In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns


from scipy.stats import skew

from imblearn.over_sampling import SMOTE

from sklearn.preprocessing import TargetEncoder, StandardScaler
from sklearn.model_selection import train_test_split, KFold, cross_val_score, Gr
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier

from sklearn.utils.class_weight import compute_class_weight
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay , roc_auc_s
```

In [ ]:
```
df=pd.read_csv("ola_driver_scaler.csv")
```

Define Problem Statement and perform Exploratory Data Analysis

Problem Statement

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

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

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

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

Column Profiling:

- MMMM-YY : Reporting Date (Monthly)
- Driver_ID : Unique id for drivers
- Age : Age of the driver

- Gender : Gender of the driver – Male : 0, Female: 1
- City : City Code of the driver
- Education_Level : Education level – 0 for 10+ ,1 for 12+ ,2 for graduate
- Income : Monthly average Income of the driver
- Date Of Joining : Joining date for the driver
- LastWorkingDate : Last date of working for the driver
- Joining Designation : Designation of the driver at the time of joining
- Grade : Grade of the driver at the time of reporting
- Total Business Value : The total business value acquired by the driver in a month (negative business indicates cancellation/refund or car EMI adjustments)
- Quarterly Rating : Quarterly rating of the driver: 1,2,3,4,5 (higher is better)

Observations in Data

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

Out[ ]:

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

In [ ]:
```
df.tail()
```

Out[ ]:

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	D
19099	19099	08/01/20	2788	30.0	0.0	C27	2	70254	
19100	19100	09/01/20	2788	30.0	0.0	C27	2	70254	
19101	19101	10/01/20	2788	30.0	0.0	C27	2	70254	
19102	19102	11/01/20	2788	30.0	0.0	C27	2	70254	
19103	19103	12/01/20	2788	30.0	0.0	C27	2	70254	

In [ ]:
```
# dropping Unnamed: 0 col
df.drop(columns="Unnamed: 0",inplace=True)
```

In [ ]:
```
# descriptive summary
df.describe()
```

Out[ ]:

	Driver_ID	Age	Gender	Education_Level	Income	Desi
count	19104.000000	19043.000000	19052.000000	19104.000000	19104.000000	19104
mean	1415.591133	34.668435	0.418749	1.021671	65652.025126	1
std	810.705321	6.257912	0.493367	0.800167	30914.515344	0
min	1.000000	21.000000	0.000000	0.000000	10747.000000	1
25%	710.000000	30.000000	0.000000	0.000000	42383.000000	1
50%	1417.000000	34.000000	0.000000	1.000000	60087.000000	1
75%	2137.000000	39.000000	1.000000	2.000000	83969.000000	2
max	2788.000000	58.000000	1.000000	2.000000	188418.000000	5

- drivers have varied ages from 21 (lowest) to 58 (highest) years of age
- there are 59% male drivers and 41% female drivers

In [ ]:

```
# checking datatyps
df.info()
```

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

In [ ]:

```
# lets check data for a given driverID
df[df['Driver_ID'] == 18]
```

Out[ ]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	La
63	01/01/19	18	27.0	1.0	C17	1	31631	01/09/19	
64	02/01/19	18	27.0	1.0	C17	1	31631	01/09/19	
65	03/01/19	18	27.0	1.0	C17	1	31631	01/09/19	
66	04/01/19	18	27.0	1.0	C17	1	31631	01/09/19	
67	05/01/19	18	27.0	1.0	C17	1	31631	01/09/19	

In [ ]:

```
val = df[['Driver_ID']].sample()
did = val.iloc[0,0]
df[df['Driver_ID'] == did]
```

Out[ ]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining
13192	01/01/19	1959	35.0	0.0	C26	2	40099	19/06/18
13193	02/01/19	1959	35.0	0.0	C26	2	40099	19/06/18
13194	03/01/19	1959	35.0	0.0	C26	2	40099	19/06/18
13195	04/01/19	1959	35.0	0.0	C26	2	40099	19/06/18
13196	05/01/19	1959	35.0	0.0	C26	2	40099	19/06/18
13197	06/01/19	1959	35.0	0.0	C26	2	40099	19/06/18
13198	07/01/19	1959	35.0	0.0	C26	2	40099	19/06/18
13199	08/01/19	1959	35.0	0.0	C26	2	40099	19/06/18
13200	09/01/19	1959	35.0	0.0	C26	2	40099	19/06/18
13201	10/01/19	1959	36.0	0.0	C26	2	40099	19/06/18
13202	11/01/19	1959	36.0	0.0	C26	2	40099	19/06/18
13203	12/01/19	1959	36.0	0.0	C26	2	40099	19/06/18
13204	01/01/20	1959	36.0	0.0	C26	2	40099	19/06/18
13205	02/01/20	1959	36.0	0.0	C26	2	40099	19/06/18

In [ ]:

```
# converting objects to datetime format
df['Dateofjoining']=pd.to_datetime(df['Dateofjoining'],errors='coerce')
df['LastWorkingDate']=pd.to_datetime(df['LastWorkingDate'],errors='coerce')
```

```
C:\Users\ashut\AppData\Local\Temp\ipykernel_32560\402060823.py:2: UserWarning: Co
uld not infer format, so each element will be parsed individually, falling back t
o `dateutil`. To ensure parsing is consistent and as-expected, please specify a f
ormat.
  df['Dateofjoining']=pd.to_datetime(df['Dateofjoining'],errors='coerce')
C:\Users\ashut\AppData\Local\Temp\ipykernel_32560\402060823.py:3: UserWarning: Co
uld not infer format, so each element will be parsed individually, falling back t
o `dateutil`. To ensure parsing is consistent and as-expected, please specify a f
ormat.
  df['LastWorkingDate']=pd.to_datetime(df['LastWorkingDate'],errors='coerce')
```

In [ ]:
```
df[df['Driver_ID'] == 18]
```

Out[ ]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	La
63	01/01/19	18	27.0	1.0	C17	1	31631	2019-01-09	
64	02/01/19	18	27.0	1.0	C17	1	31631	2019-01-09	
65	03/01/19	18	27.0	1.0	C17	1	31631	2019-01-09	
66	04/01/19	18	27.0	1.0	C17	1	31631	2019-01-09	
67	05/01/19	18	27.0	1.0	C17	1	31631	2019-01-09	

In [ ]:
```
# groupping over driverid to have our data behaviour consistent
def check(x):
    val = x.unique()
    return val[-1]

groups = df.groupby("Driver_ID")
# agg_dict = {
#     "MMM-YY" : "count",
#     "Age" : 'first',
#     "Gender" : "first",
#     "City" : 'first',
#     "Education_Level" : 'first',
#     "Income" : 'first',
#     "Dateofjoining" : 'first',
#     "LastWorkingDate" : 'last',
#     "Joining Designation" : 'first',
#     "Grade" : 'first',
#     "Total Business Value" : "sum" ,
#     "Quarterly Rating" : 'mean'
# }

dfg = groups.agg(
    total_months=("MMM-YY" ,"count"),
    age=('Age','first'),
    gender=('Gender',"first"),
    city=("City",'first'),
    education=("Education_Level" , "first"),
    income=("Income",'last'),
    DOJ= ("Dateofjoining" , 'first'),
    LWD= ("LastWorkingDate" , check) ,
    joining_designation=("Joining Designation" , 'first'),
```

```
    grade=("Grade" , 'first'),
    total_business_val=("Total Business Value" , "sum"),
    quarterly_rating=("Quarterly Rating" , 'mean')
).reset_index()
```

In [ ]:
```
print(f"Total number of unique driverID : {groups.ngroups}")
```

```
Total number of unique driverID : 2381
```

In [ ]:
```
dfg.head()
```

Out[ ]:

	Driver_ID	total_months	age	gender	city	education	income	DOJ	LWD	joinin
0	1	3	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	
1	2	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	
2	4	5	43.0	0.0	C13	2	65603	2019-12-07	2020-04-27	
3	5	3	29.0	0.0	C9	0	46368	2019-01-09	2019-03-07	
4	6	5	31.0	1.0	C11	1	78728	2020-07-31	NaT	

In [ ]:
```
# creating the target
dfg['Churn']=dfg['LWD'].fillna(0).apply(lambda x : 1 if x!=0 else 0)
dfg.drop(columns='LWD',inplace=True)
```

In [ ]:
```
dfg.head()
```

Out[ ]:

	Driver_ID	total_months	age	gender	city	education	income	DOJ	joining_desig
0	1	3	28.0	0.0	C23	2	57387	2018-12-24	
1	2	2	31.0	0.0	C7	2	67016	2020-11-06	
2	4	5	43.0	0.0	C13	2	65603	2019-12-07	
3	5	3	29.0	0.0	C9	0	46368	2019-01-09	
4	6	5	31.0	1.0	C11	1	78728	2020-07-31	

In [ ]:
```
dfg['gender'].value_counts(normalize=True)
```

Out[ ]:
```
gender
0.0    0.589668
1.0    0.410332
Name: proportion, dtype: float64
```

In [ ]:
```
# target distribution
dfg['Churn'].value_counts(normalize=True)
```

Out[ ]:
```
Churn
1    0.678706
0    0.321294
Name: proportion, dtype: float64
```

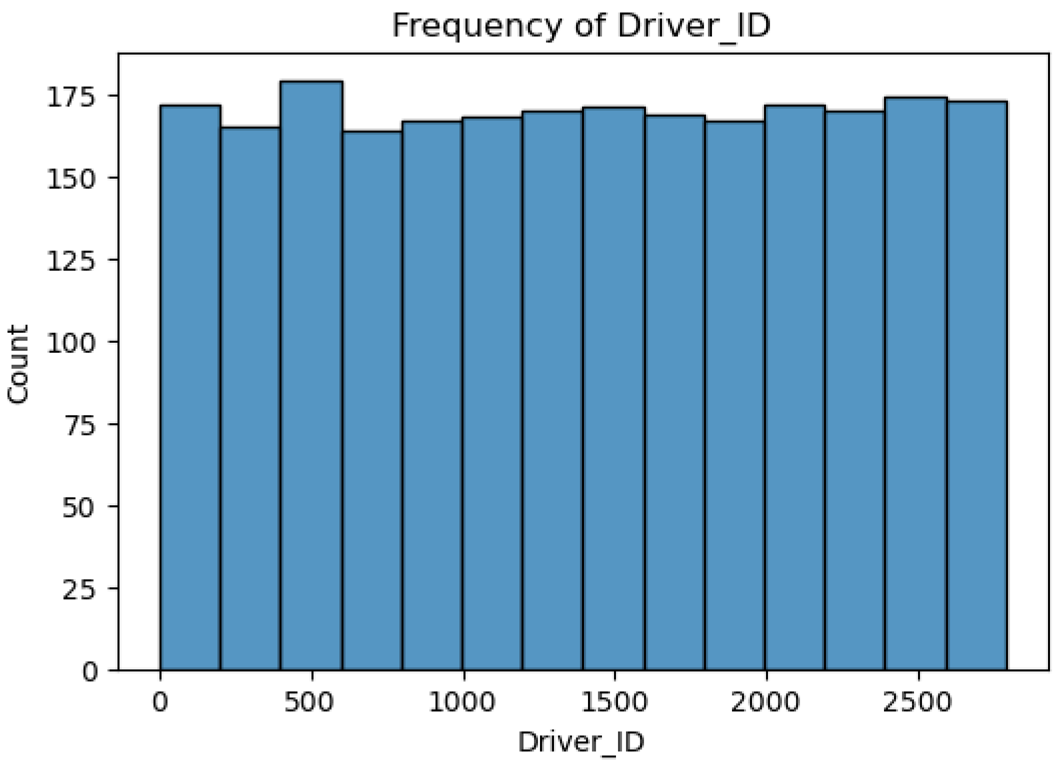
Univariate Analysis

In [ ]:
```
continuous_cols = dfg.select_dtypes(exclude='object').columns
categorical_cols = dfg.select_dtypes(include='object').columns
```

In [ ]:
```
# plotting histogram for contiuous values
continuous_cols
```

Out[ ]:
```
Index(['Driver_ID', 'total_months', 'age', 'gender', 'education', 'income',
       'DOJ', 'joining_designation', 'grade', 'total_business_val',
       'quarterly_rating', 'Churn'],
      dtype='object')
```

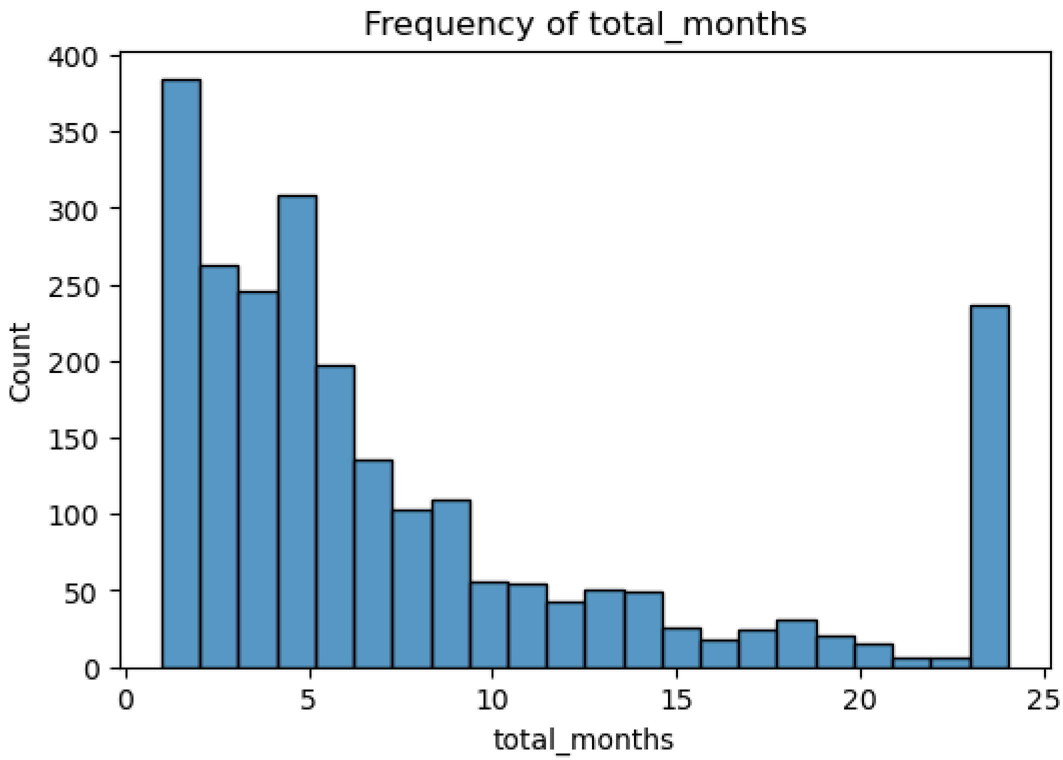
In [ ]:
```
col = "Driver_ID"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



> data is uniformly distributed

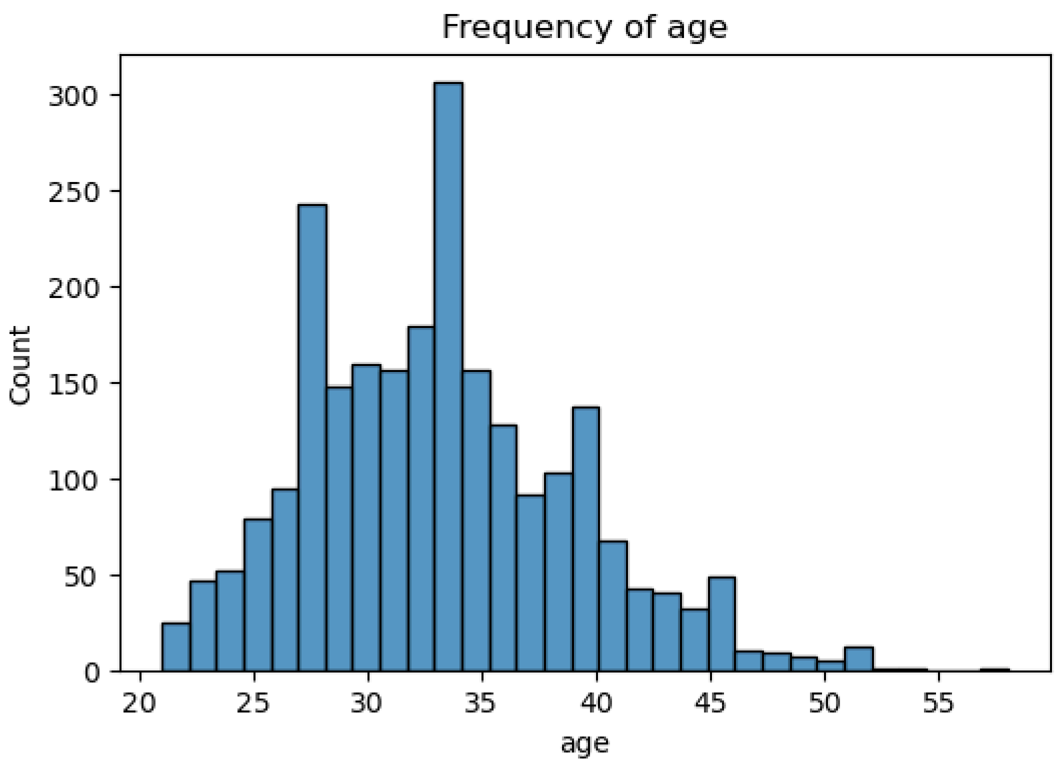
In [ ]:
```
col = "total_months"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
```

```
plt.title(f"Frequency of {col}")
plt.show()
```



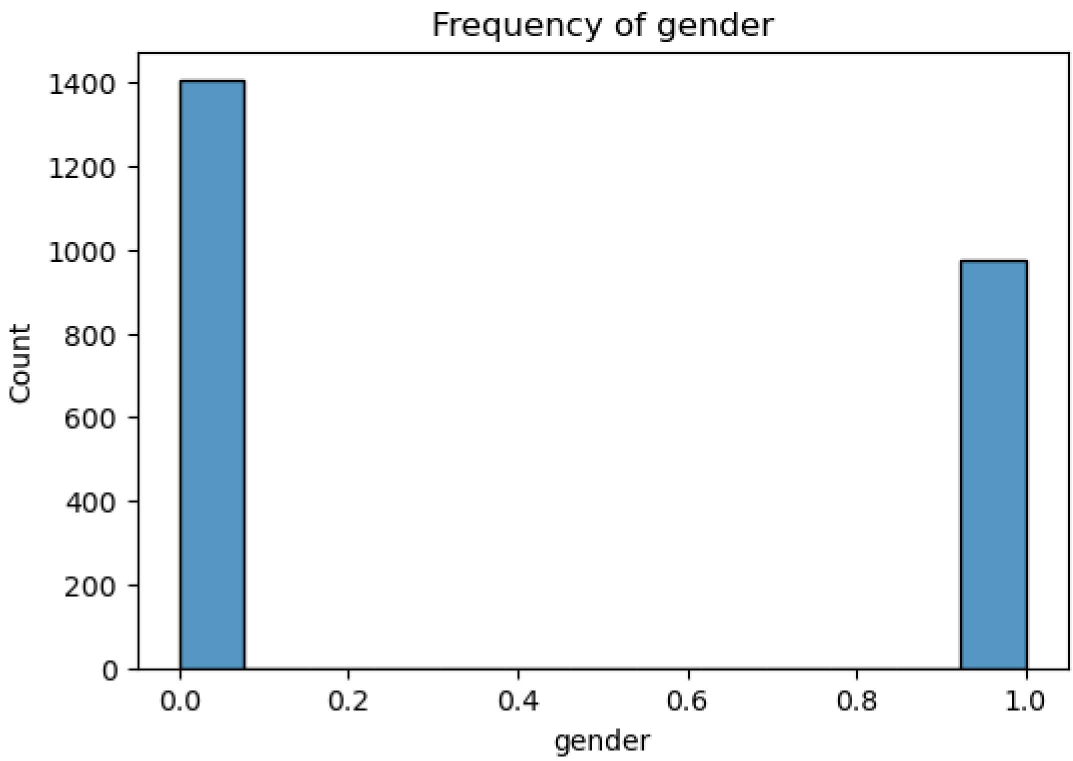
> data is right skewed, most of the drivers have records for 0-5 months [i.e most of the driver have worked 0-5 months]

In [ ]:
```
col = "age"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



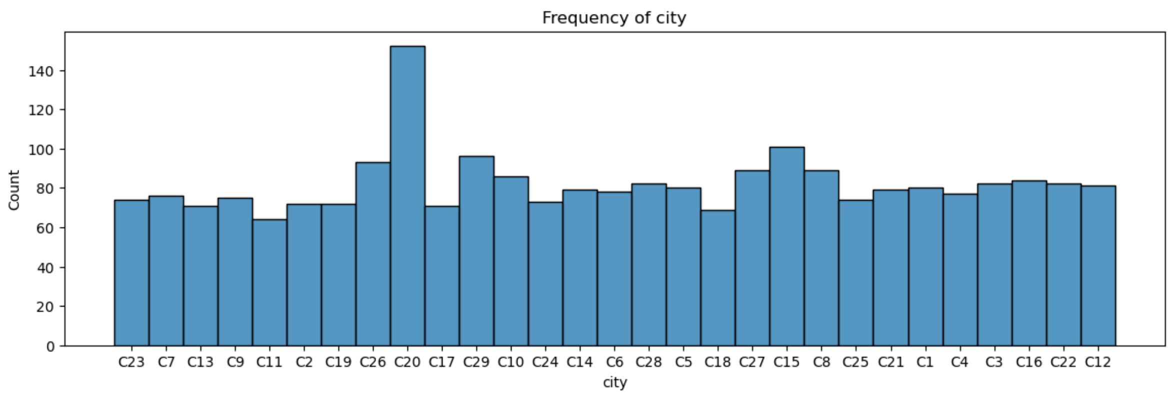
> data is almost normally distributed, with most age between 33-35

In [ ]:
```
col = "gender"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



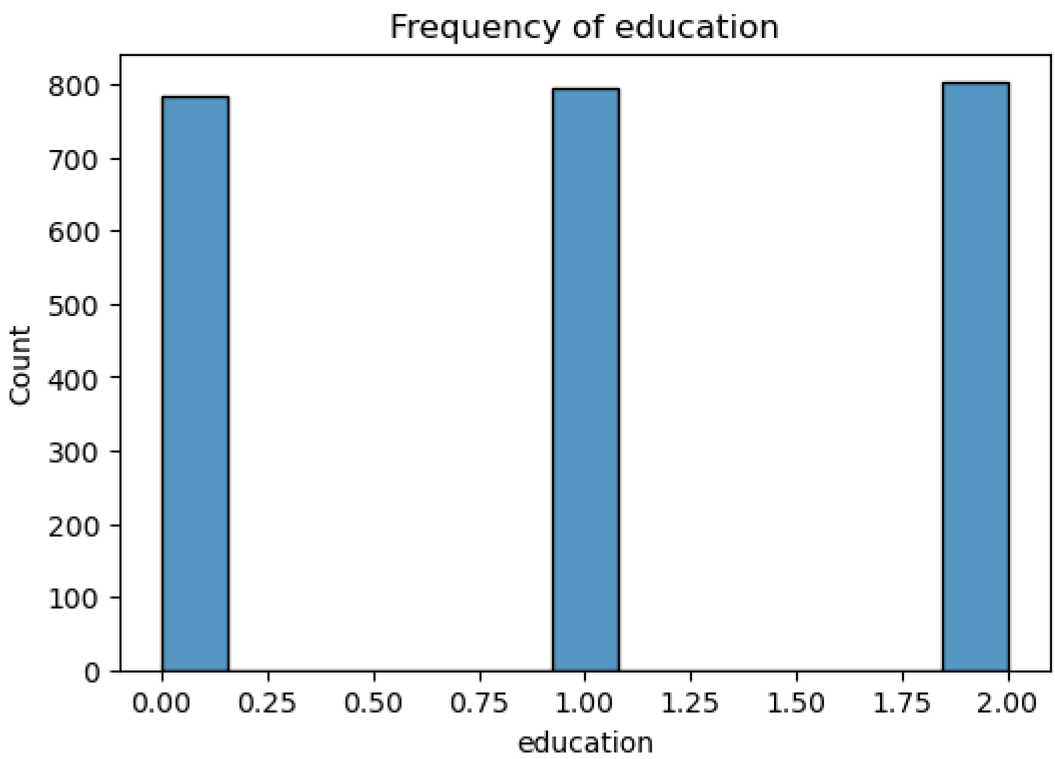
> there are more male (0) than femal (1) drivers in the data

In [ ]:
```
col = "city"
plt.figure(figsize=(14,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



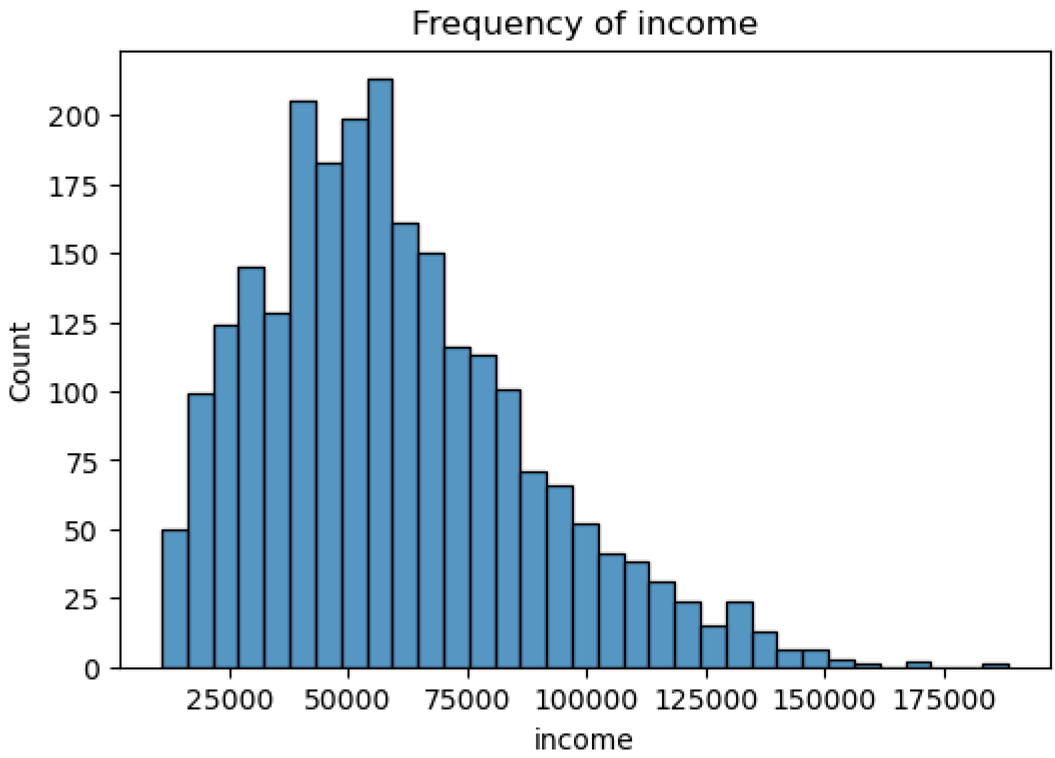
> data is uniformly distributed with city with citycode `c20` having the maximum frequency in the data

In [ ]:
```
col = "education"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



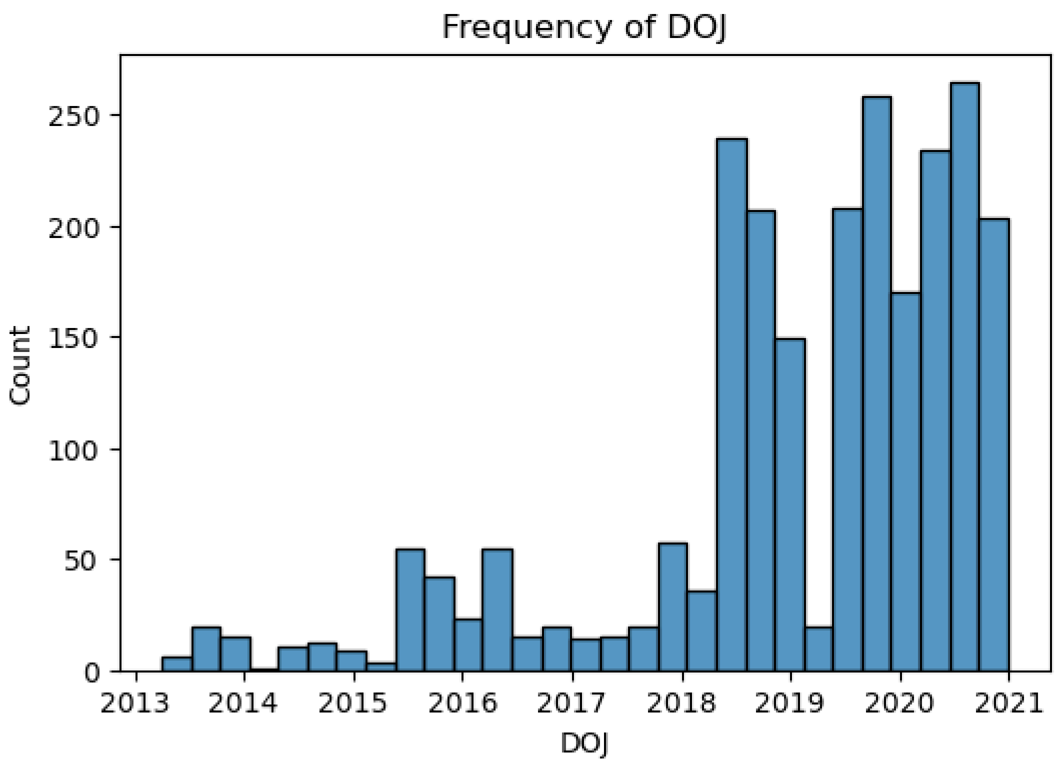
> education data is uniformly distributed (we have diverse drivers with different educational backgraounds)

In [ ]:
```
col = "income"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



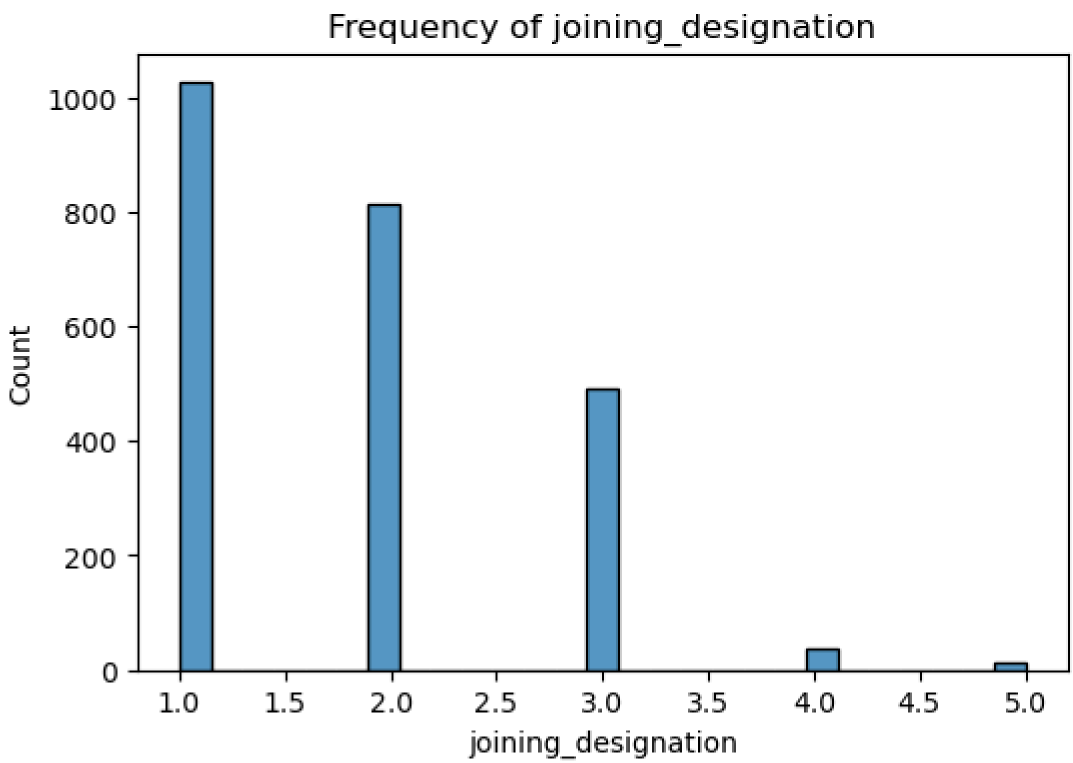
> data is having a right skewness with most drivers generating income between 50,000 - 70,000

In [ ]:
```
col = "DOJ"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



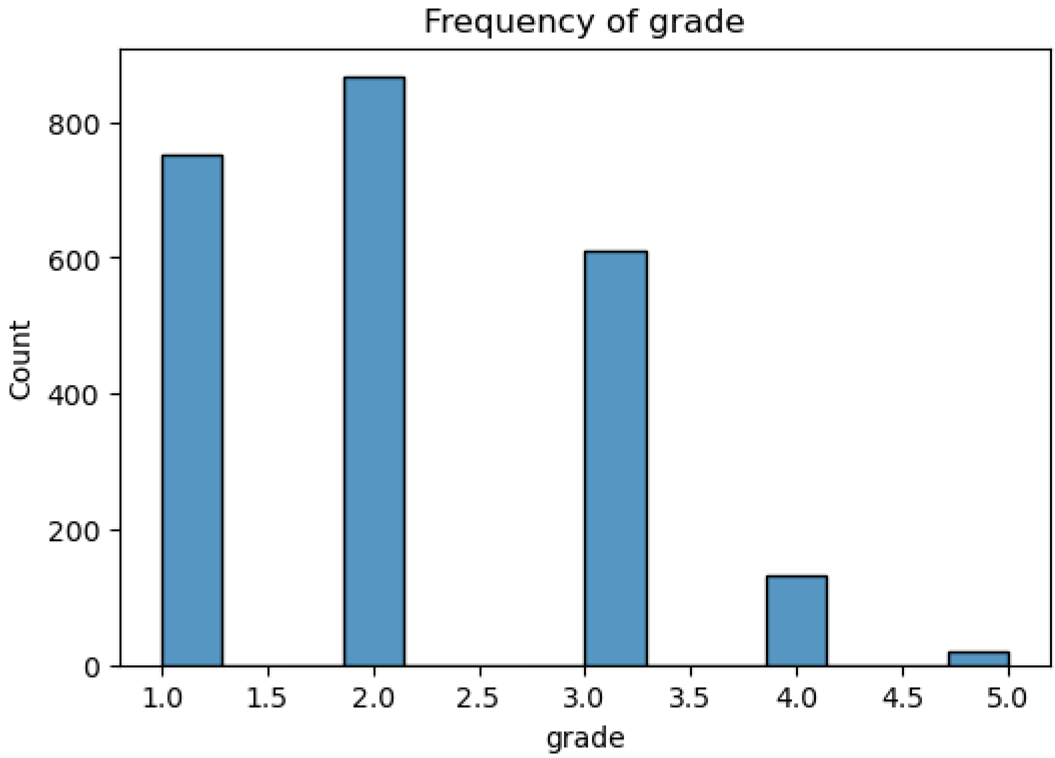
> DOJ is having left skewness; most of the drivers in the company have joined in recent years [between 2018 - 2021]

In [ ]:
```
col = "joining_designation"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



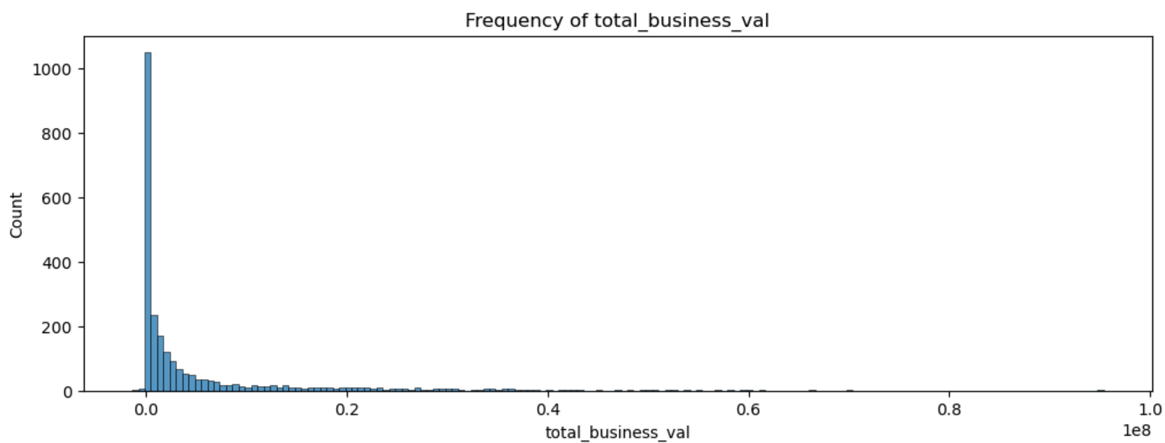
> data have a a right skewness; most of the drivers when they start working their joining degisnation is 1.0

In [ ]:
```
col = "grade"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



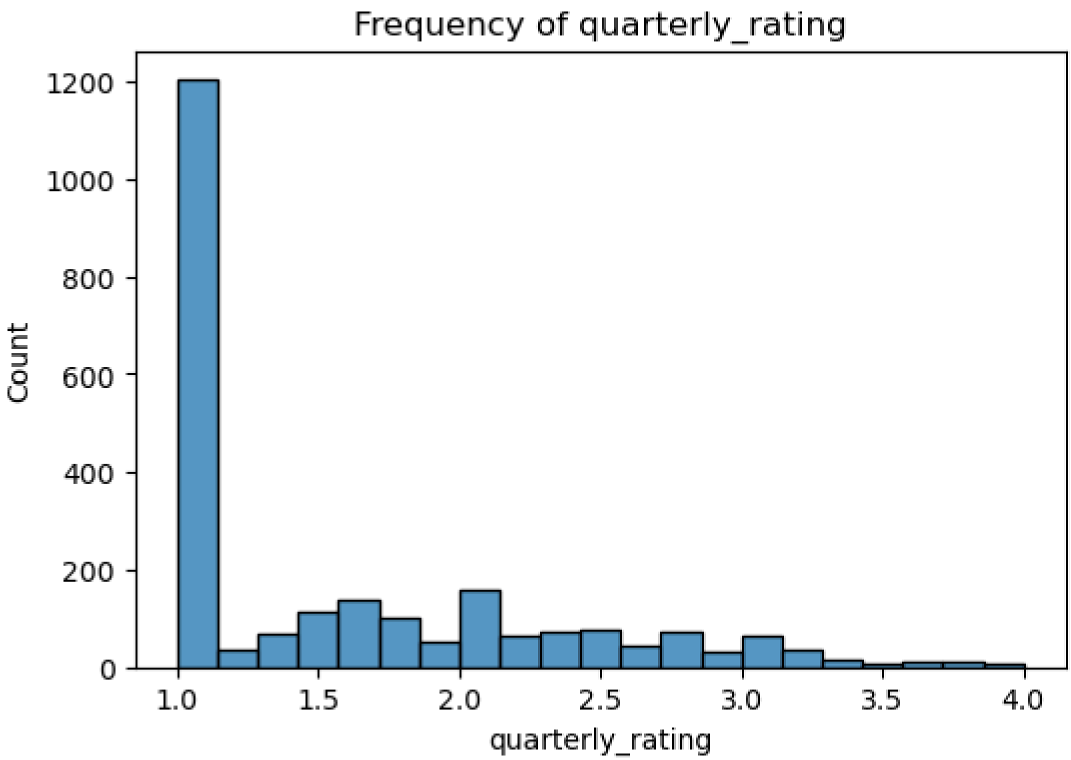
> data have right skewness with most drivers having grade of 2.0

In [ ]:
```
col = "total_business_val"
plt.figure(figsize=(12,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



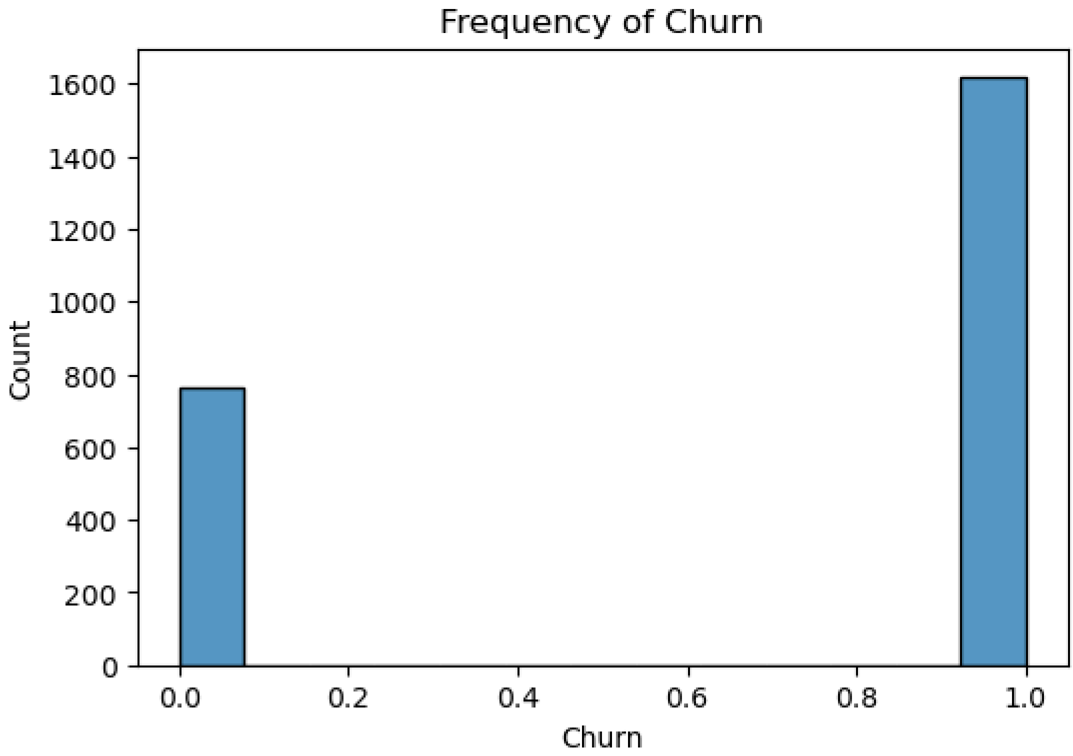
> income data is extremely right skewed

In [ ]:
```
col = "quarterly_rating"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



> data is having right skewness, with most drivering receiving a quarter rating of 1.0

In [ ]:
```
col = "Churn"
plt.figure(figsize=(6,4))
sns.histplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```

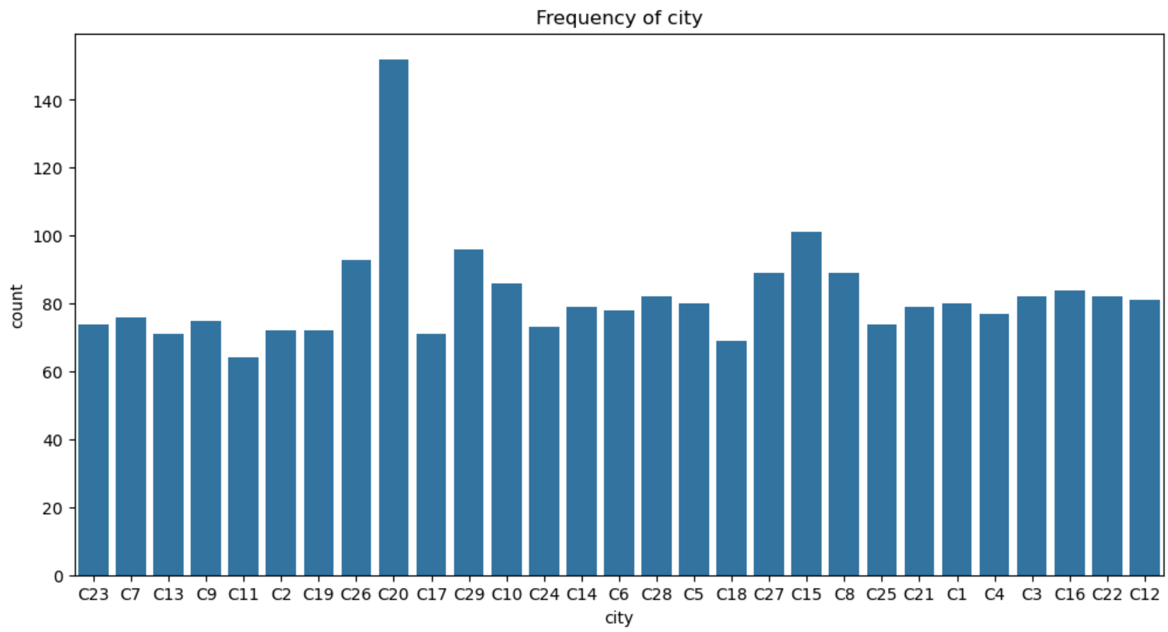


> data shows that most of the drivers have churned as compared to non-churn drivers.

In [ ]:
```
# plotting histogram for contiuous values
categorical_cols
```

Out[ ]: `Index(['city'], dtype='object')`

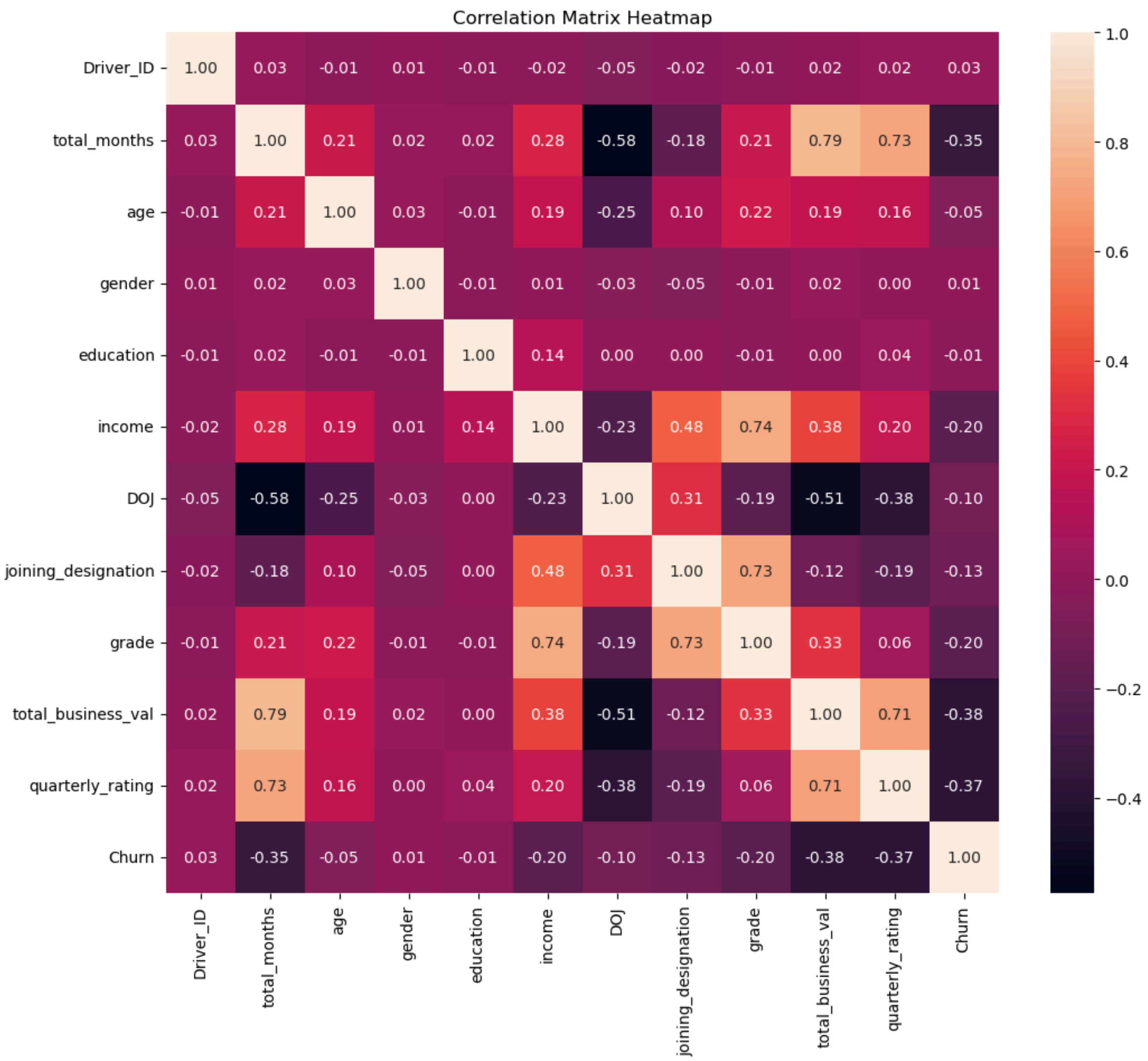
In [ ]:
```
col = "city"
plt.figure(figsize=(12,6))
sns.countplot(data=dfg,x=col)
plt.title(f"Frequency of {col}")
plt.show()
```



> city with citycode : `C20` has the highest requency in the data, this shows that this city could be a hotstop for the ride-sharing comapny

Bivariate Analysis

In [ ]:
```
# checking correlation of numerical cols
plt.figure(figsize=(12,10))
corr_matrix=dfg[continuous_cols].corr()
sns.heatmap(corr_matrix, annot=True, fmt='.2f')
plt.title('Correlation Matrix Heatmap')
plt.show()
```



In [ ]:
```
# Findinf strong correlations
threshold = 0.7

strong_positive_corrs = []
strong_negative_corrs = []

for i in range(len(corr_matrix.columns)):
    for j in range(i):
        if corr_matrix.iloc[i, j] > threshold:
            strong_positive_corrs.append((corr_matrix.columns[i], corr_matrix.cc
        elif corr_matrix.iloc[i, j] < -threshold:
            strong_negative_corrs.append((corr_matrix.columns[i], corr_matrix.cc
```

```
print(f"Strong Positive Correlations (threshold > {threshold}):")
for col1, col2, corr in strong_positive_corrs:
    print(f"{col1} and {col2}: {corr:.2f}")
print(20*"-")
print(f"Strong Negative Correlations (threshold < -{threshold}):")
for col1, col2, corr in strong_negative_corrs:
    print(f"{col1} and {col2}: {corr:.2f}")
```

```
Strong Positive Correlations (threshold > 0.7):
grade and income: 0.74
grade and joining_designation: 0.73
total_business_val and total_months: 0.79
quarterly_rating and total_months: 0.73
quarterly_rating and total_business_val: 0.71
--------------------
Strong Negative Correlations (threshold < -0.7):
```

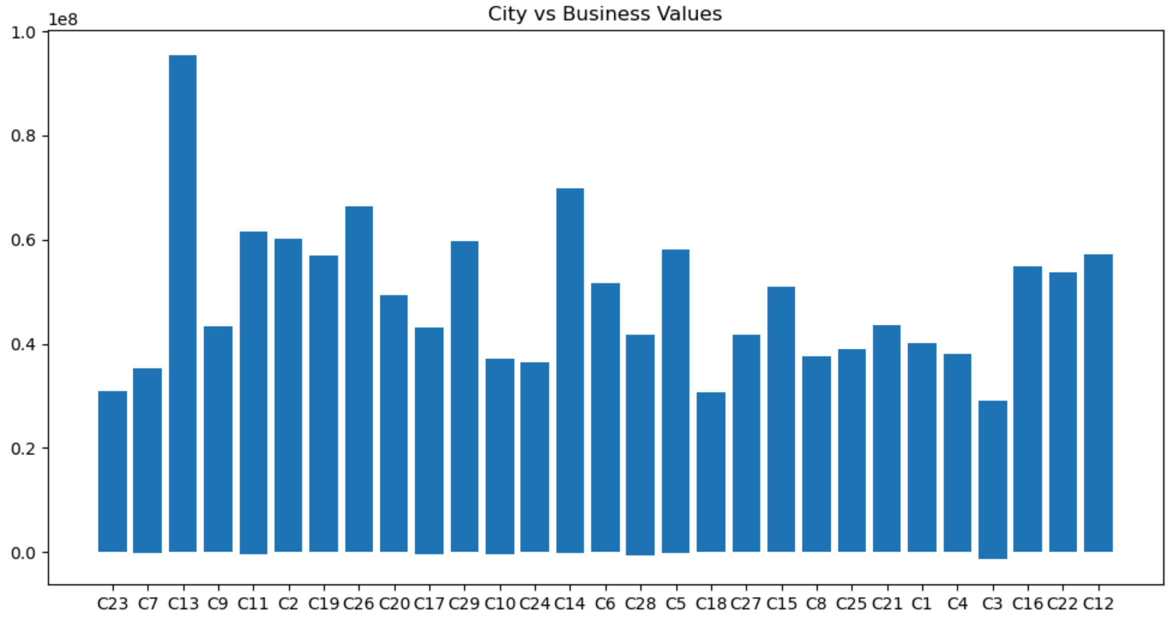
In [ ]:

```
# let change the threshol and check
threshold = 0.5

strong_positive_corrs = []
strong_negative_corrs = []

for i in range(len(corr_matrix.columns)):
    for j in range(i):
        if corr_matrix.iloc[i, j] > threshold:
            strong_positive_corrs.append((corr_matrix.columns[i], corr_matrix.cc
        elif corr_matrix.iloc[i, j] < -threshold:
            strong_negative_corrs.append((corr_matrix.columns[i], corr_matrix.cc


print(f"Strong Positive Correlations (threshold > {threshold}):")
for col1, col2, corr in strong_positive_corrs:
    print(f"{col1} and {col2}: {corr:.2f}")
print(20*"-")
print(f"Strong Negative Correlations (threshold < -{threshold}):")
for col1, col2, corr in strong_negative_corrs:
    print(f"{col1} and {col2}: {corr:.2f}")
```

```
Strong Positive Correlations (threshold > 0.5):
grade and income: 0.74
grade and joining_designation: 0.73
total_business_val and total_months: 0.79
quarterly_rating and total_months: 0.73
quarterly_rating and total_business_val: 0.71
--------------------
Strong Negative Correlations (threshold < -0.5):
DOJ and total_months: -0.58
total_business_val and DOJ: -0.51
```

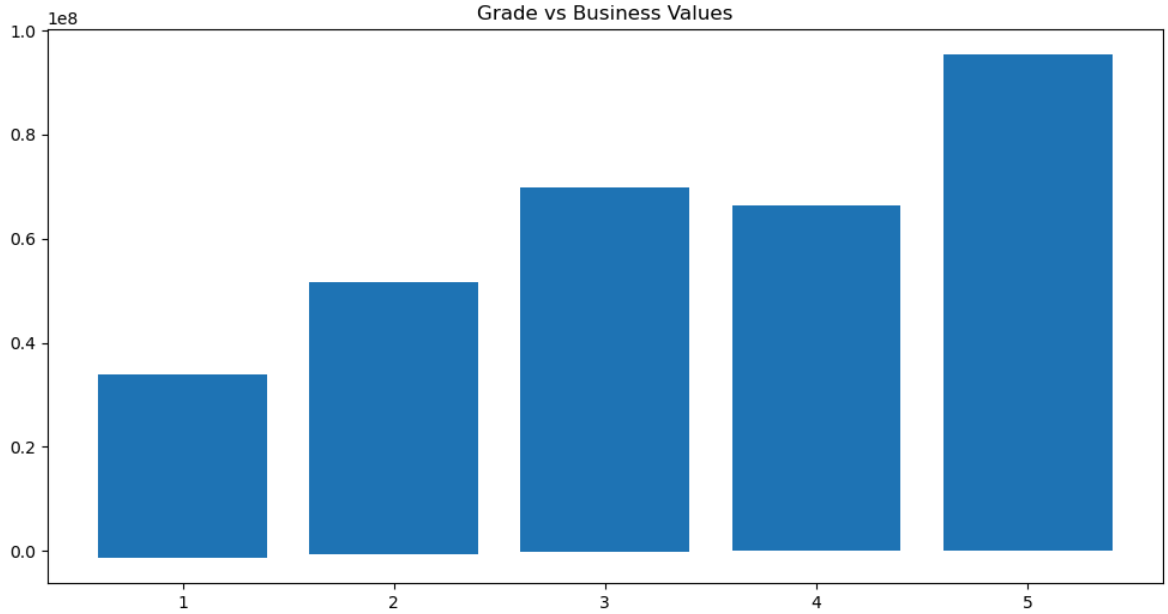
In [ ]:

```
plt.figure(figsize = (12,6))
plt.bar(dfg['city'] , dfg['total_business_val'])
plt.title("City vs Business Values")
plt.show()
```



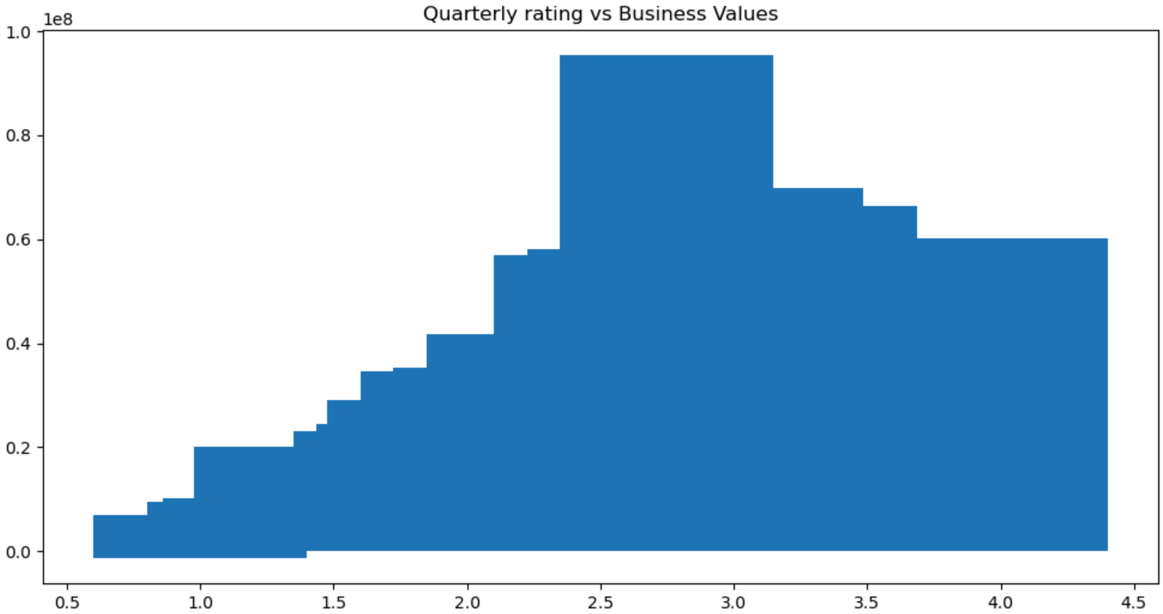
> we can see city with citycode : `C13` has the highest business value associated with it.

In [ ]:
```
plt.figure(figsize = (12,6))
plt.bar(dfg['grade'] , dfg['total_business_val'])
plt.title("Grade vs Business Values")
plt.show()
```



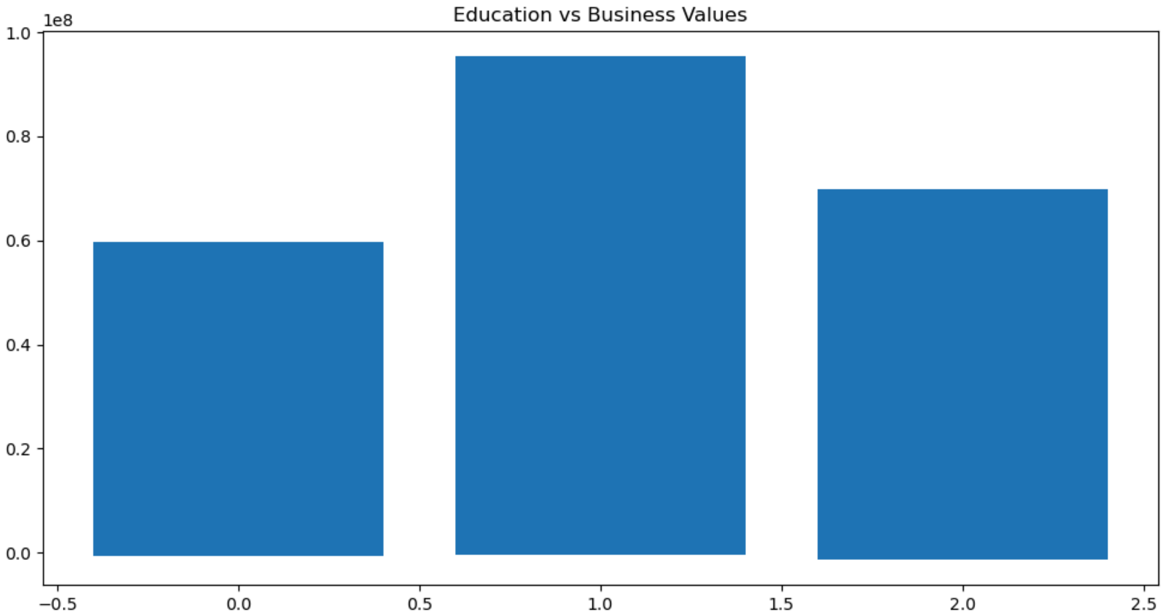
> drivers with grade 5 generated highest business values

In [ ]:
```
plt.figure(figsize = (12,6))
plt.bar(dfg['quarterly_rating'] , dfg['total_business_val'])
plt.title("Quarterly rating vs Business Values")
plt.show()
```



> quarterly rating above 2.5 brings the highest business value

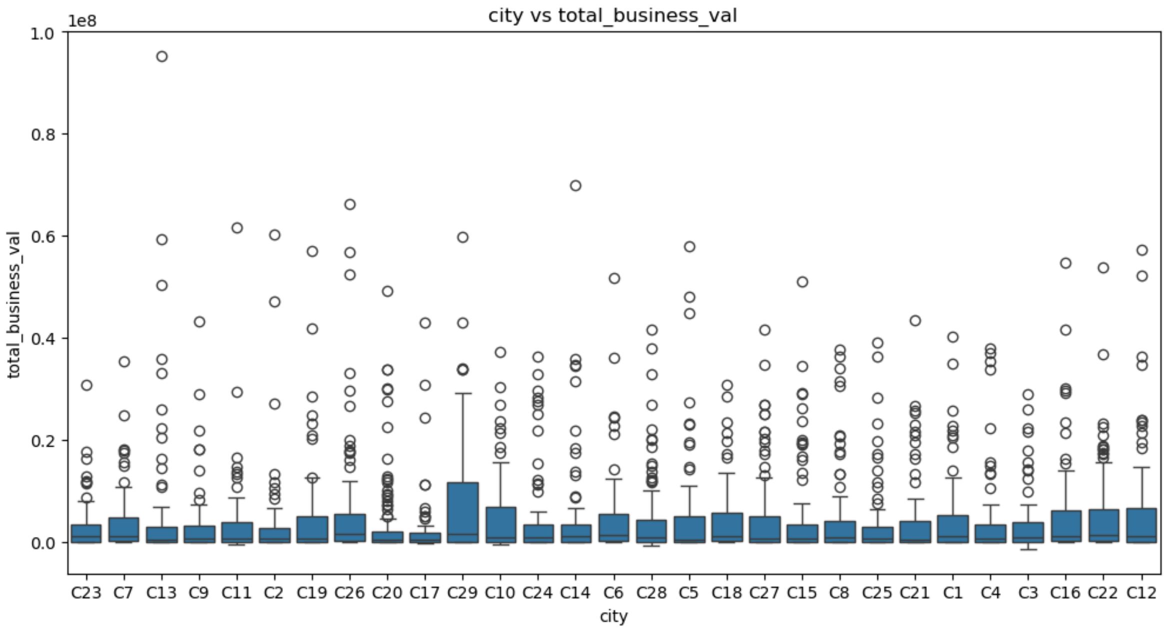
In [ ]:
```
plt.figure(figsize = (12,6))
plt.bar(dfg['education'] , dfg['total_business_val'])
plt.title("Education vs Business Values")
plt.show()
```



> data shows that drivers with education level : 1 (i.e 12th plus) generates the highest business value followed by education level : 2 (i.e graduate).

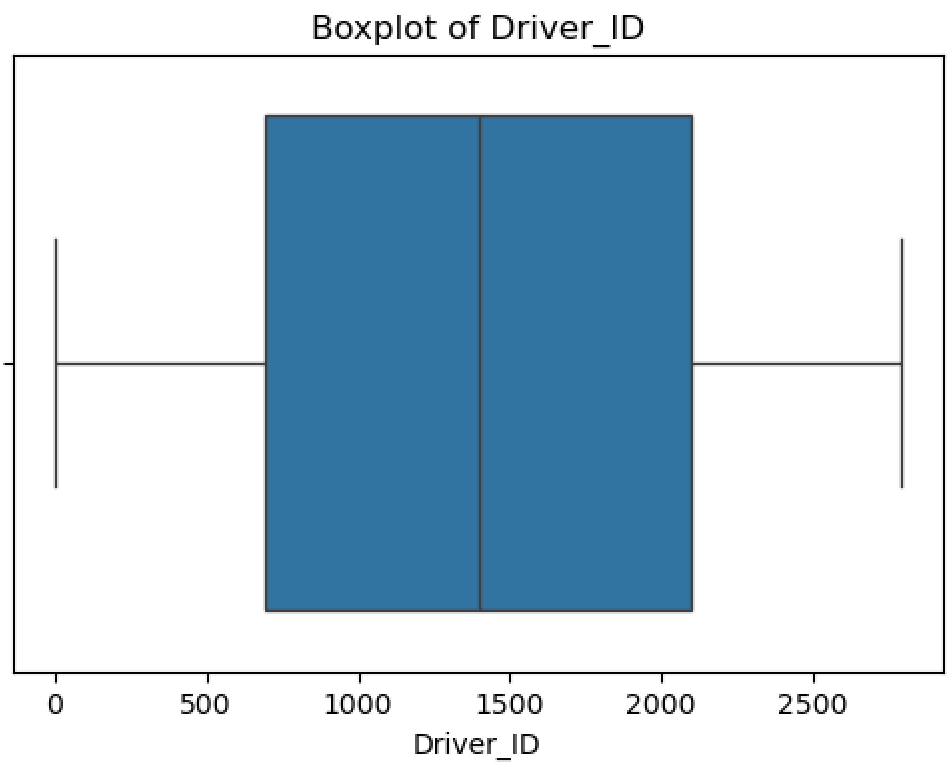
In [ ]:
```
# plotting boxplots for categorical col
cat_col='city'
num_col='total_business_val'
# for col in continuous_cols:
plt.figure(figsize = (12,6))
sns.boxplot(data=dfg,x=cat_col, y=num_col)
```

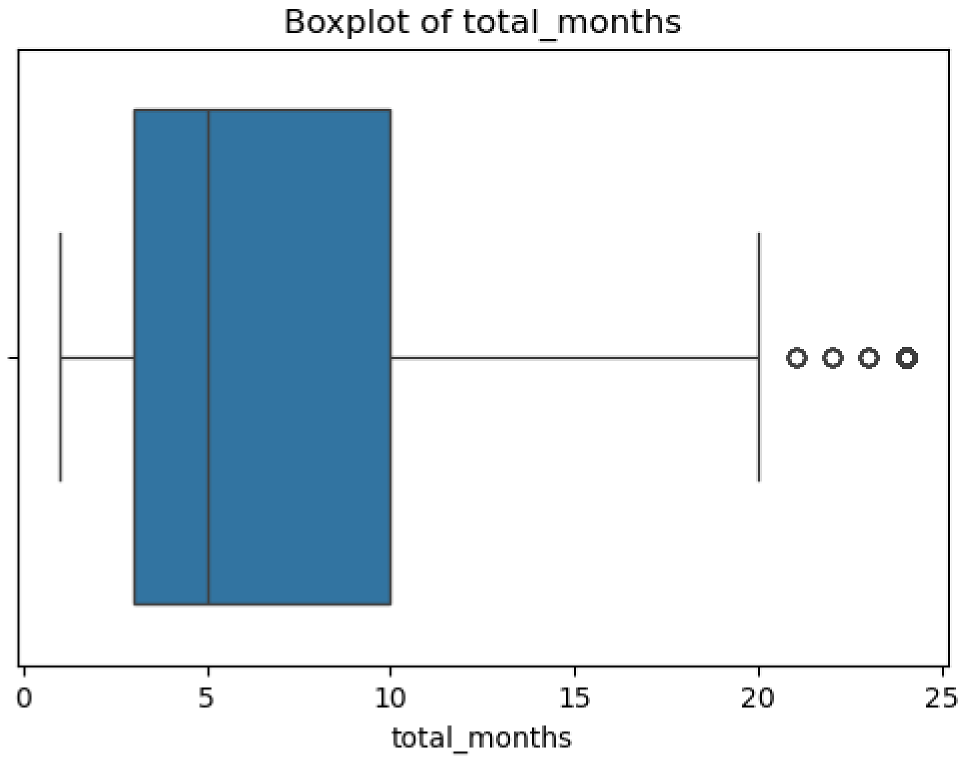
```python
plt.title(f"{cat_col} vs {num_col}")
plt.show()
```

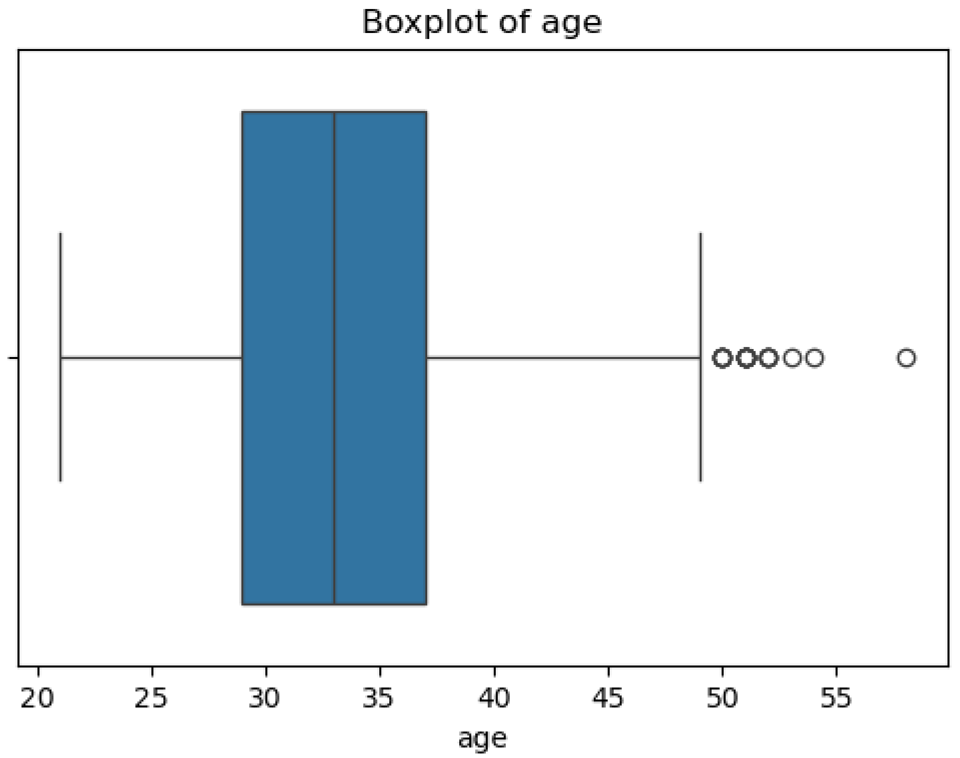


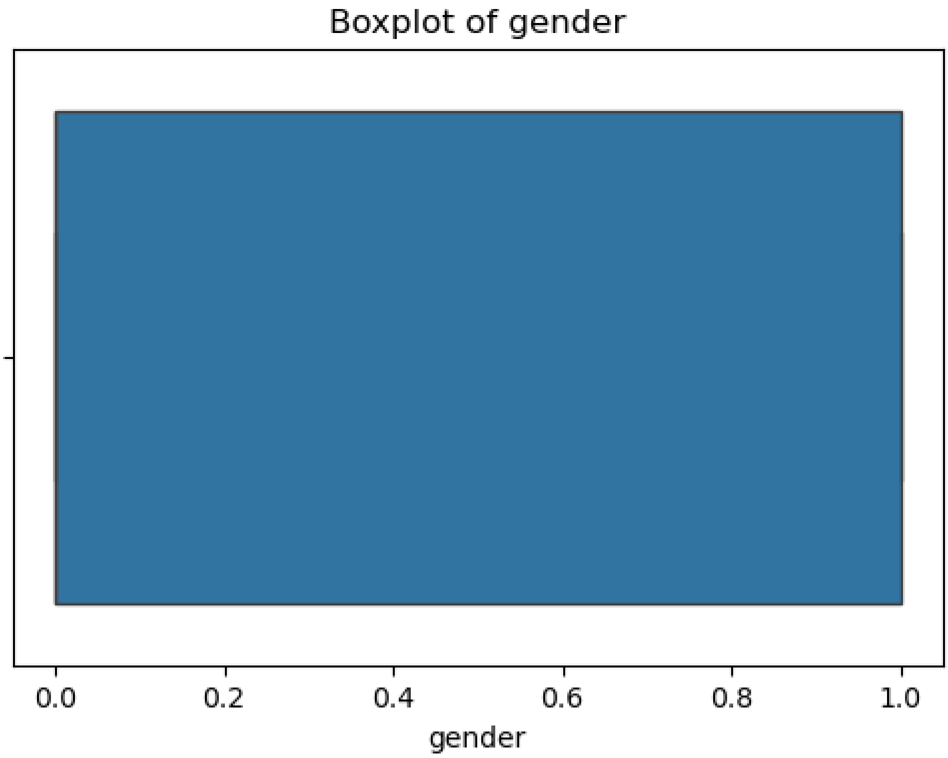
> city with citycode `C13` has the highest outlier in the data

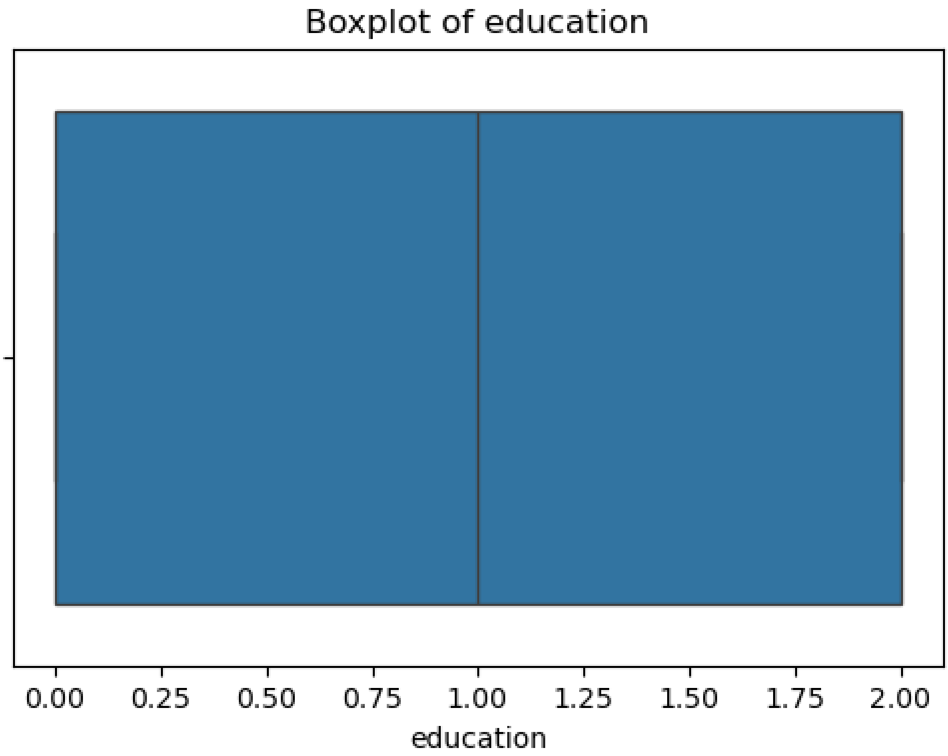
In [ ]:
```python
# outlier detection and treatment
for col in continuous_cols:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=dfg[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```

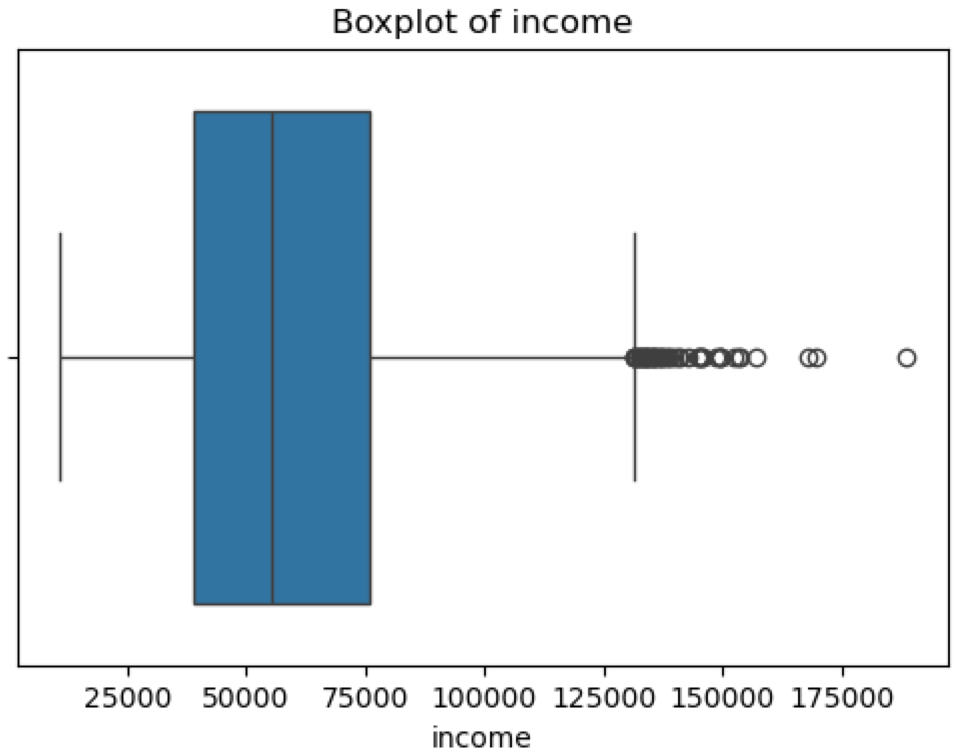


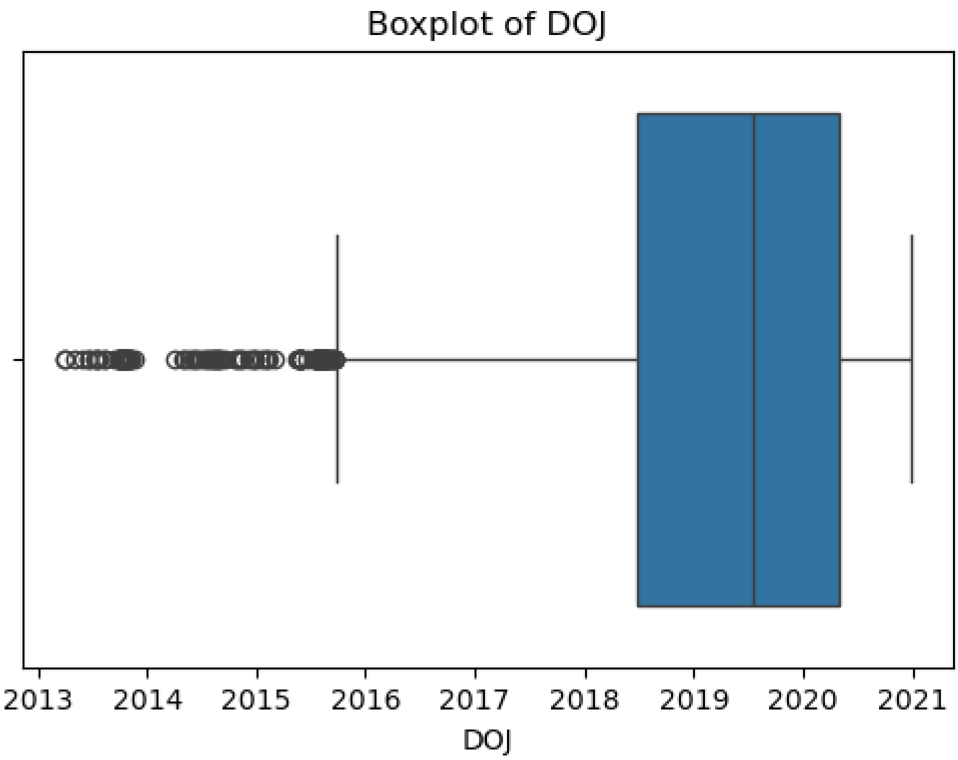

Boxplot of total_months
0
5
10
15
20
25
total_months

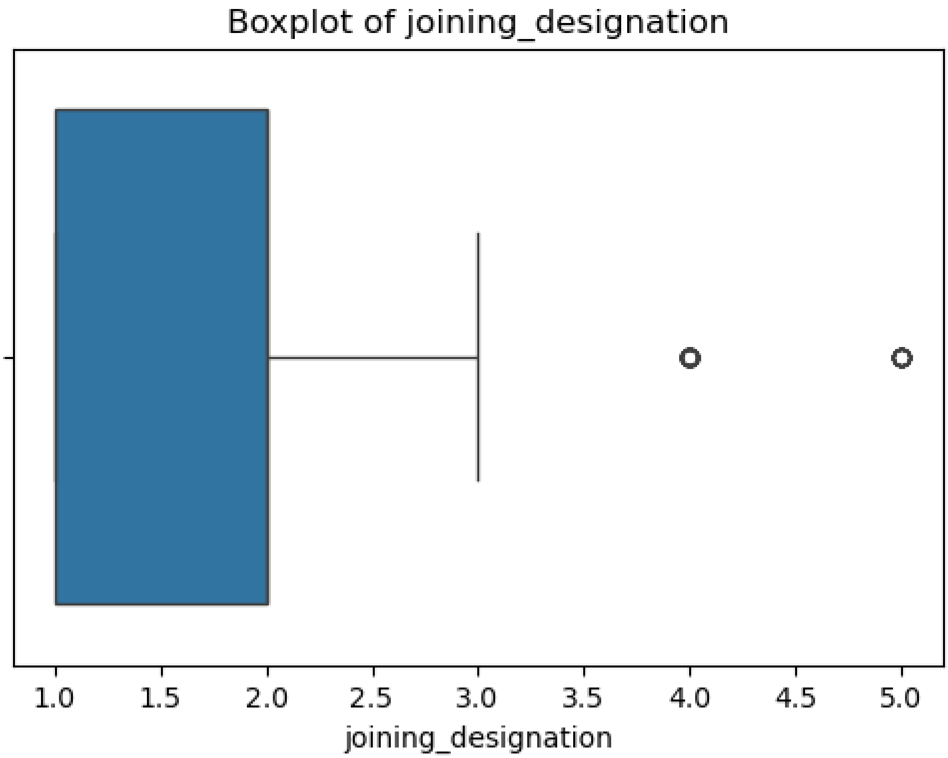

Boxplot of age
20
25
30
35
40
45
50
55
age

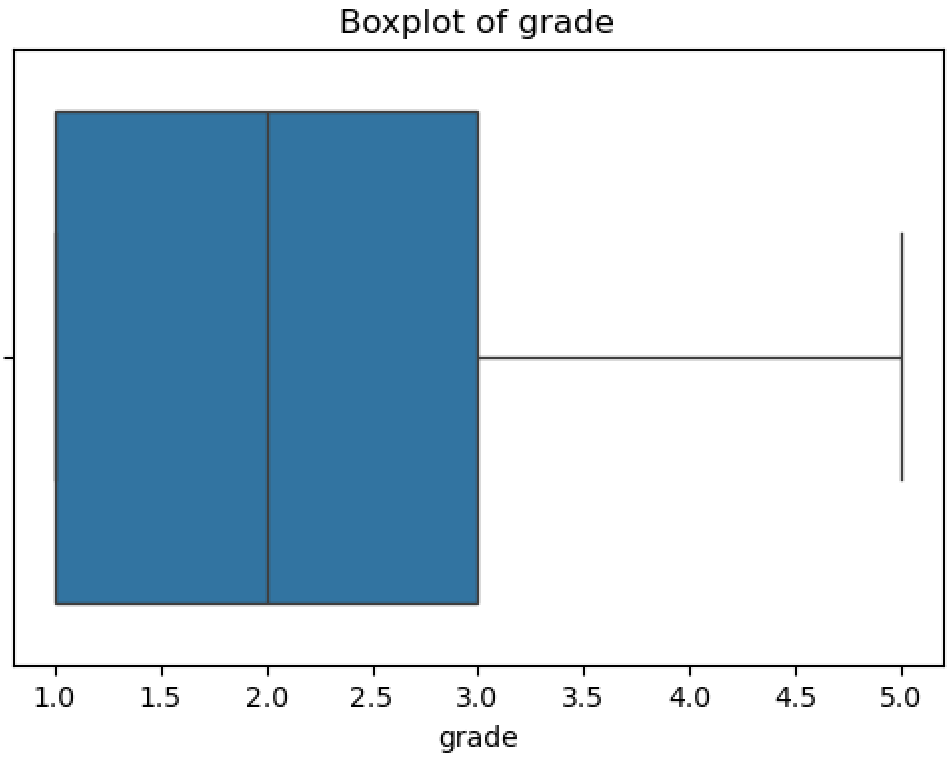

Boxplot of gender
0.0
0.2
0.4
0.6
0.8
1.0
gender

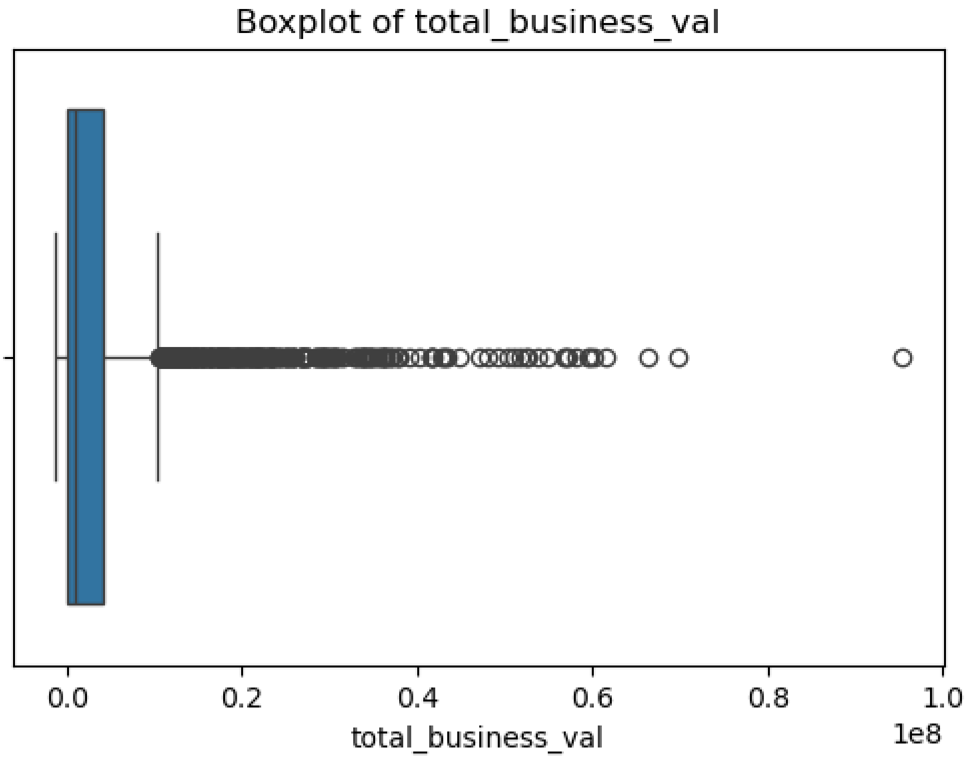

Boxplot of education
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
education

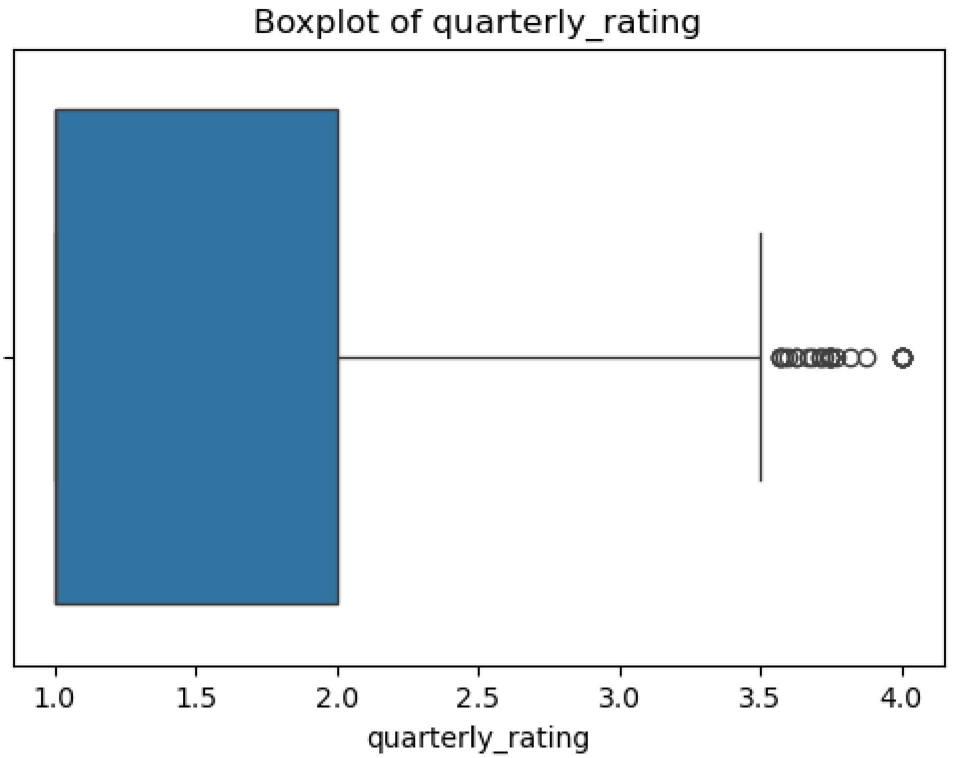

Boxplot of income
25000
50000
75000
100000
125000
150000
175000
income

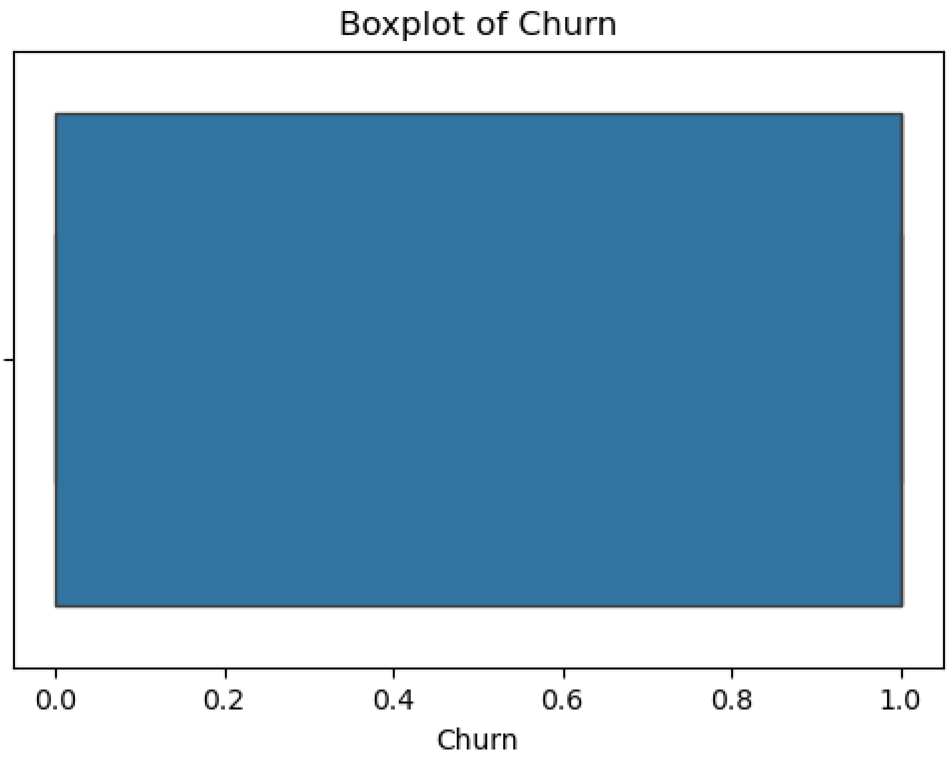

Boxplot of DOJ
2013
2014
2015
2016
2017
2018
2019
2020
2021
DOJ


Boxplot of joining_designation
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
joining_designation


Boxplot of grade
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
grade


Boxplot of total_business_val
0.0
0.2
0.4
0.6
0.8
1.0
1e8
total_business_val


Boxplot of quarterly_rating
1.0
1.5
2.0
2.5
3.0
3.5
4.0
quarterly_rating

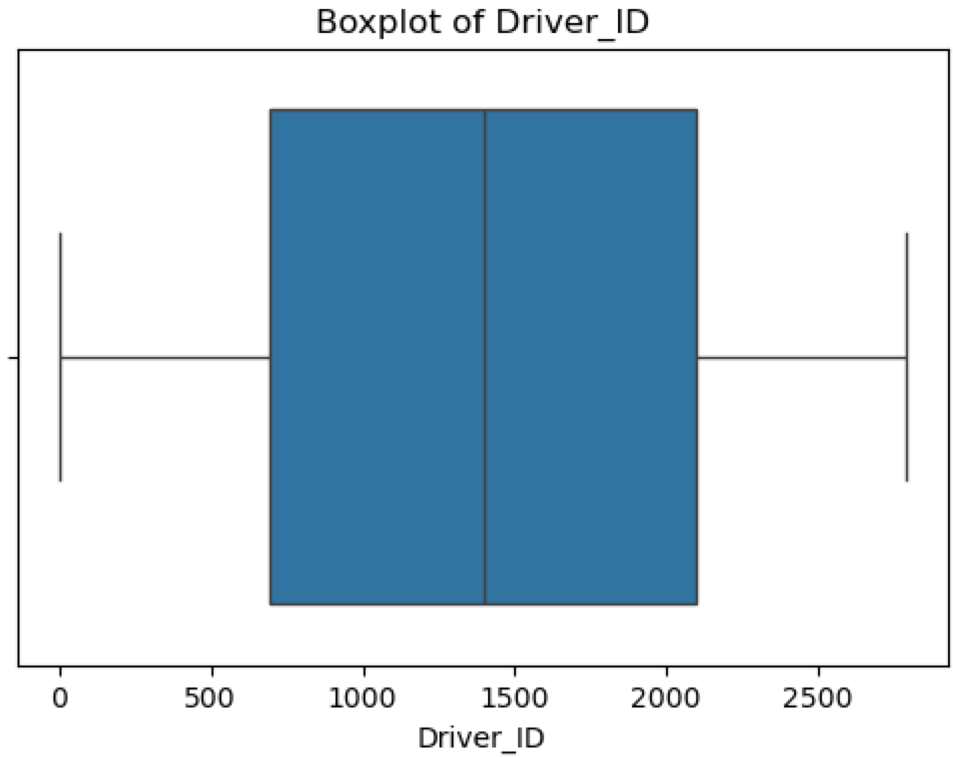


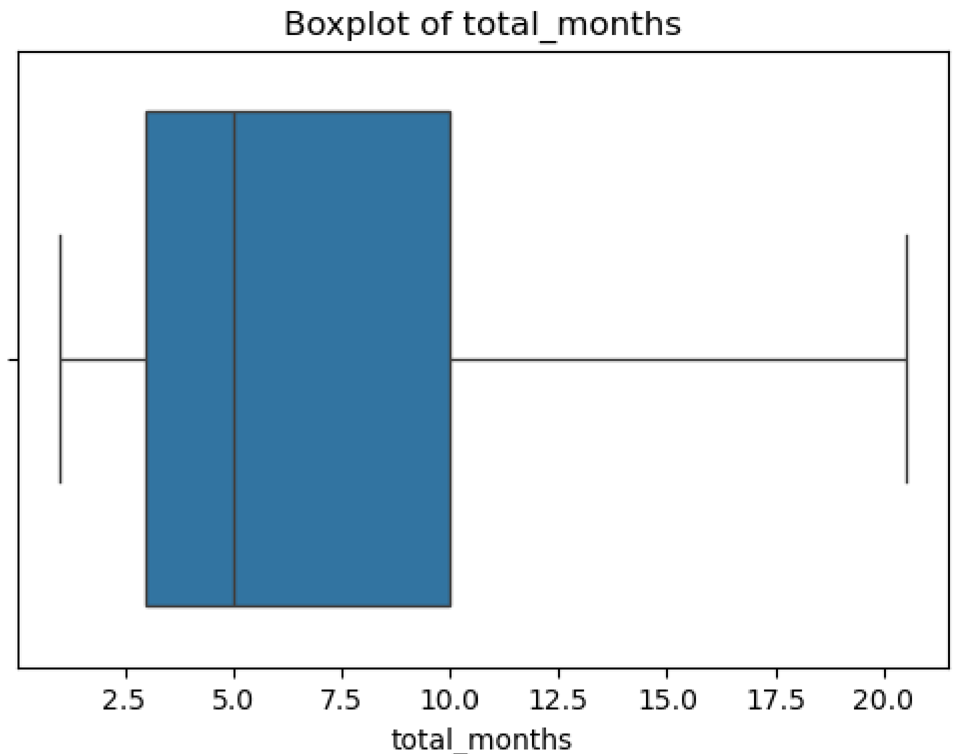
> from visual representation we can see there are columns whcih have outliers.

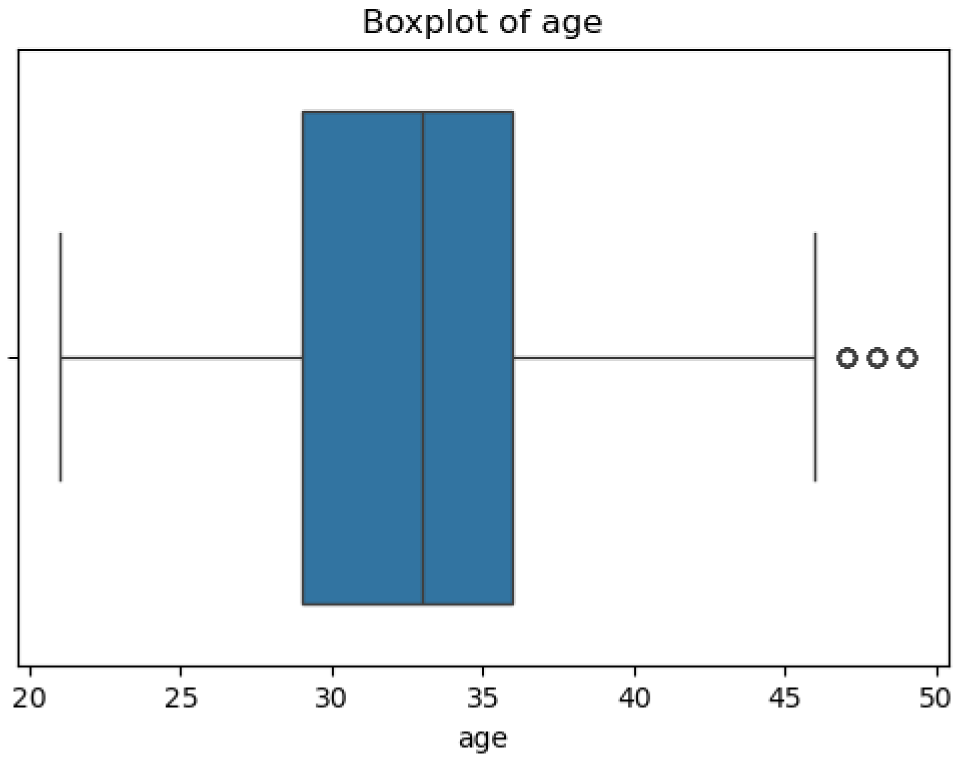
In [ ]:
```
# treamtment
# median imputation :  as it preserve the central tendency of the distribution.
# clipping : to limit their impact without distorting the underlying distributio
# leaving few cols
def outlier_detection(series):
    q1=series.quantile(0.25)
    q3=series.quantile(0.75)
    iqr=q3-q1
    lower_bound = q1 - 1.5*iqr
    upper_bound = q3 + 1.5*iqr
    if series.name in ['age' , 'income'] :
        median_value = series.median()
        output=series.apply(lambda x: median_value if x < lower_bound or x > upp
    else:
        output=series.clip(lower_bound, upper_bound)
    return output
```

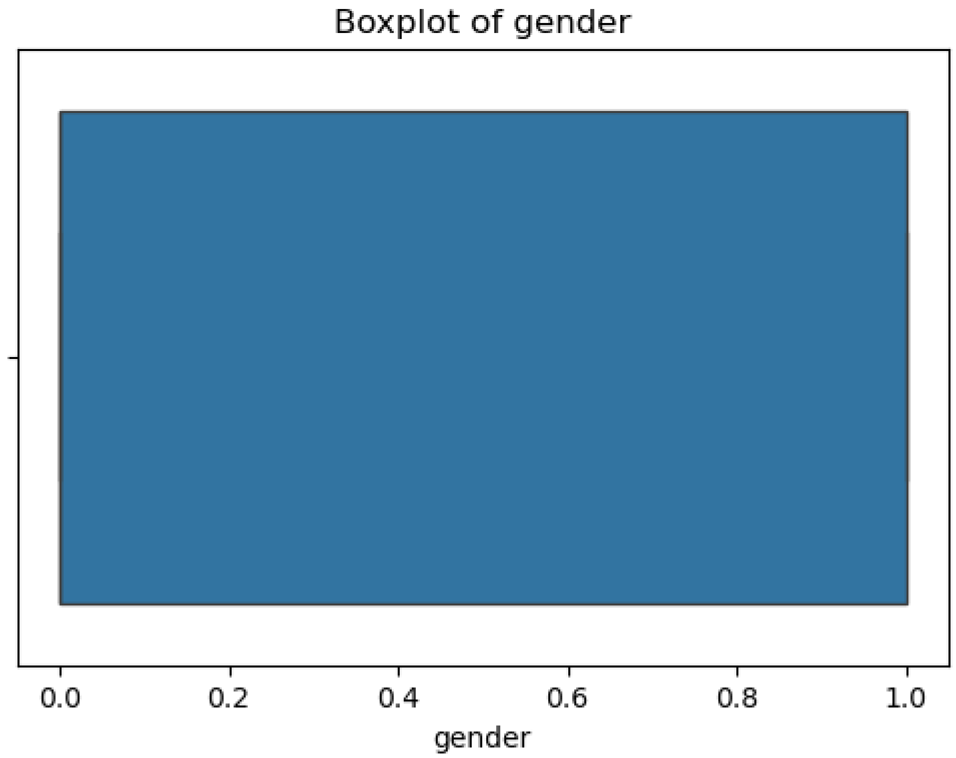
In [ ]:
```
# treatment for cols
for col in continuous_cols:
    dfg[col] = outlier_detection(dfg[col])
```

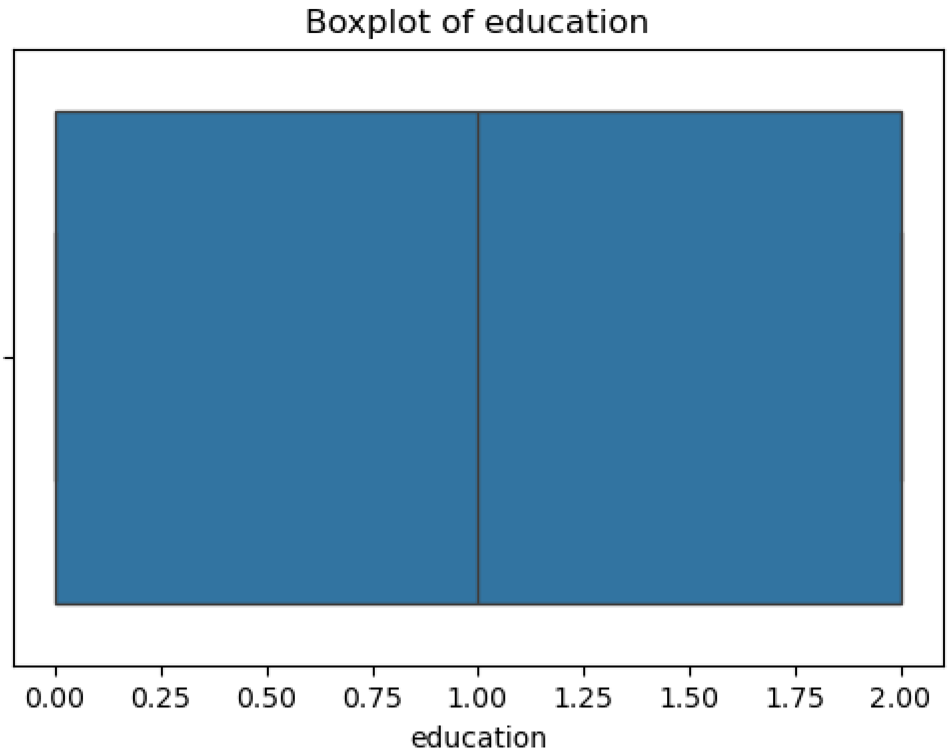
In [ ]:
```
# checking putlier treamtment effects
for col in continuous_cols:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=dfg[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```

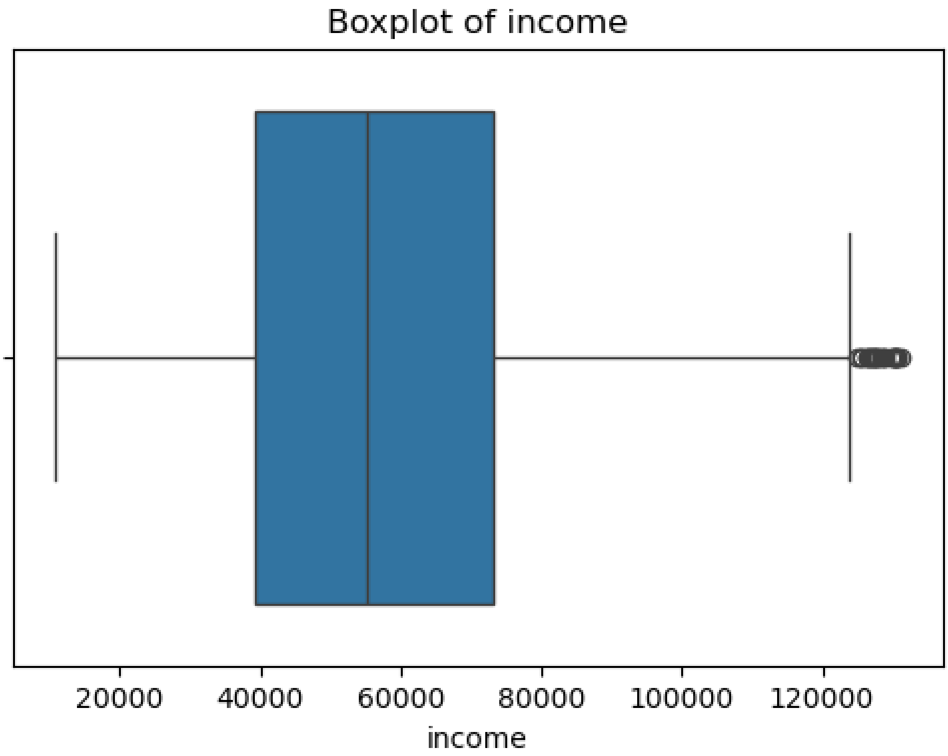

Boxplot of Driver_ID
0
500
1000
1500
2000
2500
Driver_ID

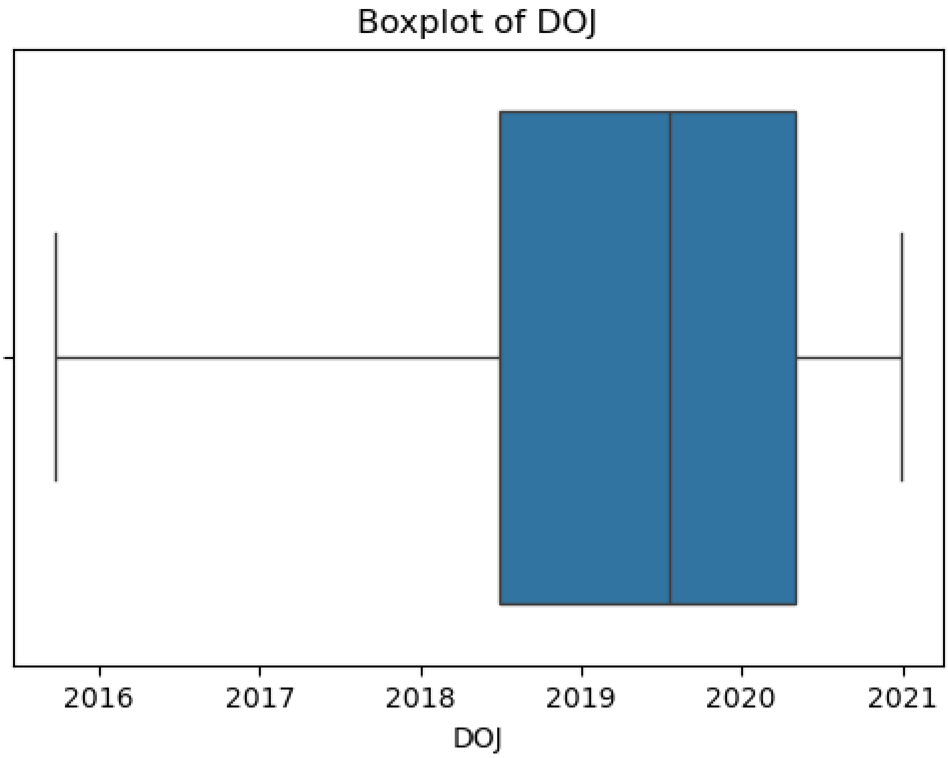

Boxplot of total_months
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
total_months

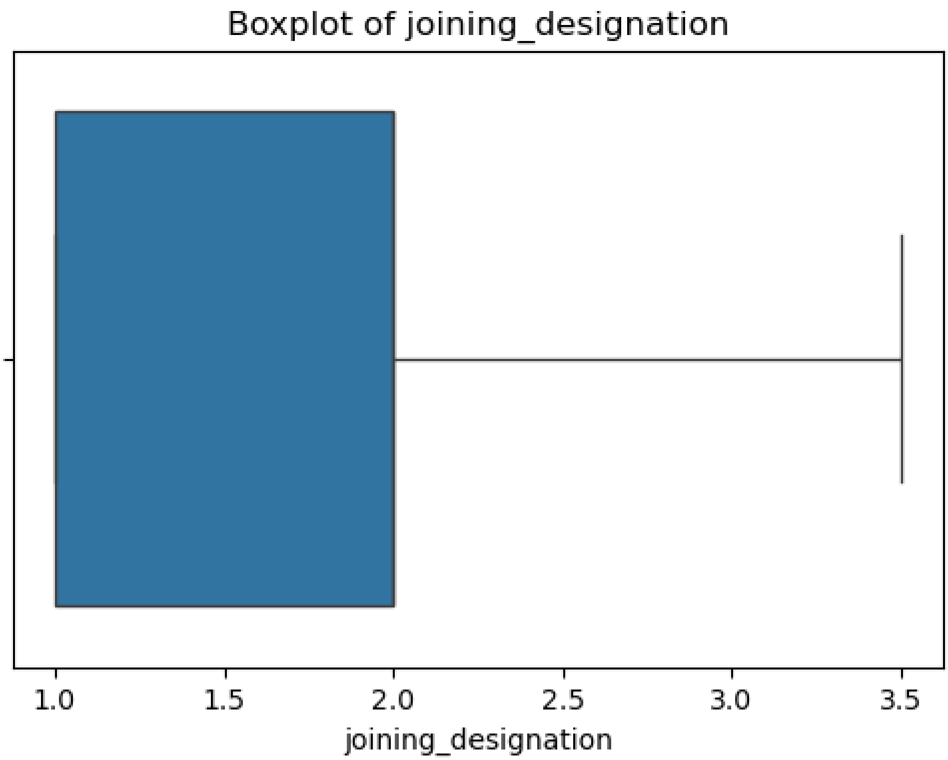

Boxplot of age
20
25
30
35
40
45
50
age

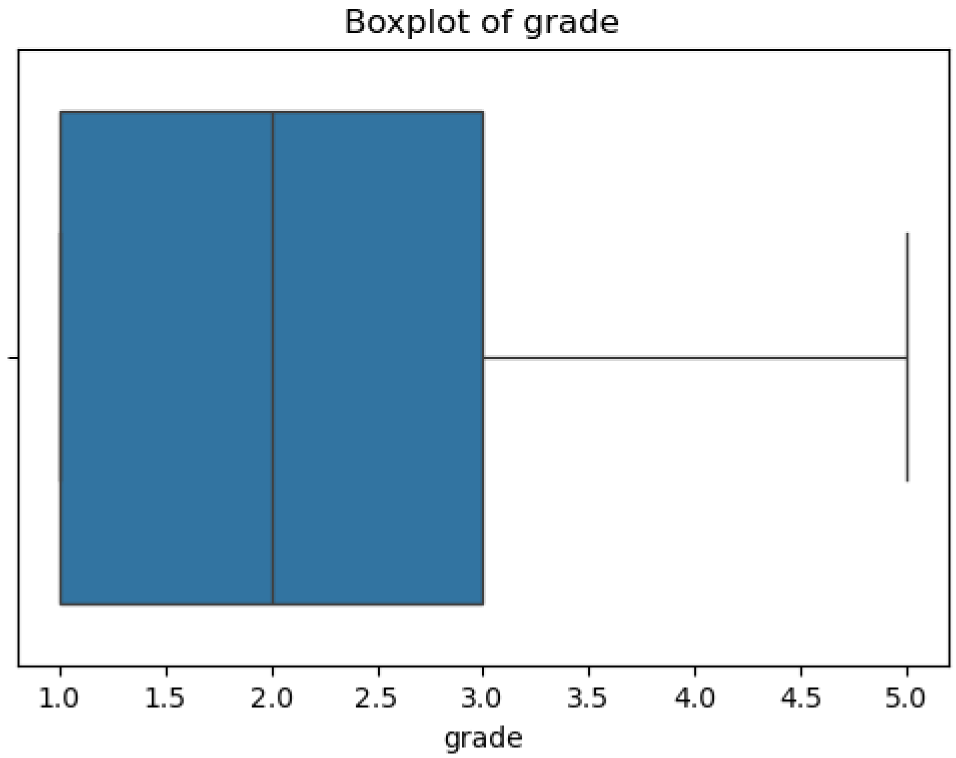

Boxplot of gender
0.0
0.2
0.4
0.6
0.8
1.0
gender

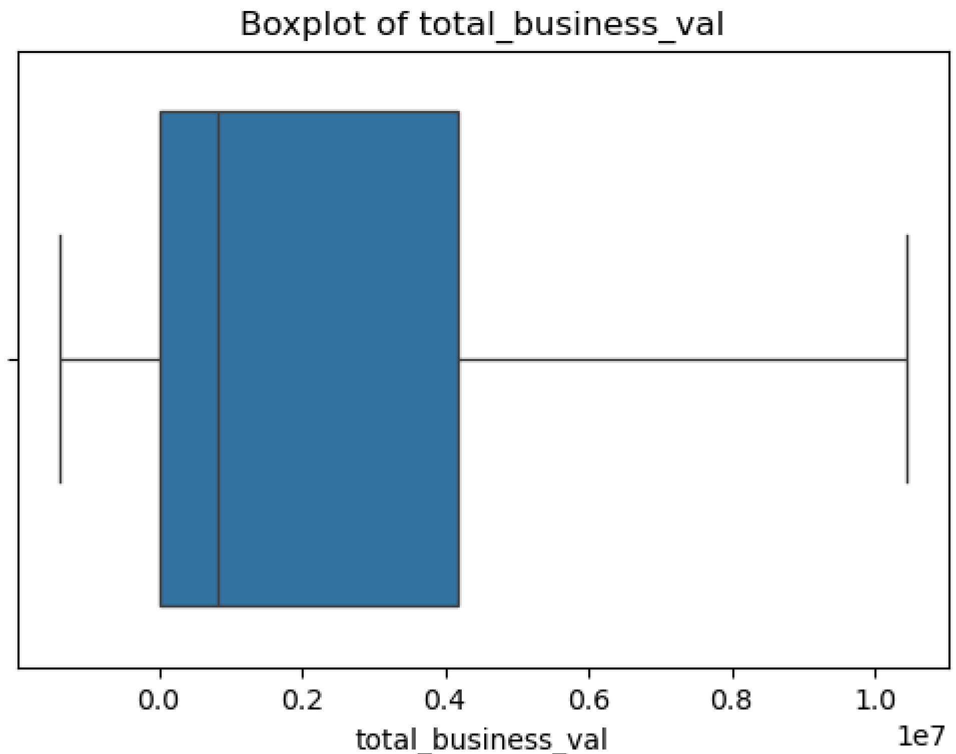

Boxplot of education
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
education

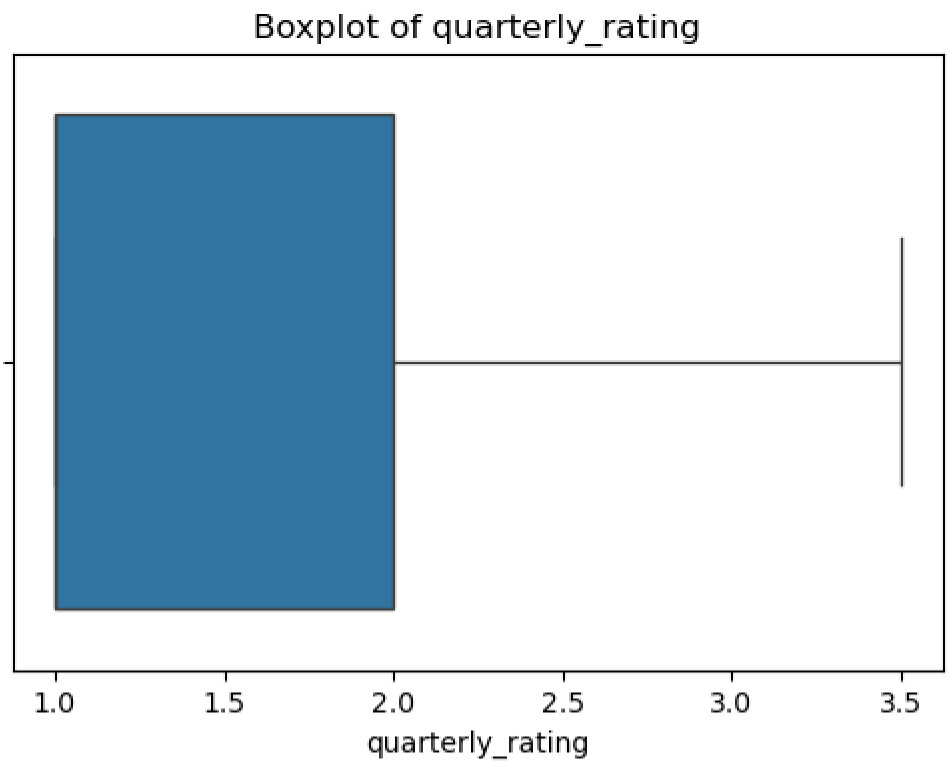

Boxplot of income
20000
40000
60000
80000
100000
120000
income

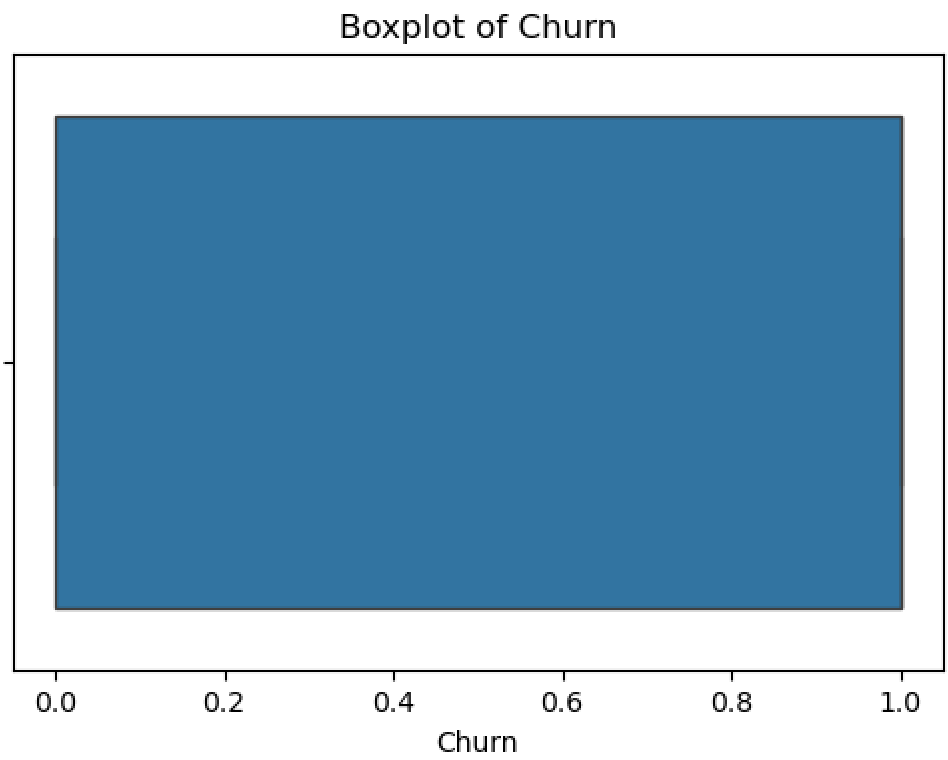

Boxplot of DOJ
2016
2017
2018
2019
2020
2021
DOJ


Boxplot of joining_designation
1.0
1.5
2.0
2.5
3.0
3.5
joining_designation


Boxplot of grade
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
grade


Boxplot of total_business_val
0.0
0.2
0.4
0.6
0.8
1.0
1e7
total_business_val





In [ ]:

```python
# checking skewness of the features
def check_skewness(series):
    if series.dtype != 'int64' and series.dtype != 'float64':
        return
    col_skewness = skew(series)
    if col_skewness < -1:
        comment = "Highly left-skewed"
    elif -1 <= col_skewness < -0.5:
        comment = "Moderately left-skewed"
    elif -0.5 <= col_skewness < 0.5:
        comment = "Approximately symmetric"
    elif 0.5 <= col_skewness < 1:
        comment = "Moderately right-skewed"
```

```
    else:
        comment = "Highly right-skewed"
    print(f"{series.name}: Skewness = {col_skewness:.2f} ({comment})")
```

In [ ]:
```
for col in continuous_cols:
    check_skewness(dfg[col])
```

```
Driver_ID: Skewness = -0.00 (Approximately symmetric)
total_months: Skewness = 1.06 (Highly right-skewed)
age: Skewness = 0.37 (Approximately symmetric)
gender: Skewness = 0.36 (Approximately symmetric)
education: Skewness = -0.01 (Approximately symmetric)
income: Skewness = 0.55 (Moderately right-skewed)
joining_designation: Skewness = 0.44 (Approximately symmetric)
grade: Skewness = 0.52 (Moderately right-skewed)
total_business_val: Skewness = 1.21 (Highly right-skewed)
quarterly_rating: Skewness = 1.03 (Highly right-skewed)
Churn: Skewness = -0.77 (Moderately left-skewed)
```

Data Preprocessing

In [ ]:
```
# checking duplicate data
dup = dfg[dfg.duplicated()]
if dup.empty:
    print("No duplicate records found.")
else:
    print("Duplicate records found:")
    print(dup)
```

```
No duplicate records found.
```

In [ ]:
```
# missing value detection and treatment
dfg.isna().sum()
```

Out[ ]:
```
Driver_ID              0
total_months           0
age                    0
gender                 0
city                   0
education              0
income                 0
DOJ                    0
joining_designation    0
grade                  0
total_business_val     0
quarterly_rating       0
Churn                  0
dtype: int64
```

In [ ]:
```
# feature engineering
dfg.head()
```

Out[ ]:

	Driver_ID	total_months	age	gender	city	education	income	DOJ	joining_desig
0	1	3.0	28.0	0.0	C23	2	57387.0	2018-12-24	
1	2	2.0	31.0	0.0	C7	2	67016.0	2020-11-06	
2	4	5.0	43.0	0.0	C13	2	65603.0	2019-12-07	
3	5	3.0	29.0	0.0	C9	0	46368.0	2019-01-09	
4	6	5.0	31.0	1.0	C11	1	78728.0	2020-07-31	

In [ ]:

```
# creating date related fields
dfg['year']=dfg['DOJ'].dt.year
dfg['month']=dfg['DOJ'].dt.month
dfg['day']=dfg['DOJ'].dt.day
dfg.drop(columns='DOJ',inplace=True)
```

In [ ]:

```
# # creating bins for ages
# print(f"min age : {dfg['age'].min()} \nmax age : {dfg['age'].max()}")

# dfg['age']=pd.cut(dfg['age'] , bins = 5 , labels=['a','b','c','d','e'])
```

In [ ]:

```
df.columns
```

Out[ ]:

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

In [ ]:

```
# new feature wrt quarterly rating increase
first_quar=df.groupby(['Driver_ID']).agg({'Quarterly Rating' : "first"})
last_quar = df.groupby(['Driver_ID']).agg({'Quarterly Rating' : "last"})

rating_change = (last_quar['Quarterly Rating'] > first_quar['Quarterly Rating'])
rating_change['Quarterly Rating']=rating_change['Quarterly Rating'].astype(int)

dfg['quarterly_rating_increased']=rating_change['Quarterly Rating']
```

In [ ]:

```
# new feature wrt income increase
first_income=df.groupby(['Driver_ID']).agg({'Income' : "first"})
last_income = df.groupby(['Driver_ID']).agg({'Income' : "last"})

income_change = (last_income['Income'] > first_income['Income']).reset_index()
income_change['Income']=income_change['Income'].astype(int)

dfg['income_increased']=income_change['Income']
```

In [ ]:

```
dfg.head()
```

Out[ ]:

	Driver_ID	total_months	age	gender	city	education	income	joining_designation
0	1	3.0	28.0	0.0	C23	2	57387.0	1.0
1	2	2.0	31.0	0.0	C7	2	67016.0	2.0
2	4	5.0	43.0	0.0	C13	2	65603.0	2.0
3	5	3.0	29.0	0.0	C9	0	46368.0	1.0
4	6	5.0	31.0	1.0	C11	1	78728.0	3.0

In [ ]:

Model building

In [ ]:

```
X = dfg.drop(columns='Churn')
y = dfg['Churn']
```

In [ ]:

```
# splitting the data
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42
```

In [ ]:

```
X_train.head()
```

Out[ ]:

	Driver_ID	total_months	age	gender	city	education	income	joining_designa
2242	2627	2.0	34.0	1.0	C7	0	104058.0	
1474	1730	1.0	42.0	0.0	C9	0	51579.0	
2132	2499	3.0	27.0	0.0	C17	1	75458.0	
1873	2200	20.5	34.0	0.0	C15	1	69756.0	
462	539	1.0	36.0	0.0	C24	0	109296.0	

In [ ]:

```
X_train.shape
```

Out[ ]:

```
(1904, 16)
```

In [ ]:

```
#encoding
te_cols = ["city"]

te = TargetEncoder()
X_train[te_cols]=te.fit_transform(X_train[te_cols],y_train)
X_test[te_cols]=te.transform(X_test[te_cols])
```

In [ ]:

```
X_train.head()
```

Out[ ]:

	Driver_ID	total_months	age	gender	city	education	income	joining_des
2242	2627	2.0	34.0	1.0	0.673188	0	104058.0	
1474	1730	1.0	42.0	0.0	0.673579	0	51579.0	
2132	2499	3.0	27.0	0.0	0.852101	1	75458.0	
1873	2200	20.5	34.0	0.0	0.656125	1	69756.0	
462	539	1.0	36.0	0.0	0.629148	0	109296.0	

In [ ]:

```
X_test.head()
```

Out[ ]:

	Driver_ID	total_months	age	gender	city	education	income	joining_desi
937	1103	5.0	26.0	0.0	0.711650	2	40318.0	
765	899	3.0	29.0	0.0	0.751551	0	28565.0	
34	46	3.0	36.0	1.0	0.753273	2	42171.0	
480	559	5.0	40.0	0.0	0.720025	0	44342.0	
303	358	14.0	39.0	1.0	0.708502	2	117830.0	

In [ ]:

```
# scalling
se = StandardScaler()

X_train = se.fit_transform(X_train)
X_test = se.transform(X_test)
```

In [ ]:

```
# handling imbalanced data
sm = SMOTE(random_state=42)

X_train_res, y_train_res = sm.fit_resample(X_train , y_train)
# X_test_res = sm.resample(X_test)
```

In [ ]:

```
print('Before OverSampling, the shape of train_X: {}'.format(X_train.shape))
print('Before OverSampling, the shape of train_y: {} \n'.format(y_train.shape))

print("Before OverSampling, counts of label '1': {}".format(sum(y_train == 1)))
print("Before OverSampling, counts of label '0': {}".format(sum(y_train == 0)))
```

```
Before OverSampling, the shape of train_X: (1904, 16)
Before OverSampling, the shape of train_y: (1904,)

Before OverSampling, counts of label '1': 1292
Before OverSampling, counts of label '0': 612
```

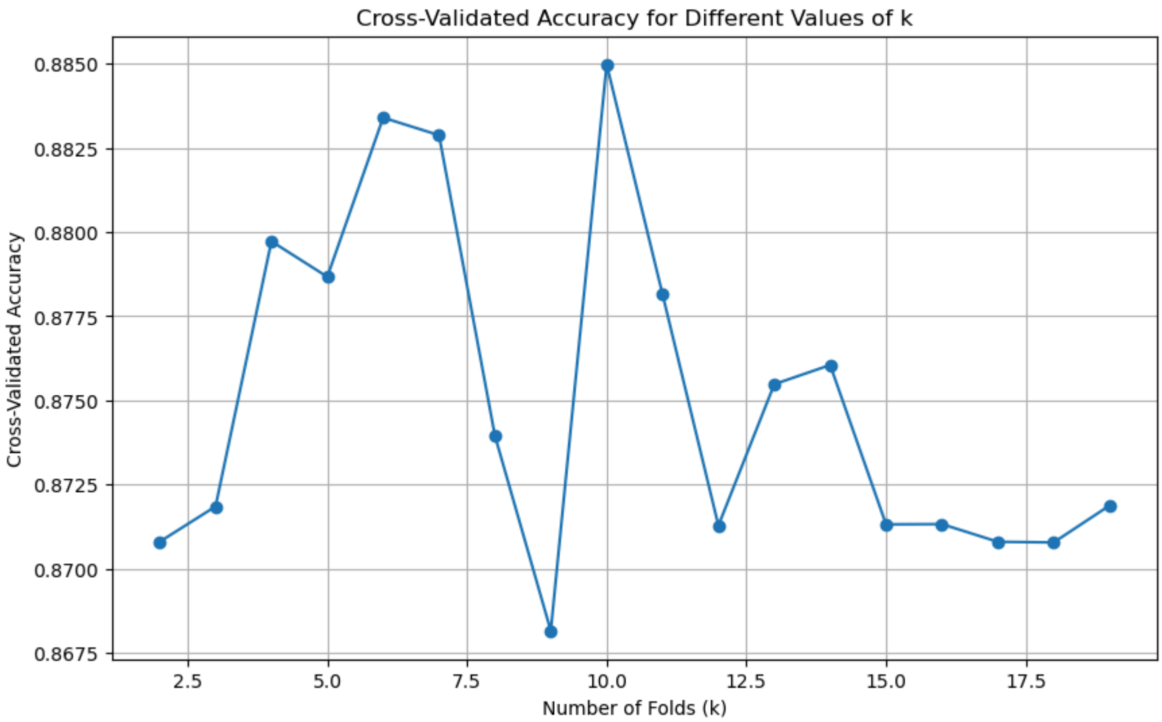
In [ ]:

```
print('After OverSampling, the shape of train_X: {}'.format(X_train_res.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_res.shape

print("After OverSampling, counts of label '1': {}".format(sum(y_train_res == 1)
print("After OverSampling, counts of label '0': {}".format(sum(y_train_res == 0)
```

```
After OverSampling, the shape of train_X: (2584, 16)
After OverSampling, the shape of train_y: (2584,)

After OverSampling, counts of label '1': 1292
After OverSampling, counts of label '0': 1292
```

Model 0 : DecisionTreeClassifier

In [ ]:
```python
# model initialization : finding the optimal value for k
model0 = DecisionTreeClassifier(random_state=7)

cv_scores = []
k_values=range(2, 20)
# selecting best value of k
for k in k_values:
     kf=StratifiedKFold(n_splits=k,shuffle=True,random_state=7)
     scores=cross_val_score(model0, X_train, y_train,cv=kf)
     cv_scores.append(np.mean(scores))

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(k_values, cv_scores, marker='o')
plt.xlabel('Number of Folds (k)')
plt.ylabel('Cross-Validated Accuracy')
plt.title('Cross-Validated Accuracy for Different Values of k')
plt.grid()
plt.show()

# Find the best value of k
best_k = k_values[np.argmax(cv_scores)]
print(f"Best value of k: {best_k} with accuracy: {max(cv_scores):.4f}")
```




```
Best value of k: 10 with accuracy: 0.8850
```

In [ ]:
```python
# training base model with best_k
kfold = StratifiedKFold(n_splits = best_k)

class_weights = compute_class_weight(class_weight='balanced', classes=np.unique(
```

```
class_weights_dict = {i: weight for i, weight in enumerate(class_weights)}

dt_clf = DecisionTreeClassifier(random_state=7,class_weight=class_weights_dict)
cv_results_dt = cross_validate(dt_clf, X_train, y_train, cv = kfold, scoring = '


print(f"K-Fold Accuracy Mean: \n Train: {cv_results_dt['train_score'].mean()*100
print(f"K-Fold Accuracy Std: \n Train: {cv_results_dt['train_score'].std()*100:.
```

```
K-Fold Accuracy Mean:
 Train: 100.00
 Validation: 86.87
K-Fold Accuracy Std:
 Train: 0.00,
 Validation: 1.49
```

In [ ]:

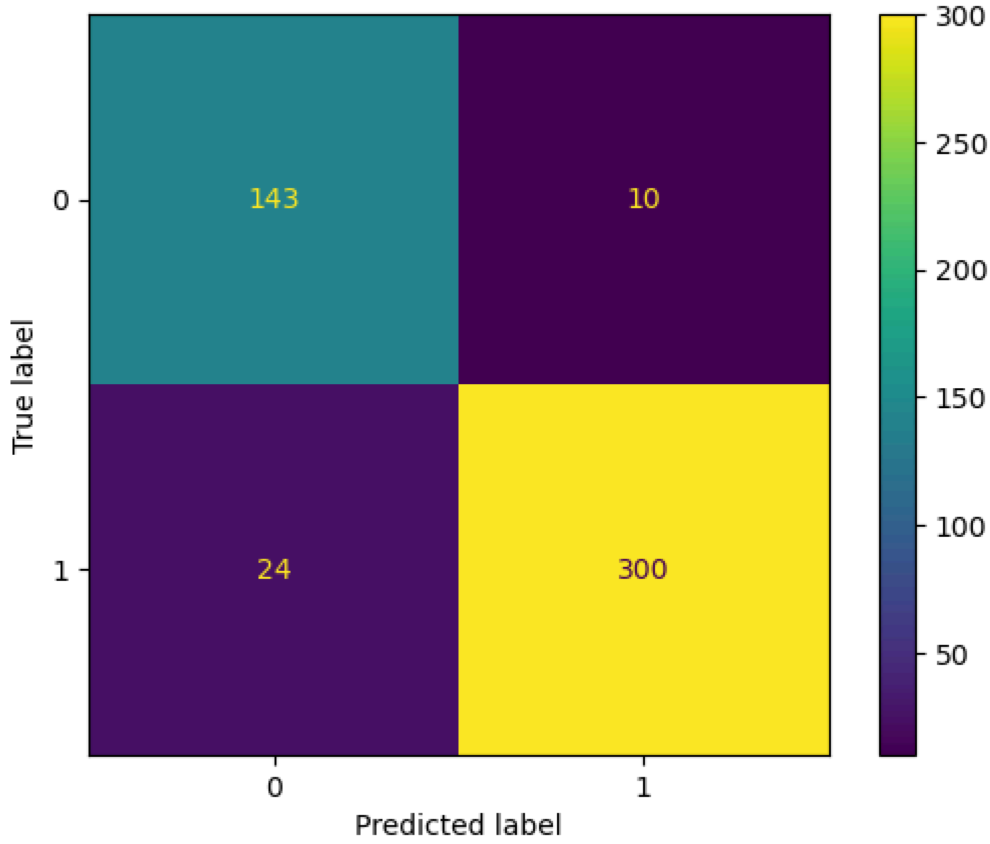
```
# initializing model : selecting best estimators
# kfold = KFold(n_splits = 10)
params = {
    "max_depth" : [3, 5, 7, 10, 15],
    "max_leaf_nodes" : [20, 40, 60 , 100],
}
grid_dt = GridSearchCV(estimator = DecisionTreeClassifier(random_state=7),
                    param_grid= params,
                    scoring = 'accuracy',
                    cv = kfold,
                    n_jobs=-1
                    )

grid_dt.fit(X_train, y_train)
```

Out[ ]:

```
GridSearchCV
best_estimator_: DecisionTreeClassifier
    DecisionTreeClassifier
```

In [ ]:

```
model_dt = grid_dt.best_estimator_
y_pred=  model_dt.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=model_dt.classes_)
disp.plot()
plt.show()
```

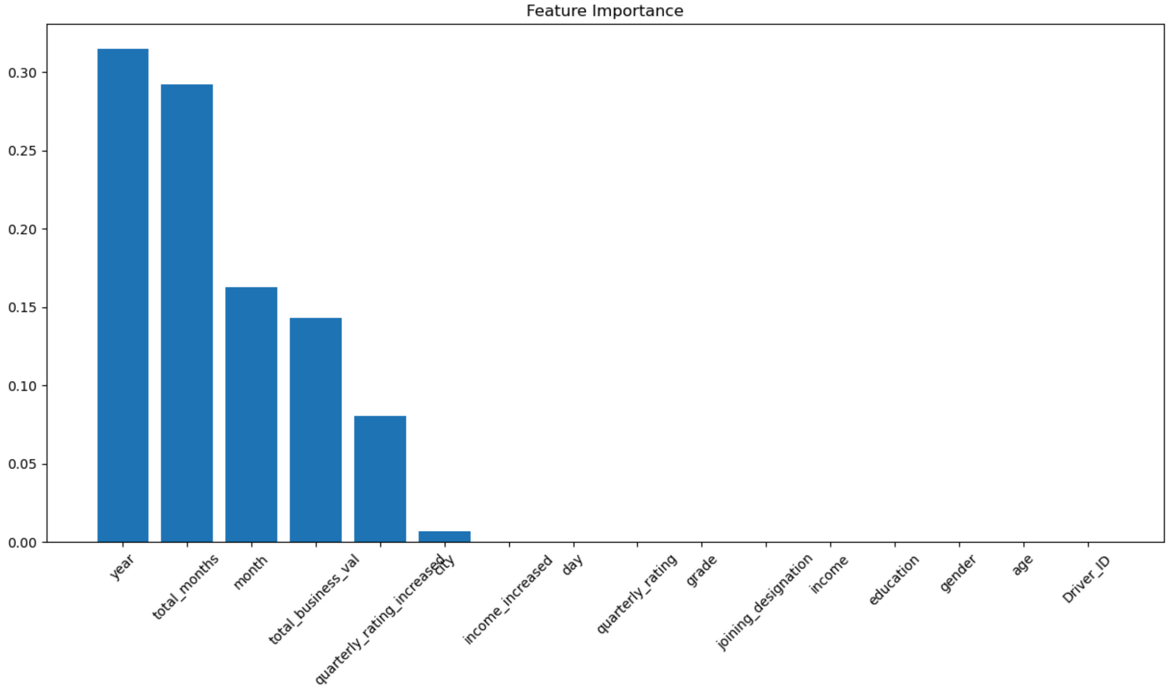


In [ ]:
```
dt_report = classification_report(y_test, y_pred, output_dict=True)
```

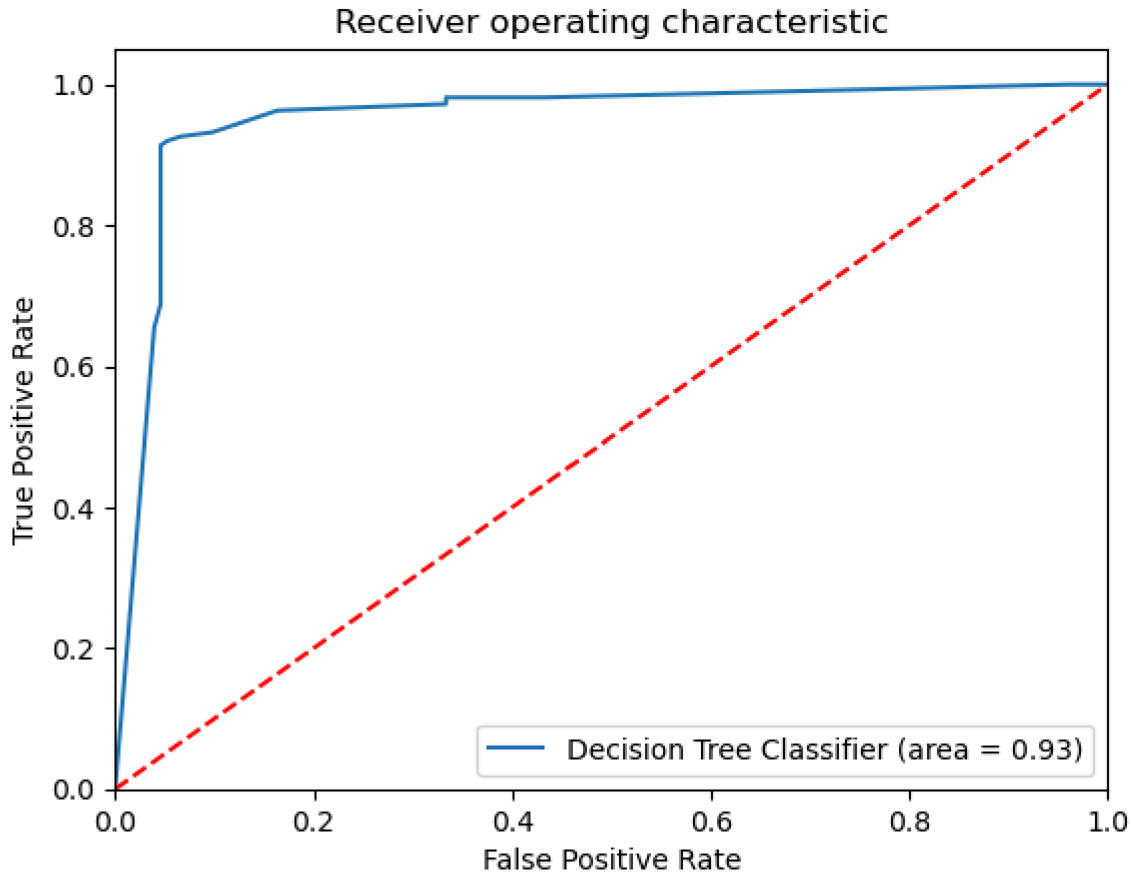
In [ ]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.93      0.89       153
           1       0.97      0.93      0.95       324

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

In [ ]:
```
importances = model_dt.feature_importances_
indices = np.argsort(importances)[::-1]
names = [X.columns[i] for i in indices]


plt.figure(figsize=(15, 7))
plt.title("Feature Importance")
plt.bar(range(X_train.shape[1]), importances[indices])
plt.xticks(range(X_train.shape[1]), names, rotation=45)
plt.show()
```

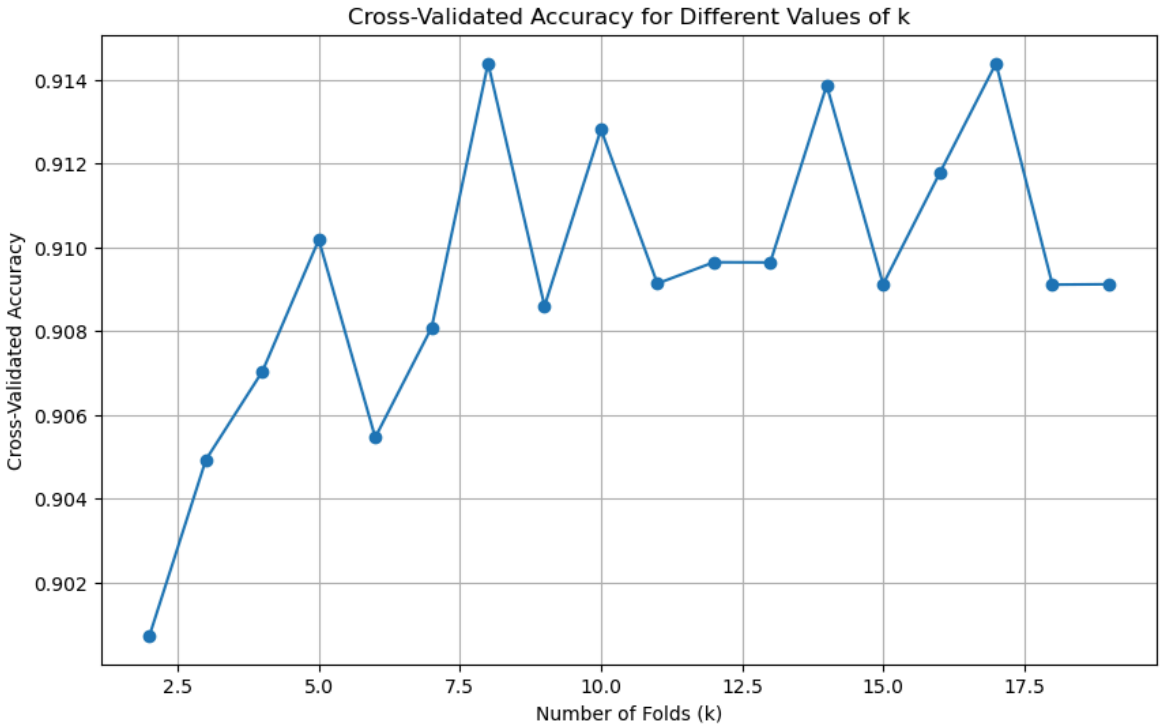


In [ ]:
```
logit_roc_auc=roc_auc_score(y_test,y_pred)
fpr,tpr,thresholds=roc_curve(y_test,model_dt.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='Decision Tree Classifier (area = %0.2f)' % logit_roc_auc
plt.plot([0,1],[0,1],'r--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



Model 1 : RandomForestClassifier

In [ ]:
```
# initialize model : finding best value for k with RF
model1 = RandomForestClassifier(random_state=7)

cv_scores = []
k_values=range(2, 20)
# selecting best value of k
for k in k_values:
     kf=StratifiedKFold(n_splits=k,shuffle=True,random_state=7)
     scores=cross_val_score(model1, X_train, y_train,cv=kf)
     cv_scores.append(np.mean(scores))

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(k_values, cv_scores, marker='o')
plt.xlabel('Number of Folds (k)')
plt.ylabel('Cross-Validated Accuracy')
plt.title('Cross-Validated Accuracy for Different Values of k')
plt.grid()
plt.show()

# Find the best value of k
best_k = k_values[np.argmax(cv_scores)]
print(f"Best value of k: {best_k} with accuracy: {max(cv_scores):.4f}")
```




```
Best value of k: 8 with accuracy: 0.9144
```

In [ ]:

```
# initialize model : model with defined classs_weight

class_weights = compute_class_weight(class_weight='balanced', classes=np.unique(
class_weights_dict = {i: weight for i, weight in enumerate(class_weights)}

kfold = StratifiedKFold(n_splits=best_k)

rf_clf = RandomForestClassifier(random_state=7, class_weight=class_weights_dict)
cv_results_rf = cross_validate(rf_clf, X_train, y_train, cv=kfold, scoring='accu

print(f"K-Fold Accuracy Mean: \n Train: {cv_results_rf['train_score'].mean()*100
print(f"K-Fold Accuracy Std: \n Train: {cv_results_rf['train_score'].std()*100:.
```

```
K-Fold Accuracy Mean:
 Train: 100.00
 Validation: 90.97
K-Fold Accuracy Std:
 Train: 0.00,
 Validation: 1.53
```

In [ ]:

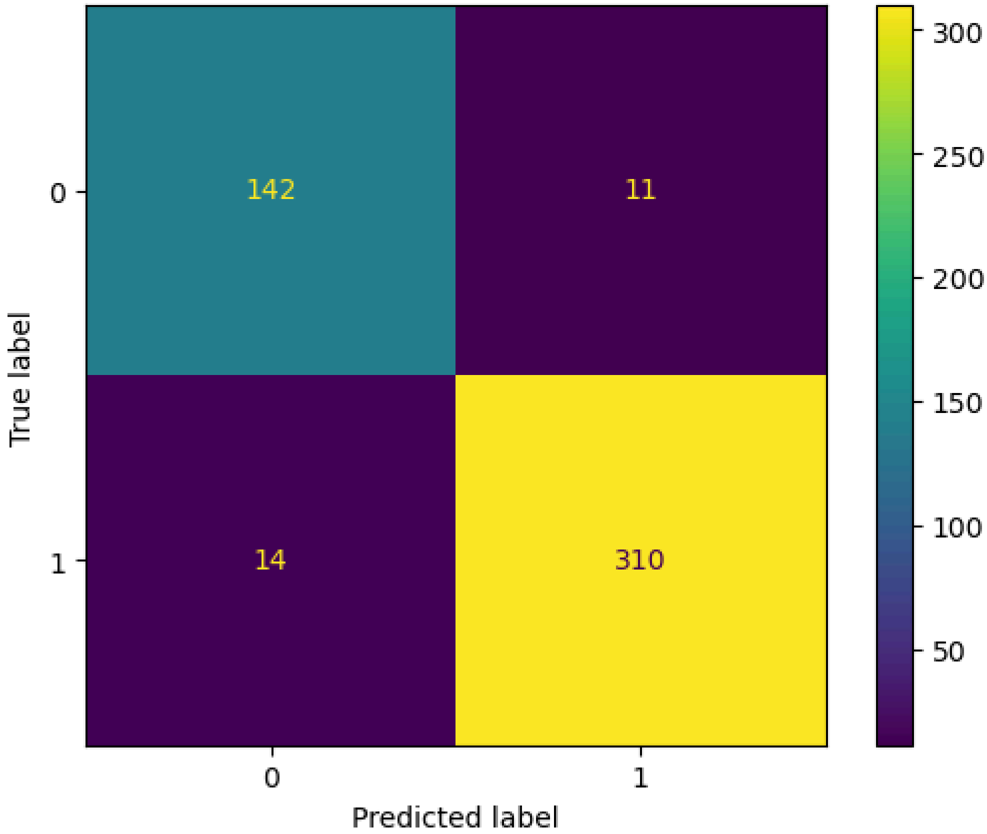
```
# initialize model : selecting best estimators
params = {
          'n_estimators' : [100,200,300,400],
          'max_depth' : [None,3,5,10],
          'criterion' : ['gini', 'entropy'],
          'bootstrap' : [True, False],
          'max_features' : [8,9,10]
         }
grid_rf = GridSearchCV(estimator = RandomForestClassifier(random_state=7, class_
                    param_grid = params,
                    scoring = 'accuracy',
                    cv = kfold ,
                    n_jobs=-1
                    )

grid_rf.fit(X_train, y_train)
```

Out[ ]:
```
▸ GridSearchCV
▸ best_estimator_: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [ ]:
```
print("Best params: ", grid_rf.best_params_)
print("Best score: ", grid_rf.best_score_)
```

```
Best params:  {'bootstrap': True, 'criterion': 'entropy', 'max_depth': 10, 'max_f
eatures': 8, 'n_estimators': 100}
Best score:  0.9191176470588236
```

In [ ]:
```
model_rf1 = grid_rf.best_estimator_
y_pred=  model_rf1.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=model_rf1.classes_)
disp.plot()
plt.show()
```

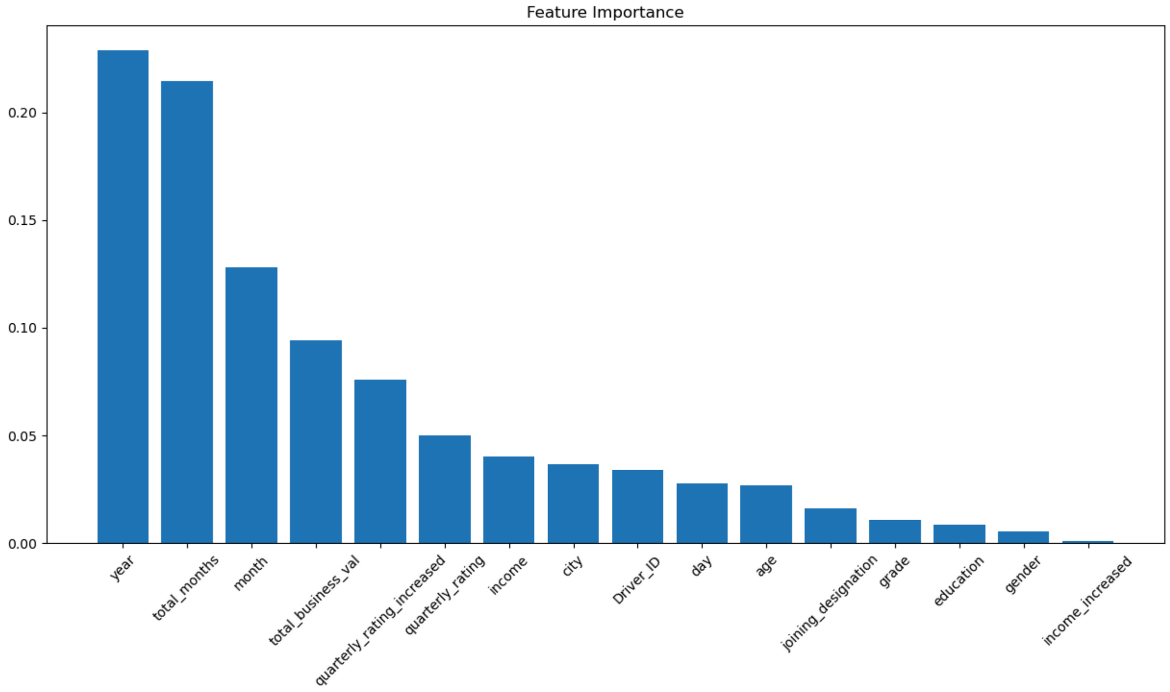


In [ ]:
```
rf_model1=classification_report(y_test, y_pred,output_dict=True)
```

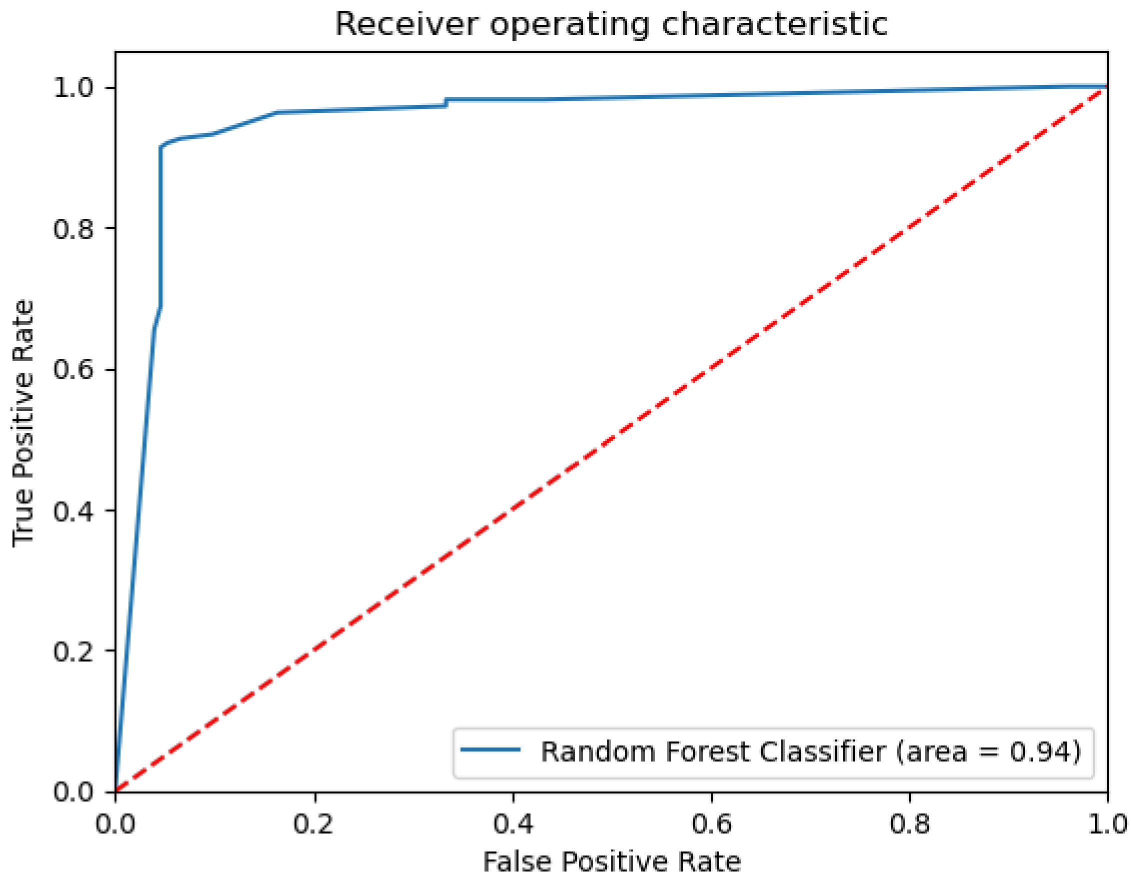
In [ ]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.93      0.92       153
           1       0.97      0.96      0.96       324

    accuracy                           0.95       477
   macro avg       0.94      0.94      0.94       477
weighted avg       0.95      0.95      0.95       477
```

In [ ]:
```
importances = model_rf1.feature_importances_
indices = np.argsort(importances)[::-1]
names = [X.columns[i] for i in indices]


plt.figure(figsize=(15, 7))
plt.title("Feature Importance")
plt.bar(range(X_train.shape[1]), importances[indices])
plt.xticks(range(X_train.shape[1]), names, rotation=45)
plt.show()
```



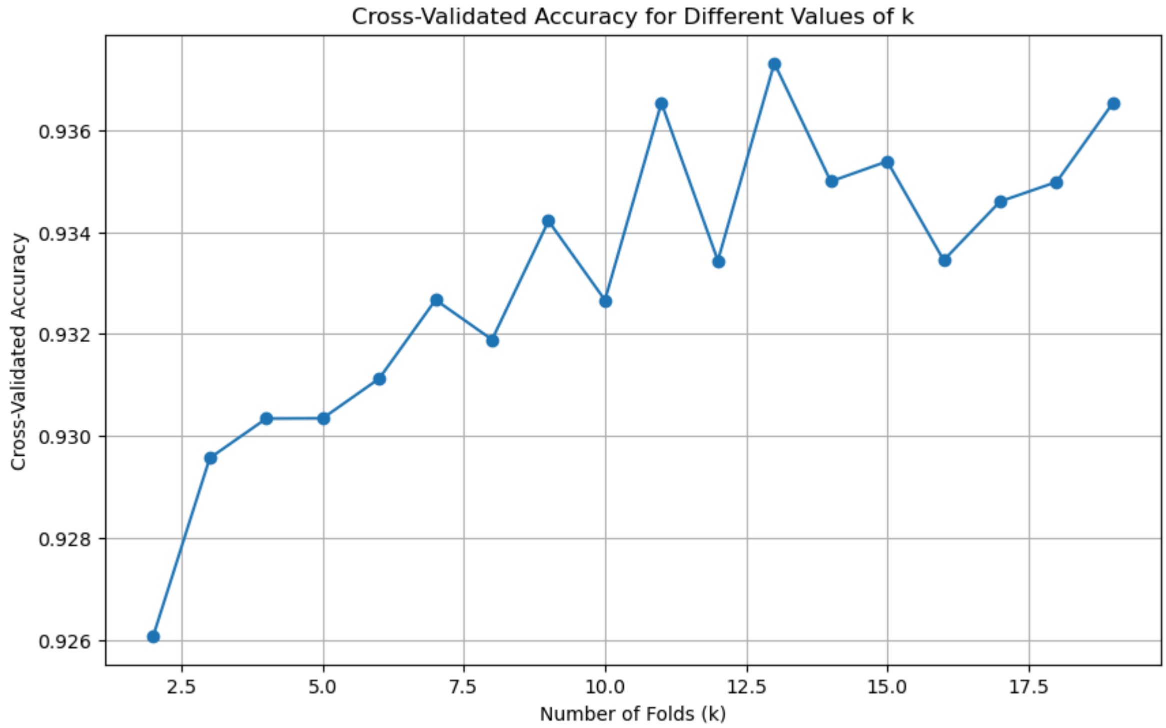
In [ ]:
```
logit_roc_auc=roc_auc_score(y_test,y_pred)
fpr,tpr,thresholds=roc_curve(y_test,model_dt.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='Random Forest Classifier (area = %0.2f)' % logit_roc_auc
plt.plot([0,1],[0,1],'r--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



In [ ]:

In [ ]:

```
# initialize model : finding optimzal k value with SMOTE data
model2 = RandomForestClassifier(random_state=7)

cv_scores = []
k_values=range(2, 20)
# selecting best value of k
for k in k_values:
     kf=StratifiedKFold(n_splits=k,shuffle=True,random_state=7)
     scores=cross_val_score(model2, X_train_res, y_train_res,cv=kf)
     cv_scores.append(np.mean(scores))

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(k_values, cv_scores, marker='o')
plt.xlabel('Number of Folds (k)')
plt.ylabel('Cross-Validated Accuracy')
plt.title('Cross-Validated Accuracy for Different Values of k')
plt.grid()
plt.show()

# Find the best value of k
best_k = k_values[np.argmax(cv_scores)]
print(f"Best value of k: {best_k} with accuracy: {max(cv_scores):.4f}")
```




```
Best value of k: 13 with accuracy: 0.9373
```

In [ ]:
```
# initialize model : training base model with SMOTE data
kfold = StratifiedKFold(n_splits=best_k)

rf_clf2 = RandomForestClassifier(random_state=7)
cv_results_rf2 = cross_validate(rf_clf, X_train_res, y_train_res, cv=kfold, scor

print(f"K-Fold Accuracy Mean: \n Train: {cv_results_rf2['train_score'].mean()*10
print(f"K-Fold Accuracy Std: \n Train: {cv_results_rf2['train_score'].std()*100:
```

```
K-Fold Accuracy Mean:
 Train: 100.00
 Validation: 93.54
K-Fold Accuracy Std:
 Train: 0.00,
 Validation: 2.33
```

In [ ]:
```
# selecting best estimators
params = {
          'n_estimators' : [100,200,300,400],
          'max_depth' : [3,5,10],
          'criterion' : ['gini', 'entropy'],
          'bootstrap' : [True, False],
          'max_features' : [8,9,10]
         }
grid_rf2 = GridSearchCV(estimator = RandomForestClassifier(random_state=7),
                        param_grid = params,
                        scoring = 'accuracy',
                        cv = kfold,
                        n_jobs=-1
                        )

grid_rf2.fit(X_train, y_train)
```

Out[ ]:

```
▸ GridSearchCV
▸ best_estimator_: RandomForestClassifier
    ▸ RandomForestClassifier
```

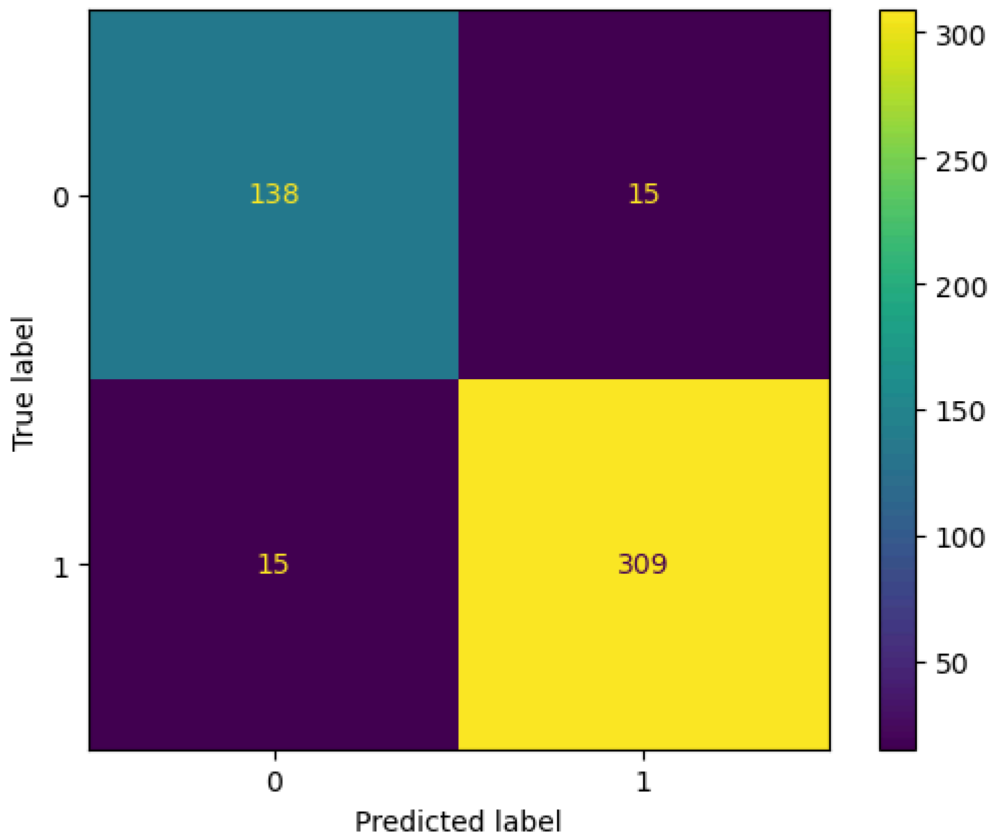
In [ ]:

```
print("Best params: ", grid_rf2.best_params_)
print("Best score: ", grid_rf2.best_score_)
```

```
Best params:  {'bootstrap': True, 'criterion': 'entropy', 'max_depth': 10, 'max_f
eatures': 8, 'n_estimators': 300}
Best score:  0.9238331792147838
```

In [ ]:

```
model_rf2 = grid_rf2.best_estimator_
y_pred=  model_rf2.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=model_rf2.classes_)
disp.plot()
plt.show()
```



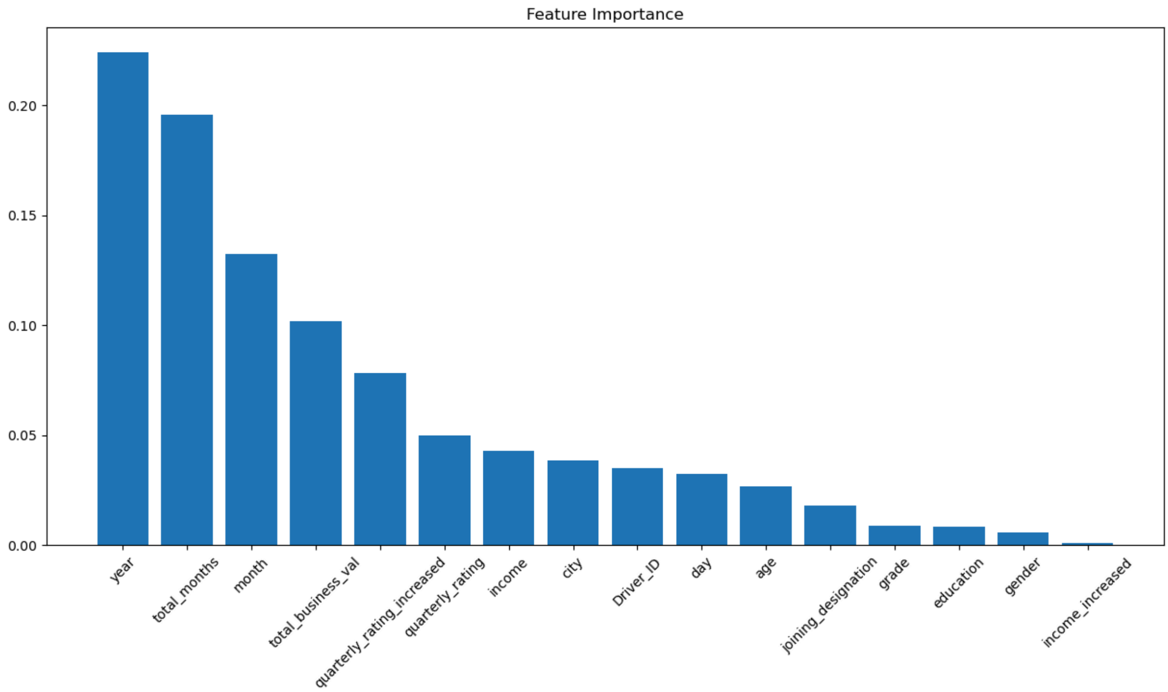
In [ ]:

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

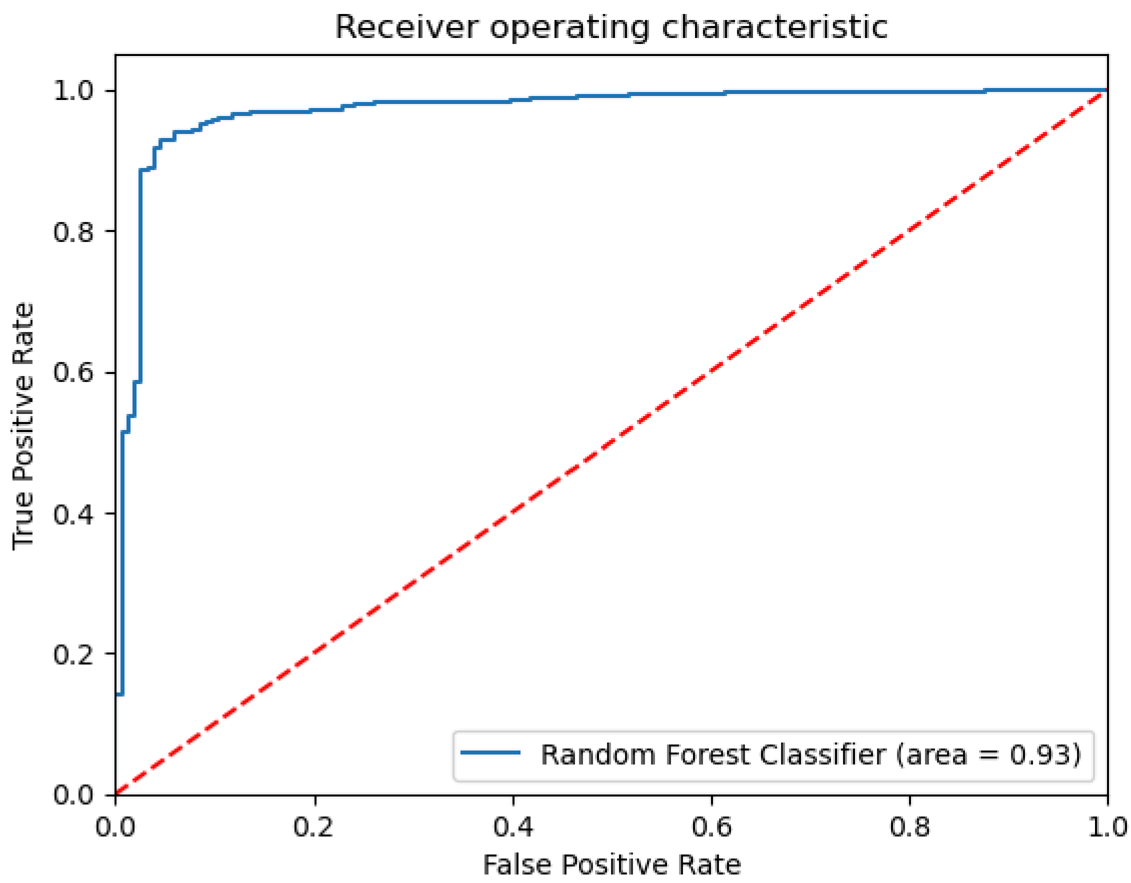
```
              precision    recall  f1-score   support

           0       0.90      0.90      0.90       153
           1       0.95      0.95      0.95       324

    accuracy                           0.94       477
   macro avg       0.93      0.93      0.93       477
weighted avg       0.94      0.94      0.94       477
```

In [ ]:
```
rf_model2=classification_report(y_test, y_pred,output_dict=True)
```

In [ ]:
```
importances = model_rf2.feature_importances_
indices = np.argsort(importances)[::-1]
names = [X.columns[i] for i in indices]


plt.figure(figsize=(15, 7))
plt.title("Feature Importance")
plt.bar(range(X_train.shape[1]), importances[indices])
plt.xticks(range(X_train.shape[1]), names, rotation=45)
plt.show()
```



In [ ]:
```
logit_roc_auc=roc_auc_score(y_test,y_pred)
fpr,tpr,thresholds=roc_curve(y_test,model_rf2.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='Random Forest Classifier (area = %0.2f)' % logit_roc_auc
plt.plot([0,1],[0,1],'r--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```

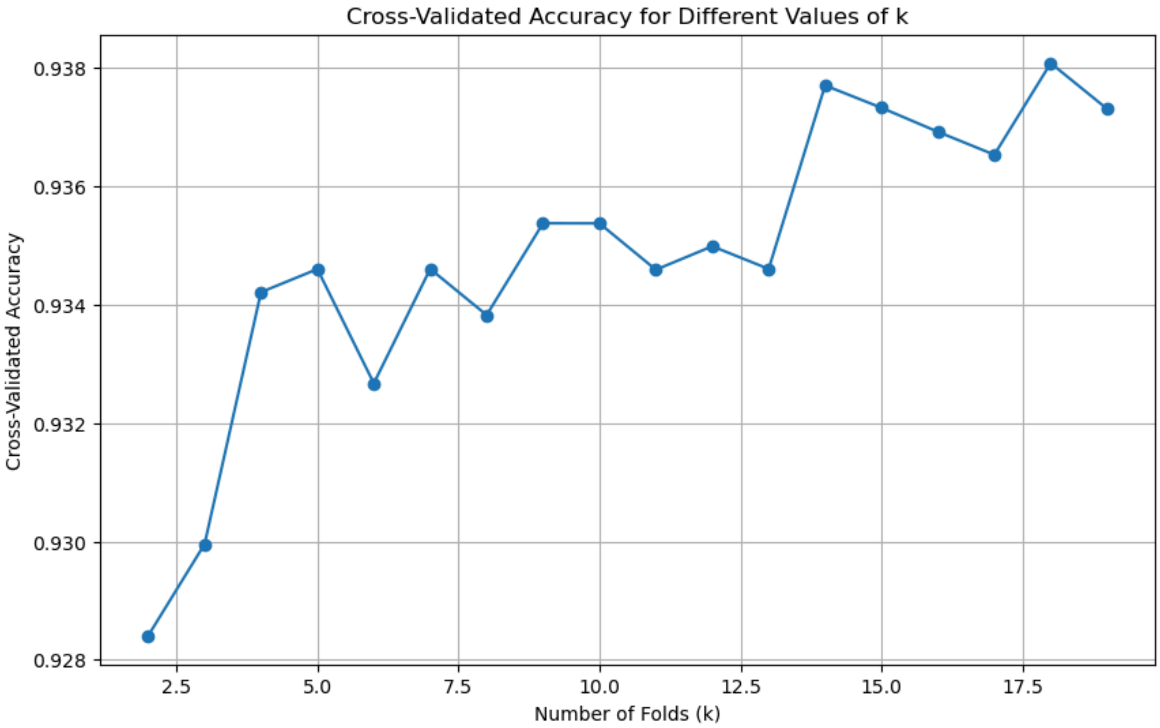


> model with class_weight and model with SMOTE performs similar

Model 2 : GradientBoostingClassifier

In [ ]:

```
# initialize model : finding best value for k with GBDT
model3 = GradientBoostingClassifier(random_state=7)

cv_scores = []
k_values=range(2, 20)
# selecting best value of k
for k in k_values:
     kf=StratifiedKFold(n_splits=k,shuffle=True,random_state=7)
     scores=cross_val_score(model3, X_train_res, y_train_res,cv=kf)
     cv_scores.append(np.mean(scores))

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(k_values, cv_scores, marker='o')
plt.xlabel('Number of Folds (k)')
plt.ylabel('Cross-Validated Accuracy')
plt.title('Cross-Validated Accuracy for Different Values of k')
plt.grid()
plt.show()

# Find the best value of k
best_k = k_values[np.argmax(cv_scores)]
print(f"Best value of k: {best_k} with accuracy: {max(cv_scores):.4f}")
```



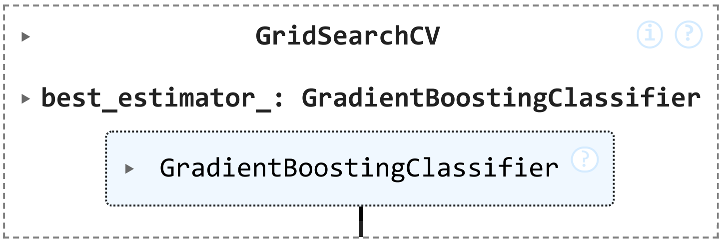

```
Best value of k: 18 with accuracy: 0.9381
```

In [ ]:
```
# training the base model with optimal k
kfold = StratifiedKFold(n_splits=best_k, shuffle=True, random_state=7)

gbdt_clf = GradientBoostingClassifier(random_state=7)
cv_results_rf = cross_validate(gbdt_clf, X_train_res, y_train_res, cv=kfold, scc

print(f"K-Fold Accuracy Mean: \n Train: {cv_results_rf['train_score'].mean()*100
print(f"K-Fold Accuracy Std: \n Train: {cv_results_rf['train_score'].std()*100:.
```

```
K-Fold Accuracy Mean:
 Train: 95.76
 Validation: 93.65
K-Fold Accuracy Std:
 Train: 0.17
 Validation: 2.38
```

In [ ]:
```
# selecting best params for the estimator
params = {
    'n_estimators': [100, 200, 300, 400],
    'max_depth': [3, 5, 10],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_features': [8, 9, 10]
}

grid_gbdt = GridSearchCV(estimator=GradientBoostingClassifier(random_state=7),
                        param_grid=params,
                        scoring='accuracy',
                        cv=kfold,
                        n_jobs=-1)

grid_gbdt.fit(X_train, y_train)
```

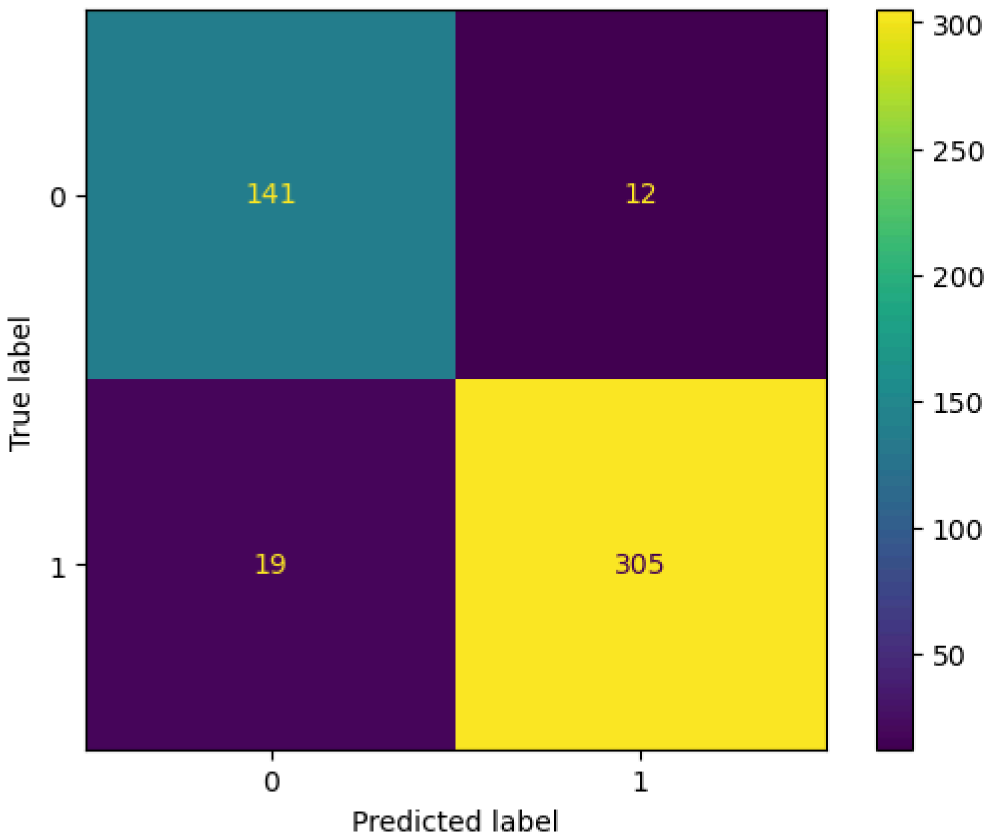
Out[ ]:



In [ ]:
```
print("Best params: ", grid_gbdt.best_params_)
print("Best score: ", grid_gbdt.best_score_)
```

```
Best params:  {'learning_rate': 0.1, 'max_depth': 5, 'max_features': 9, 'n_estima
tors': 200}
Best score:  0.9233003893381251
```

In [ ]:
```
model_gbdt = grid_gbdt.best_estimator_
y_pred=  model_gbdt.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=model_rf2.classes_)
disp.plot()
plt.show()
```

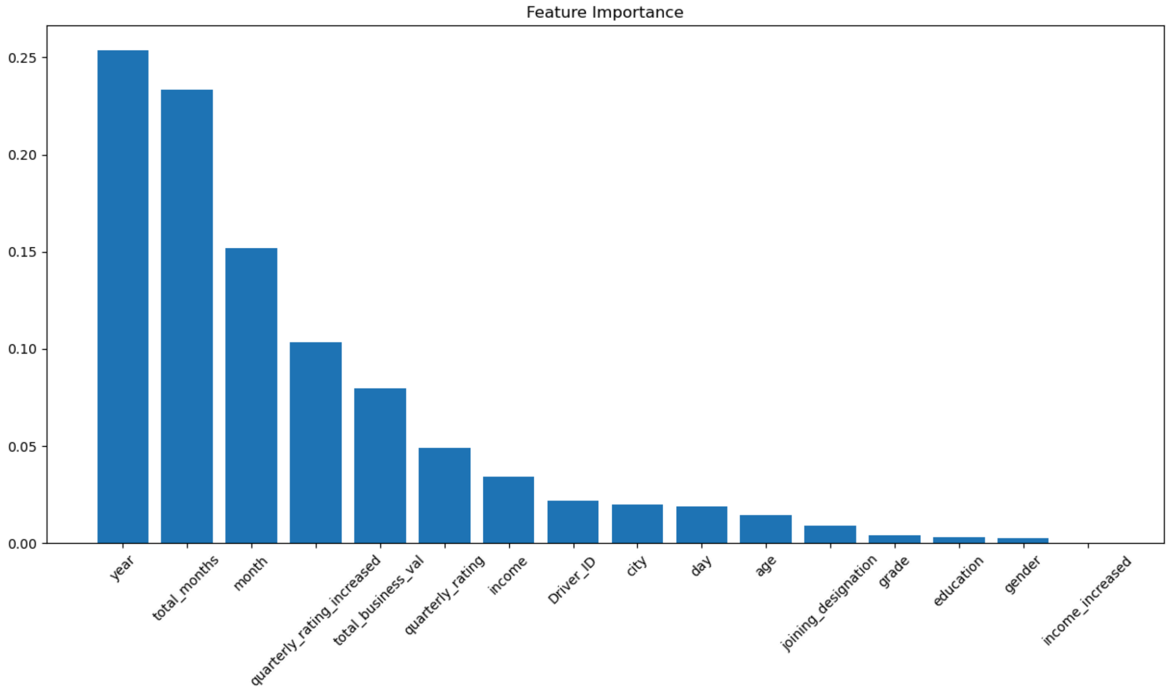


In [ ]:
```
print(classification_report(y_test, y_pred))
```

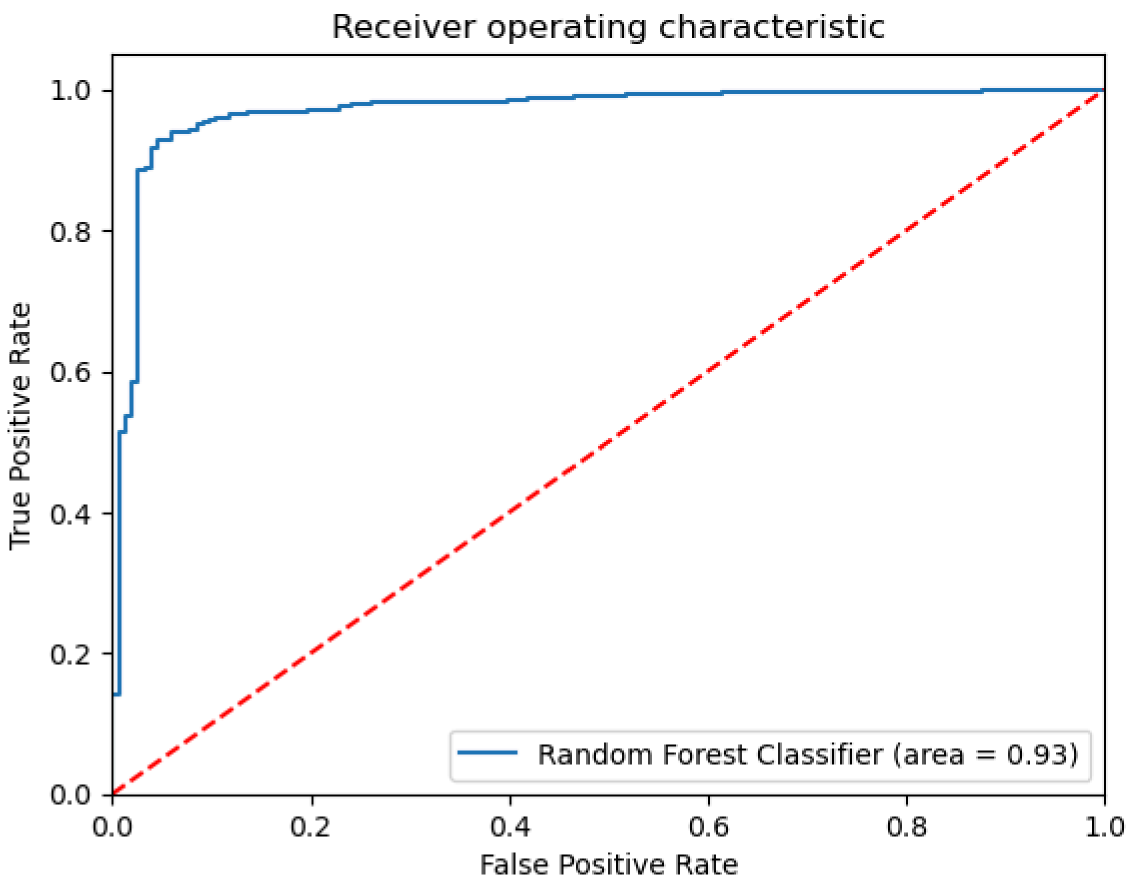
```
              precision    recall  f1-score   support

           0       0.88      0.92      0.90       153
           1       0.96      0.94      0.95       324

    accuracy                           0.94       477
   macro avg       0.92      0.93      0.93       477
weighted avg       0.94      0.94      0.94       477
```

In [ ]:
```
gbdt_model=classification_report(y_test, y_pred,output_dict=True)
```

In [ ]:
```
importances = model_gbdt.feature_importances_
indices = np.argsort(importances)[::-1]
names = [X.columns[i] for i in indices]


plt.figure(figsize=(15, 7))
plt.title("Feature Importance")
plt.bar(range(X_train.shape[1]), importances[indices])
plt.xticks(range(X_train.shape[1]), names, rotation=45)
plt.show()
```

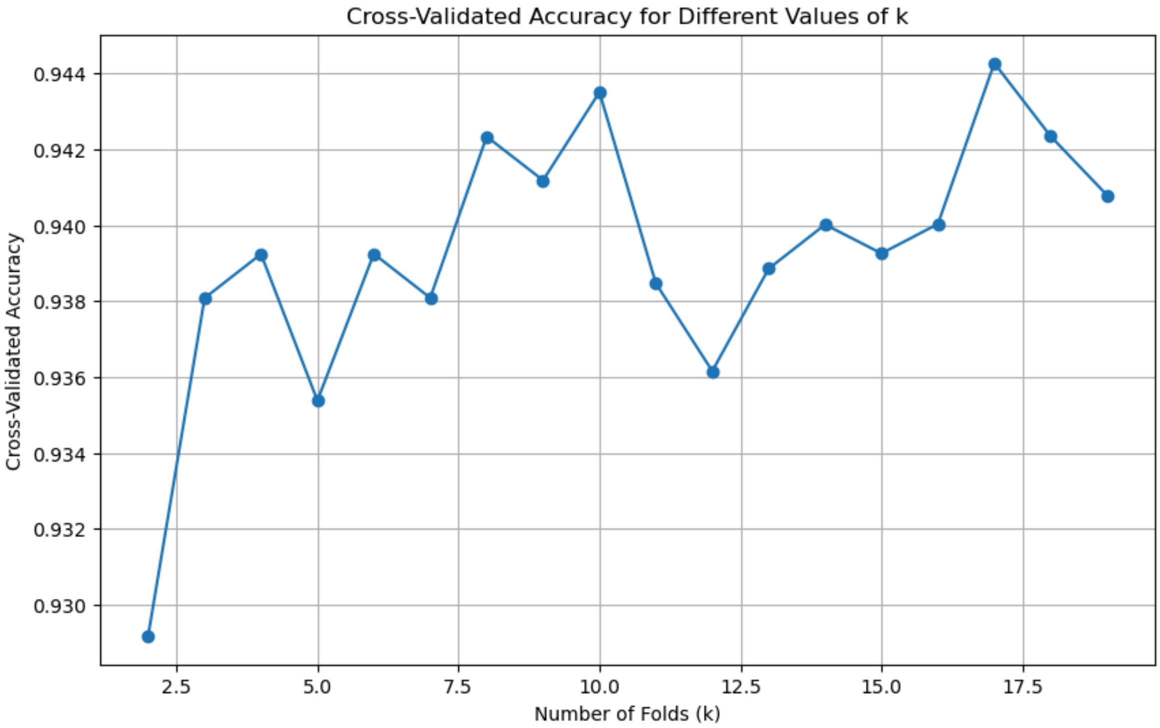


In [ ]:
```
logit_roc_auc=roc_auc_score(y_test,y_pred)
fpr,tpr,thresholds=roc_curve(y_test,model_rf2.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='Random Forest Classifier (area = %0.2f)' % logit_roc_auc
plt.plot([0,1],[0,1],'r--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



Model 3 : XGBoost

In [ ]:
```
# initialize model : finding best value for k with GBDT
model4 = XGBClassifier(random_state=7)

cv_scores = []
k_values=range(2, 20)
# selecting best value of k
for k in k_values:
     kf=StratifiedKFold(n_splits=k,shuffle=True,random_state=7)
     scores=cross_val_score(model4, X_train_res, y_train_res,cv=kf)
     cv_scores.append(np.mean(scores))

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(k_values, cv_scores, marker='o')
plt.xlabel('Number of Folds (k)')
plt.ylabel('Cross-Validated Accuracy')
plt.title('Cross-Validated Accuracy for Different Values of k')
plt.grid()
plt.show()

# Find the best value of k
best_k = k_values[np.argmax(cv_scores)]
print(f"Best value of k: {best_k} with accuracy: {max(cv_scores):.4f}")
```




```
Best value of k: 17 with accuracy: 0.9443
```

In [ ]:

```python
# training the base model with optimal k
kfold = StratifiedKFold(n_splits=best_k, shuffle=True, random_state=7)

xgb_clf = XGBClassifier(random_state=7)
cv_results_rf = cross_validate(xgb_clf , X_train_res, y_train_res, cv=kfold, scc

print(f"K-Fold Accuracy Mean: \n Train: {cv_results_rf['train_score'].mean()*100
print(f"K-Fold Accuracy Std: \n Train: {cv_results_rf['train_score'].std()*100:.
```

```
K-Fold Accuracy Mean:
 Train: 100.00
 Validation: 94.43
K-Fold Accuracy Std:
 Train: 0.00
 Validation: 2.20
```

In [ ]:

```python
# selecting best params for the estimator
params = {
    'n_estimators': [100, 200, 300, 400],
    'max_depth': [3, 5, 10],
    'learning_rate': [0.01, 0.1, 0.2],
    'gamma': [0, 0.1, 0.2],
    'reg_alpha': [0, 0.01, 0.1],
    'reg_lambda': [1, 1.5, 2]

}

grid_xgb = GridSearchCV(estimator=XGBClassifier(random_state=7),
                        param_grid=params,
                        scoring='accuracy',
                        cv=kfold,
                        n_jobs=-1)

grid_xgb.fit(X_train, y_train)
```

Out[ ]:

```
▸ GridSearchCV
▸ best_estimator_: XGBClassifier
    ▸ XGBClassifier
```

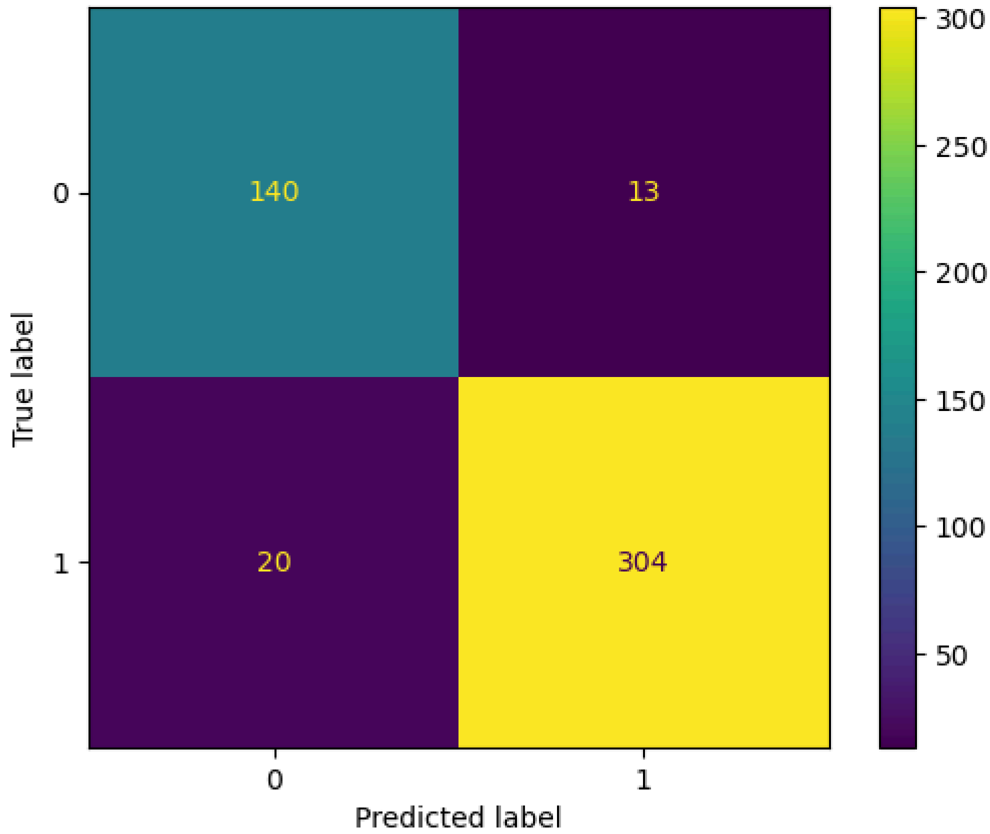
In [ ]:

```python
print("Best params: ", grid_xgb.best_params_)
print("Best score: ", grid_xgb.best_score_)
```

```
Best params:  {'gamma': 0, 'learning_rate': 0.2, 'max_depth': 10, 'n_estimators': 200, 'reg_alpha': 0, 'reg_lambda': 1.5}
Best score:  0.928046218487395
```

In [ ]:

```python
model_xgb = grid_xgb.best_estimator_
y_pred=  model_xgb.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=model_xgb.classes_)
disp.plot()
plt.show()
```



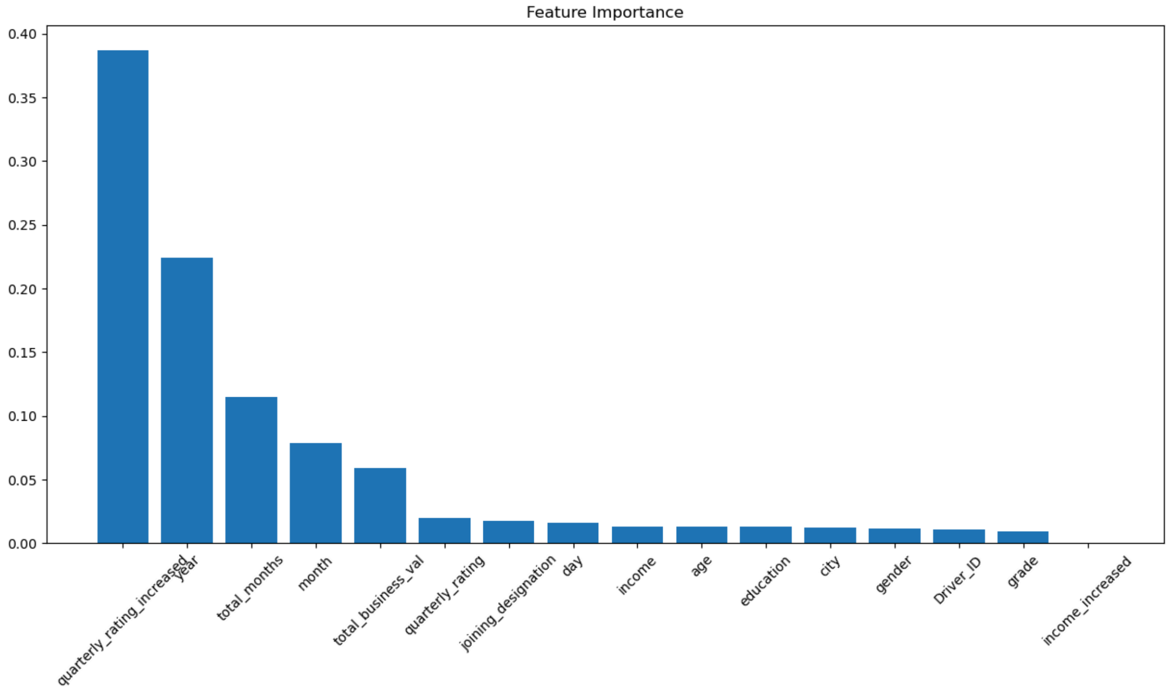
In [ ]:

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

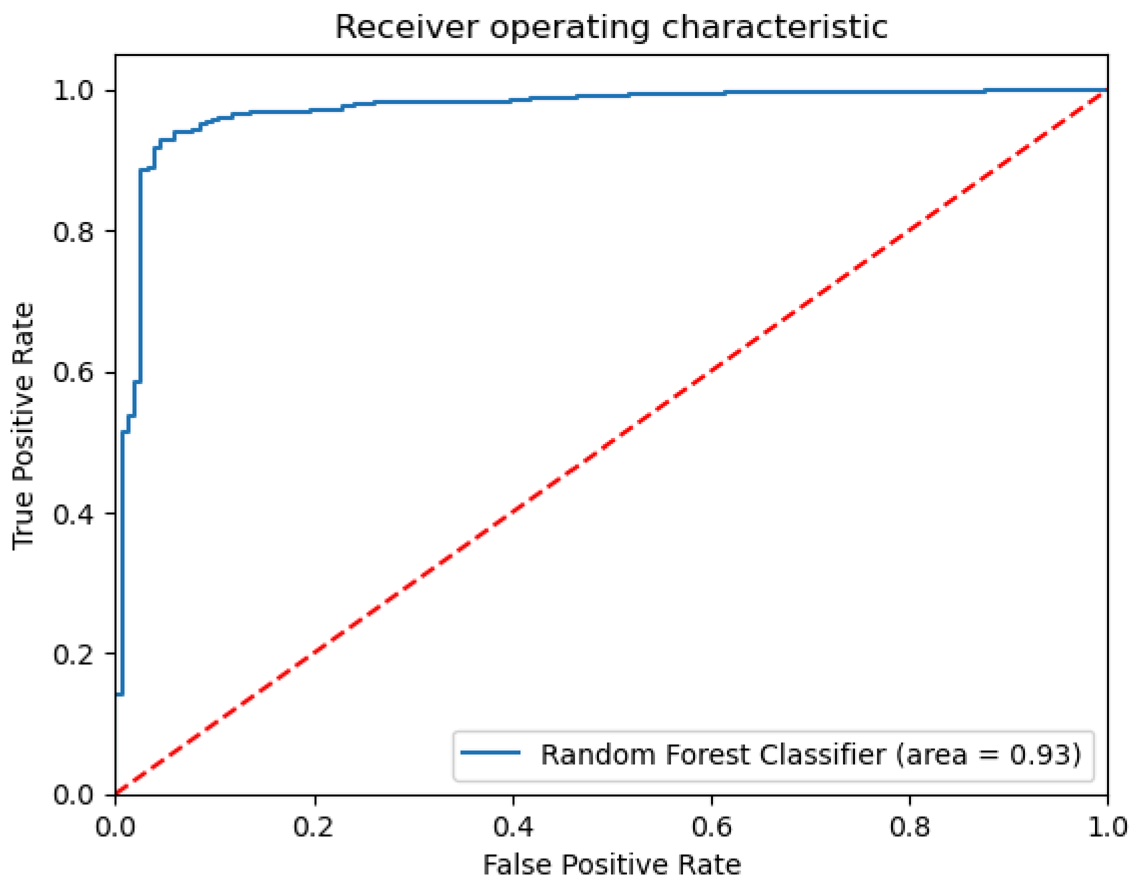
```
              precision    recall  f1-score   support

           0       0.88      0.92      0.89       153
           1       0.96      0.94      0.95       324

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

In [ ]:
```
xbg_model=classification_report(y_test, y_pred,output_dict=True)
```

In [ ]:
```
importances = model_xgb.feature_importances_
indices = np.argsort(importances)[::-1]
names = [X.columns[i] for i in indices]


plt.figure(figsize=(15, 7))
plt.title("Feature Importance")
plt.bar(range(X_train.shape[1]), importances[indices])
plt.xticks(range(X_train.shape[1]), names, rotation=45)
plt.show()
```



In [ ]:
```
logit_roc_auc=roc_auc_score(y_test,y_pred)
fpr,tpr,thresholds=roc_curve(y_test,model_rf2.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='Random Forest Classifier (area = %0.2f)' % logit_roc_auc
plt.plot([0,1],[0,1],'r--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



Model 4 : LightGBM

In [ ]:
```
# initialize model : finding best value for k with GBDT
model5 = LGBMClassifier(random_state=7)

cv_scores = []
k_values=range(2, 20)
# selecting best value of k
for k in k_values:
     kf=StratifiedKFold(n_splits=k,shuffle=True,random_state=7)
     scores=cross_val_score(model5, X_train_res, y_train_res,cv=kf)
     cv_scores.append(np.mean(scores))

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(k_values, cv_scores, marker='o')
plt.xlabel('Number of Folds (k)')
plt.ylabel('Cross-Validated Accuracy')
plt.title('Cross-Validated Accuracy for Different Values of k')
plt.grid()
plt.show()

# Find the best value of k
best_k = k_values[np.argmax(cv_scores)]
print(f"Best value of k: {best_k} with accuracy: {max(cv_scores):.4f}")
```

```
[LightGBM] [Info] Number of positive: 646, number of negative: 646
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing
was 0.000929 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 2056
[LightGBM] [Info] Number of data points in the train set: 1292, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Number of positive: 646, number of negative: 646
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000155 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2057
[LightGBM] [Info] Number of data points in the train set: 1292, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 861, number of negative: 861
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000329 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2430
[LightGBM] [Info] Number of data points in the train set: 1722, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 862, number of negative: 861
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000223 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2433
[LightGBM] [Info] Number of data points in the train set: 1723, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500290 -> initscore=0.001161
[LightGBM] [Info] Start training from score 0.001161
[LightGBM] [Info] Number of positive: 861, number of negative: 862
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000190 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2422
[LightGBM] [Info] Number of data points in the train set: 1723, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499710 -> initscore=-0.001161
[LightGBM] [Info] Start training from score -0.001161
[LightGBM] [Info] Number of positive: 969, number of negative: 969
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000199 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2512
[LightGBM] [Info] Number of data points in the train set: 1938, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 969, number of negative: 969
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000168 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2454
[LightGBM] [Info] Number of data points in the train set: 1938, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

```
[LightGBM] [Info] Number of positive: 969, number of negative: 969
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000197 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2521
[LightGBM] [Info] Number of data points in the train set: 1938, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 969, number of negative: 969
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000240 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2504
[LightGBM] [Info] Number of data points in the train set: 1938, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1034, number of negative: 1033
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000214 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2521
[LightGBM] [Info] Number of data points in the train set: 2067, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500242 -> initscore=0.000968
[LightGBM] [Info] Start training from score 0.000968
[LightGBM] [Info] Number of positive: 1034, number of negative: 1033
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000206 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2531
[LightGBM] [Info] Number of data points in the train set: 2067, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500242 -> initscore=0.000968
[LightGBM] [Info] Start training from score 0.000968
[LightGBM] [Info] Number of positive: 1033, number of negative: 1034
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000233 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2533
[LightGBM] [Info] Number of data points in the train set: 2067, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499758 -> initscore=-0.000968
[LightGBM] [Info] Start training from score -0.000968
[LightGBM] [Info] Number of positive: 1033, number of negative: 1034
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000237 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2514
[LightGBM] [Info] Number of data points in the train set: 2067, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499758 -> initscore=-0.000968
[LightGBM] [Info] Start training from score -0.000968
[LightGBM] [Info] Number of positive: 1034, number of negative: 1034
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000192 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2527
[LightGBM] [Info] Number of data points in the train set: 2068, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

```
[LightGBM] [Info] Number of positive: 1077, number of negative: 1076
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000204 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2530
[LightGBM] [Info] Number of data points in the train set: 2153, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500232 -> initscore=0.000929
[LightGBM] [Info] Start training from score 0.000929
[LightGBM] [Info] Number of positive: 1077, number of negative: 1076
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000208 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2534
[LightGBM] [Info] Number of data points in the train set: 2153, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500232 -> initscore=0.000929
[LightGBM] [Info] Start training from score 0.000929
[LightGBM] [Info] Number of positive: 1076, number of negative: 1077
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000188 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2530
[LightGBM] [Info] Number of data points in the train set: 2153, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499768 -> initscore=-0.000929
[LightGBM] [Info] Start training from score -0.000929
[LightGBM] [Info] Number of positive: 1076, number of negative: 1077
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000180 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2543
[LightGBM] [Info] Number of data points in the train set: 2153, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499768 -> initscore=-0.000929
[LightGBM] [Info] Start training from score -0.000929
[LightGBM] [Info] Number of positive: 1077, number of negative: 1077
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000192 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2526
[LightGBM] [Info] Number of data points in the train set: 2154, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1077, number of negative: 1077
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing
was 0.000237 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 2536
[LightGBM] [Info] Number of data points in the train set: 2154, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1107, number of negative: 1107
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000235 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2538
[LightGBM] [Info] Number of data points in the train set: 2214, number of used fe
atures: 16
```

```
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1108, number of negative: 1107
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000207 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2545
[LightGBM] [Info] Number of data points in the train set: 2215, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500226 -> initscore=0.000903
[LightGBM] [Info] Start training from score 0.000903
[LightGBM] [Info] Number of positive: 1108, number of negative: 1107
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000176 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2538
[LightGBM] [Info] Number of data points in the train set: 2215, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500226 -> initscore=0.000903
[LightGBM] [Info] Start training from score 0.000903
[LightGBM] [Info] Number of positive: 1108, number of negative: 1107
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000187 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2550
[LightGBM] [Info] Number of data points in the train set: 2215, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500226 -> initscore=0.000903
[LightGBM] [Info] Start training from score 0.000903
[LightGBM] [Info] Number of positive: 1107, number of negative: 1108
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000175 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2539
[LightGBM] [Info] Number of data points in the train set: 2215, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499774 -> initscore=-0.000903
[LightGBM] [Info] Start training from score -0.000903
[LightGBM] [Info] Number of positive: 1107, number of negative: 1108
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000197 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2533
[LightGBM] [Info] Number of data points in the train set: 2215, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499774 -> initscore=-0.000903
[LightGBM] [Info] Start training from score -0.000903
[LightGBM] [Info] Number of positive: 1107, number of negative: 1108
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000220 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2544
[LightGBM] [Info] Number of data points in the train set: 2215, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499774 -> initscore=-0.000903
[LightGBM] [Info] Start training from score -0.000903
[LightGBM] [Info] Number of positive: 1131, number of negative: 1130
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000197 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2542
```

```
[LightGBM] [Info] Number of data points in the train set: 2261, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500221 -> initscore=0.000885
[LightGBM] [Info] Start training from score 0.000885
[LightGBM] [Info] Number of positive: 1131, number of negative: 1130
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000203 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2549
[LightGBM] [Info] Number of data points in the train set: 2261, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500221 -> initscore=0.000885
[LightGBM] [Info] Start training from score 0.000885
[LightGBM] [Info] Number of positive: 1131, number of negative: 1130
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000225 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2547
[LightGBM] [Info] Number of data points in the train set: 2261, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500221 -> initscore=0.000885
[LightGBM] [Info] Start training from score 0.000885
[LightGBM] [Info] Number of positive: 1131, number of negative: 1130
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000200 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2547
[LightGBM] [Info] Number of data points in the train set: 2261, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500221 -> initscore=0.000885
[LightGBM] [Info] Start training from score 0.000885
[LightGBM] [Info] Number of positive: 1130, number of negative: 1131
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000277 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2261, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499779 -> initscore=-0.000885
[LightGBM] [Info] Start training from score -0.000885
[LightGBM] [Info] Number of positive: 1130, number of negative: 1131
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000196 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2540
[LightGBM] [Info] Number of data points in the train set: 2261, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499779 -> initscore=-0.000885
[LightGBM] [Info] Start training from score -0.000885
[LightGBM] [Info] Number of positive: 1130, number of negative: 1131
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000225 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2530
[LightGBM] [Info] Number of data points in the train set: 2261, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499779 -> initscore=-0.000885
[LightGBM] [Info] Start training from score -0.000885
[LightGBM] [Info] Number of positive: 1130, number of negative: 1131
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
```

```
was 0.000219 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2550
[LightGBM] [Info] Number of data points in the train set: 2261, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499779 -> initscore=-0.000885
[LightGBM] [Info] Start training from score -0.000885
[LightGBM] [Info] Number of positive: 1148, number of negative: 1148
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000150 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2544
[LightGBM] [Info] Number of data points in the train set: 2296, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1149, number of negative: 1148
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000215 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2545
[LightGBM] [Info] Number of data points in the train set: 2297, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500218 -> initscore=0.000871
[LightGBM] [Info] Start training from score 0.000871
[LightGBM] [Info] Number of positive: 1149, number of negative: 1148
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000189 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2548
[LightGBM] [Info] Number of data points in the train set: 2297, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500218 -> initscore=0.000871
[LightGBM] [Info] Start training from score 0.000871
[LightGBM] [Info] Number of positive: 1149, number of negative: 1148
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000252 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2550
[LightGBM] [Info] Number of data points in the train set: 2297, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500218 -> initscore=0.000871
[LightGBM] [Info] Start training from score 0.000871
[LightGBM] [Info] Number of positive: 1149, number of negative: 1148
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000237 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2562
[LightGBM] [Info] Number of data points in the train set: 2297, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500218 -> initscore=0.000871
[LightGBM] [Info] Start training from score 0.000871
[LightGBM] [Info] Number of positive: 1148, number of negative: 1149
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000228 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2553
[LightGBM] [Info] Number of data points in the train set: 2297, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499782 -> initscore=-0.000871
[LightGBM] [Info] Start training from score -0.000871
```

```
[LightGBM] [Info] Number of positive: 1148, number of negative: 1149
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000226 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2540
[LightGBM] [Info] Number of data points in the train set: 2297, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499782 -> initscore=-0.000871
[LightGBM] [Info] Start training from score -0.000871
[LightGBM] [Info] Number of positive: 1148, number of negative: 1149
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000204 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2541
[LightGBM] [Info] Number of data points in the train set: 2297, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499782 -> initscore=-0.000871
[LightGBM] [Info] Start training from score -0.000871
[LightGBM] [Info] Number of positive: 1148, number of negative: 1149
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000226 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2552
[LightGBM] [Info] Number of data points in the train set: 2297, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499782 -> initscore=-0.000871
[LightGBM] [Info] Start training from score -0.000871
[LightGBM] [Info] Number of positive: 1163, number of negative: 1162
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000222 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2547
[LightGBM] [Info] Number of data points in the train set: 2325, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500215 -> initscore=0.000860
[LightGBM] [Info] Start training from score 0.000860
[LightGBM] [Info] Number of positive: 1163, number of negative: 1162
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000202 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2545
[LightGBM] [Info] Number of data points in the train set: 2325, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500215 -> initscore=0.000860
[LightGBM] [Info] Start training from score 0.000860
[LightGBM] [Info] Number of positive: 1162, number of negative: 1163
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000238 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2552
[LightGBM] [Info] Number of data points in the train set: 2325, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499785 -> initscore=-0.000860
[LightGBM] [Info] Start training from score -0.000860
[LightGBM] [Info] Number of positive: 1162, number of negative: 1163
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000202 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2544
[LightGBM] [Info] Number of data points in the train set: 2325, number of used fe
```

```
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499785 -> initscore=-0.000860
[LightGBM] [Info] Start training from score -0.000860
[LightGBM] [Info] Number of positive: 1163, number of negative: 1163
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000218 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2549
[LightGBM] [Info] Number of data points in the train set: 2326, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1163, number of negative: 1163
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing
was 0.000243 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2326, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1163, number of negative: 1163
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000217 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2553
[LightGBM] [Info] Number of data points in the train set: 2326, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1163, number of negative: 1163
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000181 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2542
[LightGBM] [Info] Number of data points in the train set: 2326, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1163, number of negative: 1163
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000219 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2326, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1163, number of negative: 1163
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000187 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2326, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1175, number of negative: 1174
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000201 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2550
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500213 -> initscore=0.000851
```

```
[LightGBM] [Info] Start training from score 0.000851
[LightGBM] [Info] Number of positive: 1175, number of negative: 1174
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000198 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2552
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500213 -> initscore=0.000851
[LightGBM] [Info] Start training from score 0.000851
[LightGBM] [Info] Number of positive: 1175, number of negative: 1174
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000203 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2556
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500213 -> initscore=0.000851
[LightGBM] [Info] Start training from score 0.000851
[LightGBM] [Info] Number of positive: 1175, number of negative: 1174
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000197 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2553
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500213 -> initscore=0.000851
[LightGBM] [Info] Start training from score 0.000851
[LightGBM] [Info] Number of positive: 1175, number of negative: 1174
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000190 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500213 -> initscore=0.000851
[LightGBM] [Info] Start training from score 0.000851
[LightGBM] [Info] Number of positive: 1174, number of negative: 1175
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000230 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2559
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499787 -> initscore=-0.000851
[LightGBM] [Info] Start training from score -0.000851
[LightGBM] [Info] Number of positive: 1174, number of negative: 1175
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000229 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2559
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499787 -> initscore=-0.000851
[LightGBM] [Info] Start training from score -0.000851
[LightGBM] [Info] Number of positive: 1174, number of negative: 1175
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000207 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2550
```

```
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499787 -> initscore=-0.000851
[LightGBM] [Info] Start training from score -0.000851
[LightGBM] [Info] Number of positive: 1174, number of negative: 1175
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000205 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2545
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499787 -> initscore=-0.000851
[LightGBM] [Info] Start training from score -0.000851
[LightGBM] [Info] Number of positive: 1174, number of negative: 1175
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000237 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2552
[LightGBM] [Info] Number of data points in the train set: 2349, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499787 -> initscore=-0.000851
[LightGBM] [Info] Start training from score -0.000851
[LightGBM] [Info] Number of positive: 1175, number of negative: 1175
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000222 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2350, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1184, number of negative: 1184
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000212 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2552
[LightGBM] [Info] Number of data points in the train set: 2368, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1184, number of negative: 1184
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000184 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2368, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1184, number of negative: 1184
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000236 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2557
[LightGBM] [Info] Number of data points in the train set: 2368, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1184, number of negative: 1184
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000223 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2368, number of used fe
```

```
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1185, number of negative: 1184
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000190 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2557
[LightGBM] [Info] Number of data points in the train set: 2369, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500211 -> initscore=0.000844
[LightGBM] [Info] Start training from score 0.000844
[LightGBM] [Info] Number of positive: 1185, number of negative: 1184
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000243 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2556
[LightGBM] [Info] Number of data points in the train set: 2369, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500211 -> initscore=0.000844
[LightGBM] [Info] Start training from score 0.000844
[LightGBM] [Info] Number of positive: 1185, number of negative: 1184
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000218 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2568
[LightGBM] [Info] Number of data points in the train set: 2369, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500211 -> initscore=0.000844
[LightGBM] [Info] Start training from score 0.000844
[LightGBM] [Info] Number of positive: 1185, number of negative: 1184
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000250 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2369, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500211 -> initscore=0.000844
[LightGBM] [Info] Start training from score 0.000844
[LightGBM] [Info] Number of positive: 1184, number of negative: 1185
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000245 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2550
[LightGBM] [Info] Number of data points in the train set: 2369, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499789 -> initscore=-0.000844
[LightGBM] [Info] Start training from score -0.000844
[LightGBM] [Info] Number of positive: 1184, number of negative: 1185
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000235 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2546
[LightGBM] [Info] Number of data points in the train set: 2369, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499789 -> initscore=-0.000844
[LightGBM] [Info] Start training from score -0.000844
[LightGBM] [Info] Number of positive: 1184, number of negative: 1185
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000195 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 2554
[LightGBM] [Info] Number of data points in the train set: 2369, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499789 -> initscore=-0.000844
[LightGBM] [Info] Start training from score -0.000844
[LightGBM] [Info] Number of positive: 1184, number of negative: 1185
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000248 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2561
[LightGBM] [Info] Number of data points in the train set: 2369, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499789 -> initscore=-0.000844
[LightGBM] [Info] Start training from score -0.000844
[LightGBM] [Info] Number of positive: 1193, number of negative: 1192
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000189 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2556
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500210 -> initscore=0.000839
[LightGBM] [Info] Start training from score 0.000839
[LightGBM] [Info] Number of positive: 1193, number of negative: 1192
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000206 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500210 -> initscore=0.000839
[LightGBM] [Info] Start training from score 0.000839
[LightGBM] [Info] Number of positive: 1193, number of negative: 1192
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000241 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2559
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500210 -> initscore=0.000839
[LightGBM] [Info] Start training from score 0.000839
[LightGBM] [Info] Number of positive: 1193, number of negative: 1192
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000229 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2554
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500210 -> initscore=0.000839
[LightGBM] [Info] Start training from score 0.000839
[LightGBM] [Info] Number of positive: 1193, number of negative: 1192
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000201 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2551
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500210 -> initscore=0.000839
[LightGBM] [Info] Start training from score 0.000839
[LightGBM] [Info] Number of positive: 1192, number of negative: 1193
```

```
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000189 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499790 -> initscore=-0.000839
[LightGBM] [Info] Start training from score -0.000839
[LightGBM] [Info] Number of positive: 1192, number of negative: 1193
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000238 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2562
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499790 -> initscore=-0.000839
[LightGBM] [Info] Start training from score -0.000839
[LightGBM] [Info] Number of positive: 1192, number of negative: 1193
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000263 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499790 -> initscore=-0.000839
[LightGBM] [Info] Start training from score -0.000839
[LightGBM] [Info] Number of positive: 1192, number of negative: 1193
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000190 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2556
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499790 -> initscore=-0.000839
[LightGBM] [Info] Start training from score -0.000839
[LightGBM] [Info] Number of positive: 1192, number of negative: 1193
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000214 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2553
[LightGBM] [Info] Number of data points in the train set: 2385, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499790 -> initscore=-0.000839
[LightGBM] [Info] Start training from score -0.000839
[LightGBM] [Info] Number of positive: 1193, number of negative: 1193
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000262 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2544
[LightGBM] [Info] Number of data points in the train set: 2386, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1193, number of negative: 1193
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000217 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2720
[LightGBM] [Info] Number of data points in the train set: 2386, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

```
[LightGBM] [Info] Number of positive: 1193, number of negative: 1193
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000296 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2386, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1200, number of negative: 1199
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000200 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2399, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500208 -> initscore=0.000834
[LightGBM] [Info] Start training from score 0.000834
[LightGBM] [Info] Number of positive: 1200, number of negative: 1199
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000242 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2399, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500208 -> initscore=0.000834
[LightGBM] [Info] Start training from score 0.000834
[LightGBM] [Info] Number of positive: 1200, number of negative: 1199
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000210 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2557
[LightGBM] [Info] Number of data points in the train set: 2399, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500208 -> initscore=0.000834
[LightGBM] [Info] Start training from score 0.000834
[LightGBM] [Info] Number of positive: 1200, number of negative: 1199
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000209 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2399, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500208 -> initscore=0.000834
[LightGBM] [Info] Start training from score 0.000834
[LightGBM] [Info] Number of positive: 1199, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000233 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2399, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499792 -> initscore=-0.000834
[LightGBM] [Info] Start training from score -0.000834
[LightGBM] [Info] Number of positive: 1199, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000224 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2399, number of used fe
atures: 16
```

```
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499792 -> initscore=-0.000834
[LightGBM] [Info] Start training from score -0.000834
[LightGBM] [Info] Number of positive: 1199, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000198 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2399, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499792 -> initscore=-0.000834
[LightGBM] [Info] Start training from score -0.000834
[LightGBM] [Info] Number of positive: 1199, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000235 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2570
[LightGBM] [Info] Number of data points in the train set: 2399, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499792 -> initscore=-0.000834
[LightGBM] [Info] Start training from score -0.000834
[LightGBM] [Info] Number of positive: 1200, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000228 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2562
[LightGBM] [Info] Number of data points in the train set: 2400, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1200, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000179 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2400, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1200, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000210 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2551
[LightGBM] [Info] Number of data points in the train set: 2400, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1200, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000201 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2557
[LightGBM] [Info] Number of data points in the train set: 2400, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1200, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000278 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2721
[LightGBM] [Info] Number of data points in the train set: 2400, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

```
[LightGBM] [Info] Number of positive: 1200, number of negative: 1200
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000246 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2567
[LightGBM] [Info] Number of data points in the train set: 2400, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1205
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000218 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2411, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500207 -> initscore=0.000830
[LightGBM] [Info] Start training from score 0.000830
[LightGBM] [Info] Number of positive: 1206, number of negative: 1205
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000194 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2411, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500207 -> initscore=0.000830
[LightGBM] [Info] Start training from score 0.000830
[LightGBM] [Info] Number of positive: 1205, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000171 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2554
[LightGBM] [Info] Number of data points in the train set: 2411, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499793 -> initscore=-0.000830
[LightGBM] [Info] Start training from score -0.000830
[LightGBM] [Info] Number of positive: 1205, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000232 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2411, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499793 -> initscore=-0.000830
[LightGBM] [Info] Start training from score -0.000830
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000241 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2561
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000193 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

```
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000283 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2562
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000206 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000231 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000236 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000192 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2557
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000208 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2552
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000240 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000266 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1206, number of negative: 1206
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000237 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2567
[LightGBM] [Info] Number of data points in the train set: 2412, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1211, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000211 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2422, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1211, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000194 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2561
[LightGBM] [Info] Number of data points in the train set: 2422, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1211, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000222 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2422, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1211, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000199 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2566
[LightGBM] [Info] Number of data points in the train set: 2422, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1211, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000193 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2422, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1211, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000264 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2561
[LightGBM] [Info] Number of data points in the train set: 2422, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

```
[LightGBM] [Info] Number of positive: 1211, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000223 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2422, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1211, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000160 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2422, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1212, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000237 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2572
[LightGBM] [Info] Number of data points in the train set: 2423, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500206 -> initscore=0.000825
[LightGBM] [Info] Start training from score 0.000825
[LightGBM] [Info] Number of positive: 1212, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000248 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2423, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500206 -> initscore=0.000825
[LightGBM] [Info] Start training from score 0.000825
[LightGBM] [Info] Number of positive: 1212, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000215 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2423, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500206 -> initscore=0.000825
[LightGBM] [Info] Start training from score 0.000825
[LightGBM] [Info] Number of positive: 1212, number of negative: 1211
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000184 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2556
[LightGBM] [Info] Number of data points in the train set: 2423, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500206 -> initscore=0.000825
[LightGBM] [Info] Start training from score 0.000825
[LightGBM] [Info] Number of positive: 1211, number of negative: 1212
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000208 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2552
[LightGBM] [Info] Number of data points in the train set: 2423, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499794 -> initscore=-0.000825
```

```
[LightGBM] [Info] Start training from score -0.000825
[LightGBM] [Info] Number of positive: 1211, number of negative: 1212
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000209 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2566
[LightGBM] [Info] Number of data points in the train set: 2423, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499794 -> initscore=-0.000825
[LightGBM] [Info] Start training from score -0.000825
[LightGBM] [Info] Number of positive: 1211, number of negative: 1212
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000236 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2423, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499794 -> initscore=-0.000825
[LightGBM] [Info] Start training from score -0.000825
[LightGBM] [Info] Number of positive: 1211, number of negative: 1212
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000211 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2571
[LightGBM] [Info] Number of data points in the train set: 2423, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499794 -> initscore=-0.000825
[LightGBM] [Info] Start training from score -0.000825
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000215 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000217 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000202 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000187 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2566
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

```
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000218 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000227 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000240 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2568
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000232 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2561
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000272 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2568
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000185 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2569
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000232 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000233 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000216 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000236 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000201 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2566
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000280 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2562
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000204 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2571
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000233 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000189 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2562
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

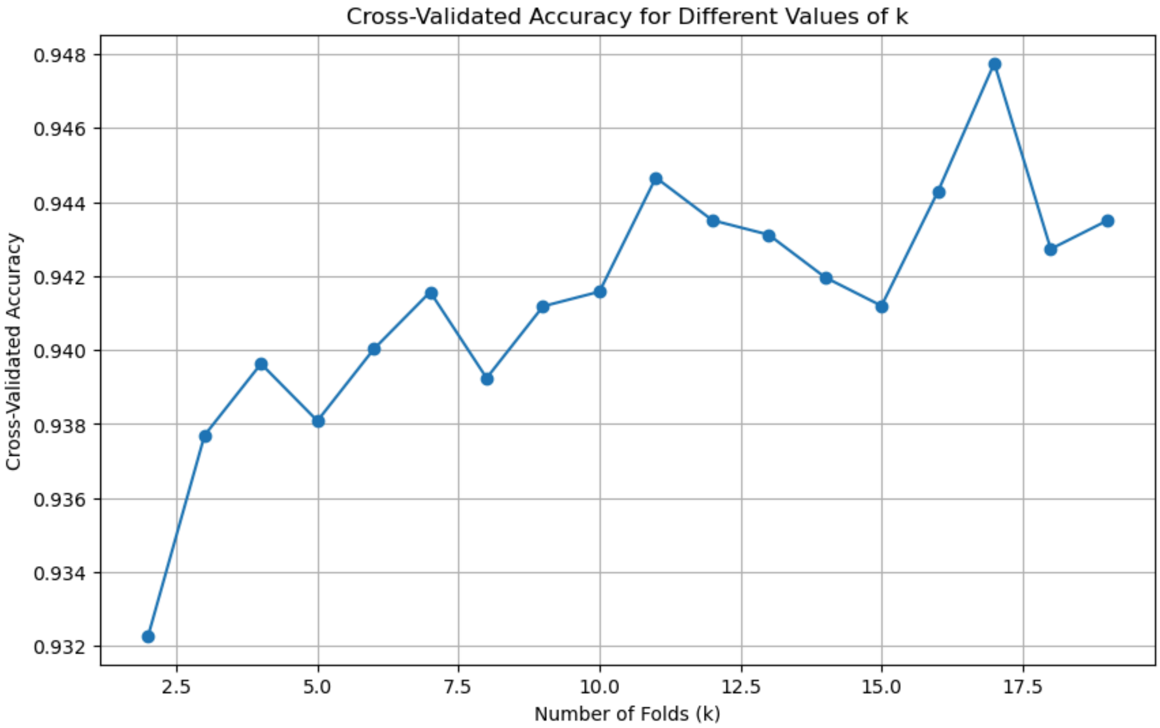
```
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000279 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000204 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2566
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000203 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2569
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000225 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000203 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000239 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000241 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2567
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1220, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000215 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 2572
[LightGBM] [Info] Number of data points in the train set: 2440, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1221, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000230 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2568
[LightGBM] [Info] Number of data points in the train set: 2441, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500205 -> initscore=0.000819
[LightGBM] [Info] Start training from score 0.000819
[LightGBM] [Info] Number of positive: 1221, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000242 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2441, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500205 -> initscore=0.000819
[LightGBM] [Info] Start training from score 0.000819
[LightGBM] [Info] Number of positive: 1221, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000249 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2441, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500205 -> initscore=0.000819
[LightGBM] [Info] Start training from score 0.000819
[LightGBM] [Info] Number of positive: 1221, number of negative: 1220
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000223 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2441, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500205 -> initscore=0.000819
[LightGBM] [Info] Start training from score 0.000819
[LightGBM] [Info] Number of positive: 1220, number of negative: 1221
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000324 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2560
[LightGBM] [Info] Number of data points in the train set: 2441, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499795 -> initscore=-0.000819
[LightGBM] [Info] Start training from score -0.000819
[LightGBM] [Info] Number of positive: 1220, number of negative: 1221
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000284 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2441, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499795 -> initscore=-0.000819
[LightGBM] [Info] Start training from score -0.000819
[LightGBM] [Info] Number of positive: 1220, number of negative: 1221
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
```

```
was 0.000235 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2562
[LightGBM] [Info] Number of data points in the train set: 2441, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499795 -> initscore=-0.000819
[LightGBM] [Info] Start training from score -0.000819
[LightGBM] [Info] Number of positive: 1220, number of negative: 1221
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000214 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2571
[LightGBM] [Info] Number of data points in the train set: 2441, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.499795 -> initscore=-0.000819
[LightGBM] [Info] Start training from score -0.000819
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000292 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000227 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2566
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000229 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000227 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2566
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000189 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2570
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000273 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000196 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2567
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000255 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000206 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2567
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000272 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2570
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000215 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2572
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000260 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000249 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

```
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000196 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000229 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2557
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000216 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing
was 0.000830 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000315 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1224, number of negative: 1224
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000356 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2571
[LightGBM] [Info] Number of data points in the train set: 2448, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```




```
Best value of k: 17 with accuracy: 0.9478
```

In [ ]:

```
# training the base model with optimal k
kfold = StratifiedKFold(n_splits=best_k, shuffle=True, random_state=7)

lgbm_clf = LGBMClassifier(random_state=7)
cv_results_rf = cross_validate(lgbm_clf , X_train_res, y_train_res, cv=kfold, sc

print(f"K-Fold Accuracy Mean: \n Train: {cv_results_rf['train_score'].mean()*100
print(f"K-Fold Accuracy Std: \n Train: {cv_results_rf['train_score'].std()*100:.
```

```
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000232 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000237 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2558
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000163 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000196 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2566
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000232 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000218 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2564
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000240 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2568
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000205 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 2561
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000229 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2568
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000236 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2569
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000214 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2565
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000345 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2563
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000224 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000180 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2555
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000220 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2566
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
```

```
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000243 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2562
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
[LightGBM] [Info] Number of positive: 1216, number of negative: 1216
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000389 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 2571
[LightGBM] [Info] Number of data points in the train set: 2432, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 -> initscore=0.000000
K-Fold Accuracy Mean:
 Train: 100.00
 Validation: 94.78
K-Fold Accuracy Std:
 Train: 0.00
 Validation: 2.10
```

In [ ]:

```
# selecting best params for the estimator
params = {
    'n_estimators': [100, 200, 300, 400],
    'max_depth': [3, 5, 10],
    'learning_rate': [0.01, 0.1, 0.2],
    'reg_alpha': [0, 0.01, 0.1],
    'reg_lambda': [1, 1.5, 2]

}

grid_lgbm = GridSearchCV(estimator=LGBMClassifier(random_state=7),
                        param_grid=params,
                        scoring='accuracy',
                        cv=kfold,
                        n_jobs=-1)

grid_lgbm.fit(X_train, y_train)
```

```
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set num_leav
es OR 2^max_depth > num_leaves. (num_leaves=31).
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set num_leav
es OR 2^max_depth > num_leaves. (num_leaves=31).
[LightGBM] [Info] Number of positive: 1292, number of negative: 612
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing
was 0.000218 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 1108
[LightGBM] [Info] Number of data points in the train set: 1904, number of used fe
atures: 16
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.678571 -> initscore=0.747214
[LightGBM] [Info] Start training from score 0.747214
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

Out[ ]:

```
▸ GridSearchCV
▸ best_estimator_: LGBMClassifier
    ▸ LGBMClassifier
```

In [ ]:

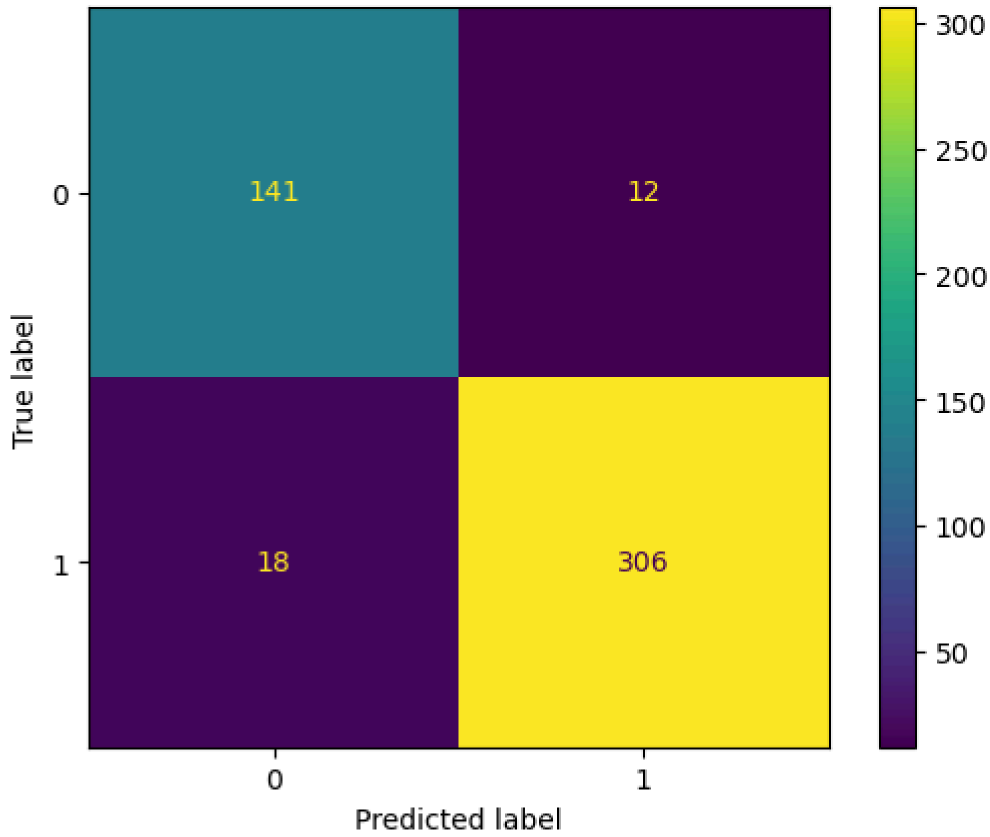
```
print("Best params: ", grid_lgbm.best_params_)
print("Best score: ", grid_lgbm.best_score_)
```

```
Best params:  {'learning_rate': 0.1, 'max_depth': 10, 'n_estimators': 100, 'reg_a
lpha': 0, 'reg_lambda': 1.5}
Best score:  0.9243697478991597
```

In [ ]:

```
model_lgbm = grid_lgbm.best_estimator_
y_pred=  model_lgbm.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=model_lgbm.classes_)
disp.plot()
plt.show()
```

```
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set num_leav
es OR 2^max_depth > num_leaves. (num_leaves=31).
```

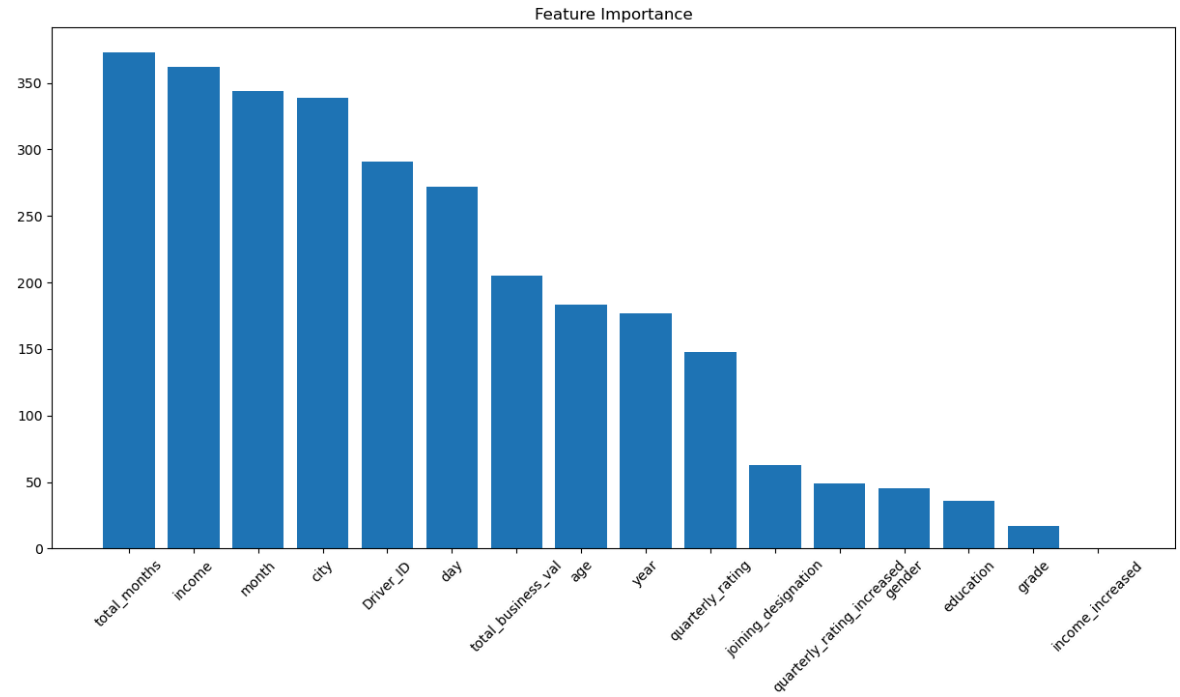


In [ ]:
```
print(classification_report(y_test, y_pred))
```

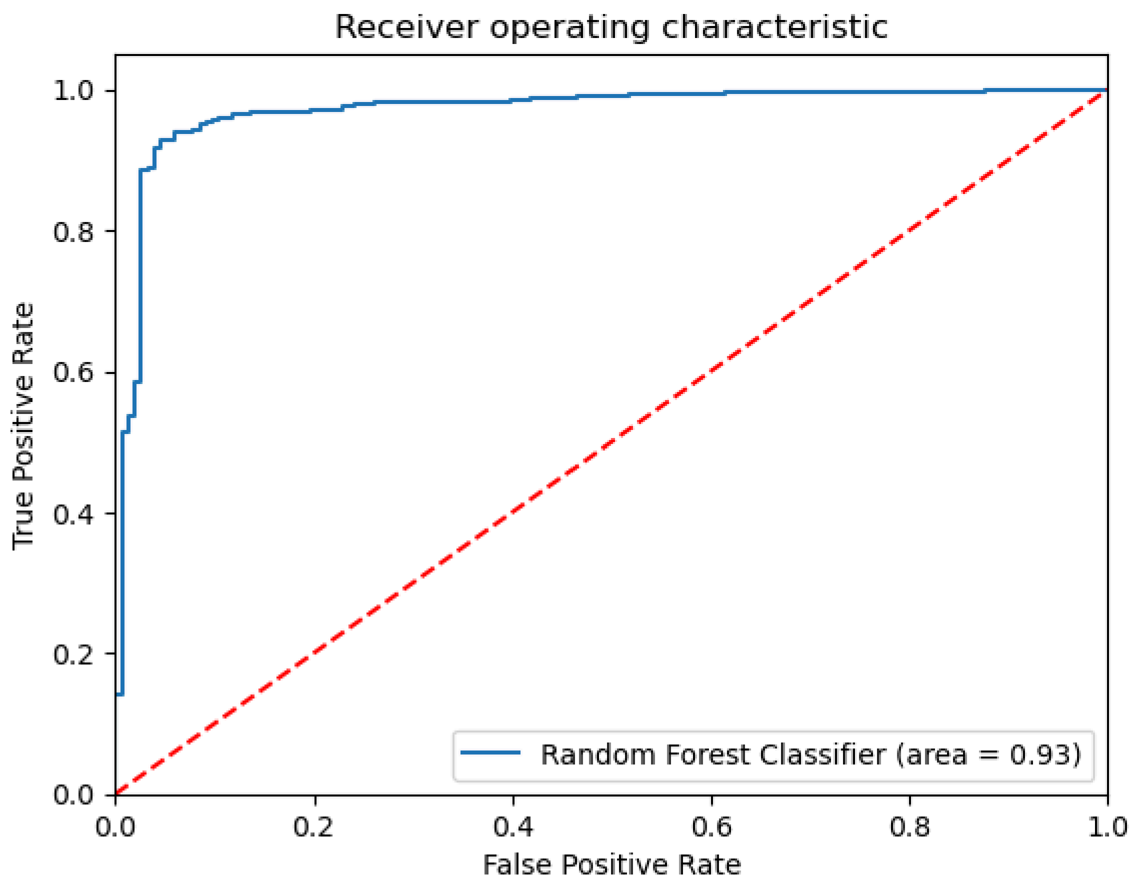
```
              precision    recall  f1-score   support

           0       0.89      0.92      0.90       153
           1       0.96      0.94      0.95       324

    accuracy                           0.94       477
   macro avg       0.92      0.93      0.93       477
weighted avg       0.94      0.94      0.94       477
```

In [ ]:
```
lgbm_model=classification_report(y_test, y_pred,output_dict=True)
```

In [ ]:
```
importances = model_lgbm.feature_importances_
indices = np.argsort(importances)[::-1]
names = [X.columns[i] for i in indices]


plt.figure(figsize=(15, 7))
plt.title("Feature Importance")
plt.bar(range(X_train.shape[1]), importances[indices])
plt.xticks(range(X_train.shape[1]), names, rotation=45)
plt.show()
```



In [ ]:
```
logit_roc_auc=roc_auc_score(y_test,y_pred)
fpr,tpr,thresholds=roc_curve(y_test,model_rf2.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='Random Forest Classifier (area = %0.2f)' % logit_roc_auc
plt.plot([0,1],[0,1],'r--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



In [ ]:
```
# aggregating all the reports in one DF
reports_df = {}

models =["DecisionTree", "RandomForest1","RandomForest2", "GradientBoosting", "X
reports =[dt_report, rf_model1,rf_model2,grid_gbdt,xbg_model,lgbm_model]

for model, r in zip(models,reports):
    try:
        print(model)
        # t=pd.DataFrame(r)
        # t['model']=model
        temp = pd.DataFrame(r).transpose()
        temp['model']=model
        reports_df[model]=temp
    except:
        continue
    # break
```

```
DecisionTree
RandomForest1
RandomForest2
GradientBoosting
XGBoost
LightGBM
```

In [ ]:
```
final_df = pd.concat(reports_df.values()).reset_index()
cols = final_df.columns.tolist()
cols = cols[-1:] + cols[:-1]
final_df = final_df[cols]
```

In [ ]:
```
final_df
```

Out[ ]:

	model	index	precision	recall	f1-score	support
0	DecisionTree	0	0.856287	0.934641	0.893750	153.000000
1	DecisionTree	1	0.967742	0.925926	0.946372	324.000000
2	DecisionTree	accuracy	0.928721	0.928721	0.928721	0.928721
3	DecisionTree	macro avg	0.912015	0.930283	0.920061	477.000000
4	DecisionTree	weighted avg	0.931992	0.928721	0.929493	477.000000
5	RandomForest1	0	0.910256	0.928105	0.919094	153.000000
6	RandomForest1	1	0.965732	0.956790	0.961240	324.000000
7	RandomForest1	accuracy	0.947589	0.947589	0.947589	0.947589
8	RandomForest1	macro avg	0.937994	0.942447	0.940167	477.000000
9	RandomForest1	weighted avg	0.947938	0.947589	0.947722	477.000000
10	RandomForest2	0	0.901961	0.901961	0.901961	153.000000
11	RandomForest2	1	0.953704	0.953704	0.953704	324.000000
12	RandomForest2	accuracy	0.937107	0.937107	0.937107	0.937107
13	RandomForest2	macro avg	0.927832	0.927832	0.927832	477.000000
14	RandomForest2	weighted avg	0.937107	0.937107	0.937107	477.000000
15	XGBoost	0	0.875000	0.915033	0.894569	153.000000
16	XGBoost	1	0.958991	0.938272	0.948518	324.000000
17	XGBoost	accuracy	0.930818	0.930818	0.930818	0.930818
18	XGBoost	macro avg	0.916995	0.926652	0.921543	477.000000
19	XGBoost	weighted avg	0.932050	0.930818	0.931213	477.000000
20	LightGBM	0	0.886792	0.921569	0.903846	153.000000
21	LightGBM	1	0.962264	0.944444	0.953271	324.000000
22	LightGBM	accuracy	0.937107	0.937107	0.937107	0.937107
23	LightGBM	macro avg	0.924528	0.933007	0.928559	477.000000
24	LightGBM	weighted avg	0.938056	0.937107	0.937418	477.000000

Model Performance Metrics

Decision Tree

- Precision (Class 0): 0.856287
- Recall (Class 0): 0.934641
- F1-score (Class 0): 0.893750
- Precision (Class 1): 0.967742
- Recall (Class 1): 0.925926
- F1-score (Class 1): 0.946372

- Accuracy: 0.928721
- Macro avg Precision: 0.912015
- Macro avg Recall: 0.930283
- Macro avg F1-score: 0.920061
- Weighted avg Precision: 0.931992
- Weighted avg Recall: 0.928721
- Weighted avg F1-score: 0.929493

Random Forest 1

- Precision (Class 0): 0.910256
- Recall (Class 0): 0.928105
- F1-score (Class 0): 0.919094
- Precision (Class 1): 0.965732
- Recall (Class 1): 0.956790
- F1-score (Class 1): 0.961240
- Accuracy: 0.947589
- Macro avg Precision: 0.937994
- Macro avg Recall: 0.942447
- Macro avg F1-score: 0.940167
- Weighted avg Precision: 0.947938
- Weighted avg Recall: 0.947589
- Weighted avg F1-score: 0.947817

Random Forest 2

- Precision (Class 0): 0.901961
- Recall (Class 0): 0.901961
- F1-score (Class 0): 0.901961
- Precision (Class 1): 0.953704
- Recall (Class 1): 0.953704
- F1-score (Class 1): 0.953704
- Accuracy: 0.937107
- Macro avg Precision: 0.927832
- Macro avg Recall: 0.927832
- Macro avg F1-score: 0.927832
- Weighted avg Precision: 0.937107
- Weighted avg Recall: 0.937107
- Weighted avg F1-score: 0.937107

XGBoost

- Precision (Class 0): 0.875000
- Recall (Class 0): 0.915033
- F1-score (Class 0): 0.894584
- Precision (Class 1): 0.958991
- Recall (Class 1): 0.938272
- F1-score (Class 1): 0.948518

- Accuracy: 0.930818
- Macro avg Precision: 0.916995
- Macro avg Recall: 0.926652
- Macro avg F1-score: 0.921451
- Weighted avg Precision: 0.932050
- Weighted avg Recall: 0.930818
- Weighted avg F1-score: 0.931213

LightGBM

- Precision (Class 0): 0.886792
- Recall (Class 0): 0.915690
- F1-score (Class 0): 0.900846
- Precision (Class 1): 0.962264
- Recall (Class 1): 0.944444
- F1-score (Class 1): 0.953256
- Accuracy: 0.937107
- Macro avg Precision: 0.924528
- Macro avg Recall: 0.930067
- Macro avg F1-score: 0.927051
- Weighted avg Precision: 0.938056
- Weighted avg Recall: 0.937107
- Weighted avg F1-score: 0.937148

Model Selection

For a ride-sharing platform focused on driver churn, the key metric depends on the business objectives:

1. High Recall (Class 1): If the goal is to catch as many potential churners as possible, recall is crucial. Random Forest 1 has the highest recall for Class 1 (0.956790).
2. Balanced Performance (F1-score): The F1-score provides a balance between precision and recall. Random Forest 1 has the highest F1-score for Class 1 (0.961240).
3. Accuracy: Overall performance across all classes can be reflected by accuracy. Random Forest 1 has the highest accuracy (0.947589).
4. Weighted Metrics: Considering the weighted averages of precision, recall, and F1-score gives an overview of the model's performance across all classes. Random Forest 1 performs best with weighted avg F1-score (0.947817).

Conclusion

Random Forest 1 stands out as the best model based on these metrics:

- It has the highest recall and F1-score for Class 1, which is important for identifying potential churners.
- It has the highest accuracy and balanced performance across all classes.

Actionable Insights and Recommendation

- based on the data we saw that ~68% of the drivers have left the company.
- after training the model, best features to represent our data are `months worked in the company`, `total business value generated`, `increase of quarterly rating`, `uareterly ratings` and `monthly average income`.
- comapny needs to employ more insentive or the drivers based on their worked monthsm business value they generate.
- also company can look at doing more frrquent rating of drivers instead of quarterly rating to see how drivers are performing and provide insentives/bonus to top performers.
- Company can also employ a feedback system where drivers can express their intent for leaving, that way company can promptly see what they can do from their based for that particular driver to make him.her stay

In [ ]: