EDA and Data Prediction on the Telcom Churn Dataset

"Churning" refers to the number of Customers or Employees that leave a Company in a given time period. Changes in a business's churn rate can provide valuable insight into an organization.

Importing librariers required for Data Analysis and Predictions

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
df=pd.read_csv("telecom_churn.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DevicePro
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	

5 rows × 21 columns

In [4]:
```
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      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

Handling Null values and then replacing them with Central Tendancies

In [5]:
```python
df[df["TotalCharges"]==" "]
#TotalCharges column has 11 rows without any value
```

Out[5]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	De
488	4472-LVYGI	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	...	
753	3115-CZMZD	Male	0	No	Yes	0	Yes	No	No	No internet service	...	
936	5709-LVOEQ	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	...	
1082	4367-NUYAO	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	...	
1340	1371-DWPAZ	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	...	
3331	7644-OMVMY	Male	0	Yes	Yes	0	Yes	No	No	No internet service	...	
3826	3213-VVOLG	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	...	
4380	2520-SGTTA	Female	0	Yes	Yes	0	Yes	No	No	No internet service	...	
5218	2923-ARZLG	Male	0	Yes	Yes	0	Yes	No	No	No internet service	...	
6670	4075-WKNIU	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	...	
6754	2775-SEFEE	Male	0	No	Yes	0	Yes	Yes	DSL	Yes	...	

11 rows × 21 columns

In [6]:
```python
df["TotalCharges"].replace(' ',np.nan, inplace=True)
df["TotalCharges"]=df["TotalCharges"].astype(float)
#Replacing the blank space with null value and converting the datatype to float
```

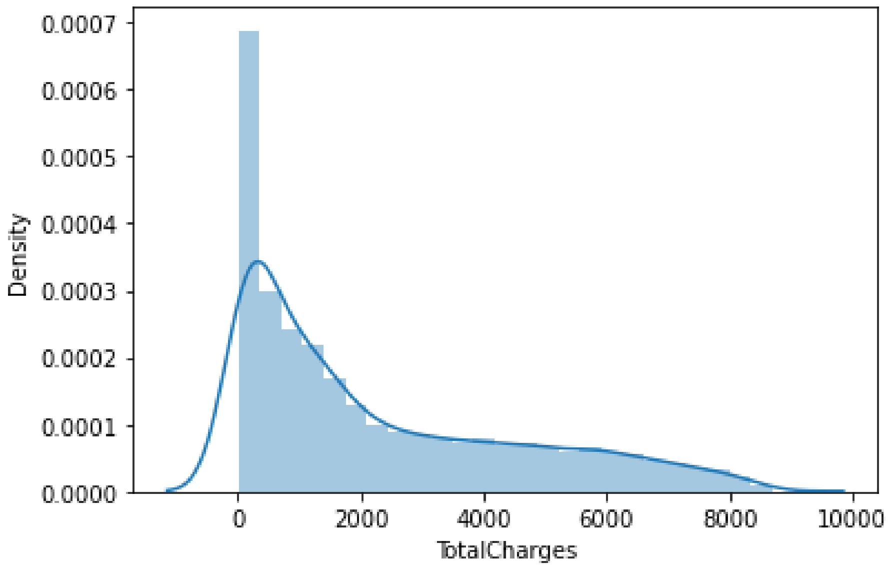
In [7]:
```
df.describe()
```

Out[7]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000	7032.000000
mean	0.162147	32.371149	64.761692	2283.300441
std	0.368612	24.559481	30.090047	2266.771362
min	0.000000	0.000000	18.250000	18.800000
25%	0.000000	9.000000	35.500000	401.450000
50%	0.000000	29.000000	70.350000	1397.475000
75%	0.000000	55.000000	89.850000	3794.737500
max	1.000000	72.000000	118.750000	8684.800000

In [8]:
```
sns.distplot(df.TotalCharges)
```

Out[8]: <AxesSubplot:xlabel='TotalCharges', ylabel='Density'>



When the data is skewed, it is good to consider using the median value for replacing the null values. Since the above Distribution Plot signifies the data is right skewed , replacing the null values with the median.

In [9]:
```
df["TotalCharges"]=df["TotalCharges"].fillna(df["TotalCharges"].median())
```

In [10]:
```
df.describe()
```

Out[10]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692	2281.916928
std	0.368612	24.559481	30.090047	2265.270398
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	1397.475000
75%	0.000000	55.000000	89.850000	3786.600000
max	1.000000	72.000000	118.750000	8684.800000

The datasets descriptions shows that the average Monthly Charges are USD 64.76 and it has maximum gone upto USD 118.75 The average tenure the telecom company has is of 32 months. The average Total Amount charged to the customer is USD 2283 and the maximum amount is USD 8684. By observation, I found that the MonthlyCharges and TotalCharges are not evenly distributed

Dropping the columns with least correlations

In [11]:
```
df.drop(['customerID'],axis=1,inplace=True)
```

Dropping the costumerID column as it has the least correlation with the Churn column

Handling Categorical Data

In [12]:
```
df_num=df.select_dtypes(['float64','int64'])
df_cat=df.select_dtypes(['object'])
```

Seperating the numerical and categorical columns

In [13]:
```
df_cat.head()
```

Out[13]:

	gender	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	S
0	Female	Yes	No	No	No phone service	DSL	No	Yes	No	No	
1	Male	No	No	Yes	No	DSL	Yes	No	Yes	No	
2	Male	No	No	Yes	No	DSL	Yes	Yes	No	No	
3	Male	No	No	No	No phone service	DSL	Yes	No	Yes	Yes	
4	Female	No	No	Yes	No	Fiber optic	No	No	No	No	

In [14]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
```

Performing Label Encoding on the categorical columns so as to convert then into the machine readable form!

In [15]:
```
for i in df_cat:
    le=LabelEncoder()
    df_cat[i]=le.fit_transform(df_cat[i])
```

In [16]:
```
df_cat.head()
```

Out[16]:

	gender	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	S
0	0	1	0	0	1	0	0	2	0	0	
1	1	0	0	1	0	0	2	0	2	0	
2	1	0	0	1	0	0	2	2	0	0	
3	1	0	0	0	1	0	2	0	2	2	
4	0	0	0	1	0	1	0	0	0	0	

In [17]:
```
df2=pd.concat([df_num,df_cat],axis=1)
```

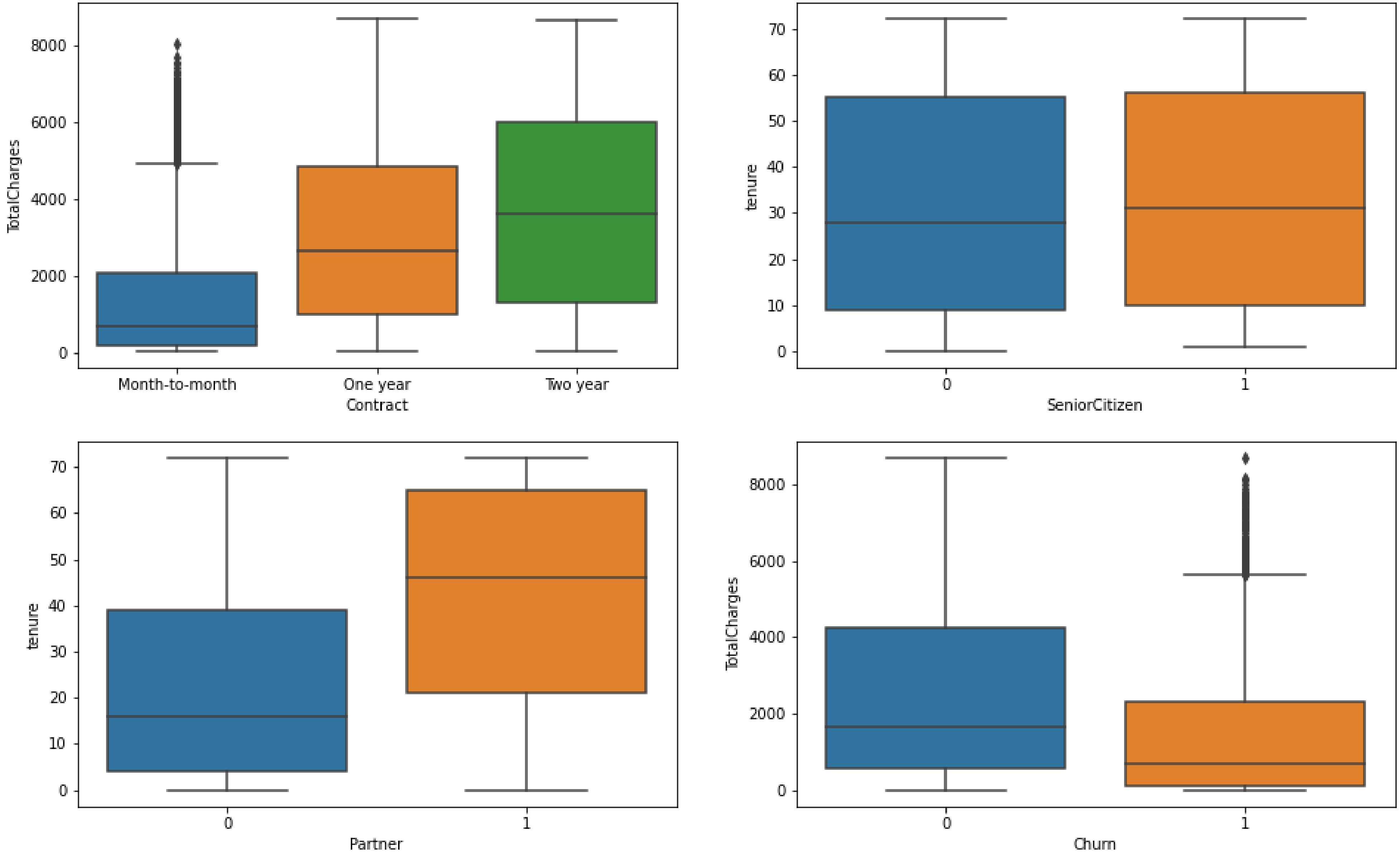
In [18]:
```
df2.head()
```

Out[18]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	gender	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSecu
0	0	1	29.85	29.85	0	1	0	0	1	0	
1	0	34	56.95	1889.50	1	0	0	1	0	0	
2	0	2	53.85	108.15	1	0	0	1	0	0	
3	0	45	42.30	1840.75	1	0	0	0	1	0	
4	0	2	70.70	151.65	0	0	0	1	0	1	

Checking For Outliers

In [19]:
```
fig,axes=plt.subplots(2,2,figsize=(16,10))
sns.boxplot(data=df, x="Contract", y="TotalCharges",ax=axes[0,0])
sns.boxplot(data=df2, x="SeniorCitizen" , y="tenure",ax=axes[0,1])
sns.boxplot(data=df2, x="Partner" , y="tenure",ax=axes[1,0])
sns.boxplot(data=df2, x="Churn" , y="TotalCharges",ax=axes[1,1])
plt.show()
```



Removing Outliers

In [20]:
```
outlier1= df.loc[(df['Contract']=='Month-to-month') & (df['TotalCharges']>8000)]
outlier2= df.loc[(df['Churn']=='Yes') & (df['TotalCharges']>8500)]
print(outlier1.index,outlier2.index)
```

```
Int64Index([3820], dtype='int64') Int64Index([4610], dtype='int64')
```

In [21]:
```
df2.drop(index=3820,inplace=True)
```

In [22]:
```
df2.drop(index=4610,inplace=True)
```

By observing the boxplots , came across some outliers and removed them

In [23]:
```
df2.head()
```

Out[23]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	gender	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSecu
0	0	1	29.85	29.85	0	1	0	0	1	0	
1	0	34	56.95	1889.50	1	0	0	1	0	0	
2	0	2	53.85	108.15	1	0	0	1	0	0	
3	0	45	42.30	1840.75	1	0	0	0	1	0	
4	0	2	70.70	151.65	0	0	0	1	0	1	

Reducing Skewness

In [24]:
```
for i in df_num:
    print(f"{i}={df2[i].skew()}")
```

```
SeniorCitizen=1.8345916532810498
tenure=0.23995276839384197
MonthlyCharges=-0.22068712827085618
TotalCharges=0.963347739293753
```

TotalCharges column is highly skewed

In [25]:
```
df2["TotalCharges"]=np.sqrt(df2["TotalCharges"])
```

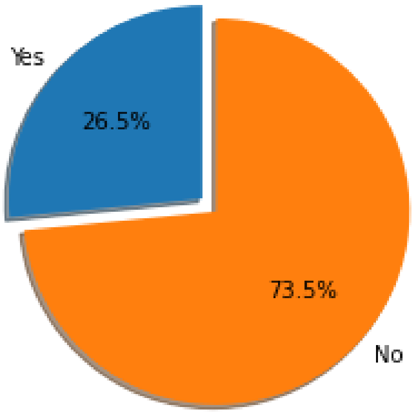
In [26]:
```
df2["TotalCharges"].skew()
```

Out[26]:
```
0.3096188474579813
```

Reduced the skewness

Data Exploration

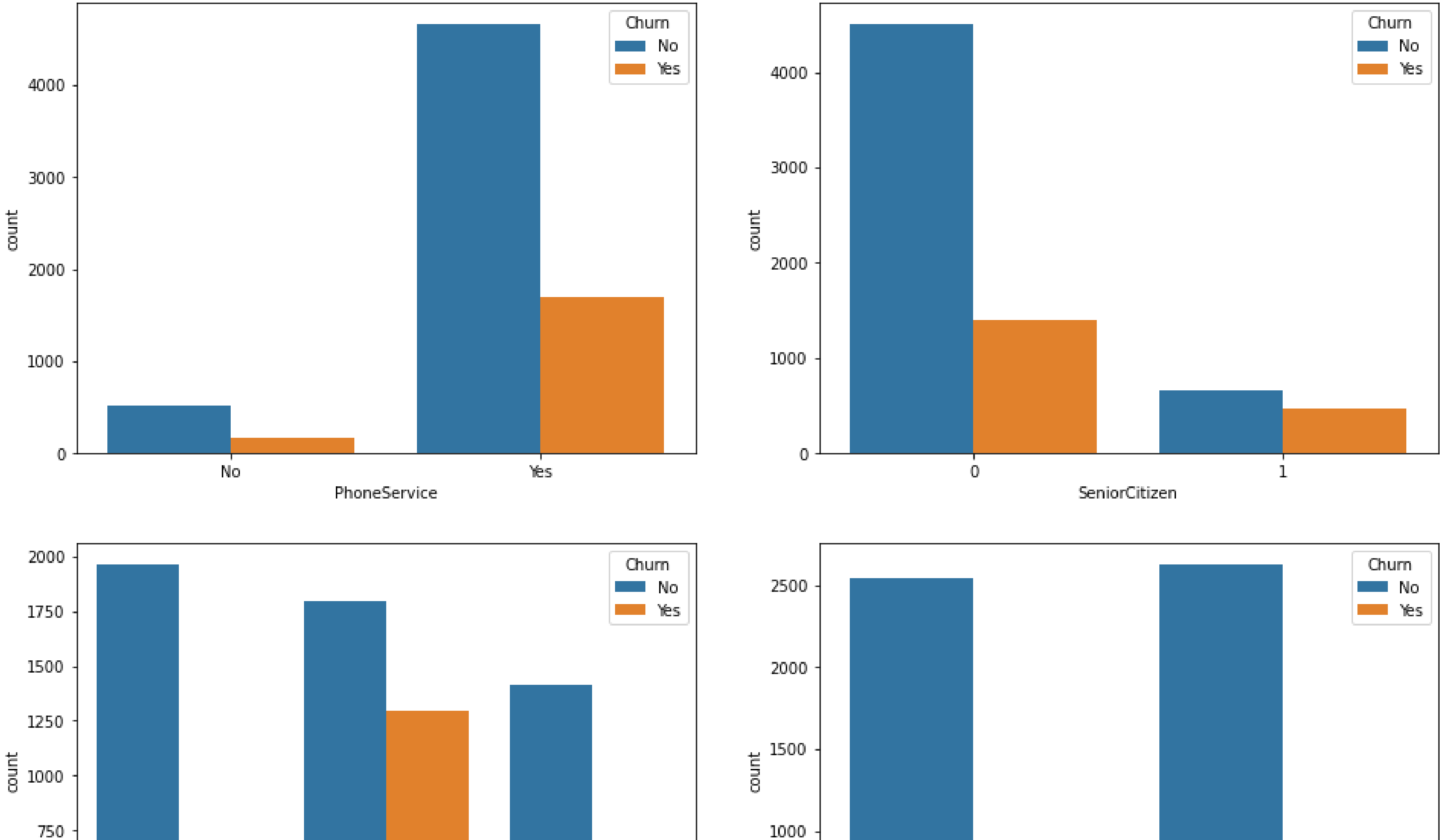
In [27]:
```
data=[df.Churn.value_counts()[1],df.Churn.value_counts()[0]]
label=['Yes','No']
plt.pie(data,labels=label, shadow=True, autopct="%0.1f%%",explode=[0,0.1],startangle=90)
plt.show()
```

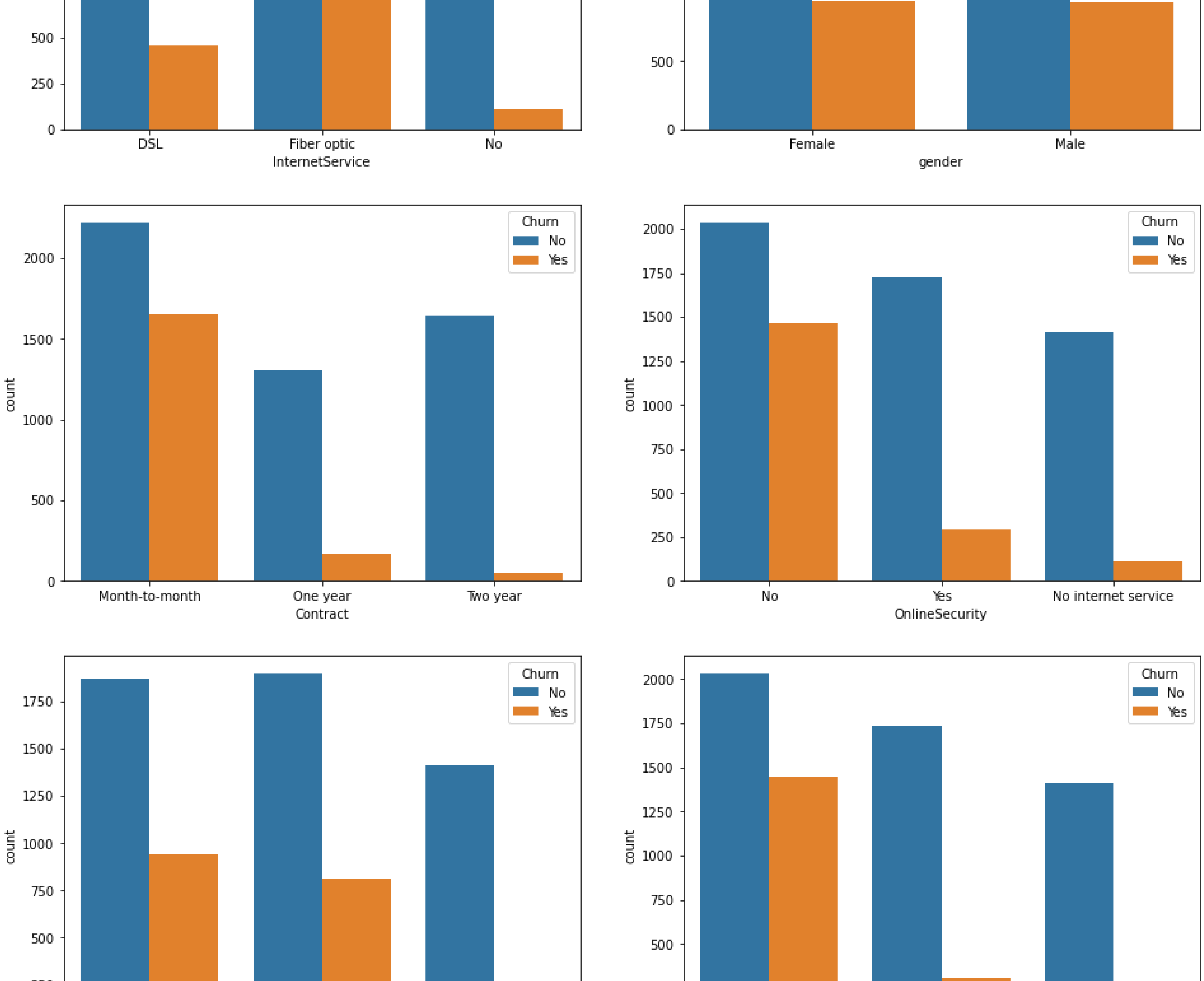


26.5% Customers have left within the last month.

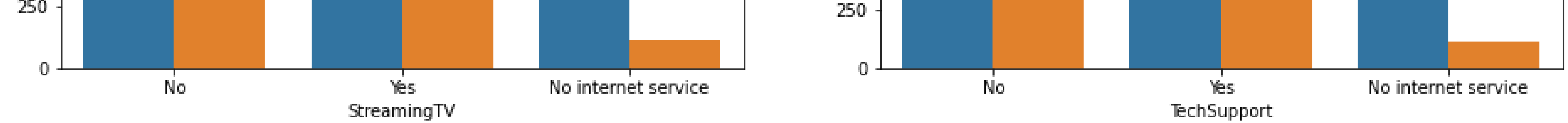
In [28]:

```
fig,axes=plt.subplots(4,2,figsize=(16,25))
sns.countplot(data=df,x='PhoneService',hue='Churn',ax=axes[0,0])
sns.countplot(data=df,x='SeniorCitizen',hue='Churn',ax=axes[0,1])
sns.countplot(data=df,x='InternetService',hue='Churn',ax=axes[1,0])
sns.countplot(data=df,x='gender',hue='Churn',ax=axes[1,1])
sns.countplot(data=df,x='Contract',hue='Churn',ax=axes[2,0])
sns.countplot(data=df,x='OnlineSecurity',hue='Churn',ax=axes[2,1])
sns.countplot(data=df,x='StreamingTV',hue='Churn',ax=axes[3,0])
sns.countplot(data=df,x='TechSupport',hue='Churn',ax=axes[3,1])
plt.show()
```



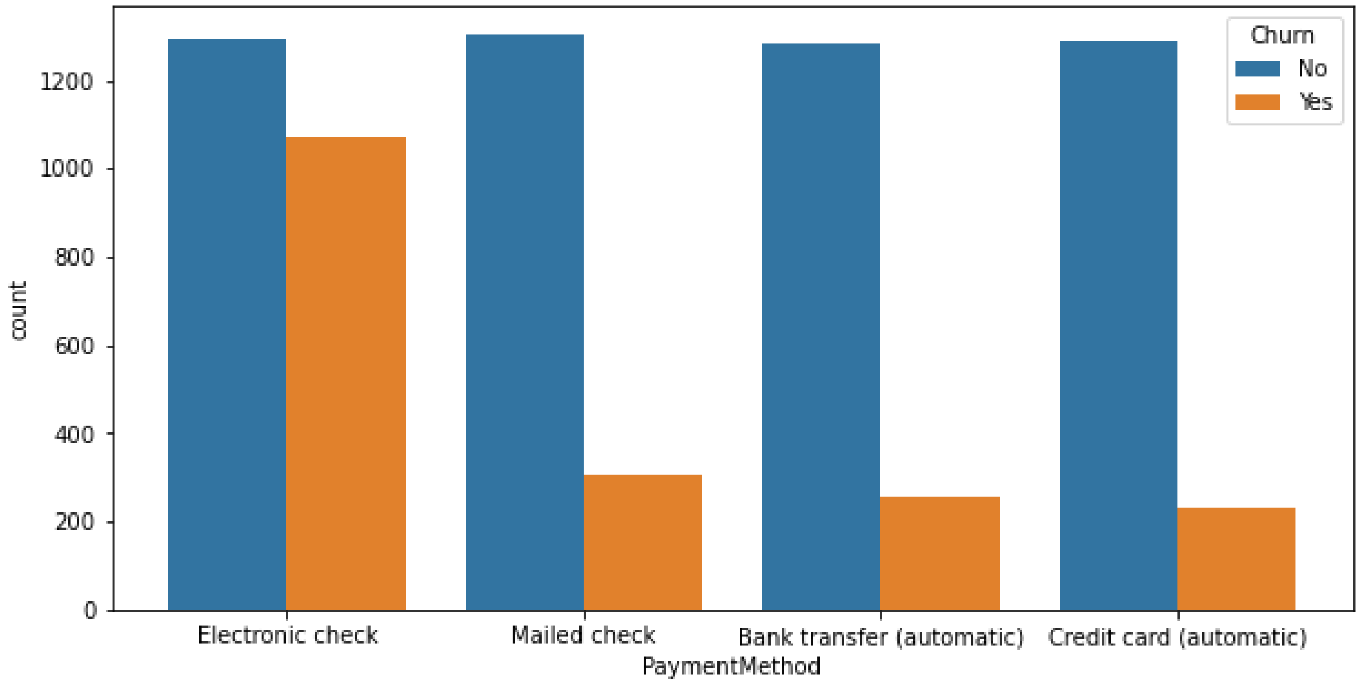


500
250
0
DSL
Fiber optic
No
InternetService
500
0
Female
Male
gender
Churn
No
Yes
count
2000
1500
1000
500
0
Month-to-month
One year
Two year
Contract
Churn
No
Yes
count
2000
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
OnlineSecurity
Churn
No
Yes
count
1750
1500
1250
1000
750
500
Churn
No
Yes
count
2000
1750
1500
1250
1000
750
500



In [29]:
```
fig,axes=plt.subplots(figsize=(10,5))
sns.countplot(data=df,x='PaymentMethod',hue='Churn')
plt.plot()
```

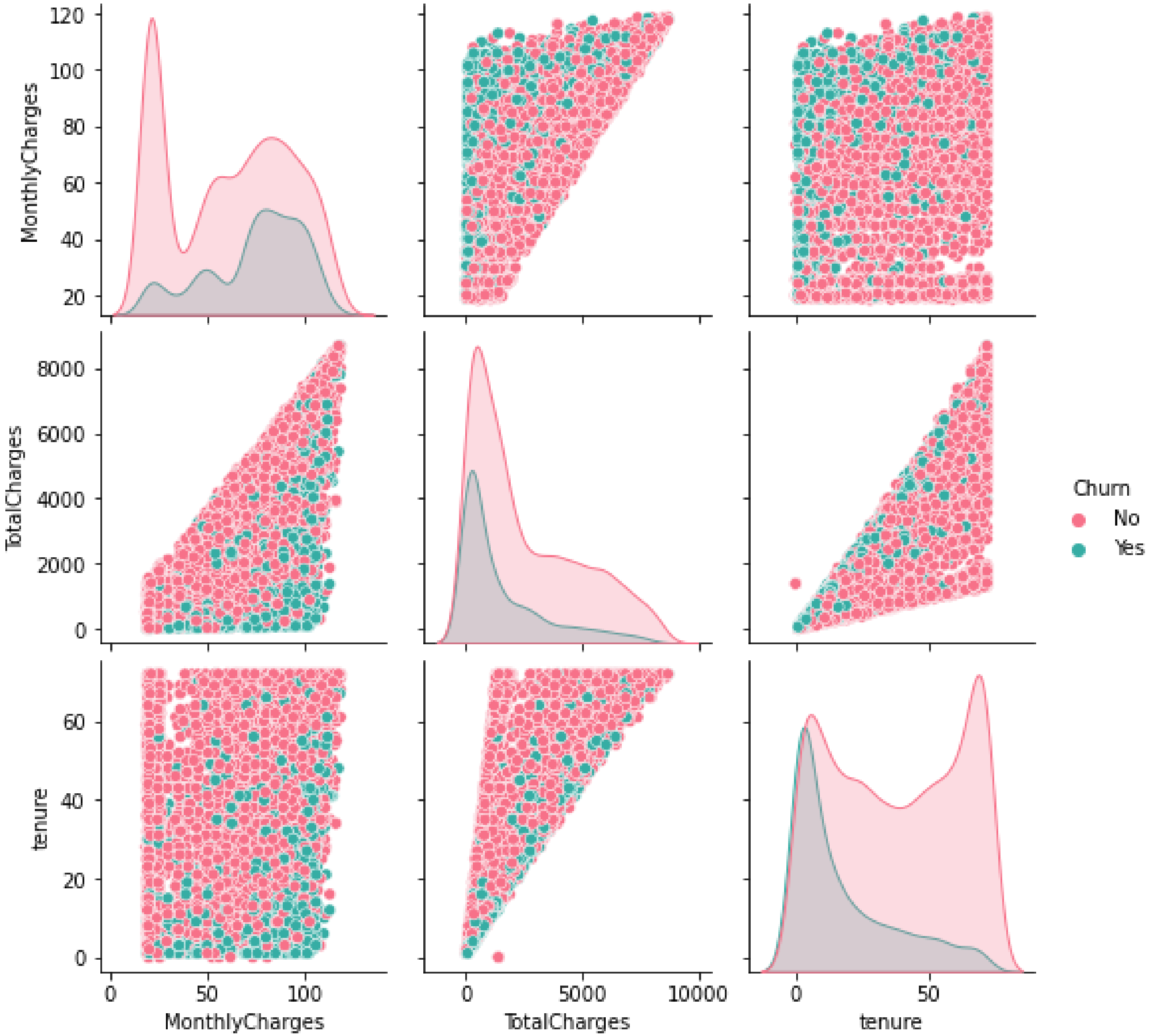
Out[29]: []



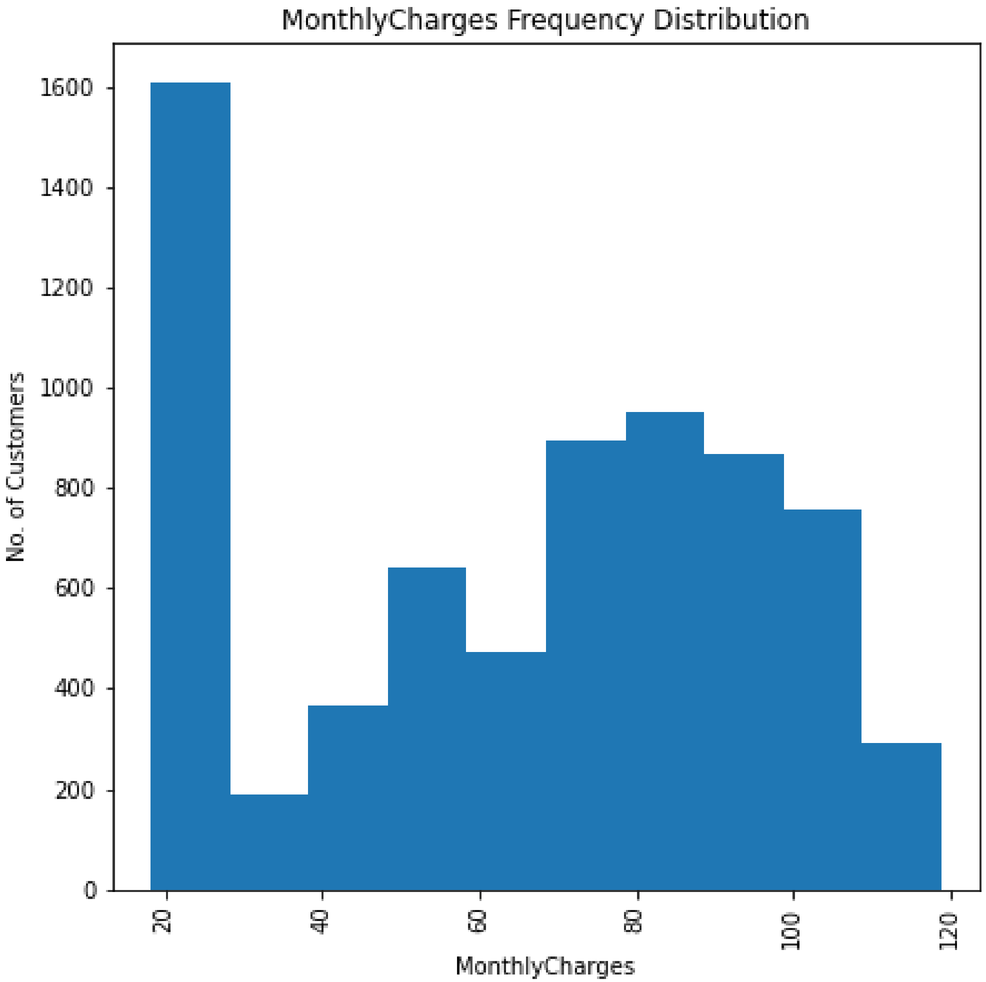
The above countplots describe the Churn analysis with other features in the dataset

```
In [30]: sns.pairplot(data=df,vars=['MonthlyCharges','TotalCharges','tenure'],hue='Churn', palette='husl')
```

```
Out[30]: <seaborn.axisgrid.PairGrid at 0x213119b1d30>
```



In [31]:
```
#Histogram of MonthlyCharges Frequency Distribution
plt.figure(figsize=(7,7))
plt.hist(df2["MonthlyCharges"], bins=10)
plt.xticks(rotation="vertical")
plt.title("MonthlyCharges Frequency Distribution")
plt.ylabel("No. of Customers")
plt.xlabel("MonthlyCharges")
plt.show()
```



Large number of customers (around 1600) pay MonthlyCharges between USD 20 to USD 30. The MonthlyCharges frequency is not evenly distrubuted

In [32]:
```
df2.corr()['Churn']
```

Out[32]:
```
SeniorCitizen       0.151278
tenure             -0.352681
MonthlyCharges      0.193197
TotalCharges       -0.225502
gender             -0.008765
Partner            -0.150660
Dependents         -0.164169
PhoneService        0.011895
MultipleLines       0.037883
InternetService    -0.047328
OnlineSecurity     -0.289667
OnlineBackup       -0.195799
DeviceProtection   -0.178401
TechSupport        -0.282844
StreamingTV        -0.036769
StreamingMovies    -0.038679
Contract           -0.396982
PaperlessBilling    0.191761
PaymentMethod       0.107407
Churn               1.000000
Name: Churn, dtype: float64
```

Correlation of the target variable with other features

According to the analysis, I came to the following conclusions:

1. 26.5% Customers have left the Company within last month.
2. The company has more no of Younger Generation than Senior Citizens with almost almost equal no of Male and Females.
3. Younger Generation Churn more than compared to the Senior Citizens. So the company must come up with more ideas in interest of the Young people.
4. The company provides phone services to many of the customers (i.e 6361 out of 7041).
5. The customers who is being provided Online Security Churn less. So the Company should increase the number of Customers with Online Security.

6. The customers with Technical Support tend to Churn less. So the Company should increase the number of Customers with Technical Support
7. The Customers with DSL as the Internet Service churn less as compared to the customers with Optical Fiber.
8. The Customers using Electronic Check as their Payment Method Churn more comparitively.
9. Customers with Yearly Contract tend to churn less as compared to customers with Monthly COntract

Scaling

In [33]:
```
from sklearn.preprocessing import MinMaxScaler
mm=MinMaxScaler()
df2[["TotalCharges"]]=mm.fit_transform(df2[["TotalCharges"]])
```

Performed Feature Scaling on Total Charges

Seperating the Dependent and Independent variables for Training and Testing of Data

In [34]:
```
x=df2.iloc[:,:-1]
x
```

Out[34]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	gender	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineS
0	0	1	29.85	0.012700	0	1	0	0	1	0	
1	0	34	56.95	0.440730	1	0	0	1	0	0	
2	0	2	53.85	0.068292	1	0	0	1	0	0	
3	0	45	42.30	0.434374	1	0	0	0	1	0	
4	0	2	70.70	0.089861	0	0	0	1	0	1	
...	...	...	...	...	...	...	...	...	...	...	
7038	0	24	84.80	0.453644	1	1	1	1	2	0	
7039	0	72	103.20	0.917574	0	1	1	1	2	1	
7040	0	11	29.60	0.160798	0	1	1	0	1	0	
7041	1	4	74.40	0.148374	1	1	0	1	2	1	
7042	0	66	105.65	0.882932	1	0	0	1	0	1	

7041 rows × 19 columns

In [35]:
```
y=df2.iloc[:,-1]
y
```
Out[35]:
```
0       0
1       0
2       1
3       0
4       1
       ..
7038    0
7039    0
7040    0
7041    1
7042    0
Name: Churn, Length: 7041, dtype: int32
```
In [36]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.25,random_state=1)
```

Model Building

Machine Learning Algorithms for Classification problems are: Logistic Regression, K Nearest Neighbor, Naive Bayes, Support Vector MAchines (SVC)

In [37]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
```

In [38]:
```
def mymodel(model):
    model.fit(xtest,ytest)
    ypred=model.predict(xtest)
    ac=accuracy_score(ytest,ypred)
    cm=confusion_matrix(ytest,ypred)
    cr=classification_report(ytest,ypred)
    print(f" Accuracy: {ac} \n {cm} \n {cr} ")
```

In [39]:
```
models=[]
models.append(("Logistic ",LogisticRegression()))
models.append(("KNN",KNeighborsClassifier()))
models.append(("Naive bayes", GaussianNB()))
models.append(("SVM", SVC()))
```

In [40]:
```python
for name,model in models:
    print(name)
    mymodel(model)
    print("\n\n")
```

```
Logistic
 Accuracy: 0.8091993185689949
 [[1198  122]
 [ 214  227]]
              precision    recall  f1-score   support

           0       0.85      0.91      0.88      1320
           1       0.65      0.51      0.57       441

    accuracy                           0.81      1761
   macro avg       0.75      0.71      0.73      1761
weighted avg       0.80      0.81      0.80      1761




KNN
 Accuracy: 0.8387279954571266
 [[1211  109]
 [ 175  266]]
              precision    recall  f1-score   support

           0       0.87      0.92      0.90      1320
           1       0.71      0.60      0.65       441

    accuracy                           0.84      1761
   macro avg       0.79      0.76      0.77      1761
weighted avg       0.83      0.84      0.83      1761




Naive bayes
 Accuracy: 0.7654741624077229
 [[1013  307]
 [ 106  335]]
```

```
              precision    recall  f1-score   support

           0       0.91      0.77      0.83      1320
           1       0.52      0.76      0.62       441

    accuracy                           0.77      1761
   macro avg       0.71      0.76      0.72      1761
weighted avg       0.81      0.77      0.78      1761
```

```
SVM
 Accuracy: 0.7995457126632595
 [[1233   87]
 [ 266  175]]
              precision    recall  f1-score   support

           0       0.82      0.93      0.87      1320
           1       0.67      0.40      0.50       441

    accuracy                           0.80      1761
   macro avg       0.75      0.67      0.69      1761
weighted avg       0.78      0.80      0.78      1761
```

Logistic Regression and KNN works well on the above dataset. However KNN gives more accuracy compared to other Machine Learning Algorithms with an accuracy of 83%