

1 Customer Churn Prediction Using Machine Learning

1.1 Importing the dependencies

```
[6]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, \
    classification_report
import pickle
```

```
[ ]:
```

1.2 2. Data Loading and Understanding

```
[33]: # load teh csv data to a pandas dataframe
df = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
```

```
[9]: df.shape
```

```
[9]: (7043, 21)
```

```
[12]: pd.set_option("display.max_columns", None)
```

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

```
[13]:
```

	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 OnlineBackup

0	No phone service	DSL	No	Yes
1	No	DSL	Yes	No
2	No	DSL	Yes	Yes
3	No phone service	DSL	Yes	No
4	No	Fiber optic	No	No

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

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

Churn

0	No
1	No
2	Yes
3	No
4	Yes

[]:

[14]: 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

```

```
[ ]:
```

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

```
[18]: df.head(2)
```

```
[18]:
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	Female	0	Yes	No	1	No	
1	Male	0	No	No	34	Yes	

	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	\
0	No phone service	DSL	No	Yes	
1	No	DSL	Yes	No	

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

	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	Yes	Electronic check	29.85	29.85	No
1	No	Mailed check	56.95	1889.5	No

```
[ ]:
```

```
[20]: df.columns
```

```
[20]: Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
        'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
        'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
```

```

        'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
        'MonthlyCharges', 'TotalCharges', 'Churn'],
        dtype='object')

```

```
[22]: print(df['gender'].unique())
```

```
['Female' 'Male']
```

```
[23]: print(df['SeniorCitizen'].unique())
```

```
[0 1]
```

```
[ ]:
```

```
[25]: # Printing the unique values in all the columns
```

```

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 (automatic)'
               'Credit card (automatic)']
-----
Churn ['No' 'Yes']
-----

```

[]:

[26]: `print(df.isnull().sum())`

```

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

```

[]:

[57]: `#df["TotalCharges"] = df["TotalCharges"].astype(float)`

[58]: `df[df["TotalCharges"]==" "]`

[58]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	\
488	4472-LVYGI	Female	0	Yes	Yes	0	
753	3115-CZMZD	Male	0	No	Yes	0	
936	5709-LV0EQ	Female	0	Yes	Yes	0	

1082	4367-NUYAO	Male	0	Yes	Yes	0
1340	1371-DWPAZ	Female	0	Yes	Yes	0
3331	7644-OMVMY	Male	0	Yes	Yes	0
3826	3213-VVOLG	Male	0	Yes	Yes	0
4380	2520-SGTTA	Female	0	Yes	Yes	0
5218	2923-ARZLG	Male	0	Yes	Yes	0
6670	4075-WKNIU	Female	0	Yes	Yes	0
6754	2775-SEFEE	Male	0	No	Yes	0

	PhoneService	MultipleLines	InternetService	OnlineSecurity \
488	No	No phone service	DSL	Yes
753	Yes	No	No	No internet service
936	Yes	No	DSL	Yes
1082	Yes	Yes	No	No internet service
1340	No	No phone service	DSL	Yes
3331	Yes	No	No	No internet service
3826	Yes	Yes	No	No internet service
4380	Yes	No	No	No internet service
5218	Yes	No	No	No internet service
6670	Yes	Yes	DSL	No
6754	Yes	Yes	DSL	Yes

	OnlineBackup	DeviceProtection	TechSupport \
488	No	Yes	Yes
753	No internet service	No internet service	No internet service
936	Yes	Yes	No
1082	No internet service	No internet service	No internet service
1340	Yes	Yes	Yes
3331	No internet service	No internet service	No internet service
3826	No internet service	No internet service	No internet service
4380	No internet service	No internet service	No internet service
5218	No internet service	No internet service	No internet service
6670	Yes	Yes	Yes
6754	Yes	No	Yes

	StreamingTV	StreamingMovies	Contract	PaperlessBilling \
488	Yes	No	Two year	Yes
753	No internet service	No internet service	Two year	No
936	Yes	Yes	Two year	No
1082	No internet service	No internet service	Two year	No
1340	Yes	No	Two year	No
3331	No internet service	No internet service	Two year	No
3826	No internet service	No internet service	Two year	No
4380	No internet service	No internet service	Two year	No
5218	No internet service	No internet service	One year	Yes
6670	Yes	No	Two year	No
6754	No	No	Two year	Yes

	PaymentMethod	MonthlyCharges	TotalCharges	Churn
488	Bank transfer (automatic)	52.55		No
753	Mailed check	20.25		No
936	Mailed check	80.85		No
1082	Mailed check	25.75		No
1340	Credit card (automatic)	56.05		No
3331	Mailed check	19.85		No
3826	Mailed check	25.35		No
4380	Mailed check	20.00		No
5218	Mailed check	19.70		No
6670	Mailed check	73.35		No
6754	Bank transfer (automatic)	61.90		No

```
[ ]:
```

```
[59]: len(df[df["TotalCharges"]==" "])
```

```
[59]: 11
```

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

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

```
[62]: 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 float64
20 Churn            7043 non-null object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB

```

[]:

```

[63]: # checking the class distribution of target column
print(df["Churn"].value_counts())

```

```

Churn
No      5174
Yes     1869
Name: count, dtype: int64

```

[]:

1.3 Insights:

1. Customer ID removed as it is not required for modelling
2. No missing values in the dataset
3. Missing values in the TotalCharges column were replaced with 0
4. Class imbalance identified in the target

[]:

1.4 3. Exploratory Data Analysis (EDA)

```

[64]: df.shape

```

```

[64]: (7043, 21)

```

```

[65]: df.columns

```

```

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

```

```

[66]: df.head(2)

```



```
[66]:
```

	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	

	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	\
0	No phone service	DSL	No	Yes	
1	No	DSL	Yes	No	

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

	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	Yes	Electronic check	29.85	29.85	No
1	No	Mailed check	56.95	1889.50	No

```
[67]: df.describe()
```

```
[67]:
```

	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

```
[ ]:
```

1.4.1 Numerical Features - Analysis

Understand the distribution of teh numerical features

```
[68]: 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}")

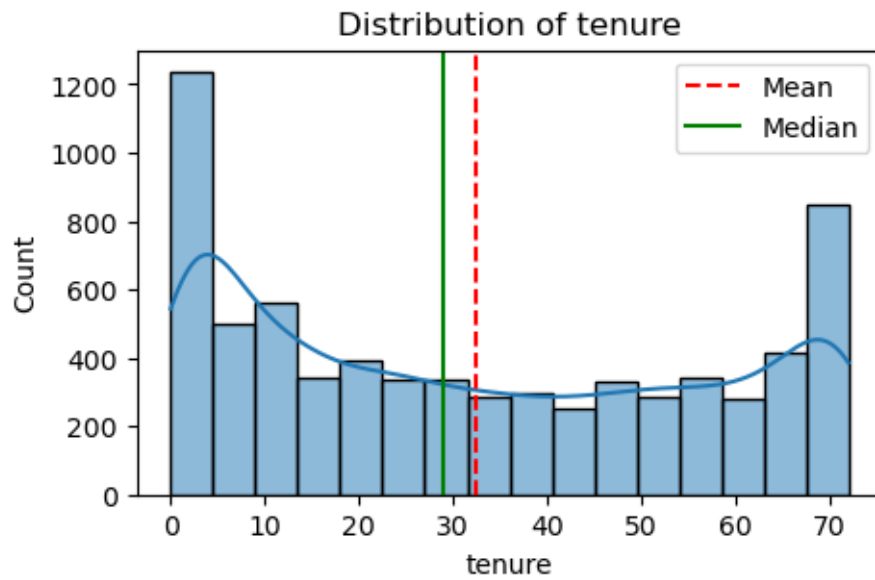
    # calculate the mean and median values for the columns
    col_mean = df[column_name].mean()
    col_median = df[column_name].median()

    # 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()
```

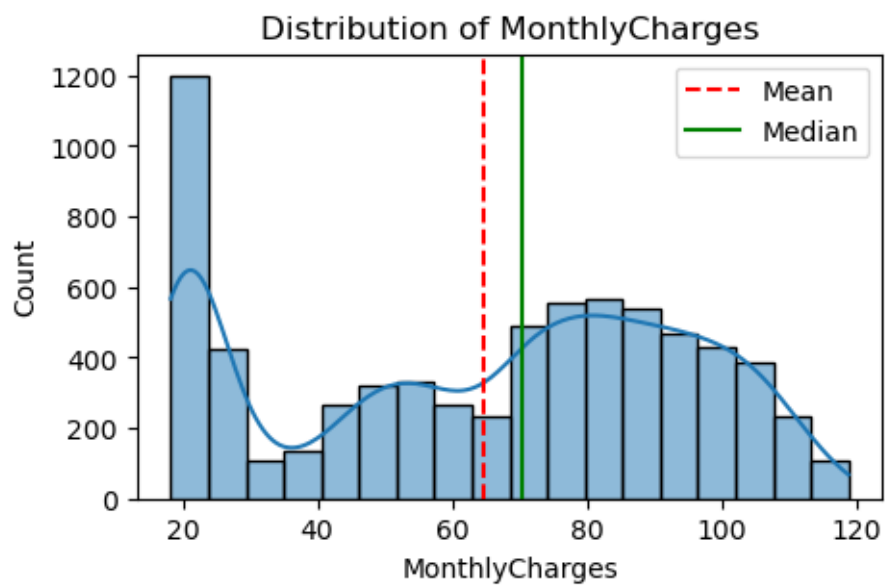
```
plt.show()
```

```
[43]: plot_histogram(df, "tenure")
```



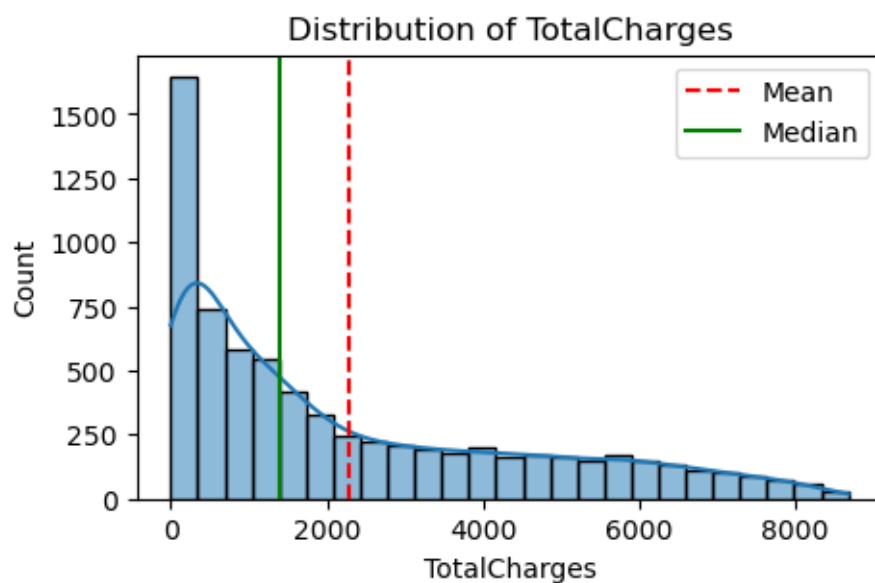
```
[ ]:
```

```
[44]: plot_histogram(df, "MonthlyCharges")
```



```
[ ]:
```

```
[73]: plot_histogram(df, "TotalCharges")
```

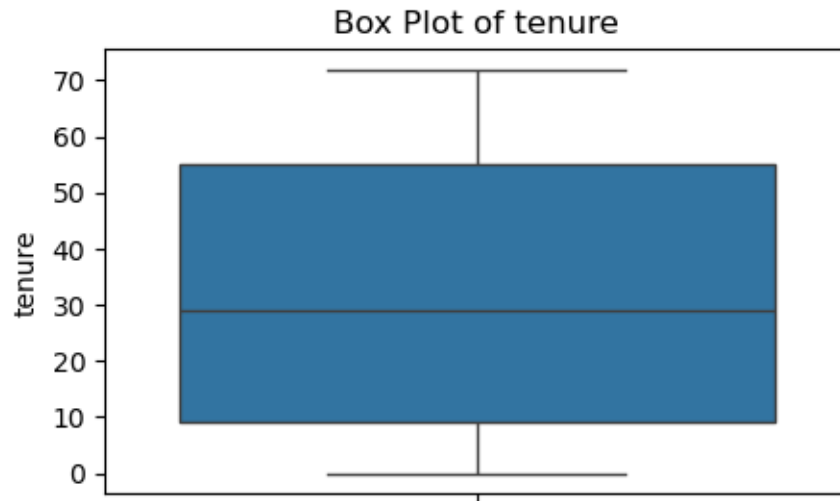


```
[ ]:
```

1.4.2 Box plot for numerical features

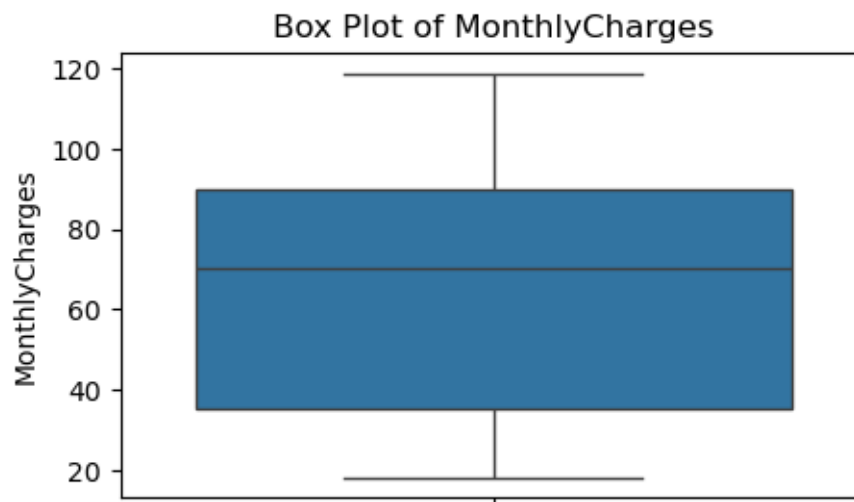
```
[49]: def plot_boxplot(df, column_name):  
  
    plt.figure(figsize=(5, 3))  
    sns.boxplot(y=df[column_name])  
    plt.title(f"Box Plot of {column_name}")  
    plt.ylabel(column_name)  
    plt.show
```

```
[50]: plot_boxplot(df, "tenure")
```



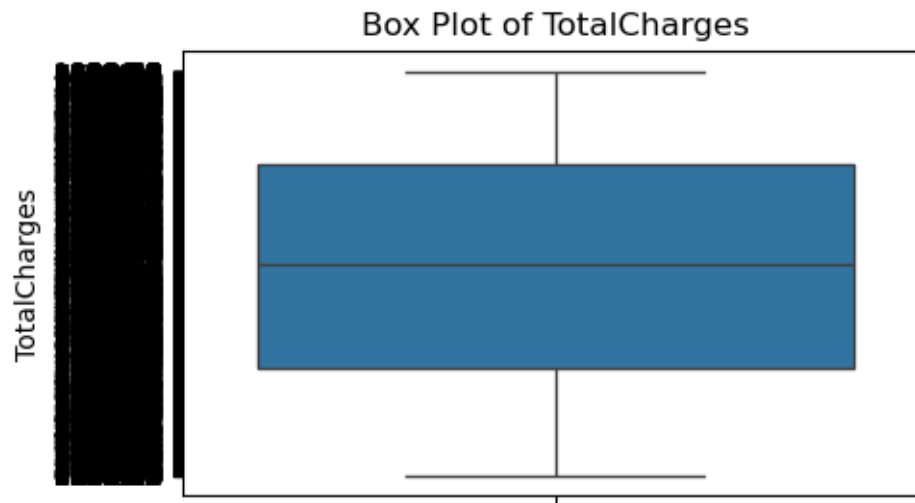
```
[ ]:
```

```
[51]: plot_boxplot(df, "MonthlyCharges")
```



```
[ ]:
```

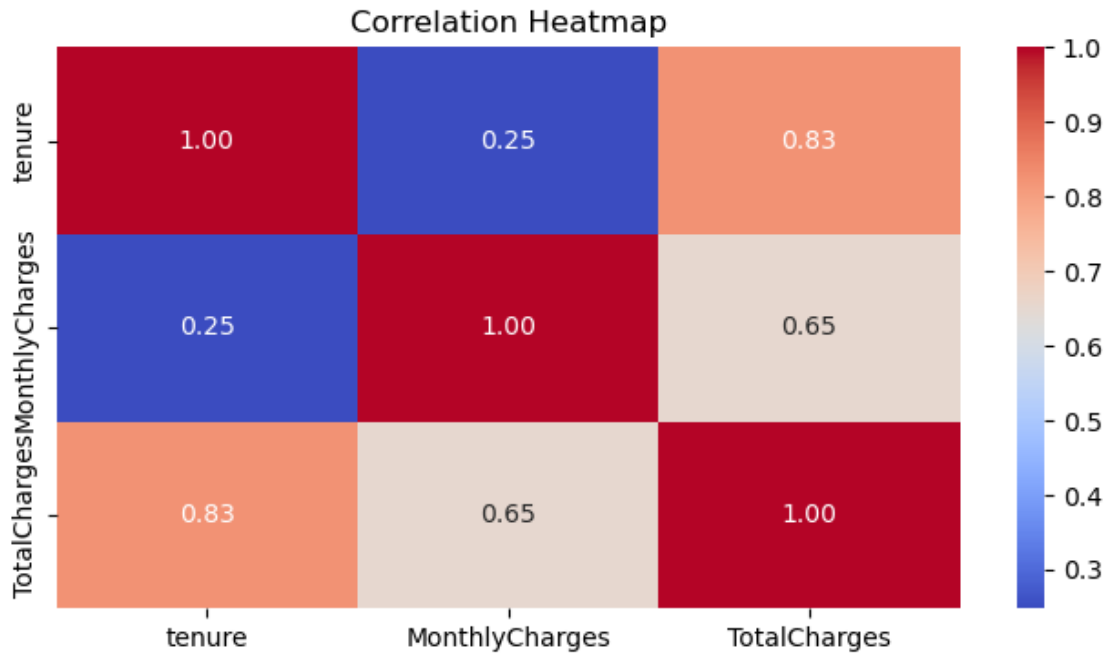
```
[53]: plot_boxplot(df, "TotalCharges")
```



[]:

1.4.3 Correlation Heatmap for numerical columns

```
[69]: # correlation matrix - heatmap
plt.figure(figsize=(8, 4))
sns.heatmap(df[["tenure", "MonthlyCharges", "TotalCharges"]].corr(),
            annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



```
[ ]:
```

1.4.4 Categorical features - Analysis

```
[70]: df.columns
```

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

```
[71]: 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   float64
20  Churn            7043 non-null   object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB

```

[]:

1.4.5 Countplot for categorical columns

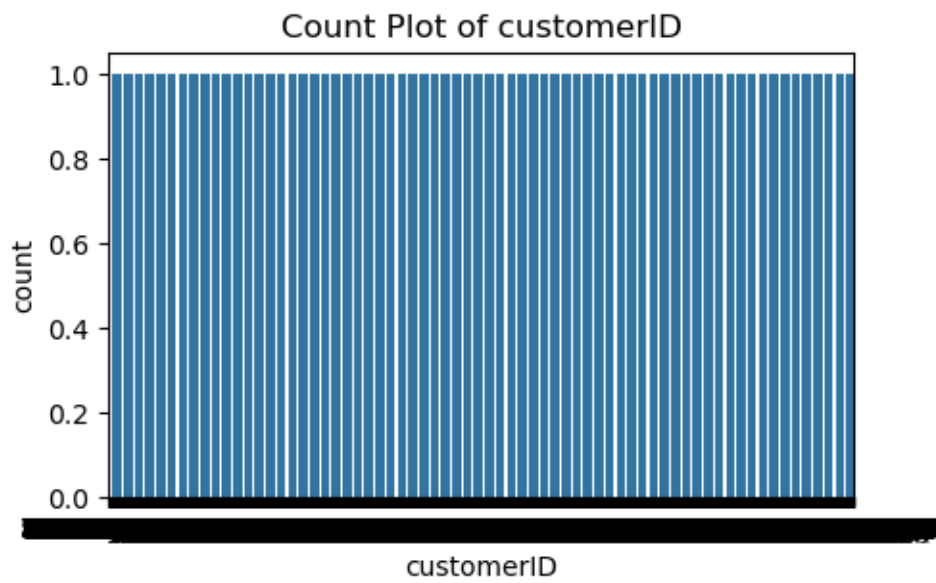
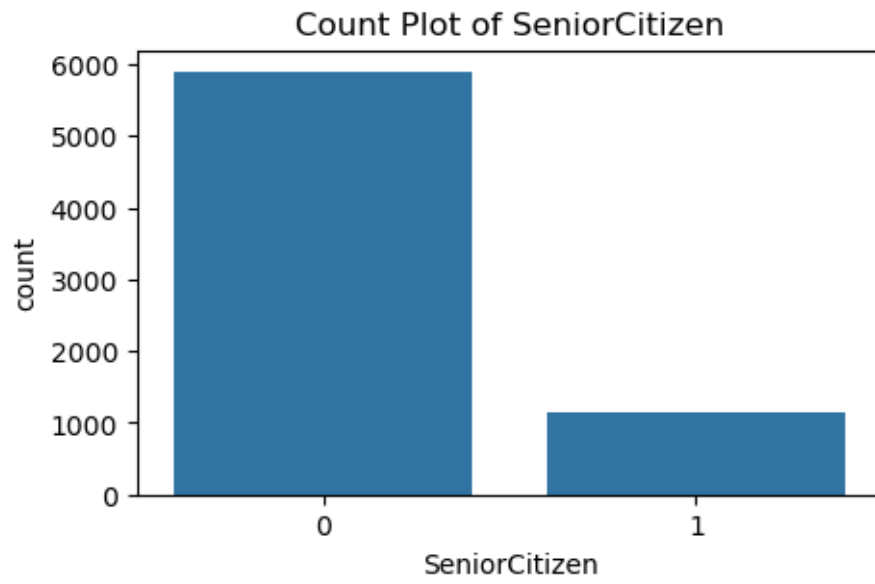
```

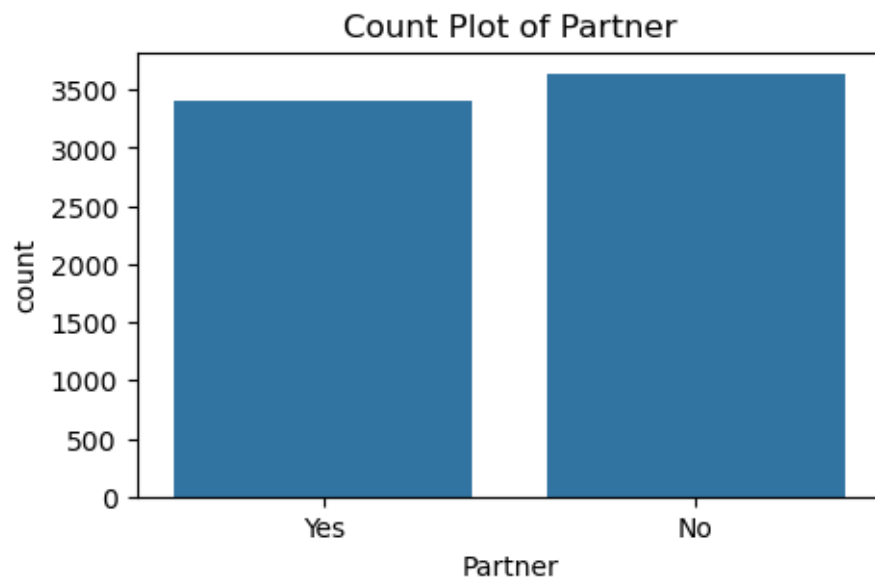
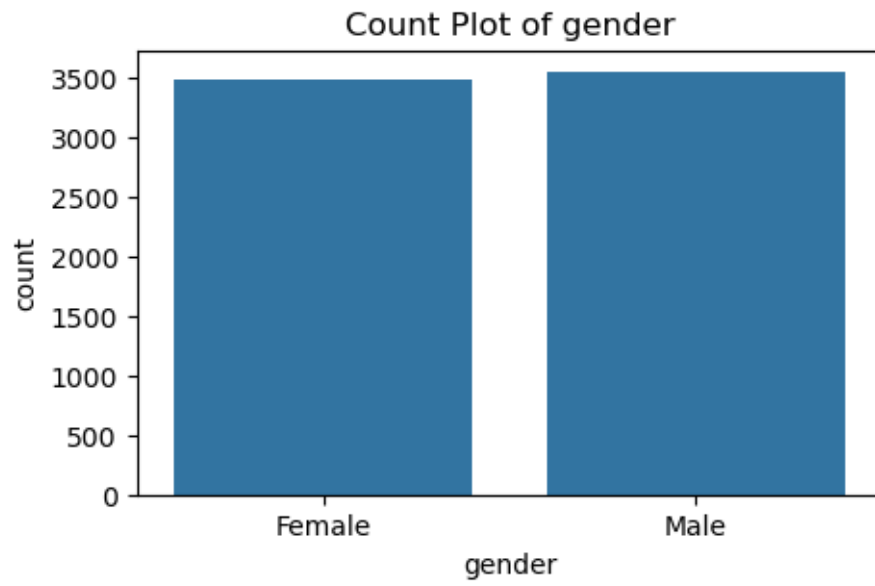
[72]: object_cols = df.select_dtypes(include="object").columns.to_list()

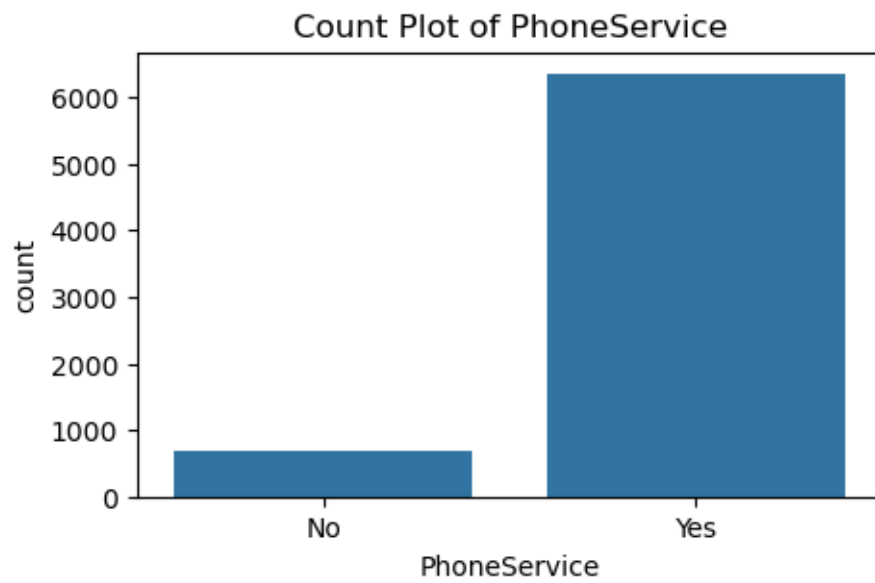
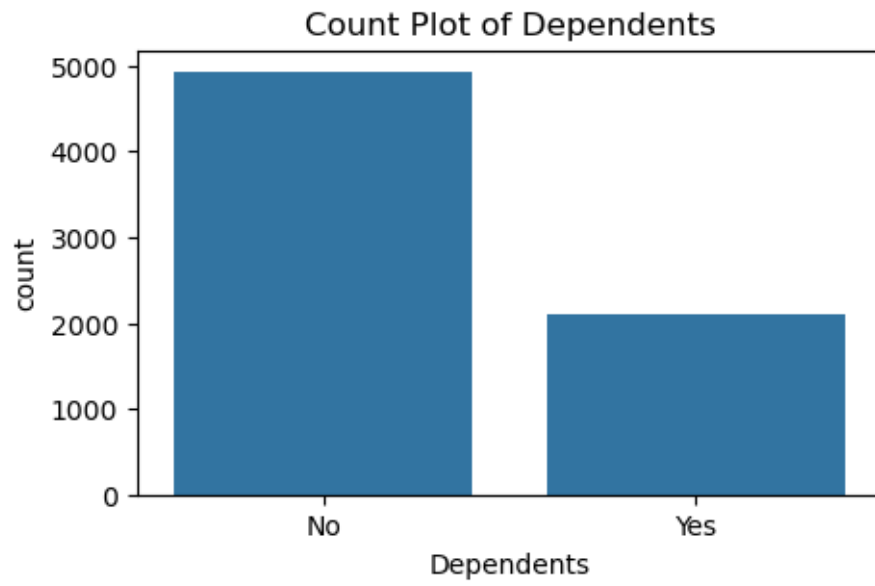
object_cols = ["SeniorCitizen"] + object_cols

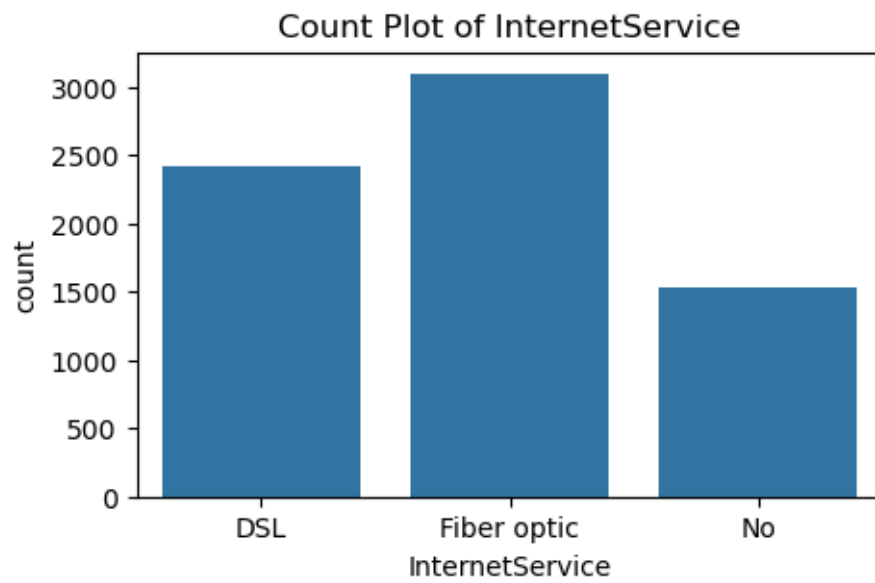
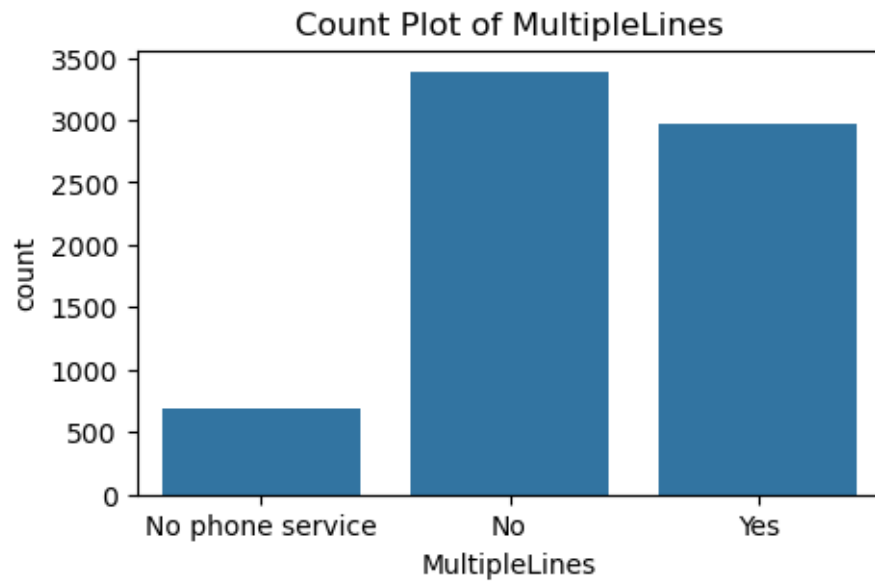
for col in object_cols:
    plt.figure(figsize=(5, 3))
    sns.countplot(x=df[col])
    plt.title(f"Count Plot of {col}")
    plt.show()

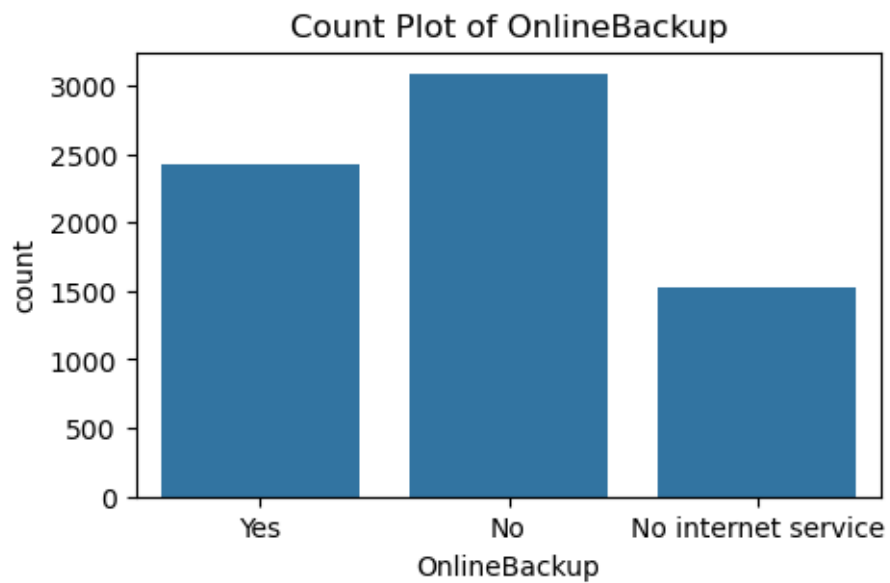
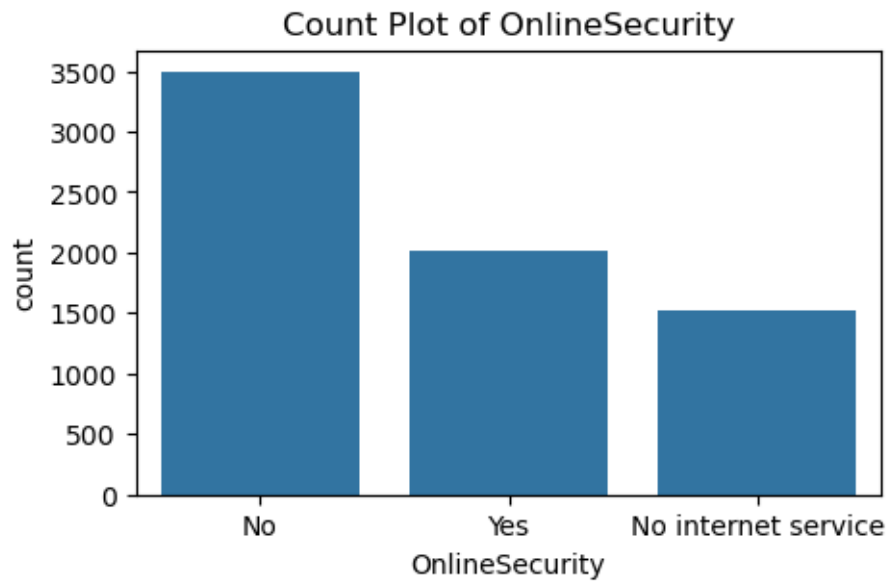
```

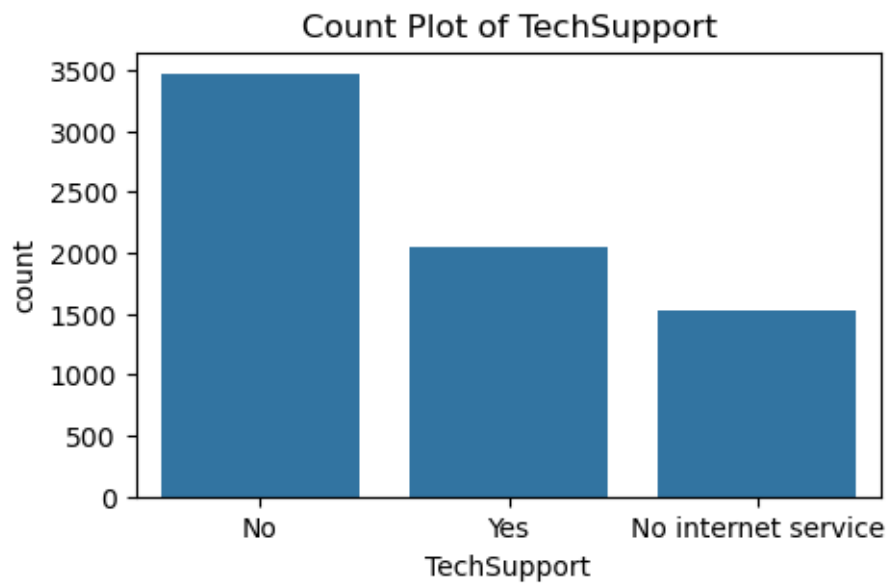
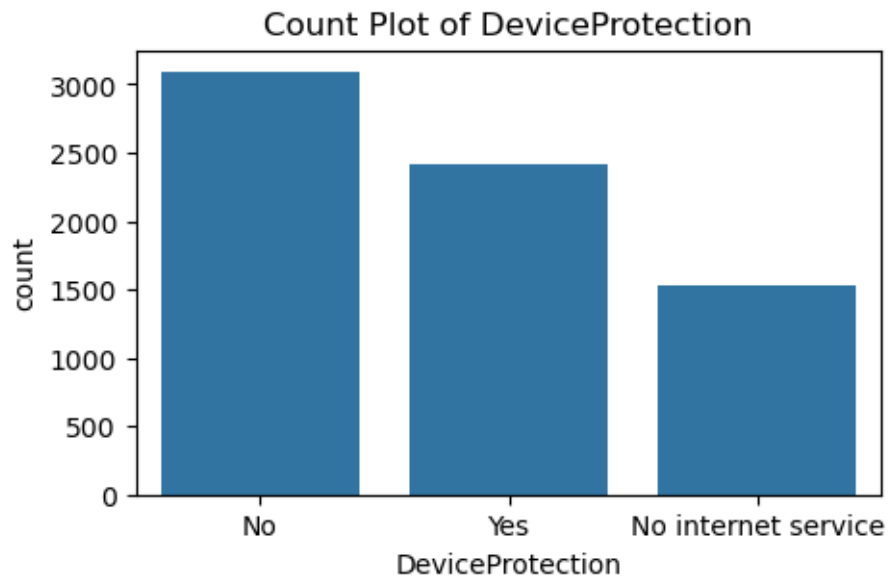


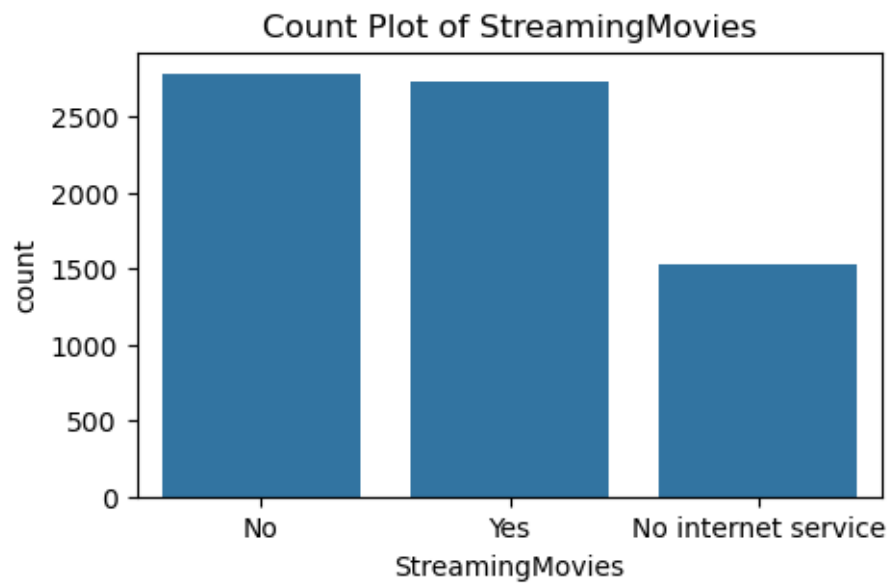
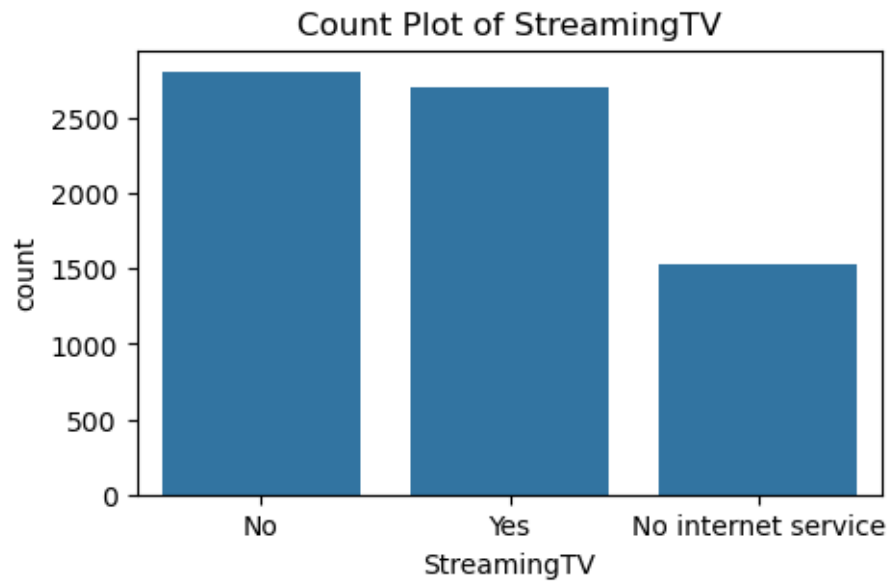


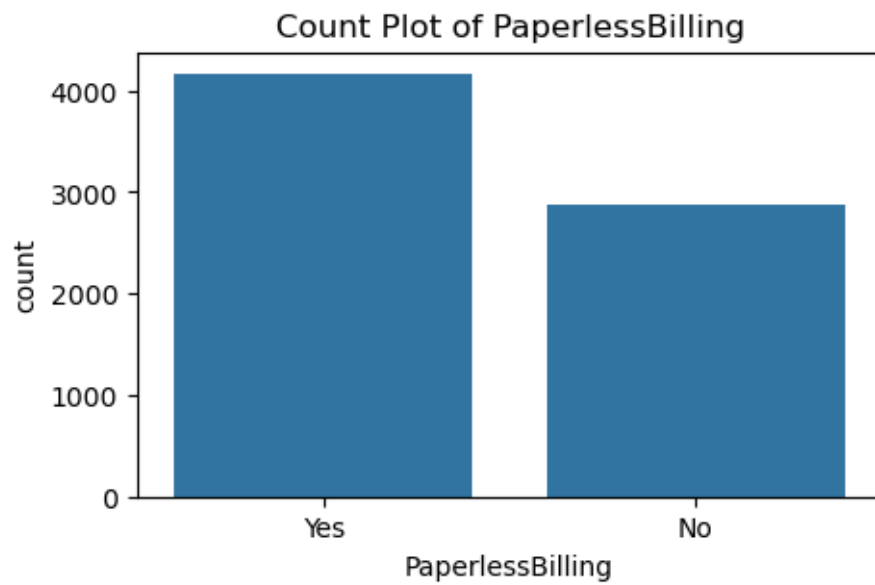
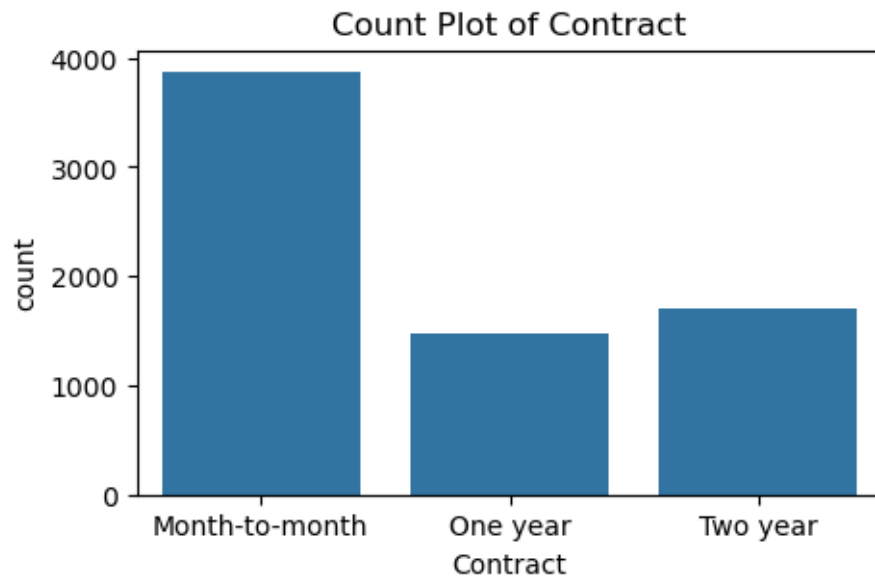


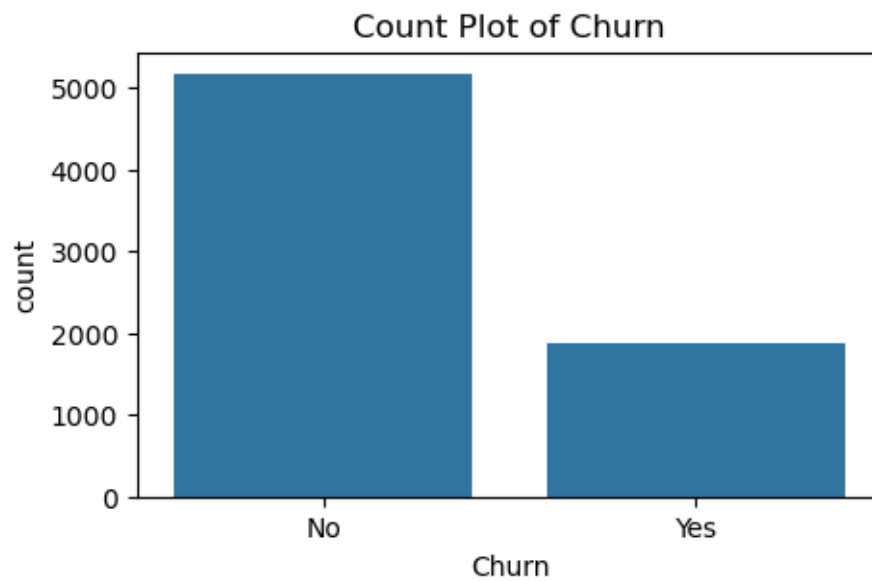
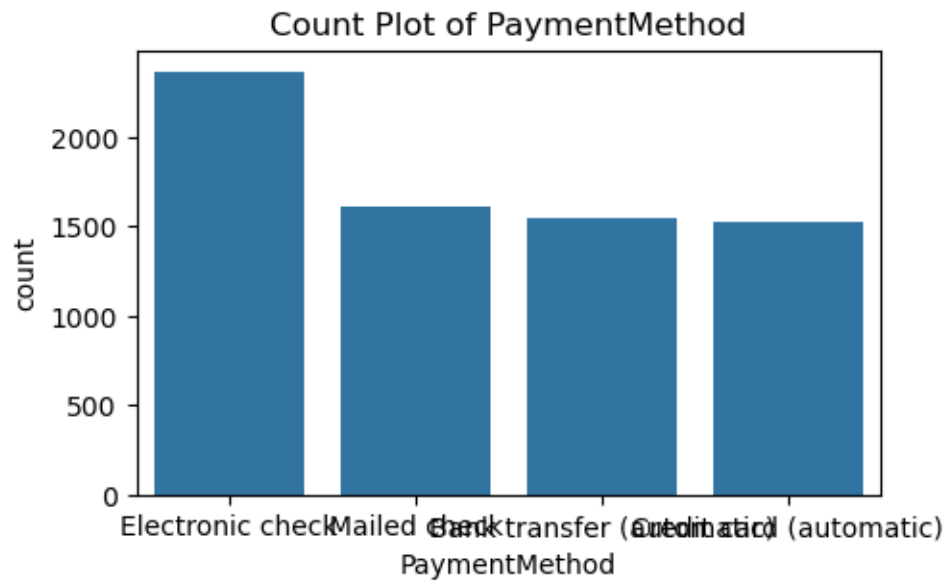












```
[ ]:
```

2 4. Data Preprocessing

```
[75]: df.head(2)
```



```
[75]: 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

MultipleLines InternetService OnlineSecurity OnlineBackup \
0 No phone service DSL No Yes
1 No DSL Yes No

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

PaperlessBilling PaymentMethod MonthlyCharges TotalCharges Churn
0 Yes Electronic check 29.85 29.85 No
1 No Mailed check 56.95 1889.50 No
```

```
[ ]:
```

2.0.1 Label encoding of target column

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

```
[ ]:
```

```
[80]: df.head(2)
```

```
[80]: 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

MultipleLines InternetService OnlineSecurity OnlineBackup \
0 No phone service DSL No Yes
1 No DSL Yes No

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

PaperlessBilling PaymentMethod MonthlyCharges TotalCharges Churn
0 Yes Electronic check 29.85 29.85 0
1 No Mailed check 56.95 1889.50 0
```

```
[ ]:
```

```
[81]: print(df["Churn"].value_counts())
```

Churn

```
0    5174
1    1869
Name: count, dtype: int64
```

```
[ ]:
```

2.0.2 Label encoding of categorical features

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

```
[83]: print(object_columns)
```

```
Index(['customerID', 'gender', 'Partner', 'Dependents', 'PhoneService',
      'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
      'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
      'Contract', 'PaperlessBilling', 'PaymentMethod'],
      dtype='object')
```

```
[ ]:
```

```
[84]: # 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)
```

```
[85]: encoders
```

```
[85]: {'customerID': LabelEncoder(),
      '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()]}
```

```
[87]: df.head(2)
```

```
[87]:   customerID  gender  SeniorCitizen  Partner  Dependents  tenure \
0         5375      0              0      1          0         1
1         3962      1              0      0          0        34

   PhoneService  MultipleLines  InternetService  OnlineSecurity  OnlineBackup \
0             0              1              0              0          2
1             1              0              0              2          0

   DeviceProtection  TechSupport  StreamingTV  StreamingMovies  Contract \
0                 0              0              0              0          0
1                 2              0              0              0          1

   PaperlessBilling  PaymentMethod  MonthlyCharges  TotalCharges  Churn
0                 1              2          29.85         29.85      0
1                 0              3          56.95        1889.50      0
```

```
[ ]:
```

2.0.3 Traianing and test data split

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

```
[89]: # split training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳ random_state=42)
```

```
[90]: print(y_train.shape)
```

```
(5634,)
```

```
[91]: print(y_train.value_counts())
```

```
Churn
0    4138
1    1496
Name: count, dtype: int64
```

```
[ ]:
```

Synthetic Minority Oversampling TEchnique (SMOTE)

```
[92]: smote = SMOTE(random_state=42)
```

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

```
[94]: print(y_train_smote.shape)
```

```
(8276,)
```

```
[95]: print(y_train_smote.value_counts())
```

```
Churn
```

```
0    4138
```

```
1    4138
```

```
Name: count, dtype: int64
```

```
[ ]:
```

3 5. Model Training

Training with default hyperparameters

```
[96]: # dictionary of models
```

```
models = {  
    "Decision Tree": DecisionTreeClassifier(random_state=42),  
    "Random Forest": RandomForestClassifier(random_state=42),  
    "XGBoost": XGBClassifier(random_state=42)  
}
```

```
[97]: # 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,  
                             scoring="accuracy")  
    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: 0.84

```
[98]: cv_scores
```

```
[98]: {'Decision Tree': array([0.68297101, 0.7081571 , 0.81873112, 0.82779456,
0.83987915]),
      'Random Forest': array([0.73248792, 0.76495468, 0.90755287, 0.89848943,
0.90574018]),
      'XGBoost': array([0.70833333, 0.74682779, 0.91359517, 0.90090634, 0.91359517])}
```

```
[ ]:
```

3.0.1 Random Forest gives the highest accuracy compared to other models with default parameters

```
[99]: rfc = RandomForestClassifier(random_state=42)
```

```
[100]: rfc.fit(X_train_smote, y_train_smote)
```

```
[100]: RandomForestClassifier(random_state=42)
```

```
[101]: print(y_test.value_counts())
```

Churn

0 1036

1 373

Name: churn, dtype: int64

```
[ ]:
```

4 6. Model Evaluation

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

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

Accuracy Score:

0.7792760823278921

Confusion Matrix:

[[875 161]

```
[150 223]]
Classification Report:
              precision    recall  f1-score   support

     0       0.85         0.84         0.85        1036
     1       0.58         0.60         0.59         373

 accuracy          0.72
 macro avg          0.72
weighted avg          0.78
```

```
[103]: # 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)
```

```
[ ]:
```

4.1 7. Load the saved model and build a Predictive System

```
[104]: # load the 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"]
```

```
[105]: print(loaded_model)
```

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

```
[106]: print(feature_names)
```

```
['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
'MonthlyCharges', 'TotalCharges']
```

```
[ ]:
```

```
[117]: 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
}

encoders.pop("customerID", None) # Remove customerID encoder

# Check for missing or extra columns
expected_features = set(loader.model.feature_names_in_) # Features expected by
↳ the model
current_features = set(input_data_df.columns)

missing_features = expected_features - current_features
extra_features = current_features - expected_features

print(f"Missing features: {missing_features}")
print(f"Extra features: {extra_features}")

```

```

Missing features: {'customerID'}
Extra features: set()

```

```
[118]: encoders
```

```

[118]: {'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()]}
```

[]:

[]:

[]: