Problem Statement

Recruiting and retaining drivers is seen by industry watchers as a tough battle for our taxi booking company. Churn among drivers is high and it's very easy for drivers to stop working for the service on the fly or jump to Uber depending on the rates.

As the companies get bigger, the high churn could become a bigger problem. To find new drivers, company is casting a wide net, including people who don't have cars for jobs. But this acquisition is really costly. Losing drivers frequently impacts the morale of the organization and acquiring new drivers is more expensive than retaining existing ones.

You are working as a data scientist with the Analytics Department of this taxi booking company, focused on driver team attrition. You are provided with the monthly information for a segment of drivers for 2019 and 2020 and tasked to predict whether a driver will be leaving the company or not based on their attributes like:-

Demographics (city, age, gender etc.) Tenure information (joining date, Last Date) Historical data regarding the performance of the driver (Quarterly rating, Monthly business acquired, grade, Income)

Column Profiling:-

MMMM-YY : Reporting Date (Monthly)

Driver_ID : Unique id for drivers

Age : Age of the driver

Gender : Gender of the driver – Male : 0, Female: 1

City : City Code of the driver

Education_Level : Education level – 0 for 10+ ,1 for 12+ ,2 for graduate

Income : Monthly average Income of the driver

Date Of Joining : Joining date for the driver

LastWorkingDate : Last date of working for the driver

Joining Designation : Designation of the driver at the time of joining

Grade : Grade of the driver at the time of reporting

Total Business Value : The total business value acquired by the driver in a month (negative business indicates cancellation/refund or car EMI adjustments) Quarterly Rating : Quarterly rating of the driver: 1,2,3,4,5 (higher is better)

```python
import pandas as pd

df = pd.read_csv("/content/taxi_driver.csv")
```

```
df

       Unnamed: 0    MMM-YY  Driver_ID   Age  Gender City
Education_Level  \
0               0  01/01/19          1  28.0     0.0  C23
2
1               1  02/01/19          1  28.0     0.0  C23
2
2               2  03/01/19          1  28.0     0.0  C23
2
3               3  11/01/20          2  31.0     0.0   C7
2
4               4  12/01/20          2  31.0     0.0   C7
2
...           ...       ...        ...   ...     ...  ...
...
19099       19099  08/01/20       2788  30.0     0.0  C27
2
19100       19100  09/01/20       2788  30.0     0.0  C27
2
19101       19101  10/01/20       2788  30.0     0.0  C27
2
19102       19102  11/01/20       2788  30.0     0.0  C27
2
19103       19103  12/01/20       2788  30.0     0.0  C27
2

       Income Dateofjoining LastWorkingDate  Joining Designation
Grade  \
0       57387      24/12/18             NaN                    1
1
1       57387      24/12/18             NaN                    1
1
2       57387      24/12/18        03/11/19                    1
1
3       67016      11/06/20             NaN                    2
2
4       67016      11/06/20             NaN                    2
2
...       ...           ...             ...                  ...    ..
.
19099   70254      06/08/20             NaN                    2
2
19100   70254      06/08/20             NaN                    2
2
19101   70254      06/08/20             NaN                    2
2
19102   70254      06/08/20             NaN                    2
2
19103   70254      06/08/20             NaN                    2
```

```
2

       Total Business Value  Quarterly Rating
0                   2381060                 2
1                   -665480                 2
2                         0                 2
3                         0                 1
4                         0                 1
...                     ...               ...
19099                740280                 3
19100                448370                 3
19101                     0                 2
19102                200420                 2
19103                411480                 2

[19104 rows x 14 columns]
```

```
df.describe()
```

```
         Unnamed: 0     Driver_ID           Age        Gender  \
count  19104.000000  19104.000000  19043.000000  19052.000000
mean    9551.500000   1415.591133     34.668435      0.418749
std     5514.994107    810.705321      6.257912      0.493367
min        0.000000      1.000000     21.000000      0.000000
25%     4775.750000    710.000000     30.000000      0.000000
50%     9551.500000   1417.000000     34.000000      0.000000
75%    14327.250000   2137.000000     39.000000      1.000000
max    19103.000000   2788.000000     58.000000      1.000000

       Education_Level         Income  Joining Designation
Grade  \
count     19104.000000   19104.000000         19104.000000
19104.000000
mean          1.021671   65652.025126             1.690536
2.252670
std           0.800167   30914.515344             0.836984
1.026512
min           0.000000   10747.000000             1.000000
1.000000
25%           0.000000   42383.000000             1.000000
1.000000
50%           1.000000   60087.000000             1.000000
2.000000
75%           2.000000   83969.000000             2.000000
3.000000
max           2.000000  188418.000000             5.000000
5.000000

       Total Business Value  Quarterly Rating
count          1.910400e+04      19104.000000
```

```
mean           5.716621e+05         2.008899
std            1.128312e+06         1.009832
min           -6.000000e+06         1.000000
25%            0.000000e+00         1.000000
50%            2.500000e+05         2.000000
75%            6.997000e+05         3.000000
max            3.374772e+07         4.000000
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19104 entries, 0 to 19103
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Unnamed: 0            19104 non-null  int64  
 1   MMM-YY                19104 non-null  object 
 2   Driver_ID             19104 non-null  int64  
 3   Age                   19043 non-null  float64
 4   Gender                19052 non-null  float64
 5   City                  19104 non-null  object 
 6   Education_Level       19104 non-null  int64  
 7   Income                19104 non-null  int64  
 8   Dateofjoining         19104 non-null  object 
 9   LastWorkingDate       1616 non-null   object 
 10  Joining Designation   19104 non-null  int64  
 11  Grade                 19104 non-null  int64  
 12  Total Business Value  19104 non-null  int64  
 13  Quarterly Rating      19104 non-null  int64  
dtypes: float64(2), int64(8), object(4)
memory usage: 2.0+ MB
```

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

```
Unnamed: 0                  0
MMM-YY                      0
Driver_ID                   0
Age                        61
Gender                     52
City                        0
Education_Level             0
Income                      0
Dateofjoining               0
LastWorkingDate         17488
Joining Designation         0
Grade                       0
Total Business Value        0
Quarterly Rating            0
dtype: int64
```

```python
#Lets drop the useless column
df.drop('Unnamed: 0',inplace=True,axis=1)

##Converting 'MMM-YY', "Dateofjoining" & "LastWorkingDate" feature to datetime type
df['MMM-YY'] = pd.to_datetime(df['MMM-YY'])
df['Dateofjoining'] = pd.to_datetime(df['Dateofjoining'])
df['LastWorkingDate'] = pd.to_datetime(df['LastWorkingDate'])

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19104 entries, 0 to 19103
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   MMM-YY                19104 non-null  datetime64[ns]
 1   Driver_ID             19104 non-null  int64
 2   Age                   19043 non-null  float64
 3   Gender                19052 non-null  float64
 4   City                  19104 non-null  object
 5   Education_Level       19104 non-null  int64
 6   Income                19104 non-null  int64
 7   Dateofjoining         19104 non-null  datetime64[ns]
 8   LastWorkingDate       1616 non-null   datetime64[ns]
 9   Joining Designation   19104 non-null  int64
 10  Grade                 19104 non-null  int64
 11  Total Business Value  19104 non-null  int64
 12  Quarterly Rating      19104 non-null  int64
dtypes: datetime64[ns](3), float64(2), int64(7), object(1)
memory usage: 1.9+ MB
```

```python
#NOW lets create seperate dataframe for numerical columns only
import numpy as np

df_num = df.select_dtypes(np.number)

#Driver ID is of no use when we are doing KNN imputation. SO lets drop it
df_num.drop("Driver_ID",inplace =True,axis = 1)
df_num.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19104 entries, 0 to 19103
Data columns (total 8 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Age                   19043 non-null  float64
 1   Gender                19052 non-null  float64
 2   Education_Level       19104 non-null  int64
 3   Income                19104 non-null  int64
```

```
 4   Joining Designation   19104 non-null  int64
 5   Grade                 19104 non-null  int64
 6   Total Business Value  19104 non-null  int64
 7   Quarterly Rating      19104 non-null  int64
dtypes: float64(2), int64(6)
memory usage: 1.2 MB
```

```
df_num.isna().sum()
```

```
Age                     61
Gender                  52
Education_Level          0
Income                   0
Joining Designation      0
Grade                    0
Total Business Value     0
Quarterly Rating         0
dtype: int64
```

```
df_num["Gender"].value_counts()
```

```
0.0    11074
1.0     7978
Name: Gender, dtype: int64
```

```
num_cols = df_num.columns.tolist()
```

KNN imputation Of Missing Values

```
#Now lets do KNN imputation for missing values in age and Gender
from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors=5, weights='uniform',
metric='nan_euclidean',)
imputer.fit(df_num)
# transform the dataset
df_num = imputer.transform(df_num)
```

```
df_num =  pd.DataFrame(df_num, columns=num_cols)
```

```
df_num
```

```
        Age  Gender  Education_Level   Income  Joining Designation
Grade  \
0      28.0     0.0              2.0  57387.0                  1.0
1.0
1      28.0     0.0              2.0  57387.0                  1.0
1.0
2      28.0     0.0              2.0  57387.0                  1.0
1.0
```

```
3      31.0     0.0                2.0  67016.0                  2.0
2.0
4      31.0     0.0                2.0  67016.0                  2.0
2.0
...     ...     ...                ...      ...                  ...
...
19099  30.0     0.0                2.0  70254.0                  2.0
2.0
19100  30.0     0.0                2.0  70254.0                  2.0
2.0
19101  30.0     0.0                2.0  70254.0                  2.0
2.0
19102  30.0     0.0                2.0  70254.0                  2.0
2.0
19103  30.0     0.0                2.0  70254.0                  2.0
2.0

       Total Business Value  Quarterly Rating
0                 2381060.0               2.0
1                 -665480.0               2.0
2                       0.0               2.0
3                       0.0               1.0
4                       0.0               1.0
...                     ...               ...
19099              740280.0               3.0
19100              448370.0               3.0
19101                   0.0               2.0
19102              200420.0               2.0
19103              411480.0               2.0

[19104 rows x 8 columns]
```

```
df_num.isna().sum()
```

```
Age                        0
Gender                     0
Education_Level            0
Income                     0
Joining Designation        0
Grade                      0
Total Business Value       0
Quarterly Rating           0
dtype: int64
```

```
df_num["Gender"].value_counts()
```

```
0.0    11082
1.0     7984
0.6       13
0.2        9
```

```
0.4        9
0.8        7
Name: Gender, dtype: int64

#if KNN imputation value came out to be greater than 0.5 then that
means majiority neighbours was of class 1

# Replace values in the 'Gender' column
df_num['Gender'].replace({0.6: 1, 0.8: 1}, inplace=True)
df_num['Gender'].replace({0.4: 0, 0.2: 0}, inplace=True)

df_num["Gender"].value_counts()

0.0    11100
1.0     8004
Name: Gender, dtype: int64

#Now lets get the remaining columns
remaining_columns=list(set(df.columns).difference(set(num_cols)))
remaining_columns

['MMM-YY', 'LastWorkingDate', 'Driver_ID', 'Dateofjoining', 'City']

#Now lets concat this with our data
df2 = pd.concat([df_num, df[remaining_columns]],axis=1)

df2

        Age  Gender  Education_Level   Income  Joining Designation
Grade  \
0      28.0     0.0              2.0  57387.0                  1.0
1.0
1      28.0     0.0              2.0  57387.0                  1.0
1.0
2      28.0     0.0              2.0  57387.0                  1.0
1.0
3      31.0     0.0              2.0  67016.0                  2.0
2.0
4      31.0     0.0              2.0  67016.0                  2.0
2.0
...     ...     ...              ...      ...                  ...
...
19099  30.0     0.0              2.0  70254.0                  2.0
2.0
19100  30.0     0.0              2.0  70254.0                  2.0
2.0
19101  30.0     0.0              2.0  70254.0                  2.0
2.0
19102  30.0     0.0              2.0  70254.0                  2.0
2.0
19103  30.0     0.0              2.0  70254.0                  2.0
```

```
2.0

       Total Business Value  Quarterly Rating     MMM-YY
LastWorkingDate  \
0                 2381060.0               2.0 2019-01-01
NaT
1                 -665480.0               2.0 2019-02-01
NaT
2                       0.0               2.0 2019-03-01      2019-03-
11
3                       0.0               1.0 2020-11-01
NaT
4                       0.0               1.0 2020-12-01
NaT
...                     ...               ...        ...             .
..
19099              740280.0               3.0 2020-08-01
NaT
19100              448370.0               3.0 2020-09-01
NaT
19101                   0.0               2.0 2020-10-01
NaT
19102              200420.0               2.0 2020-11-01
NaT
19103              411480.0               2.0 2020-12-01
NaT

       Driver_ID Dateofjoining City
0              1    2018-12-24  C23
1              1    2018-12-24  C23
2              1    2018-12-24  C23
3              2    2020-11-06   C7
4              2    2020-11-06   C7
...          ...           ...  ...
19099       2788    2020-06-08  C27
19100       2788    2020-06-08  C27
19101       2788    2020-06-08  C27
19102       2788    2020-06-08  C27
19103       2788    2020-06-08  C27

[19104 rows x 13 columns]
```

Aggregation Of Data for each Driver

```
#NOw lets aggregate values of each driver for each month
agg_dict = {'Age':'max', 'Gender':'first','City':'first',
 'Education_Level':'last', 'Income':'last',
 'Joining Designation':'last','Grade':'last',
```

```
 'Dateofjoining':'last','LastWorkingDate':'last',
 'Total Business Value':'sum','Quarterly Rating':'last'}

df2 = df2.groupby(['Driver_ID','MMM-YY']).aggregate(agg_dict)

df2
```

```
                       Age  Gender City  Education_Level   Income  \
Driver_ID MMM-YY
1         2019-01-01  28.0     0.0  C23              2.0  57387.0
          2019-02-01  28.0     0.0  C23              2.0  57387.0
          2019-03-01  28.0     0.0  C23              2.0  57387.0
2         2020-11-01  31.0     0.0   C7              2.0  67016.0
          2020-12-01  31.0     0.0   C7              2.0  67016.0
...                    ...     ...  ...              ...      ...
2788      2020-08-01  30.0     0.0  C27              2.0  70254.0
          2020-09-01  30.0     0.0  C27              2.0  70254.0
          2020-10-01  30.0     0.0  C27              2.0  70254.0
          2020-11-01  30.0     0.0  C27              2.0  70254.0
          2020-12-01  30.0     0.0  C27              2.0  70254.0

                      Joining Designation  Grade Dateofjoining  \
Driver_ID MMM-YY
1         2019-01-01                  1.0    1.0    2018-12-24
          2019-02-01                  1.0    1.0    2018-12-24
          2019-03-01                  1.0    1.0    2018-12-24
2         2020-11-01                  2.0    2.0    2020-11-06
          2020-12-01                  2.0    2.0    2020-11-06
...                                   ...    ...           ...
2788      2020-08-01                  2.0    2.0    2020-06-08
          2020-09-01                  2.0    2.0    2020-06-08
          2020-10-01                  2.0    2.0    2020-06-08
          2020-11-01                  2.0    2.0    2020-06-08
          2020-12-01                  2.0    2.0    2020-06-08

                     LastWorkingDate  Total Business Value  Quarterly
Rating
Driver_ID MMM-YY

1         2019-01-01             NaT             2381060.0
2.0
          2019-02-01             NaT             -665480.0
2.0
          2019-03-01      2019-03-11                   0.0
2.0
2         2020-11-01             NaT                   0.0
1.0
          2020-12-01             NaT                   0.0
1.0
...                              ...                   ...
```

```
...
2788      2020-08-01             NaT                 740280.0
3.0
          2020-09-01             NaT                 448370.0
3.0
          2020-10-01             NaT                      0.0
2.0
          2020-11-01             NaT                 200420.0
2.0
          2020-12-01             NaT                 411480.0
2.0

[19104 rows x 11 columns]

#NOW lets sort these indexes
df2 = df2.sort_index(ascending=[True,True])

df2

                       Age  Gender City  Education_Level   Income  \
Driver_ID MMM-YY
1         2019-01-01  28.0     0.0  C23              2.0  57387.0
          2019-02-01  28.0     0.0  C23              2.0  57387.0
          2019-03-01  28.0     0.0  C23              2.0  57387.0
2         2020-11-01  31.0     0.0   C7              2.0  67016.0
          2020-12-01  31.0     0.0   C7              2.0  67016.0
...                    ...     ...  ...              ...      ...
2788      2020-08-01  30.0     0.0  C27              2.0  70254.0
          2020-09-01  30.0     0.0  C27              2.0  70254.0
          2020-10-01  30.0     0.0  C27              2.0  70254.0
          2020-11-01  30.0     0.0  C27              2.0  70254.0
          2020-12-01  30.0     0.0  C27              2.0  70254.0

                      Joining Designation  Grade Dateofjoining  \
Driver_ID MMM-YY
1         2019-01-01                  1.0    1.0    2018-12-24
          2019-02-01                  1.0    1.0    2018-12-24
          2019-03-01                  1.0    1.0    2018-12-24
2         2020-11-01                  2.0    2.0    2020-11-06
          2020-12-01                  2.0    2.0    2020-11-06
...                                   ...    ...           ...
2788      2020-08-01                  2.0    2.0    2020-06-08
          2020-09-01                  2.0    2.0    2020-06-08
          2020-10-01                  2.0    2.0    2020-06-08
          2020-11-01                  2.0    2.0    2020-06-08
          2020-12-01                  2.0    2.0    2020-06-08

                     LastWorkingDate  Total Business Value  Quarterly
Rating
Driver_ID MMM-YY
```

```
1          2019-01-01            NaT          2381060.0
2.0
           2019-02-01            NaT          -665480.0
2.0
           2019-03-01     2019-03-11                0.0
2.0
2          2020-11-01            NaT                0.0
1.0
           2020-12-01            NaT                0.0
1.0
...                              ...                ...
...
2788       2020-08-01            NaT           740280.0
3.0
           2020-09-01            NaT           448370.0
3.0
           2020-10-01            NaT                0.0
2.0
           2020-11-01            NaT           200420.0
2.0
           2020-12-01            NaT           411480.0
2.0

[19104 rows x 11 columns]

df2.reset_index(inplace=True)
```

Creating New Features

```
#Lets find the increase/decrease in total bussiness value for each
driver with each and every reporting month

# Calculate the difference between each row and its previous row
within each group
df2['diff_bussValue'] = df2.groupby('Driver_ID')['Total Business
Value'].diff()

# Fill NaN values in the 'diff_bussValue' column with 0
df2['diff_bussValue'] = df2['diff_bussValue'].fillna(0)

# Calculate the sum of differences for each group
df2['SumOf_diff_bussValue'] = df2.groupby('Driver_ID')
['diff_bussValue'].cumsum()

df2

       Driver_ID     MMM-YY   Age  Gender City  Education_Level
Income  \
```

```
0              1 2019-01-01  28.0     0.0  C23              2.0
57387.0
1              1 2019-02-01  28.0     0.0  C23              2.0
57387.0
2              1 2019-03-01  28.0     0.0  C23              2.0
57387.0
3              2 2020-11-01  31.0     0.0   C7              2.0
67016.0
4              2 2020-12-01  31.0     0.0   C7              2.0
67016.0
...          ...        ...   ...     ...  ...              ...        .
..
19099       2788 2020-08-01  30.0     0.0  C27              2.0
70254.0
19100       2788 2020-09-01  30.0     0.0  C27              2.0
70254.0
19101       2788 2020-10-01  30.0     0.0  C27              2.0
70254.0
19102       2788 2020-11-01  30.0     0.0  C27              2.0
70254.0
19103       2788 2020-12-01  30.0     0.0  C27              2.0
70254.0

       Joining Designation  Grade Dateofjoining LastWorkingDate  \
0                      1.0    1.0    2018-12-24             NaT
1                      1.0    1.0    2018-12-24             NaT
2                      1.0    1.0    2018-12-24      2019-03-11
3                      2.0    2.0    2020-11-06             NaT
4                      2.0    2.0    2020-11-06             NaT
...                    ...    ...           ...             ...
19099                  2.0    2.0    2020-06-08             NaT
19100                  2.0    2.0    2020-06-08             NaT
19101                  2.0    2.0    2020-06-08             NaT
19102                  2.0    2.0    2020-06-08             NaT
19103                  2.0    2.0    2020-06-08             NaT

       Total Business Value  Quarterly Rating  diff_bussValue  \
0                 2381060.0               2.0             0.0
1                 -665480.0               2.0      -3046540.0
2                       0.0               2.0        665480.0
3                       0.0               1.0             0.0
4                       0.0               1.0             0.0
...                     ...               ...             ...
19099              740280.0               3.0        242590.0
19100              448370.0               3.0       -291910.0
19101                   0.0               2.0       -448370.0
19102              200420.0               2.0        200420.0
19103              411480.0               2.0        211060.0

       SumOf_diff_bussValue
```

```
0                         0.0
1                  -3046540.0
2                  -2381060.0
3                         0.0
4                         0.0
...                       ...
19099                740280.0
19100                448370.0
19101                     0.0
19102                200420.0
19103                411480.0

[19104 rows x 15 columns]
```

```
df2[df2["Driver_ID"]==2788]
```

```
       Driver_ID     MMM-YY   Age  Gender City  Education_Level
Income  \
19097       2788 2020-06-01  29.0     0.0  C27              2.0
70254.0
19098       2788 2020-07-01  30.0     0.0  C27              2.0
70254.0
19099       2788 2020-08-01  30.0     0.0  C27              2.0
70254.0
19100       2788 2020-09-01  30.0     0.0  C27              2.0
70254.0
19101       2788 2020-10-01  30.0     0.0  C27              2.0
70254.0
19102       2788 2020-11-01  30.0     0.0  C27              2.0
70254.0
19103       2788 2020-12-01  30.0     0.0  C27              2.0
70254.0

       Joining Designation  Grade Dateofjoining LastWorkingDate  \
19097                  2.0    2.0    2020-06-08             NaT
19098                  2.0    2.0    2020-06-08             NaT
19099                  2.0    2.0    2020-06-08             NaT
19100                  2.0    2.0    2020-06-08             NaT
19101                  2.0    2.0    2020-06-08             NaT
19102                  2.0    2.0    2020-06-08             NaT
19103                  2.0    2.0    2020-06-08             NaT

       Total Business Value  Quarterly Rating  diff_bussValue  \
19097                   0.0               1.0             0.0
19098              497690.0               3.0        497690.0
19099              740280.0               3.0        242590.0
19100              448370.0               3.0       -291910.0
19101                   0.0               2.0       -448370.0
19102              200420.0               2.0        200420.0
19103              411480.0               2.0        211060.0
```

	SumOf_diff_bussValue
19097	0.0
19098	497690.0
19099	740280.0
19100	448370.0
19101	0.0
19102	200420.0
19103	411480.0

```
#Now lets drop this useless column diff_bussValue
df2.drop("diff_bussValue",inplace=True,axis=1)

#Now lets create a new feature "IncomeIncrease" whose value is 1 if
income of a driver has increased over the from first reporting month
to last.
#Value will be 0 if its the same &
#Value will be -1 if monthly income of a driver has decreased from
first reporting month to last one.


# Iterate over unique Driver_IDs
income_increase_dict = {}
for driver_id, group_df in df2.groupby('Driver_ID'):
    # Check if the first value is less than the last value
    if group_df['Income'].iloc[0] < group_df['Income'].iloc[-1]:
        income_increase_dict[driver_id] = 1
    elif group_df['Income'].iloc[0] == group_df['Income'].iloc[-1]:
        income_increase_dict[driver_id] = 0
    else:
        income_increase_dict[driver_id] = -1

# Convert the dictionary to a DataFrame
income_increase_df = pd.DataFrame(list(income_increase_dict.items()),
columns=['Driver_ID', 'IncomeIncrease'])

income_increase_df
```

	Driver_ID	IncomeIncrease
0	1	0
1	2	0
2	4	0
3	5	0
4	6	0
...	...	...
2376	2784	0
2377	2785	0
2378	2786	0
2379	2787	0
2380	2788	0

```
[2381 rows x 2 columns]

income_increase_df["IncomeIncrease"].value_counts()

0    2338
1      43
Name: IncomeIncrease, dtype: int64

#Lets create a new feature GradeIncrease whose value is 1 if grade of
the driver has increased from first reporting date to last one
#It is -1 if grade has decreased and 0 if grade remained same

# Iterate over unique Driver_IDs_increase_dict = {}
grade_increase_dict={}
for driver_id, group_df in df2.groupby('Driver_ID'):
    # Check if the first value is less than the last value
    if group_df['Grade'].iloc[0] < group_df['Grade'].iloc[-1]:
        grade_increase_dict[driver_id] = 1
    elif group_df['Grade'].iloc[0] == group_df['Grade'].iloc[-1]:
        grade_increase_dict[driver_id] = 0
    else:
        grade_increase_dict[driver_id] = -1

# Convert the dictionary to a DataFrame
grade_increase_df = pd.DataFrame(list(grade_increase_dict.items()),
columns=['Driver_ID', 'GradeIncrease'])

grade_increase_df["GradeIncrease"].value_counts()

0    2338
1      43
Name: GradeIncrease, dtype: int64

#Now lets aggregate values for each driver ID
agg_dict = {'Age':'max', 'Gender':'last','City':'first',
 'Education_Level':'last', 'Income':'last',
 'Joining Designation':'last','Grade':'last',
 'Dateofjoining':'last','LastWorkingDate':'last',
 'Total Business Value':'sum','Quarterly Rating':'last',
'SumOf_diff_bussValue':'last'}

df2_agg = df2.groupby(['Driver_ID']).aggregate(agg_dict)

df2_agg.reset_index(inplace=True)
df2_agg

      Driver_ID   Age  Gender City  Education_Level   Income  \
0             1  28.0     0.0  C23              2.0  57387.0
1             2  31.0     0.0   C7              2.0  67016.0
2             4  43.0     0.0  C13              2.0  65603.0
```

```
3            5  29.0     0.0   C9              0.0  46368.0
4            6  31.0     1.0  C11              1.0  78728.0
...        ...   ...     ...  ...              ...      ...
2376      2784  34.0     0.0  C24              0.0  82815.0
2377      2785  34.0     1.0   C9              0.0  12105.0
2378      2786  45.0     0.0  C19              0.0  35370.0
2379      2787  28.0     1.0  C20              2.0  69498.0
2380      2788  30.0     0.0  C27              2.0  70254.0

      Joining Designation  Grade Dateofjoining LastWorkingDate  \
0                     1.0    1.0    2018-12-24      2019-03-11
1                     2.0    2.0    2020-11-06             NaT
2                     2.0    2.0    2019-12-07      2020-04-27
3                     1.0    1.0    2019-01-09      2019-03-07
4                     3.0    3.0    2020-07-31             NaT
...                   ...    ...           ...             ...
2376                  2.0    3.0    2015-10-15             NaT
2377                  1.0    1.0    2020-08-28      2020-10-28
2378                  2.0    2.0    2018-07-31      2019-09-22
2379                  1.0    1.0    2018-07-21      2019-06-20
2380                  2.0    2.0    2020-06-08             NaT

      Total Business Value  Quarterly Rating  SumOf_diff_bussValue
0                1715580.0               2.0            -2381060.0
1                      0.0               1.0                   0.0
2                 350000.0               1.0                   0.0
3                 120360.0               1.0                   0.0
4                1265000.0               2.0                   0.0
...                    ...               ...                   ...
2376            21748820.0               4.0             -721110.0
2377                   0.0               1.0                   0.0
2378             2815090.0               1.0             -221080.0
2379              977830.0               1.0             -408090.0
2380             2298240.0               2.0              411480.0

[2381 rows x 13 columns]
```

```python
#lets create new column RatingIncreased to check if quarterly rating of a driver increased or not

# Iterate over unique Driver_IDs
rating_increase_dict = {}
for driver_id, group_df in df2.groupby('Driver_ID'):
    # Check if the first value is less than the last value
    if group_df['Quarterly Rating'].iloc[0] < group_df['Quarterly Rating'].iloc[-1]:
        rating_increase_dict[driver_id] = 1
    elif group_df['Quarterly Rating'].iloc[0] == group_df['Quarterly Rating'].iloc[-1]:
        rating_increase_dict[driver_id] = 0
```

```
    else:
        rating_increase_dict[driver_id] = -1

# Convert the dictionary to a DataFrame
rating_increase_df = pd.DataFrame(list(rating_increase_dict.items()),
columns=['Driver_ID', 'RatingIncrease'])

rating_increase_df
```

```
      Driver_ID  RatingIncrease
0             1               0
1             2               0
2             4               0
3             5               0
4             6               1
...         ...             ...
2376       2784               1
2377       2785               0
2378       2786              -1
2379       2787              -1
2380       2788               1

[2381 rows x 2 columns]
```

```
rating_increase_df["RatingIncrease"].value_counts()
```

```
 0    1565
-1     458
 1     358
Name: RatingIncrease, dtype: int64
```

```
#Now lets add RatingIncrease column to our main df
df2_agg = pd.merge(rating_increase_df, df2_agg, on='Driver_ID')
df2_agg
```

```
      Driver_ID  RatingIncrease   Age  Gender City  Education_Level
Income  \
0             1               0  28.0     0.0  C23              2.0
57387.0
1             2               0  31.0     0.0   C7              2.0
67016.0
2             4               0  43.0     0.0  C13              2.0
65603.0
3             5               0  29.0     0.0   C9              0.0
46368.0
4             6               1  31.0     1.0  C11              1.0
78728.0
...         ...             ...   ...     ...  ...              ...
...
2376       2784               1  34.0     0.0  C24              0.0
82815.0
```

```
2377       2785                0  34.0     1.0   C9              0.0
12105.0
2378       2786               -1  45.0     0.0  C19              0.0
35370.0
2379       2787               -1  28.0     1.0  C20              2.0
69498.0
2380       2788                1  30.0     0.0  C27              2.0
70254.0

      Joining Designation  Grade Dateofjoining LastWorkingDate  \
0                     1.0    1.0    2018-12-24      2019-03-11
1                     2.0    2.0    2020-11-06             NaT
2                     2.0    2.0    2019-12-07      2020-04-27
3                     1.0    1.0    2019-01-09      2019-03-07
4                     3.0    3.0    2020-07-31             NaT
...                   ...    ...           ...             ...
2376                  2.0    3.0    2015-10-15             NaT
2377                  1.0    1.0    2020-08-28      2020-10-28
2378                  2.0    2.0    2018-07-31      2019-09-22
2379                  1.0    1.0    2018-07-21      2019-06-20
2380                  2.0    2.0    2020-06-08             NaT

      Total Business Value  Quarterly Rating  SumOf_diff_bussValue
0                1715580.0               2.0            -2381060.0
1                      0.0               1.0                   0.0
2                 350000.0               1.0                   0.0
3                 120360.0               1.0                   0.0
4                1265000.0               2.0                   0.0
...                    ...               ...                   ...
2376            21748820.0               4.0             -721110.0
2377                   0.0               1.0                   0.0
2378             2815090.0               1.0             -221080.0
2379              977830.0               1.0             -408090.0
2380             2298240.0               2.0              411480.0

[2381 rows x 14 columns]

#NOW lets add IncomeIncrease column also
df2_agg = pd.merge(income_increase_df, df2_agg, on='Driver_ID')

#Now lets also merge GradeIncrease column
df2_agg = pd.merge(grade_increase_df, df2_agg, on='Driver_ID')

df2_agg

      Driver_ID  GradeIncrease  IncomeIncrease  RatingIncrease   Age
Gender  \
0             1              0               0               0  28.0
0.0
1             2              0               0               0  31.0
```

```
0.0
2            4             0               0               0  43.0
0.0
3            5             0               0               0  29.0
0.0
4            6             0               0               1  31.0
1.0
...        ...           ...             ...             ...   ...
...
2376      2784             0               0               1  34.0
0.0
2377      2785             0               0               0  34.0
1.0
2378      2786             0               0              -1  45.0
0.0
2379      2787             0               0              -1  28.0
1.0
2380      2788             0               0               1  30.0
0.0

     City  Education_Level   Income  Joining Designation  Grade  
Dateofjoining  \
0     C23              2.0  57387.0                  1.0    1.0
2018-12-24
1      C7              2.0  67016.0                  2.0    2.0
2020-11-06
2     C13              2.0  65603.0                  2.0    2.0
2019-12-07
3      C9              0.0  46368.0                  1.0    1.0
2019-01-09
4     C11              1.0  78728.0                  3.0    3.0
2020-07-31
...   ...              ...      ...                  ...    ...
...
2376  C24              0.0  82815.0                  2.0    3.0
2015-10-15
2377   C9              0.0  12105.0                  1.0    1.0
2020-08-28
2378  C19              0.0  35370.0                  2.0    2.0
2018-07-31
2379  C20              2.0  69498.0                  1.0    1.0
2018-07-21
2380  C27              2.0  70254.0                  2.0    2.0
2020-06-08

     LastWorkingDate  Total Business Value  Quarterly Rating  \
0         2019-03-11             1715580.0               2.0
1                NaT                   0.0               1.0
2         2020-04-27              350000.0               1.0
```

```
3         2019-03-07            120360.0                  1.0
4                NaT           1265000.0                  2.0
...              ...                 ...                  ...
2376             NaT          21748820.0                  4.0
2377      2020-10-28                 0.0                  1.0
2378      2019-09-22           2815090.0                  1.0
2379      2019-06-20            977830.0                  1.0
2380             NaT           2298240.0                  2.0

      SumOf_diff_bussValue
0               -2381060.0
1                      0.0
2                      0.0
3                      0.0
4                      0.0
...                    ...
2376             -721110.0
2377                   0.0
2378             -221080.0
2379             -408090.0
2380              411480.0

[2381 rows x 16 columns]
```

```
df2_agg.nunique()
```

```
Driver_ID                2381
GradeIncrease               2
IncomeIncrease              2
RatingIncrease              3
Age                        61
Gender                      2
City                       29
Education_Level             3
Income                   2339
Joining Designation         5
Grade                       5
Dateofjoining             869
LastWorkingDate           493
Total Business Value     1629
Quarterly Rating            4
SumOf_diff_bussValue     1161
dtype: int64
```

```
df2_agg["LastWorkingDate"].isna().sum()
```

```
765
```

```
## Creating a new column "Churn" using apply function
#Churn is 1 if the driver has left otherwise it is 0
```

```
df2_agg['Churn'] = df2_agg['LastWorkingDate'].apply(lambda x: 0 if
pd.isna(x) else 1)

#Extracting Month from DateOfJoining column and creating new feature
JoiningMonth
df2_agg['JoiningMonth'] = df2_agg['Dateofjoining'].dt.month

#Now lets remove useless date columns and driver_ID from our df
df2_agg.drop(["Driver_ID","Dateofjoining","LastWorkingDate"],axis=1,in
place=True)

df2_agg
```

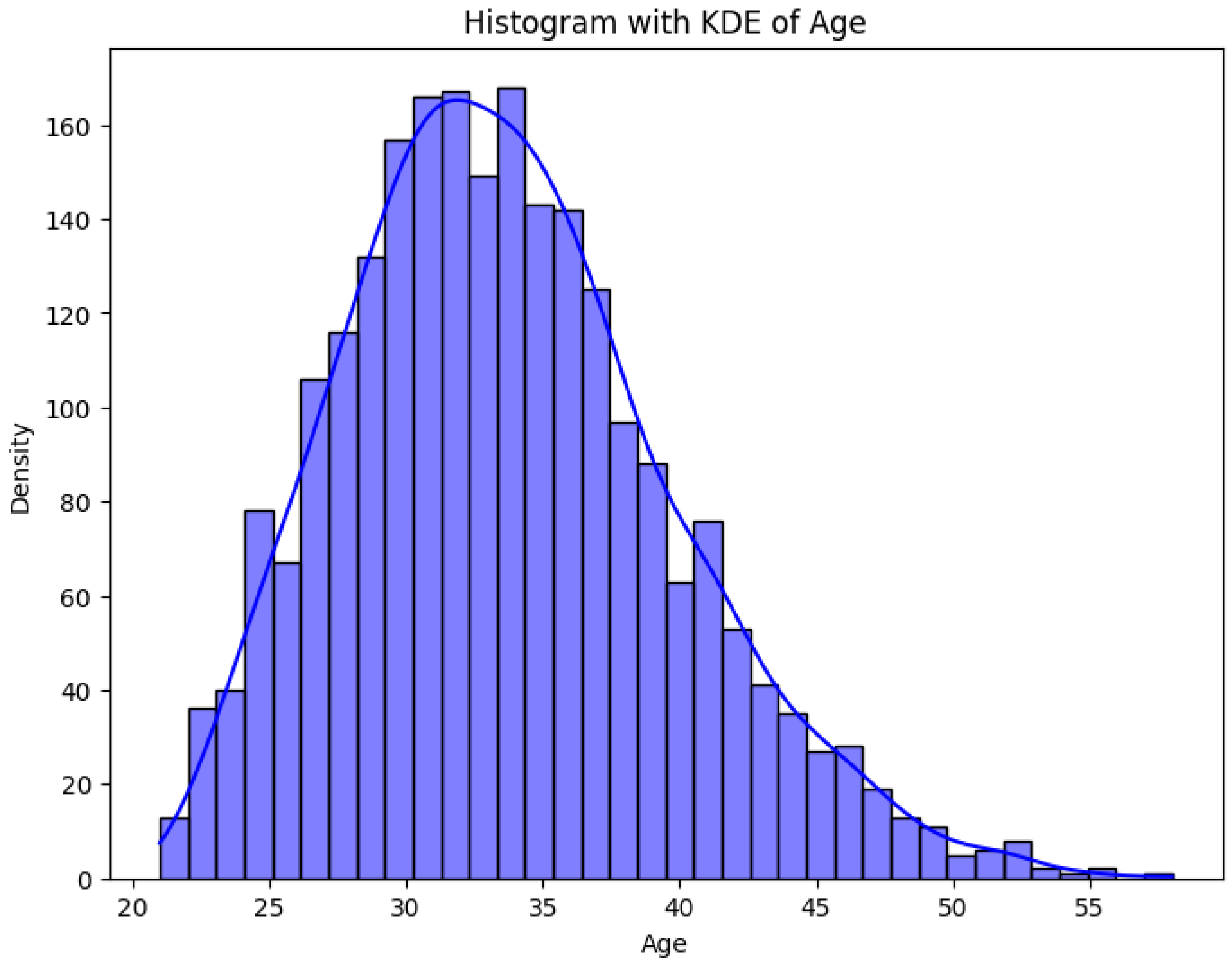
```
      GradeIncrease  IncomeIncrease  RatingIncrease   Age  Gender City
\
0                 0               0               0  28.0     0.0  C23

1                 0               0               0  31.0     0.0   C7

2                 0               0               0  43.0     0.0  C13

3                 0               0               0  29.0     0.0   C9

4                 0               0               1  31.0     1.0  C11

...             ...             ...             ...   ...     ...  ...

2376              0               0               1  34.0     0.0  C24

2377              0               0               0  34.0     1.0   C9

2378              0               0              -1  45.0     0.0  C19

2379              0               0              -1  28.0     1.0  C20

2380              0               0               1  30.0     0.0  C27


      Education_Level   Income  Joining Designation  Grade  \
0                 2.0  57387.0                  1.0    1.0
1                 2.0  67016.0                  2.0    2.0
2                 2.0  65603.0                  2.0    2.0
3                 0.0  46368.0                  1.0    1.0
4                 1.0  78728.0                  3.0    3.0
...               ...      ...                  ...    ...
2376              0.0  82815.0                  2.0    3.0
2377              0.0  12105.0                  1.0    1.0
2378              0.0  35370.0                  2.0    2.0
2379              2.0  69498.0                  1.0    1.0
2380              2.0  70254.0                  2.0    2.0
```

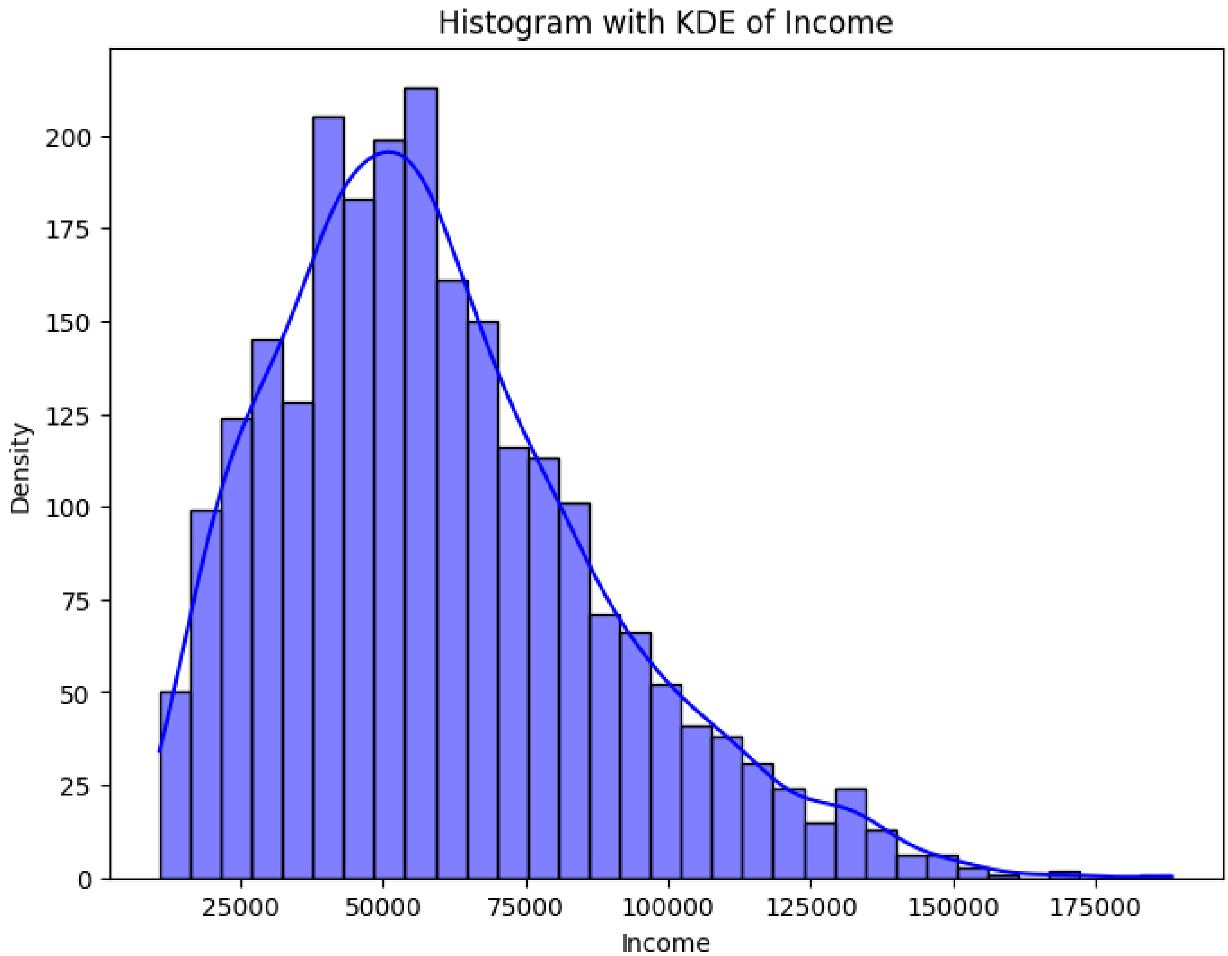
```
      Total Business Value  Quarterly Rating  SumOf_diff_bussValue
Churn  \
0                1715580.0               2.0            -2381060.0
1
1                      0.0               1.0                   0.0
0
2                 350000.0               1.0                   0.0
1
3                 120360.0               1.0                   0.0
1
4                1265000.0               2.0                   0.0
0
...                    ...               ...                   ...
...
2376            21748820.0               4.0             -721110.0
0
2377                   0.0               1.0                   0.0
1
2378             2815090.0               1.0             -221080.0
1
2379              977830.0               1.0             -408090.0
1
2380             2298240.0               2.0              411480.0
0

      JoiningMonth
0               12
1               11
2               12
3                1
4                7
...            ...
2376            10
2377             8
2378             7
2379             7
2380             6

[2381 rows x 15 columns]
```

EDA: Univariate analysis

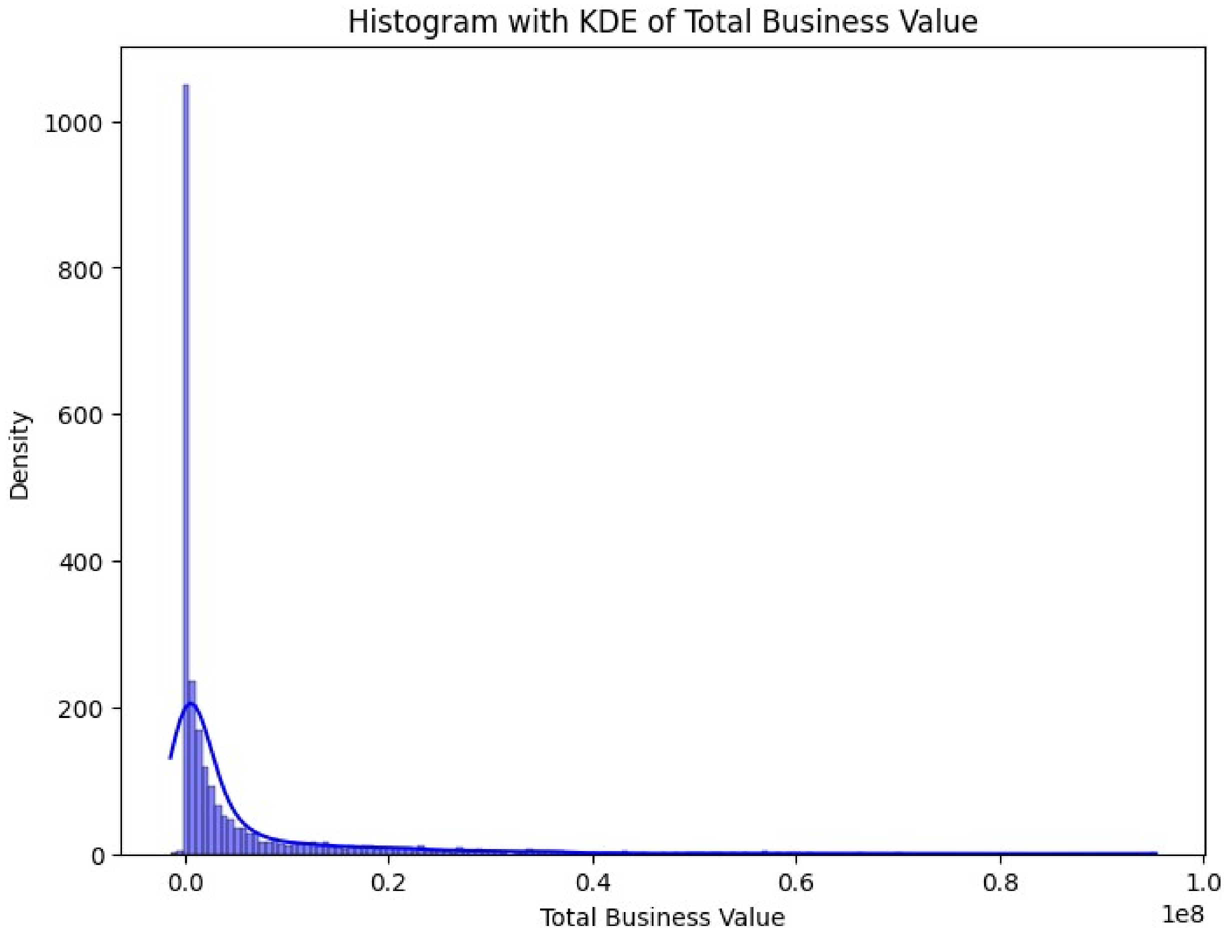
```
#Now lets seperate out numerical columns
num_cols = ["Age","Income","Total Business
Value","SumOf_diff_bussValue"]

# Plotting histograms for each numerical feature
import seaborn as sns
```

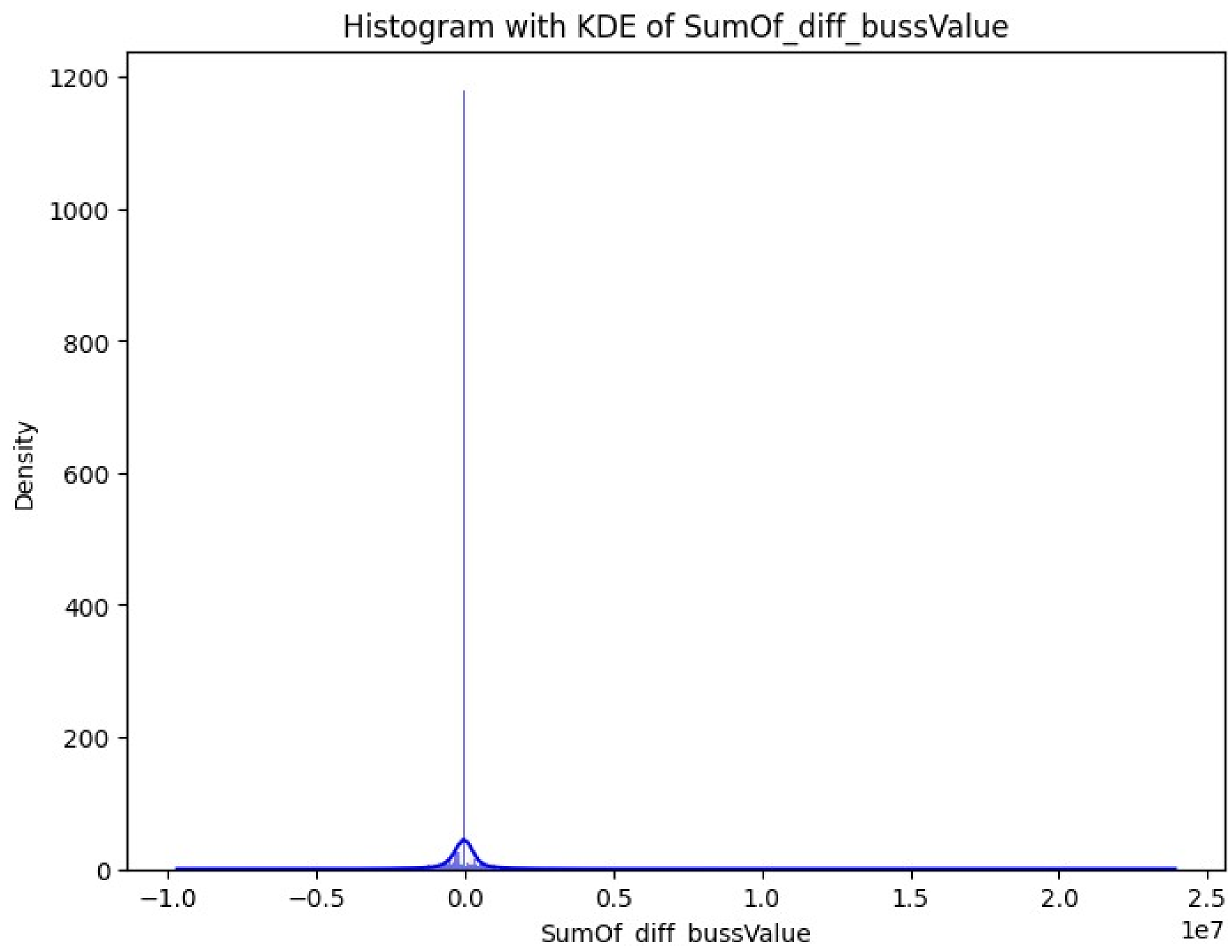
```
import matplotlib.pyplot as plt

for col in num_cols:
    plt.figure(figsize=(8, 6))
    sns.histplot(df2_agg[col], kde=True, color='blue',
edgecolor='black')
    plt.title(f'Histogram with KDE of {col}')
    plt.xlabel(col)
    plt.ylabel('Density')
    plt.show()
```





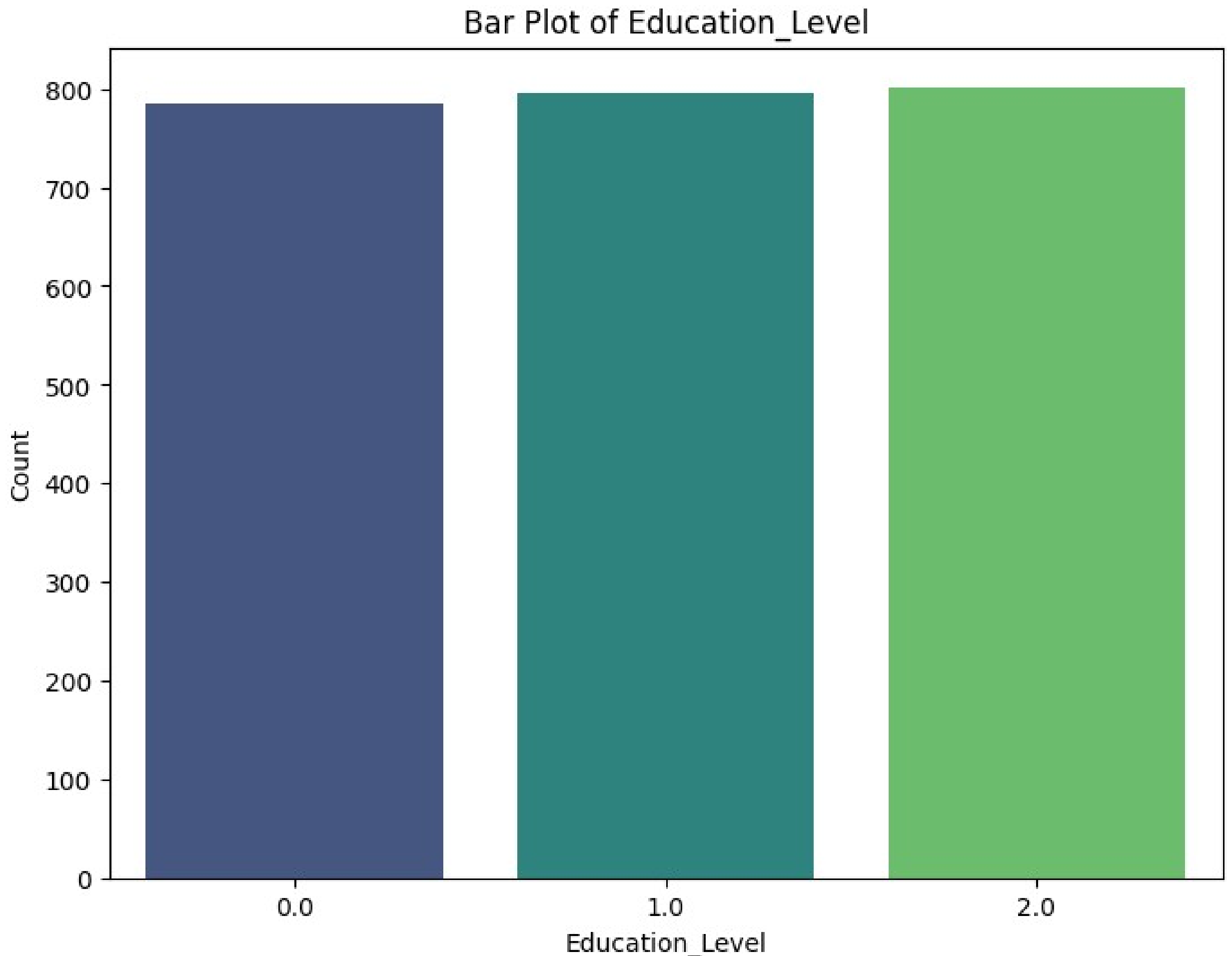
Histogram with KDE of Income
Density
0
25
50
75
100
125
150
175
200
25000
50000
75000
100000
125000
150000
175000
Income

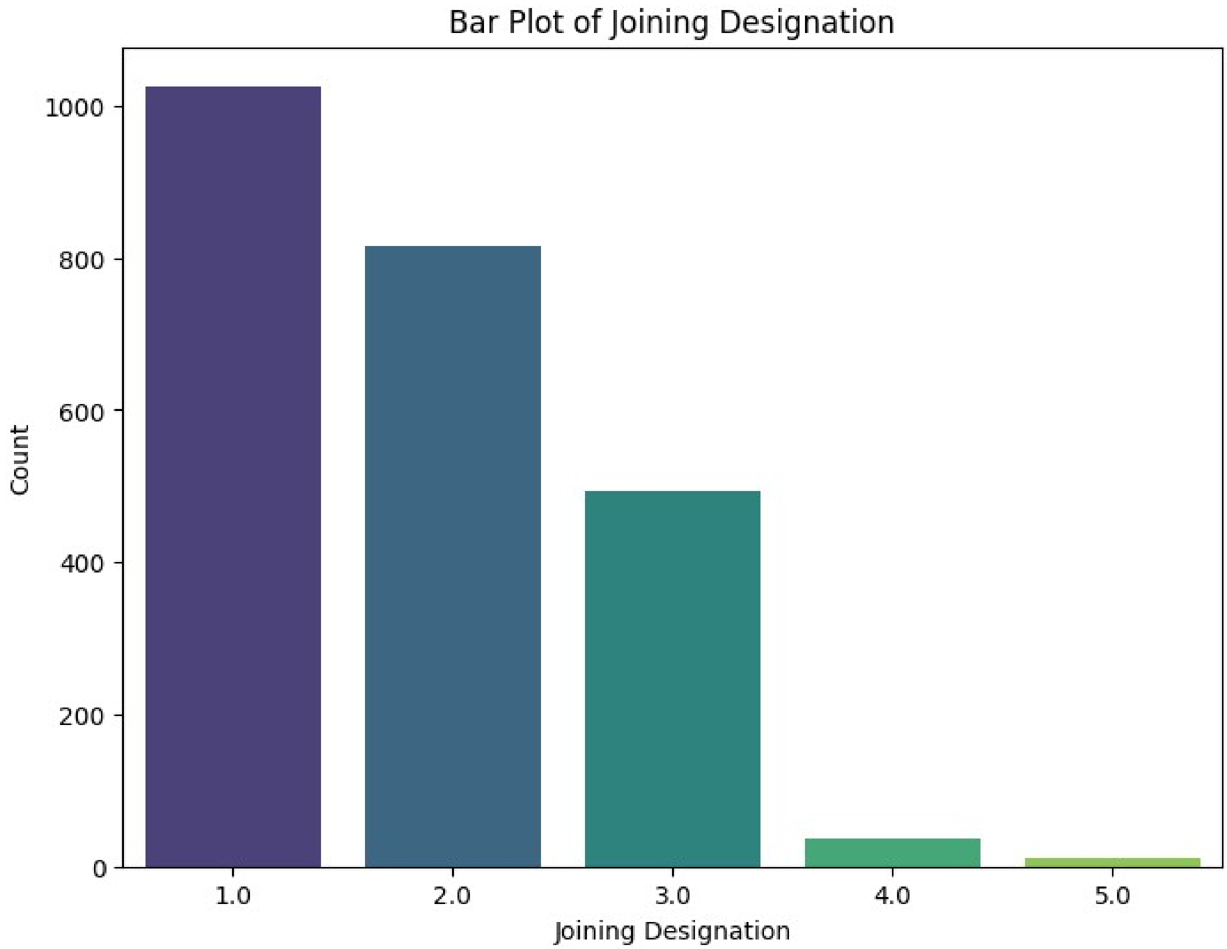

Histogram with KDE of Total Business Value
Density
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
1e8
Total Business Value

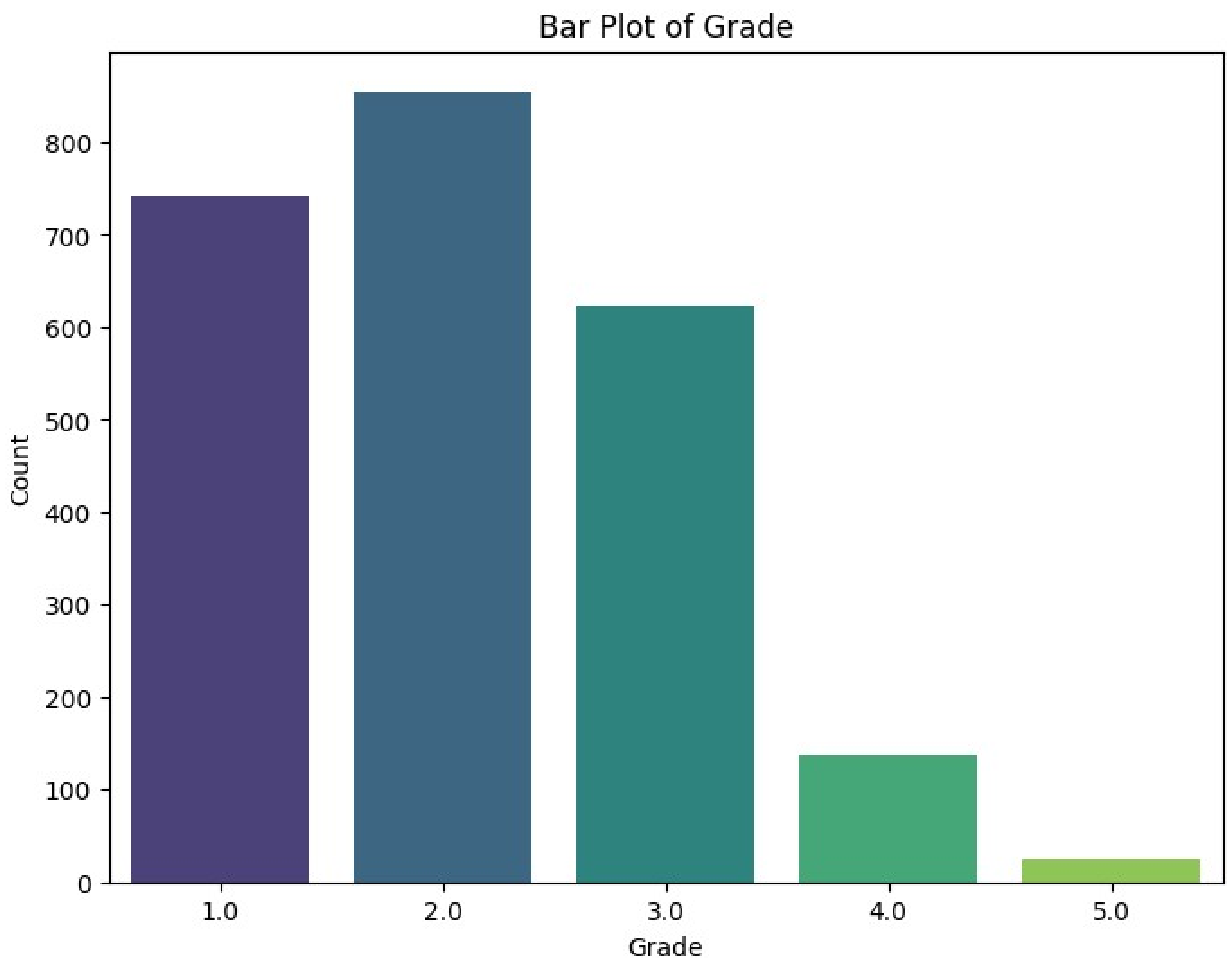


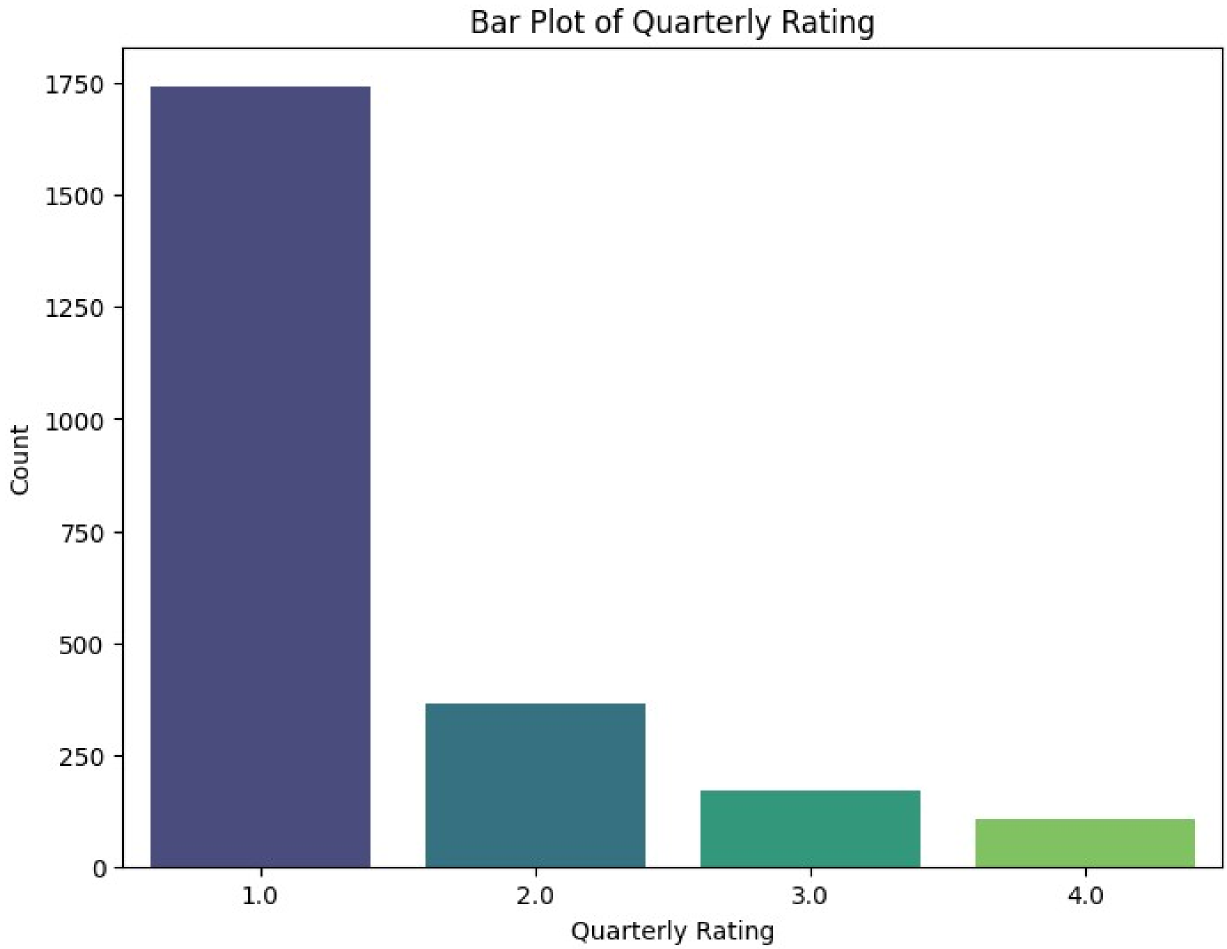
Insights All the numerical columns have gaussian like distribution but with long right tail which means there are outliers in our numerical columns.

```
cat_cols = ["Education_Level","Joining Designation","Grade","Quarterly
Rating","JoiningMonth","IncomeIncrease","RatingIncrease","GradeIncreas
e","Gender","City","Churn"]

# Plotting bar plots for each categorical feature
for col in cat_cols:
    plt.figure(figsize=(8, 6))
    sns.countplot(x=col, data=df2_agg, palette='viridis')
    plt.title(f'Bar Plot of {col}')
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.show()
```

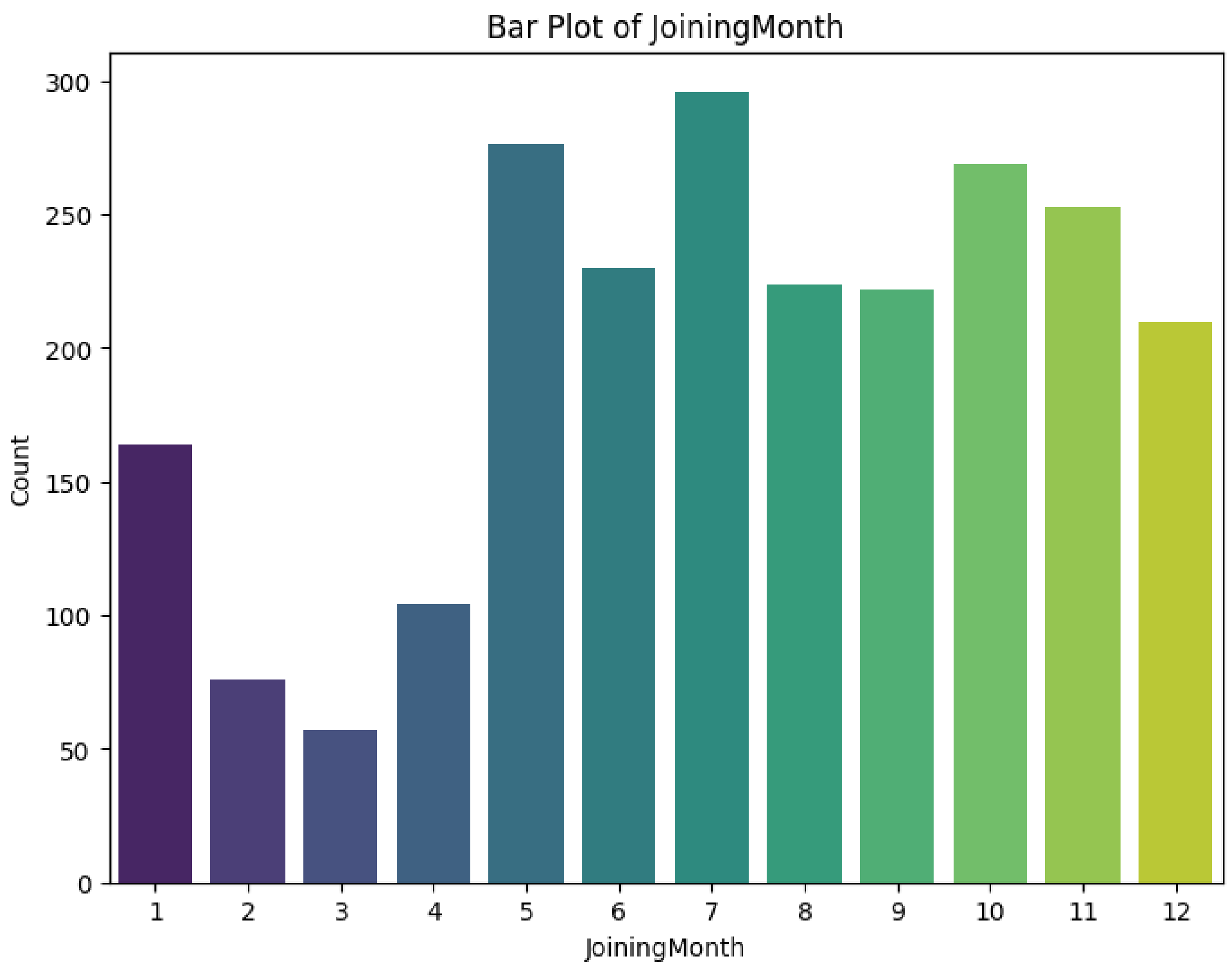

Bar Plot of Education_Level
Count
800
700
600
500
400
300
200
100
0
0.0
1.0
2.0
Education_Level

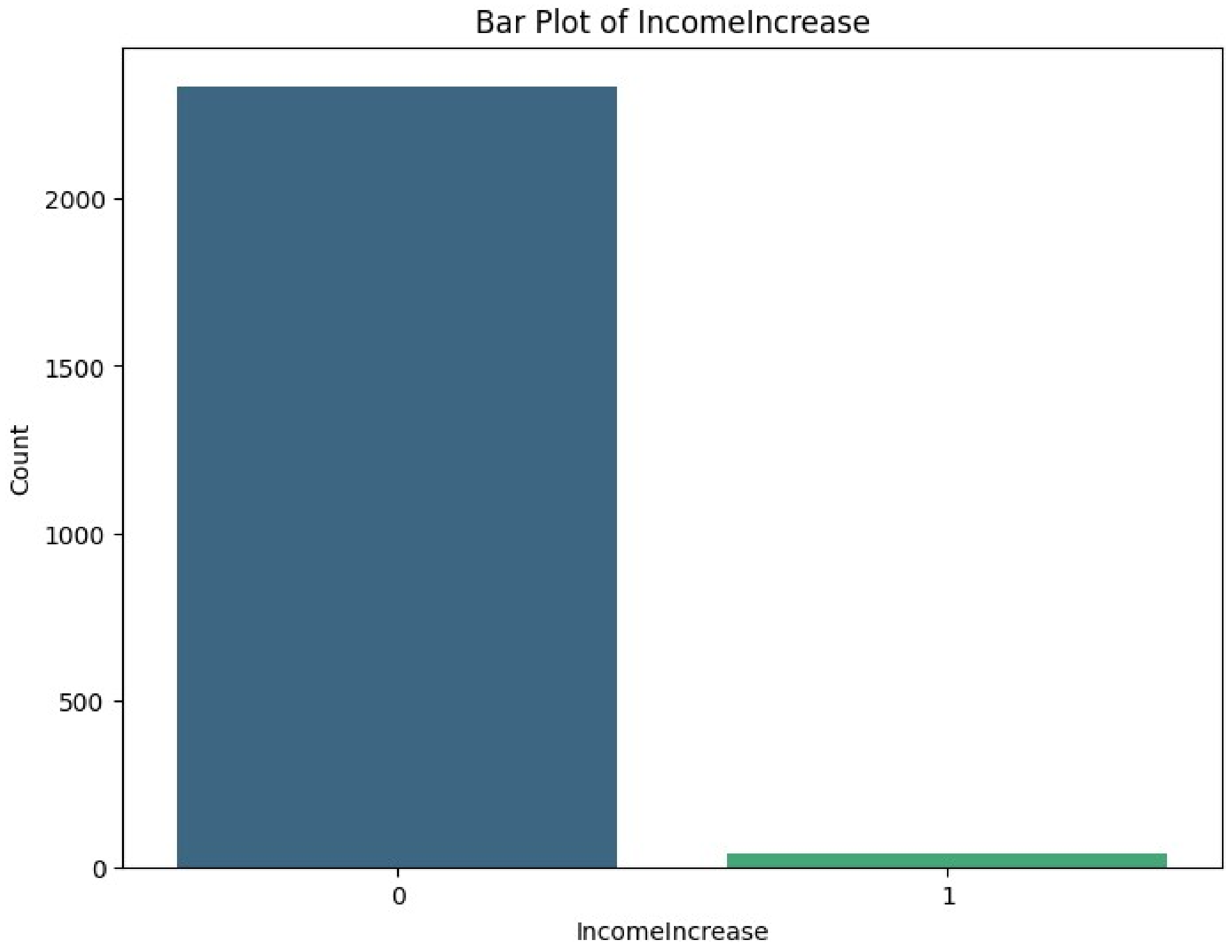

Bar Plot of Joining Designation
Count
0
200
400
600
800
1000
1.0
2.0
3.0
4.0
5.0
Joining Designation

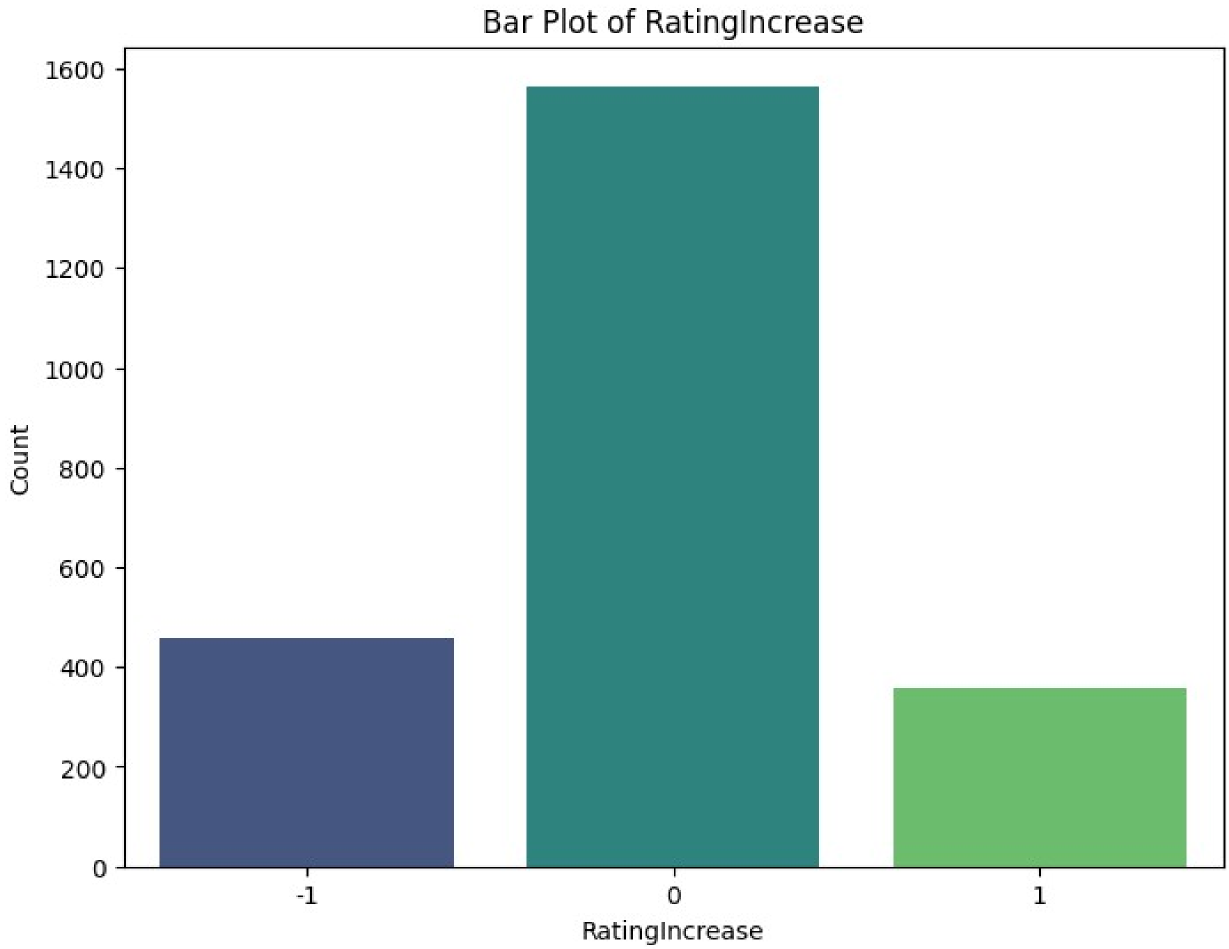

Bar Plot of Grade
Count
Grade
0
100
200
300
400
500
600
700
800
1.0
2.0
3.0
4.0
5.0



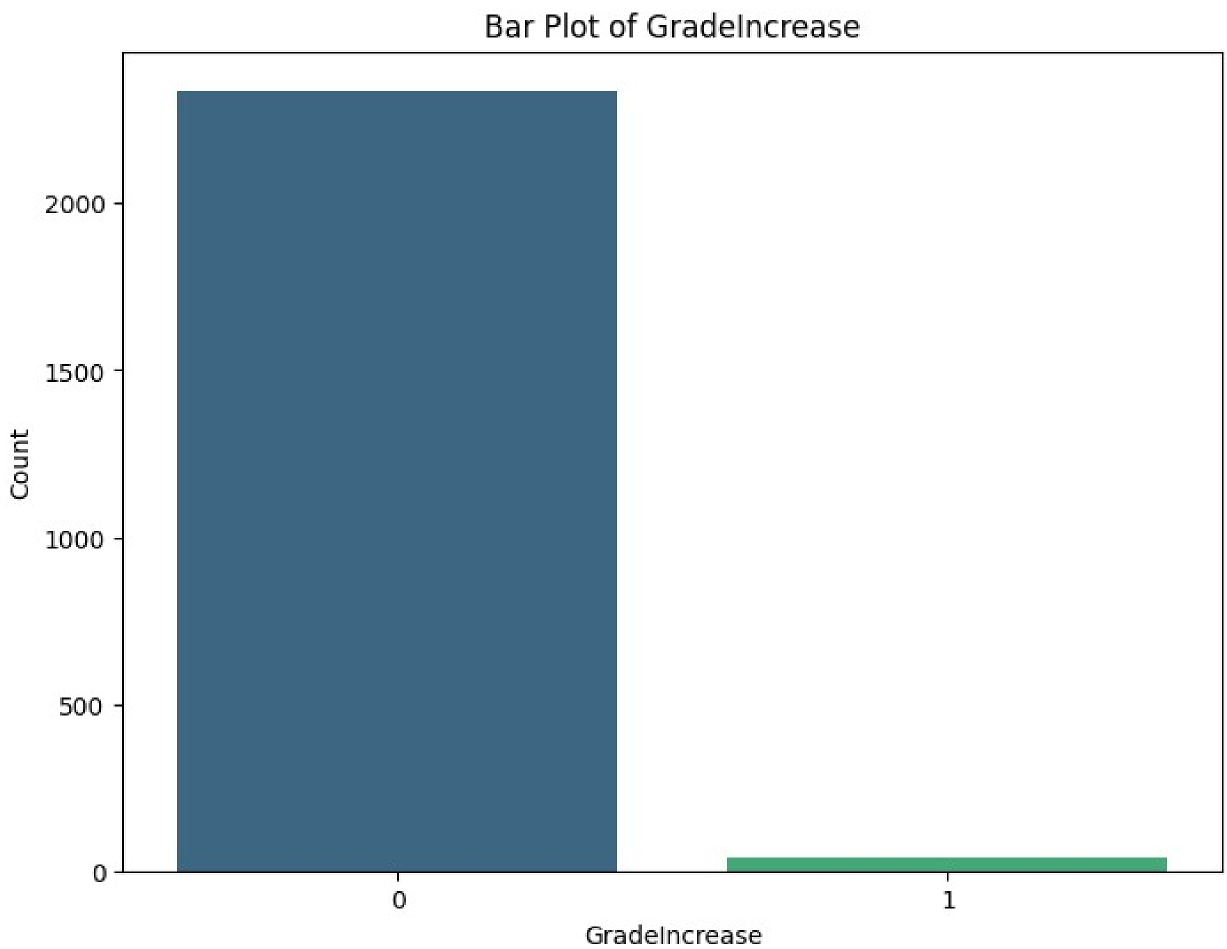
Bar Plot of Quarterly Rating
1750
1500
1250
1000
750
500
250
0
Count
1.0
2.0
3.0
4.0
Quarterly Rating

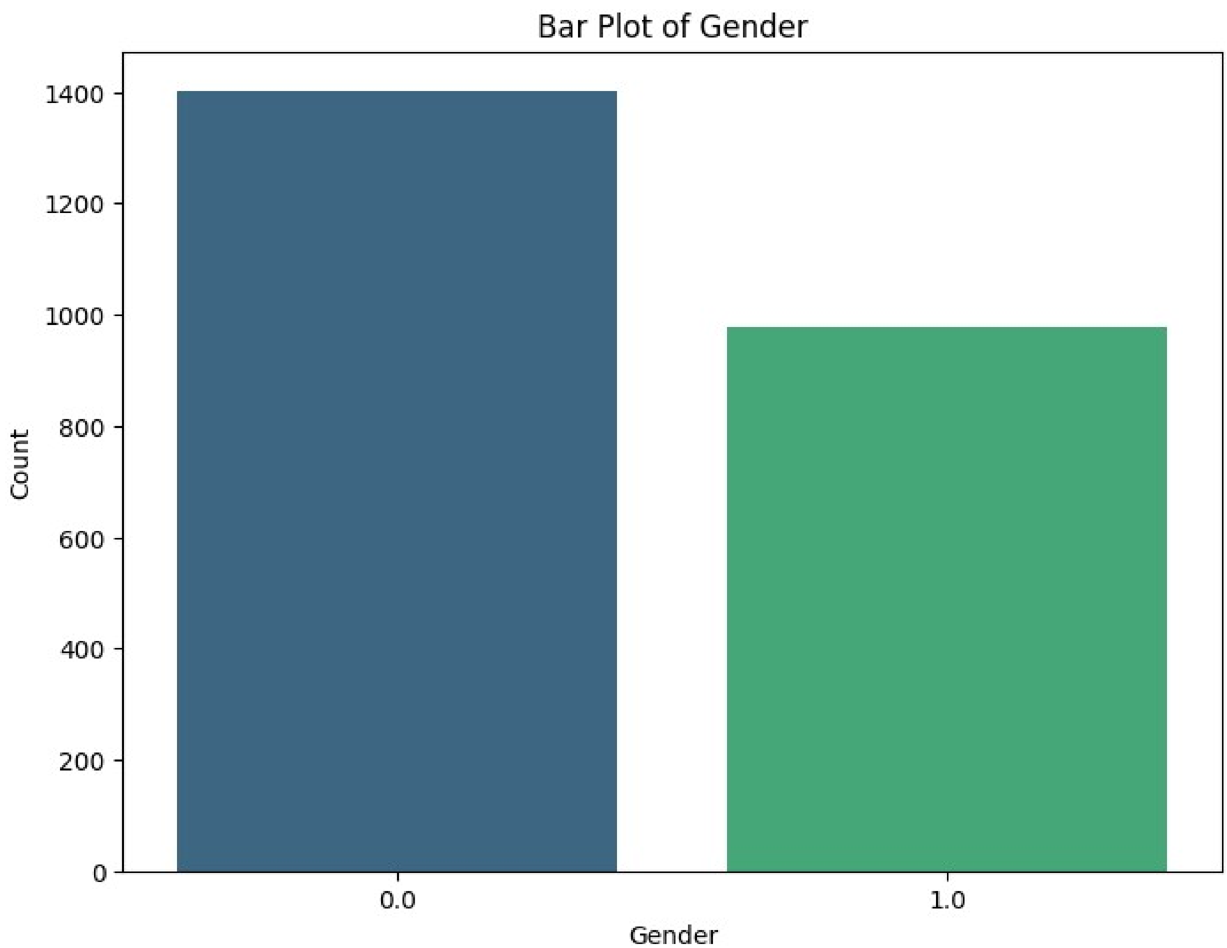

Bar Plot of JoiningMonth
Count
JoiningMonth
0
50
100
150
200
250
300
1
2
3
4
5
6
7
8
9
10
11
12


Bar Plot of IncomeIncrease
Count
2000
1500
1000
500
0
0
1
IncomeIncrease

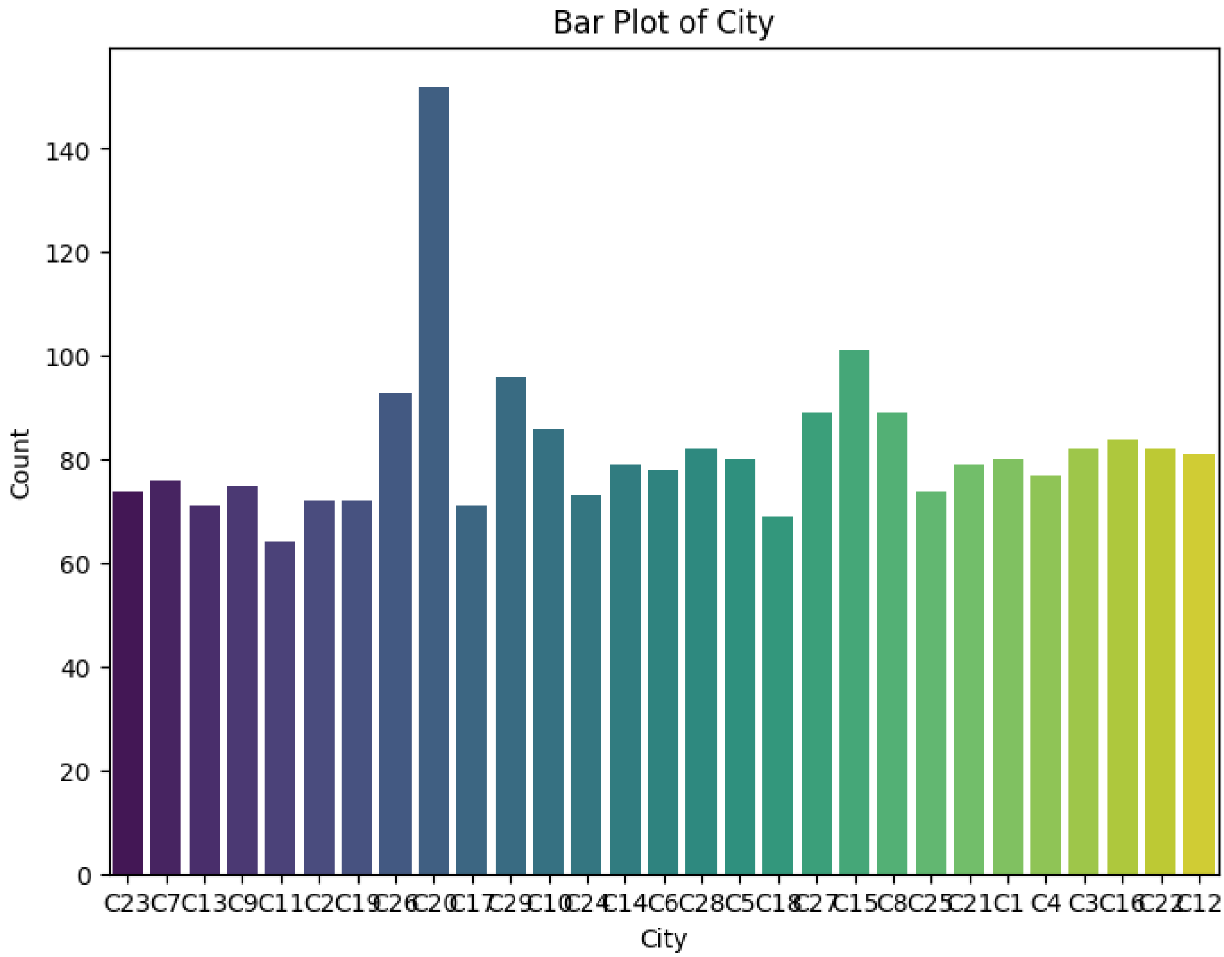


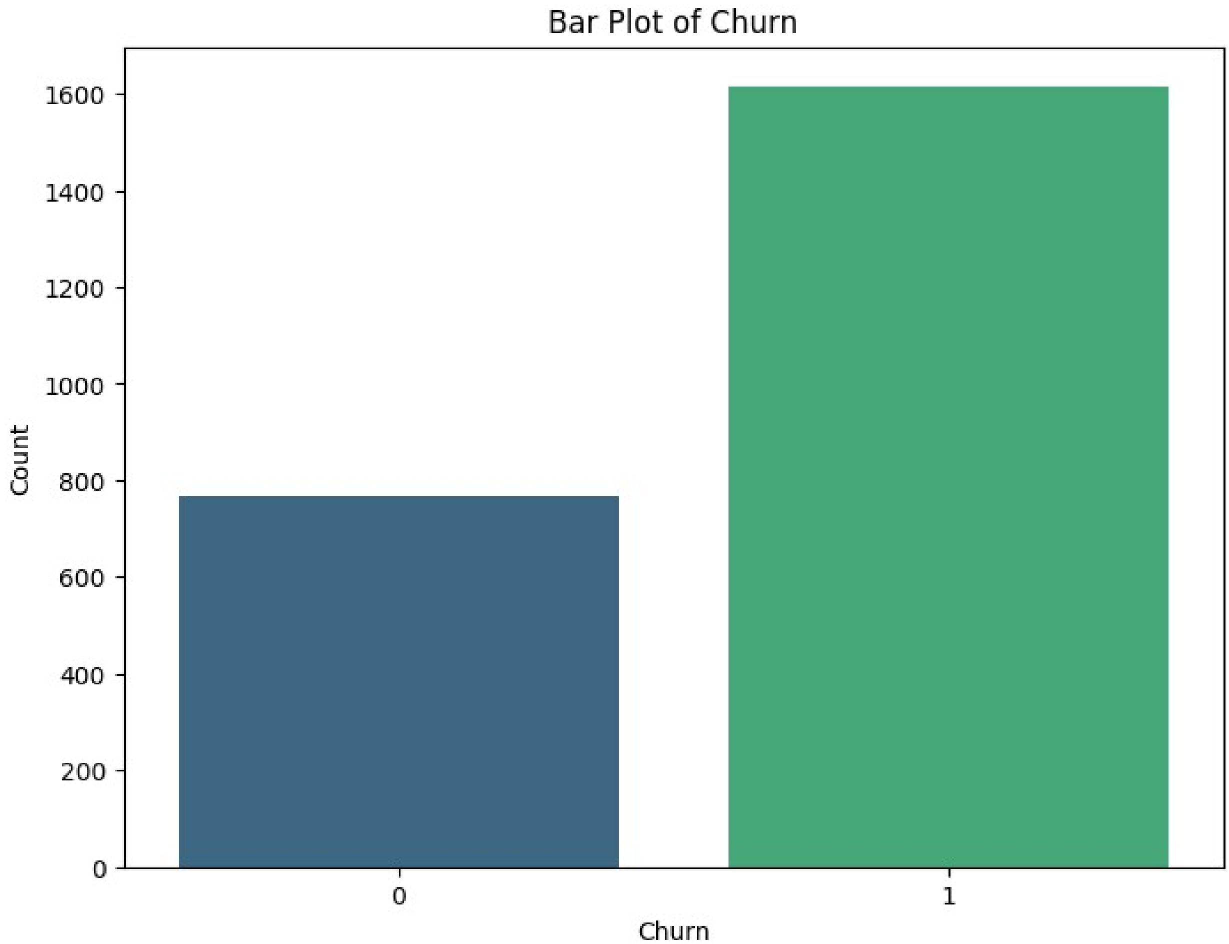
Bar Plot of RatingIncrease
1600
1400
1200
1000
800
600
400
200
0
Count
-1
0
1
RatingIncrease


Bar Plot of GradeIncrease
2000
1500
1000
500
0
Count
0
1
GradeIncrease



Bar Plot of Gender
Count
0
200
400
600
800
1000
1200
1400
0.0
1.0
Gender


Bar Plot of City
Count
0
20
40
60
80
100
120
140
C23 C7 C13 C9 C11 C2 C19 C26 C20 C17 C29 C10 C24 C14 C6 C28 C5 C18 C27 C15 C8 C25 C21 C1 C4 C3 C16 C22 C12
City



Insights 1)Number of Drivers for all education levels are almost equal.

2)Most drivers have joining designation of 1 and least has that of 5.

3)Most drivers has grade 2 and least has grade 5.

4)Most drivers have Quarterly Rating 1 & least has quarterly rating 4.

5)There is a significant increase in drivers joining after April(4rthMonth) compared to January to April period. Most drivers joining month is July and least is March month.

6)Only 1.80% Drivers income has increased. Income of Rest all the drivers remained same.

7) 19.2% of drivers had decrease in Rating & 15% drivers had increase in their rating. For rest of the drivers,rating remained same.

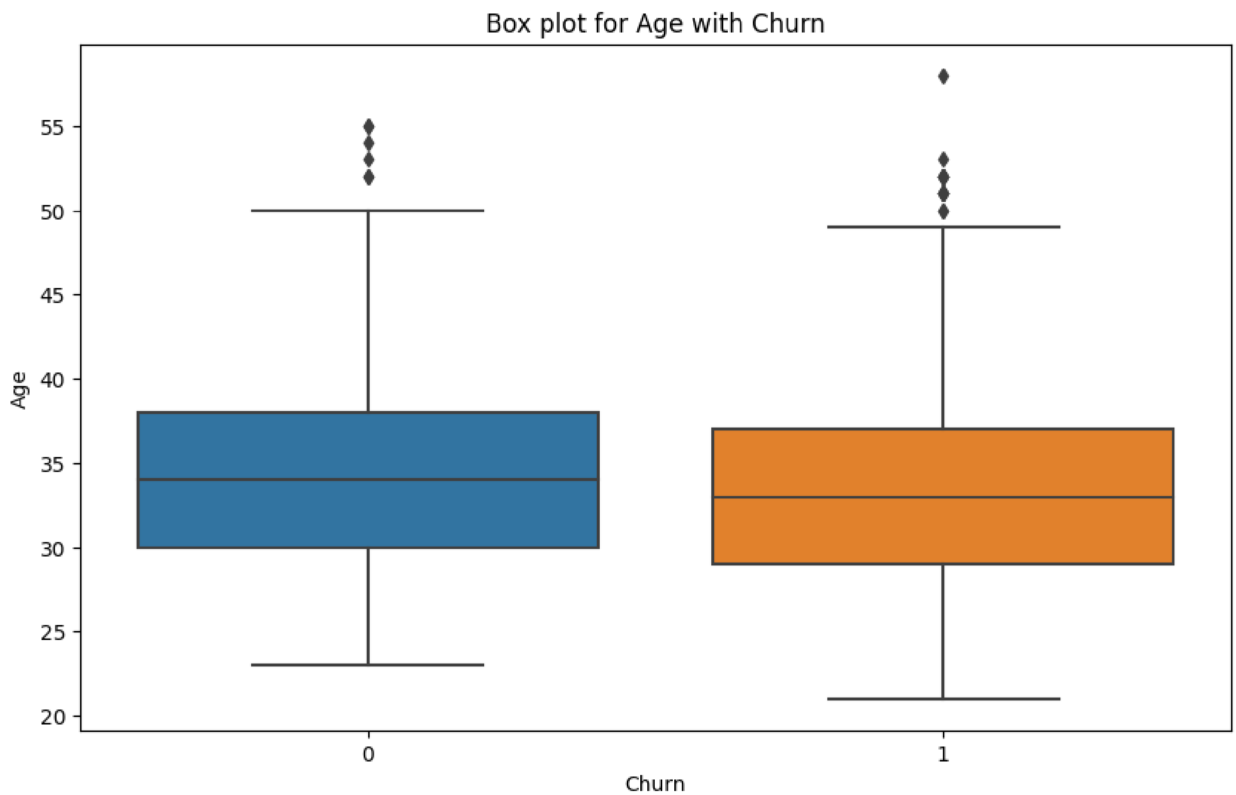
8)1.8% drivers had their grade increase. For the rest, it reamained the same.

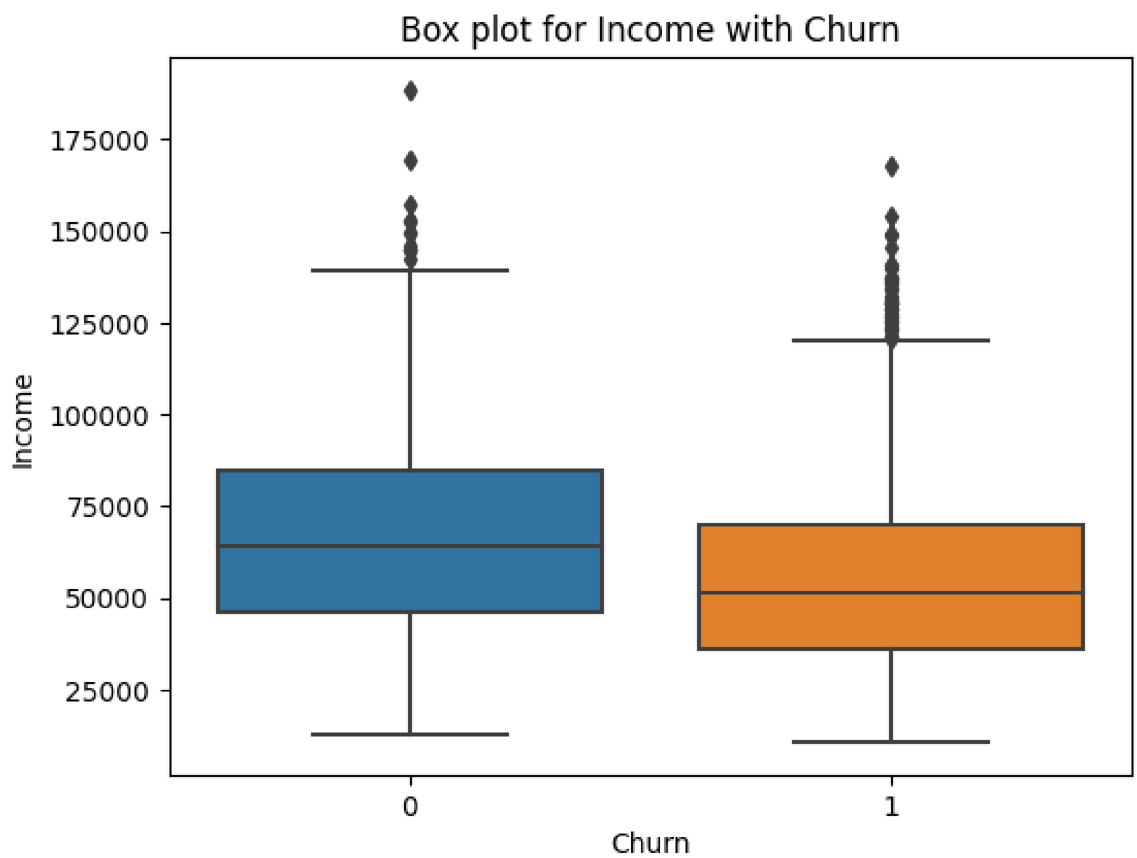
9)C20 had the highest number of occurunces in data and C11 was the least occuring city in the data.

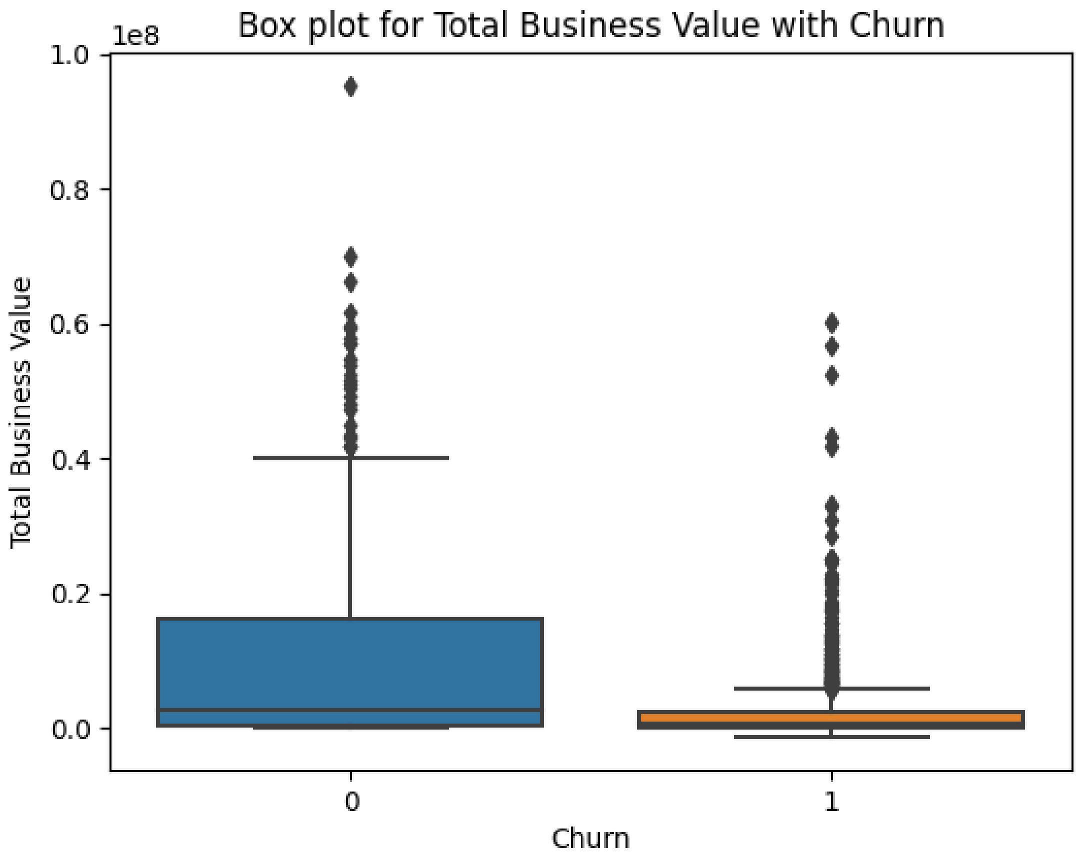
10)32.1% of drivers in our dataset has remained & rest all have churned.

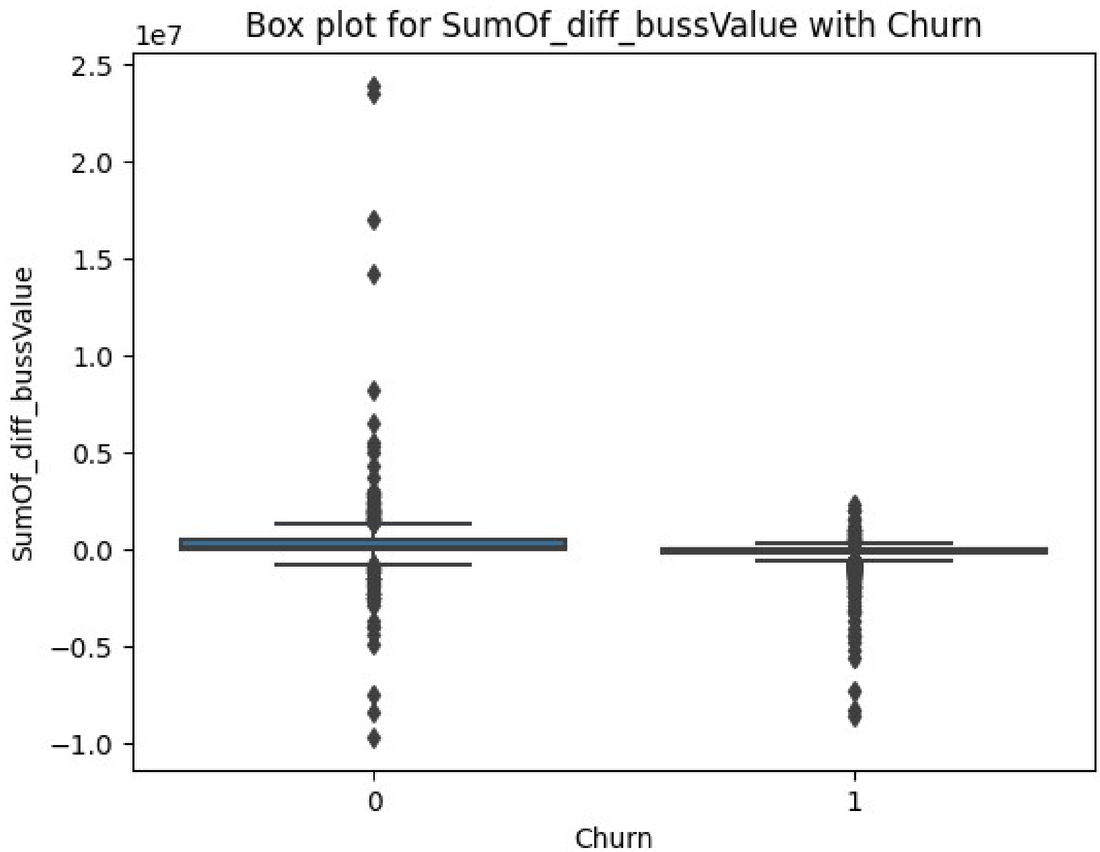
EDA: Bivariate analysis

```
plt.figure(figsize=(10, 6))
for col in num_cols:  # Exclude the target column
    sns.boxplot(x='Churn', y=col, data=df2_agg)
    plt.title(f'Box plot for {col} with Churn')
    plt.show()
```



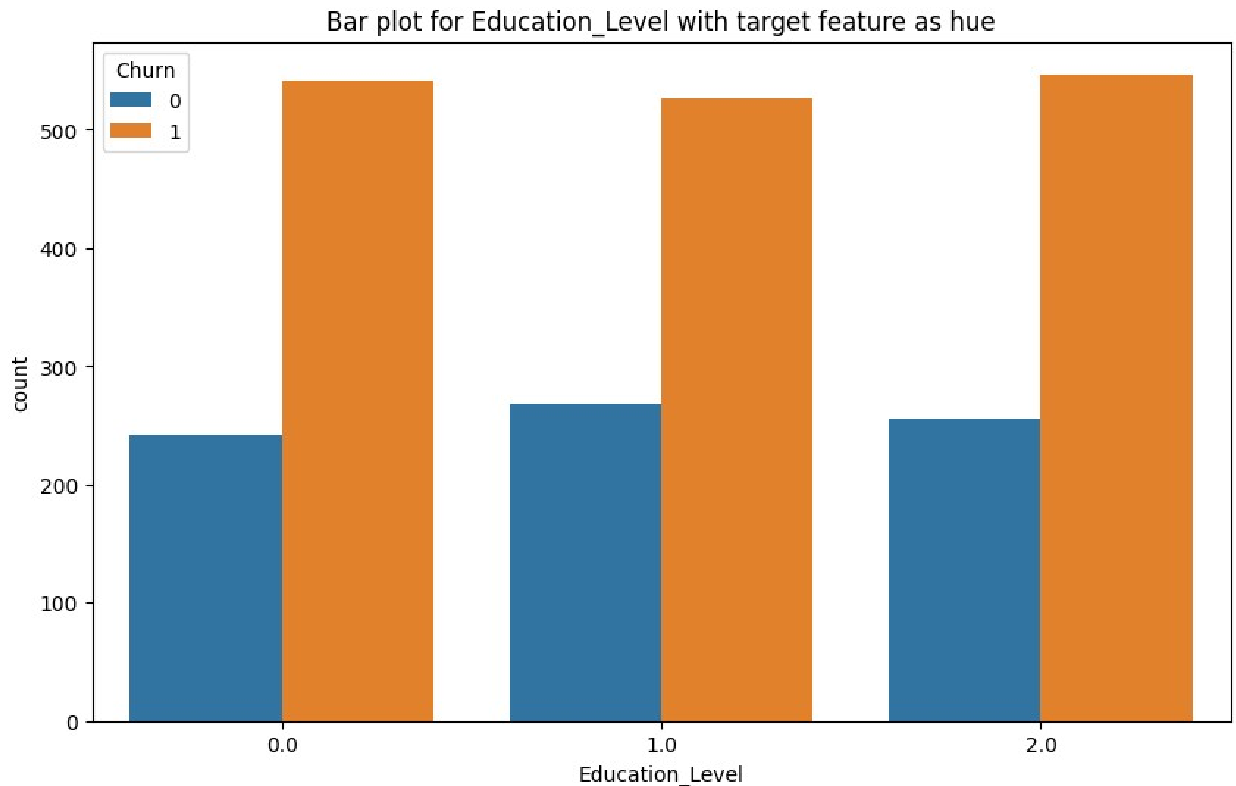

Box plot for Income with Churn
175000
150000
125000
100000
75000
50000
25000
Income
0
1
Churn

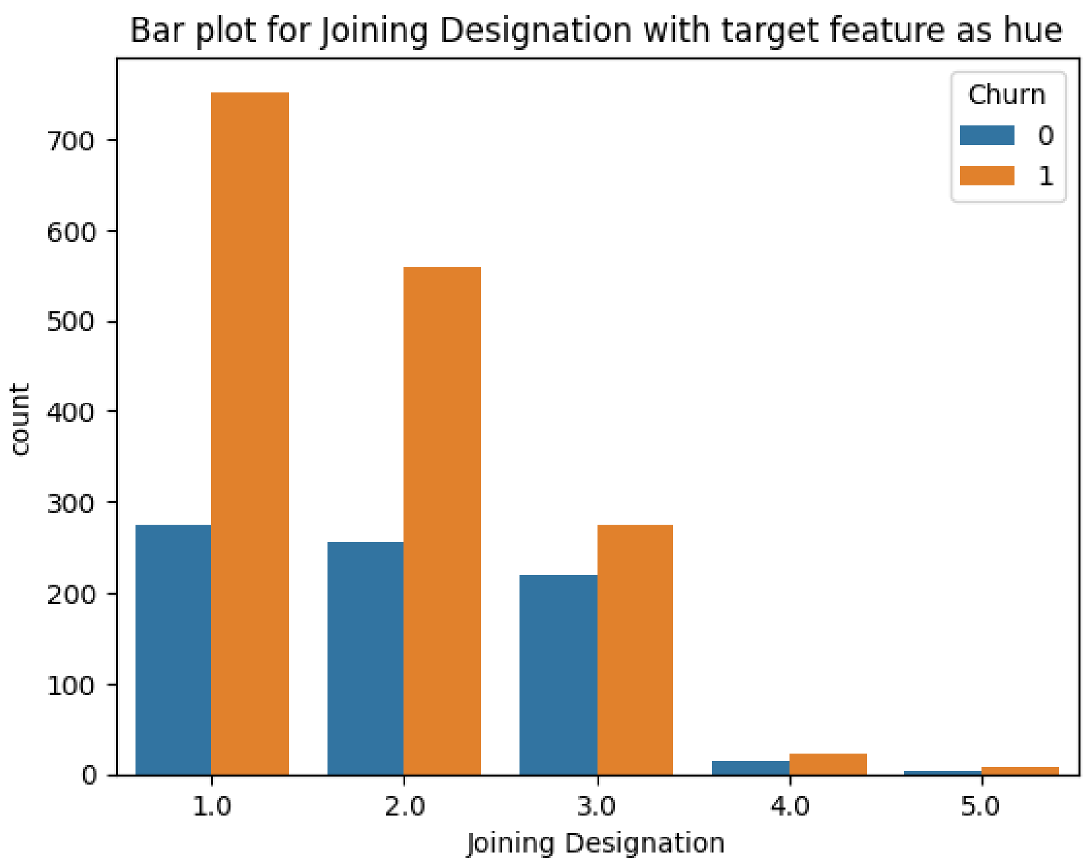

Box plot for Total Business Value with Churn
1e8
1.0
0.8
0.6
0.4
0.2
0.0
Total Business Value
0
1
Churn



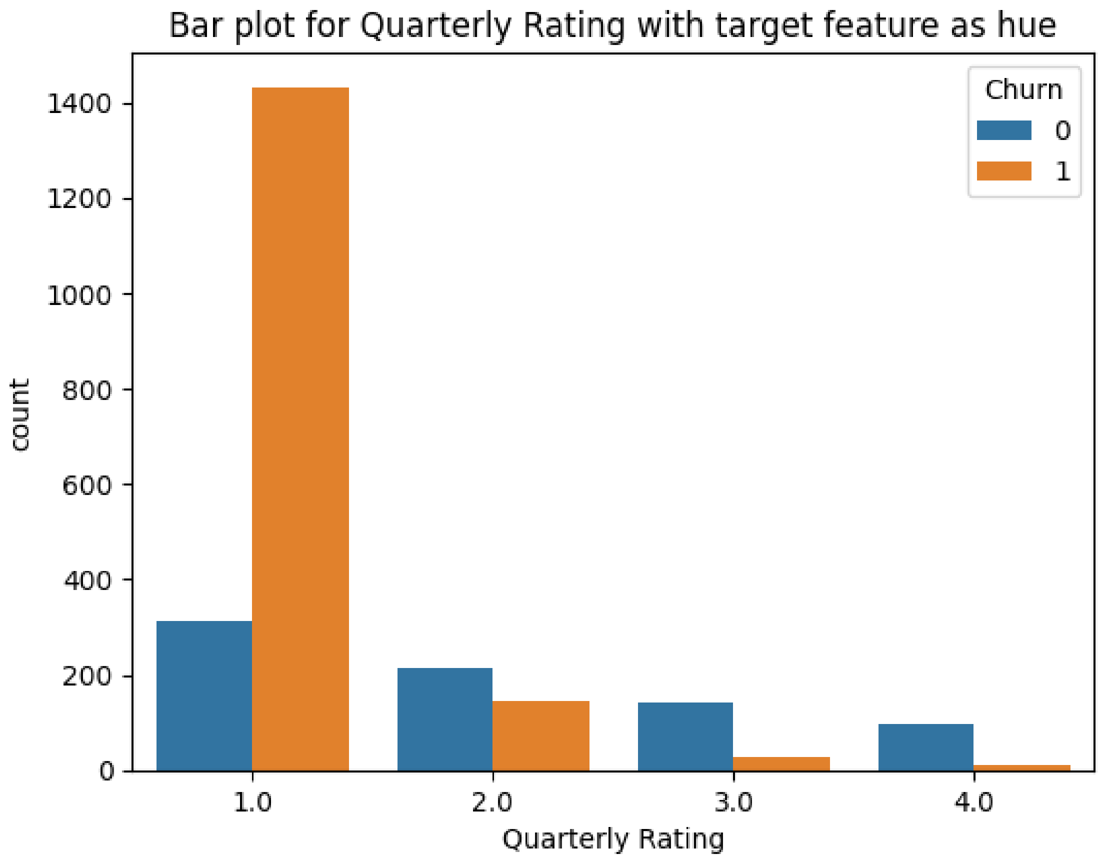
Insight For all the four features:- Age,Income,Total Bussiness Value and SumOfdiffbussValue, the Median and full boxplot of drivers who have not churned seems higher as compared to that of drivers who have churned.

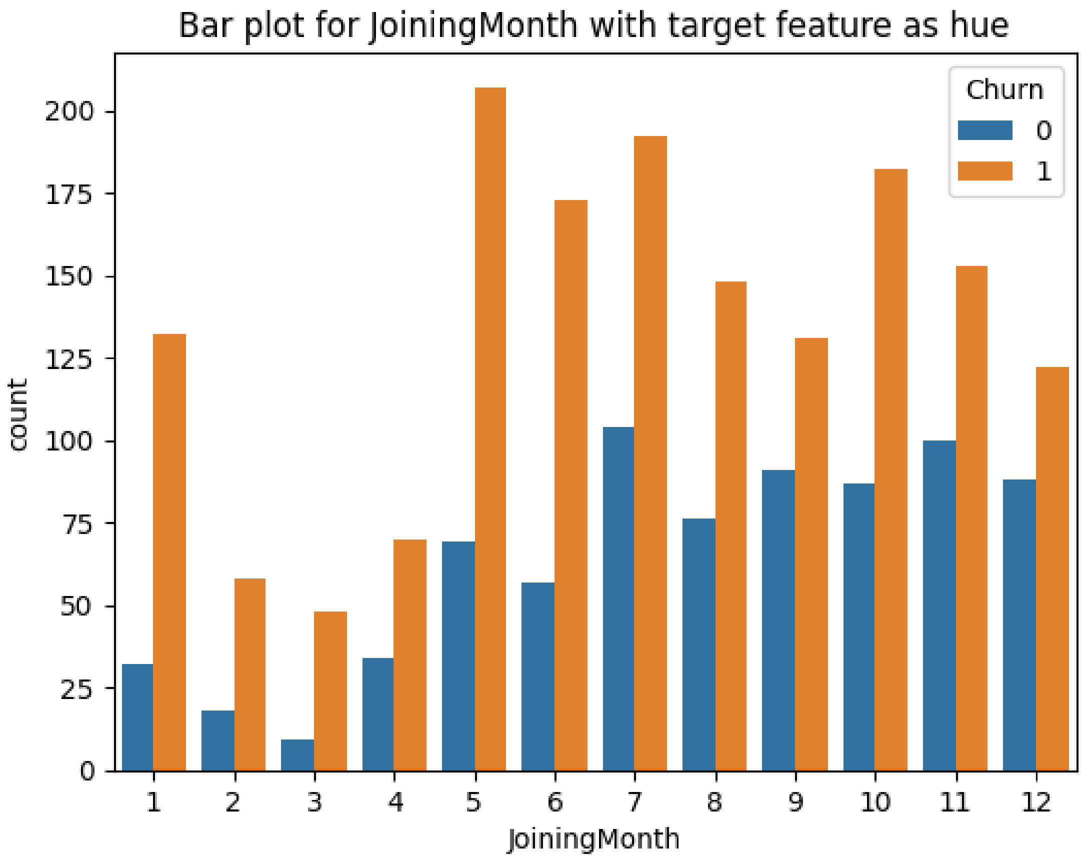
```
# Create bar plot
plt.figure(figsize=(10, 6))
for col in cat_cols:  # Exclude the target column
    sns.countplot(x=col, hue='Churn', data=df2_agg)
    plt.title(f'Bar plot for {col} with target feature as hue')
    plt.show()
```

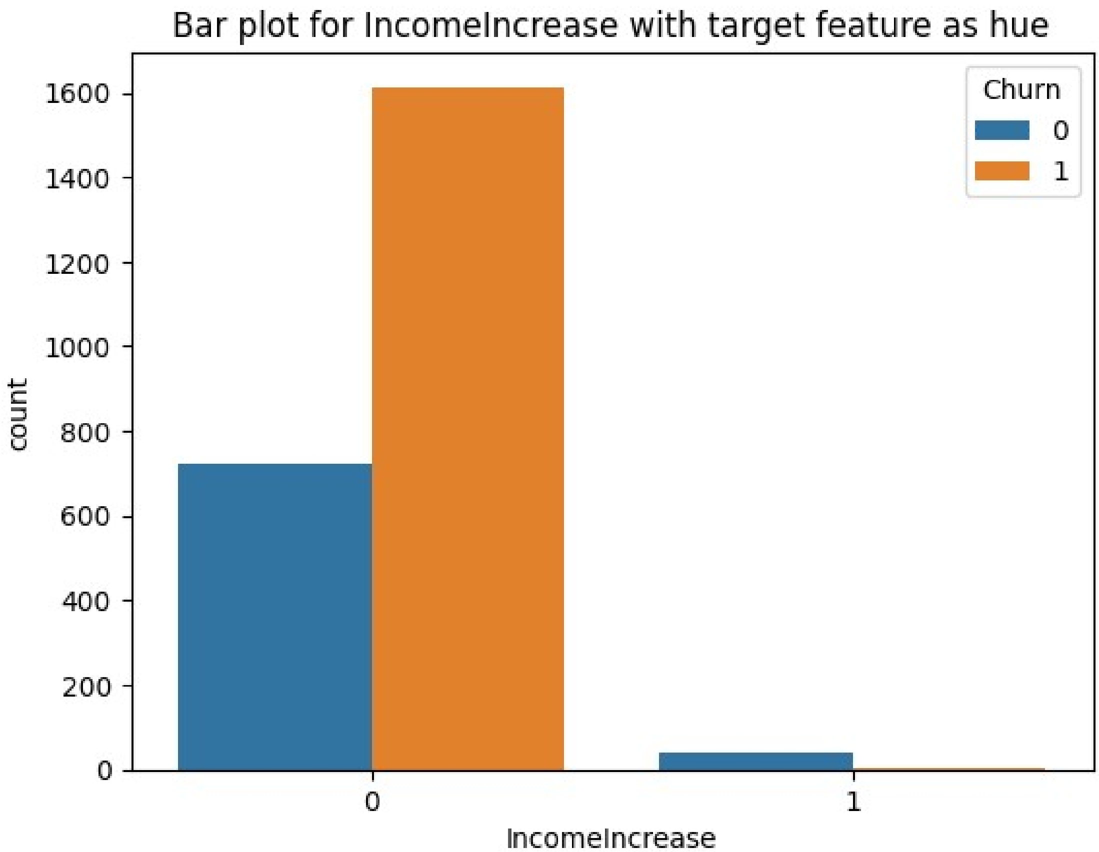

Bar plot for Education_Level with target feature as hue
Churn
0
1
count
0
100
200
300
400
500
0.0
1.0
2.0
Education_Level

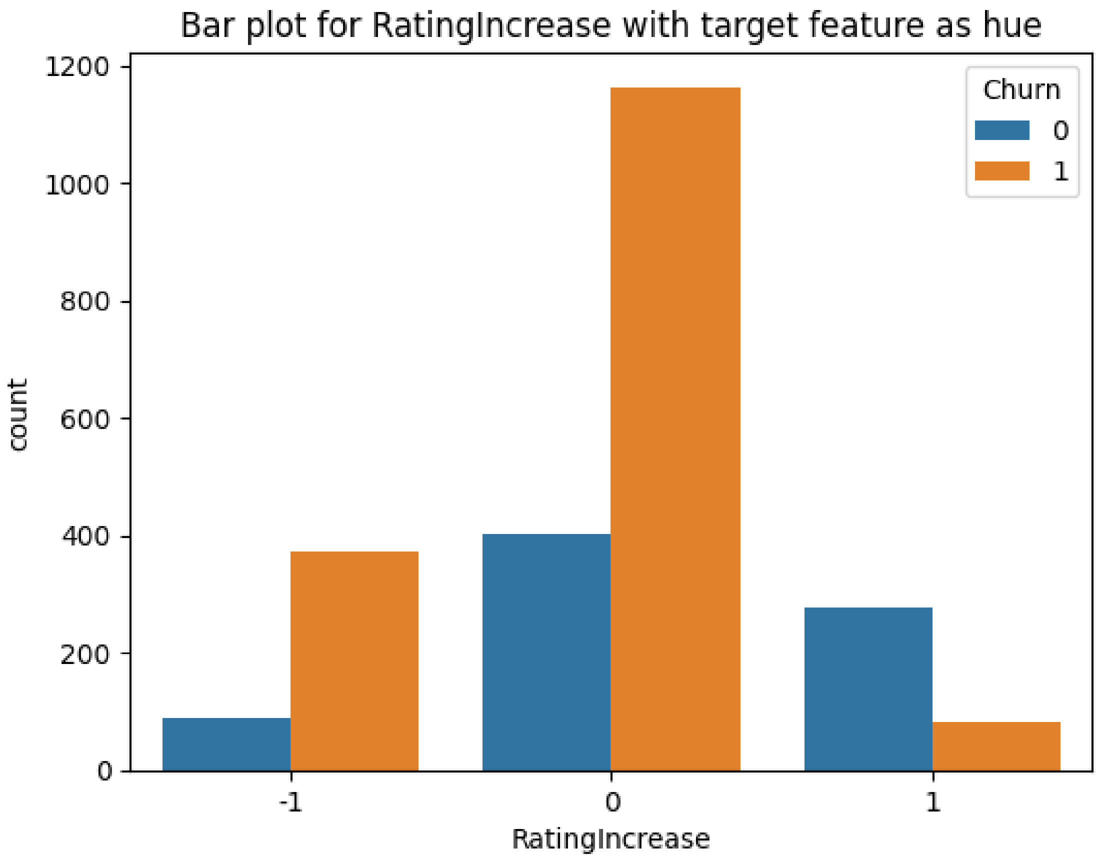

Bar plot for Joining Designation with target feature as hue
Churn
0
1
count
0
100
200
300
400
500
600
700
1.0
2.0
3.0
4.0
5.0
Joining Designation

Bar plot for Grade with target feature as hue
Churn
0
1
count
600
500
400
300
200
100
0
1.0
2.0
3.0
4.0
5.0
Grade

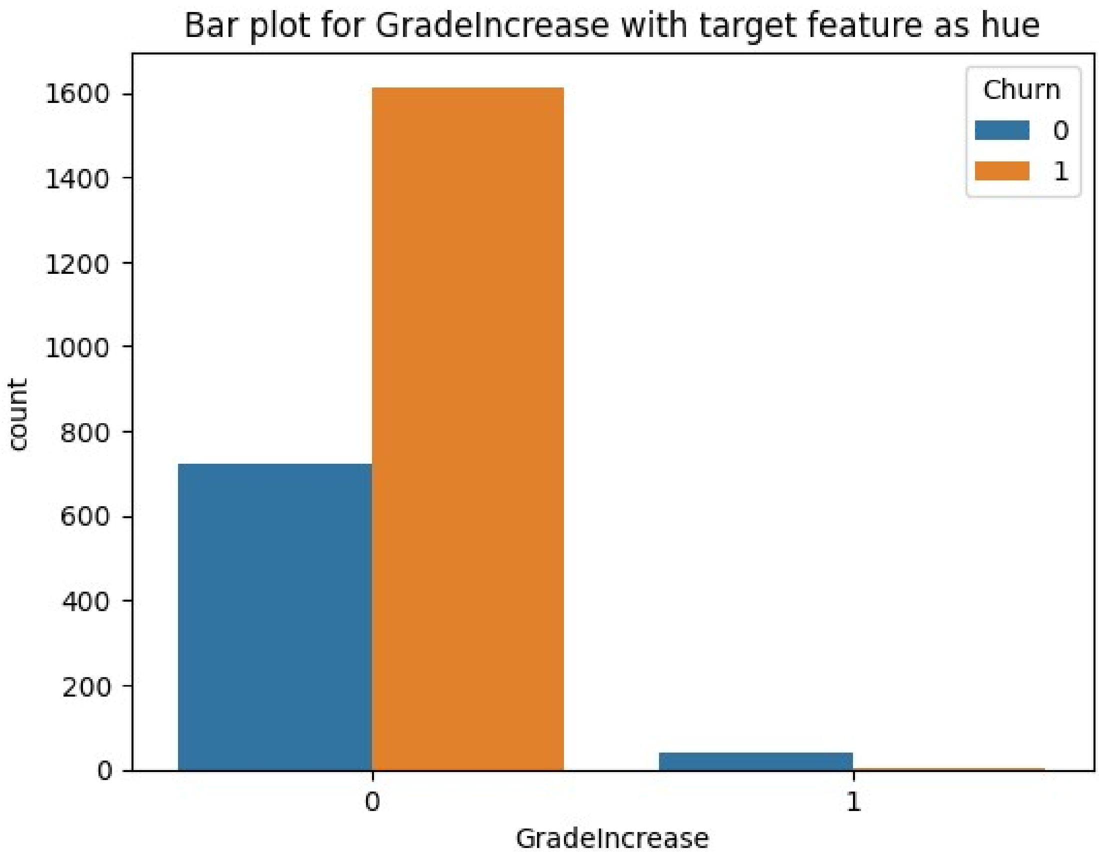

Bar plot for Quarterly Rating with target feature as hue
Churn
0
1
count
1400
1200
1000
800
600
400
200
0
1.0
2.0
3.0
4.0
Quarterly Rating

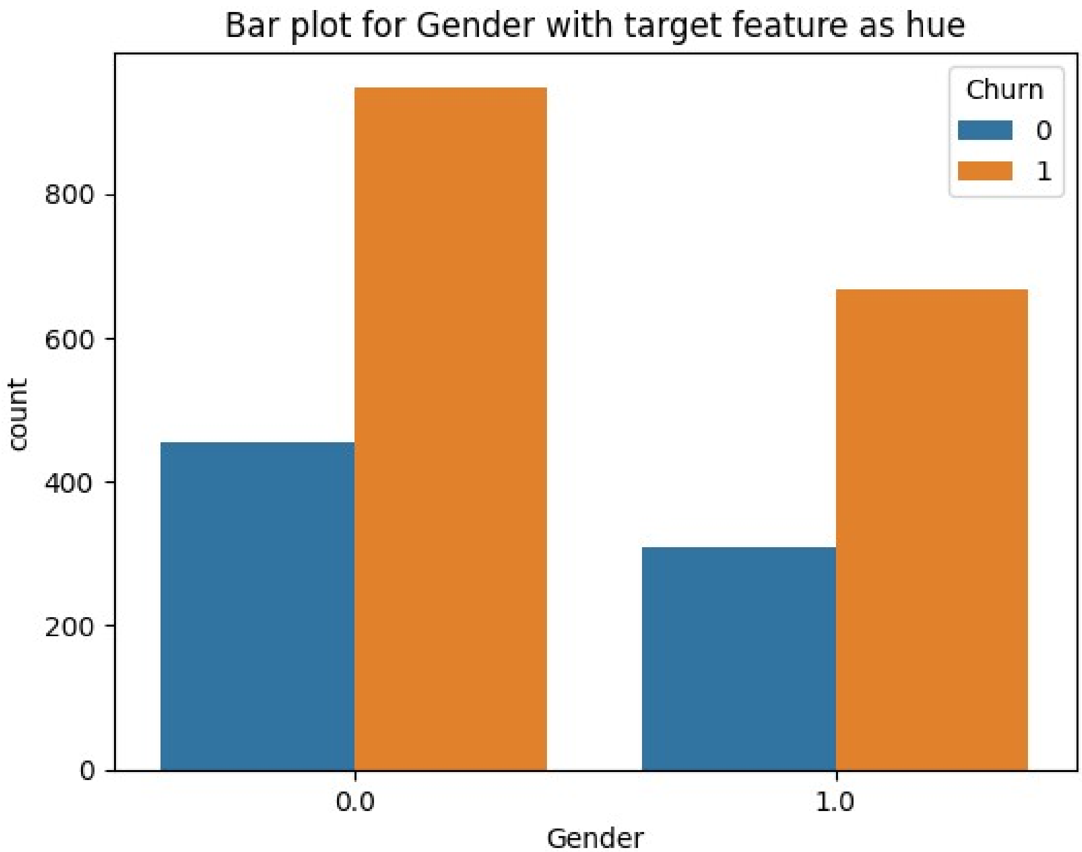

Bar plot for JoiningMonth with target feature as hue
Churn
0
1
count
0
25
50
75
100
125
150
175
200
1
2
3
4
5
6
7
8
9
10
11
12
JoiningMonth

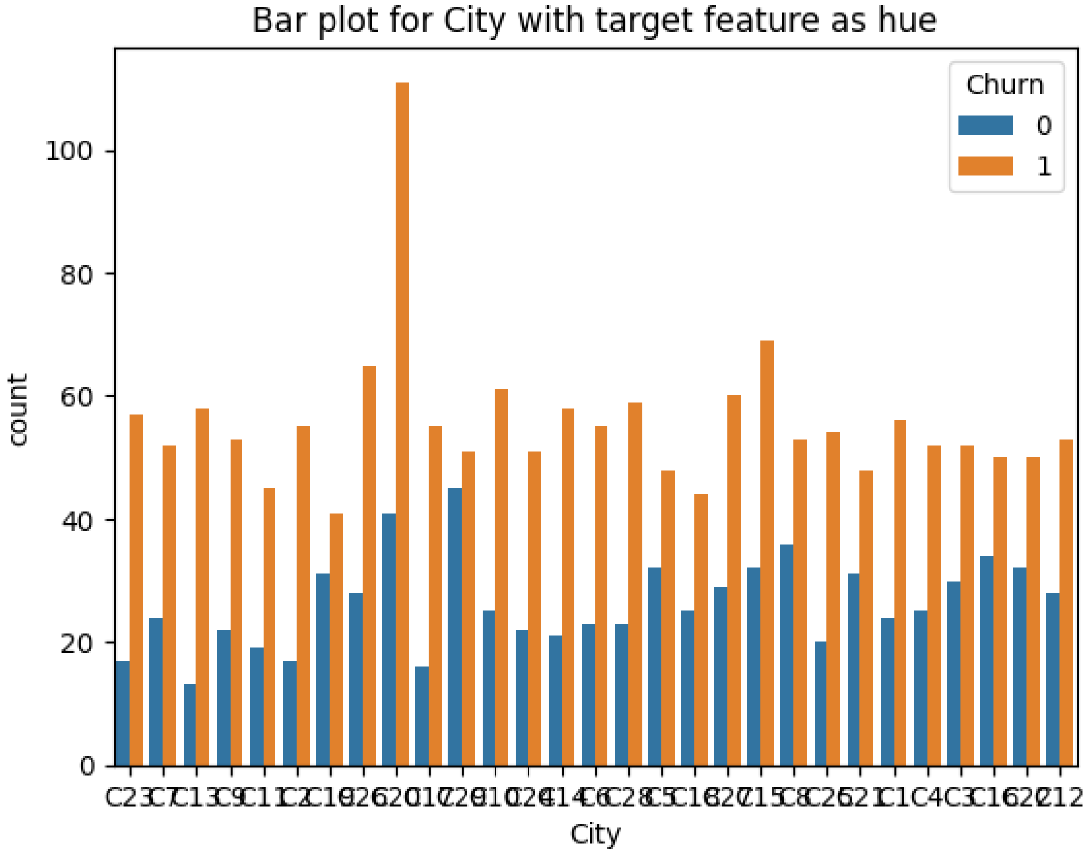

Bar plot for IncomeIncrease with target feature as hue
Churn
0
1
1600
1400
1200
1000
800
600
400
200
0
count
0
1
IncomeIncrease



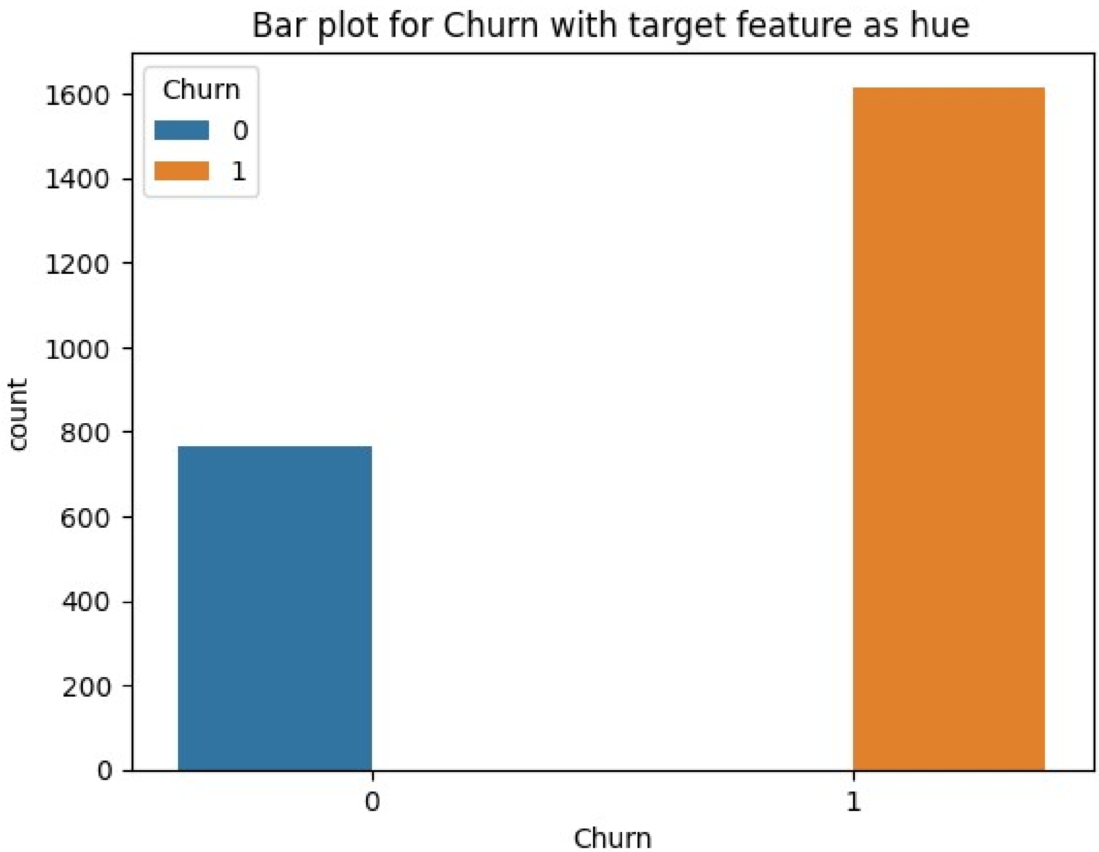
Bar plot for RatingIncrease with target feature as hue
Churn
0
1
count
0
200
400
600
800
1000
1200
-1
0
1
RatingIncrease


Bar plot for GradeIncrease with target feature as hue
Churn
0
1
count
1600
1400
1200
1000
800
600
400
200
0
0
1
GradeIncrease


Bar plot for Gender with target feature as hue
Churn
0
1
count
800
600
400
200
0
0.0
1.0
Gender



Bar plot for City with target feature as hue
Churn
0
1
count
City
0
20
40
60
80
100



Insight 1)For each joining designation, probability of churn is higher than not churn.

2)For Grade 1,2&3:- Probability of churning is higher as compared to not churning. But for Grade 4 & 5:- Probability of churn vs. not churn is almost equal.

3)If Quarterly Rating is 1, then probability of that Driver Churning is much higher than not churning. If Quarterly Rating is above 1 then Probability of Driver Not churning is higher then that of Churning.

4)If there is IncomeIncrease, then Probability of that driver to Not Churn is High.

5)IF there is RatingIncrease, then Probability of that driver to Not Churn is High. If there is decrease or remain same in Rating then driver is more likely to churn.

6)If there is GradeIncrease, then Probability of that driver to Not Churn is High.

Hypothesis Testing

```
#Now lets do hypothesis testing to see if our numerical columns affect
Churn feature
#We use ttest
from scipy.stats import ttest_ind
```

```
# Perform t-test for each numerical column
for col in num_cols:
    churn_yes = df2_agg[df2_agg['Churn'] == 1][col]
    churn_no = df2_agg[df2_agg['Churn'] == 0][col]

    t_statistic, p_value = ttest_ind(churn_yes, churn_no,
equal_var=False)
    print(f'P-value for {col}: {p_value}\n')
```

```
P-value for Age: 7.254685558389959e-05

P-value for Income: 1.1478152190994176e-21

P-value for Total Business Value: 1.2332082834621812e-45

P-value for SumOf_diff_bussValue: 4.8938992794330825e-14
```

```
from scipy.stats import mannwhitneyu
# Perform Mann-Whitney U test for each numerical column
for col in num_cols:
    churn_yes = df2_agg[df2_agg['Churn'] == 1][col]
    churn_no = df2_agg[df2_agg['Churn'] == 0][col]

    stat, p_value = mannwhitneyu(churn_yes, churn_no,
alternative='two-sided')
    print(f'P-value for {col}: {p_value}\n')
```

```
P-value for Age: 2.988960660315412e-05

P-value for Income: 2.141977374254948e-23

P-value for Total Business Value: 2.625202102681489e-46

P-value for SumOf_diff_bussValue: 3.1575856578673117e-91
```

```
#NOw lets do hypothesis testing to find if our categorical features
has any impact on target feature "Churn"
from scipy.stats import chi2_contingency

# Perform Chi-Square test for each categorical column
for col in cat_cols:
    contingency_table = pd.crosstab(df2_agg[col], df2_agg['Churn'])

    chi2, p, dof, expected = chi2_contingency(contingency_table)
    print(f'P-value for {col}: {p}\n')
```

```
P-value for Education_Level: 0.46643939521309963

P-value for Joining Designation: 5.457615375535053e-10
```

```
P-value for Grade: 2.8955519930847994e-27

P-value for Quarterly Rating: 2.5289656594512383e-142

P-value for JoiningMonth: 1.6242862540266907e-08

P-value for IncomeIncrease: 2.5729990685015372e-17

P-value for RatingIncrease: 3.8437443138819906e-87

P-value for GradeIncrease: 2.5729990685015372e-17

P-value for Gender: 0.7396634124788158

P-value for City: 0.013977549937173567

P-value for Churn: 0.0
```

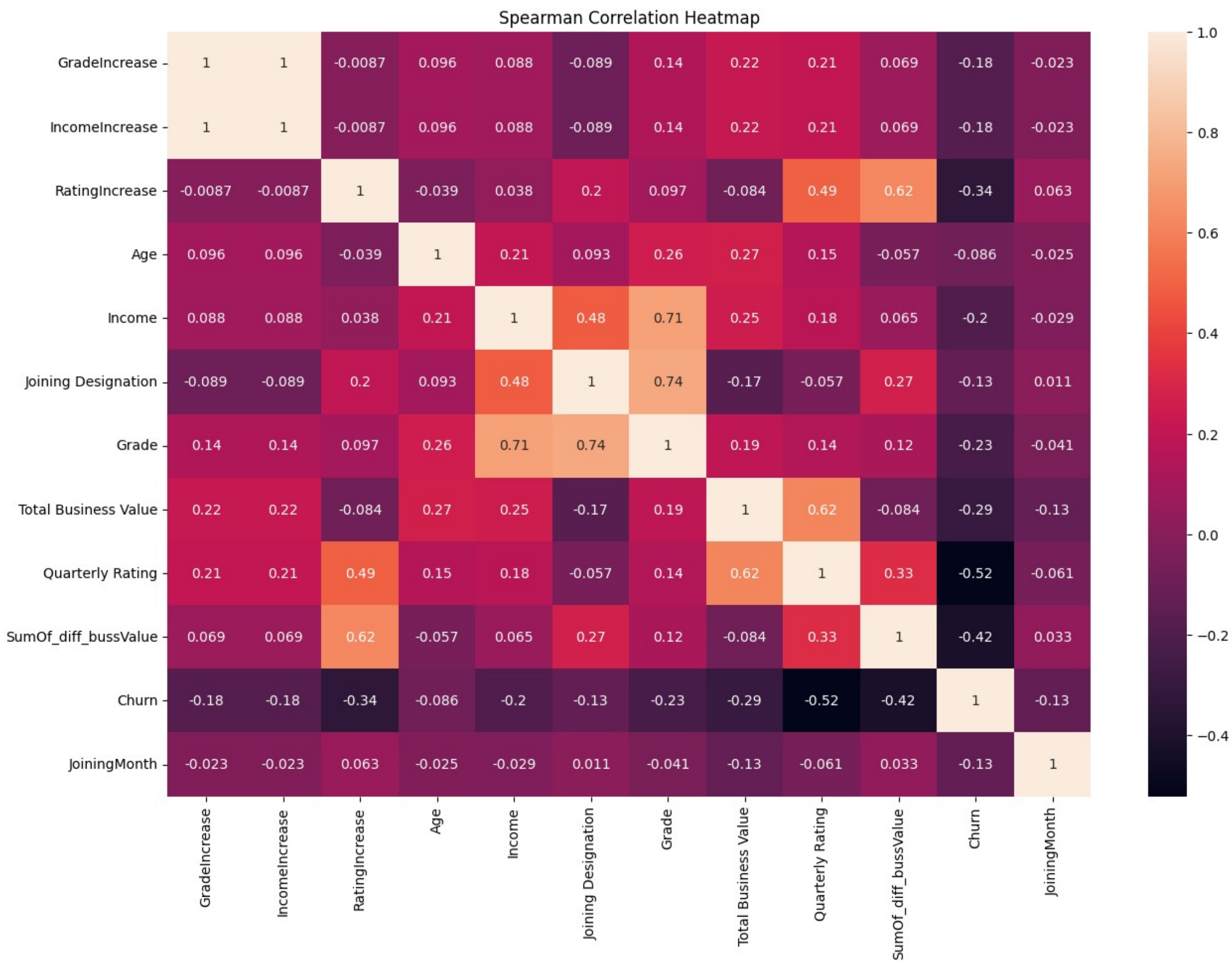
Insights Education Level & Gender has no effect on our target variable Churn.

```
#Education Level and Gender has no effect on Churn feature
#So lets drop them
df2_agg.drop(["Education_Level","Gender"],inplace=True,axis=1)
```

Spearman Correlation Heatmap

```
#Now lets find correlation heatmap
#We will use spearman correlation because our df has outliers and also
Ordinal variables
plt.figure(figsize=(15, 10))
corr_matrix = df2_agg.corr(method='spearman')
sns.heatmap(corr_matrix,annot=True)
plt.title('Spearman Correlation Heatmap')
plt.show()
```

```
<ipython-input-63-31447f95879b>:4: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  corr_matrix = df2_agg.corr(method='spearman')
```




```
#Because GradeIncrease and IncomeIncrease are correlated, we will
remove gradeIncrease column
df2_agg.drop(["GradeIncrease"],axis=1,inplace=True)

df2_agg

      IncomeIncrease  RatingIncrease   Age City   Income  Joining
Designation  \
0                  0               0  28.0  C23  57387.0
1.0
1                  0               0  31.0   C7  67016.0
2.0
2                  0               0  43.0  C13  65603.0
2.0
3                  0               0  29.0   C9  46368.0
1.0
4                  0               1  31.0  C11  78728.0
3.0
...              ...             ...   ...  ...      ...
...
2376               0               1  34.0  C24  82815.0
```

```
2.0
2377                0                0  34.0   C9  12105.0
1.0
2378                0               -1  45.0  C19  35370.0
2.0
2379                0               -1  28.0  C20  69498.0
1.0
2380                0                1  30.0  C27  70254.0
2.0

      Grade  Total Business Value  Quarterly Rating
SumOf_diff_bussValue  \
0       1.0             1715580.0               2.0             -
2381060.0
1       2.0                   0.0               1.0
0.0
2       2.0              350000.0               1.0
0.0
3       1.0              120360.0               1.0
0.0
4       3.0             1265000.0               2.0
0.0
...     ...                   ...               ...
...
2376    3.0            21748820.0               4.0              -
721110.0
2377    1.0                   0.0               1.0
0.0
2378    2.0             2815090.0               1.0              -
221080.0
2379    1.0              977830.0               1.0              -
408090.0
2380    2.0             2298240.0               2.0
411480.0

      Churn  JoiningMonth
0         1            12
1         0            11
2         1            12
3         1             1
4         0             7
...     ...           ...
2376      0            10
2377      1             8
2378      1             7
2379      1             7
2380      0             6

[2381 rows x 12 columns]
```

```
df2_agg["Churn"].value_counts()
```

```
1    1616
0     765
Name: Churn, dtype: int64
```

```
df2_agg.columns
```

```
Index(['IncomeIncrease', 'RatingIncrease', 'Age', 'City', 'Income',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating', 'SumOf_diff_bussValue', 'Churn',
'JoiningMonth'],
      dtype='object')
```

```
!pip install git+https://github.com/scikit-optimize/scikit-
optimize.git
```

```
Collecting git+https://github.com/scikit-optimize/scikit-optimize.git
  Cloning https://github.com/scikit-optimize/scikit-optimize.git to
/tmp/pip-req-build-i7x8uxyd
  Running command git clone --filter=blob:none --quiet
https://github.com/scikit-optimize/scikit-optimize.git /tmp/pip-req-
build-i7x8uxyd
  Resolved https://github.com/scikit-optimize/scikit-optimize.git to
commit a2369ddbc332d16d8ff173b12404b03fea472492
  Installing build dependencies ... ents to build wheel ... etadata
(pyproject.toml) ... ent already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize==0.9.0)
(1.3.2)
Collecting pyaml>=16.9 (from scikit-optimize==0.9.0)
  Using cached pyaml-23.12.0-py3-none-any.whl (23 kB)
Requirement already satisfied: numpy>=1.13.3 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize==0.9.0)
(1.23.5)
Requirement already satisfied: scipy>=0.19.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize==0.9.0)
(1.11.4)
Requirement already satisfied: scikit-learn>=0.20.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-optimize==0.9.0)
(1.2.2)
Requirement already satisfied: PyYAML in
/usr/local/lib/python3.10/dist-packages (from pyaml>=16.9->scikit-
optimize==0.9.0) (6.0.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0-
>scikit-optimize==0.9.0) (3.2.0)
Building wheels for collected packages: scikit-optimize
  Building wheel for scikit-optimize (pyproject.toml) ... ize:
filename=scikit_optimize-0.9.0-py2.py3-none-any.whl size=100246
sha256=83113f336d92cb1b764957fefc3dff6ed73e0b9c1a9ee815845be9c6def3e0f
```

```
a
  Stored in directory:
/tmp/pip-ephem-wheel-cache-ypn25w17/wheels/2f/f0/ed/db529a96372d05bd34
f6c3a2fa7c08ef7a8314315ac46e49d7
Successfully built scikit-optimize
Installing collected packages: pyaml, scikit-optimize
Successfully installed pyaml-23.12.0 scikit-optimize-0.9.0
```

Mean Encoding & Normalization & Train-Val-test split

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import precision_score, recall_score, f1_score,
roc_auc_score, roc_curve
from skopt import BayesSearchCV
import matplotlib.pyplot as plt
import seaborn as sns

features_to_normalize = ['RatingIncrease', 'Age', 'Income',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating', 'SumOf_diff_bussValue', 'JoiningMonth']

# Splitting the data into train, validation, and test sets
train_df, test_df = train_test_split(df2_agg, test_size=0.2,
random_state=42, stratify=df2_agg['Churn'])
train_df, val_df = train_test_split(train_df, test_size=0.2,
random_state=42, stratify=train_df['Churn'])

# Mean encoding on "City" column based on the target feature "Churn"
mean_encoded_city = train_df.groupby('City')['Churn'].mean()
train_df['City'] = train_df['City'].map(mean_encoded_city)
val_df['City'] = val_df['City'].map(mean_encoded_city)
test_df['City'] = test_df['City'].map(mean_encoded_city)

# Separating features and target variable
X_train, y_train = train_df.drop('Churn', axis=1), train_df['Churn']
X_val, y_val = val_df.drop('Churn', axis=1), val_df['Churn']
X_test, y_test = test_df.drop('Churn', axis=1), test_df['Churn']

# Normalization of features except target feature "Churn"
scaler = MinMaxScaler()

X_train[features_to_normalize] =
scaler.fit_transform(X_train[features_to_normalize])
X_val[features_to_normalize] =
```

```
scaler.transform(X_val[features_to_normalize])
X_test[features_to_normalize] =
scaler.transform(X_test[features_to_normalize])

X_train

      IncomeIncrease  RatingIncrease       Age      City    Income  \
432                0             0.0  0.513514  0.674419  0.104035
1493               0             0.5  0.378378  0.681818  0.390311
2009               0             0.5  0.351351  0.654545  0.106348
1236               0             0.5  0.270270  0.764045  0.134214
1864               0             0.5  0.216216  0.716418  0.113766
...              ...             ...       ...       ...       ...
2041               0             0.5  0.459459  0.600000  0.208650
1936               0             0.0  0.459459  0.730769  0.254380
1486               0             0.5  0.297297  0.791667  0.478834
1881               0             0.5  0.081081  0.674419  0.598094
365                0             1.0  0.486486  0.702128  0.223503

      Joining Designation  Grade  Total Business Value  Quarterly
Rating  \
432                  0.00   0.25              0.088412
0.333333
1493                 0.50   0.50              0.037072
0.000000
2009                 0.00   0.00              0.014326
0.000000
1236                 0.00   0.00              0.034564
0.333333
1864                 0.00   0.00              0.015877
0.000000
...                   ...    ...                   ...                .
..
2041                 0.25   0.25              0.014326
0.000000
1936                 0.00   0.25              0.041930
0.000000
1486                 0.50   0.50              0.014326
0.000000
1881                 0.50   0.50              0.017893
0.000000
365                  0.50   0.50              0.073420
0.666667

      SumOf_diff_bussValue  JoiningMonth
432               0.284681      0.909091
1493              0.292539      0.272727
2009              0.287653      0.909091
1236              0.282917      0.727273
1864              0.292122      0.818182
```

```
...                    ...           ...
2041              0.287653      0.363636
1936              0.245698      0.545455
1486              0.287653      0.363636
1881              0.287653      0.363636
365               0.298518      0.363636

[1523 rows x 11 columns]
```

```
X_train.columns
```

```
Index(['IncomeIncrease', 'RatingIncrease', 'Age', 'City', 'Income',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating', 'SumOf_diff_bussValue', 'JoiningMonth'],
      dtype='object')
```

```
X_val
```

```
      IncomeIncrease  RatingIncrease       Age      City    Income  \
1561               0             1.0  0.243243  0.681818  0.391853
1281               0             0.5  0.270270  0.732143  0.260932
1300               0             0.5  0.270270  0.648148  0.401275
965                0             0.5  0.270270  0.653061  0.397887
1628               0             0.5  0.540541  0.681818  0.480641
...              ...             ...       ...       ...       ...
208                0             0.0  0.513514  0.764045  0.149709
1122               0             0.5  0.621622  0.674419  0.317401
1528               0             0.5  0.108108  0.600000  0.195749
625                0             0.5  0.378378  0.730769  0.048083
1120               0             0.5  0.351351  0.764045  0.369498

      Joining Designation  Grade  Total Business Value  Quarterly
Rating  \
1561                 0.25   0.25              0.057432
1.0
1281                 0.00   0.00              0.014326
0.0
1300                 0.25   0.25              0.016362
0.0
965                  0.50   0.50              0.014326
0.0
1628                 0.50   0.50              0.054057
0.0
...                   ...    ...                   ...               .
..
208                  0.00   0.25              0.046330
0.0
1122                 0.00   0.00              0.032444
0.0
1528                 0.00   0.00              0.022275
```

```
0.0
625                  0.00   0.00              0.016693
0.0
1120                 0.25   0.25              0.019505
0.0

      SumOf_diff_bussValue  JoiningMonth
1561              0.332328      0.454545
1281              0.287653      0.636364
1300              0.293518      0.363636
965               0.287653      0.363636
1628              0.287653      0.909091
...                    ...           ...
208               0.276388      0.363636
1122              0.291892      0.636364
1528              0.287653      1.000000
625               0.280835      0.727273
1120              0.287653      0.363636

[381 rows x 11 columns]
```

X_test

```
      IncomeIncrease  RatingIncrease       Age      City    Income  \
937                0             0.5  0.135135  0.672727  0.166437
765                0             0.5  0.216216  0.764045  0.100286
34                 0             0.5  0.405405  0.761905  0.176866
480                0             1.0  0.540541  0.791667  0.189085
303                0             0.5  0.513514  0.716418  0.602704
...              ...             ...       ...       ...       ...
1934               0             0.5  0.324324  0.600000  0.198659
2031               0             1.0  0.162162  0.578947  0.213878
2155               0             0.5  0.108108  0.648148  0.030725
195                0             0.0  0.648649  0.674419  0.239983
1371               0             0.5  0.378378  0.791667  0.331793

      Joining Designation  Grade  Total Business Value  Quarterly
Rating  \
937                  0.00   0.00              0.014326
0.000000
765                  0.00   0.00              0.017501
0.000000
34                   0.00   0.00              0.017823
0.000000
480                  0.00   0.00              0.032137
0.666667
303                  0.50   0.50              0.067834
0.000000
...                   ...    ...                   ...               .
..
```

```
1934                    0.50   0.50              0.014326
0.000000
2031                    0.00   0.00              0.069158
0.666667
2155                    0.00   0.00              0.029318
0.000000
195                     0.00   0.00              0.121754
0.000000
1371                    0.25   0.25              0.145028
0.000000

      SumOf_diff_bussValue  JoiningMonth
937               0.287653      0.636364
765               0.278861      0.454545
34                0.280748      0.818182
480               0.296414      0.636364
303               0.296588      0.818182
...                    ...           ...
1934              0.287653      0.272727
2031              0.290970      0.272727
2155              0.287653      0.818182
195               0.252286      0.545455
1371              0.284578      0.818182

[477 rows x 11 columns]
```

```
#NOW lets combine # Combine X_train and X_val, y_train and y_val for
the training set
X_train = pd.concat([X_train, X_val], axis=0)
y_train = pd.concat([y_train, y_val], axis=0)

X_train
```

```
      IncomeIncrease  RatingIncrease       Age      City    Income  \
432                0             0.0  0.513514  0.674419  0.104035
1493               0             0.5  0.378378  0.681818  0.390311
2009               0             0.5  0.351351  0.654545  0.106348
1236               0             0.5  0.270270  0.764045  0.134214
1864               0             0.5  0.216216  0.716418  0.113766
...              ...             ...       ...       ...       ...
208                0             0.0  0.513514  0.764045  0.149709
1122               0             0.5  0.621622  0.674419  0.317401
1528               0             0.5  0.108108  0.600000  0.195749
625                0             0.5  0.378378  0.730769  0.048083
1120               0             0.5  0.351351  0.764045  0.369498

      Joining Designation  Grade  Total Business Value  Quarterly
Rating  \
432                     0.00   0.25              0.088412
0.333333
```

```
1493                    0.50   0.50              0.037072
0.000000
2009                    0.00   0.00              0.014326
0.000000
1236                    0.00   0.00              0.034564
0.333333
1864                    0.00   0.00              0.015877
0.000000
...                      ...    ...                   ...                .
..
208                     0.00   0.25              0.046330
0.000000
1122                    0.00   0.00              0.032444
0.000000
1528                    0.00   0.00              0.022275
0.000000
625                     0.00   0.00              0.016693
0.000000
1120                    0.25   0.25              0.019505
0.000000

      SumOf_diff_bussValue  JoiningMonth
432               0.284681      0.909091
1493              0.292539      0.272727
2009              0.287653      0.909091
1236              0.282917      0.727273
1864              0.292122      0.818182
...                    ...           ...
208               0.276388      0.363636
1122              0.291892      0.636364
1528              0.287653      1.000000
625               0.280835      0.727273
1120              0.287653      0.363636

[1904 rows x 11 columns]
```

y_train

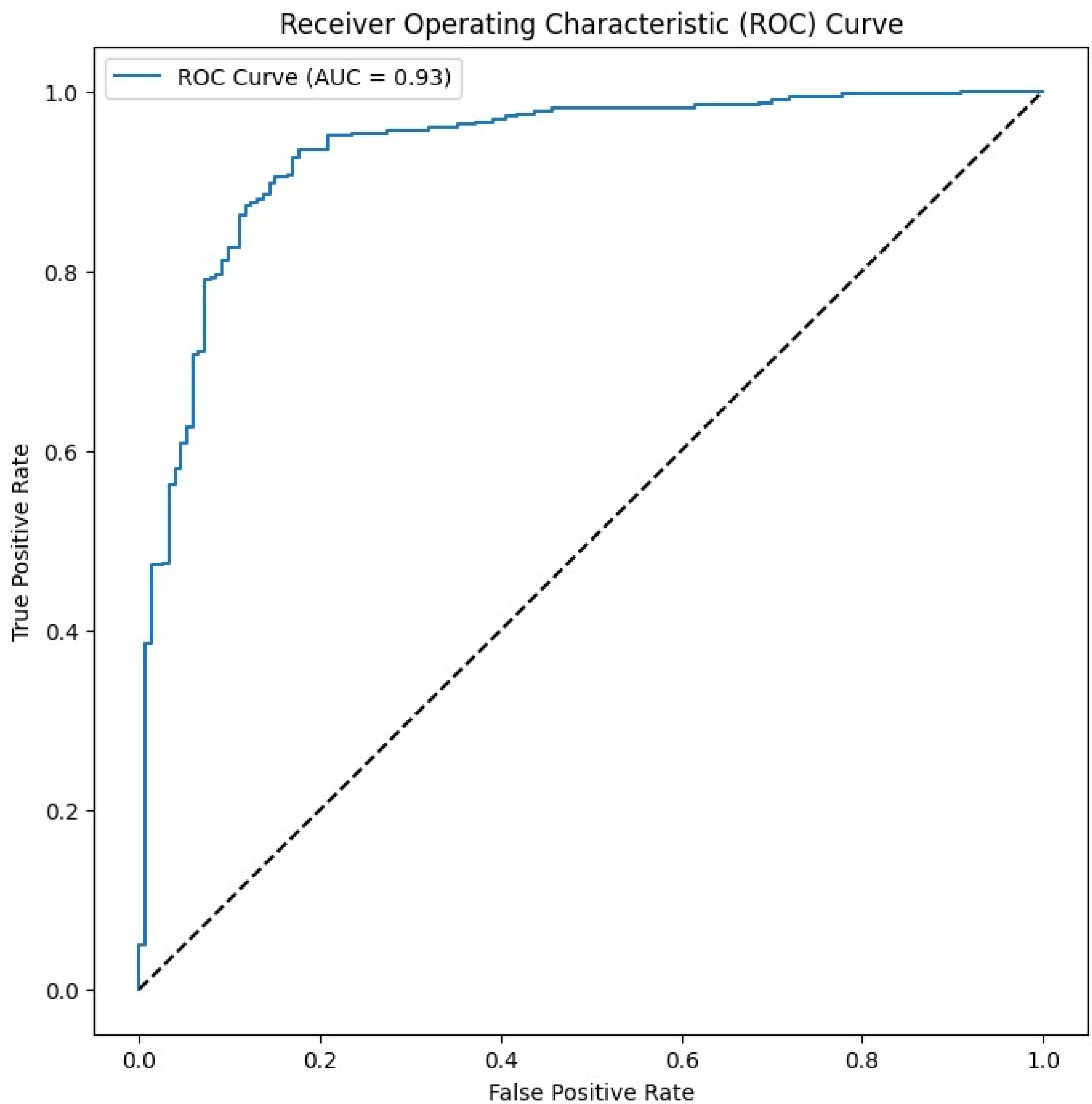
```
432     1
1493    0
2009    1
1236    1
1864    0
       ..
208     1
1122    1
1528    1
625     1
1120    1
Name: Churn, Length: 1904, dtype: int64
```

Random Forest:- Training, Hyperparameter tuning & Test Results

```
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix,
precision_score, recall_score, f1_score, roc_auc_score, roc_curve
from skopt import BayesSearchCV
from sklearn.ensemble import RandomForestClassifier


# Define the class weights because our data is imbalanced
class_weights = {0: 2, 1: 1}

# Bayesian Search CV to find the best hyperparameters
param_space = {
    'n_estimators': (10, 500),
    'max_depth': (3, 45),
    'min_samples_split': (2, 10),
    'min_samples_leaf': (1, 10),
}

rf = RandomForestClassifier(class_weight=class_weights,
random_state=42)
opt = BayesSearchCV(rf, param_space, n_iter=50,
cv=StratifiedKFold(n_splits=4, shuffle=True, random_state=42),
n_jobs=-1, scoring='roc_auc', random_state=42)
opt.fit(X_train, y_train)

# Print the best hyperparameters
print("Best Hyperparameters:", opt.best_params_)

Best Hyperparameters: OrderedDict([('max_depth', 10),
('min_samples_leaf', 1), ('min_samples_split', 10), ('n_estimators',
339)])

# Train the Random Forest model with the best hyperparameters
best_rf = opt.best_estimator_
best_rf.fit(X_train, y_train)

# Make predictions on the test set
y_pred = best_rf.predict(X_test)
y_pred_proba = best_rf.predict_proba(X_test)[:, 1]

# Calculate performance metrics
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_proba)
```

```python
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1Score: {f1}")
print(f"ROC AUC: {roc_auc}")

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, best_rf.predict_proba(X_test)[:, 1])
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```

```
Precision: 0.9297124600638977
Recall: 0.8981481481481481
F1Score: 0.9136577708006279
ROC AUC: 0.9336924070039538
```




```
from sklearn.metrics import classification_report, confusion_matrix
# Classification Report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)

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

```
              0       0.80      0.86      0.83       153
              1       0.93      0.90      0.91       324

    accuracy                              0.88       477
   macro avg       0.86      0.88      0.87       477
weighted avg       0.89      0.88      0.89       477

Confusion Matrix:
[[131  22]
 [ 33 291]]

#NOw lets also get the feature importances
feature_names = ['IncomeIncrease', 'RatingIncrease', 'Age', 'City',
'Income',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating', 'SumOf_diff_bussValue', 'JoiningMonth']


# Access feature importances
feature_importances = best_rf.feature_importances_


# Create a dictionary to pair feature names with their importances
feature_importance_dict = dict(zip(feature_names,
feature_importances))

# Sort the features based on their importances
sorted_feature_importances = sorted(feature_importance_dict.items(),
key=lambda x: x[1], reverse=True)

# Display the sorted feature importances
for feature, importance in sorted_feature_importances:
    print(f"{feature}: {importance}")

SumOf_diff_bussValue: 0.2771068033055797
Total Business Value: 0.1812008244577785
Quarterly Rating: 0.13888649111414317
JoiningMonth: 0.1079216806278633
Income: 0.06860191484873966
RatingIncrease: 0.06323353492567332
City: 0.051082216936565776
Age: 0.0484780388484003
Joining Designation: 0.030270579893077673
Grade: 0.029563549538794375
IncomeIncrease: 0.0036543655033843157
```

Conclusion of Results:

1)AUC-ROC: 0.93

2)F1score for Class 0 (Minority class):- 0.83 & For class 1:-0.91

3)55 Missclassified out of 477 test data points.

4)SumOf_diffBussValue Most important feature

```
pip install -U imbalanced-learn

Requirement already satisfied: imbalanced-learn in
/usr/local/lib/python3.10/dist-packages (0.10.1)
Collecting imbalanced-learn
  Downloading imbalanced_learn-0.11.0-py3-none-any.whl (235 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 235.6/235.6 kB 2.6 MB/s eta
0:00:00
ent already satisfied: numpy>=1.17.3 in
/usr/local/lib/python3.10/dist-packages (from imbalanced-learn)
(1.23.5)
Requirement already satisfied: scipy>=1.5.0 in
/usr/local/lib/python3.10/dist-packages (from imbalanced-learn)
(1.11.4)
Requirement already satisfied: scikit-learn>=1.0.2 in
/usr/local/lib/python3.10/dist-packages (from imbalanced-learn)
(1.2.2)
Requirement already satisfied: joblib>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from imbalanced-learn)
(1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from imbalanced-learn)
(3.2.0)
Installing collected packages: imbalanced-learn
  Attempting uninstall: imbalanced-learn
    Found existing installation: imbalanced-learn 0.10.1
    Uninstalling imbalanced-learn-0.10.1:
      Successfully uninstalled imbalanced-learn-0.10.1
Successfully installed imbalanced-learn-0.11.0
```

Balanced Random Forest Classifier

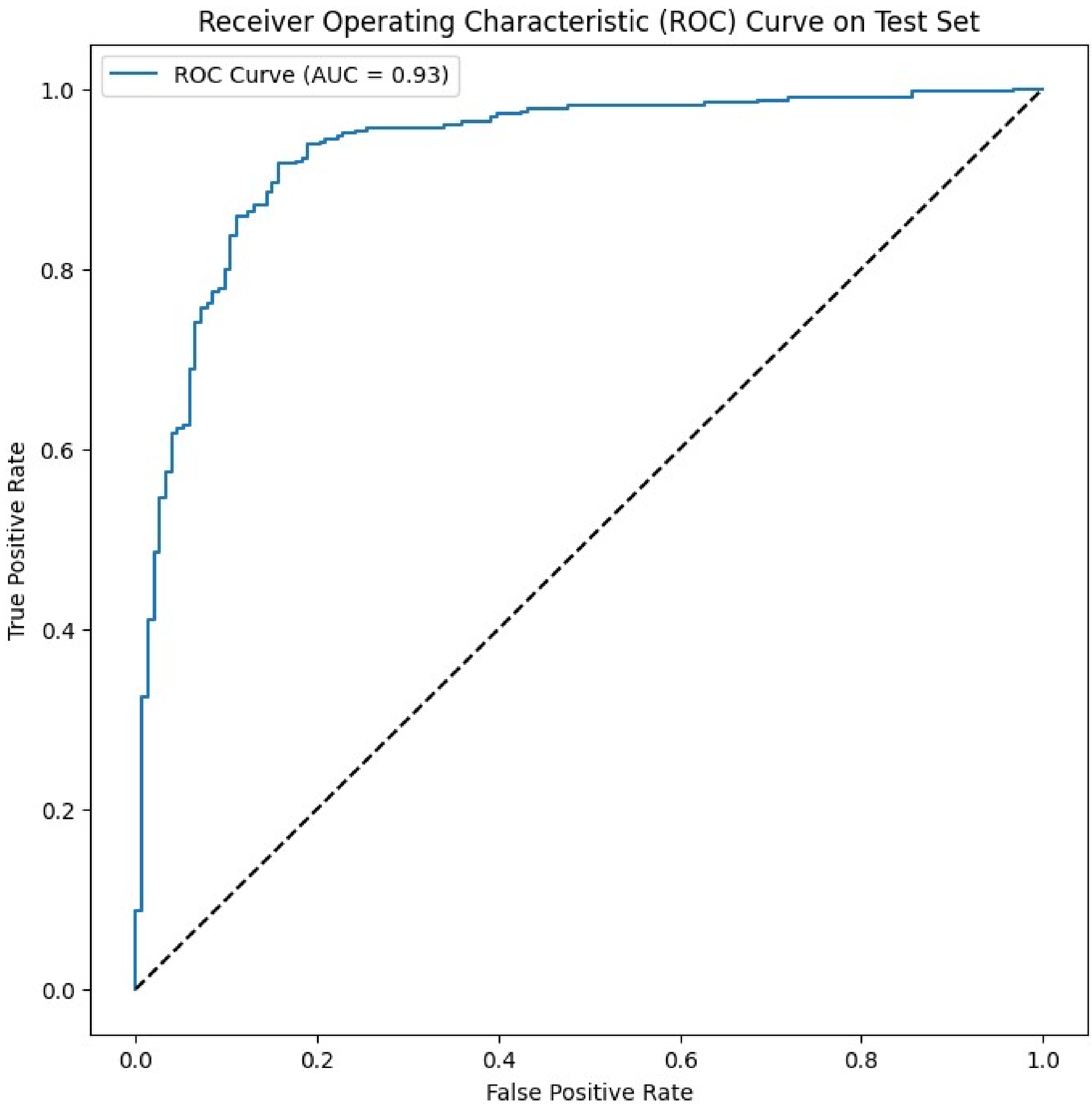
```
#Now lets try out BalancedRandomForestClassifier because our data is
imbalanced

from imblearn.ensemble import BalancedRandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,
precision_score, recall_score, f1_score, roc_auc_score, roc_curve
from skopt import BayesSearchCV
import matplotlib.pyplot as plt


# Define the search space for hyperparameters
```

```python
param_space = {
    'n_estimators': (30, 500),
    'max_depth': (3, 30),
    'min_samples_split': (2, 10),
    'min_samples_leaf': (1, 10),
}

# Create a Balanced Random Forest Classifier
brf_classifier = BalancedRandomForestClassifier(random_state=42)

# Perform Bayesian Search CV
opt = BayesSearchCV(brf_classifier, param_space, n_iter=50,
cv=StratifiedKFold(n_splits=4, shuffle=True, random_state=42),
scoring='roc_auc', n_jobs=-1, random_state=42)
opt.fit(X_train, y_train)

# Print the best hyperparameters
best_params = opt.best_params_
print("Best Hyperparameters:", best_params)

# Evaluate on the test set
best_brf_model = opt.best_estimator_
y_test_pred_prob = best_brf_model.predict_proba(X_test)[:, 1]
y_test_pred = (y_test_pred_prob > 0.5).astype(int)

# Calculate performance metrics
precision = precision_score(y_test, y_test_pred)
recall = recall_score(y_test, y_test_pred)
f1 = f1_score(y_test, y_test_pred)
roc_auc = roc_auc_score(y_test, y_test_pred_prob)

print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1Score: {f1}")
print(f"ROC AUC: {roc_auc}")

# Classification Report
print("Classification Report on Test Set:")
print(classification_report(y_test, y_test_pred))

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_test_pred)
print("Confusion Matrix on Test Set:")
print(conf_matrix)

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, y_test_pred_prob)
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'k--')
```

```python
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve on Test Set')
plt.legend()
plt.show()

# Feature Importances
feature_importances = best_brf_model.feature_importances_

# Create a dictionary to pair feature names with their importances
feature_importance_dict = dict(zip(feature_names,
feature_importances))

# Sort the features based on their importances
sorted_feature_importances = sorted(feature_importance_dict.items(),
key=lambda x: x[1], reverse=True)

# Display the sorted feature importances
for feature, importance in sorted_feature_importances:
    print(f"{feature}: {importance}")
```

```
/usr/local/lib/python3.10/dist-packages/imblearn/ensemble/
_forest.py:546: FutureWarning: The default of `sampling_strategy` will
change from `'auto'` to `'all'` in version 0.13. This change will
follow the implementation proposed in the original paper. Set to
`'all'` to silence this warning and adopt the future behaviour.
  warn(
/usr/local/lib/python3.10/dist-packages/imblearn/ensemble/_forest.py:5
58: FutureWarning: The default of `replacement` will change from
`False` to `True` in version 0.13. This change will follow the
implementation proposed in the original paper. Set to `True` to
silence this warning and adopt the future behaviour.
  warn(

Best Hyperparameters: OrderedDict([('max_depth', 10),
('min_samples_leaf', 1), ('min_samples_split', 8), ('n_estimators',
303)])
Precision: 0.9421768707482994
Recall: 0.8549382716049383
F1Score: 0.8964401294498382
ROC AUC: 0.9315541031227307
Classification Report on Test Set:
              precision    recall  f1-score   support

           0       0.74      0.89      0.81       153
           1       0.94      0.85      0.90       324

    accuracy                           0.87       477
   macro avg       0.84      0.87      0.85       477
weighted avg       0.88      0.87      0.87       477
```

```
Confusion Matrix on Test Set:
[[136  17]
 [ 47 277]]
```




```
SumOf_diff_bussValue: 0.2674973251827537
Total Business Value: 0.17979995654950406
Quarterly Rating: 0.13437260973383375
JoiningMonth: 0.10832723904953759
Income: 0.07607519802899132
RatingIncrease: 0.05958125399836072
```

```
City: 0.05758282004028386
Age: 0.05295037463445947
Joining Designation: 0.031568569394954435
Grade: 0.029539565851823872
IncomeIncrease: 0.0027050875354972586
```

Conclusion of Results:

1)AUC-ROC: 0.93

2)F1score for Class 0 (Minority class):- 0.81 & For class 1:-0.90

3)64 Missclassified out of 477 test data points.

4)SumOf_diffBussValue Most important feature

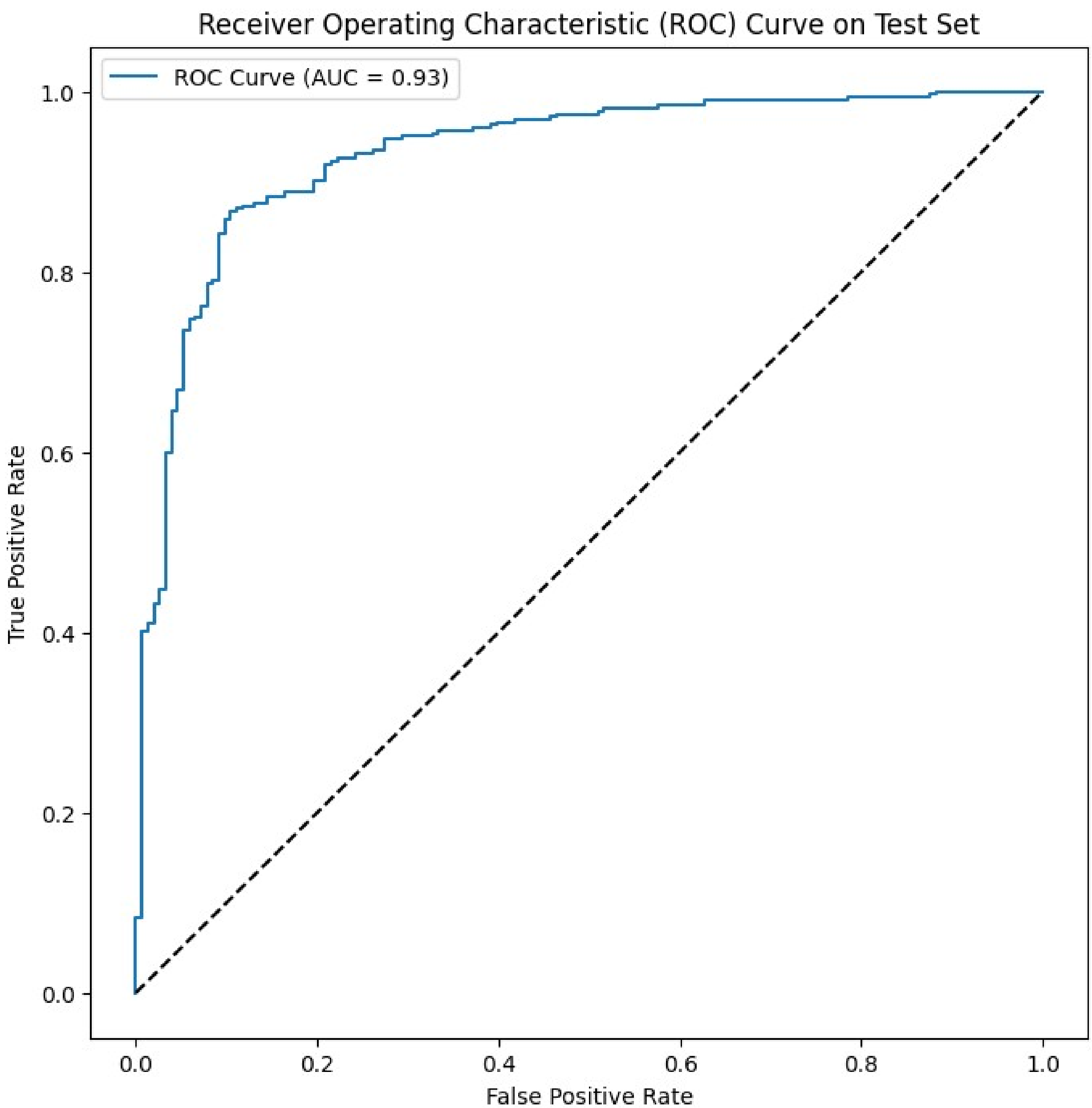
XGBoost Classifier

```
import xgboost as xgb
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix,
precision_score, recall_score, f1_score, roc_auc_score, roc_curve
from skopt import BayesSearchCV


# Define class labels
class_labels = {0: 2, 1: 1}

# Define the search space for hyperparameters
param_space = {
    'learning_rate': (0.01, 1.0, 'log-uniform'),
    'n_estimators': (30, 500),
    'max_depth': (3, 100),
    'min_child_weight': (1, 10),
    'subsample': (0.1, 1.0, 'uniform'),
    'gamma': (0, 1.0, 'uniform'),
    'colsample_bytree': (0.1, 1.0, 'uniform'),
}

# Create an XGBoost classifier
xgb_model = xgb.XGBClassifier(scale_pos_weight=class_labels[1] /
class_labels[0], random_state=42)

# Perform Bayesian Search CV
opt = BayesSearchCV(xgb_model, param_space, n_iter=50,
cv=StratifiedKFold(n_splits=4, shuffle=True, random_state=42),
scoring='roc_auc', n_jobs=-1, random_state=42)
opt.fit(X_train, y_train)
```

```
# Print the best hyperparameters
print("Best Hyperparameters:", opt.best_params_)

# Evaluate on the validation set
best_xgb_model = opt.best_estimator_
y_pred_proba = best_xgb_model.predict_proba(X_test)[:, 1]
y_pred = best_xgb_model.predict(X_test)

# Calculate performance metrics
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_proba)

print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1Score: {f1}")
print(f"ROC AUC: {roc_auc}")

# Classification Report
print("Classification Report on Test Set:")
print(classification_report(y_test, y_pred))

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix on Test Set:")
print(conf_matrix)

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, best_xgb_model.predict_proba(X_test)
[:, 1])
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve on Test Set')
plt.legend()
plt.show()
```

```
Best Hyperparameters: OrderedDict([('colsample_bytree', 1.0),
('gamma', 0), ('learning_rate', 0.01), ('max_depth', 48),
('min_child_weight', 8), ('n_estimators', 453), ('subsample',
0.5776084416838791)])
Precision: 0.9281045751633987
Recall: 0.8765432098765432
F1Score: 0.9015873015873016
ROC AUC: 0.930727023319616
Classification Report on Test Set:
```

```
              precision    recall  f1-score   support

           0       0.77      0.86      0.81       153
           1       0.93      0.88      0.90       324

    accuracy                           0.87       477
   macro avg       0.85      0.87      0.86       477
weighted avg       0.88      0.87      0.87       477

Confusion Matrix on Test Set:
[[131  22]
 [ 40 284]]
```



```python
#Now lets see feature importances for xgb model we trained

# Get the booster from the trained XGBoost model
booster = best_xgb_model.get_booster()

# Get feature importances based on how many times a feature is used for splitting
feature_importances = booster.get_score(importance_type='weight')

# Sort the features based on their importances
sorted_feature_importances = sorted(feature_importances.items(), key=lambda x: x[1], reverse=True)

# Display the sorted feature importances
for feature, importance in sorted_feature_importances:
    print(f"{feature}: {importance}")
```

```
Total Business Value: 862.0
Income: 637.0
JoiningMonth: 623.0
SumOf_diff_bussValue: 556.0
City: 510.0
Joining Designation: 366.0
Age: 356.0
Quarterly Rating: 275.0
Grade: 48.0
RatingIncrease: 16.0
```

Conclusion of Results: 1)AUC-ROC: 0.93

2)F1score for Class 0 (Minority class):- 0.81 & For class 1:-0.90

3)62 Missclassified out of 477 test data points.

4)Income & Total Bussiness Value are Most important features

LightGBM

```python
import lightgbm as lgb
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import classification_report, roc_auc_score, precision_recall_fscore_support, roc_curve
from skopt import BayesSearchCV
import matplotlib.pyplot as plt


# Define class weights
class_weights = {0: 2, 1: 1}
```

```
# Define the search space for hyperparameters
param_space = {
    'learning_rate': (0.01, 1.0, 'log-uniform'),
    'n_estimators': (30, 500),
    'max_depth': (3, 105),
    'subsample': (0.1, 1.0, 'uniform'),
    'colsample_bytree': (0.1, 1.0, 'uniform'),
    'reg_alpha': (1e-9, 20.0, 'log-uniform'),
    'reg_lambda': (1e-9, 20.0, 'log-uniform'),
}

# Create a LightGBM classifier
lgb_model = lgb.LGBMClassifier(class_weight=class_weights,
random_state=42)

# Perform Bayesian Search CV
opt = BayesSearchCV(lgb_model, param_space, n_iter=50,
cv=StratifiedKFold(n_splits=4, shuffle=True, random_state=42),
scoring='roc_auc', n_jobs=-1, random_state=42)
opt.fit(X_train, y_train)

# Print the best hyperparameters
print("Best Hyperparameters:", opt.best_params_)

# Evaluate on the test set
best_lgb_model = opt.best_estimator_
y_test_pred_prob = best_lgb_model.predict_proba(X_test)[:, 1]
y_test_pred = (y_test_pred_prob > 0.5).astype(int)


# Calculate performance metrics
precision = precision_score(y_test, y_test_pred)
recall = recall_score(y_test, y_test_pred)
f1 = f1_score(y_test, y_test_pred)
roc_auc = roc_auc_score(y_test, y_test_pred_prob)

print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 score: {f1}")
print(f"ROC-AUC: {roc_auc}")

# Classification Report
print("Classification Report on Test Set:")
print(classification_report(y_test, y_test_pred))

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, y_test_pred_prob)
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'k--')
```

```python
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve on Test Set')
plt.legend()
plt.show()

# Feature Importances
feature_importances = best_lgb_model.feature_importances_
sorted_feature_importances = sorted(zip(feature_importances,
feature_names), reverse=True)
print("Feature Importances:")
for importance, feature in sorted_feature_importances:
    print(f"{feature}: {importance}")
```

```
[LightGBM] [Warning] Found whitespace in feature_names, replace with
underlines
[LightGBM] [Info] Number of positive: 1292, number of negative: 612
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead
of testing was 0.000223 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 861
[LightGBM] [Info] Number of data points in the train set: 1904, number
of used features: 11
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.513514 ->
initscore=0.054067
[LightGBM] [Info] Start training from score 0.054067
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
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[LightGBM] [Warning] No further splits with positive gain, best gain:
```

```
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
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[LightGBM] [Warning] No further splits with positive gain, best gain:
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[LightGBM] [Warning] No further splits with positive gain, best gain:
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[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
Best Hyperparameters: OrderedDict([('colsample_bytree',
0.5473244284370286), ('learning_rate', 0.01), ('max_depth', 3),
('n_estimators', 500), ('reg_alpha', 1e-09), ('reg_lambda',
5.901137156455479e-07), ('subsample', 1.0)])
Precision: 0.9255663430420712
Recall: 0.8827160493827161
F1 score: 0.9036334913112164
ROC-AUC: 0.9298595981602518
Classification Report on Test Set:
              precision    recall  f1-score   support

           0       0.77      0.85      0.81       153
           1       0.93      0.88      0.90       324

    accuracy                           0.87       477
   macro avg       0.85      0.87      0.86       477
weighted avg       0.88      0.87      0.87       477
```
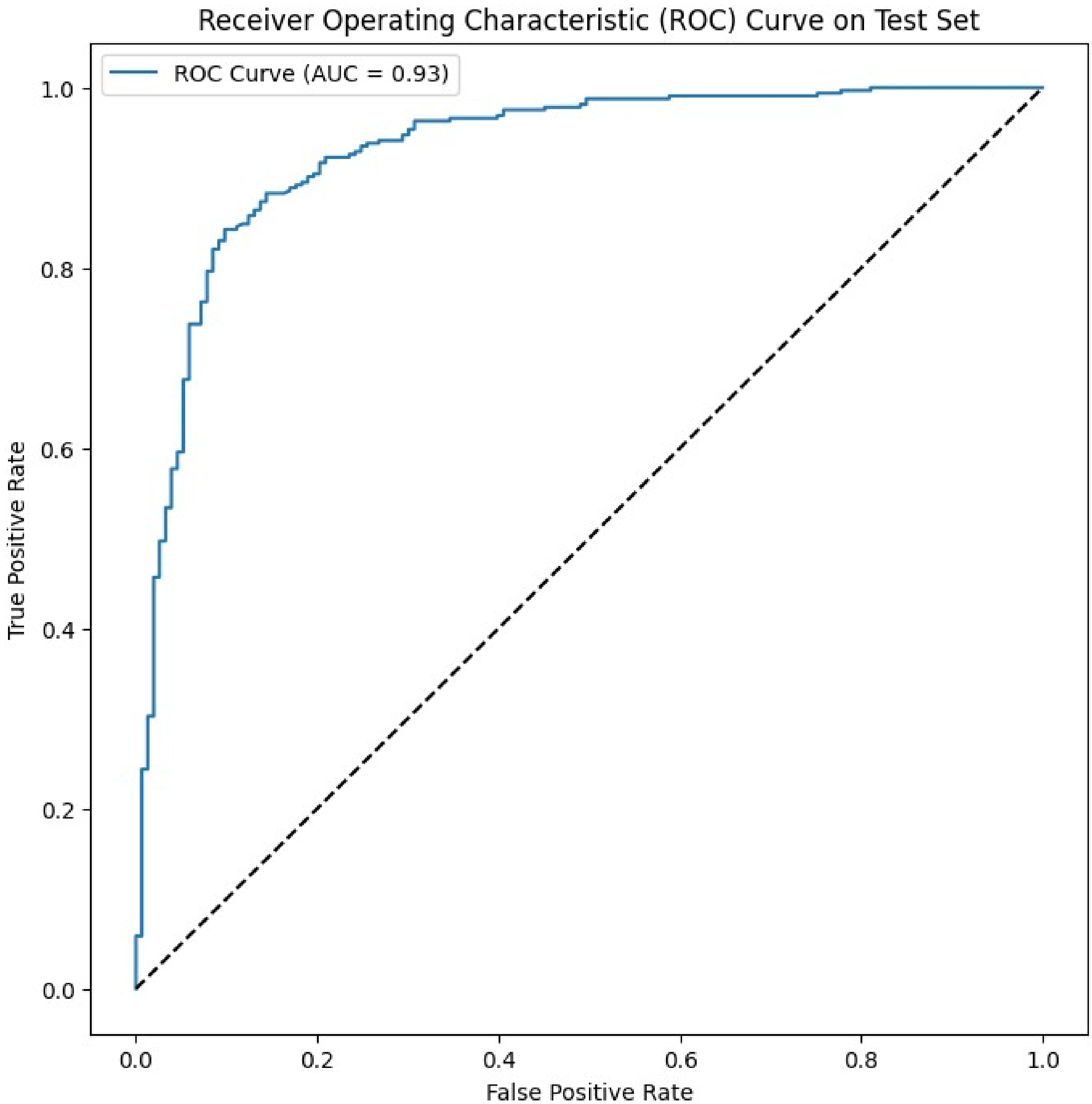




```
Feature Importances:
Total Business Value: 723
SumOf_diff_bussValue: 591
JoiningMonth: 439
City: 386
Age: 261
Quarterly Rating: 253
Income: 253
Joining Designation: 180
Grade: 169
RatingIncrease: 122
IncomeIncrease: 1
```

```
# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_test_pred)
print("Confusion Matrix on Test Set:")
print(conf_matrix)
```

```
Confusion Matrix on Test Set:
[[130  23]
 [ 38 286]]
```

Conclusion of Results:

1)AUC-ROC: 0.93

2)F1score for Class 0 (Minority class):- 0.81 & For class 1:-0.90

3)61 Missclassified out of 477 test data points.

4)Total Bussiness Value is Most important feature.

RUSBoost

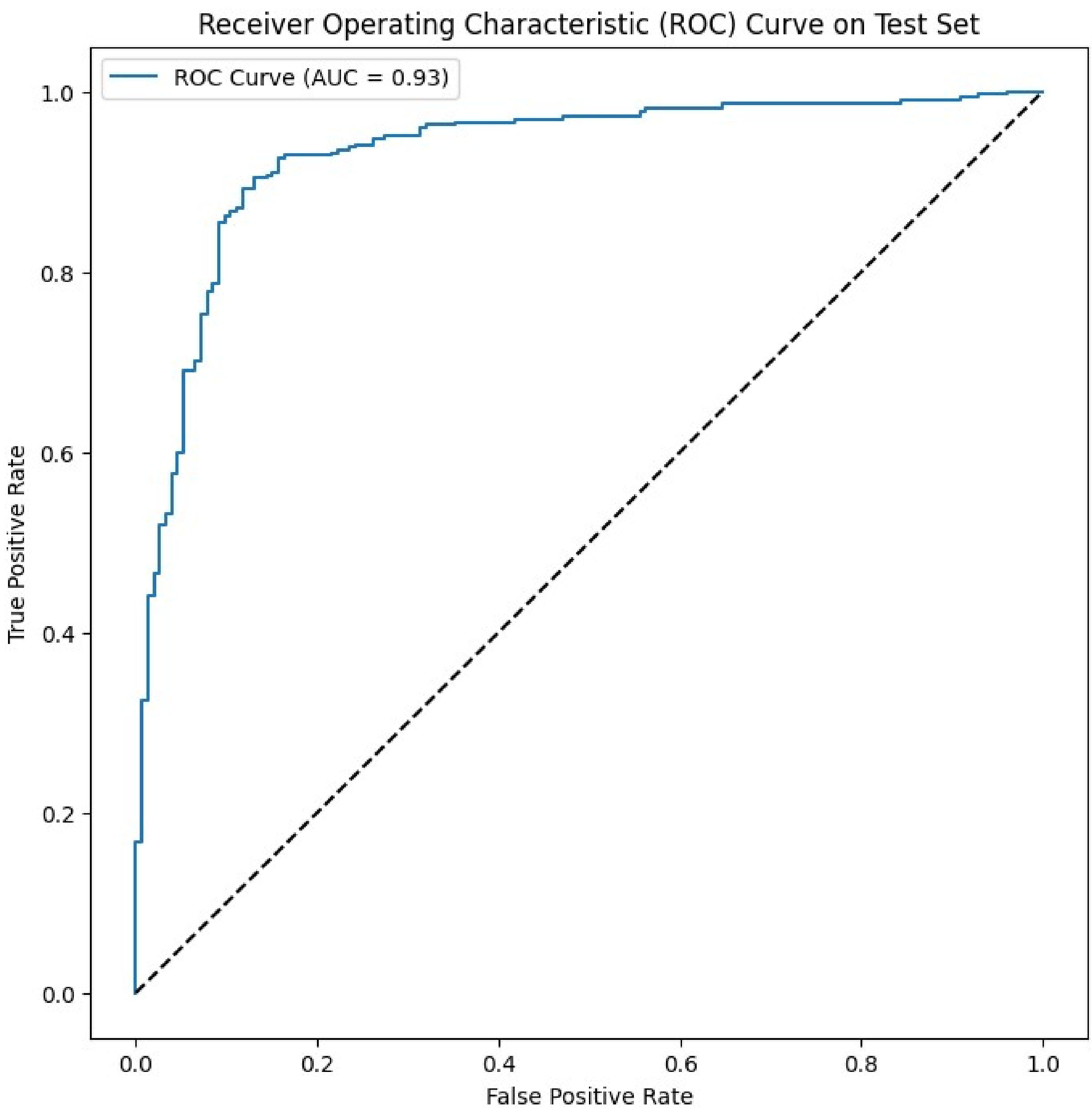
```
#Now lets use RUSBoost
from imblearn.ensemble import RUSBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix,
precision_score, recall_score, f1_score, roc_auc_score, roc_curve
from skopt import BayesSearchCV
import matplotlib.pyplot as plt

# Define the search space for hyperparameters
param_space = {
    'n_estimators': (30, 400),
    'learning_rate': (0.01, 1.0, 'log-uniform'),
    'algorithm': ['SAMME', 'SAMME.R'],
    'base_estimator__max_depth': (3, 100),
    'base_estimator__min_samples_split': (2, 10),
    'base_estimator__min_samples_leaf': (1, 10),
}


# Create a RUSBoostClassifier with DecisionTreeClassifier as base
estimator
base_estimator = DecisionTreeClassifier(random_state=42)
rusboost_classifier =
RUSBoostClassifier(base_estimator=base_estimator, random_state=42)

# Perform Bayesian Search CV
opt = BayesSearchCV(rusboost_classifier, param_space, n_iter=50,
cv=StratifiedKFold(n_splits=4, shuffle=True, random_state=42),
```

```
scoring='roc_auc', n_jobs=-1, random_state=42)
opt.fit(X_train, y_train)

# Print the best hyperparameters
best_params = opt.best_params_
print("Best Hyperparameters:", best_params)

# Evaluate on the test set
best_rusboost_model = opt.best_estimator_
y_test_pred_prob = best_rusboost_model.predict_proba(X_test)[:, 1]
y_test_pred = (y_test_pred_prob > 0.5).astype(int)

# Calculate performance metrics
precision = precision_score(y_test, y_test_pred)
recall = recall_score(y_test, y_test_pred)
f1 = f1_score(y_test, y_test_pred)
roc_auc = roc_auc_score(y_test, y_test_pred_prob)

print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 score: {f1}")
print(f"ROC-AUC: {roc_auc}")

# Classification Report
print("Classification Report on Test Set:")
print(classification_report(y_test, y_test_pred))

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_test_pred)
print("Confusion Matrix on Test Set:")
print(conf_matrix)

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, y_test_pred_prob)
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve on Test Set')
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/imblearn/ensemble/
_weight_boosting.py:271: FutureWarning: `base_estimator` was renamed
to `estimator` in version 0.10 and will be removed in 0.12.
  warnings.warn(
```

```
Best Hyperparameters: OrderedDict([('algorithm', 'SAMME.R'),
('base_estimator__max_depth', 63),
```

```
('base_estimator__min_samples_leaf', 10),
('base_estimator__min_samples_split', 10), ('learning_rate', 1.0),
('n_estimators', 400)])
Precision: 0.9361022364217252
Recall: 0.904320987654321
F1 score: 0.9199372056514914
ROC-AUC: 0.9312313402727345
Classification Report on Test Set:
              precision    recall  f1-score   support

           0       0.81      0.87      0.84       153
           1       0.94      0.90      0.92       324

    accuracy                           0.89       477
   macro avg       0.87      0.89      0.88       477
weighted avg       0.90      0.89      0.89       477

Confusion Matrix on Test Set:
[[133  20]
 [ 31 293]]
```




```python
# Feature Importances
feature_importances = best_rusboost_model.feature_importances_
sorted_feature_importances = sorted(zip(feature_importances,
feature_names), reverse=True)
print("Feature Importances:")
for importance, feature in sorted_feature_importances:
    print(f"{feature}: {importance}")
```

```
Feature Importances:
SumOf_diff_bussValue: 0.23845036308376996
Total Business Value: 0.17281148818423392
Income: 0.14053798424460073
```

```
Age: 0.1141813747518011
City: 0.11064766405278577
JoiningMonth: 0.09507094559487615
Quarterly Rating: 0.05668829112829859
Joining Designation: 0.02912089409374228
Grade: 0.01947495791205408
RatingIncrease: 0.017360179056271057
IncomeIncrease: 0.005655857897566038
```

Conclusion of Results:

1)AUC-ROC: 0.93

2)F1score for Class 0 (Minority class):- 0.84 & For class 1:-0.92

3)51 Missclassified out of 477 test data points.

4)SumOf_diff_bussValue is Most important feature.

```
X_train

      IncomeIncrease  RatingIncrease       Age      City    Income  \
432                0             0.0  0.513514  0.674419  0.104035
1493               0             0.5  0.378378  0.681818  0.390311
2009               0             0.5  0.351351  0.654545  0.106348
1236               0             0.5  0.270270  0.764045  0.134214
1864               0             0.5  0.216216  0.716418  0.113766
...              ...             ...       ...       ...       ...
208                0             0.0  0.513514  0.764045  0.149709
1122               0             0.5  0.621622  0.674419  0.317401
1528               0             0.5  0.108108  0.600000  0.195749
625                0             0.5  0.378378  0.730769  0.048083
1120               0             0.5  0.351351  0.764045  0.369498

      Joining Designation  Grade  Total Business Value  Quarterly 
Rating  \
432                  0.00   0.25              0.088412
0.333333
1493                 0.50   0.50              0.037072
0.000000
2009                 0.00   0.00              0.014326
0.000000
1236                 0.00   0.00              0.034564
0.333333
1864                 0.00   0.00              0.015877
0.000000
...                   ...    ...                   ...               .
..
208                  0.00   0.25              0.046330
0.000000
```

```
1122                    0.00   0.00              0.032444
0.000000
1528                    0.00   0.00              0.022275
0.000000
625                     0.00   0.00              0.016693
0.000000
1120                    0.25   0.25              0.019505
0.000000

      SumOf_diff_bussValue  JoiningMonth
432               0.284681      0.909091
1493              0.292539      0.272727
2009              0.287653      0.909091
1236              0.282917      0.727273
1864              0.292122      0.818182
...                    ...           ...
208               0.276388      0.363636
1122              0.291892      0.636364
1528              0.287653      1.000000
625               0.280835      0.727273
1120              0.287653      0.363636

[1904 rows x 11 columns]
```

```
y_train.value_counts()
```

```
1    1292
0     612
Name: Churn, dtype: int64
```

Resampling Using SMOTE

```
from imblearn.over_sampling import SMOTE

# Apply SMOTE to the training set
smote = SMOTE(sampling_strategy='auto', random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train,
y_train)

X_train_resampled
```

```
      IncomeIncrease  RatingIncrease       Age      City    Income  \
0                  0             0.0  0.513514  0.674419  0.104035
1                  0             0.5  0.378378  0.681818  0.390311
2                  0             0.5  0.351351  0.654545  0.106348
3                  0             0.5  0.270270  0.764045  0.134214
4                  0             0.5  0.216216  0.716418  0.113766
...              ...             ...       ...       ...       ...
2579               0             0.5  0.307871  0.544003  0.232758
```

```
2580              0           0.5  0.476864  0.705749  0.058840
2581              0           1.0  0.399697  0.629188  0.468373
2582              0           0.5  0.639591  0.698496  0.157984
2583              0           0.5  0.084361  0.669333  0.275913

      Joining Designation     Grade  Total Business Value  Quarterly
Rating  \
0                    0.00  0.250000              0.088412
0.333333
1                    0.50  0.500000              0.037072
0.000000
2                    0.00  0.000000              0.014326
0.000000
3                    0.00  0.000000              0.034564
0.333333
4                    0.00  0.000000              0.015877
0.000000
...                   ...       ...                   ...
...
2579                 0.00  0.250000              0.227613
0.666667
2580                 0.00  0.000000              0.014326
0.000000
2581                 0.25  0.608567              0.397586
1.000000
2582                 0.00  0.433243              0.155361
0.422343
2583                 0.25  0.250000              0.014326
0.000000

      SumOf_diff_bussValue  JoiningMonth
0                 0.284681      0.909091
1                 0.292539      0.272727
2                 0.287653      0.909091
3                 0.282917      0.727273
4                 0.292122      0.818182
...                    ...           ...
2579              0.296438      0.909091
2580              0.287653      0.876724
2581              0.495559      0.857661
2582              0.280443      0.496904
2583              0.287653      1.000000

[2584 rows x 11 columns]
```

```
y_train_resampled.value_counts()
```

```
1    1292
0    1292
Name: Churn, dtype: int64
```

```python
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix,
precision_score, recall_score, f1_score, roc_auc_score, roc_curve
from skopt import BayesSearchCV
from sklearn.ensemble import RandomForestClassifier




# Bayesian Search CV to find the best hyperparameters
param_space = {
    'n_estimators': (10, 1200),
    'max_depth': (3, 45),
    'min_samples_split': (2, 10),
    'min_samples_leaf': (1, 10),
}

rf = RandomForestClassifier(random_state=42)
opt = BayesSearchCV(rf, param_space, n_iter=50,
cv=StratifiedKFold(n_splits=5, shuffle=True, random_state=42),
n_jobs=-1, scoring='roc_auc', random_state=42)
opt.fit(X_train_resampled, y_train_resampled)

# Print the best hyperparameters
print("Best Hyperparameters:", opt.best_params_)
```

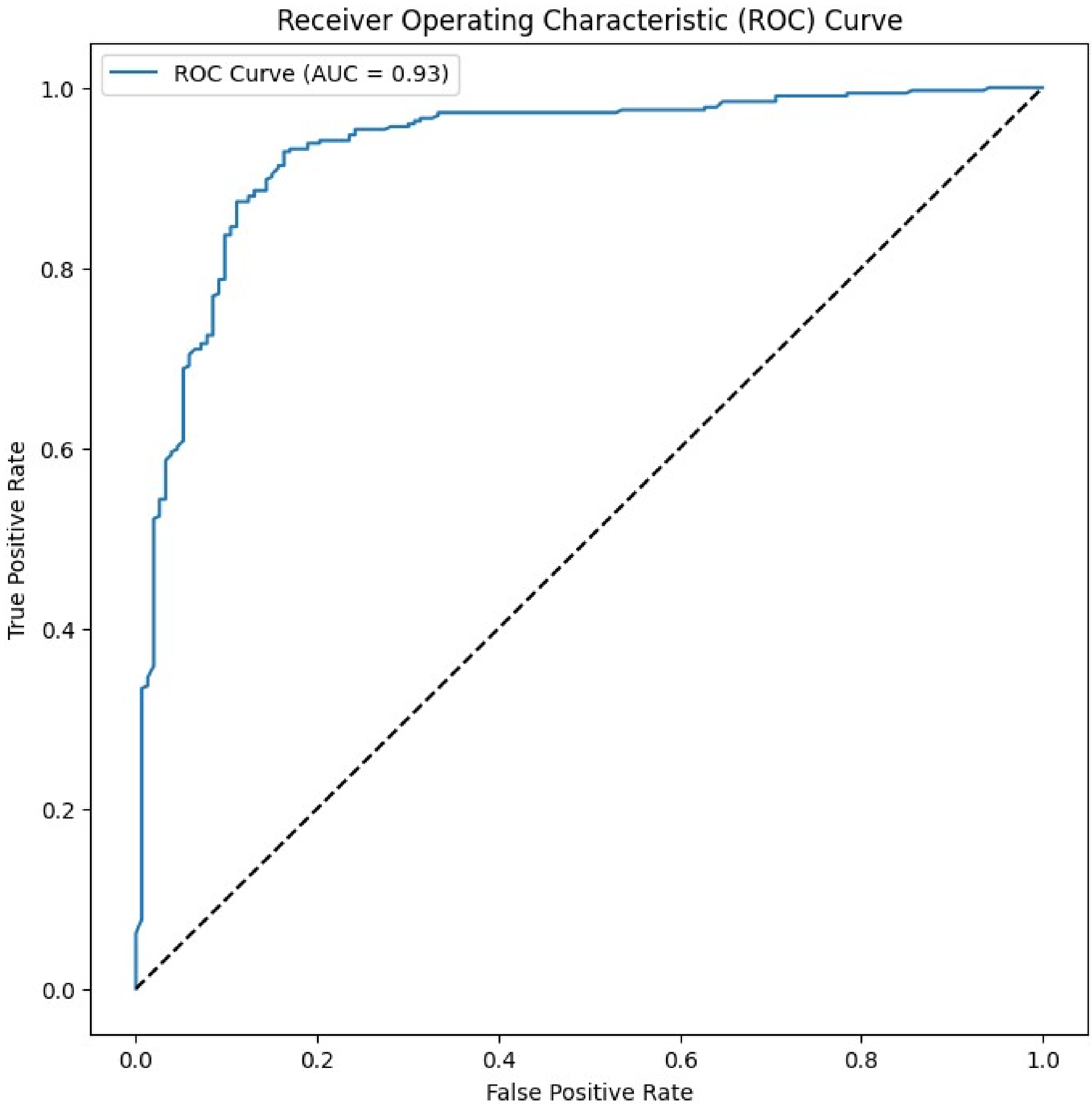
```
/usr/local/lib/python3.10/dist-packages/skopt/optimizer/
optimizer.py:449: UserWarning: The objective has been evaluated at
this point before.
  warnings.warn("The objective has been evaluated "
/usr/local/lib/python3.10/dist-packages/skopt/optimizer/optimizer.py:4
49: UserWarning: The objective has been evaluated at this point
before.
  warnings.warn("The objective has been evaluated "
/usr/local/lib/python3.10/dist-packages/skopt/optimizer/optimizer.py:4
49: UserWarning: The objective has been evaluated at this point
before.
  warnings.warn("The objective has been evaluated "
/usr/local/lib/python3.10/dist-packages/skopt/optimizer/optimizer.py:4
49: UserWarning: The objective has been evaluated at this point
before.
  warnings.warn("The objective has been evaluated "
/usr/local/lib/python3.10/dist-packages/skopt/optimizer/optimizer.py:4
49: UserWarning: The objective has been evaluated at this point
before.
  warnings.warn("The objective has been evaluated "
/usr/local/lib/python3.10/dist-packages/skopt/optimizer/optimizer.py:4
49: UserWarning: The objective has been evaluated at this point
before.
```

```
  warnings.warn("The objective has been evaluated "
/usr/local/lib/python3.10/dist-packages/skopt/optimizer/optimizer.py:4
49: UserWarning: The objective has been evaluated at this point
before.
  warnings.warn("The objective has been evaluated "
/usr/local/lib/python3.10/dist-packages/skopt/optimizer/optimizer.py:4
49: UserWarning: The objective has been evaluated at this point
before.
  warnings.warn("The objective has been evaluated "
```

```
Best Hyperparameters: OrderedDict([('max_depth', 41),
('min_samples_leaf', 1), ('min_samples_split', 2), ('n_estimators',
698)])
```

```python
# Train the Random Forest model with the best hyperparameters
best_rf_resampled = opt.best_estimator_
best_rf_resampled.fit(X_train_resampled, y_train_resampled)

# Make predictions on the test set
y_pred = best_rf_resampled.predict(X_test)
y_pred_proba = best_rf_resampled.predict_proba(X_test)[:, 1]

# Calculate performance metrics
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_proba)

print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1Score: {f1}")
print(f"ROC AUC: {roc_auc}")

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test,
best_rf_resampled.predict_proba(X_test)[:, 1])
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```

```
Precision: 0.926984126984127
Recall: 0.9012345679012346
F1Score: 0.9139280125195619
ROC AUC: 0.931836520616477
```




```
from sklearn.metrics import classification_report, confusion_matrix
# Classification Report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)

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

```
           0       0.80      0.85      0.83       153
           1       0.93      0.90      0.91       324

    accuracy                           0.88       477
   macro avg       0.86      0.88      0.87       477
weighted avg       0.89      0.88      0.89       477

Confusion Matrix:
[[130  23]
 [ 32 292]]
```

Conclusion of Results:

1)AUC-ROC: 0.93

2)F1score for Class 0 (Minority class):- 0.83 & For class 1:-0.91

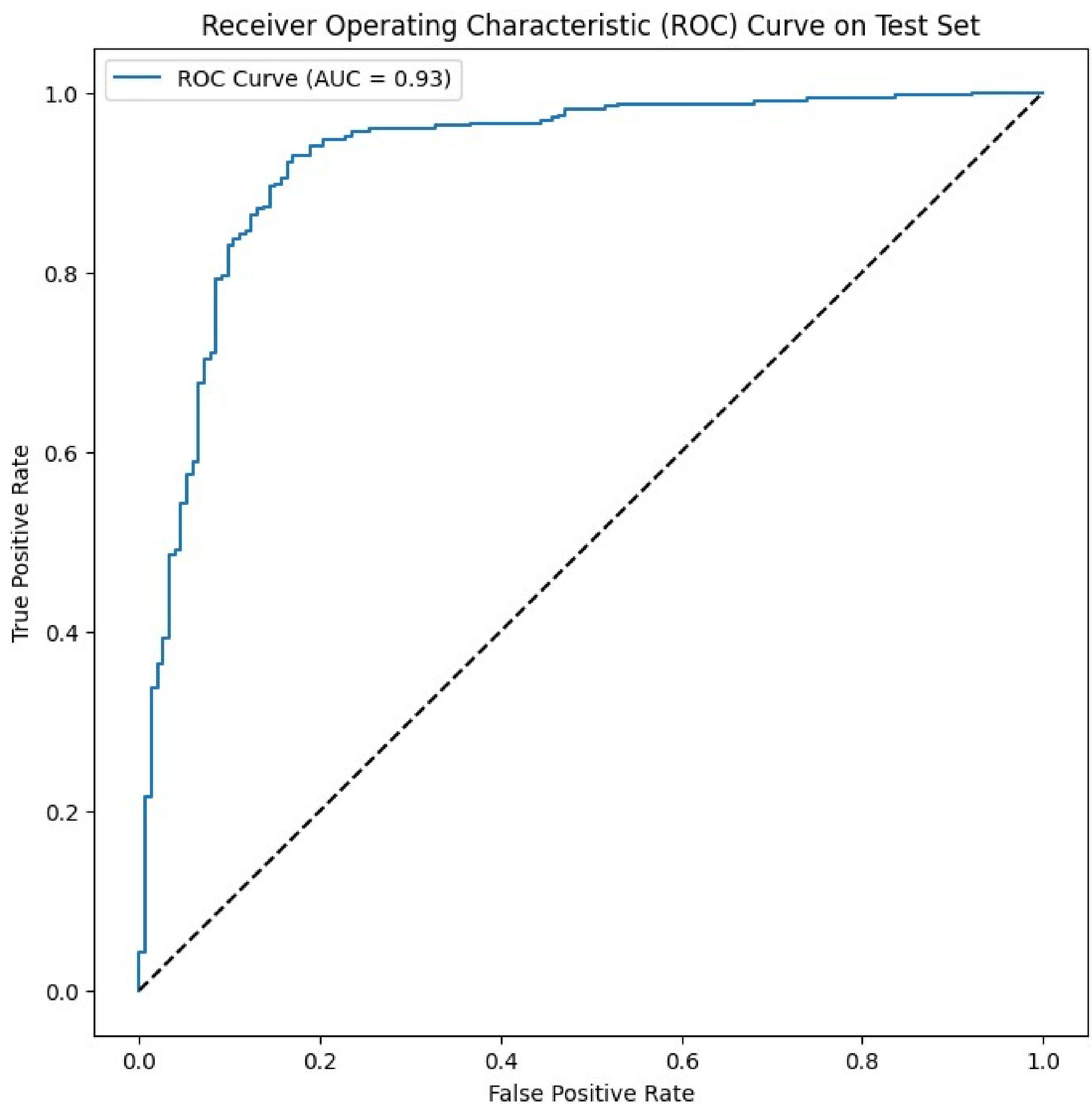
3)55 Missclassified out of 477 test data points.

```python
import xgboost as xgb
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix,
precision_score, recall_score, f1_score, roc_auc_score, roc_curve
from skopt import BayesSearchCV



# Define the search space for hyperparameters
param_space = {
    'learning_rate': (0.01, 1.0, 'log-uniform'),
    'n_estimators': (30, 500),
    'max_depth': (3, 50),
    'min_child_weight': (1, 10),
    'subsample': (0.1, 1.0, 'uniform'),
    'gamma': (0, 1.0, 'uniform'),
    'colsample_bytree': (0.1, 1.0, 'uniform'),
}

# Create an XGBoost classifier
xgb_model = xgb.XGBClassifier(random_state=42)

# Perform Bayesian Search CV
opt = BayesSearchCV(xgb_model, param_space, n_iter=50,
cv=StratifiedKFold(n_splits=5, shuffle=True, random_state=42),
scoring='roc_auc', n_jobs=-1, random_state=42)
opt.fit(X_train_resampled, y_train_resampled)

# Print the best hyperparameters
print("Best Hyperparameters:", opt.best_params_)
```

```
# Evaluate on the validation set
best_xgb_model = opt.best_estimator_
y_pred_proba = best_xgb_model.predict_proba(X_test)[:, 1]
y_pred = best_xgb_model.predict(X_test)

# Calculate performance metrics
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_proba)

print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1Score: {f1}")
print(f"ROC AUC: {roc_auc}")

# Classification Report
print("Classification Report on Test Set:")
print(classification_report(y_test, y_pred))

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix on Test Set:")
print(conf_matrix)

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, best_xgb_model.predict_proba(X_test)
[:, 1])
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve on Test Set')
plt.legend()
plt.show()
```

```
Best Hyperparameters: OrderedDict([('colsample_bytree',
0.7837945779403727), ('gamma', 0), ('learning_rate',
0.062104881739710675), ('max_depth', 26), ('min_child_weight', 1),
('n_estimators', 500), ('subsample', 0.821710323810336)])
Precision: 0.9213836477987422
Recall: 0.904320987654321
F1Score: 0.912772585669782
ROC AUC: 0.9263495521665456
Classification Report on Test Set:
              precision    recall  f1-score   support

           0       0.81      0.84      0.82       153
```

```
           1       0.92      0.90      0.91       324

    accuracy                           0.88       477
   macro avg       0.86      0.87      0.87       477
weighted avg       0.88      0.88      0.88       477

Confusion Matrix on Test Set:
[[128  25]
 [ 31 293]]
```



```
#Now lets see feature importances for xgb model we trained

# Get the booster from the trained XGBoost model
booster = best_xgb_model.get_booster()

# Get feature importances based on how many times a feature is used
for splitting
feature_importances = booster.get_score(importance_type='weight')

# Sort the features based on their importances
sorted_feature_importances = sorted(feature_importances.items(),
key=lambda x: x[1], reverse=True)

# Display the sorted feature importances
for feature, importance in sorted_feature_importances:
    print(f"{feature}: {importance}")
```

```
Income: 6220.0
Age: 4671.0
City: 4580.0
Total Business Value: 3246.0
JoiningMonth: 2961.0
SumOf_diff_bussValue: 1592.0
Joining Designation: 959.0
Grade: 620.0
Quarterly Rating: 483.0
RatingIncrease: 320.0
IncomeIncrease: 4.0
```

Conclusion of Results:

1)AUC-ROC: 0.93

2)F1score for Class 0 (Minority class):- 0.82 & For class 1:-0.91

3)56 Missclassified out of 477 test data points.

4)Income is Most important feature

LightGBM on Resampled Data

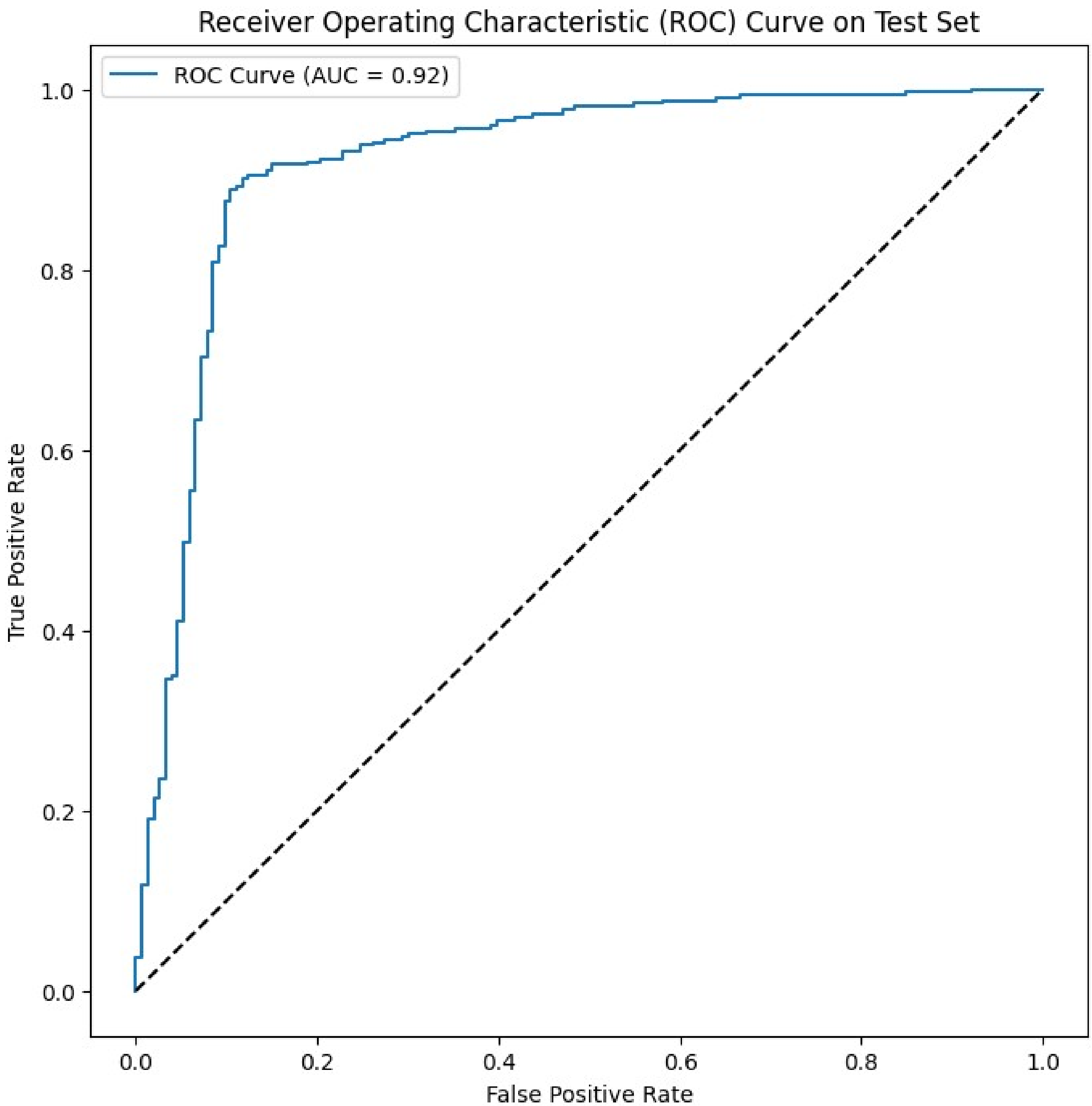
```
import lightgbm as lgb
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import classification_report, roc_auc_score,
precision_recall_fscore_support, roc_curve
from skopt import BayesSearchCV
import matplotlib.pyplot as plt
```

```python
# Define the search space for hyperparameters
param_space = {
    'learning_rate': (0.01, 1.0, 'log-uniform'),
    'n_estimators': (30, 500),
    'max_depth': (3, 100),
    'subsample': (0.1, 1.0, 'uniform'),
    'colsample_bytree': (0.1, 1.0, 'uniform'),
    'reg_alpha': (1e-9, 20.0, 'log-uniform'),
    'reg_lambda': (1e-9, 20.0, 'log-uniform'),
}

# Create a LightGBM classifier
lgb_model = lgb.LGBMClassifier(random_state=42)

# Perform Bayesian Search CV
opt = BayesSearchCV(lgb_model, param_space, n_iter=50,
cv=StratifiedKFold(n_splits=5, shuffle=True, random_state=42),
scoring='roc_auc', n_jobs=-1, random_state=42)
opt.fit(X_train_resampled, y_train_resampled)

# Print the best hyperparameters
print("Best Hyperparameters:", opt.best_params_)

# Evaluate on the test set
best_lgb_model = opt.best_estimator_
y_test_pred_prob = best_lgb_model.predict_proba(X_test)[:, 1]
y_test_pred = (y_test_pred_prob > 0.5).astype(int)


# Calculate performance metrics
precision = precision_score(y_test, y_test_pred)
recall = recall_score(y_test, y_test_pred)
f1 = f1_score(y_test, y_test_pred)
roc_auc = roc_auc_score(y_test, y_test_pred_prob)

print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 score: {f1}")
print(f"ROC-AUC: {roc_auc}")

# Classification Report
print("Classification Report on Test Set:")
print(classification_report(y_test, y_test_pred))

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, y_test_pred_prob)
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'k--')
```

```python
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve on Test Set')
plt.legend()
plt.show()

# Feature Importances
feature_importances = best_lgb_model.feature_importances_
sorted_feature_importances = sorted(zip(feature_importances,
feature_names), reverse=True)
print("Feature Importances:")
for importance, feature in sorted_feature_importances:
    print(f"{feature}: {importance}")
```

```
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly
set num_leaves OR 2^max_depth > num_leaves. (num_leaves=31).
[LightGBM] [Warning] Found whitespace in feature_names, replace with
underlines
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly
set num_leaves OR 2^max_depth > num_leaves. (num_leaves=31).
[LightGBM] [Info] Number of positive: 1292, number of negative: 1292
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead
of testing was 0.000181 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 1613
[LightGBM] [Info] Number of data points in the train set: 2584, number
of used features: 11
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 ->
initscore=0.000000
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
Best Hyperparameters: OrderedDict([('colsample_bytree', 1.0),
('learning_rate', 0.4806783064196515), ('max_depth', 100),
('n_estimators', 500), ('reg_alpha', 1e-09), ('reg_lambda', 20.0),
('subsample', 0.7325774689544908)])
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly
set num_leaves OR 2^max_depth > num_leaves. (num_leaves=31).
Precision: 0.930379746835443
Recall: 0.9074074074074074
F1 score: 0.91875
ROC-AUC: 0.9185023803760187
Classification Report on Test Set:
              precision    recall  f1-score   support
```

```
             0       0.81      0.86      0.83       153
             1       0.93      0.91      0.92       324

      accuracy                           0.89       477
     macro avg       0.87      0.88      0.88       477
  weighted avg       0.89      0.89      0.89       477
```




```
Feature Importances:
Income: 3456
```

```
Age: 2801
City: 2799
JoiningMonth: 1873
Total Business Value: 1743
SumOf_diff_bussValue: 1353
Joining Designation: 361
Quarterly Rating: 224
RatingIncrease: 179
Grade: 179
IncomeIncrease: 0
```

```
# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
Confusion Matrix:
[[128  25]
 [ 31 293]]
```

Conclusion of Results:

1)AUC-ROC: 0.93

2)F1score for Class 0 (Minority class):- 0.81 & For class 1:-0.90

3)56 Missclassified out of 477 test data points.

4)Total Bussiness value is Most important feature

Important thing to Note:- Performance of all these models is same after resampling of data using SMOTE.

Conclusion

BEST MODEL RUSBoost performed the best with the lowest number of Missclassified Points.

Results:

1)AUC-ROC: 0.93

2)F1score for Class 0 (Minority class):- 0.84 & For class 1:-0.92

3)51 Missclassified out of 477 test data points.

4)SumOf_diff_bussValue is Most important feature.

Best Model Hyperparameters

('algorithm' = 'SAMME.R'), ('base_estimator__max_depth' = 63), ('base_estimator__min_samples_leaf' = 10), ('base_estimator__min_samples_split' = 10), ('learning_rate' = 1.0), ('n_estimators' = 400)

Recommendations for the company

Recommendations:-

1)Company should work closely with drivers whose Total Bussiness value is Not increasing or decreasing month after month of reporting and help them increase it.

2)Company should do the analysis of reveiws of the users and inform the driver about why their ratings are not increasing or why it is decreasing. This should help the driver make the necessary changes which will help their Grade, Rating and Income Increase.

3)More incentives should be provided to such drivers (like:- decrease in commision that the company takes from this driver) which will make them not leave.