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 a Sata 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.

- Additional Views
  - This is the classification problem for churning, we need to track the various metrics like Recall, ROC-AUC curve etc.
  - As this industry is very competitive we need to focus more on the trained feature importances.

Installing Packages

In [410]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.impute import KNNImputer
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, GridSearchCV

from imblearn.over_sampling import SMOTE

from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifie
from sklearn.tree import DecisionTreeClassifier
import xgboost as xgb

from sklearn.metrics import classification_report, accuracy_score, confusion_m
from sklearn.metrics import roc_auc_score, roc_curve

import time
```

In [411]:
```
data = pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets

data.head()
```

Out[411]:

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	L
0	0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
1	1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
2	2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
3	3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	
4	4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	

- Removing the unwanted column Unnamed: 0

In [412]:
```
data.drop("Unnamed: 0", axis = 1, inplace = True)
```

In [413]:
```
data.head()
```

Out[413]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingI
0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	
2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	03/1
3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	
4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	

In [414]:
```
data.shape
```

Out[414]: (19104, 13)

In [415]:
```
data.nunique()
```

Out[415]:
```
MMM-YY                    24
Driver_ID               2381
Age                       36
Gender                     2
City                      29
Education_Level            3
Income                  2383
Dateofjoining            869
LastWorkingDate          493
Joining Designation        5
Grade                      5
Total Business Value   10181
Quarterly Rating           4
dtype: int64
```

In [416]:
```
data.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
```

Converting features to respective data-types

In [417]:
```
data["MMM-YY"] = pd.to_datetime(data["MMM-YY"])
data["Dateofjoining"] = pd.to_datetime(data["Dateofjoining"])
data["LastWorkingDate"] = pd.to_datetime(data["LastWorkingDate"])
```

In [418]:
```
data.info()
```

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

Check for missing values and Prepare data for KNN Imputation

In [419]:
```
data.isnull().sum() / len(data) * 100
```

Out[419]:
```
MMM-YY                   0.000000
Driver_ID                0.000000
Age                      0.319305
Gender                   0.272194
City                     0.000000
Education_Level          0.000000
Income                   0.000000
Dateofjoining            0.000000
LastWorkingDate         91.541039
Joining Designation      0.000000
Grade                    0.000000
Total Business Value     0.000000
Quarterly Rating         0.000000
dtype: float64
```

- There are missing values found in `AGE` , `Gender`
- `LastWorkingDate` feature contains missing values which indicates the driver has not left the company yet.

In [420]:
```
num_vars = data.select_dtypes(np.number)

num_vars.columns
```

Out[420]:
```
Index(['Driver_ID', 'Age', 'Gender', 'Education_Level', 'Income',
       'Joining Designation', 'Grade', 'Total Business Value',
       'Quarterly Rating'],
      dtype='object')
```

In [421]:
```
num_vars.drop(["Driver_ID"], axis = 1, inplace = True)
```

KNN Imputation

In [422]:
```
imputer = KNNImputer(n_neighbors=5, weights='uniform', metric='nan_euclidean')
imputer.fit(num_vars)
data_new = imputer.transform(num_vars)
```

In [423]:
```
data_new = pd.DataFrame(data_new)
```

In [424]:
```
data_new.columns = num_vars.columns
```

In [425]:
```
data_new.isnull().sum()
```

Out[425]:
```
Age                    0
Gender                 0
Education_Level        0
Income                 0
Joining Designation    0
Grade                  0
Total Business Value   0
Quarterly Rating       0
dtype: int64
```

- We have successfully imputed the missing values using KNNImputer

In [426]:
```
data_new.nunique()
```

Out[426]:
```
Age                       70
Gender                     6
Education_Level            3
Income                  2383
Joining Designation        5
Grade                      5
Total Business Value   10181
Quarterly Rating           4
dtype: int64
```

Concatenating dataframes

In [427]:
```
resultant_columns = list(set(data.columns).difference(set(num_vars)))

resultant_columns
```

Out[427]:
```
['MMM-YY', 'LastWorkingDate', 'Dateofjoining', 'City', 'Driver_ID']
```

In [428]:
```
new_df = pd.concat([data_new, data[resultant_columns]], axis=1)

new_df.shape
```

Out[428]:
```
(19104, 13)
```

In [429]:
```
new_df.head()
```

Out[429]:

	Age	Gender	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quarterly Rating	MMM-YY	La
0	28.0	0.0	2.0	57387.0	1.0	1.0	2381060.0	2.0	2019-01-01	
1	28.0	0.0	2.0	57387.0	1.0	1.0	-665480.0	2.0	2019-02-01	
2	28.0	0.0	2.0	57387.0	1.0	1.0	0.0	2.0	2019-03-01	
3	31.0	0.0	2.0	67016.0	2.0	2.0	0.0	1.0	2020-11-01	
4	31.0	0.0	2.0	67016.0	2.0	2.0	0.0	1.0	2020-12-01	

Data Preprocessing

Feature Engineering

In [430]:
```
agg_functions = {
    "Age": "max",
    "Gender": "first",
    "Education_Level": "last",
    "Income": "last",
    "Joining Designation": "last",
    "Grade": "last",
    "Total Business Value": "sum",
    "Quarterly Rating": "last",
    "LastWorkingDate": "last",
    "City": "first",
    "Dateofjoining": "last"
}

processed_df = new_df.groupby(["Driver_ID", "MMM-YY"]).aggregate(agg_functions

processed_df.head()
```

Out[430]:

Driver_ID	MMM-YY	Age	Gender	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quart Ra
1	2019-01-01	28.0	0.0	2.0	57387.0	1.0	1.0	2381060.0	
	2019-02-01	28.0	0.0	2.0	57387.0	1.0	1.0	-665480.0	
	2019-03-01	28.0	0.0	2.0	57387.0	1.0	1.0	0.0	
2	2020-11-01	31.0	0.0	2.0	67016.0	2.0	2.0	0.0	
	2020-12-01	31.0	0.0	2.0	67016.0	2.0	2.0	0.0	

In [431]:
```
final_data = pd.DataFrame()
```

In [432]:
```
final_data["Driver_ID"] = new_df["Driver_ID"].unique()
```

In [433]:
```
final_data['Age'] = list(processed_df.groupby('Driver_ID',axis=0).max('MMM-YY'
final_data['Gender'] = list(processed_df.groupby('Driver_ID').agg({'Gender':'l
final_data['City'] = list(processed_df.groupby('Driver_ID').agg({'City':'last'
final_data['Education'] = list(processed_df.groupby('Driver_ID').agg({'Educati
final_data['Income'] = list(processed_df.groupby('Driver_ID').agg({'Income':'l
final_data['Joining_Designation'] = list(processed_df.groupby('Driver_ID').agg
final_data['Grade'] = list(processed_df.groupby('Driver_ID').agg({'Grade':'las
final_data['Total_Business_Value'] = list(processed_df.groupby('Driver_ID',axi
final_data['Last_Quarterly_Rating'] = list(processed_df.groupby('Driver_ID').a
```

In [434]:
```
final_data.head()
```

Out[434]:

	Driver_ID	Age	Gender	City	Education	Income	Joining_Designation	Grade	Total_Busines
0	1	28.0	0.0	C23	2.0	57387.0	1.0	1.0	17
1	2	31.0	0.0	C7	2.0	67016.0	2.0	2.0	
2	4	43.0	0.0	C13	2.0	65603.0	2.0	2.0	3
3	5	29.0	0.0	C9	0.0	46368.0	1.0	1.0	1
4	6	31.0	1.0	C11	1.0	78728.0	3.0	3.0	12

In [435]:
```
final_data.shape
```

Out[435]: (2381, 10)

Create a column which tells whether the quarterly rating has increased for that driver - for those whose quarterly rating has increased we assign the value 1

In [436]:
```
first_quarter = processed_df.groupby(["Driver_ID"]).agg({"Quarterly Rating": '

last_quarter = processed_df.groupby(["Driver_ID"]).agg({"Quarterly Rating": "l

qr = (last_quarter["Quarterly Rating"] > first_quarter["Quarterly Rating"]).re

empid = qr[qr["Quarterly Rating"] == True]["Driver_ID"]

qrl = []
for i in final_data["Driver_ID"]:
    if i in empid.values:
        qrl.append(1)
    else:
        qrl.append(0)


final_data["Quarterly_Rating_Increased"] = qrl
```

In [437]:
```
final_data.head()
```

Out[437]:

	Driver_ID	Age	Gender	City	Education	Income	Joining_Designation	Grade	Total_Busines
0	1	28.0	0.0	C23	2.0	57387.0	1.0	1.0	17
1	2	31.0	0.0	C7	2.0	67016.0	2.0	2.0	
2	4	43.0	0.0	C13	2.0	65603.0	2.0	2.0	3
3	5	29.0	0.0	C9	0.0	46368.0	1.0	1.0	1
4	6	31.0	1.0	C11	1.0	78728.0	3.0	3.0	12

Target variable creation: Create a column called target which tells whether the driver has left the company- driver whose last working day is present will have the value 1

In [438]:
```
lwd = (processed_df.groupby(["Driver_ID"]).agg({"LastWorkingDate": "last"})["L

lwrid = lwd[lwd["LastWorkingDate"] == True]["Driver_ID"]
target = []

for i in final_data["Driver_ID"]:
    if i in lwrid.values:
        target.append(0)
    else:
        target.append(1)

final_data["target"] = target
```

In [439]:
```
final_data.head()
```

Out[439]:

	Driver_ID	Age	Gender	City	Education	Income	Joining_Designation	Grade	Total_Busines
0	1	28.0	0.0	C23	2.0	57387.0	1.0	1.0	17
1	2	31.0	0.0	C7	2.0	67016.0	2.0	2.0	
2	4	43.0	0.0	C13	2.0	65603.0	2.0	2.0	3
3	5	29.0	0.0	C9	0.0	46368.0	1.0	1.0	1
4	6	31.0	1.0	C11	1.0	78728.0	3.0	3.0	12

Create a column which tells whether the monthly income has increased for that driver - for those whose monthly income has increased we assign the value 1

In [440]:
```
mrf = processed_df.groupby(["Driver_ID"]).agg({"Income": "first"})

mrl = processed_df.groupby(["Driver_ID"]).agg({"Income": "last"})

mr = (mrl["Income"] > mrf["Income"]).reset_index()

empid = mr[mr["Income"] == True]["Driver_ID"]
income = []
for i in final_data["Driver_ID"]:
    if i in empid.values:
        income.append(1)
    else:
        income.append(0)

final_data["Salary_Increased"] = income
```

In [441]:
```
final_data.head()
```

Out[441]:

	Driver_ID	Age	Gender	City	Education	Income	Joining_Designation	Grade	Total_Busines
0	1	28.0	0.0	C23	2.0	57387.0	1.0	1.0	17
1	2	31.0	0.0	C7	2.0	67016.0	2.0	2.0	
2	4	43.0	0.0	C13	2.0	65603.0	2.0	2.0	3
3	5	29.0	0.0	C9	0.0	46368.0	1.0	1.0	1
4	6	31.0	1.0	C11	1.0	78728.0	3.0	3.0	12

In [442]:
```
final_data["Salary_Increased"].value_counts(normalize=True)
```

Out[442]:
```
0    0.98194
1    0.01806
Name: Salary_Increased, dtype: float64
```

- Around 1.8% drivers income have been increased.

Statistical Summary

In [443]:
```
final_data.describe().T
```

Out[443]:

	count	mean	std	min	25%	50%
Driver_ID	2381.0	1.397559e+03	8.061616e+02	1.0	695.0	1400.0
Age	2381.0	3.377018e+01	5.933265e+00	21.0	30.0	33.0
Gender	2381.0	4.105838e-01	4.914963e-01	0.0	0.0	0.0
Education	2381.0	1.007560e+00	8.162900e-01	0.0	0.0	1.0
Income	2381.0	5.933416e+04	2.838367e+04	10747.0	39104.0	55315.0
Joining_Designation	2381.0	1.820244e+00	8.414334e-01	1.0	1.0	2.0
Grade	2381.0	2.096598e+00	9.415218e-01	1.0	1.0	2.0
Total_Business_Value	2381.0	4.586742e+06	9.127115e+06	-1385530.0	0.0	817680.0
Last_Quarterly_Rating	2381.0	1.427971e+00	8.098389e-01	1.0	1.0	1.0
Quarterly_Rating_Increased	2381.0	1.503570e-01	3.574961e-01	0.0	0.0	0.0
target	2381.0	6.787064e-01	4.670713e-01	0.0	0.0	1.0
Salary_Increased	2381.0	1.805964e-02	1.331951e-01	0.0	0.0	0.0

- There are total of 2831 different drivers data.
- Age of drivers range from 21years to 58years.
- 75% drivers monthly income is <= 75986.
- 75% drivers acquired 4173650 as total business values.

In [444]:
```
final_data.describe(include = 'object')
```

Out[444]:

	City
count	2381
unique	29
top	C20
freq	152

- Majority of drivers are coming from C20 city

In [445]:
```
final_data["Gender"].value_counts()
```

Out[445]:
```
0.0    1400
1.0     975
0.6       3
0.2       2
0.4       1
Name: Gender, dtype: int64
```

- Mojority of drivers are male

In [446]:
```
final_data["Education"].value_counts()
```

Out[446]:
```
2.0    802
1.0    795
0.0    784
Name: Education, dtype: int64
```

- Majority of drivers have completed their graduation.

In [447]:
```
final_data["target"].value_counts()
```

Out[447]:
```
1    1616
0     765
Name: target, dtype: int64
```

- Out of 2381 drivers 1616 have left the company.

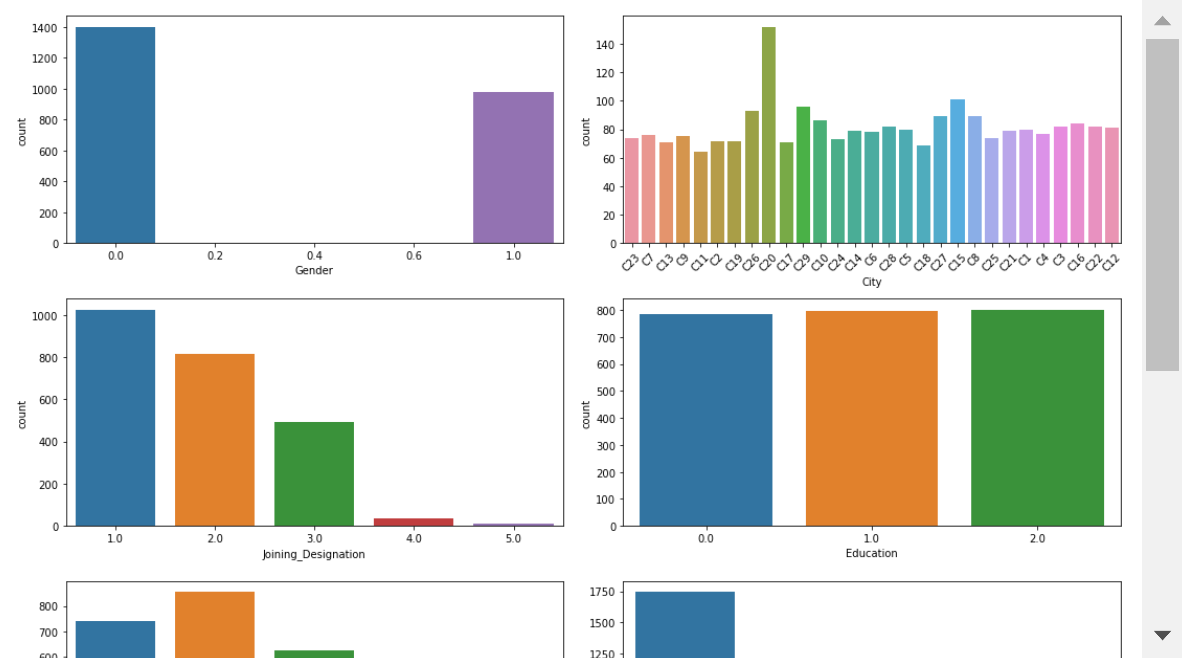
In [448]:
```
n = ['Gender','Education','Joining_Designation','Grade','Last_Quarterly_Rating

for i in n:
    print("-------------------------------------------------------------")
    print(final_data[i].value_counts(normalize=True) * 100)
```

```
------------------------------------------------------------
0.0    58.798824
1.0    40.949181
0.6     0.125997
0.2     0.083998
0.4     0.041999
Name: Gender, dtype: float64
------------------------------------------------------------
2.0    33.683326
1.0    33.389332
0.0    32.927341
Name: Education, dtype: float64
------------------------------------------------------------
1.0    43.091138
2.0    34.229315
3.0    20.705586
4.0     1.511970
5.0     0.461991
Name: Joining_Designation, dtype: float64
------------------------------------------------------------
2.0    35.909282
1.0    31.121378
3.0    26.165477
4.0     5.795884
5.0     1.007980
Name: Grade, dtype: float64
------------------------------------------------------------
1.0    73.246535
2.0    15.203696
3.0     7.055859
4.0     4.493910
Name: Last_Quarterly_Rating, dtype: float64
------------------------------------------------------------
0    84.964301
1    15.035699
Name: Quarterly_Rating_Increased, dtype: float64
```

- 58% of drivers are male while female constitutes around 40%
- 33% of drivers have completed graduation and 12+ education
- 43% of drivers have 1 as joining_designation
- Around 36% of drivers graded as 2
- Around 73% of drivers rated as 1 on last quarter
- Only 15% of drivers rating has been increased on quarterly

Univariate Analysis

In [449]:
```
plt.figure(figsize=(15, 15))
plt.subplot(421)
sns.countplot(data=final_data, x="Gender")
# final_data["Gender"].value_counts(normalize=True).plot.bar('Gender')

plt.subplot(422)
sns.countplot(data=final_data, x="City")
plt.xticks(rotation="45")

plt.subplot(423)
sns.countplot(data=final_data, x="Joining_Designation")

plt.subplot(424)
sns.countplot(data=final_data, x="Education")

plt.subplot(425)
sns.countplot(data=final_data, x="Grade")

plt.subplot(426)
sns.countplot(data=final_data, x="Last_Quarterly_Rating")

plt.subplot(427)
sns.countplot(data=final_data, x="Quarterly_Rating_Increased")

plt.subplot(428)
sns.countplot(data=final_data, x="Salary_Increased")

plt.tight_layout()
```

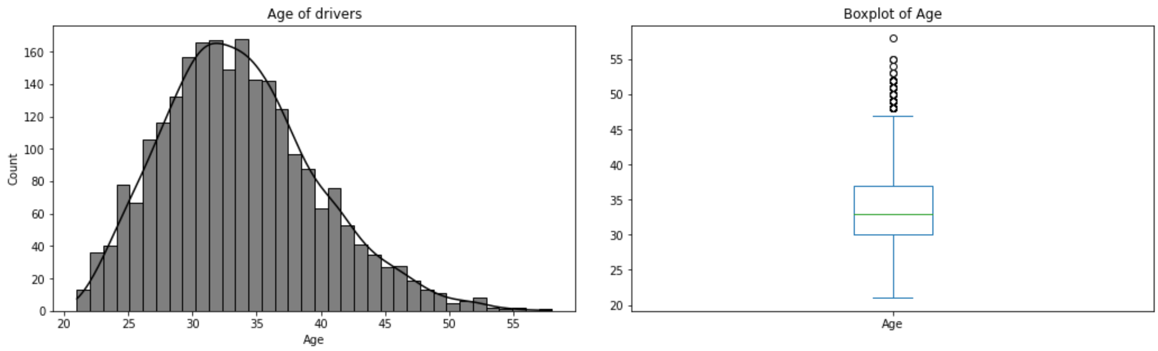


Insights

- Out of 2381 employees, 1404 employees are of the Male gender and 977 are females.
- Out of 2381 employees, 152 employees are from city C20 and 101 from city C15.
- Out of 2381 employees, 802 employees have their education as Graduate and 795 have completed their 12.
- Out of 2381 employees, 1026 joined with the grade as 1, 815 employees joined with the grade 2.
- Out of 2381 employees, 855 employees had their designation as 2 at the time of reporting.
- Out of 2381 employees, 1744 employees had their last quarterly rating as 1.
- Out of 2381 employees, the quarterly rating has not increased for 2076 employees.

- Out of 2381 employees, the quarterly rating has not increased for 2076 employees.

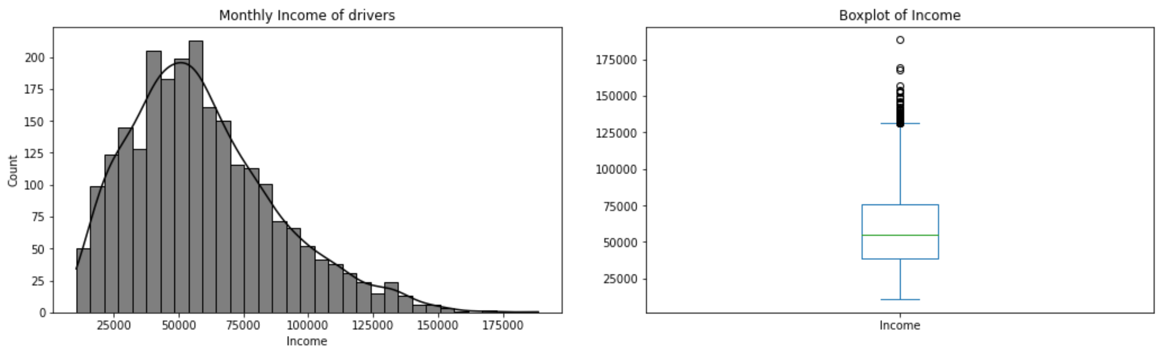
In [450]:
```
plt.subplots(figsize=(15,5))
plt.subplot(121)
sns.histplot(final_data['Age'],color='black', kde=True)
plt.title("Age of drivers")
plt.subplot(122)
final_data['Age'].plot.box(title='Boxplot of Age')
plt.tight_layout(pad=3)
```



Insights

- The distribution of age slightly skewed on right which might indicate the outliers in the data

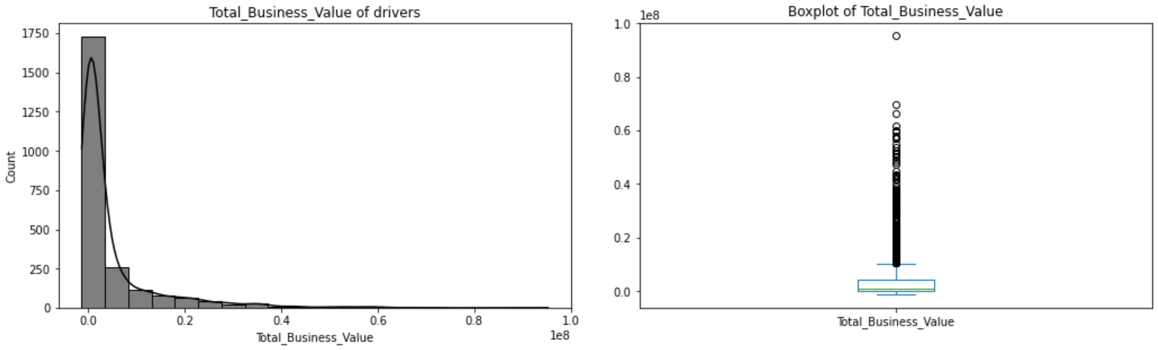
In [451]:
```
plt.subplots(figsize=(15,5))
plt.subplot(121)
sns.histplot(final_data['Income'],color='black', kde=True)
plt.title("Monthly Income of drivers")
plt.subplot(122)
final_data['Income'].plot.box(title='Boxplot of Income')
plt.tight_layout(pad=3)
```



Insights

- The distribution of monthly income skewed on right which might indicate the outliers in the data

In [452]:
```
plt.subplots(figsize=(15,5))
plt.subplot(121)
sns.histplot(final_data['Total_Business_Value'],color='black', kde=True, bins=
plt.title("Total_Business_Value of drivers")
plt.subplot(122)
final_data['Total_Business_Value'].plot.box(title='Boxplot of Total_Business_V
plt.tight_layout(pad=3)
```

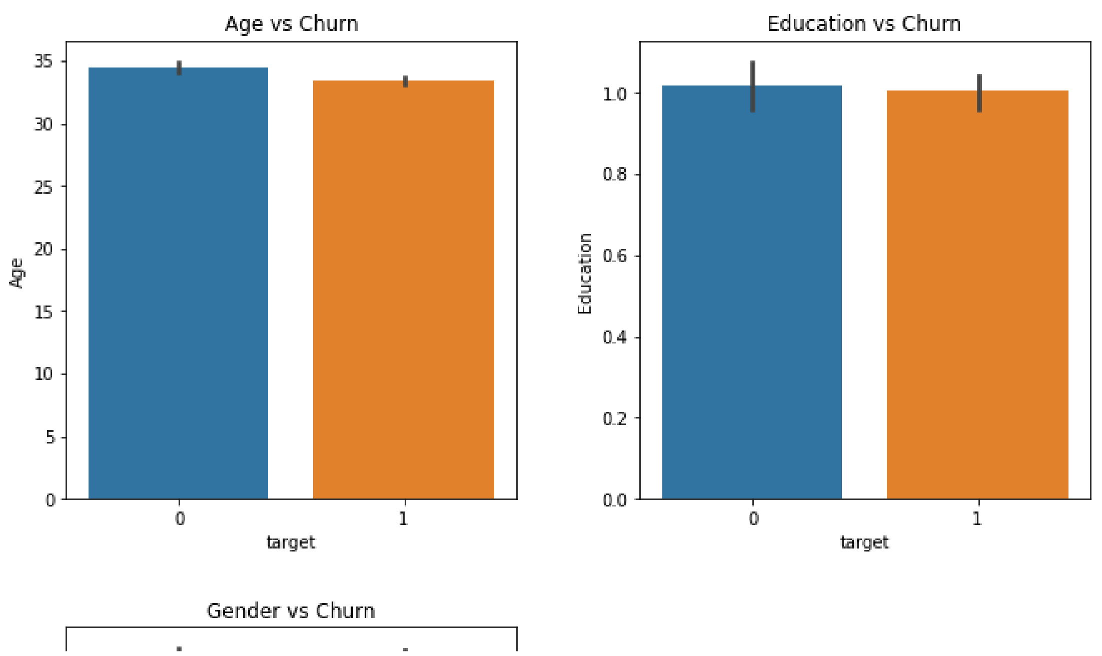


Insights

- The distribution of total business value highly skewed on right which might indicate the outliers in the data

Bi-Variate Analysis

In [453]:
```
plt.figure(figsize=(10,20))

plt.subplot(421)
sns.barplot(data=final_data, x="target", y="Age")
plt.title("Age vs Churn")

plt.subplot(422)
sns.barplot(data=final_data, x="target", y="Education")
plt.title("Education vs Churn")

plt.subplot(423)
sns.barplot(data=final_data, x="target", y="Gender")
plt.title("Gender vs Churn")

plt.subplot(425)
sns.barplot(data=final_data, x="target", y="Grade")
plt.title("Grade vs Churn")

plt.subplot(426)
sns.barplot(data=final_data, x="target", y="Joining_Designation")
plt.title("Joining_Designation vs Churn")

plt.subplot(427)
sns.barplot(data=final_data, x="target", y="Salary_Increased")
plt.title("Salary_Increased vs Churn")

plt.subplot(428)
sns.barplot(data=final_data, x="target", y="Quarterly_Rating_Increased")
plt.title("Quarterly_Rating_Increased vs Churn")

plt.tight_layout(pad=3)
```



Insights

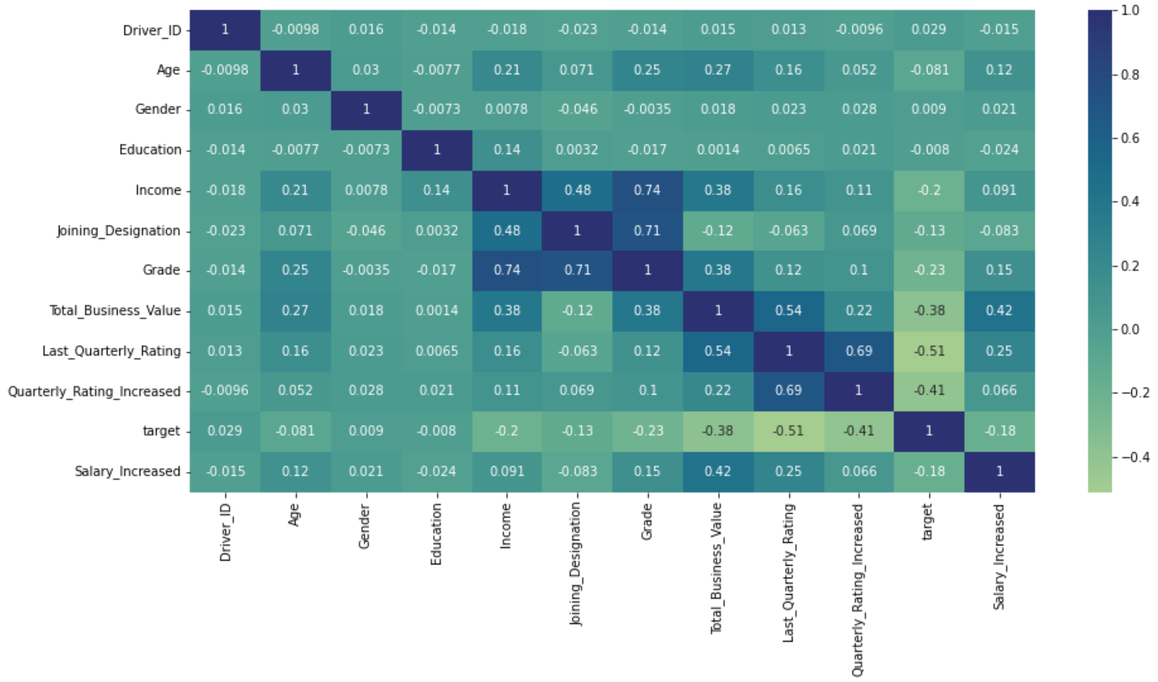
- The proportion of Age, gender and education is more or less the same for both the employees who left the organization and those who did not leave.
- The employees who have their grade as 3 or 4 at the time of joining are less likely to leave the organization.
- The employees whose quarterly rating has increased are less likely to leave the organization.
- The employees whose monthly salary has not increased are more likely to leave the

organization.

- The employees whose monthly salary has not increased are more likely to leave the organization.

Correlation Analysis

In [454]:
```
plt.figure(figsize=(15, 7))

sns.heatmap(final_data.corr(method="pearson"), annot=True, cmap="crest")
plt.show()
```



Insights

- Income and Grade is highly correlated
- Joining Designation and Grade is highly correlated
- Total Business value and salary increament is correlated

One-Hot Encoding

As there is only one categorical values in our dataset. We will opt one hot encoder to convert it to numerical.

In [455]:
```
final_data = pd.concat([final_data, final_data['City']], axis=1)
```

In [456]:
```
final_data.shape
```

Out[456]:
```
(2381, 14)
```

Standardization (for training data)

In [457]:
```
X = final_data.drop(["Driver_ID", "target", "City"], axis = 1)
X_cols = X.columns
scaler = MinMaxScaler()

X = scaler.fit_transform(X)
```

In [458]:
```
X = pd.DataFrame(X)

X.columns = X_cols

X
```

Out[458]:

	Age	Gender	Education	Income	Joining_Designation	Grade	Total_Business_Value
0	0.189189	0.0	1.0	0.262508	0.00	0.00	0.032064
1	0.270270	0.0	1.0	0.316703	0.25	0.25	0.014326
2	0.594595	0.0	1.0	0.308750	0.25	0.25	0.017944
3	0.216216	0.0	0.0	0.200489	0.00	0.00	0.015570
4	0.270270	1.0	0.5	0.382623	0.50	0.50	0.027405
...	...	...	...	...	...	...	...
2376	0.351351	0.0	0.0	0.405626	0.25	0.50	0.239197
2377	0.351351	1.0	0.0	0.007643	0.00	0.00	0.014326
2378	0.648649	0.0	0.0	0.138588	0.25	0.25	0.043432
2379	0.189189	1.0	1.0	0.330673	0.00	0.00	0.024436
2380	0.243243	0.0	1.0	0.334928	0.25	0.25	0.038088

2381 rows × 10 columns

Train & Test Split

In [459]:
```
y = final_data["target"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

In [460]:
```
print("X_train Shape: ", X_train.shape)
print("X_test Shape: ", X_test.shape)
print("y_train Shape: ", y_train.shape)
print("y_test Shape: ", y_test.shape)
```

```
X_train Shape:  (1904, 10)
X_test Shape:  (477, 10)
y_train Shape:  (1904,)
y_test Shape:  (477,)
```

Random Forest Classifier - Before Balancing

Keeping max_depth small to avoid overfitting

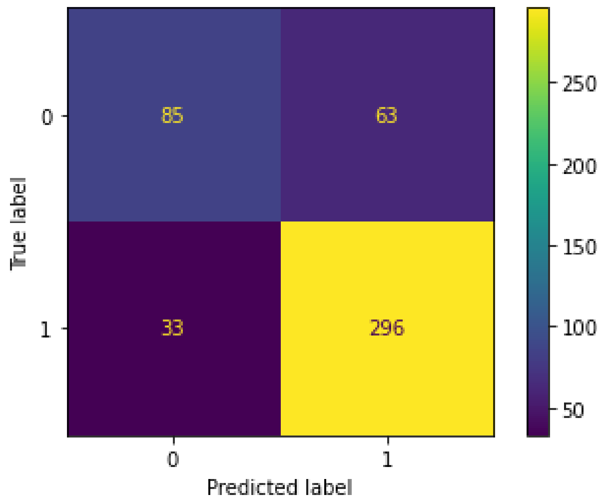
In [461]:
```
params = {
    "max_depth": [2, 3, 4],
    "n_estimators": [50, 100, 150, 200],
}

start_time = time.time()
random_forest = RandomForestClassifier(class_weight="balanced")
c = GridSearchCV(estimator=random_forest, param_grid=params, n_jobs=-1, cv=3,

c.fit(X_train, y_train)

print("Best Params: ", c.best_params_)
print("Best Score: ", c.best_score_)
elapsed_time = time.time() - start_time

print("\nElapsed Time: ", elapsed_time)
```

```
Fitting 3 folds for each of 12 candidates, totalling 36 fits
Best Params:  {'max_depth': 4, 'n_estimators': 100}
Best Score:  0.862861633218953

Elapsed Time:  5.860330104827881
```

In [462]:
```
y_pred = c.predict(X_test)

print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)

ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=c.classes_).plot()
```

```
              precision    recall  f1-score   support

           0       0.72      0.57      0.64       148
           1       0.82      0.90      0.86       329

    accuracy                           0.80       477
   macro avg       0.77      0.74      0.75       477
weighted avg       0.79      0.80      0.79       477
```

Out[462]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2416646a
580>
```



Random Forest Classifier with balanced class weight

- Out of all prediction, the measure for correctly predicted 0 is 73% and for 1 is 82% (Precision)
- Out of all actual 0, the measure for correctly predicted is 57% and for 1 is 90% (Recall)

As this is imbalanced dataset. We give importance to F1-Score metrics

- F1 Score of 0 is 64%
- F! Score of 1 is 86%

Lets try out bootstrapped random forest using subsample

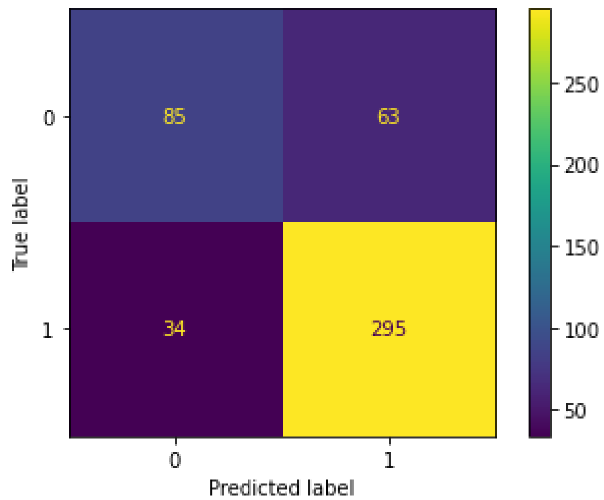
In [463]:
```
params = {
    "max_depth": [2, 3, 4],
    "n_estimators": [50, 100, 150, 200],
}

start_time = time.time()
random_forest = RandomForestClassifier(class_weight="balanced_subsample")
c = GridSearchCV(estimator=random_forest, param_grid=params, n_jobs=-1, cv=3,

c.fit(X_train, y_train)

print("Best Params: ", c.best_params_)
print("Best Score: ", c.best_score_)
elapsed_time = time.time() - start_time

print("\nElapsed Time: ", elapsed_time)
```

```
Fitting 3 folds for each of 12 candidates, totalling 36 fits
Best Params:  {'max_depth': 4, 'n_estimators': 200}
Best Score:  0.8611423652105162

Elapsed Time:  2.3675687313079834
```

In [464]:
```
y_pred = c.predict(X_test)

print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)

ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=c.classes_).plot()
```

```
              precision    recall  f1-score   support

           0       0.71      0.57      0.64       148
           1       0.82      0.90      0.86       329

    accuracy                           0.80       477
   macro avg       0.77      0.74      0.75       477
weighted avg       0.79      0.80      0.79       477
```

Out[464]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x24165642eb0>



Random Forest Classifier with balanced class weight

- Out of all prediction, the measure for correctly predicted 0 is 75% and for 1 is 83%

- Out of all prediction, the measure for correctly predicted 0 is 75% and for 1 is 83% (Precision)
- Out of all actual 0, the measure for correctly predicted is 57% and for 1 is 91% (Recall)

As this is imbalanced dataset. We give importance to F1-Score metrics

- F1 Score of 0 is 65%
- F! Score of 1 is 87%

There is not much significant difference in the matrices observed for bootstrapped Random Forest and Weighted Random Forest

Lets try balancing

Balancing Dataset using SMOTE

As the target variable is imbalanced towards 1. We will use SMOTE to balance the dataset

In [465]:
```
print("Before OverSampling, counts of label '1': {}".format(sum(y_train == 1)))
print("Before OverSampling, counts of label '0': {} \n".format(sum(y_train == 

sm = SMOTE(random_state = 7)
X_train, y_train = sm.fit_resample(X_train, y_train.ravel())

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

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

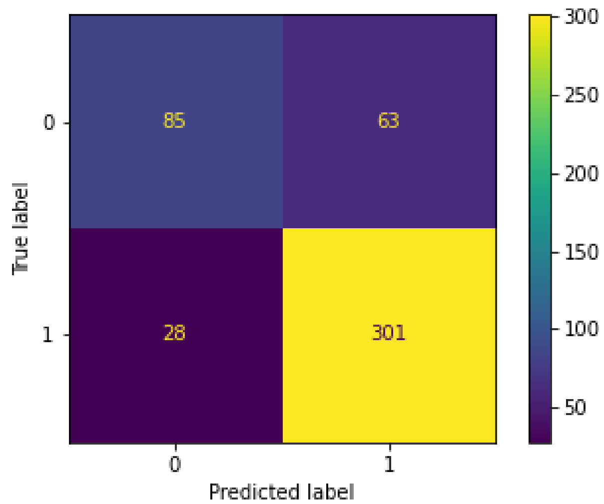
```
Before OverSampling, counts of label '1': 1287
Before OverSampling, counts of label '0': 617

After OverSampling, the shape of train_X: (2574, 10)
After OverSampling, the shape of train_y: (2574,)

After OverSampling, counts of label '1': 1287
After OverSampling, counts of label '0': 1287
```

Ensemble Learning: Bagging

In [466]:
```
params = {
    "max_depth": [2, 3, 4],
    "n_estimators": [50, 100, 150, 200],
}

start_time = time.time()
random_forest = RandomForestClassifier(class_weight="balanced_subsample")
c = GridSearchCV(estimator=random_forest, param_grid=params, n_jobs=-1, cv=3,

c.fit(X_train, y_train)

print("Best Params: ", c.best_params_)
print("Best Score: ", c.best_score_)
elapsed_time = time.time() - start_time

print("\nElapsed Time: ", elapsed_time)

y_pred = c.predict(X_test)

print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)

ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=c.classes_).plot()
```

```
Fitting 3 folds for each of 12 candidates, totalling 36 fits
Best Params:  {'max_depth': 4, 'n_estimators': 100}
Best Score:  0.7834986325743847

Elapsed Time:  2.393531084060669
              precision    recall  f1-score   support

           0       0.75      0.57      0.65       148
           1       0.83      0.91      0.87       329

    accuracy                           0.81       477
   macro avg       0.79      0.74      0.76       477
weighted avg       0.80      0.81      0.80       477
```

Out[466]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x24166205
550>
```



Random Forest Classifier with balanced class weight

- Out of all prediction, the measure for correctly predicted 0 is 74% and for 1 is 83%

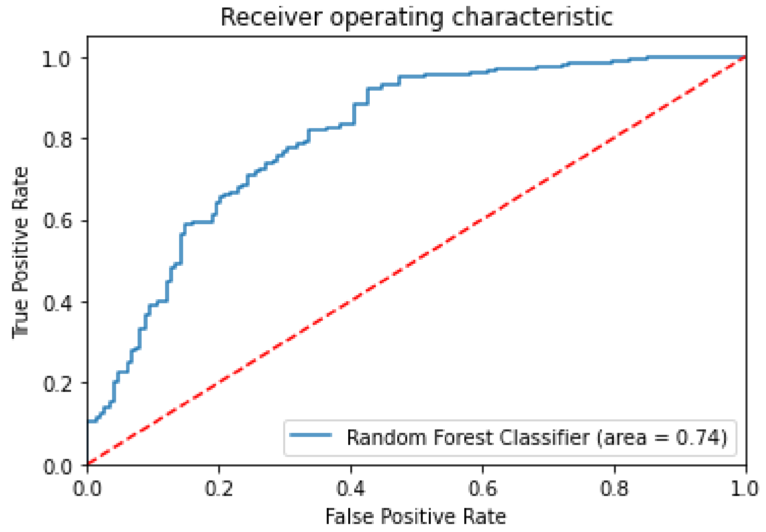
- Out of all prediction, the measure for correctly predicted 0 is 74% and for 1 is 83% (Precision)
- Out of all actual 0, the measure for correctly predicted is 57% and for 1 is 91% (Recall)

As this is imbalanced dataset. We give importance to F1-Score metrics

- F1 Score of 0 is 65%
- F! Score of 1 is 87%

ROC-AUC Curve

In [467]:
```
logit_roc_auc=roc_auc_score(y_test,y_pred)
fpr,tpr,thresholds=roc_curve(y_test,c.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='Random Forest Classifier (area = %0.2f)' % logit_roc_a
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()
```



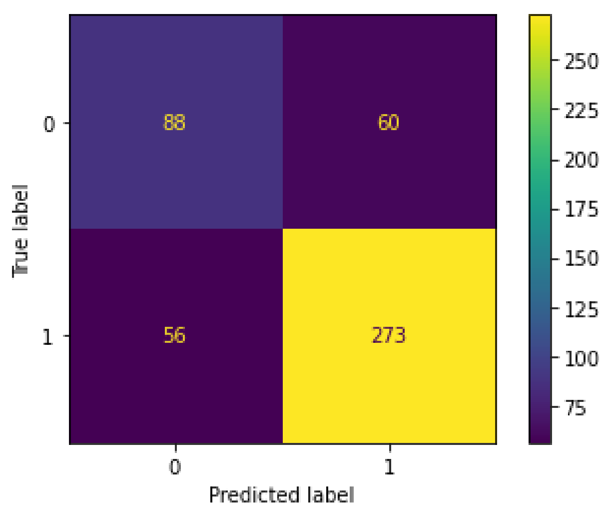
Ensemble Learning: Boosting

Gradient Boosting Classifier

In [468]:
```
params = {
    "max_depth": [2, 3, 4],
    "loss": ["log_loss", "exponential"],
    "subsample": [0.1, 0.2, 0.5, 0.8, 1],
    "learning_rate": [0.1, 0.2, 0.3],
    "n_estimators": [50,100,150,200]
}

gbdt = GradientBoostingClassifier()
start_time = time.time()
c = GridSearchCV(estimator=gbdt, cv=3, n_jobs=-1, verbose=True, param_grid=par

c.fit(X_train, y_train)
print("Best Params: ", c.best_params_)
print("Best Score: ", c.best_score_)

elapsed_time = time.time() - start_time
print("\n Elapsed Time: ", elapsed_time)

y_pred = c.predict(X_test)

print(classification_report(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)

ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=c.classes_).plot()
```

```
Fitting 3 folds for each of 360 candidates, totalling 1080 fits
Best Params:  {'learning_rate': 0.2, 'loss': 'exponential', 'max_depth': 4,
'n_estimators': 150, 'subsample': 1}
Best Score:  0.8127428127428127

 Elapsed Time:  42.14409065246582
              precision    recall  f1-score   support

           0       0.61      0.59      0.60       148
           1       0.82      0.83      0.82       329

    accuracy                           0.76       477
   macro avg       0.72      0.71      0.71       477
weighted avg       0.76      0.76      0.76       477
```

Out[468]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2416645b
280>
```



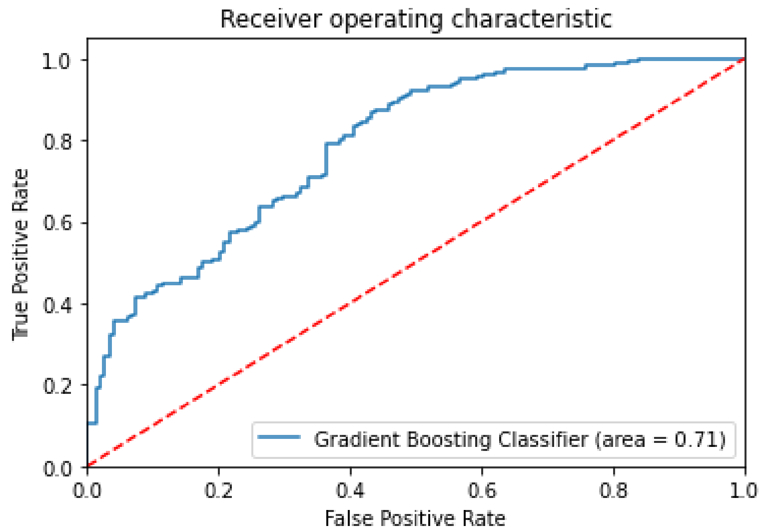
Gradient Boosting Classifier Metrics

- Out of all prediction, the measure for correctly predicted 0 is 62% and for 1 is 82% (Precision)
- Out of all actual 0, the measure for correctly predicted is 60% and for 1 is 83% (Recall)

As this is imbalanced dataset. We give importance to F1-Score metrics

- F1 Score of 0 is 61%
- F1 Score of 1 is 83%

In [469]:
```
logit_roc_auc=roc_auc_score(y_test,y_pred)
fpr,tpr,thresholds=roc_curve(y_test,c.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='Gradient Boosting Classifier (area = %0.2f)' % logit_r
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()
```

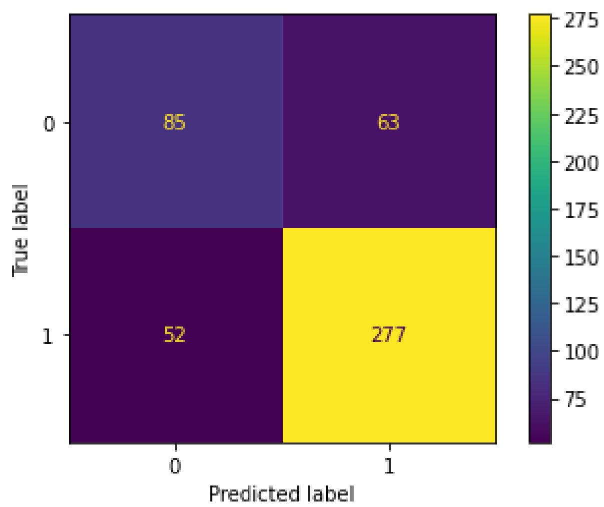


XGBoost Classifier

In [470]:
```
model = xgb.XGBClassifier(class_weight = "balanced")

model.fit(X_train, y_train)

y_pred = model.predict(X_test)
print("XGBoost Classifier Score: ", model.score(X_test, y_test))
print("\n", classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=model.classes_).plo
```

```
[19:20:38] WARNING: C:\Users\dev-admin\croot2\xgboost-split_1675461376218\wo
rk\src\learner.cc:767:
Parameters: { "class_weight" } are not used.

XGBoost Classifier Score:  0.7589098532494759

               precision    recall  f1-score   support

           0       0.62      0.57      0.60       148
           1       0.81      0.84      0.83       329

    accuracy                           0.76       477
   macro avg       0.72      0.71      0.71       477
weighted avg       0.75      0.76      0.76       477
```

Out[470]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x241661eb
220>
```



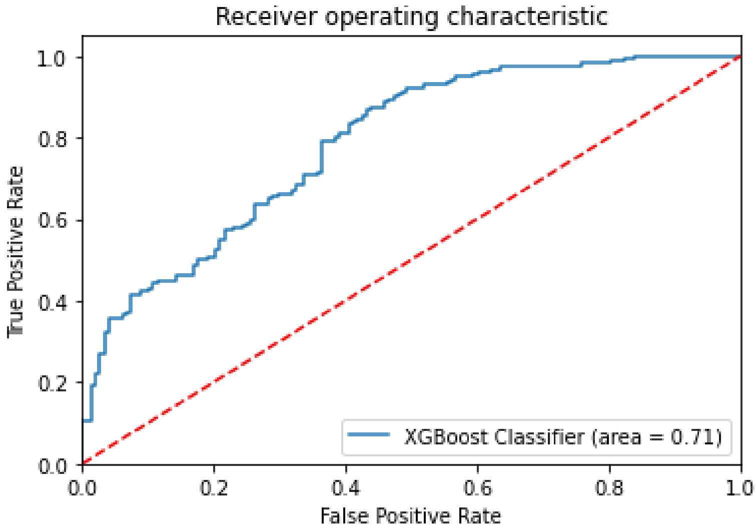
XGBoost Classifier with balanced class weight

- Out of all prediction, the measure for correctly predicted 0 is 62% and for 1 is 81% (Precision)
- Out of all actual 0, the measure for correctly predicted is 57% and for 1 is 84% (Recall)

As this is imbalanced dataset. We give importance to F1-Score metrics

- F1 Score of 0 is 60%
- F1 Score of 1 is 83%

In [471]:
```
logit_roc_auc=roc_auc_score(y_test,y_pred)
fpr,tpr,thresholds=roc_curve(y_test,c.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='XGBoost 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()
```



Final Result Evaluation

- We observe that we are not getting very high recall on target 0 which may be due to small unbalanced dataset.
- Higher precision means that an algorithm returns more relevant results than irrelevant ones, and high recall means that an algorithm returns most of the relevant results (whether or not irrelevant ones are also returned).

- **We observe that Random Forest with SMOTE outperforms rest of the models and has higher recall and precision values.**
  - The Random Forest method out of all predicted 0 the measure of correctly predicted is 73%, and for 1 it is 82%(Precision).
  - The Random Forest method out of all actual 0 the measure of correctly predicted is 56%, and for 1 it is 91%(Recall).
  - The ROC-AUC curve area for Random Forest Classifier is 0.74

- **Gradient Boosting Classifier Result**
  - Out of all prediction, the measure for correctly predicted 0 is 62% and for 1 is 82% (Precision)
  - Out of all actual 0, the measure for correctly predicted is 60% and for 1 is 83% (Recall)
  - The ROC-AUC curve area for Gradient Boosting Decision Tree Classifier is 0.71

- **XGBoost Classifier Result**

  - Out of all prediction, the measure for correctly predicted 0 is 62% and for 1 is 81%

- Out of all prediction, the measure for correctly predicted 0 is 62% and for 1 is 81% (Precision)
- Out of all actual 0, the measure for correctly predicted is 57% and for 1 is 84% (Recall)

Feature Importance of the best model so far.

Random Forest Classifier outperforms the rest of the modal.

Best parameters

Best Params: {'max_depth': 4, 'n_estimators': 50}

In [472]:
```
rf = RandomForestClassifier(max_depth = 4, n_estimators= 50, class_weight="bal

rf.fit(X_train, y_train)
print("Score of RandomForestClassifier: ", rf.score(X_test, y_test))
```

```
Score of RandomForestClassifier:  0.8113207547169812
```

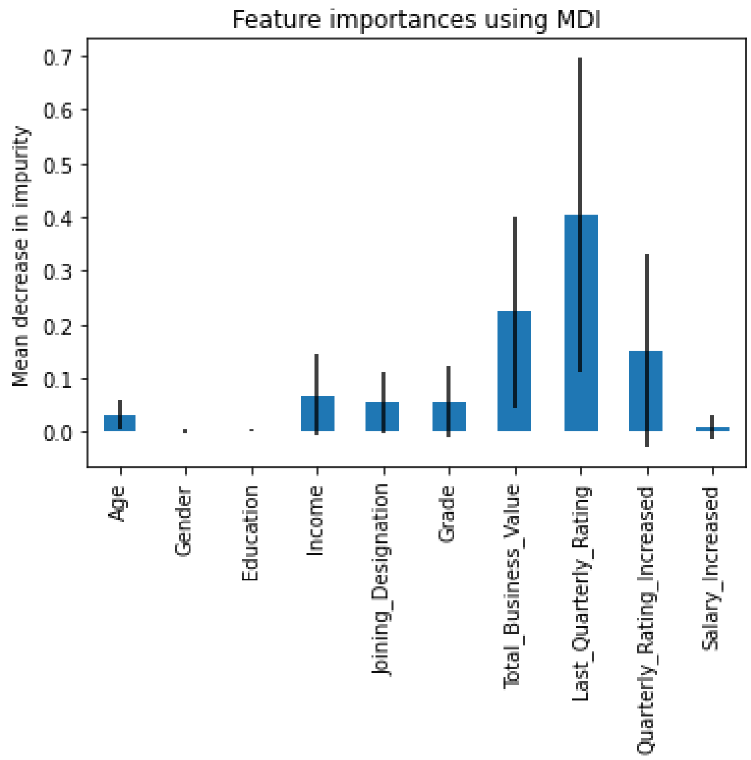
In [473]:
```
importances = rf.feature_importances_
importances
```

Out[473]:
```
array([0.03102136, 0.00163529, 0.00224746, 0.06775201, 0.05405412,
       0.0564535 , 0.22329128, 0.40343337, 0.1519475 , 0.0081641 ])
```

In [474]:
```
std = np.std([tree.feature_importances_ for tree in rf.estimators_], axis=0)
```

In [475]:
```
feature_importances = pd.Series(importances, X_train.columns)

plt.figure(figsize=(15,7))
fig, ax = plt.subplots()
feature_importances.plot.bar(yerr=std, ax=ax)
ax.set_title("Feature importances using MDI")
ax.set_ylabel("Mean decrease in impurity")

plt.show()
```

```
<Figure size 1080x504 with 0 Axes>
```



Insights

- Last_Quarterly_Rating, Total_Business_Value & Quarterly_Rating_Increased are the most important features.

Actionable Insights and Recommendation

- Out of 2381 drivers 1616 have left the company.
- We need to incentivise the drivers overtime or other perks to overcome churning
- The employees whose quarterly rating has increased are less likely to leave the organization.
- Company needs to implement the reward system for the customer who provide the feedback and rate drivers
- The employees whose monthly salary has not increased are more likely to leave the organization.
- Company needs to get in touch with those drivers whose monthly salary has not increased and help them out to earn more by provider bonus and perks.
- Out of 2381 employees, 1744 employees had their last quarterly rating as 1.

- Out of 2381 employees, the quarterly rating has not increased for 2076 employees. This is

- Out of 2381 employees, the quarterly rating has not increased for 2076 employees. This is red flag for the company which needs to regulate.
- Company needs to look why customers are not rating drivers.
- Last_Quarterly_Rating, Total_Business_Value & Quarterly_Rating_Increased are the most important features. Company needs to tracks these features as predicators
- We observe that we are not getting very high recall on target 0 which may be due to small unbalanced dataset. More data will overcome this issue.
- The Random Forest Classifier attains the Recall score of 91% for the driver who left the

In [ ]: