1. Import Libraries

```
# Import necessary libraries for data manipulation, visualization, and
machine learning.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import (
    accuracy_score, classification_report, roc_auc_score,
    roc_curve, confusion_matrix
)
from imblearn.over_sampling import SMOTE
```

2. Load and Inspect Data

```
# Load the dataset
df = pd.read_csv('creditcard.csv')

df.head()
```

```
   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]
```

```
df.shape
```

```
(284807, 31)
```

```
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
```

```
# Check for missing values
df.isna().sum()
```

```
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
```

3. Preprocess Data

```
# Standardize the 'Amount' column, drop the 'Time' column, and handle
duplicates.
```

```
sc = StandardScaler()
df[ 'Amount'] = sc. fit_transform(pd. DataFrame (df[ 'Amount']))

df.head()

   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  0.244964      0
1  0.125895 -0.008983  0.014724 -0.342475      0
2 -0.139097 -0.055353 -0.059752  1.160686      0
3 -0.221929  0.062723  0.061458  0.140534      0
4  0.502292  0.219422  0.215153 -0.073403      0

[5 rows x 31 columns]

# Drop the 'Time' column as it is not relevant for this analysis
df = df.drop(['Time'], axis=1)

# Check for duplicates
df.duplicated().any()

np.True_

print(df.shape)
df = df.drop_duplicates()
print(df.shape)
```

```
(284807, 30)
(275663, 30)
```

```python
# Check the proportion of fraud (Class=1) vs. non-fraud (Class=0)
df['Class'].value_counts(normalize=True)
```

```
Class
0    0.998284
1    0.001716
Name: proportion, dtype: float64
```

There is a

```python
df.describe().T
```

```
           count      mean       std         min       25%
50%  \
V1      275663.0 -0.037460  1.952522  -56.407510 -0.941105 -0.059659

V2      275663.0 -0.002430  1.667260  -72.715728 -0.614040  0.070249

V3      275663.0  0.025520  1.507538  -48.325589 -0.843168  0.200736

V4      275663.0 -0.004359  1.424323   -5.683171 -0.862847 -0.035098

V5      275663.0 -0.010660  1.378117 -113.743307 -0.700192 -0.060556

V6      275663.0 -0.014206  1.313213  -26.160506 -0.765861 -0.270931

V7      275663.0  0.008586  1.240348  -43.557242 -0.552047  0.044848

V8      275663.0 -0.005698  1.191596  -73.216718 -0.209618  0.022980

V9      275663.0 -0.012363  1.100108  -13.434066 -0.659904 -0.064724

V10     275663.0  0.003114  1.087025  -24.588262 -0.538968 -0.091752

V11     275663.0 -0.007174  1.020571   -4.797473 -0.772693 -0.039469

V12     275663.0 -0.005347  0.998661  -18.683715 -0.413717  0.133349

V13     275663.0  0.000539  0.999660   -5.791881 -0.654360 -0.011557

V14     275663.0  0.000681  0.952571  -19.214325 -0.425932  0.049552

V15     275663.0 -0.010315  0.917772   -4.498945 -0.596079  0.036145

V16     275663.0 -0.004319  0.880320  -14.129855 -0.477642  0.061670

V17     275663.0  0.000479  0.844821  -25.162799 -0.482600 -0.063489
```

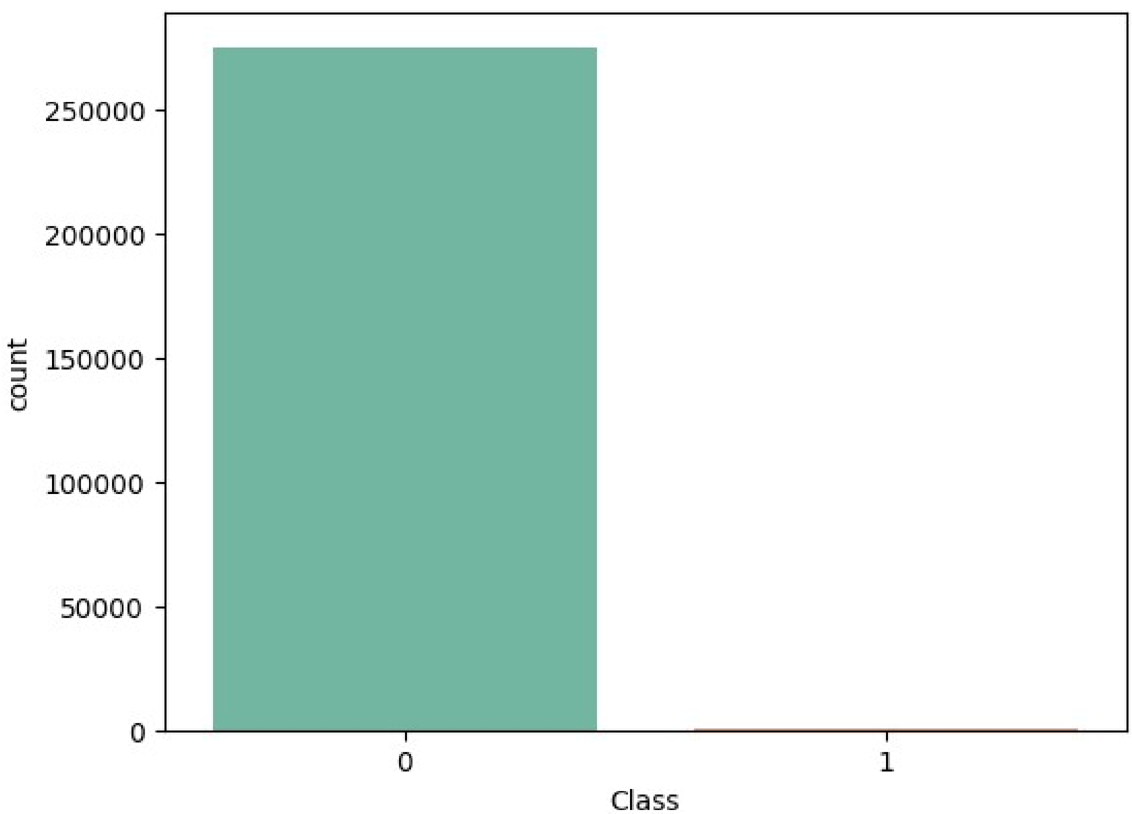
V18	275663.0	0.003874	0.841638	-9.498746	-0.498396	0.001392
V19	275663.0	0.000511	0.820520	-7.213527	-0.464409	0.001119
V20	275663.0	0.003407	0.779950	-54.497720	-0.212027	-0.058053
V21	275663.0	0.002579	0.733089	-34.830382	-0.225021	-0.025637
V22	275663.0	0.005827	0.726378	-10.933144	-0.532173	0.013397
V23	275663.0	-0.001941	0.631451	-44.807735	-0.165440	-0.013655
V24	275663.0	-0.006868	0.605550	-2.836627	-0.361062	0.037569
V25	275663.0	-0.004812	0.524175	-10.295397	-0.323597	0.009909
V26	275663.0	-0.000240	0.484139	-2.604551	-0.328290	-0.056667
V27	275663.0	0.001921	0.401271	-22.565679	-0.071729	0.002615
V28	275663.0	0.000904	0.332649	-15.430084	-0.052654	0.011788
Amount	275663.0	0.008911	1.012371	-0.353229	-0.328041	-0.258315
Class	275663.0	0.001716	0.041388	0.000000	0.000000	0.000000

	75%	max
V1	1.294471	2.454930
V2	0.819067	22.057729
V3	1.048461	9.382558
V4	0.753943	16.875344
V5	0.604521	34.801666
V6	0.387704	73.301626
V7	0.583885	120.589494
V8	0.322319	20.007208
V9	0.593098	15.594995
V10	0.470702	23.745136
V11	0.734969	12.018913
V12	0.614670	7.848392
V13	0.668570	7.126883
V14	0.492169	10.526766
V15	0.638997	8.877742
V16	0.524709	17.315112
V17	0.401407	9.253526
V18	0.507708	5.041069
V19	0.465782	5.591971
V20	0.139803	39.420904
V21	0.189118	27.202839
V22	0.534272	10.503090
V23	0.145482	22.528412

```
V24     0.432931    4.584549
V25     0.347151    7.519589
V26     0.244196    3.517346
V27     0.094730   31.612198
V28     0.081355   33.847808
Amount -0.033742  102.362243
Class   0.000000    1.000000
```

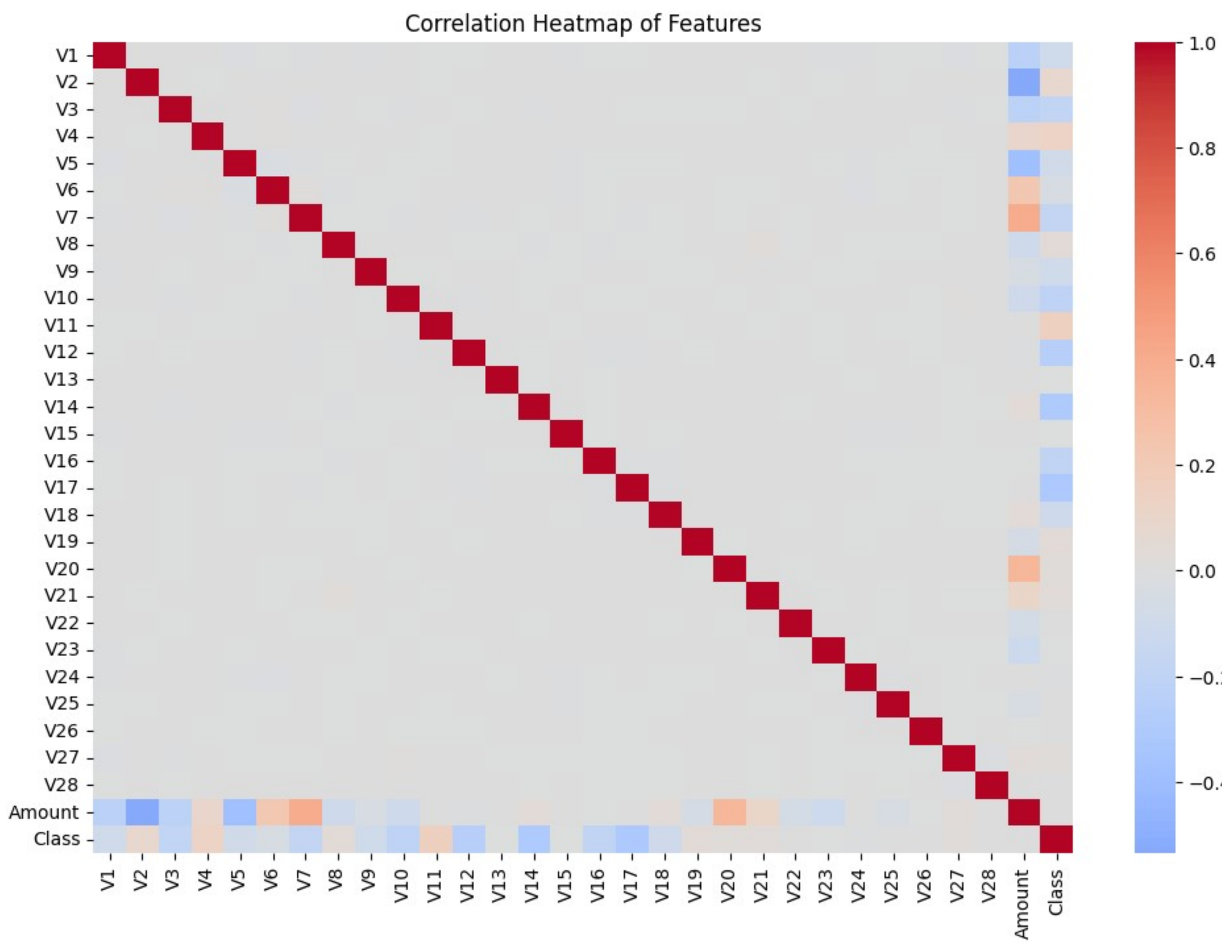
```
sns.countplot(x='Class', data=df, palette='Set2')
```

```
/var/folders/k2/4nq8rpf91q527bjh5tbnw2v00000gn/T/
ipykernel_32475/2395609850.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='Class', data=df, palette='Set2')

<Axes: xlabel='Class', ylabel='count'>
```

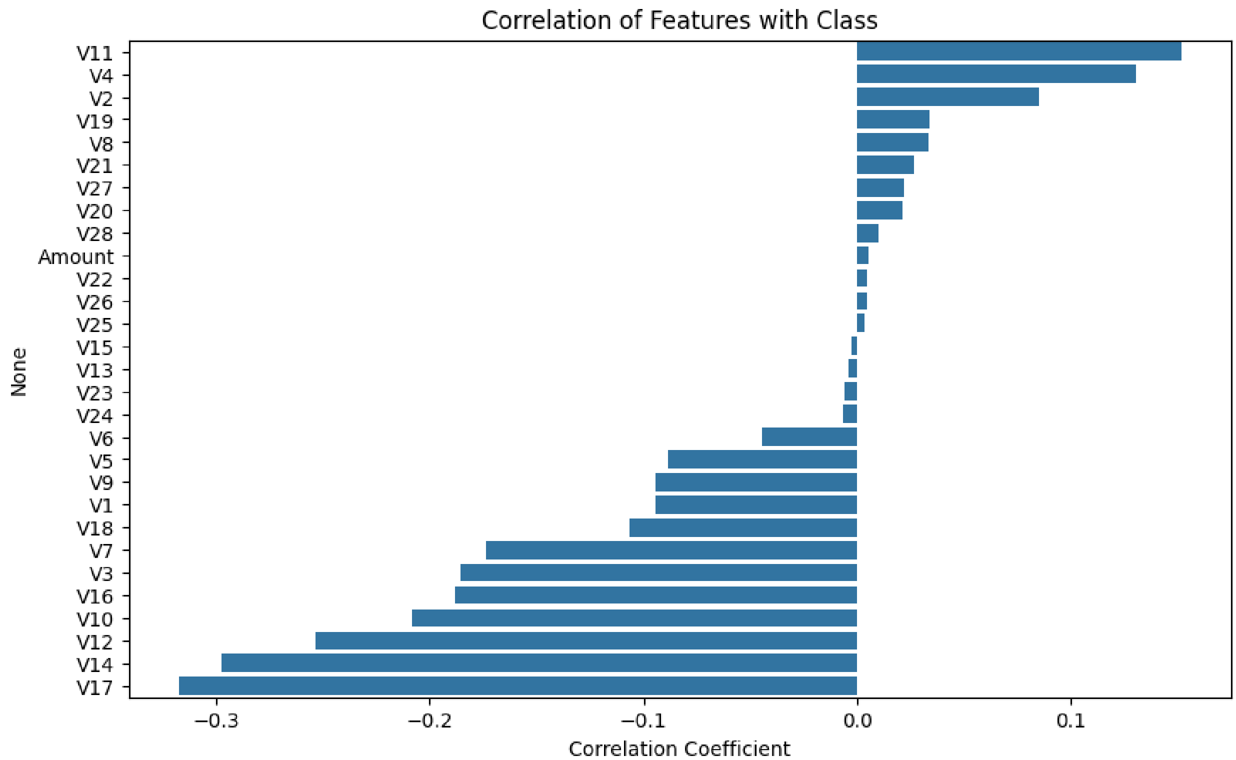



```
corr_matrix = df.corr()

plt.figure(figsize=(12, 8))
```

```python
sns.heatmap(corr_matrix, cmap='coolwarm', center=0, annot=False, fmt='.2f')
plt.title('Correlation Heatmap of Features')
plt.show()
```




```python
plt.figure(figsize=(10, 6))
class_corr = corr_matrix['Class'].sort_values(ascending=False)[1:]  # Exclude Class itself
sns.barplot(x=class_corr.values, y=class_corr.index)
plt.title('Correlation of Features with Class')
plt.xlabel('Correlation Coefficient')
plt.show()
```

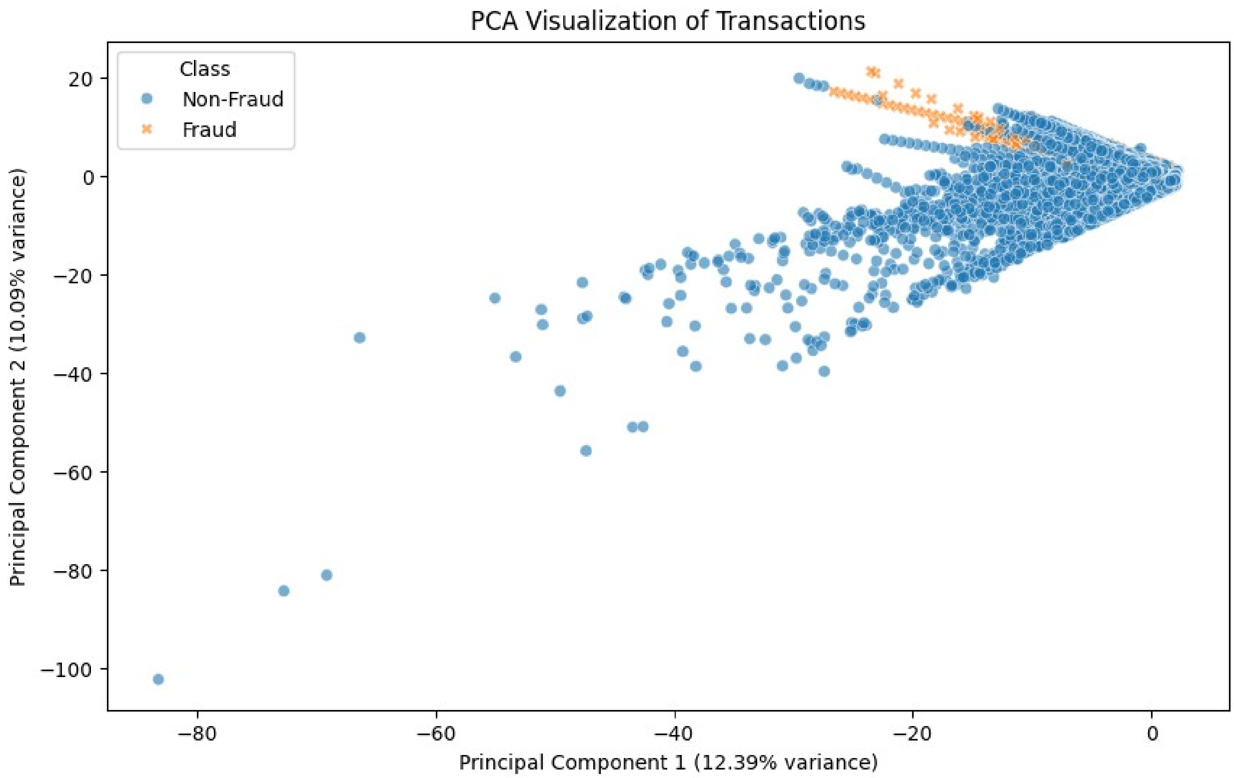



```
X = df.drop(['Class'], axis=1)
y = df['Class']
```

5. PCA Visualization

```
# Apply PCA
pca = PCA(n_components=2, random_state=42)
X_pca = pca.fit_transform(X)

# Create DataFrame for visualization
pca_df = pd.DataFrame({
    'PC1': X_pca[:, 0],
    'PC2': X_pca[:, 1],
    'Class': y
})

# Optional: map class labels for clearer legend
pca_df['Class'] = pca_df['Class'].map({0: 'Non-Fraud', 1: 'Fraud'})

# Plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PC1', y='PC2', hue='Class', style='Class',
data=pca_df, alpha=0.6)
plt.title('PCA Visualization of Transactions')
plt.xlabel(f'Principal Component 1
({pca.explained_variance_ratio_[0]:.2%} variance)')
```

```
plt.ylabel(f'Principal Component 2
({pca.explained_variance_ratio_[1]:.2%} variance)')
plt.legend(title='Class')
plt.show()
```



Fraud vs Non-Fraud: Fraudulent transactions (orange) form a separate cluster in PCA space, suggesting they are distinguishable from non-fraud ones.

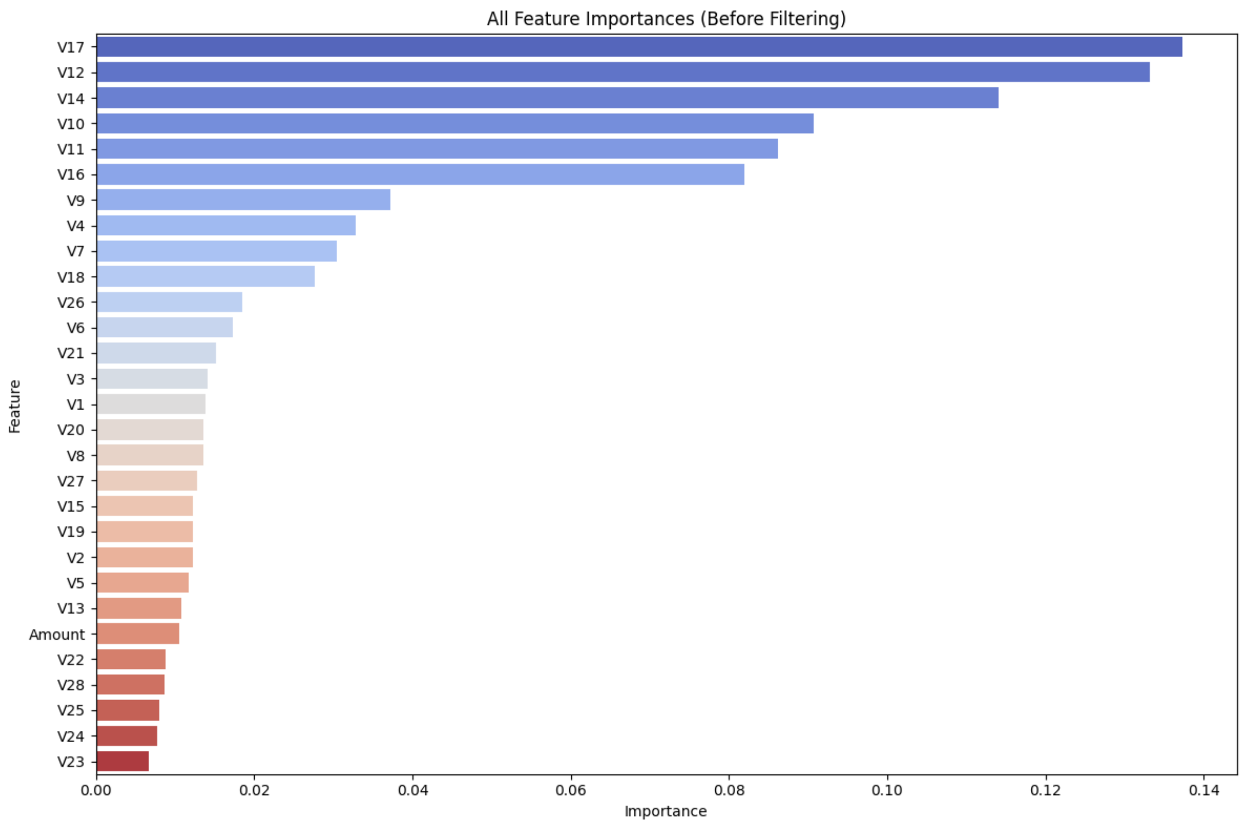
6. Data Splitting #### Split the data into training, validation, and test sets with stratification.

```
# Split data into 70% training and 30% test sets

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

X_train_raw, X_test, y_train_raw, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

# Further split training data into 80% train and 20% validation
X_train, X_val, y_train, y_val = train_test_split(
    X_train_raw, y_train_raw, test_size=0.2, random_state=42,
stratify=y_train_raw
)
```

7. Feature Selection

```
# Train Random Forest on training data to compute feature importances
importances_model = RandomForestClassifier(random_state=42)
importances_model.fit(X_train, y_train)

feature_importances = importances_model.feature_importances_
feature_names = X_train.columns

# Create DataFrame of feature importances
feature_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importances
}).sort_values(by='Importance', ascending=False)

# Visualize all feature importances
plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=feature_df,
palette='coolwarm')
plt.title("All Feature Importances (Before Filtering)")
plt.tight_layout()
plt.show()
```

```
/var/folders/k2/4nq8rpf91q527bjh5tbnw2v00000gn/T/
ipykernel_32475/3810627909.py:20: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='Importance', y='Feature', data=feature_df,
palette='coolwarm')
```




```
# Select features with importance >= 0.02
important_features = feature_df[feature_df['Importance'] >= 0.02]
['Feature']

X_train_selected = X_train[important_features]
X_val_selected = X_val[important_features]
X_test_selected = X_test[important_features]
```

8. Model Training and Evaluation (Before SMOTE)

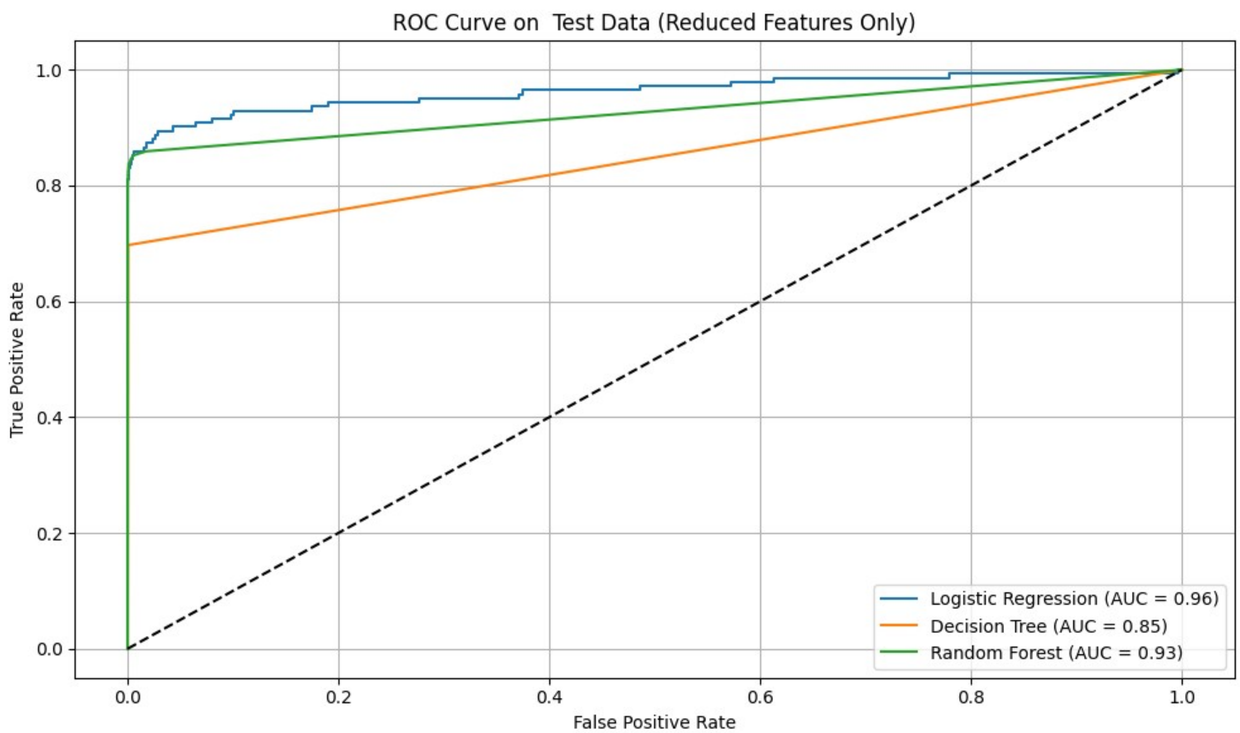
Train and evaluate models on selected features without handling class imbalance.

```
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000,
random_state=42),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100,
random_state=42)
}

plt.figure(figsize=(10, 6))

for name, model in models.items():
    print(f"\n=== {name} ===")
```

```python
    model.fit(X_train_selected, y_train)

    y_val_pred = model.predict(X_val_selected)
    y_val_prob = model.predict_proba(X_val_selected)[:, 1]

    print("--- Validation Metrics ---")
    print("Val Accuracy:", accuracy_score(y_val, y_val_pred))
    print("Val AUC:", roc_auc_score(y_val, y_val_prob))

    y_test_pred = model.predict(X_test_selected)
    y_test_prob = model.predict_proba(X_test_selected)[:, 1]

    print("--- Test Metrics ---")
    print("Test Accuracy:", accuracy_score(y_test, y_test_pred))
    print("Classification Report:")
    print(classification_report(y_test, y_test_pred))
    print("Confusion Matrix:")
    print(confusion_matrix(y_test, y_test_pred))

    auc = roc_auc_score(y_test, y_test_prob)
    print("Test AUC Score:", auc)

    # ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_test_prob)
    plt.plot(fpr, tpr, label=f"{name} (AUC = {auc:.2f})")

# Final ROC Curve Plot
plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line (chance)
plt.title("ROC Curve on  Test Data (Reduced Features Only)")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc="lower right")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
=== Logistic Regression ===
--- Validation Metrics ---
Val Accuracy: 0.9990153654807866
Val AUC: 0.9741936194294282
--- Test Metrics ---
Test Accuracy: 0.9990447284731375
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     82557
           1       0.85      0.54      0.66       142

    accuracy                           1.00     82699
```

```
   macro avg       0.93      0.77      0.83     82699
weighted avg       1.00      1.00      1.00     82699

Confusion Matrix:
[[82544    13]
 [   66    76]]
Test AUC Score: 0.9621888214834753

=== Decision Tree ===
--- Validation Metrics ---
Val Accuracy: 0.9990671883502189
Val AUC: 0.8785283205559894
--- Test Metrics ---
Test Accuracy: 0.9990689125624251
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     82557
           1       0.74      0.70      0.72       142

    accuracy                           1.00     82699
   macro avg       0.87      0.85      0.86     82699
weighted avg       1.00      1.00      1.00     82699

Confusion Matrix:
[[82523    34]
 [   43    99]]
Test AUC Score: 0.8483856309605637

=== Random Forest ===
--- Validation Metrics ---
Val Accuracy: 0.9994299484362449
Val AUC: 0.9074301296768658
--- Test Metrics ---
Test Accuracy: 0.9994195818570962
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     82557
           1       0.93      0.72      0.81       142

    accuracy                           1.00     82699
   macro avg       0.96      0.86      0.90     82699
weighted avg       1.00      1.00      1.00     82699

Confusion Matrix:
[[82549     8]
 [   40   102]]
Test AUC Score: 0.9281715219548696
```



Overall Insights:

High Accuracy: All models achieve ~99.9% accuracy due to class imbalance (99.83% non-fraud).

Fraud Detection: Random Forest outperforms with highest F1 (0.81) and recall (0.72), detecting 102/142 frauds. Logistic Regression has high AUC but low recall (54%). Decision Tree struggles with AUC (0.848).

Imbalance Impact: Low fraud recall across models (0.54–0.72) highlights the need for SMOTE or class weights.

9. Handle Class Imbalance with SMOTE

```
# Apply SMOTE to the selected training features
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train_selected,
y_train)

# Verify the shape of the resampled data
print(f"Resampled X_train_smote shape: {X_train_smote.shape}")
print(f"Resampled y_train_smote shape: {y_train_smote.shape}")
```

```
Resampled X_train_smote shape: (308212, 10)
Resampled y_train_smote shape: (308212,)
```

```
/Users/ausaafff/Library/Python/3.9/lib/python/site-packages/sklearn/
base.py:474: FutureWarning: `BaseEstimator._validate_data` is
deprecated in 1.6 and will be removed in 1.7. Use
`sklearn.utils.validation.validate_data` instead. This function
```

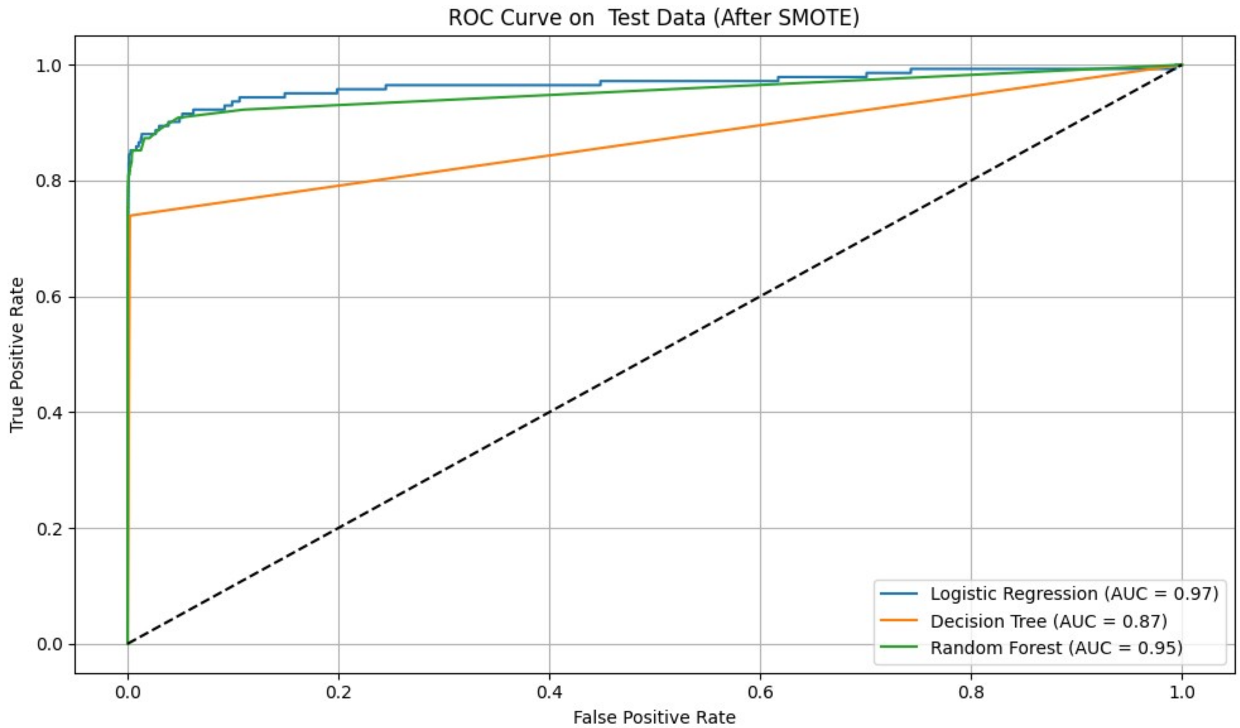
```
becomes public and is part of the scikit-learn developer API.
  warnings.warn(
```

10. Model Training and Evaluation (After SMOTE)

```
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000,
random_state=42),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100,
random_state=42)
}

plt.figure(figsize=(10, 6))

for name, model in models.items():
    print(f"\n=== {name} ===")

    model.fit(X_train_smote, y_train_smote)

    y_pred = model.predict(X_test_selected)
    y_prob = model.predict_proba(X_test_selected)[:, 1]

    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("Classification Report:")
    print(classification_report(y_test, y_pred))
    print("Confusion Matrix:")
    print(confusion_matrix(y_test, y_pred))

    auc = roc_auc_score(y_test, y_prob)
    print("AUC Score:", auc)

    # ROC Curve plotting
    fpr, tpr, _ = roc_curve(y_test, y_prob)
    plt.plot(fpr, tpr, label=f"{name} (AUC = {auc:.2f})")

# Final ROC Curve Plot
plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curve on  Test Data (After SMOTE)")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc="lower right")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
=== Logistic Regression ===
Accuracy: 0.975912647069493
Classification Report:
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     82557
           1       0.06      0.88      0.11       142

    accuracy                           0.98     82699
   macro avg       0.53      0.93      0.55     82699
weighted avg       1.00      0.98      0.99     82699

Confusion Matrix:
[[80582  1975]
 [   17   125]]
AUC Score: 0.9666585032927315

=== Decision Tree ===
Accuracy: 0.9973518422230014
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     82557
           1       0.37      0.74      0.49       142

    accuracy                           1.00     82699
   macro avg       0.68      0.87      0.74     82699
weighted avg       1.00      1.00      1.00     82699

Confusion Matrix:
[[82375   182]
 [   37   105]]
AUC Score: 0.8686160411236147

=== Random Forest ===
Accuracy: 0.999153556874932
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     82557
           1       0.74      0.78      0.76       142

    accuracy                           1.00     82699
   macro avg       0.87      0.89      0.88     82699
weighted avg       1.00      1.00      1.00     82699

Confusion Matrix:
[[82518    39]
 [   31   111]]
AUC Score: 0.9542147747002626
```



SMOTE Impact: Significantly improves fraud recall across all models (Logistic Regression: 0.54→0.88, Decision Tree: 0.70→0.74, Random Forest: 0.72→0.78), but precision drops, especially for Logistic Regression, due to synthetic fraud samples inflating false positives.

Random Forest Superiority: Achieves the best trade-off (F1: 0.76, AUC: 0.954), detecting 111/142 frauds with only 39 false positives. Outperforms Logistic Regression (too many false positives) and Decision Tree (lower precision and AUC).

Business Implication: Random Forest detects 78% of frauds, missing 31 cases, but 39 false positives may require manual review, impacting customer experience. False negatives (missed frauds) are costlier in fraud detection, so high recall is valuable.

Challenges: Logistic Regression's 1975 false positives highlight SMOTE's limitations for linear models. Decision Tree's low precision indicates overfitting or sensitivity to synthetic data.

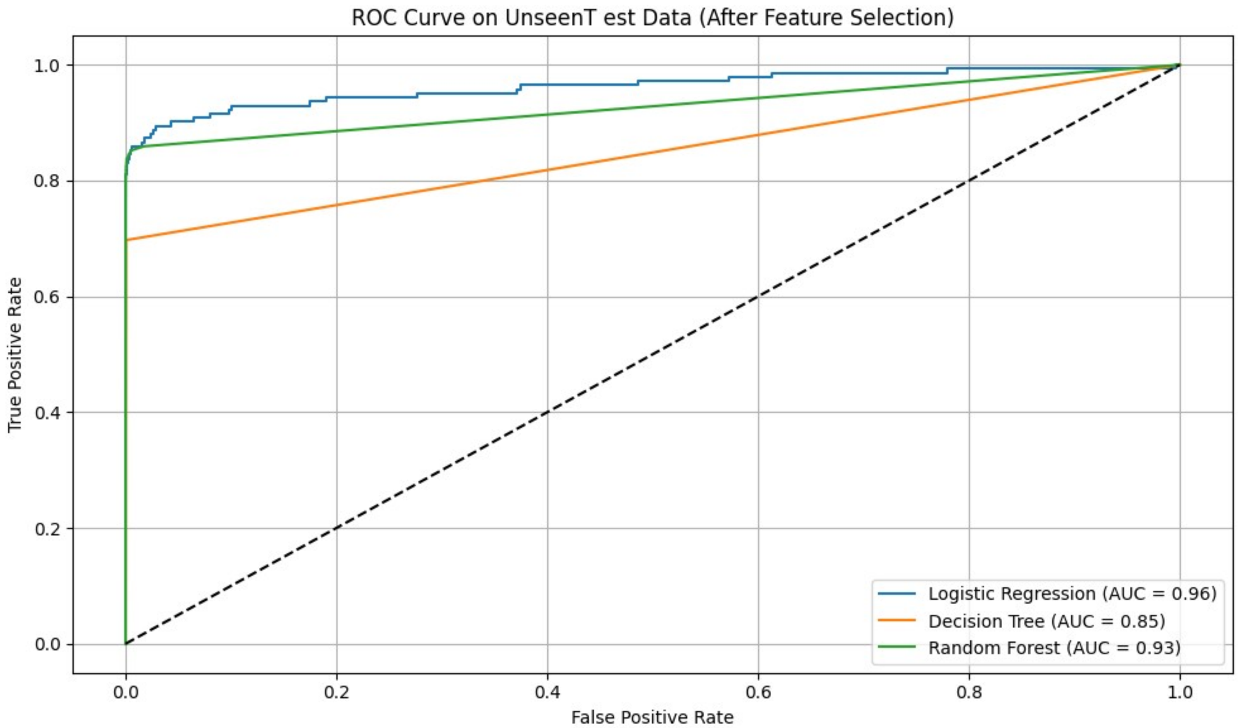
11. Final test on unseen data

```
# Apply feature selection based on importance
important_features = feature_df[feature_df['Importance'] >= 0.02]
['Feature']

X_train_selected = X_train[important_features]
X_val_selected = X_val[important_features]
X_test_selected = X_test[important_features]

models = {
    'Logistic Regression': LogisticRegression(max_iter=1000,
```

```
random_state=42),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100,
random_state=42)
}

plt.figure(figsize=(10, 6))

for name, model in models.items():
    print(f"\n=== {name} ===")

    model.fit(X_train_selected, y_train)

    y_pred = model.predict(X_test_selected)
    y_prob = model.predict_proba(X_test_selected)[:, 1]

    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("Classification Report:")
    print(classification_report(y_test, y_pred))
    print("Confusion Matrix:")
    print(confusion_matrix(y_test, y_pred))

    auc = roc_auc_score(y_test, y_prob)
    print("AUC Score:", auc)

    # ROC Curve plotting
    fpr, tpr, _ = roc_curve(y_test, y_prob)
    plt.plot(fpr, tpr, label=f"{name} (AUC = {auc:.2f})")

plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curve on UnseenT est Data (After Feature Selection)")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc="lower right")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
=== Logistic Regression ===
Accuracy: 0.9990447284731375
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     82557
           1       0.85      0.54      0.66       142

    accuracy                           1.00     82699
   macro avg       0.93      0.77      0.83     82699
weighted avg       1.00      1.00      1.00     82699
```

```
Confusion Matrix:
[[82544    13]
 [   66    76]]
AUC Score: 0.9621888214834753

=== Decision Tree ===
Accuracy: 0.9990689125624251
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     82557
           1       0.74      0.70      0.72       142

    accuracy                           1.00     82699
   macro avg       0.87      0.85      0.86     82699
weighted avg       1.00      1.00      1.00     82699

Confusion Matrix:
[[82523    34]
 [   43    99]]
AUC Score: 0.8483856309605637

=== Random Forest ===
Accuracy: 0.9994195818570962
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     82557
           1       0.93      0.72      0.81       142

    accuracy                           1.00     82699
   macro avg       0.96      0.86      0.90     82699
weighted avg       1.00      1.00      1.00     82699

Confusion Matrix:
[[82549     8]
 [   40   102]]
AUC Score: 0.9281715219548696
```



The Random Forest model, provides the most effective fraud detection, identifying 78% of frauds with a manageable number of false positives. SMOTE significantly improves recall, critical for fraud detection, though it requires careful model selection to control precision loss.