Online_Payment_Fraud_Detection

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1 Online Fraud Detection

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[1]:
```
import pandas as pd
```

[2]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

[3]:
```
from imblearn.under_sampling import RandomUnderSampler
```

2 Reading Data from CSV File

2.0.1 File Name:

- **Online_Fraud_Data.csv**

[4]:
```
Data = pd.read_csv('data/Online_Fraud_Data.csv')
```

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

[5]:
```
   step      type    amount     nameOrig  oldbalanceOrg  newbalanceOrig  \
0     1   PAYMENT   9839.64  C1231006815       170136.0       160296.36
1     1   PAYMENT   1864.28  C1666544295        21249.0        19384.72
2     1  TRANSFER    181.00  C1305486145          181.0            0.00
3     1  CASH_OUT    181.00   C840083671          181.0            0.00
4     1   PAYMENT  11668.14  C2048537720        41554.0        29885.86

      nameDest  oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud
0  M1979787155             0.0             0.0        0               0
1  M2044282225             0.0             0.0        0               0
2   C553264065             0.0             0.0        1               0
3    C38997010         21182.0             0.0        1               0
4  M1230701703             0.0             0.0        0               0
```

3 Dataset Overview

The dataset contains **6,362,620 rows** and **8 columns**. Below are the names of the features (columns):

1. **step** - The time step of the transaction.
2. **type** - The type of the transaction (e.g., PAYMENT, CASH_IN, etc.).
3. **amount** - The amount of the transaction.
4. **oldbalanceOrg** - The balance before the transaction for the sender.
5. **newbalanceOrig** - The balance after the transaction for the sender.
6. **oldbalanceDest** - The balance before the transaction for the recipient.
7. **newbalanceDest** - The balance after the transaction for the recipient.
8. **isFraud** - A binary label indicating whether the transaction was fraudulent (1) or not (0).

This dataset is used for detecting fraudulent transactions in an online system.

[6]:
```
Data.describe()
```

[6]:
```
               step        amount  oldbalanceOrg  newbalanceOrig  \
count  6.362620e+06  6.362620e+06   6.362620e+06    6.362620e+06
mean   2.433972e+02  1.798619e+05   8.338831e+05    8.551137e+05
std    1.423320e+02  6.038582e+05   2.888243e+06    2.924049e+06
min    1.000000e+00  0.000000e+00   0.000000e+00    0.000000e+00
25%    1.560000e+02  1.338957e+04   0.000000e+00    0.000000e+00
50%    2.390000e+02  7.487194e+04   1.420800e+04    0.000000e+00
75%    3.350000e+02  2.087215e+05   1.073152e+05    1.442584e+05
max    7.430000e+02  9.244552e+07   5.958504e+07    4.958504e+07

       oldbalanceDest  newbalanceDest       isFraud  isFlaggedFraud
count    6.362620e+06    6.362620e+06  6.362620e+06    6.362620e+06
mean     1.100702e+06    1.224996e+06  1.290820e-03    2.514687e-06
std      3.399180e+06    3.674129e+06  3.590480e-02    1.585775e-03
min      0.000000e+00    0.000000e+00  0.000000e+00    0.000000e+00
25%      0.000000e+00    0.000000e+00  0.000000e+00    0.000000e+00
50%      1.327057e+05    2.146614e+05  0.000000e+00    0.000000e+00
75%      9.430367e+05    1.111909e+06  0.000000e+00    0.000000e+00
max      3.560159e+08    3.561793e+08  1.000000e+00    1.000000e+00
```

4 Checking for any NULL values:

[7]:
```
Data.isna().sum()
```

[7]:
```
step              0
type              0
amount            0
nameOrig          0
oldbalanceOrg     0
newbalanceOrig    0
```

```
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

5 Data Cleaning: Dropping Unnecessary Columns

In this step, we remove the following columns from the dataset as they are not needed for our analysis:

1. **nameOrig** - The name of the sender (originating account).
2. **nameDest** - The name of the recipient (destination account).
3. **isFlaggedFraud** - A flag indicating whether the transaction was previously flagged as fraud (this column is redundant for our analysis).

[8]:
```
Data.drop(['nameOrig','nameDest','isFlaggedFraud'], axis=1, inplace=True)
```

6 Encoding Categorical Feature

We encode the **'type'** column, which is categorical, into numerical values using **LabelEncoder** from scikit-learn.

[9]:
```
from sklearn import preprocessing
encoder = preprocessing.LabelEncoder()
Data['type'] = encoder.fit_transform(Data['type'])
Data
```

[9]:
```
         step  type      amount  oldbalanceOrg  newbalanceOrig  \
0           1     3     9839.64      170136.00       160296.36
1           1     3     1864.28       21249.00        19384.72
2           1     4      181.00         181.00            0.00
3           1     1      181.00         181.00            0.00
4           1     3    11668.14       41554.00        29885.86
…         …    …           …            …              …
6362615   743     1   339682.13      339682.13            0.00
6362616   743     4  6311409.28     6311409.28            0.00
6362617   743     1  6311409.28     6311409.28            0.00
6362618   743     4   850002.52      850002.52            0.00
6362619   743     1   850002.52      850002.52            0.00

         oldbalanceDest  newbalanceDest  isFraud
0                  0.00            0.00        0
1                  0.00            0.00        0
2                  0.00            0.00        1
3              21182.00            0.00        1
```

```
4                 0.00          0.00        0
…                  …             …      …
6362615           0.00     339682.13        1
6362616           0.00          0.00        1
6362617       68488.84    6379898.11        1
6362618           0.00          0.00        1
6362619     6510099.11    7360101.63        1

[6362620 rows x 8 columns]
```

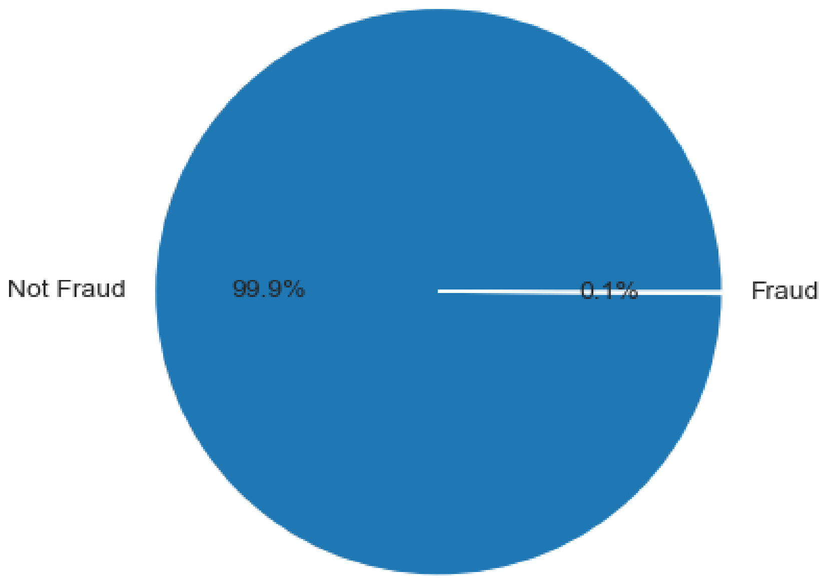
7 Visualizing Class Distribution

We visualize the distribution of the **'isFraud'** column using a pie chart. The chart shows the percentage of fraudulent vs non-fraudulent transactions in the dataset.

- **Not Fraud**: Transactions that are not fraudulent.
- **Fraud**: Transactions that are fraudulent.

[10]:
```python
class_dist = Data['isFraud'].value_counts()
plt.pie(class_dist,labels = ['Not Fraud','Fraud'],autopct='%1.1f%%')
```

[10]:
```
([<matplotlib.patches.Wedge at 0x1cff1473020>,
  <matplotlib.patches.Wedge at 0x1cff1ce16a0>],
 [Text(-1.099990955625572, 0.004460666087110192, 'Not Fraud'),
  Text(1.0999909559371663, -0.004460589247970448, 'Fraud')],
 [Text(-0.5999950667048575, 0.002433090592969195, '99.9%'),
  Text(0.599995066874818, -0.002433048680711153, '0.1%')])
```



[11]:
```
Vals = Data.drop('isFraud', axis = 1)
Ans = Data['isFraud']
```

8 Applying Random Undersampling

As classes were too much imbalance so we used **RandomUnderSampler** to address class imbalance by randomly undersampling the majority class (non-fraudulent transactions) to match the number of fraudulent transactions. This helps balance the dataset for model training.

[12]:
```
Vals, Ans = RandomUnderSampler(random_state=42).fit_resample(Vals, Ans)
```

[13]:
```
Balanced_Data = pd.concat([Vals, Ans], axis = 1)
Balanced_Data.reset_index(drop = True,inplace = True)
```

9 Dropping Duplicate Rows

We remove any duplicate rows from **T_data** to ensure the dataset contains only unique entries.

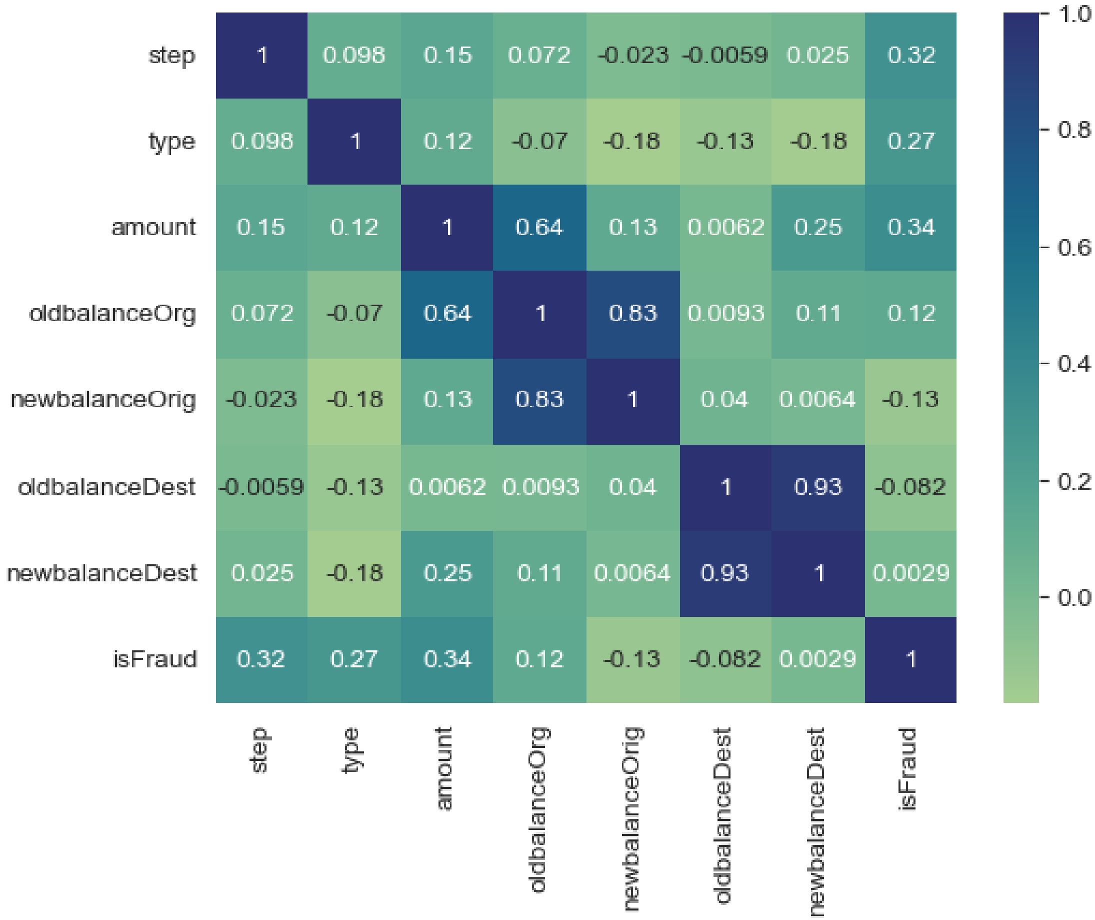
[14]:
```
Balanced_Data.drop_duplicates(inplace = True)
```

10 Correlation Heatmap

We generate a correlation heatmap of the **Balanced_Data** to visualize the relationships between different numerical features. The heatmap uses the **'crest'** color map and annotates the correlation values on the plot.

[15]:
```
sns.heatmap(Balanced_Data.corr(), annot=True, cmap = 'crest')
```

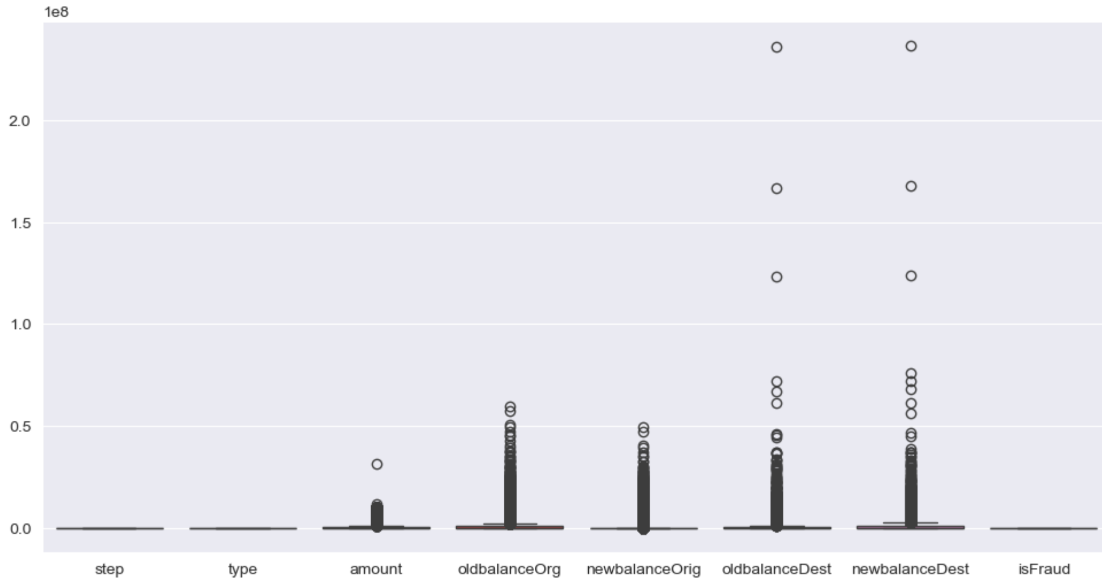
[15]: <Axes: >



11 Boxplot for Data Distribution

We create a **boxplot** to visualize the distribution and detect any potential outliers in the **Balanced_Data**. The plot is displayed with a size of 12x6 inches.

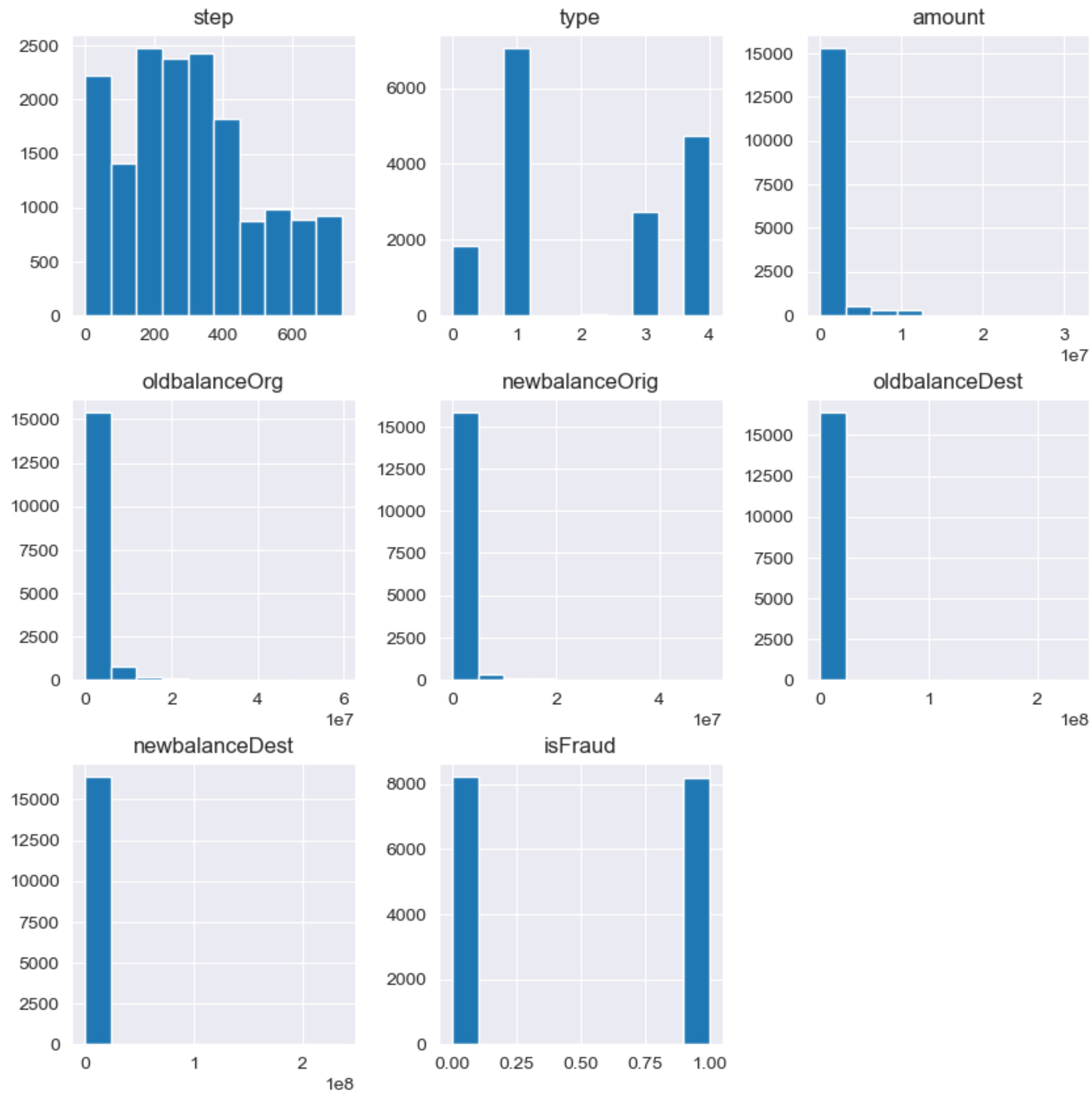
[16]:
```
plt.figure(figsize=(12,6))
sns.boxplot(data = Balanced_Data)
plt.show()
```



12 Visualizing Feature Distributions

We plot **histograms** for all numerical features in the **Balanced_Data** to observe their distributions.

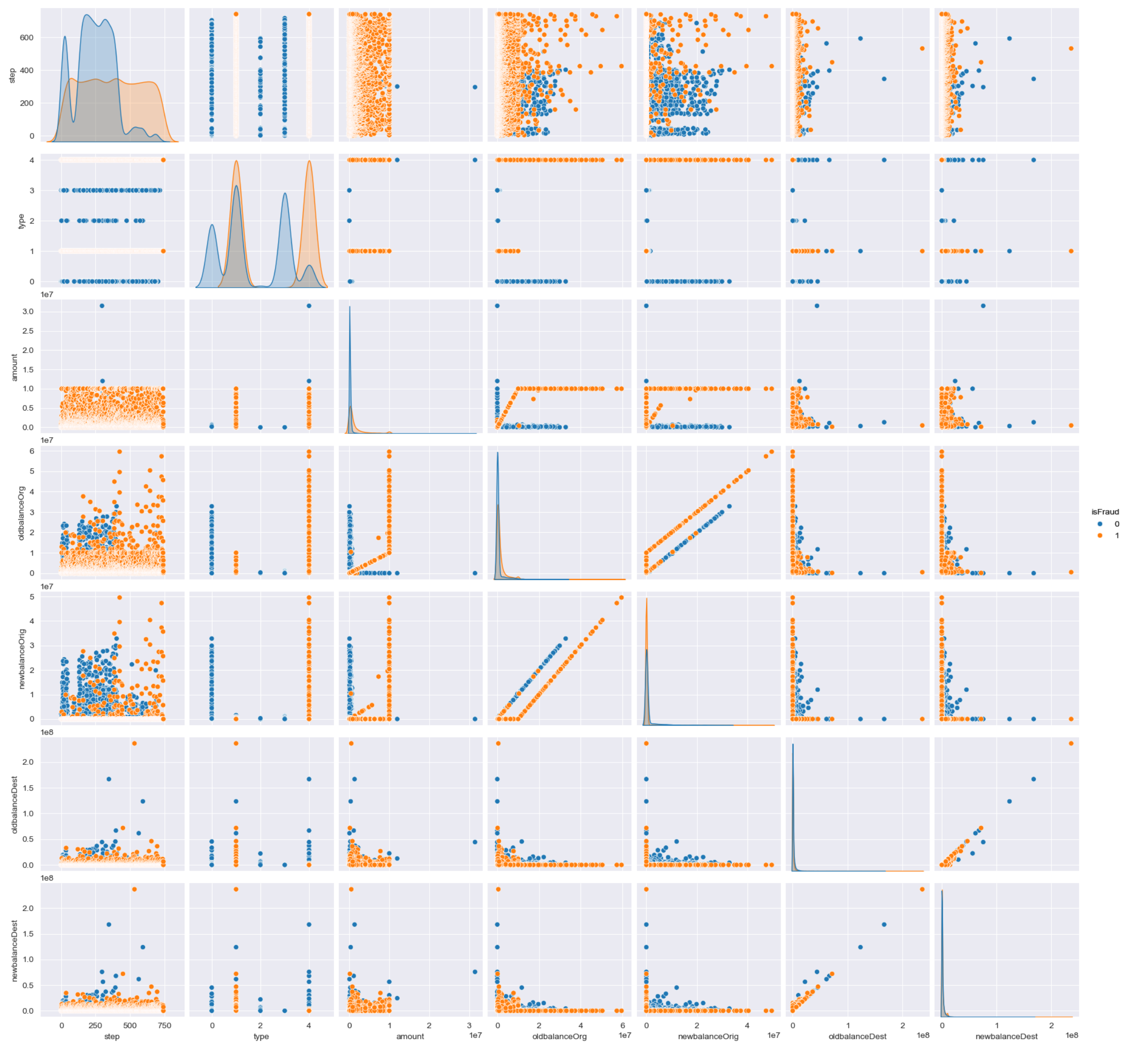
[17]:
```
Balanced_Data.hist(figsize = (10,10))
plt.show()
```



13 Pairplot of Features

We create a **pairplot** to visualize the relationships between features in the **Balanced_Data**, colored by the **'isFraud'** label. This helps in understanding how the features correlate with fraud vs. non-fraud transactions.

[18]:
```
pp = sns.pairplot(Balanced_Data, hue = 'isFraud')
pp.add_legend()
plt.show()
```




```
[19]: #Balanced_Data.to_csv("Cleaned_Data.csv", index = True)
```

```
[20]: Cols = list(Balanced_Data.columns)
```

```
[21]: Balanced_Data = pd.get_dummies(Balanced_Data, columns= ['type'])
```

14 Feature Scaling

We apply **StandardScaler** to standardize the features in **Vals**, ensuring that each feature has a mean of 0 and a standard deviation of 1.

```
[22]: from sklearn.preprocessing import StandardScaler
```

```
[23]: Scaler = StandardScaler()
```

[24]:
```
Cols.remove('isFraud')
Cols.remove('type')
```

[25]:
```
Balanced_Data[Cols] = Scaler.fit_transform(Balanced_Data[Cols])
```

[26]:
```
Balanced_Data.head()
```

[26]:
```
       step    amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest  \
0 -0.746423 -0.343380      -0.374751       -0.210007       -0.128934
1 -0.875815 -0.442849      -0.380729       -0.210007       -0.238687
2 -0.658436 -0.441245      -0.374609       -0.203473       -0.238687
3  0.252488 -0.442201      -0.378951       -0.208390       -0.238687
4  0.247312 -0.305758       0.028855        0.421103        0.539686

   newbalanceDest  isFraud  type_0  type_1  type_2  type_3  type_4
0       -0.177971        0   False    True   False   False   False
1       -0.324797        0   False   False   False    True   False
2       -0.324797        0   False   False   False    True   False
3       -0.324797        0   False   False   False    True   False
4        0.312950        0    True   False   False   False   False
```

15 Removing Outliers

We filter the scaled data (**T_data**) by removing any values with an absolute value greater than 3. This helps in removing potential outliers.

[27]:
```
Balanced_Data[abs(Balanced_Data)<=3]
```

[27]:
```
           step    amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest  \
0     -0.746423 -0.343380      -0.374751       -0.210007       -0.128934
1     -0.875815 -0.442849      -0.380729       -0.210007       -0.238687
2     -0.658436 -0.441245      -0.374609       -0.203473       -0.238687
3      0.252488 -0.442201      -0.378951       -0.208390       -0.238687
4      0.247312 -0.305758       0.028855        0.421103        0.539686
…           …         …            …              …              …
16421  2.260660 -0.258786      -0.276003       -0.210007       -0.238687
16422  2.260660  2.982084       1.565114       -0.210007       -0.238687
16423  2.260660  2.982084       1.565114       -0.210007       -0.219039
16424  2.260660  0.018166      -0.118669       -0.210007       -0.238687
16425  2.260660  0.018166      -0.118669       -0.210007        1.628940

       newbalanceDest  isFraud  type_0  type_1  type_2  type_3  type_4
0           -0.177971        0   False    True   False   False   False
1           -0.324797        0   False   False   False    True   False
2           -0.324797        0   False   False   False    True   False
3           -0.324797        0   False   False   False    True   False
4            0.312950        0    True   False   False   False   False
```

```
…              …      …      …      …      …      …      …
16421   -0.236739          1  False   True  False  False  False
16422   -0.324797          1  False  False  False  False   True
16423    1.329111          1  False   True  False  False  False
16424   -0.324797          1  False  False  False  False   True
16425    1.583217          1  False   True  False  False  False

[16410 rows x 12 columns]
```

15.0.1 Heatmap for Correlation in Balanced Data

- Visualizes the correlation matrix of features in the balanced dataset using a heatmap.
- Helps identify highly correlated variables and understand feature relationships.

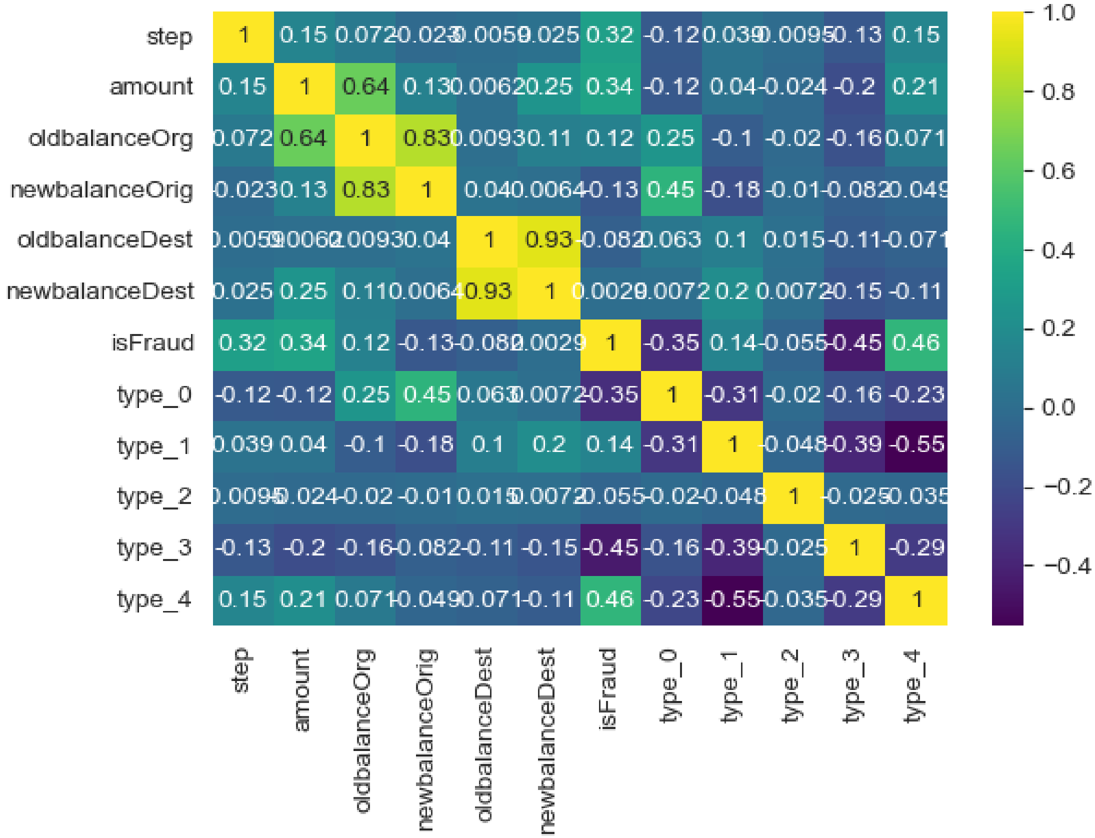
15.0.2 Dimensionality Reduction

- Removed unnecessary or less relevant features:
  - Dropped: `'oldbalanceOrg'`, `'type_2'`, `'type_1'`, `'oldbalanceDest'`, `'newbalanceDest'`, and `'type_3'`.
- Focused on retaining features that contribute most to the model's performance.

15.0.3 Heatmap for Reduced Data

- Visualized the correlation matrix of the reduced dataset using a heatmap.
- Ensured the remaining features are minimally correlated and relevant for model training.

[28]:
```
sns.heatmap(Balanced_Data.corr(), annot=True, cmap = 'viridis')
plt.tight_layout()
plt.show()
```

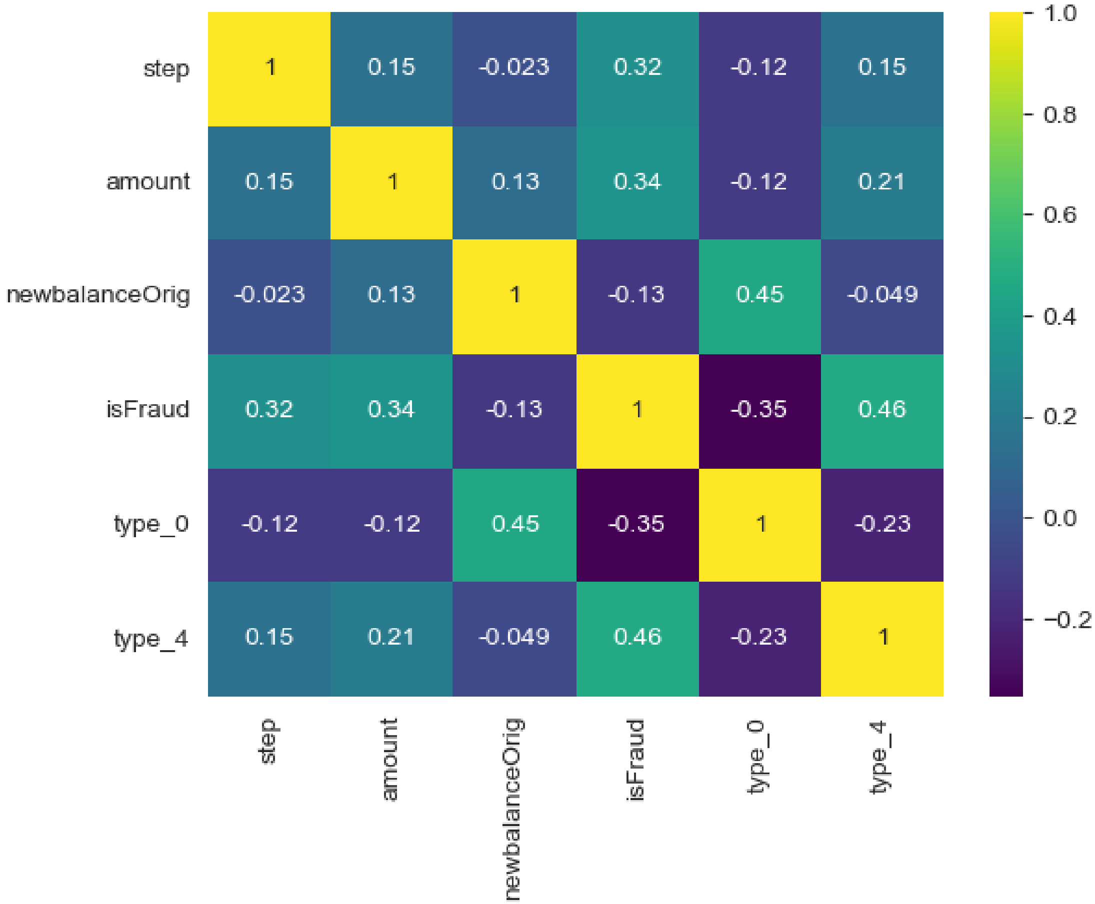


[29]:
```
Reduced_Data = Balanced_Data.
  ↪drop(['oldbalanceOrg','type_2','type_1','oldbalanceDest'], axis = 1)
```

[30]:
```
Reduced_Data.drop(['newbalanceDest','type_3'],inplace = True, axis = 1)
```

[31]:
```
sns.heatmap(Reduced_Data.corr(), annot=True, cmap = 'viridis')
```

[31]: <Axes: >



15.0.4 Train-Test Split

- Split the reduced dataset into training and testing sets.
- Features (`X`) are all columns except `'isFraud'`.
- Target variable (`y`) is `'isFraud'`.
- Used an 80-20 split ratio, with 80% of the data allocated for training and 20% for testing.
- Set `random_state=42` to ensure reproducibility of results.

[32]:
```
from sklearn.model_selection import train_test_split
x_test, x_train, y_test, y_train = train_test_split(Reduced_Data.
  ↪drop('isFraud',axis = 1),Reduced_Data['isFraud'] ,random_state = 42,␣
  ↪test_size = 0.2)
```

15.0.5 Model Selection and Training

- **Objective**: Select the best classification model based on cross-validation accuracy.

Models Evaluated:

1. Logistic Regression
2. Random Forest Classifier
3. XGBoost Classifier
4. Multi-Layer Perceptron Classifier (MLP)
    - Configured with `max_iter=1000` and `random_state=42` for stability.
5. Gaussian Naive Bayes

Process:

- Used `cross_val_score` with 5-fold cross-validation to evaluate each model's performance.
- Compared the mean accuracy of each model and selected the one with the highest score.

Best Model:

- Printed the name and accuracy of the best-performing model.
- Trained the selected model on the training data using the `fit` method.

[66]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import cross_val_score

def select_model(x_trn, y_trn):
    temp_model = None
    best = 0
    models = [LogisticRegression(), RandomForestClassifier(), XGBClassifier(),
 ↪MLPClassifier(max_iter=1000, random_state=42), GaussianNB()]
    for model in models:
        score = cross_val_score(model, x_trn, y_trn, cv = 5, scoring='accuracy')
        mean = score.mean()
        print(f"{model.__class__.__name__}: Accuracy Mean = {mean}")
        if mean  > best:
            temp_model = model
            best = mean

    print(f"Best Model: {temp_model.__class__.__name__} with Mean Accuracy =
 ↪{best}")
    return temp_model
```

[68]:
```
Model = select_model(x_train, y_train)
Model.fit(x_train, y_train)
```

```
LogisticRegression: Accuracy Mean = 0.8309003415376619
RandomForestClassifier: Accuracy Mean = 0.8613607677172663
XGBClassifier: Accuracy Mean = 0.8729387088391432
MLPClassifier: Accuracy Mean = 0.8458259086015516
```

```
GaussianNB: Accuracy Mean = 0.6099895125663585
Best Model: XGBClassifier with Mean Accuracy = 0.8729387088391432
```

[68]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, …)
```

15.0.6 Model Evaluation Metrics

Calculated Metrics:

- **Accuracy**: 0.89
- **Precision**: 0.89
- **Recall**: 0.87
- **F1-Score**: 0.88
- **AUC**: 0.96

ROC Curve: The ROC curve shows the trade-off between True Positive Rate and False Positive Rate.

Confusion Matrix:

- **Confusion Matrix**:
- **Non-Fraud (0)** vs **Fraud (1)**:
- True Positives: 5729
- True Negatives: 5892
- False Positives: 685
- False Negatives: 822

Confusion Matrix Heatmap:

- The heatmap below visualizes the confusion matrix, with darker colors representing higher values.

The model shows strong performance with high accuracy, precision, recall, and AUC. The confusion matrix and ROC curve further demonstrate its effectiveness in distinguishing between non-fraud and fraud cases.

[72]:
```
from sklearn.metrics import␣
↪accuracy_score,precision_score,recall_score,f1_score,RocCurveDisplay
```

```
y_pred = Model.predict(x_test)
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
```

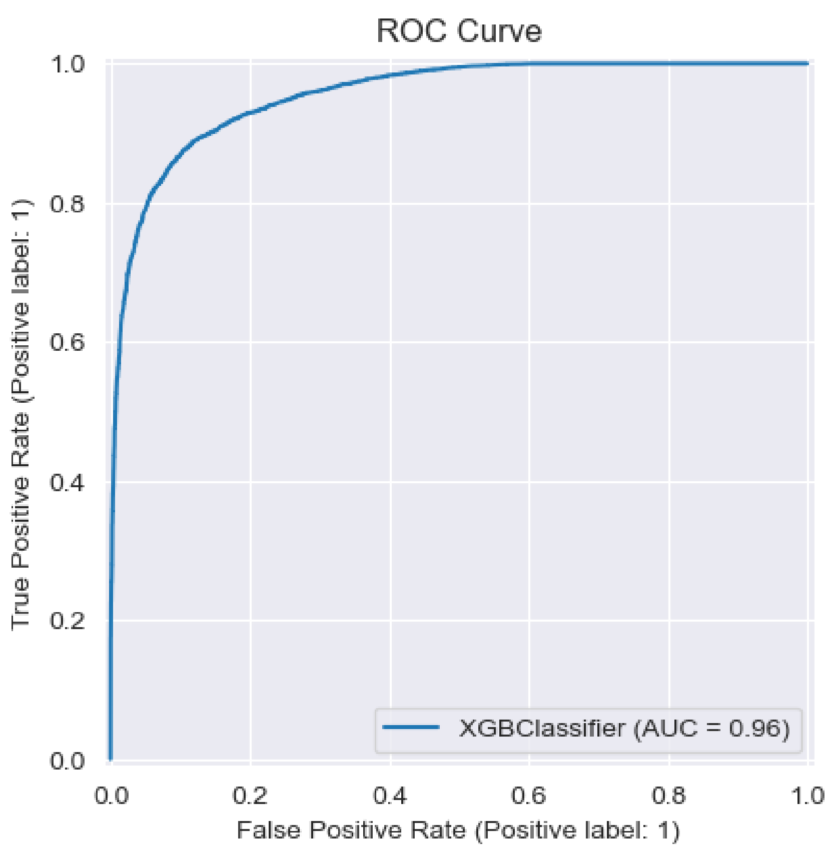
[73]:

```
print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1-Score: {f1}")
```

```
Accuracy: 0.8852071907373553
Precision: 0.8932023698160274
Recall: 0.8745229735918181
F1-Score: 0.8837639799460085
```

[74]:

```
RocCurveDisplay.from_estimator(Model, x_test, y_test)
plt.title("ROC Curve")
plt.show()
```



[70]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(confusion_matrix, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Actual Labels', fontsize=14)
plt.ylabel('Predicted Labels', fontsize=14)
plt.title('Confusion Matrix Heatmap', fontsize=16)
plt.xticks([0.5, 1.5], ['Non-Fraud', 'Fraud'], fontsize=12)
plt.yticks([0.5, 1.5], ['Non-Fraud', 'Fraud'], fontsize=12)
plt.tight_layout()
```