MENTORNESS INTERNSHIP PROGRAM
Task 2

Batch Name: MIP-ML-08

Project Name: Customer Churn Prediction

By Md. Harun-Or-Rashid Khan

Problem Statement:

Customer churn is a crucial concern for businesses across sectors. Understanding customer behaviors, identifying key factors contributing to churn, and predicting when customers are likely to churn are vital for reducing revenue loss and enhancing customer retention strategies.

Problem Type:

Classification Supervised ML

Dataset: The dataset contains the following columns:

customerID: Customer ID
gender: Customer's gender
SeniorCitizen: Whether the customer is a senior citizen (1 for yes, 0 for no)
Partner: Whether the customer has a partner
Dependents: Whether the customer has dependents
tenure: Number of months the customer has stayed with the company
PhoneService: Whether the customer has phone service
MultipleLines: Whether the customer has multiple phone lines
InternetService: Type of Internet service
OnlineSecurity: Whether the customer has online security
OnlineBackup: Whether the customer has online backup
DeviceProtection: Whether the customer has device protection
TechSupport: Whether the customer has tech support
StreamingTV: Whether the customer streams TV
StreamingMovies: Whether the customer streams movies
Contract: Type of contract (e.g., month-to-month, one year, two years)
PaperlessBilling: Whether the customer uses paperless billing
PaymentMethod: Payment method (e.g., electronic check, mailed check)
MonthlyCharges: Monthly charges
TotalCharges: Total charges
Churn: Target variable, indicating whether the customer churned (1 for yes, 0 for no)

Mission:

This internship is to leverage machine learning to predict customer churn. You will follow these key steps:

Data Preprocessing:

Prepare the data for model training. This includes handling missing values, encoding categorical variables, and scaling or normalizing features as needed.

Exploratory Data Analysis (EDA):

Dive into the dataset, conduct comprehensive EDA, and unveil valuable insights about customer behaviors. EDA will involve data visualization, summary statistics, and identifying patterns in the data.

Feature Engineering:

If required create new features or transform existing ones that can provide additional insights or improve model performance. Feature engineering might involve aggregating information, creating interaction terms, or applying domain-specific knowledge.

Machine Learning Model Development:

Train various machine learning models for classification, such as logistic regression, decision trees, random forests, and Boosting Algorithms. Experiment with different algorithms to find the best-performing model.

Model Evaluation:

Assess the performance of your models using appropriate evaluation metrics like accuracy, precision, recall, F1-score, confusion matrix, and ROC AUC. Identify the model that provides the most accurate predictions of customer churn.

Predicting Churn:

Once you've built and validated your model, use it to predict customer churn. Understand the importance of feature importance scores in interpreting the model's predictions.

Recommendations:

Based on your findings, provide actionable recommendations to the business. These recommendations should help reduce churn and improve customer retention strategies.

```python
# Import libraries for understand the dataset
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import missingno as msno
from scipy import stats

import warnings
warnings.filterwarnings('ignore')
```

```python
# read the dataset
path = r"G:\certificate-25\Mentorness\Task2\Customer_Churn.csv"
df = pd.read_csv(path)
df.head()
```

```python
df.shape
```

✓ 0.0s

```
(7043, 21)
```

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

5 rows × 21 columns

Data Preprocessing

```
df.info()
```
✓ 0.0s

```
<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
```

Observation: Individual checking of 'CustomerID', 'SeniorCitizen',and 'TotalCharges'.

```
df['customerID'].unique()
```
✓ 0.0s

```
array(['7590-VHVEG', '5575-GNVDE', '3668-QPYBK', ..., '4801-JZAZL',
       '8361-LTMKD', '3186-AJIEK'], dtype=object)
```

```
# This number are not follow any pattrn. So delete it.
df.drop(columns = 'customerID', inplace = True)
```
✓ 0.0s

```
df['SeniorCitizen'].unique()
```
✓ 0.0s

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

```
# 'SeniorCitizen' feature has binary. So, change its category.
df['SeniorCitizen'] = df['SeniorCitizen'].map({0:'No', 1:'Yes'})
```
✓ 0.0s

```
df['TotalCharges'].unique()
```
✓ 0.0s

```
array(['29.85', '1889.5', '108.15', ..., '346.45', '306.6', '6844.5'],
      dtype=object)
```

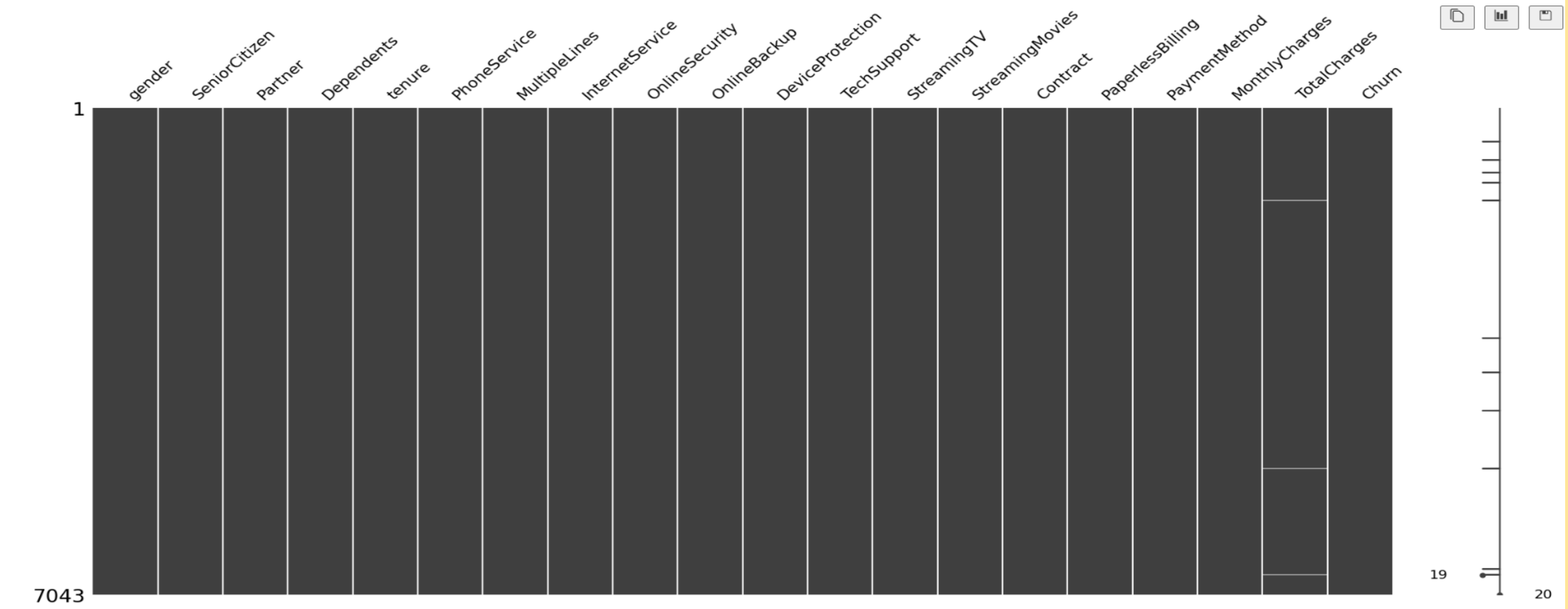
```
# 'TotalCharges' feature has string plus object. So change its data type.
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors = 'coerce')
```
✓ 0.0s

Data Preprocessing

```
# Find null values with plot
null_counts = df.isnull().sum()
null_per = ((df.isnull().sum()/len(df))*100).round(2)

result_df = pd.DataFrame({'Null Count':null_counts, 'Null_Percentage':null_per})
print(result_df)

plt.figure(figsize=(10,10))
msno.matrix(df)
plt.show()
```

✓ 0.3s

	Null Count	Null_Percentage
gender	0	0.00
SeniorCitizen	0	0.00
Partner	0	0.00
Dependents	0	0.00
tenure	0	0.00
PhoneService	0	0.00
MultipleLines	0	0.00
InternetService	0	0.00
OnlineSecurity	0	0.00
OnlineBackup	0	0.00
DeviceProtection	0	0.00
TechSupport	0	0.00
StreamingTV	0	0.00
StreamingMovies	0	0.00
Contract	0	0.00
PaperlessBilling	0	0.00
PaymentMethod	0	0.00
MonthlyCharges	0	0.00
TotalCharges	11	0.16
Churn	0	0.00



Observation : 'TotalCharges' features null values below 5% so, remove null.

```
df.dropna(inplace = True)
```

✓ 0.0s

```
df.shape
```

✓ 0.0s

(7032, 20)

Data Preprocessing

Observation: No anomaly data are not present.

```
for col in df.describe(include='object').columns:
    print(col)
    print(df[col].unique())
    print('-'*50)
```

✓ 0.0s

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

```
df.describe()
```

✓ 0.0s

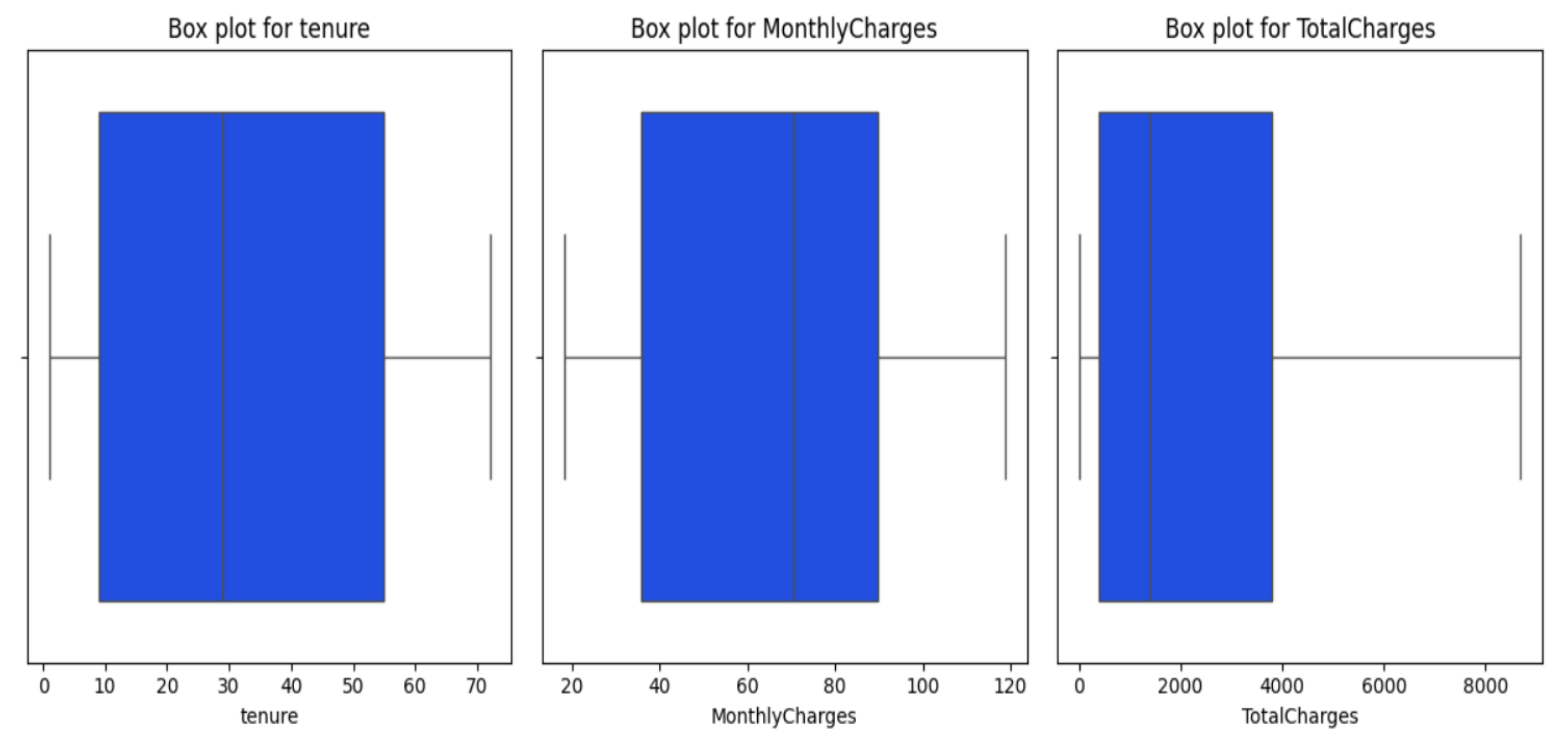
	tenure	MonthlyCharges	TotalCharges
count	7032.000000	7032.000000	7032.000000
mean	32.421786	64.798208	2283.300441
std	24.545260	30.085974	2266.771362
min	1.000000	18.250000	18.800000
25%	9.000000	35.587500	401.450000
50%	29.000000	70.350000	1397.475000
75%	55.000000	89.862500	3794.737500
max	72.000000	118.750000	8684.800000

Observation: Maybe no outliers present.
Also tenure*MonthlyCharges = TotalCharges.

Data Preprocessing

```
# For outlier
num_to_plot = ['tenure','MonthlyCharges','TotalCharges']

plt.figure(figsize=(12,5))

for i, col in enumerate(num_to_plot,1):
    plt.subplot(1,3,i)
    sns.boxplot(x = df[col], palette='bright')
    plt.title(f"Box plot for {col}")
plt.tight_layout()
plt.show()
```

✓ 0.2s



Exploratory Data Analysis (EDA)

```python
# Univeriate Analysis- First separate the features

cat_features = df.select_dtypes(include='object').columns
num_features = df.select_dtypes(include='number').columns

print(f'Categorical_feature={cat_features} \n Numerical_features={num_features}')
```

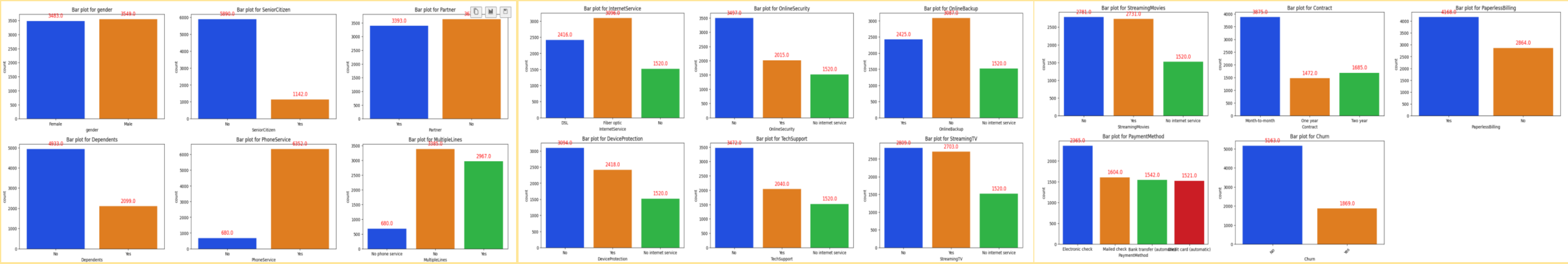
✓ 0.0s

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

```python
cat_to_plot = ['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'PhoneService',
               'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
               'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
               'Contract', 'PaperlessBilling', 'PaymentMethod', 'Churn']

plt.figure(figsize=(20,25))

for i, col in enumerate(cat_to_plot,1):
    plt.subplot(6,3,i)
    ax = sns.countplot(x=df[col], palette='bright')
    plt.title(f"Bar plot for {col}")

    # Annotating the counts
    for j in ax.patches:
        height = j.get_height()
        ax.annotate(f'{height}', (j.get_x() + j.get_width() / 2., height), ha='center',
                    va='bottom', fontsize=12, color='red', xytext=(0, 5),
                    textcoords='offset points')

plt.tight_layout()
plt.xticks(rotation=45)
plt.show()
```

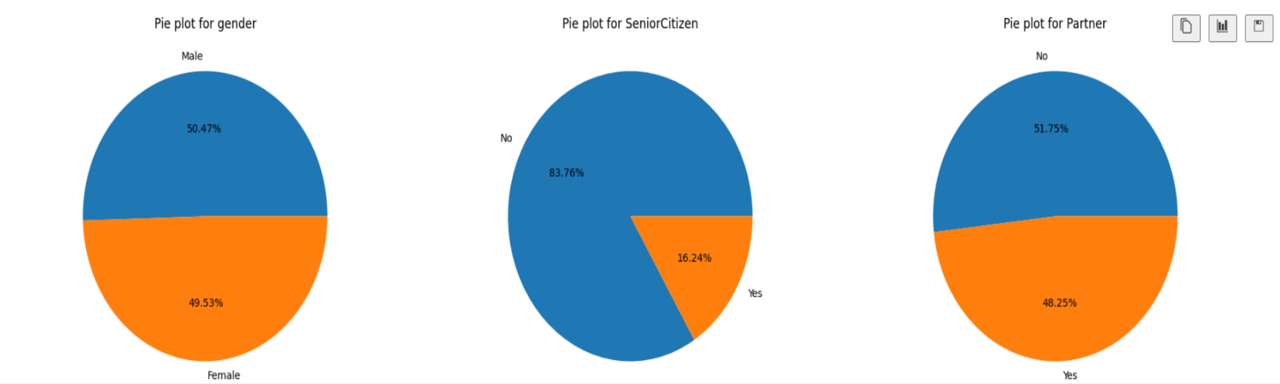
✓ 1.6s

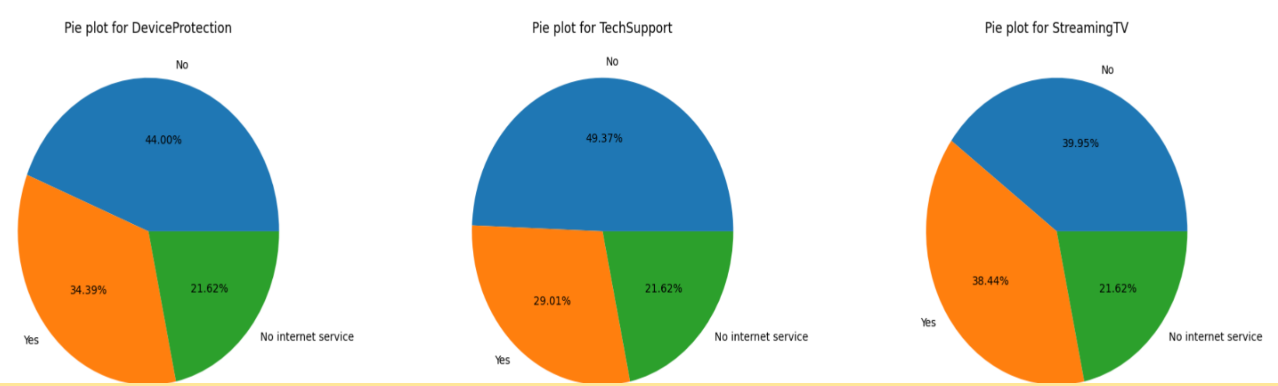
Exploratory Data Analysis (EDA)

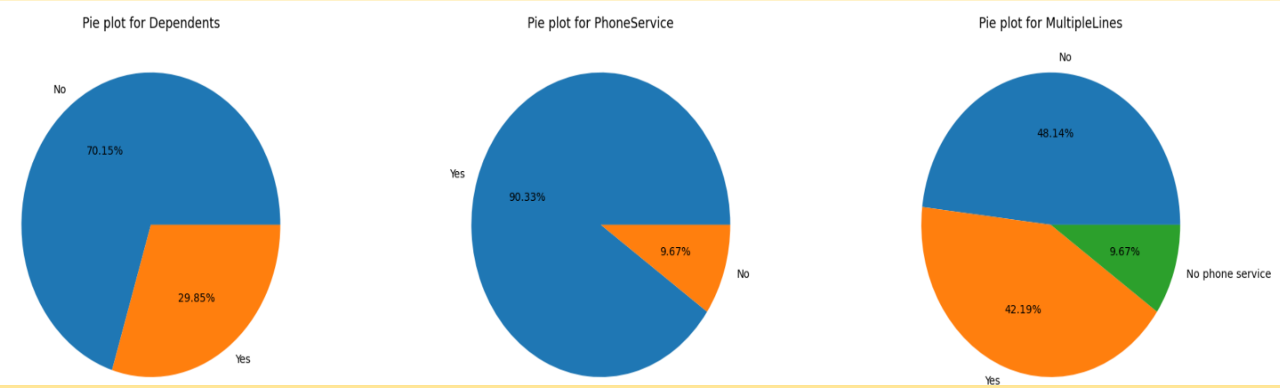


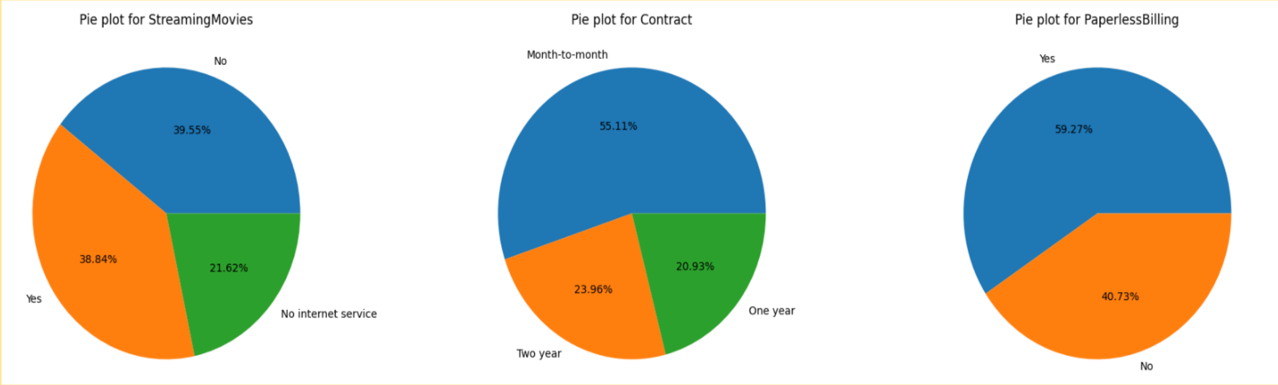

```
cat_to_plot = ['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'PhoneService',
          'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
          'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
          'Contract', 'PaperlessBilling', 'PaymentMethod', 'Churn']

plt.figure(figsize=(20,30))

for i, col in enumerate(cat_to_plot,1):
    plt.subplot(6,3,i)
    values = df[col].value_counts()
    ax = plt.pie(x=values, labels=values.index, autopct='%1.2f%%')
    plt.title(f"Pie plot for {col}")

plt.tight_layout()
plt.show()
```
✓ 0.8s

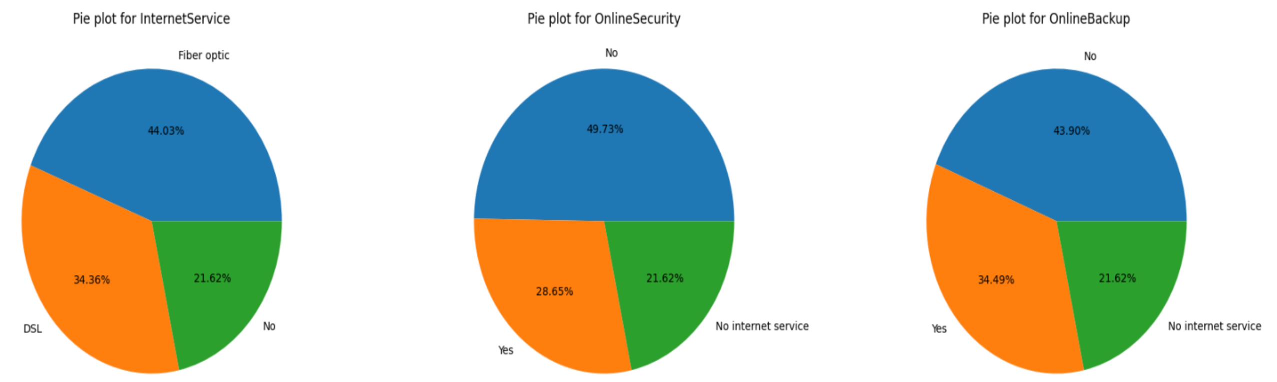
Exploratory Data Analysis (EDA)

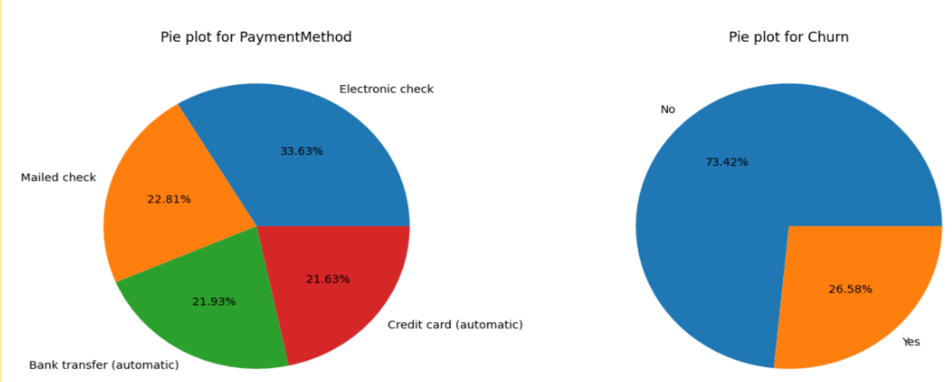










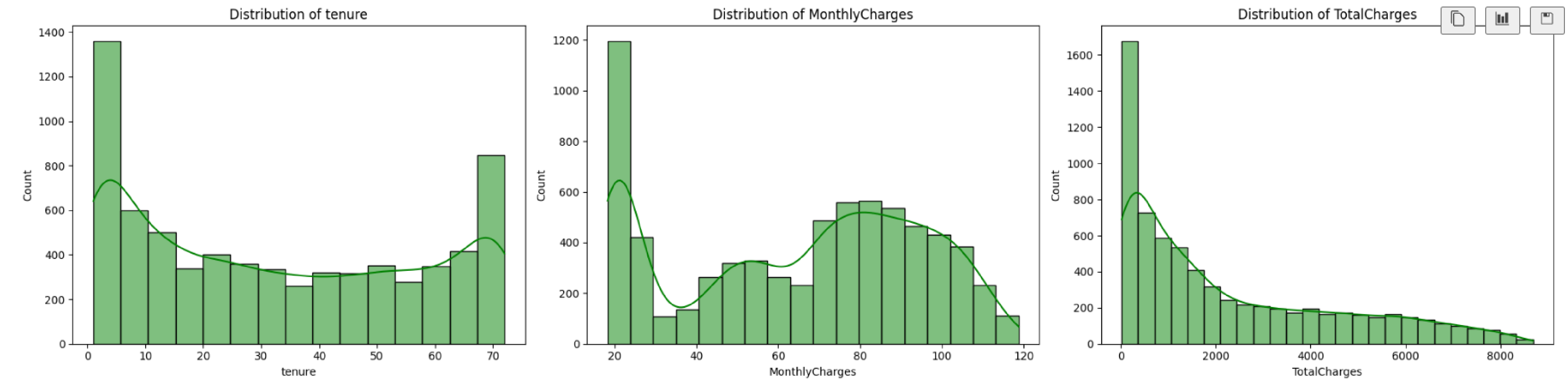


Observation: The churn rate is 26.58%.

Exploratory Data Analysis (EDA)

```
numerical_features = ['tenure', 'MonthlyCharges', 'TotalCharges']

plt.figure(figsize=(20, 5))

for i, col in enumerate(numerical_features, 1):
    plt.subplot(1, 3, i)
    sns.histplot(df[col], kde=True, color='green')
    plt.title(f"Distribution of {col}")

plt.tight_layout()
plt.show()
```

✓ 0.5s



Exploratory Data Analysis (EDA)

```python
numerical_features = ['tenure', 'MonthlyCharges', 'TotalCharges']

from scipy import stats
for col in numerical_features:
    skewness = df[col].skew()
    if skewness >0:
        skew_type = "Right Skewed"
    elif skewness <0:
        skew_type = "Left Skewed"
    else:
        skew_type = "Approximately Normal"
    print(f'Features = {col} : skewness = {skewness} Distribution = {skew_type}')
```

0.0s

```
Features = tenure : skewness = 0.23773083190513133 Distribution = Right Skewed
Features = MonthlyCharges : skewness = -0.2221029277016232 Distribution = Left Skewed
Features = TotalCharges : skewness = 0.9616424997242504 Distribution = Right Skewed
```

Observation: TotalCharges features are highly Right-skewed. In the feature Engineering section, it would convert to normal.

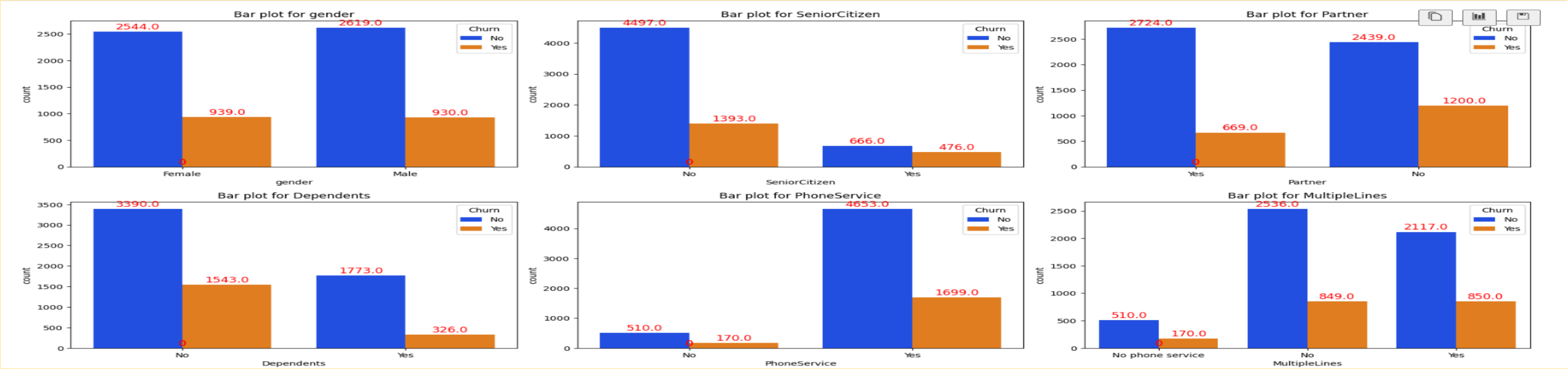
Bivariate Analysis

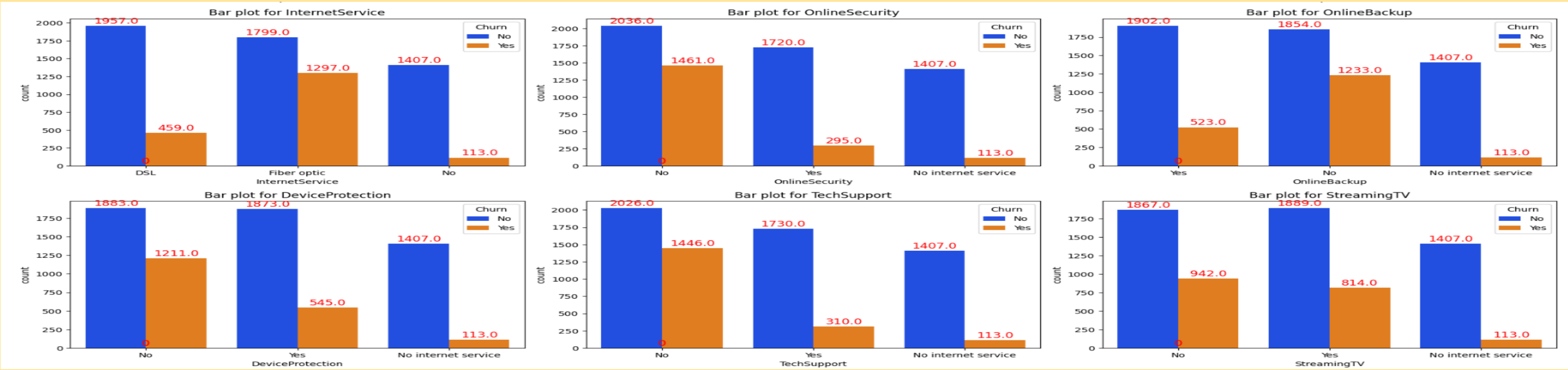
```
cat_to_plot = ['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'PhoneService',
               'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
               'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
               'Contract', 'PaperlessBilling', 'PaymentMethod']

plt.figure(figsize=(20, 25))

for i, col in enumerate(cat_to_plot, 1):
    plt.subplot(6, 3, i)
    ax = sns.countplot(x=col, data=df, hue='Churn', palette='bright')
    plt.title(f"Bar plot for {col}")

    # Annotating the counts
    for j in ax.patches:
        height = j.get_height()
        ax.annotate(f'{height}', (j.get_x() + j.get_width() / 2., height), ha='center',
                    va='bottom', fontsize=12, color='red', xytext=(0, 1),
                    textcoords='offset points')

plt.tight_layout()
plt.xticks(rotation=45)
plt.show()
```

✓ 2.2s

Exploratory Data Analysis (EDA)

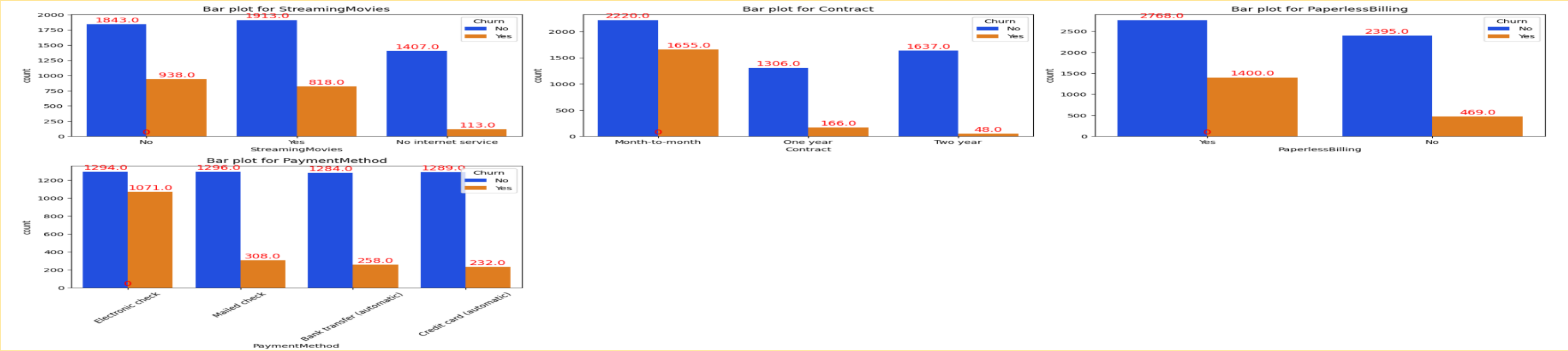
Bivariate Analysis





Exploratory Data Analysis (EDA)

Bivariate Analysis



Observation: The churn rate is higher among customers who did not utilize support, streaming TV, streaming movies, device protection, online backup, online security, multiple lines, dependents, or partners. Additionally, customers who used phone services, electronic check for payment, paperless billing, or opted for month-to-month contracts showed higher churn rates.

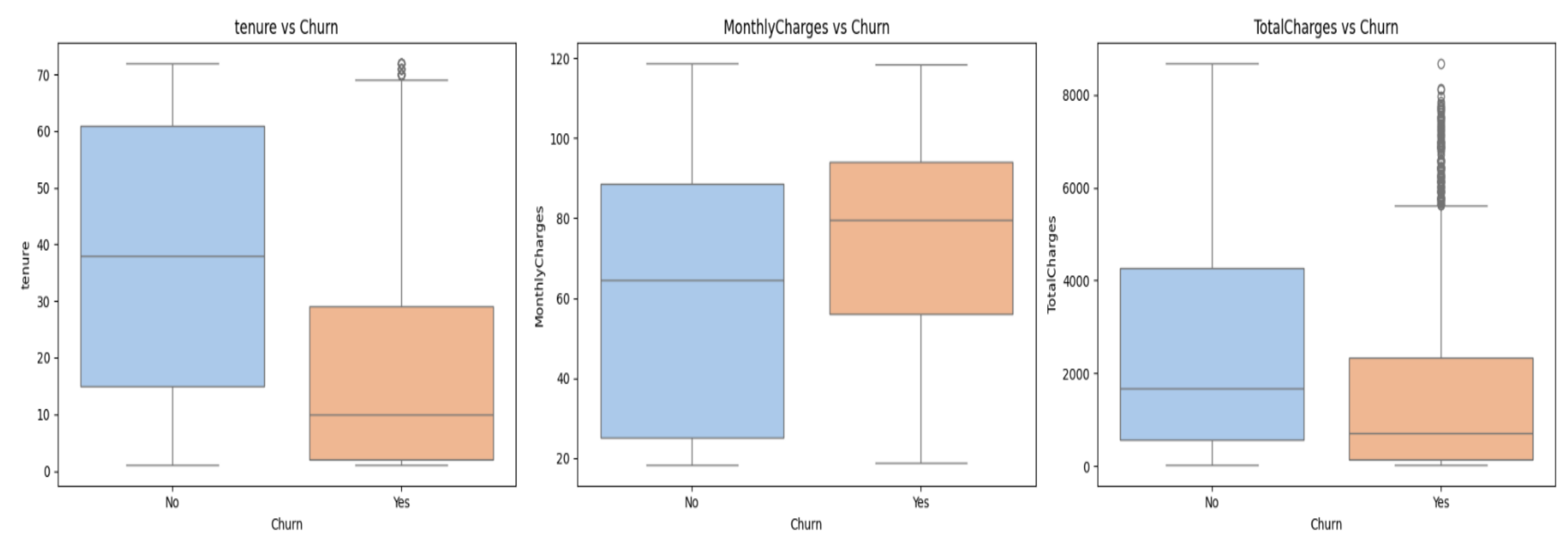
Exploratory Data Analysis (EDA)

Bivariate Analysis

```
import matplotlib.pyplot as plt
import seaborn as sns

numerical_features = ['tenure', 'MonthlyCharges', 'TotalCharges']

plt.figure(figsize=(20, 5))

for i, col in enumerate(numerical_features, 1):
    plt.subplot(1, 3, i)
    sns.boxplot(x='Churn', y=col, data=df, palette='pastel')
    plt.title(f'{col} vs Churn')

plt.tight_layout()
plt.show()
```

✓ 0.3s

Observation: It appears that the product of tenure and MonthlyCharges equals TotalCharges. Therefore, it is advisable to drop both tenure and MonthlyCharges from the analysis.



Feature Engineering

```python
df1 = df.copy()
```
✓ 0.0s

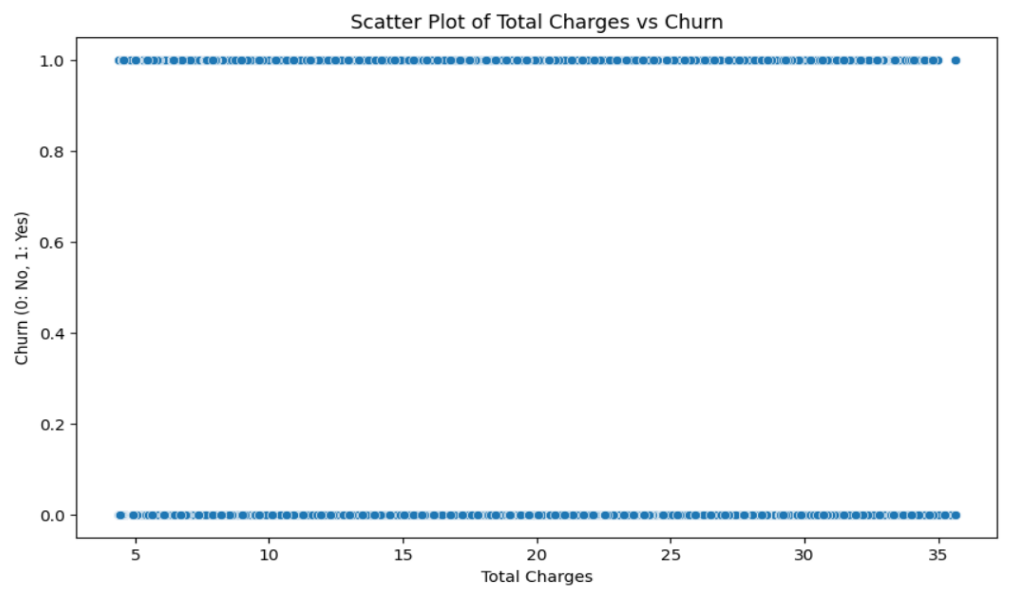
```python
# Since 'tenure'*'MonthlyCharges'='TotalCharges'. So remove 'tenure' and 'MonthlyCharges'
df1.drop(columns=['tenure','MonthlyCharges'], inplace= True)
```
✓ 0.0s

```python
from scipy.stats import boxcox

# Apply Box-Cox transformation to 'MonthlyCharges' column
df1['TotalCharges'], _ = boxcox(df1['TotalCharges'])

# Check the transformed 'MonthlyCharges' column
print(df1['TotalCharges'].skew())
```
✓ 0.0s

```
-0.1457578689928088
```

```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df1['Churn'] = le.fit_transform(df1['Churn'])
```
✓ 0.0s

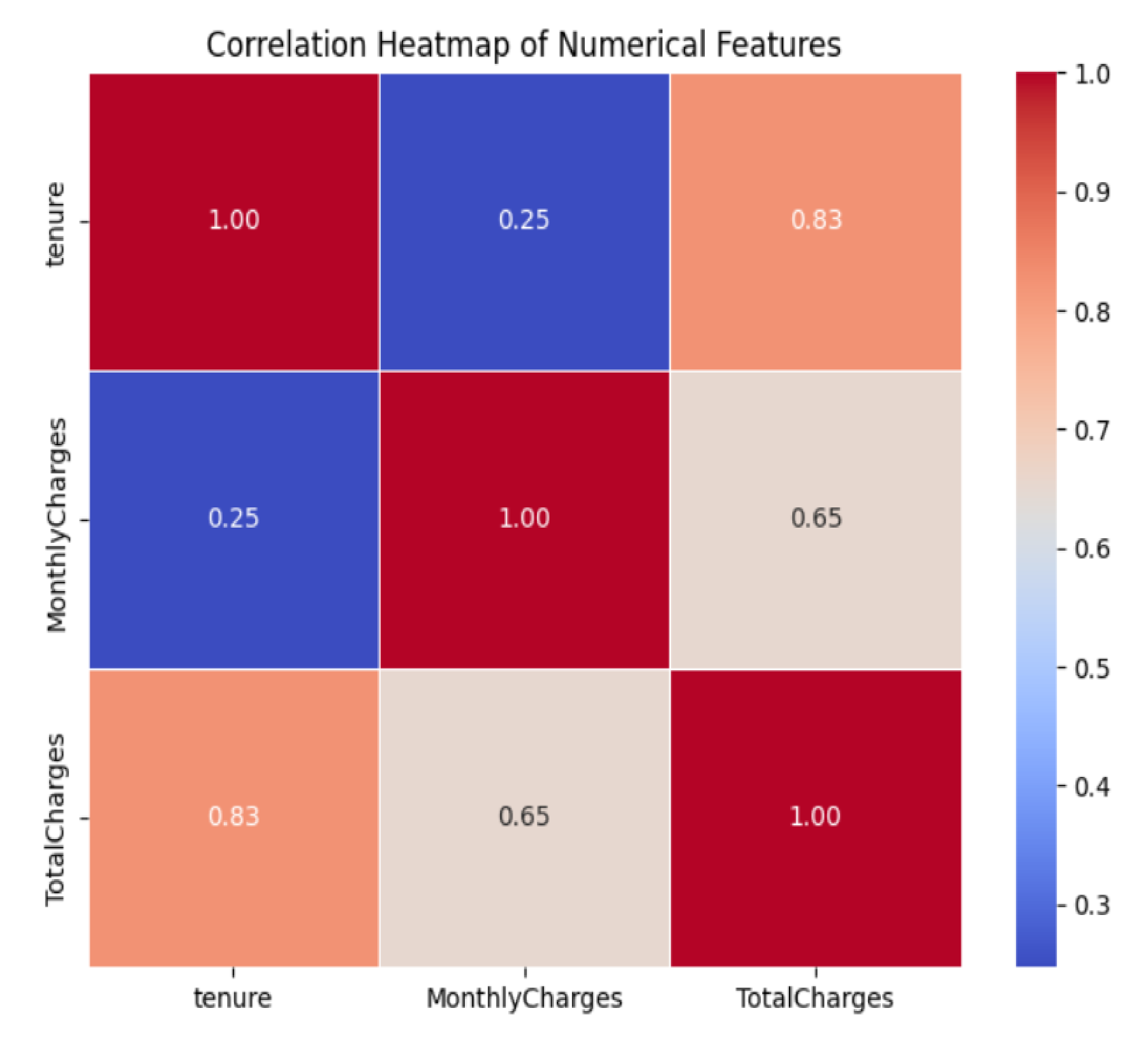
```python
plt.figure(figsize=(10, 6))

# Create scatter plot for 'TotalCharges' vs 'Churn_numeric'
sns.scatterplot(x='TotalCharges', y='Churn', data=df1, palette='Set1')

plt.title('Scatter Plot of Total Charges vs Churn')
plt.xlabel('Total Charges')
plt.ylabel('Churn (0: No, 1: Yes)')

plt.show()
```
✓ 0.1s



Feature Engineering

```python
import seaborn as sns
import matplotlib.pyplot as plt

numerical_features = ['tenure', 'MonthlyCharges', 'TotalCharges']

# Compute the correlation matrix
correlation = df[numerical_features].corr()

plt.figure(figsize=(8, 6))

# Create a heatmap
sns.heatmap(correlation, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)

plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```

✓ 0.1s



Feature Engineering

```python
from scipy.stats import chi2_contingency

# Initialize an empty list to store the results
results = []

# Iterate over each categorical feature in df1
for feature in df.select_dtypes(include='object').columns:
    # Create a contingency table
    contingency_table = pd.crosstab(df[feature], df['Churn'])

    # Perform chi-square test
    chi2, p_value, _, _ = chi2_contingency(contingency_table)

    # Determine whether to accept or reject null hypothesis based on p-value
    if p_value <= 0.05:  # Using a significance level of 0.05
        hypothesis_status = 'Reject Null Hypothesis'
    else:
        hypothesis_status = 'Accept Null Hypothesis'

    # Append the results to the list
    results.append({'Feature': feature,
                    'Chi-squared statistic': round(chi2, 2),
                    'p-value': round(p_value, 6),
                    'Hypothesis Status': hypothesis_status})

# Convert the list of dictionaries to a DataFrame
results_df = pd.DataFrame(results)

# Display the results DataFrame
print(results_df)
```

✓ 0.0s

	Feature	Chi-squared statistic	p-value	Hypothesis Status
0	gender	0.48	0.490488	Accept Null Hypothesis
1	SeniorCitizen	158.44	0.000000	Reject Null Hypothesis
2	Partner	157.50	0.000000	Reject Null Hypothesis
3	Dependents	186.32	0.000000	Reject Null Hypothesis
4	PhoneService	0.87	0.349924	Accept Null Hypothesis
5	MultipleLines	11.27	0.003568	Reject Null Hypothesis
6	InternetService	728.70	0.000000	Reject Null Hypothesis
7	OnlineSecurity	846.68	0.000000	Reject Null Hypothesis
8	OnlineBackup	599.18	0.000000	Reject Null Hypothesis
9	DeviceProtection	555.88	0.000000	Reject Null Hypothesis
10	TechSupport	824.93	0.000000	Reject Null Hypothesis
11	StreamingTV	372.46	0.000000	Reject Null Hypothesis
12	StreamingMovies	374.27	0.000000	Reject Null Hypothesis
13	Contract	1179.55	0.000000	Reject Null Hypothesis
14	PaperlessBilling	256.87	0.000000	Reject Null Hypothesis
15	PaymentMethod	645.43	0.000000	Reject Null Hypothesis
16	Churn	7026.88	0.000000	Reject Null Hypothesis

Feature Engineering

```python
from scipy.stats import f_oneway

# Define the numerical features and the categorical features
numerical_features = ['tenure','MonthlyCharges','TotalCharges']
categorical_features = df.select_dtypes(include='object').columns.tolist()

# Initialize an empty list to store the results
anova_results = []

# Iterate over each categorical feature
for cat_feature in categorical_features:
    # Iterate over each numerical feature
    for num_feature in numerical_features:
        # Group the numerical data by the categorical feature
        groups = df.groupby(cat_feature)[num_feature].apply(list)

        # Perform ANOVA test
        f_statistic, p_value = f_oneway(*groups)

        # Determine whether to accept or reject null hypothesis based on p-value
        if p_value <= 0.05:  # Using a significance level of 0.05
            hypothesis_status = 'Reject Null Hypothesis'
        else:
            hypothesis_status = 'Accept Null Hypothesis'

        # Append the results to the list
        anova_results.append({'Categorical Feature': cat_feature,
                              'Numerical Feature': num_feature,
                              'F-statistic': round(f_statistic, 2),
                              'p-value': round(p_value, 6),
                              'Hypothesis Status': hypothesis_status})

# Convert the list of dictionaries to a DataFrame
anova_results_df = pd.DataFrame(anova_results)

# Display the ANOVA results DataFrame
anova_results_df
```

✓ 0.0s

	Categorical Feature	Numerical Feature	F-statistic	p-value	Hypothesis Status
0	gender	tenure	0.20	0.657665	Accept Null Hypothesis
1	gender	MonthlyCharges	1.34	0.247950	Accept Null Hypothesis
2	gender	TotalCharges	0.00	0.996800	Accept Null Hypothesis
3	SeniorCitizen	tenure	1.73	0.188504	Accept Null Hypothesis
4	SeniorCitizen	MonthlyCharges	357.13	0.000000	Reject Null Hypothesis
5	SeniorCitizen	TotalCharges	74.51	0.000000	Reject Null Hypothesis
6	Partner	tenure	1200.47	0.000000	Reject Null Hypothesis
7	Partner	MonthlyCharges	67.93	0.000000	Reject Null Hypothesis
8	Partner	TotalCharges	796.83	0.000000	Reject Null Hypothesis
9	Dependents	tenure	192.81	0.000000	Reject Null Hypothesis
10	Dependents	MonthlyCharges	89.86	0.000000	Reject Null Hypothesis
11	Dependents	TotalCharges	29.51	0.000000	Reject Null Hypothesis
12	PhoneService	tenure	0.44	0.508957	Accept Null Hypothesis
13	PhoneService	MonthlyCharges	460.84	0.000000	Reject Null Hypothesis
14	PhoneService	TotalCharges	90.94	0.000000	Reject Null Hypothesis
15	MultipleLines	tenure	471.70	0.000000	Reject Null Hypothesis
16	MultipleLines	MonthlyCharges	1198.61	0.000000	Reject Null Hypothesis
17	MultipleLines	TotalCharges	993.33	0.000000	Reject Null Hypothesis
18	InternetService	tenure	4.96	0.007053	Reject Null Hypothesis
19	InternetService	MonthlyCharges	16065.03	0.000000	Reject Null Hypothesis
20	InternetService	TotalCharges	796.69	0.000000	Reject Null Hypothesis
21	OnlineSecurity	tenure	450.26	0.000000	Reject Null Hypothesis
22	OnlineSecurity	MonthlyCharges	4943.73	0.000000	Reject Null Hypothesis
23	OnlineSecurity	TotalCharges	1071.93	0.000000	Reject Null Hypothesis
24	OnlineBackup	tenure	582.29	0.000000	Reject Null Hypothesis
25	OnlineBackup	MonthlyCharges	5475.11	0.000000	Reject Null Hypothesis
26	OnlineBackup	TotalCharges	1494.26	0.000000	Reject Null Hypothesis
27	DeviceProtection	tenure	583.39	0.000000	Reject Null Hypothesis
28	DeviceProtection	MonthlyCharges	5876.71	0.000000	Reject Null Hypothesis
29	DeviceProtection	TotalCharges	1576.45	0.000000	Reject Null Hypothesis
30	TechSupport	tenure	441.49	0.000000	Reject Null Hypothesis
31	TechSupport	MonthlyCharges	5058.65	0.000000	Reject Null Hypothesis
32	TechSupport	TotalCharges	1151.40	0.000000	Reject Null Hypothesis
33	StreamingTV	tenure	330.86	0.000000	Reject Null Hypothesis
34	StreamingTV	MonthlyCharges	8231.54	0.000000	Reject Null Hypothesis
35	StreamingTV	TotalCharges	1486.38	0.000000	Reject Null Hypothesis
36	StreamingMovies	tenure	345.83	0.000000	Reject Null Hypothesis
37	StreamingMovies	MonthlyCharges	8098.69	0.000000	Reject Null Hypothesis
38	StreamingMovies	TotalCharges	1508.17	0.000000	Reject Null Hypothesis
39	Contract	tenure	3034.74	0.000000	Reject Null Hypothesis
40	Contract	MonthlyCharges	20.00	0.000000	Reject Null Hypothesis

Feature Engineering

41	Contract	TotalCharges	934.74	0.000000	Reject Null Hypothesis
42	PaperlessBilling	tenure	0.16	0.685929	Accept Null Hypothesis
43	PaperlessBilling	MonthlyCharges	993.79	0.000000	Reject Null Hypothesis
44	PaperlessBilling	TotalCharges	179.59	0.000000	Reject Null Hypothesis
45	PaymentMethod	tenure	445.63	0.000000	Reject Null Hypothesis
46	PaymentMethod	MonthlyCharges	447.40	0.000000	Reject Null Hypothesis
47	PaymentMethod	TotalCharges	327.52	0.000000	Reject Null Hypothesis
48	Churn	tenure	1007.51	0.000000	Reject Null Hypothesis
49	Churn	MonthlyCharges	271.58	0.000000	Reject Null Hypothesis
50	Churn	TotalCharges	291.34	0.000000	Reject Null Hypothesis

Feature Engineering

```python
from scipy.stats import f_oneway

# Define the numerical features and the categorical features
numerical_features = ['TotalCharges']
categorical_features = df.select_dtypes(include='object').columns.tolist()

# Initialize an empty list to store the results
anova_results = []

# Iterate over each categorical feature
for cat_feature in categorical_features:
    # Iterate over each numerical feature
    for num_feature in numerical_features:
        # Group the numerical data by the categorical feature
        groups = df.groupby(cat_feature)[num_feature].apply(list)

        # Perform ANOVA test
        f_statistic, p_value = f_oneway(*groups)

        # Determine whether to accept or reject null hypothesis based on p-value
        if p_value <= 0.05:  # Using a significance level of 0.05
            hypothesis_status = 'Reject Null Hypothesis'
        else:
            hypothesis_status = 'Accept Null Hypothesis'
         # Append the results to the list
         anova_results.append({'Categorical Feature': cat_feature,
                              'Numerical Feature': num_feature,
                              'F-statistic': round(f_statistic, 2),
                              'p-value': round(p_value, 6),
                              'Hypothesis Status': hypothesis_status})

# Convert the list of dictionaries to a DataFrame
anova_results_df = pd.DataFrame(anova_results)

# Display the ANOVA results DataFrame
anova_results_df
```
0.0s

	Categorical Feature	Numerical Feature	F-statistic	p-value	Hypothesis Status
0	gender	TotalCharges	0.00	0.9968	Accept Null Hypothesis
1	SeniorCitizen	TotalCharges	74.51	0.0000	Reject Null Hypothesis
2	Partner	TotalCharges	796.83	0.0000	Reject Null Hypothesis
3	Dependents	TotalCharges	29.51	0.0000	Reject Null Hypothesis
4	PhoneService	TotalCharges	90.94	0.0000	Reject Null Hypothesis
5	MultipleLines	TotalCharges	993.33	0.0000	Reject Null Hypothesis
6	InternetService	TotalCharges	796.69	0.0000	Reject Null Hypothesis
7	OnlineSecurity	TotalCharges	1071.93	0.0000	Reject Null Hypothesis
8	OnlineBackup	TotalCharges	1494.26	0.0000	Reject Null Hypothesis
9	DeviceProtection	TotalCharges	1576.45	0.0000	Reject Null Hypothesis
10	TechSupport	TotalCharges	1151.40	0.0000	Reject Null Hypothesis
11	StreamingTV	TotalCharges	1486.38	0.0000	Reject Null Hypothesis
12	StreamingMovies	TotalCharges	1508.17	0.0000	Reject Null Hypothesis
13	Contract	TotalCharges	934.74	0.0000	Reject Null Hypothesis
14	PaperlessBilling	TotalCharges	179.59	0.0000	Reject Null Hypothesis
15	PaymentMethod	TotalCharges	327.52	0.0000	Reject Null Hypothesis
16	Churn	TotalCharges	291.34	0.0000	Reject Null Hypothesis

Feature Engineering

Remark: This suggests that both 'gender' and 'Dependents' are not useful for predicting the target variable and can be safely dropped from the dataset without losing important predictive information.

```
# Drop the features
df1.drop(columns=['gender','Dependents'], inplace=True)
```

✓ 0.0s

Model Building

```
cat_features = df1.select_dtypes(include='object').columns
num_features = df1.select_dtypes(include='number').columns

print(f'Categorical_feature={cat_features} \n Numerical_features={num_features}')
```

✓ 0.0s

```
Categorical_feature=Index(['SeniorCitizen', 'Partner', 'PhoneService', 'MultipleLines',
       'InternetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract',
       'PaperlessBilling', 'PaymentMethod'],
      dtype='object')
 Numerical_features=Index(['TotalCharges', 'Churn'], dtype='object')
```

Model Building

```python
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder, OrdinalEncoder
from sklearn.pipeline import Pipeline

# Assuming df, numeric_features, categorical_features, and ordinal_feature are defined

X = df1.drop(['Churn'], axis=1)
y = df1['Churn']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=0)

numeric_features = ['TotalCharges']
categorical_features = ['SeniorCitizen', 'Partner',  'PhoneService',
       'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
       'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
       'Contract', 'PaperlessBilling', 'PaymentMethod']


preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_features),
        ('cat', OneHotEncoder(), categorical_features)
        ]
    )
```

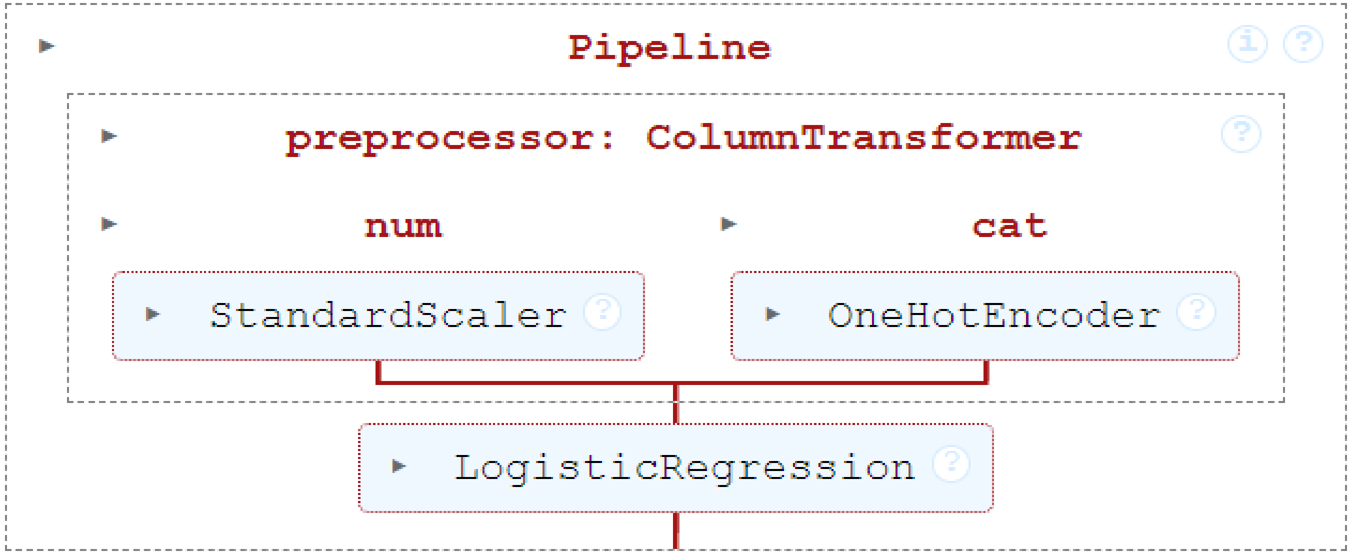
✓ 0.0s

Model Building

LogisticRegression

```python
from sklearn.linear_model import LogisticRegression
pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(random_state=42, max_iter=1000))
])

# Fit the pipeline on your data and target variable
pipeline.fit(X, y)
```

✓ 0.0s



Model Building

```python
y_pred_train = pipeline.predict(X_train)
y_pred_test = pipeline.predict(X_test)

accuracy_train_lgr = accuracy_score(y_train,y_pred_train)
accuracy_test_lgr = accuracy_score(y_test,y_pred_test)
cm = confusion_matrix(y_test,y_pred_test)

print("Accuracy on train-lgr :", accuracy_train_lgr)
print("Accuracy on test-lgr :", accuracy_test_lgr)
print("Confusion Matrix-lgr :\n", cm)
print("For LogisticRegression:", classification_report(y_test,y_pred_test))
```

✓ 0.0s

```
Accuracy on train-lgr : 0.812068264932954
Accuracy on test-lgr : 0.8052132701421801
Confusion Matrix-lgr :
 [[1416  139]
 [ 272  283]]
For LogisticRegression:               precision    recall  f1-score   support

           0       0.84      0.91      0.87      1555
           1       0.67      0.51      0.58       555

    accuracy                           0.81      2110
   macro avg       0.75      0.71      0.73      2110
weighted avg       0.79      0.81      0.80      2110
```

```python
# Define cross-validation strategy
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Perform cross-validation
scores = cross_val_score(pipeline, X, y, cv=cv, scoring='accuracy')

# Print the cross-validation results
print("Cross-Validation Scores:", scores)
print("Mean Accuracy:", np.mean(scores))
```

✓ 0.2s

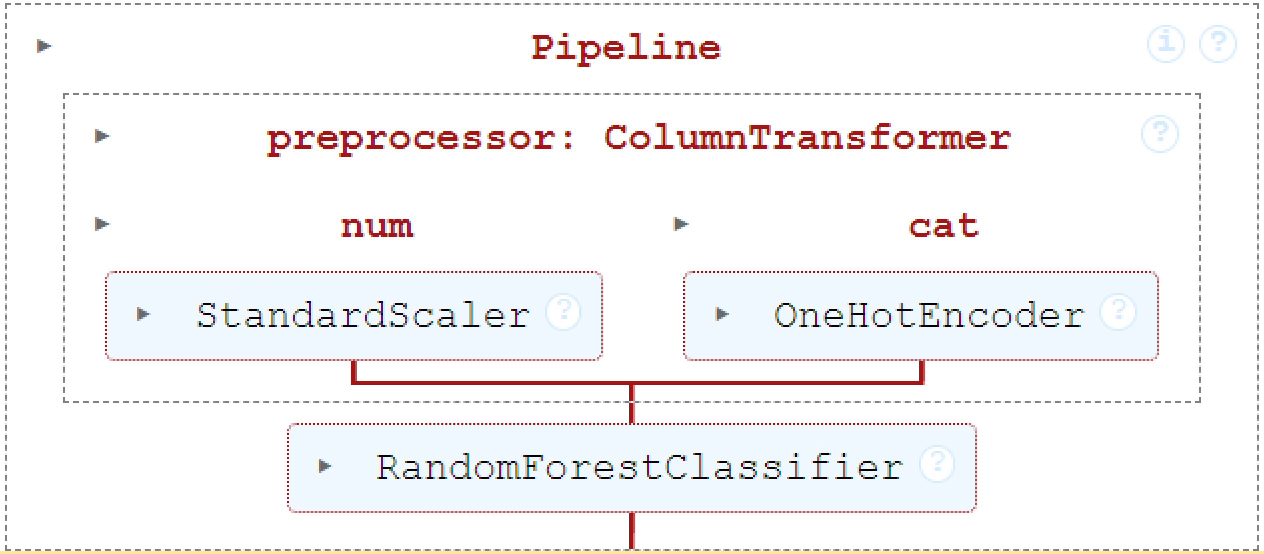
```
Cross-Validation Scores: [0.81307747 0.80454869 0.80227596 0.80156472 0.8200569 ]
Mean Accuracy: 0.8083047473463812
```

Model Building

2. RandomForestClassifier

```python
# Create a pipeline with ColumnTransformer and a Random Forest classifier
rf_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(random_state=42, n_estimators=100))
])

# Fit the pipeline on your data and target variable
rf_pipeline.fit(X, y)
```

✓ 0.5s



Model Building

2. RandomForestClassifier

```
y_pred_train_rf = rf_pipeline.predict(X_train)
y_pred_test_rf = rf_pipeline.predict(X_test)

accuracy_train_rf = accuracy_score(y_train,y_pred_train_rf)
accuracy_test_rf = accuracy_score(y_test,y_pred_test_rf)
cm = confusion_matrix(y_test,y_pred_test_rf)

print("Accuracy on train-rf :", accuracy_train_rf)
print("Accuracy on test-rf :", accuracy_test_rf)
print("Confusion Matrix-rf :\n", cm)
print("For RandomForestClassifier:", classification_report(y_test,y_pred_test_rf))
```

✓ 0.1s

```
Accuracy on train-rf : 0.9965461194636327
Accuracy on test-rf : 0.9966824644549763
Confusion Matrix-rf :
 [[1550    5]
 [   2  553]]
For RandomForestClassifier:               precision    recall  f1-score   support

           0       1.00      1.00      1.00      1555
           1       0.99      1.00      0.99       555

    accuracy                           1.00      2110
   macro avg       0.99      1.00      1.00      2110
weighted avg       1.00      1.00      1.00      2110
```

Model Building

2. RandomForestClassifier

```python
from sklearn.model_selection import cross_val_score, StratifiedKFold

# Define cross-validation strategy
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Perform cross-validation
scores = cross_val_score(rf_pipeline, X, y, cv=cv, scoring='accuracy')

# Print the cross-validation results
print("Cross-Validation Scores:", scores)
print("Mean Accuracy:", np.mean(scores))
```

✓ 2.0s

```
Cross-Validation Scores: [0.7782516  0.78109453 0.75960171 0.76458037 0.7745377 ]
Mean Accuracy: 0.7716131797828577
```

Remark:

The RandomForest model exhibits superior accuracy compared to the others and shows no signs of overfitting.

Recommendations

Improve Service Offerings: Enhance the quality and range of services, such as support, streaming TV, streaming movies, device protection, online backup, and online security, to better meet customer needs and expectations.

-**Personalized Customer Support:** Provide personalized and proactive customer support to address individual needs and concerns, thereby increasing customer satisfaction and loyalty.

-**Promote Bundled Services:** Encourage customers to subscribe to bundled services, such as multiple lines, to increase their perceived value and reduce the likelihood of churn.

-**Enhance Dependability:** Ensure consistent and reliable service delivery to instill trust and confidence in customers, particularly those with dependents or partners who may rely heavily on the services.

-**Optimize Billing Process:** Streamline the billing process, offer flexible payment options, and minimize issues related to electronic check payments to improve customer convenience and satisfaction.

-**Offer Incentives for Longer Contracts:** Encourage customers to opt for longer contract durations by providing incentives or discounts, thereby reducing the churn associated with month-to-month contracts.

-**Engage in Targeted Marketing:** Identify and target customers who are more likely to churn based on their usage patterns and preferences, and implement personalized marketing campaigns to retain them.

-**Continuous Monitoring and Feedback:** Continuously monitor customer feedback and usage data to identify potential churn indicators early and take proactive measures to address them effectively.

-**Improve Communication:** Maintain open and transparent communication with customers regarding service updates, new offerings, and promotions to keep them engaged and informed.

-**Loyalty Programs:** Implement loyalty programs or rewards schemes to incentivize long-term commitment and foster stronger customer relationships.

Thanks to All