About Ola

Ola is a major player in the ride-hailing industry, known for its vast network of drivers and vehicles, providing convenient and affordable transportation options. However, it faces significant challenges in driver recruitment and retention, which directly impact its operational efficiency and customer satisfaction.

Problem Statement

Ola is struggling with high attrition rates among its drivers. This churn creates multiple challenges:

1. **Operational Challenges**: A constant need to recruit new drivers, which is costly and resource-intensive.
2. **Retention Issues**: Difficulty in retaining existing drivers who might leave due to dissatisfaction, better offers, or other factors.
3. **Business Impact**: Frequent driver exits impact morale, operational consistency, and financial stability since acquiring new drivers is more expensive than retaining current ones.

The goal is to predict whether a driver will leave the company based on historical and demographic data, enabling Ola to take proactive steps to improve retention.

Objective

The primary objective is:

- **Predict driver attrition** using available data (demographics, tenure, performance, etc.).
- This prediction will help Ola identify at-risk drivers and design targeted interventions (e.g., incentives, support programs, or policy changes) to retain them and reduce operational costs.

Concepts Used

This project incorporates the following key data science and machine learning techniques:

1. **Ensemble Learning - Bagging**:

    - A technique that combines predictions from multiple models (e.g., Random Forest) to reduce variance and improve prediction stability and accuracy.

2. **Ensemble Learning - Boosting**:

    - An iterative approach that focuses on correcting errors made by weak models in the previous iterations (e.g., Gradient Boosting, XGBoost).

3. **KNN Imputation of Missing Values**:

    - A method to handle missing data by imputing values based on the similarity (proximity) of data points.

4. **Working with an Imbalanced Dataset**:

    - Addressing class imbalance where attrition (leaving drivers) might be a minority class compared to non-attrition. Techniques such as SMOTE (Synthetic Minority Oversampling Technique), under-sampling, or class-weighted algorithms may be used to balance the dataset for better model performance.

Libraries

In [2]:
```
import numpy as np
import pandas as pd
```

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

from sklearn.preprocessing import MinMaxScaler

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classifi
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import roc_curve, roc_auc_score

from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RandomizedSearchCV
import datetime as dt

import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```python
pd.set_option('display.max_columns', None)
```

Exploring the data...

In [4]:
```python
data = pd.read_csv('ola_driver_scaler.csv')
```

In [5]:
```python
data.head()
```

Out[5]:

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Da
0	0	01/01/19	1	28.0	0.0	C23	2	57387	
1	1	02/01/19	1	28.0	0.0	C23	2	57387	
2	2	03/01/19	1	28.0	0.0	C23	2	57387	
3	3	11/01/20	2	31.0	0.0	C7	2	67016	
4	4	12/01/20	2	31.0	0.0	C7	2	67016	

In [6]:
```python
# Checking the number of rows and columns
print(f"The number of rows: {data.shape[0]:,} \nThe number of columns: {data.s
```

```
The number of rows: 19,104
The number of columns: 14
```

In [7]:
```python
# Check all column names
data.columns
```

Out[7]:
```
Index(['Unnamed: 0', 'MMM-YY', 'Driver_ID', 'Age', 'Gender', 'City',
       'Education_Level', 'Income', 'Dateofjoining', 'LastWorkingDate',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating'],
      dtype='object')
```

Observations on Data

In [8]:
```python
data.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
```

OBSERVATION

1. **Data Overview**:
    - Total entries: **19,104 rows**
    - Total columns: **14**
    - Missing data in columns:
        - **Age**: 61 missing values.
        - **Gender**: 52 missing values.
        - **LastWorkingDate**: Majority missing (17,488 missing values, only 1,616 non-null). Likely indicates currently active drivers.
2. **Columns Details**:

- `MMMM-YY` (object): Monthly reporting date. Time-based feature for trend analysis.
- `Driver_ID` (int64): Unique identifier for drivers.
- `Age` (float64): Driver's age, has 61 missing values.
- `Gender` (float64): Encoded (Male = 0, Female = 1). Missing values need imputation.
- `City` (object): Categorical variable, encoded city codes.
- `Education_Level` (int64): Encoded education levels (0 = 10+, 1 = 12+, 2 = graduate).
- `Income` (int64): Monthly average income of the driver.
- `DateOfJoining` (object): Date when the driver joined the company.
- `LastWorkingDate` (object): Date when the driver left (or null if still active).
- `Joining Designation` (int64): Initial designation of the driver.
- `Grade` (int64): Grade assigned to the driver during the reporting period.
- `Total Business Value` (int64): Monthly business value, with potential for negative values indicating cancellations or refunds.
- `Quarterly Rating` (int64): Driver performance rating (1 to 5).

3. **Data Challenges**:

    - **Missing Values**: Key variables like `Age`, `Gender`, and especially `LastWorkingDate` have missing values requiring appropriate handling.
    - **Imbalanced Dataset**: Drivers with `LastWorkingDate` populated are likely those who have left, potentially creating an imbalance in attrition prediction.
    - **Temporal Features**: `MMMM-YY`, `DateOfJoining`, and `LastWorkingDate` need preprocessing to derive tenure and time-based features.

4. **Potential Derived Features**:

    - **Driver Tenure**: Difference between reporting date (`MMMM-YY`) and joining date (`DateOfJoining`).
    - **Activity Status**: Binary column indicating whether the driver is active (`LastWorkingDate` is null) or has left (`LastWorkingDate` populated).

- **Income Trends**: Calculate income trends over time for active drivers.
- **Performance Metrics**: Analyze `Quarterly Rating` and `Total Business Value` trends.

In [9]:
```
# Number of unique values in each coluumn and datatype:
print("Number of unique values in each coluumn and datatype:")
print("-" * 55)
for i, elem in (enumerate(data.columns)):
  print(f"{i+1}. {elem}: {data[elem].nunique(), data[elem].dtypes}")
```

```
Number of unique values in each coluumn and datatype:
-------------------------------------------------------
1. Unnamed: 0: (19104, dtype('int64'))
2. MMM-YY: (24, dtype('O'))
3. Driver_ID: (2381, dtype('int64'))
4. Age: (36, dtype('float64'))
5. Gender: (2, dtype('float64'))
6. City: (29, dtype('O'))
7. Education_Level: (3, dtype('int64'))
8. Income: (2383, dtype('int64'))
9. Dateofjoining: (869, dtype('O'))
10. LastWorkingDate: (493, dtype('O'))
11. Joining Designation: (5, dtype('int64'))
12. Grade: (5, dtype('int64'))
13. Total Business Value: (10181, dtype('int64'))
14. Quarterly Rating: (4, dtype('int64'))
```

Processing the data

In [10]:
```
# Creating a deep copy
df1 = data.copy()
```

In [11]:
```
# Remove Unnamed column
df1.drop('Unnamed: 0', axis=1,inplace=True)
```

In [12]:
```
# Doing the required operations for each columns
df1 = df1.rename(columns={'MMM-YY': 'Reporting_Date'})
df1['Reporting_Date'] = pd.to_datetime(df1['Reporting_Date'], format='mixed',e
df1['Dateofjoining'] = pd.to_datetime(df1['Dateofjoining'], format='mixed',err
df1['LastWorkingDate'] = pd.to_datetime(df1['LastWorkingDate'], format='mixed'
df1['City'] = df1['City'].astype('category') #OHE
df1["Gender"].replace({0.0:"Male",1.0:"Female"},inplace=True)
df1['Gender'] = df1['Gender'].astype('category') #Convert to int after EDA
df1['Education_Level'] = df1['Education_Level'].astype('category') #Convert to
df1['Joining Designation'] = df1['Joining Designation'].astype('category') #Co
df1['Grade'] = df1['Grade'].astype('category') #Convert to int after EDA
```

In [13]:
```
print(df1.dtypes)
```

```
Reporting_Date          datetime64[ns]
Driver_ID                        int64
Age                            float64
Gender                        category
City                          category
Education_Level               category
Income                           int64
Dateofjoining           datetime64[ns]
LastWorkingDate         datetime64[ns]
Joining Designation           category
Grade                         category
Total Business Value             int64
Quarterly Rating                 int64
dtype: object
```

Feature Engineering

Creating Target feature

In [14]:
```python
df1.head(15)
```

Out[14]:

	Reporting_Date	Driver_ID	Age	Gender	City	Education_Level	Income	Dat
0	2019-01-01	1	28.0	Male	C23	2	57387	
1	2019-02-01	1	28.0	Male	C23	2	57387	
2	2019-03-01	1	28.0	Male	C23	2	57387	
3	2020-11-01	2	31.0	Male	C7	2	67016	
4	2020-12-01	2	31.0	Male	C7	2	67016	
5	2019-12-01	4	43.0	Male	C13	2	65603	
6	2020-01-01	4	43.0	Male	C13	2	65603	
7	2020-02-01	4	43.0	Male	C13	2	65603	
8	2020-03-01	4	43.0	Male	C13	2	65603	
9	2020-04-01	4	43.0	Male	C13	2	65603	
10	2019-01-01	5	29.0	Male	C9	0	46368	
11	2019-02-01	5	29.0	Male	C9	0	46368	
12	2019-03-01	5	29.0	Male	C9	0	46368	
13	2020-08-01	6	31.0	Female	C11	1	78728	
14	2020-09-01	6	31.0	Female	C11	1	78728	

In [15]:
```python
churn =  (df1.groupby('Driver_ID').agg({'LastWorkingDate':'last'})['LastWorkir
```

```python
churn['LastWorkingDate'].replace({True:0,False:1},inplace=True) # Churned -> 1
churn.rename(columns={'LastWorkingDate':'churn'},inplace=True)
churn.head()
```

Out[15]:

	Driver_ID	churn
0	1	1
1	2	0
2	4	1
3	5	1
4	6	0

Quarterly Rating

In [16]:
```python
# If Quarterly Rating has increased than value 1 else 0
QR1 =  (df1.groupby('Driver_ID').agg({'Quarterly Rating':'first'})).reset_inde
QR2 = (df1.groupby('Driver_ID').agg({'Quarterly Rating':'last'})).reset_index(
```

In [17]:
```python
QR1.isna().sum(),QR2.isna().sum()
```

Out[17]:
```
(Driver_ID           0
 Quarterly Rating    0
 dtype: int64,
 Driver_ID           0
 Quarterly Rating    0
 dtype: int64)
```

In [18]:
```python
churn = churn.merge(QR1,on='Driver_ID')
churn = churn.merge(QR2,on='Driver_ID')
churn['Rating_increase']=np.where(churn['Quarterly Rating_x'] < churn['Quarter
```

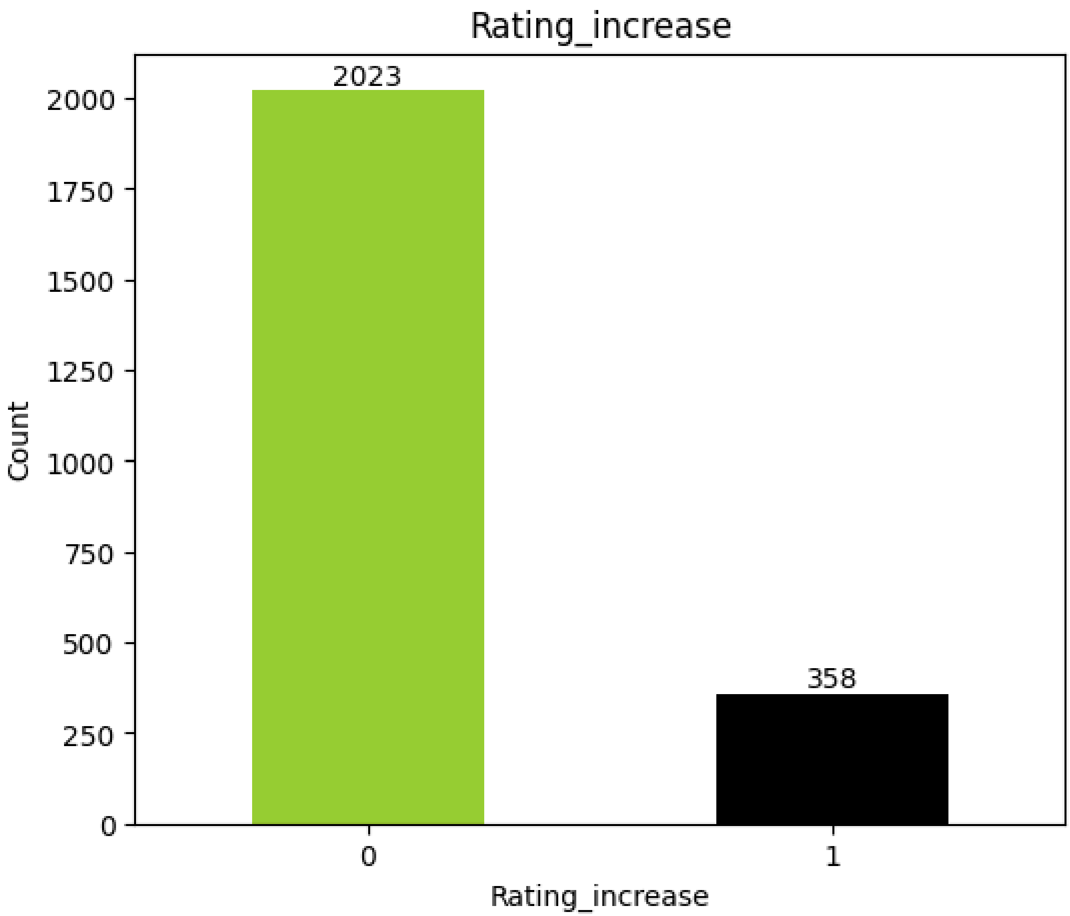
In [19]:
```python
churn.head()
```

Out[19]:

	Driver_ID	churn	Quarterly Rating_x	Quarterly Rating_y	Rating_increase
0	1	1	2	2	0
1	2	0	1	1	0
2	4	1	1	1	0
3	5	1	1	1	0
4	6	0	1	2	1

In [20]:
```python
plt.figure(figsize=(6,5))
label = churn['Rating_increase'].value_counts().plot(kind="bar", color=['yello
for i in label.containers:
    label.bar_label(i)
```

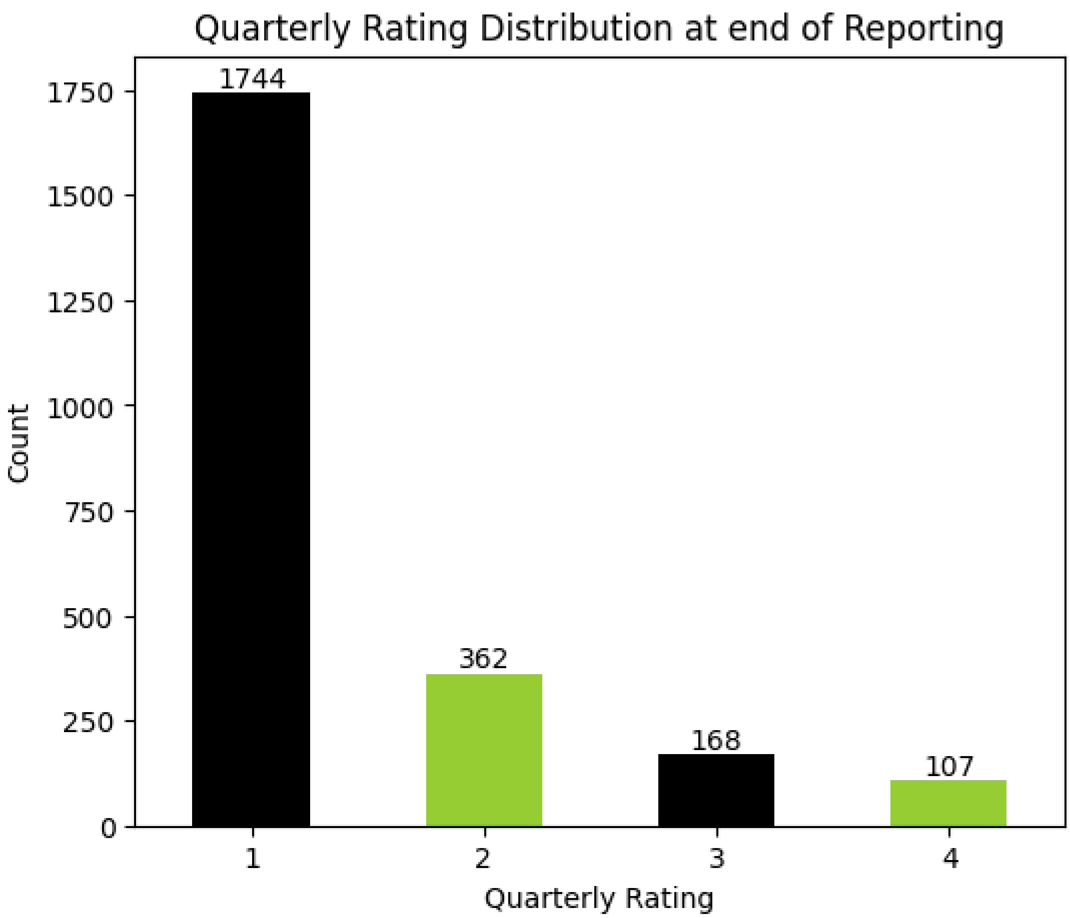
```
plt.xticks(rotation=360)
plt.xlabel("Rating_increase")
plt.ylabel("Count")
plt.title("Rating_increase")
plt.show()
```



🔍**OBSERVATION**🔎

- This indicates that a significant majority 2023 (approximately 85%) of the drivers are either maintaining the same rating or experiencing a decline.
- Only 358 drivers (approximately 15%) showed an improvement in their ratings during the same period.

In [21]:
```
plt.figure(figsize=(6,5))
label = churn['Quarterly Rating_y'].value_counts().plot(kind="bar", color=['bl
for i in label.containers:
    label.bar_label(i)
plt.xticks(rotation=360)
plt.xlabel("Quarterly Rating")
plt.ylabel("Count")
plt.title("Quarterly Rating Distribution at end of Reporting")
plt.show()
```



🔍**OBSERVATION**🔎

- The majority of drivers (1,744 out of the total) have a Quarterly Rating of 1. This indicates that most drivers are rated poorly on their quarterly performance metrics.
- The small number of drivers with higher ratings (3 or 4) suggests that most drivers are underperforming or the rating system is stringent.

Income

In [22]:
```
income1 =  (df1.groupby('Driver_ID').agg({'Income':'first'})['Income']).reset_
income2 = (df1.groupby('Driver_ID').agg({'Income':'last'})['Income']).reset_ir
```

In [23]:
```
income1.shape,income2.shape
```

Out[23]: ((2381, 2), (2381, 2))

In [24]:
```
income1.isna().sum(),income2.isna().sum()
```

Out[24]:
```
(Driver_ID    0
 Income       0
 dtype: int64,
 Driver_ID    0
 Income       0
 dtype: int64)
```

In [25]:
```
churn = churn.merge(income1,on='Driver_ID')
churn = churn.merge(income2,on='Driver_ID')
churn['Income_increase'] = np.where(churn['Income_x'] < churn['Income_y'], 1,0
```

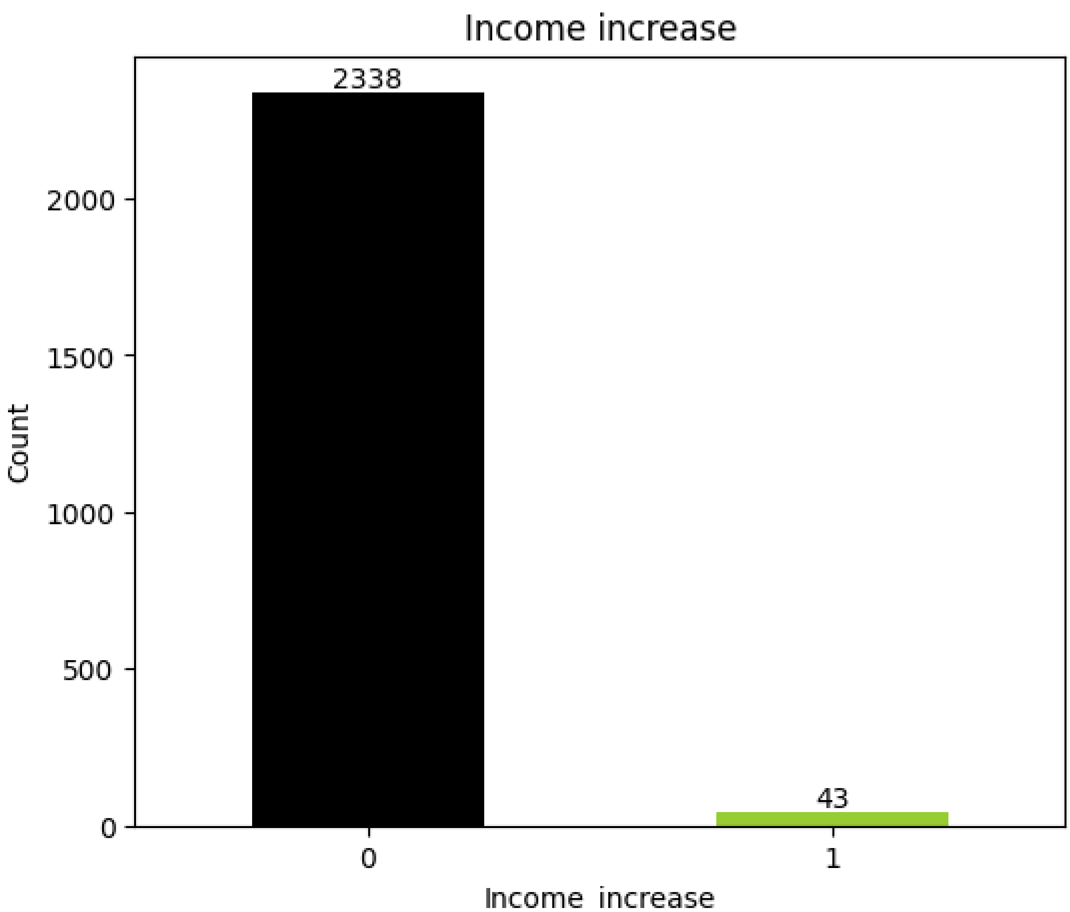
In [26]:
```
churn['Income_increase'].value_counts()
```

Out[26]:

Income_increase	count
0	2338
1	43

dtype: int64

In [27]:
```
plt.figure(figsize=(6,5))
label = churn['Income_increase'].value_counts().plot(kind="bar", color=['black
for i in label.containers:
    label.bar_label(i)
plt.xticks(rotation=360)
plt.xlabel("Income_increase")
plt.ylabel("Count")
plt.title("Income increase")
plt.show()
```



🔍**OBSERVATION**🔎

- Out of the total drivers, 2,338 drivers (approximately 98%) either experienced no increase or a decrease in their income over the observed period. This reflects a significant challenge in driver satisfaction, as stagnant or declining income can lead to dissatisfaction and potentially higher churn.
- Only 43 drivers (approximately 2%) experienced an increase in income during the period. This extremely low percentage indicates that income progression is rare, which could discourage drivers from staying loyal to Ola.

In [28]:
```
churn.columns
```

Out[28]:
```
Index(['Driver_ID', 'churn', 'Quarterly Rating_x', 'Quarterly Rating_y',
       'Rating_increase', 'Income_x', 'Income_y', 'Income_increase'],
      dtype='object')
```

In [29]:
```
target = churn[['Driver_ID','churn','Rating_increase','Income_increase']]
target.head()
```

Out[29]:

	Driver_ID	churn	Rating_increase	Income_increase
0	1	1	0	0
1	2	0	0	0
2	4	1	0	0
3	5	1	0	0
4	6	0	1	0

Aggregated dataframe

In [30]:
```
# Creating a deep copy
df = df1.copy()
```

In [31]:
```
functions = {'Reporting_Date':'count',
             'Driver_ID':'first',
             'Age':'max',
             'Gender':'last',
             'City':'last',
             'Education_Level':'last',
             'Dateofjoining':'first',
             'LastWorkingDate':'last',
             'Grade':'last',
             'Total Business Value':'sum',
             'Income':'last',
             'Joining Designation':'last',
             'Quarterly Rating':'mean'} #last
df = df.groupby('Driver_ID').aggregate(functions).reset_index(drop=True)
df.rename(columns={'Reporting_Date':'Reportings'},inplace=True)
```

In [32]:
```
# Merge with target
df = df.merge(target,on='Driver_ID')
```

In [33]:
```
# Maintaining decimal places
df['Quarterly Rating'] = round(df['Quarterly Rating'],1)
```

In [34]:
```
df.head()
```

Out[34]:

	Reportings	Driver_ID	Age	Gender	City	Education_Level	Dateofjoining	La
0	3	1	28.0	Male	C23	2	2018-12-24	
1	2	2	31.0	Male	C7	2	2020-11-06	
2	5	4	43.0	Male	C13	2	2019-12-07	
3	3	5	29.0	Male	C9	0	2019-01-09	
4	5	6	31.0	Female	C11	1	2020-07-31	

In [35]:
```
df.shape
```

Out[35]:
```
(2381, 16)
```

In [36]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2381 entries, 0 to 2380
Data columns (total 16 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Reportings            2381 non-null   int64
 1   Driver_ID             2381 non-null   int64
 2   Age                   2381 non-null   float64
 3   Gender                2381 non-null   category
 4   City                  2381 non-null   category
 5   Education_Level       2381 non-null   category
 6   Dateofjoining         2381 non-null   datetime64[ns]
 7   LastWorkingDate       1616 non-null   datetime64[ns]
 8   Grade                 2381 non-null   category
 9   Total Business Value  2381 non-null   int64
 10  Income                2381 non-null   int64
 11  Joining Designation   2381 non-null   category
 12  Quarterly Rating      2381 non-null   float64
 13  churn                 2381 non-null   int64
 14  Rating_increase       2381 non-null   int64
 15  Income_increase       2381 non-null   int64
dtypes: category(5), datetime64[ns](2), float64(2), int64(7)
memory usage: 218.3 KB
```

In [37]:
```
# Doing the required operations for each columns
#df['Reportings'] = df['Reportings'].astype('category')
df['Age'] = df['Age'].astype('int')
df['churn'] = df['churn'].astype('category')
#df['Quarterly Rating'] = df['Quarterly Rating'].astype('category')
df['Rating_increase'] = df['Rating_increase'].astype('category')
df['Income_increase'] = df['Income_increase'].astype('category')
```

In [38]:
```
print(df.dtypes)
```

```
Reportings                         int64
Driver_ID                          int64
Age                                int64
Gender                          category
City                            category
Education_Level                 category
Dateofjoining             datetime64[ns]
LastWorkingDate           datetime64[ns]
Grade                           category
Total Business Value               int64
Income                             int64
Joining Designation             category
Quarterly Rating                 float64
churn                           category
Rating_increase                 category
Income_increase                 category
dtype: object
```

In [39]:

```
# Number of unique values in each column and datatype:
print("Number of unique values in each column and datatype:")
print("-" * 55)
for i, elem in (enumerate(df.columns)):
  print(f"{i+1}. {elem}: {df[elem].nunique(), df[elem].dtypes}")
```

```
Number of unique values in each column and datatype:
-------------------------------------------------------
1. Reportings: (24, dtype('int64'))
2. Driver_ID: (2381, dtype('int64'))
3. Age: (36, dtype('int64'))
4. Gender: (2, CategoricalDtype(categories=['Female', 'Male'], ordered=False, c
ategories_dtype=object))
5. City: (29, CategoricalDtype(categories=['C1', 'C10', 'C11', 'C12', 'C13', 'C
14', 'C15', 'C16', 'C17',
                  'C18', 'C19', 'C2', 'C20', 'C21', 'C22', 'C23', 'C24', 'C25',
                  'C26', 'C27', 'C28', 'C29', 'C3', 'C4', 'C5', 'C6', 'C7',
                  'C8', 'C9'],
, ordered=False, categories_dtype=object))
6. Education_Level: (3, CategoricalDtype(categories=[0, 1, 2], ordered=False, c
ategories_dtype=int64))
7. Dateofjoining: (869, dtype('<M8[ns]'))
8. LastWorkingDate: (493, dtype('<M8[ns]'))
9. Grade: (5, CategoricalDtype(categories=[1, 2, 3, 4, 5], ordered=False, categ
ories_dtype=int64))
10. Total Business Value: (1629, dtype('int64'))
11. Income: (2339, dtype('int64'))
12. Joining Designation: (5, CategoricalDtype(categories=[1, 2, 3, 4, 5], order
ed=False, categories_dtype=int64))
13. Quarterly Rating: (31, dtype('float64'))
14. churn: (2, CategoricalDtype(categories=[0, 1], ordered=False, categories_dt
ype=int64))
15. Rating_increase: (2, CategoricalDtype(categories=[0, 1], ordered=False, cat
egories_dtype=int64))
16. Income_increase: (2, CategoricalDtype(categories=[0, 1], ordered=False, cat
egories_dtype=int64))
```

Check for Duplicate

> Add blockquote

In [40]:
```
df[df.duplicated]
```

Out[40]:

Reportings	Driver_ID	Age	Gender	City	Education_Level	Dateofjoining	Last

Missing value treatment

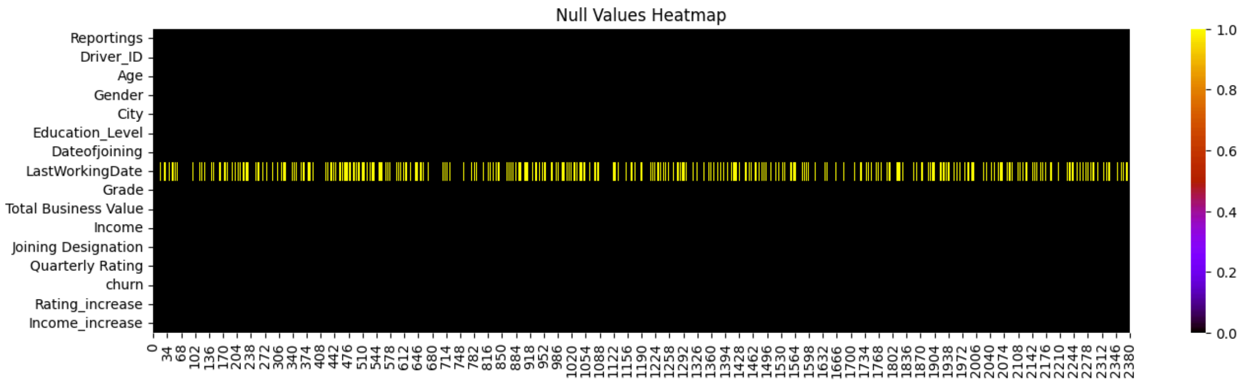
In [41]:
```
# How many percentage of data is missing in each column
missing_value = pd.DataFrame({'Missing Value': df.isnull().sum(), 'Percentage'
missing_value.sort_values(by='Percentage', ascending=False)
```

Out[41]:

	Missing Value	Percentage
LastWorkingDate	765	32.13
Reportings	0	0.00
Age	0	0.00
Driver_ID	0	0.00
Gender	0	0.00
City	0	0.00
Education_Level	0	0.00
Dateofjoining	0	0.00
Grade	0	0.00
Total Business Value	0	0.00
Income	0	0.00
Joining Designation	0	0.00
Quarterly Rating	0	0.00
churn	0	0.00
Rating_increase	0	0.00
Income_increase	0	0.00

In [42]:
```
# Null value heatmap:
plt.figure(figsize = (16,4))
sns.heatmap(df.isnull().T, cmap='gnuplot')
plt.title('Null Values Heatmap')
```

```
plt.show()
```



🔍OBSERVATION🔎

- Lets keep the last working dat as it is because if it is null then the person is still working

In [43]:
```
df.head()
```

Out[43]:

	Reportings	Driver_ID	Age	Gender	City	Education_Level	Dateofjoining	La
0	3	1	28	Male	C23	2	2018-12-24	
1	2	2	31	Male	C7	2	2020-11-06	
2	5	4	43	Male	C13	2	2019-12-07	
3	3	5	29	Male	C9	0	2019-01-09	
4	5	6	31	Female	C11	1	2020-07-31	

In [44]:
```
# Display the range of attributes
print("Range of attributes:")
print("-" * 20)
df.describe(include='all').T
```

```
Range of attributes:
--------------------
```

Out[44]:

	count	unique	top	freq	mean	min
Reportings	2381.0	NaN	NaN	NaN	8.02352	1.0
Driver_ID	2381.0	NaN	NaN	NaN	1397.559009	1.0
Age	2381.0	NaN	NaN	NaN	33.663167	21.0
Gender	2381	2	Male	1404	NaN	NaN
City	2381	29	C20	152	NaN	NaN
Education_Level	2381.0	3.0	2.0	802.0	NaN	NaN
Dateofjoining	2381	NaN	NaN	NaN	2019-02-08 07:14:50.550189056	2013-04-01 00:00:00
LastWorkingDate	1616	NaN	NaN	NaN	2019-12-21 20:59:06.534653440	2018-12-31 00:00:00
Grade	2381.0	5.0	2.0	855.0	NaN	NaN
Total Business Value	2381.0	NaN	NaN	NaN	4586741.822764	-1385530.0
Income	2381.0	NaN	NaN	NaN	59334.157077	10747.0
Joining Designation	2381.0	5.0	1.0	1026.0	NaN	NaN
Quarterly Rating	2381.0	NaN	NaN	NaN	1.567535	1.0
churn	2381.0	2.0	1.0	1616.0	NaN	NaN
Rating_increase	2381.0	2.0	0.0	2023.0	NaN	NaN
Income_increase	2381.0	2.0	0.0	2338.0	NaN	NaN

In [45]:

```
# Display the statistical summary
print("statistical summary:")
print("-" * 20)
df.describe().T
```

```
statistical summary:
--------------------
```

Out[45]:

	count	mean	min	25%	50%
Reportings	2381.0	8.02352	1.0	3.0	5.0
Driver_ID	2381.0	1397.559009	1.0	695.0	1400.0
Age	2381.0	33.663167	21.0	29.0	33.0
Dateofjoining	2381	2019-02-08 07:14:50.550189056	2013-04-01 00:00:00	2018-06-29 00:00:00	2019-07-21 00:00:00
LastWorkingDate	1616	2019-12-21 20:59:06.534653440	2018-12-31 00:00:00	2019-06-06 00:00:00	2019-12-20 12:00:00
Total Business Value	2381.0	4586741.822764	-1385530.0	0.0	817680.0
Income	2381.0	59334.157077	10747.0	39104.0	55315.0
Quarterly Rating	2381.0	1.567535	1.0	1.0	1.0

🔍OBSERVATION🔎

1. **Age**:
    - The average age of drivers is approximately 33.66 years.
    - The age ranges from 21 to 58 years, with a standard deviation of around 5.98 years.
2. **Gender**:
    - The dataset is predominantly male, with 1404 male drivers (around 59% of the dataset) and the remaining being female.
3. **City**:
    - The most frequent city is `C20`, with 152 drivers working there, but there are 29 distinct cities, showing a diverse distribution of drivers.
4. **Total Business Value**:
    - The average total business value per driver is around 4.59 million, but the values range from a minimum of -1.39 million to a maximum of 95.33 million, suggesting significant variation in business performance among drivers.
5. **Income**:
    - The average income is approximately 59,334, with a minimum income of 10,747 and a maximum of 188,418, indicating a wide spread of earnings among drivers.

Exploratory data analysis📊📈

Univariate Analysis

In [46]:
```
# Selecting the categorical columns
categorical_cols = df.select_dtypes(include='category').columns
categorical_cols
```

Out[46]:
```
Index(['Gender', 'City', 'Education_Level', 'Grade', 'Joining Designation',
       'churn', 'Rating_increase', 'Income_increase'],
      dtype='object')
```

In [47]:
```
# Required colour palette
green_palette = ['#187c19', '#69b41e', '#8dc71e', '#b8d53d'] #'#0d5b11',
#green_palette = ['#F5FAD1', '#D1EBA1', '#A6D577', '#76C352', '#438032', '#189
```

In [48]:
```
# Value couts for categorical columns
for elem in categorical_cols:
  print(f"Column Name: {elem}")
  print(df[elem].value_counts())
  print()
  print(round(((df[elem].value_counts(normalize=True)) * 100),2))
  print("_" * 35)
  print()
```

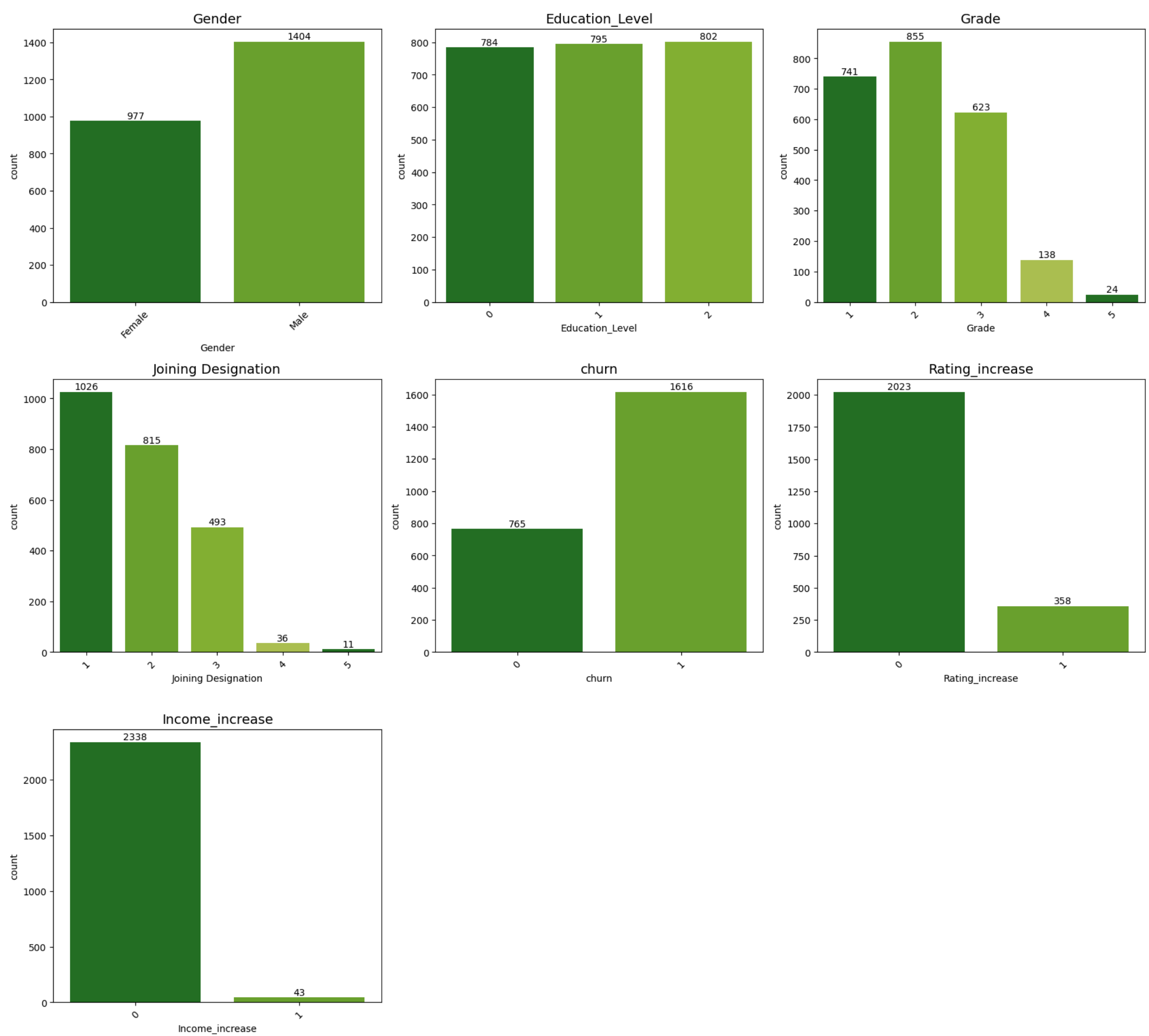
```
Column Name: Gender
Gender
Male      1404
Female     977
Name: count, dtype: int64

Gender
Male      58.97
Female    41.03
Name: proportion, dtype: float64
___________________________________

Column Name: City
City
C20    152
C15    101
C29     96
C26     93
C8      89
C27     89
C10     86
C16     84
C22     82
C3      82
C28     82
C12     81
C1      80
C5      80
C21     79
C14     79
C6      78
C4      77
C7      76
C9      75
C23     74
C25     74
C24     73
C19     72
C2      72
C13     71
C17     71
C18     69
C11     64
Name: count, dtype: int64

City
C20    6.38
C15    4.24
C29    4.03
C26    3.91
C8     3.74
C27    3.74
C10    3.61
C16    3.53
```

```
C22    3.44
C3     3.44
C28    3.44
C12    3.40
C1     3.36
C5     3.36
C21    3.32
C14    3.32
C6     3.28
C4     3.23
C7     3.19
C9     3.15
C23    3.11
C25    3.11
C24    3.07
C19    3.02
C2     3.02
C13    2.98
C17    2.98
C18    2.90
C11    2.69
Name: proportion, dtype: float64
___________________________________

Column Name: Education_Level
Education_Level
2    802
1    795
0    784
Name: count, dtype: int64

Education_Level
2    33.68
1    33.39
0    32.93
Name: proportion, dtype: float64
___________________________________

Column Name: Grade
Grade
2    855
1    741
3    623
4    138
5     24
Name: count, dtype: int64

Grade
2    35.91
1    31.12
3    26.17
4     5.80
5     1.01
Name: proportion, dtype: float64
```

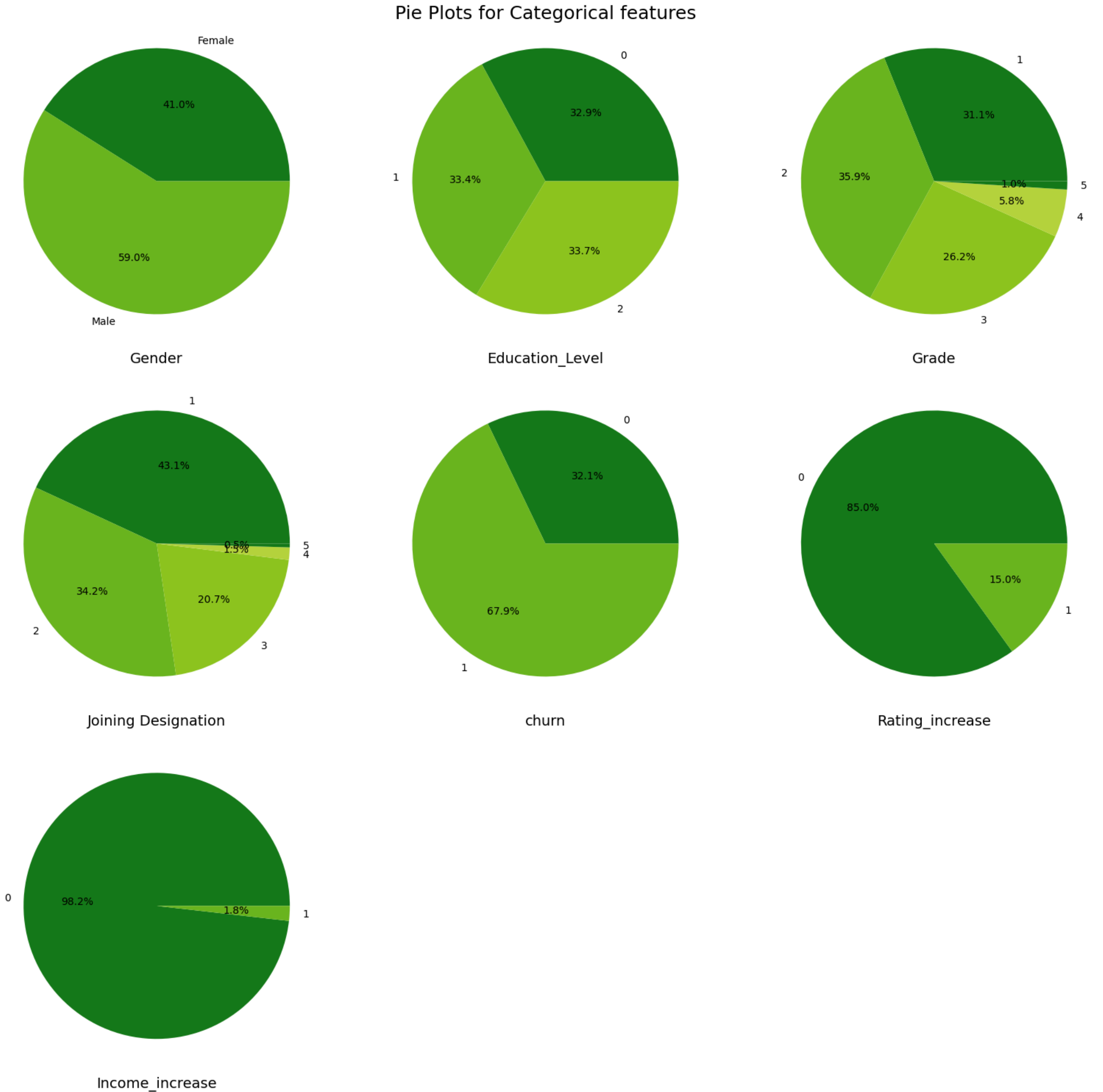
```
----------------------------------------

Column Name: Joining Designation
Joining Designation
1    1026
2     815
3     493
4      36
5      11
Name: count, dtype: int64

Joining Designation
1    43.09
2    34.23
3    20.71
4     1.51
5     0.46
Name: proportion, dtype: float64
----------------------------------------

Column Name: churn
churn
1    1616
0     765
Name: count, dtype: int64

churn
1    67.87
0    32.13
Name: proportion, dtype: float64
----------------------------------------

Column Name: Rating_increase
Rating_increase
0    2023
1     358
Name: count, dtype: int64

Rating_increase
0    84.96
1    15.04
Name: proportion, dtype: float64
----------------------------------------

Column Name: Income_increase
Income_increase
0    2338
1      43
Name: count, dtype: int64

Income_increase
0    98.19
1     1.81
Name: proportion, dtype: float64
```

In [49]:

```
# Count Plots for Categorical features
req_cat_col_plot = ['Gender', 'Education_Level', 'Grade', 'Joining Designation

plt.figure(figsize=(17,20))
for i, elem in enumerate(req_cat_col_plot):
  plt.subplot(4,3,i+1)
  label = sns.countplot(data = df, x = elem, palette = green_palette)
  for i in label.containers:
    label.bar_label(i)

  plt.xticks(rotation = 45)
  plt.ylabel('count')
  plt.title(elem, fontsize=14)

#plt.suptitle("Count Plots for Categorical features", fontsize = 18)
plt.tight_layout()
plt.show()
```

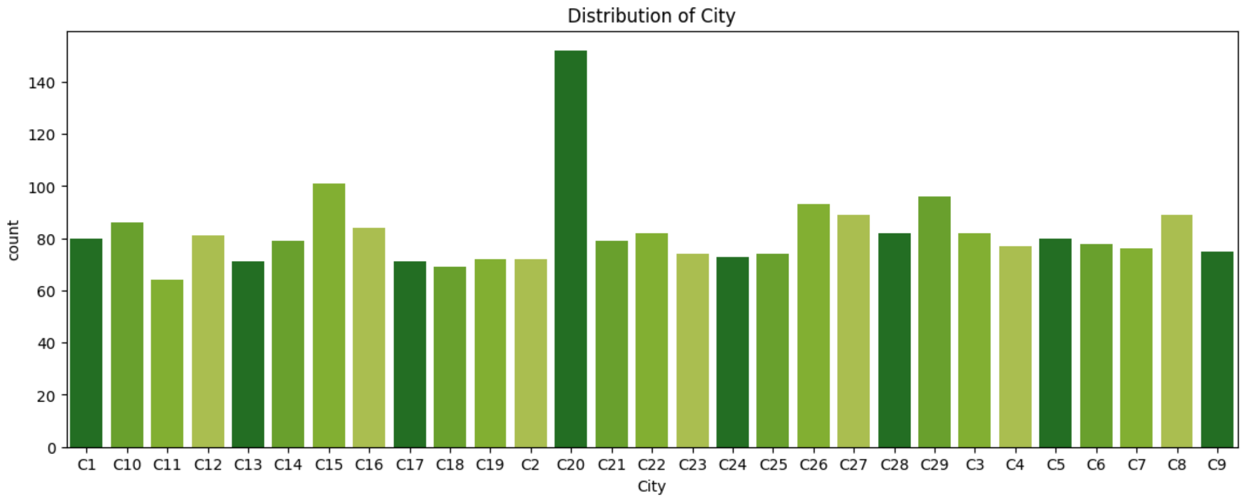


In [50]:
```
# Pie Plots for Categorical features
plt.figure(figsize=(16,20))
for i, elem in enumerate(req_cat_col_plot):
  plt.subplot(4,3,i+1)
  labels = df.groupby(elem)[elem].count().index.categories
  plt.pie(df.groupby(elem)[elem].count().values, labels = labels, autopct = "%
  plt.xlabel(elem, fontsize=14)

plt.suptitle("Pie Plots for Categorical features", fontsize = 18)
plt.tight_layout()
plt.show()
```



In [51]:
```
plt.figure(figsize=(14,5))
sns.countplot(x=df['City'], palette = green_palette)
plt.title('Distribution of City')
```

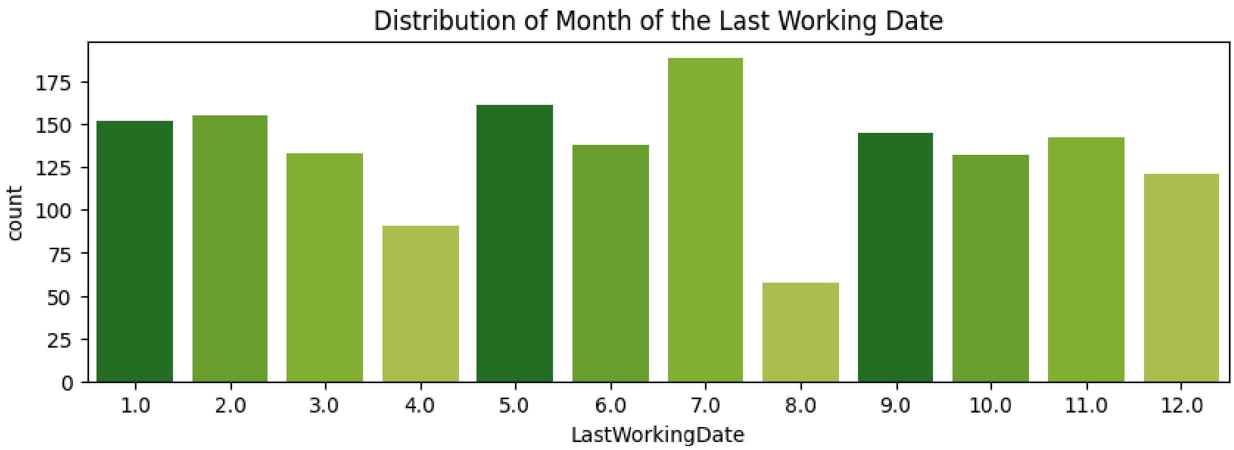
Out[51]: Text(0.5, 1.0, 'Distribution of City')

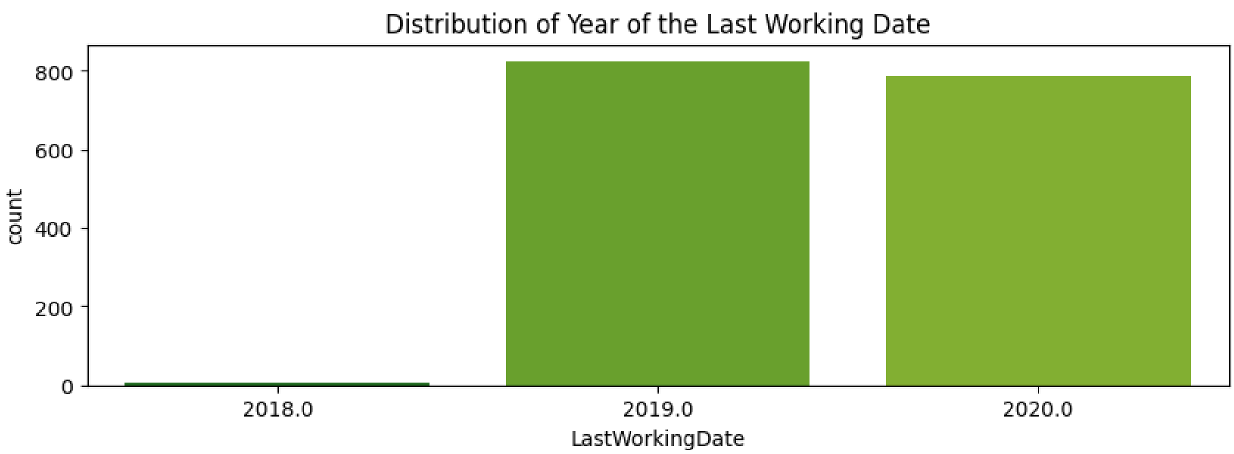


🔍**OBSERVATION**🔎

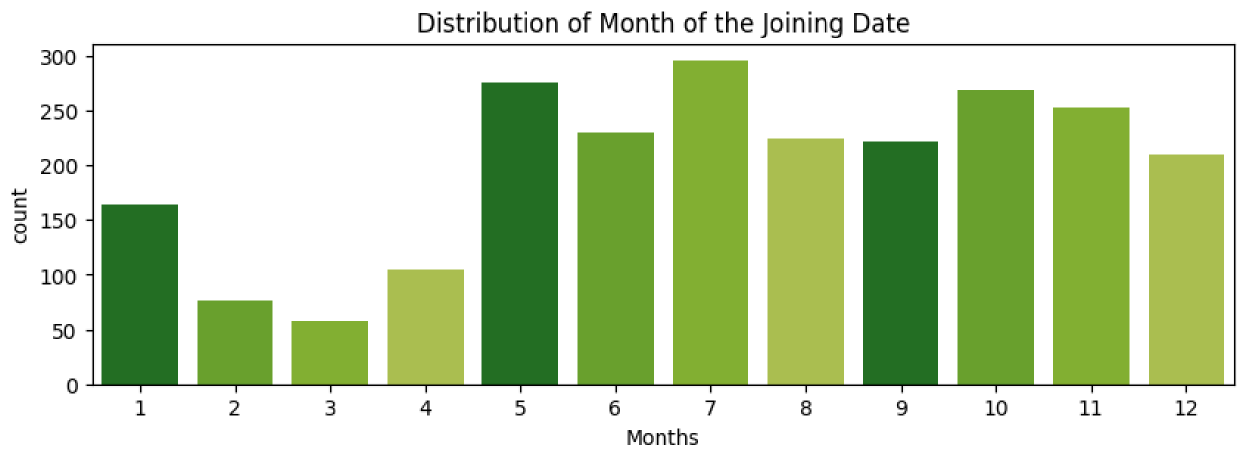
1. **Gender**:
    - The majority of drivers are **Male (58.97%)**.
2. **City**:
    - The most common city is **C20 (6.38%)**.
3. **Education Level**:
    - The most frequent education level is **2 (33.68%)**, which could indicate a moderate educational background.
4. **Grade**:
    - The most prevalent grade is **Grade 2 (35.91%)**, representing a significant portion of drivers.
5. **Joining Designation**:
    - Most drivers started with **Joining Designation 1 (43.09%)**.
6. **Churn**:
    - The churn rate is high, with **67.87% of drivers leaving**.
7. **Rating Increase**:
    - A majority of drivers (**84.96%**) did not experience a rating increase.
8. **Income Increase**:
    - Almost all drivers (**98.19%**) did not receive an income increase.

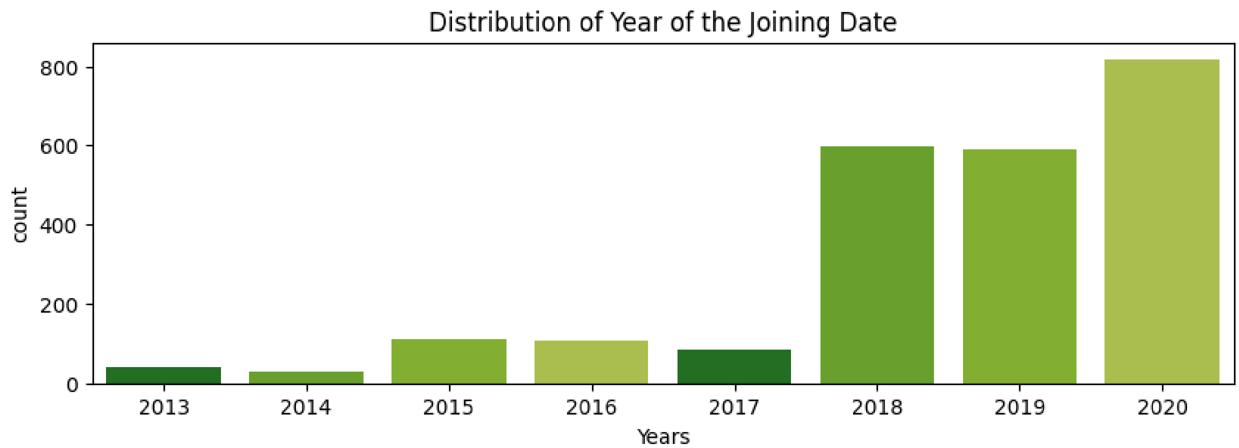
In [52]:
```
plt.figure(figsize=(10,3))
sns.countplot(x=df['LastWorkingDate'].dt.month, palette = green_palette)
plt.title('Distribution of Month of the Last Working Date')

plt.figure(figsize=(10,3))
sns.countplot(x=df['LastWorkingDate'].dt.year, palette = green_palette)
plt.title('Distribution of Year of the Last Working Date')

plt.show()
```





In [53]:
```
plt.figure(figsize=(10,3))
sns.countplot(x=df['Dateofjoining'].dt.month, palette = green_palette)
plt.title('Distribution of Month of the Joining Date')
plt.xlabel('Months')

plt.figure(figsize=(10,3))
sns.countplot(x=df['Dateofjoining'].dt.year, palette = green_palette)
plt.title('Distribution of Year of the Joining Date')
plt.xlabel('Years')

plt.show()
```





In [54]:
```
df.columns
```

Out[54]:
```
Index(['Reportings', 'Driver_ID', 'Age', 'Gender', 'City', 'Education_Level',
       'Dateofjoining', 'LastWorkingDate', 'Grade', 'Total Business Value',
       'Income', 'Joining Designation', 'Quarterly Rating', 'churn',
       'Rating_increase', 'Income_increase'],
      dtype='object')
```

In [55]:
```
df.Age.dtype
```

Out[55]:
```
dtype('int64')
```

In [56]:
```
df.select_dtypes(include=['int32','int64','float64'])
```

Out[56]:

	Reportings	Driver_ID	Age	Total Business Value	Income	Quarterly Rating
0	3	1	28	1715580	57387	2.0
1	2	2	31	0	67016	1.0
2	5	4	43	350000	65603	1.0
3	3	5	29	120360	46368	1.0
4	5	6	31	1265000	78728	1.6
...	...	...	...	...	...	...
2376	24	2784	34	21748820	82815	2.6
2377	3	2785	34	0	12105	1.0
2378	9	2786	45	2815090	35370	1.7
2379	6	2787	28	977830	69498	1.5
2380	7	2788	30	2298240	70254	2.3

2381 rows × 6 columns

In [57]:

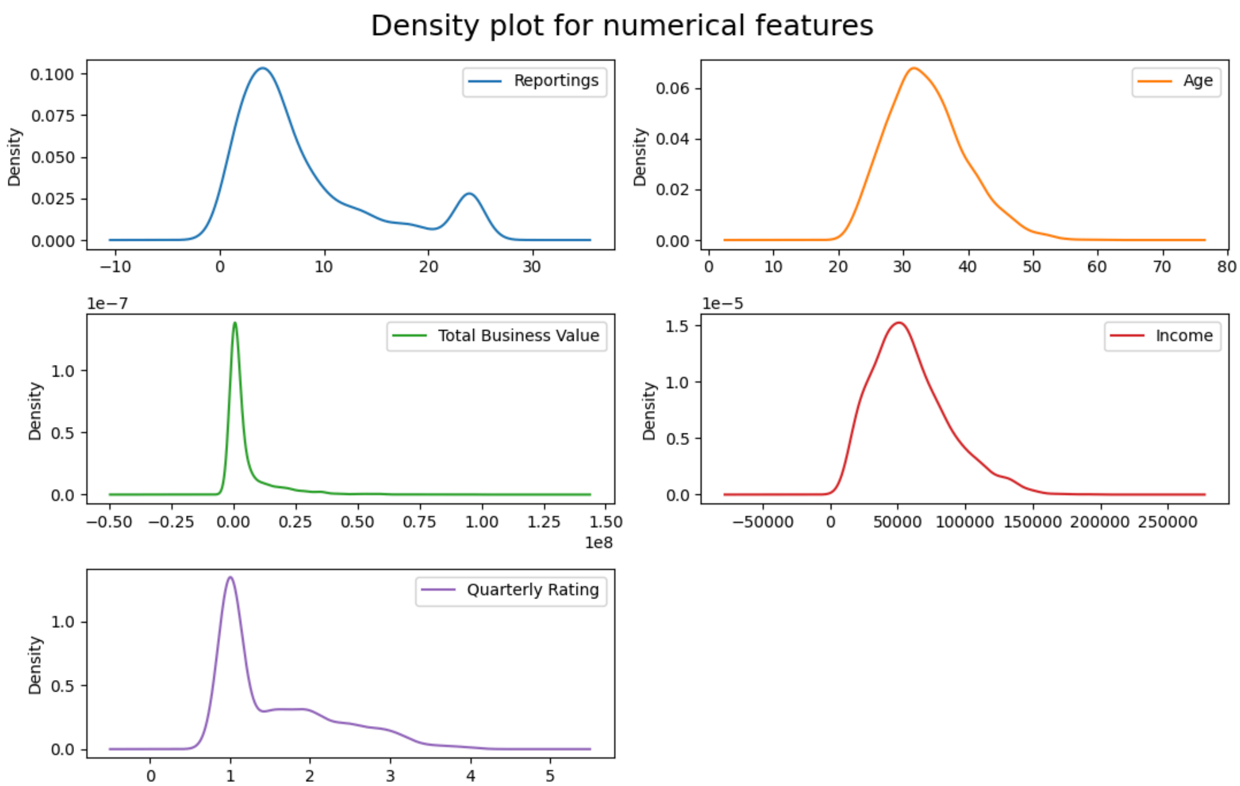
```
# Selecting the categorical columns
numerical_df = df.select_dtypes(include=['int32','int64','float64'])
numerical_df_req = numerical_df[['Reportings', 'Age', 'Total Business Value',
numerical_df_req.columns
```

Out[57]:

```
Index(['Reportings', 'Age', 'Total Business Value', 'Income',
       'Quarterly Rating'],
      dtype='object')
```

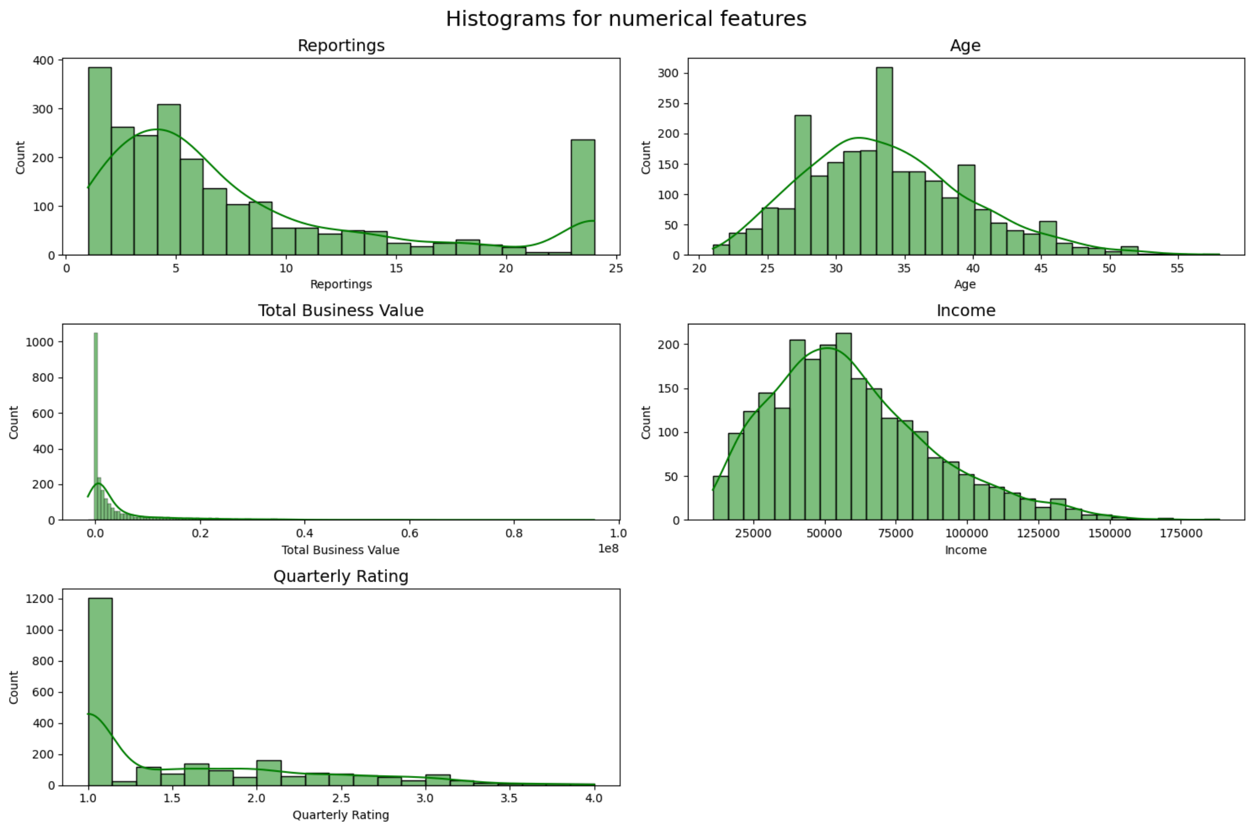
In [58]:

```
# Density plot for numerical columns
plt.rcParams["figure.figsize"] = [11,7]
numerical_df_req.plot(kind="density", subplots = True, layout = (3,2), sharex
plt.suptitle("Density plot for numerical features", fontsize = 18)
plt.tight_layout()
plt.show()
```



In [59]:

```
# Histograms for numerical columns
numerical_cols = numerical_df_req.columns

plt.figure(figsize=(15,10))
for i, elem in enumerate(numerical_cols):
  plt.subplot(3,2,i+1)
  sns.histplot(df[elem], kde=True, color='green')
  plt.title(elem, fontsize=14)

plt.suptitle("Histograms for numerical features", fontsize = 18)
plt.tight_layout()
plt.show()
```



In [60]:
```python
# Skewness Coefficient:
print("Skewness Coefficient")
print("-" * 20)
print(numerical_df_req.skew().round(4))
```

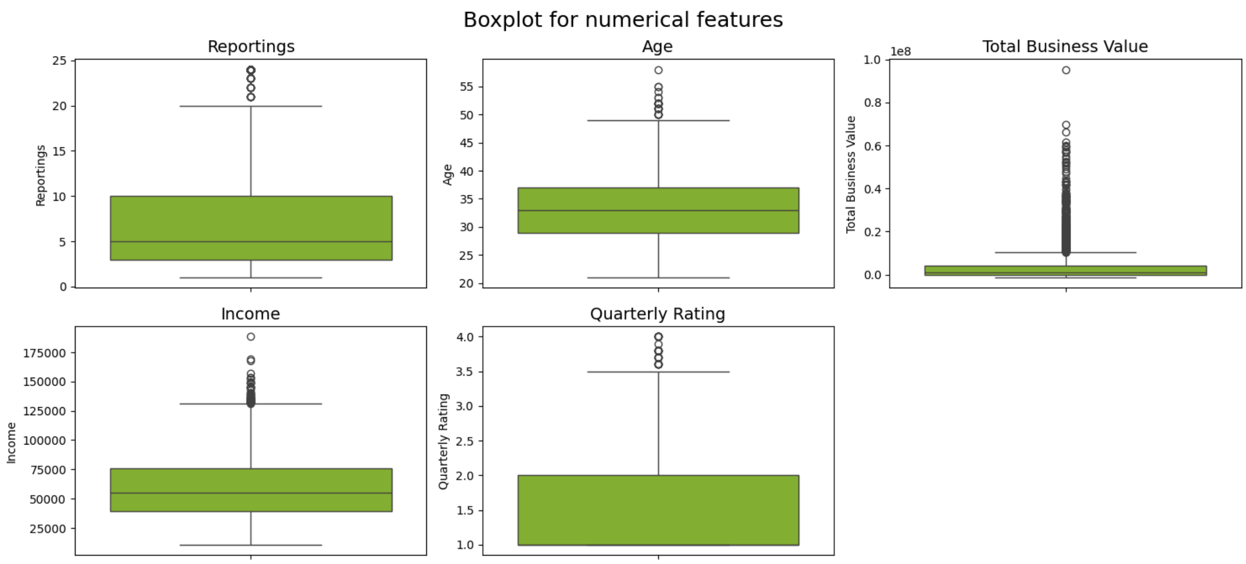
```
Skewness Coefficient
--------------------
Reportings              1.2970
Age                     0.5391
Total Business Value    3.3613
Income                  0.7795
Quarterly Rating        1.0882
dtype: float64
```

🔍OBSERVATION🔎

1. **Reportings**: Skewed positively with a skewness of **1.2970**, indicating a longer tail on the right side.
2. **Age**: Slightly positively skewed with a skewness of **0.5391**, showing a near-normal distribution.
3. **Total Business Value**: Highly positively skewed with a skewness of **3.3613**, suggesting a strong concentration of lower values.
4. **Income**: Positively skewed with a skewness of **0.7795**, indicating a moderate tail of higher income values.
5. **Quarterly Rating**: Positively skewed with a skewness of **1.0882**,

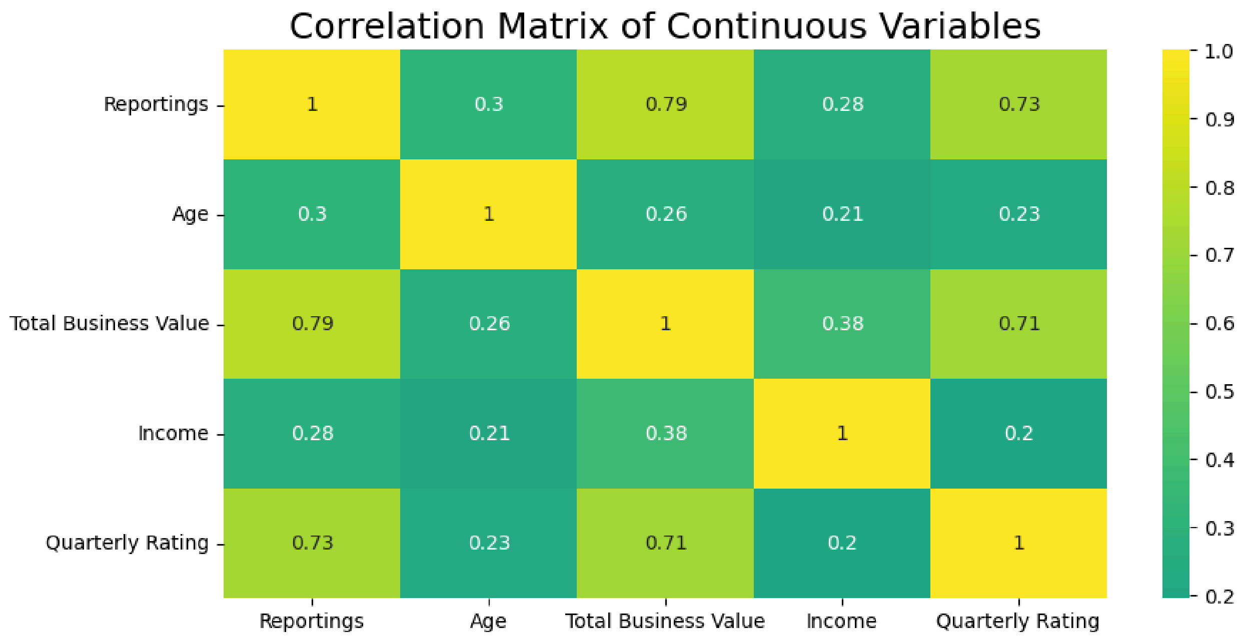
reflecting more drivers with lower ratings.

In [61]:
```
# Box plots for numerical columns
green = ['#8dc71e']

plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols):
    plt.subplot(3, 3, i+1)
    sns.boxplot(df[col],palette = green)
    plt.title(col, fontsize=14)

plt.suptitle("Boxplot for numerical features", fontsize = 18)
plt.tight_layout()
plt.show()
```

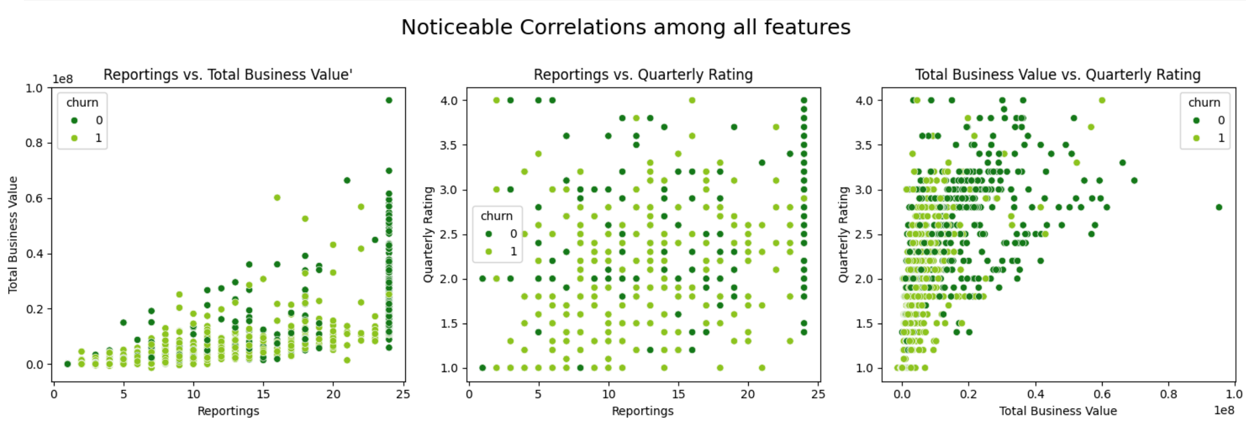


Multivariate Analysis

In [62]:
```
# Correlation Matrix of Continuous Variables
corr_matrix = numerical_df[numerical_cols].corr()
plt.figure(figsize=(10, 5))
sns.heatmap(corr_matrix, annot=True, cmap='viridis', center=0)
plt.title('Correlation Matrix of Continuous Variables', fontsize = 18)
plt.yticks(rotation=360)
plt.show()
```

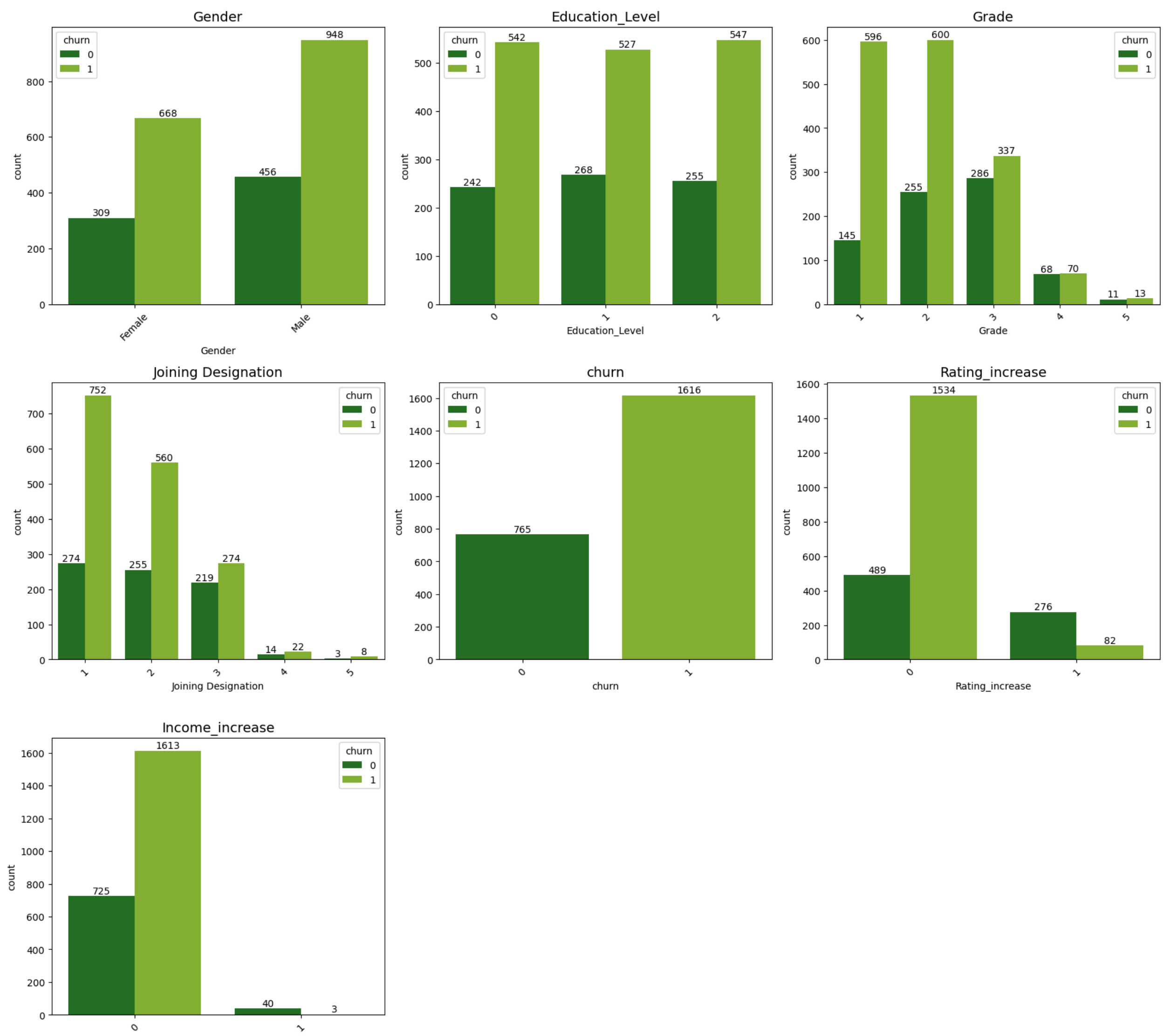


In [63]:
```python
req_palette = ['#187c19', '#8dc71e']
plt.figure(figsize=(15, 5))

plt.subplot(1, 3, 1)
sns.scatterplot(x='Reportings', y='Total Business Value', hue='churn', data=df
plt.title("Reportings vs. Total Business Value'")

plt.subplot(1, 3, 2)
sns.scatterplot(x='Reportings', y='Quarterly Rating', hue='churn', data=df, pa
plt.title("Reportings vs. Quarterly Rating")

plt.subplot(1, 3, 3)
sns.scatterplot(x='Total Business Value', y='Quarterly Rating', hue='churn', d
plt.title("Total Business Value vs. Quarterly Rating")

plt.suptitle("Noticeable Correlations among all features", fontsize = 18)
plt.tight_layout()
plt.show()
```



In [64]:
```python
# Count Plots for Categorical features
```

```
req_cat_col_plot = ['Gender', 'Education_Level', 'Grade', 'Joining Designatior

plt.figure(figsize=(17,20))
for i, elem in enumerate(req_cat_col_plot):
  plt.subplot(4,3,i+1)
  label = sns.countplot(data = df, x = elem, hue='churn', palette = req_palett
  for i in label.containers:
    label.bar_label(i)

  plt.xticks(rotation = 45)
  plt.ylabel('count')
  plt.title(elem, fontsize=14)

#plt.suptitle("Count Plots for Categorical features", fontsize = 18)
plt.tight_layout()
plt.show()
```



In [65]:
```
# Comparisons of Median values of all numerical features by loan status
print("Comparisons of Median values of all numerical features by loan status")
print("-" * 72)
```

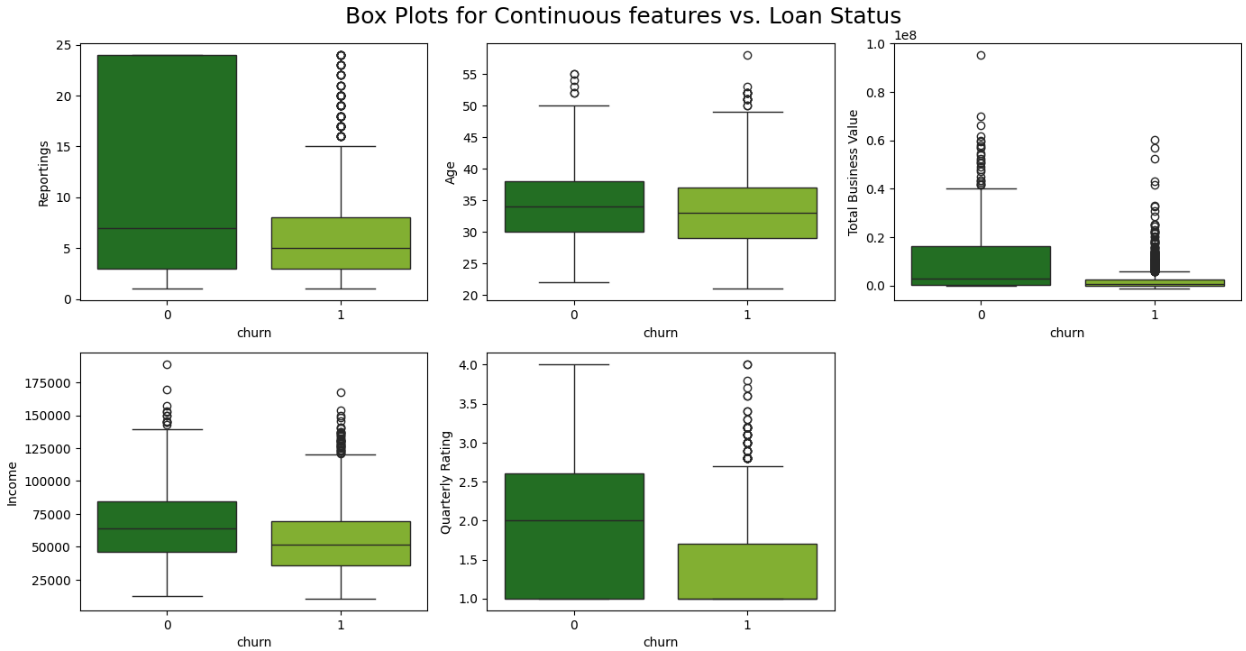
```
for elem in numerical_cols:
  print(f"Column Name: {elem}")
  print(df.groupby('churn')[elem].median())
  print("_" * 35)
  print()
```

```
Comparisons of Median values of all numerical features by loan status
-------------------------------------------------------------------------
Column Name: Reportings
churn
0    7.0
1    5.0
Name: Reportings, dtype: float64
___________________________________

Column Name: Age
churn
0    34.0
1    33.0
Name: Age, dtype: float64
___________________________________

Column Name: Total Business Value
churn
0    2636210.0
1     465025.0
Name: Total Business Value, dtype: float64
___________________________________

Column Name: Income
churn
0    64154.0
1    51630.0
Name: Income, dtype: float64
___________________________________

Column Name: Quarterly Rating
churn
0    2.0
1    1.0
Name: Quarterly Rating, dtype: float64
___________________________________
```

In [66]:

```
# Box Plots for Continuous features vs. Loan Status

plt.figure(figsize=(14, 14))
for i, col in enumerate(numerical_cols):
    plt.subplot(4, 3, i+1)
    sns.boxplot(x='churn', y=col, data=df, palette = req_palette)

plt.suptitle("Box Plots for Continuous features vs. Loan Status", fontsize = 1
plt.tight_layout()
```

```
plt.show()
```



🔍**OBSERVATION**🔎

1. **Reportings**: Non-churned drivers have a higher median value (**7.0**) compared to churned drivers (**5.0**), indicating more reportings are linked to retention.
2. **Age**: Non-churned drivers have a slightly higher median age (**34**) compared to churned drivers (**33**), suggesting age might have a minor influence.
3. **Total Business Value**: Non-churned drivers have a significantly higher median total business value (**2,636,210**) than churned drivers (**465,025**), showing a strong correlation with retention.
4. **Income**: Non-churned drivers have a higher median income (**64,154**) compared to churned drivers (**51,630**), suggesting better pay may reduce churn.
5. **Quarterly Rating**: Non-churned drivers have a higher median quarterly rating (**2.0**) compared to churned drivers (**1.0**), indicating performance rating impacts churn behavior.

Churn Analysis

In [67]:
```
# Feature Engineering
df_churned = df[df['churn'] == 1]
```

In [68]:
```
df_churned['tenure_days'] = (df_churned['LastWorkingDate'] - df_churned['Datec
```

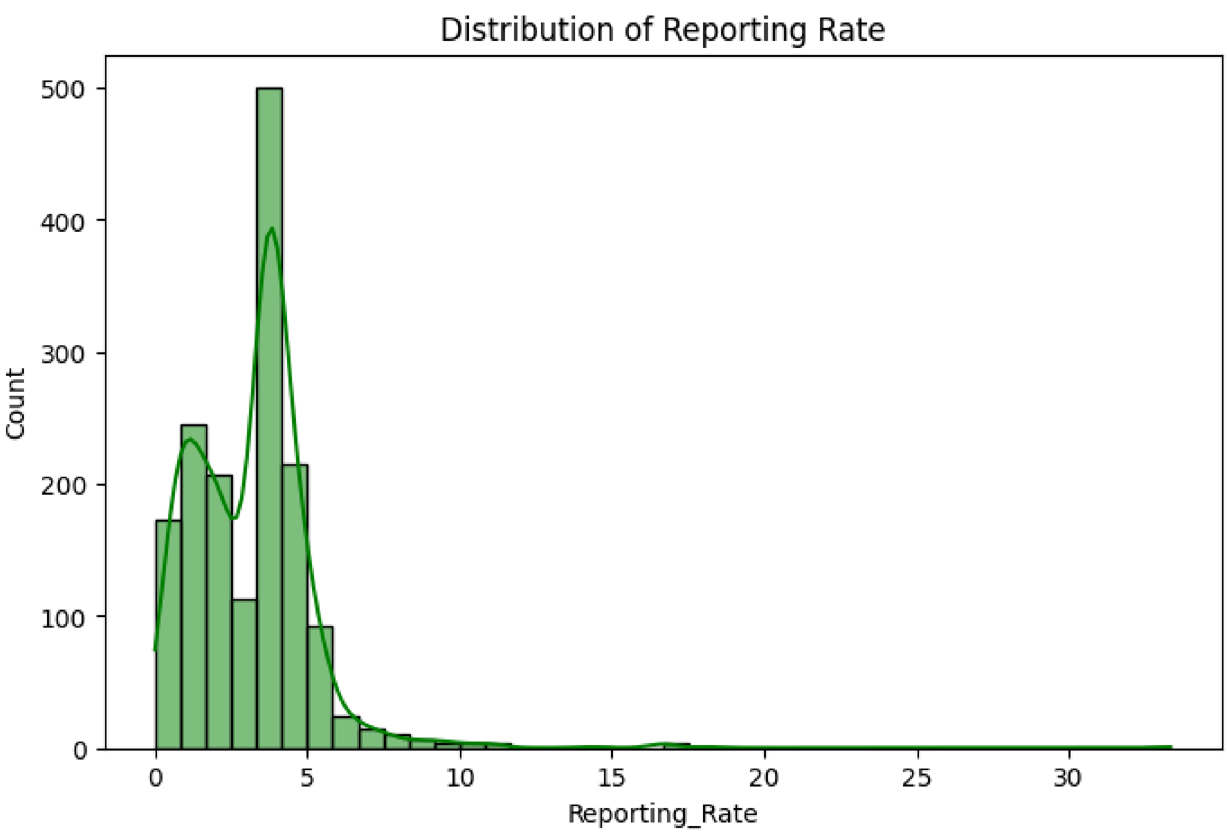
In [69]:
```
df_churned['Reporting_Rate'] = (df_churned['Reportings'] / df_churned['tenure_
df_churned['Reporting_Rate'] = df_churned['Reporting_Rate'].fillna(0)
df_churned['Reporting_Rate'] = df_churned['Reporting_Rate'].round(2)
```

In [70]:
```
df_churned.head()
```

Out[70]:

	Reportings	Driver_ID	Age	Gender	City	Education_Level	Dateofjoining	La
0	3	1	28	Male	C23	2	2018-12-24	
2	5	4	43	Male	C13	2	2019-12-07	
3	3	5	29	Male	C9	0	2019-01-09	
5	3	8	34	Male	C2	0	2020-09-19	
7	6	12	35	Male	C23	2	2019-06-29	

In [71]:
```
# Histogram
plt.figure(figsize=(8, 5))
sns.histplot(data=df_churned, x ='Reporting_Rate', bins=40, kde=True, color='g
plt.title("Distribution of Reporting Rate")
plt.show()
```



In [72]:
```
df_churned['Reporting_Rate'].describe()
```

Out[72]:

	Reporting_Rate
count	1616.000000
mean	3.155736
std	2.048271
min	0.000000
25%	1.600000
50%	3.470000
75%	4.092500
max	33.330000

dtype: float64

🔍**OBSERVATION**🔎

- The mean reporting rate for churned drivers is 3.16, indicating that, on average, churned drivers had moderate reporting rates before leaving.
- The median reporting rate is 3.47, which is close to the mean, indicating a relatively symmetric distribution for most churned drivers.
- The reporting rates vary widely, from a minimum of 0.00 to a maximum of 33.33, suggesting that while some churned drivers had no reports, a few had exceptionally high reporting rates.

Data preparation for modeling🔢

In [73]:
```
# Creating a deep copy
df_model = df.copy()
```

In [74]:
```
df_model.drop(columns=['Driver_ID', 'LastWorkingDate'], inplace=True)
df_model['Month_of_joining'] = df_model['Dateofjoining'].dt.month
df_model['Year_of_joining']= df_model['Dateofjoining'].dt.year
df_model.drop(columns='Dateofjoining', inplace=True)
```

In [75]:
```
df_model.head()
```

Out[75]:

	Reportings	Age	Gender	City	Education_Level	Grade	Total Business Value	Income	D
0	3	28	Male	C23	2	1	1715580	57387	
1	2	31	Male	C7	2	2	0	67016	
2	5	43	Male	C13	2	2	350000	65603	
3	3	29	Male	C9	0	1	120360	46368	
4	5	31	Female	C11	1	3	1265000	78728	

In [76]:

```
df_model.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2381 entries, 0 to 2380
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Reportings            2381 non-null   int64
 1   Age                   2381 non-null   int64
 2   Gender                2381 non-null   category
 3   City                  2381 non-null   category
 4   Education_Level       2381 non-null   category
 5   Grade                 2381 non-null   category
 6   Total Business Value  2381 non-null   int64
 7   Income                2381 non-null   int64
 8   Joining Designation   2381 non-null   category
 9   Quarterly Rating      2381 non-null   float64
 10  churn                 2381 non-null   category
 11  Rating_increase       2381 non-null   category
 12  Income_increase       2381 non-null   category
 13  Month_of_joining      2381 non-null   int32
 14  Year_of_joining       2381 non-null   int32
dtypes: category(8), float64(1), int32(2), int64(4)
memory usage: 132.6 KB
```

In [77]:

```
df_model_category_columns = df_model.select_dtypes(include='category')
df_model_category_columns.head()
```

Out[77]:

	Gender	City	Education_Level	Grade	Joining Designation	churn	Rating_increase	I
0	Male	C23	2	1	1	1	0	
1	Male	C7	2	2	2	0	0	
2	Male	C13	2	2	2	1	0	
3	Male	C9	0	1	1	1	0	
4	Female	C11	1	3	3	0	1	

Label Encoding

In [78]:
```
# Convert the following columns directly to int since they are ordinal
columns = ['Education_Level', 'Grade', 'Joining Designation', 'churn', 'Rating

for cols in columns:
  df_model[cols] = df_model[cols].astype('int')
```

In [79]:
```
# Encode (Male = 0, Female = 1)
df_model['Gender'] = df_model['Gender'].map({"Male": 0, "Female": 1})
df_model['Gender'] = df_model['Gender'].astype('int')
```

In [80]:
```
df_model['City'].nunique(), df_model['City'].unique()
```

Out[80]:
```
(29,
 ['C23', 'C7', 'C13', 'C9', 'C11', ..., 'C4', 'C3', 'C16', 'C22', 'C12']
 Length: 29
 Categories (29, object): ['C1', 'C10', 'C11', 'C12', ..., 'C6', 'C7', 'C8',
'C9'])
```

One Hot Encodeing

In [81]:
```
# Perform one-hot encoding for 'City' column and drop the first category
df_encoded = pd.get_dummies(df_model, columns=['City'], prefix='City', drop_fi
```

In [82]:
```
df_encoded.head()
```

Out[82]:

	Reportings	Age	Gender	Education_Level	Grade	Total Business Value	Income	Joi Design
0	3	28	0	2	1	1715580	57387	
1	2	31	0	2	2	0	67016	
2	5	43	0	2	2	350000	65603	
3	3	29	0	0	1	120360	46368	
4	5	31	1	1	3	1265000	78728	

In [83]:
```
df_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2381 entries, 0 to 2380
Data columns (total 42 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Reportings            2381 non-null   int64  
 1   Age                   2381 non-null   int64  
 2   Gender                2381 non-null   int64  
 3   Education_Level       2381 non-null   int64  
 4   Grade                 2381 non-null   int64  
 5   Total Business Value  2381 non-null   int64  
 6   Income                2381 non-null   int64  
 7   Joining Designation   2381 non-null   int64  
 8   Quarterly Rating      2381 non-null   float64
 9   churn                 2381 non-null   int64  
 10  Rating_increase       2381 non-null   int64  
 11  Income_increase       2381 non-null   int64  
 12  Month_of_joining      2381 non-null   int32  
 13  Year_of_joining       2381 non-null   int32  
 14  City_C10              2381 non-null   int64  
 15  City_C11              2381 non-null   int64  
 16  City_C12              2381 non-null   int64  
 17  City_C13              2381 non-null   int64  
 18  City_C14              2381 non-null   int64  
 19  City_C15              2381 non-null   int64  
 20  City_C16              2381 non-null   int64  
 21  City_C17              2381 non-null   int64  
 22  City_C18              2381 non-null   int64  
 23  City_C19              2381 non-null   int64  
 24  City_C2               2381 non-null   int64  
 25  City_C20              2381 non-null   int64  
 26  City_C21              2381 non-null   int64  
 27  City_C22              2381 non-null   int64  
 28  City_C23              2381 non-null   int64  
 29  City_C24              2381 non-null   int64  
 30  City_C25              2381 non-null   int64  
 31  City_C26              2381 non-null   int64  
 32  City_C27              2381 non-null   int64  
 33  City_C28              2381 non-null   int64  
 34  City_C29              2381 non-null   int64  
 35  City_C3               2381 non-null   int64  
 36  City_C4               2381 non-null   int64  
 37  City_C5               2381 non-null   int64  
 38  City_C6               2381 non-null   int64  
 39  City_C7               2381 non-null   int64  
 40  City_C8               2381 non-null   int64  
 41  City_C9               2381 non-null   int64  
dtypes: float64(1), int32(2), int64(39)
memory usage: 762.8 KB
```

Train Test Split

In [84]:
```
# Lets split the data into Independent feature and dependent feature
```

```
y = df_encoded['churn']
X = df_encoded.drop('churn', axis = 1)
X.shape, y.shape
```

Out[84]: ((2381, 41), (2381,))

In [85]:
```
# Lets split the data into train and test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randc
```

In [86]:
```
# After_train_test_split
# X_train | y_train
# X_test | y_test
```

Scaling

In general:

- Bagging and Boosting with Decision Trees: No scaling required.
- Other weak learners (KNN, SVM, etc.) in Bagging/Boosting: Scaling is needed.

Best Practices: For Tree-Based Methods (Bagging/Boosting):

- Scaling is not necessary, but you can still standardize or normalize if you are preprocessing the dataset for consistency across models.

In [87]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

X_train_scaled = pd.DataFrame(X_train_scaled, columns=X.columns)
X_test_scaled = pd.DataFrame(X_test_scaled, columns=X.columns)
```

In [88]:
```
# After_train_test_split       After Scaling
# X_train | y_train  -->   X_train_scaled | y_train
# X_test | y_test    -->   X_test_scaled | y_test
```

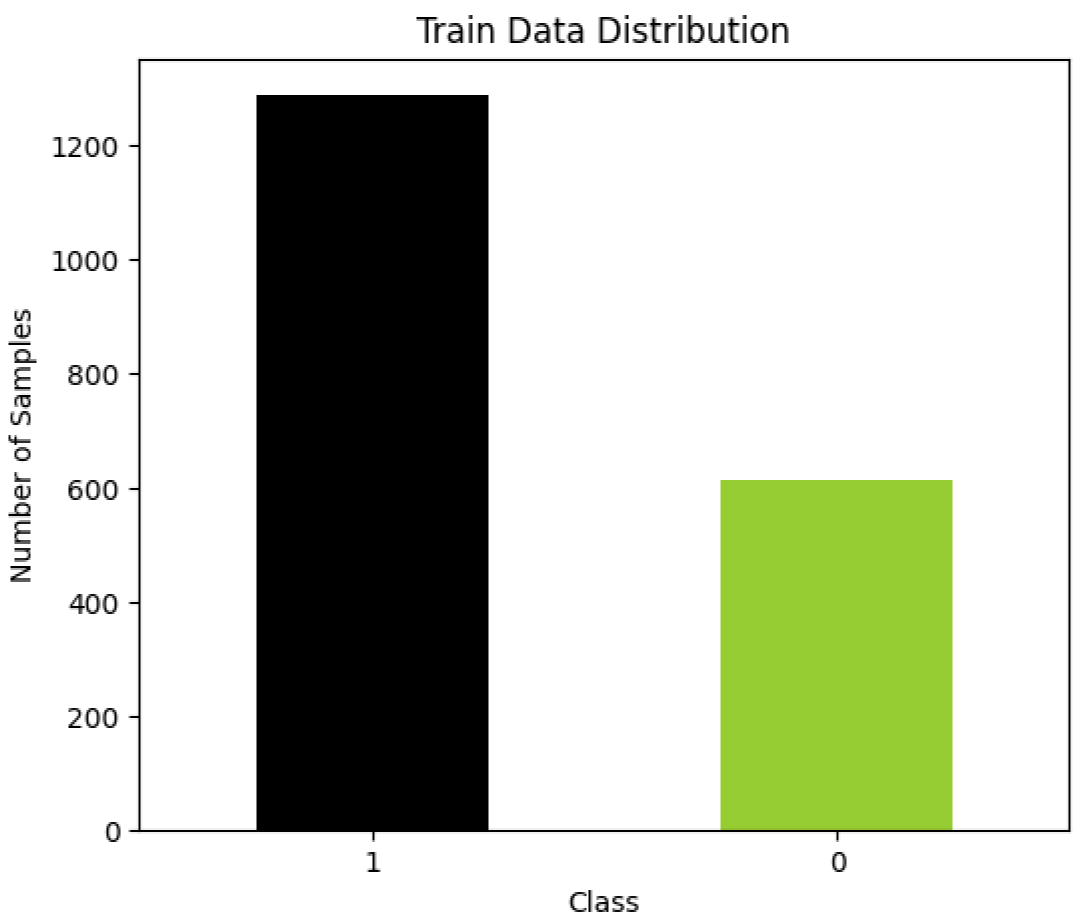
Handling Class Imbalance

In [89]:
```
print(((y_train.value_counts(normalize=True)) * 100).round(2))
```

```
churn
1    67.7
0    32.3
Name: proportion, dtype: float64
```

In [90]:
```
plt.figure(figsize=(6, 5))
```

```
y_train.value_counts().plot(kind='bar', color=['black', 'yellowgreen'])
plt.xlabel('Class')
plt.ylabel('Number of Samples')
plt.title('Train Data Distribution')
plt.xticks(rotation=0)
plt.show()
```



SMOTE

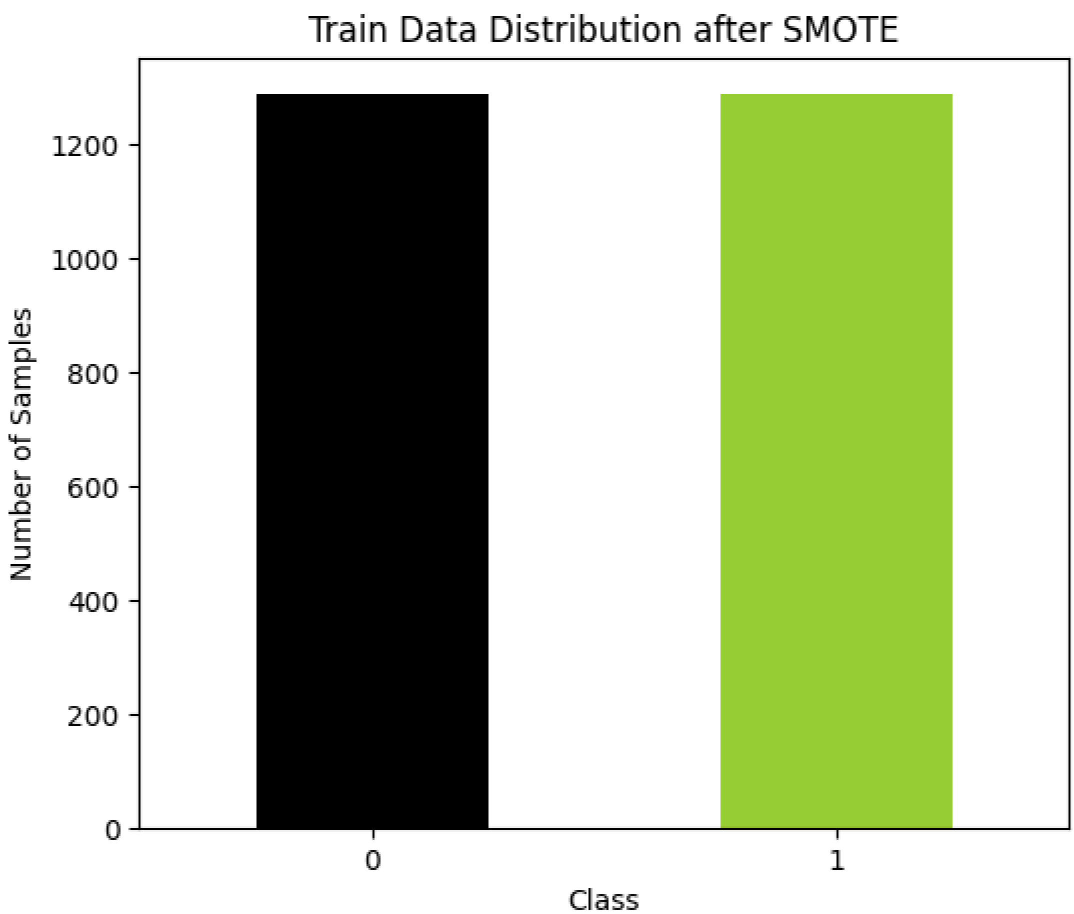
In [91]:
```
from imblearn.over_sampling import SMOTE

# Create an instance of SMOTE
smote = SMOTE()

# Perform SMOTE on the training data
# Oversample the training data using SMOTE
X_train_balanced, y_train_balanced  = smote.fit_resample(X_train_scaled, y_tra
```

In [92]:
```
# After_train_test_split        After Scaling                        After SMOTE
# X_train | y_train  -->   X_train_scaled | y_train    -->   X_train_balanced |
# X_test | y_test    -->   X_test_scaled | y_test      -->   X_test_scaled | y_
```

In [93]:
```
print(((y_train_balanced.value_counts(normalize=True)) * 100).round(2))
```

```
churn
0    50.0
1    50.0
Name: proportion, dtype: float64
```

In [94]:
```
plt.figure(figsize=(6, 5))
y_train_balanced.value_counts().plot(kind='bar', color=['black', 'yellowgreen'
plt.xlabel('Class')
plt.ylabel('Number of Samples')
plt.title('Train Data Distribution after SMOTE')
plt.xticks(rotation=0)
plt.show()
```



Model Building - Ensemble Learning💻

Bagging Random Forest Classifier

What is Bagging in Ensemble Learning?

Bagging (Bootstrap Aggregating) is an ensemble learning technique that combines predictions from multiple models (base estimators) to improve overall performance and reduce variance. The key idea is:

- **Bootstrap Sampling:** Random subsets of data are sampled with replacement to train each model.

- **Aggregation:** Predictions are averaged (for regression) or voted (for classification) to create the final prediction. Example: Random Forest is a popular bagging algorithm that uses decision trees as base estimators.

Advantages:

- Reduces overfitting by combining weak learners.
- Improves model stability and accuracy.

Hyperparameter Tuning Using RandomizedSearchCV

Define hyperparameters to tune a bagging model (e.g., Random Forest).

These are the hyperparameters for a **Random Forest** model, which is a commonly used **Bagging algorithm**. Here's what each hyperparameter represents:

- `n_estimators` : The number of trees in the forest.

- `max_depth` : The maximum depth of each decision tree.

- `min_samples_split` : The minimum number of samples required to split an internal node.

- `min_samples_leaf` : The minimum number of samples required to be at a leaf node.

- `bootstrap` : Whether to use bootstrap sampling (random sampling with replacement) when building trees.

In [95]:
```
# Hyperparameters for RandomizedSearchCV
param_dist = {
    'n_estimators': [50, 100, 200, 500, 1000],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 3, 4],
    'bootstrap': [True, False]
}
```

In [96]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RandomizedSearchCV
```

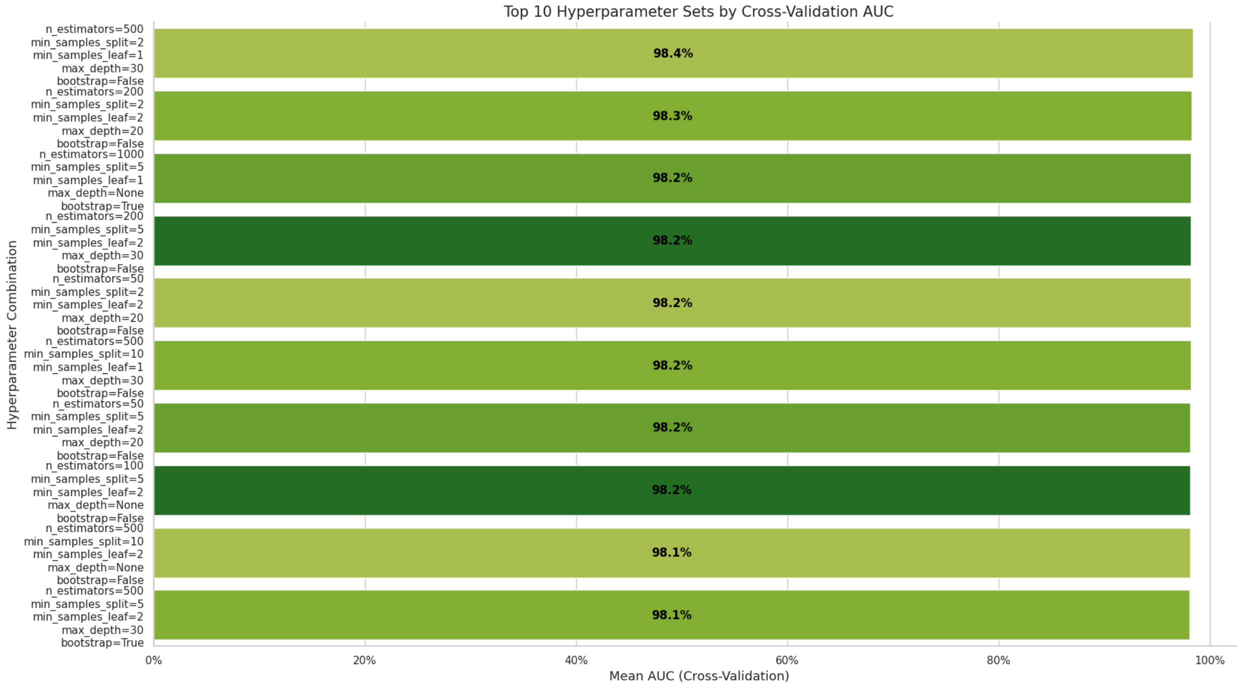
```python
import datetime as dt

# Define the model
rf = RandomForestClassifier(random_state=42)

# Perform RandomizedSearchCV
random_search = RandomizedSearchCV(
                                    estimator=rf,
                                    param_distributions=param_dist,
                                    n_iter=50,
                                    scoring='roc_auc',
                                    cv=5,
                                    verbose=2,
                                    random_state=42,
                                    n_jobs=-1
                                  )

# Fit the model
start = dt.datetime.now()
random_search.fit(X_train_balanced, y_train_balanced)
end = dt.datetime.now()

# Best parameters
print("Best Parameters:", random_search.best_params_)
print("Best cross-validation score achieved: ", random_search.best_score_)
print(f"Time taken for RandomizedSearchCV(fits) : {end - start}")
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
Best Parameters: {'n_estimators': 500, 'min_samples_split': 2, 'min_samples_lea
f': 1, 'max_depth': 30, 'bootstrap': False}
Best cross-validation score achieved:  0.9841618914139447
Time taken for RandomizedSearchCV(fits) : 0:05:15.726154
```

In [97]:

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

# Create the DataFrame from cv_results_
cv_results_df = pd.DataFrame(random_search.cv_results_)

# Sort by mean_test_score descending
cv_results_df = cv_results_df.sort_values(by='mean_test_score', ascending=Fals

# Define top_n to display
top_n = 10
top_results = cv_results_df.head(top_n).copy()

# Convert hyperparameters dict to readable multiline string
top_results['param_str'] = top_results['params'].apply(
    lambda x: '\n'.join(f"{k}={v}" for k, v in x.items())
)

# Convert AUC scores to percentages
```

```python
top_results['mean_test_score'] = top_results['mean_test_score'] * 100

# Set style and palette
sns.set(style="whitegrid")
# green_palette = sns.color_palette("Greens", n_colors=top_n)

# Plotting
fig, ax = plt.subplots(figsize=(18, 10))
bars = sns.barplot(
    y='param_str',
    x='mean_test_score',
    data=top_results,
    palette=green_palette[::-1],
    ax=ax
)

# Add labels inside bars
for container in bars.containers:
    bars.bar_label(container,
                   labels=[f"{v.get_width():.1f}%" for v in container],
                   label_type='center',
                   color='black',
                   fontsize=12,
                   weight='bold')

# Axis formatting
ax.set_xlabel("Mean AUC (Cross-Validation)", fontsize=13)
ax.set_ylabel("Hyperparameter Combination", fontsize=13)
ax.set_title(f"Top {top_n} Hyperparameter Sets by Cross-Validation AUC", fonts

# Format x-axis ticks as percentages
ax.xaxis.set_major_formatter(FuncFormatter(lambda x, _: f"{x:.0f}%"))

# Expand left margin
plt.subplots_adjust(left=0.4)
plt.tight_layout()
sns.despine()
plt.show()
```



In [98]:
```python
tree = random_search.best_estimator_.estimators_[0]
tree
```

Out[98]:

DecisionTreeClassifier

```
DecisionTreeClassifier(max_depth=30, max_features='sqrt',
                       random_state=1608637542)
```

In [99]:
```python
from sklearn.tree import export_graphviz

for depth in [5, 10, 15, 20, 25, 30]:
    filename = f"tree_depth_{depth}.pdf"
    export_graphviz(tree,
                    out_file=filename,
                    feature_names=X_train_balanced.columns,
                    class_names=True,
                    max_depth=depth,
                    filled=True,
                    rounded=True)
    print(f"Exported tree to {filename}")
```

```
Exported tree to tree_depth_5.pdf
Exported tree to tree_depth_10.pdf
Exported tree to tree_depth_15.pdf
Exported tree to tree_depth_20.pdf
Exported tree to tree_depth_25.pdf
Exported tree to tree_depth_30.pdf
```

In [100…
```python
y_train_balanced = pd.Series(y_train_balanced)
```

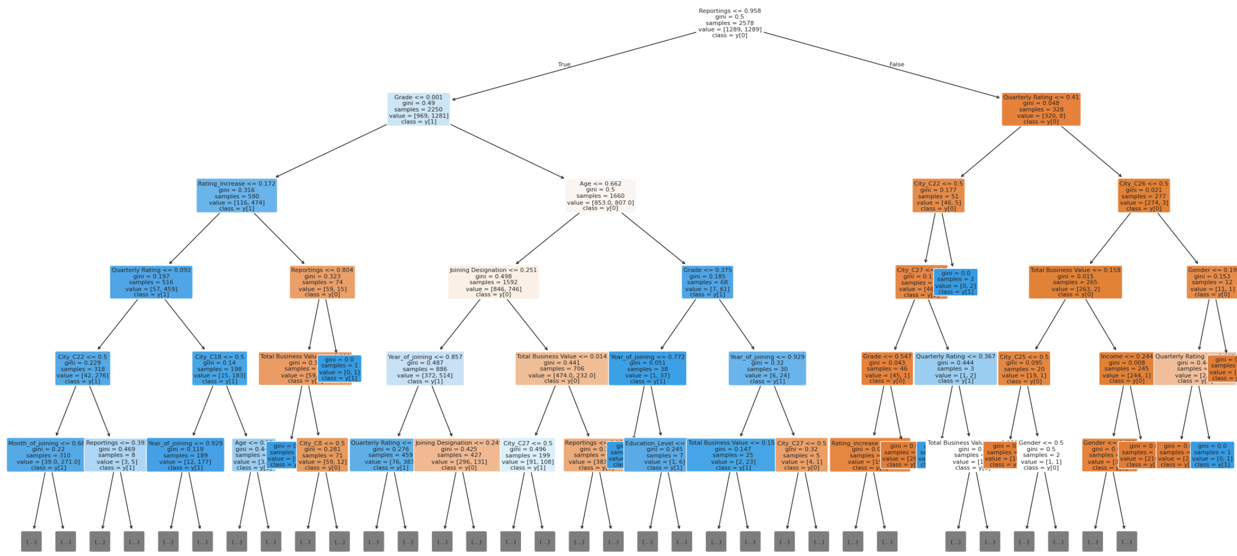
In [101…
```python
# from dtreeviz import dtreeviz
```

```
# # Ensure y_train_balanced is a pandas Series or numpy array
# if not hasattr(y_train_balanced, "__iter__"):
#     raise ValueError("y_train_balanced must be an array-like object")

# # Create a list of class names based on unique classes in y_train_balanced
# class_labels = sorted(set(y_train_balanced))  # e.g., [0, 1]
# class_names = [str(label) for label in class_labels]

# # Visualize the decision tree
# viz = dtreeviz(
#     tree,
#     X_train_balanced,
#     y_train_balanced,
#     feature_names=X_train_balanced.columns.tolist(),
#     class_names=class_names,
#     fancy=True
# )

# viz.view()
```

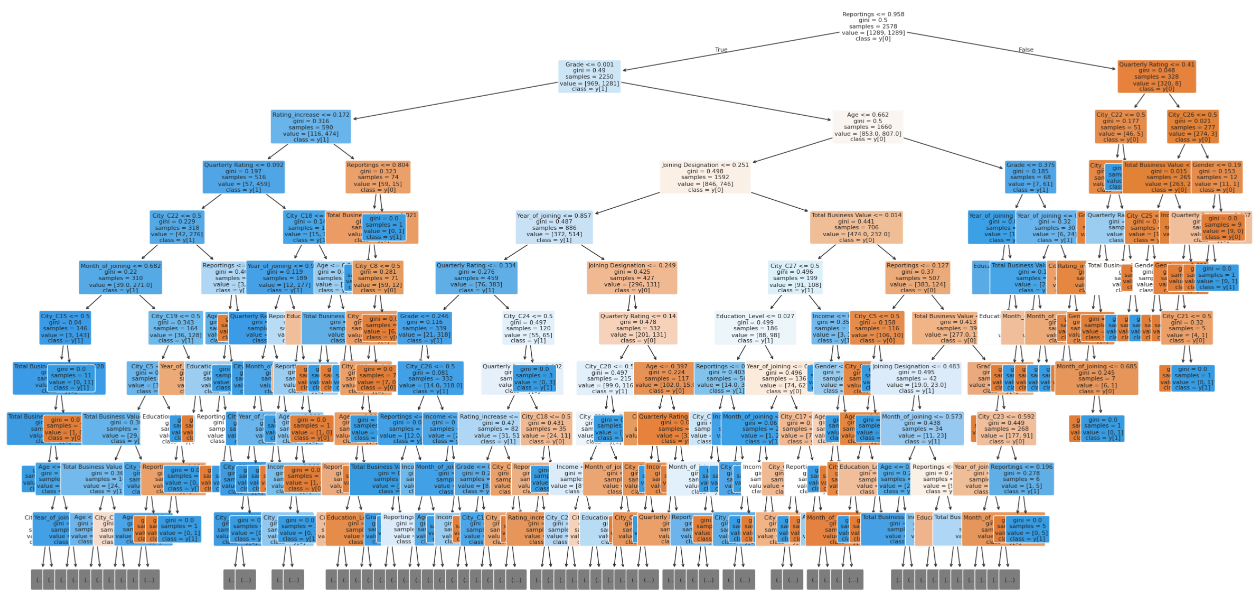
In [102…

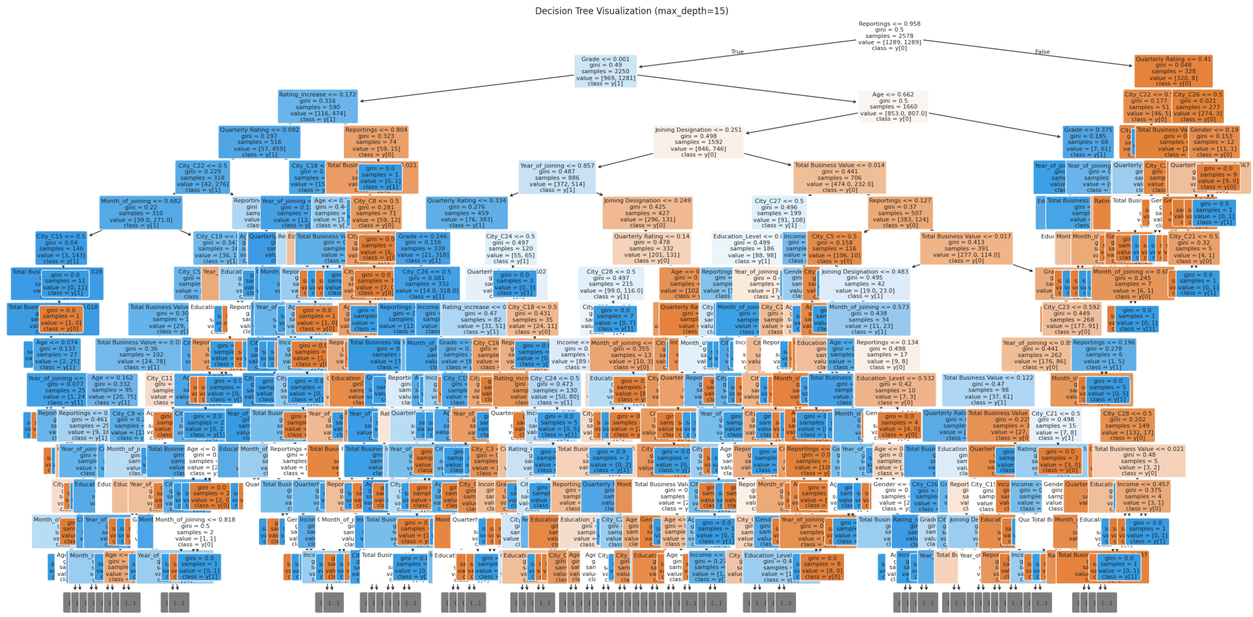
```
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

# Get the first tree from the trained Random Forest
tree = random_search.best_estimator_.estimators_[0]

# Set the depth intervals
depth_intervals = [5, 10, 15, 20, 25, 30]

# Plot trees at different depths
for depth in depth_intervals:
    plt.figure(figsize=(24, 12))
    plot_tree(tree,
              max_depth=depth,
              filled=True,
              feature_names=X_train_balanced.columns,
              class_names=True,
              rounded=True,
              fontsize=8)
    plt.title(f"Decision Tree Visualization (max_depth={depth})")
    plt.tight_layout()
    sns.despine()
    plt.show()
```

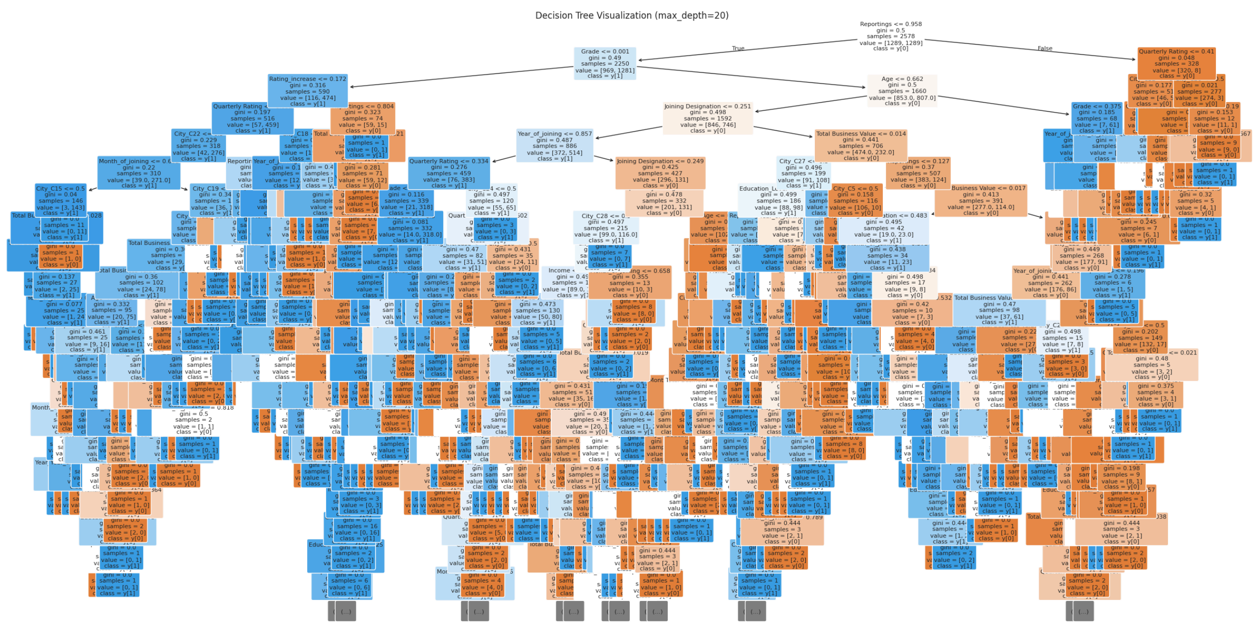
Decision Tree Visualization (max_depth=5)

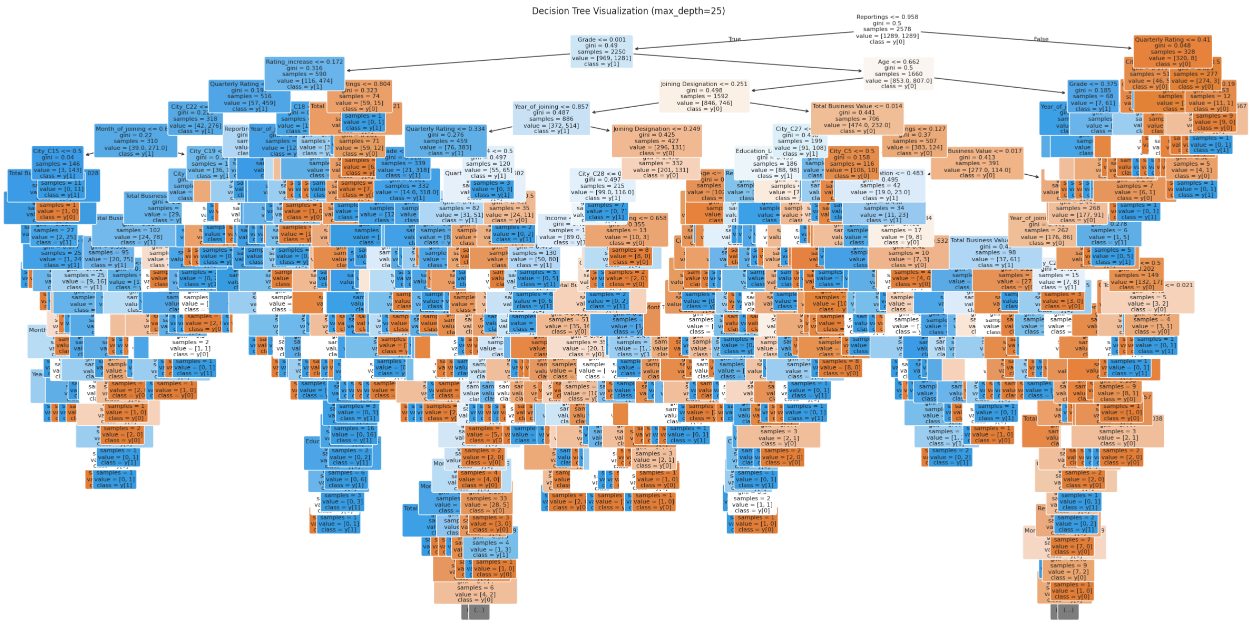


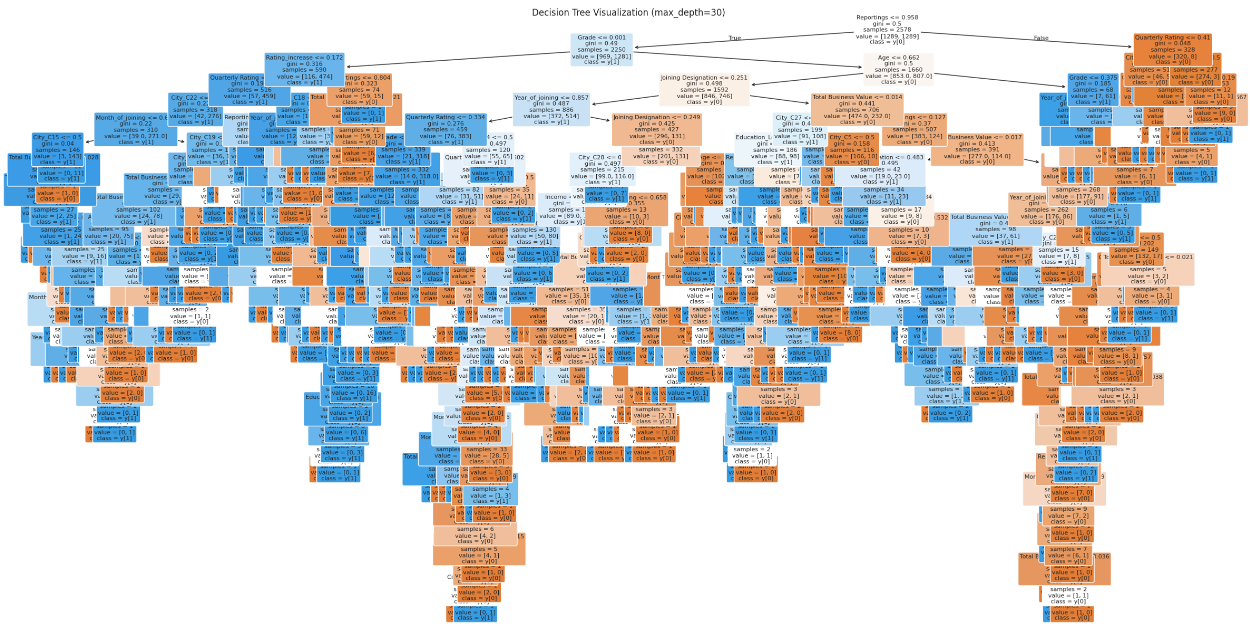
Decision Tree Visualization (max_depth=10)




Decision Tree Visualization (max_depth=15)


Decision Tree Visualization (max_depth=20)





Train the Model with Best Hyperparameters

Use the best parameters from `RandomizedSearchCV` to train the model.

In [103…

```python
# Train the best model
best_rf = random_search.best_estimator_
best_rf.fit(X_train_balanced, y_train_balanced)
```

Out[103…

RandomForestClassifier

```
RandomForestClassifier(bootstrap=False, max_depth=30, n_estimators=50
0,
                       random_state=42)
```

Model Score / Accuracy Measurement

Evaluate the model's accuracy on the training and testing datasets.

In [104…

```
# After_train_test_split       After Scaling                     After SMOTE
# X_train | y_train  -->   X_train_scaled | y_train   -->   X_train_balanced |
# X_test | y_test    -->   X_test_scaled | y_test     -->   X_test_scaled | y_
```

In [105…

```
# Accuracy on train and test sets
train_accuracy = best_rf.score(X_train_balanced, y_train_balanced)
test_accuracy = best_rf.score(X_test_scaled, y_test)

print(f"Train Accuracy: {train_accuracy:.2f}")
print(f"Test Accuracy: {test_accuracy:.2f}")
```

```
Train Accuracy: 1.00
Test Accuracy: 0.92
```

In [106…

```
# Make predictions on the test set
y_train_pred = best_rf.predict(X_train_balanced)
y_test_pred = best_rf.predict(X_test_scaled)

# Evaluate the model
# Accuracy on predictions of train and test sets
train_accuracy = accuracy_score(y_train_balanced, y_train_pred)
print(f"Training Accuracy: {train_accuracy:.2f}")

test_accuracy = accuracy_score(y_test, y_test_pred)
print(f"Test Accuracy: {test_accuracy:.2f}")
```

```
Training Accuracy: 1.00
Test Accuracy: 0.92
```

Confusion Matrix

Use the confusion matrix to evaluate classification performance.

In [107…

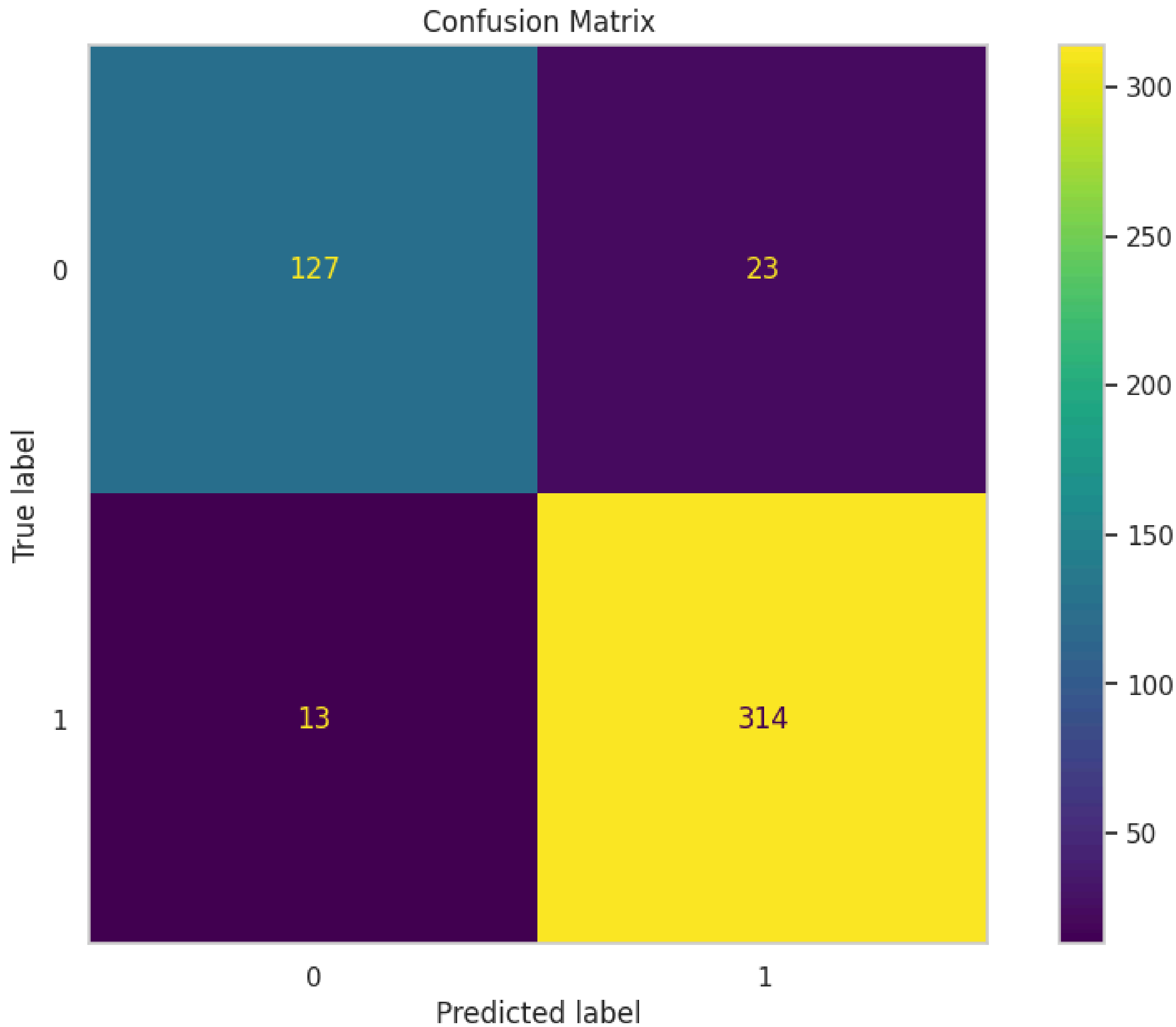
```
# After_train_test_split       After Scaling                     After SMOTE
# X_train | y_train  -->   X_train_scaled | y_train   -->   X_train_balanced |
# X_test | y_test    -->   X_test_scaled | y_test     -->   X_test_scaled | y_
```

In [108…

```
from sklearn.metrics import confusion_matrix, classification_report

# Predictions on test set
y_pred = best_rf.predict(X_test_scaled)

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", cm)

#plt.figure(figsize=(5, 4))
ConfusionMatrixDisplay(cm).plot()
```

```
plt.title('Confusion Matrix')
plt.grid(False)
plt.show()

# Classification Report
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[127  23]
 [ 13 314]]
```



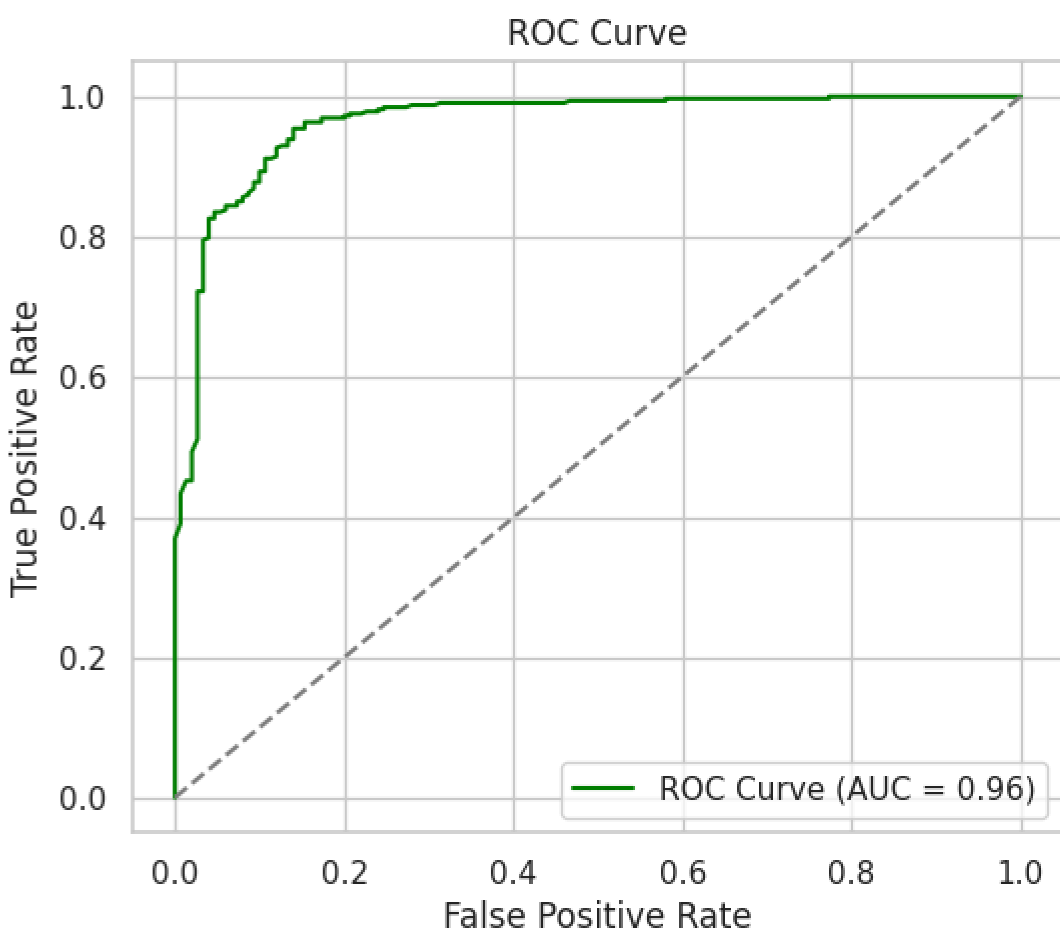

```
Classification Report:
               precision    recall  f1-score   support

           0       0.91      0.85      0.88       150
           1       0.93      0.96      0.95       327

    accuracy                           0.92       477
   macro avg       0.92      0.90      0.91       477
weighted avg       0.92      0.92      0.92       477
```

ROC Curve & AUC

Evaluate the ROC Curve and calculate the AUC score.

In [109…

```
from sklearn.metrics import roc_curve, auc, roc_auc_score
import matplotlib.pyplot as plt

# Predict probabilities for ROC curve
y_prob = best_rf.predict_proba(X_test_scaled)[:, 1]

# ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr) # roc_auc_score(y_test, y_prob) also works

# Plot the ROC Curve
plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='green', label=f'ROC Curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='grey', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



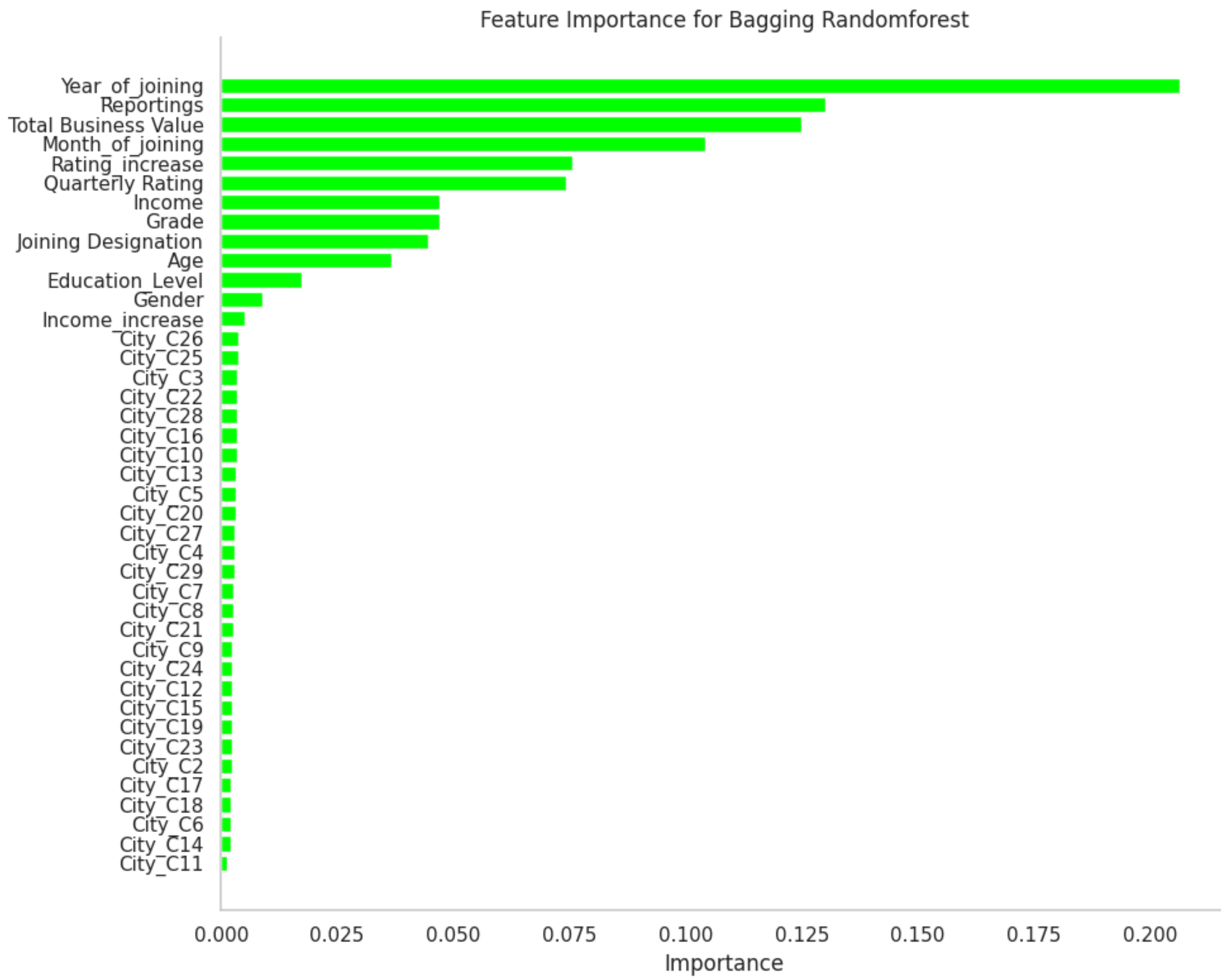
Feature Importance

Identify the features that contribute most to the model's predictions.

In [110…

```
# Feature Importance
importances = best_rf.feature_importances_
features = X.columns

# Sort feature importances
importance_df = pd.DataFrame({'Feature': features, 'Importance': importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

print("Top Features:\n", importance_df.head())

# Plot feature importances
plt.figure(figsize=(10, 8))
plt.barh(importance_df['Feature'], importance_df['Importance'], color='lime')
plt.gca().invert_yaxis()
plt.xlabel('Importance')
plt.title('Feature Importance for Bagging Randomforest')
sns.despine()
plt.tight_layout()
plt.grid(False)
plt.show()
```

```
Top Features:
                   Feature  Importance
12       Year_of_joining    0.206403
0             Reportings    0.130169
5   Total Business Value    0.124994
11      Month_of_joining    0.104284
9        Rating_increase    0.075790
```



Observations

1. **Model Accuracy:**

- **Observation:** Train accuracy is 1.00, and test accuracy is 0.92.
- **Insight:** The model performs excellently on both train and test data. However, perfect training accuracy could indicate slight overfitting. Despite this, the high test accuracy demonstrates that the model generalizes well to unseen data.

2. **Class Balance Performance:**

- **Observation:** The recall for churned drivers (class 1) is 0.94, while the precision is 0.93. The false negatives (18) are low, which means the model is not missing many actual churned drivers.
- **Insight:** High recall ensures most churned drivers are identified, aligning with the business objective to capture churn risks. Slightly lower precision indicates occasional over-targeting, but this is

acceptable given the priority to minimize churn.

3. **AUC-ROC Curve:**

- **Observation:** AUC of 0.96 signifies excellent discriminatory power between churned and non-churned drivers.
- **Insight:** This allows confident ranking of drivers based on their churn probability. High AUC ensures the model can effectively prioritize drivers for retention actions with minimal misclassification.

4. **Feature Importance:**

- **Observation:** The top 5 features contributing to churn predictions are:
    1. **Year of Joining (0.207):** Recent joiners are at a higher churn risk.
    2. **Reportings (0.129):** Management structure significantly impacts churn.
    3. **Total Business Value (0.125):** Drivers with lower business contributions are more likely to churn.
    4. **Month of Joining (0.109):** Seasonal or onboarding timing affects churn.
    5. **Quarterly Rating (0.074):** Drivers with poor performance ratings are more likely to leave.
- **Insight:** These features provide actionable levers for improving retention strategies. For instance, better onboarding for recent joiners or addressing low ratings can mitigate churn risks.

5. **Misclassification Insights:**

- **Observation:** The confusion matrix shows 22 false positives (non-churned misclassified as churned) and 18 false negatives (churned misclassified as non-churned).
- **Insight:** False negatives (churned drivers missed by the model) are more critical in this context as they represent missed opportunities to prevent churn. The low number of false negatives indicates the model is well-suited for identifying high-risk drivers for targeted interventions.

Overall Insight:

The Bagging Random Forest model is highly effective for this business problem, with strong recall and precision for churned drivers. It identifies critical factors influencing churn, offering actionable insights to design retention strategies while maintaining excellent predictive performance.

Boosting (XGBoost)

What is Boosting in Ensemble Learning?

Boosting is an ensemble learning technique that combines multiple weak learners (e.g., decision trees) to create a strong learner. It focuses on improving the performance iteratively:

- Initially, a weak learner is trained.
- In subsequent iterations, the model gives higher weight to misclassified instances, allowing the next learner to focus on correcting these errors.
- Popular algorithms include XGBoost, LightGBM, and AdaBoost.

Hyperparameter Tuning Using RandomizedSearchCV

Let's use XGBoost as the boosting algorithm. We'll tune the following hyperparameters:

- `n_estimators`: Number of trees.
- `max_depth`: Maximum depth of trees.
- `learning_rate`: How quickly the model learns (shrinkage rate).
- `subsample`: Fraction of data to sample for each tree.
- `colsample_bytree`: Fraction of features to consider per split.

In [111…

```
# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 250, 300, 400],
    'max_depth': [3, 5, 7, 10],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'subsample': [0.7, 0.8, 0.9, 1],
    'colsample_bytree': [0.7, 0.8, 0.9, 1]
}
```

In [112…

```
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV

# Define the model
xgb_model = XGBClassifier(random_state=42, use_label_encoder=False, eval_metri

# Randomized Search with Cross Validation
random_search = RandomizedSearchCV(
                                    estimator=xgb_model,
                                    param_distributions=param_grid,
                                    n_iter=50,
                                    scoring='roc_auc',
                                    cv=3,
```

```python
                                    verbose=2,
                                    random_state=42,
                                    n_jobs=-1
                                  )

# Fit the model
start = dt.datetime.now()
random_search.fit(X_train_balanced, y_train_balanced)
end = dt.datetime.now()

# Best parameters
best_params = random_search.best_params_
print("Best Hyperparameters:", best_params)
print("Best cross-validation score achieved: ", random_search.best_score_)
print(f"Time taken for RandomizedSearchCV(fits) : {end - start}")
```

```
Fitting 3 folds for each of 50 candidates, totalling 150 fits
Best Hyperparameters: {'subsample': 0.8, 'n_estimators': 100, 'max_depth': 10,
'learning_rate': 0.1, 'colsample_bytree': 0.7}
Best cross-validation score achieved:  0.9819959464848593
Time taken for RandomizedSearchCV(fits) : 0:00:51.590566
```

In [113…

```python
import lightgbm as lgb
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier
import datetime as dt

# Define the models
xgb_model = XGBClassifier(random_state=42, use_label_encoder=False, eval_metri
lgb_model = lgb.LGBMClassifier(random_state=42)
ada_model = AdaBoostClassifier(random_state=42)
vgb_model = GradientBoostingClassifier(random_state=42)

# Define the parameter grids for RandomizedSearchCV
param_grid_xgb = {
    'n_estimators': [100, 200, 250, 300, 400],
    'max_depth': [3, 5, 7, 10],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'subsample': [0.7, 0.8, 0.9, 1],
    'colsample_bytree': [0.7, 0.8, 0.9, 1]
}

param_grid_lgb = {
    'n_estimators': [100, 200, 250, 300, 400],
    'max_depth': [3, 5, 7, 10],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'subsample': [0.7, 0.8, 0.9, 1],
    'colsample_bytree': [0.7, 0.8, 0.9, 1]
}

param_grid_ada = {
    'n_estimators': [50, 100, 150, 200],
    'learning_rate': [0.01, 0.1, 0.5, 1.0]
```

```
}

param_grid_vgb = {
    'n_estimators': [100, 200, 250, 300, 400],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'max_depth': [3, 5, 7, 10]
}

# Create a dictionary of all models and their parameter grids
models = {
    'XGBoost': (xgb_model, param_grid_xgb),
    'LightGBM': (lgb_model, param_grid_lgb),
    'AdaBoost': (ada_model, param_grid_ada),
    'GradientBoosting': (vgb_model, param_grid_vgb)
}

# Store the best models after RandomizedSearchCV
best_models = {}
start = dt.datetime.now()

# Perform RandomizedSearchCV for each model
for model_name, (model, param_grid) in models.items():
    print(f"Running RandomizedSearchCV for {model_name}...")
    random_search = RandomizedSearchCV(
        estimator=model,
        param_distributions=param_grid,
        n_iter=50,
        scoring='roc_auc',
        cv=3,
        verbose=2,
        random_state=42,
        n_jobs=-1
    )

    # Fit the model
    random_search.fit(X_train_balanced, y_train_balanced)
    best_models[model_name] = random_search.best_estimator_

    # Output the results for each model
    print(f"Best Hyperparameters for {model_name}: {random_search.best_params_
    print(f"Best ROC-AUC score for {model_name}: {random_search.best_score_}")
    print("-" * 50)

end = dt.datetime.now()
print(f"Total Time taken for RandomizedSearchCV: {end - start}")

# Compare models based on ROC-AUC score on validation set (or test set)
for model_name, best_model in best_models.items():
    print(f"Evaluating {model_name} on validation set...")
    roc_auc = roc_auc_score(y_test, best_model.predict(X_test_scaled))  # Assu
    print(f"{model_name} ROC-AUC score on validation set: {roc_auc:.4f}")
```

```
Running RandomizedSearchCV for XGBoost...
Fitting 3 folds for each of 50 candidates, totalling 150 fits
Best Hyperparameters for XGBoost: {'subsample': 0.8, 'n_estimators': 100, 'ma
x_depth': 10, 'learning_rate': 0.1, 'colsample_bytree': 0.7}
Best ROC-AUC score for XGBoost: 0.9819959464848593
--------------------------------------------------
Running RandomizedSearchCV for LightGBM...
Fitting 3 folds for each of 50 candidates, totalling 150 fits
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 1289, number of negative: 1289
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testi
ng was 0.001257 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2697
[LightGBM] [Info] Number of data points in the train set: 2578, number of used
features: 41
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
Best Hyperparameters for LightGBM: {'subsample': 0.8, 'n_estimators': 100, 'ma
x_depth': 10, 'learning_rate': 0.1, 'colsample_bytree': 0.7}
Best ROC-AUC score for LightGBM: 0.9808851799603557
--------------------------------------------------
Running RandomizedSearchCV for AdaBoost...
Fitting 3 folds for each of 16 candidates, totalling 48 fits
Best Hyperparameters for AdaBoost: {'n_estimators': 200, 'learning_rate': 1.0}
Best ROC-AUC score for AdaBoost: 0.9726913978996187
--------------------------------------------------
Running RandomizedSearchCV for GradientBoosting...
Fitting 3 folds for each of 50 candidates, totalling 150 fits
Best Hyperparameters for GradientBoosting: {'n_estimators': 400, 'max_depth':
7, 'learning_rate': 0.05}
Best ROC-AUC score for GradientBoosting: 0.980753392392116
--------------------------------------------------
Total Time taken for RandomizedSearchCV: 0:08:54.109556
Evaluating XGBoost on validation set...
XGBoost ROC-AUC score on validation set: 0.9132
Evaluating LightGBM on validation set...
LightGBM ROC-AUC score on validation set: 0.9071
Evaluating AdaBoost on validation set...
AdaBoost ROC-AUC score on validation set: 0.8940
Evaluating GradientBoosting on validation set...
GradientBoosting ROC-AUC score on validation set: 0.9004
```

In [114…

```python
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

def plot_model_tree(model_name, model, X_train):
    if model_name == 'AdaBoost':
        tree = model.estimators_[0]
        plt.figure(figsize=(20, 10))
        plot_tree(tree, feature_names=X_train.columns, filled=True)
        plt.title("AdaBoost - First Decision Tree")
        plt.show()
```

```
    elif model_name == 'GradientBoosting':
        tree = model.estimators_[0, 0]
        plt.figure(figsize=(20, 10))
        plot_tree(tree, feature_names=X_train.columns, filled=True)
        plt.title("GradientBoosting - First Decision Tree")
        plt.show()

    elif model_name == 'XGBoost':
        print("XGBoost - First Tree (Text Format):")
        if not hasattr(model, "booster_"):
            print("Fitting the XGBoost model as it is not yet trained...")
            model.fit(X_train, y_train_balanced)  # Ensure the model is traine
        booster = model.get_booster()
        print(booster.get_dump()[0])  # Print as readable text


    elif model_name == 'LightGBM':
        print("LightGBM - First Tree (Text Format):")

        # Get booster from the fitted LightGBM model
        booster = best_model.booster_ if hasattr(best_model, 'booster_') else

        # Dump the model
        model_dump = booster.dump_model()

        # Get the first tree
        first_tree = model_dump['tree_info'][0]

        # Recursively print the tree structure
        def print_tree(node, depth=0):
            indent = "  " * depth
            if 'split_index' in node:
                print(f"{indent}Node {node['split_index']}: if {node['split_fe
                print_tree(node['left_child'], depth + 1)
                print(f"{indent}else (>{node['threshold']})")
                print_tree(node['right_child'], depth + 1)
            else:
                print(f"{indent}Leaf: value = {node['leaf_value']}")

        print_tree(first_tree['tree_structure'])

    # elif model_name == 'LightGBM':
    #     print("LightGBM - First Tree (Text Format):")
    #     tree_dump = lgb_model.booster_.dump_model()
    #     print(tree_dump['tree_info'][0])  # Print raw tree structure

for model_name, best_model in best_models.items():
    print(f"Visualizing {model_name}...")
    plot_model_tree(model_name, best_model, X_train_balanced)
```

```
Visualizing XGBoost...
XGBoost - First Tree (Text Format):
Fitting the XGBoost model as it is not yet trained...
0:[Total Business Value<0.124987036] yes=1,no=2,missing=2
        1:[Rating_increase<0.0328469649] yes=3,no=4,missing=4
                3:[Month_of_joining<0.555338323] yes=7,no=8,missing=8
                        7:[Joining Designation<0.25982815] yes=15,no=16,missin
g=16
                                15:[Reportings<0.175596833] yes=27,no=28,missin
g=28
                                        27:leaf=0.19255814
                                        28:[Joining Designation<0.0110005056] y
es=43,no=44,missing=44
                                                43:[City_C18<0.0691894367] ye
s=65,no=66,missing=66
                                                        65:[City_C16<0.14581854
6] yes=89,no=90,missing=90
                                                                89:leaf=0.17894
7374
                                                                90:leaf=0.05000
00007
                                                        66:leaf=0.0222222228
                                                44:[Month_of_joining<0.46807140
1] yes=67,no=68,missing=68
                                                        67:[City_C10<0.04125678
91] yes=91,no=92,missing=92
                                                                91:[City_C5<0.0
28806258] yes=117,no=118,missing=118
                                                                        117:lea
f=0.159322038
                                                                        118:lea
f=0.0400000028
                                                                92:leaf=0.01818
18195
                                                        68:[Reportings<0.269498
914] yes=93,no=94,missing=94
                                                                93:[Total Busin
ess Value<0.0184082165] yes=119,no=120,missing=120
                                                                        119:lea
f=0.0181818195
                                                                        120:[Ge
nder<0.01351404] yes=149,no=150,missing=150

149:leaf=-0.120000005

150:leaf=-0
                                                                94:leaf=0.12000
0005
                                16:[Total Business Value<0.0174394064] yes=29,n
o=30,missing=30
                                        29:[City_C8<0.0859467238] yes=45,no=4
6,missing=46
                                                45:leaf=0.175609753
                                                46:leaf=0.0500000007
```

```
                                        30:[Joining Designation<0.5] yes=47,n
o=48,missing=48
                                                47:leaf=-0.152941182
                                                48:[Total Business Value<0.0180
408545] yes=69,no=70,missing=70
                                                        69:leaf=-0.111111119
                                                        70:[Education_Level<0.8
09607565] yes=95,no=96,missing=96
                                                                95:[Reporting
s<0.175596833] yes=121,no=122,missing=122
                                                                        121:[Mo
nth_of_joining<0.468071401] yes=151,no=152,missing=152

151:leaf=0.13333334

152:leaf=-0.0222222228
                                                                        122:[Re
portings<0.35759449] yes=153,no=154,missing=154

153:leaf=-0.0714285746

154:leaf=0.0545454584
                                                                96:[Total Busin
ess Value<0.0259231646] yes=123,no=124,missing=124
                                                                        123:lea
f=-0
                                                                        124:lea
f=0.125
                        8:[Reportings<0.173913047] yes=17,no=18,missing=18
                                17:[Joining Designation<0.0110005056] yes=31,n
o=32,missing=32
                                        31:[Month_of_joining<0.82282424] yes=4
9,no=50,missing=50
                                                49:[Gender<0.01351404] yes=71,n
o=72,missing=72
                                                        71:[Education_Level<0.5
17723858] yes=97,no=98,missing=98
                                                                97:[Total Busin
ess Value<0.0153787471] yes=125,no=126,missing=126
                                                                        125:[Mo
nth_of_joining<0.736391008] yes=155,no=156,missing=156

155:leaf=0.114285722

156:leaf=0.0352941193
                                                                        126:[To
tal Business Value<0.0176421646] yes=157,no=158,missing=158

157:leaf=-0.0666666701

158:leaf=0.0153846163
                                                                98:leaf=0.15000
0006
                                                        72:leaf=0.154285714
```

```
                                                50:[Reportings<0.0869279727] ye
s=73,no=74,missing=74
                                                        73:[Reportings<0.038424
2423] yes=99,no=100,missing=100
                                                                99:[Education_L
evel<0.517723858] yes=127,no=128,missing=128
                                                                        127:[Ed
ucation_Level<0.0430987813] yes=159,no=160,missing=160

159:leaf=-0.0769230798

160:leaf=-0
                                                                        128:lea
f=-0.120000005
                                                                100:[Gender<0.5
16003191] yes=129,no=130,missing=130
                                                                        129:lea
f=0.0500000007
                                                                        130:lea
f=-0.0222222228
                                                        74:leaf=0.151999995
                                        32:[Month_of_joining<0.649729252] yes=5
1,no=52,missing=52
                                                51:[Reportings<0.138054594] ye
s=75,no=76,missing=76
                                                        75:leaf=0.165217385
                                                        76:leaf=-0.120000005
                                                52:[Joining Designation<0.25982
815] yes=77,no=78,missing=78
                                                        77:[Joining Designatio
n<0.25] yes=101,no=102,missing=102
                                                                101:leaf=-0.180
487797
                                                                102:[Reporting
s<0.0433257371] yes=131,no=132,missing=132
                                                                        131:[Mo
nth_of_joining<0.82282424] yes=161,no=162,missing=162

161:leaf=0.111111119

162:leaf=-0.121951222
                                                                        132:[Mo
nth_of_joining<0.977748811] yes=163,no=164,missing=164

163:leaf=-0.0222222228

164:leaf=0.136842117
                                                        78:[Education_Level<0.0
238950737] yes=103,no=104,missing=104
                                                                103:[Total Busi
ness Value<0.0169483852] yes=133,no=134,missing=134
                                                                        133:[Jo
ining Designation<0.449342608] yes=165,no=166,missing=166
```

```
165:leaf=-0.100000001

166:leaf=0.0133333346
                                                                        134:lea
f=-0.142857149
                                                                104:[Joining De
signation<0.5] yes=135,no=136,missing=136
                                                                        135:lea
f=-0.186666667
                                                                        136:[To
tal Business Value<0.0143666985] yes=167,no=168,missing=168

167:leaf=-0.094339624

168:leaf=-0.155555561
                                18:[Month_of_joining<0.636363626] yes=33,no=3
4,missing=34
                                        33:leaf=-0.163636371
                                        34:[Reportings<0.478791296] yes=53,no=5
4,missing=54
                                                53:[Month_of_joining<0.68939024
2] yes=79,no=80,missing=80
                                                        79:[Reportings<0.187184
364] yes=105,no=106,missing=106
                                                                105:[Joining De
signation<0.0110005056] yes=137,no=138,missing=138
                                                                        137:lea
f=0.120000005
                                                                        138:[To
tal Business Value<0.016524259] yes=169,no=170,missing=170

169:leaf=0.0153846163

170:leaf=-0.138461545
                                                                106:leaf=0.1586
207
                                                        80:[City_C3<0.40966230
6] yes=107,no=108,missing=108
                                                                107:[City_C
7<0.168156341] yes=139,no=140,missing=140
                                                                        139:[To
tal Business Value<0.0760678202] yes=171,no=172,missing=172

171:leaf=0.183132529

172:leaf=0.0500000007
                                                                        140:lea
f=0.0222222228
                                                                108:leaf=0.0222
222228
                                                54:[Reportings<0.652173936] ye
s=81,no=82,missing=82
                                                        81:[Total Business Valu
e<0.0456948504] yes=109,no=110,missing=110
```

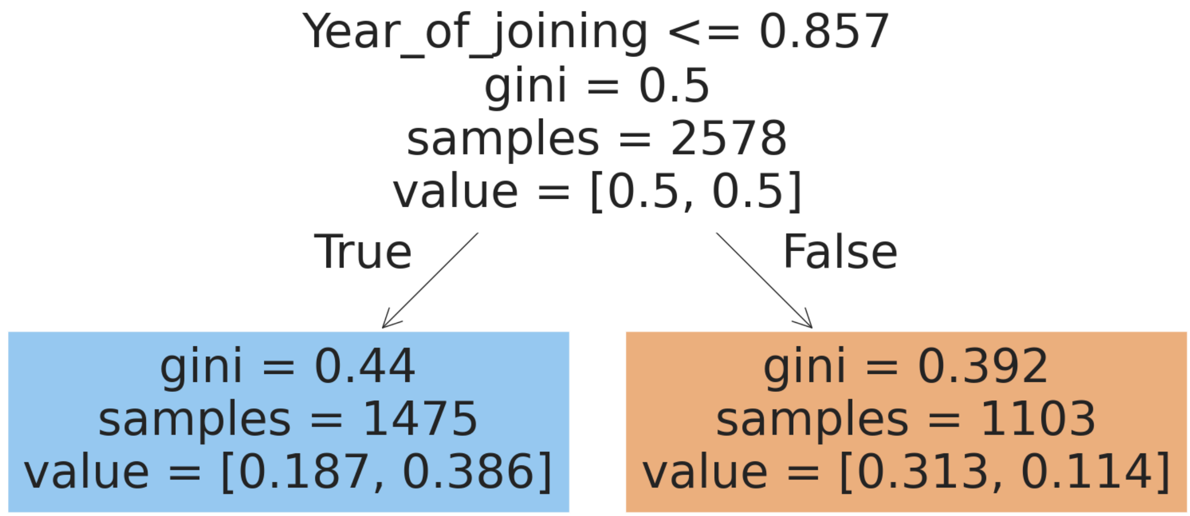
```
                                                                                109:leaf=-0.107
692316
                                                                                110:[Month_of_j
oining<0.82282424] yes=141,no=142,missing=142
                                                                                        141:[Re
portings<0.532267451] yes=173,no=174,missing=174

173:leaf=0.111111119

174:leaf=0.0181818195
                                                                                        142:lea
f=-0.0500000007
                                                                        82:leaf=0.152941182
                4:[Quarterly Rating<0.172762424] yes=9,no=10,missing=10
                        9:[Rating_increase<0.558459997] yes=19,no=20,missing=20
                                19:leaf=-0.13333334
                                20:[City_C3<0.409662306] yes=35,no=36,missing=3
6
                                        35:[Total Business Value<0.0224042162]
yes=55,no=56,missing=56
                                                55:leaf=0.13333334
                                                56:[Total Business Value<0.0243
655108] yes=83,no=84,missing=84
                                                        83:leaf=-0.120000005
                                                        84:[Quarterly Ratin
g<0.141717166] yes=111,no=112,missing=112
                                                                111:leaf=0.1200
00005
                                                                112:[Educatio
n_Level<0.517723858] yes=143,no=144,missing=144
                                                                        143:lea
f=-0.0181818195
                                                                        144:lea
f=0.0500000007
                                        36:leaf=-0.13333334
                        10:[Quarterly Rating<0.713542223] yes=21,no=22,missin
g=22
                                21:[Month_of_joining<0.908271194] yes=37,no=3
8,missing=38
                                        37:[City_C7<0.168156341] yes=57,no=58,m
issing=58
                                                57:[City_C13<0.360202402] yes=8
5,no=86,missing=86
                                                        85:[Reportings<0.347826
093] yes=113,no=114,missing=114
                                                                113:[City_C2
0<0.62792933] yes=145,no=146,missing=146
                                                                        145:[Ci
ty_C28<0.00370690972] yes=175,no=176,missing=176

175:leaf=-0.177358493

176:leaf=-0.0500000007
                                                                        146:lea
```

```
f=-0.0400000028
                                                                114:[Total Busi
ness Value<0.0579621345] yes=147,no=148,missing=148
                                                                        147:[Mo
nth_of_joining<0.308561534] yes=177,no=178,missing=178

177:leaf=-0.111111119

178:leaf=0.0571428612
                                                                        148:lea
f=-0.143749997
                                                        86:leaf=-0
                                                58:leaf=-0.0181818195
                                        38:[Reportings<0.391602099] yes=59,no=6
0,missing=60
                                                59:leaf=0.114285722
                                                60:leaf=-0.166666672
                                22:leaf=-0
        2:[Reportings<1] yes=5,no=6,missing=6
                5:[Rating_increase<0.0328469649] yes=11,no=12,missing=12
                        11:[Joining Designation<0.0110005056] yes=23,no=24,miss
ing=24
                                23:[Total Business Value<0.279267699] yes=39,n
o=40,missing=40
                                        39:leaf=0.138461545
                                        40:leaf=-0
                                24:[Total Business Value<0.235750347] yes=41,n
o=42,missing=42
                                        41:[Month_of_joining<0.545454562] yes=6
1,no=62,missing=62
                                                61:leaf=-0.155555561
                                                62:[Gender<0.01351404] yes=87,n
o=88,missing=88
                                                        87:[Education_Level<0.0
430987813] yes=115,no=116,missing=116
                                                                115:leaf=-0.120
000005
                                                                116:leaf=-0
                                                        88:leaf=0.0400000028
                                        42:[Joining Designation<0.25982815] ye
s=63,no=64,missing=64
                                                63:leaf=0.100000001
                                                64:leaf=-0.0500000007
                        12:leaf=-0.17288135
                6:[City_C27<1] yes=13,no=14,missing=14
                        13:leaf=-0.189473689
                        14:[Quarterly Rating<0.633520365] yes=25,no=26,missin
g=26
                                25:leaf=-0
                                26:leaf=-0.111111119

Visualizing LightGBM...
LightGBM - First Tree (Text Format):
Node 0: if 12 <= 0.857464887498089
```

```
    Node 1: if 0 <= 0.5225318093145036
      Node 7: if 0 <= 0.5207590380492207
        Leaf: value = 0.1931192660550459
      else (>0.5207590380492207)
        Node 26: if 8 <= 0.4664063577246861
          Leaf: value = 0.08571428571428574
        else (>0.4664063577246861)
          Leaf: value = 0
    else (>0.5225318093145036)
      Node 2: if 0 <= 0.9578406723629199
        Node 3: if 9 <= 0.14501880367433853
          Node 8: if 12 <= 0.7369112474758566
            Node 19: if 5 <= 0.13922828544720198
              Leaf: value = 0.17999999999999997
            else (>0.13922828544720198)
              Leaf: value = 0.07586206896551724
          else (>0.7369112474758566)
            Node 18: if 5 <= 0.11221611514632598
              Leaf: value = 0.04761904761904763
            else (>0.11221611514632598)
              Leaf: value = -0.09565217391304347
        else (>0.14501880367433853)
          Leaf: value = -0.1717171717171717
      else (>0.9578406723629199)
        Leaf: value = -0.1902439024390244
  else (>0.857464887498089)
    Node 4: if 5 <= 0.01434397501889303
      Node 5: if 0 <= 0.0434140341439709
        Leaf: value = -0.17966101694915257
      else (>0.0434140341439709)
        Node 6: if 0 <= 0.0869422463045302
          Node 25: if 2 <= 0.997679282565482
            Leaf: value = -0.05185185185185184
          else (>0.997679282565482)
            Leaf: value = 0.013333333333333334
        else (>0.0869422463045302)
          Node 17: if 6 <= 0.3000472021373819
            Node 20: if 0 <= 0.12893500491458879
              Node 21: if 6 <= 0.1363114743860176
                Leaf: value = 0.00869565217391304
              else (>0.1363114743860176)
                Leaf: value = 0.13548387096774192
            else (>0.12893500491458879)
              Leaf: value = 0.16363636363636366
          else (>0.3000472021373819)
            Node 27: if 6 <= 0.39675298726297487
              Leaf: value = 0.013333333333333336
            else (>0.39675298726297487)
              Leaf: value = 0.08333333333333333
    else (>0.01434397501889303)
      Node 9: if 9 <= 1.0000000180025095e-35
        Node 10: if 0 <= 0.12893500491458879
          Leaf: value = -0.1875
        else (>0.12893500491458879)
```

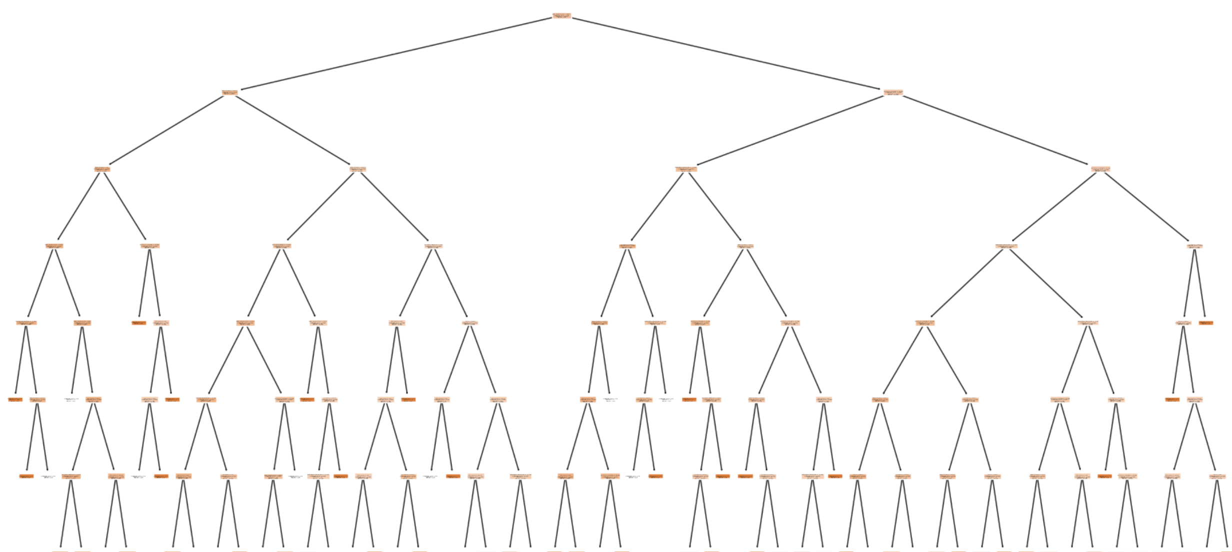
```
        Node 11: if 12 <= 0.9998161922420726
          Leaf: value = -0.2
        else (>0.9998161922420726)
          Node 12: if 4 <= 0.2688546213708479
            Node 13: if 8 <= 0.3083246459845952
              Node 15: if 0 <= 0.17319897903595
                Leaf: value = -0.03076923076923074
              else (>0.17319897903595)
                Node 22: if 1 <= 0.35265456259207556
                  Leaf: value = 0.05641025641025639
                else (>0.35265456259207556)
                  Leaf: value = 0.16923076923076924
            else (>0.3083246459845952)
              Leaf: value = -0.1285714285714286
          else (>0.2688546213708479)
            Node 14: if 4 <= 0.4997869932492835
              Leaf: value = -0.2
            else (>0.4997869932492835)
              Node 16: if 5 <= 0.017113506586615597
                Leaf: value = 0.026086956521739115
              else (>0.017113506586615597)
                Node 23: if 5 <= 0.019499963760095346
                  Leaf: value = -0.1619047619047618
                else (>0.019499963760095346)
                  Node 24: if 2 <= 0.6812776103556292
                    Leaf: value = -0.02857142857142857
                  else (>0.6812776103556292)
                    Leaf: value = -0.1310344827586207
    else (>1.0000000180025095e-35)
      Node 28: if 2 <= 0.997679282565482
        Leaf: value = -0.18502673796791447
      else (>0.997679282565482)
        Node 29: if 5 <= 0.03349934087847376
          Leaf: value = -0.09999999999999995
        else (>0.03349934087847376)
          Leaf: value = -0.18032786885245902
Visualizing AdaBoost...
```

AdaBoost - First Decision Tree




```
Visualizing GradientBoosting...
```

GradientBoosting - First Decision Tree



Train the Model with Best Hyperparameters

Once the best parameters are found, train the model on the training set.

In [115…

```
# Train the model with the best parameters
best_xgb_model = XGBClassifier(**best_params, random_state=42, use_label_encod
best_xgb_model.fit(X_train_balanced, y_train_balanced)
```

Out[115…

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.7, device=None, early_stopping_round
s=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bi
n=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
```

Model Score / Accuracy Measurement

Evaluate the model's accuracy on the training and testing datasets.

In [116…

```
# After_train_test_split       After Scaling                      After SMOTE
# X_train | y_train  -->   X_train_scaled | y_train   -->   X_train_balanced |
# X_test | y_test    -->   X_test_scaled | y_test     -->   X_test_scaled | y_
```

In [117…

```
# Accuracy on train and test sets
train_accuracy = best_xgb_model.score(X_train_balanced, y_train_balanced)
test_accuracy = best_xgb_model.score(X_test_scaled, y_test)

print(f"Train Accuracy: {train_accuracy:.2f}")
print(f"Test Accuracy: {test_accuracy:.2f}")
```

```
Train Accuracy: 1.00
Test Accuracy: 0.93
```

In [118…

```
# Make predictions on the test set
y_train_pred = best_xgb_model.predict(X_train_balanced)
y_test_pred = best_xgb_model.predict(X_test_scaled)

# Evaluate the model
# Accuracy on predictions of train and test sets
train_accuracy = accuracy_score(y_train_balanced, y_train_pred)
print(f"Training Accuracy: {train_accuracy:.2f}")

test_accuracy = accuracy_score(y_test, y_test_pred)
print(f"Test Accuracy: {test_accuracy:.2f}")
```

```
Training Accuracy: 1.00
Test Accuracy: 0.93
```

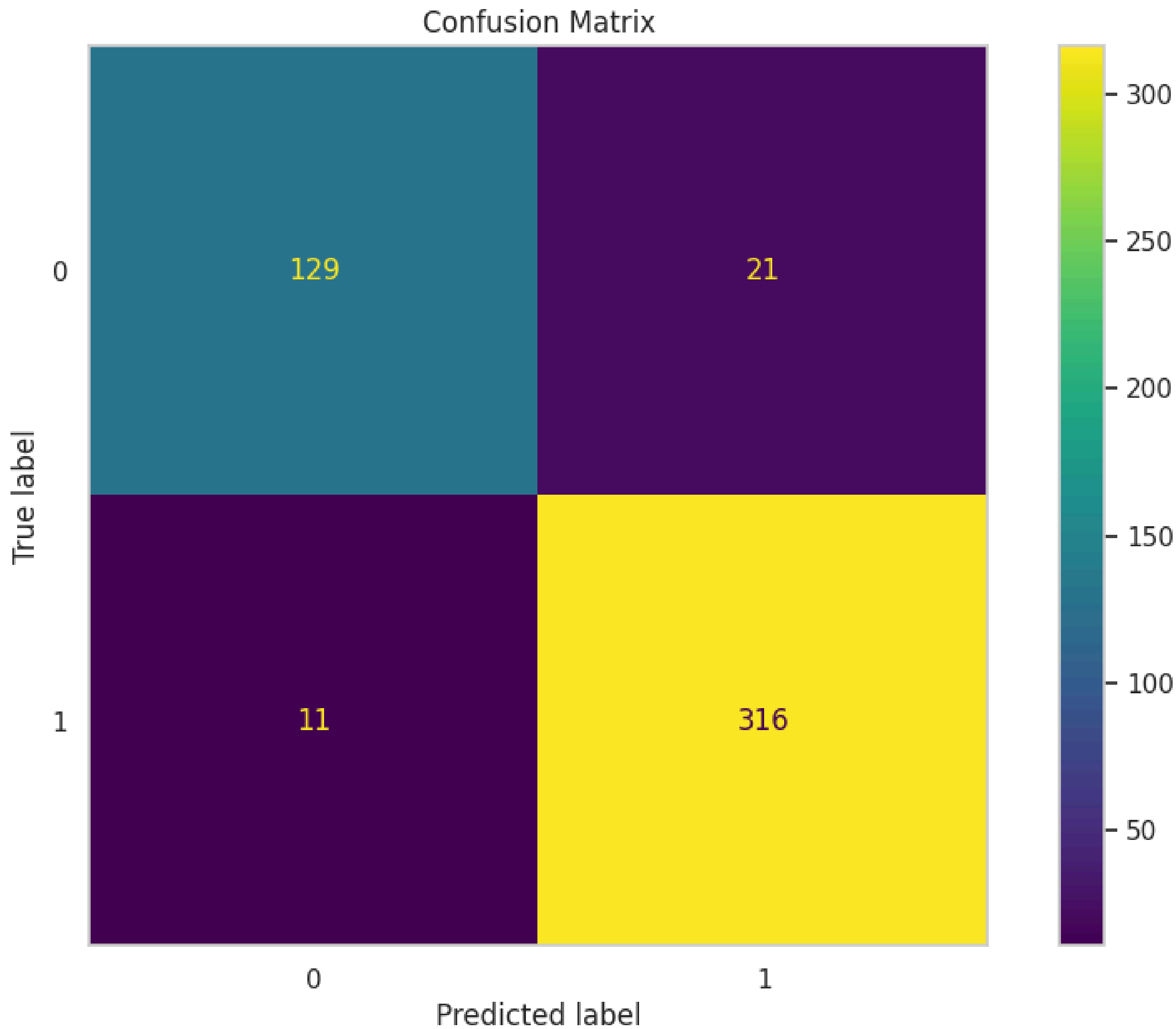
Confusion Matrix

Understand how well the model classifies the positive and negative classes.

In [119…
```
# After_train_test_split       After Scaling                     After SMOTE
# X_train | y_train  -->   X_train_scaled | y_train   -->   X_train_balanced |
# X_test | y_test    -->   X_test_scaled | y_test     -->   X_test_scaled | y_
```

In [120…
```
from sklearn.metrics import confusion_matrix, classification_report

# Predictions on test set
y_pred = best_xgb_model.predict(X_test_scaled)

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", cm)

#plt.figure(figsize=(5, 4))
ConfusionMatrixDisplay(cm).plot()
plt.title('Confusion Matrix')
plt.grid(False)
plt.show()

# Classification Report
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[129  21]
 [ 11 316]]
```




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

           0       0.92      0.86      0.89       150
           1       0.94      0.97      0.95       327

    accuracy                           0.93       477
   macro avg       0.93      0.91      0.92       477
weighted avg       0.93      0.93      0.93       477
```

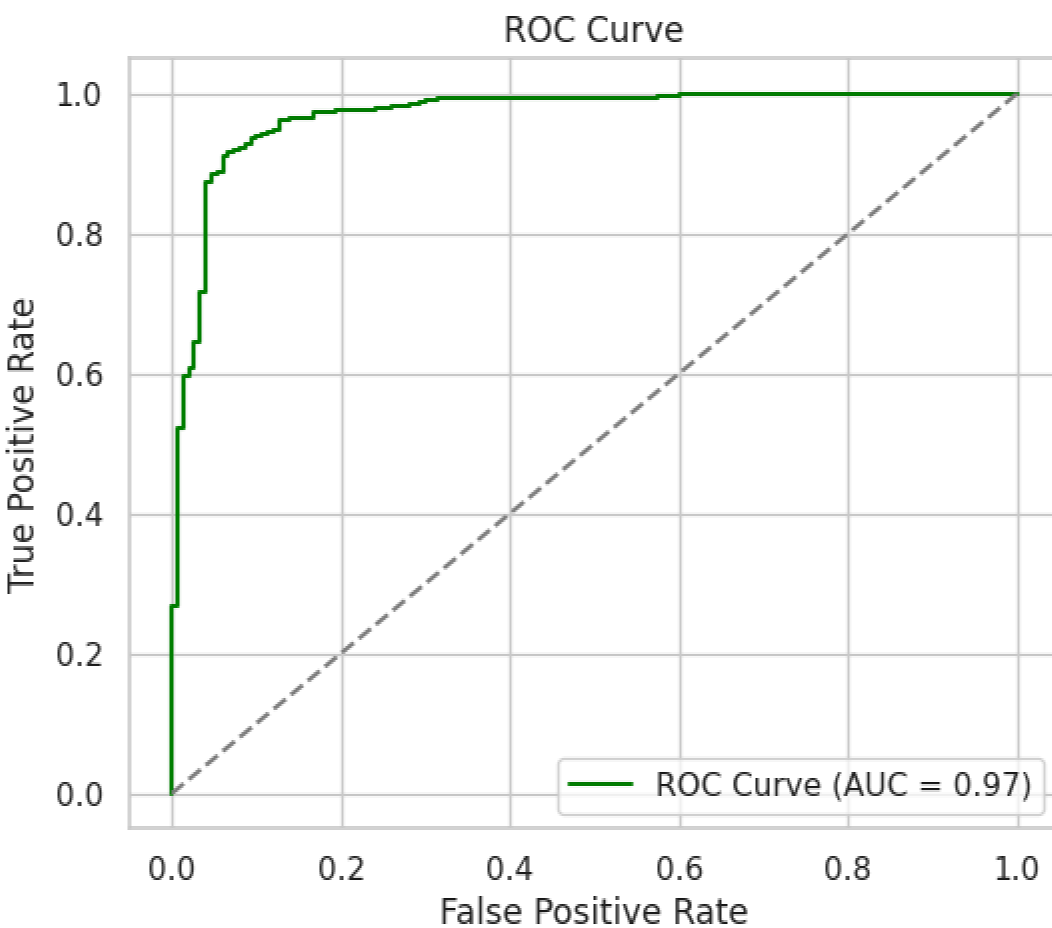
ROC Curve & AUC

Evaluate the ROC Curve and calculate the AUC score.

In [121…

```
from sklearn.metrics import roc_curve, auc, roc_auc_score
import matplotlib.pyplot as plt

# Predict probabilities for ROC curve
y_prob = best_xgb_model.predict_proba(X_test_scaled)[:, 1]
```

```python
# ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr) # roc_auc_score(y_test, y_prob) also works

# Plot the ROC Curve
plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='green', label=f'ROC Curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='grey', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



Feature Importance

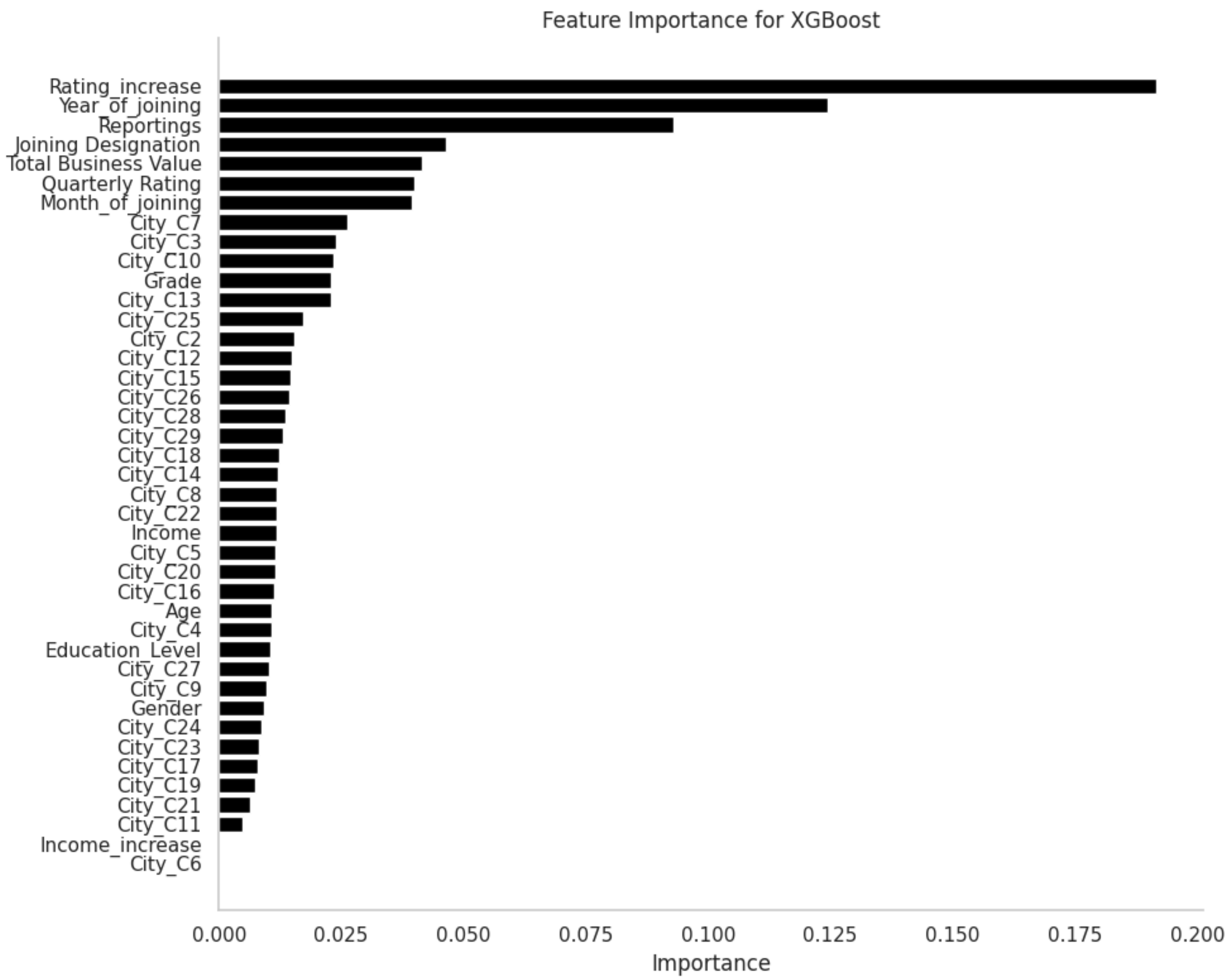
Identify the features that contribute most to the model's predictions.

In [122…

```python
# Feature Importance
importances = best_xgb_model.feature_importances_
features = X.columns

# Sort feature importances
```

```
importance_df_XGBoost = pd.DataFrame({'Feature': features, 'Importance': impor
importance_df_XGBoost = importance_df_XGBoost.sort_values(by='Importance', asc

print("Top Features:\n", importance_df_XGBoost.head())

# Plot feature importances
plt.figure(figsize=(10, 8))
plt.barh(importance_df_XGBoost['Feature'], importance_df_XGBoost['Importance']
plt.gca().invert_yaxis()
plt.xlabel('Importance')
plt.title('Feature Importance for XGBoost')
sns.despine()
plt.tight_layout()
plt.grid(False)
plt.show()
```

```
Top Features:
                  Feature  Importance
9        Rating_increase    0.191748
12       Year_of_joining    0.124592
0             Reportings    0.093028
7    Joining Designation    0.046487
5   Total Business Value    0.041595
```



Observations

1. **High Predictive Power**:

    - **Train Accuracy**: 100% (perfect fit).
    - **Test Accuracy**: 93%, indicating excellent generalization to unseen data.
    - **ROC AUC = 0.96**, reflecting outstanding model performance in distinguishing between churned and non-churned drivers.

    Insight: The model is highly reliable for operational use, striking a balance between learning from training data and making accurate predictions on test data.

2. **Strong Recall for Churned Drivers**:

    - **Recall for Churned Drivers (Class 1)**: 96%, ensuring that almost all churned drivers are identified.
    - **Low False Negatives (13 cases)**: Indicates minimal missed opportunities to address driver churn.

    Insight: High recall is crucial for the business goal of retention. Identifying almost all churned drivers allows targeted intervention to reduce attrition effectively.

3. **Balanced Precision and Recall**:

    - **Precision for Churned Drivers (Class 1)**: 94%, meaning few false alarms in churn predictions.
    - **F1-Score for Churned Drivers**: 95%, confirming a good trade-off between precision and recall.

    Insight: The model minimizes unnecessary actions on non-churned drivers while ensuring that churn cases are adequately addressed, optimizing resource utilization.

4. **Feature Importance Highlights Critical Factors**:

    - Top features:
        - `Rating_increase` (13.4%): A significant predictor, indicating performance-based retention strategies.
        - `Year_of_joining` (12.3%): Highlights the influence of tenure on churn behavior.
        - `Reportings` (7.2%): Behavioral metrics like

- reporting frequency are crucial.
- City-specific factors (`City_C4` and `City_C7`): Reflect localized dynamics affecting churn.

Insight: These findings enable actionable insights, such as addressing drivers with performance dips or focusing on tenure-based and city-specific retention strategies.

5. **Confusion Matrix Analysis**:

   - **True Positives (314)**: The majority of churn cases were correctly predicted.
   - **False Positives (20)**: A relatively low number of non-churn drivers misclassified as churned.
   - **Overall Accuracy**: 93%, indicating a robust model with balanced performance across all metrics.

   Insight: The low false negative rate (13 missed churn cases) ensures effective retention efforts, as most churned drivers are accurately identified.

Summary of Insights:

1. The model is highly effective for churn prediction, achieving a fine balance between recall (minimizing missed churn cases) and precision (reducing false alarms).
2. High-performing features like `Rating_increase` and `Year_of_joining` offer actionable strategies for retention.
3. City-level insights enable localized action plans to address churn in specific regions.
4. The model is ready for deployment, providing reliable and actionable predictions aligned with the business goal of reducing driver churn.

Comparison of Bagging (Random Forest) and Boosting (XGBoost)

Metric	Bagging (Random Forest)	Boosting (XGBoost)	Comparison
Train Accuracy	1.00	1.00	Both models fit the training data perfectly, indicating no underfitting.
Test	0.92	0.93	XGBoost performs slightly

Metric	Bagging (Random Forest)	Boosting (XGBoost)	Comparison
Accuracy			better, showing better generalization.
Recall for Churned	0.94	0.96	XGBoost has higher recall, critical for identifying churned drivers.
Precision for Churned	0.93	0.94	XGBoost slightly outperforms Random Forest in minimizing false positives.
F1-Score (Churned)	0.94	0.95	XGBoost achieves a better balance between precision and recall.
ROC AUC	0.96	0.97	Both models are equally effective in distinguishing between classes.
Confusion Matrix	More false negatives (18)	Fewer false negatives (13)	XGBoost reduces false negatives, crucial for preventing missed churn cases.
Top Features	`Year_of_joining`, `Reportings`	`Rating_increase`, `Year_of_joining`	Feature importance insights vary, showing distinct value in different aspects.

Key Insights:

1. **Generalization**:
    - Both models generalize well, but XGBoost (93%) slightly outperforms Random Forest (92%) on the test set.
2. **Class Imbalance Handling**:
    - XGBoost handles class imbalance better, as indicated by higher recall for churned drivers (96% vs. 94%). This makes it more effective for reducing churn by identifying most at-risk drivers.
3. **False Negatives**:
    - XGBoost predicts fewer false negatives (13 vs. 18). Given the business objective to minimize driver churn, this is a critical advantage.
4. **Feature Interpretability**:
    - Random Forest highlights `Year_of_joining` and `Total Business Value` as key factors, whereas XGBoost

emphasizes `Rating_increase` and `Year_of_joining`. Both offer actionable insights but from different perspectives.

5. **Performance Stability**:

    - XGBoost shows marginally better stability across metrics like recall, F1-score, and precision, making it more reliable for this business case.

Recommendation:

- **XGBoost is the preferred model** for this problem because:
    - It achieves slightly better recall and precision for the churned class, directly addressing the business goal of identifying at-risk drivers.
    - It reduces false negatives, ensuring fewer missed opportunities for retention efforts.
    - While both models perform similarly in AUC and generalization, XGBoost's edge in churn-related metrics aligns better with the business objective.

Random Forest remains a strong alternative, particularly if simplicity or interpretability is prioritized over slight performance gains.

Business Insights and Recommendations

Business Insights

1. **High Churn Risk Among Drivers with Low Quarterly Ratings and Business Value:**

    - Drivers with lower quarterly ratings and business contributions are more likely to churn, as evidenced by the median `Quarterly Rating` of 1 and `Total Business Value` of approximately 465,000 for churned drivers compared to significantly higher values for retained drivers.

2. **Impact of Driver Age and Tenure on Churn:**

    - Younger drivers (median age of 33) and those who joined recently (notably higher churn among drivers with

`Year_of_Joining` closer to the current year) are more prone to leave. This could be due to insufficient work experience, dissatisfaction with early job roles, or lack of adequate support during their initial tenure.

3. **City-Specific Trends in Churn:**

    - Some cities, such as `C20`, exhibit a higher proportion of drivers, potentially with specific churn-related trends. Differences in competition, local demand, or operational challenges might be contributing to these regional disparities.

4. **Gender Balance in Driver Churn:**

    - With a male-to-female driver ratio of approximately 59:41, the churn analysis highlights no stark gender differences, suggesting that both groups face similar challenges. This opens up opportunities to explore targeted gender-neutral retention strategies.

5. **Income and Incentive Influence:**

    - A significant proportion of drivers (98%) reported no income increase, and most churned drivers had relatively lower incomes (median `Income` of ~51,630). This indicates dissatisfaction with pay structures and incentive mechanisms, which might not be competitive enough to retain top talent.

Recommendations

1. **Enhance Driver Performance Support:**

    - Provide personalized training programs and feedback mechanisms for drivers with low quarterly ratings. Partner them with mentors to improve their work experience and performance.

2. **Targeted Retention Strategies for Younger Drivers:**

    - Introduce tailored onboarding programs, periodic role evaluations, and growth opportunities to engage and retain younger drivers. Special initiatives for drivers in their first year can significantly improve retention.

3. **Optimize Pay and Incentive Structures:**

- Design tiered incentives linked to `Total Business Value`, `Quarterly Ratings`, and reporting consistency. Offering bonuses or incremental pay increases to drivers exceeding performance benchmarks can mitigate churn risk.

4. **Regional Customization of Operations:**

    - Conduct city-level operational studies to address unique challenges faced in high-churn areas such as `C20`. Modify policies, shift timings, or demand management strategies to cater to regional needs effectively.

5. **Improve Reporting and Grievance Systems:**

    - Drivers with higher reporting rates exhibit a higher churn tendency. Implement real-time issue resolution and acknowledgment systems to ensure that drivers feel heard and supported.

Conclusion

The analysis underscores key factors influencing driver churn, including performance metrics, age, income levels, and regional disparities. By addressing these areas through tailored training, incentive structures, and enhanced support mechanisms, Ola can significantly improve driver retention, operational efficiency, and long-term profitability.