In [137…
```python
# basic libraries
import pandas as pd
import numpy as np
```

In [138…
```python
#import our excel file in pyhton as df
df=pd.read_excel("fraud_data.xlsx")
df.head(6) # first 6 rows of data
```

Out[138…

	TransactionID	Amount	Time	Location	MerchantCategory	CardHolderAge
0	1	375.17	47605	Houston	Travel	18.0
1	2	950.76	38088	Los Angeles	Electronics	28.0
2	3	732.26	78752	Miami	Travel	20.0
3	4	599.06	55284	New York	Groceries	69.0
4	5	156.86	57043	New York	Groceries	79.0
5	6	156.84	35547	Chicago	Clothing	40.0

In [139…
```python
df.describe()
```

Out[139…

	TransactionID	Amount	Time	CardHolderAge	IsFraud
count	500.000000	475.000000	500.000000	476.000000	500.000000
mean	250.500000	641.112753	41141.482000	47.518908	0.054000
std	144.481833	1044.448065	25614.468967	18.677362	0.226244
min	1.000000	6.060000	55.000000	5.000000	0.000000
25%	125.750000	243.780000	18726.250000	32.000000	0.000000
50%	250.500000	518.810000	40772.000000	47.000000	0.000000
75%	375.250000	776.000000	63463.250000	63.000000	0.000000
max	500.000000	9691.578643	86066.000000	120.000000	1.000000

In [140…
```python
df.isnull().sum()    # this shows number of missing values in our data.
                     # we can not fit model on this data now
```

Out[140…
```
TransactionID        0
Amount              25
Time                 0
Location            25
MerchantCategory     0
CardHolderAge       24
IsFraud              0
dtype: int64
```

In [141…
```python
#to get percentage of data missing in each data
```

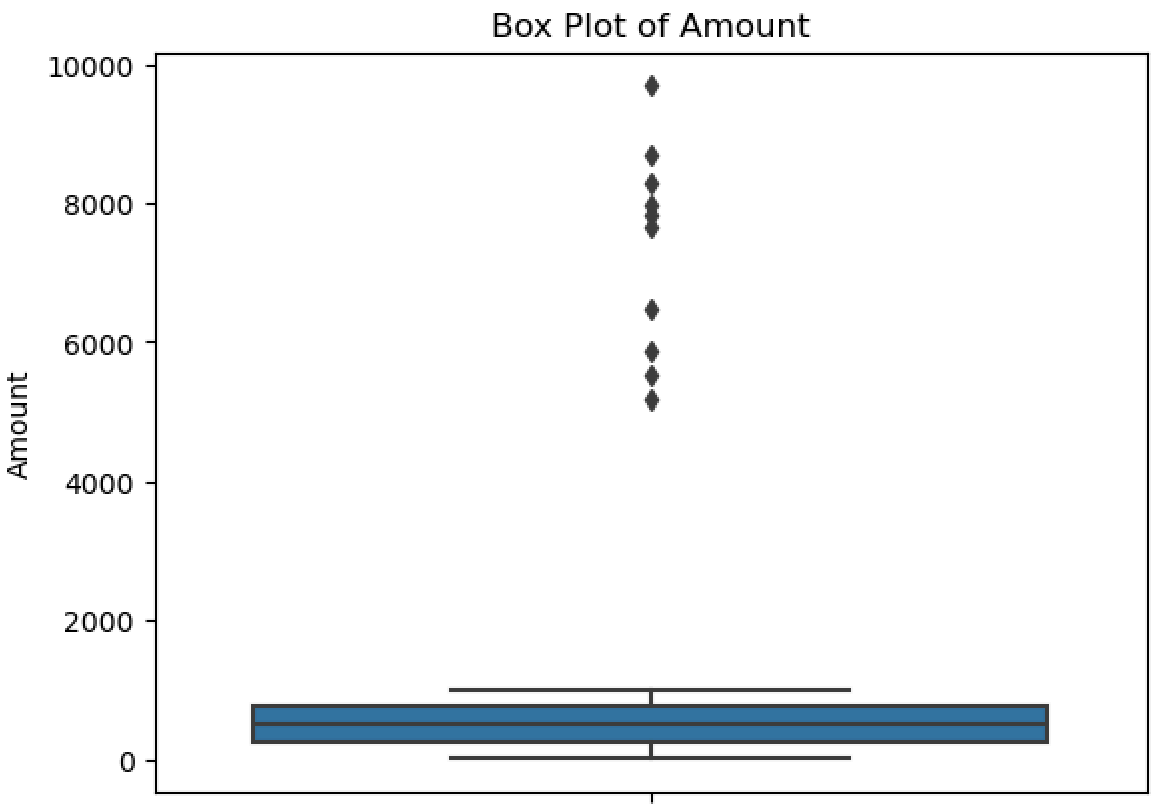
```python
(df.isnull().sum() / len(df)) * 100
```

Out[141…

```
TransactionID       0.0
Amount              5.0
Time                0.0
Location            5.0
MerchantCategory    0.0
CardHolderAge       4.8
IsFraud             0.0
dtype: float64
```

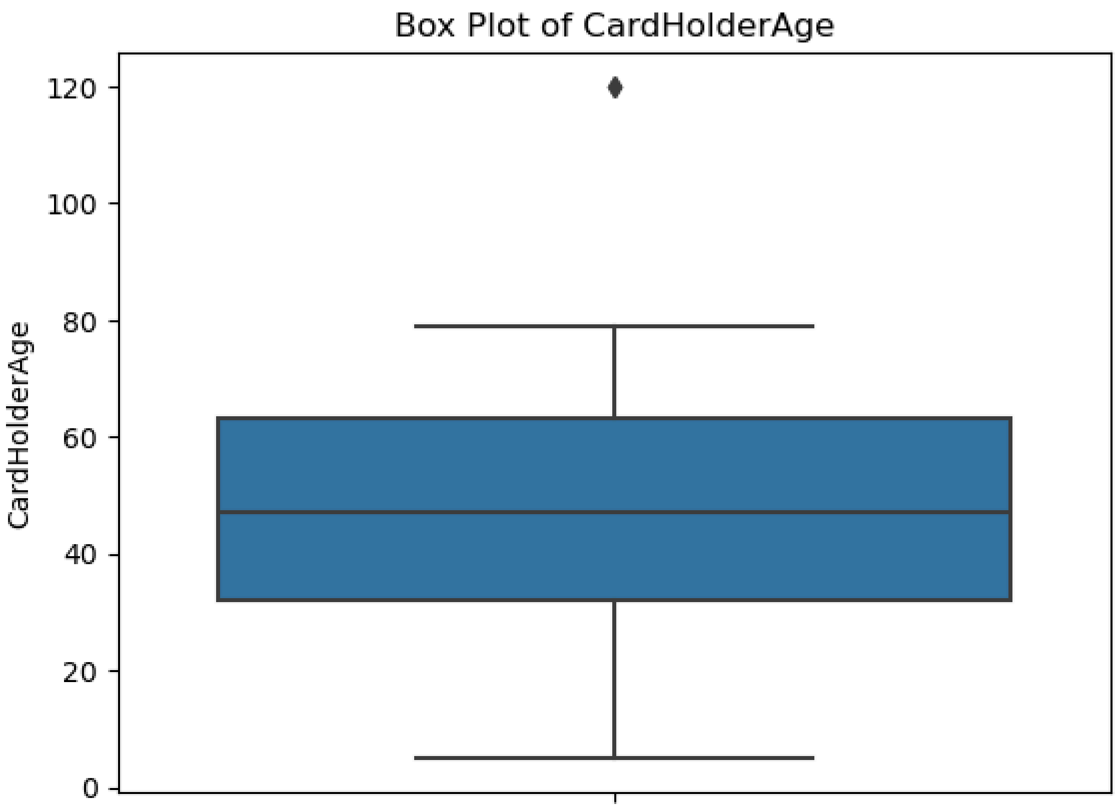
In [142…

```python
import seaborn as sns
sns.boxplot(y=df['Amount'])
plt.title("Box Plot of Amount")
plt.show()
# here we can see that it contain outliers( very extreme values)
# we have to use median as substitute vlaue of missing values in amount.
```



In [143…

```python
# also check for cardeholder age
sns.boxplot(y=df['CardHolderAge'])
plt.title("Box Plot of CardHolderAge")
plt.show()
# it has outlier so we also use median here.
```



In [144…
```
# for location we use mode because it is categorical variable.
# for Amount we will use median
# for Cardholderage we will use median
df['Amount'].fillna(df['Amount'].median(), inplace=True)
df['CardHolderAge'].fillna(df['CardHolderAge'].median(), inplace=True)
df['Location'].fillna(df['Location'].mode()[0], inplace=True)
```

In [145…
```
# now our data have no missing values.
df.isnull().sum()
```

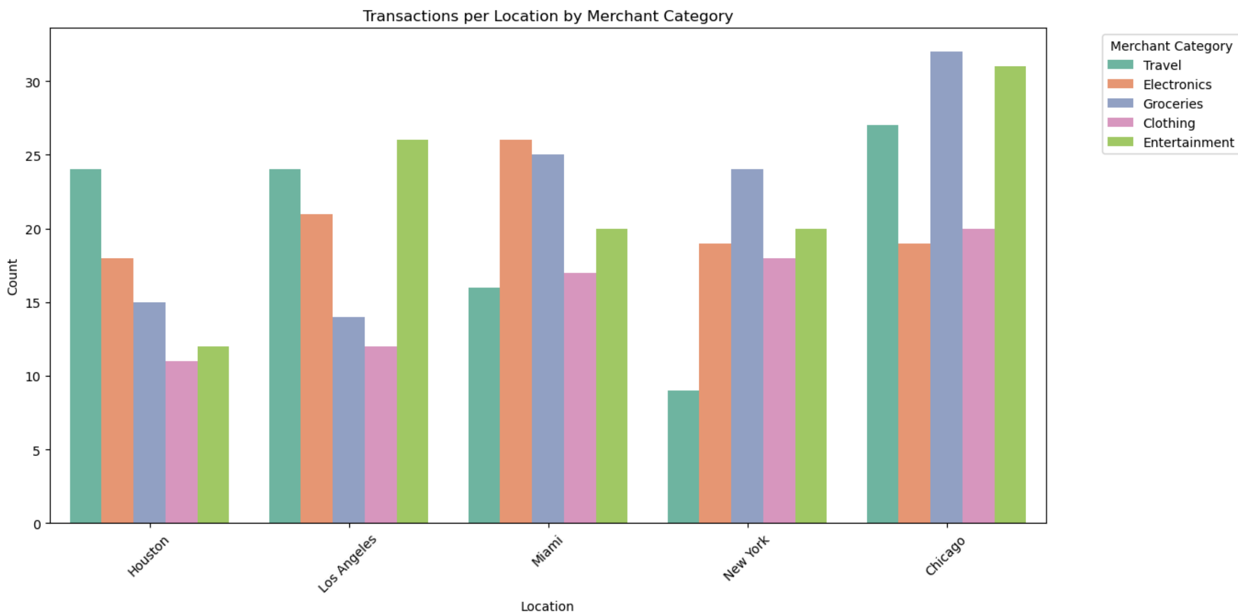
Out[145…
```
TransactionID       0
Amount              0
Time                0
Location            0
MerchantCategory    0
CardHolderAge       0
IsFraud             0
dtype: int64
```

In [146…
```
# check for data is balance or not.
print(df['IsFraud'].value_counts())
```

```
IsFraud
0    473
1     27
Name: count, dtype: int64
```

In [147…
```
plt.figure(figsize=(14,7))
```

```python
sns.countplot(data=df, x="Location", hue="MerchantCategory", palette="Set2")
plt.title("Transactions per Location by Merchant Category")
plt.xlabel("Location")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.legend(title="Merchant Category", bbox_to_anchor=(1.05, 1), loc='upper lef
plt.show()
# we have 5 merchant category and 5 locations.
```



In [148…

```python
df.drop('TransactionID',axis=1,inplace=True)
df.head()
# Transactionsid doesn't have any significant relation with fruad transaction
```

Out[148…

	Amount	Time	Location	MerchantCategory	CardHolderAge	IsFraud
0	375.17	47605	Houston	Travel	18.0	0
1	950.76	38088	Los Angeles	Electronics	28.0	0
2	732.26	78752	Miami	Travel	20.0	0
3	599.06	55284	New York	Groceries	69.0	0
4	156.86	57043	New York	Groceries	79.0	0

In [149…

```python
# Encode categorical variables Location and MerchantCategory.
encoded_df = pd.get_dummies(df, columns=["Location", "MerchantCategory"], drop
encoded_df.head()
```

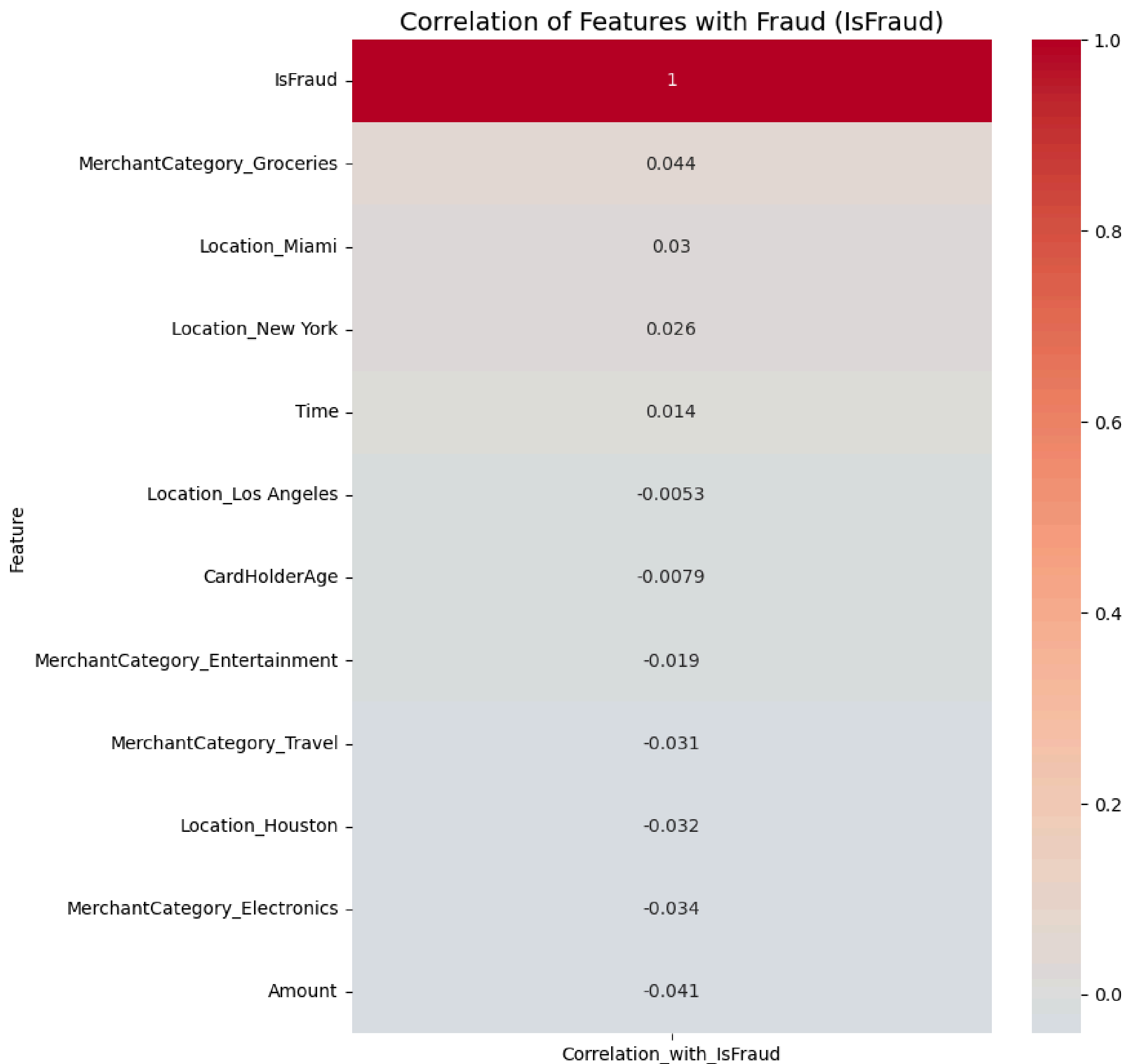
Out[149…

	Amount	Time	CardHolderAge	IsFraud	Location_Houston	Location_Los Angeles	Lo
0	375.17	47605	18.0	0	True	False	
1	950.76	38088	28.0	0	False	True	
2	732.26	78752	20.0	0	False	False	
3	599.06	55284	69.0	0	False	False	
4	156.86	57043	79.0	0	False	False	

In [150…

```python
# we have to check correlation between variables to select important features
corr_matrix = encoded_df.corr()

fraud_corr = corr_matrix["IsFraud"].sort_values(ascending=False)

fraud_corr_df = fraud_corr.reset_index()
fraud_corr_df.columns = ["Feature", "Correlation_with_IsFraud"]

# Print correlation values
print(fraud_corr_df)

# Heatmap for correlations with IsFraud only
plt.figure(figsize=(8, 10))
sns.heatmap(fraud_corr_df.set_index("Feature"), annot=True, cmap="coolwarm", c
plt.title("Correlation of Features with Fraud (IsFraud)", fontsize=14)
plt.show()
```

```
                         Feature  Correlation_with_IsFraud
0                        IsFraud                  1.000000
1       MerchantCategory_Groceries                  0.044004
2                 Location_Miami                  0.030174
3              Location_New York                  0.026257
4                           Time                  0.014175
5           Location_Los Angeles                 -0.005326
6                  CardHolderAge                 -0.007941
7   MerchantCategory_Entertainment                 -0.018988
8          MerchantCategory_Travel                 -0.030971
9               Location_Houston                 -0.031861
10    MerchantCategory_Electronics                 -0.034176
11                        Amount                 -0.041102
```



In [151…
```
# now we are going to separate target variable from data.
X = encoded_df.drop("IsFraud", axis=1)
y = encoded_df["IsFraud"]
# it is important for train-test split part.
```

In [152…
```
y.head()
```

Out[152…
```
0    0
1    0
2    0
3    0
4    0
Name: IsFraud, dtype: int64
```

In [153…
```
# these are important libraries for model fitting and selection

from sklearn.model_selection import train_test_split
```

```python
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_
from imblearn.over_sampling import SMOTE
```

In [154…
```python
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
) # we have now divided data into training and testing data.
# 20% for test and 80% for training.
```

In [157…
```python
# Because we have imbalance dataset , so we have to use SMOTE to balance out c

smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
print("Before SMOTE:", y_train.value_counts().to_dict())
print("After SMOTE:", y_train_resampled.value_counts().to_dict())
```

```
Before SMOTE: {0: 378, 1: 22}
After SMOTE: {0: 378, 1: 378}
```

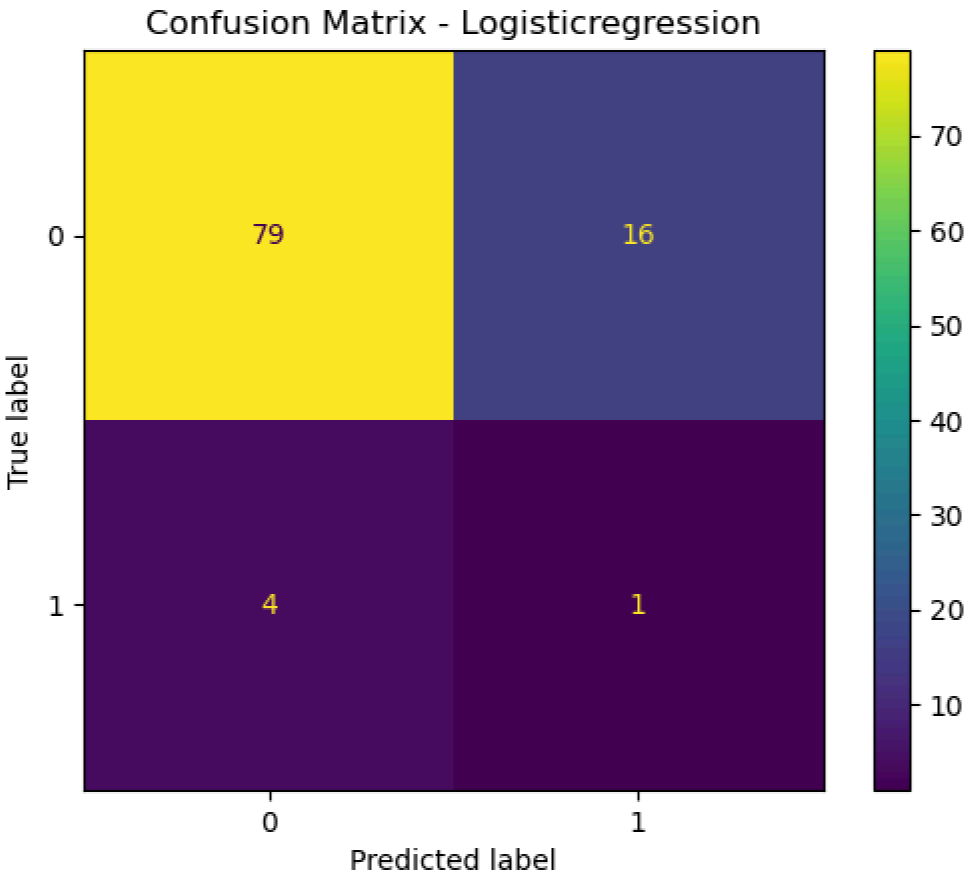
In [158…
```python
#Our data contains outliers ,so we have to use standardization for scaling.
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_resampled)
X_test_scaled = scaler.transform(X_test)
```

In [170…
```python
# Logistic Regression model fitting.
model = LogisticRegression(max_iter=1000)
model.fit(X_train_scaled, y_train_resampled)

# Predictions
y_pred = model.predict(X_test_scaled)

# Evaluation
print("\n=== Logistic regression Evaluation ===")
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
=== Logistic regression Evaluation ===
Accuracy: 0.8

Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.83      0.89        95
           1       0.06      0.20      0.09         5

    accuracy                           0.80       100
   macro avg       0.51      0.52      0.49       100
weighted avg       0.91      0.80      0.85       100
```

In [164…
```python
# For confussion matrix representation.
from sklearn.metrics import confusion_matrix
```

```python
from sklearn.metrics import ConfusionMatrixDisplay

ConfusionMatrixDisplay(confusion_matrix(y_test, y_pred)).plot()
plt.title("Confusion Matrix - Logisticregression")
plt.show() # verifying quantity of TP and TN on confusion matrix...
```



In [167…

```python
# Random Forest model fitting.
rf_model = RandomForestClassifier(
    n_estimators=200,
    max_depth=6,
    min_samples_split=15,
    min_samples_leaf=8,
    random_state=42,
    n_jobs=-1
)
rf_model.fit(X_train_scaled, y_train_resampled)

y_pred_rf = rf_model.predict(X_test_scaled)
y_prob_rf = rf_model.predict_proba(X_test_scaled)[:, 1]

print("\n=== Random Forest Evaluation ===")
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
print("\nClassification Report:\n", classification_report(y_test, y_pred_rf))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))
print("ROC-AUC:", roc_auc_score(y_test, y_prob_rf))
print("PR-AUC:", average_precision_score(y_test, y_prob_rf))
```

```
=== Random Forest Evaluation ===
Accuracy: 0.88

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.93      0.94        95
           1       0.00      0.00      0.00         5

    accuracy                           0.88       100
   macro avg       0.47      0.46      0.47       100
weighted avg       0.90      0.88      0.89       100

Confusion Matrix:
 [[88  7]
 [ 5  0]]
ROC-AUC: 0.34947368421052627
PR-AUC: 0.04739696835672068
```

In [172…

```
# Side by side comparison of both models in terms for minority group(Fraud).
# Logistic Regression
log_metrics = {
    "Accuracy": accuracy_score(y_test, y_pred),
    "Minority Precision": classification_report(y_test, y_pred, output_dict=Tr
    "Minority Recall": classification_report(y_test, y_pred, output_dict=True)
    "Minority F1": classification_report(y_test, y_pred, output_dict=True)['1'
    "ROC-AUC": roc_auc_score(y_test, y_prob),
    "PR-AUC": average_precision_score(y_test, y_prob)
}

# Random Forest
rf_metrics = {
    "Accuracy": accuracy_score(y_test, y_pred_rf),
    "Minority Precision": classification_report(y_test, y_pred_rf, output_dict
    "Minority Recall": classification_report(y_test, y_pred_rf, output_dict=Tr
    "Minority F1": classification_report(y_test, y_pred_rf, output_dict=True)[
    "ROC-AUC": roc_auc_score(y_test, y_prob_rf),
    "PR-AUC": average_precision_score(y_test, y_prob_rf)
}

# Combine into a DataFrame
df_comparison = pd.DataFrame([log_metrics, rf_metrics], index=["Logistic Regre
print(df_comparison)
```

```
                     Accuracy  Minority Precision  Minority Recall  \
Logistic Regression      0.80            0.058824              0.2
Random Forest            0.88            0.000000              0.0

                     Minority F1   ROC-AUC    PR-AUC
Logistic Regression     0.090909  0.349474  0.047397
Random Forest           0.000000  0.349474  0.047397
```

In [ ]:

```
# since we had imbalance data set so we cannot perfer accuracy for model valic
# As we can see that logistic regression is performing better when it comes tc
```

```
# our logistic regression model capturing fraud tranctision more effectivel wh
# we can conclude that LR model is bettern than Random Forest model.....
```