Final_results

April 12, 2025

[4]:
```
import pandas as pd
data = pd.read_csv("/content/default_of_credit_card_clients.csv")
print(data.head())
```

```
   ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0   1      20000    2          2         1   24      2      2     -1     -1
1   2     120000    2          2         2   26     -1      2      0      0
2   3      90000    2          2         2   34      0      0      0      0
3   4      50000    2          2         1   37      0      0      0      0
4   5      50000    1          2         1   57     -1      0     -1      0

   …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  \
0  …          0          0          0         0       689         0
1  …       3272       3455       3261         0      1000      1000
2  …      14331      14948      15549      1518      1500      1000
3  …      28314      28959      29547      2000      2019      1200
4  …      20940      19146      19131      2000     36681     10000

   PAY_AMT4  PAY_AMT5  PAY_AMT6  default.payment.next.month
0         0         0         0                           1
1      1000         0      2000                           1
2      1000      1000      5000                           0
3      1100      1069      1000                           0
4      9000       689       679                           0

[5 rows x 25 columns]
```

[5]:
```
# Replacing education values = 0, 5 and 6 with 4, since 0, 5 and 6 are not␣
 ↪defined

fill = (data.EDUCATION == 0) | (data.EDUCATION == 5) | (data.EDUCATION == 6)
data.loc[fill, 'EDUCATION'] = 4

print('EDUCATION ' + str(sorted(data['EDUCATION'].unique())))
```

```
EDUCATION [np.int64(1), np.int64(2), np.int64(3), np.int64(4)]
```

[6]:

```python
# Replacing marital status value = 0 to 3, since 0 is not defined

fill = (data.MARRIAGE == 0)
data.loc[fill, 'MARRIAGE'] = 3

print('MARRIAGE ' + str(sorted(data['MARRIAGE'].unique())))
```

```
MARRIAGE [np.int64(1), np.int64(2), np.int64(3)]
```

[7]:

```python
# Applying feature engineering to add derived variables
data['BillAverage'] = data[['BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4',␣
↪'BILL_AMT5', 'BILL_AMT6']].mean(axis=1).round()
data['PayAverage'] = data[['PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4',␣
↪'PAY_AMT5', 'PAY_AMT6']].mean(axis=1).round()
data.head()
```

[7]:

```
   ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0   1      20000    2          2         1   24      2      2     -1     -1
1   2     120000    2          2         2   26     -1      2      0      0
2   3      90000    2          2         2   34      0      0      0      0
3   4      50000    2          2         1   37      0      0      0      0
4   5      50000    1          2         1   57     -1      0     -1      0

   …  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  \
0  …          0         0       689         0         0         0         0
1  …       3261         0      1000      1000      1000         0      2000
2  …      15549      1518      1500      1000      1000      1000      5000
3  …      29547      2000      2019      1200      1100      1069      1000
4  …      19131      2000     36681     10000      9000       689       679

   default.payment.next.month  BillAverage  PayAverage
0                           1       1284.0       115.0
1                           1       2846.0       833.0
2                           0      16942.0      1836.0
3                           0      38556.0      1398.0
4                           0      18223.0      9842.0

[5 rows x 27 columns]
```

[8]:

```python
categorical_variables = ['SEX', 'EDUCATION', 'MARRIAGE','PAY_0', 'PAY_2',␣
↪'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']
numeric_variables = ['LIMIT_BAL', 'AGE',␣
↪'BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AMT6',␣
↪'PAY_AMT1','PAY_AMT2','PAY_AMT3','PAY_AMT4','PAY_AMT5','PAY_AMT6',␣
↪'BillAverage', 'PayAverage']
```

[9]:
```python
#Calculating and printing the Pearson correlation matrix
print("Pearson Correlation Matrix of numeric variables:")
pearson_correlation_matrix = data[numeric_variables].corr().round(2)
pearson_correlation_matrix
```

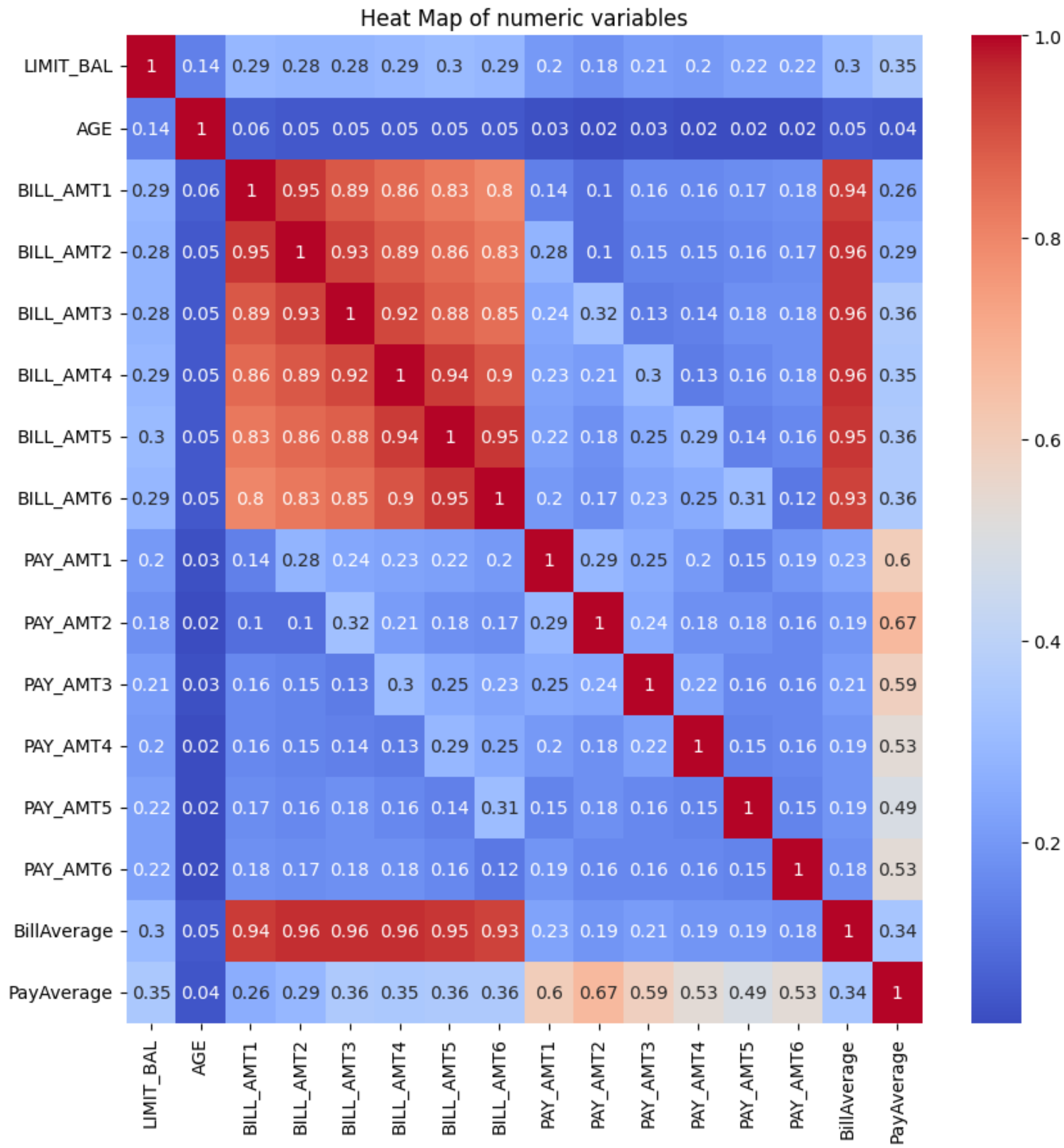
```
Pearson Correlation Matrix of numeric variables:
```

[9]:
```
             LIMIT_BAL   AGE  BILL_AMT1  BILL_AMT2  BILL_AMT3  BILL_AMT4  \
LIMIT_BAL         1.00  0.14       0.29       0.28       0.28       0.29
AGE               0.14  1.00       0.06       0.05       0.05       0.05
BILL_AMT1         0.29  0.06       1.00       0.95       0.89       0.86
BILL_AMT2         0.28  0.05       0.95       1.00       0.93       0.89
BILL_AMT3         0.28  0.05       0.89       0.93       1.00       0.92
BILL_AMT4         0.29  0.05       0.86       0.89       0.92       1.00
BILL_AMT5         0.30  0.05       0.83       0.86       0.88       0.94
BILL_AMT6         0.29  0.05       0.80       0.83       0.85       0.90
PAY_AMT1          0.20  0.03       0.14       0.28       0.24       0.23
PAY_AMT2          0.18  0.02       0.10       0.10       0.32       0.21
PAY_AMT3          0.21  0.03       0.16       0.15       0.13       0.30
PAY_AMT4          0.20  0.02       0.16       0.15       0.14       0.13
PAY_AMT5          0.22  0.02       0.17       0.16       0.18       0.16
PAY_AMT6          0.22  0.02       0.18       0.17       0.18       0.18
BillAverage       0.30  0.05       0.94       0.96       0.96       0.96
PayAverage        0.35  0.04       0.26       0.29       0.36       0.35

             BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  PAY_AMT4  \
LIMIT_BAL         0.30       0.29      0.20      0.18      0.21      0.20
AGE               0.05       0.05      0.03      0.02      0.03      0.02
BILL_AMT1         0.83       0.80      0.14      0.10      0.16      0.16
BILL_AMT2         0.86       0.83      0.28      0.10      0.15      0.15
BILL_AMT3         0.88       0.85      0.24      0.32      0.13      0.14
BILL_AMT4         0.94       0.90      0.23      0.21      0.30      0.13
BILL_AMT5         1.00       0.95      0.22      0.18      0.25      0.29
BILL_AMT6         0.95       1.00      0.20      0.17      0.23      0.25
PAY_AMT1          0.22       0.20      1.00      0.29      0.25      0.20
PAY_AMT2          0.18       0.17      0.29      1.00      0.24      0.18
PAY_AMT3          0.25       0.23      0.25      0.24      1.00      0.22
PAY_AMT4          0.29       0.25      0.20      0.18      0.22      1.00
PAY_AMT5          0.14       0.31      0.15      0.18      0.16      0.15
PAY_AMT6          0.16       0.12      0.19      0.16      0.16      0.16
BillAverage       0.95       0.93      0.23      0.19      0.21      0.19
PayAverage        0.36       0.36      0.60      0.67      0.59      0.53

             PAY_AMT5  PAY_AMT6  BillAverage  PayAverage
LIMIT_BAL        0.22      0.22         0.30        0.35
AGE              0.02      0.02         0.05        0.04
BILL_AMT1        0.17      0.18         0.94        0.26
```

```
BILL_AMT2        0.16     0.17       0.96       0.29
BILL_AMT3        0.18     0.18       0.96       0.36
BILL_AMT4        0.16     0.18       0.96       0.35
BILL_AMT5        0.14     0.16       0.95       0.36
BILL_AMT6        0.31     0.12       0.93       0.36
PAY_AMT1         0.15     0.19       0.23       0.60
PAY_AMT2         0.18     0.16       0.19       0.67
PAY_AMT3         0.16     0.16       0.21       0.59
PAY_AMT4         0.15     0.16       0.19       0.53
PAY_AMT5         1.00     0.15       0.19       0.49
PAY_AMT6         0.15     1.00       0.18       0.53
BillAverage      0.19     0.18       1.00       0.34
PayAverage       0.49     0.53       0.34       1.00
```

[10]:

```
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(pearson_correlation_matrix, cmap='coolwarm', annot=True, ax=ax)
plt.title('Heat Map of numeric variables')
plt.show()
```



[11]:
```python
# Printing summary statistics of numeric variables:
print("\nSummary Statistics of numeric variables:")
data[numeric_variables].describe().transpose()
```

```
Summary Statistics of numeric variables:
```

[11]:
```
              count           mean            std        min       25%  \
LIMIT_BAL   30000.0  167484.322667  129747.661567    10000.0  50000.00
AGE         30000.0      35.485500       9.217904       21.0     28.00
BILL_AMT1   30000.0   51223.330900   73635.860576  -165580.0   3558.75
```

```
BILL_AMT2    30000.0   49179.075167   71173.768783  -69777.0   2984.75
BILL_AMT3    30000.0   47013.154800   69349.387427 -157264.0   2666.25
BILL_AMT4    30000.0   43262.948967   64332.856134 -170000.0   2326.75
BILL_AMT5    30000.0   40311.400967   60797.155770  -81334.0   1763.00
BILL_AMT6    30000.0   38871.760400   59554.107537 -339603.0   1256.00
PAY_AMT1     30000.0    5663.580500   16563.280354       0.0   1000.00
PAY_AMT2     30000.0    5921.163500   23040.870402       0.0    833.00
PAY_AMT3     30000.0    5225.681500   17606.961470       0.0    390.00
PAY_AMT4     30000.0    4826.076867   15666.159744       0.0    296.00
PAY_AMT5     30000.0    4799.387633   15278.305679       0.0    252.50
PAY_AMT6     30000.0    5215.502567   17777.465775       0.0    117.75
BillAverage  30000.0   44976.943700   63260.722001  -56043.0   4781.75
PayAverage   30000.0    5275.231633   10137.946665       0.0   1113.00

                  50%        75%        max
LIMIT_BAL    140000.0  240000.00  1000000.0
AGE              34.0      41.00       79.0
BILL_AMT1     22381.5   67091.00   964511.0
BILL_AMT2     21200.0   64006.25   983931.0
BILL_AMT3     20088.5   60164.75  1664089.0
BILL_AMT4     19052.0   54506.00   891586.0
BILL_AMT5     18104.5   50190.50   927171.0
BILL_AMT6     17071.0   49198.25   961664.0
PAY_AMT1       2100.0    5006.00   873552.0
PAY_AMT2       2009.0    5000.00  1684259.0
PAY_AMT3       1800.0    4505.00   896040.0
PAY_AMT4       1500.0    4013.25   621000.0
PAY_AMT5       1500.0    4031.50   426529.0
PAY_AMT6       1500.0    4000.00   528666.0
BillAverage   21052.0   57104.25   877314.0
PayAverage     2397.5    5584.00   627344.0
```

[12]:
```python
print(data.columns)
```

```
Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
       'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
       'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
       'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6',
       'default.payment.next.month', 'BillAverage', 'PayAverage'],
      dtype='object')
```

[13]:
```python
# Removing ID column and Bill Amount columns based on high correlation with␣
↪variable BillAverage
data = data.drop(columns=['ID', 'BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3',␣
↪'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6'])
print(data.columns)
```

```
Index(['LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0', 'PAY_2',
       'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3',
       'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6', 'default.payment.next.month',
       'BillAverage', 'PayAverage'],
      dtype='object')
```

[14]:

```
# Applying One-Hot Encoding technique to categorical variables Sex, Education␣
↪and Marriage

from sklearn.preprocessing import OneHotEncoder

cat_variables = ['SEX','EDUCATION', 'MARRIAGE']

encoder = OneHotEncoder(sparse_output=False)
one_hot_encoded = encoder.fit_transform(data[cat_variables])

one_hot_df = pd.DataFrame(one_hot_encoded, columns=encoder.
↪get_feature_names_out(cat_variables))

encoded_df = pd.concat([data, one_hot_df], axis=1)

encoded_df = encoded_df.drop(['SEX', 'EDUCATION', 'MARRIAGE'], axis=1)
print(f"Encoded dataframe: \n{encoded_df}")
```

```
Encoded dataframe:
       LIMIT_BAL  AGE  PAY_0  PAY_2  PAY_3  PAY_4  PAY_5  PAY_6  PAY_AMT1  \
0          20000   24      2      2     -1     -1     -2     -2         0
1         120000   26     -1      2      0      0      0      2         0
2          90000   34      0      0      0      0      0      0      1518
3          50000   37      0      0      0      0      0      0      2000
4          50000   57     -1      0     -1      0      0      0      2000
…            …  …    …    …    …    …    …    …       …
29995     220000   39      0      0      0      0      0      0      8500
29996     150000   43     -1     -1     -1     -1      0      0      1837
29997      30000   37      4      3      2     -1      0      0         0
29998      80000   41      1     -1      0      0      0     -1     85900
29999      50000   46      0      0      0      0      0      0      2078

       PAY_AMT2  …  PayAverage  SEX_1  SEX_2  EDUCATION_1  EDUCATION_2  \
0           689  …       115.0    0.0    1.0          0.0          1.0
1          1000  …       833.0    0.0    1.0          0.0          1.0
2          1500  …      1836.0    0.0    1.0          0.0          1.0
3          2019  …      1398.0    0.0    1.0          0.0          1.0
4         36681  …      9842.0    1.0    0.0          0.0          1.0
…           …  …         …    …    …          …          …
29995     20000  …      7092.0    1.0    0.0          0.0          0.0
29996      3526  …      2415.0    1.0    0.0          0.0          0.0
29997         0  …      5217.0    1.0    0.0          0.0          1.0
```

```
29998      3409  …     24530.0    1.0    0.0          0.0          0.0
29999      1800  …      1385.0    1.0    0.0          0.0          1.0

       EDUCATION_3  EDUCATION_4  MARRIAGE_1  MARRIAGE_2  MARRIAGE_3
0              0.0          0.0         1.0         0.0         0.0
1              0.0          0.0         0.0         1.0         0.0
2              0.0          0.0         0.0         1.0         0.0
3              0.0          0.0         1.0         0.0         0.0
4              0.0          0.0         1.0         0.0         0.0
…              …          …         …         …         …
29995          1.0          0.0         1.0         0.0         0.0
29996          1.0          0.0         0.0         1.0         0.0
29997          0.0          0.0         0.0         1.0         0.0
29998          1.0          0.0         1.0         0.0         0.0
29999          0.0          0.0         1.0         0.0         0.0

[30000 rows x 26 columns]
```

[15]:
```
print(encoded_df.columns)
```

```
Index(['LIMIT_BAL', 'AGE', 'PAY_0', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5',
       'PAY_6', 'PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5',
       'PAY_AMT6', 'default.payment.next.month', 'BillAverage', 'PayAverage',
       'SEX_1', 'SEX_2', 'EDUCATION_1', 'EDUCATION_2', 'EDUCATION_3',
       'EDUCATION_4', 'MARRIAGE_1', 'MARRIAGE_2', 'MARRIAGE_3'],
      dtype='object')
```

[16]:
```
#Normalizing the numeric attributes
from sklearn.preprocessing import MinMaxScaler

# Initializing the scaler
scaler = MinMaxScaler()

# Fitting and transforming the data
normalized_data = scaler.fit_transform(encoded_df)
normalized_df = pd.DataFrame(scaler.transform(encoded_df), index=encoded_df.
 ↪index, columns=encoded_df.columns)
```

[17]:
```
# Validating minimum and maximum values are set as 0.00 and 1.00 respectively
pd.DataFrame(normalized_df).describe()
```

[17]:
```
          LIMIT_BAL           AGE        PAY_0         PAY_2         PAY_3  \
count  30000.000000  30000.000000  30000.00000  30000.000000  30000.000000
mean       0.159075      0.249750      0.19833      0.186623      0.183380
std        0.131058      0.158929      0.11238      0.119719      0.119687
min        0.000000      0.000000      0.00000      0.000000      0.000000
25%        0.040404      0.120690      0.10000      0.100000      0.100000
```

```
50%        0.131313     0.224138     0.20000     0.200000     0.200000
75%        0.232323     0.344828     0.20000     0.200000     0.200000
max        1.000000     1.000000     1.00000     1.000000     1.000000

              PAY_4        PAY_5        PAY_6     PAY_AMT1     PAY_AMT2  \
count  30000.000000 30000.000000 30000.000000 30000.000000 30000.000000
mean       0.177933     0.173380     0.170890     0.006483     0.003516
std        0.116914     0.113319     0.114999     0.018961     0.013680
min        0.000000     0.000000     0.000000     0.000000     0.000000
25%        0.100000     0.100000     0.100000     0.001145     0.000495
50%        0.200000     0.200000     0.200000     0.002404     0.001193
75%        0.200000     0.200000     0.200000     0.005731     0.002969
max        1.000000     1.000000     1.000000     1.000000     1.000000

       …    PayAverage        SEX_1        SEX_2  EDUCATION_1  \
count  …  30000.000000 30000.000000 30000.000000 30000.000000
mean   …      0.008409     0.396267     0.603733     0.352833
std    …      0.016160     0.489129     0.489129     0.477859
min    …      0.000000     0.000000     0.000000     0.000000
25%    …      0.001774     0.000000     0.000000     0.000000
50%    …      0.003822     0.000000     1.000000     0.000000
75%    …      0.008901     1.000000     1.000000     1.000000
max    …      1.000000     1.000000     1.000000     1.000000

        EDUCATION_2  EDUCATION_3  EDUCATION_4   MARRIAGE_1   MARRIAGE_2  \
count  30000.000000 30000.000000 30000.000000 30000.000000 30000.000000
mean       0.467667     0.163900     0.015600     0.455300     0.532133
std        0.498962     0.370191     0.123924     0.498006     0.498975
min        0.000000     0.000000     0.000000     0.000000     0.000000
25%        0.000000     0.000000     0.000000     0.000000     0.000000
50%        0.000000     0.000000     0.000000     0.000000     1.000000
75%        1.000000     0.000000     0.000000     1.000000     1.000000
max        1.000000     1.000000     1.000000     1.000000     1.000000

         MARRIAGE_3
count  30000.000000
mean       0.012567
std        0.111396
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000

[8 rows x 26 columns]
```

[19]:
```python
# Dataset partition
X = pd.DataFrame(normalized_df).drop('default.payment.next.month', axis=1,␣
↪inplace=False)
X.head()
```

[19]:
```
   LIMIT_BAL       AGE  PAY_0  PAY_2  PAY_3  PAY_4  PAY_5  PAY_6  PAY_AMT1  \
0   0.010101  0.051724    0.4    0.4    0.1    0.1    0.0    0.0  0.000000
1   0.111111  0.086207    0.1    0.4    0.2    0.2    0.2    0.4  0.000000
2   0.080808  0.224138    0.2    0.2    0.2    0.2    0.2    0.2  0.001738
3   0.040404  0.275862    0.2    0.2    0.2    0.2    0.2    0.2  0.002290
4   0.040404  0.620690    0.1    0.2    0.1    0.2    0.2    0.2  0.002290

   PAY_AMT2  …  PayAverage  SEX_1  SEX_2  EDUCATION_1  EDUCATION_2  \
0  0.000409  …    0.000183    0.0    1.0          0.0          1.0
1  0.000594  …    0.001328    0.0    1.0          0.0          1.0
2  0.000891  …    0.002927    0.0    1.0          0.0          1.0
3  0.001199  …    0.002228    0.0    1.0          0.0          1.0
4  0.021779  …    0.015688    1.0    0.0          0.0          1.0

   EDUCATION_3  EDUCATION_4  MARRIAGE_1  MARRIAGE_2  MARRIAGE_3
0          0.0          0.0         1.0         0.0         0.0
1          0.0          0.0         0.0         1.0         0.0
2          0.0          0.0         0.0         1.0         0.0
3          0.0          0.0         1.0         0.0         0.0
4          0.0          0.0         1.0         0.0         0.0

[5 rows x 25 columns]
```

[20]:
```python
y = data['default.payment.next.month']
```

[21]:
```python
from sklearn.model_selection import train_test_split
# Splitting data into training and testing sets: training set 70%, test set 30%
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪stratify=y, random_state=42)
```

[ ]:
```python
print(X_train.shape, X_test.shape)
```

```
(21000, 25) (9000, 25)
```

[22]:
```python
print("Train->")
print(y_train.value_counts(normalize=True))
print("Test->")
print(y_test.value_counts(normalize=True))
```

```
Train->
default.payment.next.month
0    0.77881
```

```
1    0.22119
Name: proportion, dtype: float64
Test->
default.payment.next.month
0    0.778778
1    0.221222
Name: proportion, dtype: float64
```

[23]:
```
from collections import Counter
# summarizing class distribution before applying SMOTE
print(Counter(y_train))
```

```
Counter({0: 16355, 1: 4645})
```

[24]:
```
from imblearn.over_sampling import SMOTE
# Applying SMOTE to transform the dataset
oversample = SMOTE()

#Fitting and applying the transform
X_train, y_train = oversample.fit_resample(X_train, y_train)

# summarizing the new class distribution after applying SMOTE
print(Counter(y_train))
```

```
Counter({0: 16355, 1: 16355})
```

[25]:
```
# Starting the timer to measure the time the Logistic Regression model takes to
 ↪be trained and tested
import time

# Start the timer
start_time_log_reg = time.time()
```

[26]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
# Initializing the logistic regression model as baseline model

log_reg = LogisticRegression()
```

[27]:
```
# Performing stratified cross-validation for Logistic Regression on the
 ↪training set
from sklearn.model_selection import StratifiedKFold, cross_val_score

sk_folds = StratifiedKFold(n_splits = 5, shuffle=True, random_state=42)

scores = cross_val_score(log_reg, X_train, y_train, cv = sk_folds)
```

```
print("Cross Validation Scores: ", scores)
print("Average CV Score: ", scores.mean())
print("Number of CV Scores used in Average: ", len(scores))
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465:
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(
```

```
Cross Validation Scores:  [0.67471721 0.67823296 0.6718129  0.67853867
0.67487007]
Average CV Score:  0.6756343625802506
Number of CV Scores used in Average:  5
```

[28]:
```
# Training the logistic regression model on the full training set
log_reg.fit(X_train, y_train)
```

[28]:
```
LogisticRegression()
```

[29]:
```
# Making predictions with Logistic Regression on the test set
y_pred = log_reg.predict(X_test)
```

[30]:
```
# End the timer for Logistic Regression
end_time_log_reg = time.time()

# Calculating the time for Logistic Regression model
elapsed_time = end_time_log_reg - start_time_log_reg
print(f"Time Logistic Regression model takes to be trained and tested:␣
 ↪{elapsed_time:.2f} seconds")
```

```
Time Logistic Regression model takes to be trained and tested: 22.10 seconds
```

[32]:
```
from sklearn.metrics import confusion_matrix, accuracy_score, recall_score,␣
 ↪precision_score, f1_score

# Calculating evaluation metrics for Logistic Regression
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)

conf_matrix = pd.DataFrame(confusion_matrix(y_test, y_pred))
```

```python
print("Confusion Matrix Logistic Regression before hyperparameter tuning:\n",␣
 ↪conf_matrix)
print("Accuracy Logistic Regression:", accuracy)
print("Precision Logistic Regression:", precision)
print("Recall Logistic Regression:", recall)
print("F1 score Logistic Regression:", f1)
```

```
Confusion Matrix Logistic Regression before hyperparameter tuning:
       0     1
0  4784  2225
1   709  1282
Accuracy Logistic Regression: 0.674
Precision Logistic Regression: 0.36555460507556314
Recall Logistic Regression: 0.6438975389251632
F1 score Logistic Regression: 0.4663514005092761
```

[33]:

```python
# Printing precision, recall, f1-score and accuracy from the perspective of␣
 ↪each of the class (0 and 1)
from sklearn.metrics import classification_report
from sklearn import metrics

print("Classification Report for Logistic Regression before hyperparameter␣
 ↪tuning:\n")
print(classification_report(y_test, y_pred))
```

```
Classification Report for Logistic Regression before hyperparameter tuning:

              precision    recall  f1-score   support

           0       0.87      0.68      0.77      7009
           1       0.37      0.64      0.47      1991

    accuracy                           0.67      9000
   macro avg       0.62      0.66      0.62      9000
weighted avg       0.76      0.67      0.70      9000
```

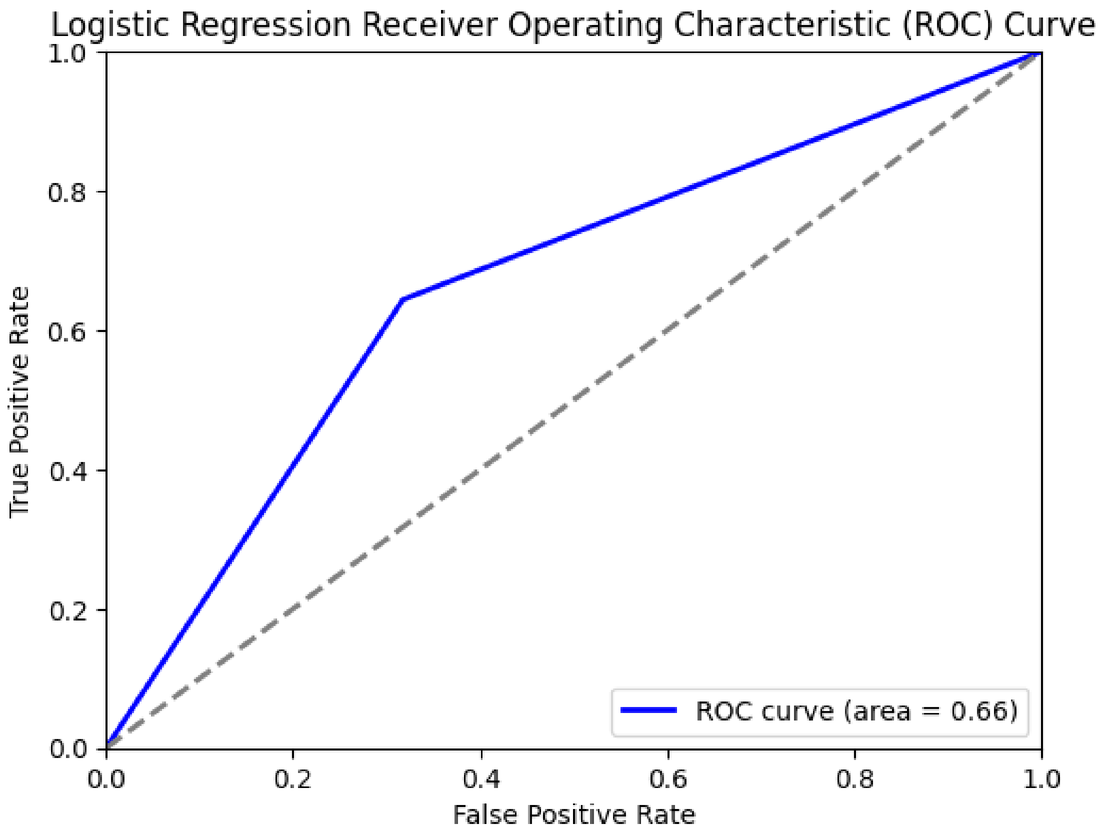
[34]:

```python
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print("True Negatives_LG (TN):", tn)
print("False Positives_LG (FP):", fp)
print("False Negatives_LG (FN):", fn)
print("True Positives_LG (TP):", tp)
```

```
True Negatives_LG (TN): 4784
False Positives_LG (FP): 2225
False Negatives_LG (FN): 709
True Positives_LG (TP): 1282
```

[35]:
```
from sklearn.metrics import roc_auc_score, roc_curve
from matplotlib import pyplot
import matplotlib.pyplot as plt

# Calculating AUC-ROC
auc = roc_auc_score(y_test, y_pred)
print(f'AUC-ROC for Logistic Regression before hyperparameter tuning: {auc:.
 ↪2f}')

# Plotting the ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred)
plt.figure()
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

from sklearn.metrics import roc_curve, auc
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

```
AUC-ROC for Logistic Regression before hyperparameter tuning: 0.66
```



[35]: np.float64(0.6632242723873926)

[36]:
```
# Performing hyperparameter tuning for Logistic Regression
from sklearn.model_selection import RandomizedSearchCV

param_lr = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear']
}

random_search = RandomizedSearchCV(log_reg, param_distributions=param_lr,
 ↪n_iter=10, cv=3, verbose=2, n_jobs=-1, random_state=42)
random_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

[36]:
```
RandomizedSearchCV(cv=3, estimator=LogisticRegression(), n_jobs=-1,
                   param_distributions={'C': [0.001, 0.01, 0.1, 1, 10, 100],
                                        'penalty': ['l1', 'l2'],
```

```
                                    'solver': ['liblinear']},
                    random_state=42, verbose=2)
```

[37]:
```
print("Best Hyperparameters for Logistic Regression:", random_search.
 ↪best_params_)
print("Best Cross-Validation Score:", random_search.best_score_)
```

```
Best Hyperparameters for Logistic Regression: {'solver': 'liblinear', 'penalty':
'l2', 'C': 1}
Best Cross-Validation Score: 0.6749314140274337
```

[38]:
```
best_log_reg = LogisticRegression(solver= 'liblinear', penalty= 'l2', C= 1)

best_log_reg.fit(X_train, y_train)
```

[38]:
```
LogisticRegression(C=1, solver='liblinear')
```

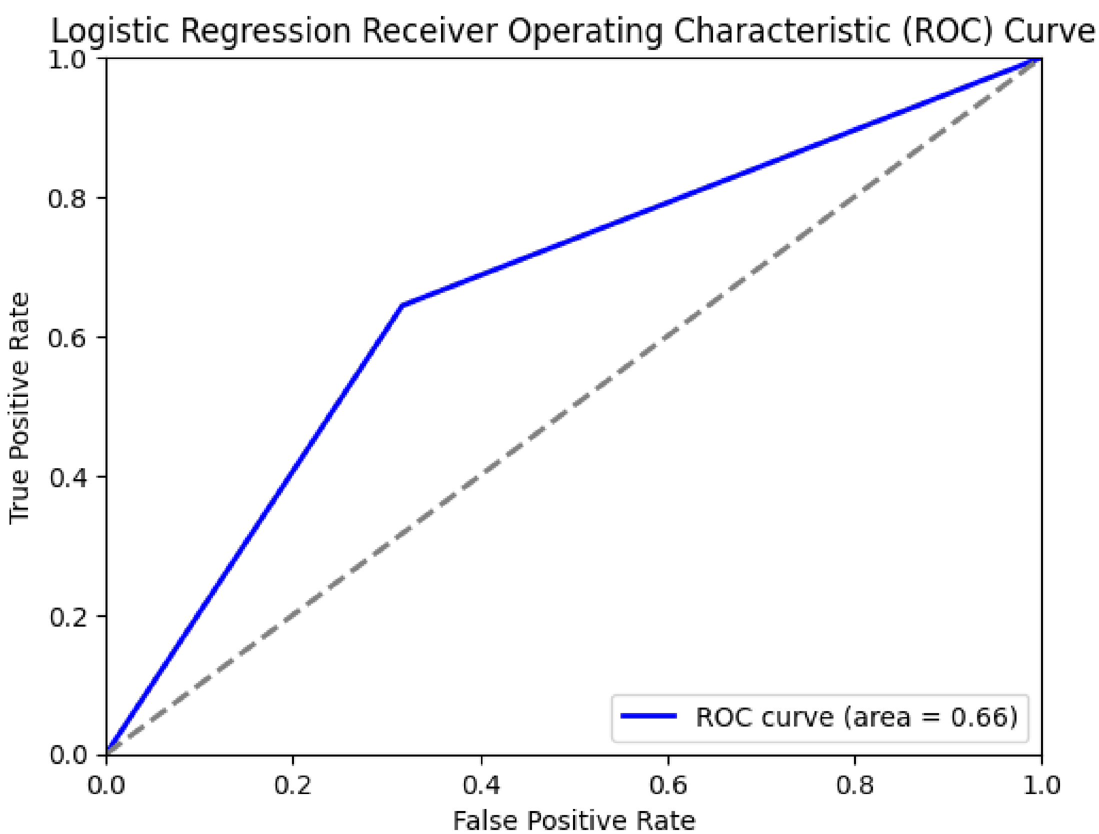
[39]:
```
y_pred = best_log_reg.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Test Accuracy: {accuracy:.4f}")

print("Classification Report for Logistic Regression after hyperparameter␣
 ↪tuning:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
auc = roc_auc_score(y_test, y_pred)
print(f'AUC-ROC for Logistic Regression after hyperparameter tuning: {auc:.2f}')
```

```
Test Accuracy: 0.6746
Classification Report for Logistic Regression after hyperparameter tuning:
               precision    recall  f1-score   support

           0       0.87      0.68      0.77      7009
           1       0.37      0.64      0.47      1991

    accuracy                           0.67      9000
   macro avg       0.62      0.66      0.62      9000
weighted avg       0.76      0.67      0.70      9000

Confusion Matrix:
 [[4789 2220]
 [ 709 1282]]
AUC-ROC for Logistic Regression after hyperparameter tuning: 0.66
```

[40]:
```
# Calculating AUC-ROC
auc = roc_auc_score(y_test, y_pred)
print(f'AUC-ROC for Logistic Regression after hyperparameter tuning: {auc:.2f}')
```

```python
# Plotting the ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred)
plt.figure()
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

from sklearn.metrics import roc_curve, auc
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

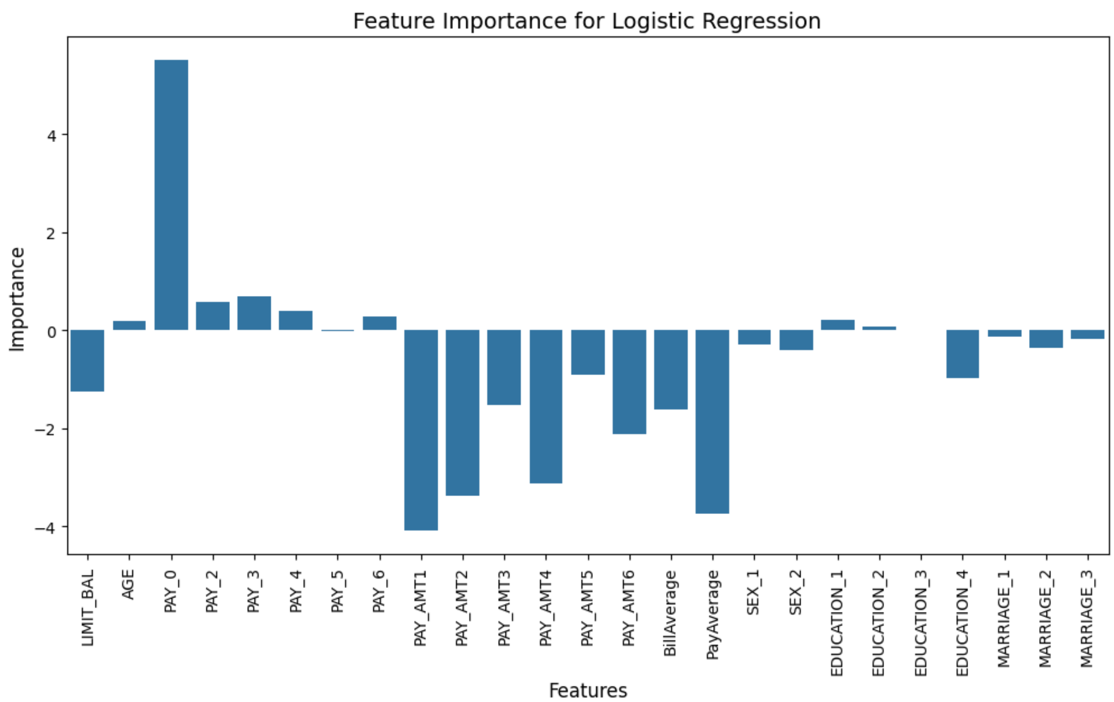
```
AUC-ROC for Logistic Regression after hyperparameter tuning: 0.66
```



[40]: np.float64(0.6635809566504829)

[41]:
```
# Building feature importance for Logistic Regression
importance = best_log_reg.coef_[0]

feature_names = X.columns
feature_imp_df = pd.DataFrame({'Feature': feature_names, 'Importance':␣
↪importance}).sort_values('Importance', ascending=False)
print(feature_imp_df)

# Plotting feature importance
features = X.columns
plt.figure(figsize=(12, 6))
sns.barplot(x=features, y=importance)
plt.title('Feature Importance for Logistic Regression', fontsize=14)
plt.xlabel('Features', fontsize=12)
plt.ylabel('Importance', fontsize=12)
plt.xticks(rotation=90)
plt.savefig("feature_importance_tuned.png", transparent=True)
plt.show()
```

```
        Feature  Importance
2         PAY_0    5.513111
4         PAY_3    0.683906
3         PAY_2    0.573585
5         PAY_4    0.391358
7         PAY_6    0.281144
18  EDUCATION_1    0.209200
1           AGE    0.180915
19  EDUCATION_2    0.080706
20  EDUCATION_3    0.017270
6         PAY_5   -0.023273
22   MARRIAGE_1   -0.136642
24   MARRIAGE_3   -0.180589
16        SEX_1   -0.281881
23   MARRIAGE_2   -0.361449
17        SEX_2   -0.396799
12     PAY_AMT5   -0.914096
21  EDUCATION_4   -0.985856
0     LIMIT_BAL   -1.258508
10     PAY_AMT3   -1.532369
14  BillAverage   -1.618102
13     PAY_AMT6   -2.111717
11     PAY_AMT4   -3.130799
9      PAY_AMT2   -3.369230
15   PayAverage   -3.739289
8      PAY_AMT1   -4.094235
```



[42]:
```
# Starting the timer to measure the time the Random Forest model takes to be␣
↪trained and tested
import time

# Start the timer
start_time_rf_classifier = time.time()
```

[43]:
```
from sklearn.ensemble import RandomForestClassifier
# Initializing the Random Forest classifier
rf_classifier = RandomForestClassifier()
```

[44]:
```
# Performing stratified cross-validation for Random Forest on the training set
sk_folds = StratifiedKFold(n_splits = 5, shuffle=True, random_state=42)

scores = cross_val_score(rf_classifier, X_train, y_train, cv = sk_folds)

print("Cross Validation Scores: ", scores)
print("Average CV Score: ", scores.mean())
print("Number of CV Scores used in Average: ", len(scores))
```

```
Cross Validation Scores:  [0.86105167 0.86105167 0.84974014 0.86105167
0.85661877]
Average CV Score:  0.8579027820238461
Number of CV Scores used in Average:  5
```

[45]:
```
# Training the Random Forest classifier
rf_classifier.fit(X_train, y_train)
```

[45]: RandomForestClassifier()

[46]:
```
# Making predictions with Random Forest classifier on the test set
y_pred = rf_classifier.predict(X_test)
```

[ ]:
```
# End the timer for Random Forest
end_time_rf_classifier = time.time()

# Calculating the time for Random Forest model
elapsed_time = end_time_rf_classifier - start_time_rf_classifier
print(f"Time Random Forest model takes to be trained and tested: {elapsed_time:.
↪2f} seconds")
```

```
Time Random Forest model takes to be trained and tested: 39.30 seconds
```

[47]:
```
# Calculating evaluation metrics for Random Forest
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)

conf_matrix = pd.DataFrame(confusion_matrix(y_test, y_pred))
print("Confusion Matrix Random Forest before hyperparameter tuning:\n",␣
↪conf_matrix)
print("Accuracy Random Forest:", accuracy)
print("Precision Random Forest:", precision)
print("Recall Random Forest:", recall)
print("F1 score Random Forest:", f1)
```

```
Confusion Matrix Random Forest before hyperparameter tuning:
       0    1
0   6278  731
1   1094  897
Accuracy Random Forest: 0.7972222222222223
Precision Random Forest: 0.550982800982801
Recall Random Forest: 0.45052737317930686
F1 score Random Forest: 0.4957170489085383
```

[48]:
```
# Printing precision, recall, f1-score and accuracy from the perspective of␣
↪each of the class (0 and 1)
from sklearn.metrics import classification_report
from sklearn import metrics

print('Classification Report for Random Forest before hyperparameter tuning:')
```

```
print(classification_report(y_test, y_pred))
```

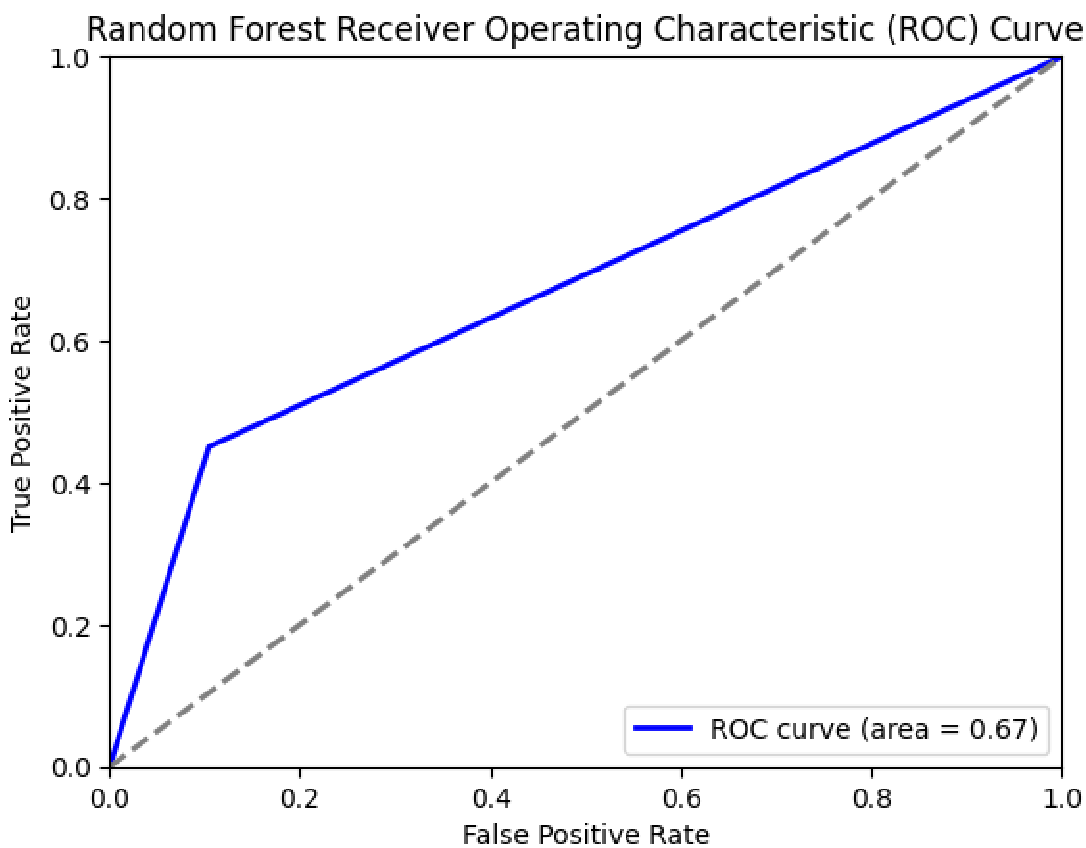
```
Classification Report for Random Forest before hyperparameter tuning:
              precision    recall  f1-score   support

           0       0.85      0.90      0.87      7009
           1       0.55      0.45      0.50      1991

    accuracy                           0.80      9000
   macro avg       0.70      0.67      0.68      9000
weighted avg       0.79      0.80      0.79      9000
```

[49]:
```
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print("True Negatives_LG (TN):", tn)
print("False Positives_LG (FP):", fp)
print("False Negatives_LG (FN):", fn)
print("True Positives_LG (TP):", tp)
```

```
True Negatives_LG (TN): 6278
False Positives_LG (FP): 731
False Negatives_LG (FN): 1094
True Positives_LG (TP): 897
```

[50]:
```
# Calculating AUC-ROC for Random Forest
auc = roc_auc_score(y_test, y_pred)
print(f'AUC-ROC for Random Forest before hyperparameter tuning: {auc:.2f}')

# Plotting the ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred)
plt.figure()
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Random Forest Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

from sklearn.metrics import roc_curve, auc
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

```
AUC-ROC for Random Forest before hyperparameter tuning: 0.67
```



[50]: np.float64(0.6731164473258499)

[51]:
```
# Performing hyperparameter tuning for Random Forest
# Defining the parameters
param_rf = {
'n_estimators': [50, 100, 200],
'max_depth': [None, 10],
'min_samples_split': [2, 5, 10],
'min_samples_leaf': [1, 2, 4],
'max_features': ['sqrt', 'log2']
}

# Creating the RandomizedSearchCV object
random_search = RandomizedSearchCV(estimator=rf_classifier,␣
↪param_distributions=param_rf, cv=3, n_jobs=-1, verbose=2, n_iter=5)

# Fitting the search to the data
random_search.fit(X_train, y_train)

# Printing the best parameters
```

```python
print("Best Hyperparameters:", random_search.best_params_)
print("Best Cross-Validation Score:", random_search.best_score_)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
Best Hyperparameters: {'n_estimators': 50, 'min_samples_split': 5,
'min_samples_leaf': 1, 'max_features': 'log2', 'max_depth': None}
Best Cross-Validation Score: 0.831796935546289
```

[52]:
```python
best_rf = RandomForestClassifier(n_estimators= 50, min_samples_split= 5,␣
↪min_samples_leaf= 1, max_features= 'log2', max_depth= None)

best_rf.fit(X_train, y_train)
```

[52]:
```
RandomForestClassifier(max_features='log2', min_samples_split=5,
                       n_estimators=50)
```

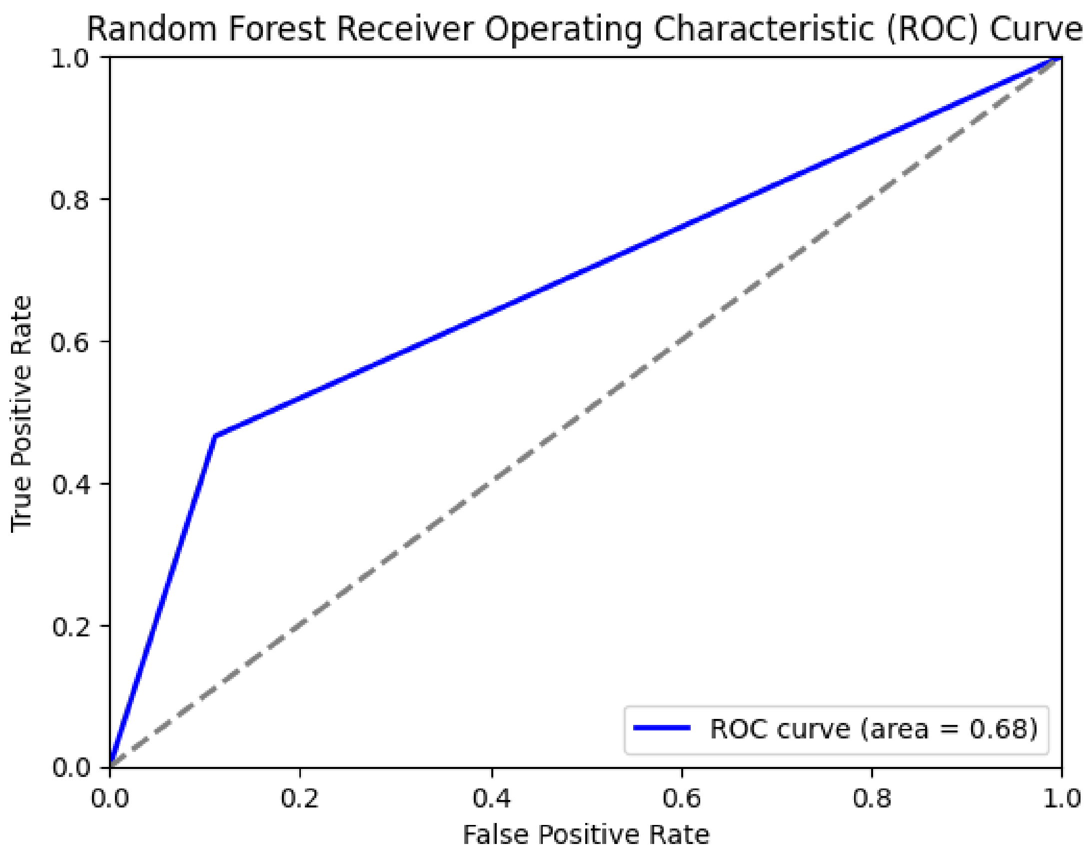
[53]:
```python
y_pred = best_rf.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Test Accuracy: {accuracy:.4f}")

print("Classification Report for Random Forest after hyperparameter tuning:\n",␣
↪classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
auc = roc_auc_score(y_test, y_pred)
print(f'AUC-ROC for Random Forest after hyperparameter tuning: {auc:.2f}')
```

```
Test Accuracy: 0.7953
Classification Report for Random Forest after hyperparameter tuning:
               precision    recall  f1-score   support

           0       0.85      0.89      0.87      7009
           1       0.54      0.47      0.50      1991

    accuracy                           0.80      9000
   macro avg       0.70      0.68      0.69      9000
weighted avg       0.79      0.80      0.79      9000

Confusion Matrix:
 [[6232  777]
 [1065  926]]
AUC-ROC for Random Forest after hyperparameter tuning: 0.68
```

[54]:
```python
# Calculating AUC-ROC for Random Forest
auc = roc_auc_score(y_test, y_pred)
print(f'AUC-ROC for Random Forest after hyperparameter tuning: {auc:.2f}')
```

```
# Plotting the ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred)
plt.figure()
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Random Forest Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

from sklearn.metrics import roc_curve, auc
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

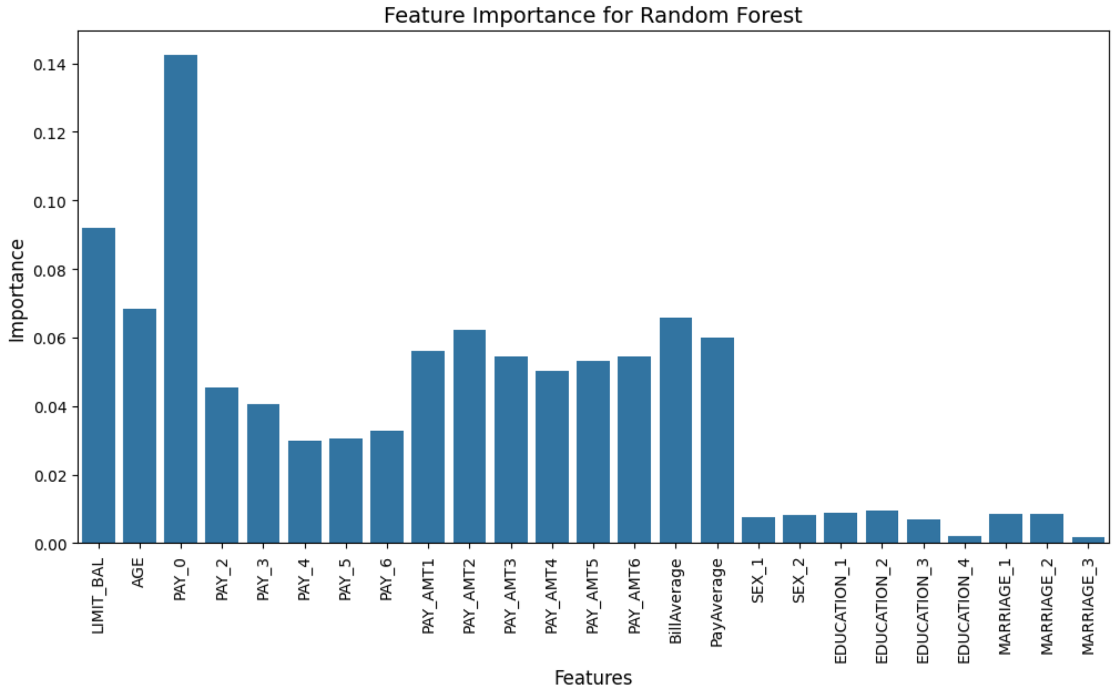
```
AUC-ROC for Random Forest after hyperparameter tuning: 0.68
```



[54]: np.float64(0.6771177245815615)

[55]:
```
importance = best_rf.feature_importances_

feature_names = X.columns
feature_imp_df = pd.DataFrame({'Feature': feature_names, 'Importance':␣
↪importance}).sort_values('Importance', ascending=False)
print(feature_imp_df)

features = X.columns
plt.figure(figsize=(12, 6))
sns.barplot(x=features, y=importance)
plt.title('Feature Importance for Random Forest', fontsize=14)
plt.xlabel('Features', fontsize=12)
plt.ylabel('Importance', fontsize=12)
plt.xticks(rotation=90)
plt.savefig("feature_importance_tuned.png", transparent=True)
plt.show()
```

```
        Feature  Importance
2         PAY_0    0.142349
0     LIMIT_BAL    0.092095
1           AGE    0.068333
14  BillAverage    0.065802
9      PAY_AMT2    0.062079
15   PayAverage    0.060097
8      PAY_AMT1    0.056128
10     PAY_AMT3    0.054445
13     PAY_AMT6    0.054430
12     PAY_AMT5    0.053185
11     PAY_AMT4    0.050372
3         PAY_2    0.045291
4         PAY_3    0.040514
7         PAY_6    0.032653
6         PAY_5    0.030525
5         PAY_4    0.029863
19  EDUCATION_2    0.009479
18  EDUCATION_1    0.008730
22   MARRIAGE_1    0.008412
23   MARRIAGE_2    0.008392
17        SEX_2    0.008192
16        SEX_1    0.007698
20  EDUCATION_3    0.007057
21  EDUCATION_4    0.002136
24   MARRIAGE_3    0.001741
```



[56]:
```
# Starting the timer to measure the time the Gradient Boosting model takes to␣
↪be trained and tested
import time

# Start the timer
start_time_gb_clf = time.time()
```

[57]:
```
from sklearn.ensemble import GradientBoostingClassifier
# Initializing the Gradient Boosting Classifier
gb_clf = GradientBoostingClassifier()
```

[58]:
```
# Performing stratified cross-validation for Gradient Boosting on the training␣
↪set
sk_folds = StratifiedKFold(n_splits = 5, shuffle=True, random_state=42)

scores = cross_val_score(gb_clf, X_train, y_train, cv = sk_folds)

print("Cross Validation Scores: ", scores)
print("Average CV Score: ", scores.mean())
print("Number of CV Scores used in Average: ", len(scores))
```

```
Cross Validation Scores:  [0.80755121 0.81228982 0.80051972 0.80923265
0.79914399]
Average CV Score:  0.8057474778355243
Number of CV Scores used in Average:  5
```

[59]:
```
# Training the Gradient Boosting model
gb_clf.fit(X_train, y_train)
```

[59]:
```
GradientBoostingClassifier()
```

[60]:
```
# Making predictions with Gradient Boosting classifier
y_pred = gb_clf.predict(X_test)
```

[61]:
```
# End the timer for Gradient Boosting
end_time_gb_clf = time.time()

# Calculating the time for Gradient Boosting model
elapsed_time = end_time_gb_clf - start_time_gb_clf
print(f"Time Gradient Boosting model takes to be trained and tested:␣
 ↪{elapsed_time:.2f} seconds")
```

```
Time Gradient Boosting model takes to be trained and tested: 99.69 seconds
```

[62]:
```
# Calculating evaluation metrics for Gradient Boosting
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)

conf_matrix = pd.DataFrame(confusion_matrix(y_test, y_pred))
print("Confusion Matrix Gradient Boosting before hyperparameter tuning:\n",␣
 ↪conf_matrix)
print("Accuracy Gradient Boosting:", accuracy)
print("Precision Gradient Boosting:", precision)
print("Recall Gradient Boosting:", recall)
print("F1 score Gradient Boosting:", f1)
```

```
Confusion Matrix Gradient Boosting before hyperparameter tuning:
       0    1
0  6259  750
1  1040  951
Accuracy Gradient Boosting: 0.8011111111111111
Precision Gradient Boosting: 0.5590828924162258
Recall Gradient Boosting: 0.4776494224008036
F1 score Gradient Boosting: 0.5151679306608884
```

[63]:
```
# Printing precision, recall, f1-score and accuracy from the perspective of␣
 ↪each of the class (0 and 1)
from sklearn.metrics import classification_report
from sklearn import metrics
```

```
print('Classification Report for Gradient Boosting before hyperparameter tuning:
 ↪')
print(classification_report(y_test, y_pred))
```

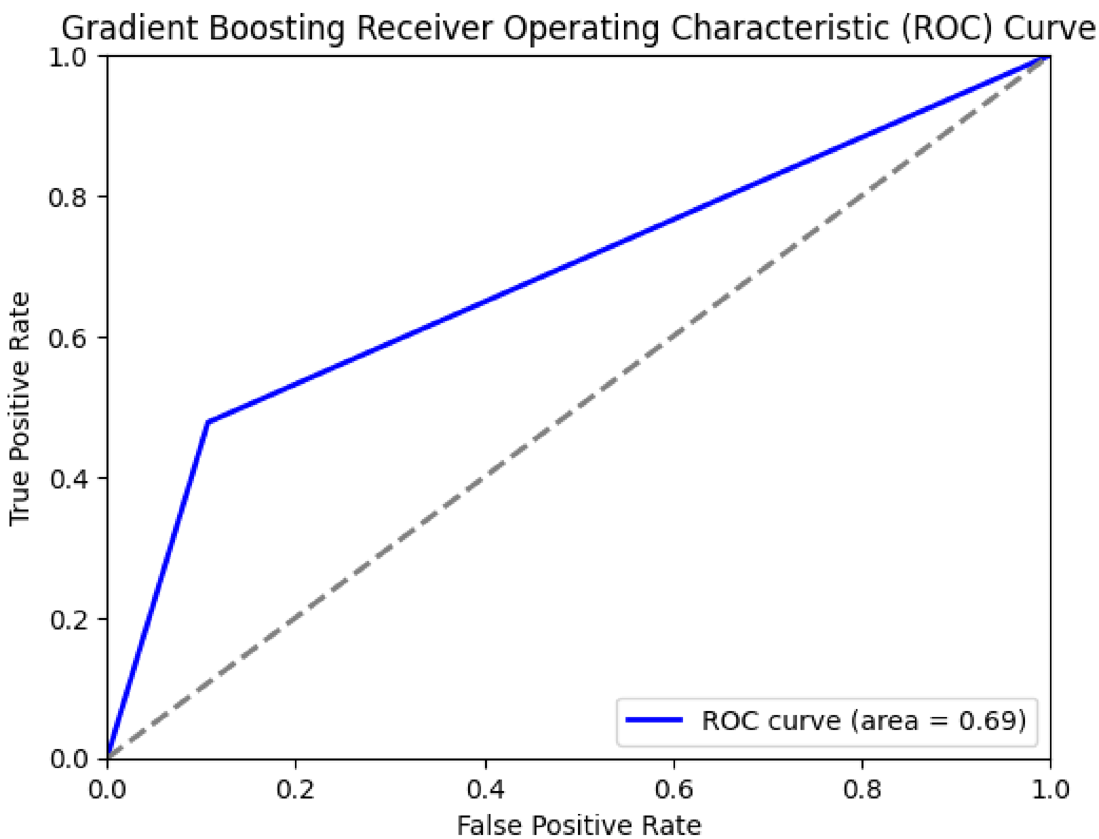
```
Classification Report for Gradient Boosting before hyperparameter tuning:
              precision    recall  f1-score   support

           0       0.86      0.89      0.87      7009
           1       0.56      0.48      0.52      1991

    accuracy                           0.80      9000
   macro avg       0.71      0.69      0.70      9000
weighted avg       0.79      0.80      0.80      9000
```

[64]:
```
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print("True Negatives_LG (TN):", tn)
print("False Positives_LG (FP):", fp)
print("False Negatives_LG (FN):", fn)
print("True Positives_LG (TP):", tp)
```

```
True Negatives_LG (TN): 6259
False Positives_LG (FP): 750
False Negatives_LG (FN): 1040
True Positives_LG (TP): 951
```

[65]:
```
# Calculating AUC-ROC
auc = roc_auc_score(y_test, y_pred)
print(f'AUC-ROC for Gradient Boosting before hyperparameter tuning: {auc:.2f}')

# Plotting the ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred)
plt.figure()
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Gradient Boosting Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

from sklearn.metrics import roc_curve, auc
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

```
AUC-ROC for Gradient Boosting before hyperparameter tuning: 0.69
```



[65]:
```
np.float64(0.6853220717368549)
```

[66]:
```python
import numpy as np

# Performing hyperparameter tuning for Gradient Boosting
# Defining the parameters
param_gb = {
'learning_rate': np.arange(0.01, 0.2, 0.01),
'n_estimators': [100, 200, 300],
'max_depth': [3, 5, 7]
}

# Creating the RandomizedSearchCV object
random_search = RandomizedSearchCV(estimator=gb_clf,␣
 ↪param_distributions=param_gb, cv=3, n_jobs=-1, verbose=2, n_iter=3)

# Fitting the search to the data
random_search.fit(X_train, y_train)
```

```
# Printing the best parameters
print("Best Hyperparameters:", random_search.best_params_)
print("Best Cross-Validation Score:", random_search.best_score_)
best_model_random = random_search.best_estimator_
```

```
Fitting 3 folds for each of 3 candidates, totalling 9 fits
Best Hyperparameters: {'n_estimators': 300, 'max_depth': 5, 'learning_rate':
np.float64(0.08)}
Best Cross-Validation Score: 0.8194804209251608
```

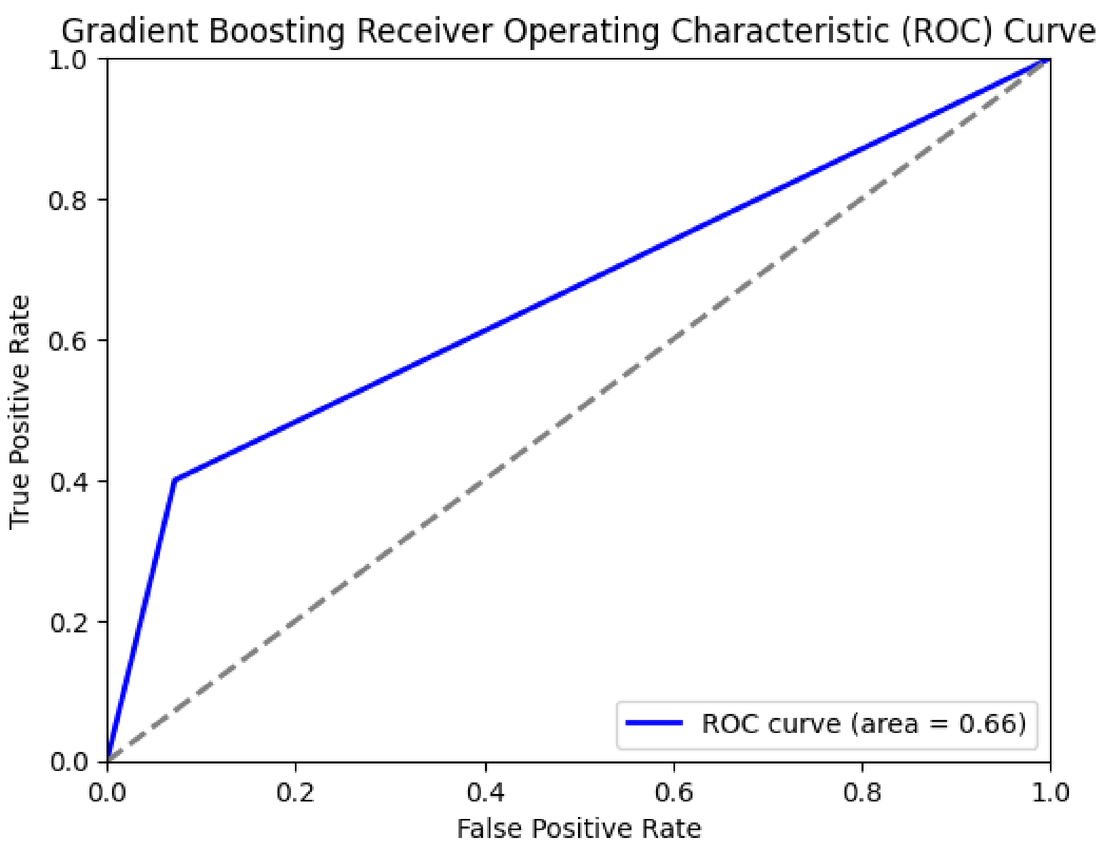
[67]:
```
best_gb = GradientBoostingClassifier(n_estimators= 300, max_depth= 5,␣
 ↪learning_rate= 0.08)
best_gb.fit(X_train, y_train)

y_pred = best_gb.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Test Accuracy: {accuracy:.4f}")

print("Classification Report for Gradient Boosting after hyperparameter tuning:
 ↪\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
auc = roc_auc_score(y_test, y_pred)
print(f'AUC-ROC for Gradient Boosting after hyperparameter tuning: {auc:.2f}')
```

```
Test Accuracy: 0.8113
Classification Report for Gradient Boosting after hyperparameter tuning:
               precision    recall  f1-score   support

           0       0.84      0.93      0.88      7009
           1       0.61      0.40      0.48      1991

    accuracy                           0.81      9000
   macro avg       0.73      0.66      0.68      9000
weighted avg       0.79      0.81      0.80      9000

Confusion Matrix:
 [[6506  503]
 [1195  796]]
AUC-ROC for Gradient Boosting after hyperparameter tuning: 0.66
```

[68]:
```
# Calculating AUC-ROC
auc = roc_auc_score(y_test, y_pred)
print(f'AUC-ROC for Gradient Boosting after hyperparameter tuning: {auc:.2f}')

# Plotting the ROC Curve
```

```
fpr, tpr, _ = roc_curve(y_test, y_pred)
plt.figure()
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Gradient Boosting Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

from sklearn.metrics import roc_curve, auc
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

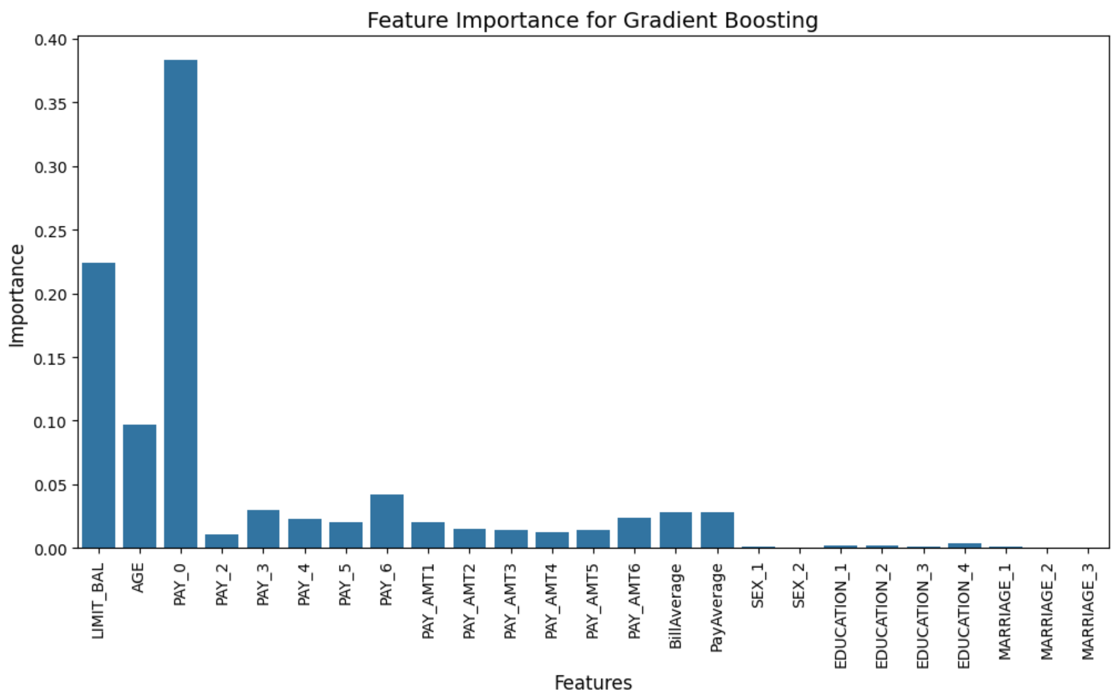
```
AUC-ROC for Gradient Boosting after hyperparameter tuning: 0.66
```




```
[68]: np.float64(0.6640171110989609)
```

[69]:
```python
import seaborn as sns
#Feature Importances after Hyperparameter Tuning
importances = best_gb.feature_importances_

feature_names = X.columns
feature_imp_df = pd.DataFrame({'Feature': feature_names, 'Importance':␣
↪importances}).sort_values('Importance', ascending=False)
print(feature_imp_df)

features = X.columns
plt.figure(figsize=(12, 6))
sns.barplot(x=features, y=importances)
plt.title('Feature Importance for Gradient Boosting', fontsize=14)
plt.xlabel('Features', fontsize=12)
plt.ylabel('Importance', fontsize=12)
plt.xticks(rotation=90)
plt.savefig("feature_importance_tuned.png", transparent=True)
plt.show()
```

```
        Feature  Importance
2         PAY_0    0.383101
0     LIMIT_BAL    0.224334
1           AGE    0.096891
7         PAY_6    0.042047
4         PAY_3    0.029737
15   PayAverage    0.028561
14  BillAverage    0.028496
13     PAY_AMT6    0.023523
5         PAY_4    0.023244
6         PAY_5    0.020635
8      PAY_AMT1    0.020494
9      PAY_AMT2    0.015146
12     PAY_AMT5    0.014518
10     PAY_AMT3    0.013896
11     PAY_AMT4    0.012209
3         PAY_2    0.011003
21  EDUCATION_4    0.003576
18  EDUCATION_1    0.001827
19  EDUCATION_2    0.001670
22   MARRIAGE_1    0.001437
16        SEX_1    0.001431
20  EDUCATION_3    0.000862
17        SEX_2    0.000728
23   MARRIAGE_2    0.000429
24   MARRIAGE_3    0.000206
```



[ ]:
```
#!apt-get install -y texlive-xetex texlive-fonts-recommended texlive-latex-extra
#!apt-get install texlive texlive-latex-extra pandoc
#!jupyter nbconvert --to pdf "/content/Big_Data_Analytics_Project_Data␣
↪Transformation & Modeling_Mar16.ipynb"
```