AcadGild_Capstone_Project_7

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1 AcadGild_Capstone_Project_7

1. Domain Introduction There has been customer data for the teleccom company which provides many entertainment and communication services like phone, internet , Mobile streaming , TV streaming etc.

2. Problem Statement The company is concerned about their customers leaving their landline business for cable competitors and they want to knoe who is leaving & why. object is to create and find best model to identify customer behaviour to retain customers.

3. Data Source Data Source is available at [IBM watson analytics page]

4. Data Set description This data set provides info to help you predict behavior to retain customers. You can analyze all relevant customer data and develop focused customer retention programs.

A telecommunications company is concerned about the number of customers leaving their landline business for cable competitors. They need to understand who is leaving. Imagine that you're an analyst at this company and you have to find out who is leaving and why.

The data set includes information about:

- Customers who left within the last month – the column is called Churn
- Services that each customer has signed up for – phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies
- Customer account information – how long they've been a customer, contract, payment method,paperless billing, monthly charges, and total charges
- Demographic info about customers – gender, age range, and if they have partners and dependents

5. Identifying target fetaure/variable The Goal is to predict whether or not a particular customer is likely to retain services.

This is represented by the Churn column in dataset. Churn=Yes means customer leaves the company, whereas Churn=No implies customer is retained by the company.

6. Reading the DataSet form source path/url Before reading the dataset from data source , let's collect some important python modules requored for data analysis.

In [1]:
```
# python modules

import pandas as pd  # for dataframe and other data strture realted opeartions
import numpy as np # for numerical computation
import matplotlib.pyplot  as plt #  for data visualisation
import seaborn as sns #  for data visualisation
# for plotting the graph/data with in Jupyter notebook
%matplotlib inline

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

In [2]:
```
# To prevent depreciation warnings

import warnings

def fxn():
    warnings.warn("deprecated", DeprecationWarning)

with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    fxn()
```

In [3]:
```
def get_data_from_source(dataset_path):
    '''this function will load data from the source'''
    df_data = pd.read_csv(dataset_path)
    return df_data

## Apply function and get data

dataset_path = 'https://community.watsonanalytics.com/wp-content/uploads/2015/03/WA_Fn
#dataset_path ='WA_Fn-UseC_-Telco-Customer-Churn.csv'
df_telecomData = get_data_from_source(dataset_path) # crete datafraame values return b

# Sample rows from data set
df_telecomData.head(3)
```

Out[3]:
```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity  ... DeviceProtection  \
0  No phone service             DSL             No  ...               No
1                No             DSL            Yes  ...              Yes
2                No             DSL            Yes  ...               No
```

```
  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes

      PaymentMethod MonthlyCharges  TotalCharges Churn
0  Electronic check          29.85         29.85    No
1      Mailed check          56.95        1889.5    No
2      Mailed check          53.85        108.15   Yes

[3 rows x 21 columns]
```

As we can see data set contains features/columns with numerical and categorcal(binary and others) data and out of that the " customerID " is the unique features which's values get changes for every customer. So we can re-frame our dataset with making curomerID as Index value.

In [4]:
```
df_telecomData.set_index('customerID' , inplace=True) # apply inplace if want to make 
# Sample rows of data set after changing index value
df_telecomData.head(3)
```

Out[4]:
```
            gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
customerID
7590-VHVEG  Female              0     Yes         No       1           No
5575-GNVDE    Male              0      No         No      34          Yes
3668-QPYBK    Male              0      No         No       2          Yes

               MultipleLines InternetService OnlineSecurity OnlineBackup  \
customerID
7590-VHVEG  No phone service             DSL             No          Yes
5575-GNVDE                No             DSL            Yes           No
3668-QPYBK                No             DSL            Yes          Yes

           DeviceProtection TechSupport StreamingTV StreamingMovies  \
customerID
7590-VHVEG               No          No          No              No
5575-GNVDE              Yes          No          No              No
3668-QPYBK               No          No          No              No

                  Contract PaperlessBilling     PaymentMethod  MonthlyCharges  \
customerID
7590-VHVEG  Month-to-month              Yes  Electronic check           29.85
5575-GNVDE        One year               No      Mailed check           56.95
3668-QPYBK  Month-to-month              Yes      Mailed check           53.85

           TotalCharges Churn
customerID
7590-VHVEG        29.85    No
```

```
5575-GNVDE        1889.5     No
3668-QPYBK        108.15    Yes
```

7. Inspection Of Data

```
In [5]: # function to Get insights of data

        def  get_insights_from_dataframe(dataframe):
            '''This function return insights from data set. The function return values in folo
            0-index ,1-columns , 2-datatypes of columns  ,3-shape of data set   '''
            index_values = dataframe.index
            df_columns = dataframe.columns
            datatypes = dataframe.dtypes
            shape_dataset = dataframe.shape
            return index_values , df_columns , datatypes,shape_dataset


        # Apply function on dataframe
        df_telecomData_insights = get_insights_from_dataframe(df_telecomData)
```

```
In [6]: print("Index values froom dataset")
        df_telecomData_insights[0]
```

```
Index values froom dataset
```

```
Out[6]: Index(['7590-VHVEG', '5575-GNVDE', '3668-QPYBK', '7795-CFOCW', '9237-HQITU',
               '9305-CDSKC', '1452-KIOVK', '6713-OKOMC', '7892-POOKP', '6388-TABGU',
               ...
               '9767-FFLEM', '0639-TSIQW', '8456-QDAVC', '7750-EYXWZ', '2569-WGERO',
               '6840-RESVB', '2234-XADUH', '4801-JZAZL', '8361-LTMKD', '3186-AJIEK'],
              dtype='object', name='customerID', length=7043)
```

```
In [7]: print("Columns form dataset")
        df_telecomData_insights[1]
```

```
Columns form dataset
```

```
Out[7]: Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
               'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
               'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
               'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
               'MonthlyCharges', 'TotalCharges', 'Churn'],
              dtype='object')
```

```
In [8]: print("datatypes information about columns in dataset")
        df_telecomData_insights[2]
```

```
datatypes information about columns in dataset
```

```
Out[8]: gender                object
        SeniorCitizen          int64
        Partner               object
        Dependents            object
        tenure                 int64
        PhoneService          object
        MultipleLines         object
        InternetService       object
        OnlineSecurity        object
        OnlineBackup          object
        DeviceProtection      object
        TechSupport           object
        StreamingTV           object
        StreamingMovies       object
        Contract              object
        PaperlessBilling      object
        PaymentMethod         object
        MonthlyCharges       float64
        TotalCharges          object
        Churn                 object
        dtype: object
```

```
In [9]: print("Shape (no. of rows and column) of dataset")
        df_telecomData_insights[3]
```

```
Shape (no. of rows and column) of dataset
```

```
Out[9]: (7043, 20)
```

Thus our data set has 7043 rows and 20 features

8. Data Manipulation

```
In [10]: # Check if data set contains null values
         df_telecomData.isna().sum()
```

```
Out[10]: gender              0
         SeniorCitizen       0
         Partner             0
         Dependents          0
         tenure              0
         PhoneService        0
         MultipleLines       0
         InternetService     0
         OnlineSecurity      0
```

```
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [11]:
```
# get unique values in each column in dataset

def get_unique_values_for_stringtype_Data(df):
    '''this function will display string /categorical type data from dataset'''
    # np.object is numpy variable to detect string/object type data
    for col in df.select_dtypes(include=[np.object]).columns:
        print(col , " :" , df[col].unique(),"\n")


# Applu dataframe on function
print('Columns with unique values\n')
get_unique_values_for_stringtype_Data(df_telecomData)
```

```
Columns with unique values

gender  : ['Female' 'Male']

Partner  : ['Yes' 'No']

Dependents  : ['No' 'Yes']

PhoneService  : ['No' 'Yes']

MultipleLines  : ['No phone service' 'No' 'Yes']

InternetService  : ['DSL' 'Fiber optic' 'No']

OnlineSecurity  : ['No' 'Yes' 'No internet service']

OnlineBackup  : ['Yes' 'No' 'No internet service']

DeviceProtection  : ['No' 'Yes' 'No internet service']

TechSupport  : ['No' 'Yes' 'No internet service']
```

```
StreamingTV  : ['No' 'Yes' 'No internet service']

StreamingMovies  : ['No' 'Yes' 'No internet service']

Contract  : ['Month-to-month' 'One year' 'Two year']

PaperlessBilling  : ['Yes' 'No']

PaymentMethod  : ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']

TotalCharges  : ['29.85' '1889.5' '108.15' ... '346.45' '306.6' '6844.5']

Churn  : ['No' 'Yes']
```

In [12]:
```
# Check if dataset contains duplicate values
df_telecomData.duplicated().all()
```

Out[12]:
```
False
```

In [13]:
```
df_telecomData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7043 entries, 7590-VHVEG to 3186-AJIEK
Data columns (total 20 columns):
gender              7043 non-null object
SeniorCitizen       7043 non-null int64
Partner             7043 non-null object
Dependents          7043 non-null object
tenure              7043 non-null int64
PhoneService        7043 non-null object
MultipleLines       7043 non-null object
InternetService     7043 non-null object
OnlineSecurity      7043 non-null object
OnlineBackup        7043 non-null object
DeviceProtection    7043 non-null object
TechSupport         7043 non-null object
StreamingTV         7043 non-null object
StreamingMovies     7043 non-null object
Contract            7043 non-null object
PaperlessBilling    7043 non-null object
PaymentMethod       7043 non-null object
MonthlyCharges      7043 non-null float64
TotalCharges        7043 non-null object
Churn               7043 non-null object
dtypes: float64(1), int64(2), object(17)
```

```
memory usage: 1.1+ MB
```

In [14]:
```python
df_telecomData.head()
```

Out[14]:
```
                gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
customerID
7590-VHVEG  Female              0     Yes         No       1           No
5575-GNVDE    Male              0      No         No      34          Yes
3668-QPYBK    Male              0      No         No       2          Yes
7795-CFOCW    Male              0      No         No      45           No
9237-HQITU  Female              0      No         No       2          Yes

               MultipleLines InternetService OnlineSecurity OnlineBackup  \
customerID
7590-VHVEG  No phone service             DSL             No          Yes
5575-GNVDE                No             DSL            Yes           No
3668-QPYBK                No             DSL            Yes          Yes
7795-CFOCW  No phone service             DSL            Yes           No
9237-HQITU                No     Fiber optic             No           No

           DeviceProtection TechSupport StreamingTV StreamingMovies  \
customerID
7590-VHVEG               No          No          No              No
5575-GNVDE              Yes          No          No              No
3668-QPYBK               No          No          No              No
7795-CFOCW              Yes         Yes          No              No
9237-HQITU               No          No          No              No

                  Contract PaperlessBilling              PaymentMethod  \
customerID
7590-VHVEG  Month-to-month              Yes           Electronic check
5575-GNVDE        One year               No               Mailed check
3668-QPYBK  Month-to-month              Yes               Mailed check
7795-CFOCW        One year               No  Bank transfer (automatic)
9237-HQITU  Month-to-month              Yes           Electronic check

            MonthlyCharges TotalCharges Churn
customerID
7590-VHVEG           29.85        29.85    No
5575-GNVDE           56.95       1889.5    No
3668-QPYBK           53.85       108.15   Yes
7795-CFOCW           42.30      1840.75    No
9237-HQITU           70.70       151.65   Yes
```

As seen in dataset " Total Charges " contains numerical but it's datatype is object type. hence it needs to be convert into numerical.

In [15]:
```python
# We need to convert the Total Charges from object type to Numeric
df_telecomData['TotalCharges'] = df_telecomData['TotalCharges'].replace(r'\s+', np.nan
```

```
df_telecomData['TotalCharges'] = pd.to_numeric(df_telecomData['TotalCharges'])
df_telecomData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7043 entries, 7590-VHVEG to 3186-AJIEK
Data columns (total 20 columns):
gender              7043 non-null object
SeniorCitizen       7043 non-null int64
Partner             7043 non-null object
Dependents          7043 non-null object
tenure              7043 non-null int64
PhoneService        7043 non-null object
MultipleLines       7043 non-null object
InternetService     7043 non-null object
OnlineSecurity      7043 non-null object
OnlineBackup        7043 non-null object
DeviceProtection    7043 non-null object
TechSupport         7043 non-null object
StreamingTV         7043 non-null object
StreamingMovies     7043 non-null object
Contract            7043 non-null object
PaperlessBilling    7043 non-null object
PaymentMethod       7043 non-null object
MonthlyCharges      7043 non-null float64
TotalCharges        7032 non-null float64
Churn               7043 non-null object
dtypes: float64(2), int64(2), object(16)
memory usage: 1.1+ MB
```

In [16]:
```
# Check null values in dataframe
print(" datatype of TotalCharge :" , df_telecomData.TotalCharges.dtype)
df_telecomData.isna().sum()
```

```
 datatype of TotalCharge : float64
```

Out[16]:
```
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
```

```
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64
```

As seen " Total Chanrges " contains missing values and now "TotalCharge" is it of float64 type. thus those missing values may get raplce with the mean of TotalCharge

```
In [17]: df_telecomData['TotalCharges'] = df_telecomData['TotalCharges'].fillna((df_telecomData
         #
         df_telecomData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7043 entries, 7590-VHVEG to 3186-AJIEK
Data columns (total 20 columns):
gender              7043 non-null object
SeniorCitizen       7043 non-null int64
Partner             7043 non-null object
Dependents          7043 non-null object
tenure              7043 non-null int64
PhoneService        7043 non-null object
MultipleLines       7043 non-null object
InternetService     7043 non-null object
OnlineSecurity      7043 non-null object
OnlineBackup        7043 non-null object
DeviceProtection    7043 non-null object
TechSupport         7043 non-null object
StreamingTV         7043 non-null object
StreamingMovies     7043 non-null object
Contract            7043 non-null object
PaperlessBilling    7043 non-null object
PaymentMethod       7043 non-null object
MonthlyCharges      7043 non-null float64
TotalCharges        7043 non-null float64
Churn               7043 non-null object
dtypes: float64(2), int64(2), object(16)
memory usage: 1.1+ MB
```

9. Basline Accuracy Our object is to identify the count of customer who are leaving the subscription from the telecom company or who are reating with them based upon " Churn " column. Thus let's form baseline accuracy based upon existing data

```
In [18]: # Baseline accuracy

         df_telecomData['Churn'].value_counts()
```

```
Out[18]: No     5174
         Yes    1869
         Name: Churn, dtype: int64
```

```
In [19]: df_telecomData['Churn'].value_counts(normalize=True)
```

```
Out[19]: No     0.73463
         Yes    0.26537
         Name: Churn, dtype: float64
```

10. Exploratory Data Analysis Based upon above opted baseline accuracy we can predict that 73 % (5174 cutomers out of 7043) has decided to retain the subscription with company. Rest has decided to quit.

```
In [20]: # Statitistical Analysis of dataset

         df_telecomData.describe()  # return information about fetaures with numerical data
```

```
Out[20]:        SeniorCitizen       tenure  MonthlyCharges  TotalCharges
         count    7043.000000  7043.000000     7043.000000   7043.000000
         mean        0.162147    32.371149       64.761692   2283.300441
         std         0.368612    24.559481       30.090047   2265.000258
         min         0.000000     0.000000       18.250000     18.800000
         25%         0.000000     9.000000       35.500000    402.225000
         50%         0.000000    29.000000       70.350000   1400.550000
         75%         0.000000    55.000000       89.850000   3786.600000
         max         1.000000    72.000000      118.750000   8684.800000
```

```
In [21]: # Statitistical Analysis of dataset with object type feature
         df_telecomData.describe(include=np.object)
```

```
Out[21]:       gender Partner Dependents PhoneService MultipleLines InternetService  \
         count    7043    7043       7043         7043          7043            7043
         unique      2       2          2            2             3               3
         top      Male      No         No          Yes            No     Fiber optic
         freq     3555    3641       4933         6361          3390            3096

               OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV  \
         count           7043         7043             7043        7043        7043
         unique             3            3                3           3           3
         top               No           No               No          No          No
         freq            3498         3088             3095        3473        2810

               StreamingMovies        Contract PaperlessBilling     PaymentMethod  \
         count            7043            7043             7043              7043
```

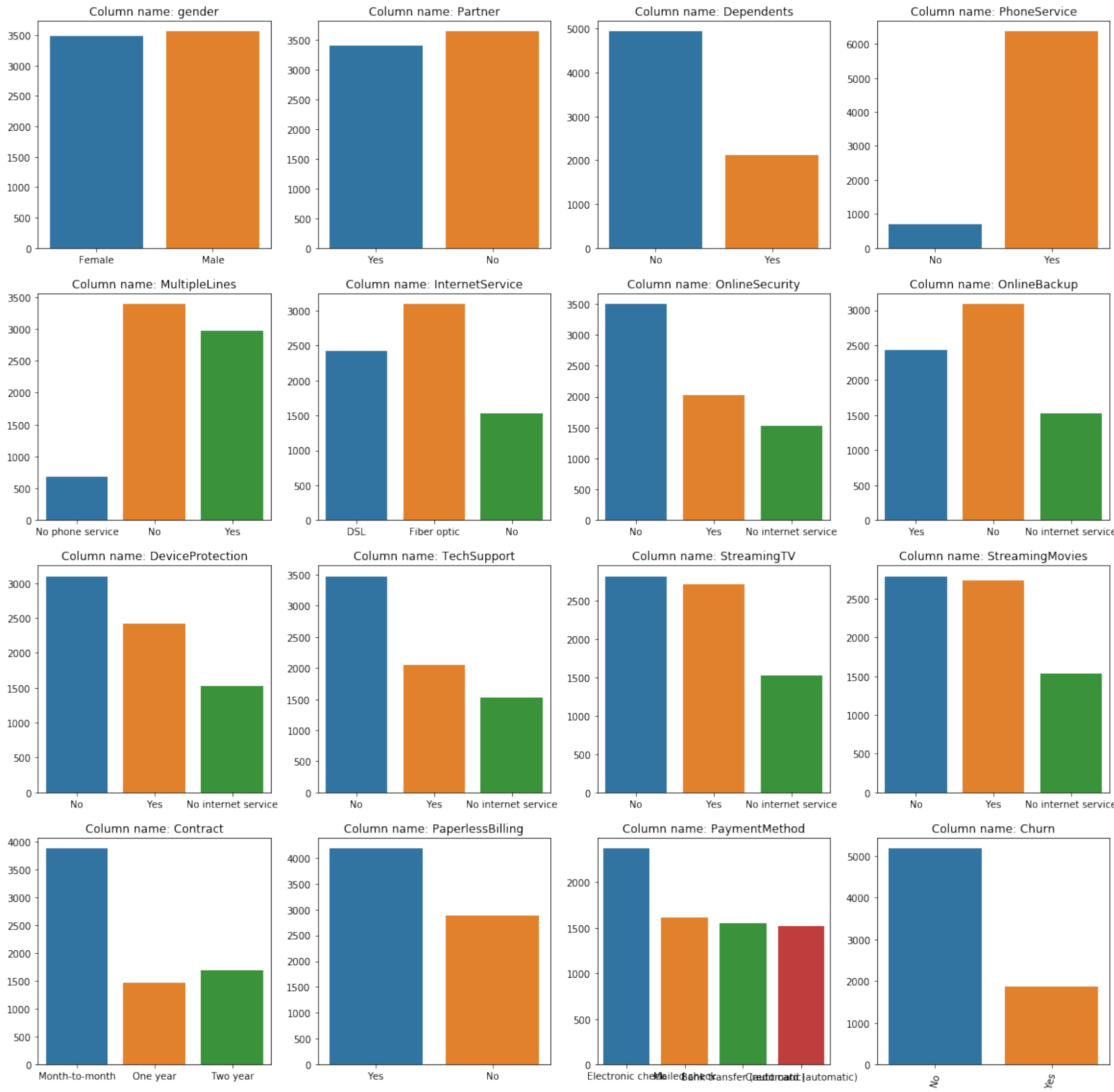
```
unique               3               3               2                 4
top                 No  Month-to-month             Yes  Electronic check
freq              2785            3875            4171              2365

       Churn
count   7043
unique     2
top       No
freq    5174
```

10.1 Univariate Analysis

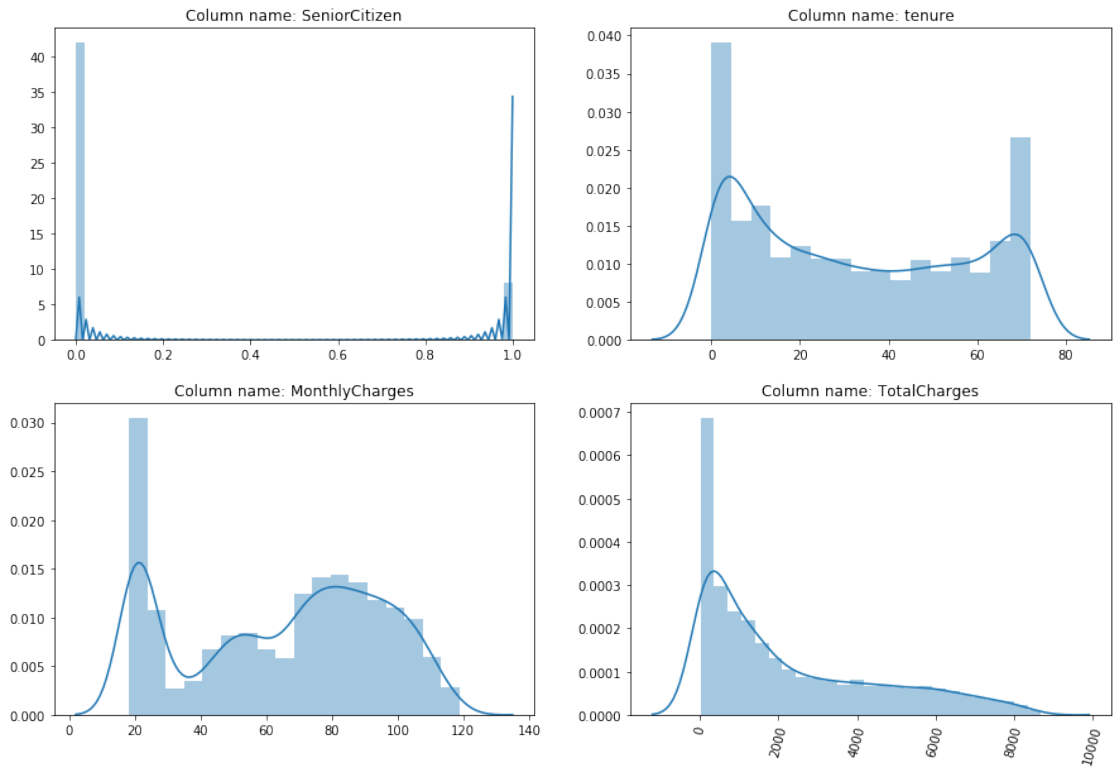
In [22]:
```python
# Create function to get graphical analysis of data

def get_visualize_data( df, col_to_exclude, object_mode = True ):
    """
     This function plots the count or distribution of each column in the dataframe ba
     @Args
       df: pandas dataframe
       col_to_exclude: specific column to exclude from the plot, used for excluded ke
       object_mode: whether to plot on object data types or not (default: True)

     Return
       No object returned but visualized plot will return based on specified inputs
    """

    num = 0
    cols_add = []

    # temp vairbale for object cols to add or not
    if object_mode :
        nrows = 4
        ncols = 4
        width =20
        height= 20
    else:
        nrows = 2
        ncols = 2
        width = 15
        height= 10

    for col in df.columns:
        if object_mode:
            if (df[col].dtypes == 'O') & (col != col_to_exclude):
                cols_add.append(col)

        else:
            if (df[col].dtypes != 'O'):
```

```
                cols_add.append(col)

        # graph
        fig, ax = plt.subplots(nrows, ncols, sharex=False, sharey=False, figsize=(width, l

        for row in range(nrows):
            for column in range(ncols):
                if object_mode:
                    graph = sns.countplot(df[cols_add[num]], ax=ax[row][column])
                else:
                    graph = sns.distplot(df[cols_add[num]], ax = ax[row][column])

                ax[row, column].set_title("Column name: {}".format(cols_add[num]))
                ax[row, column].set_xlabel("")
                ax[row, column].set_ylabel("")
                num += 1
        plt.xticks(rotation=75)
        plt.show();
        return None
```

In [23]:
```
# get visualisation of dat with including object type data

get_visualize_data(df_telecomData, 'customerid', object_mode = True)
```



In [24]:
```
# get visualisation of dat with excluding object type data

get_visualize_data(df_telecomData, 'customerid', object_mode = False)
```



10.2 Feature Engineering

In [25]:
```
df_telecomData.head()
```

Out[25]:
```
                gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
customerID
7590-VHVEG  Female              0     Yes         No       1           No
5575-GNVDE    Male              0      No         No      34          Yes
3668-QPYBK    Male              0      No         No       2          Yes
7795-CFOCW    Male              0      No         No      45           No
9237-HQITU  Female              0      No         No       2          Yes

               MultipleLines InternetService OnlineSecurity OnlineBackup  \
customerID
7590-VHVEG  No phone service             DSL             No          Yes
5575-GNVDE                No             DSL            Yes           No
3668-QPYBK                No             DSL            Yes          Yes
7795-CFOCW  No phone service             DSL            Yes           No
9237-HQITU                No     Fiber optic             No           No

           DeviceProtection TechSupport StreamingTV StreamingMovies  \
customerID
7590-VHVEG               No          No          No              No
```

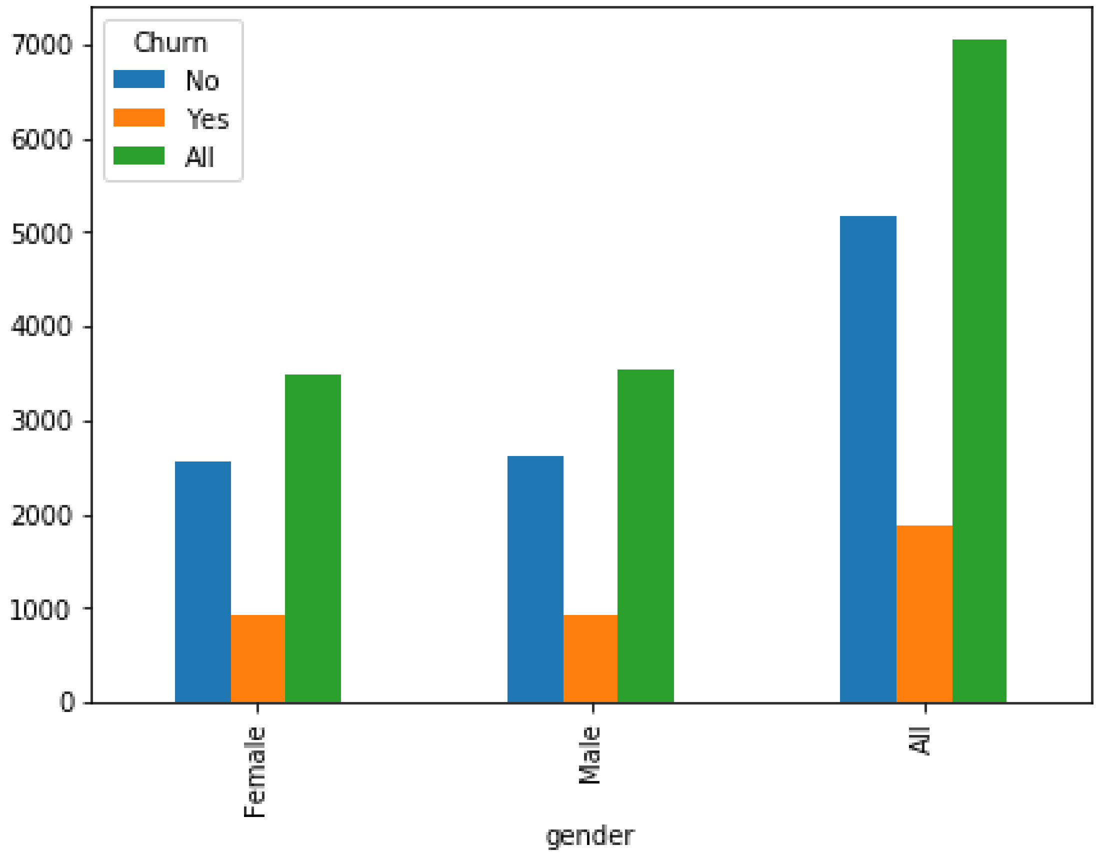
```
5575-GNVDE              Yes         No          No              No
3668-QPYBK               No         No          No              No
7795-CFOCW              Yes        Yes          No              No
9237-HQITU               No         No          No              No

                  Contract PaperlessBilling             PaymentMethod  \
customerID
7590-VHVEG  Month-to-month              Yes          Electronic check
5575-GNVDE        One year               No              Mailed check
3668-QPYBK  Month-to-month              Yes              Mailed check
7795-CFOCW        One year               No  Bank transfer (automatic)
9237-HQITU  Month-to-month              Yes          Electronic check

            MonthlyCharges  TotalCharges Churn
customerID
7590-VHVEG           29.85         29.85    No
5575-GNVDE           56.95       1889.50    No
3668-QPYBK           53.85        108.15   Yes
7795-CFOCW           42.30       1840.75    No
9237-HQITU           70.70        151.65   Yes
```

In this section , we do analysis between features of dataset as wether customer churn the subscriptioon or not , it's based upon services provided by company and other features related to them.

```
In [26]: def get_cross_realtionship_between_features ( df , feature_a , feature_b):
             '''This function returns cross relationship between features'''
             df_temp = pd.crosstab(index=df[feature_a] ,columns= df[feature_b] , margins=True)
             df_temp.plot(kind='bar',figsize=(7,5))
             plt.show()
             return df_temp
```

a . Gender vs Churn Identify which category of gender churn the subscription

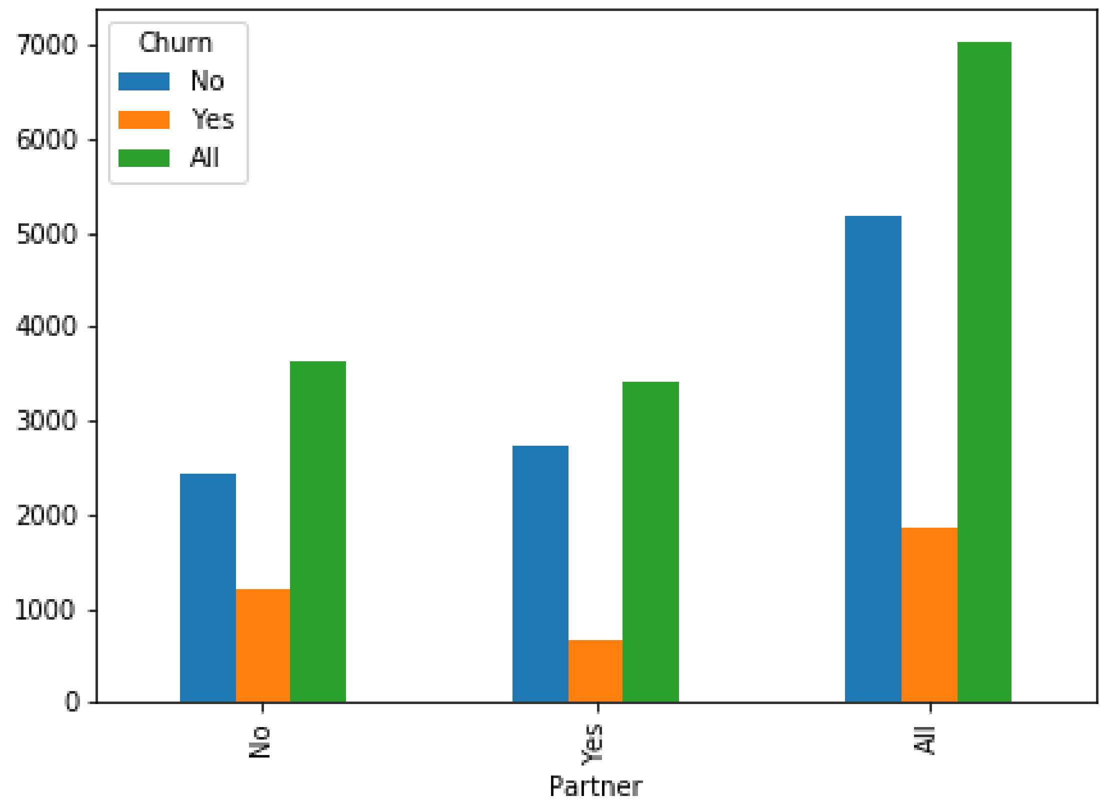
```
In [27]: get_cross_realtionship_between_features(df= df_telecomData , feature_a='gender' , fea
```




```
Out[27]: Churn      No   Yes   All
         gender
         Female  2549   939  3488
         Male    2625   930  3555
         All     5174  1869  7043
```

b . Partner vs Churn Identify wether Customer with Partners, churn the subscription

```
In [28]: get_cross_realtionship_between_features(df= df_telecomData , feature_a='Partner' , fea
```

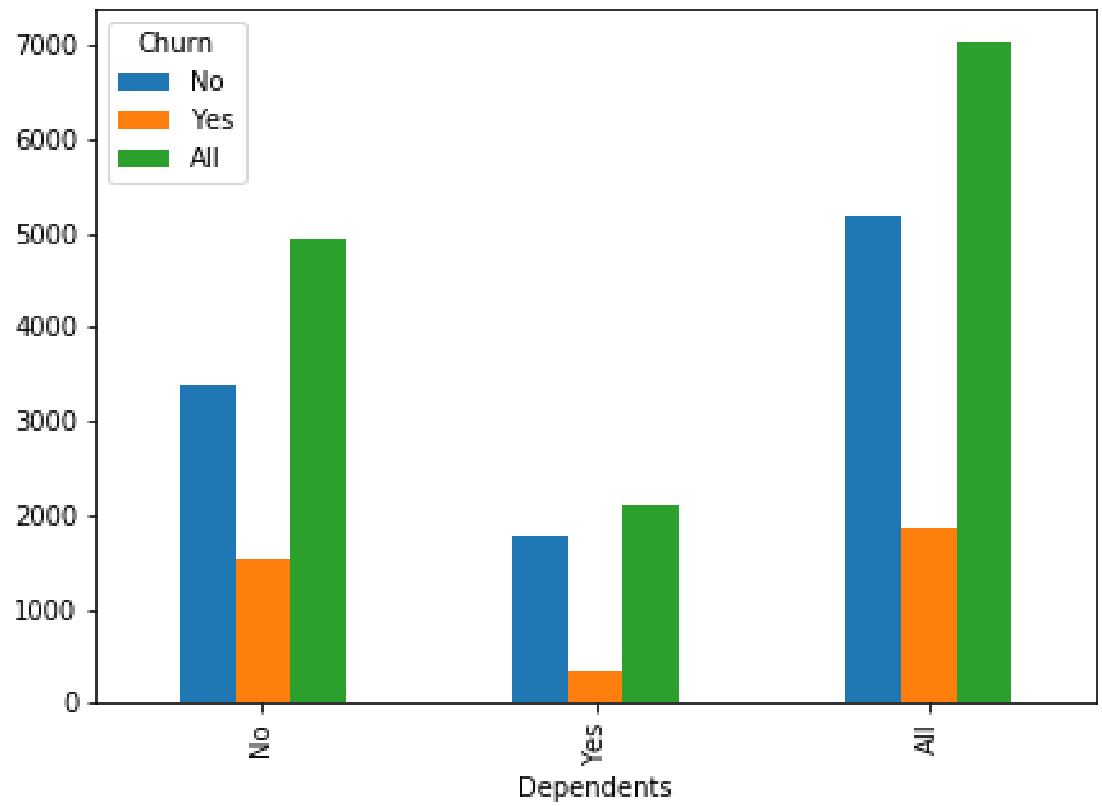


Out[28]:

Churn	No	Yes	All
Partner			
No	2441	1200	3641
Yes	2733	669	3402
All	5174	1869	7043

c . Dependents vs Churn Identify wether Customer with Dependents, churn the subscription

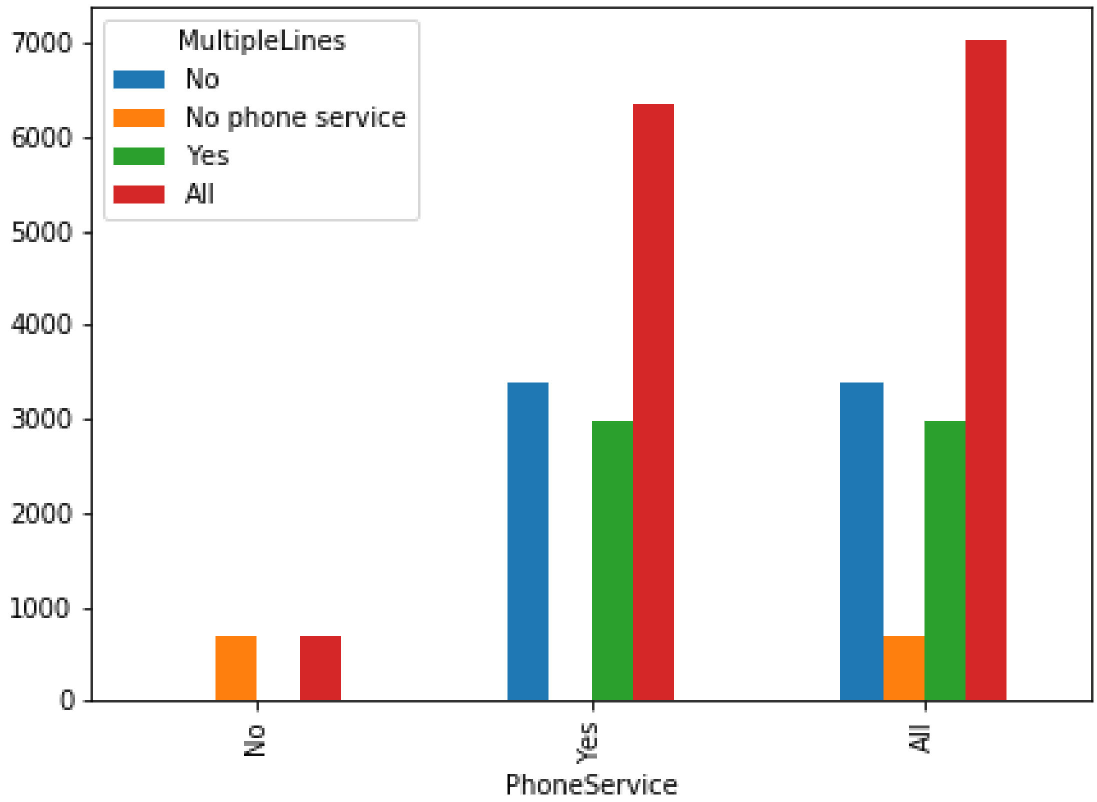
In [29]:
```
get_cross_realtionship_between_features(df= df_telecomData , feature_a='Dependents' ,
```




```
Out[29]: Churn          No   Yes   All
         Dependents
         No           3390  1543  4933
         Yes          1784   326  2110
         All          5174  1869  7043
```

d . PhoneServices vs MultipleLines - If the subscribers have phone service, they may have multiple lines (yes or no). - But if the subscribers don't have phone service, the subscribers will never have multiple lines.

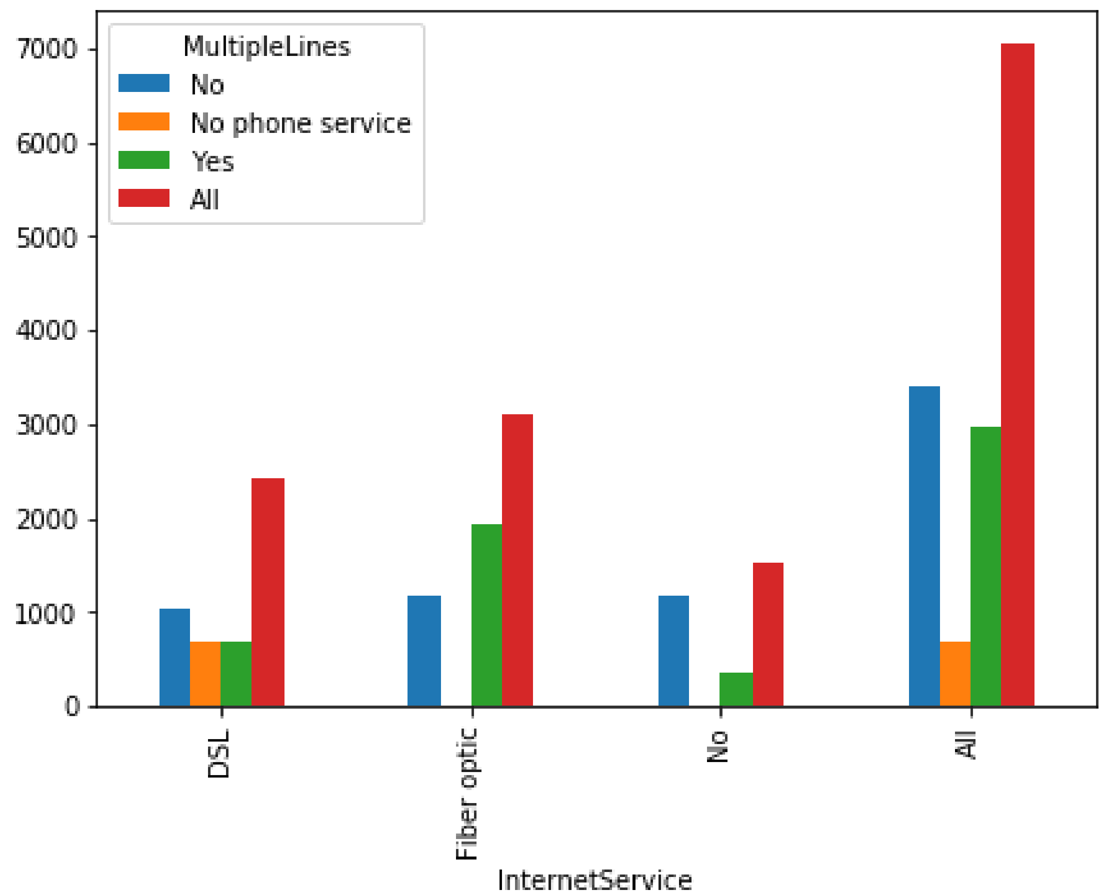
```
In [30]: get_cross_realtionship_between_features(df=df_telecomData , feature_a='PhoneService'
```




```
Out[30]: MultipleLines     No  No phone service   Yes   All
         PhoneService
         No                 0               682     0   682
         Yes             3390                 0  2971  6361
         All             3390               682  2971  7043
```

e . InternetServices vs MultipleLines - If the subscribers have Internet service, they may have multiple lines (yes or no). - But if the subscribers don't have Internet service, the subscribers will may or may not have multiple lines.

```
In [31]: get_cross_realtionship_between_features(df=df_telecomData , feature_a='InternetServic
```



Out[31]:

MultipleLines	No	No phone service	Yes	All
InternetService				
DSL	1048	682	691	2421
Fiber optic	1158	0	1938	3096
No	1184	0	342	1526
All	3390	682	2971	7043

As seen in dataset , various features contains muliplt No Values like No , NO Phone/internet Service. In context it is similar to No because customer is lacking a service and as alternative they using another service either phone or internet service.

In [32]:

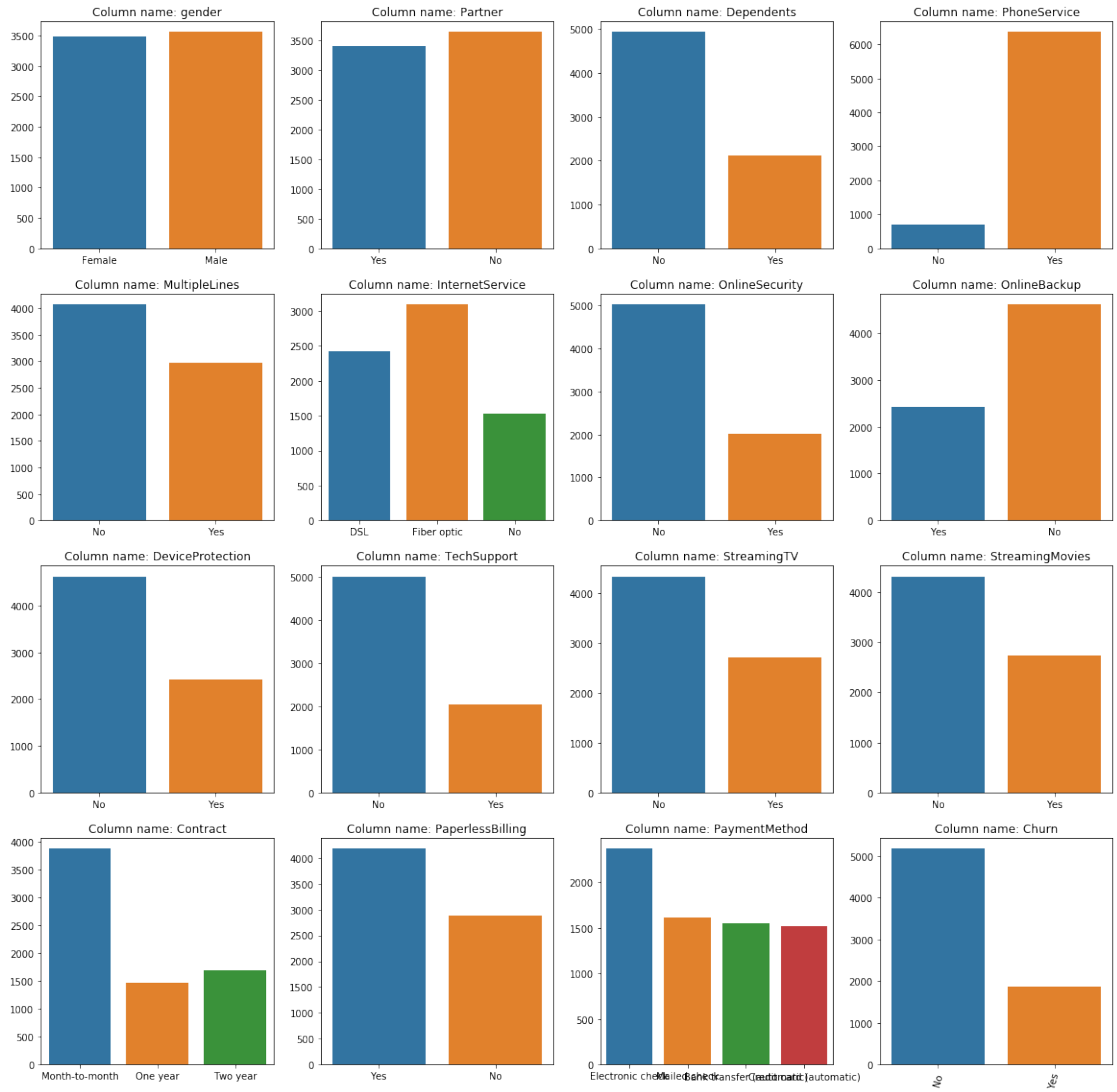
```
# Function to transfrom No Service

def transform_no_service (dataframe):
    '''This Function will transfrom features with multiple no values to single No val
    columns_to_transform = []
    for col in dataframe.columns:
        if (dataframe[col].dtype == 'O'):
            if len(dataframe[dataframe[col].str.contains("No")][col].unique())>1 :
```

```
                    columns_to_transform.append(col)

        print("Total column(s) to transform: {}".format(columns_to_transform))
        for col in columns_to_transform:
            dataframe.loc[dataframe[col].str.contains("No"), col] = 'No'

        return dataframe


    # Apply  function on dataframe

    df_telecomData = transform_no_service(df_telecomData)

    print(" Unique values in features after transforming values")
    get_unique_values_for_stringtype_Data(df_telecomData)
```

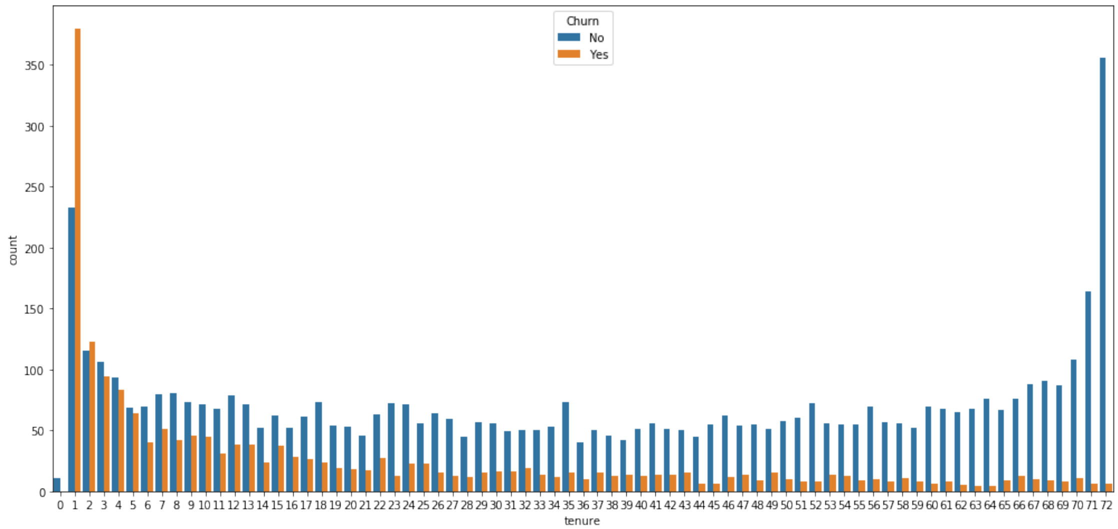
```
Total column(s) to transform: ['MultipleLines', 'OnlineSecurity', 'OnlineBackup', 'DeviceProte
 Unique values in features after transforming values
gender  : ['Female' 'Male']

Partner  : ['Yes' 'No']

Dependents  : ['No' 'Yes']

PhoneService  : ['No' 'Yes']

MultipleLines  : ['No' 'Yes']

InternetService  : ['DSL' 'Fiber optic' 'No']

OnlineSecurity  : ['No' 'Yes']

OnlineBackup  : ['Yes' 'No']

DeviceProtection  : ['No' 'Yes']

TechSupport  : ['No' 'Yes']

StreamingTV  : ['No' 'Yes']

StreamingMovies  : ['No' 'Yes']

Contract  : ['Month-to-month' 'One year' 'Two year']

PaperlessBilling  : ['Yes' 'No']

PaymentMethod  : ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
```

```
Churn  : ['No' 'Yes']
```

```
In [33]: # data visualisation after transforming values

         get_visualize_data(df_telecomData, 'customerid', object_mode = True)
```



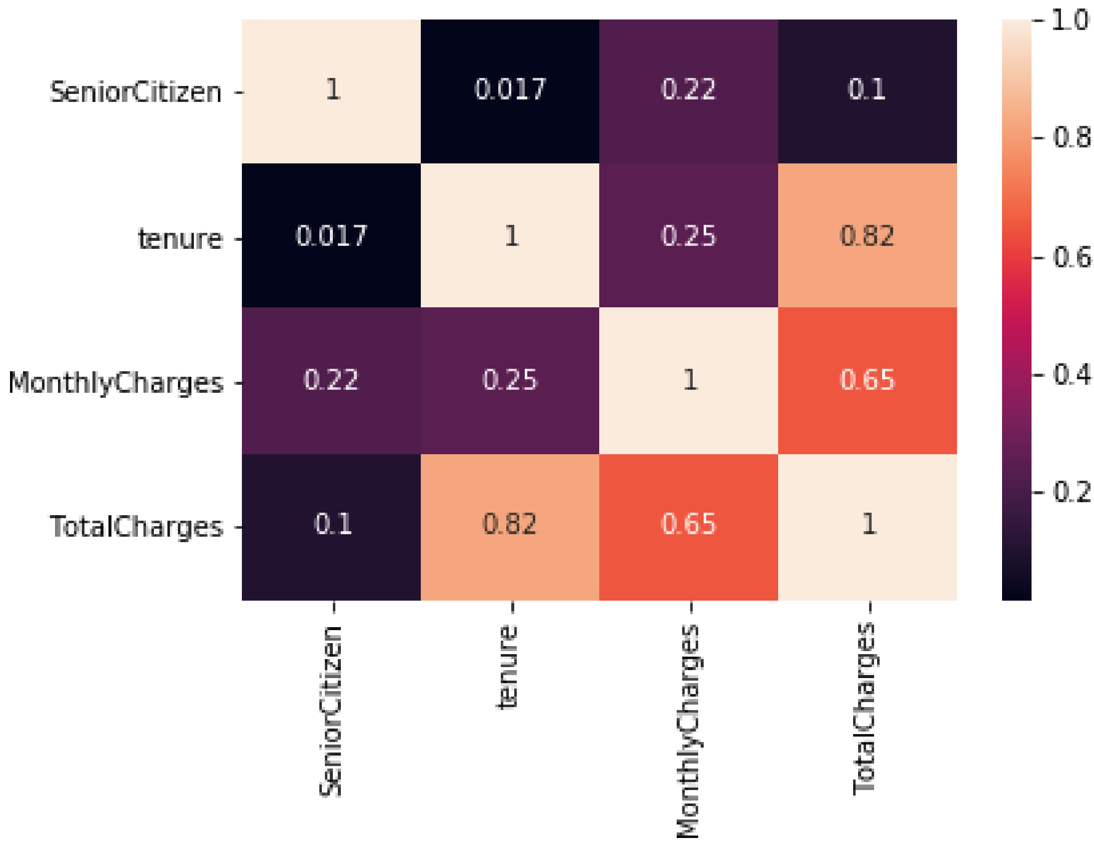

```
In [34]: # relationShip between tenure and
         plt.figure(figsize=(17,8))
         sns.countplot(x=df_telecomData['tenure'],hue=df_telecomData.Churn);
```



10.3 Correlation between features

In [35]:
```
# Function to get correlation between features

def correlation_between_features(dataframe):
    ''' This function returns correlation between features from dataframe'''
    print("Correlation values between features \n",dataframe.corr())
    sns.heatmap(dataframe.corr(),xticklabels=dataframe.corr().columns.values,yticklabe
    plt.show()


# Apply dataframe on function

correlation_between_features(df_telecomData)
```

```
Correlation values between features
                SeniorCitizen    tenure  MonthlyCharges  TotalCharges
SeniorCitizen        1.000000  0.016567        0.220173      0.102395
tenure               0.016567  1.000000        0.247900      0.824757
MonthlyCharges       0.220173  0.247900        1.000000      0.650468
TotalCharges         0.102395  0.824757        0.650468      1.000000
```



As seen Correlation between tenure and Total Charges is much higher. Similar is the case with Monthly charges and Total Charges.

The reason may be presumablw as calulation of **Total Charges ~ Monthly Charges * Tenure + Additional Charges(Tax).**

As seen in dataset , tenure is contaning linear range as values which may transform into group to seperate them in classification.

```
In [36]: #Tenure to categorical column
         def tenure_lab(telcom) :
             ''' This function cretaes catgorical values based upon range of values'''

             if telcom["tenure"] <= 12 :
                 return "Tenure_0-12"
             elif (telcom["tenure"] > 12) & (telcom["tenure"] <= 24 ):
                 return "Tenure_12-24"
             elif (telcom["tenure"] > 24) & (telcom["tenure"] <= 48) :
                 return "Tenure_24-48"
             elif (telcom["tenure"] > 48) & (telcom["tenure"] <= 60) :
                 return "Tenure_48-60"
             elif telcom["tenure"] > 60 :
                 return "Tenure_gt_60"
```

```python
# Create new feature in dataframe based on tenure
df_telecomData["tenure_group"] = df_telecomData.apply(lambda x:tenure_lab(x),axis = 1)
```

In [37]:
```python
# Sample rows after adding new column/feature
df_telecomData.head()
```

Out[37]:
```
            gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
customerID
7590-VHVEG  Female              0     Yes         No       1           No
5575-GNVDE    Male              0      No         No      34          Yes
3668-QPYBK    Male              0      No         No       2          Yes
7795-CFOCW    Male              0      No         No      45           No
9237-HQITU  Female              0      No         No       2          Yes

           MultipleLines InternetService OnlineSecurity OnlineBackup  \
customerID
7590-VHVEG            No             DSL             No          Yes
5575-GNVDE            No             DSL            Yes           No
3668-QPYBK            No             DSL            Yes          Yes
7795-CFOCW            No             DSL            Yes           No
9237-HQITU            No     Fiber optic             No           No

                ...      TechSupport StreamingTV StreamingMovies  \
customerID      ...
7590-VHVEG      ...               No          No              No
5575-GNVDE      ...               No          No              No
3668-QPYBK      ...               No          No              No
7795-CFOCW      ...              Yes          No              No
9237-HQITU      ...               No          No              No

                  Contract PaperlessBilling              PaymentMethod  \
customerID
7590-VHVEG  Month-to-month              Yes           Electronic check
5575-GNVDE        One year               No               Mailed check
3668-QPYBK  Month-to-month              Yes               Mailed check
7795-CFOCW        One year               No  Bank transfer (automatic)
9237-HQITU  Month-to-month              Yes           Electronic check

           MonthlyCharges  TotalCharges  Churn  tenure_group
customerID
7590-VHVEG          29.85         29.85     No    Tenure_0-12
5575-GNVDE          56.95       1889.50     No   Tenure_24-48
3668-QPYBK          53.85        108.15    Yes    Tenure_0-12
7795-CFOCW          42.30       1840.75     No   Tenure_24-48
9237-HQITU          70.70        151.65    Yes    Tenure_0-12

[5 rows x 21 columns]
```

11 . Data Preprocessing

11.1 Encoding categorical variable As seen in dataset " SenoirCitizon " only two unique values , 0 and 1 . Thus Encoding it into boolean may help to understand data better.

```
In [38]: df_telecomData['SeniorCitizen'].unique()

Out[38]: array([0, 1], dtype=int64)

In [39]: df_telecomData['SeniorCitizen'] = df_telecomData['SeniorCitizen'].replace({0:"No" , 1

In [40]: # unqiue data in dataset after encoding
         get_unique_values_for_stringtype_Data(df_telecomData)
```

```
gender  : ['Female' 'Male']

SeniorCitizen  : ['No' 'Yes']

Partner  : ['Yes' 'No']

Dependents  : ['No' 'Yes']

PhoneService  : ['No' 'Yes']

MultipleLines  : ['No' 'Yes']

InternetService  : ['DSL' 'Fiber optic' 'No']

OnlineSecurity  : ['No' 'Yes']

OnlineBackup  : ['Yes' 'No']

DeviceProtection  : ['No' 'Yes']

TechSupport  : ['No' 'Yes']

StreamingTV  : ['No' 'Yes']

StreamingMovies  : ['No' 'Yes']

Contract  : ['Month-to-month' 'One year' 'Two year']

PaperlessBilling  : ['Yes' 'No']

PaymentMethod  : ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']

Churn  : ['No' 'Yes']
```

```
tenure_group  : ['Tenure_0-12' 'Tenure_24-48' 'Tenure_12-24' 'Tenure_gt_60' 'Tenure_48-60']
```

```
In [41]: # Selection of encoding method for data preprocessing
         from sklearn.preprocessing import LabelEncoder , StandardScaler
```

As we know our dataset contains multiple type of columns including int, float and object. Thus before processing seperating them into individual group may ease preprocessing step.

```
In [42]: # Columns in dataset
         df_telecomData.columns
```

```
Out[42]: Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
                'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
                'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
                'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
                'MonthlyCharges', 'TotalCharges', 'Churn', 'tenure_group'],
               dtype='object')
```

```
In [43]: # We already know that Churn is our target variable

         target_col = ['Churn']


         #categorical columns   df_telecomData.nunique() return number of unique values in fea
         catg_cols   = df_telecomData.nunique()[df_telecomData.nunique() < 6].keys().tolist()

         #Selection of colum with category
         catg_col = [ x for x in catg_cols if x not in target_col]

         # Columns with numerical data
         number_col = [x for x in df_telecomData.columns if x not in  catg_col + target_col]

         # Selection of columns with two classes
         binary_col = df_telecomData.nunique()[df_telecomData.nunique() ==2].keys().tolist()

         #Columns more than 2 classes
         multi_cols = [x for x in catg_cols if x not in binary_col]


         print("Columns with  2 classes :" ,binary_col)
         print('-'*80)
         print("Columns with more than 2 classes :" ,multi_cols)
         print('-'*80)
         print("Number columns :" , number_col)
```

```
Columns with  2 classes : ['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'PhoneService',
--------------------------------------------------------------------------------
```

```
Columns with more than 2 classes : ['InternetService', 'Contract', 'PaymentMethod', 'tenure_gro
--------------------------------------------------------------------------------
Number columns : ['tenure', 'MonthlyCharges', 'TotalCharges']
```

In [44]:
```python
# Lable encoding on binary columns
le = LabelEncoder()
#Apply encoding on binary columns
for col in binary_col:
    df_telecomData[col] = le.fit_transform(df_telecomData[col])


# Creating dummy variable form columns with morethan trwo classes
df_telecomData = pd.get_dummies(data = df_telecomData,columns = multi_cols )


# Sample rows from dataset after label encoding and dummy variable adding

df_telecomData.head(2)
```

Out[44]:
```
            gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  \
customerID
7590-VHVEG       0              0        1           0       1             0
5575-GNVDE       1              0        0           0      34             1

            MultipleLines  OnlineSecurity  OnlineBackup  DeviceProtection  \
customerID
7590-VHVEG              0               0             1                 0
5575-GNVDE              0               1             0                 1

                      ...              Contract_Two year  \
customerID            ...
7590-VHVEG            ...                              0
5575-GNVDE            ...                              0

            PaymentMethod_Bank transfer (automatic)  \
customerID
7590-VHVEG                                        0
5575-GNVDE                                        0

            PaymentMethod_Credit card (automatic)  \
customerID
7590-VHVEG                                      0
5575-GNVDE                                      0

            PaymentMethod_Electronic check  PaymentMethod_Mailed check  \
customerID
7590-VHVEG                               1                           0
```

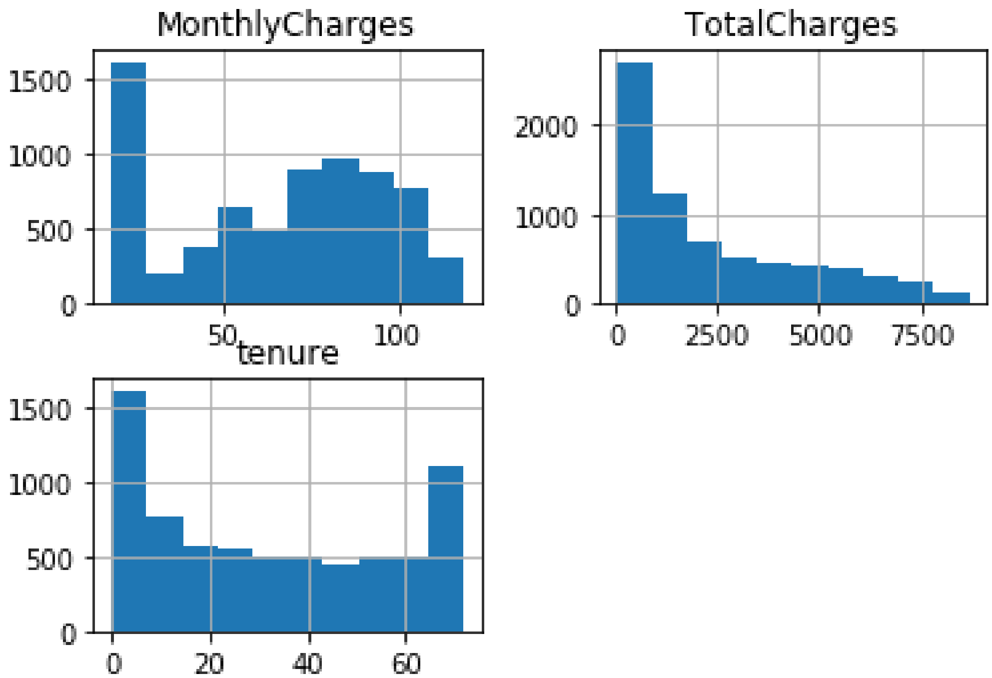
```
5575-GNVDE                              0                             1

               tenure_group_Tenure_0-12  tenure_group_Tenure_12-24  \
customerID
7590-VHVEG                            1                          0
5575-GNVDE                            0                          0

               tenure_group_Tenure_24-48  tenure_group_Tenure_48-60  \
customerID
7590-VHVEG                             0                          0
5575-GNVDE                             1                          0

               tenure_group_Tenure_gt_60
customerID
7590-VHVEG                             0
5575-GNVDE                             0

[2 rows x 32 columns]
```

In [45]:
```python
# Columns in data set after label encoding
df_telecomData.columns
```

Out[45]:
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'OnlineSecurity', 'OnlineBackup',
       'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
       'PaperlessBilling', 'MonthlyCharges', 'TotalCharges', 'Churn',
       'InternetService_DSL', 'InternetService_Fiber optic',
       'InternetService_No', 'Contract_Month-to-month', 'Contract_One year',
       'Contract_Two year', 'PaymentMethod_Bank transfer (automatic)',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check',
       'tenure_group_Tenure_0-12', 'tenure_group_Tenure_12-24',
       'tenure_group_Tenure_24-48', 'tenure_group_Tenure_48-60',
       'tenure_group_Tenure_gt_60'],
      dtype='object')
```

11.2 Normalizing Features As seen in dataset, it contains some numerical data(other than 0 & 1). The data have un-even distribution , which may hamper analysis while building the model. Thus Normalizing it may solve our problem.

In [46]:
```python
# Select numerical data from dataset - hist() distribution
df_telecomData[number_col].hist()
plt.show()
```



In [47]:
```
# Calling Statndard scalar method for preprocessing

std = StandardScaler()
# Apply scaling on dataframe with numerical columns
scaled_data = std.fit_transform(df_telecomData[number_col])
scaled_data = pd.DataFrame(scaled_data,columns=number_col)
# Sample rows from scaled data
scaled_data.head()
```

Out[47]:

	tenure	MonthlyCharges	TotalCharges
0	-1.277445	-1.160323	-0.994971
1	0.066327	-0.259629	-0.173876
2	-1.236724	-0.362660	-0.960399
3	0.514251	-0.746535	-0.195400
4	-1.236724	0.197365	-0.941193

In [48]:
```
# Drop existing numerical features from dataset
print(" Shape of dataset before dropping the features ", df_telecomData.shape)

df_telecomData.drop( columns= number_col , axis=1 , inplace=True ) # axis =1 for perf
print(" Shape of dataset after dropping the features ", df_telecomData.shape)
```

```
 Shape of dataset before dropping the features  (7043, 32)
 Shape of dataset after dropping the features  (7043, 29)
```

In [49]: df_telecomData.head()

Out[49]:
```
            gender  SeniorCitizen  Partner  Dependents  PhoneService  \
customerID
7590-VHVEG       0              0        1           0             0
5575-GNVDE       1              0        0           0             1
3668-QPYBK       1              0        0           0             1
7795-CFOCW       1              0        0           0             0
9237-HQITU       0              0        0           0             1

            MultipleLines  OnlineSecurity  OnlineBackup  DeviceProtection  \
customerID
7590-VHVEG              0               0             1                 0
5575-GNVDE              0               1             0                 1
3668-QPYBK              0               1             1                 0
7795-CFOCW              0               1             0                 1
9237-HQITU              0               0             0                 0

            TechSupport            ...                Contract_Two year  \
customerID                         ...
7590-VHVEG            0            ...                                0
5575-GNVDE            0            ...                                0
3668-QPYBK            0            ...                                0
7795-CFOCW            1            ...                                0
9237-HQITU            0            ...                                0

            PaymentMethod_Bank transfer (automatic)  \
customerID
7590-VHVEG                                        0
5575-GNVDE                                        0
3668-QPYBK                                        0
7795-CFOCW                                        1
9237-HQITU                                        0

            PaymentMethod_Credit card (automatic)  \
customerID
7590-VHVEG                                      0
5575-GNVDE                                      0
3668-QPYBK                                      0
7795-CFOCW                                      0
9237-HQITU                                      0

            PaymentMethod_Electronic check  PaymentMethod_Mailed check  \
customerID
7590-VHVEG                               1                           0
5575-GNVDE                               0                           1
3668-QPYBK                               0                           1
7795-CFOCW                               0                           0
```

```
9237-HQITU                              1                          0

            tenure_group_Tenure_0-12  tenure_group_Tenure_12-24  \
customerID
7590-VHVEG                         1                          0
5575-GNVDE                         0                          0
3668-QPYBK                         1                          0
7795-CFOCW                         0                          0
9237-HQITU                         1                          0

            tenure_group_Tenure_24-48  tenure_group_Tenure_48-60  \
customerID
7590-VHVEG                          0                          0
5575-GNVDE                          1                          0
3668-QPYBK                          0                          0
7795-CFOCW                          1                          0
9237-HQITU                          0                          0

            tenure_group_Tenure_gt_60
customerID
7590-VHVEG                          0
5575-GNVDE                          0
3668-QPYBK                          0
7795-CFOCW                          0
9237-HQITU                          0

[5 rows x 29 columns]
```

In [50]:
```python
# apply scaled features on dataset
df_telecomData.reset_index(drop=False, inplace=True)

df_telecomData = pd.concat([df_telecomData, scaled_data], axis=1)

df_telecomData.set_index('customerID', inplace=True)

df_telecomData.head()
```

Out[50]:
```
            gender  SeniorCitizen  Partner  Dependents  PhoneService  \
customerID
7590-VHVEG       0              0        1           0             0
5575-GNVDE       1              0        0           0             1
3668-QPYBK       1              0        0           0             1
7795-CFOCW       1              0        0           0             0
9237-HQITU       0              0        0           0             1

            MultipleLines  OnlineSecurity  OnlineBackup  DeviceProtection  \
customerID
7590-VHVEG              0               0             1                 0
```

```
5575-GNVDE             0               1              0                  1
3668-QPYBK             0               1              1                  0
7795-CFOCW             0               1              0                  1
9237-HQITU             0               0              0                  0

            TechSupport      ...      PaymentMethod_Electronic check  \
customerID                   ...
7590-VHVEG            0      ...                                   1
5575-GNVDE            0      ...                                   0
3668-QPYBK            0      ...                                   0
7795-CFOCW            1      ...                                   0
9237-HQITU            0      ...                                   1

            PaymentMethod_Mailed check  tenure_group_Tenure_0-12  \
customerID
7590-VHVEG                           0                         1
5575-GNVDE                           1                         0
3668-QPYBK                           1                         1
7795-CFOCW                           0                         0
9237-HQITU                           0                         1

            tenure_group_Tenure_12-24  tenure_group_Tenure_24-48  \
customerID
7590-VHVEG                          0                          0
5575-GNVDE                          0                          1
3668-QPYBK                          0                          0
7795-CFOCW                          0                          1
9237-HQITU                          0                          0

            tenure_group_Tenure_48-60  tenure_group_Tenure_gt_60    tenure  \
customerID
7590-VHVEG                          0                          0 -1.277445
5575-GNVDE                          0                          0  0.066327
3668-QPYBK                          0                          0 -1.236724
7795-CFOCW                          0                          0  0.514251
9237-HQITU                          0                          0 -1.236724

            MonthlyCharges  TotalCharges
customerID
7590-VHVEG       -1.160323     -0.994971
5575-GNVDE       -0.259629     -0.173876
3668-QPYBK       -0.362660     -0.960399
7795-CFOCW       -0.746535     -0.195400
9237-HQITU        0.197365     -0.941193

[5 rows x 32 columns]
```

11.3 Split the data into train and test Set

```
In [51]: # Calling sklearn.model_selection for splitting data into train and test
         from sklearn.model_selection import train_test_split
```

```
In [52]: # Seprating dataset bet ween dependent and indepndent features

         dep_feature = ["Churn"]
         indep_feature = [ x for x in df_telecomData.columns if x not in dep_feature ]

         X = df_telecomData[indep_feature]
         y= df_telecomData[dep_feature]

         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state

         print(" Shape of train set ( feature):",X_train.shape)
         print(" Shape of train set ( target):",y_train.shape)
         print("\n")
         print(" Shape of test set ( feature):",X_test.shape)
         print(" Shape of test set ( target):",y_test.shape)
```

```
 Shape of train set ( feature): (4718, 31)
 Shape of train set ( target): (4718, 1)


 Shape of test set ( feature): (2325, 31)
 Shape of test set ( target): (2325, 1)
```

12 . Model Building

```
In [53]: # Loading required librarires for machine lerning model building

         # dummy classifier
         from sklearn.dummy import DummyClassifier
         # Classification Models
         from sklearn.linear_model import LogisticRegression
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.ensemble import RandomForestClassifier , GradientBoostingClassifier
         from xgboost.sklearn import XGBClassifier
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.naive_bayes import GaussianNB
         # model evaluation
         from sklearn.metrics import confusion_matrix , classification_report ,  precision_reca
         from sklearn.metrics import f1_score , accuracy_score , precision_score , recall_score
         from sklearn.metrics import roc_curve ,auc , precision_recall_curve

         # Model validation
         import scipy.stats as st
```

```
from scipy.stats import randint as sp_randint
from sklearn.model_selection import GridSearchCV , RandomizedSearchCV

# Utilies

import time
import io, os, sys, types, time, datetime, math, random
```

12.1 Model evaluation function

```
In [54]: # (A ) Function for model fit using training dataset

         def model_fitting(ml_algo,feature_variable_train,target_variable_train,cross_validati
             ''' This function fit's the model and  returns  prdicted values from feature vari
             Following classifier used for model prediction LogisticRegression , DecisionTreeC
                                         RandomForestClassifier , GradientBoostingClassifier,
                                         XGBClassifier , KNeighborsClassifier , GaussianNB'''
             # Model fitting
             ml_model = ml_algo.fit(feature_variable_train, target_variable_train)

             if (isinstance(ml_algo , (LogisticRegression , DecisionTreeClassifier,
                                         RandomForestClassifier , GradientBoostingClassifier,
                                         XGBClassifier , KNeighborsClassifier , GaussianNB))):
                 model_pred_prob = ml_model.predict_proba(feature_variable_train)[:,1]
             else:
                 model_pred_prob = "Not available"
             acc_score_train = round(ml_model.score(feature_variable_train, target_variable_tr
             # Cross Validation
             from sklearn.model_selection import cross_val_predict
             from sklearn.metrics import accuracy_score

             pred_val_train = cross_val_predict(ml_algo,feature_variable_train,target_variable
             acc_cv = round(accuracy_score(target_variable_train, pred_val_train) * 100, 2)

             return ml_model, pred_val_train , model_pred_prob , acc_score_train , acc_cv

         #----------------------------------------------------------------------------------


         # (B) Function to predict target variable based on test features and ml_model


         def predict_target(feature_variable_test , ml_model):
             '''This function return predicted tartget variable based on model'''
             pred_test = ml_model.predict(feature_variable_test)
             pred_test_prob = ml_model.predict_proba(feature_variable_test)[:,1]
             return pred_test , pred_test_prob
```

```
#--------------------------------------------------------------------------------

# (C) Function for model evalution score

def get_model_evaluation_scores(actual_target_variable , predicted_target_variable):
    '''This function return model evaluation scores . The function return values in f
    precision_score , recall_score ,f1_score , roc_auc_score ,log_loss'''
    from sklearn.metrics import  accuracy_score , precision_score , recall_score ,f1_s

    accu_score = accuracy_score(y_true= actual_target_variable , y_pred= predicted_ta
    precision_score = precision_score(y_true= actual_target_variable , y_pred= predic
    recall_score = recall_score(y_true= actual_target_variable , y_pred= predicted_ta
    f1_score = f1_score( y_true= actual_target_variable , y_pred=predicted_target_var
    roc_auc_score = roc_auc_score(y_true= actual_target_variable , y_score= predicted
    log_loss_score = log_loss( y_true= actual_target_variable , y_pred= predicted_tar

    return accu_score , precision_score , recall_score , f1_score , roc_auc_score ,lo

#--------------------------------------------------------------------------------

# (D) Function for Confusion matrix

def get_visual_confusion_matrix(actual_target_variable , predicted_target_variable):
    '''This function returns the visual representaion of Confusion matix'''
    from sklearn.metrics import confusion_matrix
    import seaborn as sns

    matrix = confusion_matrix(y_true= actual_target_variable , y_pred= predicted_targ
    confusion_matrix_graph = pd.DataFrame(matrix, range(2), range(2))
    sns.set(font_scale=0.9)#for label size
    graph = sns.heatmap(confusion_matrix_graph, annot=True, annot_kws={"size": 25},
                fmt='.4g',xticklabels=['Pred : False(NO:0)','Pred : True(Yes:1)'],
                yticklabels=['Actual : False(NO:0)','Actual : True(Yes:1)'])
    plt.show()
    return graph

#--------------------------------------------------------------------------------

# ( E) unction for classification report
def get_classification_report(actual_target_variable,predicted_target_variable):
    '''This function will return classification report based upon actual and predicte
    from sklearn.metrics import classification_report
    report = classification_report(y_true=actual_target_variable , y_pred=predicted_t
                                   target_names=['No :0' , 'Yes:1'])
    return report

#--------------------------------------------------------------------------------
```

```
# (F ) Function for plotting ROC-AUC curve

def plot_roc_auc_curve(actual_target_variable , predicted_target_variable):
    '''This function returns graph between model's roc and auc score '''
    from sklearn.metrics import roc_curve , auc
    import matplotlib.pyplot as plt
    fpr , tpr, threshold = roc_curve(y_true= actual_target_variable , y_score= predict
    auc_score = auc(x=fpr,y=tpr )
    plt.title('Receiver Operating Characteristic')
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % auc_score)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([-0.01, 1.01])
    plt.ylim([-0.01, 1.01])
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()

#-----------------------------------------------------------------------------------

#  ( G) Function for plotting Precision-Recall curve

def plot_precision_recall_curve(actual_target_variable , predicted_target_variable):
    '''This function returns precision-recall curve for model '''
    from sklearn.metrics import precision_recall_curve
    import matplotlib.pyplot as plt
    precision , recall , threshold = precision_recall_curve(y_true= actual_target_vari
                                                            probas_pred=predicted_targ

    closest_zero = np.argmin(np.abs(threshold))
    closest_zero_p = precision[closest_zero]
    closest_zero_r = recall[closest_zero]
    plt.figure()
    plt.xlim([0.0, 1.01])
    plt.ylim([0.0, 1.01])
    plt.plot(precision, recall, label='Precision-Recall Curve')
    plt.plot(closest_zero_p, closest_zero_r, 'o' , markersize = 12, fillstyle = 'none
    plt.xlabel('Precision', fontsize=16)
    plt.ylabel('Recall', fontsize=16)
    plt.axes().set_aspect('equal')
    plt.title('Precision-Recall curve for Test dataset', fontsize=16)
    plt.show()


# (H ) Function foe=r float value
def float_value(x):
    '''This function return float values till 2 decimal places'''
    return round((x*100),2)
```

12.2 Basline Accuracy with dummy classifier

```
In [55]: # Convert Traget variable from dataframe  to 1-D array

         # training Test variable
         y_train = np.ravel(y_train)
         # target Test variable
         y_test = np.ravel(y_test)

         # Training Variable
         print( "Training data - shape : Feature variable  'X_train'{0},\t Target variable 'y_
               .format(X_train.shape ,y_train.shape ))

         # test variable
         print( "Test data - shape : Feature variable  'X_test' {0},\t Target variable 'y_test
               .format(X_test.shape ,y_test.shape ))
```

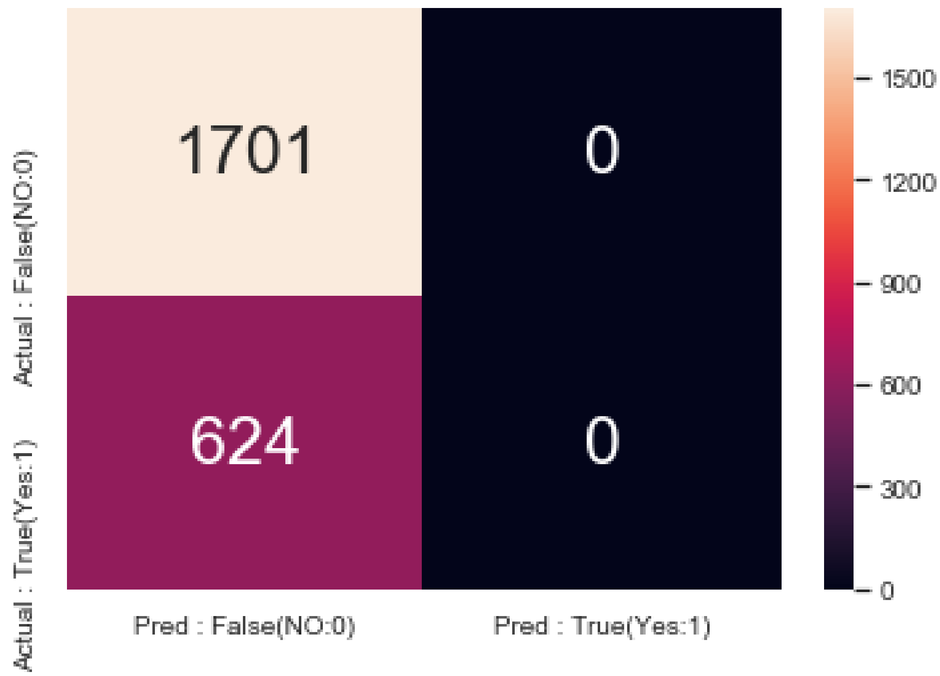
```
Training data - shape : Feature variable  'X_train'(4718, 31),         Target variable 'y_trai
Test data - shape : Feature variable  'X_test' (2325, 31),         Target variable 'y_test' (2
```

```
In [56]: # Apply training data into dummy classifier

         dummy_clf = DummyClassifier(strategy='most_frequent', random_state=0)

         # Apply training's feature and target variable
         start_time = time.time() # Start timer before model fitting
         dummy_model = model_fitting(ml_algo= dummy_clf , feature_variable_train= X_train ,\
                                     target_variable_train= y_train , cross_validation= 10 )
         dummy_time = (time.time() - start_time)

         print("* ML-Model :", dummy_model[0])
         print("* Accuracy (on training set): %s" % dummy_model[3])
         print("* Accuracy CV 10-Fold(on training set): %s" % dummy_model[4])
         print("* Running Time: %s" % datetime.timedelta(seconds=dummy_time))

         # Predict Target variable (test set)
         # Apply values on function " predict_target "
         pred_test_dummy , pred_test_prob_dummy = predict_target(feature_variable_test= X_test
         print("\n")

         print("* Dummy ClassifierModel Evaluation  (test set)\n")
         dummy_model_score = get_model_evaluation_scores(actual_target_variable= y_test ,\
                                                         predicted_target_variable= pred_test_d
         print("* Dummy Classifier evaluation score (on test set)\n\tAccuracy Score: {0}\n\tPre
               \n\tRecall Score: {2}\n\tF1_score: {3}\n\tROC_AUC_score: {4}\n\tLog_Loss_Score
```

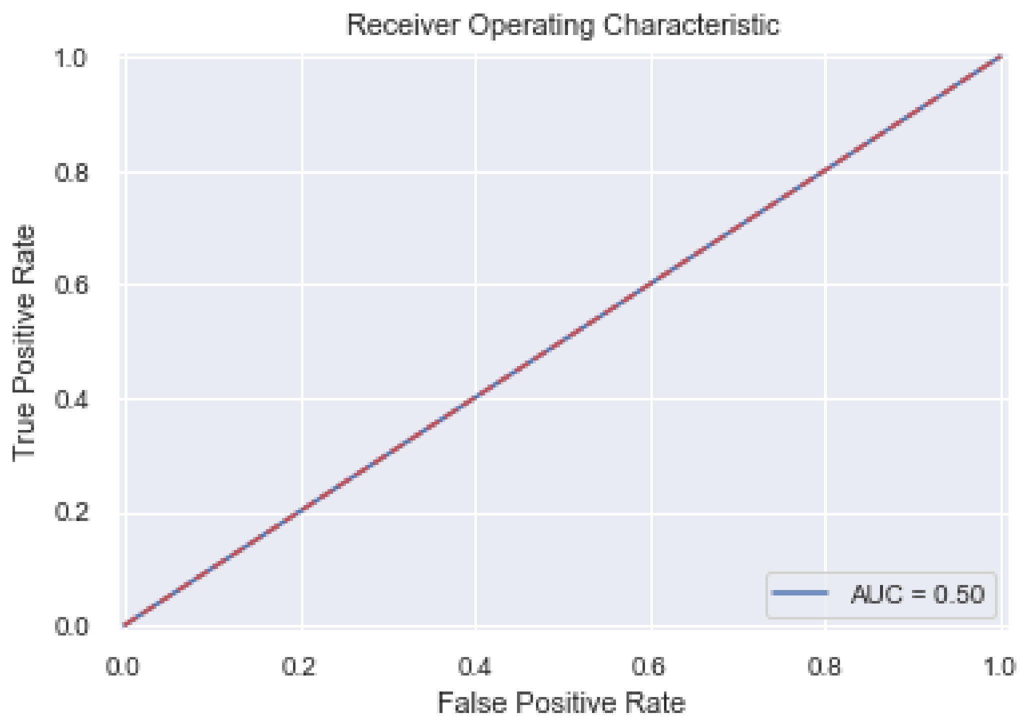
```
            dummy_model_score[0], dummy_model_score[1], dummy_model_score[2],\
            dummy_model_score[3],dummy_model_score[4],dummy_model_score[5]))

        # Model Classification report (test set)
        print("\n")
        # Apply values on function " get_classification_report "
        print("* Dummy classifier  -Classification Report (on test set)\n",get_classification_
                                                predicted_target_variable= pred_test_dumm
        print("\n")

        # Model's Confusion matrix (test set)
        # Apply values on function " get_visual_confusion_matrix "
        print("* Dummy classifier -Confusion matrix (test set)\n")
        get_visual_confusion_matrix(actual_target_variable= y_test ,predicted_target_variable=
        print("\n")

        # Model's ROC-AUC curve
        # Apply values on function " plot_roc_auc_curve " with actual target and predicted pr

        print("* ROC-AUC curve on Dummy classifier b/w actual target and Predicted probabilit
        plot_roc_auc_curve (actual_target_variable= y_test ,predicted_target_variable= pred_te
```

```
* ML-Model : DummyClassifier(constant=None, random_state=0, strategy='most_frequent')
* Accuracy (on training set): 73.61
* Accuracy CV 10-Fold(on training set): 73.61
* Running Time: 0:00:09.536563


* Dummy ClassifierModel Evaluation  (test set)

* Dummy Classifier evaluation score (on test set)
      Accuracy Score: 0.7316129032258064
      Precision Score: 0.0
      Recall Score: 0.0
      F1_score: 0.0
      ROC_AUC_score: 0.5
      Log_Loss_Score: 9.269761922763125


* Dummy classifier  -Classification Report (on test set)
              precision    recall  f1-score   support

       No :0       0.73      1.00      0.85      1701
       Yes:1       0.00      0.00      0.00       624

   micro avg       0.73      0.73      0.73      2325
   macro avg       0.37      0.50      0.42      2325
weighted avg       0.54      0.73      0.62      2325
```

* Dummy classifier -Confusion matrix (test set)



* ROC-AUC curve on Dummy classifier b/w actual target and Predicted probabilities



12.3 Selection of Best Classification Model and their Hyper-parameter Machine Lerning classifier provides many classification algorithms. Few of them are LogisticRegression , DecisionTreeClassifier, RandomForestClassifier , GradientBoostingClassifier, XGBClassifier , KNeighborsClassifier , GaussianNB

In order to predict classification accuracy from model it is required to train the model with suitable hyperparamter. Thus selection of best hyper-paramter can be done through either GridSearchCV or RandomSearchCV.

Here I used RandomSearchCV because Random search tries random combinations of a range of values and while training it takes less time. On the other hand Grid search will give the best combination but it can take a lot of time.

```
In [57]: # Function for Hyper parameter selection
         def hyper_param_selection_RandomSearchCV(ml_algo , parms_dict , no_of_iteration , fea
             ''' This function return the best values of hyperparameters for ML algorithm'''
             from sklearn.model_selection import RandomizedSearchCV

             random_search = RandomizedSearchCV(estimator= ml_algo ,
                                                param_distributions= parms_dict ,
                                                n_iter= no_of_iteration, n_jobs= -1,
                                                cv=5 ,random_state=50)

             # Model fittin with feature_variable & target_variable
             random_search.fit(feature_variable , target_variable)
```

```
    return random_search.cv_results_ , random_search.best_params_

# Utility function to report best scores
def report(results, n_top=5):
    '''Utility function to report best scores'''
    for i in range(1, n_top + 1):
        candidates = np.flatnonzero(results['rank_test_score'] == i)
        for candidate in candidates:
            print("Model with rank: {0}".format(i))
            print("Mean validation score: {0:.3f} (std: {1:.3f})".format(
                  results['mean_test_score'][candidate],
                  results['std_test_score'][candidate]))
            print("Parameters: {0}".format(results['params'][candidate]))
            print("")
```

Selection Of Candidate Algorithms

- LogisticRegression
- DecisionTreeClassifier
- RandomForestClassifier
- GradientBoostingClassifier
- KNeighborsClassifier
- GaussianNB
- XGBClassifier

12.3.1 Logistic Regression Classifier Selection Of Hyper Paramter for Logistics regression

In [58]:
```
# Selection Of Hyper Paramter for Logistics regression

# Hyper paramter for logistic regression
params_dist = {'penalty': ['l2', 'l1'],
               'class_weight': [None, 'balanced'],
               'intercept_scaling': np.logspace(-20, 20, 10000),
               'C': np.logspace(-20, 20, 10000)
              }

# Logistic regression alogorithm
from sklearn.linear_model import LogisticRegression
logRegrClf = LogisticRegression()

# Apply values on function "hyper_param_selection_RandomSearchCV" to get best hyperpa
hyper_params_logReg , best_hyperParam_logreg = hyper_param_selection_RandomSearchCV(ml
                                                  parms_dict= params_dist ,no_of_ite
                                                  feature_variable = X_train , targe

print("Hyper Paramter for Logistics Regression\n")
report(hyper_params_logReg)
```

```
print("Best Hyperparameter for Logistics Regresion")
print(best_hyperParam_logreg)
```

```
Hyper Paramter for Logistics Regression

Model with rank: 1
Mean validation score: 0.815 (std: 0.007)
Parameters: {'penalty': 'l1', 'intercept_scaling': 1.5886202787099985e-10, 'class_weight': None

Model with rank: 2
Mean validation score: 0.813 (std: 0.006)
Parameters: {'penalty': 'l1', 'intercept_scaling': 26732692588.850086, 'class_weight': None, '

Model with rank: 3
Mean validation score: 0.736 (std: 0.000)
Parameters: {'penalty': 'l2', 'intercept_scaling': 0.2477076355991714, 'class_weight': None, '

Model with rank: 3
Mean validation score: 0.736 (std: 0.000)
Parameters: {'penalty': 'l1', 'intercept_scaling': 4.074375072391666, 'class_weight': 'balance

Model with rank: 3
Mean validation score: 0.736 (std: 0.000)
Parameters: {'penalty': 'l2', 'intercept_scaling': 345.34551912178443, 'class_weight': None, '

Model with rank: 3
Mean validation score: 0.736 (std: 0.000)
Parameters: {'penalty': 'l1', 'intercept_scaling': 3.440754332237622e-14, 'class_weight': 'bal

Model with rank: 3
Mean validation score: 0.736 (std: 0.000)
Parameters: {'penalty': 'l1', 'intercept_scaling': 5.447203715024437e-19, 'class_weight': 'bal

Model with rank: 3
Mean validation score: 0.736 (std: 0.000)
Parameters: {'penalty': 'l2', 'intercept_scaling': 3.63041268157839e+19, 'class_weight': None,

Best Hyperparameter for Logistics Regresion
{'penalty': 'l1', 'intercept_scaling': 1.5886202787099985e-10, 'class_weight': None, 'C': 8855
```

12.3.1.1 Logistic Regression Model Model Evaluation on Training Set

In [59]:
```
# Logistic Regression
start_time = time.time()

# Initialize Logistics Regression with hyper-parameters
```

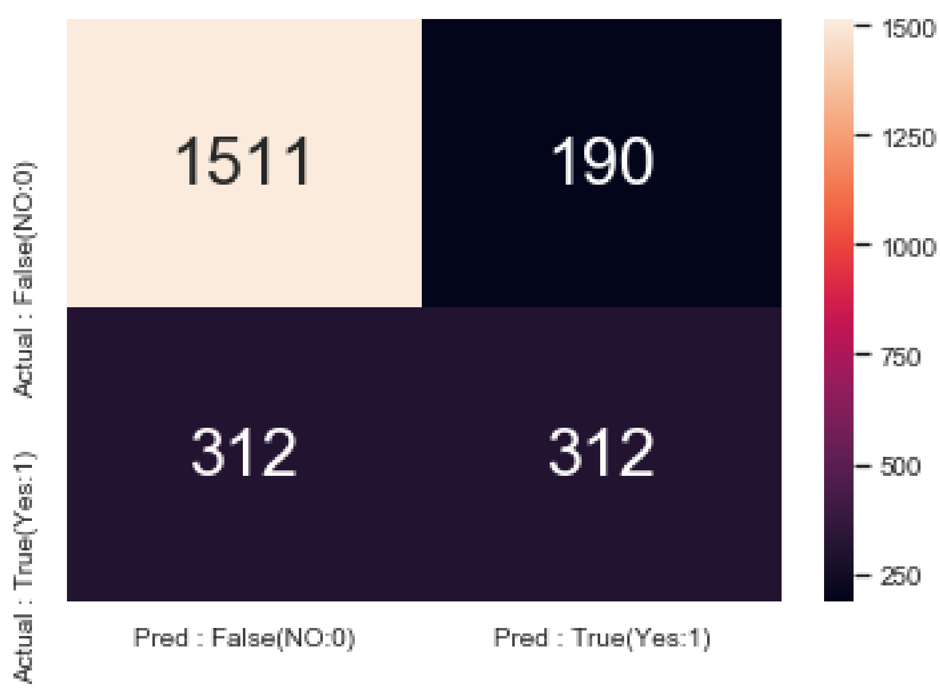
```python
logisticsRegressionClf = LogisticRegression(**best_hyperParam_logreg)

# Start timer before model fitting
start_time = time.time()

# 1. model fitting with LogisticRegression
logisticsRegression_model = model_fitting(ml_algo= logisticsRegressionClf , \
                            feature_variable_train= X_train , target_variable_train= y

dummy_time = (time.time() - start_time)
print("Logistics Regression : Model Evaluation on Training dataset\n")
print("Running Time: %s" % datetime.timedelta(seconds=dummy_time) ,"\n")
print("* ML-Model:", logisticsRegression_model[0],"\n")
print("* Logistics Regression-Predicted Values (on training set):", logisticsRegressio
print("* Logistics Regression-Predicted Probabilities (on training set):", logisticsRe
print("* Logistics Regression-Accuracy (on training set): %s" % logisticsRegression_mo
print("* Logistics Regression-Accuracy CV 10-Fold(on training set): %s" % logisticsReg
print("* Logistics Regression-Classification Report (on training set):\n",get_classifi
                                                    predicted_target_variable= logisti
```

```
Logistics Regression : Model Evaluation on Training dataset

Running Time: 0:00:11.149131

* ML-Model: LogisticRegression(C=885512547609.7212, class_weight=None, dual=False,
          fit_intercept=True, intercept_scaling=1.5886202787099985e-10,
          max_iter=100, multi_class='warn', n_jobs=None, penalty='l1',
          random_state=None, solver='warn', tol=0.0001, verbose=0,
          warm_start=False)

* Logistics Regression-Predicted Values (on training set): [0 1 0 ... 0 1 1]

* Logistics Regression-Predicted Probabilities (on training set): [0.42871147 0.61107544 0.1685

* Logistics Regression-Accuracy (on training set): 81.73

* Logistics Regression-Accuracy CV 10-Fold(on training set): 81.26

* Logistics Regression-Classification Report (on training set):
               precision    recall  f1-score   support

       No :0       0.85      0.90      0.88      3473
       Yes:1       0.68      0.56      0.61      1245

   micro avg       0.81      0.81      0.81      4718
   macro avg       0.76      0.73      0.74      4718
weighted avg       0.80      0.81      0.81      4718
```

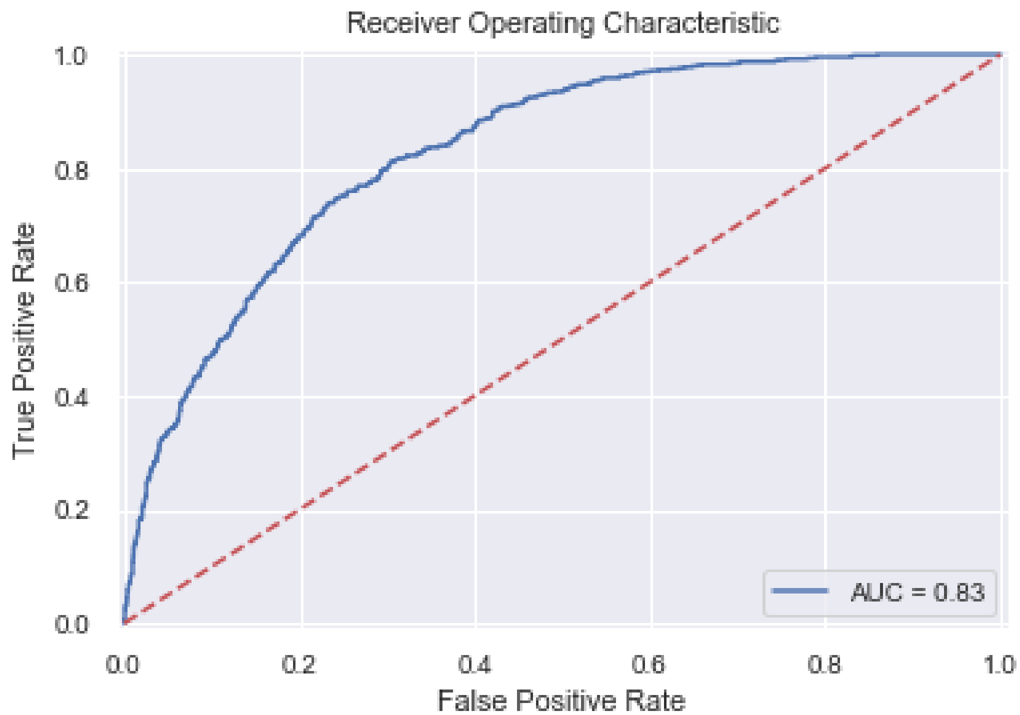
Model Evaluation on Test Set

In [60]:
```
# Predict Target variable (test set)

# 2. Apply values on function " predict_target "
logisticsRegclf_test_pred , logisticsRegclf_test_prob_pred = predict_target(feature_va
                                                            ml_model= logisticsRegres

print("Logistics Regression : Model Evaluation  (on test set)\n")

# 3. Apply values on function " get_model_evaluation_scores "
logisticsRegclf_model_score = get_model_evaluation_scores(actual_target_variable= y_te
                                                  predicted_target_variable= logistics

print("* Logistics Regression : Evaluation score (on test set)\n\tAccuracy Score: {0}
       \n\tRecall Score: {2}\n\tF1_score: {3}\n\tROC_AUC_score: {4}\n\tLog_Loss_Score
    logisticsRegclf_model_score[0], logisticsRegclf_model_score[1], logisticsRegclf_mo
    logisticsRegclf_model_score[3],logisticsRegclf_model_score[4],logisticsRegclf_mode


# Model Classification report (test set)
# 4.  Apply values on function " get_classification_report "
print("* Logistics Regression-Classification Report (on test set)\n",\
    get_classification_report(actual_target_variable= y_test ,\
      predicted_target_variable= logisticsRegclf_test_pred))
print("\n")

# Model's Confusion matrix (test set)
# 5. Apply values on function " get_visual_confusion_matrix "
print("* Logistics Regression-Confusion matrix (on test set)\n")
get_visual_confusion_matrix(actual_target_variable= y_test ,\
       predicted_target_variable= logisticsRegclf_test_pred)
print("\n")

# Model's ROC-AUC curve (test set)
# 6. Apply values on function " plot_roc_auc_curve "
print("* ROC-AUC curve on Logistics Regression classifier (on test set) \n")
plot_roc_auc_curve (actual_target_variable= y_test ,\
      predicted_target_variable= logisticsRegclf_test_prob_pred)

# Model's Precision-Recall curve (test set)
# 7. Apply values on function " plot_precision_recall_curve "
print("* Precision-Recall curve on Logistics Regression classifier (on test set)\n")
plot_precision_recall_curve(actual_target_variable= y_test ,\
      predicted_target_variable= logisticsRegclf_test_pred)
```

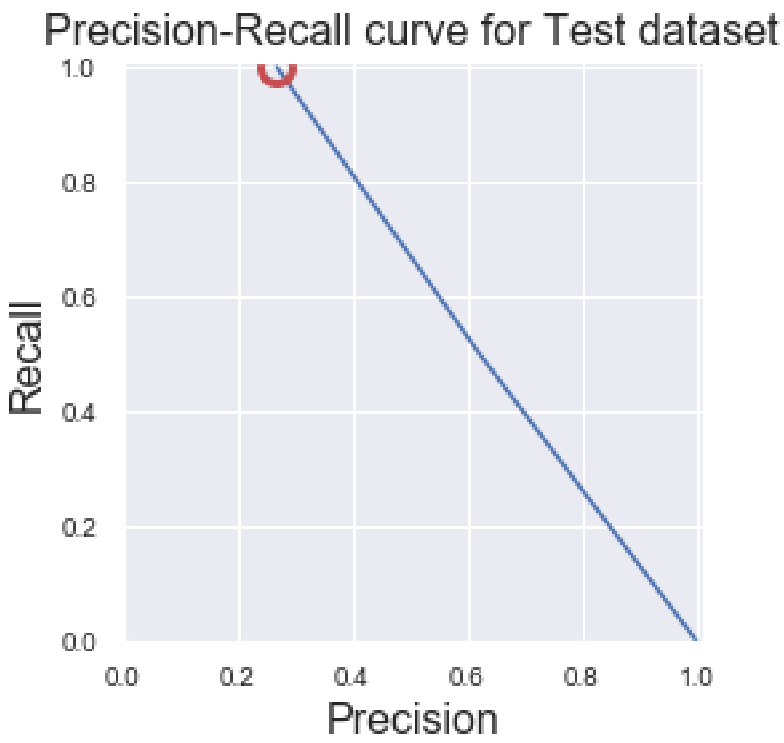
```
Logistics Regression : Model Evaluation  (on test set)

* Logistics Regression : Evaluation score (on test set)
        Accuracy Score: 0.7840860215053763
        Precision Score: 0.6215139442231076
        Recall Score: 0.5
        F1_score: 0.5541740674955595
        ROC_AUC_score: 0.6941504997060552
        Log_Loss_Score: 7.457469967207269

* Logistics Regression-Classification Report (on test set)
               precision    recall  f1-score   support

       No :0       0.83      0.89      0.86      1701
       Yes:1       0.62      0.50      0.55       624

   micro avg       0.78      0.78      0.78      2325
   macro avg       0.73      0.69      0.71      2325
weighted avg       0.77      0.78      0.78      2325


* Logistics Regression-Confusion matrix (on test set)
```



* ROC-AUC curve on Logistics Regression classifier (on test set)



* Precision-Recall curve on Logistics Regression classifier (on test set)



12.3.2 DecisionTree Classifier Selection Of Hyper Paramter for DecisionTree

```
In [61]: # Hyper paramter for logistic regression
         params_dist = {"criterion": ["gini", "entropy"],
                        "min_samples_split": [2, 10, 20],
                        "max_depth": [None, 2, 5, 10],
                        "min_samples_leaf": [1, 5, 10],
                        "max_leaf_nodes": [None, 5, 10, 20],
                        }

         # Logistic regression alogorithm
         from sklearn.tree import DecisionTreeClassifier
         decTreeclf = DecisionTreeClassifier()

         # Apply values on function "hyper_param_selection_RandomSearchCV" to get best hyperpa
         hyper_params_decTreeclf , best_hyperParam_decTreeclf = hyper_param_selection_RandomSea
                                                                 parms_dict= params_dist , no_
                                                                  feature_variable = X_train ,

         print("Hyper Paramter for DecisionTreeClassifier\n")
         report(hyper_params_decTreeclf)
```

```
print("Best Hyperparameter for DecisionTreeClassifier")
print(best_hyperParam_decTreeclf)
```

```
Hyper Paramter for DecisionTreeClassifier

Model with rank: 1
Mean validation score: 0.799 (std: 0.009)
Parameters: {'min_samples_split': 10, 'min_samples_leaf': 1, 'max_leaf_nodes': None, 'max_deptl

Model with rank: 1
Mean validation score: 0.799 (std: 0.018)
Parameters: {'min_samples_split': 2, 'min_samples_leaf': 5, 'max_leaf_nodes': 20, 'max_depth':

Model with rank: 3
Mean validation score: 0.798 (std: 0.016)
Parameters: {'min_samples_split': 20, 'min_samples_leaf': 1, 'max_leaf_nodes': 10, 'max_depth'

Model with rank: 4
Mean validation score: 0.797 (std: 0.013)
Parameters: {'min_samples_split': 20, 'min_samples_leaf': 1, 'max_leaf_nodes': None, 'max_deptl

Model with rank: 5
Mean validation score: 0.793 (std: 0.014)
Parameters: {'min_samples_split': 10, 'min_samples_leaf': 5, 'max_leaf_nodes': 10, 'max_depth'

Model with rank: 5
Mean validation score: 0.793 (std: 0.014)
Parameters: {'min_samples_split': 20, 'min_samples_leaf': 1, 'max_leaf_nodes': 10, 'max_depth'

Best Hyperparameter for DecisionTreeClassifier
{'min_samples_split': 10, 'min_samples_leaf': 1, 'max_leaf_nodes': None, 'max_depth': 5, 'crit
```

12.3.2.1 Decision Tree Model
Model Evaluation on Training Set

In [62]:
```
# Decision Tree Regression
start_time = time.time()

# Initialize DecisionTree with hyper-parameters

from sklearn.tree import DecisionTreeClassifier

decisionTreeClf = DecisionTreeClassifier(**best_hyperParam_decTreeclf)

# Start timer before model fitting
start_time = time.time()
```

```python
    # 1. model fitting with LogisticRegression
    decisionTree_model = model_fitting(ml_algo= decisionTreeClf , feature_variable_train=
                                       target_variable_train= y_train , cross_validation=

    dummy_time = (time.time() - start_time)

    print("DecisionTreeClassifier : Model Evaluation on Training dataset\n")
    print("Running Time: %s" % datetime.timedelta(seconds=dummy_time) ,"\n")
    print("* ML-Model:", decisionTree_model[0],"\n")
    print("* Predicted Values (on training set):", decisionTree_model[1],"\n")
    print("* Predicted Probabilities (on training set):", decisionTree_model[2],"\n")
    print("* Accuracy (on training set): %s" % decisionTree_model[3],"\n")
    print("* Accuracy CV 10-Fold(on training set): %s" % decisionTree_model[4],"\n")
    print("* Decision Tree - Classification Report (on training set):\n",\
          get_classification_report(actual_target_variable= y_train ,
          predicted_target_variable= decisionTree_model[1]),"\n")
```

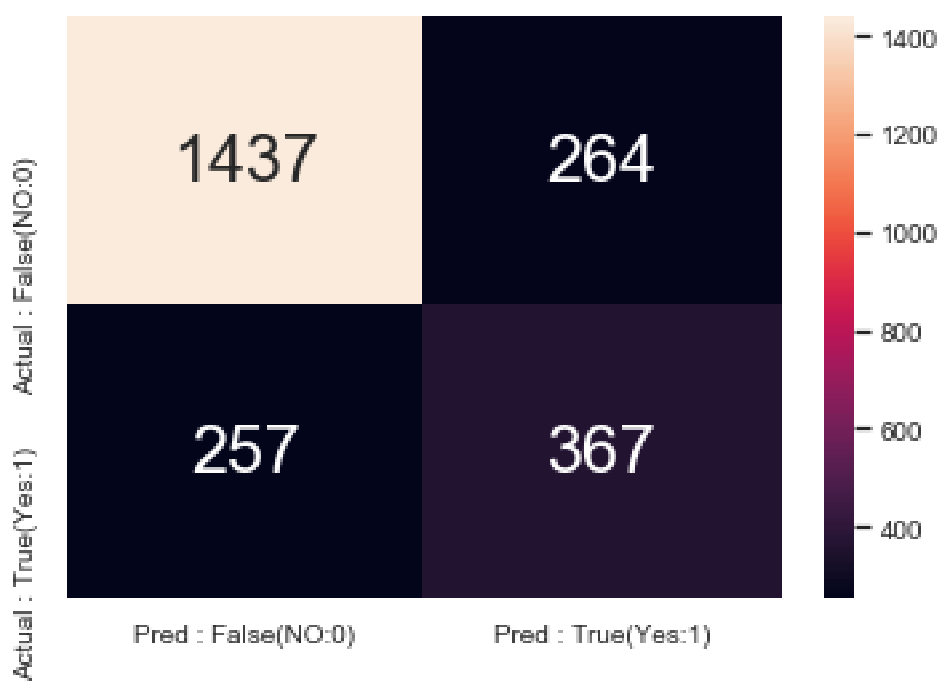
```
DecisionTreeClassifier : Model Evaluation on Training dataset

Running Time: 0:00:00.455719

* ML-Model: DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=5,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=10,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')

* Predicted Values (on training set): [0 1 0 ... 0 1 1]

* Predicted Probabilities (on training set): [0.36929461 0.51256281 0.17283951 ... 0.         0

* Accuracy (on training set): 80.82

* Accuracy CV 10-Fold(on training set): 79.97

* Decision Tree - Classification Report (on training set):
               precision    recall  f1-score   support

       No :0       0.87      0.86      0.86      3473
       Yes:1       0.62      0.62      0.62      1245

   micro avg       0.80      0.80      0.80      4718
   macro avg       0.74      0.74      0.74      4718
weighted avg       0.80      0.80      0.80      4718
```

Model Evaluation on Test Set

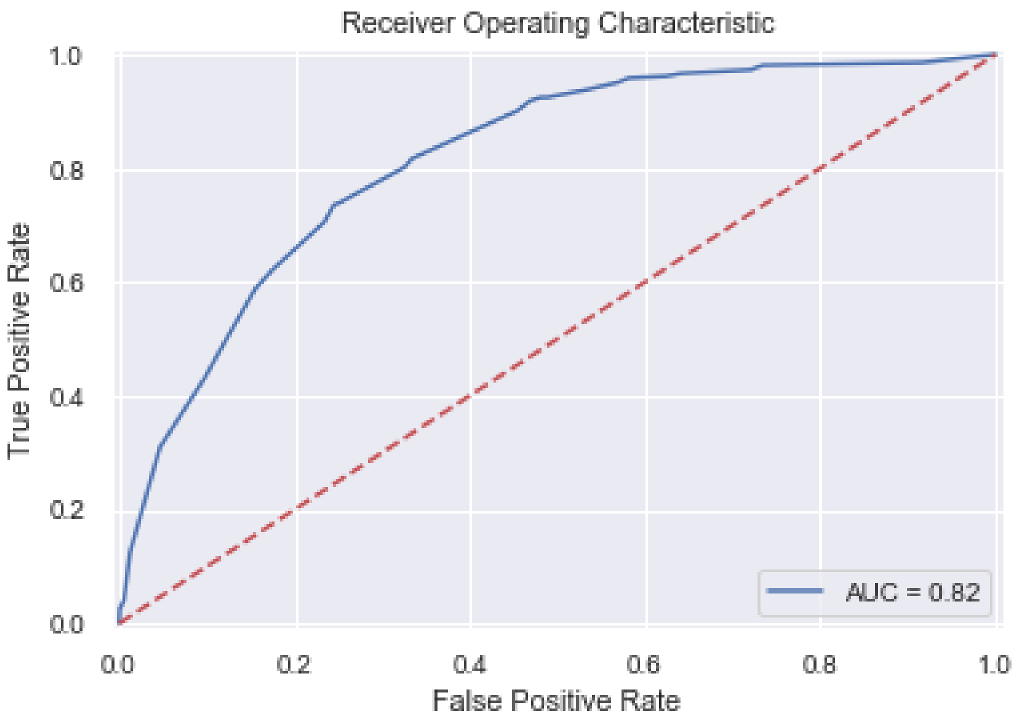
```
In [63]: # Predict Target variable (test set)

         # 2. Apply values on function " predict_target "
         decisionTree_model_test_pred ,decisionTree_model_test_prob_pred  = predict_target(fea
                                                      ml_model= decisionTree_model[0])

         print("DecisionTreeClassifier : Model Evaluation  (on test set)\n")

         # 3. Apply values on function " get_model_evaluation_scores "
         decisionTree_model_score = get_model_evaluation_scores(actual_target_variable= y_test
                                    predicted_target_variable= decisionTree_model_test_pred)

         print("* DecisionTree : Evaluation score (on test set)\n\tAccuracy Score: {0}\n\tPrec
                \n\tRecall Score: {2}\n\tF1_score: {3}\n\tROC_AUC_score: {4}\n\tLog_Loss_Score
                decisionTree_model_score[0], decisionTree_model_score[1], decisionTree_model_s
                decisionTree_model_score[3],decisionTree_model_score[4],decisionTree_model_sco


         # Model Classification report (test set)
         # 4.  Apply values on function " get_classification_report "
         print("* DecisionTree - Classification Report (on test set)\n",\
               get_classification_report(actual_target_variable= y_test , \
               predicted_target_variable= decisionTree_model_test_pred))

         print("\n")

         # Model's Confusion matrix (test set)
         # 5. Apply values on function " get_visual_confusion_matrix "
         print("* DecisionTree - Confusion matrix (on test set)\n")
         get_visual_confusion_matrix(actual_target_variable= y_test , \
               predicted_target_variable= decisionTree_model_test_pred)

         print("\n")

         # Model's ROC-AUC curve
         # 6. Apply values on function " plot_roc_auc_curve "
         print("* ROC-AUC curve on DecisionTreeClassifier (on test set) \n")
         plot_roc_auc_curve (actual_target_variable= y_test , \
               predicted_target_variable= decisionTree_model_test_prob_pred)

         # Model's ROC-AUC curve
         # 7. Apply values on function " plot_roc_auc_curve "
         print("* Precision-Recall curve on DecisionTreeClassifier (on test set)  \n")
         plot_precision_recall_curve (actual_target_variable= y_test , \
               predicted_target_variable= decisionTree_model_test_pred)
```

```
DecisionTreeClassifier : Model Evaluation  (on test set)
```

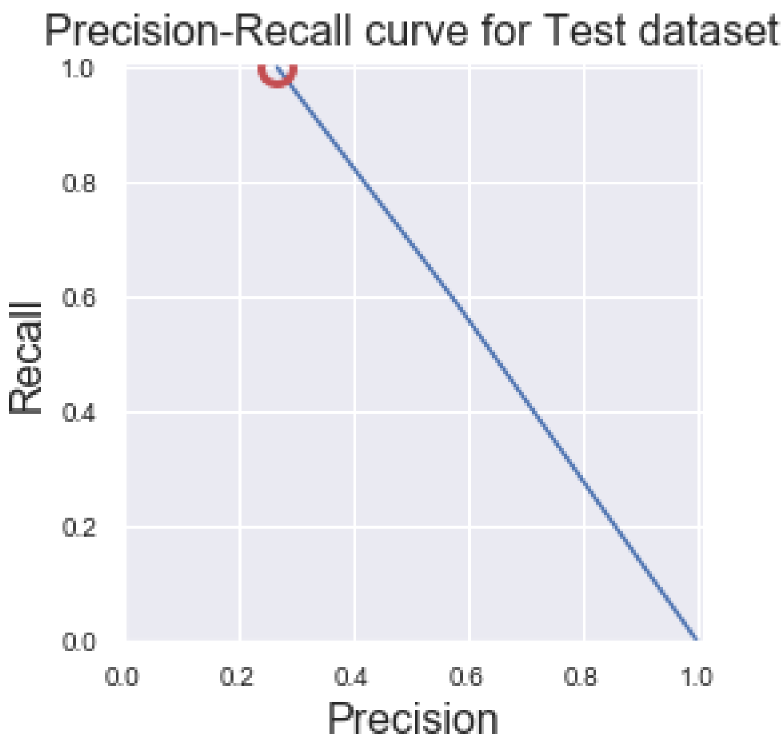
```
* DecisionTree : Evaluation score (on test set)
        Accuracy Score: 0.7759139784946236
        Precision Score: 0.5816164817749604
        Recall Score: 0.5881410256410257
        F1_score: 0.5848605577689243
        ROC_AUC_score: 0.7164691018857685
        Log_Loss_Score: 7.739747782997867

* DecisionTree - Classification Report (on test set)
               precision    recall  f1-score   support

       No :0       0.85      0.84      0.85      1701
       Yes:1       0.58      0.59      0.58       624

   micro avg       0.78      0.78      0.78      2325
   macro avg       0.71      0.72      0.72      2325
weighted avg       0.78      0.78      0.78      2325


* DecisionTree - Confusion matrix (on test set)
```



* ROC-AUC curve on DecisionTreeClassifier (on test set)



* Precision-Recall curve on DecisionTreeClassifier (on test set)



12.3.3 Random Forest Classifier Selection Of Hyper Paramter for RandomForest

```
In [64]: # Selection Of Hyper Paramter for RandomForest

         # Hyper paramter for logistic regression
         params_dist = {"criterion": ["gini", "entropy"],
                        "min_samples_split": [2, 10, 20],
                        "max_depth": [2, 5, 10],
                        "min_samples_leaf": [2, 5, 10],
                        "max_leaf_nodes": [2, 5, 10, 20],
                        "n_estimators":[10,100]
                        }

         # Logistic regression alogorithm
         from sklearn.ensemble import RandomForestClassifier
         randomForestclf = RandomForestClassifier()

         # Apply values on function "hyper_param_selection_RandomSearchCV" to get best hyperpa
         hyper_params_randomForestclf , best_hyperParam_randomForest = hyper_param_selection_Ra
                                        parms_dict= params_dist , no_of_iteration =10 ,\
                                        feature_variable = X_train , target_variable =y_train

         print("Hyper Paramter for RandomForestClassifier\n")
```

```
report(hyper_params_randomForestclf)

print("Best Hyperparameter for RandomForestClassifier")
print(best_hyperParam_randomForest)
```

```
Hyper Paramter for RandomForestClassifier

Model with rank: 1
Mean validation score: 0.800 (std: 0.012)
Parameters: {'n_estimators': 10, 'min_samples_split': 10, 'min_samples_leaf': 10, 'max_leaf_noc

Model with rank: 2
Mean validation score: 0.797 (std: 0.010)
Parameters: {'n_estimators': 10, 'min_samples_split': 2, 'min_samples_leaf': 10, 'max_leaf_node

Model with rank: 3
Mean validation score: 0.793 (std: 0.011)
Parameters: {'n_estimators': 10, 'min_samples_split': 20, 'min_samples_leaf': 5, 'max_leaf_node

Model with rank: 4
Mean validation score: 0.792 (std: 0.012)
Parameters: {'n_estimators': 100, 'min_samples_split': 10, 'min_samples_leaf': 10, 'max_leaf_nc

Model with rank: 5
Mean validation score: 0.790 (std: 0.011)
Parameters: {'n_estimators': 10, 'min_samples_split': 2, 'min_samples_leaf': 10, 'max_leaf_node

Best Hyperparameter for RandomForestClassifier
{'n_estimators': 10, 'min_samples_split': 10, 'min_samples_leaf': 10, 'max_leaf_nodes': 20, 'ma
```

12.3.3.1 Random Forest Classification Model Model Evaluation on Training Set

In [65]:
```
# Random Forest Classification


# Initialize Random Forest Classification with hyper-parameters

from sklearn.ensemble import RandomForestClassifier

randomForestClf = RandomForestClassifier(**best_hyperParam_randomForest)

# Start timer before model fitting
start_time = time.time()

# 1. model fitting with RandomForestClassifier
randomForest_model = model_fitting(ml_algo= randomForestClf , feature_variable_train=
                                   target_variable_train= y_train , cross_validation=
```

```
    dummy_time = (time.time() - start_time)

    print("RandomForestClassifier : Model Evaluation on Training dataset\n")
    print("Running Time: %s" % datetime.timedelta(seconds=dummy_time) ,"\n")
    print("* ML-Model:", randomForest_model[0],"\n")
    print("* Predicted Values (on training set):", randomForest_model[1],"\n")
    print("* Predicted Probabilities (on training set):", randomForest_model[2],"\n")
    print("* Accuracy (on training set): %s" % randomForest_model[3],"\n")
    print("* Accuracy CV 10-Fold(on training set): %s" % randomForest_model[4],"\n")
    print("* RandomForest - Classification Report (on training set):\n",\
          get_classification_report(actual_target_variable= y_train , \
          predicted_target_variable= randomForest_model[1]),"\n")
```

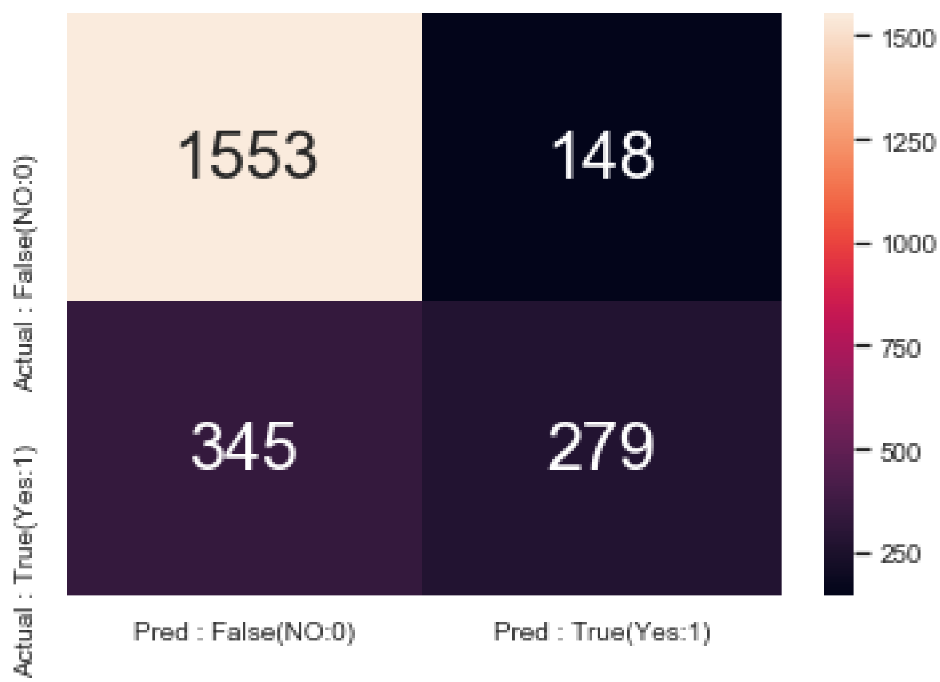
```
RandomForestClassifier : Model Evaluation on Training dataset

Running Time: 0:00:00.996386

* ML-Model: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entropy',
            max_depth=10, max_features='auto', max_leaf_nodes=20,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=10, min_samples_split=10,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

* Predicted Values (on training set): [0 0 0 ... 0 1 1]

* Predicted Probabilities (on training set): [0.24466664 0.50588613 0.36120906 ... 0.01561311 0

* Accuracy (on training set): 81.26

* Accuracy CV 10-Fold(on training set): 80.44

* RandomForest - Classification Report (on training set):
               precision    recall  f1-score   support

       No :0       0.83      0.92      0.87      3473
       Yes:1       0.69      0.48      0.56      1245

   micro avg       0.80      0.80      0.80      4718
   macro avg       0.76      0.70      0.72      4718
weighted avg       0.79      0.80      0.79      4718
```

```
In [66]: # Predict Target variable (test set)
```

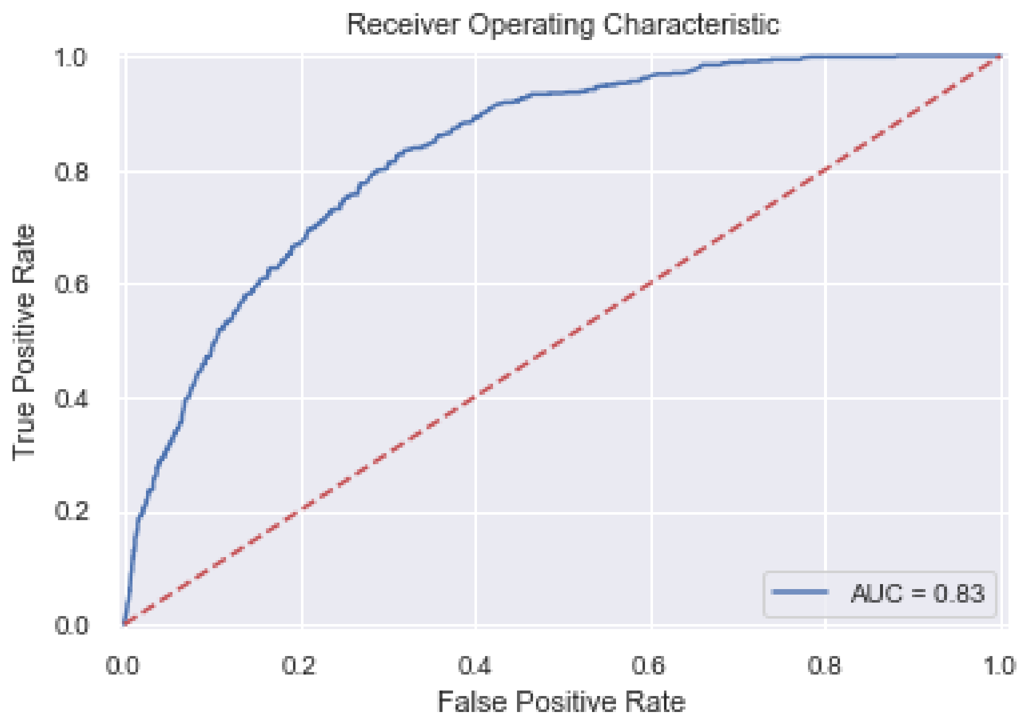
```
# 2. Apply values on function " predict_target "
randomForest_model_test_pred , randomForest_model_test_prob_pred = predict_target(fea
                                                     ml_model= randomForest_model[0])

print("RandomForestClassifier : Model Evaluation  (on test set)\n")

# 3. Apply values on function " get_model_evaluation_scores "
randomForest_model_score = get_model_evaluation_scores(actual_target_variable= y_test
                           predicted_target_variable= randomForest_model_test_pred)

print("* Random Forest : Evaluation score (on test set)\n\tAccuracy Score: {0}\n\tPre
       \n\tRecall Score: {2}\n\tF1_score: {3}\n\tROC_AUC_score: {4}\n\tLog_Loss_Score
       randomForest_model_score[0], randomForest_model_score[1], randomForest_model_s
       randomForest_model_score[3],randomForest_model_score[4],randomForest_model_sco


# Model Classification report (test set)
# 4.  Apply values on function " get_classification_report "
print("* Random Forest - Classification Report (on test set)\n",\
      get_classification_report(actual_target_variable= y_test , \
      predicted_target_variable= randomForest_model_test_pred))

print("\n")

# Model's Confusion matrix (test set)
# 5. Apply values on function " get_visual_confusion_matrix "
print("* Random Forest -Confusion matrix (on test set)\n")
get_visual_confusion_matrix(actual_target_variable= y_test , \
      predicted_target_variable= randomForest_model_test_pred)

print("\n")

# Model's ROC-AUC curve
# 6. Apply values on function " plot_roc_auc_curve "
print("* ROC-AUC curve on RandomForestClassifier (on test set) \n")
plot_roc_auc_curve (actual_target_variable= y_test , \
      predicted_target_variable= randomForest_model_test_prob_pred)

# Model's ROC-AUC curve
# 7. Apply values on function " plot_roc_auc_curve "
print("* Precision-Recall curve on RandomForestClassifier (on test set)  \n")
plot_precision_recall_curve (actual_target_variable= y_test , \
      predicted_target_variable= randomForest_model_test_pred)
```

```
RandomForestClassifier : Model Evaluation  (on test set)

* Random Forest : Evaluation score (on test set)
        Accuracy Score: 0.7879569892473118
```

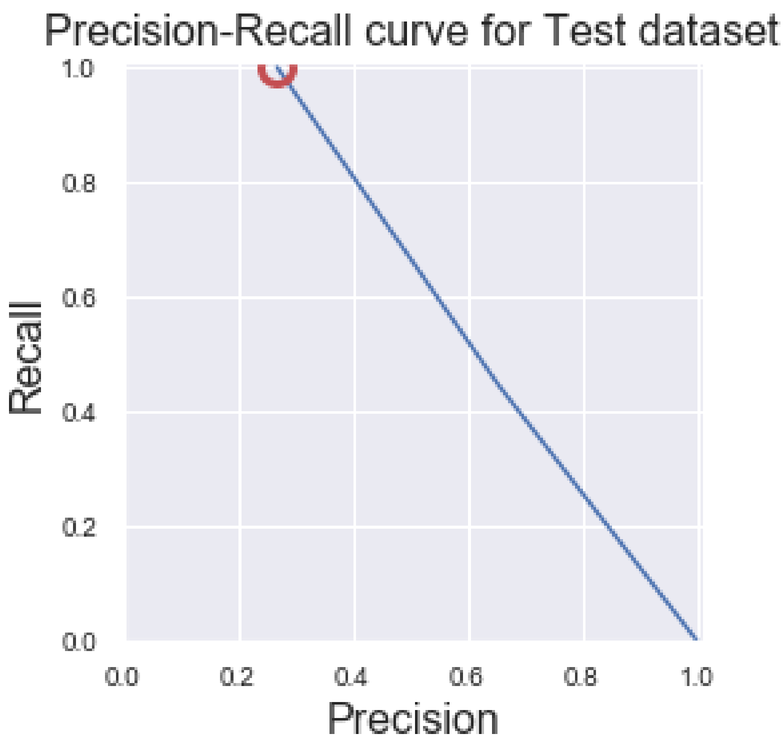
```
        Precision Score: 0.6533957845433255
        Recall Score: 0.44711538461538464
        F1_score: 0.5309229305423405
        ROC_AUC_score: 0.6800538710260932
        Log_Loss_Score: 7.323757033595973

* Random Forest - Classification Report (on test set)
              precision    recall  f1-score   support

       No :0       0.82      0.91      0.86      1701
       Yes:1       0.65      0.45      0.53       624

   micro avg       0.79      0.79      0.79      2325
   macro avg       0.74      0.68      0.70      2325
weighted avg       0.77      0.79      0.77      2325



* Random Forest -Confusion matrix (on test set)
```




```
* ROC-AUC curve on RandomForestClassifier (on test set)
```




```
* Precision-Recall curve on RandomForestClassifier (on test set)
```



12.4 GradientBoostingClassifier Selection Of Hyper Paramter for GradientBoostingClassifier

In [67]:
```
# Selection Of Hyper Paramter for GradientBoostingClassifier

# Hyper paramter for GradientBoostingClassifier
params_dist = {"loss": ["deviance", "exponential"],
               "learning_rate" :[0.01, 0.1],
              "max_depth": [2, 5, 10],
              "min_samples_split" :[2,10,20],
              "min_samples_leaf": [2, 5, 10],
              "max_leaf_nodes": [2, 5, 10, 20],
              "n_estimators":[10,100]
              }

# GradientBoostingClassifier alogorithm
from sklearn.ensemble import GradientBoostingClassifier
gradientBoostclf = GradientBoostingClassifier()

# Apply values on function "hyper_param_selection_RandomSearchCV" to get best hyperpa
hyper_params_gradientBoostclf, best_hyperParam_gradientBoostclf = hyper_param_selecti
                              parms_dict= params_dist , no_of_iteration =10 ,\
                              feature_variable = X_train , target_variable =y_train
```

```
print("Hyper Paramter for GradientBoostingClassifier\n")
report(hyper_params_gradientBoostclf)

print("Best Hyperparameter for GradientBoostingClassifier")
print(best_hyperParam_gradientBoostclf)
```

```
Hyper Paramter for GradientBoostingClassifier

Model with rank: 1
Mean validation score: 0.805 (std: 0.011)
Parameters: {'n_estimators': 100, 'min_samples_split': 20, 'min_samples_leaf': 10, 'max_leaf_no

Model with rank: 2
Mean validation score: 0.805 (std: 0.010)
Parameters: {'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf': 2, 'max_leaf_node

Model with rank: 3
Mean validation score: 0.805 (std: 0.009)
Parameters: {'n_estimators': 100, 'min_samples_split': 20, 'min_samples_leaf': 5, 'max_leaf_noc

Model with rank: 4
Mean validation score: 0.804 (std: 0.006)
Parameters: {'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf': 2, 'max_leaf_node

Model with rank: 5
Mean validation score: 0.791 (std: 0.011)
Parameters: {'n_estimators': 10, 'min_samples_split': 10, 'min_samples_leaf': 10, 'max_leaf_noc

Best Hyperparameter for GradientBoostingClassifier
{'n_estimators': 100, 'min_samples_split': 20, 'min_samples_leaf': 10, 'max_leaf_nodes': 5, 'ma
```

12.4.1 GradientBoostingClassifier Model Model Evaluation on Training Set

In [68]:
```
# GradientBoostingClassifier  Classification


# Initialize GradientBoostingClassifier  with hyper-parameters

from sklearn.ensemble import GradientBoostingClassifier

gradientBoostClf = GradientBoostingClassifier(**best_hyperParam_gradientBoostclf)

# Start timer before model fitting
start_time = time.time()

# 1. model fitting with Random Forest Classifier
gradientBoostClf_model = model_fitting(ml_algo= gradientBoostClf , feature_variable_tr
```

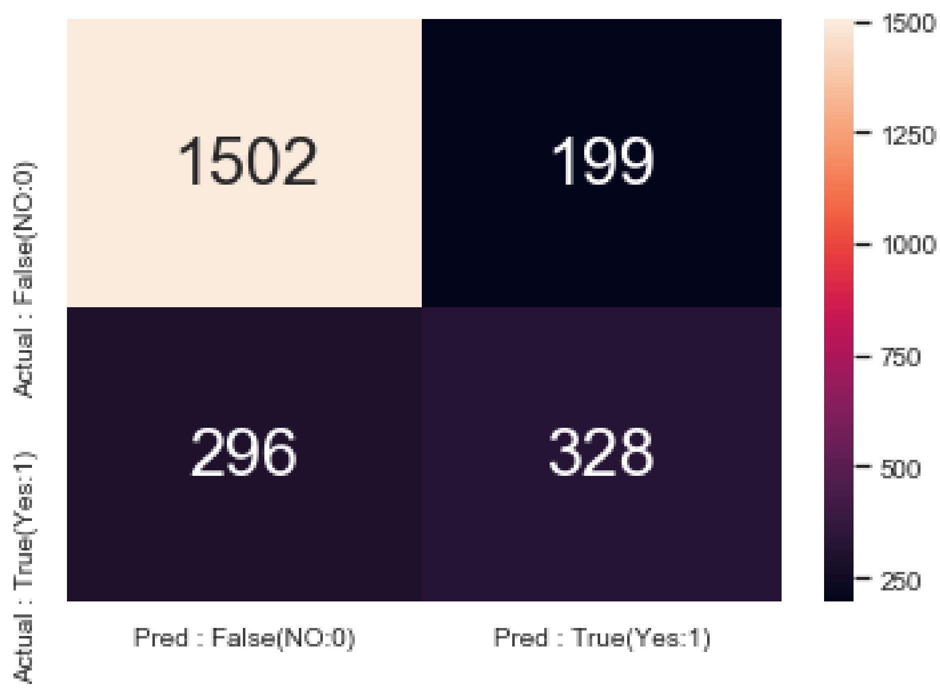
```
                                               target_variable_train= y_train , cross_validation=

        dummy_time = (time.time() - start_time)

        print("GradientBoostingClassifier - Model Evaluation on Training dataset\n")
        print("Running Time: %s" % datetime.timedelta(seconds=dummy_time) ,"\n")
        print("* ML-Model:", gradientBoostClf_model[0],"\n")
        print("* Predicted Values (on training set):", gradientBoostClf_model[1],"\n")
        print("* Predicted Probabilities (on training set):", gradientBoostClf_model[2],"\n")
        print("* Accuracy (on training set): %s" % gradientBoostClf_model[3],"\n")
        print("* Accuracy CV 10-Fold(on training set): %s" % gradientBoostClf_model[4],"\n")
        print("* GradientBoostingClassifier  - Classification Report (on training set):\n",\
              get_classification_report(actual_target_variable= y_train , \
              predicted_target_variable= gradientBoostClf_model[1]),"\n")
```

```
GradientBoostingClassifier - Model Evaluation on Training dataset

Running Time: 0:00:10.057800

* ML-Model: GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='exponential', max_depth=5,
              max_features=None, max_leaf_nodes=5,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=10, min_samples_split=20,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              n_iter_no_change=None, presort='auto', random_state=None,
              subsample=1.0, tol=0.0001, validation_fraction=0.1,
              verbose=0, warm_start=False)

* Predicted Values (on training set): [0 1 0 ... 0 1 1]

* Predicted Probabilities (on training set): [0.38109967 0.61724741 0.19648421 ... 0.00914905 0

* Accuracy (on training set): 82.87

* Accuracy CV 10-Fold(on training set): 81.05

* GradientBoostingClassifier  - Classification Report (on training set):
               precision    recall  f1-score   support

       No :0       0.85      0.90      0.87      3473
       Yes:1       0.67      0.56      0.61      1245

   micro avg       0.81      0.81      0.81      4718
   macro avg       0.76      0.73      0.74      4718
weighted avg       0.80      0.81      0.80      4718
```

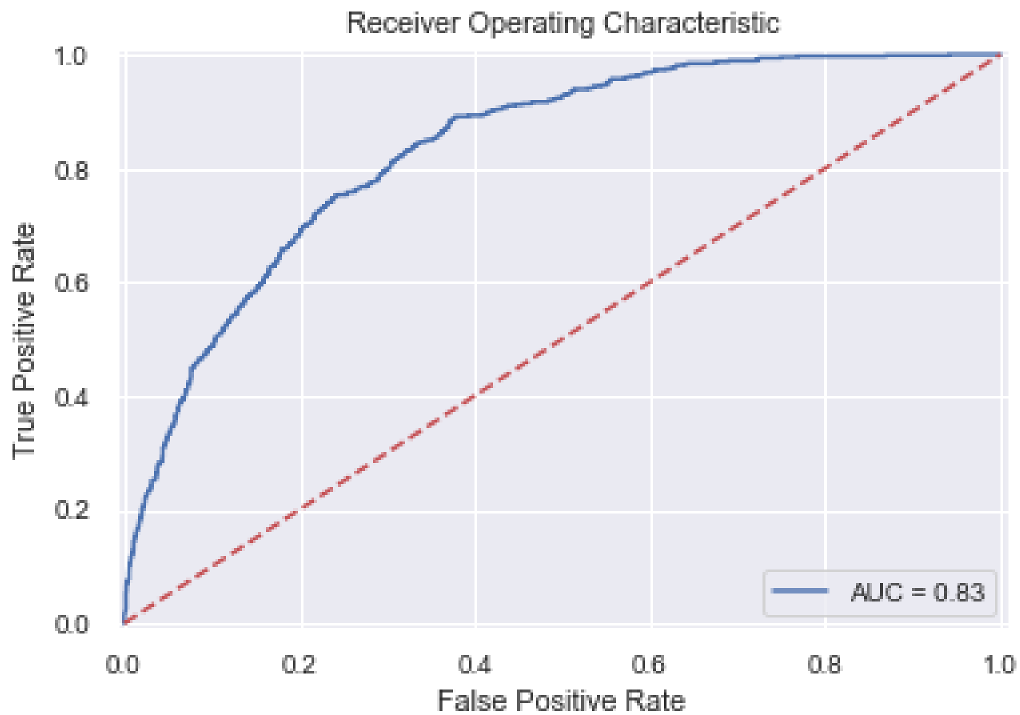
Model Evaluation on Test Set

```
In [69]: # Predict Target variable (test set)

         # 2. Apply values on function " predict_target "
         gradientBoostClf_model_test_pred , gradientBoostClf_model_test_prob_pred = predict_ta
                                                       ml_model= gradientBoostClf_model[0])

         print("GradientBoostingClassifier : Model Evaluation  (on test set)\n")

         # 3. Apply values on function " get_model_evaluation_scores "
         gradientBoostClf_model_score = get_model_evaluation_scores(actual_target_variable= y_
                                    predicted_target_variable= gradientBoostClf_model_test_pre

         print("* GradientBoosting Classifier : Evaluation score (on test set)\n\tAccuracy Sco
                \n\tRecall Score: {2}\n\tF1_score: {3}\n\tROC_AUC_score: {4}\n\tLog_Loss_Score
                gradientBoostClf_model_score[0], gradientBoostClf_model_score[1], gradientBoos
                gradientBoostClf_model_score[3],gradientBoostClf_model_score[4],gradientBoostC


         # Model Classification report (test set)
         # 4.  Apply values on function " get_classification_report "
         print("* GradientBoosting Classifier - Classification Report (on test set)\n",\
               get_classification_report(actual_target_variable= y_test , \
               predicted_target_variable= gradientBoostClf_model_test_pred))

         print("\n")

         # Model's Confusion matrix (test set)
         # 5. Apply values on function " get_visual_confusion_matrix "
         print("* GradientBoosting Classifier -Confusion matrix (on test set)\n")
         get_visual_confusion_matrix(actual_target_variable= y_test , \
               predicted_target_variable= gradientBoostClf_model_test_pred)

         print("\n")

         # Model's ROC-AUC curve
         # 6. Apply values on function " plot_roc_auc_curve "
         print("* ROC-AUC curve on GradientBoosting Classifier (on test set) \n")
         plot_roc_auc_curve (actual_target_variable= y_test , \
               predicted_target_variable= gradientBoostClf_model_test_prob_pred)

         # Model's ROC-AUC curve
         # 7. Apply values on function " plot_roc_auc_curve "
         print("* Precision-Recall curve on GradientBoosting Classifier (on test set)  \n")
         plot_precision_recall_curve (actual_target_variable= y_test , \
               predicted_target_variable= gradientBoostClf_model_test_pred)
```

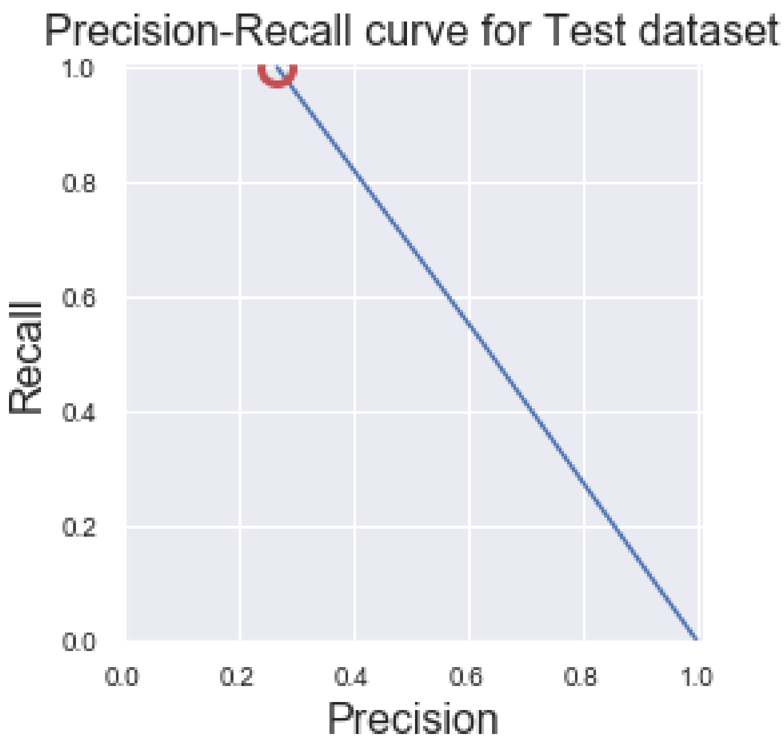
```
GradientBoostingClassifier : Model Evaluation  (on test set)

* GradientBoosting Classifier : Evaluation score (on test set)
        Accuracy Score: 0.7870967741935484
        Precision Score: 0.6223908918406073
        Recall Score: 0.5256410256410257
        F1_score: 0.5699391833188532
        ROC_AUC_score: 0.7043255098810653
        Log_Loss_Score: 7.353485348545978

* GradientBoosting Classifier - Classification Report (on test set)
              precision    recall  f1-score   support

       No :0       0.84      0.88      0.86      1701
       Yes:1       0.62      0.53      0.57       624

   micro avg       0.79      0.79      0.79      2325
   macro avg       0.73      0.70      0.71      2325
weighted avg       0.78      0.79      0.78      2325


* GradientBoosting Classifier -Confusion matrix (on test set)
```



* ROC-AUC curve on GradientBoosting Classifier (on test set)



* Precision-Recall curve on GradientBoosting Classifier (on test set)



12.5 KNeighborclassifier Selection Of Hyper Paramter for KNeighborclassifier

In [70]:
```
# Selection Of Hyper Paramter for GradientBoostingClassifier

# Hyper paramter for KNeighborsClassifier
params_dist = {"n_neighbors": [5,8,10],
               "leaf_size" :[30,60]
               }

# KNeighborsClassifier alogorithm
from sklearn.neighbors import KNeighborsClassifier
kNeighborsclf = KNeighborsClassifier()

# Apply values on function
hyper_params_kNeighborsclf ,best_hyperParam_kNeighborsclf = hyper_param_selection_Ranc
                               parms_dict= params_dist , no_of_iteration =20 ,\
                               feature_variable = X_train , target_variable =y_train

print("Hyper Paramter for KNeighborsClassifier\n")
report(hyper_params_kNeighborsclf)

print("Best Hyperparameter for KNeighborsClassifier")
print(best_hyperParam_kNeighborsclf)
```

```
Hyper Paramter for KNeighborsClassifier

Model with rank: 1
Mean validation score: 0.789 (std: 0.010)
Parameters: {'n_neighbors': 8, 'leaf_size': 30}

Model with rank: 1
Mean validation score: 0.789 (std: 0.010)
Parameters: {'n_neighbors': 8, 'leaf_size': 60}

Model with rank: 3
Mean validation score: 0.786 (std: 0.011)
Parameters: {'n_neighbors': 10, 'leaf_size': 30}

Model with rank: 3
Mean validation score: 0.786 (std: 0.011)
Parameters: {'n_neighbors': 10, 'leaf_size': 60}

Model with rank: 5
Mean validation score: 0.776 (std: 0.008)
Parameters: {'n_neighbors': 5, 'leaf_size': 30}

Model with rank: 5
Mean validation score: 0.776 (std: 0.008)
Parameters: {'n_neighbors': 5, 'leaf_size': 60}

Best Hyperparameter for KNeighborsClassifier
{'n_neighbors': 8, 'leaf_size': 30}
```

12.5.1 KNeighborclassifier Model Model Evaluation on Training Set

In [71]:
```
# KNeighborsClassifier  Classification


# Initialize KNeighborsClassifier  with hyper-parameters

from sklearn.neighbors import KNeighborsClassifier

Parameters= { 'weights':'distance', 'algorithm': 'brute', 'p': 2, 'n_jobs': -1, **bes

kNeighborClf = KNeighborsClassifier(**Parameters)

# Start timer before model fitting
start_time = time.time()

# 1. model fitting with KNeighborsClassifier
kNeighborClf_model = model_fitting(ml_algo= kNeighborClf , feature_variable_train= X_
```

```
                                        target_variable_train= y_train , cross_validation=

        dummy_time = (time.time() - start_time)

        print("KNeighborsClassifier - Model Evaluation on Training dataset\n")
        print("Running Time: %s" % datetime.timedelta(seconds=dummy_time) ,"\n")
        print("* ML-Model:", kNeighborClf_model[0],"\n")
        print("* Predicted Values (on training set):", kNeighborClf_model[1],"\n")
        print("* Predicted Probabilities (on training set):", kNeighborClf_model[2],"\n")
        print("* Accuracy (on training set): %s" % kNeighborClf_model[3],"\n")
        print("* Accuracy CV 10-Fold(on training set): %s" % kNeighborClf_model[4],"\n")
        print("* KNeighborsClassifier  - Classification Report (on training set):\n",\
              get_classification_report(actual_target_variable= y_train , \
              predicted_target_variable= kNeighborClf_model[1]),"\n")
```

```
KNeighborsClassifier - Model Evaluation on Training dataset

Running Time: 0:00:11.844353

* ML-Model: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=-1, n_neighbors=8, p=2,
           weights='distance')

* Predicted Values (on training set): [0 1 1 ... 0 1 1]

* Predicted Probabilities (on training set): [0. 0. 0. ... 0. 1. 1.]

* Accuracy (on training set): 99.77

* Accuracy CV 10-Fold(on training set): 77.28

* KNeighborsClassifier  - Classification Report (on training set):
               precision    recall  f1-score   support

       No :0       0.83      0.86      0.85      3473
       Yes:1       0.58      0.52      0.55      1245

   micro avg       0.77      0.77      0.77      4718
   macro avg       0.71      0.69      0.70      4718
weighted avg       0.77      0.77      0.77      4718
```

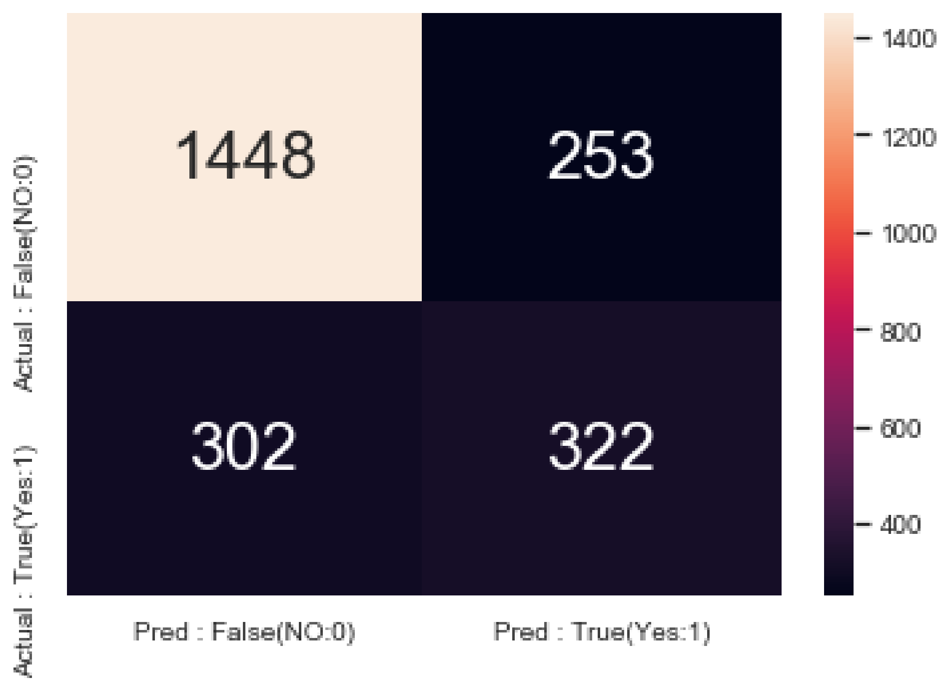
Model Evaluation on Test Set

```
In [72]: # Predict Target variable (test set)
```

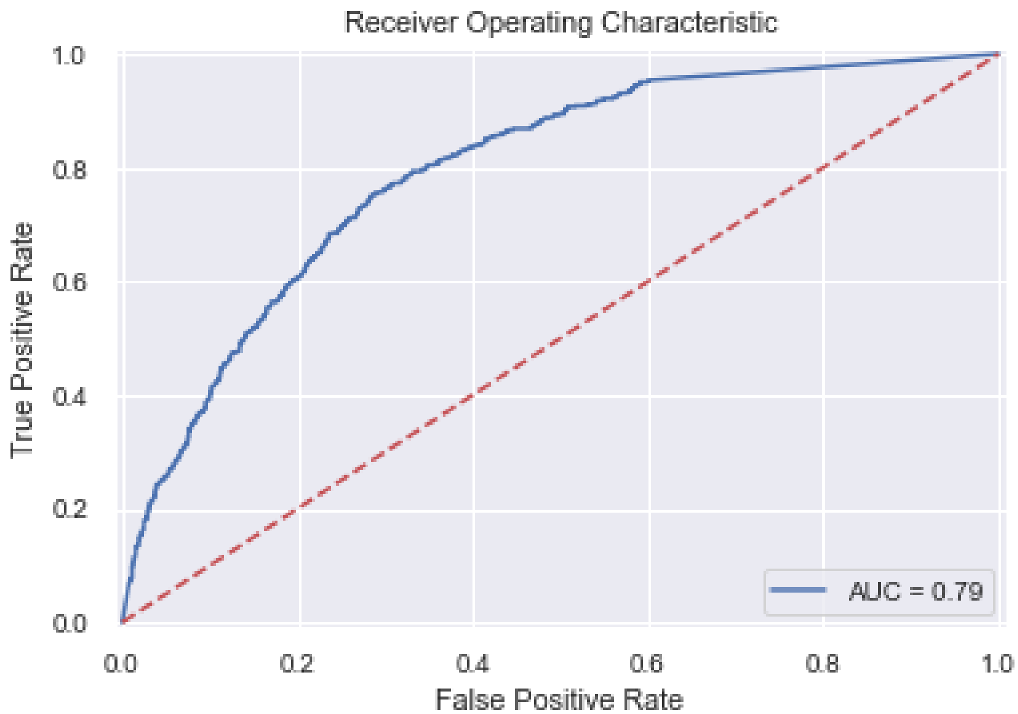
```python
        # 2. Apply values on function " predict_target "
        kNeighborClf_model_test_pred , kNeighborClf_model_test_prob_pred = predict_target(fea
                                                        ml_model= kNeighborClf_model[0])

        print("KNeighborsClassifier : Model Evaluation  (on test set)\n")

        # 3. Apply values on function " get_model_evaluation_scores "
        kNeighborClf_model_score = get_model_evaluation_scores(actual_target_variable= y_test
                                   predicted_target_variable= kNeighborClf_model_test_pred)

        print("KNeighborsClassifier : Evaluation score (on test set)\n\tAccuracy Score: {0}\n
               \n\tRecall Score: {2}\n\tF1_score: {3}\n\tROC_AUC_score: {4}\n\tLog_Loss_Score
               kNeighborClf_model_score[0], kNeighborClf_model_score[1], kNeighborClf_model_s
               kNeighborClf_model_score[3],kNeighborClf_model_score[4],kNeighborClf_model_sco


        # Model Classification report (test set)
        # 4.  Apply values on function " get_classification_report "
        print("KNeighborsClassifier - Classification Report (on test set)\n",\
              get_classification_report(actual_target_variable= y_test , \
              predicted_target_variable= kNeighborClf_model_test_pred))

        print("\n")

        # Model's Confusion matrix (test set)
        # 5. Apply values on function " get_visual_confusion_matrix "
        print("KNeighborsClassifier -Confusion matrix (on test set)\n")
        get_visual_confusion_matrix(actual_target_variable= y_test , \
              predicted_target_variable= kNeighborClf_model_test_pred)

        print("\n")

        # Model's ROC-AUC curve
        # 6. Apply values on function " plot_roc_auc_curve "
        print("ROC-AUC curve on KNeighborsClassifier (on test set) \n")
        plot_roc_auc_curve (actual_target_variable= y_test , \
              predicted_target_variable= kNeighborClf_model_test_prob_pred)

        # Model's ROC-AUC curve
        # 7. Apply values on function " plot_roc_auc_curve "
        print("Precision-Recall curve on KNeighborsClassifier (on test set)  \n")
        plot_precision_recall_curve (actual_target_variable= y_test , \
              predicted_target_variable= kNeighborClf_model_test_pred)
```

```
KNeighborsClassifier : Model Evaluation  (on test set)

KNeighborsClassifier : Evaluation score (on test set)
        Accuracy Score: 0.7612903225806451
```

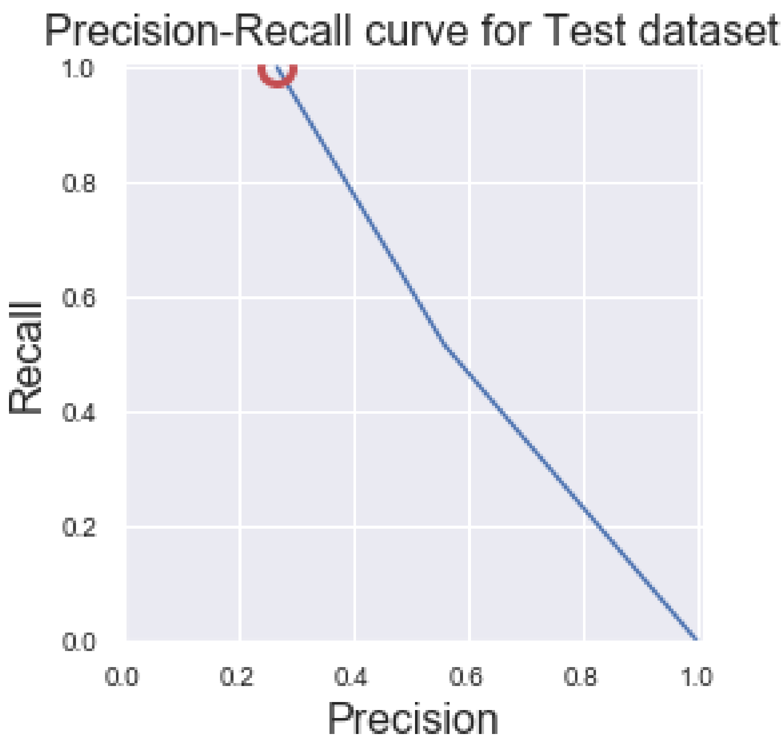
```
        Precision Score: 0.56
        Recall Score: 0.5160256410256411
        F1_score: 0.5371142618849042
        ROC_AUC_score: 0.6836448017003572
        Log_Loss_Score: 8.244827181645277

KNeighborsClassifier - Classification Report (on test set)
               precision    recall  f1-score   support

       No :0       0.83      0.85      0.84      1701
       Yes:1       0.56      0.52      0.54       624

   micro avg       0.76      0.76      0.76      2325
   macro avg       0.69      0.68      0.69      2325
weighted avg       0.76      0.76      0.76      2325



KNeighborsClassifier -Confusion matrix (on test set)
```




```
ROC-AUC curve on KNeighborsClassifier (on test set)
```



Precision-Recall curve on KNeighborsClassifier (on test set)



12.6 GaussianNB

12.6.1 GaussianNB Classifier Model   Model Evaluation on Training Set

In [73]:
```
# GaussianNB Classifier  Classification


# Initialize GaussianNB Classifier  with hyper-parameters

from sklearn.naive_bayes import GaussianNB

#Parameters= {'priors': None, 'var_smoothing': 1e-09}

#gaussianNBClf = GaussianNB(**Parameters)
gaussianNBClf = GaussianNB()

# Start timer before model fitting
start_time = time.time()

# 1. model fitting with GaussianNB Classifier
gaussianNBClf_model = model_fitting(ml_algo= gaussianNBClf , feature_variable_train= X
                                   target_variable_train= y_train , cross_validation=
```

```
dummy_time = (time.time() - start_time)

print("GaussianNB Classifier - Model Evaluation on Training dataset\n")
print("Running Time: %s" % datetime.timedelta(seconds=dummy_time) ,"\n")
print("* ML-Model:", gaussianNBClf_model[0],"\n")
print("* Predicted Values (on training set):", gaussianNBClf_model[1],"\n")
print("* Predicted Probabilities (on training set):", gaussianNBClf_model[2],"\n")
print("* Accuracy (on training set): %s" % gaussianNBClf_model[3],"\n")
print("* Accuracy CV 10-Fold(on training set): %s" % gaussianNBClf_model[4],"\n")
print("* GaussianNB Classifier  - Classification Report (on training set):\n",\
      get_classification_report(actual_target_variable= y_train , \
      predicted_target_variable= gaussianNBClf_model[1]),"\n")
```

```
GaussianNB Classifier - Model Evaluation on Training dataset

Running Time: 0:00:00.630314

* ML-Model: GaussianNB(priors=None, var_smoothing=1e-09)

* Predicted Values (on training set): [0 1 0 ... 0 1 1]

* Predicted Probabilities (on training set): [1.09852423e-03 9.85500837e-01 2.81700188e-01 ...
 9.99874116e-01 9.99979698e-01]

* Accuracy (on training set): 75.29

* Accuracy CV 10-Fold(on training set): 75.18

* GaussianNB Classifier  - Classification Report (on training set):
               precision    recall  f1-score   support

       No :0       0.91      0.74      0.81      3473
       Yes:1       0.52      0.79      0.63      1245

   micro avg       0.75      0.75      0.75      4718
   macro avg       0.71      0.76      0.72      4718
weighted avg       0.81      0.75      0.76      4718
```

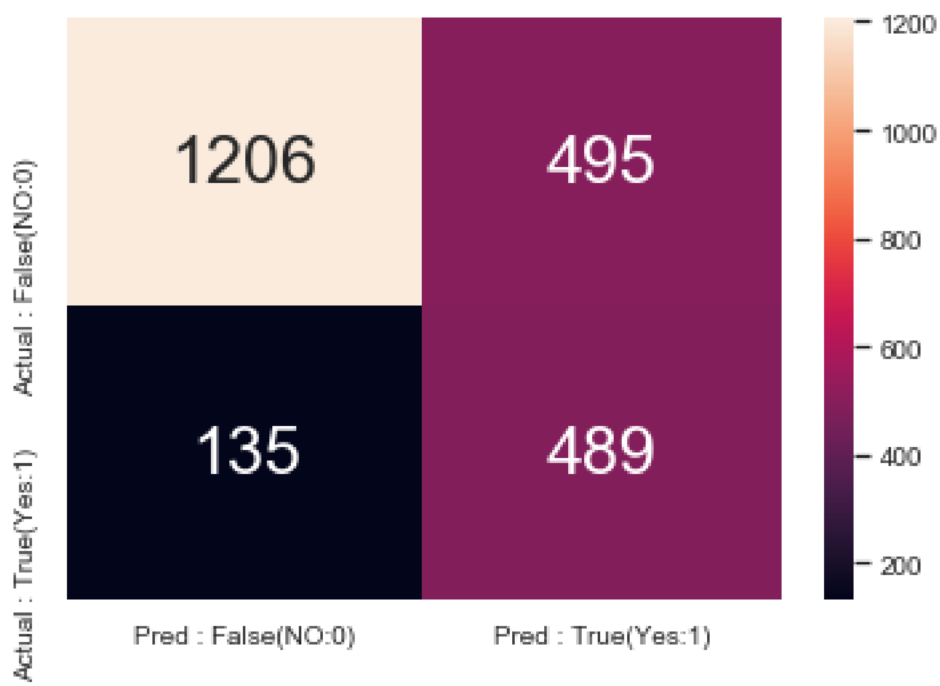
Model Evaluation on Test Set

In [74]:
```
# Predict Target variable (test set)

# 2. Apply values on function " predict_target "
gaussianNBClf_model_test_pred , gaussianNBClf_model_test_prob_pred = predict_target(fe
```

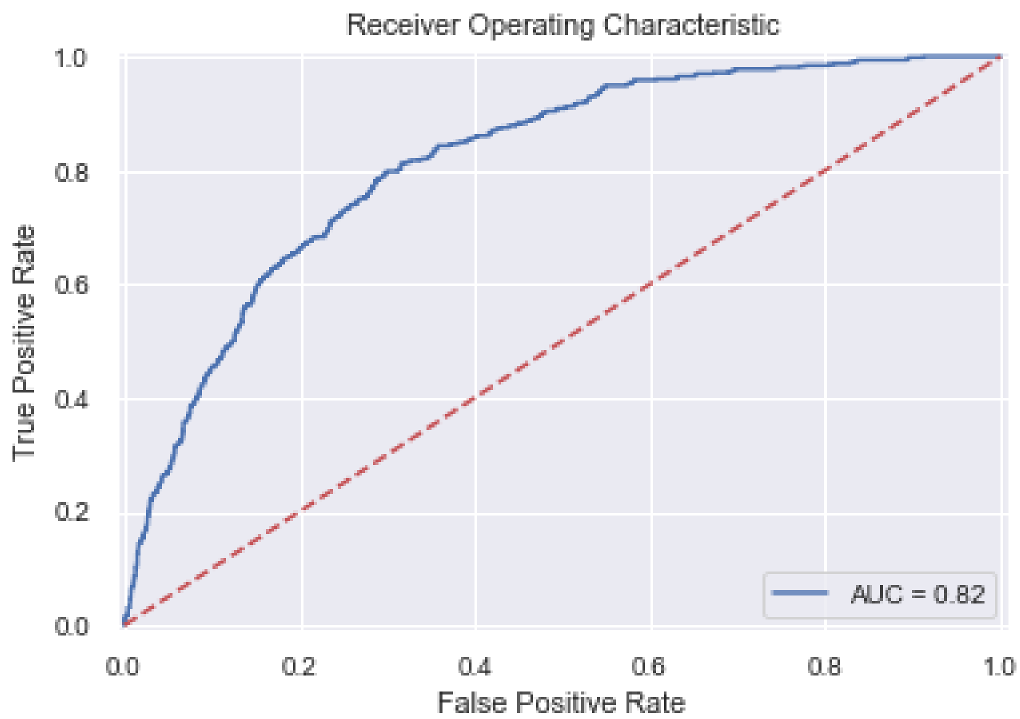
```
                                    ml_model= gaussianNBClf_model[0])

        print("GaussianNB Classifier : Model Evaluation  (on test set)\n")

        # 3. Apply values on function " get_model_evaluation_scores "
        gaussianNBClf_model_score = get_model_evaluation_scores(actual_target_variable= y_tes
                                    predicted_target_variable= gaussianNBClf_model_test_pred)

        print("GaussianNB Classifier : Evaluation score (on test set)\n\tAccuracy Score: {0}\
               \n\tRecall Score: {2}\n\tF1_score: {3}\n\tROC_AUC_score: {4}\n\tLog_Loss_Score
               gaussianNBClf_model_score[0], gaussianNBClf_model_score[1], gaussianNBClf_mode
               gaussianNBClf_model_score[3],gaussianNBClf_model_score[4],gaussianNBClf_model_


        # Model Classification report (test set)
        # 4.  Apply values on function " get_classification_report "
        print("GaussianNB Classifier - Classification Report (on test set)\n",\
              get_classification_report(actual_target_variable= y_test , \
              predicted_target_variable= gaussianNBClf_model_test_pred))

        print("\n")

        # Model's Confusion matrix (test set)
        # 5. Apply values on function " get_visual_confusion_matrix "
        print("GaussianNB Classifier -Confusion matrix (on test set)\n")
        get_visual_confusion_matrix(actual_target_variable= y_test , \
              predicted_target_variable= gaussianNBClf_model_test_pred)

        print("\n")

        # Model's ROC-AUC curve
        # 6. Apply values on function " plot_roc_auc_curve "
        print("ROC-AUC curve on GaussianNB Classifier (on test set) \n")
        plot_roc_auc_curve (actual_target_variable= y_test , \
              predicted_target_variable= gaussianNBClf_model_test_prob_pred)

        # Model's ROC-AUC curve
        # 7. Apply values on function " plot_roc_auc_curve "
        print("Precision-Recall curve on GaussianNB Classifier (on test set)  \n")
        plot_precision_recall_curve (actual_target_variable= y_test , \
              predicted_target_variable= gaussianNBClf_model_test_pred)
```

```
GaussianNB Classifier : Model Evaluation  (on test set)

GaussianNB Classifier : Evaluation score (on test set)
        Accuracy Score: 0.7290322580645161
        Precision Score: 0.4969512195121951
        Recall Score: 0.7836538461538461
```

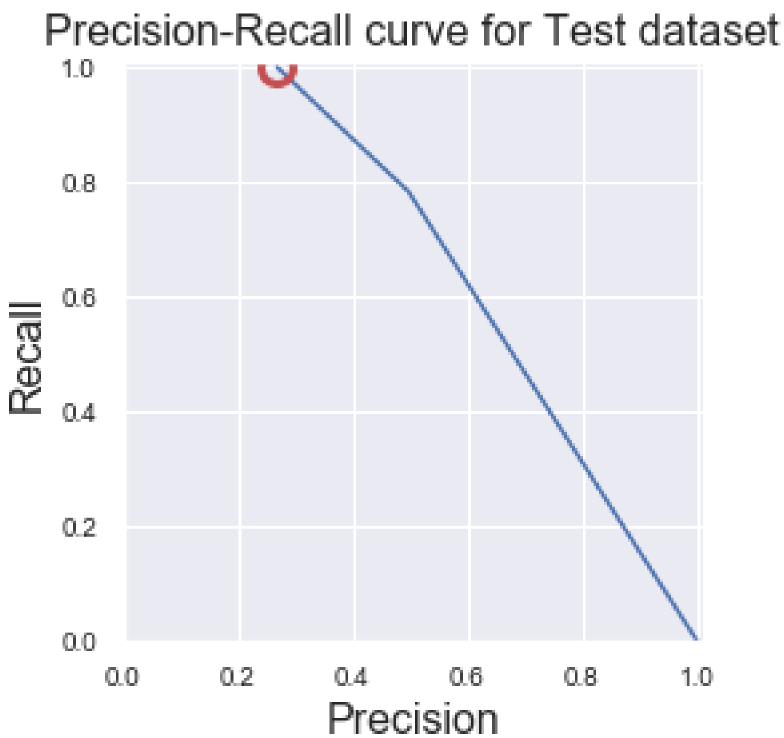
```
        F1_score: 0.6082089552238806
        ROC_AUC_score: 0.7463242775742777
        Log_Loss_Score: 9.359064485815777

GaussianNB Classifier - Classification Report (on test set)
               precision    recall  f1-score   support

       No :0       0.90      0.71      0.79      1701
       Yes:1       0.50      0.78      0.61       624

   micro avg       0.73      0.73      0.73      2325
   macro avg       0.70      0.75      0.70      2325
weighted avg       0.79      0.73      0.74      2325



GaussianNB Classifier -Confusion matrix (on test set)
```




```
ROC-AUC curve on GaussianNB Classifier (on test set)
```



Precision-Recall curve on GaussianNB Classifier (on test set)



12.7 XGBoostClassifier

12.7.1 XGBoostClassifier Model   Model Evaluation on Training Set

In [75]:
```
# XGBoostClassifier Classifier  Classification


# Initialize XGBoostClassifier  with hyper-parameters

from xgboost import XGBClassifier

# Hyper parameter for XGBClassifier
Param_dist = { 'booster':'gbtree',
               'verbosity':0,
               'max_depth':40,
               'learning_rate':0.2,
               'gamma':0.9,
               'subsample':0.9,
               'eval_metric':'error',
               'n_estimators':400,
               'colsample_bytree':1,
               'objective':'binary:logistic',
```

```
                  'silent':True,
                  'nthread':-1,
                  'scale_pos_weight':1
                }


xgBoostClf = XGBClassifier(**Param_dist)

# Start timer before model fitting
start_time = time.time()

# 1. model fitting with XGBClassifier
xgBoostClf_model = model_fitting(ml_algo= xgBoostClf , feature_variable_train= X_trai
                                  target_variable_train= y_train , cross_validation=

dummy_time = (time.time() - start_time)

print("XGBoostClassifier - Model Evaluation on Training dataset\n")
print("Running Time: %s" % datetime.timedelta(seconds=dummy_time) ,"\n")
print("* ML-Model:", xgBoostClf_model[0],"\n")
print("* Predicted Values (on training set):", xgBoostClf_model[1],"\n")
print("* Predicted Probabilities (on training set):", xgBoostClf_model[2],"\n")
print("* Accuracy (on training set): %s" % xgBoostClf_model[3],"\n")
print("* Accuracy CV 10-Fold(on training set): %s" % xgBoostClf_model[4],"\n")
print("* XGBoostClassifier  - Classification Report (on training set):\n",\
      get_classification_report(actual_target_variable= y_train , \
      predicted_target_variable= xgBoostClf_model[1]),"\n")
```

```
XGBoostClassifier - Model Evaluation on Training dataset

Running Time: 0:04:44.170782

* ML-Model: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, eval_metric='error', gamma=0.9,
       learning_rate=0.2, max_delta_step=0, max_depth=40,
       min_child_weight=1, missing=None, n_estimators=400, n_jobs=1,
       nthread=-1, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=0.9, verbosity=0)

* Predicted Values (on training set): [0 1 0 ... 0 1 1]

* Predicted Probabilities (on training set): [4.35406305e-02 2.75124848e-01 1.08111896e-01 ...
 9.18952465e-01 9.91299927e-01]

* Accuracy (on training set): 99.64

* Accuracy CV 10-Fold(on training set): 78.0
```

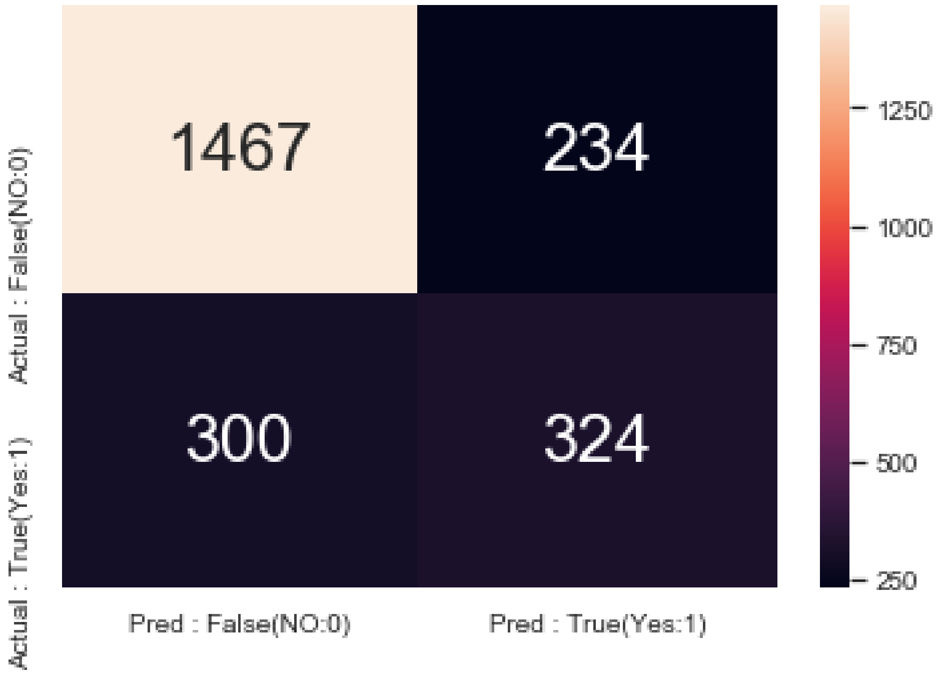
```
* XGBoostClassifier  - Classification Report (on training set):
               precision    recall  f1-score   support

       No :0       0.83      0.88      0.85      3473
       Yes:1       0.60      0.51      0.55      1245

   micro avg       0.78      0.78      0.78      4718
   macro avg       0.72      0.69      0.70      4718
weighted avg       0.77      0.78      0.77      4718
```

Model Evaluation on Test Set

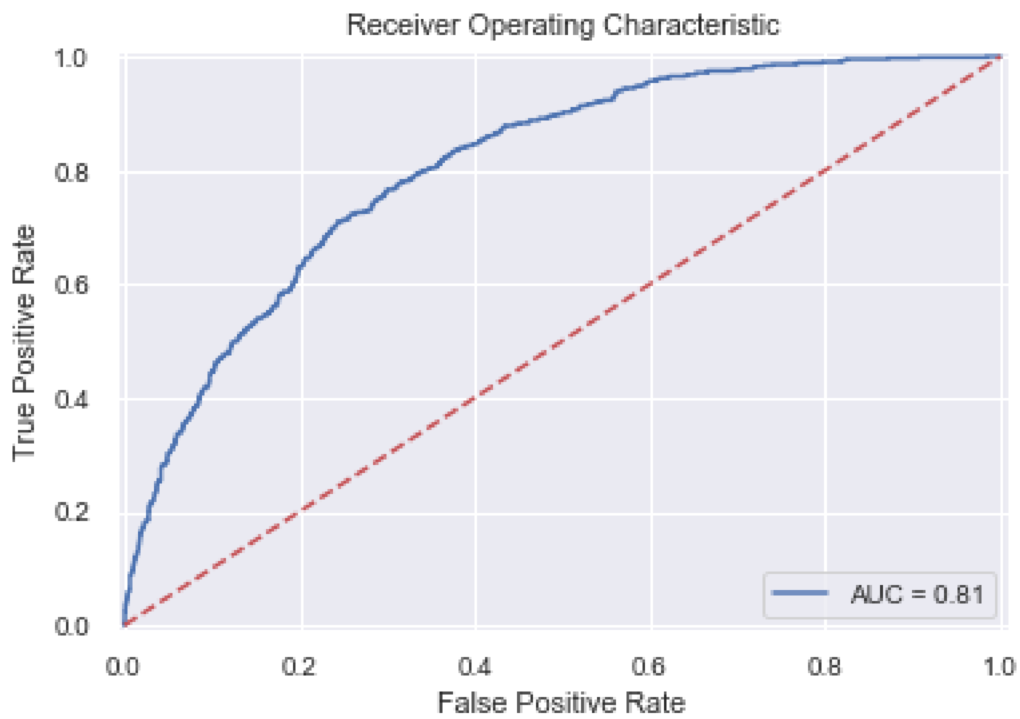
In [76]:
```python
# Predict Target variable (test set)

# 2. Apply values on function " predict_target " and target probabilities
xgBoostClf_model_test_pred , xgBoostClf_model_test_prob_pred = predict_target(feature_
                                              ml_model= xgBoostClf_model[0])

print("XGBoost Classifier : Model Evaluation  (on test set)\n")

# 3. Apply values on function " get_model_evaluation_scores "
xgBoostClf_model_score = get_model_evaluation_scores(actual_target_variable= y_test ,
                           predicted_target_variable= xgBoostClf_model_test_pred)

print("XGBoost Classifier : Evaluation score (on test set)\n\tAccuracy Score: {0}\n\tP
       \n\tRecall Score: {2}\n\tF1_score: {3}\n\tROC_AUC_score: {4}\n\tLog_Loss_Score
       xgBoostClf_model_score[0], xgBoostClf_model_score[1], xgBoostClf_model_score[2]
       xgBoostClf_model_score[3],xgBoostClf_model_score[4],xgBoostClf_model_score[5])


# Model Classification report (test set)
# 4.  Apply values on function " get_classification_report "
print("XGBoost Classifier - Classification Report (on test set)\n",\
      get_classification_report(actual_target_variable= y_test , \
      predicted_target_variable= xgBoostClf_model_test_pred))

print("\n")

# Model's Confusion matrix (test set)
# 5. Apply values on function " get_visual_confusion_matrix "
print("XGBoost Classifier -Confusion matrix (on test set)\n")
get_visual_confusion_matrix(actual_target_variable= y_test , \
      predicted_target_variable= xgBoostClf_model_test_pred)
```

```
    print("\n")

    # Model's ROC-AUC curve
    # 6. Apply values on function " plot_roc_auc_curve "
    print("ROC-AUC curve on XGBoost Classifier (on test set) \n")
    plot_roc_auc_curve (actual_target_variable= y_test , \
          predicted_target_variable= xgBoostClf_model_test_prob_pred)

    # Model's ROC-AUC curve
    # 7. Apply values on function " plot_roc_auc_curve "
    print("Precision-Recall curve on XGBoost Classifier (on test set)  \n")
    plot_precision_recall_curve (actual_target_variable= y_test , \
          predicted_target_variable= xgBoostClf_model_test_pred)
```

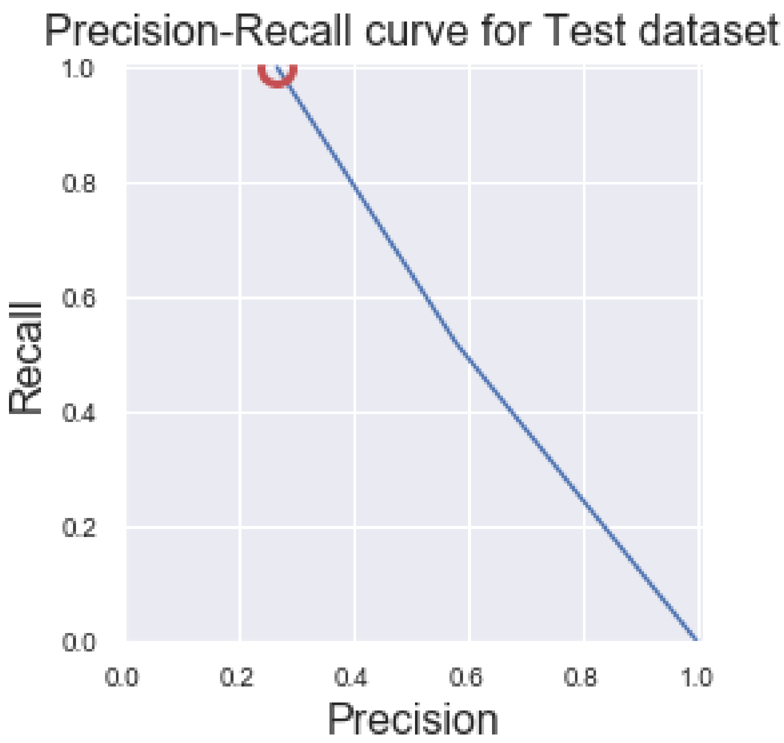
```
XGBoost Classifier : Model Evaluation  (on test set)

XGBoost Classifier : Evaluation score (on test set)
        Accuracy Score: 0.7703225806451612
        Precision Score: 0.5806451612903226
        Recall Score: 0.5192307692307693
        F1_score: 0.5482233502538072
        ROC_AUC_score: 0.6908323158323157
        Log_Loss_Score: 7.932857505669234

XGBoost Classifier - Classification Report (on test set)
               precision    recall  f1-score   support

       No :0       0.83      0.86      0.85      1701
       Yes:1       0.58      0.52      0.55       624

   micro avg       0.77      0.77      0.77      2325
   macro avg       0.71      0.69      0.70      2325
weighted avg       0.76      0.77      0.77      2325



XGBoost Classifier -Confusion matrix (on test set)
```



ROC-AUC curve on XGBoost Classifier (on test set)



Precision-Recall curve on XGBoost Classifier (on test set)



Feature Importance ratio (through xgboost classifier)

In [77]:
```
# Create Temporary dataframe for feature and their importance ratio

df_Feature_importance =pd.DataFrame(list(zip(X_test.columns, np.round(xgBoostClf.featu
df_Feature_importance.sort_values(by='Importance_ratio', ascending=False , inplace=Tru
df_Feature_importance
```

Out[77]:

	Feature	Importance_ratio
30	TotalCharges	0.316
29	MonthlyCharges	0.316
28	tenure	0.099
0	gender	0.027
12	PaperlessBilling	0.023
2	Partner	0.020
7	OnlineBackup	0.016
3	Dependents	0.015
1	SeniorCitizen	0.014
21	PaymentMethod_Electronic check	0.014
6	OnlineSecurity	0.013
9	TechSupport	0.013
19	PaymentMethod_Bank transfer (automatic)	0.012
5	MultipleLines	0.012
8	DeviceProtection	0.011

11	StreamingMovies	0.011
22	PaymentMethod_Mailed check	0.011
10	StreamingTV	0.010
20	PaymentMethod_Credit card (automatic)	0.010
25	tenure_group_Tenure_24-48	0.006
16	Contract_Month-to-month	0.005
24	tenure_group_Tenure_12-24	0.005
26	tenure_group_Tenure_48-60	0.004
4	PhoneService	0.004
17	Contract_One year	0.004
14	InternetService_Fiber optic	0.003
23	tenure_group_Tenure_0-12	0.002
18	Contract_Two year	0.002
13	InternetService_DSL	0.002
15	InternetService_No	0.001
27	tenure_group_Tenure_gt_60	0.000

In [78]:
```
# Select features whose importance ration is more than or equal to 1.2% or 0.012

df_Feature_importance =df_Feature_importance[df_Feature_importance.Importance_ratio>=(
df_Feature_importance
```

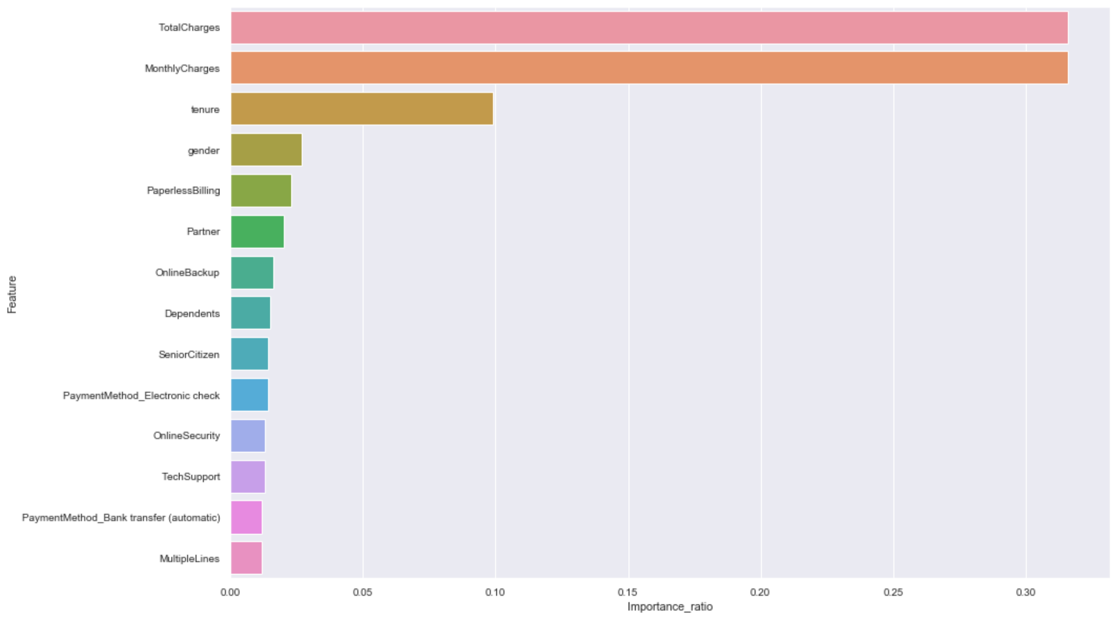
Out[78]:

	Feature	Importance_ratio
30	TotalCharges	0.316
29	MonthlyCharges	0.316
28	tenure	0.099
0	gender	0.027
12	PaperlessBilling	0.023
2	Partner	0.020
7	OnlineBackup	0.016
3	Dependents	0.015
1	SeniorCitizen	0.014
21	PaymentMethod_Electronic check	0.014
6	OnlineSecurity	0.013
9	TechSupport	0.013
19	PaymentMethod_Bank transfer (automatic)	0.012
5	MultipleLines	0.012

In [79]:
```
# Visual analysis of important features


def plot_feature_importance(df_feature):
    '''This function plot feature importance ratio'''
    plt.figure(figsize=(15,10))
    print(sns.barplot(x=df_Feature_importance.iloc[:,1],y=df_Feature_importance.iloc[
    plt.show()
```

```
# Apply values on function

plot_feature_importance(df_Feature_importance)
```

AxesSubplot(0.125,0.125;0.775x0.755)



13. Classification Model Comparison Let's comapare different classification model based upon their evaluation score performed on test dataset.

```
In [80]: print("Based on : Test Dataset\n")
         # Model Evaluation score based on test set
         model_scores =[logisticsRegclf_model_score,decisionTree_model_score , randomForest_moc
                        gradientBoostClf_model_score,kNeighborClf_model_score,  gaussianNBClf_moc
         # Model scores ( columns for dataframe)
         score_list = ['Test-Accuracy_score','Test-Precision_score' , 'Test-Recall_score' ,'Tes
         # Model scores ( row for dataframe)
         clf_Models = ['Logistics Regression','DecisionTree Classification','RandomForest Class

         # temp list to store model scores
         eval_score=[]
         # iterate model scores
         for  i, score in list(enumerate(model_scores)):
             eval_score.append(score)

         # Temporary dataframe for classification model scores
         df_Evaluation_Score = pd.DataFrame(data=eval_score,index=clf_Models, columns=score_lis
```

```
df_Evaluation_Score
```

```
Based on : Test Dataset
```

Out[80]:

	Test-Accuracy_score	Test-Precision_score
Logistics Regression	0.784086	0.621514
DecisionTree Classification	0.775914	0.581616
RandomForest Classifiaction	0.787957	0.653396
GradientBoosting	0.787097	0.622391
KNeighbor Classifiaction	0.761290	0.560000
GaussianNB Classifiaction	0.729032	0.496951
XGBoost Classifiaction	0.770323	0.580645

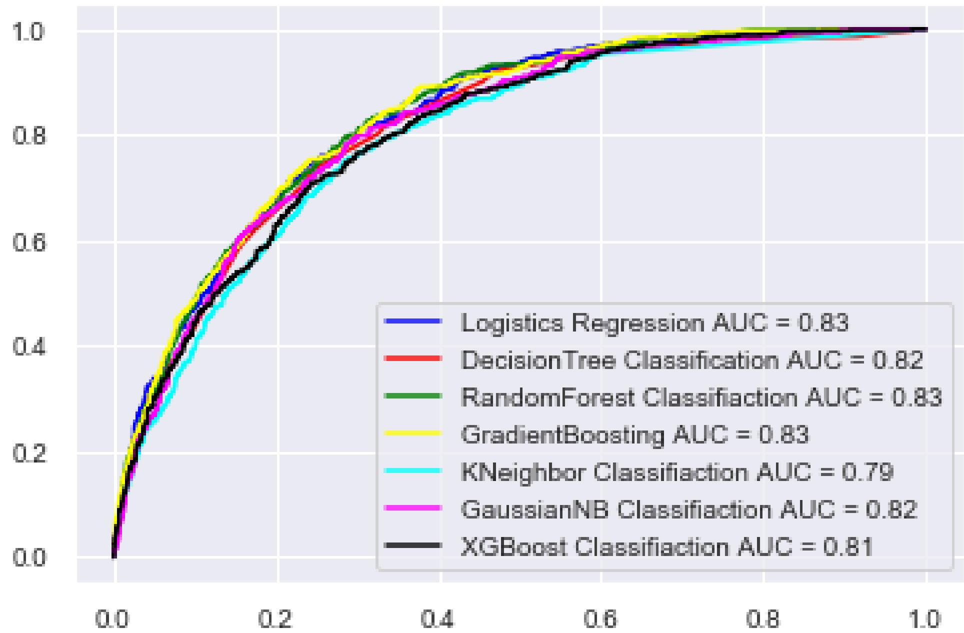
	Test-Recall_score	Test-F1_score
Logistics Regression	0.500000	0.554174
DecisionTree Classification	0.588141	0.584861
RandomForest Classifiaction	0.447115	0.530923
GradientBoosting	0.525641	0.569939
KNeighbor Classifiaction	0.516026	0.537114
GaussianNB Classifiaction	0.783654	0.608209
XGBoost Classifiaction	0.519231	0.548223

	Test-ROC_AUC_score	Test-Log_loss_score
Logistics Regression	0.694150	7.457470
DecisionTree Classification	0.716469	7.739748
RandomForest Classifiaction	0.680054	7.323757
GradientBoosting	0.704326	7.353485
KNeighbor Classifiaction	0.683645	8.244827
GaussianNB Classifiaction	0.746324	9.359064
XGBoost Classifiaction	0.690832	7.932858

In [81]:
```
# Function to compare Classification Model's performance through ROC_AUC Curve ( base

colors_name = ['blue','red','green','yellow','cyan','magenta','black']

predict_target = [logisticsRegclf_test_prob_pred , decisionTree_model_test_prob_pred
                  gradientBoostClf_model_test_prob_pred,kNeighborClf_model_test_prob_p
                  gaussianNBClf_model_test_prob_pred, xgBoostClf_model_test_prob_pred ]
```

In [82]:
```
# Model's comparison based on ROC curve

def plot_roc_curve(actual_traget , predict_target, colors , model):
    '''This function return AUC score and ROC-AUC curve between actual target and tar
    from sklearn.metrics import roc_curve , auc
    fpr, tpr, threshold = roc_curve(actual_traget, predict_target)
    auc_score= auc(fpr,tpr)
```

```
    plt.plot(fpr, tpr, 'b', label = model + ' AUC = %0.2f' % auc_score, color=colors[i
    plt.legend(loc = 'lower right')


 # Loop to iterate classification model, for plotting ROC curve
for i, model in list(enumerate(clf_Models)):
    plot_roc_curve(actual_traget=y_test,predict_target= predict_target[i], model= clf_

plt.figure(figsize=(15,10))
plt.show()
```




```
<Figure size 1080x720 with 0 Axes>
```

14. Model Interpreation and Conclusion

- Based on above analysis we can predict that , with the RandomForest Classifiaction algorithm (test accuracy : 78.7 % and Log-loss ratio :7.32) , we can classify Churn rate for organization.
- Also feature like Total Charges, Monthly Chanrges, Tenure & gender play vital role in Churn rate whether customers want to retain the services with organization or want to leave the company services.

```
In [ ]:
```