1.Importing the dependencies

In [104…
```
import numpy as np
import pandas as pd
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
```

2. Data Loading and Understanding

In [107…
```
# load thecsv data to a pandas dataframe
df = pd.read_csv("WA_Fn-UseC_-Telco-Customer-Churn.csv")
```

In [109…
```
df.shape
```

Out[109… (7043, 21)

In [110…
```
df.head()
```

Out[110…

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	C
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	

In [111…
```
df.tail()
```

Out[111…

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	DSL	Yes
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	No
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	DSL	Yes
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes	Fiber optic	No
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	Fiber optic	Yes

In [112…
```
pd.set_option("display.max_columns", None)
```

In [113…
```
df.head(2)
```

Out[113…

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	C
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	

In [114…
```
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
```

In [115…
```
# dropping customerID column as this is not required for modelling
df = df.drop(columns=["customerID"])
```

In [116…
```
df.head(2)
```

Out[116…

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes
1	Male	0	No	No	34	Yes	No	DSL	Yes	No

In [117…
```
df.columns
```

Out[117…
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
       'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
       'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [118…
```
print(df["gender"].unique())
```

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

In [119…
```
print(df["SeniorCitizen"].unique())
```

```
[0 1]
```

In [120…
```
# 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']
--------------------------------------------------
```

In [121…
```
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
```

In [122…
```
#df["TotalCharges"] = df["TotalCharges"].astype(float)
```

In [123…
```
df[df["TotalCharges"]==" "]
```

Out[123…

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBack
488	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	
753	Male	0	No	Yes	0	Yes	No	No	No internet service	No inter serv
936	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	Y
1082	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No inter serv
1340	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	Y
3331	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No inter serv
3826	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No inter serv
4380	Female	0	Yes	Yes	0	Yes	No	No	No internet service	No inter serv
5218	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No inter serv
6670	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	Y
6754	Male	0	No	Yes	0	Yes	Yes	DSL	Yes	Y

In [124…
```
len(df[df["TotalCharges"]==" "])
```

Out[124… 11

In [125…
```
df["TotalCharges"] = df["TotalCharges"].replace({" ": "0.0"})
```

In [126…
```
df["TotalCharges"] = df["TotalCharges"].astype(float)
```

In [127…
```
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 [128…
```
# checking the class distribution of target column
print(df["Churn"].value_counts())
```

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

Insights:

Customer ID removed as it is not required for modelling

No mmissing values in the dataset

Missing values in the TotalCharges column were replaced with 0

Class imbalance identified in the target

3.. Exploratory Data Analysis (EDA)

In [129…
```
df.shape
```

Out[129…
```
(7043, 20)
```

In [130…
```
df.columns
```

Out[130…
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
       'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
       'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [131…
```
df.head(2)
```

Out[131…

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes
1	Male	0	No	No	34	Yes	No	DSL	Yes	No

In [133…
```
df.describe()
```

Out[133…

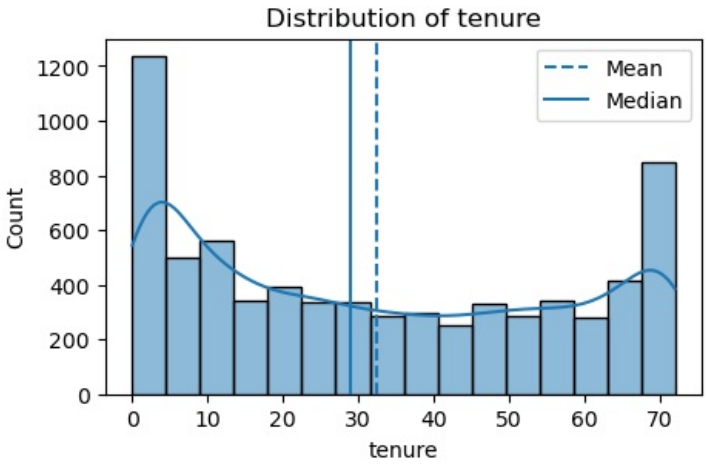
	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692	2279.734304
std	0.368612	24.559481	30.090047	2266.794470
min	0.000000	0.000000	18.250000	0.000000
25%	0.000000	9.000000	35.500000	398.550000
50%	0.000000	29.000000	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

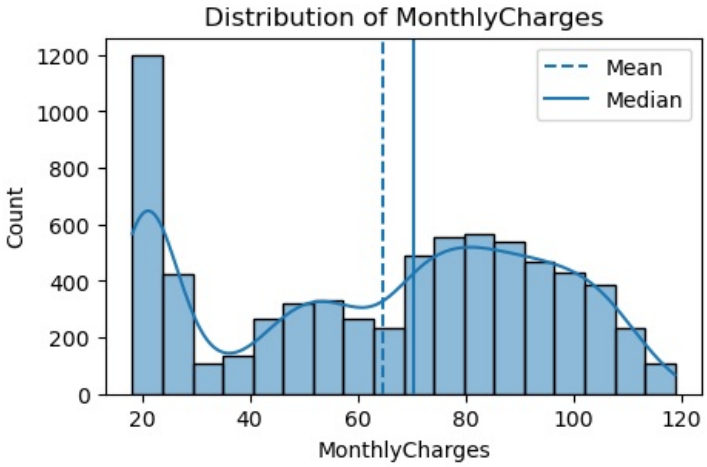
Understand the distribution of teh numerical features

In [135…
```
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 mean and median
    col_mean = df[column_name].mean()
    col_median = df[column_name].median()

    # add vertical lines
    plt.axvline(col_mean, linestyle="--", label="Mean")
    plt.axvline(col_median, linestyle="-", label="Median")

    plt.legend()
    plt.show()
```

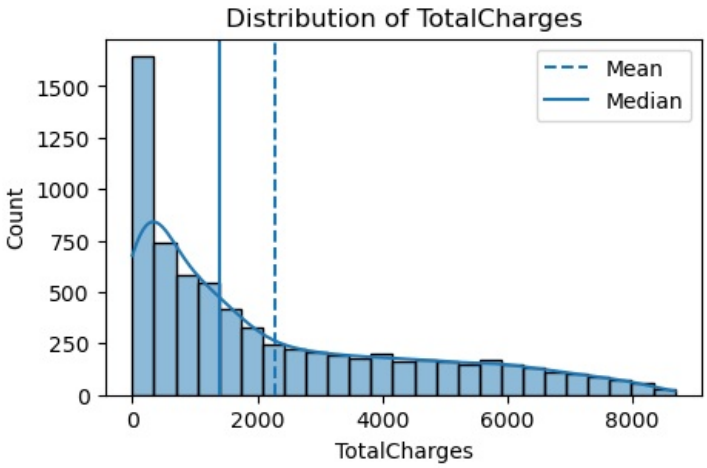
In [136…
```
plot_histogram(df, "tenure")
```



In [137…
```
plot_histogram(df, "MonthlyCharges")
```



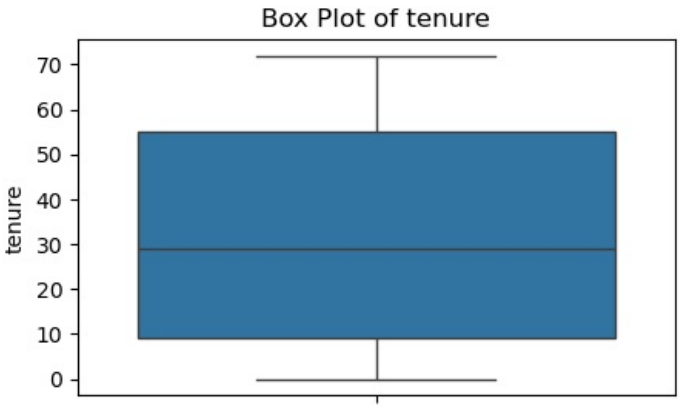
In [138…
```
plot_histogram(df, "TotalCharges")
```



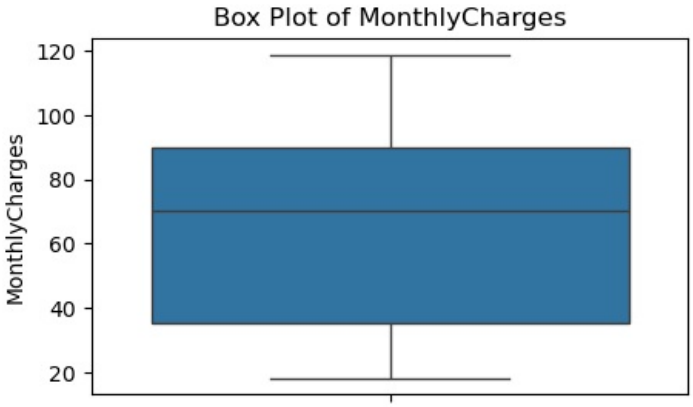
Box plot for numerical features

In [141…
```
import matplotlib.pyplot as plt

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()
```

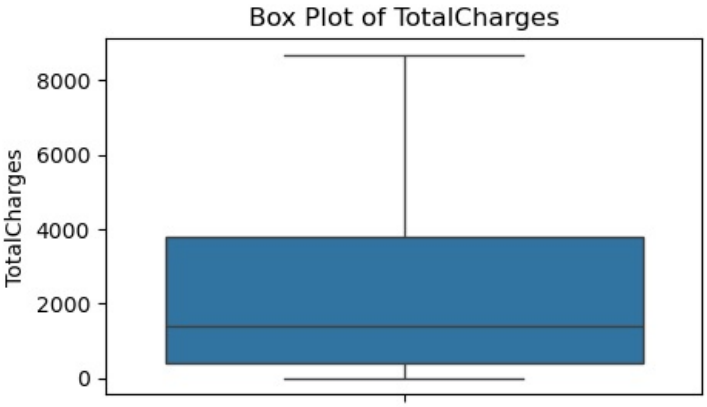
In [142…
```
plot_boxplot(df, "tenure")
```



In [143…
```
plot_boxplot(df, "MonthlyCharges")
```

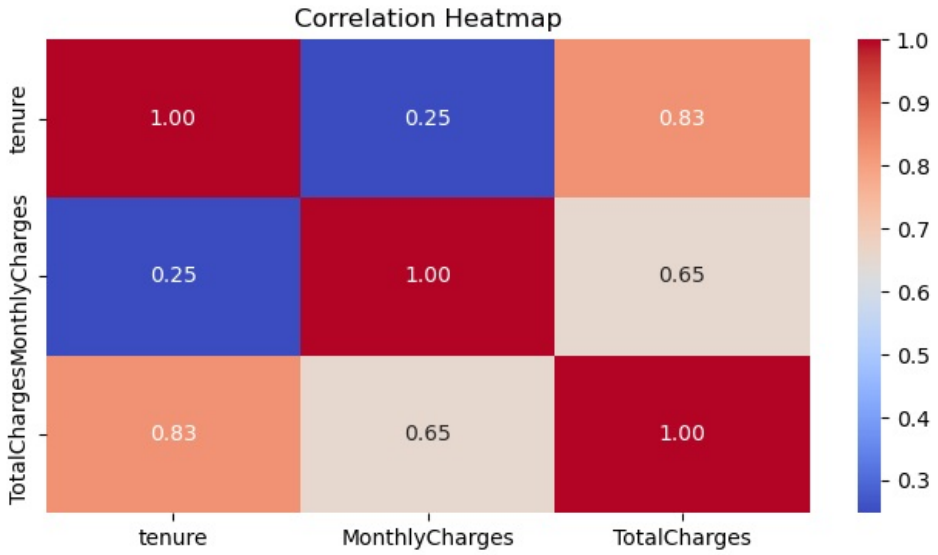


In [144…
```
plot_boxplot(df, "TotalCharges")
```



Correlation Heatmap for numerical columns

In [145…
```
# 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()
```



Categorical features - Analysis

In [147…
```
df.columns
```

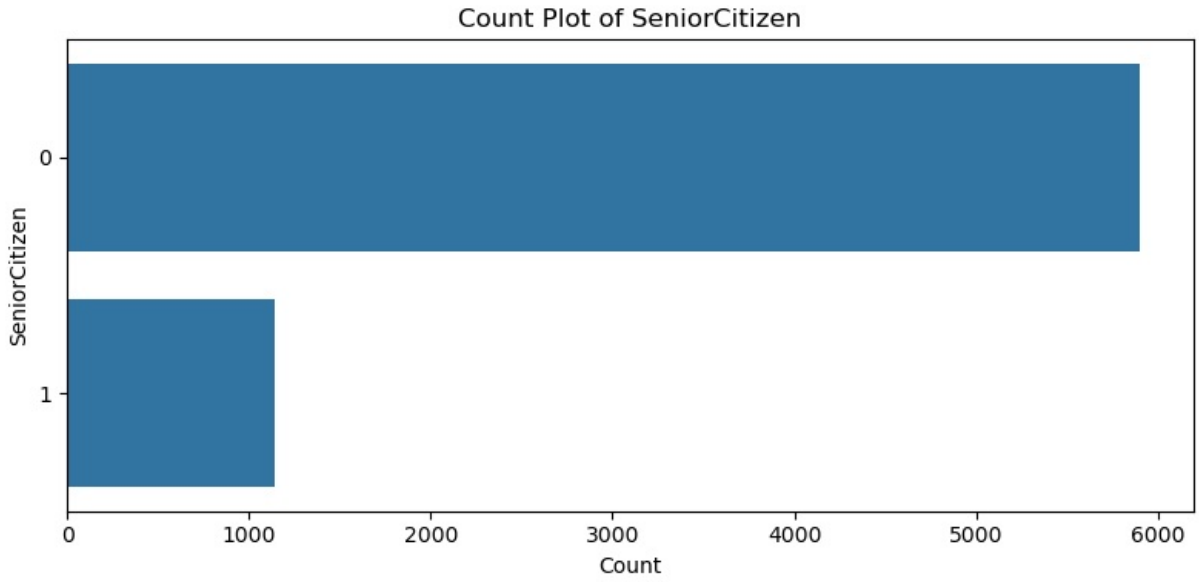
Out[147…
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
       'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
       'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

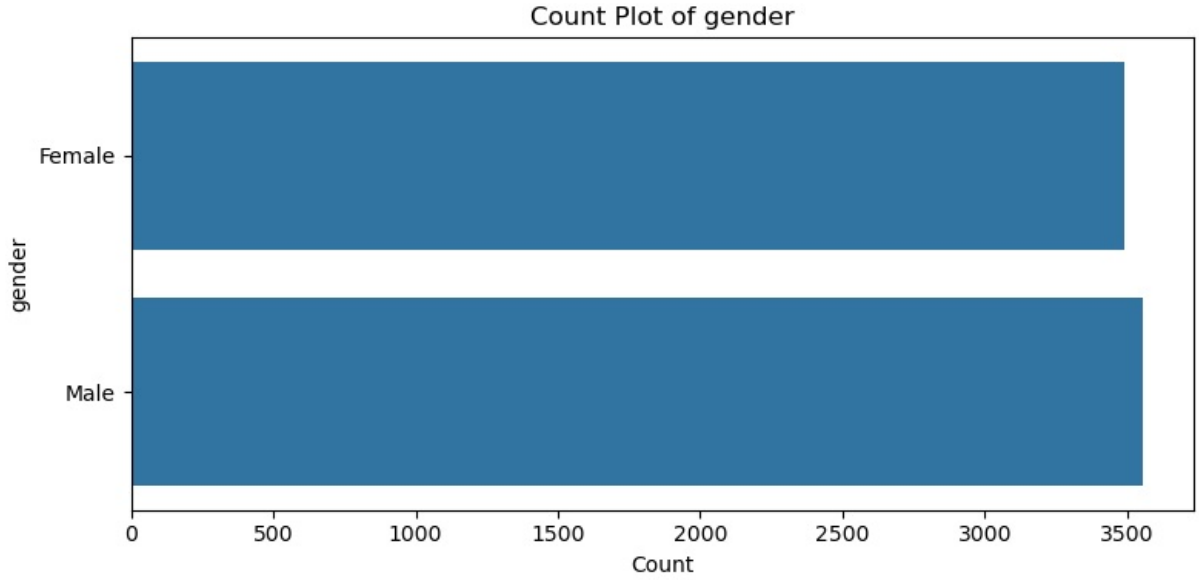
In [148…
```
df.info()
```

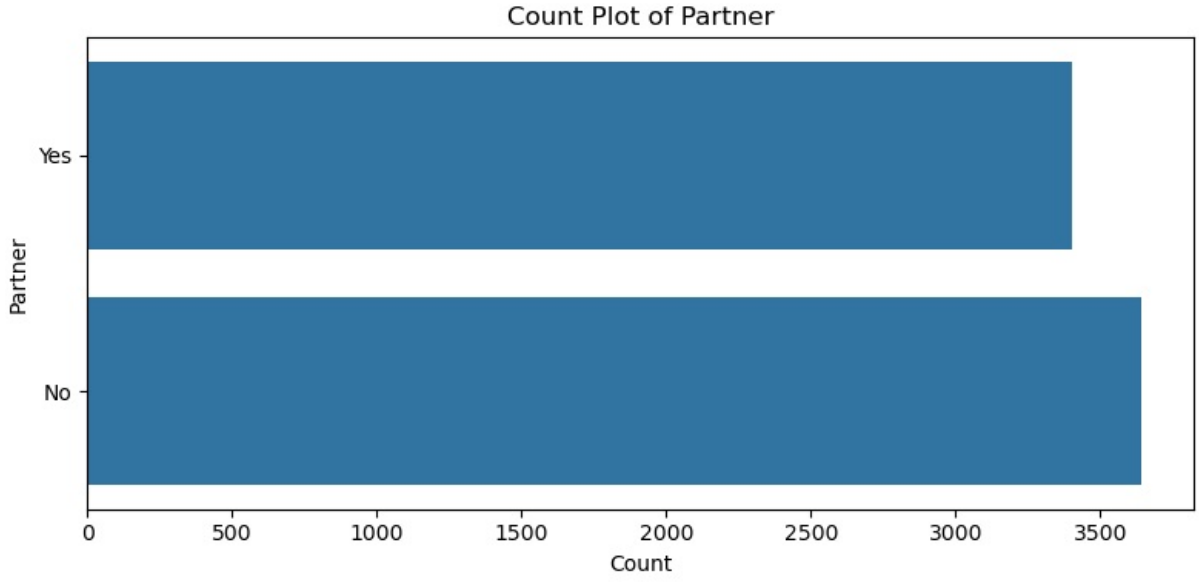
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   gender            7043 non-null   object 
 1   SeniorCitizen     7043 non-null   int64  
 2   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
```

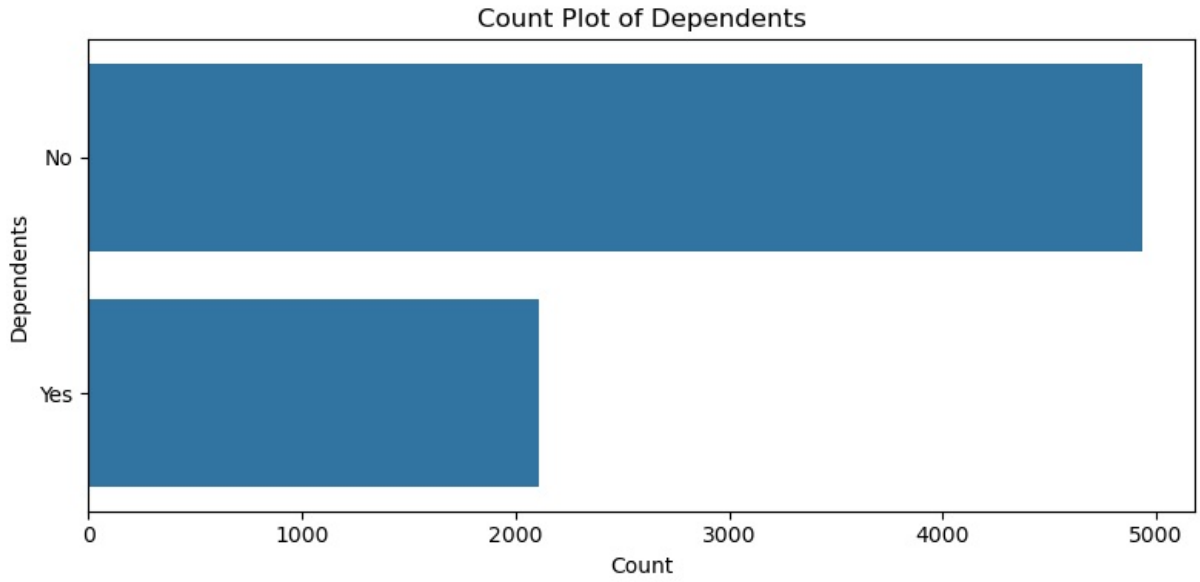
Countplot for categorical columns

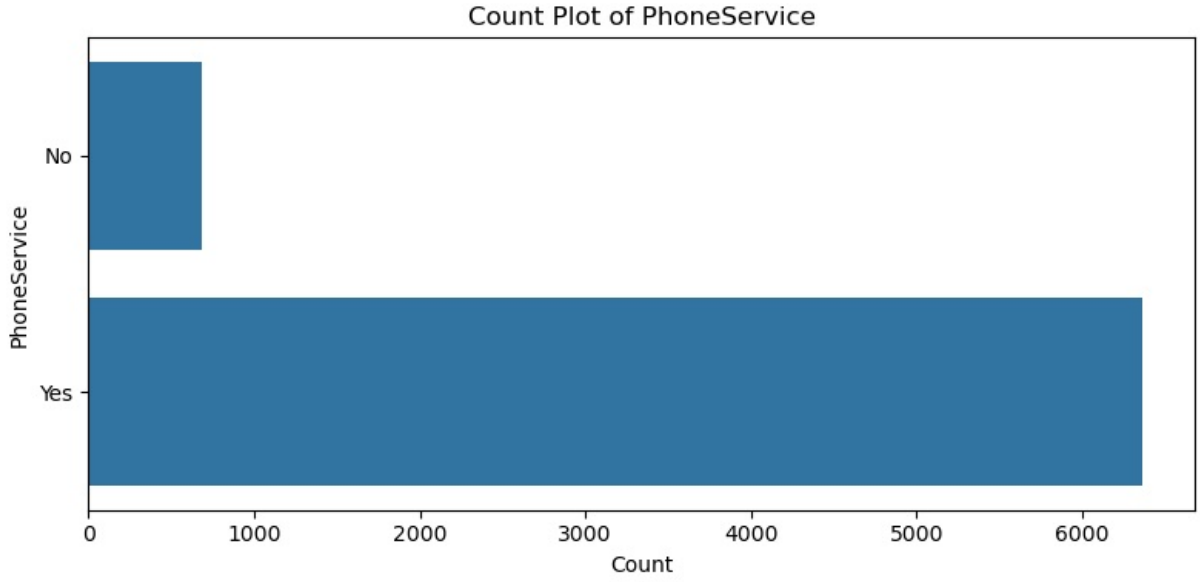
In [151…
```
for col in object_cols:
    plt.figure(figsize=(8, 4))
    sns.countplot(y=df[col])
    plt.title(f"Count Plot of {col}")
    plt.xlabel("Count")
    plt.ylabel(col)
    plt.tight_layout()
    plt.show()
```

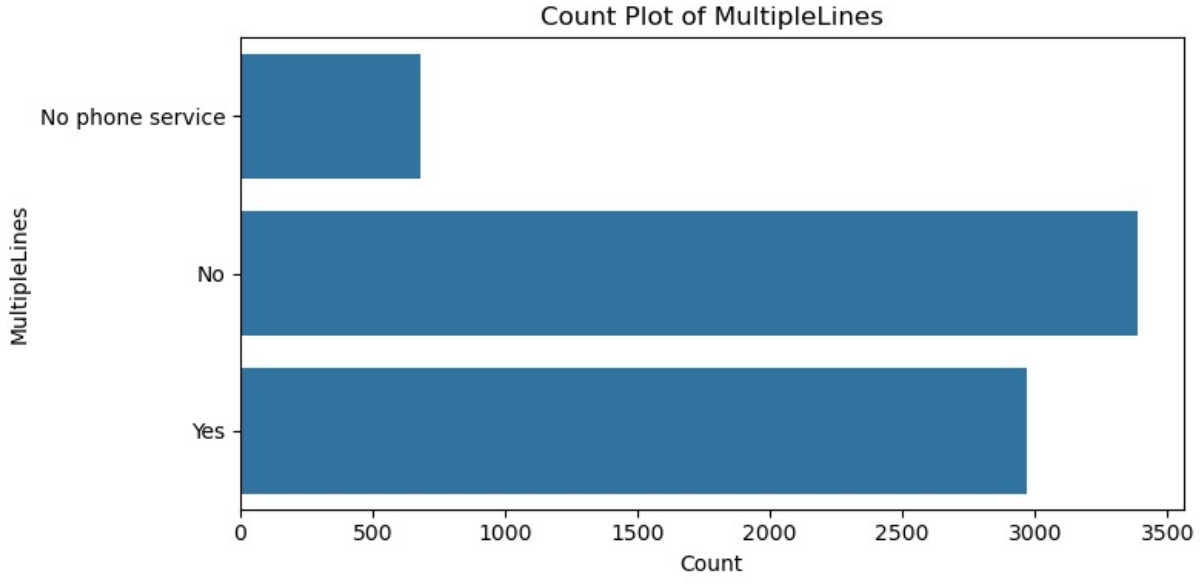

Count Plot of SeniorCitizen
SeniorCitizen
0
1
0
1000
2000
3000
4000
5000
6000
Count

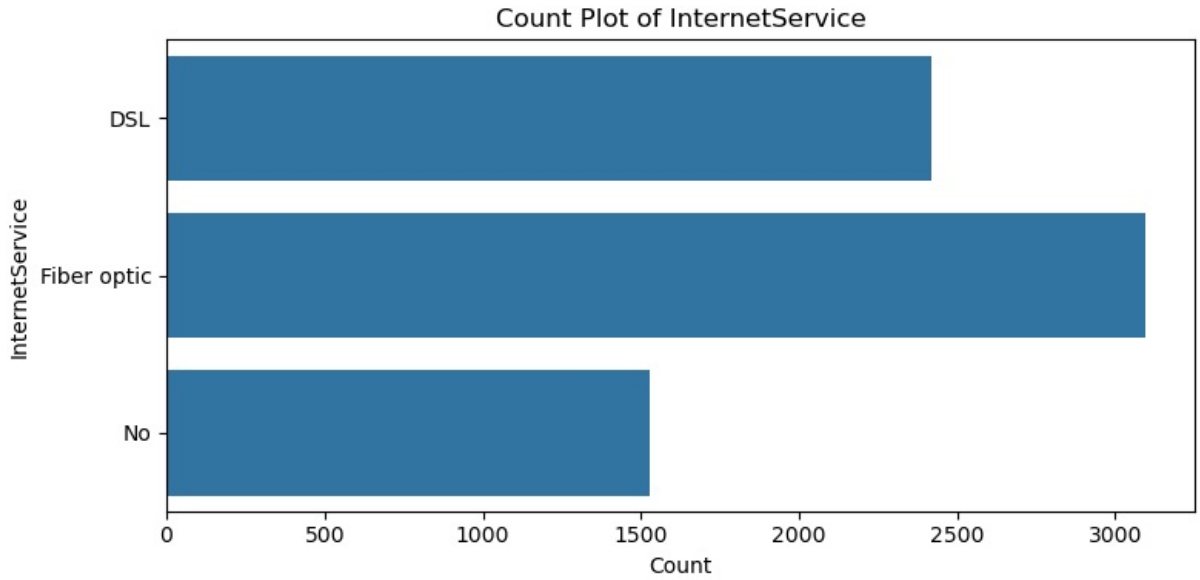

Count Plot of gender
gender
Female
Male
0
500
1000
1500
2000
2500
3000
3500
Count

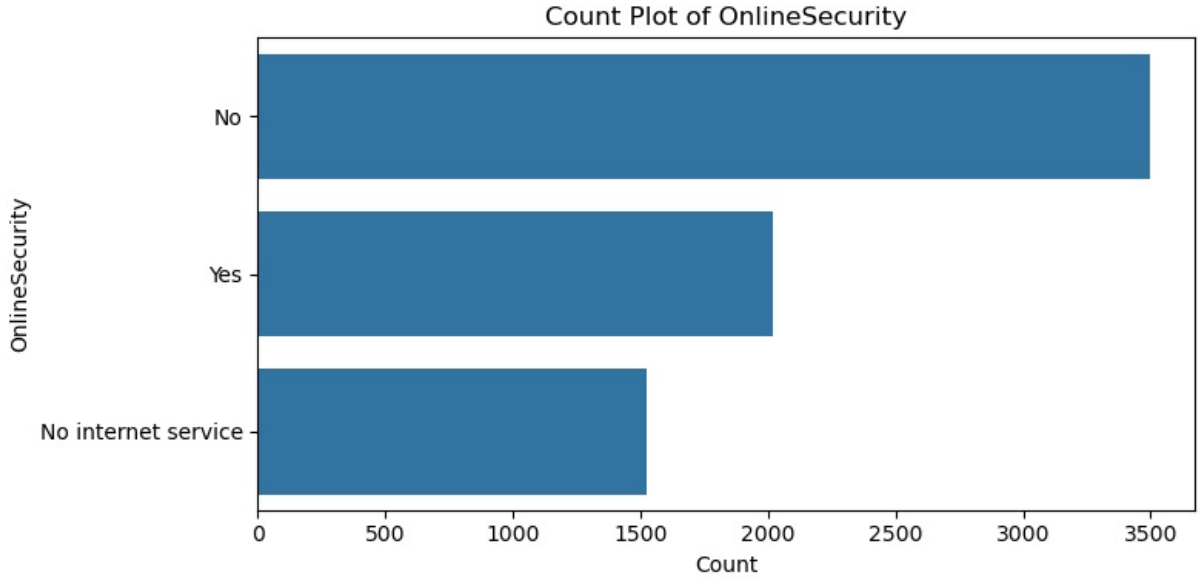

Count Plot of Partner
Partner
Yes
No
0
500
1000
1500
2000
2500
3000
3500
Count

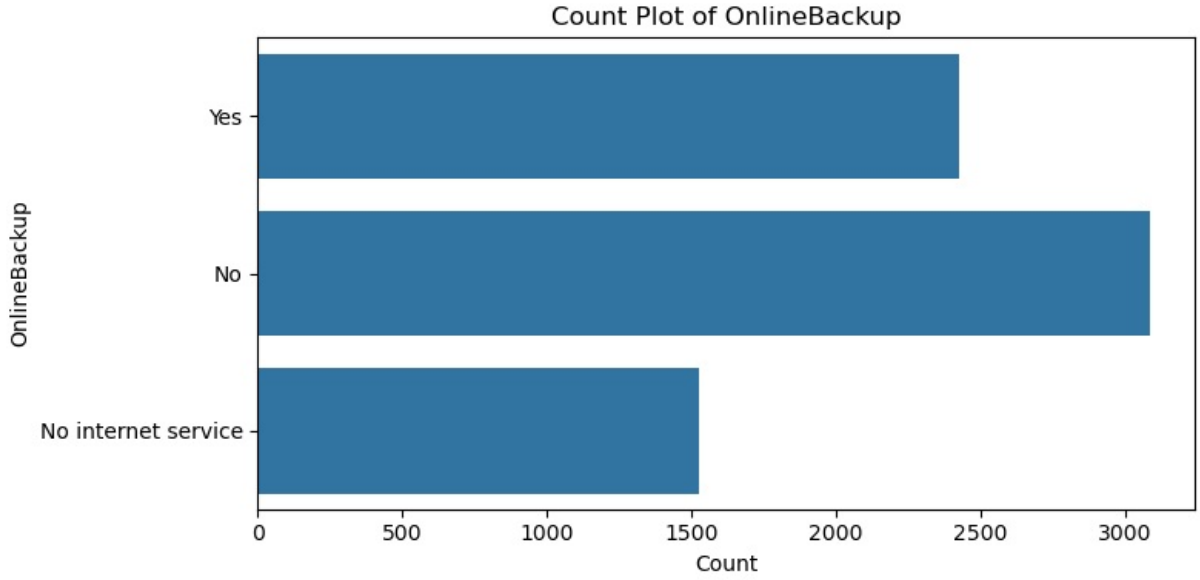

Count Plot of Dependents
Dependents
No
Yes
0
1000
2000
3000
4000
5000
Count

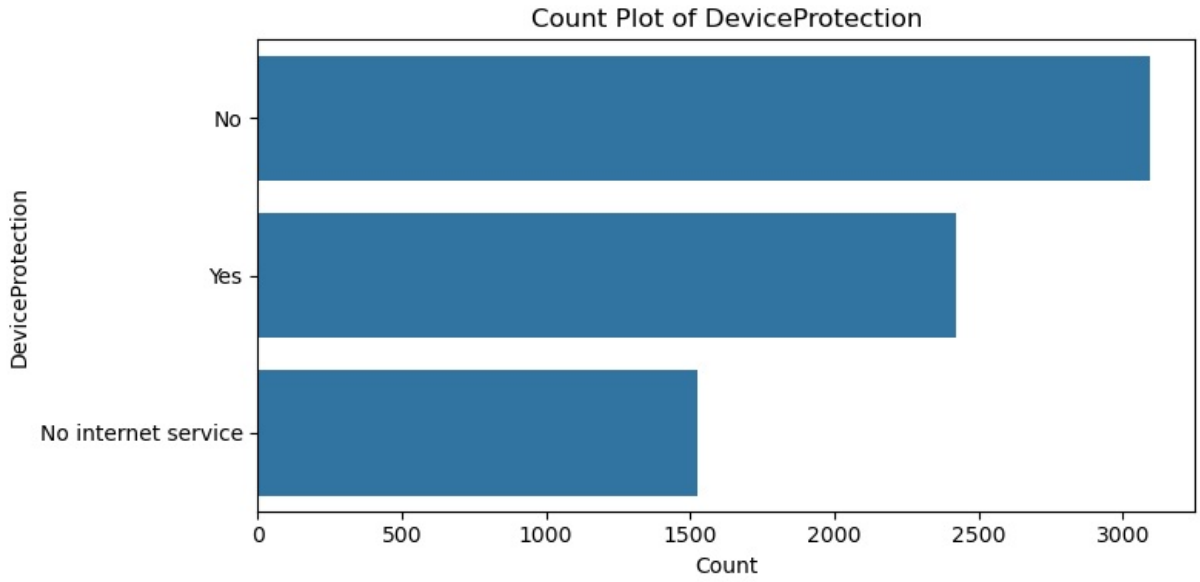

Count Plot of PhoneService
PhoneService
No
Yes
0
1000
2000
3000
4000
5000
6000
Count

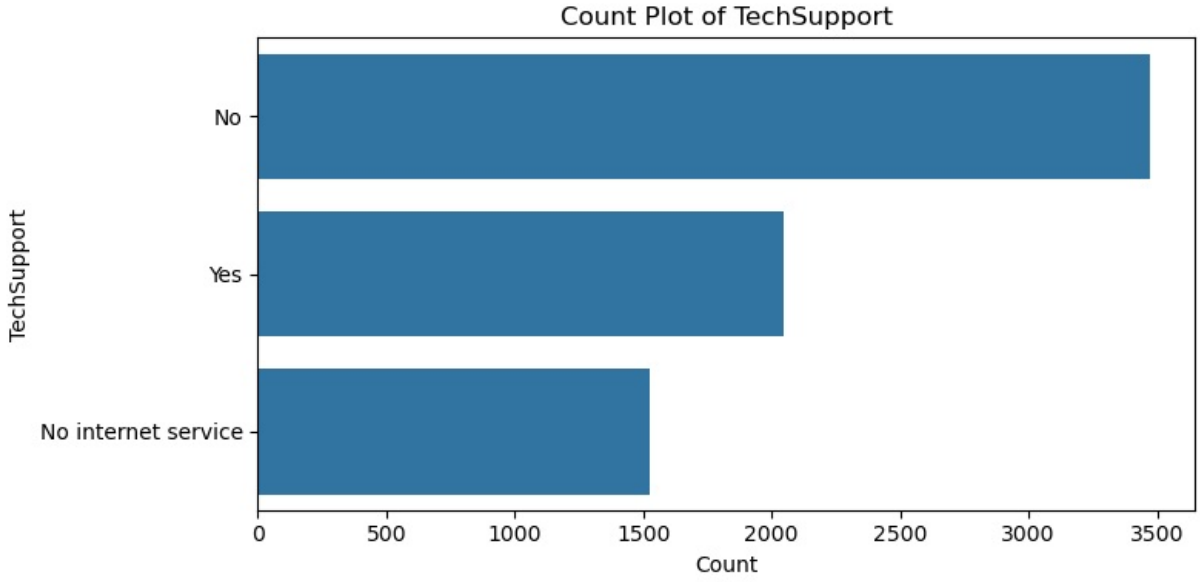

Count Plot of MultipleLines
MultipleLines
No phone service
No
Yes
0
500
1000
1500
2000
2500
3000
3500
Count

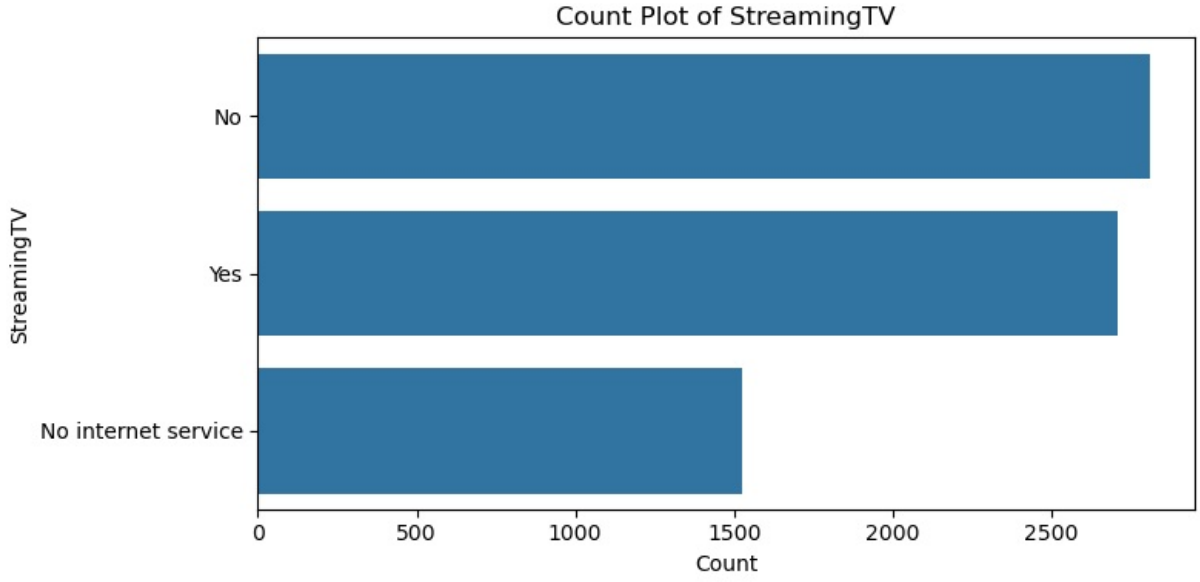

Count Plot of InternetService
InternetService
DSL
Fiber optic
No
0
500
1000
1500
2000
2500
3000
Count

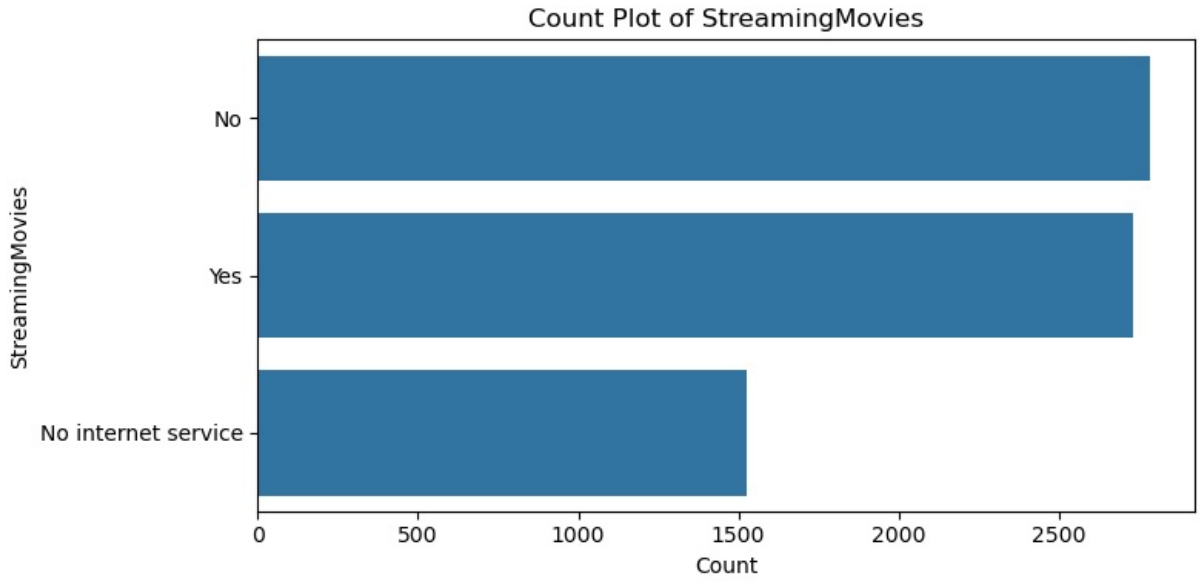

Count Plot of OnlineSecurity
OnlineSecurity
No
Yes
No internet service
0
500
1000
1500
2000
2500
3000
3500
Count

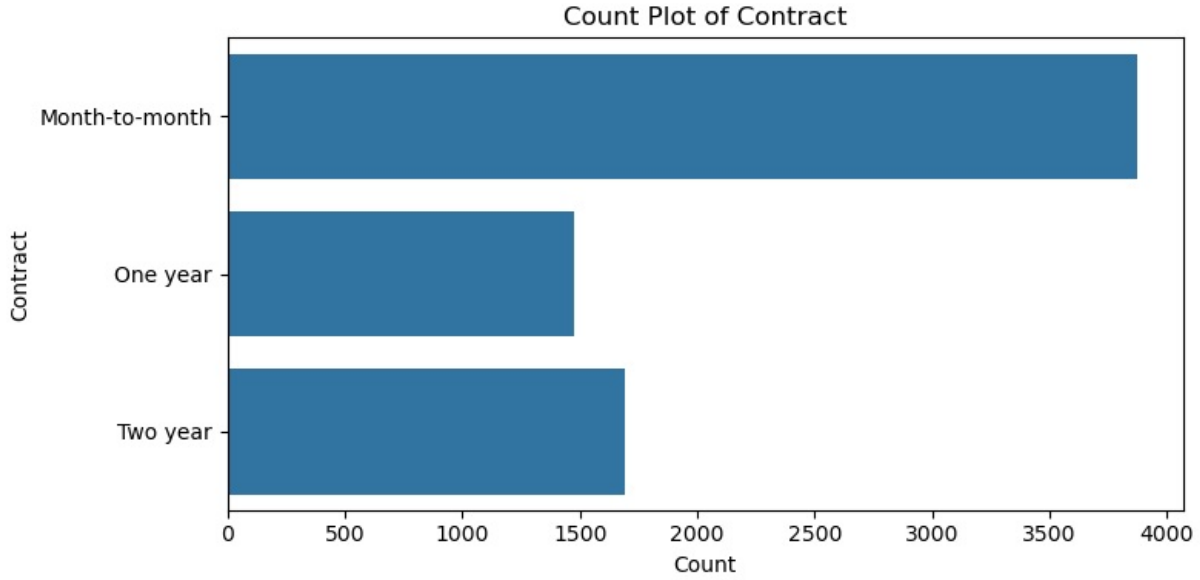

Count Plot of OnlineBackup
OnlineBackup
Yes
No
No internet service
0
500
1000
1500
2000
2500
3000
Count

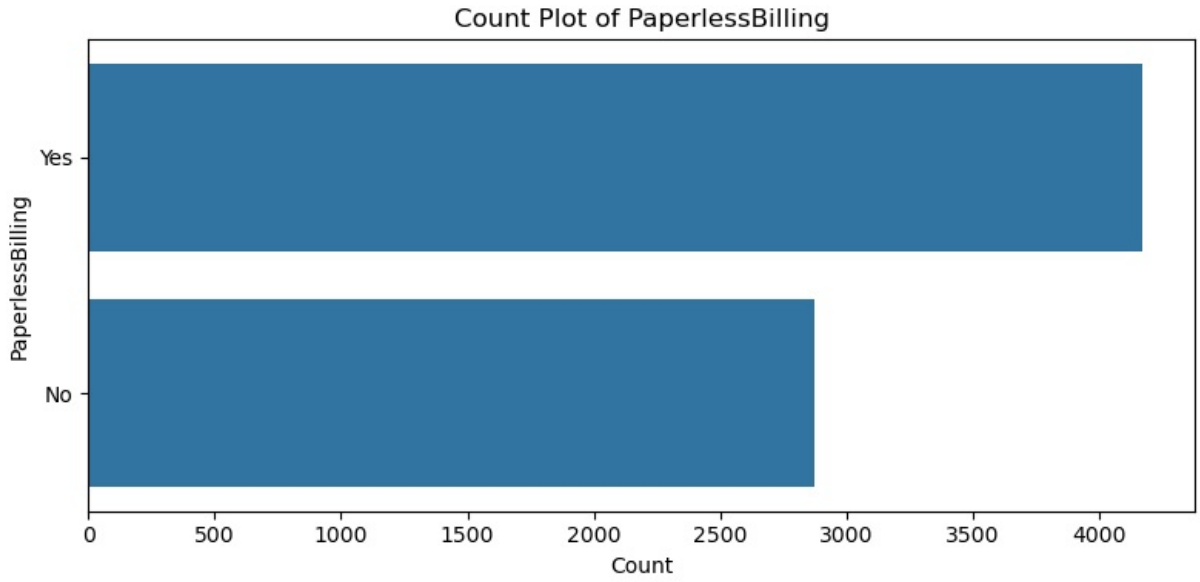

Count Plot of DeviceProtection
DeviceProtection
No
Yes
No internet service
0
500
1000
1500
2000
2500
3000
Count

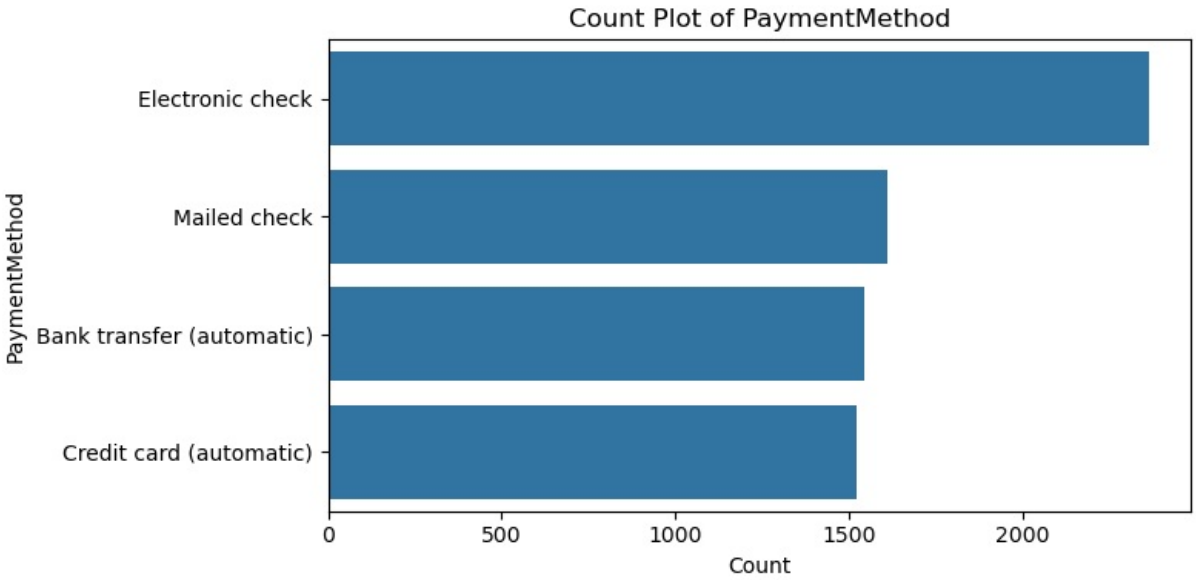

Count Plot of TechSupport
TechSupport
No
Yes
No internet service
0
500
1000
1500
2000
2500
3000
3500
Count

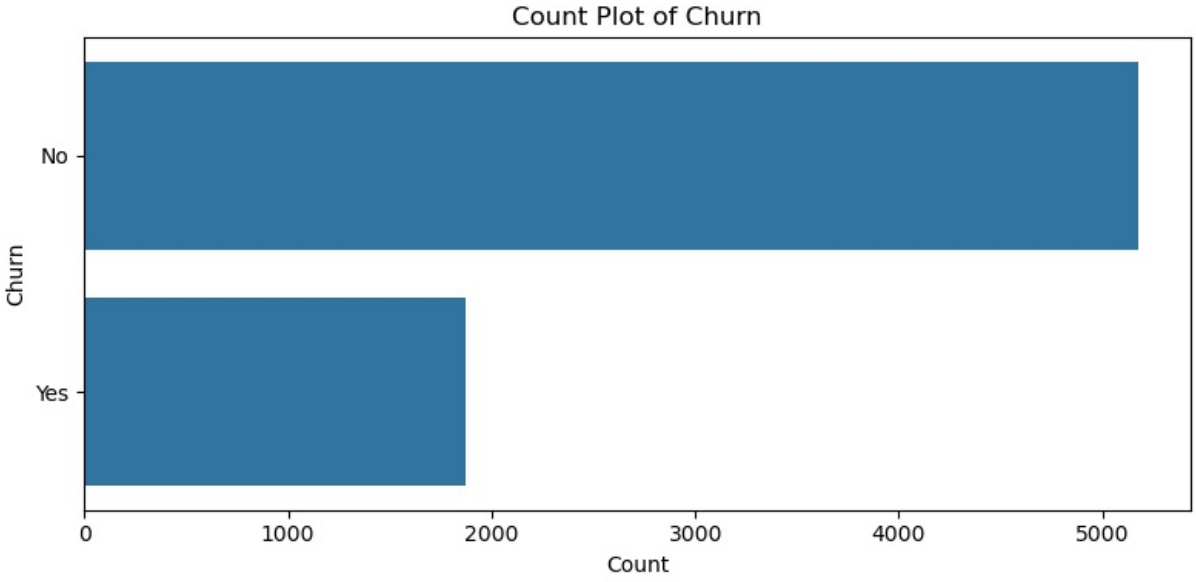

Count Plot of StreamingTV
StreamingTV
No
Yes
No internet service
0
500
1000
1500
2000
2500
Count


Count Plot of StreamingMovies
StreamingMovies
No
Yes
No internet service
0
500
1000
1500
2000
2500
Count


Count Plot of Contract
Contract
Month-to-month
One year
Two year
0
500
1000
1500
2000
2500
3000
3500
4000
Count


Count Plot of PaperlessBilling
PaperlessBilling
Yes
No
0
500
1000
1500
2000
2500
3000
3500
4000
Count





4. Data Preprocessing

In [152…
```
df.head(3)
```

Out[152…

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes
1	Male	0	No	No	34	Yes	No	DSL	Yes	No
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes

Label encoding of target column

In [153…
```
df["Churn"] = df["Churn"].replace({"Yes": 1, "No": 0})
```

```
C:\Users\asusl\AppData\Local\Temp\ipykernel_27480\2364848822.py:1: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df["Churn"] = df["Churn"].replace({"Yes": 1, "No": 0})
```

In [154…
```
df.head()
```

Out[154…

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes
1	Male	0	No	No	34	Yes	No	DSL	Yes	No
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No
4	Female	0	No	No	2	Yes	No	Fiber optic	No	No

In [155…
```
print(df["Churn"].value_counts())
```

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

Label encoding of categorical fetaures

In [156…
```
# identifying columns with object data type
object_columns = df.select_dtypes(include="object").columns
```

In [157…
```
print(object_columns)
```

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

In [158…
```
# 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 [159…
```
encoders
```

Out[159…
```
{'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 [160…
```
df.head()
```

Out[160…

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup
0	0	0	1	0	1	0	1	0	0	2
1	1	0	0	0	34	1	0	0	2	0
2	1	0	0	0	2	1	0	0	2	2
3	1	0	0	0	45	0	1	0	2	0
4	0	0	0	0	2	1	0	1	0	0

In [161…
```
df.tail()
```

Out[161…

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBack
7038	1	0	1	1	24	1	2	0	2	
7039	0	0	1	1	72	1	2	1	0	
7040	0	0	1	1	11	0	1	0	2	
7041	1	1	1	0	4	1	2	1	0	
7042	1	0	0	0	66	1	0	1	2	

Traianing and test data split

In [162…
```
# splitting the features and target
X = df.drop(columns=["Churn"])
y = df["Churn"]
```

In [163…
```
# 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)
```

In [164…
```
print(y_train.shape)
```

```
(5634,)
```

In [165…
```
print(y_train.value_counts())
```

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

Synthetic Minority Oversampling TEchnique (SMOTE)

In [166…
```
smote = SMOTE(random_state=42)
```

In [167…
```
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
```

In [168…
```
print(y_train_smote.shape)
```

```
(8276,)
```

In [169…
```
print(y_train_smote.value_counts())
```

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

5. Model Training

Training with default hyperparameters

In [170…
```
# dictionary of models
models = {
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42),
    "XGBoost": XGBClassifier(random_state=42)
}
```

In [171…
```
# 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: 0.83
--------------------------------------------------------------------
```

In [172…
```
cv_scores
```

Out[172…
```
{'Decision Tree': array([0.68115942, 0.71903323, 0.81752266, 0.84350453, 0.84350453]),
 'Random Forest': array([0.72705314, 0.76676737, 0.90453172, 0.89244713, 0.89848943]),
 'XGBoost': array([0.71074879, 0.75226586, 0.90271903, 0.89123867, 0.89909366])}
```

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

In [173…
```
rfc = RandomForestClassifier(random_state=42)
```

In [174…
```
rfc.fit(X_train_smote, y_train_smote)
```

Out[174…

RandomForestClassifier

RandomForestClassifier(random_state=42)

In [175…
```
print(y_test.value_counts())
```

```
Churn
0    1036
1     373
Name: count, dtype: int64
```

6. Model Evaluation

In [176…
```
# 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:
 0.7771469127040455
Confsuion Matrix:
 [[880 156]
 [158 215]]
Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.85      0.85      1036
           1       0.58      0.58      0.58       373

    accuracy                           0.78      1409
   macro avg       0.71      0.71      0.71      1409
weighted avg       0.78      0.78      0.78      1409
```

In [177…
```
# 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)
```

7. Load the saved model and build a Predictive System

In [178…
```
# 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 [179…
```
print(loaded_model)
```

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

In [180…
```
print(feature_names)
```

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

In [181…
```
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: [[0.83 0.17]]
```

Conclusion

This project demonstrates an end-to-end machine learning workflow for predicting customer churn.

Through effective data analysis, preprocessing, and model building, meaningful churn patterns were identified.

The final model provides actionable insights that can help businesses improve customer retention.

Overall, this project reflects practical application of machine learning in a real-world business scenario.

In [ ]: