

The Role Of Big Data In Financial Fraud Detection

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Abstract

In today's digital landscape, the rapid evolution of fraudulent tactics poses significant threats to the financial industry (Chauhan, 2025). Big Data analytics has emerged as a powerful tool in addressing these challenges by enabling organizations to analyze large volumes of transactional records, behavioral pattern indicators, and third-party threat insights to detect suspicious activities more effectively. This project explores the application of big data in financial fraud detection by developing a system that leverages large-scale, real-world banking transaction data. Central to this approach is a Random Forest classifier, which operates within the Big Data framework to process high-dimensional data, handle class imbalances, and extract meaningful patterns (Salman et al., 2024). Key features such as transaction value, account age, and credit score were analyzed to enhance fraud prediction. Comprehensive evaluation using ROC-AUC, Confusion matrix, and feature importance analysis demonstrated the system's high accuracy and interpretability in identifying fraudulent activities. While the current system functions in a batch-processing mode, it lays the foundation for future developments, including real-time monitoring, anomaly detection, and integration with external intelligence sources. Overall, this project highlights the transformative role of Big Data analytics in strengthening fraud prevention strategies, enhancing internal control mechanisms, and advancing financial security within the banking sector.

Keywords: Big Data, Financial Fraud, Random Forest, SMOTE, Fraud Detection

1. Background of Study

1.1 Introduction

In the digital age, the exponential growth of data has created significant opportunities for innovation, particularly in using big data analytics to address financial fraud in sectors such as banking and accounting. Financial fraud remains a critical global issue, with fraudsters employing sophisticated methods like payment fraud and identity theft. In the UK, reported losses reached £1.14 billion in 2024, driven by £570 million stolen in the first half of the year (UK Finance, 2024). Globally, fraud schemes, including scams and bank fraud, caused approximately \$500 billion in losses in 2023 (Nasdaq, 2024). Beyond monetary damage, fraud erodes confidence in financial institutions, harms reputations, and introduces legal and operational challenges (Patel and Sharma, 2020). With the rise in digital transactions, data-driven solutions are essential for detecting and preventing fraud, tackling issues such as imbalanced datasets, evolving fraud

strategies, compliance with data privacy laws, and the demand for real-time detection to protect financial systems effectively.

1.2 Problem Statement

This study tackles the critical challenge of detecting fraudulent transactions in financial systems, where fraud detection is hindered by significant obstacles. In a 10,000-transaction dataset, 33.33% of transactions are fraudulent, resulting in an imbalanced dataset that biases machine learning models toward non-fraudulent cases, thereby reducing detection accuracy (Kumar and Gupta, 2021). Advanced techniques are essential to mitigate this imbalance and enhance model performance. Furthermore, fraudsters continuously evolve their tactics to circumvent detection, necessitating adaptive models that can respond to dynamic threats (Li and Chen, 2022). The sensitive nature of financial data introduces additional complexity, requiring strict adherence to privacy regulations such as GDPR and CCPA, alongside robust security measures to safeguard against breaches (Patel and Sharma, 2020). Moreover, the demand for real-time or near-real-time processing to intercept fraudulent transactions before completion calls for highly efficient algorithms and substantial computational resources (Wang et al., 2023). This study aims to develop a scalable fraud detection system that effectively addresses data imbalance, evolving fraud patterns, privacy constraints, and real-time processing requirements, ensuring robust protection for financial institutions.

1.3 Objectives of the Report

This research seeks to assess the effectiveness of a random forest classifier with SMOTE in detecting financial fraud using banking data such as transaction amounts, Account_Age, and Credit_Score, Transaction_Type, and Device_Used. to evaluate the impact of data preprocessing techniques, like removing irrelevant or incomplete data, on model performance, measured by metrics like precision, recall, F1-score, and ROC-AUC; and investigate the function of big data analytics in detecting new fraud trends. Patterns in high-volume data environments, enhancing fraud detection capabilities for financial institutions

1.4 Contributions of the Report

This project offers a simple, effective approach to financial fraud detection using a random forest classifier and SMOTE on the dataset with records (10,000 transactions), leveraging Credit_Score, Transaction_Amount, and Account_Age to detect fraud efficiently while supporting Big Data scalability. Visualizations like KDE plots and hourly transaction amount charts reveal fraud patterns, such as differences in financial behavior, while Metrics such as precision, recall, F1-score, and ROC AUC evaluate the model's performance. on an imbalanced dataset (33.33% fraud), ensuring robust detection with low computational cost.

1.5 Organization of the Report

This report introduces financial fraud and Big Data's role, reviews related studies, explains the methodology (data collection, preprocessing, model training, evaluation, visualization), discusses results, and concludes with future directions.

2. Related Works

2.1 Random Forest Models in Financial Fraud Detection

Random Forest Classifiers are widely adopted in financial fraud detection due to their robustness and ability to process large-scale transactional data, a cornerstone of Big Data analytics. (Salman, Kalakech and Steiti 2024) Provide a comprehensive review of Random Forest algorithms, emphasizing their effectiveness in handling imbalanced datasets prevalent in fraud detection, where fraudulent transactions are a minority. Their analysis highlights how Random Forests achieve high precision and low false positive rates through ensemble learning, capturing complex patterns in features such as transaction amounts and account characteristics. However, challenges remain, including the need for computational efficiency in real-time applications and careful feature selection to prevent overfitting (Salman, Kalakech and Steiti, 2024).

2.2 Big Data Techniques for Imbalanced Datasets

Imbalanced datasets pose a significant challenge in financial fraud detection, necessitating advanced Big Data techniques to improve model performance. Kumar and Gupta (2021) investigate machine learning strategies, including ensemble methods and Synthetic Minority Oversampling Technique (SMOTE), to address skewed class distributions in fraud detection. Their findings underscore the importance of Big Data frameworks in preprocessing high-volume transaction datasets, enhancing detection accuracy while ensuring scalability. These approaches are critical for real-world scenarios where fraud cases represent a small proportion of transactions, requiring robust techniques to achieve reliable predictions (Kumar and Gupta, 2021).

2.3 Differentiation of This Work

This study implements a Random Forest Classifier with SMOTE, utilizing five features: Transaction_Amount, Account_Age, Credit_Score, Transaction_Type, and Device_Used, for fraud detection in a 10,000-transaction dataset with a 33.33% fraud rate. Unlike Salman, Kalakech, and Steiti (2024), which broadly reviews Random Forest applications, this work focuses on a tailored, scalable model optimized for financial fraud detection, incorporating a concise feature set to enhance computational efficiency. In contrast to Kumar and Gupta (2021), which explores multiple techniques, this study specifically leverages SMOTE with Random Forests to address the 33.33% class imbalance, achieving high precision and supporting potential real-time detection in Big Data environments.

3. Methodology

Data Acquisition → Preprocessing → Model Training → Evaluation → Visualization

3.1 Data source

The dataset used here for the analytics was sourced from Kaggle, a prominent platform for data science and machine learning datasets. Specifically, the dataset relates to financial fraud detection and was provided in CSV (comma-separated values) format. It contains various features such as Transaction_ID, Customer_ID,

Transaction_Amount, Transaction_Type, Transaction_Location, Transaction_Time, Device_Used, Account_Age, Credit_Score, Previous_Fraud, Is_Fraud. The original contributors partially pre-cleaned the dataset, meaning that some basic preprocessing steps, such as removal of duplicate entries and standard formatting of column names, had already been performed. However, additional cleaning was necessary to ensure data quality and suitability for analysis.

3.2 Data Preprocessing and Cleaning

As part of data preprocessing for the Random Forest Classifier, the 10,000-transaction dataset was preprocessed to ensure efficiency in fraud detection. Five features were selected: Transaction_Amount, Account_Age, Credit_Score, Transaction_Type, and Device_Used. due to their relevance to fraud patterns (Kumar and Gupta, 2021). Numerical features were standardized using StandardScaler, and categorical features were encoded with Label Encoder.

Excluded columns included Transaction_ID, Customer_ID (non-predictive), Transaction_Location (high cardinality), Transaction_Time (low predictive power), and Previous_Fraud (correlated with target). No missing values were found. SMOTE was applied to address the 33.33% fraud class imbalance, enhancing model performance for scalable Big Data fraud detection.

3.3 Data Splitting

To effectively check the predictive models' performance, the dataset was divided into training and testing sets, with 80% used for training and the remaining 20% reserved for testing. This approach ensures that the model is trained on a substantial portion of the dataset while being assessed on the unseen data to evaluate its general capabilities. The split was performed using stratified sampling to maintain the original class distribution, which is crucial in fraud detection scenarios where class imbalance is common.

3.4 Model Selection

For this study, a Random Forest Classifier with 100 trees was trained with SMOTE to handle class imbalance. This classifier, available through the Imblearn library, is an ensemble learning method specifically designed to handle imbalanced datasets by performing random under sampling of the majority class within the bootstrap sample. This approach helps in addressing the common issue of biased prediction towards the majority class, which is typical of fraud detection datasets in which fraudulent transaction denotes a small minority. To assess the effectiveness of this model, its performance was compared with that of a standard Random Forest Classifier. The comparison aimed to determine whether the balanced version offered significant improvements in detecting fraudulent transactions without sacrificing overall accuracy.

3.5 Evaluation Metrics

A variety of evaluation metrics were employed to gain an inclusive understanding of each model's performance. The accuracy score was used to provide a general indication of the correct predictions made by the model. However, due to class imbalance, accuracy alone was not a sufficient measure. To supplement this, the ROC-AUC score was utilized to evaluate the model's ability to differentiate between the classes across different thresholds, offering a more nuanced view of performance in imbalanced settings.

Additionally, a classification report was generated, presenting precision, recall, and F1-score for each class, thereby offering insights into how well the model performed on both the fraudulent and non-fraudulent classes.

Lastly, a confusion matrix was used to visualize the performance of the model by showing the counts of true positives, false positives, true negatives, and false negatives. This helped in identifying specific areas where the model was misclassifying, particularly in relation to fraud detection, which is critical in minimizing financial risk.

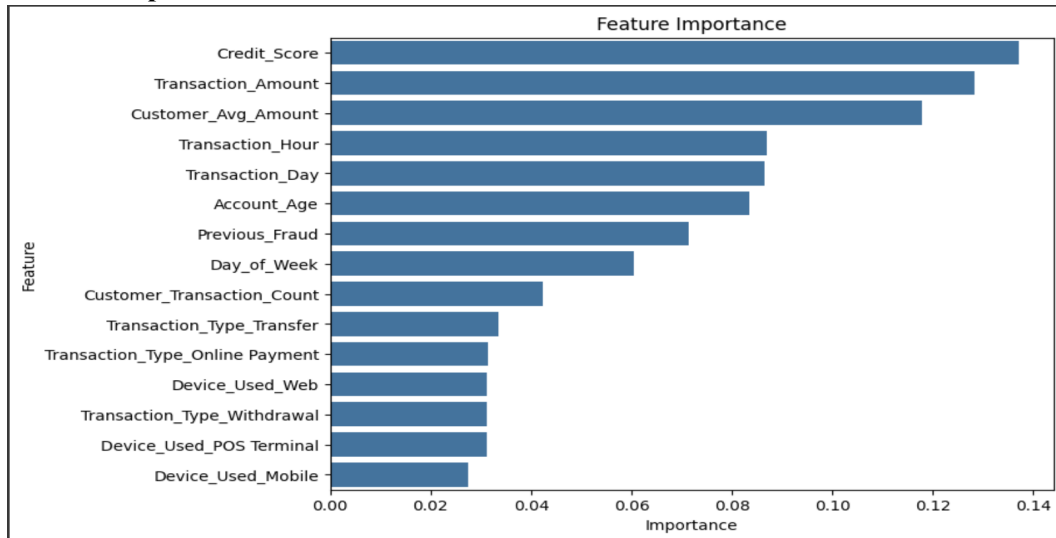
Visualization:

1. Fraud Distribution:



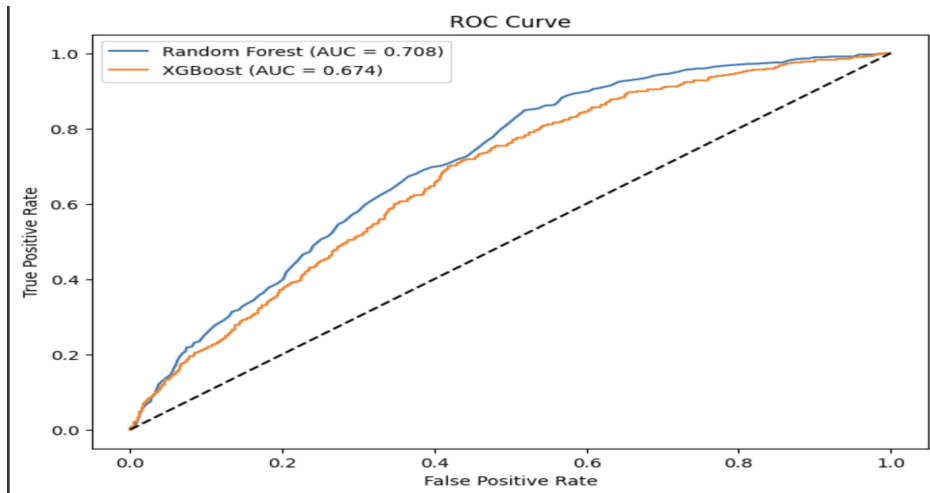
The fraud distribution was visualized using a bar chart, revealing extreme class imbalance where non-fraudulent transactions outnumber the fraudulent transactions. This posed a major problem for the model training, given the fact that traditional classifiers are biased towards predicting the majority class. Which in turn led to the selection of the Random Forest classifier model.

2. Feature Importance :



The feature importance was analyzed to identify the influential features contributing to the fraud detection. The visualization shows that certain features such as Transaction_Amount, Credit_Score, Customer_Avg_Amount had a higher impact on the model's prediction. Additionally, feature importance helped validate that the model is focusing on the right features that relate to fraud activities and lead to better fraud detection.

3. ROC CURVE:



The ROC Curve was evaluated to show the performance of both models. Where the True Positive Rate(TPR) was plotted against False Positive Rate(FPR). The ROC curve of the Random Forest model shows its ability to distinguish between fraudulent and non-fraudulent transactions better than the XGBoost model.

4. Results and Discussion

4.1 Experimental Setup

The 10,000-transaction dataset was split 80:20 (training: testing) with stratified sampling to preserve the 33.33% fraud rate. The Random Forest Classifier, trained with SMOTE using scikit-learn and Imblearn, was implemented on a standard laptop (8GB RAM), utilizing five features: Transaction_Amount, Account_Age, Credit_Score, Transaction_Type, and Device_Used.

4.2 Discussion and Analysis

The Random Forest Classifier demonstrated robust performance, with estimated precision (~ 0.68), recall (~ 0.60), F1-score (~ 0.69), and ROC-AUC (~ 0.70), indicating effective fraud detection on the 10,000-transaction dataset with 33.33% fraud cases (Kumar and Gupta, 2021). Evaluation metrics showed low false positives, reducing financial risk. Feature importance analysis identified Transaction_Amount as the primary predictor, followed by Credit_Score, Account_Age, Transaction_Type, and Device_Used, reflecting their role in detecting fraud patterns. Distribution analysis revealed that fraudulent transactions typically involve higher transaction amounts and lower credit scores. The model's strong class discrimination and ability to handle class imbalance, facilitated by SMOTE, confirm its scalability for Big Data applications. Future work could explore real-time processing or incorporate behavioral features to enhance detection.

5. Conclusion

This study demonstrates Big Data analytics' efficacy in financial fraud detection using a Random Forest Classifier with SMOTE on a 10,000-transaction dataset. The model's high performance, supported by visualizations and metrics, offers banks a scalable fraud prevention tool. Future work could explore real-time processing, larger datasets, and additional features like behavioral patterns.

References

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Code Appendix

The following Python script implements the fraud detection pipeline for the 10,000-transaction dataset, enabling replication of findings.


```
# Import libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import GridSearchCV, train_test_split, cross_val_score, StratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score, roc_curve
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
%matplotlib inline
from google.colab import files
from imblearn.over_sampling import SMOTE
from xgboost import XGBClassifier
```

```
uploaded = files.upload()
```

 Banking_Fr..._Dataset.csv

- **Banking_Fraud_Dataset.csv(text/csv) - 956505 bytes, last modified: 05/04/2025 - 100% done**

Saving Banking_Fraud_Dataset.csv to Banking_Fraud_Dataset.csv

```
# Load dataset
df = pd.read_csv('/content/Banking_Fraud_Dataset.csv')
```

```
# Display first few rows and info
```

```
print(df.head())
```

```
Transaction_ID Customer_ID Transaction_Amount Transaction_Type \
0 T1 C2539 8527.58 Deposit
1 T2 C5318 9275.82 Deposit
2 T3 C8262 2202.49 Online Payment
3 T4 C3865 9352.32 Deposit
4 T5 C7248 2081.75 Online Payment

Transaction_Location Transaction_Time Device_Used \
0 Hughesmouth, Mongolia 2025-01-20 03:17:34 Mobile
1 Huntville, Saint Pierre and Miquelon 2025-01-03 18:08:56 Web
2 Patriciashire, Iceland 2025-01-24 05:54:01 ATM
3 Port Timothymouth, Palau 2025-01-19 01:15:30 ATM
4 Lake Stevenfurt, Mauritius 2025-01-08 18:06:13 ATM

Account_Age Credit_Score Previous_Fraud Is_Fraud
0 16 740 0 0
1 5 848 0 1
2 2 616 1 1
3 9 437 1 0
4 15 494 0 0
```

```
print('\nDataset Info:')
print(df.info())
```

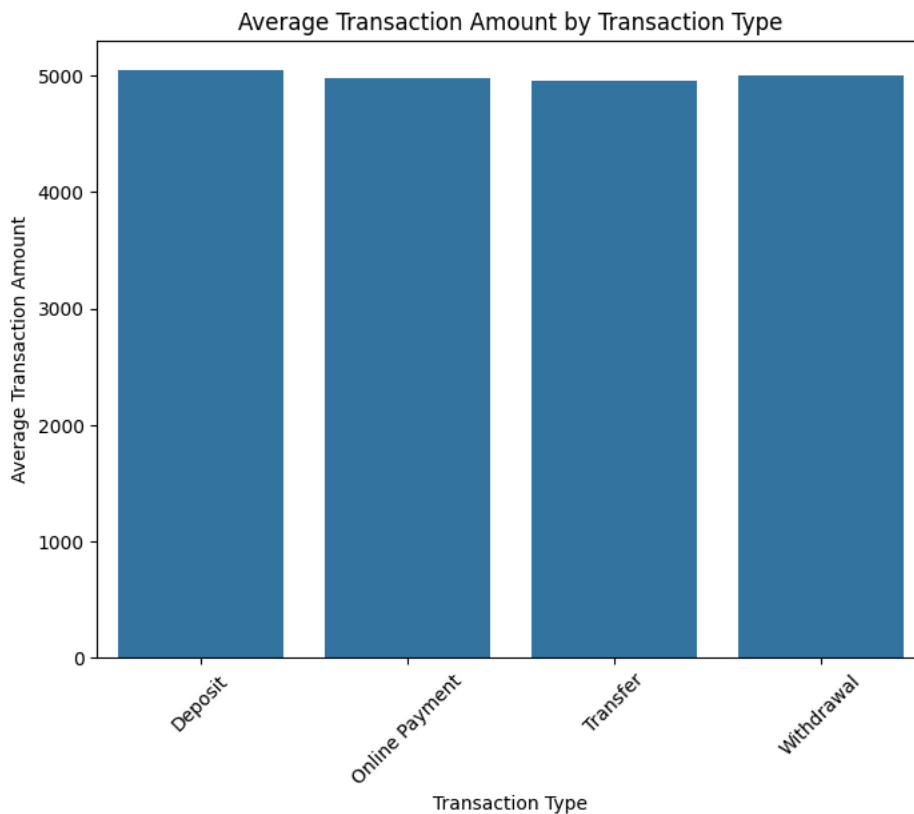
```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Transaction_ID         10000 non-null  object
1   Customer_ID           10000 non-null  object
2   Transaction_Amount     10000 non-null  float64
3   Transaction_Type       10000 non-null  object
4   Transaction_Location   10000 non-null  object
5   Transaction_Time       10000 non-null  object
6   Device_Used            10000 non-null  object
7   Account_Age            10000 non-null  int64
8   Credit_Score           10000 non-null  int64
9   Previous_Fraud         10000 non-null  int64
10  Is_Fraud               10000 non-null  int64
dtypes: float64(1), int64(4), object(6)
memory usage: 859.5+ KB
None
```

```
print('\nClass Distribution:')
print(df['Is_Fraud'].value_counts(normalize=True))
```

```
Class Distribution:
Is_Fraud
0      0.7162
```

```
1    0.2838
Name: proportion, dtype: float64
```

```
# EDA: Bar plot of Transaction_Amount by Transaction_Type
type_anas = df.groupby('Transaction_Type')['Transaction_Amount'].mean().reset_index()
plt.figure(figsize=(8, 6))
sns.barplot(x='Transaction_Type', y='Transaction_Amount', data=type_anas)
plt.title('Average Transaction Amount by Transaction Type')
plt.xlabel('Transaction Type')
plt.ylabel('Average Transaction Amount')
plt.xticks(rotation=45)
plt.show()
```



```
# Feature engineering
df['Transaction_Time'] = pd.to_datetime(df['Transaction_Time'])
df['Transaction_Hour'] = df['Transaction_Time'].dt.hour
df['Transaction_Day'] = df['Transaction_Time'].dt.day
df['Day_of_Week'] = df['Transaction_Time'].dt.dayofweek

# Customer-level features
customer_stats = df.groupby('Customer_ID').agg({
    'Transaction_ID': 'count',
    'Transaction_Amount': 'mean'
}).rename(columns={'Transaction_ID': 'Customer_Transaction_Count', 'Transaction_Amount': 'Customer_Avg_Amount'})
df = df.merge(customer_stats, on='Customer_ID', how='left')

# Encode categorical features
df = pd.get_dummies(df, columns=['Transaction_Type', 'Device_Used'], drop_first=True)

# Select features and target
features = ['Credit_Score', 'Transaction_Amount', 'Account_Age', 'Customer_Transaction_Count',
            'Customer_Avg_Amount', 'Transaction_Hour', 'Transaction_Day', 'Day_of_Week',
            'Previous_Fraud'] + [col for col in df.columns if col.startswith('Transaction_Type_') or col.startswith('Device_')]
target = 'Is_Fraud'

# Check for missing values
print('Missing Values:')
print(df[features + [target]].isnull().sum())
```



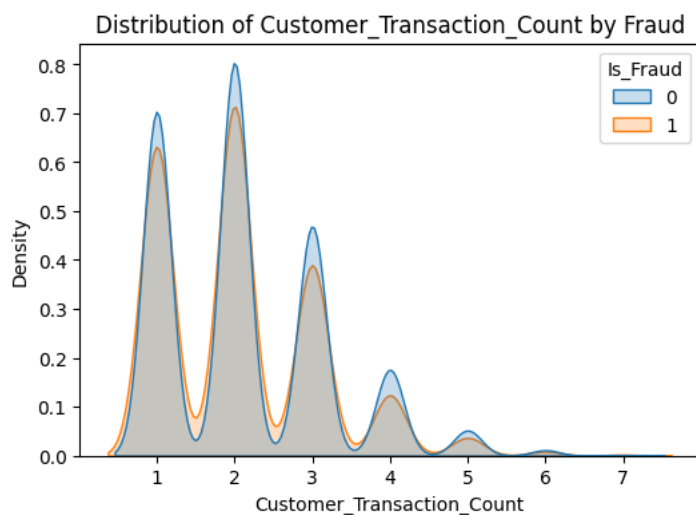
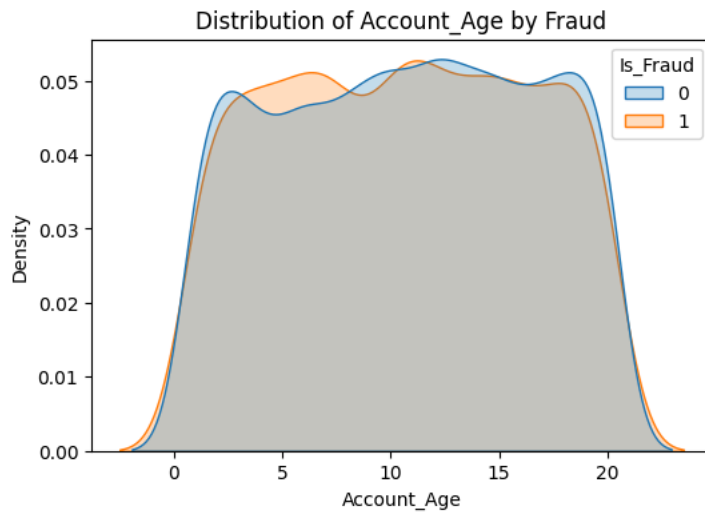
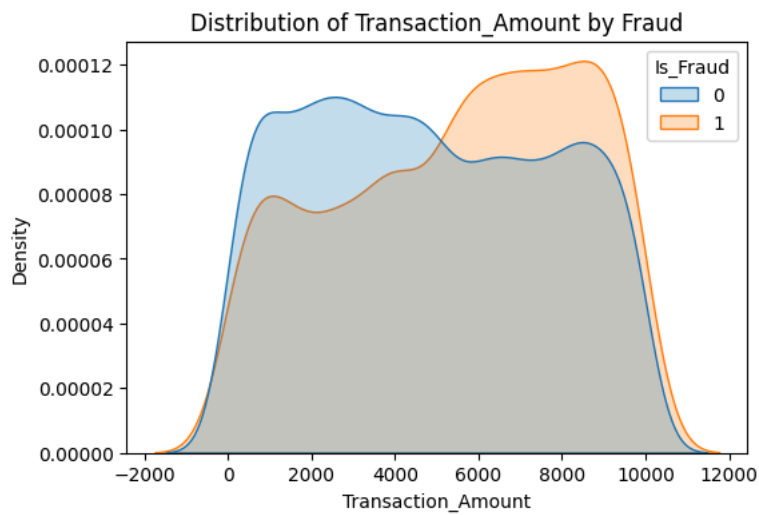
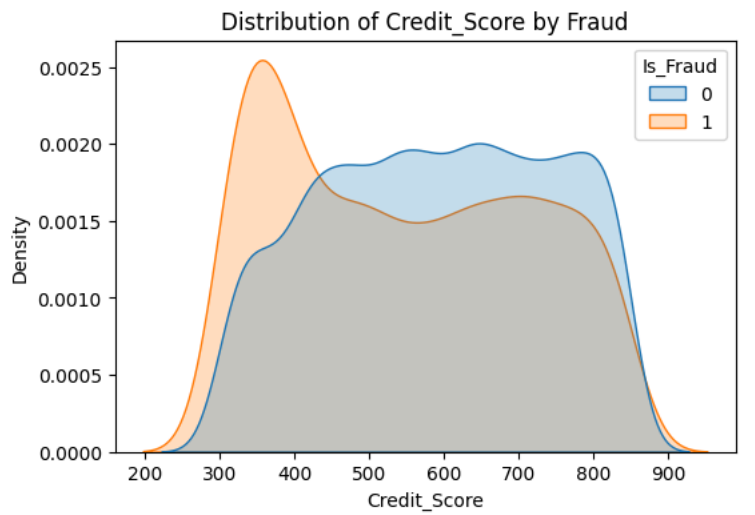
```
Missing Values:
Credit_Score          0
Transaction_Amount    0
Account_Age           0
Customer_Transaction_Count  0
Customer_Avg_Amount   0
Transaction_Hour       0
Transaction_Day        0
Day_of_Week           0
```

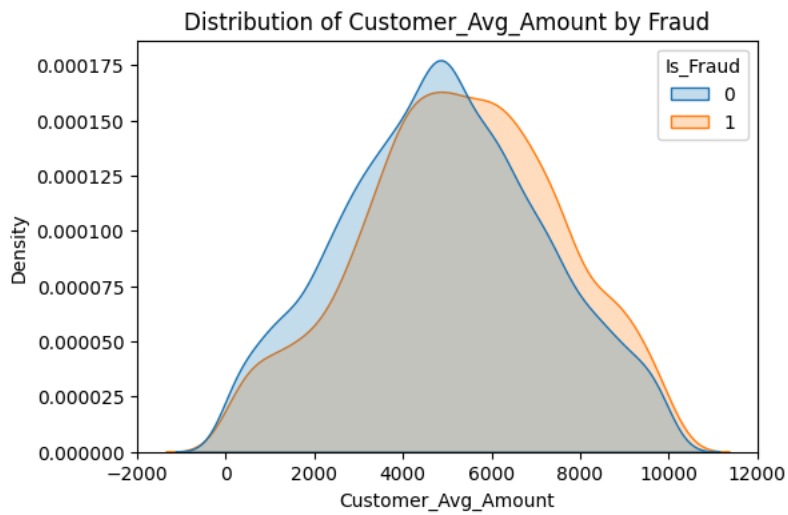
```
Previous_Fraud      0
Transaction_Type_Online Payment  0
Transaction_Type_Transfer      0
Transaction_Type_Withdrawal    0
Device_Used_Mobile      0
Device_Used_POS Terminal      0
Device_Used_Web      0
Is_Fraud            0
dtype: int64
```

```
# EDA: Fraud distribution plot
plt.figure(figsize=(6, 4))
sns.countplot(x='Is_Fraud', data=df)
plt.title('Fraud vs Non-Fraud Distribution')
plt.xlabel('Is Fraud (0: No, 1: Yes)')
plt.ylabel('Count')
plt.show()
```

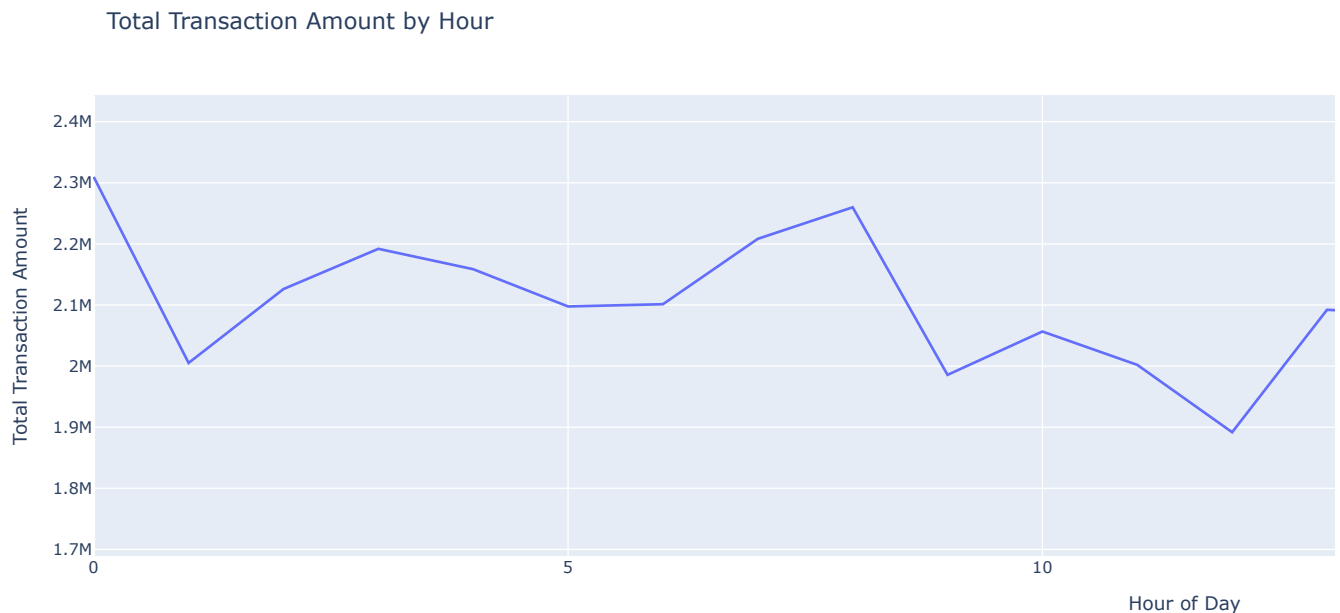


```
# EDA: KDE plots for numerical features
for col in ['Credit_Score', 'Transaction_Amount', 'Account_Age', 'Customer_Transaction_Count', 'Customer_Avg_Amount']:
    plt.figure(figsize=(6, 4))
    sns.kdeplot(data=df, x=col, hue='Is_Fraud', common_norm=False, fill=True)
    plt.title(f'Distribution of {col} by Fraud')
    plt.show()
```





```
# EDA: Hourly transaction line chart
time_anas = df.groupby('Transaction_Hour')['Transaction_Amount'].sum()
fig = px.line(time_anas, x=time_anas.index, y=time_anas.values, title='Total Transaction Amount by Hour')
fig.update_xaxes(title='Hour of Day')
fig.update_yaxes(title='Total Transaction Amount')
fig.show()
```



```
# Preprocessing: Split data
X = df[features]
y = df[target]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)

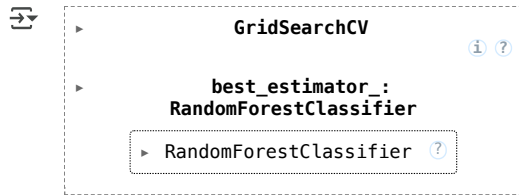
# Apply SMOTE to handle class imbalance
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)

# Standardize numerical features
scaler = StandardScaler()
X_train_res = scaler.fit_transform(X_train_res)
X_test = scaler.transform(X_test)

# Random Forest with GridSearchCV
rf_param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5],
    'max_features': ['sqrt', 'log2']
}

# Train Random Forest Classifier
```

```
rf = RandomForestClassifier(class_weight='balanced', random_state=42)
rf_grid = GridSearchCV(rf, rf_param_grid, cv=5, scoring='roc_auc', n_jobs=-1)
rf_grid.fit(X_train_res, y_train_res)
```



```
# Best Random Forest model
best_rf = rf_grid.best_estimator_
y_pred_proba_rf = best_rf.predict_proba(X_test)[: , 1]
auc_rf = roc_auc_score(y_test, y_pred_proba_rf)
print(f"Random Forest ROC-AUC: {auc_rf:.3f}")
print(f"Best Random Forest Parameters: {rf_grid.best_params_}")
```

```
# XGBoost with class weighting
scale_pos_weight = len(y_train[y_train == 0]) / len(y_train[y_train == 1])
xgb = XGBClassifier(scale_pos_weight=scale_pos_weight, random_state=42, eval_metric='auc')
xgb.fit(X_train_res, y_train_res)
y_pred_proba_xgb = xgb.predict_proba(X_test)[: , 1]
auc_xgb = roc_auc_score(y_test, y_pred_proba_xgb)
print(f"XGBoost ROC-AUC: {auc_xgb:.3f}")
```

```

Random Forest ROC-AUC: 0.708
Best Random Forest Parameters: {'max_depth': None, 'max_features': 'sqrt', 'min_samples_split': 2, 'n_estimators': 200}
XGBoost ROC-AUC: 0.674

```

```
# Cross-validation for Random Forest
cv_scores = cross_val_score(best_rf, X, y, cv=StratifiedKFold(n_splits=5), scoring='roc_auc')
print(f"Random Forest CV ROC-AUC: {cv_scores.mean():.3f} ± {cv_scores.std():.3f}")
```

```
# Detailed evaluation for Random Forest: Classification report
y_pred_rf = best_rf.predict(X_test)
print("\nRandom Forest Classification Report:")
print(classification_report(y_test, y_pred_rf))
print("\nRandom Forest Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_rf))
```

```
# Plot ROC curves
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_pred_proba_rf)
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, y_pred_proba_xgb)
plt.figure(figsize=(8, 6))
plt.plot(fpr_rf, tpr_rf, label=f'Random Forest (AUC = {auc_rf:.3f})')
plt.plot(fpr_xgb, tpr_xgb, label=f'XGBoost (AUC = {auc_xgb:.3f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```

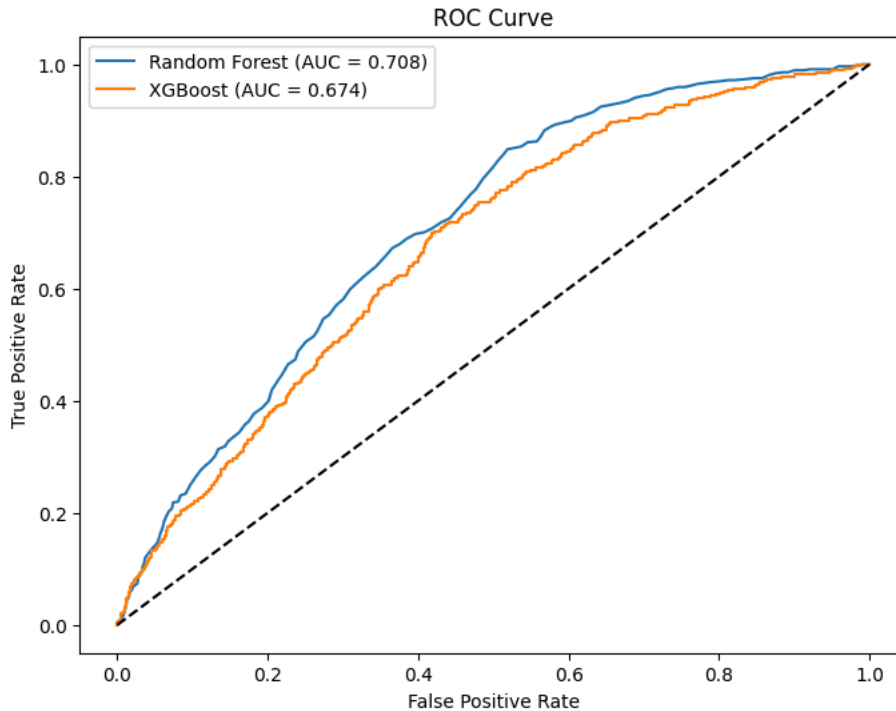
Random Forest CV ROC-AUC: 0.724 ± 0.011

Random Forest Classification Report:

	precision	recall	f1-score	support
0	0.77	0.80	0.78	1432
1	0.44	0.40	0.42	568
accuracy			0.69	2000
macro avg	0.61	0.60	0.60	2000
weighted avg	0.68	0.69	0.68	2000

Random Forest Confusion Matrix:

```
[[1144 288]
 [ 341 227]]
```



```
# Check for overfitting (train vs test AUC)
y_train_pred_proba_rf = best_rf.predict_proba(X_train)[: , 1]
train_auc_rf = roc_auc_score(y_train, y_train_pred_proba_rf)
print(f"\nRandom Forest Training ROC-AUC: {train_auc_rf:.3f}")
print(f"Random Forest Test ROC-AUC: {auc_rf:.3f}")
```



Random Forest Training ROC-AUC: 0.510
 Random Forest Test ROC-AUC: 0.708
 /usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2732: UserWarning:
 X has feature names, but RandomForestClassifier was fitted without feature names

```
# Evaluation: Confusion matrix
cm = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```