Project Proposal

1. **Title of the Project-** Telecom Customer Churn Prediction Using Machine Learning
2. **Brief on the project:** This project aims to develop a predictive model to identify customers likely to churn (i.e., discontinue service) from a telecom company. Customer churn is a critical issue in the highly competitive telecom sector, as retaining existing customers is more cost-effective than acquiring new ones.

The **primary goal** is to use customer behavioral and service usage data to predict churn using supervised machine learning techniques. The project falls under the **classification** category of machine learning problems.

Motivation: Churn prediction enables proactive retention strategies. Reducing churn can lead to significant cost savings and better resource planning for telecom companies. This project is especially relevant for data-driven decision-making in customer relationship management.

Previous Work: Several studies and business use-cases have shown the effectiveness of machine learning in predicting customer churn, often using models like Logistic Regression, Random Forest, and XGBoost, which are also explored in this project.

Tentative Approach:

- Perform Exploratory Data Analysis (EDA)
- Preprocess and balance the data (using SMOTE)
- Train and evaluate multiple classification models
- Deploy a prediction system

3. Deliverables of the project: General Approach:

- **Data Preprocessing:** Handling missing values, encoding categorical variables, and standardizing features.
- **Data Balancing:** Applying **SMOTE** to handle class imbalance in the target variable (churn).
- **Model Building:** Training and evaluating models including **Random Forest**, **XGBoost**, and **Logistic Regression**.
- **Model Evaluation:** Using accuracy, confusion matrix, precision, recall, and ROC-AUC score to compare models.

Deployment: Creating a churn prediction system and serializing the model using pickle.

List of Questions the Project Aims to Answer:

- Which customers are more likely to churn based on their usage and service patterns?
- What features contribute most significantly to customer churn?
- Which machine learning model offers the best performance in churn prediction?
- Can we use the model to proactively identify and retain at-risk customers?

Important Findings:

- The dataset showed a class imbalance, which was addressed using SMOTE.
- **Random Forest** yielded the highest accuracy among all models.
- Key indicators of churn include service subscription features, tenure, and monthly charges.

4. Expected Observations & Outcomes:

- A reliable model that can predict churn with high accuracy.

- Insights into factors affecting customer retention.
- A working prediction system that can be used in real-world telecom applications.

5. **Resources**

Platform: Kaggle

- **Data set source: Dataset Title:** Telco Customer Churn

○ **Software**: And Tools Used

- **Python**: Primary programming language used for the entire project
- **Jupyter Notebook**: For writing and organizing code, analysis, and documentation
- **Pandas & NumPy**: For data manipulation and numerical operations
- **Matplotlib & Seaborn**: For data visualization and exploratory data analysis (EDA)
- **Scikit-learn**: For preprocessing, model building (Logistic Regression, Random Forest), and evaluation
- **XGBoost**: For implementing gradient-boosted tree models
- **Imbalanced-learn (SMOTE)**: To balance the target class distribution
- **Pickle**: For saving the final trained model

6. **Individual Details:** Shreya Chittranshi, shreyachitranshi3@gmail.com and 9555958031

Title of the Project : # Telecom Churn Prediction

Photo credit: Superoffice.com

1. Introduction

Dataset, Features and Target Value

Source: Telco Customer Churn - Kaggle- [https://www.kaggle.com/datasets/blastchar/telco-customer-churn (https://www.kaggle.com/datasets/blastchar/telco-customer-churn)](https://www.kaggle.com/datasets/blastchar/telco-customer-churn)

Objective: Analyze churn behavior and build strategies to improve customer retention.

Assumption: The dataset does not contain time-based data, so all records are assumed to represent a single snapshot in time (monthly).

Features

- Demographic
  - Gender (Male/Female)
  - Partner, Dependents, SeniorCitizen (indirect age indicators)
- Services

-Phone Service (including Multiline)

-Internet Services (Online Security, Backup, Device Protection, Tech Support, Streaming TV/Movies)

- Account Info

  -Tenure

  -Contract Type (Month-to-month, One-year, Two-year)

  -Paperless Billing

  -Payment Method (Mailed check, Electronic check, Credit card, Bank transfer)

  - Usage

    -Monthly Charges

    -Total Charges

- Target

  -Churn: Binary classification

  -0: Customer is active

  -1: Customer has churned

Reducing churn is essential for business growth as acquiring new customers is often more costly than retaining existing ones.

Problem Description

- Why do customers churn? -High service charges -Better offers from competitors -Poor service experience -Unknown personal reasons

How to detect high-risk customers?

- Usage pattern analysis
- Complaint data
- Competitive benchmarking

How to reduce churn?

- Targeted retention plans
- Enhanced customer support and engagement#

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1. Introduction

Dataset, Features and Target value

Dataset: Source: [https://www.kaggle.com/datasets/blastchar/telco-customer-churn (https://www.kaggle.com/datasets/blastchar/telco-customer-churn)](https://www.kaggle.com/datasets/blastchar/telco-customer-churn)

Main objective here is to analyze churn customers' behavior and develop strategies to increase customer retention. Assumption — Here, data source has not provided any information related to time; So I have assumed that all the records are specific to the particular month.

Dataset has information related to,

Demographic:

- Gender - Male / Female
- Age range - In terms of Partner, Dependent and Senior Citizen

Services:

- Phone service - If customer has Phone service, then services related to Phone like;
  - Multiline Phone service
- Internet Service - If customer has Internet service, then services related to Internet like;
  - Online security
  - Online backup
  - Device protection
  - Tech support
  - Streaming TV
  - Streaming Movies

Account type:

- Tenure - How long customer is with the company?
- Contract type - What kind of contract they have with a company? Like
  - Monthly bases
  - On going bases - If on going bases, then One month contract or Two year contract
- Paperless billing - Customer is paperless billion option or not?
- Payment method - What kind of payment method customer has?
  - Mailed check
  - Electronic check
  - Credit card (Automatic)
  - Bank transfer (Automatic)

Usage:

- Monthly charges
- Total charges

Target:

- Churn - Whether customer left the company or still with the company?

Problem Description

Why customers leaving the company?

The reasons behind the customer leaving company could be

- High charges
- Better offer from competitor
- Poor customer service
- Some unknown reasons

How to detect the churn customer?

- Monitoring usage
- Analysing complains
- Analyzing competitors offers

How to prevent customers from leaving a company?

Once you detect high risk customers, apply

- Retention plans

In [ ]:
```
Import Libraries
```

In [114]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

from sklearn.preprocessing import LabelEncoder
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split, cross_val_score
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn import metrics
from sklearn.metrics import accuracy_score, confusion_matrix, classificatio
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.svm import SVC
import pickle
```

Importing Dataset 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

Dataset: Source: https://www.kaggle.com/datasets/blastchar/telco-customer-churn (https://www.kaggle.com/datasets/blastchar/telco-customer-churn)

In [3]:
```
df = pd.read_csv("Telco_Customer_Churn.csv")
df.head(5)
```

Out[3]:

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

5 rows × 21 columns

In [4]:
```
df.tail()
```

Out[4]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLi
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No ph ser
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	
7042	3186-AJIEK	Male	0	No	No	66	Yes	

5 rows × 21 columns

Dataset knowledge

In [7]:
```
df.shape
```

Out[7]:
```
(7043, 21)
```

In [8]:
```
df.columns
```

Out[8]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSuppor
t',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [9]:
```
df.duplicated().sum()
```
Out[9]:
```
0
```

In [10]:
```
df.nunique()
```
Out[10]:
```
customerID          7043
gender                 2
SeniorCitizen          2
Partner                2
Dependents             2
tenure                73
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      1585
TotalCharges        6531
Churn                  2
dtype: int64
```

In [11]:
```
# dropping customerID column as this is not required for modelling
df = df.drop(columns=["customerID"])
```

In [12]:
```
df.head(5)
```
Out[12]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetServ
0	Female	0	Yes	No	1	No	No phone service	[
1	Male	0	No	No	34	Yes	No	[
2	Male	0	No	No	2	Yes	No	[
3	Male	0	No	No	45	No	No phone service	[
4	Female	0	No	No	2	Yes	No	Fiber o

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

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

In [14]:
```
df.columns
```

Out[14]:
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurit
y',
       'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMetho
d',
       'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [15]:
```
df.isnull().sum()
```

Out[15]:
```
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 [16]:
```
df["gender"].unique()
```

Out[16]:
```
array(['Female', 'Male'], dtype=object)
```

In [17]:
```
df["SeniorCitizen"].unique()
```

Out[17]:
```
array([0, 1], dtype=int64)
```

In [18]:
```
for col in df.columns:
    print(col, df[col].unique())
    print("-"*50)
```

```
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  0
 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 (automati
c)'
 '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']
--------------------------------------------------
```

In [19]:
```
numerical_features_list = ["tenure", "MonthlyCharges", "TotalCharges"]

for col in df.columns:
  if col not in numerical_features_list:
    print(col, df[col].unique())
    print("-"*50)
```

```
gender ['Female' 'Male']
--------------------------------------------------
SeniorCitizen [0 1]
--------------------------------------------------
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 (automati
c)'
 'Credit card (automatic)']
--------------------------------------------------
Churn ['No' 'Yes']
--------------------------------------------------
```

In [20]:
```
df.describe().T
```

Out[20]:

	count	mean	std	min	25%	50%	75%	max
SeniorCitizen	7043.0	0.162147	0.368612	0.00	0.0	0.00	0.00	1.00
tenure	7043.0	32.371149	24.559481	0.00	9.0	29.00	55.00	72.00
MonthlyCharges	7043.0	64.761692	30.090047	18.25	35.5	70.35	89.85	118.75

In [21]:
```
df[df["TotalCharges"]==" "]
```

Out[21]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetS
488	Female	0	Yes	Yes	0	No	No phone service	
753	Male	0	No	Yes	0	Yes	No	
936	Female	0	Yes	Yes	0	Yes	No	
1082	Male	0	Yes	Yes	0	Yes	Yes	
1340	Female	0	Yes	Yes	0	No	No phone service	
3331	Male	0	Yes	Yes	0	Yes	No	
3826	Male	0	Yes	Yes	0	Yes	Yes	
4380	Female	0	Yes	Yes	0	Yes	No	
5218	Male	0	Yes	Yes	0	Yes	No	
6670	Female	0	Yes	Yes	0	Yes	Yes	
6754	Male	0	No	Yes	0	Yes	Yes	

In [22]:
```
len(df[df["TotalCharges"]==" "])
```

Out[22]: 11

In [23]:
```
df["TotalCharges"] = df["TotalCharges"].replace({" ": "0.0"})
```

In [24]:
```
df["TotalCharges"] = df["TotalCharges"].astype(float)
```

In [25]:
```
df.info()
```

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

In [26]:
```
# checking the class distribution of target column
df["Churn"].value_counts()
```

Out[26]:
```
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

Insights:

- Customer ID was excluded as it’s not relevant for modeling.
- The dataset contains no missing values.
- Missing entries in the TotalCharges column were imputed with 0.
- The target variable exhibits class imbalance.

In [27]:
```
df.describe()
```

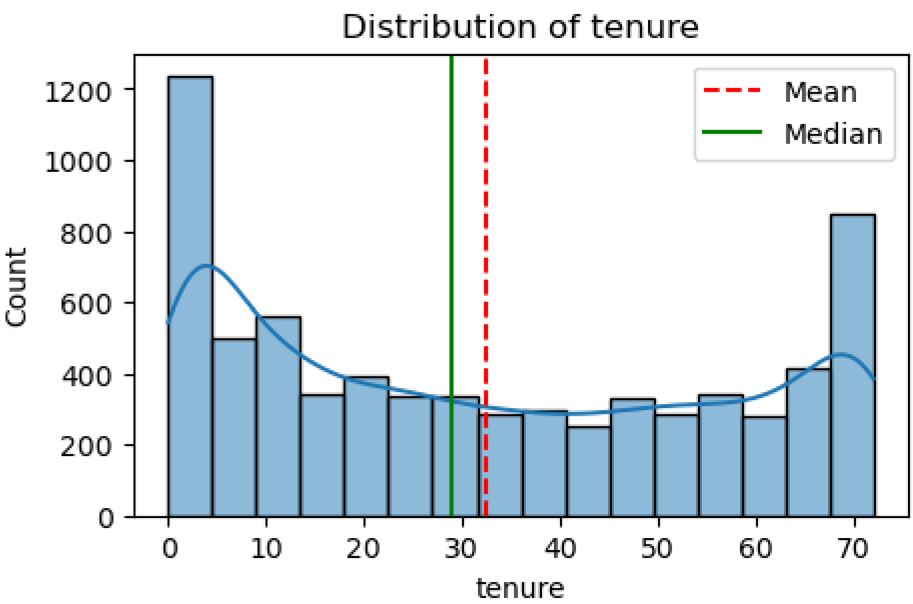
Out[27]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692	2279.734304
std	0.368612	24.559481	30.090047	2266.794470
min	0.000000	0.000000	18.250000	0.000000
25%	0.000000	9.000000	35.500000	398.550000
50%	0.000000	29.000000	70.350000	1394.550000
75%	0.000000	55.000000	89.850000	3786.600000
max	1.000000	72.000000	118.750000	8684.800000

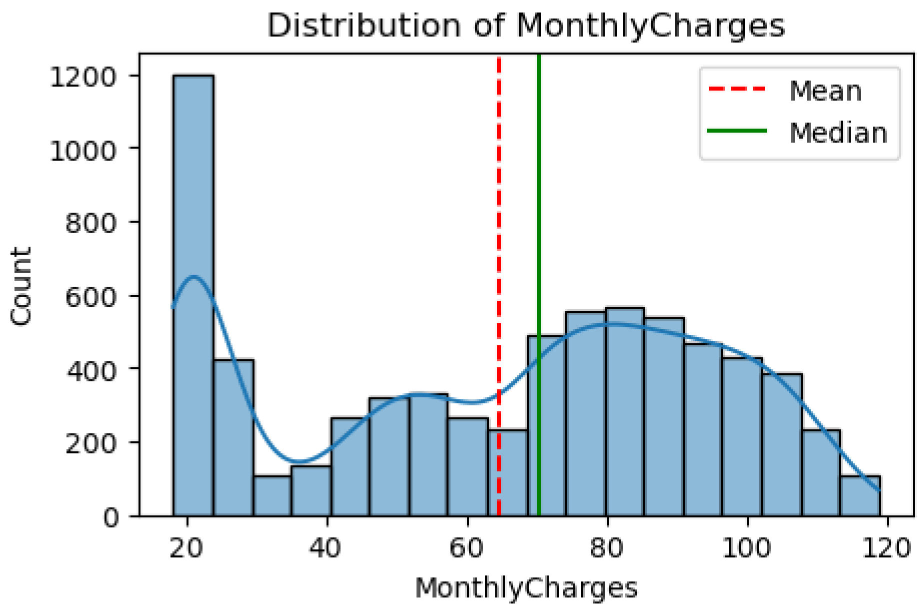
Numerical Features - Analysis Understand the distribution of the numerical features

In [28]:
```
def plot_histogram(df, column_name):

  plt.figure(figsize=(5, 3))
  sns.histplot(df[column_name], kde=True)
  plt.title(f"Distribution of {column_name}")

  # calculate the mean and median values for the columns
  col_mean = df[column_name].mean()
  col_median = df[column_name].median()

  # add vertical lines for mean and median
  plt.axvline(col_mean, color="red", linestyle="--", label="Mean")
  plt.axvline(col_median, color="green", linestyle="-", label="Median")
  plt.legend()
  plt.show()
```

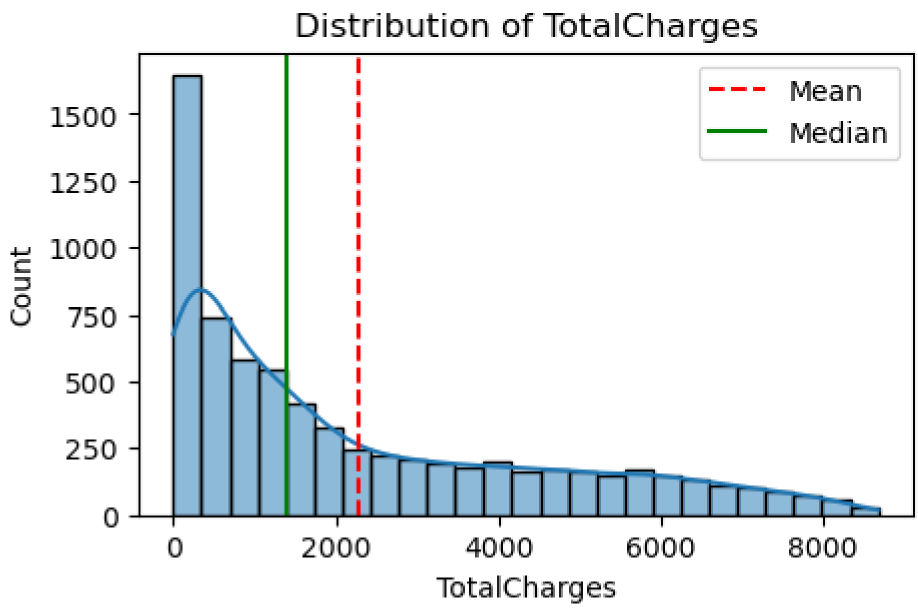
In [29]:
```
plot_histogram(df, "tenure")
```



In [30]:
```
plot_histogram(df, "MonthlyCharges")
```



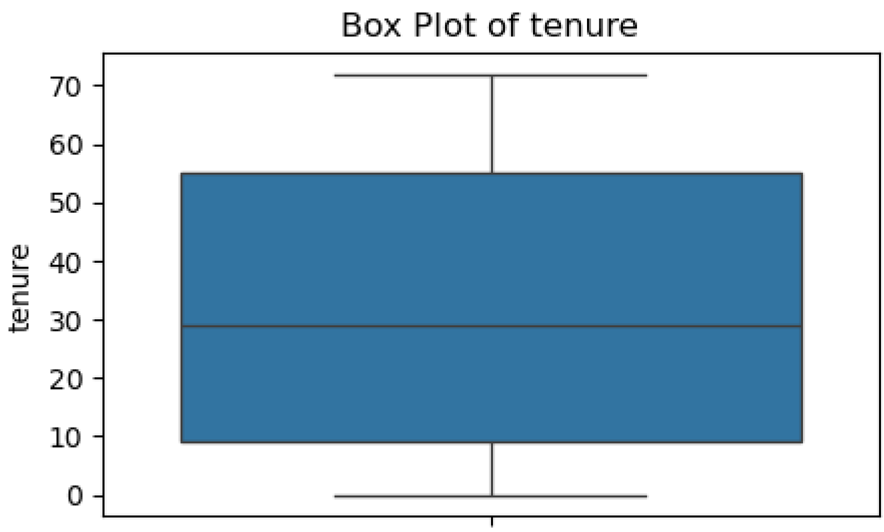
In [31]:
```
plot_histogram(df, "TotalCharges")
```



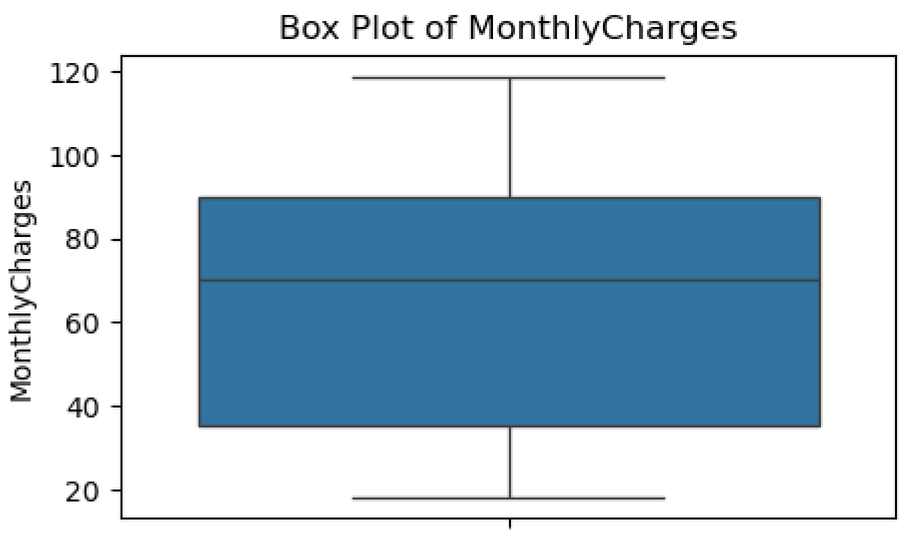
Box Plot for numerical features

In [32]:
```
def plot_boxplot(df, column_name):
    plt.figure(figsize=(5, 3))
    sns.boxplot(y=df[column_name])
    plt.title(f"Box Plot of {column_name}")
    plt.ylabel(column_name)
    plt.show()
```

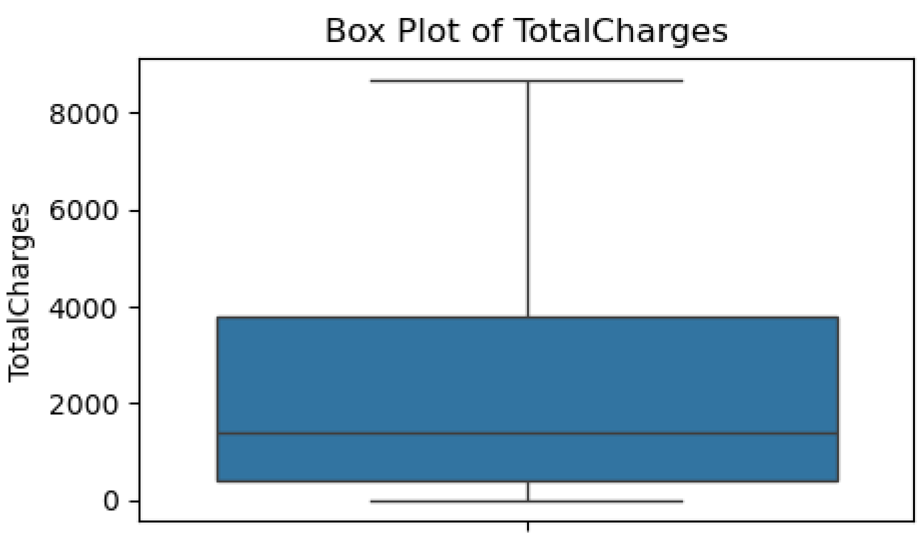
In [33]:
```
plot_boxplot(df, "tenure")
```



In [34]:
```
plot_boxplot(df, "MonthlyCharges")
```

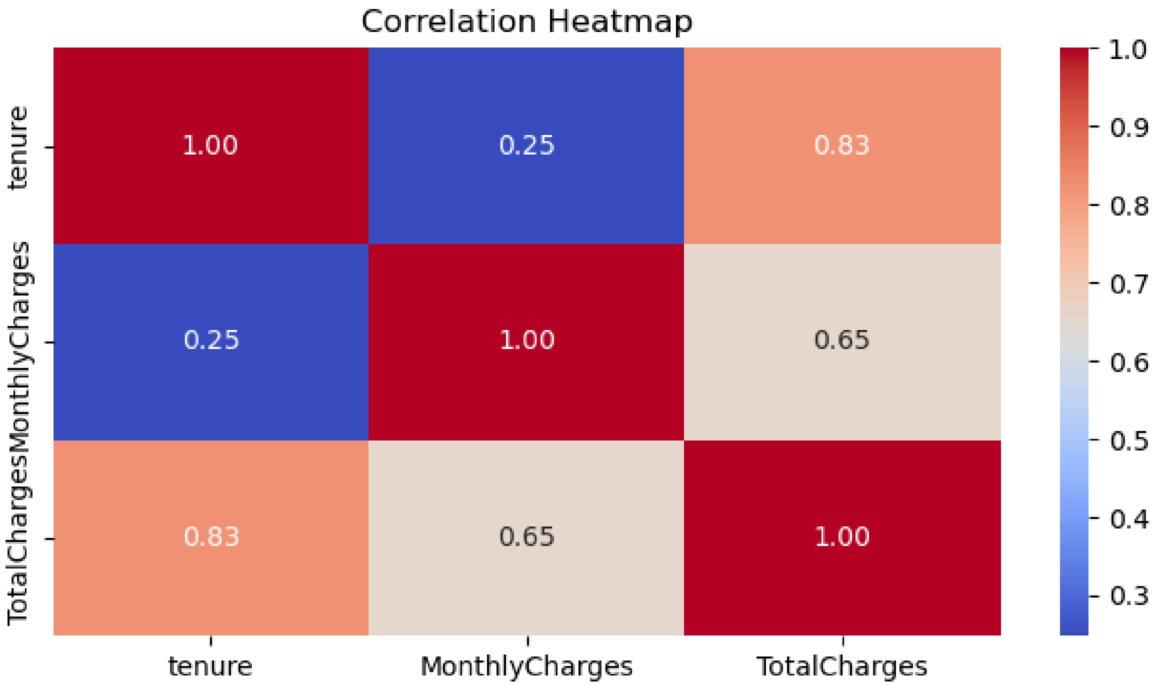


In [35]:
```
plot_boxplot(df, "TotalCharges")
```



corelation

In [36]:
```
# correlation matrix - heatmap
plt.figure(figsize=(8, 4))
sns.heatmap(df[["tenure", "MonthlyCharges", "TotalCharges"]].corr(), annot:
plt.title("Correlation Heatmap")
plt.show()
```

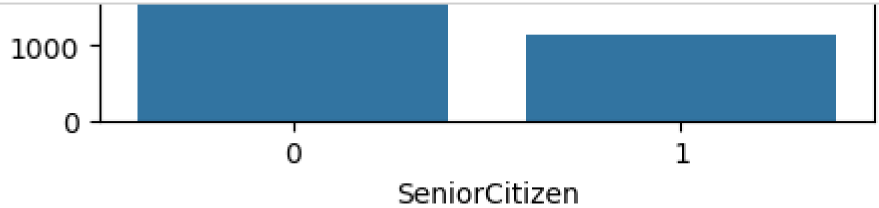


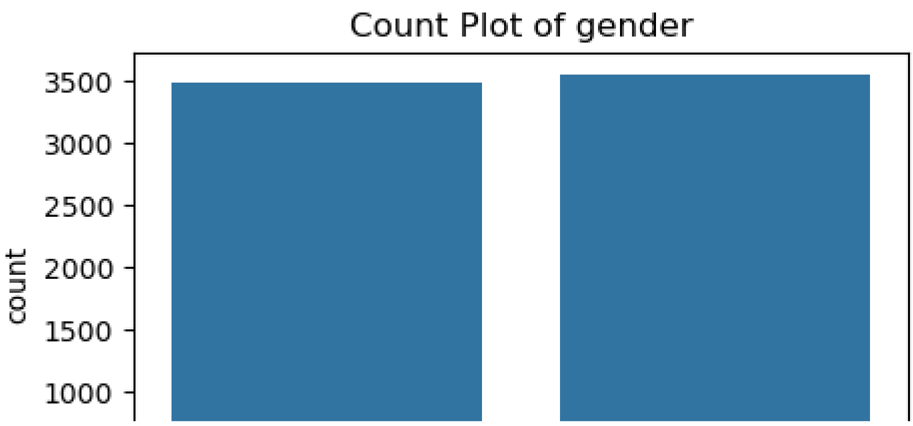
Categorical features - Analysis

In [37]:
```
df.info()
```

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

In [38]:
```
object_cols = df.select_dtypes(include="object").columns.to_list()
object_cols = ["SeniorCitizen"] + object_cols
for col in object_cols:
  plt.figure(figsize=(5, 3))
  sns.countplot(x=df[col])
  plt.title(f"Count Plot of {col}")
  plt.show()
```

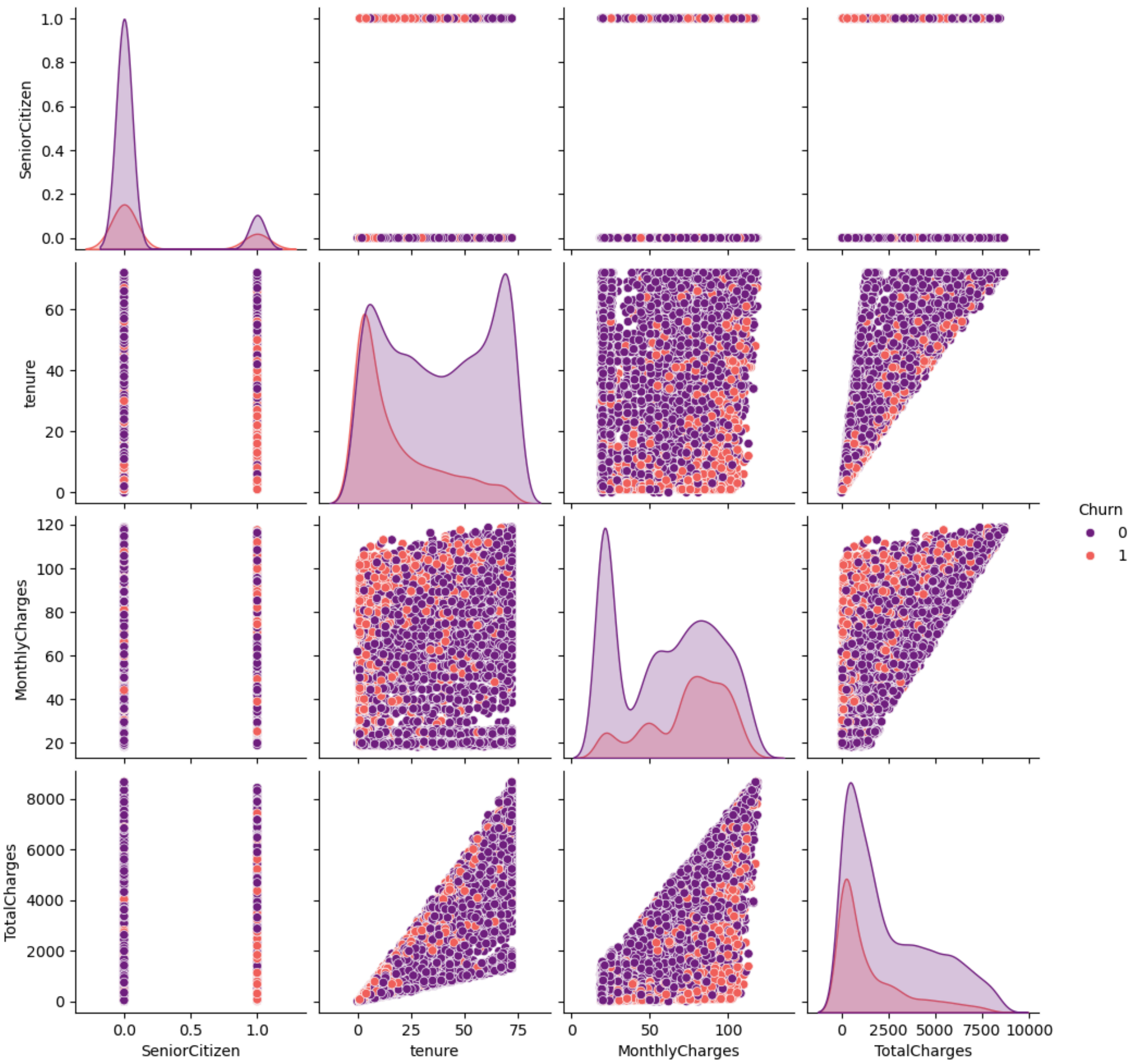




In [ ]:
```
Distribution
```

In [46]:
```
plt.figure(dpi=200, figsize=(8,6))
sns.pairplot(df,hue="Churn",palette="magma")
plt.show()
```

```
<Figure size 1600x1200 with 0 Axes>
```

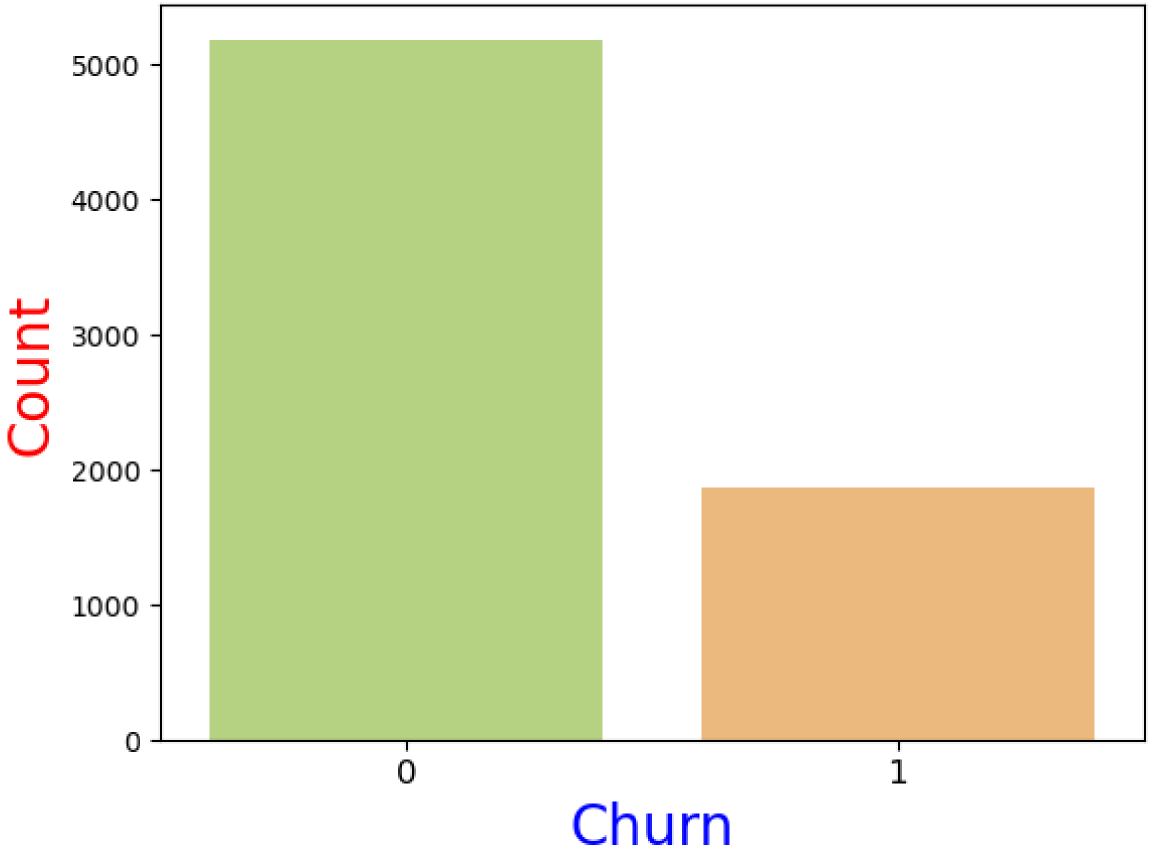


Churn is high when Monthly Charges are high. Churn is high at starting tenure and churn is low as tenure increases.

In [47]:
```
df['Churn'].value_counts()
```

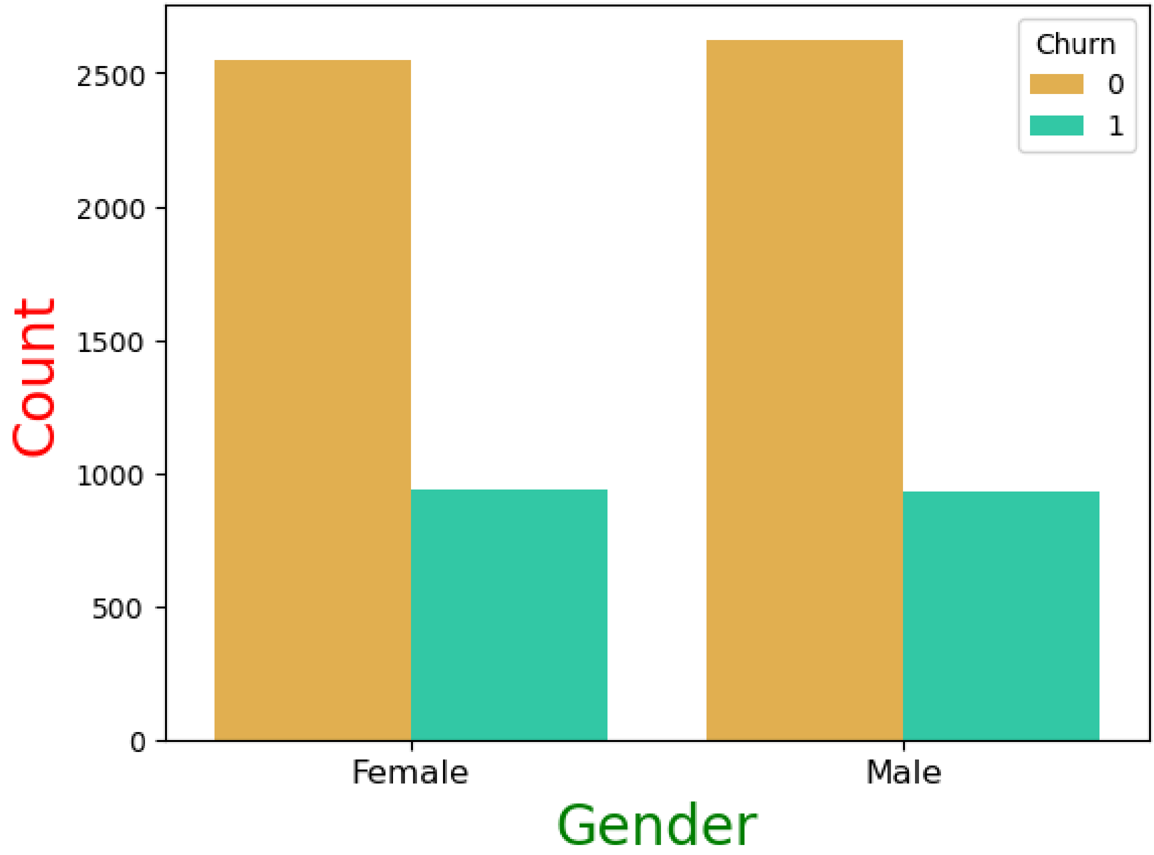
Out[47]:
```
Churn
0    5174
1    1869
Name: count, dtype: int64
```

In [48]:
```
sns.countplot(x= "Churn", data= df, palette= "RdYlGn_r")
plt.xticks(fontsize = 12)
plt.xlabel("Churn", fontsize = 20, c= "b")
plt.ylabel("Count", fontsize = 20, c= "r")
plt.show()
```



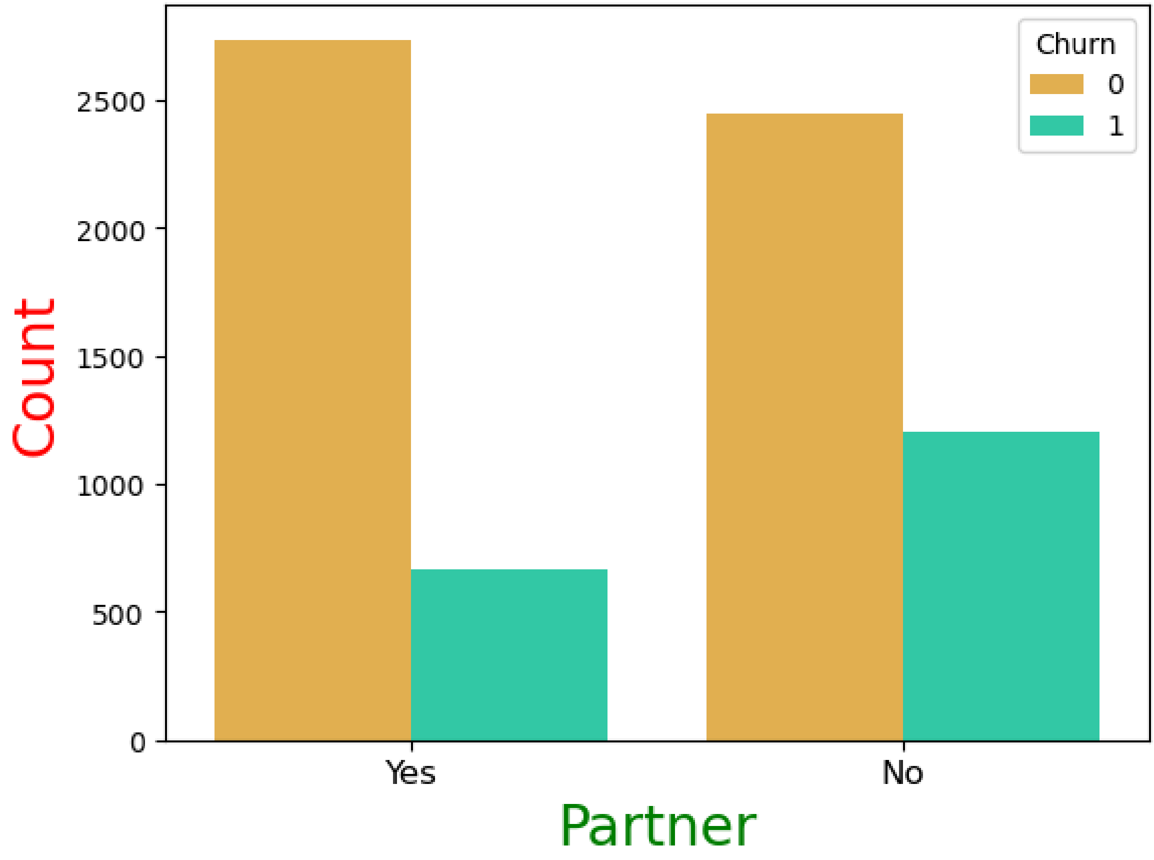
Here we can see Churn data is imbalance. It shows No churn is high.

In [49]:
```
sns.countplot(x= "gender", data= df, hue = "Churn", palette= "turbo_r")
plt.xticks(fontsize = 12)
plt.xlabel("Gender", fontsize = 20, c= "g")
plt.ylabel("Count", fontsize = 20, c= "r")
plt.show()
```



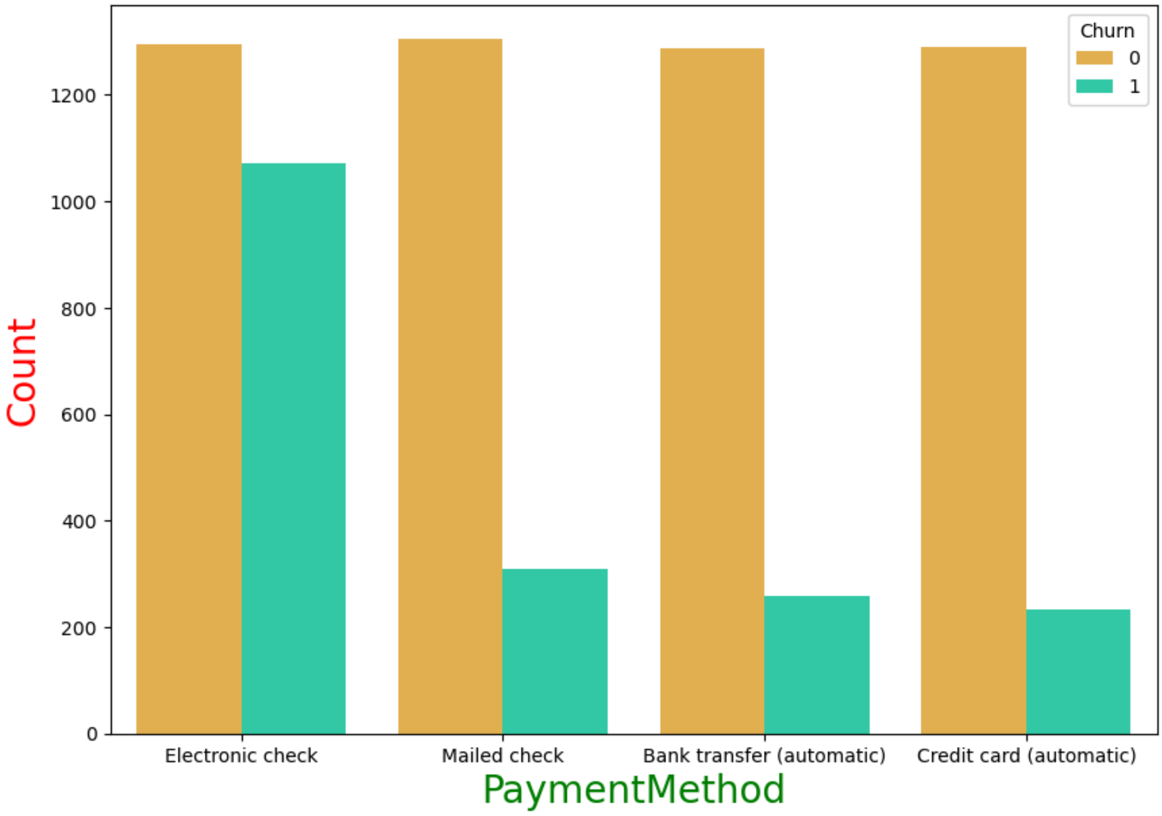
In [ ]:
```
Churn in male and female is approximately same whereas in the No-churn male
```

In [50]:
```
sns.countplot(x="Partner",hue="Churn",palette="turbo_r",data=df)
plt.xticks(fontsize = 12)
plt.xlabel("Partner", fontsize = 20, c= "g")
plt.ylabel("Count", fontsize = 20, c= "r")
plt.show()
```



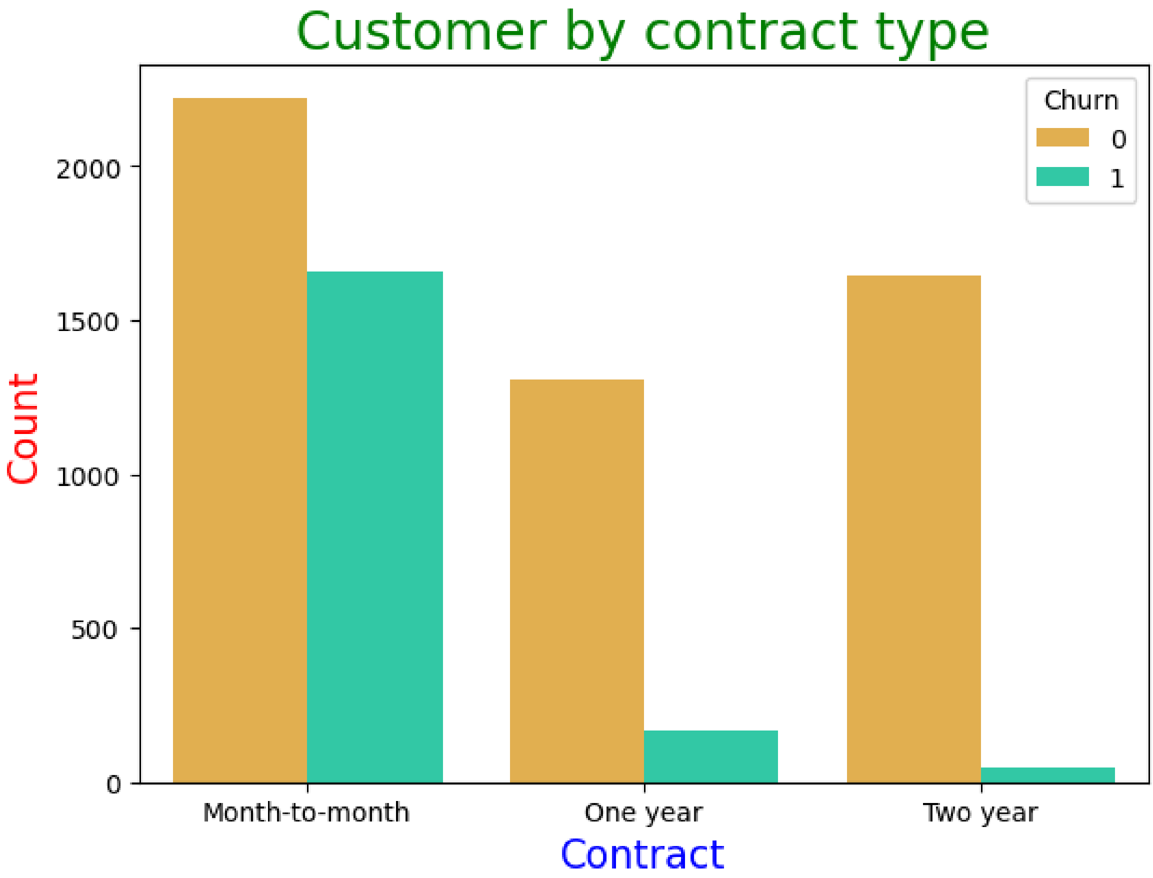
People have partners are less churn.

In [51]:
```
plt.figure(figsize= (10, 7))
sns.countplot(x="PaymentMethod",hue="Churn",palette="turbo_r",data=df)
plt.xticks(fontsize = 10)
plt.xlabel("PaymentMethod", fontsize = 20, c= "g")
plt.ylabel("Count", fontsize = 20, c= "r")
plt.show()
```



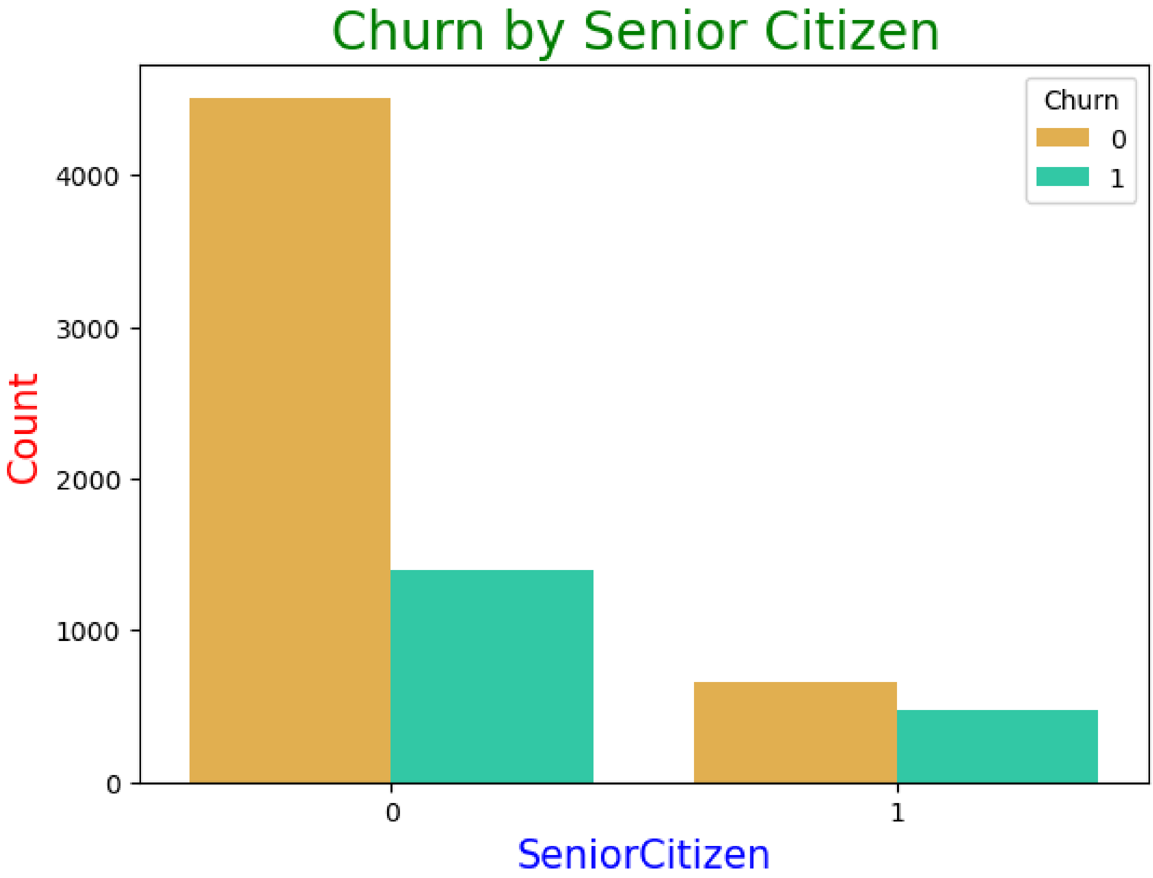
In Electronic check payment have high churn.

In [52]:
```
plt.figure(figsize=(7,5))
sns.countplot(x= "Contract", data= df ,palette="turbo_r", hue="Churn")
plt.xlabel("Contract", fontsize= 15, c = "b")
plt.ylabel("Count", fontsize= 15, c = "r")
plt.title("Customer by contract type", fontsize = 20, c= "g")
plt.show()
```



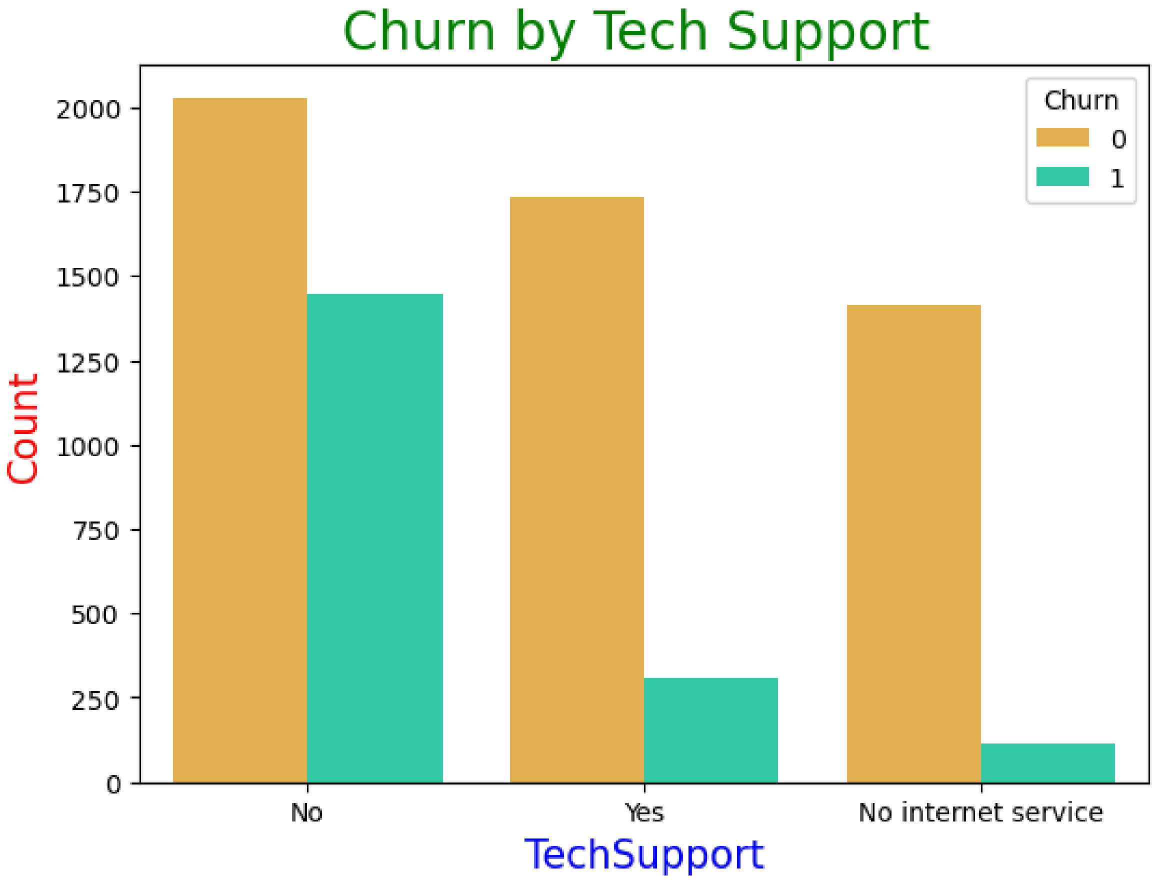
In [ ]:
```
Month to Month contract has high churn
```

In [53]:
```
plt.figure(figsize=(7,5))
sns.countplot(x= "SeniorCitizen", data= df ,palette="turbo_r", hue="Churn")
plt.xlabel("SeniorCitizen", fontsize= 15, c = "b")
plt.ylabel("Count", fontsize= 15, c = "r")
plt.title("Churn by Senior Citizen ", fontsize = 20, c= "g")
plt.show()
```



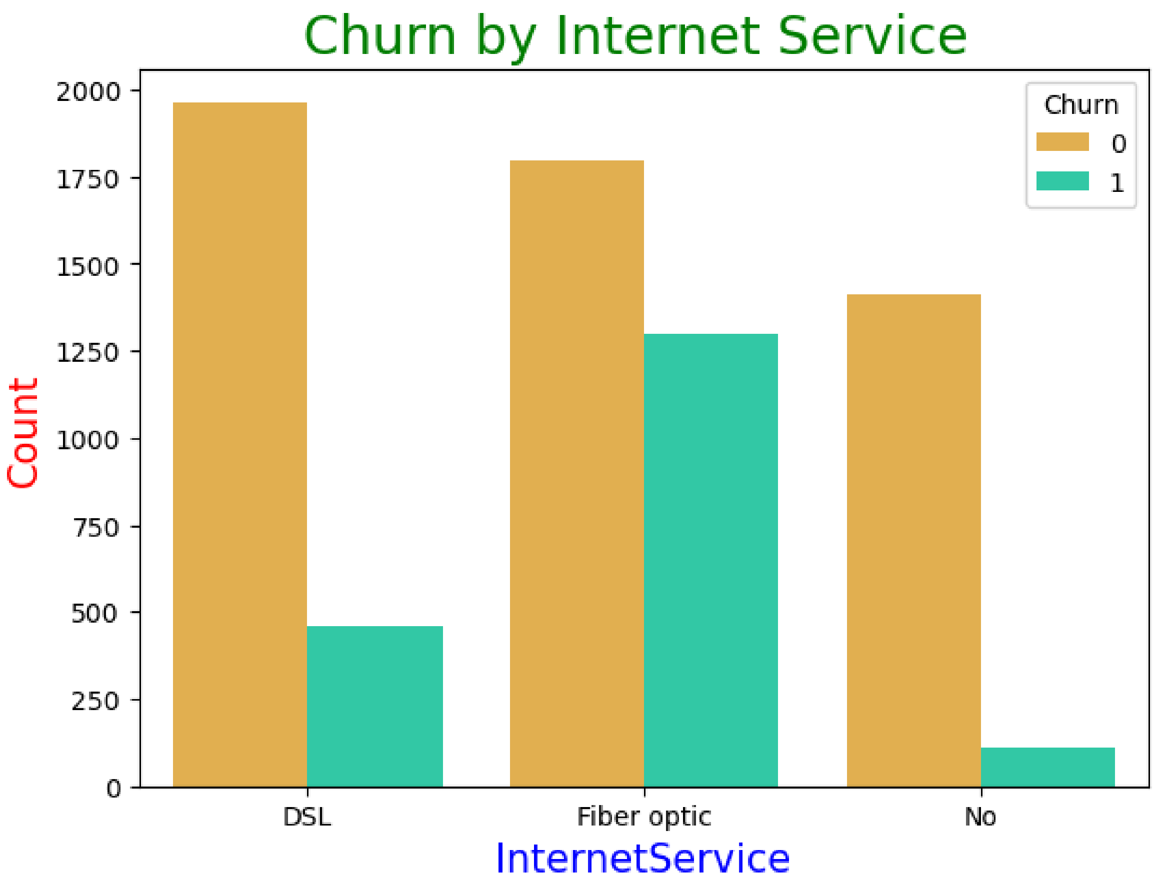
In [ ]:
```
Here we can see Senior Citizen has low churn
```

In [54]:
```
plt.figure(figsize=(7,5))
sns.countplot(x= "TechSupport", data= df ,palette="turbo_r", hue="Churn")
plt.xlabel("TechSupport", fontsize= 15, c = "b")
plt.ylabel("Count", fontsize= 15, c = "r")
plt.title("Churn by Tech Support ", fontsize = 20, c= "g")
plt.show()
```



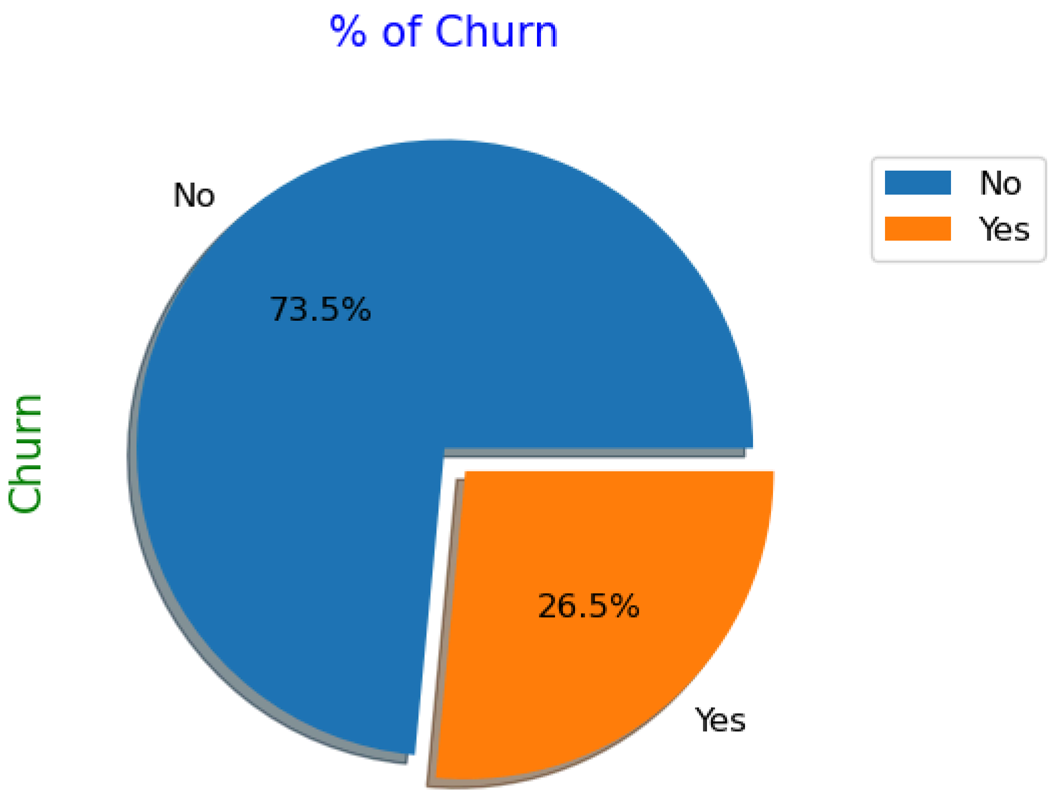
In [ ]:
```
No Tech support category has high Churn
```

In [55]:
```
plt.figure(figsize=(7,5))
sns.countplot(x= "InternetService", data= df ,palette="turbo_r", hue="Churn
plt.xlabel("InternetService", fontsize= 15, c = "b")
plt.ylabel("Count", fontsize= 15, c = "r")
plt.title("Churn by Internet Service ", fontsize = 20, c= "g")
plt.show()
```



In [ ]:
```
No Internet service has low churn
```

In [56]:
```
ax = (df['Churn'].value_counts()*100.0 /len(df))\
.plot.pie(autopct='%.1f%%', labels = ['No', 'Yes'],figsize =(5,5), fontsize
ax.set_ylabel('Churn',fontsize = 15, c = "g")
ax.set_title('% of Churn', fontsize = 15, c= "b")
plt.legend(loc='upper right', bbox_to_anchor =(1.3,0.9), fontsize=12)
plt.show()
df.Churn.value_counts()
```



Out[56]:
```
Churn
0    5174
1    1869
Name: count, dtype: int64
```

Here we can see Churn is 26.5% and No Churn is 73.5%. Data is imbalance.

In [ ]:
```
Label Encoding of Target Column
```

In [59]:
```
df["Churn"] = df["Churn"].replace({"Yes": 1, "No": 0})
```

In [60]:
```
df.head()
```

Out[60]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetServ
0	Female	0	Yes	No	1	No	No phone service	[
1	Male	0	No	No	34	Yes	No	[
2	Male	0	No	No	2	Yes	No	[
3	Male	0	No	No	45	No	No phone service	[
4	Female	0	No	No	2	Yes	No	Fiber o

In [61]:
```
# identifying columns with object data type
object_columns = df.select_dtypes(include="object").columns
```

In [62]:
```
df.columns
```

Out[62]:
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurit
y',
       'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMetho
d',
       'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [63]:
```
# initialize a dictionary to save the encoders
encoders = {}

# apply label encoding and store the encoders
for column in object_columns:
  label_encoder = LabelEncoder()
  df[column] = label_encoder.fit_transform(df[column])
  encoders[column] = label_encoder

# save the encoders to a pickle file
with open("encoders.pkl", "wb") as f:
  pickle.dump(encoders, f)
```

In [64]:
```
encoders
```

Out[64]:
```
{'gender': LabelEncoder(),
 'Partner': LabelEncoder(),
 'Dependents': LabelEncoder(),
 'PhoneService': LabelEncoder(),
 'MultipleLines': LabelEncoder(),
 'InternetService': LabelEncoder(),
 'OnlineSecurity': LabelEncoder(),
 'OnlineBackup': LabelEncoder(),
 'DeviceProtection': LabelEncoder(),
 'TechSupport': LabelEncoder(),
 'StreamingTV': LabelEncoder(),
 'StreamingMovies': LabelEncoder(),
 'Contract': LabelEncoder(),
 'PaperlessBilling': LabelEncoder(),
 'PaymentMethod': LabelEncoder()}
```

In [65]:
```
df.head()
```

Out[65]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetServ
0	0	0	1	0	1	0	1	
1	1	0	0	0	34	1	0	
2	1	0	0	0	2	1	0	
3	1	0	0	0	45	0	1	
4	0	0	0	0	2	1	0	

In [ ]:
```
Traianing and test data split
```

In [66]:
```
# splitting the features and target
X = df.drop(columns=["Churn"])
y = df["Churn"]
```

In [67]:
```
# split training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra
```

In [71]:
```
y_train.shape
```

Out[71]:
```
(5634,)
```

In [72]:
```
X_train.shape
```

Out[72]:
```
(5634, 19)
```

In [74]:
```
y_train.value_counts()
```

Out[74]:
```
Churn
0    4138
1    1496
Name: count, dtype: int64
```

In [ ]:
```
Synthetic Minority Oversampling TEchnique (SMOTE)
```

In [79]:
```
smote = SMOTE(random_state=42)
```

In [81]:
```
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
```

In [82]:
```
print(y_train_smote.shape)
```

```
(8276,)
```

In [83]:
```
y_train_smote.value_counts()
```

Out[83]:
```
Churn
0    4138
1    4138
Name: count, dtype: int64
```

In [ ]:
```
Building a Model
```

In [84]:
```
# dictionary of models
models = {
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42),
    "XGBoost": XGBClassifier(random_state=42)
}
```

In [85]:
```
# dictionary to store the cross validation results
cv_scores = {}

# perform 5-fold cross validation for each model
for model_name, model in models.items():
  print(f"Training {model_name} with default parameters")
  scores = cross_val_score(model, X_train_smote, y_train_smote, cv=5, scor
  cv_scores[model_name] = scores
  print(f"{model_name} cross-validation accuracy: {np.mean(scores):.2f}")
  print("-"*70)
```

```
Training Decision Tree with default parameters
Decision Tree cross-validation accuracy: 0.78
----------------------------------------------------------------------
Training Random Forest with default parameters
Random Forest cross-validation accuracy: 0.84
----------------------------------------------------------------------
Training XGBoost with default parameters
XGBoost cross-validation accuracy: 0.83
----------------------------------------------------------------------
```

In [86]:
```
cv_scores
```

Out[86]:
```
{'Decision Tree': array([0.69202899, 0.70574018, 0.82537764, 0.83806647,
0.84350453]),
 'Random Forest': array([0.73067633, 0.77039275, 0.90392749, 0.89969789,
0.90030211]),
 'XGBoost': array([0.70833333, 0.76132931, 0.90453172, 0.88821752, 0.9075
5287])}
```

In [ ]:
```
Random Forest gives the highest accuracy compared to other models with defa
```

In [89]:
```
rfc = RandomForestClassifier(random_state=42)
rfc.fit(X_train_smote, y_train_smote)
```

Out[89]:
```
RandomForestClassifier(random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [90]:
```
y_test.value_counts()
```

Out[90]:
```
Churn
0    1036
1     373
Name: count, dtype: int64
```

In [ ]:
```
Model Evaluation
```

In [91]:
```
# evaluate on test data
y_test_pred = rfc.predict(X_test)

print("Accuracy Score:\n", accuracy_score(y_test, y_test_pred))
print("Confsuion Matrix:\n", confusion_matrix(y_test, y_test_pred))
print("Classification Report:\n", classification_report(y_test, y_test_pred
```

```
Accuracy Score:
 0.7785663591199432
Confsuion Matrix:
 [[878 158]
 [154 219]]
Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.85      0.85      1036
           1       0.58      0.59      0.58       373

    accuracy                           0.78      1409
   macro avg       0.72      0.72      0.72      1409
weighted avg       0.78      0.78      0.78      1409
```

In [92]:
```
# save the trained model as a pickle file
model_data = {"model": rfc, "features_names": X.columns.tolist()}


with open("customer_churn_model.pkl", "wb") as f:
  pickle.dump(model_data, f)
```

In [ ]:
```
 Load the saved model and build a Predictive System
```

In [93]:
```
# Load teh saved model and the feature names

with open("customer_churn_model.pkl", "rb") as f:
  model_data = pickle.load(f)

loaded_model = model_data["model"]
feature_names = model_data["features_names"]
```

In [94]:
```
print(loaded_model)
```

```
RandomForestClassifier(random_state=42)
```

In [95]:
```
print(feature_names)
```

```
['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure', 'PhoneServ
ice', 'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBacku
p', 'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
'Contract', 'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges', 'Total
Charges']
```

In [96]:
```
input_data = {
    'gender': 'Female',
    'SeniorCitizen': 0,
    'Partner': 'Yes',
    'Dependents': 'No',
    'tenure': 1,
    'PhoneService': 'No',
    'MultipleLines': 'No phone service',
    'InternetService': 'DSL',
    'OnlineSecurity': 'No',
    'OnlineBackup': 'Yes',
    'DeviceProtection': 'No',
    'TechSupport': 'No',
    'StreamingTV': 'No',
    'StreamingMovies': 'No',
    'Contract': 'Month-to-month',
    'PaperlessBilling': 'Yes',
    'PaymentMethod': 'Electronic check',
    'MonthlyCharges': 29.85,
    'TotalCharges': 29.85
}


input_data_df = pd.DataFrame([input_data])

with open("encoders.pkl", "rb") as f:
  encoders = pickle.load(f)


# encode categorical featires using teh saved encoders
for column, encoder in encoders.items():
  input_data_df[column] = encoder.transform(input_data_df[column])

# make a prediction
prediction = loaded_model.predict(input_data_df)
pred_prob = loaded_model.predict_proba(input_data_df)

print(prediction)

# results
print(f"Prediction: {'Churn' if prediction[0] == 1 else 'No Churn'}")
print(f"Prediciton Probability: {pred_prob}")
```

```
[0]
Prediction: No Churn
Prediciton Probability: [[0.79 0.21]]
```

In [97]:
```
encoders
```

Out[97]:
```
{'gender': LabelEncoder(),
 'Partner': LabelEncoder(),
 'Dependents': LabelEncoder(),
 'PhoneService': LabelEncoder(),
 'MultipleLines': LabelEncoder(),
 'InternetService': LabelEncoder(),
 'OnlineSecurity': LabelEncoder(),
 'OnlineBackup': LabelEncoder(),
 'DeviceProtection': LabelEncoder(),
 'TechSupport': LabelEncoder(),
 'StreamingTV': LabelEncoder(),
 'StreamingMovies': LabelEncoder(),
 'Contract': LabelEncoder(),
 'PaperlessBilling': LabelEncoder(),
 'PaymentMethod': LabelEncoder()}
```

In [ ]:
```
Logistic Regression Model
```

In [102]:
```
log_reg=LogisticRegression()
log_reg.fit(X_train_smote,y_train_smote)
y_train_pred=log_reg.predict(X_train_smote)
y_test_pred=log_reg.predict(X_test)
```

In [104]:
```
accuracy = accuracy_score(y_train_smote, y_train_pred)
accuracy = accuracy_score(y_test, y_test_pred)
conf_matrix = confusion_matrix(y_test, y_test_pred)
class_report = classification_report(y_test, y_test_pred)
```

In [106]:
```
accuracy = accuracy_score(y_train_smote, y_train_pred)
print(f"Logistic Regression Accuracy: {accuracy * 100:.2f}%")
```

```
Logistic Regression Accuracy: 78.99%
```

In [107]:
```
print(conf_matrix)
```

```
[[785 251]
 [ 83 290]]
```

In [109]:
```
print(class_report)
```

```
              precision    recall  f1-score   support

           0       0.90      0.76      0.82      1036
           1       0.54      0.78      0.63       373

    accuracy                           0.76      1409
   macro avg       0.72      0.77      0.73      1409
weighted avg       0.81      0.76      0.77      1409
```

In [ ]:
```
Random Forest Model
```

In [110]:
```
rf=RandomForestClassifier()
rf.fit(X_train_smote,y_train_smote)
y_train_pred=rf.predict(X_train_smote)
y_test_pred=rf.predict(X_test)
```

In [111]:
```
accuracy = accuracy_score(y_test, y_test_pred)
```

In [112]:
```
print(f"Random Forest Accuracy: {accuracy * 100:.2f}%")
```

```
Random Forest Accuracy: 77.71%
```

In [ ]:
```
Hyperparameter Tuning
```

In [126]:
```
from sklearn.model_selection import GridSearchCV
```

In [128]:
```
param_grid = {'C':[0.1,1,10],'gamma':[1,0.1,0.01],'kernel':['rbf'],'class_w
grid = GridSearchCV(SVC(),param_grid,refit=True,verbose=2,cv=2)
grid.fit(X_train,y_train)
```

```
Fitting 2 folds for each of 9 candidates, totalling 18 fits
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time
=   1.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time
=   1.4s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.5s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.5s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.3s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.4s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=
1.5s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.5s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=
1.5s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.6s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=
1.4s
```

Out[128]:
```
GridSearchCV(cv=2, estimator=SVC(),
             param_grid={'C': [0.1, 1, 10], 'class_weight': ['balanced'],
                         'gamma': [1, 0.1, 0.01], 'kernel': ['rbf']},
             verbose=2)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [129]:
```
print(grid.best_estimator_)
```

```
SVC(C=10, class_weight='balanced', gamma=0.1)
```

In [131]:
```
grid_predictions = grid.predict(X_test)
```

In [132]:
```
confusion_matrix(y_test, grid_predictions)
```

Out[132]:
```
array([[982,  54],
       [270, 103]], dtype=int64)
```

In [133]:
```
print(classification_report(y_test, grid_predictions))
```

```
              precision    recall  f1-score   support

           0       0.78      0.95      0.86      1036
           1       0.66      0.28      0.39       373

    accuracy                           0.77      1409
   macro avg       0.72      0.61      0.62      1409
weighted avg       0.75      0.77      0.73      1409
```

In [ ]:
```
Model Evaluation
we have used Hyperparameter tuning
overall accuracy of 77%
recall is 95% and precision=78%
```

Retention Plan We should focus on below Churn is high when Monthly Charges are high. Churn is high at starting tenure People have partners are less churn. In Electronic check payment have high churn. Month to Month contract has high churn Senior Citizen has low churn No Tech support category has high Churn No Internet service has low churn