bank-transaction-fraud-detection

August 11, 2025

0.1 import Libraries

[2]:
```
# import Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score,precision_score, recall_score, f1_score
from sklearn.metrics import roc_auc_score
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import AdaBoostClassifier
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
import warnings
#ignore warnings
warnings.filterwarnings("ignore")
```

0.2 Read the data

[4]:
```
df = pd.read_csv('Bank_Transaction_Fraud_Detection.csv')
df.head(5)
```

[4]:
```
                            Customer_ID        Customer_Name  Gender  Age  \
0  d5f6ec07-d69e-4f47-b9b4-7c58ff17c19e           Osha Tella    Male   60
1  7c14ad51-781a-4db9-b7bd-67439c175262      Hredhaan Khosla  Female   51
2  3a73a0e5-d4da-45aa-85f3-528413900a35       Ekani Nazareth    Male   20
3  7902f4ef-9050-4a79-857d-9c2ea3181940  Yamini Ramachandran  Female   57
4  3a4bba70-d9a9-4c5f-8b92-1735fd8c19e9         Kritika Rege  Female   43

        State                City                 Bank_Branch Account_Type  \
0      Kerala  Thiruvananthapuram  Thiruvananthapuram Branch      Savings
```

```
1  Maharashtra              Nashik          Nashik Branch     Business
2        Bihar           Bhagalpur       Bhagalpur Branch      Savings
3   Tamil Nadu             Chennai         Chennai Branch     Business
4       Punjab            Amritsar        Amritsar Branch      Savings

                         Transaction_ID Transaction_Date  …  \
0  4fa3208f-9e23-42dc-b330-844829d0c12c       23-01-2025  …
1  c9de0c06-2c4c-40a9-97ed-3c7b8f97c79c       11-01-2025  …
2  e41c55f9-c016-4ff3-872b-cae72467c75c       25-01-2025  …
3  7f7ee11b-ff2c-45a3-802a-49bc47c02ecb       19-01-2025  …
4  f8e6ac6f-81a1-4985-bf12-f60967d852ef       30-01-2025  …

  Merchant_Category  Account_Balance Transaction_Device  \
0        Restaurant         74557.27    Voice Assistant
1        Restaurant         74622.66  POS Mobile Device
2         Groceries         66817.99                ATM
3     Entertainment         58177.08     POS Mobile App
4     Entertainment         16108.56       Virtual Card

        Transaction_Location Device_Type  Is_Fraud Transaction_Currency  \
0  Thiruvananthapuram, Kerala         POS         0                  INR
1         Nashik, Maharashtra     Desktop         0                  INR
2            Bhagalpur, Bihar     Desktop         0                  INR
3         Chennai, Tamil Nadu      Mobile         0                  INR
4            Amritsar, Punjab      Mobile         0                  INR

  Customer_Contact Transaction_Description           Customer_Email
0   +9198579XXXXXX     Bitcoin transaction       oshaXXXXX@XXXXX.com
1   +9191074XXXXXX        Grocery delivery  hredhaanXXXX@XXXXXX.com
2   +9197745XXXXXX  Mutual fund investment       ekaniXXX@XXXXXX.com
3   +9195889XXXXXX           Food delivery  yaminiXXXXX@XXXXXXX.com
4   +9195316XXXXXX          Debt repayment   kritikaXXXX@XXXXXX.com

[5 rows x 24 columns]
```

0.3 Data Cleaning

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

[6]:
```
(200000, 24)
```

[7]:
```python
df.columns
```

[7]:
```
Index(['Customer_ID', 'Customer_Name', 'Gender', 'Age', 'State', 'City',
       'Bank_Branch', 'Account_Type', 'Transaction_ID', 'Transaction_Date',
       'Transaction_Time', 'Transaction_Amount', 'Merchant_ID',
       'Transaction_Type', 'Merchant_Category', 'Account_Balance',
```

```
       'Transaction_Device', 'Transaction_Location', 'Device_Type', 'Is_Fraud',
       'Transaction_Currency', 'Customer_Contact', 'Transaction_Description',
       'Customer_Email'],
      dtype='object')
```

[8]:
```
df.Customer_Name.value_counts()
```

[8]:
```
Customer_Name
Aahana Kala        8
Krishna Sani       7
Madhav Kala        7
Jonathan Dara      7
Mitali Lad         7
                  ..
Chaitaly Parekh    1
Omkaar Gandhi      1
Oviya Chokshi      1
Theodore Hari      1
Gopal Rout         1
Name: count, Length: 142699, dtype: int64
```

[9]:
```
df.
↪drop(columns=['Customer_ID','Merchant_ID','Transaction_ID','Customer_Email','Customer_Conta
↪, inplace=True , axis=1 )
```

[10]:
```
df.shape
```

[10]:
```
(200000, 18)
```

[11]:
```
df.head()
```

[11]:
```
         Customer_Name  Gender  Age        State                City  \
0           Osha Tella    Male   60       Kerala  Thiruvananthapuram
1      Hredhaan Khosla  Female   51  Maharashtra              Nashik
2       Ekani Nazareth    Male   20        Bihar           Bhagalpur
3  Yamini Ramachandran  Female   57   Tamil Nadu             Chennai
4         Kritika Rege  Female   43       Punjab            Amritsar

                Bank_Branch Account_Type Transaction_Date Transaction_Time  \
0  Thiruvananthapuram Branch      Savings       23-01-2025         16:04:07
1              Nashik Branch     Business       11-01-2025         17:14:53
2           Bhagalpur Branch      Savings       25-01-2025         03:09:52
3             Chennai Branch     Business       19-01-2025         12:27:02
4            Amritsar Branch      Savings       30-01-2025         18:30:46

   Transaction_Amount Transaction_Type Merchant_Category  Account_Balance  \
0            32415.45         Transfer        Restaurant         74557.27
```

```
1            43622.60     Bill Payment       Restaurant         74622.66
2            63062.56     Bill Payment        Groceries         66817.99
3            14000.72            Debit    Entertainment         58177.08
4            18335.16         Transfer    Entertainment         16108.56

  Transaction_Device        Transaction_Location Device_Type  Is_Fraud  \
0    Voice Assistant  Thiruvananthapuram, Kerala         POS         0
1  POS Mobile Device          Nashik, Maharashtra     Desktop         0
2                ATM            Bhagalpur, Bihar     Desktop         0
3     POS Mobile App          Chennai, Tamil Nadu      Mobile         0
4       Virtual Card            Amritsar, Punjab      Mobile         0

  Transaction_Currency
0                  INR
1                  INR
2                  INR
3                  INR
4                  INR
```

[12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 18 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   Customer_Name         200000 non-null  object 
 1   Gender                200000 non-null  object 
 2   Age                   200000 non-null  int64  
 3   State                 200000 non-null  object 
 4   City                  200000 non-null  object 
 5   Bank_Branch           200000 non-null  object 
 6   Account_Type          200000 non-null  object 
 7   Transaction_Date      200000 non-null  object 
 8   Transaction_Time      200000 non-null  object 
 9   Transaction_Amount    200000 non-null  float64
 10  Transaction_Type      200000 non-null  object 
 11  Merchant_Category     200000 non-null  object 
 12  Account_Balance       200000 non-null  float64
 13  Transaction_Device    200000 non-null  object 
 14  Transaction_Location  200000 non-null  object 
 15  Device_Type           200000 non-null  object 
 16  Is_Fraud              200000 non-null  int64  
 17  Transaction_Currency  200000 non-null  object 
dtypes: float64(2), int64(2), object(14)
memory usage: 27.5+ MB
```

[13]:
```python
df['year'] = pd.to_datetime(df['Transaction_Date']).dt.year
df['month'] = pd.to_datetime(df['Transaction_Date']).dt.month
df['day'] = pd.to_datetime(df['Transaction_Date']).dt.day
df['hour'] = pd.to_datetime(df['Transaction_Time'], format='%H:%M:%S').dt.hour
df['minute'] = pd.to_datetime(df['Transaction_Time'], format='%H:%M:%S').dt.
↪minute
df['second'] = pd.to_datetime(df['Transaction_Time'], format='%H:%M:%S').dt.
↪second
```

[14]:
```python
df.head()
```

[14]:
```
        Customer_Name  Gender  Age        State                City  \
0          Osha Tella    Male   60       Kerala  Thiruvananthapuram
1      Hredhaan Khosla  Female   51  Maharashtra              Nashik
2       Ekani Nazareth    Male   20        Bihar           Bhagalpur
3  Yamini Ramachandran  Female   57   Tamil Nadu             Chennai
4         Kritika Rege  Female   43       Punjab            Amritsar

                Bank_Branch Account_Type Transaction_Date Transaction_Time  \
0  Thiruvananthapuram Branch      Savings       23-01-2025         16:04:07
1              Nashik Branch     Business       11-01-2025         17:14:53
2           Bhagalpur Branch      Savings       25-01-2025         03:09:52
3             Chennai Branch     Business       19-01-2025         12:27:02
4            Amritsar Branch      Savings       30-01-2025         18:30:46

   Transaction_Amount  …          Transaction_Location Device_Type  Is_Fraud  \
0            32415.45  …  Thiruvananthapuram, Kerala         POS         0
1            43622.60  …         Nashik, Maharashtra     Desktop         0
2            63062.56  …            Bhagalpur, Bihar     Desktop         0
3            14000.72  …         Chennai, Tamil Nadu      Mobile         0
4            18335.16  …            Amritsar, Punjab      Mobile         0

  Transaction_Currency  year month  day hour  minute  second
0                  INR  2025     1   23   16       4       7
1                  INR  2025     1   11   17      14      53
2                  INR  2025     1   25    3       9      52
3                  INR  2025     1   19   12      27       2
4                  INR  2025     1   30   18      30      46

[5 rows x 24 columns]
```

[15]:
```python
df.drop(columns=['Transaction_Date','Transaction_Time'],inplace=True)
```

[16]:
```python
#since all the transaction_currency is in rupees
df.drop(columns=['Transaction_Currency'],inplace=True ,axis=1)
```

[17]:
```python
df.drop(columns=['Customer_Name'],inplace=True ,axis=1)
```

[18]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 20 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   Gender                200000 non-null  object
 1   Age                   200000 non-null  int64
 2   State                 200000 non-null  object
 3   City                  200000 non-null  object
 4   Bank_Branch           200000 non-null  object
 5   Account_Type          200000 non-null  object
 6   Transaction_Amount    200000 non-null  float64
 7   Transaction_Type      200000 non-null  object
 8   Merchant_Category     200000 non-null  object
 9   Account_Balance       200000 non-null  float64
 10  Transaction_Device    200000 non-null  object
 11  Transaction_Location  200000 non-null  object
 12  Device_Type           200000 non-null  object
 13  Is_Fraud              200000 non-null  int64
 14  year                  200000 non-null  int32
 15  month                 200000 non-null  int32
 16  day                   200000 non-null  int32
 17  hour                  200000 non-null  int32
 18  minute                200000 non-null  int32
 19  second                200000 non-null  int32
dtypes: float64(2), int32(6), int64(2), object(10)
memory usage: 25.9+ MB
```

[19]:
```
df.duplicated().sum()
```

[19]:
```
0
```

[20]:
```
df.isna().sum()
```

[20]:
```
Gender                 0
Age                    0
State                  0
City                   0
Bank_Branch            0
Account_Type           0
Transaction_Amount     0
Transaction_Type       0
Merchant_Category      0
Account_Balance        0
Transaction_Device     0
```

```
Transaction_Location    0
Device_Type             0
Is_Fraud                0
year                    0
month                   0
day                     0
hour                    0
minute                  0
second                  0
dtype: int64
```

0.4 Exploratory Data Analysis

[22]:
```
Categorical = [i for i in df.columns if df[i].dtype == 'O']
Numerical = [i for i in df.columns if df[i].dtype != 'O']
```

[23]:
```
Categorical
```

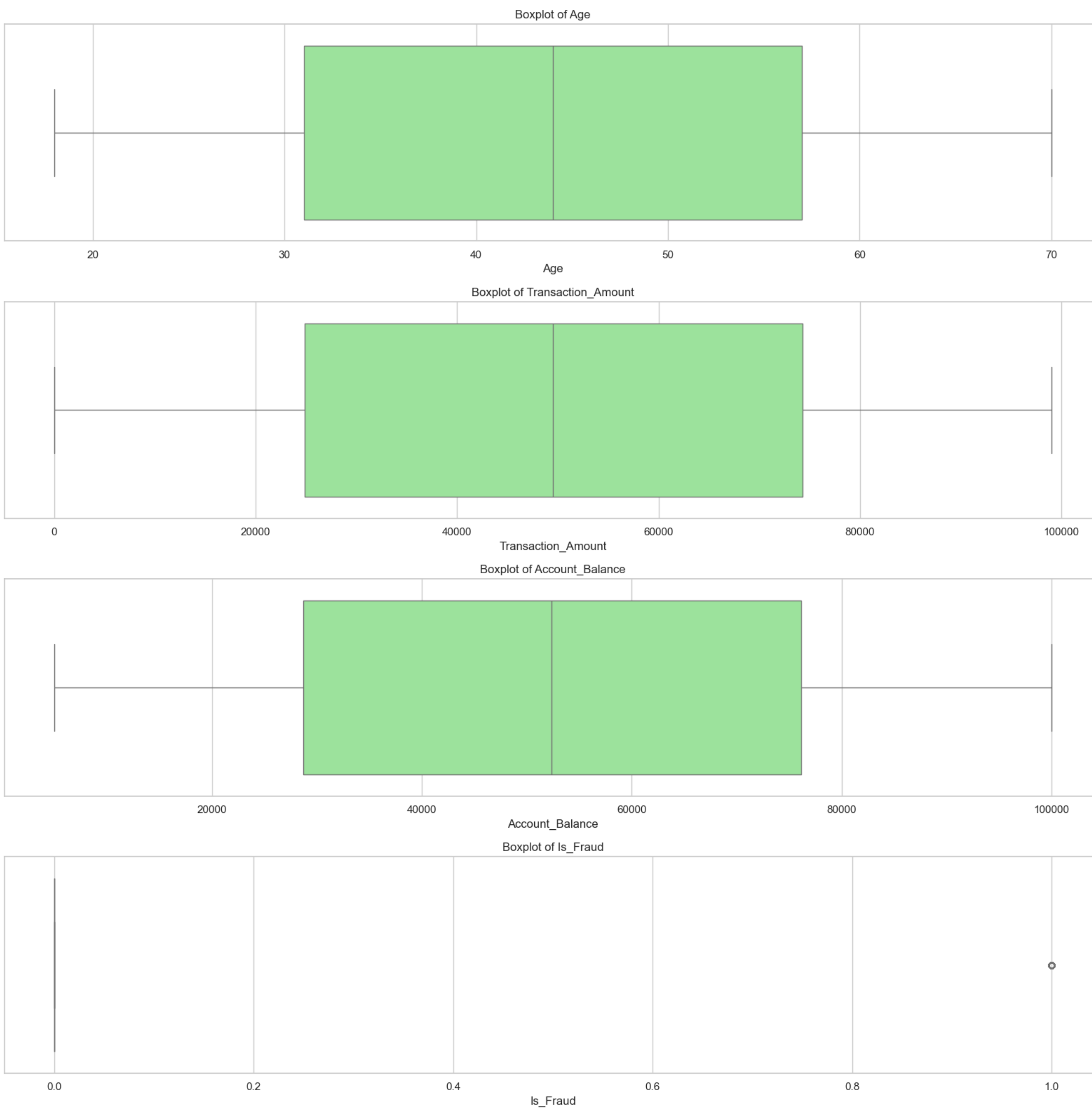
[23]:
```
['Gender',
 'State',
 'City',
 'Bank_Branch',
 'Account_Type',
 'Transaction_Type',
 'Merchant_Category',
 'Transaction_Device',
 'Transaction_Location',
 'Device_Type']
```

[24]:
```
Numerical
```

[24]:
```
['Age',
 'Transaction_Amount',
 'Account_Balance',
 'Is_Fraud',
 'year',
 'month',
 'day',
 'hour',
 'minute',
 'second']
```

[25]:
```
#checking for outliers
# Select only numeric columns
numeric_columns = df.select_dtypes(include=['int64', 'float64']).columns

# Set plot style
```

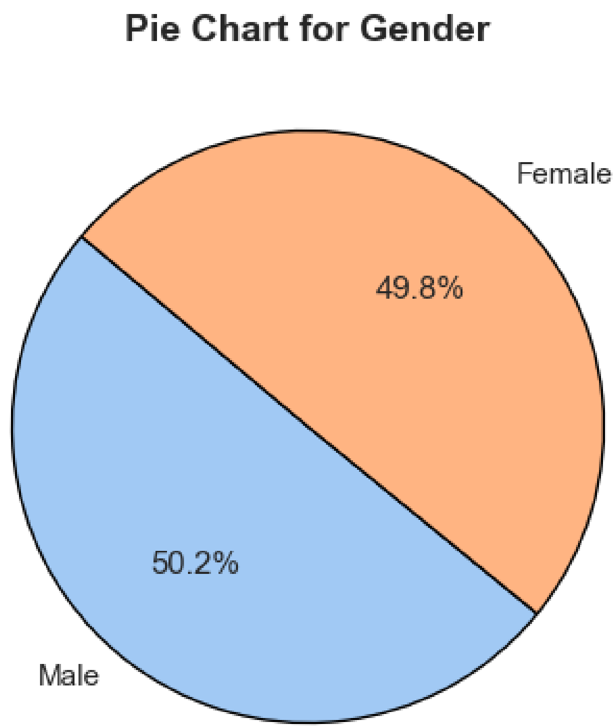
```
sns.set(style="whitegrid")
plt.figure(figsize=(16, 4 * len(numeric_columns)))

# Create boxplots for each numeric column
for i, column in enumerate(numeric_columns, 1):
    plt.subplot(len(numeric_columns), 1, i)
    sns.boxplot(data=df, x=column, color='lightgreen')
    plt.title(f'Boxplot of {column}')
    plt.tight_layout()

plt.show()
```



[26]:

```
sns.set_theme(style="whitegrid")

for i in Categorical:
    print(f"Value counts for column '{i}':")
    value_counts = df[i].value_counts()
    unique_count = len(value_counts)

    plt.figure(figsize=(7, 5))

    if 1 < unique_count < 5:
        colors = sns.color_palette("pastel")
        plt.pie(value_counts, labels=value_counts.index, autopct='%1.1f%%',␣
↪colors=colors,
                startangle=140, wedgeprops={'edgecolor': 'black'})
        plt.title(f"Pie Chart for {i}", fontsize=14, fontweight="bold")

    elif 5 <= unique_count <= 15:
        sns.barplot(x=value_counts.index, y=value_counts.values,␣
↪palette="viridis")
        plt.title(f"Bar Chart for {i}", fontsize=14, fontweight="bold")
        plt.xlabel(i, fontsize=12)
        plt.ylabel('Count', fontsize=12)
        plt.xticks(rotation=45, fontsize=10)
    else :
        print(value_counts)

    plt.show()
    print("-" * 25)
```

```
Value counts for column 'Gender':
```




```
-------------------------
Value counts for column 'State':
State
Nagaland                                   6031
Meghalaya                                  6003
Uttar Pradesh                              6002
Uttarakhand                                5985
Lakshadweep                                5954
Telangana                                  5952
Haryana                                    5947
Delhi                                      5943
Kerala                                     5933
Madhya Pradesh                             5928
Arunachal Pradesh                          5919
Punjab                                     5912
Gujarat                                    5901
Odisha                                     5899
Jharkhand                                  5898
Mizoram                                    5892
Himachal Pradesh                           5875
Goa                                        5871
Tripura                                    5869
```

```
Manipur                                       5869
Bihar                                         5857
Dadra and Nagar Haveli and Daman and Diu      5857
West Bengal                                   5851
Tamil Nadu                                    5841
Andaman and Nicobar Islands                   5832
Puducherry                                    5828
Chhattisgarh                                  5818
Assam                                         5816
Chandigarh                                    5797
Rajasthan                                     5795
Sikkim                                        5793
Maharashtra                                   5784
Karnataka                                     5775
Andhra Pradesh                                5773
Name: count, dtype: int64
```

```
<Figure size 700x500 with 0 Axes>
```

```
-------------------------
Value counts for column 'City':
City
Chandigarh     8135
Kavaratti      5954
Udaipur        2681
Daman          2022
Car Nicobar    1956
               …
Nashik         1125
Guwahati       1122
Asansol        1118
Jaipur         1115
Silchar        1112
Name: count, Length: 145, dtype: int64
```

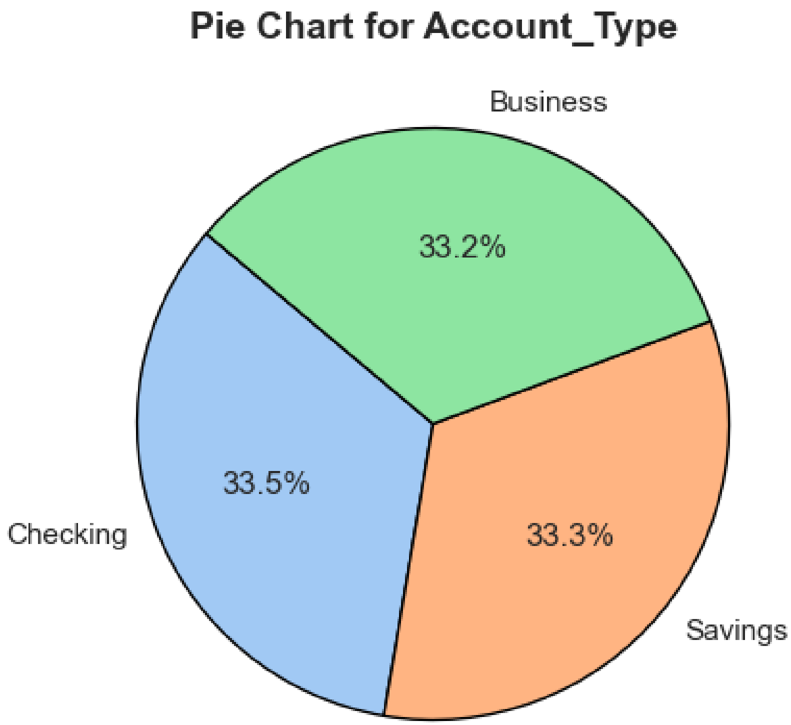
```
<Figure size 700x500 with 0 Axes>
```

```
-------------------------
Value counts for column 'Bank_Branch':
Bank_Branch
Chandigarh Branch     8135
Kavaratti Branch      5954
Udaipur Branch        2681
Daman Branch          2022
Car Nicobar Branch    1956
                      …
Nashik Branch         1125
Guwahati Branch       1122
Asansol Branch        1118
Jaipur Branch         1115
```

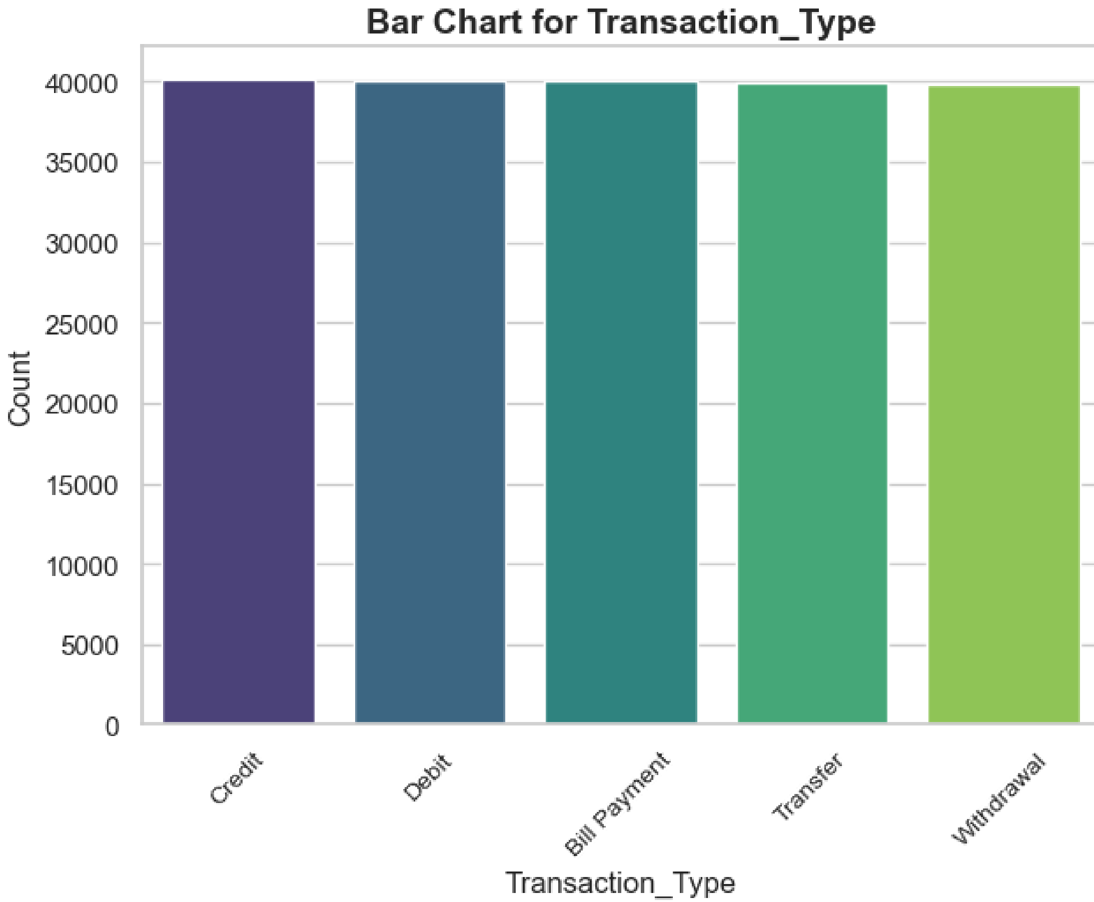
```
Silchar Branch        1112
Name: count, Length: 145, dtype: int64
```

```
<Figure size 700x500 with 0 Axes>
```

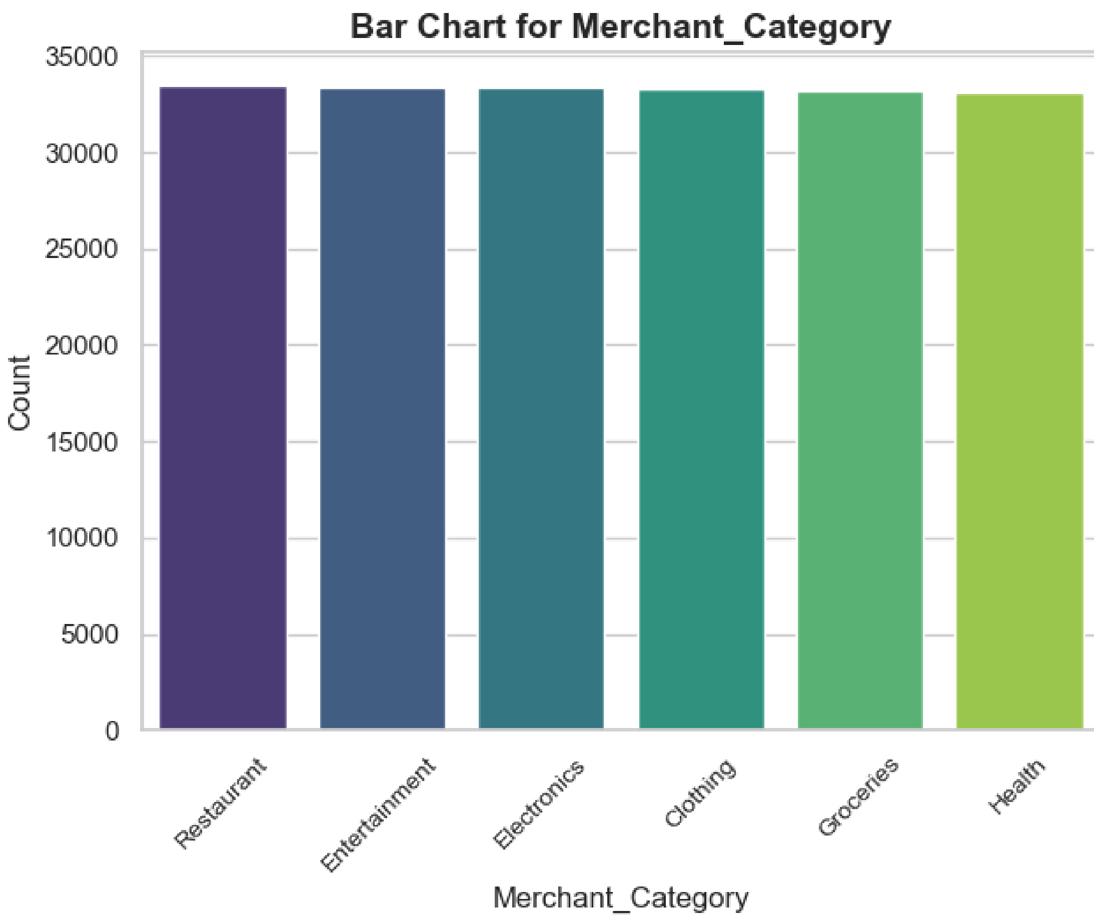
```
-------------------------
Value counts for column 'Account_Type':
```




```
-------------------------
Value counts for column 'Transaction_Type':
```




```
-------------------------
Value counts for column 'Merchant_Category':
```




```
-------------------------
Value counts for column 'Transaction_Device':
Transaction_Device
Self-service Banking Machine    21707
ATM                             21200
ATM Booth Kiosk                 21149
Debit/Credit Card                8273
Smart Card                       8133
Wearable Device                  8128
Virtual Card                     8059
Tablet                           8059
Desktop/Laptop                   8057
Voice Assistant                  8039
POS Mobile Device                8006
Banking Chatbot                  7995
Web Browser                      7981
Biometric Scanner                7952
QR Code Scanner                  7938
```

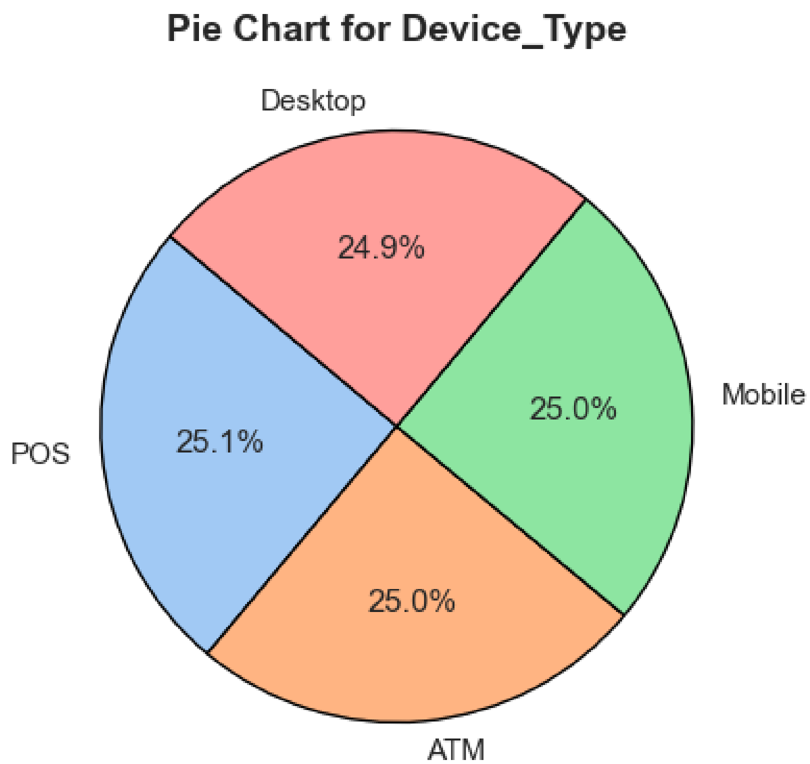
```
Mobile Device                    7879
Payment Gateway Device           7874
POS Mobile App                   7868
Bank Branch                      7855
POS Terminal                     7848
Name: count, dtype: int64
```

```
<Figure size 700x500 with 0 Axes>
```

```
-------------------------
Value counts for column 'Transaction_Location':
Transaction_Location
Kavaratti, Lakshadweep                             5954
Chandigarh, Chandigarh                             5797
Daman, Dadra and Nagar Haveli and Daman and Diu    2022
Car Nicobar, Andaman and Nicobar Islands           1956
Port Blair, Andaman and Nicobar Islands            1950
                                                   …
Nashik, Maharashtra                                1125
Guwahati, Assam                                    1122
Asansol, West Bengal                               1118
Jaipur, Rajasthan                                  1115
Silchar, Assam                                     1112
Name: count, Length: 148, dtype: int64
```

```
<Figure size 700x500 with 0 Axes>
```

```
-------------------------
Value counts for column 'Device_Type':
```

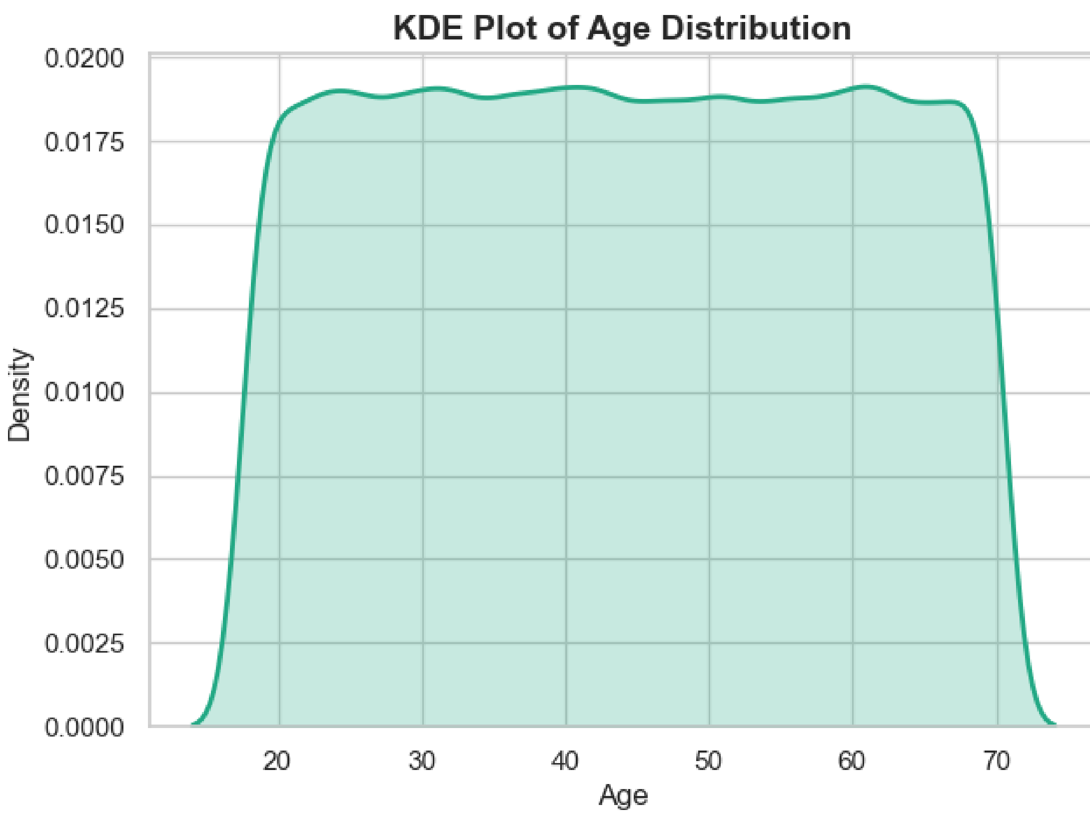


----

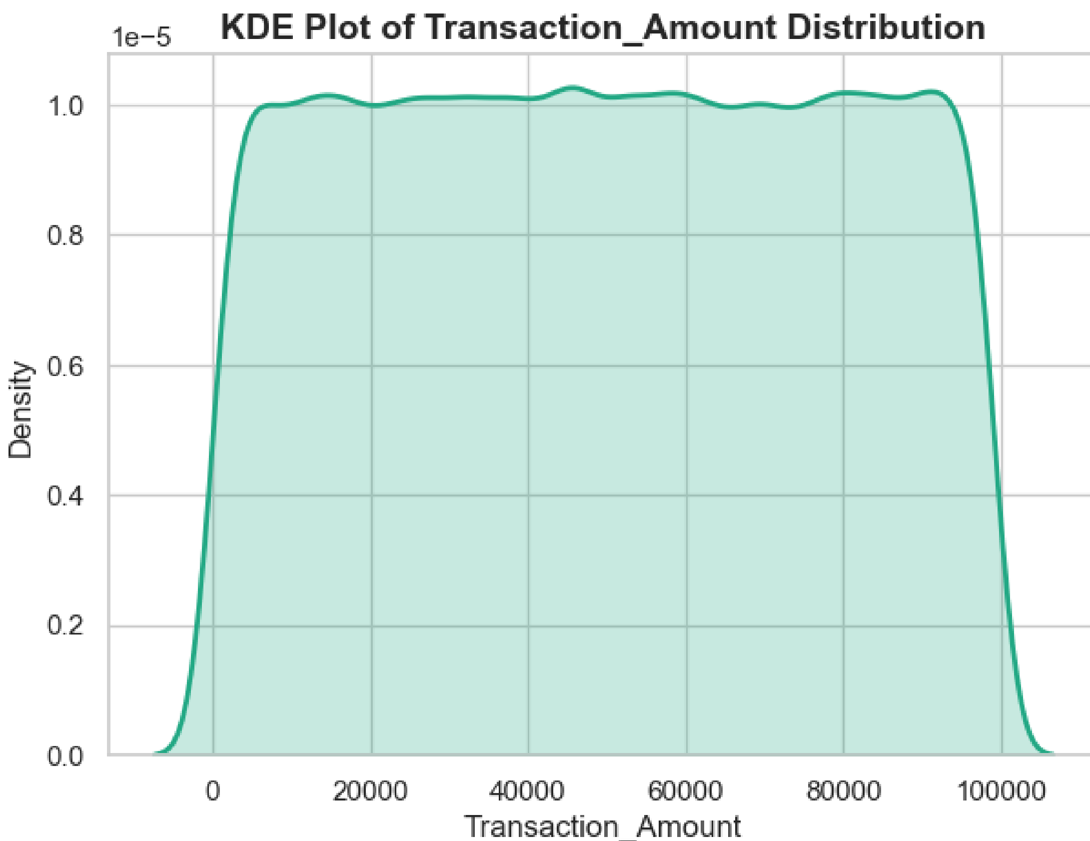
[27]:
```
def kdePlotForNumericalData(x):
    plt.figure(figsize=(7, 5))
    sns.set_theme(style="whitegrid")

    color = sns.color_palette("viridis", as_cmap=True)(0.6)

    sns.kdeplot(df[x], fill=True, color=color, linewidth=2)

    plt.title(f"KDE Plot of {x} Distribution", fontsize=14, fontweight="bold")
    plt.xlabel(x, fontsize=12)
    plt.ylabel("Density", fontsize=12)

    plt.show()
```

[28]:
```
for i in Numerical:
    if i != 'year' and i != 'month':
        print(i, '\n', df[i].describe())
        kdePlotForNumericalData(i)
        print("-" * 25)
```

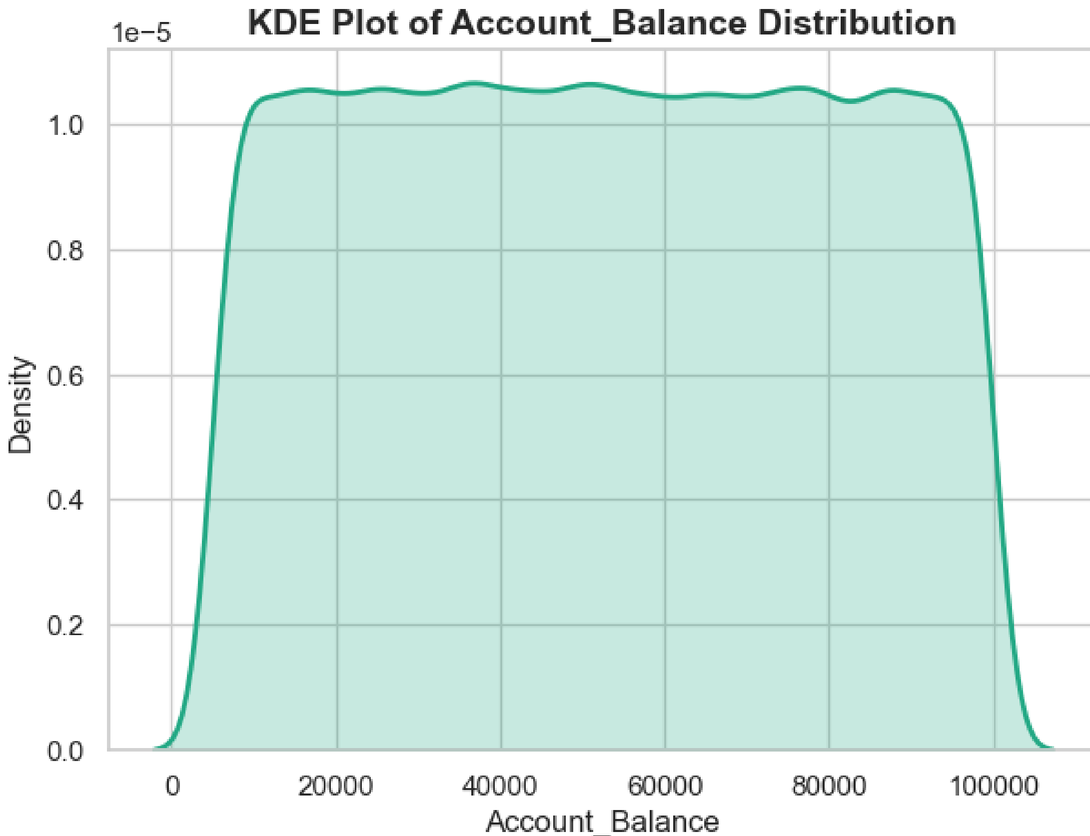
```
Age
 count    200000.000000
mean         44.015110
std          15.288774
min          18.000000
25%          31.000000
50%          44.000000
75%          57.000000
max          70.000000
Name: Age, dtype: float64
```



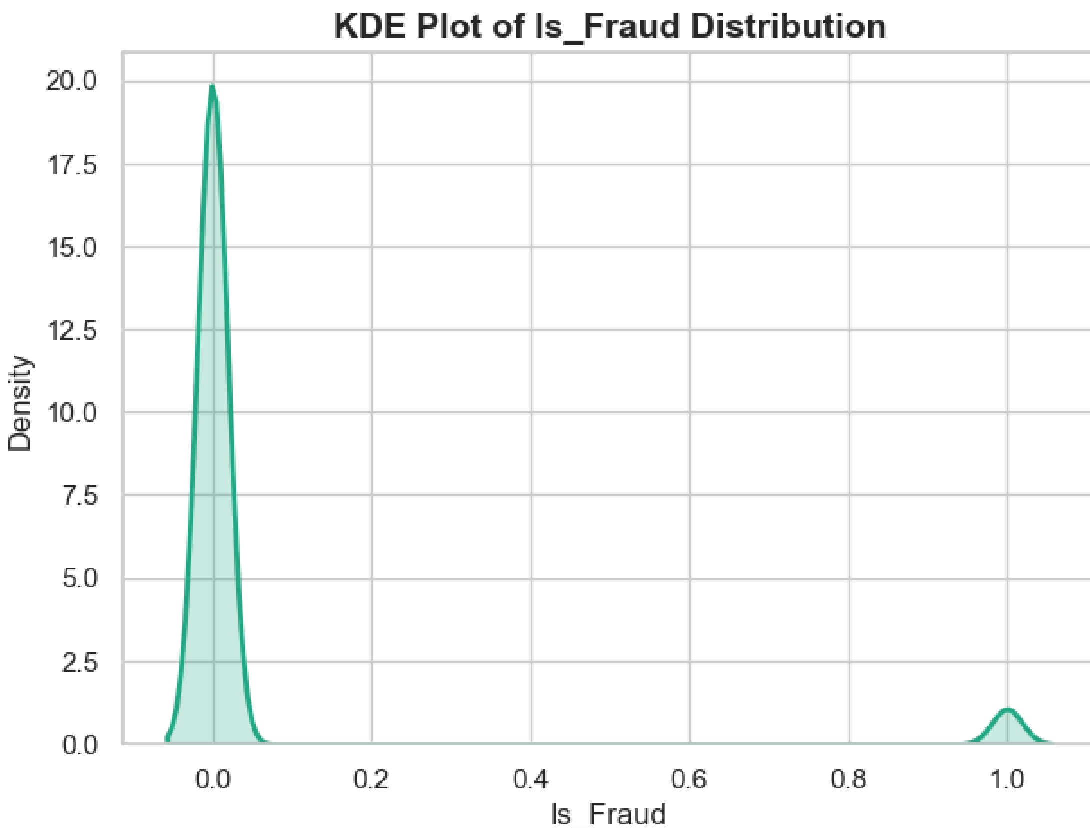

```
-------------------------
Transaction_Amount
 count    200000.000000
mean      49538.015554
std       28551.874004
min          10.290000
25%       24851.345000
50%       49502.440000
75%       74314.625000
max       98999.980000
Name: Transaction_Amount, dtype: float64
```



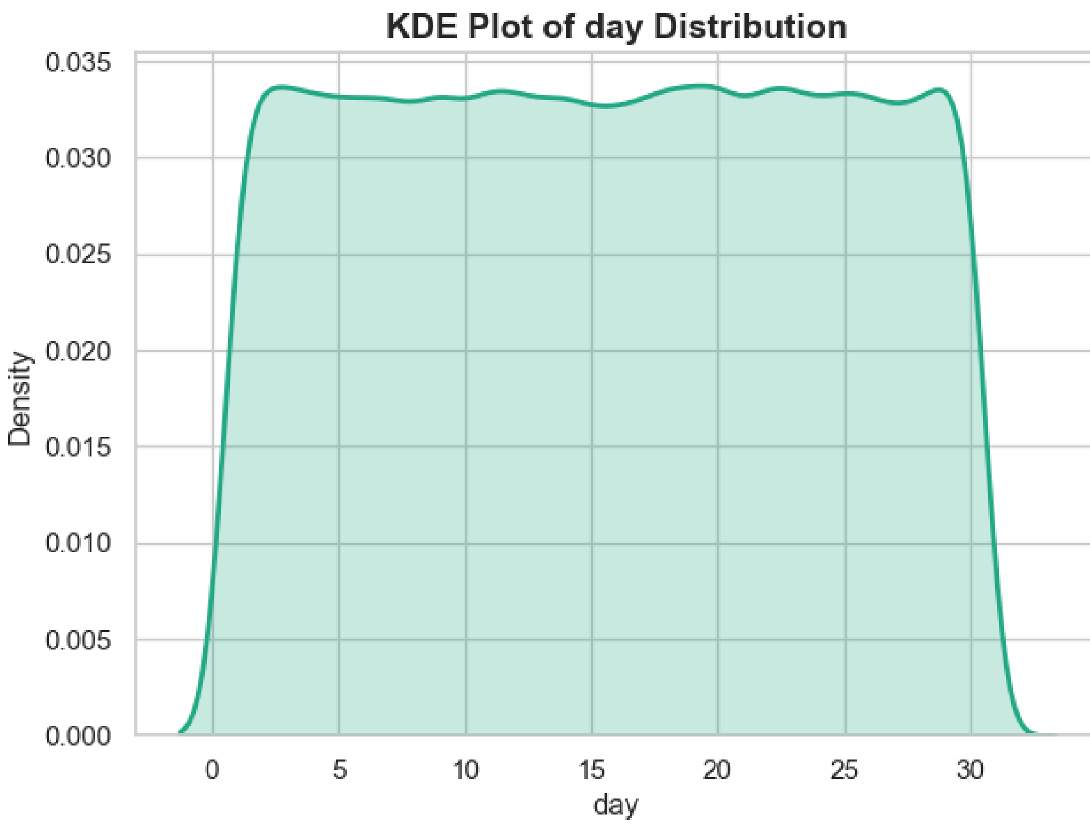

```
-------------------------
Account_Balance
 count    200000.000000
mean       52437.988784
std        27399.507128
min         5000.820000
25%        28742.395000
50%        52372.555000
75%        76147.670000
max        99999.950000
Name: Account_Balance, dtype: float64
```



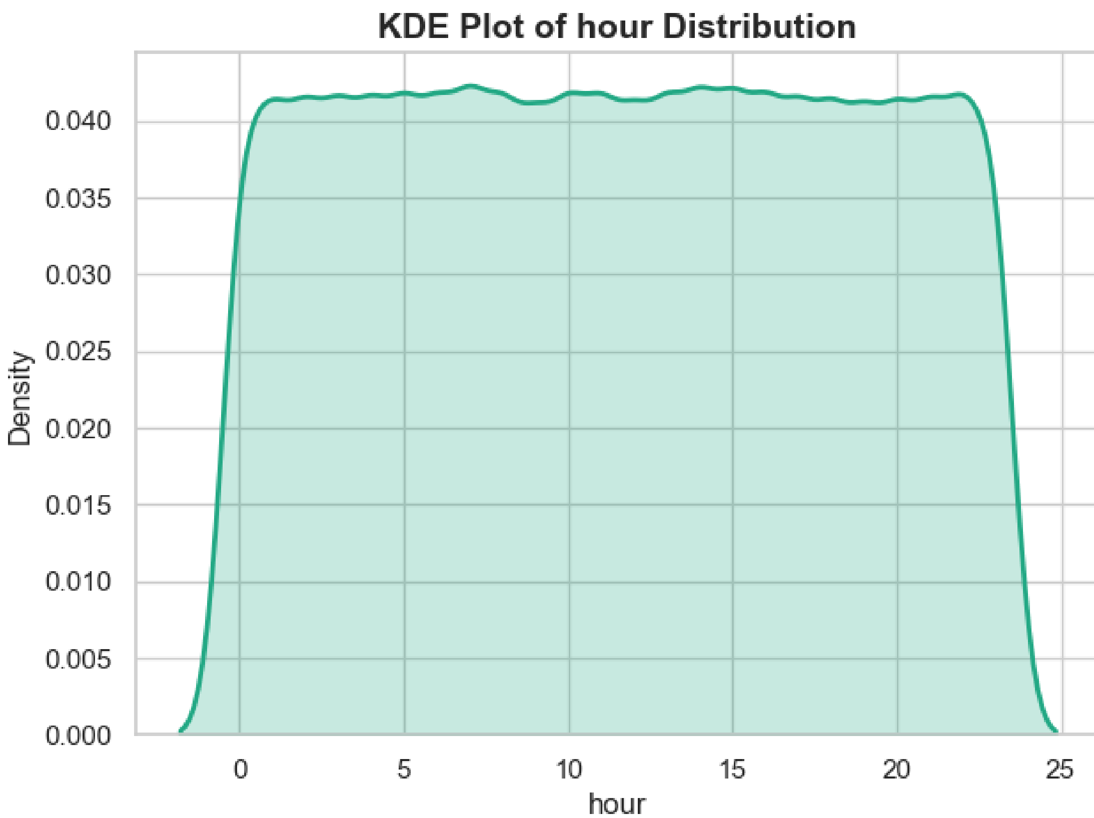

```
-------------------------
Is_Fraud
 count    200000.000000
mean          0.050440
std           0.218852
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max           1.000000
Name: Is_Fraud, dtype: float64
```



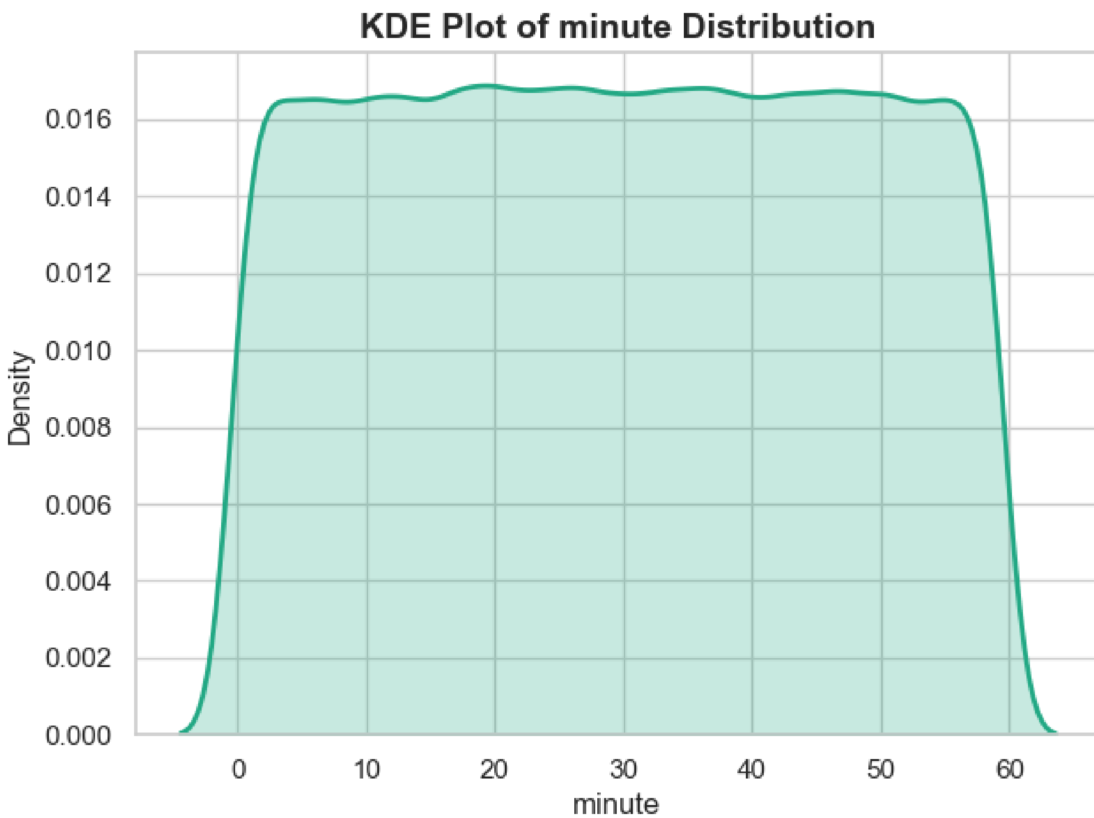

```
-------------------------
day
 count    200000.000000
mean          15.515985
std            8.672289
min            1.000000
25%            8.000000
50%           16.000000
75%           23.000000
max           31.000000
Name: day, dtype: float64
```



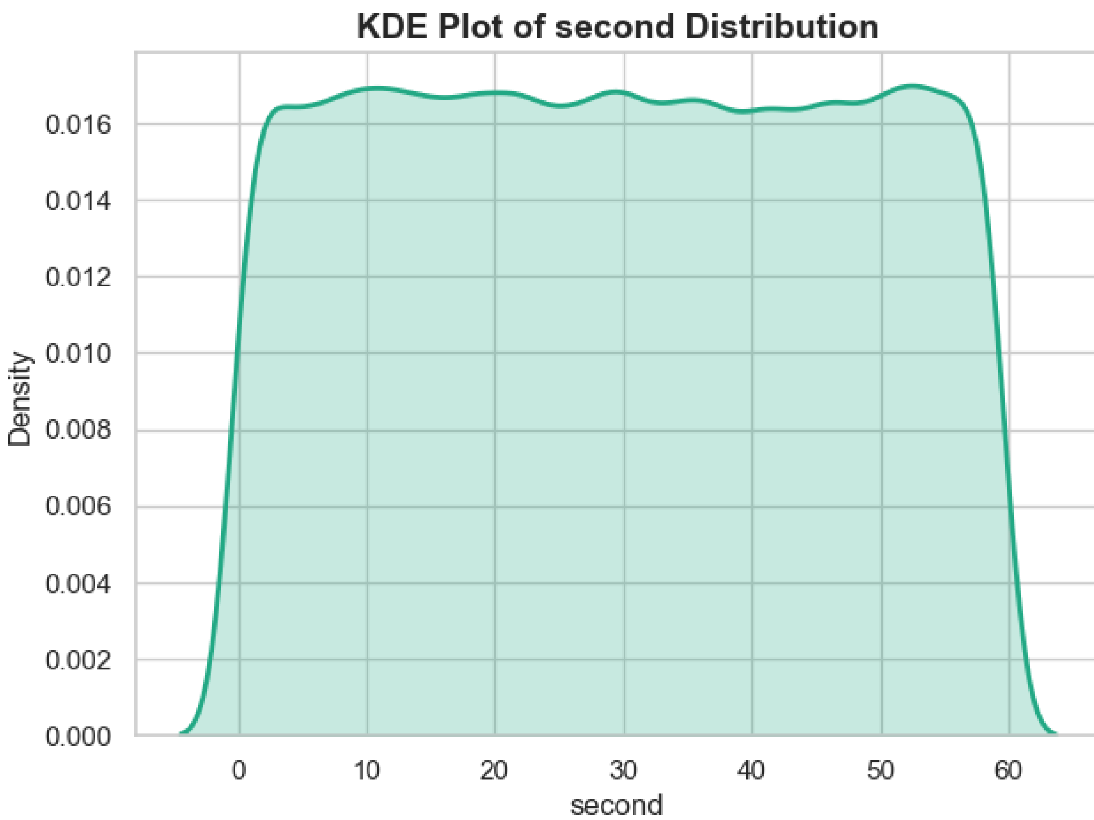

```
-------------------------
hour
 count    200000.000000
mean         11.490420
std           6.917094
min           0.000000
25%           6.000000
50%          11.000000
75%          17.000000
max          23.000000
Name: hour, dtype: float64
```




```
-------------------------
minute
 count    200000.00000
mean          29.48192
std           17.28522
min            0.00000
25%           15.00000
50%           29.00000
75%           44.00000
max           59.00000
Name: minute, dtype: float64
```




```
-------------------------
second
 count    200000.00000
mean         29.50111
std          17.33988
min           0.00000
25%          14.00000
50%          29.00000
75%          45.00000
max          59.00000
Name: second, dtype: float64
```



0.5 Preprocessing

0.5.1 Encoding

[31]:
```
label_encoder = LabelEncoder()
```

[32]:
```
for i in Categorical :
    df[i] = label_encoder.fit_transform(df[i])
```

[33]:
```
df
```

[33]:

	Gender	Age	State	City	Bank_Branch	Account_Type	\
0	1	60	15	127	127	2	
1	0	51	18	100	100	0	
2	1	20	4	13	13	2	
3	0	57	28	22	22	0	
4	0	43	25	7	7	2	
…	…	…	…	…	…	…	
199995	0	55	7	33	33	0	

```
199996        1   51      19    63            63             0
199997        0   41       5    21            21             2
199998        0   28      29   103           103             1
199999        1   34      22    71            71             0

        Transaction_Amount  Transaction_Type  Merchant_Category  \
0                 32415.45                 3                  5
1                 43622.60                 0                  5
2                 63062.56                 0                  3
3                 14000.72                 2                  2
4                 18335.16                 3                  2
…                      …                …                …
199995            98513.74                 1                  5
199996            40593.55                 4                  3
199997            61579.70                 4                  4
199998            39488.22                 2                  1
199999            58622.49                 2                  1

        Account_Balance  Transaction_Device  Transaction_Location  \
0              74557.27                  17                   129
1              74622.66                   9                   102
2              66817.99                   0                    13
3              58177.08                   8                    24
4              16108.56                  16                     7
…                   …                …                  …
199995         37475.11                   6                    35
199996         53037.20                   0                    65
199997         96225.36                   0                    21
199998         89599.90                  17                   105
199999         15066.24                  16                    73

        Device_Type  Is_Fraud  year  month  day  hour  minute  second
0                 3         0  2025      1   23    16       4       7
1                 1         0  2025      1   11    17      14      53
2                 1         0  2025      1   25     3       9      52
3                 2         0  2025      1   19    12      27       2
4                 2         0  2025      1   30    18      30      46
…              …       …    …     …   …     …      …
199995            0         0  2025      1    8    18      42       9
199996            0         0  2025      1    1    20      51      21
199997            1         0  2025      1   28    10      47      40
199998            1         0  2025      1    8     6      26      41
199999            2         0  2025      1    8    15      26      19

[200000 rows x 20 columns]
```

[34]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 20 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   Gender                200000 non-null  int32
 1   Age                   200000 non-null  int64
 2   State                 200000 non-null  int32
 3   City                  200000 non-null  int32
 4   Bank_Branch           200000 non-null  int32
 5   Account_Type          200000 non-null  int32
 6   Transaction_Amount    200000 non-null  float64
 7   Transaction_Type      200000 non-null  int32
 8   Merchant_Category     200000 non-null  int32
 9   Account_Balance       200000 non-null  float64
 10  Transaction_Device    200000 non-null  int32
 11  Transaction_Location  200000 non-null  int32
 12  Device_Type           200000 non-null  int32
 13  Is_Fraud              200000 non-null  int64
 14  year                  200000 non-null  int32
 15  month                 200000 non-null  int32
 16  day                   200000 non-null  int32
 17  hour                  200000 non-null  int32
 18  minute                200000 non-null  int32
 19  second                200000 non-null  int32
dtypes: float64(2), int32(16), int64(2)
memory usage: 18.3 MB
```

[35]:
```
X = df.drop(columns=['Is_Fraud'])
```

[36]:
```
Y = df['Is_Fraud']
```

[37]:
```
x_train,x_test,y_train,y_test = train_test_split(X , Y , test_size=0.2 ,␣
↪random_state=42 )
```

0.5.2 Scaling

[39]:
```
Scaling = StandardScaler()
```

[40]:
```
scaledData = Scaling.fit_transform(x_train)
```

[41]:
```
x_train_scaled = pd.DataFrame(scaledData,columns=x_train.columns)
```

[42]:
```
x_train_scaled
```

[42]:
```
          Gender       Age     State      City  Bank_Branch  Account_Type  \
0      -1.005088 -0.524942 -1.482329  1.750748     1.750748     -1.226545
```

```
1      -1.005088 -0.655753  1.679690 -0.541664    -0.541664     -1.226545
2      -1.005088 -0.263320  1.271687 -0.087957    -0.087957     -0.000421
3      -1.005088  1.110193 -1.584329  1.392558     1.392558      1.225702
4       0.994938 -1.309807  0.965686 -0.278992    -0.278992      1.225702
…            …         …         …         …            …            …
159995 -1.005088  1.633437 -1.584329  1.631351     1.631351     -0.000421
159996 -1.005088 -1.048185  0.659684  1.129886     1.129886     -1.226545
159997 -1.005088 -1.113590 -0.360322 -0.589422    -0.589422      1.225702
159998 -1.005088  0.979383 -1.380328 -0.231233    -0.231233     -1.226545
159999  0.994938  0.979383  1.679690 -1.496835    -1.496835     -1.226545

        Transaction_Amount  Transaction_Type  Merchant_Category  \
0                -1.243502         -0.705631           0.878821
1                 1.659210          0.001503           0.293689
2                -0.525214         -0.705631          -1.461708
3                 0.724717          0.708637           0.293689
4                 1.160714          0.708637           0.878821
…                      …               …                 …
159995            1.712250          0.001503          -0.291443
159996           -1.510608          0.001503          -0.291443
159997           -0.732904          0.001503           0.878821
159998            1.344078         -0.705631          -1.461708
159999            1.492668          1.415771           0.878821

        Account_Balance  Transaction_Device  Transaction_Location  \
0             -0.571419           -0.092887              1.755799
1             -0.055549           -0.420169             -0.528198
2              0.132145           -0.747451             -0.080817
3              1.055514            1.379883              1.379057
4             -0.944140           -1.074734             -0.269188
…                  …                 …                    …
159995         0.666064           -0.911092              1.638067
159996        -0.247549            0.398037              1.120047
159997         0.750419           -0.420169             -0.575290
159998         1.573536            0.725319             -0.222095
159999         0.491915           -1.402016             -1.517145

        Device_Type  year  month       day      hour    minute    second
0         -0.447120   0.0    0.0  0.171485 -1.083895 -0.202656 -1.469352
1          0.446026   0.0    0.0  0.402100 -0.939299  1.069960 -1.584697
2         -0.447120   0.0    0.0  0.978637  0.940444  0.317960 -0.661936
3          0.446026   0.0    0.0 -0.520360 -1.662277 -1.301733 -1.296334
4         -0.447120   0.0    0.0  0.748022 -0.939299 -0.376194  1.414276
…                 …   …     …       …         …         …         …
159995     1.339173   0.0    0.0 -0.520360  0.072870 -0.954656  1.125913
159996    -1.340267   0.0    0.0  0.748022  1.229635 -0.838964  0.895223
159997     1.339173   0.0    0.0  1.439867 -0.360917 -0.029117 -0.777281
```

```
159998     1.339173   0.0    0.0  0.056177 -0.650108 -0.665425 -1.238662
159999     0.446026   0.0    0.0  0.286792  0.940444  0.317960  0.376170

[160000 rows x 19 columns]
```

[43]:
```
y_train
```

[43]:
```
153248    0
67802     0
148889    0
103093    0
104681    0
         ..
119879    0
103694    1
131932    0
146867    0
121958    0
Name: Is_Fraud, Length: 160000, dtype: int64
```

0.6 Modeling

0.6.1 Logistic Regression

[46]:
```
logisticRegressionModel = LogisticRegression(class_weight='balanced')
```

[47]:
```
logisticRegressionModel.fit(x_train_scaled,y_train)
```

[47]:
```
LogisticRegression(class_weight='balanced')
```

[48]:
```
y_pred = logisticRegressionModel.predict(x_test)
```

[49]:
```
y_pred
```

[49]:
```
array([0, 0, 0, …, 0, 0, 0], dtype=int64)
```

[50]:
```
score = confusion_matrix(y_test,y_pred)
```

[51]:
```
score
```

[51]:
```
array([[37955,     0],
       [ 2045,     0]], dtype=int64)
```

[52]:
```
report = classification_report(y_test,y_pred)
```

[53]:
```
print(report)
```

```
              precision    recall  f1-score   support

           0       0.95      1.00      0.97     37955
           1       0.00      0.00      0.00      2045

    accuracy                           0.95     40000
   macro avg       0.47      0.50      0.49     40000
weighted avg       0.90      0.95      0.92     40000
```

0.6.2 Random Forest

[55]:
```
model = RandomForestClassifier(random_state=42 , class_weight = 'balanced')
```

[56]:
```
model.fit(x_train_scaled, y_train)
```

[56]:
```
RandomForestClassifier(class_weight='balanced', random_state=42)
```

[57]:
```
y_pred_for_RFC = model.predict(x_test)
```

[58]:
```
print(classification_report(y_test, y_pred_for_RFC))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_for_RFC))
```

```
              precision    recall  f1-score   support

           0       0.95      1.00      0.97     37955
           1       0.00      0.00      0.00      2045

    accuracy                           0.95     40000
   macro avg       0.47      0.50      0.49     40000
weighted avg       0.90      0.95      0.92     40000

ROC-AUC Score: 0.5
```

0.6.3 AdaBoost

[60]:
```
scale_pos_weight = len(y_train[y_train == 0]) / len(y_train[y_train == 1])
```

[61]:
```
adamodel = AdaBoostClassifier(n_estimators=100, learning_rate=0.8,␣
↪random_state=42)
```

[62]:
```
adamodel.fit(x_train_scaled, y_train)
```

[62]:
```
AdaBoostClassifier(learning_rate=0.8, n_estimators=100, random_state=42)
```

[63]:
```
y_pred_for_adamodel = adamodel.predict(x_test)
```

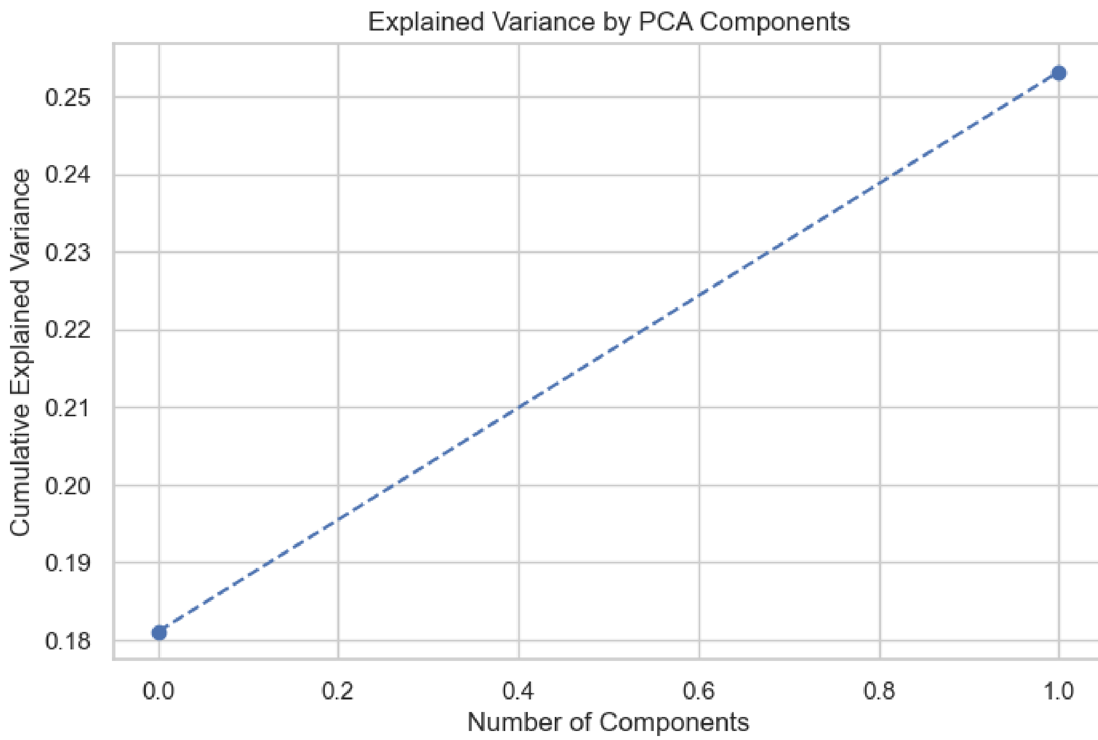
[64]:
```
print("Classification Report:\n", classification_report(y_test,␣
 ↪y_pred_for_adamodel))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_for_adamodel))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00     37955
           1       0.05      1.00      0.10      2045

    accuracy                           0.05     40000
   macro avg       0.03      0.50      0.05     40000
weighted avg       0.00      0.05      0.00     40000

ROC-AUC Score: 0.5
```

0.7 Sampling

[66]:
```
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(x_train_scaled, y_train)
```

[67]:
```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_resampled)

# Plot explained variance to decide components
plt.figure(figsize=(8, 5))
plt.plot(np.cumsum(pca.explained_variance_ratio_), marker='o', linestyle='--')
plt.title("Explained Variance by PCA Components")
plt.xlabel("Number of Components")
plt.ylabel("Cumulative Explained Variance")
plt.grid(True)
plt.show()
```



0.7.1 Logistic Regression with Over Sampling

[69]:
```
logisticRegressionModelSampled = LogisticRegression(random_state=42)
```

[70]:
```
logisticRegressionModelSampled.fit(X_resampled,y_resampled)
```

[70]:
```
LogisticRegression(random_state=42)
```

[71]:
```
LR_y_pred_sampled = logisticRegressionModel.predict(x_test)
```

[72]:
```
score = confusion_matrix(y_test,LR_y_pred_sampled)
```

[73]:
```
score
```

[73]:
```
array([[37955,     0],
       [ 2045,     0]], dtype=int64)
```

[74]:
```
report = classification_report(y_test,LR_y_pred_sampled)
```

[75]:
```
print(report)
```

```
              precision    recall  f1-score   support
```

```
           0       0.95      1.00      0.97     37955
           1       0.00      0.00      0.00      2045

    accuracy                           0.95     40000
   macro avg       0.47      0.50      0.49     40000
weighted avg       0.90      0.95      0.92     40000
```

0.7.2 KNeighbours with over Sampling

[77]:
```
knn = KNeighborsClassifier()
```

[78]:
```
knn.fit(X_resampled, y_resampled)
```

[78]:
```
KNeighborsClassifier()
```

[79]:
```
y_pred_for_KNN = knn.predict(x_test)
```

[80]:
```
print("  K-Nearest Neighbors")
print("Accuracy:", accuracy_score(y_test, y_pred_for_KNN))
print("ROC AUC:", roc_auc_score(y_test, knn.predict_proba(x_test)[:, 1]))
print(confusion_matrix(y_test, y_pred_for_KNN))
print(classification_report(y_test, y_pred_for_KNN))
```

```
  K-Nearest Neighbors
Accuracy: 0.948875
ROC AUC: 0.4998618039184866
[[37955     0]
 [ 2045     0]]
              precision    recall  f1-score   support

           0       0.95      1.00      0.97     37955
           1       0.00      0.00      0.00      2045

    accuracy                           0.95     40000
   macro avg       0.47      0.50      0.49     40000
weighted avg       0.90      0.95      0.92     40000
```

0.7.3 Random Forest With over sampling

[82]:
```
RFmodelOverSampled = RandomForestClassifier(random_state=42)
```

[83]:
```
RFmodelOverSampled.fit(X_resampled, y_resampled)
```

[83]:
```
RandomForestClassifier(random_state=42)
```

[84]:
```python
y_pred_for_RFC2 = RFmodelOverSampled.predict(x_test)
```

[85]:
```python
print(classification_report(y_test, y_pred_for_RFC2))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_for_RFC2))
```

```
              precision    recall  f1-score   support

           0       0.95      0.84      0.89     37955
           1       0.05      0.15      0.07      2045

    accuracy                           0.81     40000
   macro avg       0.50      0.50      0.48     40000
weighted avg       0.90      0.81      0.85     40000

ROC-AUC Score: 0.4974766154360507
```

0.7.4 AdaBoost with Over Sampling

[87]:
```python
adamodel_sampled = AdaBoostClassifier(random_state=42)
```

[88]:
```python
adamodel_sampled.fit(X_resampled, y_resampled)
```

[88]:
```
AdaBoostClassifier(random_state=42)
```

[89]:
```python
y_pred_for_ada_sampled = adamodel_sampled.predict(x_test)
```

[90]:
```python
print("Classification Report:\n", classification_report(y_test,␣
↪y_pred_for_ada_sampled))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_for_ada_sampled))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.90      0.92     37955
           1       0.05      0.09      0.06      2045

    accuracy                           0.86     40000
   macro avg       0.50      0.50      0.49     40000
weighted avg       0.90      0.86      0.88     40000

ROC-AUC Score: 0.4958564366050519
```

[91]:
```python
#leadership board
# Create a leaderboard for model comparison
models = {
    "K-Nearest Neighbors": knn,
    "Random Forest": RFmodelOverSampled,
```

```
    "Logistic Regression": logisticRegressionModelSampled,
    "AdaBoost": adamodel_sampled
}

# Initialize leaderboard list
leaderboard = []

# Evaluate each model
for name, model in models.items():
    y_pred = model.predict(x_test)
    y_prob = model.predict_proba(x_test)[:, 1] if hasattr(model,␣
 ↪"predict_proba") else None

    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, zero_division=0)
    recall = recall_score(y_test, y_pred, zero_division=0)
    f1 = f1_score(y_test, y_pred, zero_division=0)
    roc_auc = roc_auc_score(y_test, y_prob) if y_prob is not None else None

    leaderboard.append({
        "Model": name,
        "Accuracy": round(accuracy, 4),
        "Precision": round(precision, 4),
        "Recall": round(recall, 4),
        "F1 Score": round(f1, 4),
        "ROC AUC": round(roc_auc, 4) if roc_auc is not None else "N/A"
    })

# Convert to DataFrame
leaderboard_df = pd.DataFrame(leaderboard)
leaderboard_df.sort_values(by="F1 Score", ascending=False, inplace=True)

# Display leaderboard
print("\nModel Leaderboard:\n")
print(leaderboard_df.to_string(index=False))
```

```
Model Leaderboard:

              Model  Accuracy  Precision  Recall  F1 Score  ROC AUC
      Random Forest    0.8089     0.0495  0.1506    0.0746   0.4936
           AdaBoost    0.8607     0.0470  0.0895    0.0616   0.4911
K-Nearest Neighbors    0.9489     0.0000  0.0000    0.0000   0.4999
Logistic Regression    0.9489     0.0000  0.0000    0.0000   0.5000
```

[ ]:

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```