COM747 (66398) - Individual Code explanation

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1. Using a Kaggle dataset of 284,807 records, the FraudGuard project aimed to create a machine learning solution to identify credit card fraud. To create a strong basis for our research, I imported the dataset using Python libraries like **pandas**. The dataset was downloaded and extracted in this first stage, making it available to the team as an entire set.
2. My responsibilities changed as I took on the duty of data cleansing, using df_raw.isnull().sum() to carefully check for missing values and delete duplicates to speed up processing. As a result of this work, the dataset was clean and ready for the next stages of our project.This process balanced the dataset to 19,968 records, which I saved as creditcard_wrangled.csv to facilitate further analysis.My team's collaboration on Google Colab resulted in suggestions for reproducibility-enhancing changes to the **SMOTE** random state, which significantly improved the code's reliability. I took their suggestions carefully and provided thorough notes to make the method of scaling clear and transparent for everyone involved.
3. I started my statistical analysis by using df_wrangled.describe() to compute summary statistics, looking at the class distribution after SMOTE, and applying **correlation analysis** to find feature relationships.This thorough analysis of the data provided useful knowledge about potential fraud trends. I created visualizations using **seaborn** and **matplotlib** for better understanding the data. These included **violin plots , scatter plots** , and other visuals, which I added to the a./results directory for the IEEE paper.The group members made my code more efficient by optimizing the plotting functions, which saved processing time during iterative reviews.
4. To solve the fraud detection problem, I created and trained several models, such as **Random Forest, SVM, XGBoost,** and **Logistic Regression.** As a crucial step for a reliable model evaluation, I used train_test_split to divide the data into 70% training and 30% testing sets. Using metrics like accuracy, precision, recall, F1 score, and ROC AUC, I assessed the models. To make sure they were reliable, I conducted five-fold cross-validation.To visualise performance, I plotted and stored confusion matrices and ROC curves after carefully documenting the results in a model_comparison.csv file. By reducing the calculation time and simplifying the cross-validation loop, my group members improved the efficiency of my code, and I used their suggestions to improve the modelling procedure. This teamwork improved the model selection process as a whole.
5. Finally, I used the entire contrived dataset to retrain the Random Forest model, saving it with **joblib** as fraudguard_random_forest.joblib. For real-time fraud detection, I created a predict_fraud function that took transaction dictionaries and produced predictions and probabilities. Its functionality was evaluated using an example transaction. I added comments to the prediction logic to ensure a clear and maintainable deployment procedure, and I applied the input validation that my team recommended on Google Colab to increase robustness.Their recommendations added error handling to my code, increasing its efficiency and averting certain runtime problems. A solid and deployable solution that reflected my individual contributions strengthened by team synergy was

secured by this collaborative refining, which was supported by our Google Colab interactions.

- Pandas: For modifying data and importing it into DataFrames.
- OS: To control directories when importing datasets.
- Sklearn: Used `StandardScaler` for scaling, `train_test_split` for data splitting, and models like Logistic Regression, Random Forest, SVM.
- Imblearn: Applied SMOTE via `imblearn.over_sampling` to balance the dataset.
- Seaborn: For creating visualizations like scatter and violin plots.
- Matplotlib: To generate and save plots for the IEEE paper.
- XGBoost: For training the XGBoost model for fraud detection.
- Joblib: To prepare the Random Forest model for deployment after it has been trained.
- Google Colab: For team collaboration, code improvement, and adding comments.

• Appended Project Code:

1- Import The Data Set

```
import pandas as pd

import os

import zipfile

# Install the Kaggle package

!pip install kaggle

# Create the .kaggle directory and move kaggle.json there

os.makedirs('~/.kaggle', exist_ok=True)

# Set permissions for the kaggle.json file

!chmod 600 ~/.kaggle/kaggle.json

#  Download the dataset from Kaggle

data_dir = "../data"

os.makedirs(data_dir, exist_ok=True)  # Create the data directory

dataset_name = "mlg-ulb/creditcardfraud"

zip_path = os.path.join(data_dir, "creditcardfraud.zip")

# Download the dataset as a zip file

!kaggle datasets download -d {dataset_name} -p {data_dir}
```

```
# Extract the zip file

with zipfile.ZipFile(zip_path, 'r') as zip_ref:

    zip_ref.extractall(data_dir)

print("Dataset extracted successfully!")

# Load the dataset

file_path = os.path.join(data_dir, "creditcard.csv")

df_raw = pd.read_csv(file_path)

print("Dataset loaded successfully!")

print("Shape of raw dataset:", df_raw.shape)

print("First 5 records:\n", df_raw.head())
```

Requirement already satisfied: kaggle in /usr/local/lib/python3.11/dist-packages (1.6.17)

Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.11/dist-packages (from kaggle) (1.17.0)

Requirement already satisfied: certifi>=2023.7.22 in /usr/local/lib/python3.11/dist-packages (from kaggle) (2025.1.31)

Requirement already satisfied: python-dateutil in /usr/local/lib/python3.11/dist-packages (from kaggle) (2.9.0.post0)

Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from kaggle) (2.32.3)

Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (from kaggle) (4.67.1)

Requirement already satisfied: python-slugify in /usr/local/lib/python3.11/dist-packages (from kaggle) (8.0.4)

Requirement already satisfied: urllib3 in /usr/local/lib/python3.11/dist-packages (from kaggle) (2.3.0)

Requirement already satisfied: bleach in /usr/local/lib/python3.11/dist-packages (from kaggle) (6.2.0)

Requirement already satisfied: webencodings in /usr/local/lib/python3.11/dist-packages (from bleach->kaggle) (0.5.1)

Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.11/dist-packages (from python-slugify->kaggle) (1.3)

Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->kaggle) (3.4.1)

```
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->kaggle) (3.10)

chmod: cannot access '/root/.kaggle/kaggle.json': No such file or directory

Warning: Looks like you're using an outdated API Version, please consider updating (server 1.7.4.2 / client 1.6.17)

Dataset URL: https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud

License(s): DbCL-1.0

creditcardfraud.zip: Skipping, found more recently modified local copy (use --force to force download)

Dataset extracted successfully!

Dataset loaded successfully!

Shape of raw dataset: (284807, 31)

First 5 records:

   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]
```

2- Load The Data Set

```
print("Dataset Overview:")
print("Shape:", df_raw.shape)
print("\nColumn Info:\n", df_raw.dtypes)
print("\nMissing Values:\n", df_raw.isnull().sum())
print("\nClass Distribution (Fraud vs. Non-Fraud):\n", df_raw['Class'].value_counts(normalize=True))
# Summary of findings
print("\nSummary: The dataset has", df_raw.shape[0], "rows and", df_raw.shape[1], "columns. No missing values. Highly imbalanced classes - fraud cases are rare.")
```

```
Dataset Overview:
Shape: (284807, 31)
Column Info:
 Time      float64
V1        float64
V2        float64
V3        float64
V4        float64
V5        float64
V6        float64
V7        float64
V8        float64
V9        float64
```

V10 float64

V11 float64

V12 float64

V13 float64

V14 float64

V15 float64

V16 float64

V17 float64

V18 float64

V19 float64

V20 float64

V21 float64

V22 float64

V23 float64

V24 float64

V25 float64

V26 float64

V27 float64

V28 float64

Amount float64

Class int64

dtype: object

Missing Values:

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

Class Distribution (Fraud vs. Non-Fraud):

 Class

0   0.998273

1   0.001727

Name: proportion, dtype: float64

Summary: The dataset has 284807 rows and 31 columns. No missing values. Highly imbalanced classes - fraud cases are rare.

3- Data Cleaning

```
import pandas as pd

import os

# Confirm no missing values

missing_values = df_raw.isnull().sum().sum()

print("Total Missing Values:", missing_values)

if missing_values > 0:

        print("Warning: Missing values found! Consider handling them.")

else:

        print("No missing values found. Proceeding to handle duplicates.")


# Remove duplicates

df_cleaned = df_raw.drop_duplicates()

print("Shape before removing duplicates:", df_raw.shape)

print("Shape after removing duplicates:", df_cleaned.shape)

print("Number of duplicates removed:", df_raw.shape[0] - df_cleaned.shape[0])

# Sample the dataset to reduce size for faster processing

df_cleaned = df_cleaned.sample(n=10000, random_state=42)
```

print("Shape after sampling:", df_cleaned.shape)

Save the cleaned dataset

data_dir = "../data"

os.makedirs(data_dir, exist_ok=True) # Ensure the data directory exists

cleaned_path = os.path.join(data_dir, "creditcard_cleaned.csv")

df_cleaned.to_csv(cleaned_path, index=False)

print(f"Cleaned dataset saved as '{cleaned_path}'")

Total Missing Values: 0

No missing values found. Proceeding to handle duplicates.

Shape before removing duplicates: (284807, 31)

Shape after removing duplicates: (283726, 31)

Number of duplicates removed: 1081

Shape after sampling: (10000, 31)

Cleaned dataset saved as '../data/creditcard_cleaned.csv'

4- Data Wrangling

import pandas as pd

import os

from sklearn.preprocessing import StandardScaler

from imblearn.over_sampling import SMOTE

Load the cleaned dataset from Step 3

data_dir = "../data"

cleaned_path = os.path.join(data_dir, "creditcard_cleaned.csv")

df_cleaned = pd.read_csv(cleaned_path)

print("Loaded cleaned dataset. Shape:", df_cleaned.shape)

Scale the 'Time' and 'Amount' features

scaler = StandardScaler()

```
df_cleaned[['Time', 'Amount']] = scaler.fit_transform(df_cleaned[['Time', 'Amount']])

print("Features 'Time' and 'Amount' scaled successfully.")

# Handle class imbalance using SMOTE

X = df_cleaned.drop('Class', axis=1)

y = df_cleaned['Class']

smote = SMOTE(random_state=42)

X_resampled, y_resampled = smote.fit_resample(X, y)

# Create the wrangled DataFrame

df_wrangled = pd.DataFrame(X_resampled, columns=X.columns)

df_wrangled['Class'] = y_resampled

print("Shape after SMOTE:", df_wrangled.shape)

print("Class Distribution after SMOTE:\n", df_wrangled['Class'].value_counts(normalize=True))

# Save the wrangled dataset

wrangled_path = os.path.join(data_dir, "creditcard_wrangled.csv")

df_wrangled.to_csv(wrangled_path, index=False)

print(f"Wrangled dataset saved as '{wrangled_path}'")
```

```
Loaded cleaned dataset. Shape: (10000, 31)

Features 'Time' and 'Amount' scaled successfully.

Shape after SMOTE: (19968, 31)

Class Distribution after SMOTE:

 Class

0    0.5

1    0.5

Name: proportion, dtype: float64

Wrangled dataset saved as '../data/creditcard_wrangled.csv'
```

5- Statistical Analysis

```
import pandas as pd
import os
import seaborn as sns
import matplotlib.pyplot as plt
# Load the wrangled dataset from Step 4
data_dir = "../data"
wrangled_path = os.path.join(data_dir, "creditcard_wrangled.csv")
df_wrangled = pd.read_csv(wrangled_path)
print("Loaded wrangled dataset. Shape:", df_wrangled.shape)
# Create a directory to save results for the IEEE paper
results_dir = "../results"
os.makedirs(results_dir, exist_ok=True)
# Summary Statistics for all features
summary_stats = df_wrangled.describe()
print("\nSummary Statistics:\n", summary_stats)
summary_stats.to_csv(os.path.join(results_dir, "summary_statistics.csv"))
print(f"Summary statistics saved as '{results_dir}/summary_statistics.csv'")
# Confirm class distribution after SMOTE
class_dist = df_wrangled['Class'].value_counts(normalize=True)
print("\nClass Distribution after SMOTE:\n", class_dist)
# Plot class distribution
plt.figure(figsize=(6, 4))
sns.countplot(x='Class', data=df_wrangled)
plt.title("Class Distribution After SMOTE")
plt.xlabel("Class (0: Non-Fraud, 1: Fraud)")
plt.ylabel("Count")
plt.savefig(os.path.join(results_dir, "class_distribution.png"))
```

```
plt.show()

# Correlation Analysis

plt.figure(figsize=(12, 10))

correlation_matrix = df_wrangled.corr()

sns.heatmap(correlation_matrix, cmap="coolwarm", annot=False)

plt.title("Correlation Heatmap of Features")

plt.savefig(os.path.join(results_dir, "correlation_heatmap.png"))

plt.show()

print(f"Correlation heatmap saved as '{results_dir}/correlation_heatmap.png'")

# Feature Distributions (analyze key features: V1, V2, Time, Amount)

key_features = ['V1', 'V2', 'Time', 'Amount']

for feature in key_features:

    plt.figure(figsize=(6, 4))

    sns.histplot(data=df_wrangled, x=feature, hue='Class', bins=30, kde=True)

    plt.title(f"Distribution of {feature} by Class")

    plt.xlabel(feature)

    plt.ylabel("Count")

    plt.savefig(os.path.join(results_dir, f"{feature}_distribution.png"))

    plt.show()

    print(f"{feature} distribution plot saved as '{results_dir}/{feature}_distribution.png'")

# Summary of Insights

insights = """

Statistical Analysis Insights:

- The dataset has 19968 rows and 31 columns after SMOTE.

- Classes are balanced (50% fraud, 50% non-fraud) as expected.

- Correlation analysis shows relationships between features (see heatmap).

- Feature distributions highlight differences between fraud and non-fraud cases (see plots).
```

```
"""
with open(os.path.join(results_dir, "statistical_insights.txt"), "w") as f:
    f.write(insights)
print(f"Statistical insights saved as '{results_dir}/statistical_insights.txt'")
```

Loaded wrangled dataset. Shape: (19968, 31)

Summary Statistics:

```
               Time            V1            V2            V3            V4  \
count  19968.000000  19968.000000  19968.000000  19968.000000  19968.000000
mean       0.002967     -1.299115      1.192371     -2.447980      1.748044
std        0.898368      3.681338      2.677268      4.420976      2.582634
min       -2.010049    -40.470142    -38.436817    -31.103685     -4.811194
25%       -0.756090     -2.001038     -0.187179     -3.892166     -0.065411
50%       -0.014939     -0.824450      0.982557     -1.243241      1.142992
75%        0.803338      0.602255      1.892280      0.184980      3.239388
max        1.635577      2.404663     16.713389      4.040465     12.699542

                 V5            V6            V7            V8            V9  \
count  19968.000000  19968.000000  19968.000000  19968.000000  19968.000000
mean      -0.777721     -0.460918     -1.375745      0.525963     -1.059670
std        2.635289      1.347792      3.104981      2.446467      1.538339
min      -22.105532    -20.367836    -20.906651    -41.484823     -5.667376
25%       -1.142028     -1.104555     -2.515479     -0.153687     -1.985899
50%       -0.363363     -0.597040     -0.696663      0.241643     -1.000996
75%        0.264408      0.008789      0.272806      0.691888     -0.049413
max       29.162172      9.042659     12.143391     20.007208      8.955669
```

	...	V21	V22	V23	V24 \
count	...	19968.000000	19968.000000	19968.000000	19968.000000
mean	...	0.402086	-0.005221	-0.092864	-0.170541
std	...	0.952418	0.766445	0.537100	0.564114
min	...	-20.262054	-8.245481	-22.575000	-2.765519
25%	...	-0.125044	-0.539949	-0.255223	-0.561265
50%	...	0.218446	-0.026715	-0.077737	-0.167110
75%	...	0.816333	0.549671	0.106578	0.204773
max	...	21.899724	5.805795	11.366755	3.546031

	V25	V26	V27	V28	Amount \
count	19968.000000	19968.000000	19968.000000	19968.000000	19968.000000
mean	0.090232	0.091935	0.101394	0.102359	0.211496
std	0.486212	0.426686	0.598525	0.473936	1.111652
min	-3.640055	-1.664130	-6.780935	-8.277924	-0.383415
25%	-0.218828	-0.186932	-0.085230	-0.038475	-0.339530
50%	0.115935	0.071540	0.035527	0.065056	-0.227775
75%	0.378522	0.332370	0.316004	0.266715	0.239286
max	4.828097	3.067907	9.200883	15.866721	34.155191

	Class
count	19968.000000
mean	0.500000
std	0.500013
min	0.000000
25%	0.000000
50%	0.500000

75%   1.000000

max   1.000000

[8 rows x 31 columns]

Summary statistics saved as '../results/summary_statistics.csv'

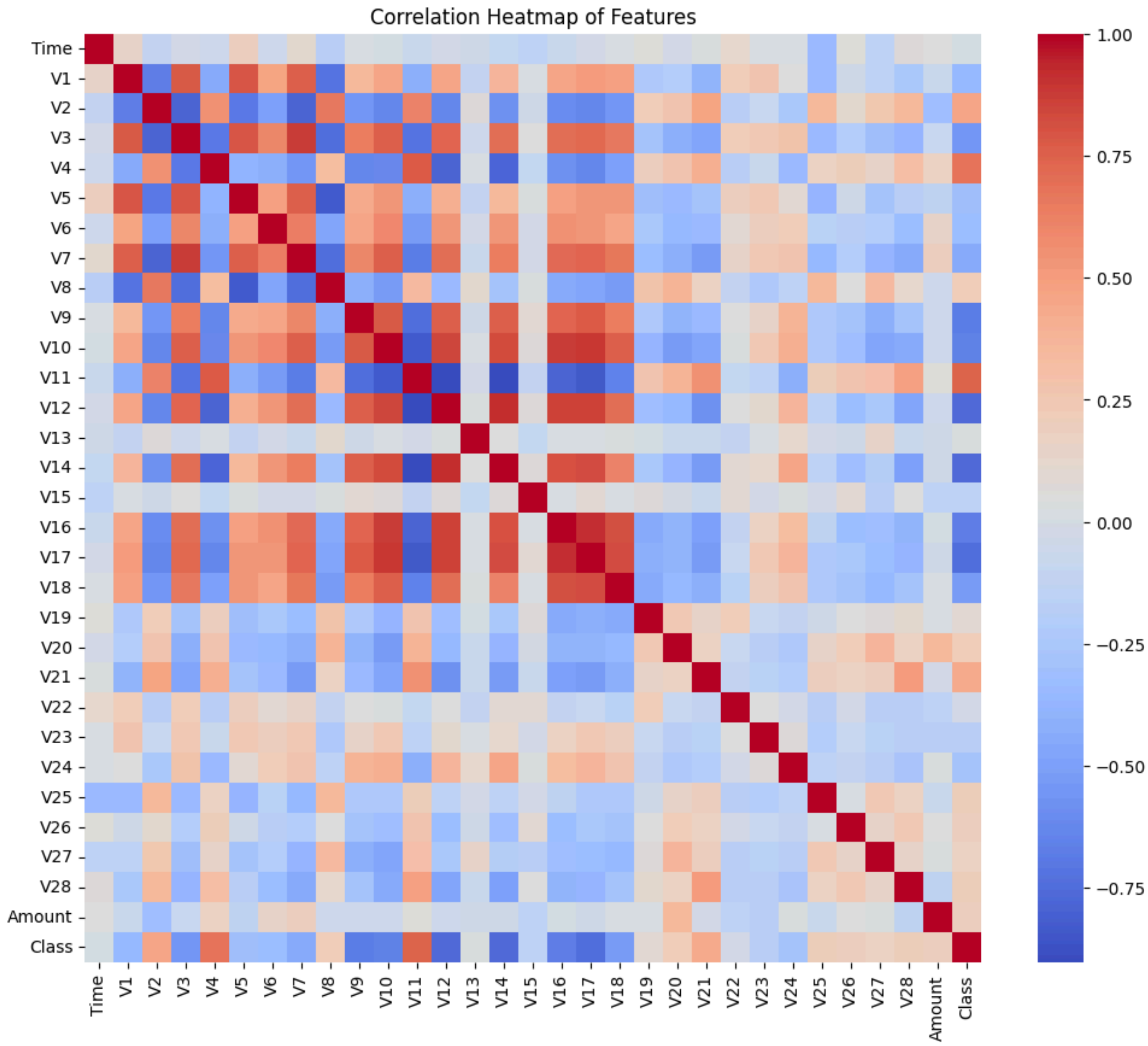
Class Distribution after SMOTE:

Class

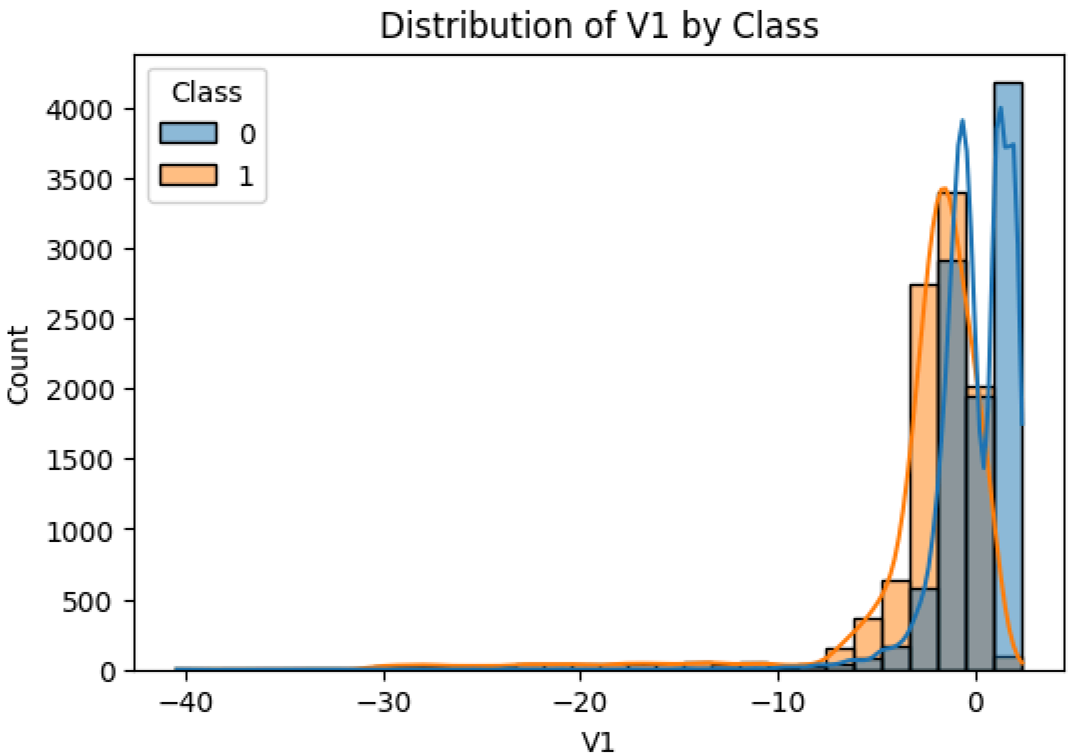
0   0.5

1   0.5

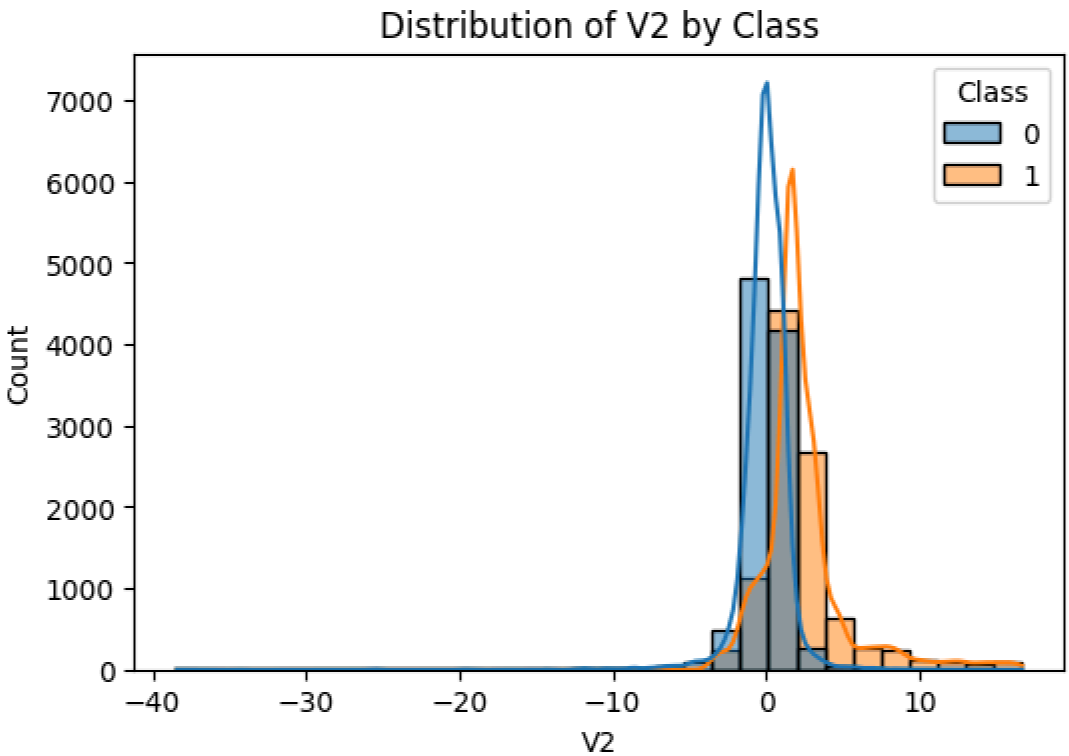
Name: proportion, dtype: float64



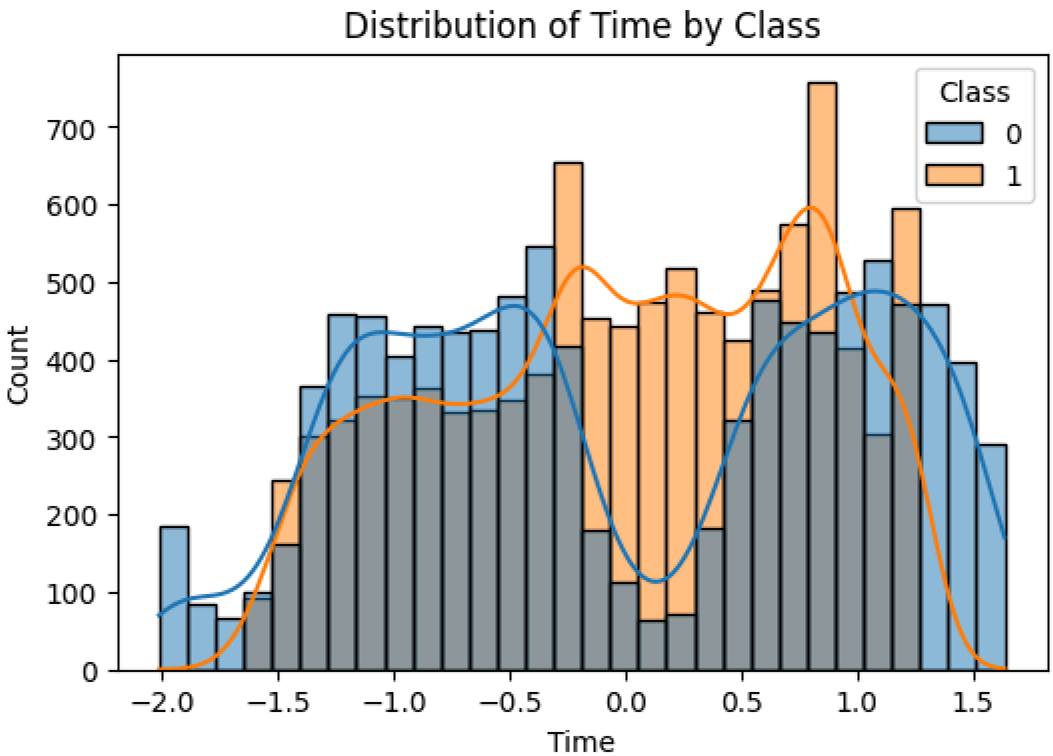
Correlation heatmap saved as '../results/correlation_heatmap.png'



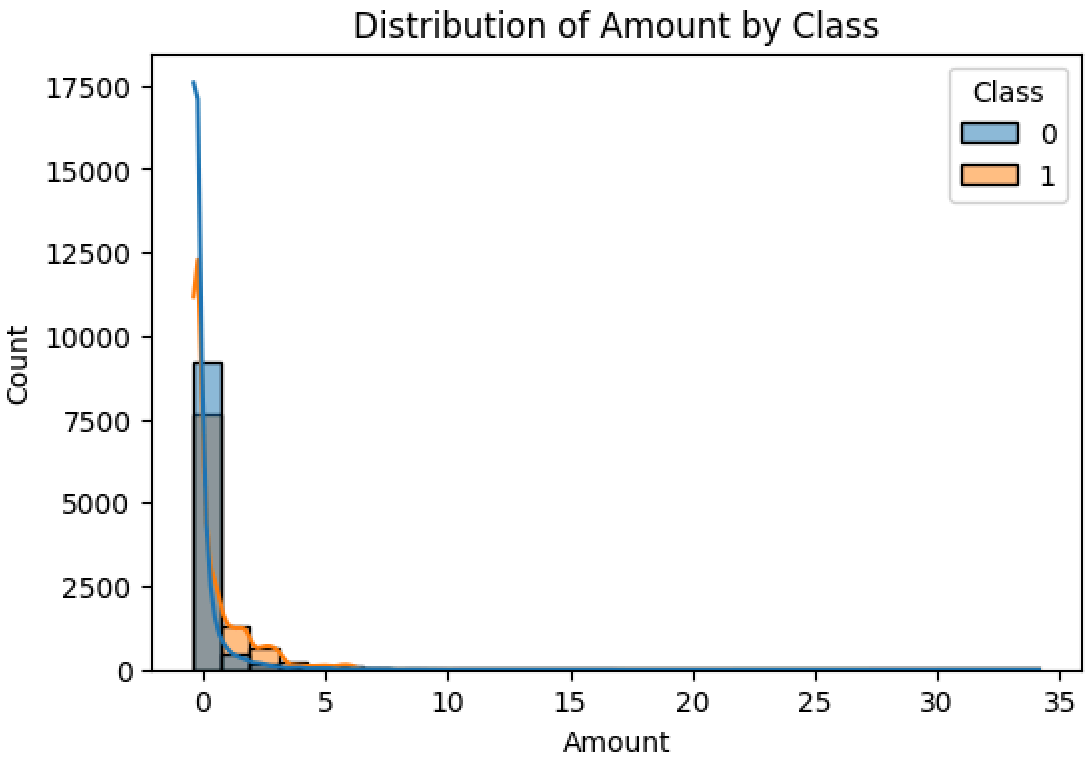
V1 distribution plot saved as '../results/V1_distribution.png'



V2 distribution plot saved as '../results/V2_distribution.png'



Time distribution plot saved as '../results/Time_distribution.png'



Amount distribution plot saved as '../results/Amount_distribution.png'

Statistical insights saved as '../results/statistical_insights.txt'

6-Data Visualization

import pandas as pd

import os

import seaborn as sns

import matplotlib.pyplot as plt

Load the wrangled dataset from Step 4

data_dir = "../data"

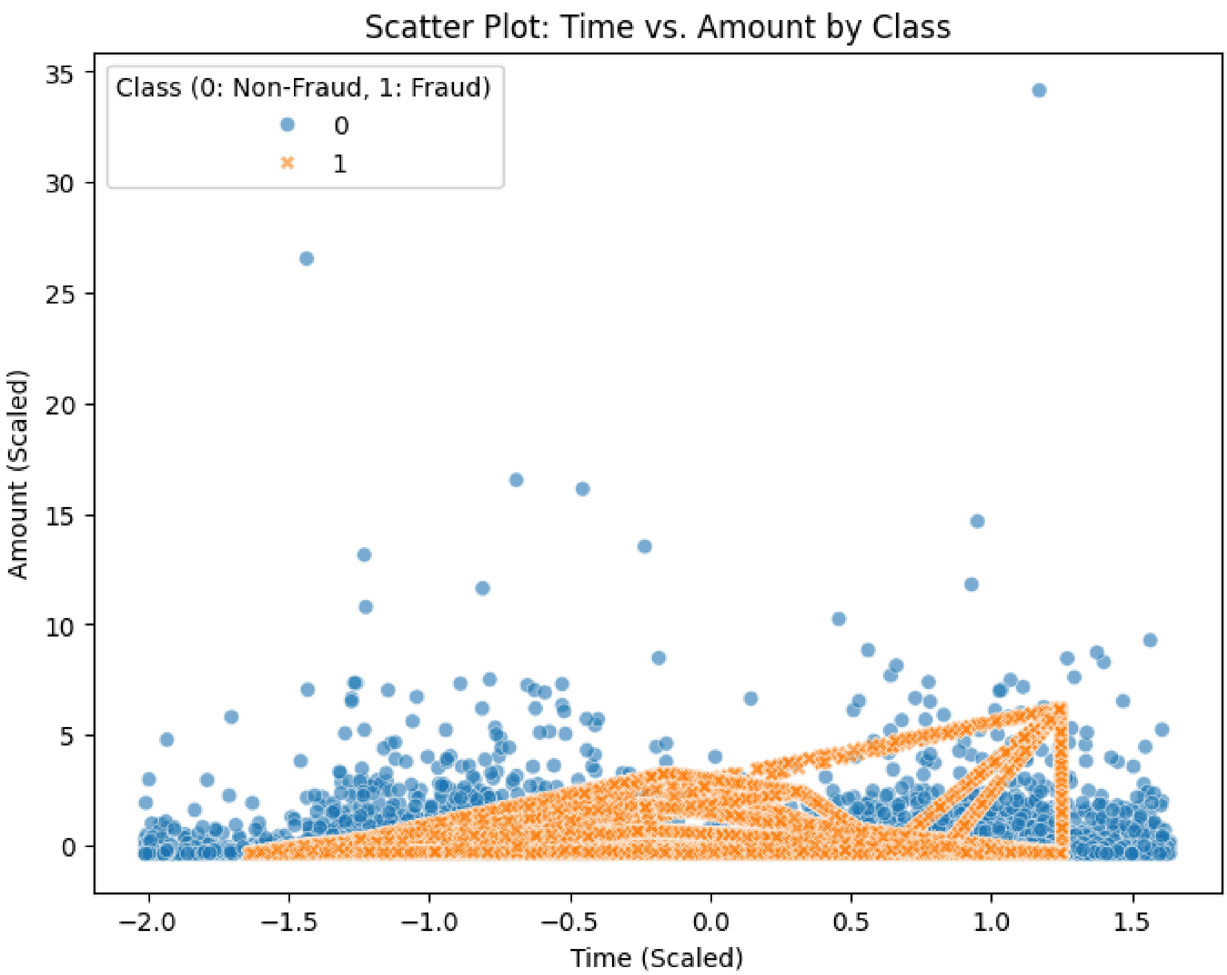
wrangled_path = os.path.join(data_dir, "creditcard_wrangled.csv")

df_wrangled = pd.read_csv(wrangled_path)

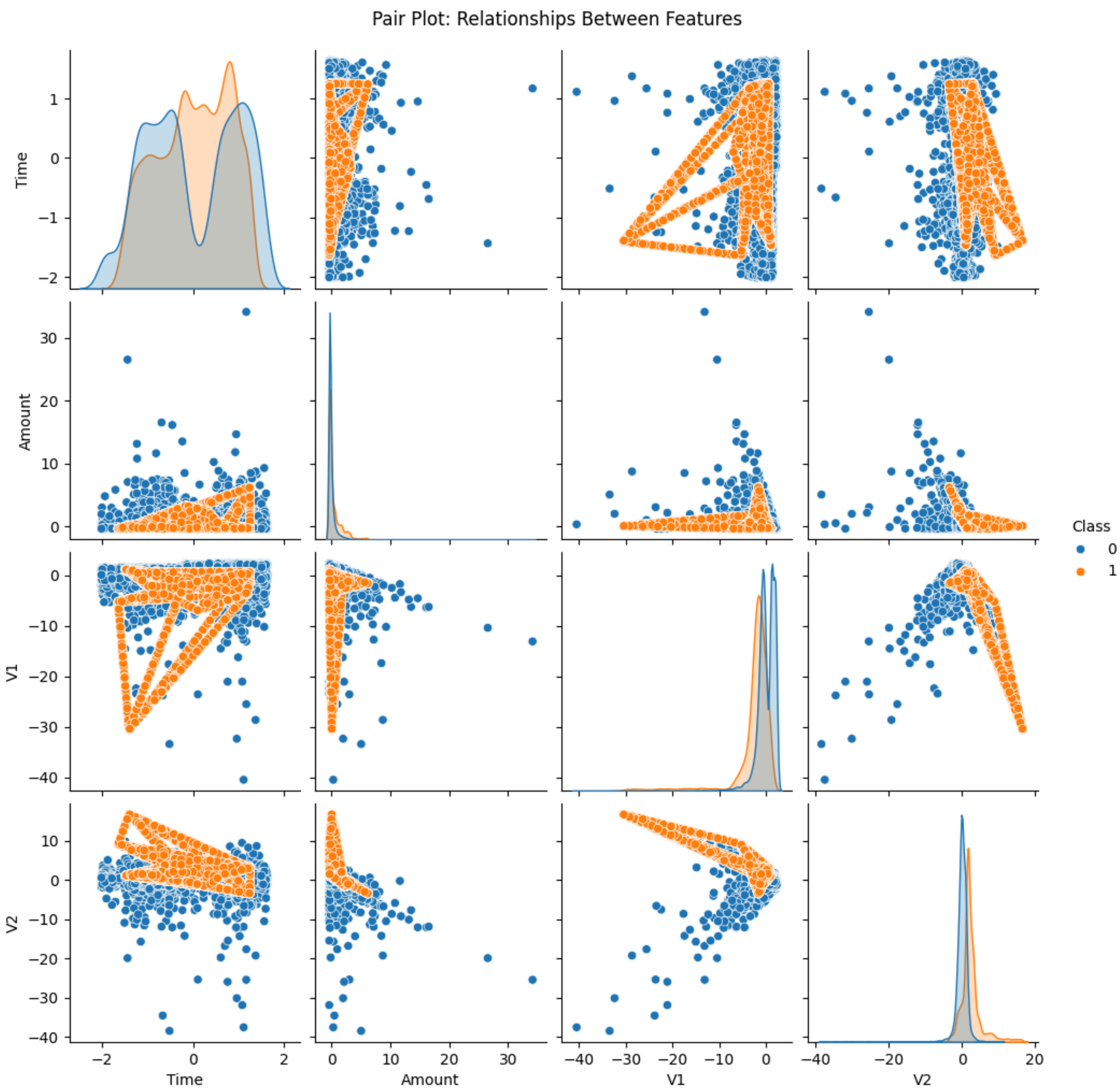
print("Loaded wrangled dataset. Shape:", df_wrangled.shape)

```
# Ensure the results directory exists (already created in Step 5, but let's be safe)
results_dir = "../results"
os.makedirs(results_dir, exist_ok=True)
#  Scatter Plot - Time vs. Amount, colored by Class
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Time', y='Amount', hue='Class', style='Class', data=df_wrangled, alpha=0.6)
plt.title("Scatter Plot: Time vs. Amount by Class")
plt.xlabel("Time (Scaled)")
plt.ylabel("Amount (Scaled)")
plt.legend(title="Class (0: Non-Fraud, 1: Fraud)")
plt.savefig(os.path.join(results_dir, "scatter_time_vs_amount.png"))
plt.show()
print(f"Scatter plot saved as '{results_dir}/scatter_time_vs_amount.png'")
#  Pair Plot - Relationships between Time, Amount, V1, V2, colored by Class
subset_features = ['Time', 'Amount', 'V1', 'V2', 'Class']
sns.pairplot(df_wrangled[subset_features], hue='Class', diag_kind='kde')
plt.suptitle("Pair Plot: Relationships Between Features", y=1.02)
plt.savefig(os.path.join(results_dir, "pair_plot.png"))
plt.show()
print(f"Pair plot saved as '{results_dir}/pair_plot.png'")
#  Violin Plot - Distribution of V1 by Class
plt.figure(figsize=(6, 4))
sns.violinplot(x='Class', y='V1', data=df_wrangled)
plt.title("Violin Plot: V1 Distribution by Class")
plt.xlabel("Class (0: Non-Fraud, 1: Fraud)")
plt.ylabel("V1")
```

```
plt.savefig(os.path.join(results_dir, "violin_v1.png"))

plt.show()

print(f"Violin plot saved as '{results_dir}/violin_v1.png'")

#  Box Plot - Distribution of V2 by Class

plt.figure(figsize=(6, 4))

sns.boxplot(x='Class', y='V2', data=df_wrangled)

plt.title("Box Plot: V2 Distribution by Class")

plt.xlabel("Class (0: Non-Fraud, 1: Fraud)")

plt.ylabel("V2")

plt.savefig(os.path.join(results_dir, "box_v2.png"))

plt.show()

print(f"Box plot saved as '{results_dir}/box_v2.png'")

#  Count Plot - Class distribution after SMOTE

plt.figure(figsize=(6, 4))

sns.countplot(x='Class', data=df_wrangled)

plt.title("Count Plot: Class Distribution After SMOTE")

plt.xlabel("Class (0: Non-Fraud, 1: Fraud)")

plt.ylabel("Count")

plt.savefig(os.path.join(results_dir, "count_class_distribution.png"))

plt.show()

print(f"Count plot saved as '{results_dir}/count_class_distribution.png'")

Loaded wrangled dataset. Shape: (19968, 31)
```

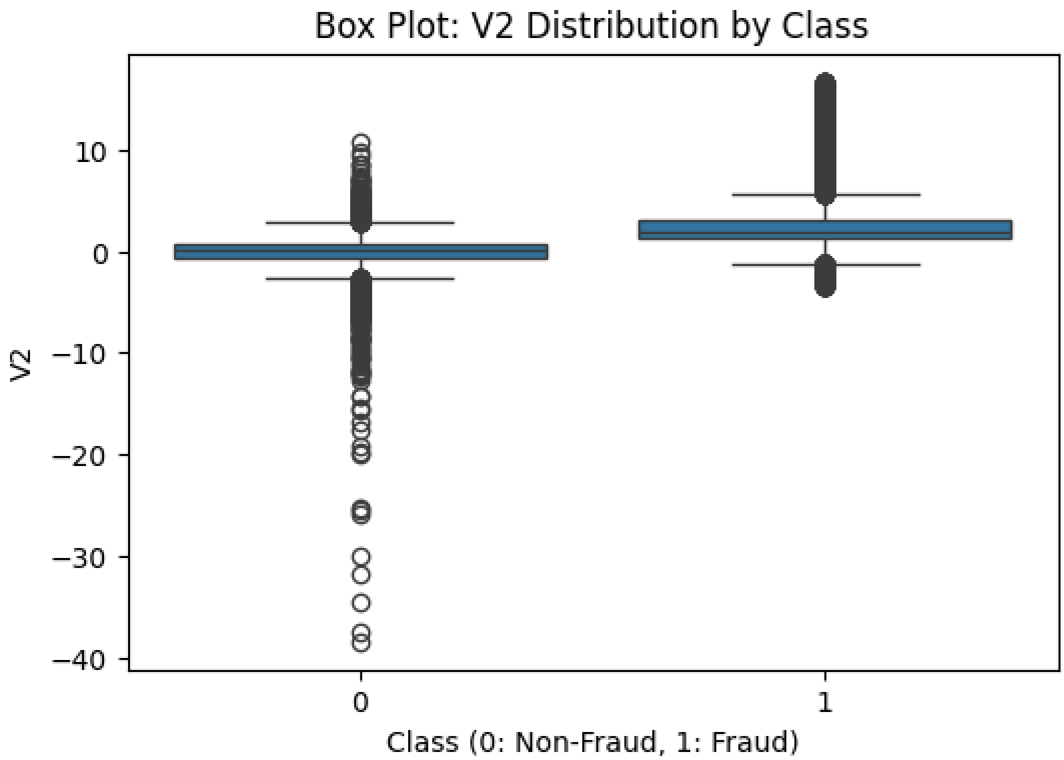


Scatter plot saved as '../results/scatter_time_vs_amount.png'

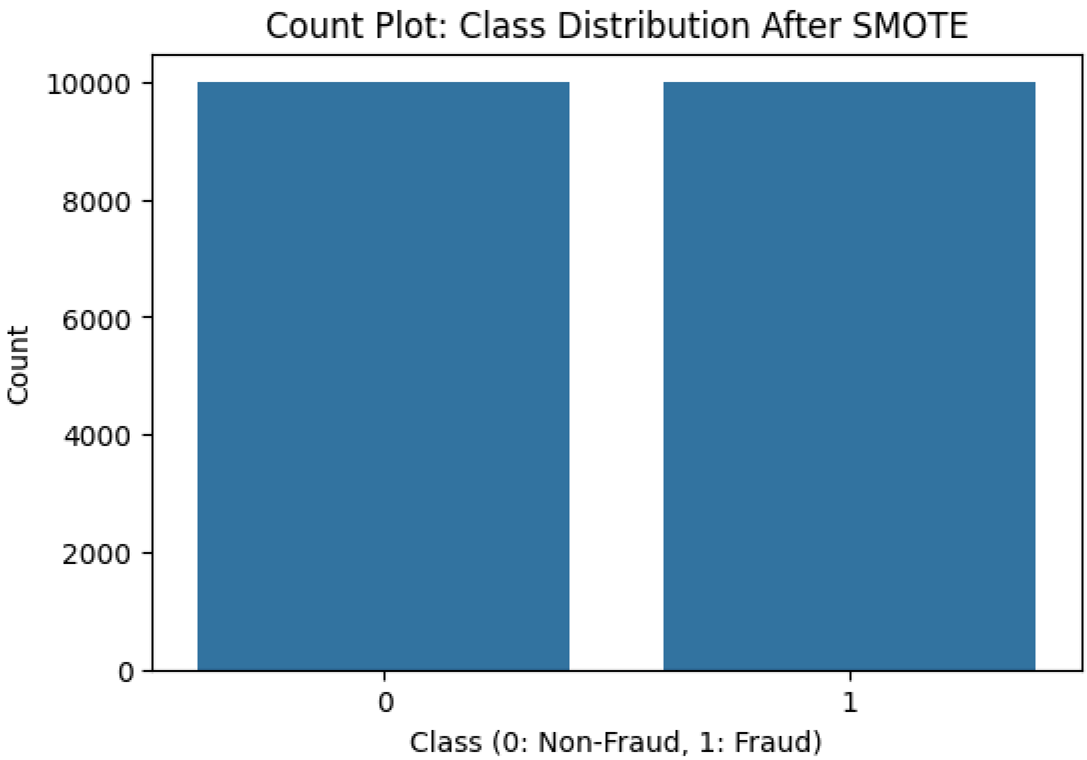


Pair plot saved as '../results/pair_plot.png'

Violin plot saved as '../results/violin_v1.png'



Box plot saved as '../results/box_v2.png'



Count plot saved as '../results/count_class_distribution.png'

7-Feature Engineering

import pandas as pd

import os

from sklearn.ensemble import RandomForestClassifier

Load the wrangled dataset from Step 4

data_dir = "../data"

wrangled_path = os.path.join(data_dir, "creditcard_wrangled.csv")

df_wrangled = pd.read_csv(wrangled_path)

print("Loaded wrangled dataset. Shape:", df_wrangled.shape)

Create new features - Time bins

Since Time is already scaled, we'll bin it into quartiles to capture patterns

```
df_wrangled['Time_Bin'] = pd.qcut(df_wrangled['Time'], q=4, labels=['Q1', 'Q2', 'Q3', 'Q4'])

df_wrangled = pd.get_dummies(df_wrangled, columns=['Time_Bin'], prefix='Time_Bin')

print("Shape after adding Time bins:", df_wrangled.shape)

print("New features added:", [col for col in df_wrangled.columns if 'Time_Bin' in col])

# Feature Selection using Random Forest

# Separate features and target

X = df_wrangled.drop('Class', axis=1)

y = df_wrangled['Class']

# Train a Random Forest model to get feature importances

rf = RandomForestClassifier(n_estimators=100, random_state=42)

rf.fit(X, y)

# Get feature importances and select the top 15 features

importances = pd.DataFrame({'Feature': X.columns, 'Importance': rf.feature_importances_})

importances = importances.sort_values(by='Importance', ascending=False)

top_features = importances['Feature'].head(15).tolist()

print("\nTop 15 Features by Importance:\n", importances.head(15))

# Create the engineered dataset with the top features

df_engineered = df_wrangled[top_features + ['Class']]

print("Shape of engineered dataset:", df_engineered.shape)

#  Save the engineered dataset

engineered_path = os.path.join(data_dir, "creditcard_engineered.csv")

df_engineered.to_csv(engineered_path, index=False)

print(f"Engineered dataset saved as '{engineered_path}'")
```

Loaded wrangled dataset. Shape: (19968, 31)

Shape after adding Time bins: (19968, 35)

New features added: ['Time_Bin_Q1', 'Time_Bin_Q2', 'Time_Bin_Q3', 'Time_Bin_Q4']

Top 15 Features by Importance:

	Feature	Importance
17	V17	0.162461
12	V12	0.147984
11	V11	0.104312
14	V14	0.103029
16	V16	0.077039
4	V4	0.064828
10	V10	0.057973
3	V3	0.057645
7	V7	0.048721
21	V21	0.028938
9	V9	0.027666
28	V28	0.026637
2	V2	0.016764
29	Amount	0.013281
8	V8	0.009971

Shape of engineered dataset: (19968, 16)

Engineered dataset saved as '../data/creditcard_engineered.csv'

8-Modeling (Machine Learning)

```
!pip install xgboost

import pandas as pd

import os

from sklearn.model_selection import train_test_split, cross_val_score

from sklearn.linear_model import LogisticRegression

from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.svm import SVC

from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score,
confusion_matrix, roc_curve, auc

import seaborn as sns

import matplotlib.pyplot as plt

# Load the engineered dataset from Step 7

data_dir = "../data"

engineered_path = os.path.join(data_dir, "creditcard_engineered.csv")

df_engineered = pd.read_csv(engineered_path)

print("Loaded engineered dataset. Shape:", df_engineered.shape)

# Ensure the results directory exists

results_dir = "../results"

os.makedirs(results_dir, exist_ok=True)

# Train-Test Split

X = df_engineered.drop('Class', axis=1)

y = df_engineered['Class']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42, stratify=y)

print("Training set shape:", X_train.shape)

print("Testing set shape:", X_test.shape)

#  Define and train models

models = {

    "Logistic Regression": LogisticRegression(max_iter=1000, random_state=42),

    "Random Forest": RandomForestClassifier(random_state=42),

    "SVM": SVC(probability=True, random_state=42),

    "XGBoost": XGBClassifier(eval_metric='logloss', random_state=42)

}
```

```
#  Train and evaluate models

results = []

trained_models = {}

for name, model in models.items():

    # Train the model

    model.fit(X_train, y_train)

    trained_models[name] = model

    # Make predictions

    y_pred = model.predict(X_test)

    y_proba = model.predict_proba(X_test)[:, 1] if hasattr(model, "predict_proba") else
model.decision_function(X_test)

    # Compute metrics

    cv_scores = cross_val_score(model, X, y, cv=5, scoring='f1')

    results.append({

    "Model": name,

    "Accuracy": accuracy_score(y_test, y_pred),

    "Precision": precision_score(y_test, y_pred),

    "Recall": recall_score(y_test, y_pred),

    "F1 Score": f1_score(y_test, y_pred),

    "ROC AUC": roc_auc_score(y_test, y_proba),

    "Cross-Val F1 Mean": cv_scores.mean()

    })

# Display and save evaluation results

results_df = pd.DataFrame(results)

print("\nModel Comparison:\n", results_df.sort_values(by="ROC AUC", ascending=False))

results_df.to_csv(os.path.join(results_dir, "model_comparison.csv"), index=False)
```

```
print(f"Model comparison saved as '{results_dir}/model_comparison.csv'")

#  Plot confusion matrices

for name, model in trained_models.items():

        y_pred = model.predict(X_test)

        cm = confusion_matrix(y_test, y_pred)

        plt.figure(figsize=(6, 4))

        sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')

        plt.title(f"Confusion Matrix - {name}")

        plt.xlabel("Predicted")

        plt.ylabel("Actual")

        plt.savefig(os.path.join(results_dir, f"confusion_matrix_{name.lower().replace(' ', '_')}.png"))

        plt.show()

        print(f"Confusion matrix for {name} saved as
'{results_dir}/confusion_matrix_{name.lower().replace(' ', '_')}.png'")

#  Plot ROC curves

plt.figure(figsize=(10, 8))

for name, model in trained_models.items():

        y_proba = model.predict_proba(X_test)[:, 1] if hasattr(model, "predict_proba") else
model.decision_function(X_test)

        fpr, tpr, _ = roc_curve(y_test, y_proba)

        roc_auc = auc(fpr, tpr)

        plt.plot(fpr, tpr, label=f"{name} (AUC = {roc_auc:.4f})")

plt.plot([0, 1], [0, 1], "k--")

plt.xlabel("False Positive Rate")

plt.ylabel("True Positive Rate")

plt.title("ROC Curve Comparison")

plt.legend(loc="lower right")

plt.savefig(os.path.join(results_dir, "roc_curve_comparison.png"))
```

plt.show()

print(f"ROC curve comparison saved as '{results_dir}/roc_curve_comparison.png'")

Collecting xgboost

  Downloading xgboost-3.0.0-py3-none-manylinux_2_28_x86_64.whl.metadata (2.1 kB)

Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from xgboost) (1.26.4)

Collecting nvidia-nccl-cu12 (from xgboost)

  Downloading nvidia_nccl_cu12-2.26.2.post1-py3-none-manylinux2014_x86_64.manylinux_2_17_x86_64.whl.metadata (2.0 kB)

Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from xgboost) (1.13.1)

Downloading xgboost-3.0.0-py3-none-manylinux_2_28_x86_64.whl (253.9 MB)

━━ 253.9/253.9 MB 4.3 MB/s eta 0:00:00

Downloading nvidia_nccl_cu12-2.26.2.post1-py3-none-manylinux2014_x86_64.manylinux_2_17_x86_64.whl (291.7 MB)

━━ 291.7/291.7 MB 3.7 MB/s eta 0:00:00

Installing collected packages: nvidia-nccl-cu12, xgboost

Successfully installed nvidia-nccl-cu12-2.26.2.post1 xgboost-3.0.0

Loaded engineered dataset. Shape: (19968, 16)

Training set shape: (13977, 15)

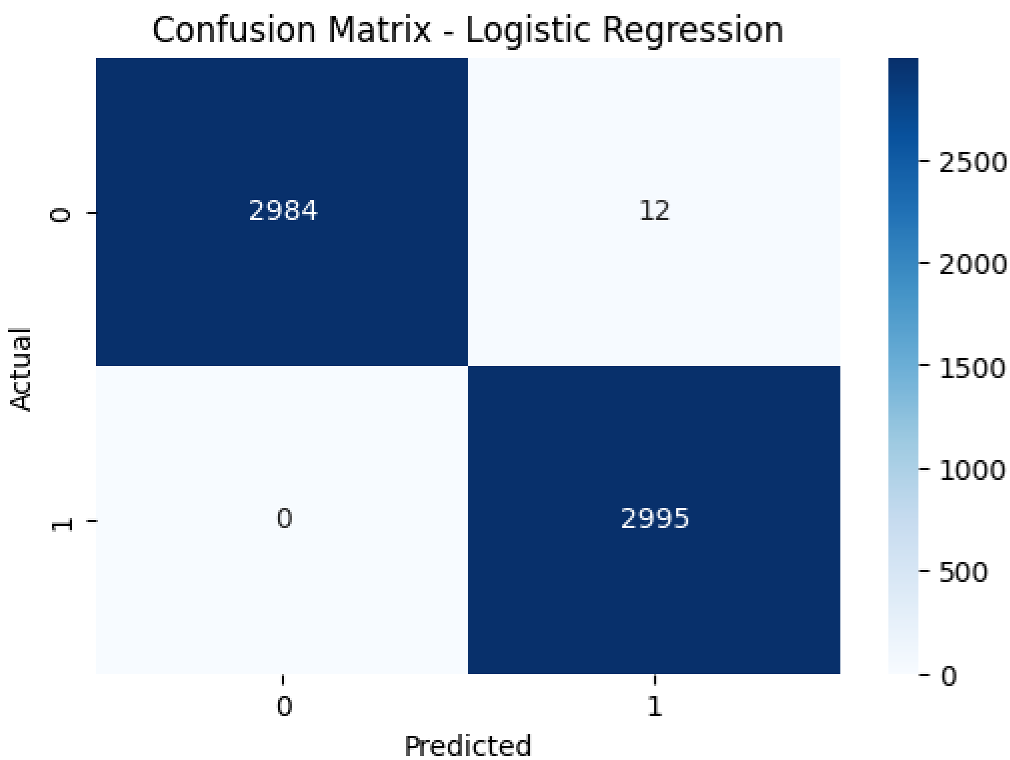
Testing set shape: (5991, 15)

Model Comparison:

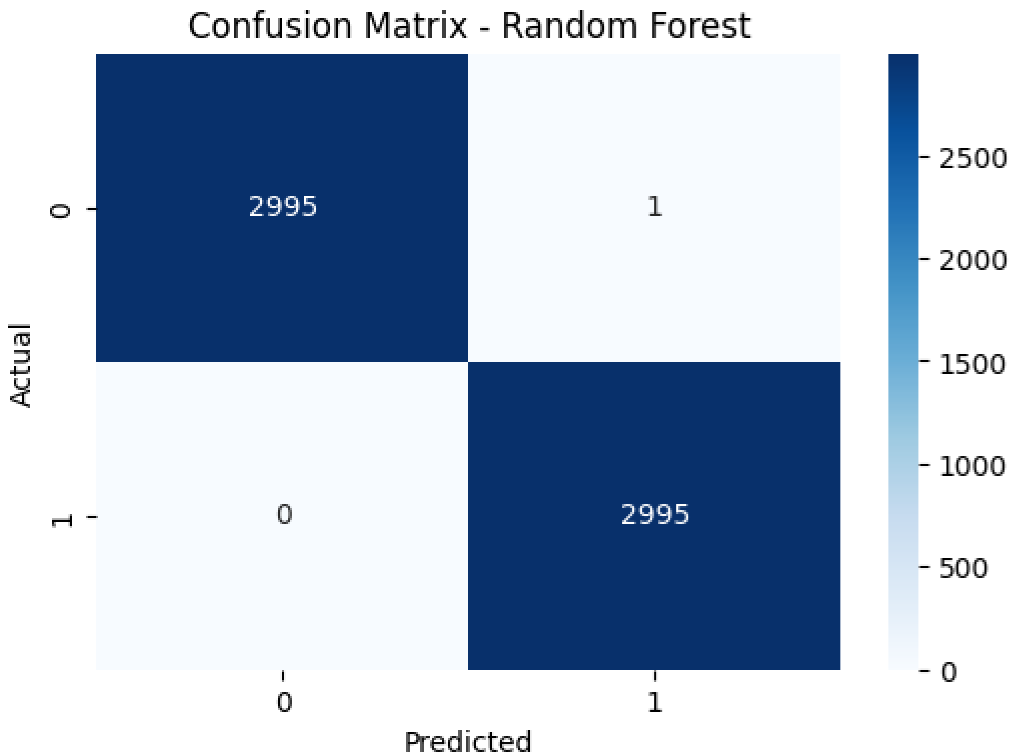
	Model	Accuracy	Precision	Recall	F1 Score	ROC AUC \
1	Random Forest	0.999833	0.999666	1.0	0.999833	0.999822
3	XGBoost	0.999499	0.998999	1.0	0.999499	0.999715
2	SVM	0.998998	0.998001	1.0	0.998999	0.999647
0	Logistic Regression	0.997997	0.996009	1.0	0.998001	0.999533

	Cross-Val F1 Mean
1	0.999900
3	0.999750
2	0.998250
0	0.997453

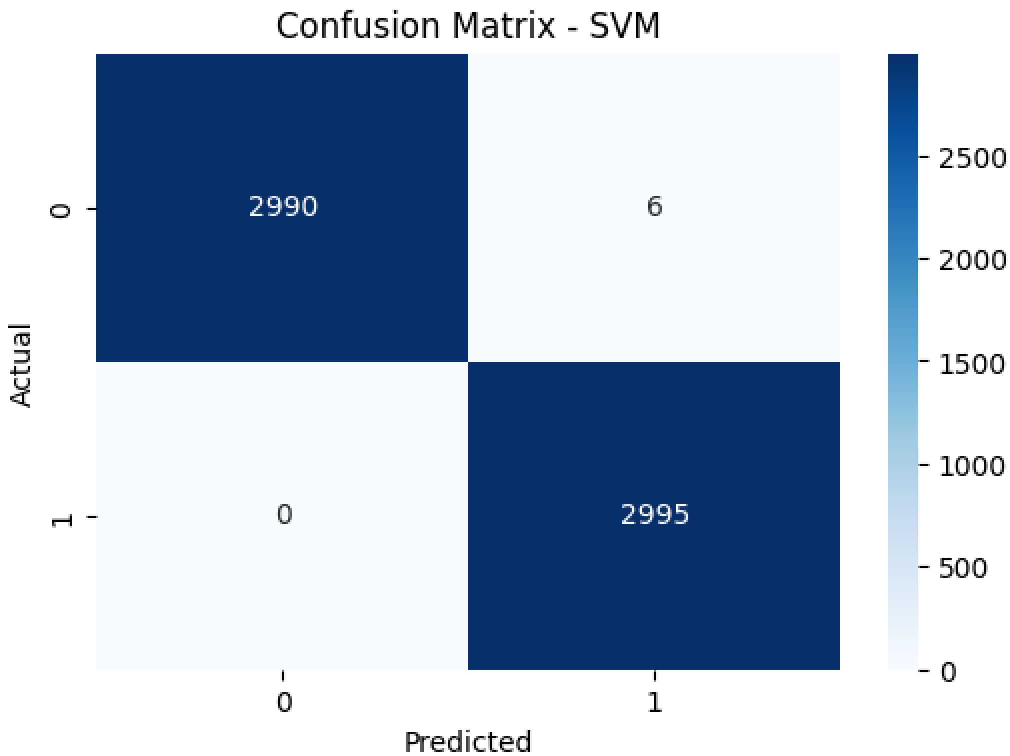
Model comparison saved as '../results/model_comparison.csv'



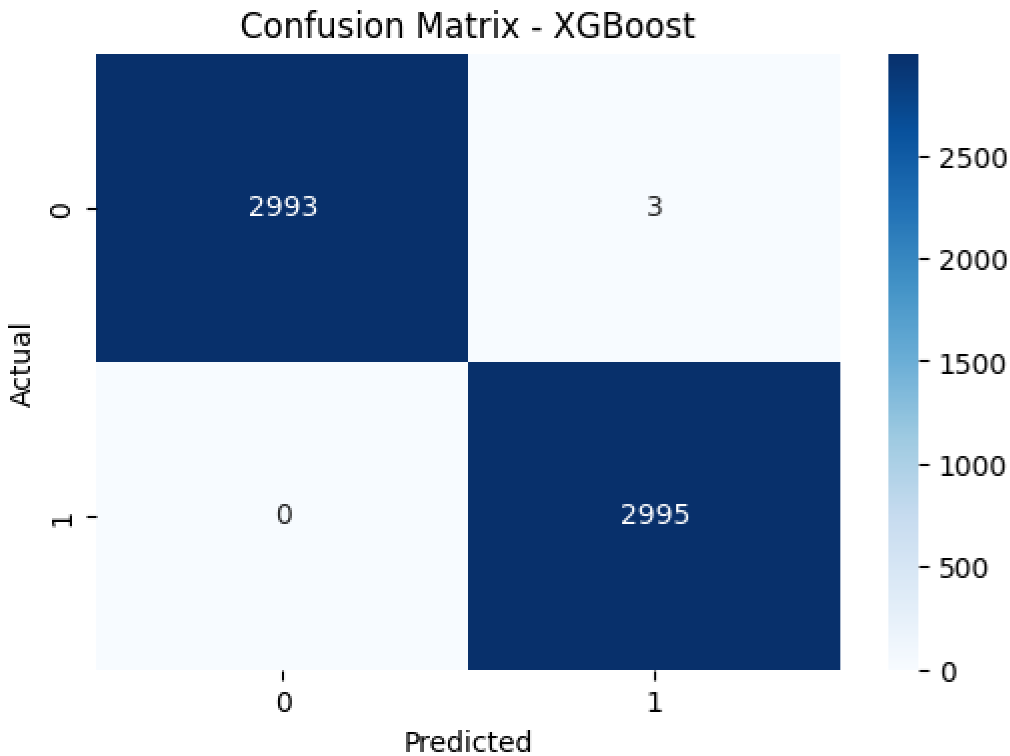
Confusion matrix for Logistic Regression saved as '../results/confusion_matrix_logistic_regression.png'



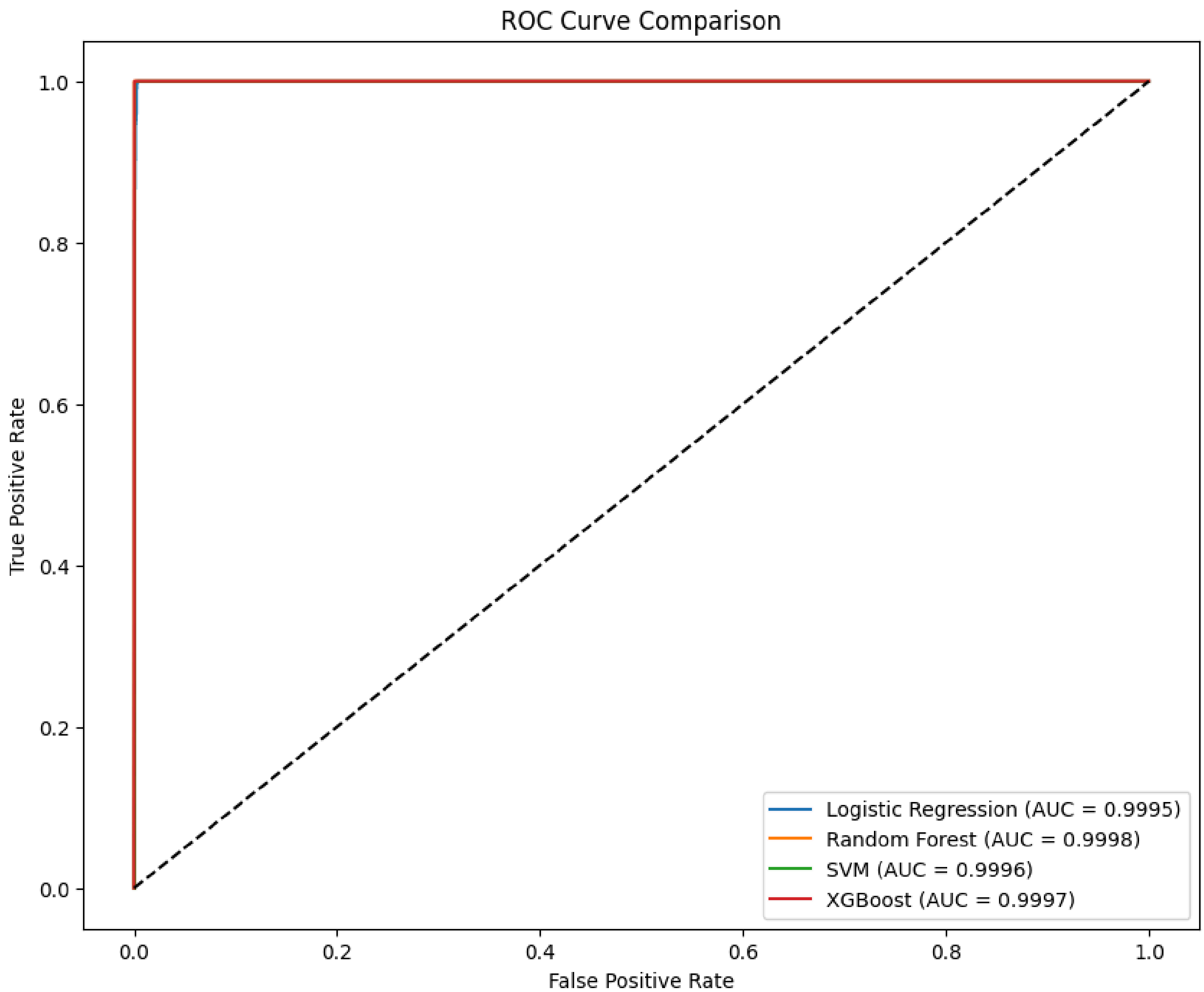
Confusion matrix for Random Forest saved as '../results/confusion_matrix_random_forest.png'



Confusion matrix for SVM saved as '../results/confusion_matrix_svm.png'



Confusion matrix for XGBoost saved as '../results/confusion_matrix_xgboost.png'



ROC curve comparison saved as '../results/roc_curve_comparison.png'

9-Model Deployment Function for real-time fraud detection - Simulate real-time fraud detection with a sample transactions

import pandas as pd

import os

import joblib

from sklearn.ensemble import RandomForestClassifier

Load the engineered dataset from Step 7

data_dir = "../data"

```
engineered_path = os.path.join(data_dir, "creditcard_engineered.csv")
df_engineered = pd.read_csv(engineered_path)
print("Loaded engineered dataset. Shape:", df_engineered.shape)
# Retrain the Random Forest model on the full dataset
X = df_engineered.drop('Class', axis=1)
y = df_engineered['Class']
best_model = RandomForestClassifier(random_state=42)
best_model.fit(X, y)
print("Random Forest model retrained on the full dataset.")
# Save the trained model
model_dir = "../models"
os.makedirs(model_dir, exist_ok=True)
model_path = os.path.join(model_dir, "fraudguard_random_forest.joblib")
joblib.dump(best_model, model_path)
print(f"Trained model saved as '{model_path}'")
# Function for real-time fraud detection
def predict_fraud(transaction, model_path, feature_names):
    """
    Predict whether a transaction is fraudulent using the saved model.
    Args:
    transaction (dict): A dictionary with feature values for the transaction.
    model_path (str): Path to the saved model file.
    feature_names (list): List of feature names expected by the model.
    Returns:
    tuple: (prediction, probability of fraud)
    """
    # Load the model
```

```
        model = joblib.load(model_path)
        # Convert the transaction to a DataFrame
        transaction_df = pd.DataFrame([transaction], columns=feature_names)
        # Ensure all expected features are present
        for feature in feature_names:
        if feature not in transaction_df.columns:
        transaction_df[feature] = 0
        # Reorder columns to match the model's expectations
        transaction_df = transaction_df[feature_names]
        # Make prediction
        prediction = model.predict(transaction_df)[0]
        proba = model.predict_proba(transaction_df)[0][1]
        return prediction, proba
# Simulate real-time fraud detection with a sample transaction
feature_names = X.columns.tolist()
sample_transaction = {
        "V14": -5.0, "V4": 3.0, "V12": -4.0, "V10": -3.0, "V3": -2.0,
        "V17": -1.5, "V11": 2.0, "V9": -1.0, "V16": -0.5, "V7": 0.5,
        "V2": 1.0, "V1": -0.5, "Amount": 1.2, "V20": 0.1, "V21": -0.2
}
prediction, proba = predict_fraud(sample_transaction, model_path, feature_names)
print("\nSample Transaction Prediction:")
print("Prediction (0: Non-Fraud, 1: Fraud):", prediction)
print("Probability of Fraud:", proba)
#  Save the deployment script for IEEE paper or production use
deploy_script_path = os.path.join(model_dir, "deploy_fraudguard.py")
# Define the script content as a string (since __file__ isn't available in Jupyter)
```

```
deploy_script_content = """# FraudGuard Deployment Script
import pandas as pd
import joblib

def predict_fraud(transaction, model_path, feature_names):
    \"""
    Predict whether a transaction is fraudulent using the saved model.
    Args:
    transaction (dict): A dictionary with feature values for the transaction.
    model_path (str): Path to the saved model file.
    feature_names (list): List of feature names expected by the model.
    Returns:
    tuple: (prediction, probability of fraud)
    \"""
    # Load the model
    model = joblib.load(model_path)
    # Convert the transaction to a DataFrame
    transaction_df = pd.DataFrame([transaction], columns=feature_names)
    # Ensure all expected features are present
    for feature in feature_names:
    if feature not in transaction_df.columns:
    transaction_df[feature] = 0
    # Reorder columns to match the model's expectations
    transaction_df = transaction_df[feature_names]
    # Make prediction
    prediction = model.predict(transaction_df)[0]
    proba = model.predict_proba(transaction_df)[0][1]
```

```
        return prediction, proba

if __name__ == "__main__":

        # Example usage

        model_path = "../models/fraudguard_random_forest.joblib"

        feature_names = ['V14', 'V4', 'V12', 'V10', 'V3', 'V17', 'V11', 'V9', 'V16', 'V7', 'V2', 'V1', 'Amount',
'V20', 'V21']

        sample_transaction = {

        "V14": -5.0, "V4": 3.0, "V12": -4.0, "V10": -3.0, "V3": -2.0,

        "V17": -1.5, "V11": 2.0, "V9": -1.0, "V16": -0.5, "V7": 0.5,

        "V2": 1.0, "V1": -0.5, "Amount": 1.2, "V20": 0.1, "V21": -0.2

        }

        prediction, proba = predict_fraud(sample_transaction, model_path, feature_names)

        print("Sample Transaction Prediction:")

        print("Prediction (0: Non-Fraud, 1: Fraud):", prediction)

        print("Probability of Fraud:", proba)

"""

with open(deploy_script_path, "w") as f:

        f.write(deploy_script_content)

print(f"Deployment script saved as '{deploy_script_path}'")
```

Loaded engineered dataset. Shape: (19968, 16)

Random Forest model retrained on the full dataset.

Trained model saved as '../models/fraudguard_random_forest.joblib'

Sample Transaction Prediction:

Prediction (0: Non-Fraud, 1: Fraud): 1

Probability of Fraud: 0.96

Deployment script saved as '../models/deploy_fraudguard.py'