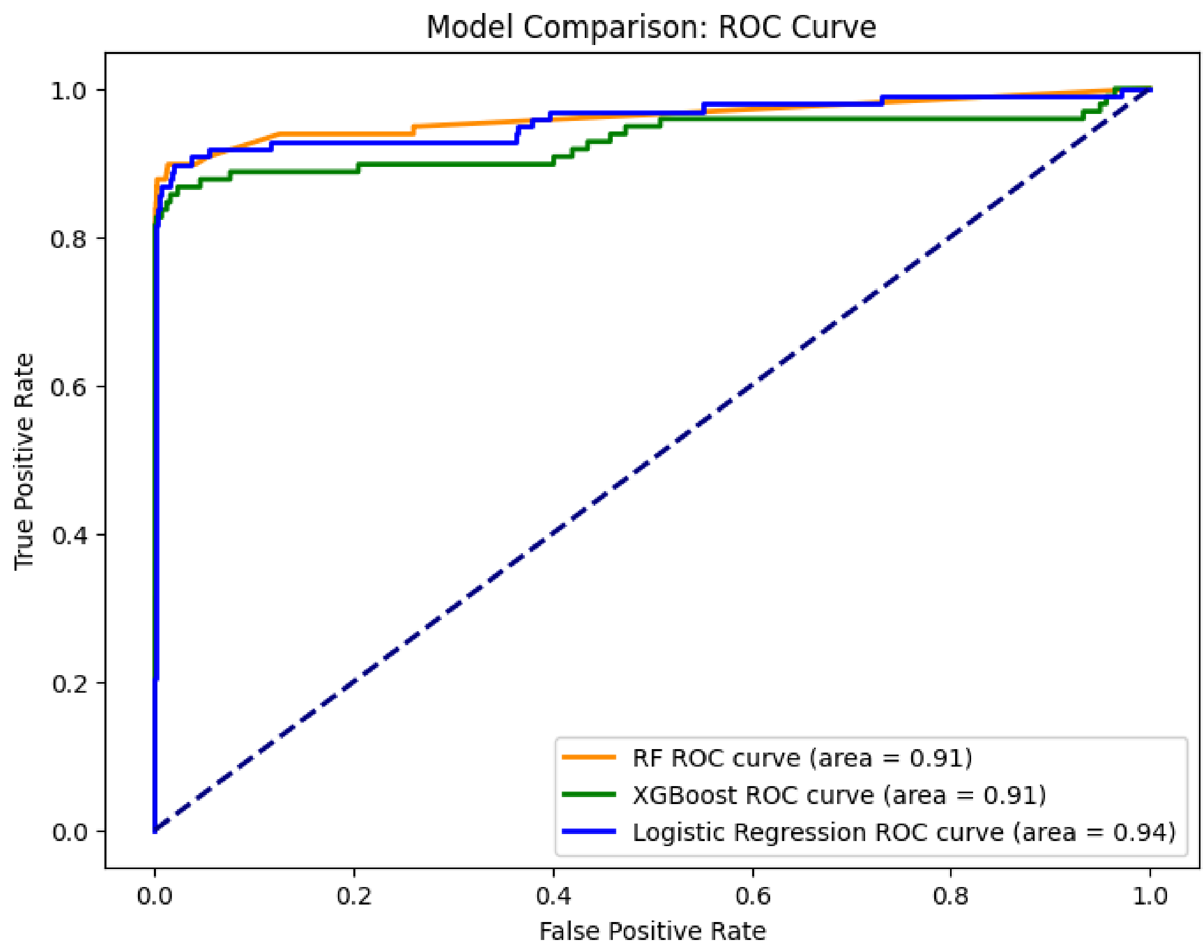
In [62]:
```
# Logistic Regression Confusion Matrix
conf_matrix_lr = confusion_matrix(y_test, y_pred_lr)
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix_lr, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Logistic Regression Confusion Matrix')
plt.xlabel('Predicted')
```

```python
plt.ylabel('True')
plt.show()
```




In [63]:
```python
# Compare Logistic Regression vs Random Forest vs XGBoost (ROC Curve)
fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test, log_reg.predict_proba(X_test)[:,
roc_auc_lr = roc_auc_score(y_test, y_pred_lr)
```

In [64]:
```python
plt.figure(figsize=(8, 6))
plt.plot(fpr_best, tpr_best, color='darkorange', lw=2, label=f'RF ROC curve (area =
plt.plot(fpr_xgb, tpr_xgb, color='green', lw=2, label=f'XGBoost ROC curve (area = {
plt.plot(fpr_lr, tpr_lr, color='blue', lw=2, label=f'Logistic Regression ROC curve
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Model Comparison: ROC Curve')
plt.legend(loc='lower right')
plt.show()
```




In [65]:

```
# Hyperparameter Tuning Logistic Regression (GridSearchCV)
param_grid_lr = {
    'C': [0.01, 0.1, 1, 10],
    'solver': ['liblinear', 'saga']
}
grid_search_lr = GridSearchCV(log_reg, param_grid=param_grid_lr, cv=3, n_jobs=-1, v
grid_search_lr.fit(X_train_res, y_train_res)
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
```

Out[65]:

```
▸ GridSearchCV
▸ best_estimator_: LogisticRegression
  ▸ LogisticRegression
```

In [66]:

```
# Best Parameters for Logistic Regression
print("Best Parameters (Logistic Regression):", grid_search_lr.best_params_)
```

```
Best Parameters (Logistic Regression): {'C': 1, 'solver': 'saga'}
```

In [67]:

```
# Re-training Logistic Regression with Best Parameters
best_log_reg = grid_search_lr.best_estimator_
```

```
best_log_reg.fit(X_train_res, y_train_res)
y_pred_best_lr = best_log_reg.predict(X_test)
```

In [68]:
```
# Logistic Regression - Final Evaluation
print(classification_report(y_test, y_pred_best_lr))
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     56864
           1       0.07      0.90      0.12        98

    accuracy                           0.98     56962
   macro avg       0.53      0.94      0.56     56962
weighted avg       1.00      0.98      0.99     56962
```

In [104…
```
# Feature Engineering: Adding Interaction Features
df['V1_V2'] = df['V1'] * df['V2']
df['V3_V4'] = df['V3'] * df['V4']
# Add more features based on domain knowledge and intuition
df_new_features = df.drop(columns=['Time', 'Class'])
```

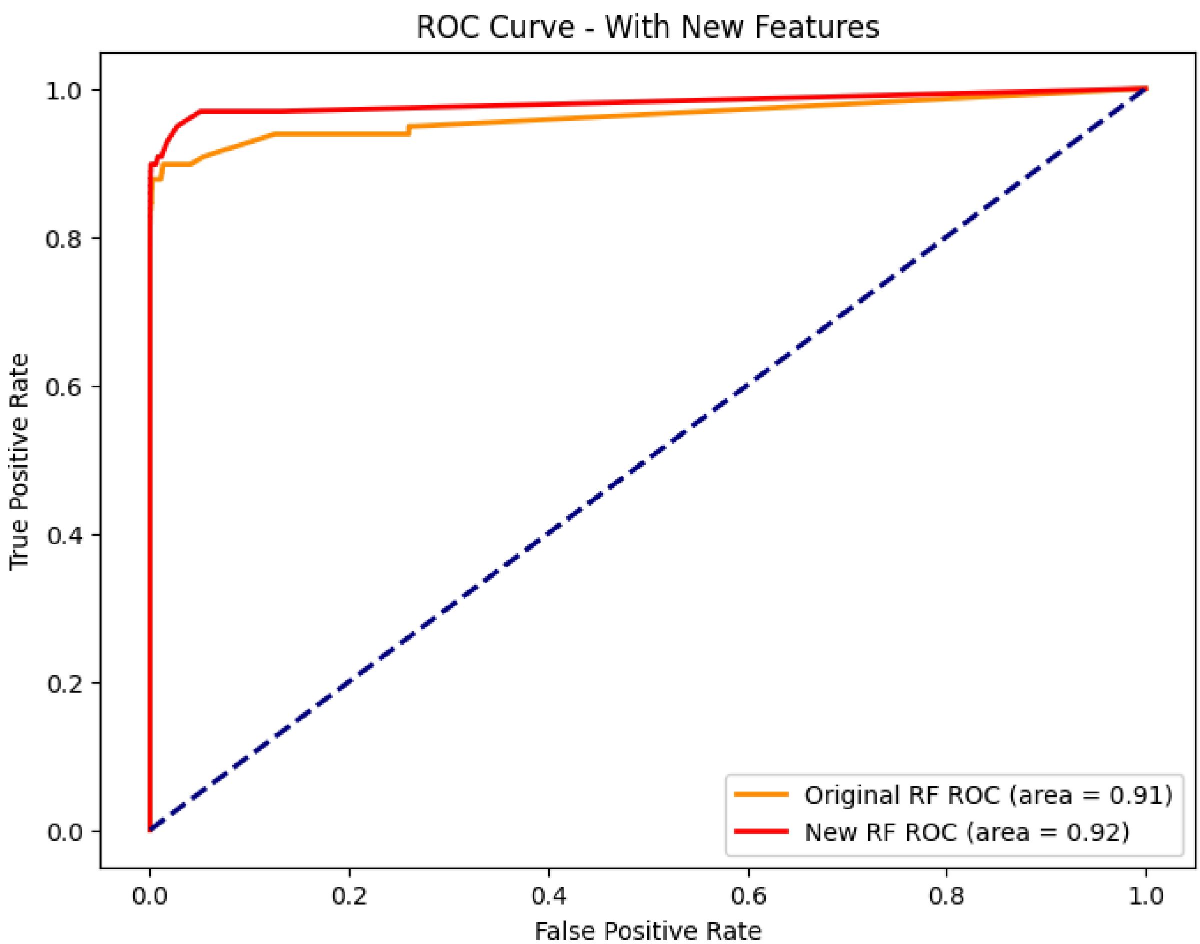
In [105…
```
# Re-training with New Features
X_new = df_new_features
X_train_new, X_test_new, y_train_new, y_test_new = train_test_split(X_new, df['Clas
X_train_res_new, y_train_res_new = smote.fit_resample(X_train_new, y_train_new)
rf.fit(X_train_res_new, y_train_res_new)
y_pred_new = rf.predict(X_test_new)
```

In [106…
```
# Re-evaluating Model with New Features
print(classification_report(y_test_new, y_pred_new))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.88      0.85      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
```

In [107…
```
# ROC Curve with New Features
fpr_new, tpr_new, thresholds_new = roc_curve(y_test_new, rf.predict_proba(X_test_ne
roc_auc_new = roc_auc_score(y_test_new, y_pred_new)
```

In [108…
```
plt.figure(figsize=(8, 6))
plt.plot(fpr_best, tpr_best, color='darkorange', lw=2, label=f'Original RF ROC (are
plt.plot(fpr_new, tpr_new, color='red', lw=2, label=f'New RF ROC (area = {roc_auc_n
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - With New Features')
plt.legend(loc='lower right')
plt.show()
```




In [118…

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.utils.class_weight import compute_class_weight


# Compute class weights for 'y_train_res'
class_weights = compute_class_weight('balanced', classes=np.unique(y_train_res), y=
class_weight_dict = dict(zip(np.unique(y_train_res), class_weights))

# Define models
models = {
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42, clas
    'Logistic Regression': LogisticRegression(max_iter=1000, class_weight='balanced
}

# Evaluate models using cross-validation
for model_name, model in models.items():
    cv_scores = cross_val_score(model, X_train_res, y_train_res, cv=5, scoring='acc
    print(f"{model_name} - Cross-Validation Accuracy: {cv_scores.mean():.4f} ± {cv_
```

```
Random Forest - Cross-Validation Accuracy: 0.9998 ± 0.0001
Logistic Regression - Cross-Validation Accuracy: 0.9289 ± 0.0009
```

In [119…

```
# Save the Model and New Features for Future Use
joblib.dump(rf, 'fraud_detection_model_with_new_features.pkl')
df_new_features.to_csv('fraud_detection_with_new_features.csv', index=False)
```