Fraud_Detection_Model

May 19, 2024

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter('ignore')
```

1 Data Collection

[2]:
```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call
drive.mount("/content/gdrive", force_remount=True).
```

[3]:
```
main_df = pd.read_csv('/content/gdrive/MyDrive/Fraud.csv')
main_df.shape
```

[3]:
```
(6362620, 11)
```

[4]:
```
df = main_df.sample(frac=0.1, random_state=42)
```

[5]:
```
df.head()
```

[5]:
```
         step      type     amount     nameOrig  oldbalanceOrg  \
3737323   278   CASH_IN  330218.42   C632336343       20866.00
264914     15   PAYMENT   11647.08  C1264712553       30370.00
85647      10   CASH_IN  152264.21  C1746846248      106589.00
5899326   403  TRANSFER 1551760.63   C333676753           0.00
2544263   206   CASH_IN   78172.30   C813403091     2921331.58

         newbalanceOrig     nameDest  oldbalanceDest  newbalanceDest  isFraud  \
3737323       351084.42   C834976624       452419.57       122201.15        0
264914         18722.92   M215391829            0.00            0.00        0
85647         258853.21  C1607284477       201303.01        49038.80        0
5899326            0.00  C1564353608      3198359.45      4750120.08        0
2544263      2999503.88  C1091768874       415821.90       337649.60        0
```

```
         isFlaggedFraud
3737323               0
264914                0
85647                 0
5899326               0
2544263               0
```

[6]:
```
df.shape
```

[6]:
```
(636262, 11)
```

2 Data Cleaning

[7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 636262 entries, 3737323 to 759063
Data columns (total 11 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   step            636262 non-null  int64  
 1   type            636262 non-null  object 
 2   amount          636262 non-null  float64
 3   nameOrig        636262 non-null  object 
 4   oldbalanceOrg   636262 non-null  float64
 5   newbalanceOrig  636262 non-null  float64
 6   nameDest        636262 non-null  object 
 7   oldbalanceDest  636262 non-null  float64
 8   newbalanceDest  636262 non-null  float64
 9   isFraud         636262 non-null  int64  
 10  isFlaggedFraud  636262 non-null  int64  
dtypes: float64(5), int64(3), object(3)
memory usage: 58.3+ MB
```

[8]:
```
pd.options.display.float_format = '{:,.2f}'.format
```

[9]:
```
df.describe()
```

[9]:
```
                step        amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest  \
count 636,262.00    636,262.00     636,262.00      636,262.00      636,262.00   
mean      243.53    181,042.06     828,545.16      849,906.52    1,106,789.79   
std       142.49    613,686.71   2,877,270.65    2,913,448.98    3,396,119.42   
min         1.00          0.00           0.00            0.00            0.00   
25%       156.00     13,362.92           0.00            0.00            0.00   
50%       239.00     74,949.35      14,111.81            0.00      133,047.96   
75%       335.00    209,477.17     106,956.50      143,667.23      950,528.96   
max       742.00 69,337,316.27  37,919,816.48   37,950,093.25  327,998,074.22   
```

```
       newbalanceDest    isFraud  isFlaggedFraud
count      636,262.00 636,262.00      636,262.00
mean     1,232,760.41       0.00            0.00
std      3,685,490.05       0.04            0.00
min              0.00       0.00            0.00
25%              0.00       0.00            0.00
50%        215,936.31       0.00            0.00
75%      1,119,455.24       0.00            0.00
max    328,431,698.23       1.00            1.00
```

[10]:
```
df.isnull().sum()
```

[10]:
```
step              0
type              0
amount            0
nameOrig          0
oldbalanceOrg     0
newbalanceOrig    0
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

[11]:
```
df.duplicated().sum()
```

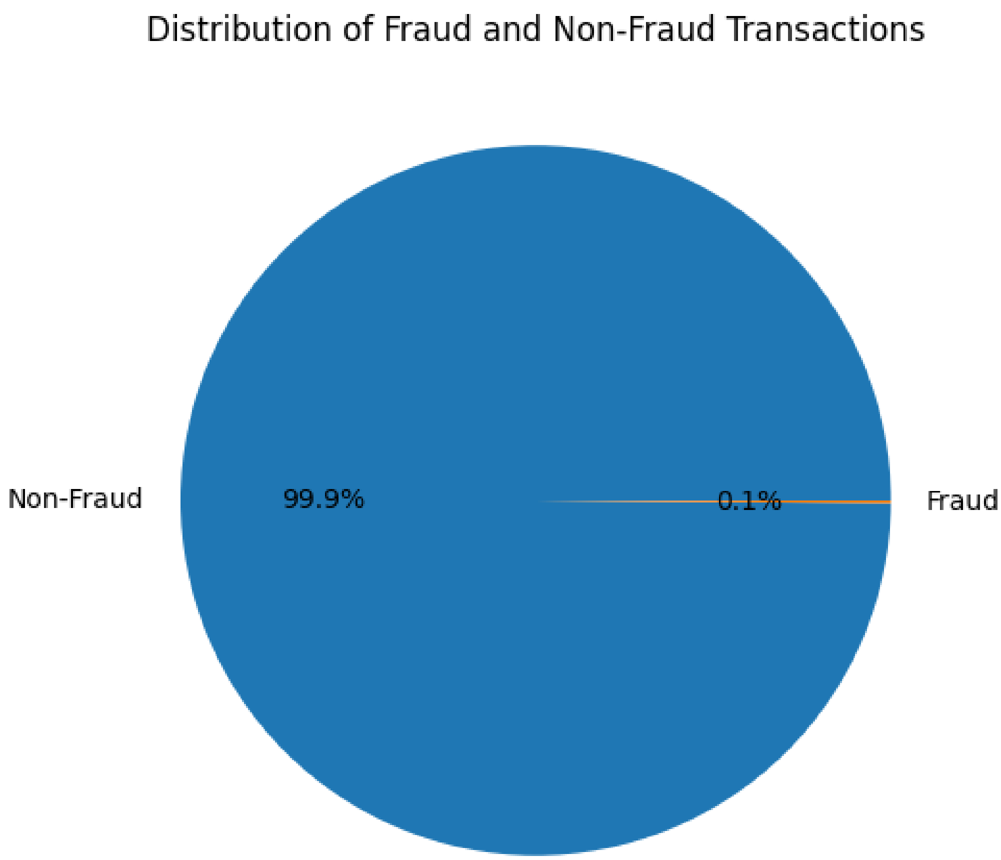
[11]:
```
0
```

3 EDA

[12]:
```
fraud_counts = df['isFraud'].value_counts()
fraud_counts
```

[12]:
```
isFraud
0    635445
1       817
Name: count, dtype: int64
```

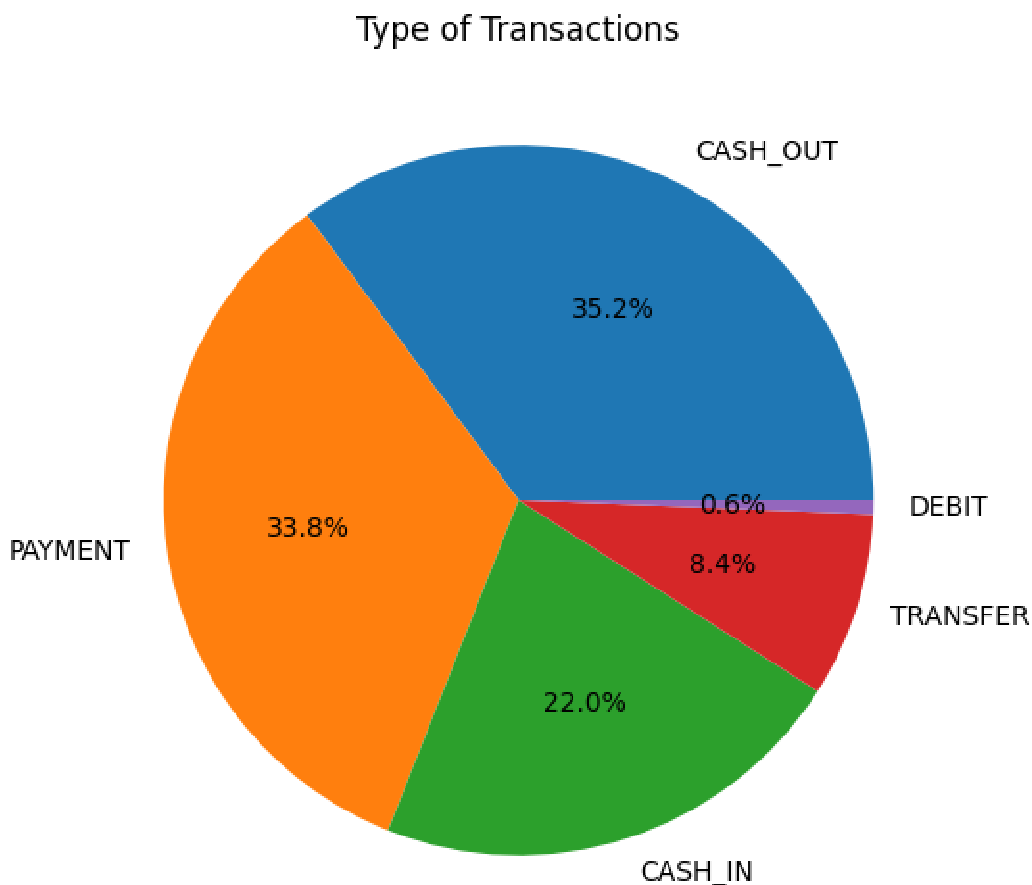
[13]:
```
# Distribution of Fraud and Non-Fraud Transactions
fraud_counts = df['isFraud'].value_counts()
plt.figure(figsize=(8, 6))
plt.pie(fraud_counts, labels=['Non-Fraud', 'Fraud'], autopct='%1.1f%%')
plt.title('Distribution of Fraud and Non-Fraud Transactions')
plt.show()
```



[14]:
```
type_counts = df['type'].value_counts()
type_counts
```

[14]:
```
type
CASH_OUT    223689
PAYMENT     215342
CASH_IN     139694
TRANSFER     53444
DEBIT         4093
Name: count, dtype: int64
```

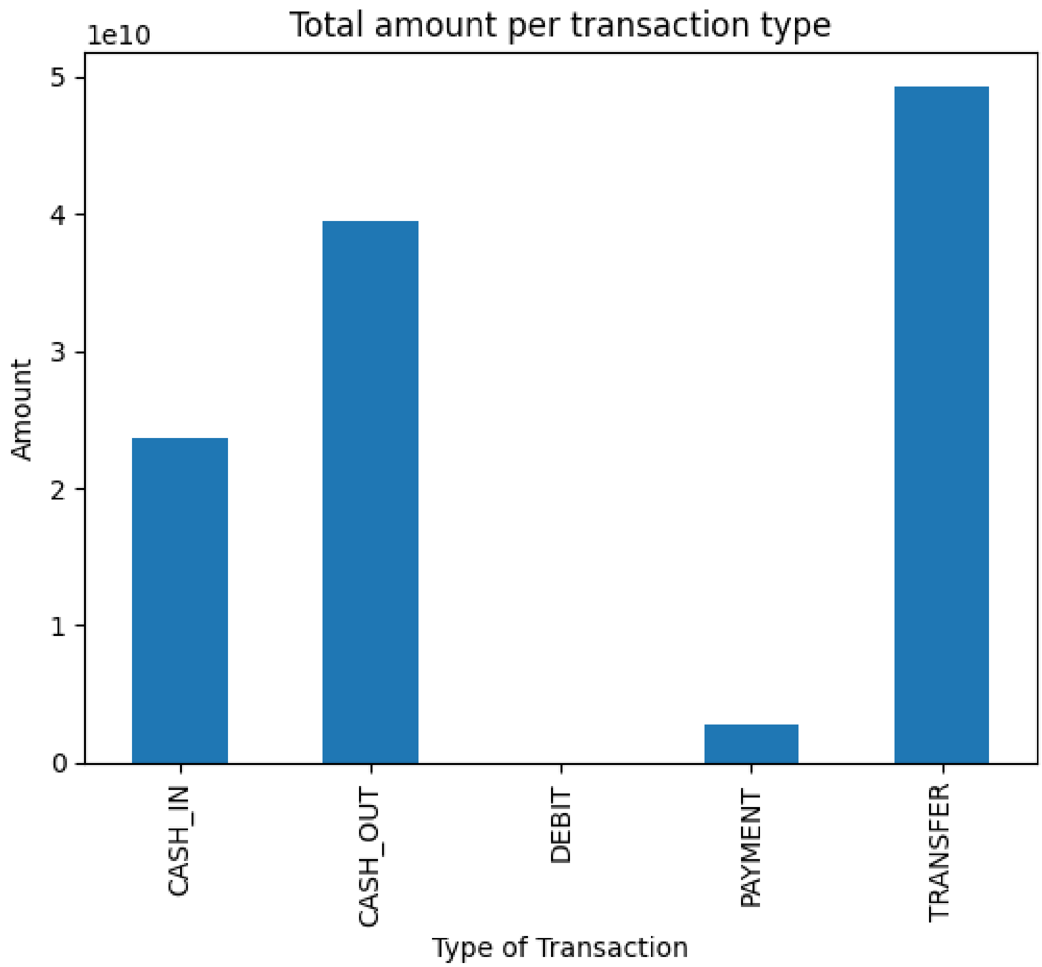
[15]:
```
# Distribution of Transactions Type
plt.figure(figsize=(8, 6))
plt.pie(type_counts,labels=type_counts.index, autopct='%1.1f%%')
plt.title('Type of Transactions')
plt.show()
```



[16]:
```
# Type of transaction having Fraud Transactions
df.groupby('type')['isFraud'].value_counts().unstack()
```

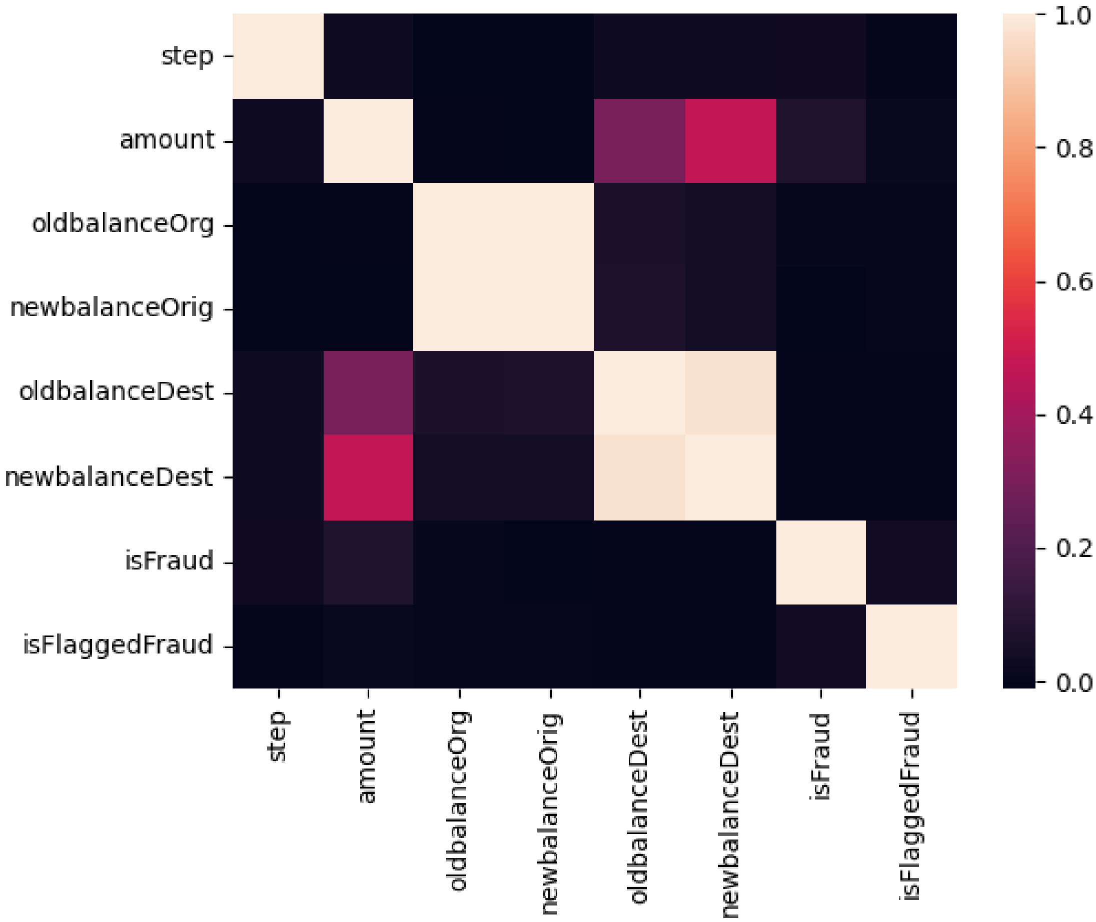
[16]:
```
isFraud           0      1
type
CASH_IN  139,694.00    NaN
CASH_OUT 223,287.00 402.00
DEBIT      4,093.00    NaN
PAYMENT  215,342.00    NaN
TRANSFER  53,029.00 415.00
```

[17]:
```
# Total amount per transaction type
var = df.groupby('type').amount.sum()
var.plot(kind='bar', title='Total amount per transaction type')
plt.xlabel('Type of Transaction')
plt.ylabel('Amount')
plt.show()
```



[18]:
```python
# Corellation
sns.heatmap(df.corr(numeric_only=True))
```

[18]: <Axes: >



4 Data Preprocessing

[19]:
```
# Dropping highly correlated features
df.drop(['isFlaggedFraud'], axis=1, inplace=True)
```

[20]:
```
# Feature Engineering
df['errorBalanceOrig'] = df['newbalanceOrig'] + df['amount'] -␣
↪df['oldbalanceOrg']
df['errorBalanceDest'] = df['oldbalanceDest'] + df['amount'] -␣
↪df['newbalanceDest']
```

[21]:
```
# one hot encoding for type
df = pd.get_dummies(df, columns=['type'],dtype=int)
```

[22]:
```
# Label Encoding for nameOrig and nameDest
from sklearn.preprocessing import LabelEncoder
```

```
df['nameOrig'] = LabelEncoder().fit_transform(df['nameOrig'])
df['nameDest'] = LabelEncoder().fit_transform(df['nameDest'])
```

[23]:

```
df.head()
```

[23]:

	step	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	\
3737323	278	330,218.42	515158	20,866.00	351,084.42	221549	
264914	15	11,647.08	87134	30,370.00	18,722.92	370005	
85647	10	152,264.21	246139	106,589.00	258,853.21	76027	
5899326	403	1,551,760.63	416801	0.00	0.00	70612	
2544263	206	78,172.30	574944	2,921,331.58	2,999,503.88	11530	

	oldbalanceDest	newbalanceDest	isFraud	errorBalanceOrig	\
3737323	452,419.57	122,201.15	0	660,436.84	
264914	0.00	0.00	0	0.00	
85647	201,303.01	49,038.80	0	304,528.42	
5899326	3,198,359.45	4,750,120.08	0	1,551,760.63	
2544263	415,821.90	337,649.60	0	156,344.60	

	errorBalanceDest	type_CASH_IN	type_CASH_OUT	type_DEBIT	\
3737323	660,436.84	1	0	0	
264914	11,647.08	0	0	0	
85647	304,528.42	1	0	0	
5899326	0.00	0	0	0	
2544263	156,344.60	1	0	0	

	type_PAYMENT	type_TRANSFER
3737323	0	0
264914	1	0
85647	0	0
5899326	0	1
2544263	0	0

[32]:

```
# Multicollinearity using Variance Inflation Factor (VIF)
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm

predictors =␣
 ↪df[['step','amount',        'nameOrig',        'oldbalanceOrg'        ,'newbalanceOrig',
                ␣
 ↪'isFraud',        'errorBalanceOrig',        'errorBalanceDest',        'type_CASH_IN',
c = sm.add_constant(predictors)
```

[33]:

```
vif_data = pd.DataFrame()
vif_data["feature"] = c.columns
vif_data["VIF"] = [variance_inflation_factor(c.values, i) for i in range(c.
 ↪shape[1])]
```

```
print(vif_data)
```

```
              feature  VIF
0               const 0.00
1                step 1.00
2              amount  inf
3            nameOrig 1.00
4       oldbalanceOrg  inf
5      newbalanceOrig  inf
6            nameDest 3.58
7      oldbalanceDest  inf
8      newbalanceDest  inf
9             isFraud 1.21
10   errorBalanceOrig  inf
11   errorBalanceDest  inf
12       type_CASH_IN  inf
13      type_CASH_OUT  inf
14         type_DEBIT  inf
15       type_PAYMENT  inf
16      type_TRANSFER  inf
```

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

[26]:
```
# Spliting data into Train and Test
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y, test_size=0.
 ↪2,random_state=42)
```

[27]:
```
# SMOTE
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)
X_train, y_train = smote.fit_resample(X_train, y_train)
```

[28]:
```
# Scalling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

5 Modeling and Evaluation

[29]:
```
# Modeling, Prediction, Accuracy Score and CV Score
from sklearn.ensemble import RandomForestClassifier
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train,y_train)
```

```python
train_pred = rf_model.predict(X_train)
y_pred = rf_model.predict(X_test)

from sklearn.metrics import accuracy_score
print('Train Accuracy: ',accuracy_score(train_pred,y_train))
print('Test Accuracy: ',accuracy_score(y_pred,y_test))

from sklearn.model_selection import cross_val_score
score = cross_val_score(rf_model,X,y,cv=5)
print('CV score: ',score.mean())
```

```
Train Accuracy:  1.0
Test Accuracy:  0.9999921416390969
CV score:  0.9999968566432879
```

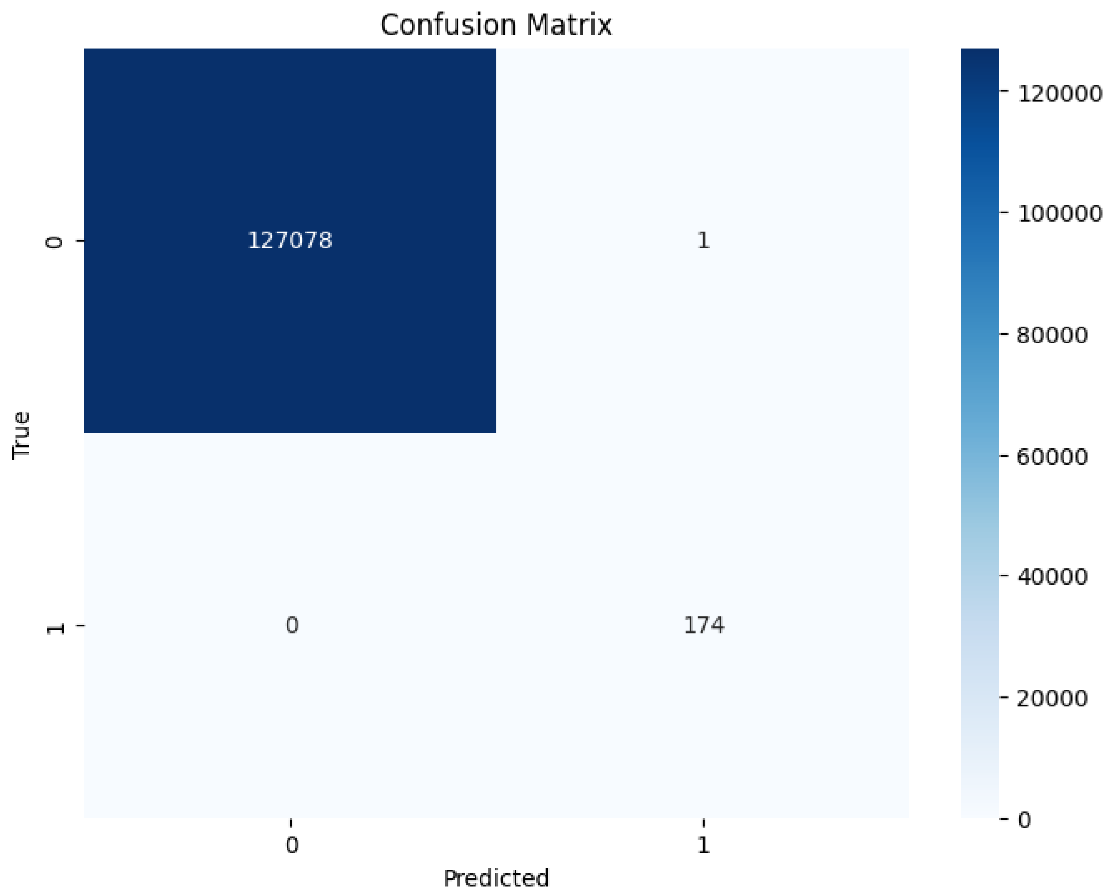
[30]:
```python
# Feature Importance
rf_model.feature_importances_
pd.DataFrame(index=X.columns,data=rf_model.
 ↪feature_importances_,columns=['Feature Importances'])
```

[30]:

	Feature Importances
step	0.02
amount	0.07
nameOrig	0.00
oldbalanceOrg	0.14
newbalanceOrig	0.16
nameDest	0.05
oldbalanceDest	0.02
newbalanceDest	0.03
errorBalanceOrig	0.36
errorBalanceDest	0.04
type_CASH_IN	0.02
type_CASH_OUT	0.01
type_DEBIT	0.00
type_PAYMENT	0.04
type_TRANSFER	0.04

[31]:
```python
# Confusion Matrix
from sklearn.metrics import confusion_matrix

conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues")
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



[32]:
```
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(y_pred,y_test))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    127078
           1       1.00      0.99      1.00       175

    accuracy                           1.00    127253
   macro avg       1.00      1.00      1.00    127253
weighted avg       1.00      1.00      1.00    127253
```

[33]:
```
# ROC AUC Score
from sklearn.metrics import roc_auc_score, roc_curve

y_pred_proba = rf_model.predict_proba(X_test)[:, 1]
roc_auc = roc_auc_score(y_test, y_pred_proba)
```

```
print(f"ROC-AUC: {roc_auc:.2f}")
```

ROC-AUC: 1.00

[34]:

```
# Generate ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {roc_auc:.
 ↪2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```