```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler,
RobustScaler, Normalizer, LabelEncoder, OneHotEncoder
from sklearn.impute import SimpleImputer, KNNImputer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier, AdaBoostClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix, classification_report
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
from sklearn.metrics import roc_auc_score, roc_curve

df=pd.read_csv(r"C:\Users\arjun\Downloads\BankChurners (1).csv")
df.head()
```

```
   CLIENTNUM     Attrition_Flag  Customer_Age Gender  Dependent_count
\
0  768805383  Existing Customer            45      M                3

1  818770008  Existing Customer            49      F                5

2  713982108  Existing Customer            51      M                3

3  769911858  Existing Customer            40      F                4

4  709106358  Existing Customer            40      M                3


  Education_Level Marital_Status Income_Category Card_Category  \
0     High School        Married     $60K - $80K          Blue
1        Graduate         Single  Less than $40K          Blue
2        Graduate        Married    $80K - $120K          Blue
3     High School        Unknown  Less than $40K          Blue
4      Uneducated        Married     $60K - $80K          Blue

   Months_on_book  ...  Months_Inactive_12_mon  Contacts_Count_12_mon
\
0              39  ...                       1                      3

1              44  ...                       1                      2
```

```
2              36  ...                        1                       0

3              34  ...                        4                       1

4              21  ...                        1                       0


   Credit_Limit  Total_Revolving_Bal  Avg_Open_To_Buy
Total_Amt_Chng_Q4_Q1  \
0       12691.0                  777          11914.0
1.335
1        8256.0                  864           7392.0
1.541
2        3418.0                    0           3418.0
2.594
3        3313.0                 2517            796.0
1.405
4        4716.0                    0           4716.0
2.175

   Total_Trans_Amt  Total_Trans_Ct  Total_Ct_Chng_Q4_Q1
Avg_Utilization_Ratio
0             1144              42                1.625
0.061
1             1291              33                3.714
0.105
2             1887              20                2.333
0.000
3             1171              20                2.333
0.760
4              816              28                2.500
0.000

[5 rows x 21 columns]
```

```
df.isna().sum()
```

```
CLIENTNUM                   0
Attrition_Flag              0
Customer_Age                0
Gender                      0
Dependent_count             0
Education_Level             0
Marital_Status              0
Income_Category             0
Card_Category               0
Months_on_book              0
Total_Relationship_Count    0
Months_Inactive_12_mon      0
Contacts_Count_12_mon       0
```

```
Credit_Limit                0
Total_Revolving_Bal         0
Avg_Open_To_Buy             0
Total_Amt_Chng_Q4_Q1        0
Total_Trans_Amt             0
Total_Trans_Ct              0
Total_Ct_Chng_Q4_Q1         0
Avg_Utilization_Ratio       0
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   CLIENTNUM                 10127 non-null  int64
 1   Attrition_Flag            10127 non-null  object
 2   Customer_Age              10127 non-null  int64
 3   Gender                    10127 non-null  object
 4   Dependent_count           10127 non-null  int64
 5   Education_Level           10127 non-null  object
 6   Marital_Status            10127 non-null  object
 7   Income_Category           10127 non-null  object
 8   Card_Category             10127 non-null  object
 9   Months_on_book            10127 non-null  int64
 10  Total_Relationship_Count  10127 non-null  int64
 11  Months_Inactive_12_mon    10127 non-null  int64
 12  Contacts_Count_12_mon     10127 non-null  int64
 13  Credit_Limit              10127 non-null  float64
 14  Total_Revolving_Bal       10127 non-null  int64
 15  Avg_Open_To_Buy           10127 non-null  float64
 16  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 17  Total_Trans_Amt           10127 non-null  int64
 18  Total_Trans_Ct            10127 non-null  int64
 19  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 20  Avg_Utilization_Ratio     10127 non-null  float64
dtypes: float64(5), int64(10), object(6)
memory usage: 1.6+ MB
```

```
df['Attrition_Flag'].value_counts()
```

```
Attrition_Flag
Existing Customer    8500
Attrited Customer    1627
Name: count, dtype: int64
```

```
df['Attrition_Flag'] = df['Attrition_Flag'].map({'Existing Customer':
0, 'Attrited Customer': 1})
```

```python
df['Gender'].value_counts()
```

```
Gender
F    5358
M    4769
Name: count, dtype: int64
```

```python
df['Gender'] = df['Gender'].map({'F': 0, 'M': 1})

df = pd.get_dummies(df, columns=['Education_Level'], dtype=int)


df.head()
```

```
   CLIENTNUM  Attrition_Flag  Customer_Age  Gender  Dependent_count  \
0  768805383               0            45       1                3
1  818770008               0            49       0                5
2  713982108               0            51       1                3
3  769911858               0            40       0                4
4  709106358               0            40       1                3

  Marital_Status Income_Category Card_Category  Months_on_book  \
0        Married     $60K - $80K          Blue              39
1         Single  Less than $40K          Blue              44
2        Married    $80K - $120K          Blue              36
3        Unknown  Less than $40K          Blue              34
4        Married     $60K - $80K          Blue              21

   Total_Relationship_Count  ...  Total_Trans_Ct  Total_Ct_Chng_Q4_Q1
\
0                         5  ...              42                1.625

1                         6  ...              33                3.714

2                         4  ...              20                2.333

3                         3  ...              20                2.333

4                         5  ...              28                2.500


   Avg_Utilization_Ratio  Education_Level_College
Education_Level_Doctorate  \
0                  0.061                        0
0
1                  0.105                        0
0
2                  0.000                        0
0
3                  0.760                        0
0
```

```
4                    0.000                        0
0

   Education_Level_Graduate  Education_Level_High School  \
0                         0                            1
1                         1                            0
2                         1                            0
3                         0                            1
4                         0                            0

   Education_Level_Post-Graduate  Education_Level_Uneducated  \
0                              0                           0
1                              0                           0
2                              0                           0
3                              0                           0
4                              0                           1

   Education_Level_Unknown
0                        0
1                        0
2                        0
3                        0
4                        0

[5 rows x 27 columns]
```

```
df = pd.get_dummies(df, columns=['Marital_Status'], dtype=int)

df.head()
```

```
   CLIENTNUM  Attrition_Flag  Customer_Age  Gender  Dependent_count  \
0  768805383               0            45       1                3
1  818770008               0            49       0                5
2  713982108               0            51       1                3
3  769911858               0            40       0                4
4  709106358               0            40       1                3

  Income_Category Card_Category  Months_on_book
Total_Relationship_Count  \
0     $60K - $80K          Blue              39
5
1  Less than $40K          Blue              44
6
2    $80K - $120K          Blue              36
4
3  Less than $40K          Blue              34
3
4     $60K - $80K          Blue              21
5

   Months_Inactive_12_mon  ...  Education_Level_Doctorate  \
```

```
0                        1  ...                              0
1                        1  ...                              0
2                        1  ...                              0
3                        4  ...                              0
4                        1  ...                              0

   Education_Level_Graduate  Education_Level_High School  \
0                          0                            1
1                          1                            0
2                          1                            0
3                          0                            1
4                          0                            0

   Education_Level_Post-Graduate  Education_Level_Uneducated  \
0                              0                           0
1                              0                           0
2                              0                           0
3                              0                           0
4                              0                           1

   Education_Level_Unknown  Marital_Status_Divorced
Marital_Status_Married  \
0                        0                        0
1
1                        0                        0
0
2                        0                        0
1
3                        0                        0
0
4                        0                        0
1

   Marital_Status_Single  Marital_Status_Unknown
0                      0                       0
1                      1                       0
2                      0                       0
3                      0                       1
4                      0                       0

[5 rows x 30 columns]
```

```
income_mapping = {
    'Unknown':0,
    'Less than $40K': 1,
    '$40K - $60K': 2,
    '$60K - $80K': 3,
    '$80K - $120K': 4,
    '$120K +': 5
}
```

```
df['Income_Category'] = df['Income_Category'].map(income_mapping)

df.head()

   CLIENTNUM  Attrition_Flag  Customer_Age  Gender  Dependent_count  \
0  768805383               0            45       1                3
1  818770008               0            49       0                5
2  713982108               0            51       1                3
3  769911858               0            40       0                4
4  709106358               0            40       1                3

   Income_Category Card_Category  Months_on_book
Total_Relationship_Count  \
0                3          Blue              39
5
1                1          Blue              44
6
2                4          Blue              36
4
3                1          Blue              34
3
4                3          Blue              21
5

   Months_Inactive_12_mon  ...  Education_Level_Doctorate  \
0                       1  ...                          0
1                       1  ...                          0
2                       1  ...                          0
3                       4  ...                          0
4                       1  ...                          0

   Education_Level_Graduate  Education_Level_High School  \
0                         0                            1
1                         1                            0
2                         1                            0
3                         0                            1
4                         0                            0

   Education_Level_Post-Graduate  Education_Level_Uneducated  \
0                              0                           0
1                              0                           0
2                              0                           0
3                              0                           0
4                              0                           1

   Education_Level_Unknown  Marital_Status_Divorced
Marital_Status_Married  \
0                        0                        0
1
```

```
1                        0                        0
0
2                        0                        0
1
3                        0                        0
0
4                        0                        0
1

   Marital_Status_Single  Marital_Status_Unknown
0                      0                       0
1                      1                       0
2                      0                       0
3                      0                       1
4                      0                       0

[5 rows x 30 columns]
```

```
df = pd.get_dummies(df, columns=['Card_Category'], dtype=int)

df.head()
```

```
   CLIENTNUM  Attrition_Flag  Customer_Age  Gender  Dependent_count  \
0  768805383               0            45       1                3
1  818770008               0            49       0                5
2  713982108               0            51       1                3
3  769911858               0            40       0                4
4  709106358               0            40       1                3

   Income_Category  Months_on_book  Total_Relationship_Count  \
0                3              39                         5
1                1              44                         6
2                4              36                         4
3                1              34                         3
4                3              21                         5

   Months_Inactive_12_mon  Contacts_Count_12_mon  ...  \
0                       1                      3  ...
1                       1                      2  ...
2                       1                      0  ...
3                       4                      1  ...
4                       1                      0  ...

   Education_Level_Uneducated  Education_Level_Unknown  \
0                           0                        0
1                           0                        0
2                           0                        0
3                           0                        0
4                           1                        0

   Marital_Status_Divorced  Marital_Status_Married
```

```
Marital_Status_Single  \
0                         0                       1
0
1                         0                       0
1
2                         0                       1
0
3                         0                       0
0
4                         0                       1
0

   Marital_Status_Unknown  Card_Category_Blue  Card_Category_Gold  \
0                       0                   1                   0
1                       0                   1                   0
2                       0                   1                   0
3                       1                   1                   0
4                       0                   1                   0

   Card_Category_Platinum  Card_Category_Silver
0                       0                     0
1                       0                     0
2                       0                     0
3                       0                     0
4                       0                     0

[5 rows x 33 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 33 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   CLIENTNUM                           10127 non-null  int64
 1   Attrition_Flag                      10127 non-null  int64
 2   Customer_Age                        10127 non-null  int64
 3   Gender                              10127 non-null  int64
 4   Dependent_count                     10127 non-null  int64
 5   Income_Category                     10127 non-null  int64
 6   Months_on_book                      10127 non-null  int64
 7   Total_Relationship_Count            10127 non-null  int64
 8   Months_Inactive_12_mon              10127 non-null  int64
 9   Contacts_Count_12_mon               10127 non-null  int64
 10  Credit_Limit                        10127 non-null  float64
 11  Total_Revolving_Bal                 10127 non-null  int64
 12  Avg_Open_To_Buy                     10127 non-null  float64
 13  Total_Amt_Chng_Q4_Q1                10127 non-null  float64
 14  Total_Trans_Amt                     10127 non-null  int64
```

```
 15  Total_Trans_Ct                  10127 non-null  int64
 16  Total_Ct_Chng_Q4_Q1             10127 non-null  float64
 17  Avg_Utilization_Ratio           10127 non-null  float64
 18  Education_Level_College         10127 non-null  int32
 19  Education_Level_Doctorate       10127 non-null  int32
 20  Education_Level_Graduate        10127 non-null  int32
 21  Education_Level_High School     10127 non-null  int32
 22  Education_Level_Post-Graduate   10127 non-null  int32
 23  Education_Level_Uneducated      10127 non-null  int32
 24  Education_Level_Unknown         10127 non-null  int32
 25  Marital_Status_Divorced         10127 non-null  int32
 26  Marital_Status_Married          10127 non-null  int32
 27  Marital_Status_Single           10127 non-null  int32
 28  Marital_Status_Unknown          10127 non-null  int32
 29  Card_Category_Blue              10127 non-null  int32
 30  Card_Category_Gold              10127 non-null  int32
 31  Card_Category_Platinum          10127 non-null  int32
 32  Card_Category_Silver            10127 non-null  int32
dtypes: float64(5), int32(15), int64(13)
memory usage: 2.0 MB
```

```python
df.drop(columns=["CLIENTNUM"], inplace=True)

from scipy.stats import skew

# List of columns to check for skewness
skew_columns = [
    "Credit_Limit", "Total_Revolving_Bal", "Avg_Open_To_Buy",
"Total_Amt_Chng_Q4_Q1",
    "Total_Trans_Amt", "Total_Trans_Ct", "Total_Ct_Chng_Q4_Q1",
"Avg_Utilization_Ratio"
]

# Calculate skewness for each column
skewness_values = {col: skew(df[col], nan_policy='omit') for col in
skew_columns}

# Display skewness values
for col, skew_val in skewness_values.items():
    print(f"Skewness of {col}: {skew_val:.2f}")
```

```
Skewness of Credit_Limit: 1.67
Skewness of Total_Revolving_Bal: -0.15
Skewness of Avg_Open_To_Buy: 1.66
Skewness of Total_Amt_Chng_Q4_Q1: 1.73
Skewness of Total_Trans_Amt: 2.04
Skewness of Total_Trans_Ct: 0.15
Skewness of Total_Ct_Chng_Q4_Q1: 2.06
Skewness of Avg_Utilization_Ratio: 0.72
```

```
"""import numpy as np

# Apply log transformation for highly skewed columns
columns_to_transform = ["Credit_Limit", "Avg_Open_To_Buy",
"Total_Amt_Chng_Q4_Q1", "Total_Trans_Amt", "Total_Ct_Chng_Q4_Q1"]

for col in columns_to_transform:
    df[col] = np.log1p(df[col])  # log1p to avoid log(0) issues

print("Transformation applied to highly skewed columns!")"""
```

```
'import numpy as np\n\n# Apply log transformation for highly skewed
columns\ncolumns_to_transform = ["Credit_Limit", "Avg_Open_To_Buy",
"Total_Amt_Chng_Q4_Q1", "Total_Trans_Amt", "Total_Ct_Chng_Q4_Q1"]\n\
nfor col in columns_to_transform:\n    df[col] = np.log1p(df[col])  #
log1p to avoid log(0) issues\n\nprint("Transformation applied to
highly skewed columns!")'
```

```
"""from sklearn.preprocessing import RobustScaler

scaler = RobustScaler()
df[['Credit_Limit', 'Total_Revolving_Bal', 'Avg_Open_To_Buy',
'Total_Trans_Amt']] = scaler.fit_transform(df[['Credit_Limit',
'Total_Revolving_Bal', 'Avg_Open_To_Buy', 'Total_Trans_Amt']])"""
```

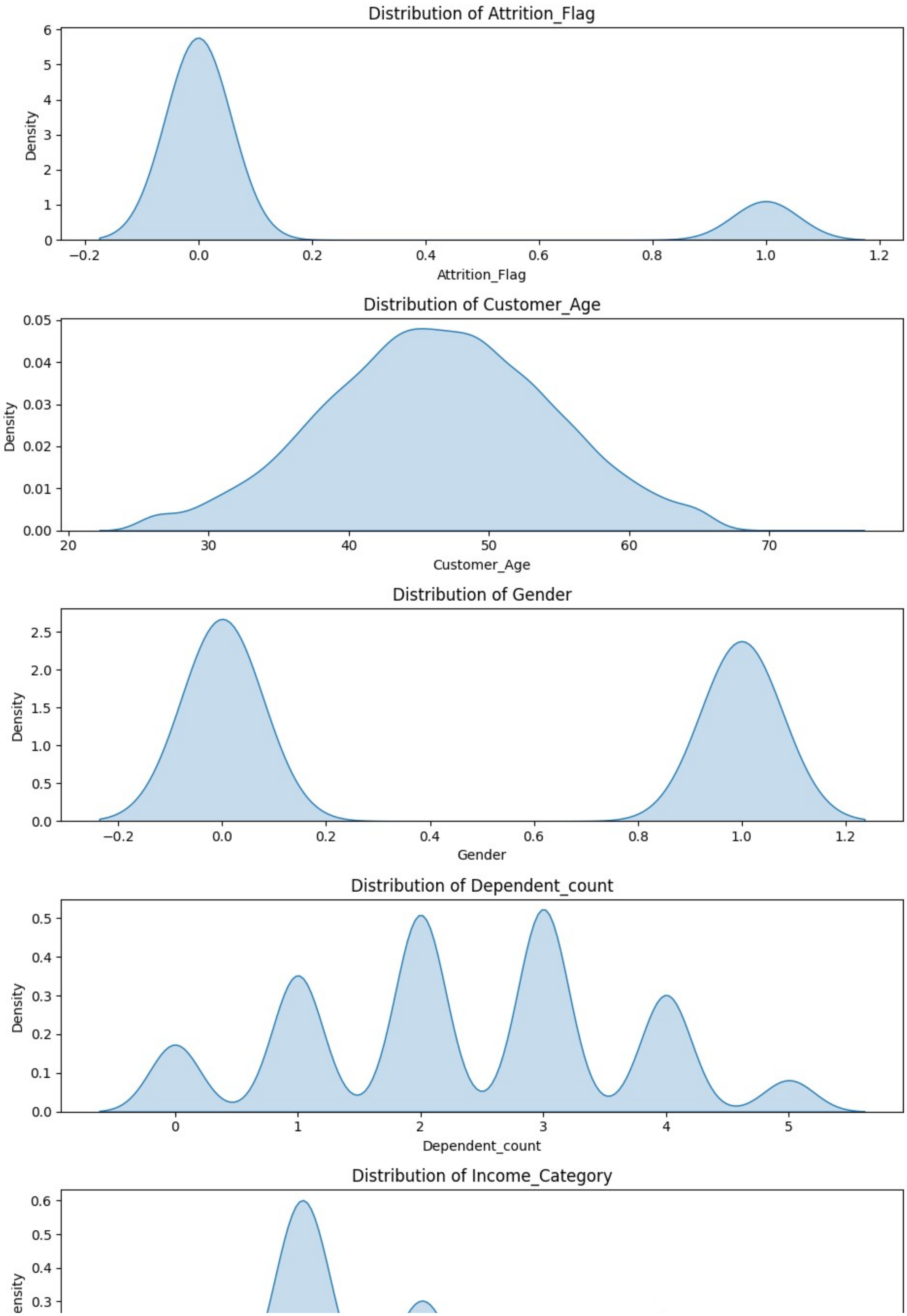
```
"from sklearn.preprocessing import RobustScaler\n\nscaler =
RobustScaler()\ndf[['Credit_Limit', 'Total_Revolving_Bal',
'Avg_Open_To_Buy', 'Total_Trans_Amt']] =
scaler.fit_transform(df[['Credit_Limit', 'Total_Revolving_Bal',
'Avg_Open_To_Buy', 'Total_Trans_Amt']])"
```

```
"""import numpy as np

# List of columns to check for outliers
outlier_columns = [
    "Credit_Limit", "Total_Revolving_Bal", "Avg_Open_To_Buy",
"Total_Amt_Chng_Q4_Q1",
    "Total_Trans_Amt", "Total_Trans_Ct", "Total_Ct_Chng_Q4_Q1",
"Avg_Utilization_Ratio"
]

# Function to remove outliers using IQR
def remove_outliers(df, columns):
    for col in columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
```

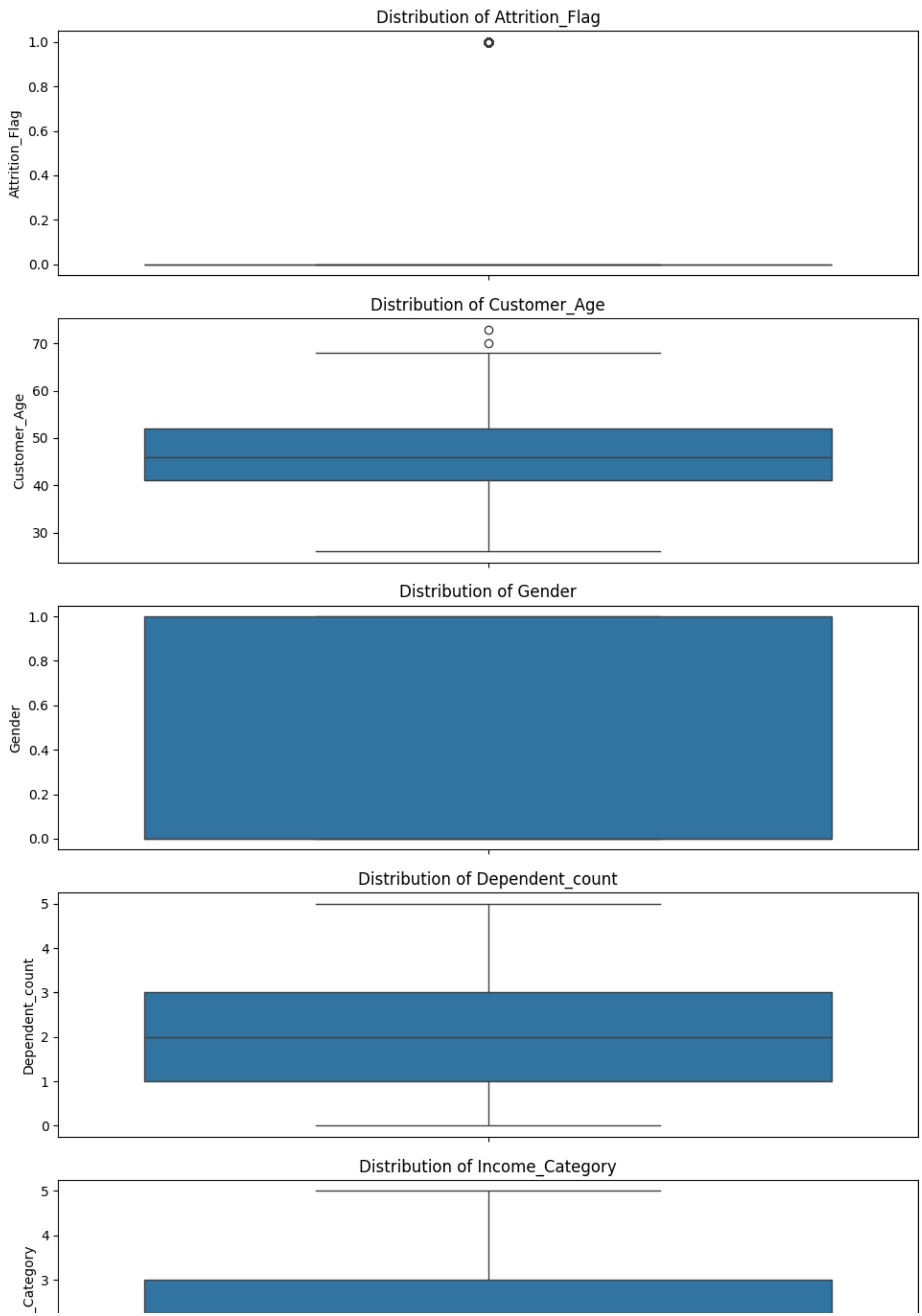
```
    return df

# Apply outlier removal
df1 = remove_outliers(df, outlier_columns)

# Display the new shape of the dataset
print(f"Original shape: {df.shape}")
print(f"New shape after outlier removal: {df1.shape}")"""
```

```
'import numpy as np\n\n# List of columns to check for outliers\
noutlier_columns = [\n    "Credit_Limit", "Total_Revolving_Bal",
"Avg_Open_To_Buy", "Total_Amt_Chng_Q4_Q1",\n    "Total_Trans_Amt",
"Total_Trans_Ct", "Total_Ct_Chng_Q4_Q1", "Avg_Utilization_Ratio"\n]\n\
n# Function to remove outliers using IQR\ndef remove_outliers(df,
columns):\n    for col in columns:\n        Q1 =
df[col].quantile(0.25)\n        Q3 = df[col].quantile(0.75)\n
IQR = Q3 - Q1\n        lower_bound = Q1 - 1.5 * IQR\n
upper_bound = Q3 + 1.5 * IQR\n        df = df[(df[col] >= lower_bound)
& (df[col] <= upper_bound)]\n    return df\n\n# Apply outlier removal\
ndf1 = remove_outliers(df, outlier_columns)\n\n# Display the new shape
of the dataset\nprint(f"Original shape: {df.shape}")\nprint(f"New
shape after outlier removal: {df1.shape}")'
```

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# Select numeric columns
numeric_cols = df.select_dtypes(include=['int64', 'float64',
'int32']).columns

# Create subplots
fig, axes = plt.subplots(nrows=len(numeric_cols), ncols=1,
figsize=(10, len(numeric_cols) * 3))

# Loop through each column and plot in a separate subplot
for i, column in enumerate(numeric_cols):
    sns.kdeplot(df[column], ax=axes[i], fill=True)
    axes[i].set_title(f"Distribution of {column}")

# Adjust layout
plt.tight_layout()
plt.show()
```


Distribution of Attrition_Flag
Density
0
1
2
3
4
5
6
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Attrition_Flag
Distribution of Customer_Age
Density
0.00
0.01
0.02
0.03
0.04
0.05
20
30
40
50
60
70
Customer_Age
Distribution of Gender
Density
0.0
0.5
1.0
1.5
2.0
2.5
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Gender
Distribution of Dependent_count
Density
0.0
0.1
0.2
0.3
0.4
0.5
0
1
2
3
4
5
Dependent_count
Distribution of Income_Category
0.3
0.4
0.5
0.6

```python
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# Select numeric columns
numeric_cols = df.select_dtypes(include=['int64', 'float64',
'int32']).columns

# Create subplots
fig, axes = plt.subplots(nrows=len(numeric_cols), ncols=1,
figsize=(10, len(numeric_cols) * 3))

# Loop through each column and plot in a separate subplot
for i, column in enumerate(numeric_cols):
    sns.boxplot(df[column], ax=axes[i], fill=True)
    axes[i].set_title(f"Distribution of {column}")

# Adjust layout
plt.tight_layout()
plt.show()
```


Distribution of Attrition_Flag
Attrition_Flag
0.0
0.2
0.4
0.6
0.8
1.0
Distribution of Customer_Age
Customer_Age
30
40
50
60
70
Distribution of Gender
Gender
0.0
0.2
0.4
0.6
0.8
1.0
Distribution of Dependent_count
Dependent_count
0
1
2
3
4
5
Distribution of Income_Category
_Category
3
4
5

```
df.head()

   Attrition_Flag  Customer_Age  Gender  Dependent_count
Income_Category  \
0               0            45       1                3
3
1               0            49       0                5
1
2               0            51       1                3
4
3               0            40       0                4
1
4               0            40       1                3
3

   Months_on_book  Total_Relationship_Count  Months_Inactive_12_mon  \
0              39                         5                       1
1              44                         6                       1
2              36                         4                       1
3              34                         3                       4
4              21                         5                       1

   Contacts_Count_12_mon  Credit_Limit  ...
Education_Level_Uneducated  \
0                      3       12691.0  ...
0
1                      2        8256.0  ...
0
2                      0        3418.0  ...
0
3                      1        3313.0  ...
0
4                      0        4716.0  ...
1

   Education_Level_Unknown  Marital_Status_Divorced
Marital_Status_Married  \
0                        0                        0
1
1                        0                        0
0
2                        0                        0
1
3                        0                        0
0
4                        0                        0
1
```

```
   Marital_Status_Single  Marital_Status_Unknown
Card_Category_Blue  \
0                      0                        0                    1

1                      1                        0                    1

2                      0                        0                    1

3                      0                        1                    1

4                      0                        0                    1


   Card_Category_Gold  Card_Category_Platinum  Card_Category_Silver
0                   0                       0                     0
1                   0                       0                     0
2                   0                       0                     0
3                   0                       0                     0
4                   0                       0                     0

[5 rows x 32 columns]
```

```python
correlation = df.corr()["Attrition_Flag"].sort_values(ascending=False)
print(correlation)
```

```
Attrition_Flag                    1.000000
Contacts_Count_12_mon             0.204491
Months_Inactive_12_mon            0.152449
Education_Level_Doctorate         0.029386
Marital_Status_Single             0.019037
Dependent_count                   0.018991
Customer_Age                      0.018203
Months_on_book                    0.013687
Education_Level_Post-Graduate     0.011127
Card_Category_Platinum            0.010823
Education_Level_Unknown           0.009005
Marital_Status_Unknown            0.008904
Card_Category_Gold                0.005973
Card_Category_Blue                0.003216
Marital_Status_Divorced           0.000850
Avg_Open_To_Buy                  -0.000285
Education_Level_Uneducated       -0.001444
Education_Level_College          -0.007840
Card_Category_Silver             -0.008467
Education_Level_Graduate         -0.009046
Education_Level_High School      -0.011730
Income_Category                  -0.013577
Marital_Status_Married           -0.023735
Credit_Limit                     -0.023873
```

```
Gender                              -0.037272
Total_Amt_Chng_Q4_Q1                -0.131063
Total_Relationship_Count            -0.150005
Total_Trans_Amt                     -0.168598
Avg_Utilization_Ratio               -0.178410
Total_Revolving_Bal                 -0.263053
Total_Ct_Chng_Q4_Q1                 -0.290054
Total_Trans_Ct                      -0.371403
Name: Attrition_Flag, dtype: float64
```

```
from scipy.stats import skew

# List of columns to check for skewness
skew_columns = [
     "Total_Revolving_Bal",  "Total_Ct_Chng_Q4_Q1",
     "Total_Trans_Ct",
"Contacts_Count_12_mon",'Months_Inactive_12_mon'
]

# Calculate skewness for each column
skewness_values = {col: skew(df[col], nan_policy='omit') for col in
skew_columns}

# Display skewness values
for col, skew_val in skewness_values.items():
    print(f"Skewness of {col}: {skew_val:.2f}")
```

```
Skewness of Total_Revolving_Bal: -0.15
Skewness of Total_Ct_Chng_Q4_Q1: 2.06
Skewness of Total_Trans_Ct: 0.15
Skewness of Contacts_Count_12_mon: 0.01
Skewness of Months_Inactive_12_mon: 0.63
```

```
df.describe()
```

| | Attrition_Flag | Customer_Age | Gender | Dependent_count |
|---|---|---|---|---|
| count | 10127.000000 | 10127.000000 | 10127.000000 | 10127.000000 |
| mean | 0.160660 | 46.325960 | 0.470919 | 2.346203 |
| std | 0.367235 | 8.016814 | 0.499178 | 1.298908 |
| min | 0.000000 | 26.000000 | 0.000000 | 0.000000 |
| 25% | 0.000000 | 41.000000 | 0.000000 | 1.000000 |
| 50% | 0.000000 | 46.000000 | 0.000000 | 2.000000 |
| 75% | 0.000000 | 52.000000 | 1.000000 | 3.000000 |
| max | 1.000000 | 73.000000 | 1.000000 | 5.000000 |

| | Income_Category | Months_on_book | Total_Relationship_Count |
|---|---|---|---|
| count | 10127.000000 | 10127.000000 | 10127.000000 |
| mean | 2.085711 | 35.928409 | 3.812580 |
| std | 1.474639 | 7.986416 | 1.554408 |
| min | 0.000000 | 13.000000 | 1.000000 |
| 25% | 1.000000 | 31.000000 | 3.000000 |

```
50%           2.000000      36.000000                        4.000000
75%           3.000000      40.000000                        5.000000
max           5.000000      56.000000                        6.000000

       Months_Inactive_12_mon  Contacts_Count_12_mon
Credit_Limit  ...  \
count             10127.000000           10127.000000
10127.000000  ...
mean                  2.341167               2.455317
8631.953698  ...
std                   1.010622               1.106225
9088.776650  ...
min                   0.000000               0.000000
1438.300000  ...
25%                   2.000000               2.000000
2555.000000  ...
50%                   2.000000               2.000000
4549.000000  ...
75%                   3.000000               3.000000
11067.500000  ...
max                   6.000000               6.000000
34516.000000  ...

       Education_Level_Uneducated  Education_Level_Unknown  \
count                10127.000000             10127.000000
mean                     0.146835                 0.149995
std                      0.353959                 0.357084
min                      0.000000                 0.000000
25%                      0.000000                 0.000000
50%                      0.000000                 0.000000
75%                      0.000000                 0.000000
max                      1.000000                 1.000000

       Marital_Status_Divorced  Marital_Status_Married
Marital_Status_Single  \
count             10127.000000            10127.000000
10127.000000
mean                  0.073862                0.462822
0.389355
std                   0.261559                0.498641
0.487628
min                   0.000000                0.000000
0.000000
25%                   0.000000                0.000000
0.000000
50%                   0.000000                0.000000
0.000000
75%                   0.000000                1.000000
1.000000
max                   1.000000                1.000000
```

```
1.000000

       Marital_Status_Unknown  Card_Category_Blue  Card_Category_Gold
\
count            10127.000000        10127.000000        10127.000000

mean                 0.073961            0.931767            0.011455

std                  0.261720            0.252159            0.106416

min                  0.000000            0.000000            0.000000

25%                  0.000000            1.000000            0.000000

50%                  0.000000            1.000000            0.000000

75%                  0.000000            1.000000            0.000000

max                  1.000000            1.000000            1.000000


       Card_Category_Platinum  Card_Category_Silver
count            10127.000000          10127.000000
mean                 0.001975              0.054804
std                  0.044398              0.227608
min                  0.000000              0.000000
25%                  0.000000              0.000000
50%                  0.000000              0.000000
75%                  0.000000              0.000000
max                  1.000000              1.000000

[8 rows x 32 columns]
```

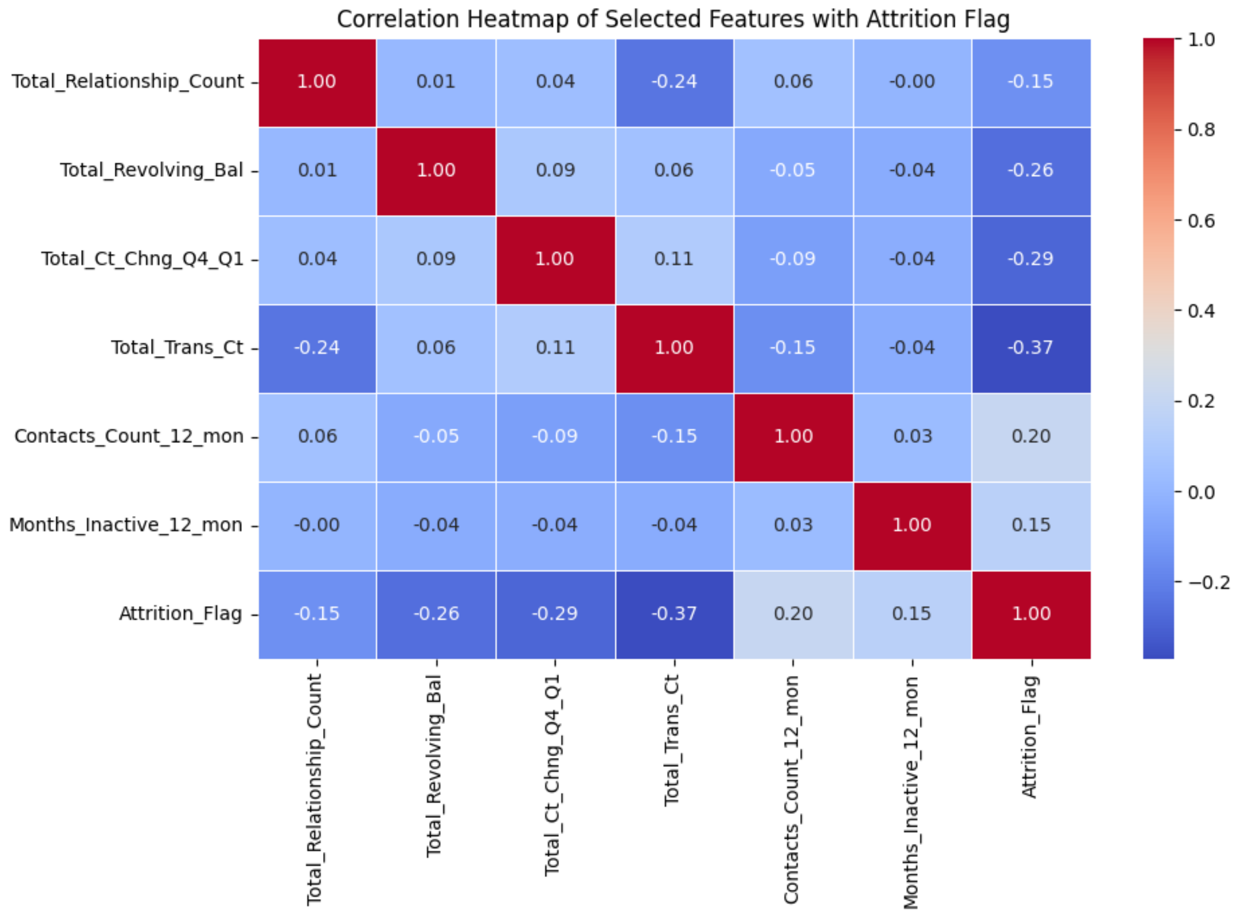
## model

```
"""selected_features = ['Total_Amt_Chng_Q4_Q1',
'Total_Relationship_Count', 'Total_Trans_Amt',
        'Avg_Utilization_Ratio', 'Total_Revolving_Bal',
'Total_Ct_Chng_Q4_Q1',
        'Total_Trans_Ct', 'Contacts_Count_12_mon',
'Months_Inactive_12_mon']"""
selected_features = [ 'Total_Relationship_Count',
                      'Total_Revolving_Bal', 'Total_Ct_Chng_Q4_Q1',
                     'Total_Trans_Ct', 'Contacts_Count_12_mon',
'Months_Inactive_12_mon']
X = df[selected_features]
y = df["Attrition_Flag"]  # Target variable

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

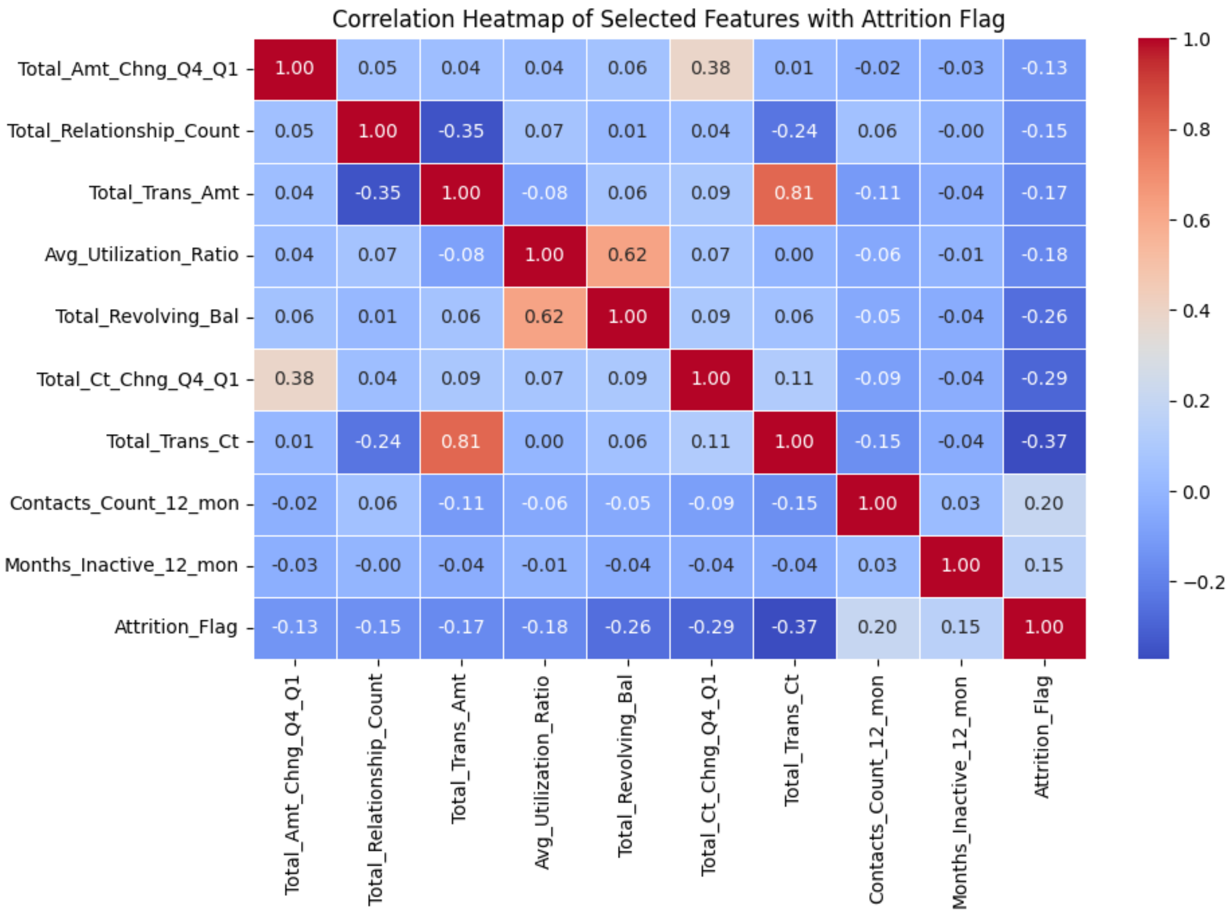
```python
from imblearn.over_sampling import SMOTE
smote = SMOTE(sampling_strategy=0.5, random_state=42)  # Only 50%
oversampling
X_train_resampled, y_train_resampled = smote.fit_resample(X_train,
y_train)

# Train logistic regression model on balanced data
model = LogisticRegression()
model.fit(X_train_resampled, y_train_resampled)

# Make predictions
y_pred = model.predict(X_test)

# Evaluation
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

# Print results
print(f"Accuracy after SMOTE: {accuracy * 100:.2f}%")
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(class_report)
```

```
Accuracy after SMOTE: 88.25%
Confusion Matrix:
[[1563  136]
 [ 102  225]]
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.92      0.93      1699
           1       0.62      0.69      0.65       327

    accuracy                           0.88      2026
   macro avg       0.78      0.80      0.79      2026
weighted avg       0.89      0.88      0.88      2026


C:\Users\arjun\AppData\Roaming\Python\Python310\site-packages\sklearn\
linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
```

```
https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(

selected_features = [ 'Total_Relationship_Count',
                      'Total_Revolving_Bal', 'Total_Ct_Chng_Q4_Q1',
                     'Total_Trans_Ct', 'Contacts_Count_12_mon',
'Months_Inactive_12_mon', 'Attrition_Flag']

# Filter dataset with selected features
df_selected = df[selected_features]

# Compute correlation matrix
corr_matrix = df_selected.corr()

# Plot heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",
linewidths=0.5)
plt.title("Correlation Heatmap of Selected Features with Attrition
Flag")
plt.show()
```




```
selected_features = ['Total_Amt_Chng_Q4_Q1',
'Total_Relationship_Count', 'Total_Trans_Amt',
                     'Avg_Utilization_Ratio', 'Total_Revolving_Bal',
'Total_Ct_Chng_Q4_Q1',
                     'Total_Trans_Ct', 'Contacts_Count_12_mon',
'Months_Inactive_12_mon', 'Attrition_Flag']

# Filter dataset with selected features
df_selected = df[selected_features]

# Compute correlation matrix
corr_matrix = df_selected.corr()

# Plot heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",
linewidths=0.5)
plt.title("Correlation Heatmap of Selected Features with Attrition
Flag")
plt.show()
```




```
import numpy as np
from sklearn.preprocessing import MinMaxScaler

# Load your trained model and scaler
# model = your_trained_model
# scaler = your_fitted_scaler

# Selected features as per your specification
selected_features = [
    'Total_Relationship_Count',
    'Total_Revolving_Bal',
    'Total_Ct_Chng_Q4_Q1',
    'Total_Trans_Ct',
    'Contacts_Count_12_mon',
    'Months_Inactive_12_mon'
]

# Creating a single sample using the values you provided
new_sample = np.array([[
    5,        # Total_Relationship_Count
    777,      # Total_Revolving_Bal
    1.625,    # Total_Ct_Chng_Q4_Q1
```

```
    42,      # Total_Trans_Ct
    3,       # Contacts_Count_12_mon
    1        # Months_Inactive_12_mon
]])

# Scale the features using your trained scaler
# scaled_sample = scaler.transform(new_sample)

# Make prediction
# prediction = model.predict(scaled_sample)
# probability = model.predict_proba(scaled_sample)[0][1]  #
Probability of attrition (class 1)

# For demonstration (replace with actual prediction)
prediction = model.predict(new_sample)  # Example prediction (0=stay,
1=attrite)


print("Customer data:", new_sample[0])
print("Prediction:", "Will attrite" if prediction == 1 else "Will
stay")
```

```
Customer data: [  5.    777.      1.625  42.      3.      1.   ]
Prediction: Will stay
```

```
C:\Users\arjun\AppData\Roaming\Python\Python310\site-packages\sklearn\
base.py:493: UserWarning: X does not have valid feature names, but
LogisticRegression was fitted with feature names
  warnings.warn(
```

```
import numpy as np
from sklearn.preprocessing import MinMaxScaler

# Load your trained model and scaler
# model = your_trained_model
# scaler = your_fitted_scaler

# Selected features as per your specification
selected_features = [
    'Total_Relationship_Count',
    'Total_Revolving_Bal',
    'Total_Ct_Chng_Q4_Q1',
    'Total_Trans_Ct',
    'Contacts_Count_12_mon',
    'Months_Inactive_12_mon'
]

# Creating a single sample using the values you provided
new_sample = np.array([[
    2,       # Total_Relationship_Count
    0,     # Total_Revolving_Bal
```

```
    0.6,   # Total_Ct_Chng_Q4_Q1
    16,      # Total_Trans_Ct
    3,       # Contacts_Count_12_mon
    3        # Months_Inactive_12_mon
]])

# Scale the features using your trained scaler
# scaled_sample = scaler.transform(new_sample)

# Make prediction
# prediction = model.predict(scaled_sample)
# probability = model.predict_proba(scaled_sample)[0][1]  #
Probability of attrition (class 1)

# For demonstration (replace with actual prediction)
prediction = model.predict(new_sample)  # Example prediction (0=stay,
1=attrite)


print("Customer data:", new_sample[0])
print("Prediction:", "Will attrite" if prediction == 1 else "Will
stay")
```

```
Customer data: [ 2.   0.   0.6 16.   3.   3. ]
Prediction: Will attrite
```

```
C:\Users\arjun\AppData\Roaming\Python\Python310\site-packages\sklearn\
base.py:493: UserWarning: X does not have valid feature names, but
LogisticRegression was fitted with feature names
  warnings.warn(
```

## KNN

```
"""from imblearn.over_sampling import SMOTE
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
from sklearn.preprocessing import RobustScaler  # For scaling with
outliers

# Apply robust scaling that's less sensitive to outliers
robust_scaler = RobustScaler()
X_train_scaled = robust_scaler.fit_transform(X_train)
X_test_scaled = robust_scaler.transform(X_test)

# Apply SMOTE on scaled data
smote = SMOTE(sampling_strategy=0.5, random_state=42)
X_train_resampled, y_train_resampled =
smote.fit_resample(X_train_scaled, y_train)
```

```
# Train KNN model on scaled and balanced data
model = KNeighborsClassifier(n_neighbors=5)
model.fit(X_train_resampled, y_train_resampled)

# Make predictions on scaled test data
y_pred = model.predict(X_test_scaled)

# Evaluation
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

# Print results
print(f"Accuracy after robust scaling, SMOTE, with KNN: {accuracy *
100:.2f}%")
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(class_report)"""
```

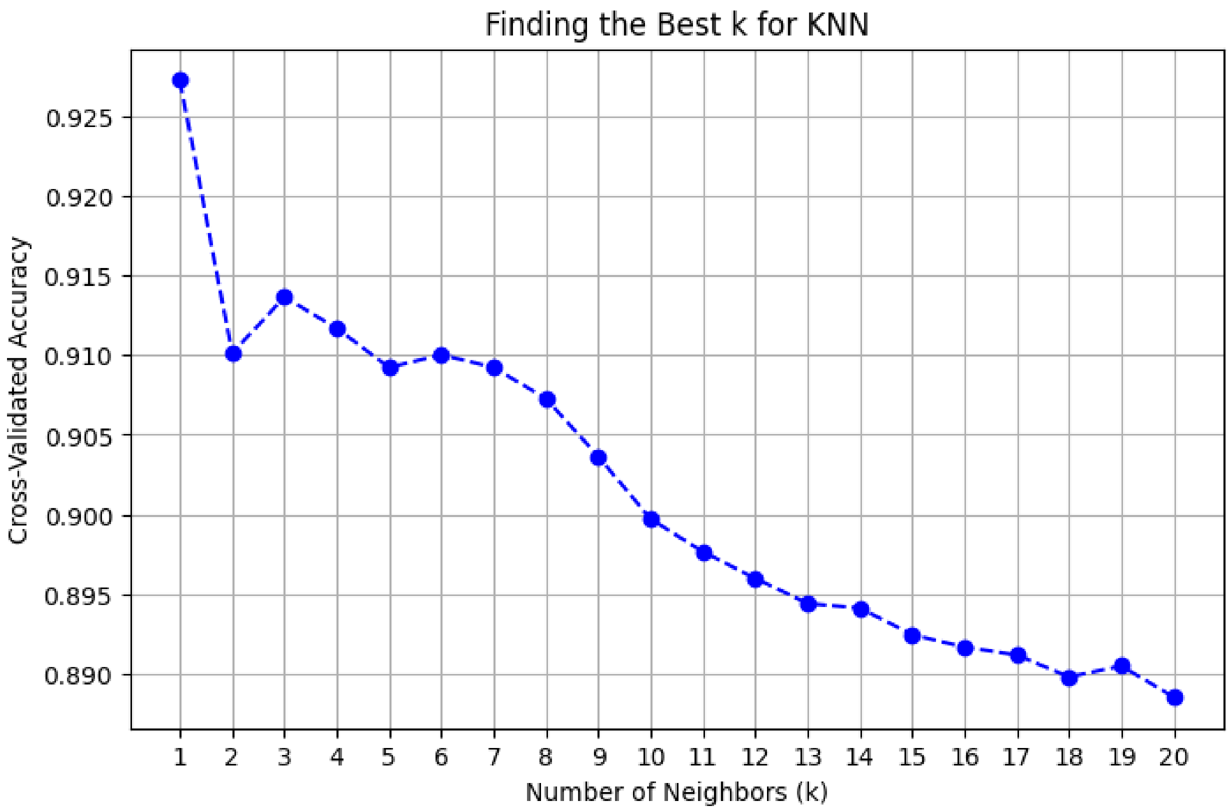
```
'from imblearn.over_sampling import SMOTE\nfrom sklearn.neighbors
import KNeighborsClassifier\nfrom sklearn.metrics import
accuracy_score, confusion_matrix, classification_report\nfrom
sklearn.preprocessing import RobustScaler  # For scaling with
outliers\n\n# Apply robust scaling that\'s less sensitive to outliers\
nrobust_scaler = RobustScaler()\nX_train_scaled =
robust_scaler.fit_transform(X_train)\nX_test_scaled =
robust_scaler.transform(X_test)\n\n# Apply SMOTE on scaled data\nsmote
= SMOTE(sampling_strategy=0.5, random_state=42)\nX_train_resampled,
y_train_resampled = smote.fit_resample(X_train_scaled, y_train)\n\n#
Train KNN model on scaled and balanced data\nmodel =
KNeighborsClassifier(n_neighbors=5)\nmodel.fit(X_train_resampled,
y_train_resampled)\n\n# Make predictions on scaled test data\ny_pred =
model.predict(X_test_scaled)\n\n# Evaluation\naccuracy =
accuracy_score(y_test, y_pred)\nconf_matrix = confusion_matrix(y_test,
y_pred)\nclass_report = classification_report(y_test, y_pred)\n\n#
Print results\nprint(f"Accuracy after robust scaling, SMOTE, with KNN:
{accuracy * 100:.2f}%")\nprint("Confusion Matrix:")\
nprint(conf_matrix)\nprint("Classification Report:")\
nprint(class_report)'
```

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score
from imblearn.over_sampling import SMOTE
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import RobustScaler

# Step 1: Apply RobustScaler to handle outliers
robust_scaler = RobustScaler()
```

```
X_train_scaled = robust_scaler.fit_transform(X_train)
X_test_scaled = robust_scaler.transform(X_test)

# Step 2: Apply SMOTE on the scaled training data
smote = SMOTE(sampling_strategy=0.5, random_state=42)
X_train_resampled, y_train_resampled =
smote.fit_resample(X_train_scaled, y_train)

# Step 3: Cross-validation to find the best k
k_values = range(1, 21)  # Testing k from 1 to 20
cv_scores = []

for k in k_values:
    model = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(model, X_train_resampled,
y_train_resampled, cv=5, scoring='accuracy')  # 5-fold CV
    cv_scores.append(scores.mean())

# Find the best k
best_k = k_values[np.argmax(cv_scores)]
print(f"Best k: {best_k}")

# Step 4: Plot Accuracy vs. k
plt.figure(figsize=(8, 5))
plt.plot(k_values, cv_scores, marker='o', linestyle='dashed',
color='b')
plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Cross-Validated Accuracy')
plt.title('Finding the Best k for KNN')
plt.xticks(k_values)
plt.grid()
plt.show()

# Step 5: Train final model with the best k
best_knn_model = KNeighborsClassifier(n_neighbors=best_k)
best_knn_model.fit(X_train_resampled, y_train_resampled)

# Step 6: Make predictions on scaled test data
y_pred_best = best_knn_model.predict(X_test_scaled)

# Step 7: Evaluate the final model
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
accuracy_best = accuracy_score(y_test, y_pred_best)
print(f"Final Model Accuracy with k={best_k}: {accuracy_best *
100:.2f}%")

conf_matrix = confusion_matrix(y_test, y_pred_best)
class_report = classification_report(y_test, y_pred_best)
```

```
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(class_report)
```

```
Best k: 1
```




```
Final Model Accuracy with k=1: 88.25%
Confusion Matrix:
[[1585  114]
 [ 124  203]]
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.93      0.93      1699
           1       0.64      0.62      0.63       327

    accuracy                           0.88      2026
   macro avg       0.78      0.78      0.78      2026
weighted avg       0.88      0.88      0.88      2026
```

```
import numpy as np
from sklearn.preprocessing import MinMaxScaler
```

```
# Load your trained model and scaler
# model = your_trained_model
# scaler = your_fitted_scaler

# Selected features as per your specification
selected_features = [
    'Total_Relationship_Count',
    'Total_Revolving_Bal',
    'Total_Ct_Chng_Q4_Q1',
    'Total_Trans_Ct',
    'Contacts_Count_12_mon',
    'Months_Inactive_12_mon'
]

# Creating a single sample using the values you provided
new_sample = np.array([[-1.5        ,  0.3125    , -0.10212766,
0.88888889,  1.        ,
         1.        ]])

# Scale the features using your trained scaler
# scaled_sample = scaler.transform(new_sample)

# Make prediction
# prediction = model.predict(scaled_sample)
# probability = model.predict_proba(scaled_sample)[0][1]  #
Probability of attrition (class 1)

# For demonstration (replace with actual prediction)
prediction = best_knn_model.predict(new_sample)


print("Customer data:", new_sample[0])
print("Prediction:", "Will attrite" if prediction == 1 else "Will
stay")
```

```
Customer data: [-1.5         0.3125     -0.10212766  0.88888889  1.
1.        ]
Prediction: Will stay
```

```
X_train_resampled
```

```
array([[-1.5       ,  0.3125    , -0.10212766,  0.88888889,  1.
,
         1.        ],
       [-1.5       ,  0.36401099, -1.31489362, -0.77777778,  1.
,
         2.        ],
       [ 1.        ,  0.25755495,  2.33191489, -0.86111111,  1.
,
        -1.        ],
       ...,
```

```
       [-1.        ,  0.8543956 , -0.26857441, -0.53821286,  1.
,
         1.10828913],
       [-0.5       , -0.75829704, -0.3301146 , -1.10582922,  1.
,
         1.        ],
       [-0.2969941 , -0.36722024, -1.59248204, -0.64411046, -1.
,
         1.        ]])
```