telecom-customer-churn-prediction

October 9, 2023

1 Telecom Customer Churn Prediction

The aim of this project is to analyze customer demographics, services, tenure and other variables to predict whether a particular customer will churn or not.

2 Import libraries :-

Data Analysis and visualization libraries :

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
# sns.set_style("whitegrid")
import warnings
warnings.filterwarnings('ignore')
np.random.seed(42)
```

[2]:
```
df=pd.read_csv("/content/WA_Fn-UseC_-Telco-Customer-Churn.xls")
df
```

[2]:
```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
0     7590-VHVEG  Female              0     Yes         No       1
1     5575-GNVDE    Male              0      No         No      34
2     3668-QPYBK    Male              0      No         No       2
3     7795-CFOCW    Male              0      No         No      45
4     9237-HQITU  Female              0      No         No       2
…            …       …              …       …          …       …
7038  6840-RESVB    Male              0     Yes        Yes      24
7039  2234-XADUH  Female              0     Yes        Yes      72
7040  4801-JZAZL  Female              0     Yes        Yes      11
7041  8361-LTMKD    Male              1     Yes         No       4
7042  3186-AJIEK    Male              0      No         No      66

     PhoneService     MultipleLines InternetService OnlineSecurity  …  \
```

```
0              No  No phone service             DSL             No  …
1             Yes                No             DSL            Yes  …
2             Yes                No             DSL            Yes  …
3              No  No phone service             DSL            Yes  …
4             Yes                No     Fiber optic             No  …
…             …                 …            …             …   …
7038          Yes               Yes             DSL            Yes  …
7039          Yes               Yes     Fiber optic             No  …
7040           No  No phone service             DSL            Yes  …
7041          Yes               Yes     Fiber optic             No  …
7042          Yes                No     Fiber optic            Yes  …

     DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0                  No          No          No              No  Month-to-month
1                 Yes          No          No              No        One year
2                  No          No          No              No  Month-to-month
3                 Yes         Yes          No              No        One year
4                  No          No          No              No  Month-to-month
…                 …          …          …              …             …
7038              Yes         Yes         Yes             Yes        One year
7039              Yes          No         Yes             Yes        One year
7040               No          No          No              No  Month-to-month
7041               No          No          No              No  Month-to-month
7042              Yes         Yes         Yes             Yes        Two year

     PaperlessBilling              PaymentMethod MonthlyCharges  TotalCharges  \
0                 Yes           Electronic check          29.85         29.85
1                  No               Mailed check          56.95        1889.5
2                 Yes               Mailed check          53.85        108.15
3                  No  Bank transfer (automatic)          42.30       1840.75
4                 Yes           Electronic check          70.70        151.65
…                 …                        …             …            …
7038              Yes               Mailed check          84.80        1990.5
7039              Yes    Credit card (automatic)         103.20        7362.9
7040              Yes           Electronic check          29.60        346.45
7041              Yes               Mailed check          74.40         306.6
7042              Yes  Bank transfer (automatic)         105.65        6844.5

     Churn
0       No
1       No
2      Yes
3       No
4      Yes
…     …
7038    No
7039    No
```

```
7040     No
7041    Yes
7042     No

[7043 rows x 21 columns]
```

[3]:
```
df.shape
```

[3]:
```
(7043, 21)
```

[4]:
```
df.head()
```

[4]:
```
   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
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              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
3  No phone service             DSL            Yes  …              Yes
4                No     Fiber optic             No  …               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
3         Yes          No              No        One year               No
4          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  Bank transfer (automatic)          42.30       1840.75    No
4           Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

[5]:
```
df.tail()
```

[5]:
```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
7038  6840-RESVB    Male              0     Yes        Yes      24
7039  2234-XADUH  Female              0     Yes        Yes      72
```

```
7040  4801-JZAZL  Female              0     Yes        Yes       11
7041  8361-LTMKD    Male              1     Yes         No        4
7042  3186-AJIEK    Male              0      No         No       66

     PhoneService     MultipleLines InternetService OnlineSecurity  …  \
7038          Yes               Yes             DSL            Yes  …
7039          Yes               Yes     Fiber optic             No  …
7040           No  No phone service             DSL            Yes  …
7041          Yes               Yes     Fiber optic             No  …
7042          Yes                No     Fiber optic            Yes  …

     DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
7038              Yes         Yes         Yes             Yes        One year
7039              Yes          No         Yes             Yes        One year
7040               No          No          No              No  Month-to-month
7041               No          No          No              No  Month-to-month
7042              Yes         Yes         Yes             Yes        Two year

     PaperlessBilling              PaymentMethod MonthlyCharges  TotalCharges  \
7038              Yes               Mailed check          84.80        1990.5
7039              Yes    Credit card (automatic)         103.20        7362.9
7040              Yes           Electronic check          29.60        346.45
7041              Yes               Mailed check          74.40         306.6
7042              Yes  Bank transfer (automatic)         105.65        6844.5

     Churn
7038    No
7039    No
7040    No
7041   Yes
7042    No

[5 rows x 21 columns]
```

[6]:
```
df.dtypes
```

[6]:
```
customerID           object
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
```

[7]:

```python
df.describe().T
```

[7]:

```
                 count       mean        std    min   25%    50%    75%  \
SeniorCitizen   7043.0   0.162147   0.368612   0.00   0.0   0.00   0.00
tenure          7043.0  32.371149  24.559481   0.00   9.0  29.00  55.00
MonthlyCharges  7043.0  64.761692  30.090047  18.25  35.5  70.35  89.85

                   max
SeniorCitizen     1.00
tenure           72.00
MonthlyCharges  118.75
```

Statistical description of Categorical features

[8]:

```python
df.describe(include='object')
```

[8]:

```
        customerID gender Partner Dependents PhoneService MultipleLines  \
count         7043   7043    7043       7043         7043          7043
unique        7043      2       2          2            2             3
top     7590-VHVEG   Male      No         No          Yes            No
freq             1   3555    3641       4933         6361          3390

       InternetService OnlineSecurity OnlineBackup DeviceProtection  \
count             7043           7043         7043             7043
unique               3              3            3                3
top        Fiber optic             No           No               No
freq              3096           3498         3088             3095

       TechSupport StreamingTV StreamingMovies        Contract  \
count         7043        7043            7043            7043
unique           3           3               3               3
top             No          No              No  Month-to-month
freq          3473        2810            2785            3875

       PaperlessBilling     PaymentMethod TotalCharges Churn
```

```
count              7043              7043     7043  7043
unique                2                 4     6531     2
top                 Yes  Electronic check             No
freq               4171              2365       11  5174
```

[9]:
```
df.duplicated().sum()
```

[9]:
```
0
```

[10]:
```
#covert 'TotalCharges' in to numerical datatype(some row contains " ")
df['TotalCharges']=df['TotalCharges'].replace(" ",np.nan)
df['TotalCharges']=pd.to_numeric(df['TotalCharges'])
```

[11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7032 non-null   float64
 20  Churn             7043 non-null   object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
```

[12]:
```
#checking for null values

df.isnull().sum()
```

[12]:
```
customerID           0
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
```

11 missing datapoints can be observed in the Total Changes column

[13]:
```
#Removal of rows with missing data
df.dropna(inplace=True)
df.reset_index()
```

[13]:
```
      index  customerID  gender  SeniorCitizen Partner Dependents  tenure  \
0         0  7590-VHVEG  Female              0     Yes         No       1
1         1  5575-GNVDE    Male              0      No         No      34
2         2  3668-QPYBK    Male              0      No         No       2
3         3  7795-CFOCW    Male              0      No         No      45
4         4  9237-HQITU  Female              0      No         No       2
…         …         …       …             …       …          …     …
7027   7038  6840-RESVB    Male              0     Yes        Yes      24
7028   7039  2234-XADUH  Female              0     Yes        Yes      72
7029   7040  4801-JZAZL  Female              0     Yes        Yes      11
7030   7041  8361-LTMKD    Male              1     Yes         No       4
7031   7042  3186-AJIEK    Male              0      No         No      66

     PhoneService     MultipleLines InternetService  … DeviceProtection  \
0              No  No phone service             DSL  …               No
1             Yes                No             DSL  …              Yes
2             Yes                No             DSL  …               No
3              No  No phone service             DSL  …              Yes
```

```
4             Yes                No     Fiber optic  ...              No
...          ...              ...           ...  ...              ...
7027          Yes               Yes            DSL  ...             Yes
7028          Yes               Yes    Fiber optic  ...             Yes
7029           No  No phone service            DSL  ...              No
7030          Yes               Yes    Fiber optic  ...              No
7031          Yes                No    Fiber optic  ...             Yes

     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
3            Yes          No              No        One year               No
4             No          No              No  Month-to-month              Yes
...          ...         ...             ...             ...              ...
7027         Yes         Yes             Yes        One year              Yes
7028          No         Yes             Yes        One year              Yes
7029          No          No              No  Month-to-month              Yes
7030          No          No              No  Month-to-month              Yes
7031         Yes         Yes             Yes        Two year              Yes

                  PaymentMethod MonthlyCharges TotalCharges  Churn
0              Electronic check          29.85        29.85     No
1                  Mailed check          56.95      1889.50     No
2                  Mailed check          53.85       108.15    Yes
3     Bank transfer (automatic)          42.30      1840.75     No
4              Electronic check          70.70       151.65    Yes
...                         ...            ...          ...    ...
7027               Mailed check          84.80      1990.50     No
7028    Credit card (automatic)         103.20      7362.90     No
7029           Electronic check          29.60       346.45     No
7030               Mailed check          74.40       306.60    Yes
7031  Bank transfer (automatic)         105.65      6844.50     No

[7032 rows x 22 columns]
```

[14]:
```python
df.isnull().sum()
```

[14]:
```
customerID          0
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
```

[15]:
```
#checking for duplicate values

df.duplicated().sum()
```

[15]:
```
0
```

[16]:
```
#checking number of unique value in each column
df.nunique()
```

[16]:
```
customerID          7032
gender                 2
SeniorCitizen          2
Partner                2
Dependents             2
tenure                72
PhoneService           2
MultipleLines          3
InternetService        3
OnlineSecurity         3
OnlineBackup           3
DeviceProtection       3
TechSupport            3
StreamingTV            3
StreamingMovies        3
Contract               3
PaperlessBilling       2
PaymentMethod          4
MonthlyCharges      1584
TotalCharges        6530
Churn                  2
dtype: int64
```

[17]:

```python
#to print unique value of each column
cols=df.columns
for i in cols:
  print(i, df[i].unique(), '\n')
```

```
customerID ['7590-VHVEG' '5575-GNVDE' '3668-QPYBK' … '4801-JZAZL' '8361-LTMKD'
 '3186-AJIEK']

gender ['Female' 'Male']

SeniorCitizen [0 1]

Partner ['Yes' 'No']

Dependents ['No' 'Yes']

tenure [ 1 34  2 45  8 22 10 28 62 13 16 58 49 25 69 52 71 21 12 30 47 72 17 27
  5 46 11 70 63 43 15 60 18 66  9  3 31 50 64 56  7 42 35 48 29 65 38 68
 32 55 37 36 41  6  4 33 67 23 57 61 14 20 53 40 59 24 44 19 54 51 26 39]

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)']

MonthlyCharges [29.85 56.95 53.85 … 63.1  44.2  78.7 ]
```

```
TotalCharges [  29.85 1889.5   108.15 …  346.45  306.6  6844.5 ]

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

[18]:
```python
df['PhoneService'].value_counts()
```

[18]:
```
Yes    6352
No      680
Name: PhoneService, dtype: int64
```

[19]:
```python
df['MultipleLines'].value_counts()
```

[19]:
```
No                  3385
Yes                 2967
No phone service     680
Name: MultipleLines, dtype: int64
```

[20]:
```python
df['InternetService'].value_counts()
```

[20]:
```
Fiber optic    3096
DSL            2416
No             1520
Name: InternetService, dtype: int64
```

[21]:
```python
df['OnlineSecurity'].value_counts()
```

[21]:
```
No                     3497
Yes                    2015
No internet service    1520
Name: OnlineSecurity, dtype: int64
```

[22]:
```python
#create a list for each object column

lst=df.select_dtypes(include='object').columns.tolist()
lst
```

[22]:
```
['customerID',
 'gender',
 'Partner',
 'Dependents',
 'PhoneService',
 'MultipleLines',
 'InternetService',
 'OnlineSecurity',
 'OnlineBackup',
 'DeviceProtection',
```

```
 'TechSupport',
 'StreamingTV',
 'StreamingMovies',
 'Contract',
 'PaperlessBilling',
 'PaymentMethod',
 'Churn']
```

[23]:
```
#Uploading wrongly labeled data points : some data cells has 'No phone servicee␣
↪and : 'No ,internetservice' instead of 'No'
for i in lst:
  df[i]=df[i].replace('No phone service','No')
  df[i]=df[i].replace('No internet service','No')
```

[24]:
```
df
```

[24]:
```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
0     7590-VHVEG  Female              0     Yes         No       1
1     5575-GNVDE    Male              0      No         No      34
2     3668-QPYBK    Male              0      No         No       2
3     7795-CFOCW    Male              0      No         No      45
4     9237-HQITU  Female              0      No         No       2
…            …     …             …     …        …     …
7038  6840-RESVB    Male              0     Yes        Yes      24
7039  2234-XADUH  Female              0     Yes        Yes      72
7040  4801-JZAZL  Female              0     Yes        Yes      11
7041  8361-LTMKD    Male              1     Yes         No       4
7042  3186-AJIEK    Male              0      No         No      66

     PhoneService MultipleLines InternetService OnlineSecurity  …  \
0              No            No             DSL             No  …
1             Yes            No             DSL            Yes  …
2             Yes            No             DSL            Yes  …
3              No            No             DSL            Yes  …
4             Yes            No     Fiber optic             No  …
…           …           …            …            …  …
7038          Yes           Yes             DSL            Yes  …
7039          Yes           Yes     Fiber optic             No  …
7040           No            No             DSL            Yes  …
7041          Yes           Yes     Fiber optic             No  …
7042          Yes            No     Fiber optic            Yes  …

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

```
4                    No           No           No                No  Month-to-month
…                 …          …          …              …              …
7038                Yes          Yes          Yes               Yes        One year
7039                Yes           No          Yes               Yes        One year
7040                 No           No           No                No  Month-to-month
7041                 No           No           No                No  Month-to-month
7042                Yes          Yes          Yes               Yes        Two year

     PaperlessBilling              PaymentMethod MonthlyCharges  TotalCharges  \
0                 Yes           Electronic check          29.85         29.85
1                  No               Mailed check          56.95       1889.50
2                 Yes               Mailed check          53.85        108.15
3                  No  Bank transfer (automatic)          42.30       1840.75
4                 Yes           Electronic check          70.70        151.65
…                 …                        …            …           …
7038              Yes               Mailed check          84.80       1990.50
7039              Yes    Credit card (automatic)         103.20       7362.90
7040              Yes           Electronic check          29.60        346.45
7041              Yes               Mailed check          74.40        306.60
7042              Yes  Bank transfer (automatic)         105.65       6844.50

      Churn
0        No
1        No
2       Yes
3        No
4       Yes
…       …
7038     No
7039     No
7040     No
7041    Yes
7042     No

[7032 rows x 21 columns]
```

3 Exploratory Data Analysis

Visualization Of Data

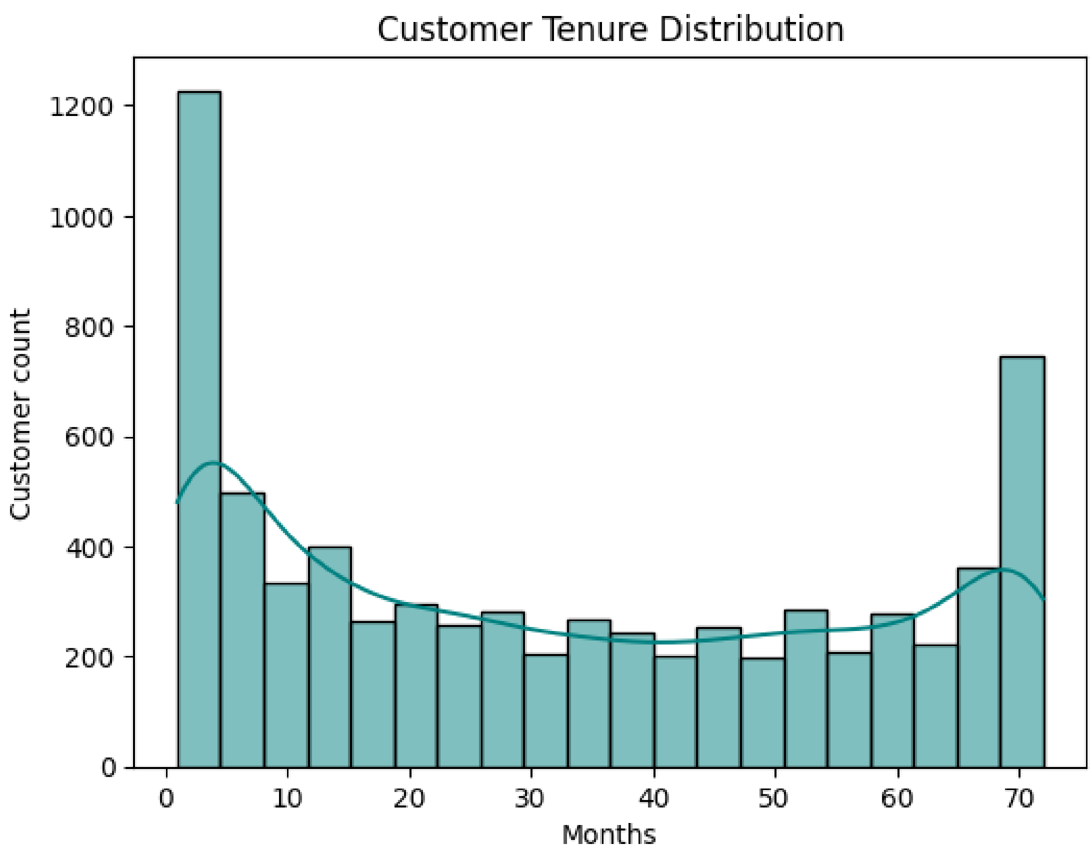
---

for better understanding of data and to find relationship between dependent variables and the target variable

[25]:
```
#distribution of customer tenure
# plt.figure(figsize=(12,4))
```

```
sns.histplot(df['tenure'],color='teal',edgecolor='black',bins=20,kde=True)
plt.title('Customer Tenure Distribution')
plt.xlabel('Months')
plt.ylabel('Customer count')
```

[25]: Text(0, 0.5, 'Customer count')



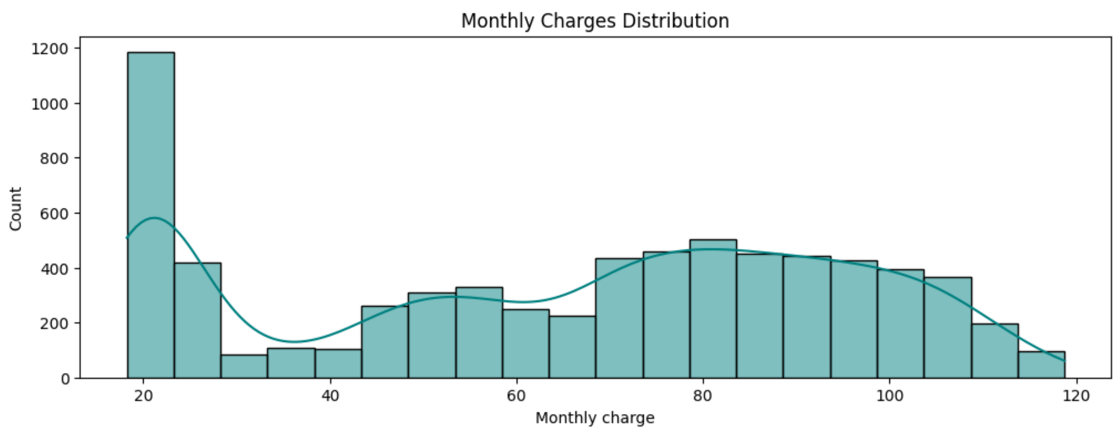
[26]:
```
df['tenure']
```

[26]:
```
0        1
1       34
2        2
3       45
4        2
        ..
7038    24
7039    72
7040    11
7041     4
7042    66
```

```
Name: tenure, Length: 7032, dtype: int64
```

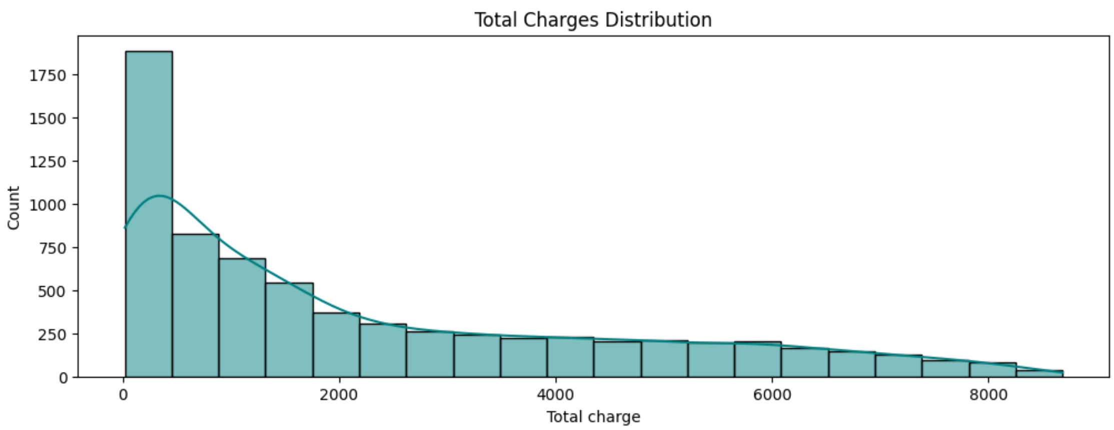
[27]:
```
#distribution of monthly charges
plt.figure(figsize=(12,4))
sns.
 ↪histplot(df['MonthlyCharges'],color='teal',edgecolor='black',bins=20,kde=True)
plt.title('Monthly Charges Distribution')
plt.xlabel('Monthly charge')
plt.ylabel('Count')
```

[27]:
```
Text(0, 0.5, 'Count')
```



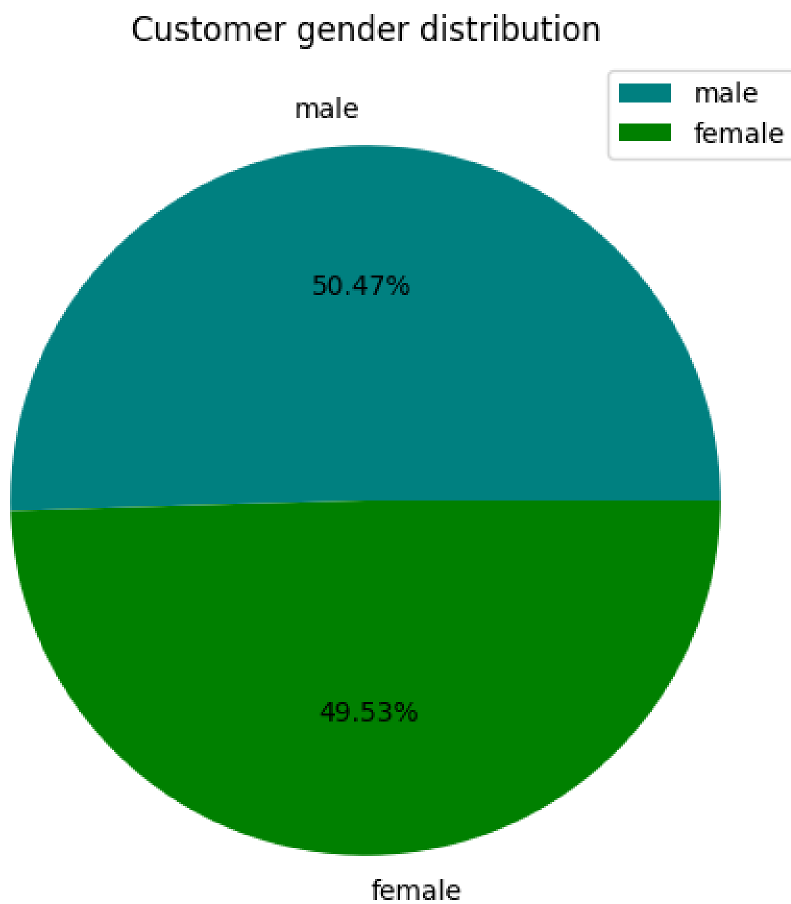
[28]:
```
#distribution of total charges
plt.figure(figsize=(12,4))
sns.histplot(df['TotalCharges'],color='teal',edgecolor='black',bins=20,kde=True)
plt.title('Total Charges Distribution')
plt.xlabel('Total charge')
plt.ylabel('Count')
```

[28]:
```
Text(0, 0.5, 'Count')
```



[29]:
```
#customer gender distribution
plt.figure(figsize=(10,6))
color=['teal','green']
label=['male','female']
plt.pie(df['gender'].value_counts(),labels=label,colors=color,autopct='%1.2f%%')
plt.title('Customer gender distribution')

plt.legend()
```

[29]: <matplotlib.legend.Legend at 0x7df11d1e7be0>

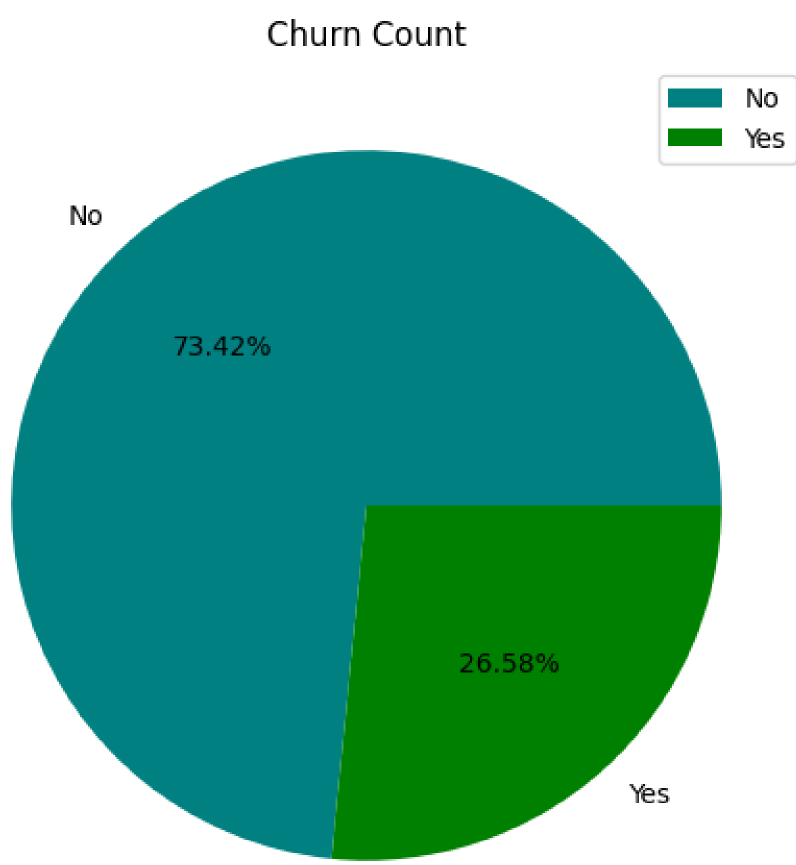


Gender distribution is approximately the same between males and females

COUNT OF CUSTOMER CHURN

[30]:
```
plt.figure(figsize=(14,6))
color=['teal','green']
plt.pie(x=  df['Churn'].value_counts(),labels= df['Churn'].
  ↪unique(),colors=color,autopct='%1.2f%%')
plt.title('Churn Count')
plt.legend()
```

[30]: <matplotlib.legend.Legend at 0x7df11d1a7070>



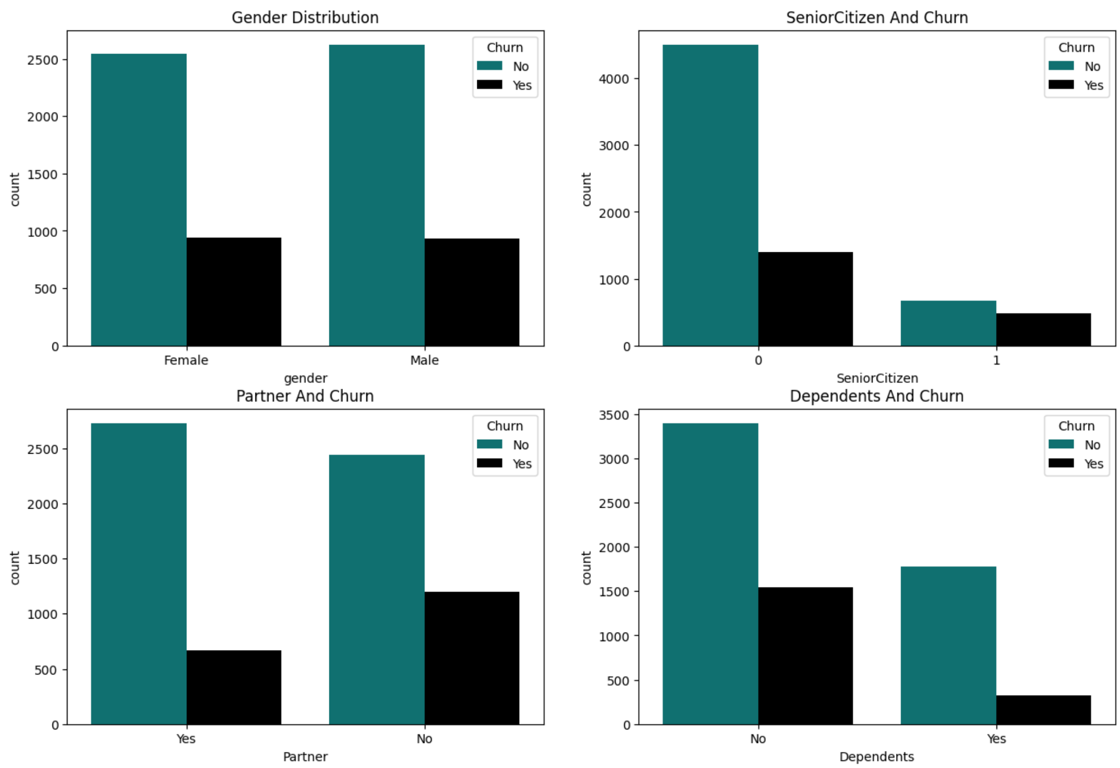
In the dataset, the number of churning customers is very less as compared to non churning. Only 26.49% churnned from the telecom company.This could be a potential proof, that company is quite good at retaning its customers.

Customer Demographics and Churn

[31]:
```
fig,ax=plt.subplots(2,2,figsize=(15,10))



#gender distribution
color=['teal','black']
sns.countplot(x='gender',data=df,hue='Churn',palette=color,ax=ax[0,0])
ax[0,0].set_title('Gender Distribution')

#senior citizen distriburion

sns.countplot(x='SeniorCitizen',data=df,hue='Churn',palette=color,ax=ax[0,1])
ax[0,1].set_title('SeniorCitizen And Churn')
```

```
#partner distribution

sns.countplot(x='Partner',data=df,hue='Churn',palette=color,ax=ax[1,0])
ax[1,0].set_title('Partner And Churn')

#Dependents distribution

sns.countplot(x='Dependents',data=df,hue='Churn',palette=color,ax=ax[1,1])
ax[1,1].set_title('Dependents And Churn')
```

[31]: Text(0.5, 1.0, 'Dependents And Churn')



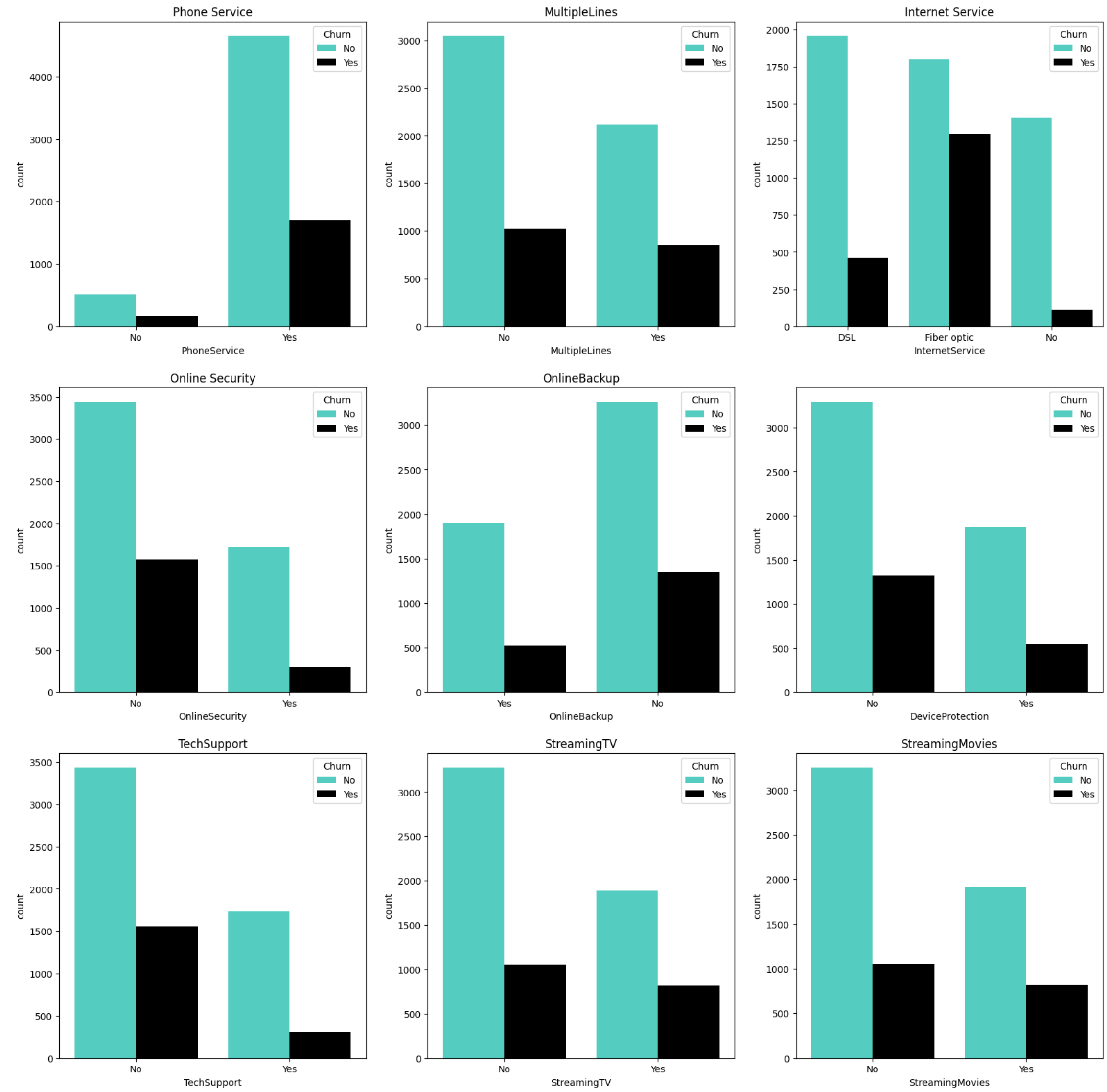
from above graph it is clear that male and female have same churn count.However, the senior citizens have a lesser churn count as compared to non senior citizens,The customers with no partners have higher churn count as compared to customers with partners. customers with no dependents have higher churn count as compared to customers with dependents.

CUSTOMER SERVICES AND CHURN

These graphs visualizes the relation between customer churn based on services opted by the customer

[32]:
```python
fig,ax=plt.subplots(3,3,figsize=(20,20))
color=['turquoise','black']

#phone service
sns.countplot(x='PhoneService',data=df,hue='Churn',palette=color,ax=ax[0,0])
ax[0,0].set_title('Phone Service')

#multiplelines
sns.countplot(x='MultipleLines',data=df,hue='Churn',palette=color,ax=ax[0,1])
ax[0,1].set_title('MultipleLines')
#internet service
sns.countplot(x='InternetService',data=df,hue='Churn',palette=color,ax=ax[0,2])
ax[0,2].set_title('Internet Service')

#online security service
sns.countplot(x='OnlineSecurity',data=df,hue='Churn',palette=color,ax=ax[1,0])
ax[1,0].set_title('Online Security')

#online backup
sns.countplot(x='OnlineBackup',data=df,hue='Churn',palette=color,ax=ax[1,1])
ax[1,1].set_title('OnlineBackup')

#Device protection
sns.countplot(x='DeviceProtection',data=df,hue='Churn',palette=color,ax=ax[1,2])
ax[2,0].set_title('Device protection')

#tech support

sns.countplot(x='TechSupport',data=df,hue='Churn',palette=color,ax=ax[2,0])
ax[2,0].set_title('TechSupport')

#streaming TV
sns.countplot(x='StreamingTV',data=df,hue='Churn',palette=color,ax=ax[2,1])
ax[2,1].set_title('StreamingTV')

#Streaming Movies
sns.countplot(x='StreamingMovies',data=df,hue='Churn',palette=color,ax=ax[2,2])
ax[2,2].set_title('StreamingMovies')
```

[32]:
```
Text(0.5, 1.0, 'StreamingMovies')
```

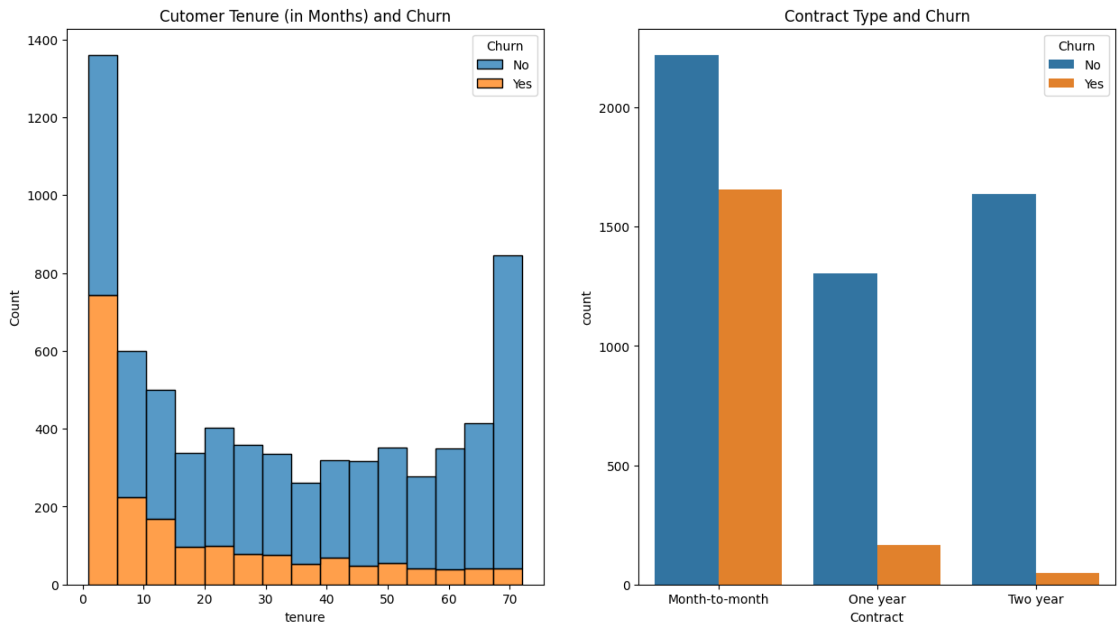


These graphs visualizes the relation between customer churn based on services opted by the customer. churn count is higher for the customers, who have taken multiple lines. the customers with streaming services have lower churn count

TENURE/CONTRACT AND CHURN

[33]:
```
fig, ax = plt.subplots(1, 2, figsize=(15, 8))
sns.histplot(x = 'tenure', data = df, ax= ax[0], hue = 'Churn', multiple =␣
↪'stack').set_title('Cutomer Tenure (in Months) and Churn')
sns.countplot(x = 'Contract', data = df, ax= ax[1], hue = 'Churn').
↪set_title('Contract Type and Churn')
```

[33]:
```
Text(0.5, 1.0, 'Contract Type and Churn')
```



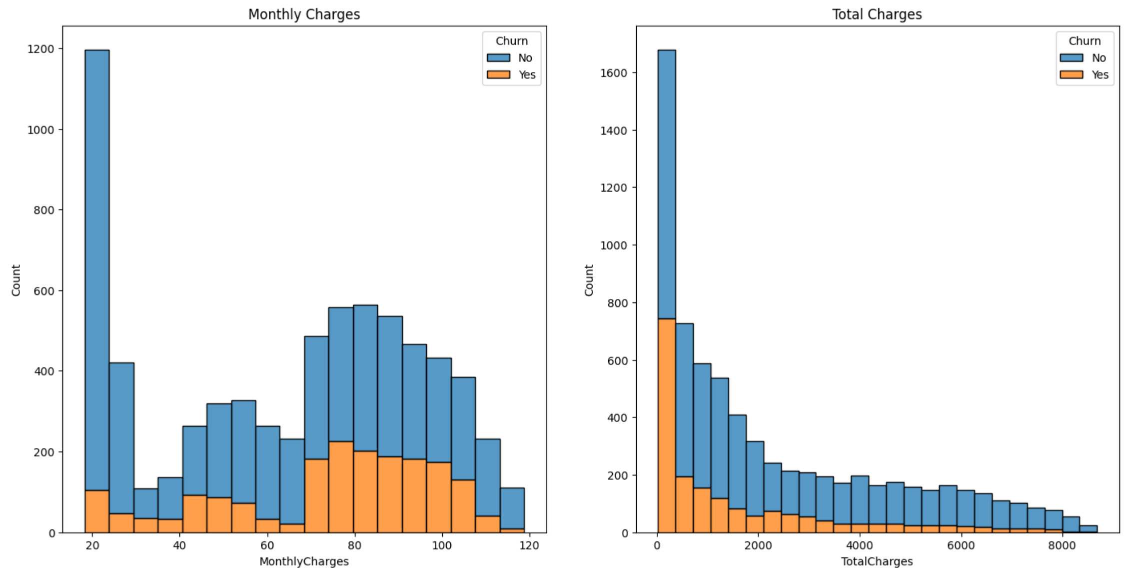
customer with long tenure have lowest churn rate,and cutsomer with month to month contract have highest churn count than one or more year contract

Monthly Charges Distribution By Customer Churn

Charges And Churn

[35]:
```
fig, ax = plt.subplots(1, 2, figsize=(15, 8))
fig.tight_layout(pad=5.0)
sns.histplot(x = 'MonthlyCharges', data = df, ax= ax[0], hue = 'Churn',␣
 ↪multiple = 'stack').set_title('Monthly Charges')
sns.histplot(x = 'TotalCharges', data = df, ax= ax[1], hue = 'Churn', multiple␣
 ↪= 'stack').set_title('Total Charges')
```

[35]:
```
Text(0.5, 1.0, 'Total Charges')
```



Customer with higher monthly charges have higher churn count,But customer with highest Total charges have the lower churn count.This could be possible when the customer has a long tenure and use lot of services.Therefore the company sholud focus on lowering the monthly charges inorder to reduce churn count.

[36]:
```
# Mean of monthly charges for churned and retained customers
mean_monthly_charges_churned = df[df['Churn']== 'Yes']['MonthlyCharges'].mean()
mean_monthly_charges_retained = df[df['Churn'] == 'No']['MonthlyCharges'].mean()


print(f"Mean Monthly Charges for Churned Customers:␣
 ↪{mean_monthly_charges_churned:.2f}")
print(f"Mean Monthly Charges for Retained Customers:␣
 ↪{mean_monthly_charges_retained:.2f}")
```

```
Mean Monthly Charges for Churned Customers: 74.44
Mean Monthly Charges for Retained Customers: 61.31
```

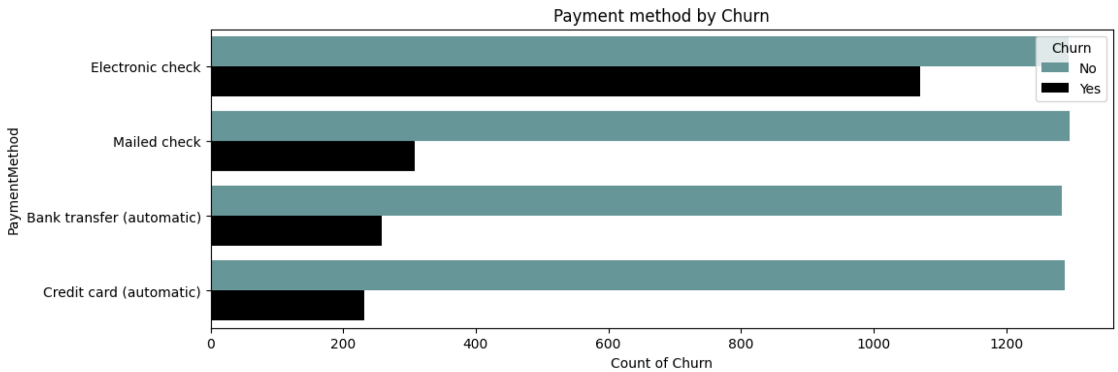
[37]:
```
# Calculation of sum monthly charges by customer churn
monthly_charges_by_churn = df.groupby('Churn')['MonthlyCharges'].sum().
 ↪reset_index()
print(monthly_charges_by_churn)
```

```
  Churn  MonthlyCharges
0    No       316530.15
1   Yes       139130.85
```

Payment method by customer churn

```
[38]: # Payment method by customer churn
plt.figure(figsize=(12,4))
color=['cadetblue','black']
sns.countplot(data=df, y = 'PaymentMethod', hue = 'Churn',palette=color)
plt.xlabel('Count of Churn')
plt.title('Payment method by Churn')
```

```
[38]: Text(0.5, 1.0, 'Payment method by Churn')
```



Most of churn customers using electronic check for payment.

CORRELATION

Correlation in machine learning refers to the statistical relationship between two or more variables. It measures how closely the values of these variables are related to each other. Correlation is often used to understand the association between features (independent variables) and the target variable (dependent variable) in a dataset

```
[39]: df.corr()
```

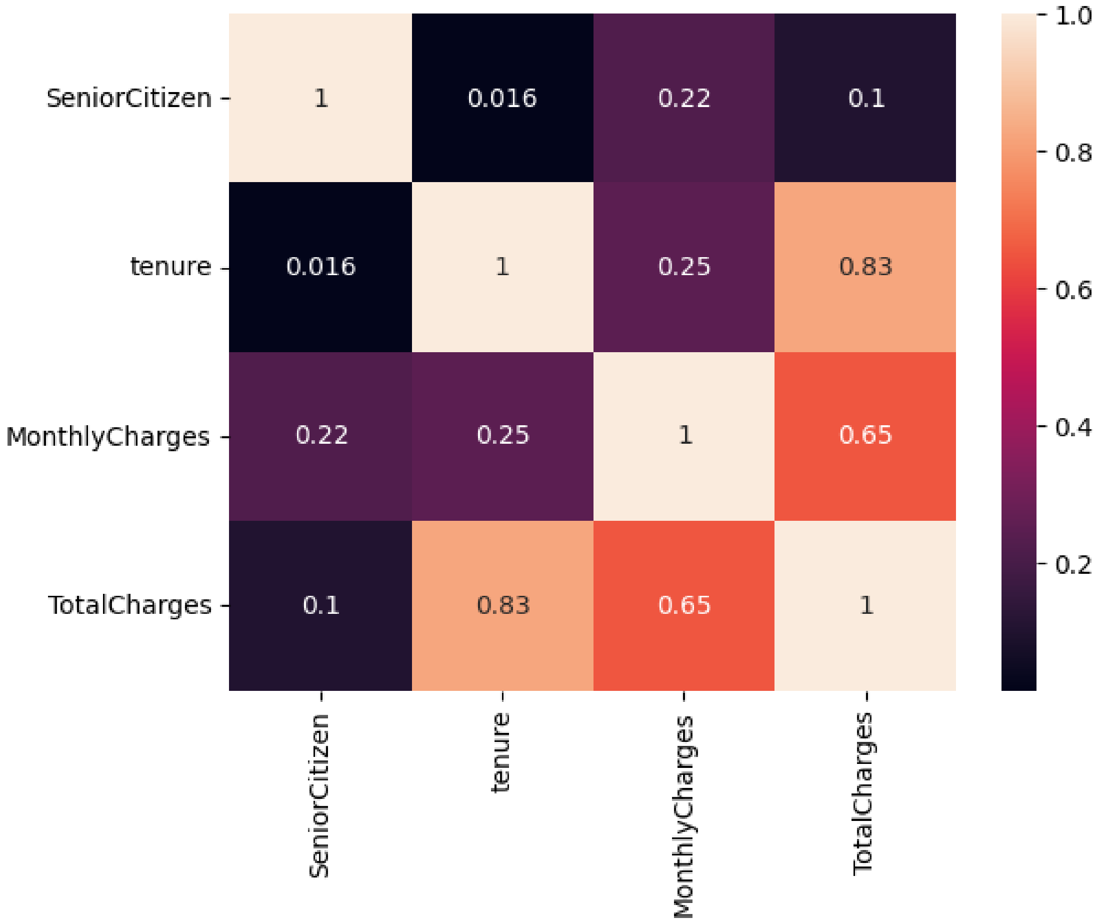
[39]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
SeniorCitizen	1.000000	0.015683	0.219874	0.102411
tenure	0.015683	1.000000	0.246862	0.825880
MonthlyCharges	0.219874	0.246862	1.000000	0.651065
TotalCharges	0.102411	0.825880	0.651065	1.000000

GRAPHICAL REPRESENTATION OF CORRELATION(HEAT MAP)

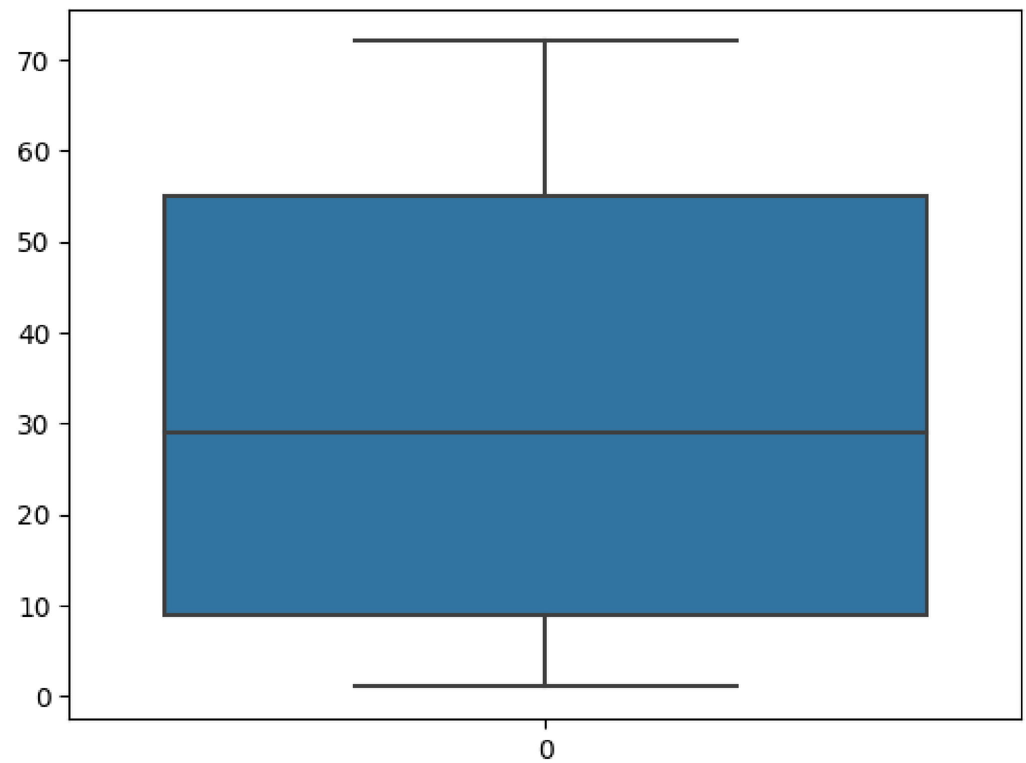
```
[40]: sns.heatmap(df.corr(),annot=True)
```

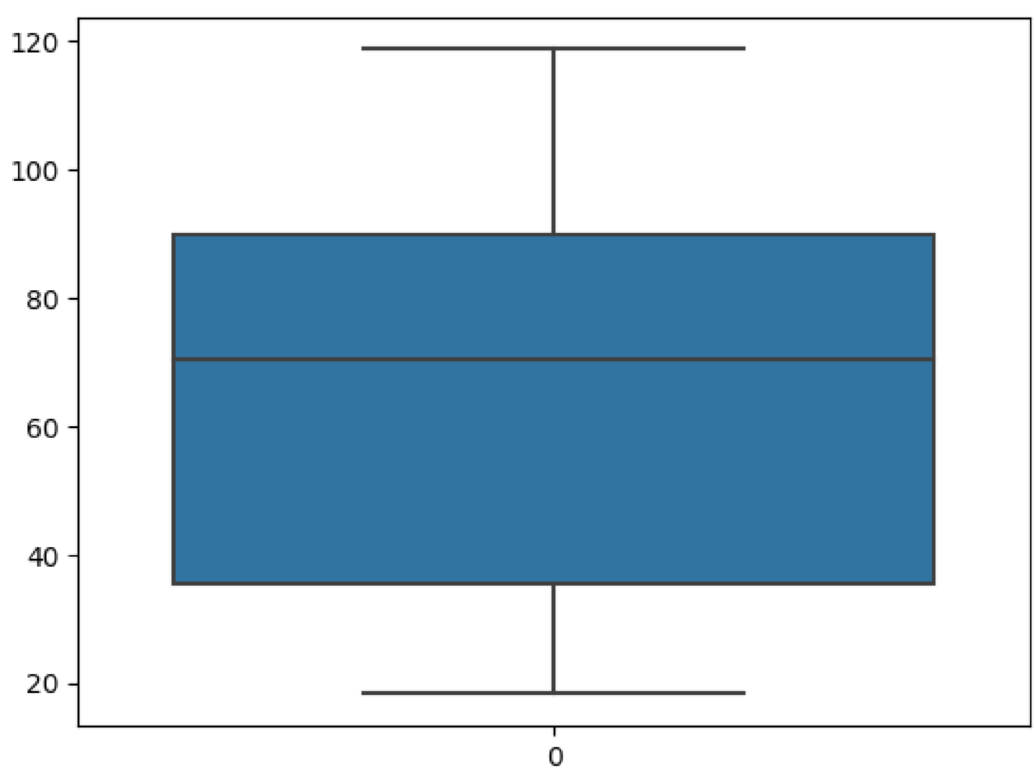
```
[40]: <Axes: >
```

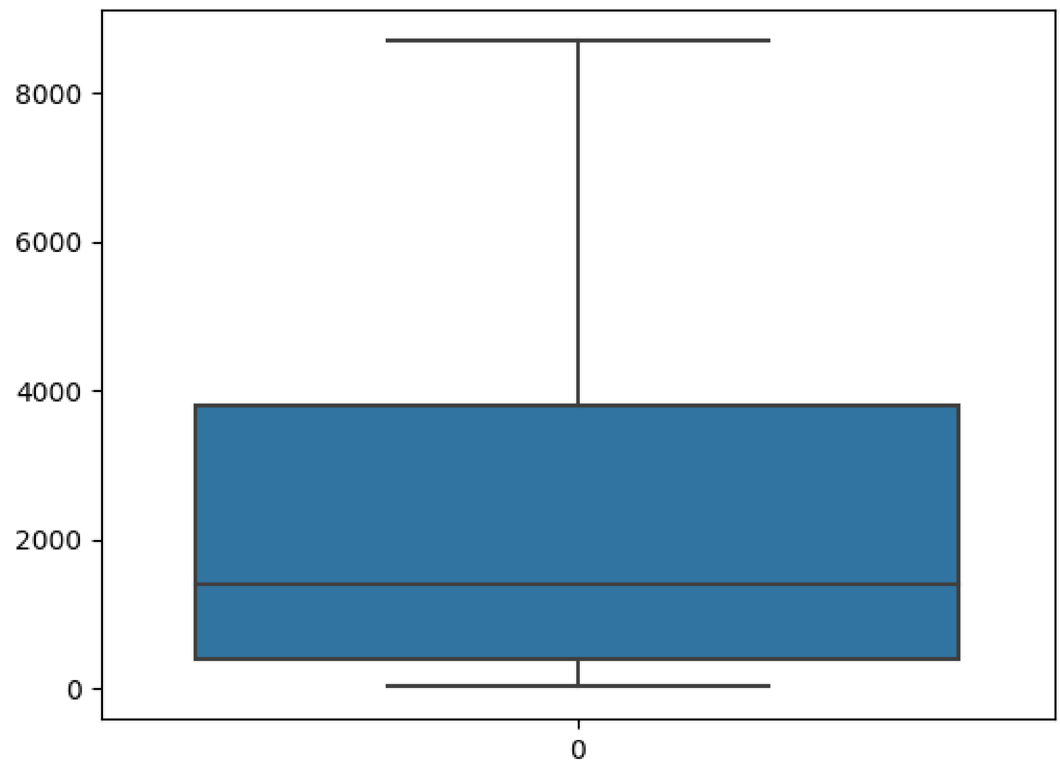


checking Outliers

[41]:
```
lst1=['tenure','MonthlyCharges','TotalCharges']
for i in lst1:
    sns.boxplot(df[i])
    plt.show()
```


70
60
50
40
30
20
10
0
0


120
100
80
60
40
20
0



[42]:
```
df['customerID'].value_counts()
```

[42]:
```
7590-VHVEG    1
0265-PSUAE    1
2956-GGUCQ    1
6008-NAIXK    1
5956-YHHRX    1
             ..
7874-ECPQJ    1
9796-MVYXX    1
2637-FKFSY    1
1552-AAGRX    1
3186-AJIEK    1
Name: customerID, Length: 7032, dtype: int64
```

[43]:
```
#large no of unique values so drop customer ID
df.drop(['customerID'],axis=1,inplace=True)
```

3.1 LABEL ENCODING

[44]:
```
df['Contract'].value_counts()
```

[44]:
```
Month-to-month    3875
Two year          1685
One year          1472
Name: Contract, dtype: int64
```

[45]:
```
from sklearn.preprocessing import LabelEncoder
#colums for label encoding
cols = df.columns[df.dtypes == 'object']
#Label encoder object
le = LabelEncoder()
#Label encoding the columns
for i in cols:
    le.fit(df[i])
    df[i] = le.transform(df[i])
    print(i, df[i].unique(), '\n')
```

```
gender [0 1]

Partner [1 0]

Dependents [0 1]

PhoneService [0 1]

MultipleLines [0 1]

InternetService [0 1 2]

OnlineSecurity [0 1]

OnlineBackup [1 0]

DeviceProtection [0 1]

TechSupport [0 1]

StreamingTV [0 1]

StreamingMovies [0 1]

Contract [0 1 2]

PaperlessBilling [1 0]
```

```
PaymentMethod [2 3 0 1]

Churn [0 1]
```

X AND Y SEPERATION

[46]:
```
x=df.drop(columns='Churn',axis=1)
y=df['Churn']
x
```

[46]:
```
      gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  \
0          0              0        1           0       1             0
1          1              0        0           0      34             1
2          1              0        0           0       2             1
3          1              0        0           0      45             0
4          0              0        0           0       2             1
…         …              …        …         …      …             …
7038       1              0        1           1      24             1
7039       0              0        1           1      72             1
7040       0              0        1           1      11             0
7041       1              1        1           0       4             1
7042       1              0        0           0      66             1

      MultipleLines  InternetService  OnlineSecurity  OnlineBackup  \
0                 0                0               0             1
1                 0                0               1             0
2                 0                0               1             1
3                 0                0               1             0
4                 0                1               0             0
…                …                …               …            …
7038              1                0               1             0
7039              1                1               0             1
7040              0                0               1             0
7041              1                1               0             0
7042              0                1               1             0

      DeviceProtection  TechSupport  StreamingTV  StreamingMovies  Contract  \
0                    0            0            0                0         0
1                    1            0            0                0         1
2                    0            0            0                0         0
3                    1            1            0                0         1
4                    0            0            0                0         0
…                   …           …           …               …        …
7038                 1            1            1                1         1
7039                 1            0            1                1         1
7040                 0            0            0                0         0
7041                 0            0            0                0         0
```

```
7042                 1            1            1                1          2

      PaperlessBilling  PaymentMethod  MonthlyCharges  TotalCharges
0                    1              2           29.85         29.85
1                    0              3           56.95       1889.50
2                    1              3           53.85        108.15
3                    0              0           42.30       1840.75
4                    1              2           70.70        151.65
…                  …            …             …            …
7038                 1              3           84.80       1990.50
7039                 1              1          103.20       7362.90
7040                 1              2           29.60        346.45
7041                 1              3           74.40        306.60
7042                 1              0          105.65       6844.50

[7032 rows x 19 columns]
```

[47]:
```
y
```

[47]:
```
0       0
1       0
2       1
3       0
4       1
       ..
7038    0
7039    0
7040    0
7041    1
7042    0
Name: Churn, Length: 7032, dtype: int64
```

FEATURE SCALING

[48]:
```
from sklearn.preprocessing import MinMaxScaler
mm=MinMaxScaler()
sc_x=mm.fit_transform(x)
sc_x
```

[48]:
```
array([[0.        , 0.        , 1.        , …, 0.66666667, 0.11542289,
        0.0012751 ],
       [1.        , 0.        , 0.        , …, 1.        , 0.38507463,
        0.21586661],
       [1.        , 0.        , 0.        , …, 1.        , 0.35422886,
        0.01031041],
       …,
       [0.        , 0.        , 1.        , …, 0.66666667, 0.11293532,
```

```
 0.03780868],
[1.        , 1.        , 1.        , …, 1.        , 0.55870647,
 0.03321025],
[1.        , 0.        , 0.        , …, 0.        , 0.86965174,
 0.78764136]])
```

SPLIT DATA INTO TRAINING AND TESTING SETS

[49]:
```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(sc_x,y,test_size=0.
↪3,random_state=42)
```

[50]:
```
y.value_counts()
```

[50]:
```
0    5163
1    1869
Name: Churn, dtype: int64
```

Here, we can see that accuracy of the dataset is pretty good but this is an imbalanced data set. So the chance of false prediction in the class with lower value counts is high. Inorder to rectify that problem, we use the oversampling method

Balance dataset- Over Sampliing

[51]:
```
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)
x_train_resampled, y_train_resampled = smote.fit_resample(x_train, y_train)
```

[52]:
```
y_train_resampled.value_counts()
```

[52]:
```
1    3614
0    3614
Name: Churn, dtype: int64
```

[53]:
```
mm=MinMaxScaler()
sc_x1=mm.fit_transform(x_train_resampled)
sc_x1
```

[53]:
```
array([[0.        , 0.        , 0.        , …, 1.        , 0.40109616,
        0.06012036],
       [1.        , 0.        , 0.        , …, 0.66666667, 0.43148979,
        0.18037261],
       [0.        , 0.        , 0.        , …, 0.66666667, 0.51519681,
        0.02326346],
       …,
       [1.        , 0.        , 0.        , …, 0.43142225, 0.88224269,
        0.49283617],
```

```
[0.        , 0.        , 0.        , …, 0.66666667, 0.60096037,
 0.05156806],
[1.        , 0.        , 0.05846709, …, 1.        , 0.33049549,
 0.09687183]])
```

[54]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(sc_x1,y_train_resampled)
```

[ ]:
```
# from sklearn.model_selection import train_test_split
#␣
↪x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=42,test_size=0.
↪20)
```

[ ]:
```
# from sklearn.preprocessing import StandardScaler
# scaler=StandardScaler()
# scaler.fit(x_train)
# x_train=scaler.fit_transform(x_train)
# x_test=scaler.fit_transform(x_test)
```

3.2 MODEL BUILDING

K Nearest Neighbor Classifier

NAIVE BAYES

SVM

RANDOM FOREST CLASSIFIER

MODEL EVALUATION TOOLS

ACCURACY SCORE

CLASSIFICATION REPORT

CONFUSION MATRIX

importing classification report and accuracy score for model evaluation

[55]:
```
from sklearn.metrics import␣
↪accuracy_score,classification_report,ConfusionMatrixDisplay
```

1.KNN

[56]:
```
from sklearn.neighbors import KNeighborsClassifier

knn=KNeighborsClassifier()
```

Hyperparameter Tuning using GridSearchCV

[96]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.metrics.pairwise import distance
```

```
np.random.seed(42)

param={'n_neighbors':[1,3,5,7,9],
       'weights':['uniform','distance'],
       'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute']
}
gsv_knn=GridSearchCV(knn,param,cv=10,scoring='accuracy')

gsv_knn.fit(x_train,y_train)

#Best parameters
print(gsv_knn.best_params_)
```

```
{'algorithm': 'ball_tree', 'n_neighbors': 1, 'weights': 'uniform'}
```

MODEL CREATION

[97]:
```
knn=KNeighborsClassifier(algorithm='ball_tree',n_neighbors=1,weights='uniform')
knn.fit(x_train,y_train)
knn_pred=knn.predict(x_test)
```

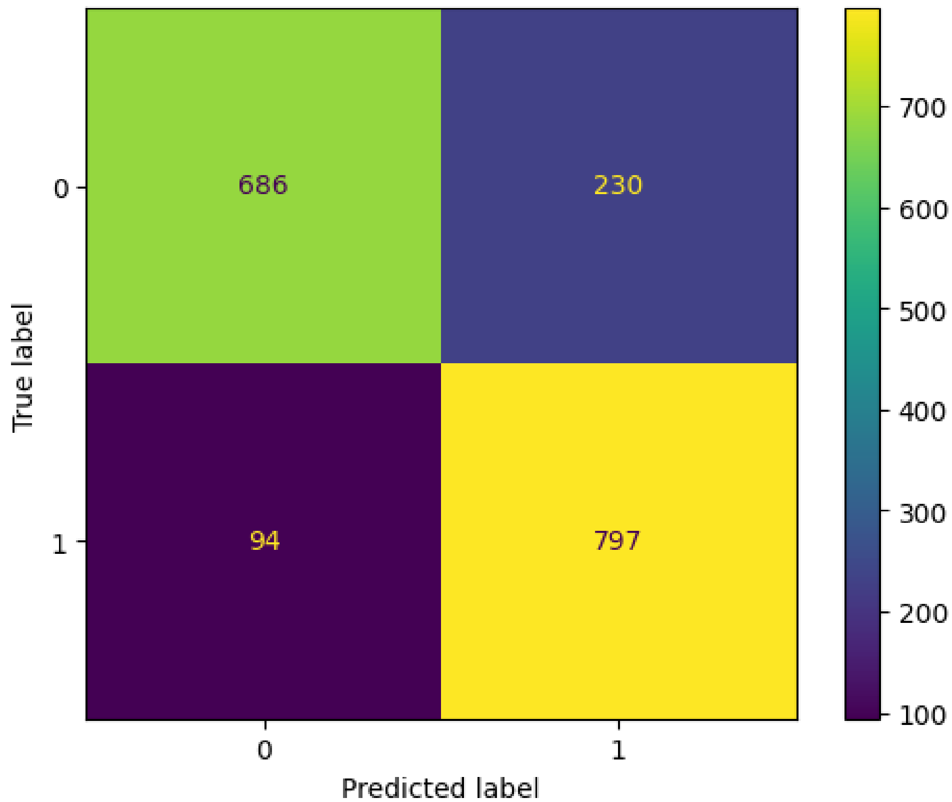
MODEL EVALUATION

[59]:
```
#accuracy score
knn_acc=accuracy_score(y_test,knn_pred)
knn_acc
```

[59]: 0.8206972883231876

[60]:
```
#classification report and confusion matrix
print(classification_report(y_test,knn_pred))
print(ConfusionMatrixDisplay.from_predictions(y_test,knn_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.75      0.81       916
           1       0.78      0.89      0.83       891

    accuracy                           0.82      1807
   macro avg       0.83      0.82      0.82      1807
weighted avg       0.83      0.82      0.82      1807

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x7df117fd2560>
```



2. SVM (SUPPORT VECTOR MACHINE)

[61]:
```
from sklearn.svm import SVC
svm=SVC()
```

Hyperparameter Tuning using GridSearchCV

[63]:
```
param_grid_svm ={'C': [0.1, 1, 10],
'kernel': ['linear', 'rbf'],
'gamma': ['scale', 'auto', 0.1,1]}

grid_search_svm = GridSearchCV(svm, param_grid_svm, scoring='recall', cv=10)
grid_search_svm.fit(x_train, y_train)

print(grid_search_svm.best_params_)
```

```
{'C': 10, 'gamma': 1, 'kernel': 'rbf'}
```

MODEL CREATION

[67]:
```
svm=SVC(C=10,gamma=1,kernel='rbf')
svm.fit(x_train,y_train)
svm_pred=svm.predict(x_test)
```

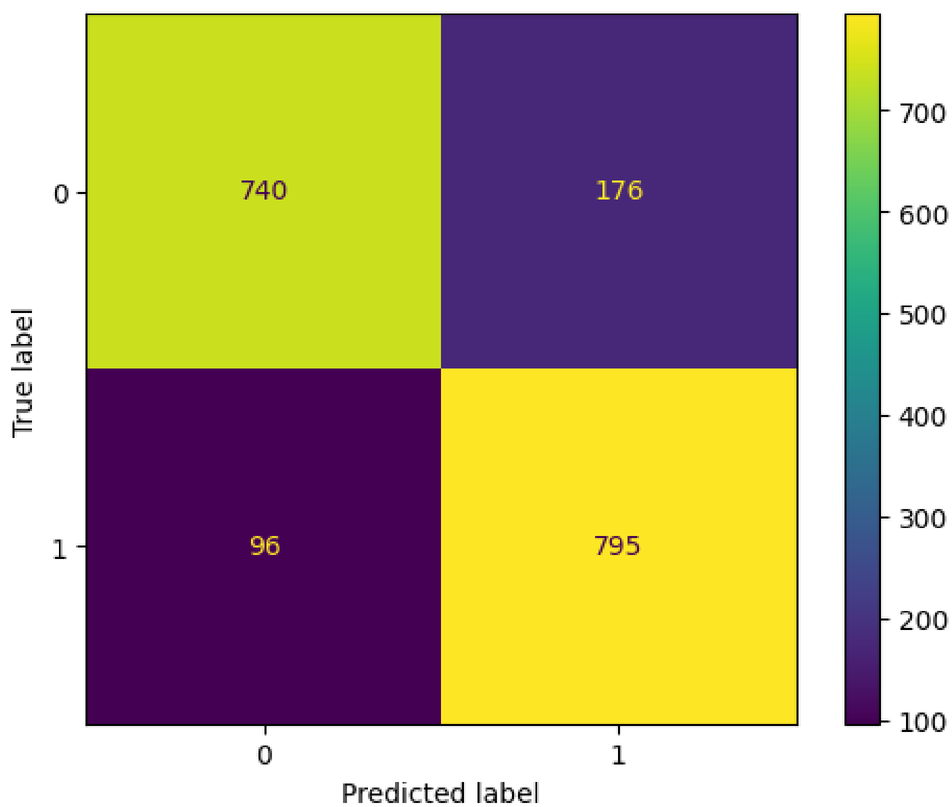
MODEL EVALUATION

[68]:
```
#accuracy score
svm_acc=accuracy_score(y_test,svm_pred)
svm_acc
```

[68]: 0.8494742667404538

[69]:
```
#classification report and confusion matrix
print(classification_report(y_test,svm_pred))
print(ConfusionMatrixDisplay.from_predictions(y_test,svm_pred))
```

```
              precision    recall  f1-score   support

           0       0.89      0.81      0.84       916
           1       0.82      0.89      0.85       891

    accuracy                           0.85      1807
   macro avg       0.85      0.85      0.85      1807
weighted avg       0.85      0.85      0.85      1807

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x7df115f335e0>
```



3. DECISION TREE CLASSIFIER

[70]:
```
from sklearn.tree import DecisionTreeClassifier
#Decision Tree Classifier Object
dtree = DecisionTreeClassifier()
```

Hyperparameter Tuning using GridSearchCV

[72]:
```
from sklearn.model_selection import GridSearchCV

#parameter grid
param_grid = {
    'max_depth': [2,4,6,8,10],
    'min_samples_leaf': [2,4,6,8,10],
    'min_samples_split': [2,4,6,8,10],
    'criterion': ['gini', 'entropy'],
    'random_state': [0,42]
}

#Grid Search Object with Decision Tree Classifier
grid_search_d = GridSearchCV(estimator = dtree, param_grid = param_grid, cv =␣
↪3, n_jobs = -1, verbose = 2, scoring='accuracy')

#Fitting the data
grid_search_d.fit(x_train, y_train)
```

```
Fitting 3 folds for each of 500 candidates, totalling 1500 fits
```

[72]:
```
GridSearchCV(cv=3, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [2, 4, 6, 8, 10],
                         'min_samples_leaf': [2, 4, 6, 8, 10],
                         'min_samples_split': [2, 4, 6, 8, 10],
                         'random_state': [0, 42]},
             scoring='accuracy', verbose=2)
```

[73]:
```
#Best parameters
print(grid_search_d.best_params_)
```

```
{'criterion': 'entropy', 'max_depth': 8, 'min_samples_leaf': 8,
'min_samples_split': 2, 'random_state': 42}
```

MODEL CREATION

[74]:
```
dtree  = DecisionTreeClassifier(criterion='entropy', max_depth=8,␣
↪min_samples_leaf=8,min_samples_split=2, random_state=42)
dtree.fit(x_train,y_train)
```

```
dtree_pred=dtree.predict(x_test)
```

MODEL EVALUATION

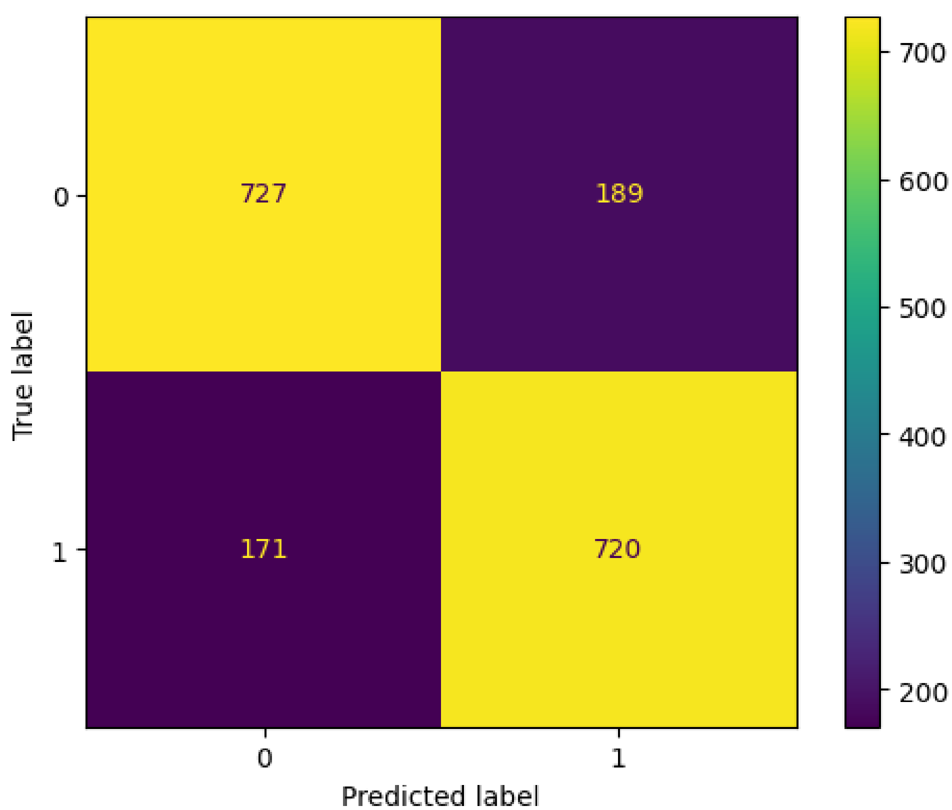
[75]:
```
dtree_acc=accuracy_score(y_test,dtree_pred)
dtree_acc
```

[75]: 0.8007747648035418

[76]:
```
#classification report and confusion matrix
print(classification_report(y_test,dtree_pred))
print(ConfusionMatrixDisplay.from_predictions(y_test,dtree_pred))
```

```
              precision    recall  f1-score   support

           0       0.81      0.79      0.80       916
           1       0.79      0.81      0.80       891

    accuracy                           0.80      1807
   macro avg       0.80      0.80      0.80      1807
weighted avg       0.80      0.80      0.80      1807
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x7df115eef310>
```



4.RANDOM FOREST

[77]:
```
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier()
rf.get_params()
```

[77]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'sqrt',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': None,
 'verbose': 0,
 'warm_start': False}
```

Hyperparameter Tuning using GridSearchCV

[78]:
```
param_rf = {'n_estimators': [50, 100, 150],
            'max_depth': [ 10, 20, 30,40,50]
}

grid_search_rf = GridSearchCV(rf, param_rf, scoring ='accuracy', cv=10)
grid_search_rf.fit(x_train, y_train)


print(grid_search_rf.best_params_)
```

```
{'max_depth': 50, 'n_estimators': 150}
```

MODEL CREATION

[83]:
```
rf=RandomForestClassifier(max_depth=50,n_estimators=150)
rf.fit(x_train,y_train)
rf_pred=rf.predict(x_test)
```

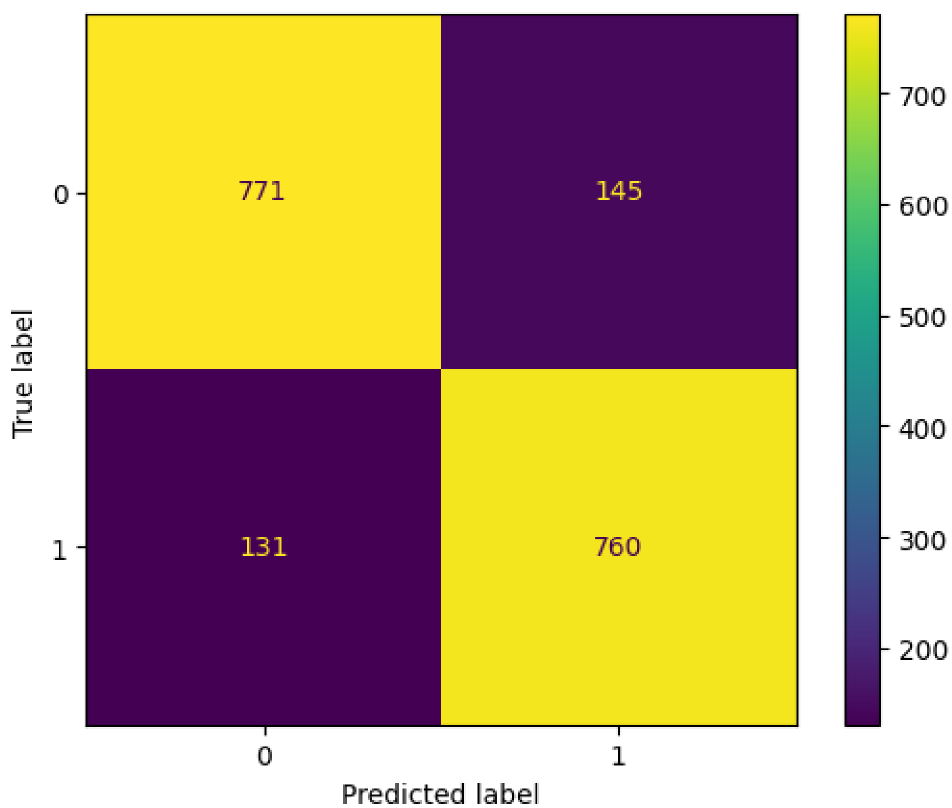
MODEL EVALUATION

[84]:
```python
#accuracy score
rf_acc=accuracy_score(y_test,rf_pred)
rf_acc
```

[84]: 0.8472606530160487

[85]:
```python
#classification report and confusion matrix
print(classification_report(y_test,rf_pred))
print(ConfusionMatrixDisplay.from_predictions(y_test,rf_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.84      0.85       916
           1       0.84      0.85      0.85       891

    accuracy                           0.85      1807
   macro avg       0.85      0.85      0.85      1807
weighted avg       0.85      0.85      0.85      1807

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x7df115eed7b0>
```



5. NAIVE BAYES CLASSIFIER

[86]:
```python
from sklearn.naive_bayes import GaussianNB
nb=GaussianNB()
nb.fit(x_train,y_train)
nb_pred=nb.predict(x_test)
```

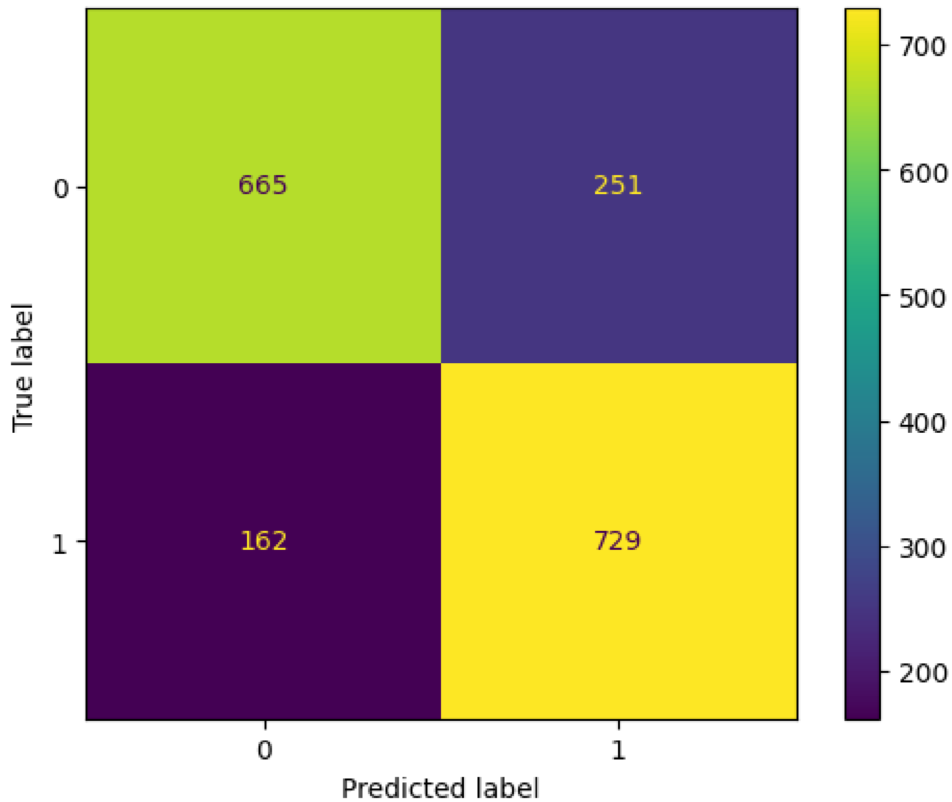
MODEL EVALUATION

[87]:
```python
nb_acc=(accuracy_score(y_test,nb_pred))
nb_acc
```

[87]: 0.7714443829551744

[88]:
```python
#classification report and confusion matrix
print(classification_report(y_test,nb_pred))
print(ConfusionMatrixDisplay.from_predictions(y_test,nb_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.73      0.76       916
           1       0.74      0.82      0.78       891

    accuracy                           0.77      1807
   macro avg       0.77      0.77      0.77      1807
weighted avg       0.77      0.77      0.77      1807

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at
0x7df117fa5600>
```



MODEL EVALUATION - Accuracy_Score visualization

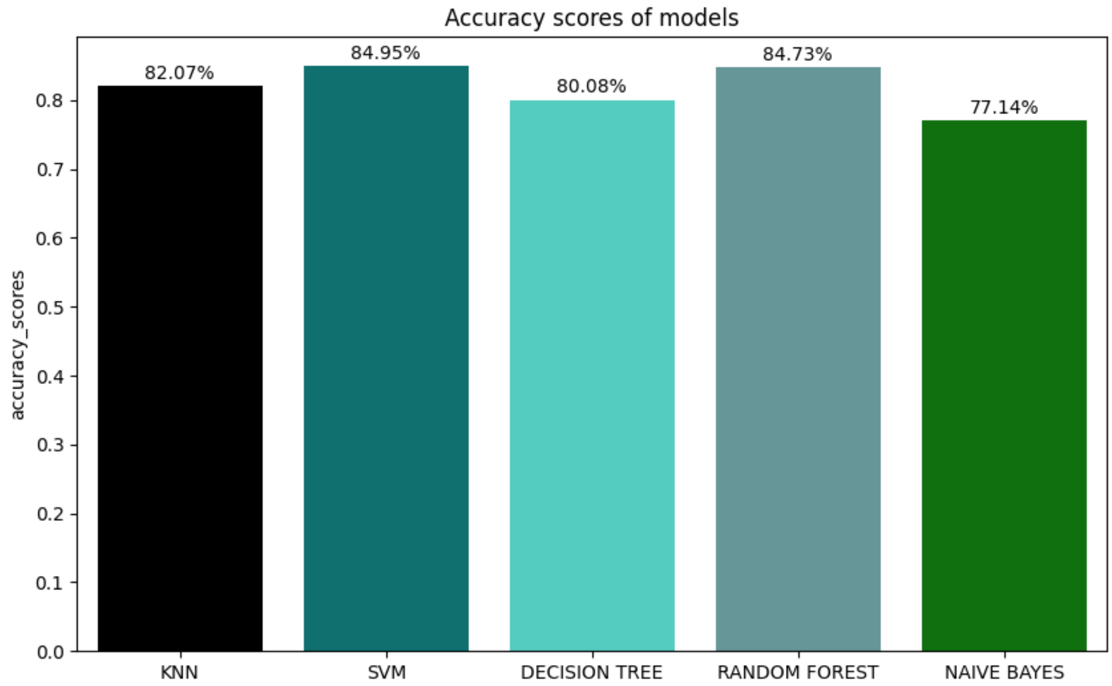
ACCURACY SCORE COMPARISON BETWEEN MODELS

[89]:
```
model=['KNN','SVM','DECISION TREE','RANDOM FOREST','NAIVE BAYES']
accuracy_scores=[knn_acc,svm_acc,dtree_acc,rf_acc,nb_acc]
accuracy_scores
```

[89]:
```
[0.8206972883231876,
 0.8494742667404538,
 0.8007747648035418,
 0.8472606530160487,
 0.7714443829551744]
```

[90]:
```
color=['black','teal','turquoise','cadetblue','green']
plt.figure(figsize=(10,6))
sns.barplot(x=model,y=accuracy_scores,palette=color)
plt.ylabel('accuracy_scores')
plt.title('Accuracy scores of models')
# Adding percentage labels
for i, score in enumerate(accuracy_scores):
    plt.text(i, score +0.01, f'{score*100:.2f}%' , ha = 'center')
```

```
plt.show()
```



By plotting accuracy score with percentage label,it is clear that support vector machine classifier and Random forest classifier shows highest accurcy score than other models.

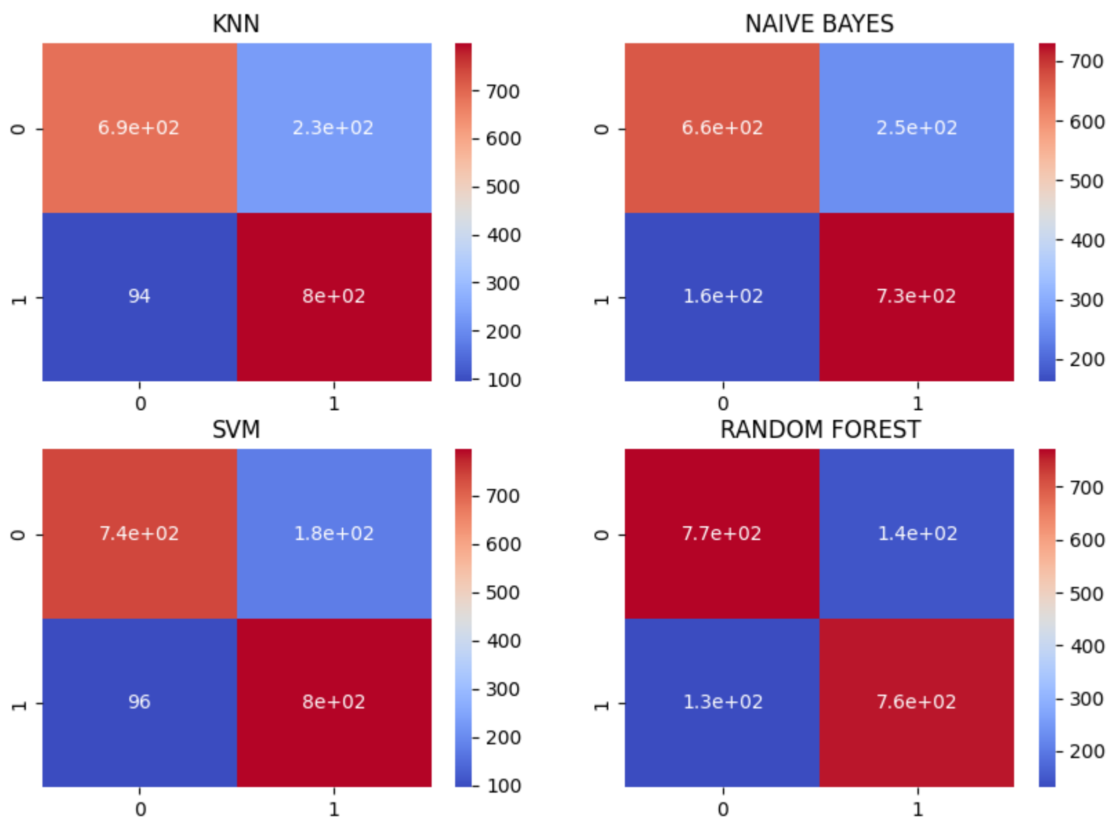
3.3 Confusion Matrix Heatmap

A confusion matrix is a common tool used in machine learning to evaluate the performance of a classification algorithm.

[95]:
```
# #from sklearn.metrics import confusion_matrix
# fig, ax = plt.subplots(2, 2, figsize=(10, 7))

# #KNN Confusion Matrix
# sns.heatmap(confusion_matrix(y_test, knn_pred), annot=True, ax=ax[0,0],␣
↪cmap='coolwarm')
# ax[0,0].set_title('KNN')

# #NAIVE BAYES confusion matrix
# sns.heatmap(confusion_matrix(y_test, nb_pred), annot=True, ax=ax[0,1],␣
↪cmap='coolwarm')
# ax[0,1].set_title('NAIVE BAYES')


# #SVM Confusion Matrix
```

```
# sns.heatmap(confusion_matrix(y_test, svm_pred), annot=True, ax=ax[1,0],␣
↪cmap='coolwarm')
# ax[1,0].set_title('SVM')


# #RANDOM FORESTConfusion Matrix
# sns.heatmap(confusion_matrix(y_test, rf_pred), annot=True, ax=ax[1,1],␣
↪cmap='coolwarm')
# ax[1,1].set_title('RANDOM FOREST')
```

[95]: Text(0.5, 1.0, 'RANDOM FOREST')



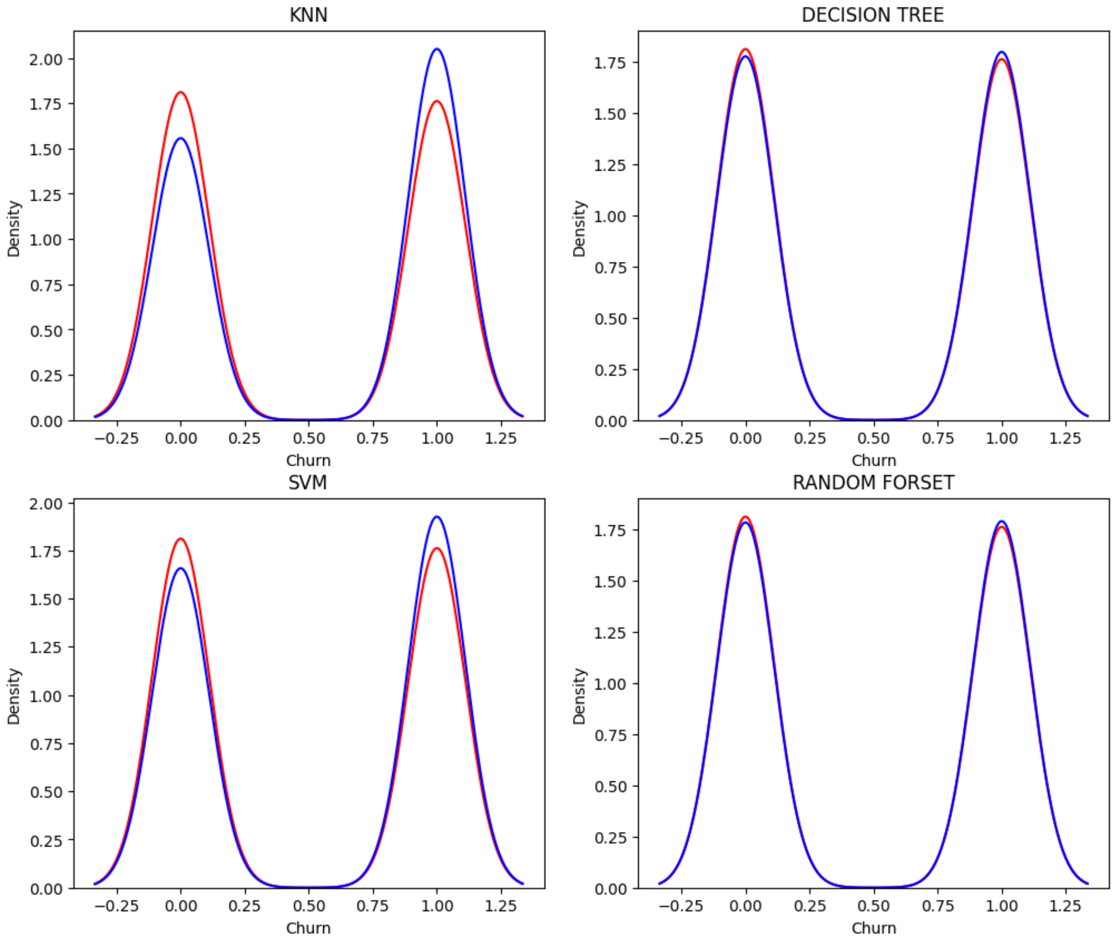
The confusion matrix heatmaps visulaizes the true positive and true negative results from the machine learning model.

DISTRIBUTION PLOT(Y_TEST V/S Y_PREDICTED VALUES)

[93]:
```
fig, ax = plt.subplots(2, 2, figsize=(12, 10))

#KNN
```

```
sns.distplot(y_test, hist=False, color="r", label="Actual Value", ax=ax[0,0]).
    ↪set_title('KNN')
sns.distplot(knn_pred, hist=False, color="b", label="Fitted Values" ,␣
    ↪ax=ax[0,0])


#DECISION TREE
sns.distplot(y_test, hist=False, color="r", label="Actual Value", ax=ax[0,1]).
    ↪set_title('DECISION TREE')
sns.distplot(dtree_pred, hist=False, color="b", label="Fitted Values" ,␣
    ↪ax=ax[0,1])


#SVM
sns.distplot(y_test, hist=False, color="r", label="Actual Value", ax=ax[1,0]).
    ↪set_title('SVM')
sns.distplot(svm_pred, hist=False, color="b", label="Fitted Values" ,␣
    ↪ax=ax[1,0])


# #RANDOM FOREST
sns.distplot(y_test, hist=False, color="r", label="Actual Value", ax=ax[1,1]).
    ↪set_title('RANDOM FORSET')
sns.distplot(rf_pred, hist=False, color="b", label="Fitted Values" , ax=ax[1,1])
```

[93]:
```
<Axes: title={'center': 'RANDOM FORSET'}, xlabel='Churn', ylabel='Density'>
```

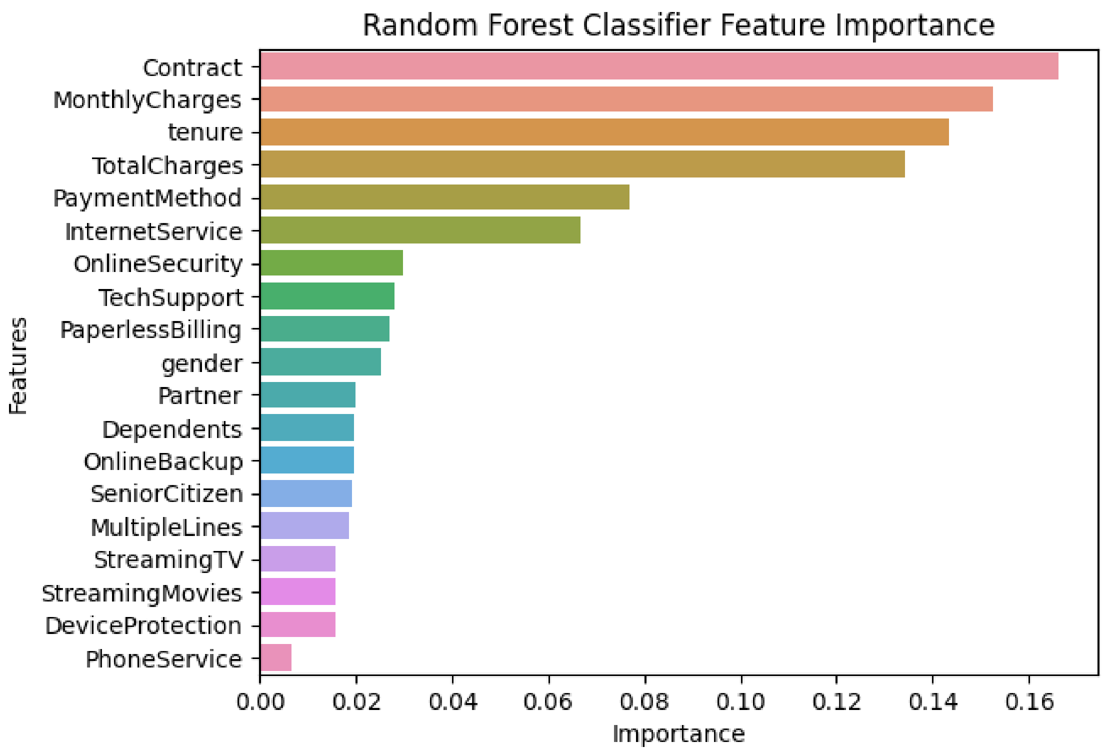


Distribution plots allow you to visually compare the distribution of your model's predictions (fitted values) with the distribution of the actual values.it provide a visual way to assess the goodness of fit of your model, understand the quality of predictions, and identify potential issues or areas for improvement.

Feature Importance

[94]:
```
# Random Forest Classifier Feature Importance

x_train = pd.DataFrame(x_train, columns = x.columns)
feature_df = pd.DataFrame({'Features': x_train.columns, 'Importance': rf.
 ↪feature_importances_})
feature_df.sort_values('Importance', ascending=False, inplace=True)
sns.barplot(x = 'Importance', y = 'Features', data = feature_df).
 ↪set_title('Random Forest Classifier Feature Importance')
```

[94]:
```
Text(0.5, 1.0, 'Random Forest Classifier Feature Importance')
```



Total charges,Monthly charges,tenure,contract are the most important features for predicting the customer churn hence company should focus on this features to reduce churn rate

CONCLUSION

I have used five models - K Nearest Neighbor classifier, Naive bayes classifier,Support vector machine(SVM),Decision tree classifier, Random Forest Classifier. The Support vector machine Classifier and Random Forest Cllasifier shows the highest accuracy score and F1 Score. Therefore, the support vector machine Classifier and random forest classifier is good fit for predicting the customer churn.