

Submitted By:

Name: Tanishk Raj: 03

A.H.V Sriram: 04

Amrit Raj: 05

# Customer Churnout Prediction

April 10, 2024

```
[336]: # Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Load the dataset
telco_data = pd.read_csv("telco_customer_churn.csv")

# Display basic information about the dataset
print("Shape of the dataset:", telco_data.shape)
print("\nColumns in the dataset:")
print(telco_data.columns)
print("\nSample data:")
print(telco_data.head())

# Summary statistics
print("\nSummary statistics:")
print(telco_data.describe())

# Check for missing values
print("\nMissing values:")
print(telco_data.isnull().sum())

print("\nColumn names : ")
print(telco_data.columns.values)

print("\nColumns Data Types : ")
print(telco_data.dtypes)
# Check for duplicate rows
print("\nDuplicate rows:", telco_data.duplicated().sum())

# Visualize the distribution of the target variable 'Churn'
plt.figure(figsize=(8, 6))
```

```
sns.countplot(x=Churn, data=telco_data)

plt.title('Distribution of Churn') plt.show()
```

```

# Visualize the distribution of numerical features
numerical_features = telco_data.select_dtypes(include=[np.number]).columns.
    tolist()
telco_data[numerical_features].hist(figsize=(12, 10))
plt.suptitle('Distribution of Numerical Features')
plt.show()

# Visualize the correlation matrix
plt.figure(figsize=(10, 8))
correlation_matrix = telco_data[numerical_features].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()

```

Shape of the dataset: (7043, 21)

Columns in the dataset:

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

Sample data:

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

	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling
0	No	No	No	Month-to-month	Yes
1	No	No	No	One year	No
2	No	No	No	Month-to-month	Yes
3	Yes	No	No	One year	No
4	No	No	No	Month-to-month	Yes

	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	Electronic check	29.85	29.85	No
1	Mailed check	56.95	1889.5	No
2	Mailed check	53.85	108.15	Yes
3	Bank transfer (automatic)	42.30	1840.75	No
4	Electronic check	70.70	151.65	Yes

[5 rows x 21 columns]

Summary statistics:

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

Missing values:

customerID	0
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

Column names :

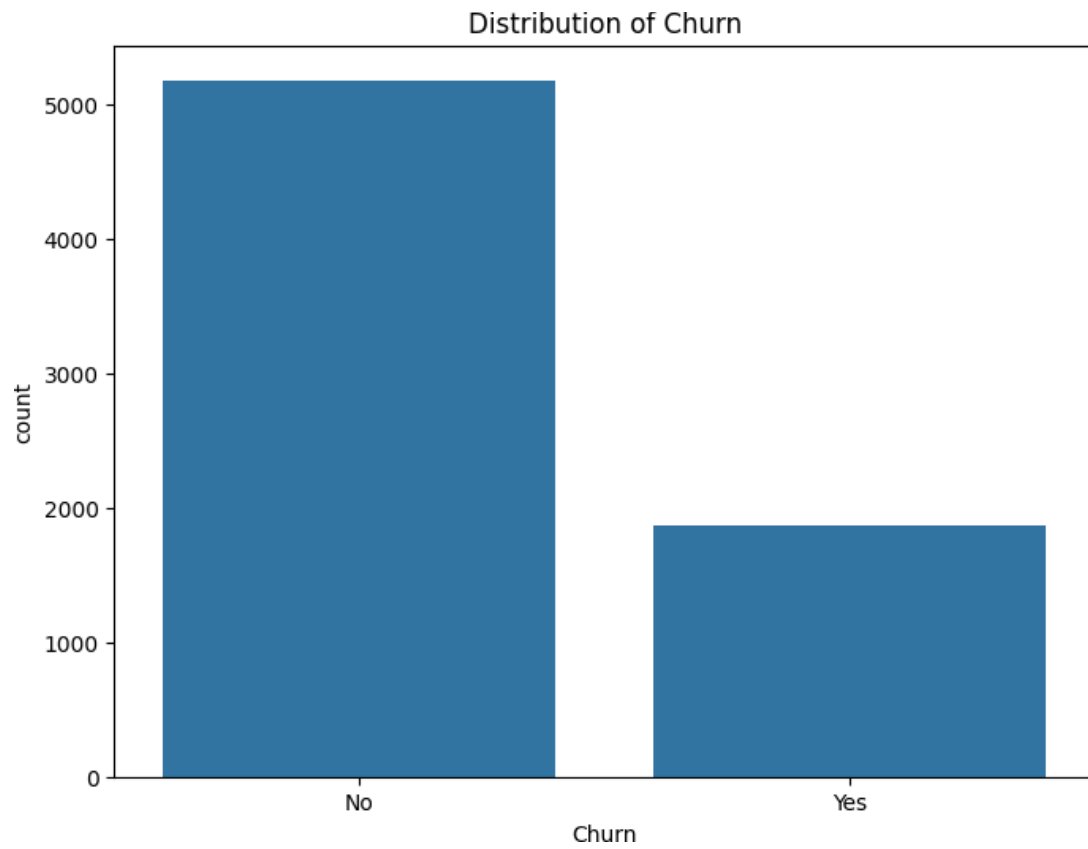
['customerID' 'gender' 'SeniorCitizen' 'Partner' 'Dependents' 'tenure'  
 'PhoneService' 'MultipleLines' 'InternetService' 'OnlineSecurity'  
 'OnlineBackup' 'DeviceProtection' 'TechSupport' 'StreamingTV']

'StreamingMovies' 'Contract' 'PaperlessBilling' 'PaymentMethod'  
'MonthlyCharges' 'TotalCharges' 'Churn']

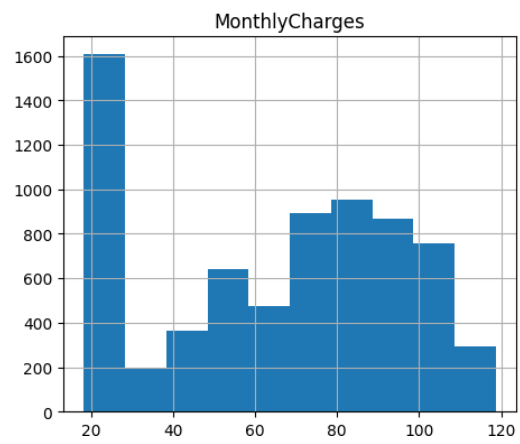
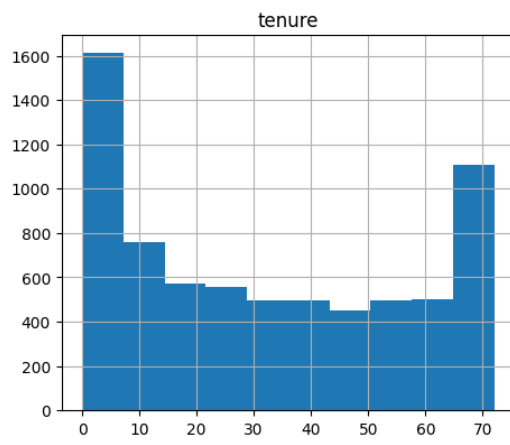
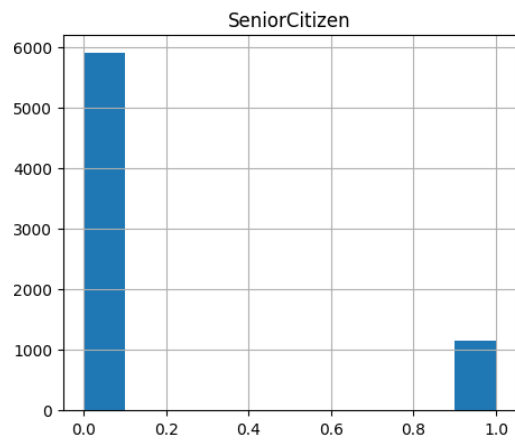
Columns Data Types :

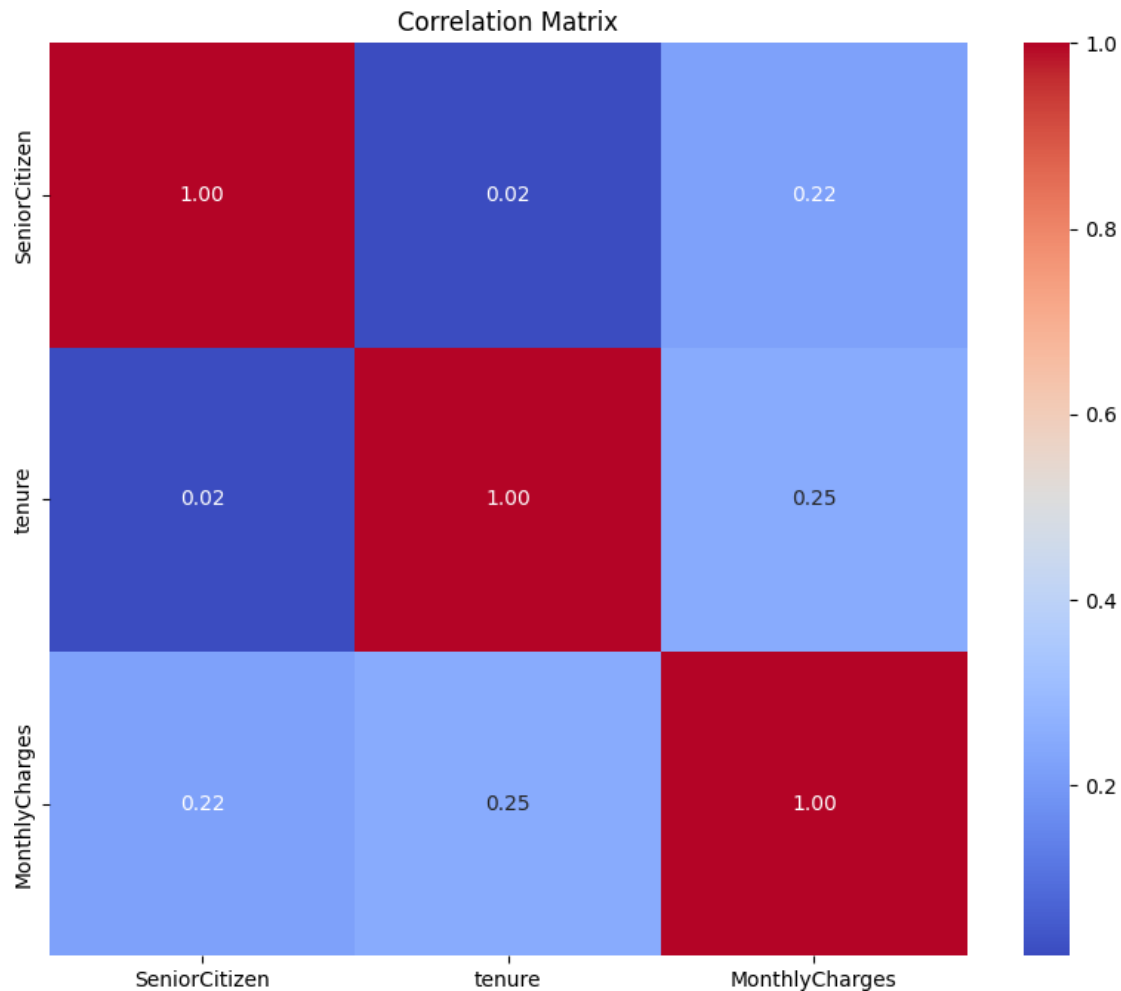
customerID	object
gender	object
SeniorCitizen	int64
Partner	object
Dependents	object
tenure	int64
PhoneService	object
MultipleLines	object
InternetService	object
OnlineSecurity	object
OnlineBackup	object
DeviceProtection	object
TechSupport	object
StreamingTV	object
StreamingMovies	object
Contract	object
PaperlessBilling	object
PaymentMethod	object
MonthlyCharges	float64
TotalCharges	object
Churn	object
dtype:	object

Duplicate rows: 0



## Distribution of Numerical Features





[337]: *# 1. Understanding Target Variable*

```
print(100*telco_data["Churn"].value_counts()/len(telco_data["Churn"]))
print(telco_data["Churn"].value_counts())
telco_base_data=telco_data.copy()
```

```
No    73.463013
Yes   26.536987
Name: Churn, dtype: float64
No     5174
Yes    1869
Name: Churn, dtype: int64
```

[338]: *# 2. Handling Missing Values*

```
telco_data.TotalCharges=pd.to_numeric(telco_data.TotalCharges, errors='coerce')
telco_data.isnull().sum()
```



```
[338]: customerID      0
      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    11
      Churn           0
      dtype: int64
```

```
[339]: # 2.1 Handling Missing Values by dropping NULL containing rows
      telco_data.loc[telco_data['TotalCharges'].isnull()==True]
      telco_data.dropna(how='any',inplace=True)
      telco_data.shape
```

```
[339]: (7032, 21)
```

```
[340]: telco_data
```

```
[340]:   customerID  gender  SeniorCitizen  Partner  Dependents  tenure  \
0    7590-VHVEG  Female              0    Yes           No        1
1    5575-GNVDE   Male              0    No            No       34
2    3668-QPYBK   Male              0    No            No        2
3    7795-CFOCW   Male              0    No            No       45
4    9237-HQITU  Female              0    No            No        2
...         ...      ...            ...    ...          ...
7038  6840-RESVB   Male              0    Yes           Yes       24
7039  2234-XADUH  Female              0    Yes           Yes       72
7040  4801-JAZL   Female              0    Yes           Yes       11
7041  8361-LTMKD   Male              1    Yes           No        4
7042  3186-AJIEK   Male              0    No            No       66

      PhoneService  MultipleLines  InternetService  OnlineSecurity  ...  \
0                No  No phone service              DSL              No  ...
```

1	Yes	No	DSL	Yes	...
2	Yes	No	DSL	Yes	...
3	No	No phone service	DSL	Yes	...
4	Yes	No	Fiber optic	No	...
...	...	...	...	...	...
7038	Yes	Yes	DSL	Yes	...
7039	Yes	Yes	Fiber optic	No	...
7040	No	No phone service	DSL	Yes	...
7041	Yes	Yes	Fiber optic	No	...
7042	Yes	No	Fiber optic	Yes	...

	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	
...	...	...	...	...	...	
7038	Yes	Yes	Yes	Yes	One year	
7039	Yes	No	Yes	Yes	One year	
7040	No	No	No	No	Month-to-month	
7041	No	No	No	No	Month-to-month	
7042	Yes	Yes	Yes	Yes	Two year	

	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	\
0	Yes	Electronic check	29.85	29.85	
1	No	Mailed check	56.95	1889.50	
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	
...	...	...	...	...	
7038	Yes	Mailed check	84.80	1990.50	
7039	Yes	Credit card (automatic)	103.20	7362.90	
7040	Yes	Electronic check	29.60	346.45	
7041	Yes	Mailed check	74.40	306.60	
7042	Yes	Bank transfer (automatic)	105.65	6844.50	

	Churn
0	No
1	No
2	Yes
3	No
4	Yes
...	...
7038	No
7039	No
7040	No

7041 Yes  
7042 No

[7032 rows x 21 columns]

```
[341]: telco_data.drop(columns=["customerID"],axis=1,inplace=True)
telco_data
```

```
[341]:
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	Female	0	Yes	No	1	No	
1	Male	0	No	No	34	Yes	
2	Male	0	No	No	2	Yes	
3	Male	0	No	No	45	No	
4	Female	0	No	No	2	Yes	
...	...	...	...	...	...	...	
7038	Male	0	Yes	Yes	24	Yes	
7039	Female	0	Yes	Yes	72	Yes	
7040	Female	0	Yes	Yes	11	No	
7041	Male	1	Yes	No	4	Yes	
7042	Male	0	No	No	66	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	
...	...	...	...	...	
7038	Yes	DSL	Yes	No	
7039	Yes	Fiber optic	No	Yes	
7040	No phone service	DSL	Yes	No	
7041	Yes	Fiber optic	No	No	
7042	No	Fiber optic	Yes	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	
...	...	...	...	...	...	
7038	Yes	Yes	Yes	Yes	One year	
7039	Yes	No	Yes	Yes	One year	
7040	No	No	No	No	Month-to-month	
7041	No	No	No	No	Month-to-month	
7042	Yes	Yes	Yes	Yes	Two year	

	PaperlessBilling	PaymentMethod	MonthlyCharges \
0	Yes	Electronic check	29.85
1	No	Mailed check	56.95
2	Yes	Mailed check	53.85
3	No	Bank transfer (automatic)	42.30
4	Yes	Electronic check	70.70
...	...	...	...
7038	Yes	Mailed check	84.80
7039	Yes	Credit card (automatic)	103.20
7040	Yes	Electronic check	29.60
7041	Yes	Mailed check	74.40
7042	Yes	Bank transfer (automatic)	105.65

	TotalCharges	Churn
0	29.85	No
1	1889.50	No
2	108.15	Yes
3	1840.75	No
4	151.65	Yes
...	...	...
7038	1990.50	No
7039	7362.90	No
7040	346.45	No
7041	306.60	Yes
7042	6844.50	No

[7032 rows x 20 columns]

```
[342]: Data=telco_data.copy()
telco_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 7032 entries, 0 to 7042
```

```
Data columns (total 20 columns):
```

#	Column	Non-Null Count	Dtype
0	gender	7032 non-null	object
1	SeniorCitizen	7032 non-null	int64
2	Partner	7032 non-null	object
3	Dependents	7032 non-null	object
4	tenure	7032 non-null	int64
5	PhoneService	7032 non-null	object
6	MultipleLines	7032 non-null	object
7	InternetService	7032 non-null	object
8	OnlineSecurity	7032 non-null	object
9	OnlineBackup	7032 non-null	object
10	DeviceProtection	7032 non-null	object

11	TechSupport	7032	non-null	object
12	StreamingTV	7032	non-null	object
13	StreamingMovies	7032	non-null	object
14	Contract	7032	non-null	object
15	PaperlessBilling	7032	non-null	object
16	PaymentMethod	7032	non-null	object
17	MonthlyCharges	7032	non-null	float64
18	TotalCharges	7032	non-null	float64
19	Churn	7032	non-null	object

dtypes: float64(2), int64(2), object(16)

memory usage: 1.1+ MB

```
[343]: from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for i in telco_data.columns:
    if(telco_data[i].dtype==object):
        telco_data[i]=le.fit_transform(telco_data[i])
telco_data
```

```
[343]:      gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  \
0          0              0        1           0         1           0
1          1              0        0           0        34           1
2          1              0        0           0         2           1
3          1              0        0           0        45           0
4          0              0        0           0         2           1
...
7038       1              0        1           1        24           1
7039       0              0        1           1        72           1
7040       0              0        1           1        11           0
7041       1              1        1           0         4           1
7042       1              0        0           0        66           1

      MultipleLines  InternetService  OnlineSecurity  OnlineBackup  \
0                  1                0                0                2
1                  0                0                2                0
2                  0                0                2                2
3                  1                0                2                0
4                  0                1                0                0
...
7038               2                0                2                0
7039               2                1                0                2
7040               1                0                2                0
7041               2                1                0                0
7042               0                1                2                0

      DeviceProtection  TechSupport  StreamingTV  StreamingMovies  Contract  \
0                    0            0            0            0            0
```

1	2	0	0	0	1
2	0	0	0	0	0
3	2	2	0	0	1
4	0	0	0	0	0
...	...	...	...	...	...
7038	2	2	2	2	1
7039	2	0	2	2	1
7040	0	0	0	0	0
7041	0	0	0	0	0
7042	2	2	2	2	2

	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	1	2	29.85	29.85	0
1	0	3	56.95	1889.50	0
2	1	3	53.85	108.15	1
3	0	0	42.30	1840.75	0
4	1	2	70.70	151.65	1
...	...	...	...	...	...
7038	1	3	84.80	1990.50	0
7039	1	1	103.20	7362.90	0
7040	1	2	29.60	346.45	0
7041	1	3	74.40	306.60	1
7042	1	0	105.65	6844.50	0

[7032 rows x 20 columns]

[344]: telco\_data.corr()

[344]:

	gender	SeniorCitizen	Partner	Dependents	tenure \
gender	1.000000	-0.001819	-0.001379	0.010349	0.005285
SeniorCitizen	-0.001819	1.000000	0.016957	-0.210550	0.015683
Partner	-0.001379	0.016957	1.000000	0.452269	0.381912
Dependents	0.010349	-0.210550	0.452269	1.000000	0.163386
tenure	0.005285	0.015683	0.381912	0.163386	1.000000
PhoneService	-0.007515	0.008392	0.018397	-0.001078	0.007877
MultipleLines	-0.006908	0.146287	0.142717	-0.024975	0.343673
InternetService	-0.002236	-0.032160	0.000513	0.044030	-0.029835
OnlineSecurity	-0.014899	-0.127937	0.150610	0.151198	0.327283
OnlineBackup	-0.011920	-0.013355	0.153045	0.090231	0.372434
DeviceProtection	0.001348	-0.021124	0.165614	0.079723	0.372669
TechSupport	-0.006695	-0.151007	0.126488	0.132530	0.324729
StreamingTV	-0.005624	0.031019	0.136679	0.046214	0.290572
StreamingMovies	-0.008920	0.047088	0.129907	0.022088	0.296785
Contract	0.000095	-0.141820	0.294094	0.240556	0.676734
PaperlessBilling	-0.011902	0.156258	-0.013957	-0.110131	0.004823
PaymentMethod	0.016942	-0.038158	-0.156232	-0.041989	-0.370087
MonthlyCharges	-0.013779	0.219874	0.097825	-0.112343	0.246862

TotalCharges	0.000048	0.102411	0.319072	0.064653	0.825880
Churn	-0.008545	0.150541	-0.149982	-0.163128	-0.354049

	PhoneService	MultipleLines	InternetService	\
gender	-0.007515	-0.006908	-0.002236	
SeniorCitizen	0.008392	0.146287	-0.032160	
Partner	0.018397	0.142717	0.000513	
Dependents	-0.001078	-0.024975	0.044030	
tenure	0.007877	0.343673	-0.029835	
PhoneService	1.000000	-0.020504	0.387266	
MultipleLines	-0.020504	1.000000	-0.108849	
InternetService	0.387266	-0.108849	1.000000	
OnlineSecurity	-0.014163	0.007306	-0.028003	
OnlineBackup	0.024040	0.117276	0.036735	
DeviceProtection	0.004718	0.122614	0.045558	
TechSupport	-0.018136	0.010941	-0.025626	
StreamingTV	0.056393	0.175403	0.108190	
StreamingMovies	0.043025	0.181705	0.097967	
Contract	0.003019	0.111029	0.099579	
PaperlessBilling	0.016696	0.165306	-0.138166	
PaymentMethod	-0.005499	-0.176598	0.084504	
MonthlyCharges	0.248033	0.433905	-0.322173	
TotalCharges	0.113008	0.453202	-0.175691	
Churn	0.011691	0.038043	-0.047097	

	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	\
gender	-0.014899	-0.011920	0.001348	-0.006695	
SeniorCitizen	-0.127937	-0.013355	-0.021124	-0.151007	
Partner	0.150610	0.153045	0.165614	0.126488	
Dependents	0.151198	0.090231	0.079723	0.132530	
tenure	0.327283	0.372434	0.372669	0.324729	
PhoneService	-0.014163	0.024040	0.004718	-0.018136	
MultipleLines	0.007306	0.117276	0.122614	0.010941	
InternetService	-0.028003	0.036735	0.045558	-0.025626	
OnlineSecurity	1.000000	0.184942	0.175789	0.284875	
OnlineBackup	0.184942	1.000000	0.187646	0.195581	
DeviceProtection	0.175789	0.187646	1.000000	0.240476	
TechSupport	0.284875	0.195581	0.240476	1.000000	
StreamingTV	0.044399	0.147085	0.275947	0.161168	
StreamingMovies	0.056313	0.137083	0.289309	0.162530	
Contract	0.373980	0.280617	0.350067	0.425072	
PaperlessBilling	-0.157723	-0.012697	-0.037596	-0.113617	
PaymentMethod	-0.096593	-0.125534	-0.136460	-0.104544	
MonthlyCharges	-0.053576	0.119943	0.163984	-0.008237	
TotalCharges	0.254473	0.375556	0.389066	0.276890	
Churn	-0.289050	-0.195290	-0.177883	-0.282232	

	StreamingTV	StreamingMovies	Contract	PaperlessBilling	\
gender	-0.005624	-0.008920	0.000095	-0.011902	
SeniorCitizen	0.031019	0.047088	-0.141820	0.156258	
Partner	0.136679	0.129907	0.294094	-0.013957	
Dependents	0.046214	0.022088	0.240556	-0.110131	
tenure	0.290572	0.296785	0.676734	0.004823	
PhoneService	0.056393	0.043025	0.003019	0.016696	
MultipleLines	0.175403	0.181705	0.111029	0.165306	
InternetService	0.108190	0.097967	0.099579	-0.138166	
OnlineSecurity	0.044399	0.056313	0.373980	-0.157723	
OnlineBackup	0.147085	0.137083	0.280617	-0.012697	
DeviceProtection	0.275947	0.289309	0.350067	-0.037596	
TechSupport	0.161168	0.162530	0.425072	-0.113617	
StreamingTV	1.000000	0.435354	0.226826	0.097379	
StreamingMovies	0.435354	1.000000	0.232478	0.083901	
Contract	0.226826	0.232478	1.000000	-0.175475	
PaperlessBilling	0.097379	0.083901	-0.175475	1.000000	
PaymentMethod	-0.104782	-0.112009	-0.229636	-0.061348	
MonthlyCharges	0.337156	0.335761	-0.072739	0.351930	
TotalCharges	0.392472	0.398088	0.450306	0.157830	
Churn	-0.036303	-0.038802	-0.396150	0.191454	

	PaymentMethod	MonthlyCharges	TotalCharges	Churn
gender	0.016942	-0.013779	0.000048	-0.008545
SeniorCitizen	-0.038158	0.219874	0.102411	0.150541
Partner	-0.156232	0.097825	0.319072	-0.149982
Dependents	-0.041989	-0.112343	0.064653	-0.163128
tenure	-0.370087	0.246862	0.825880	-0.354049
PhoneService	-0.005499	0.248033	0.113008	0.011691
MultipleLines	-0.176598	0.433905	0.453202	0.038043
InternetService	0.084504	-0.322173	-0.175691	-0.047097
OnlineSecurity	-0.096593	-0.053576	0.254473	-0.289050
OnlineBackup	-0.125534	0.119943	0.375556	-0.195290
DeviceProtection	-0.136460	0.163984	0.389066	-0.177883
TechSupport	-0.104544	-0.008237	0.276890	-0.282232
StreamingTV	-0.104782	0.337156	0.392472	-0.036303
StreamingMovies	-0.112009	0.335761	0.398088	-0.038802
Contract	-0.229636	-0.072739	0.450306	-0.396150
PaperlessBilling	-0.061348	0.351930	0.157830	0.191454
PaymentMethod	1.000000	-0.192500	-0.330594	0.107852
MonthlyCharges	-0.192500	1.000000	0.651065	0.192858
TotalCharges	-0.330594	0.651065	1.000000	-0.199484
Churn	0.107852	0.192858	-0.199484	1.000000

```
[345]: for i in telco_data.columns:
        if abs(telco_data["Churn"].corr(telco_data[i]))<0.15:
            telco_data.drop(columns=i,inplace=True)
```



```
telco_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 7032 entries, 0 to 7042
```

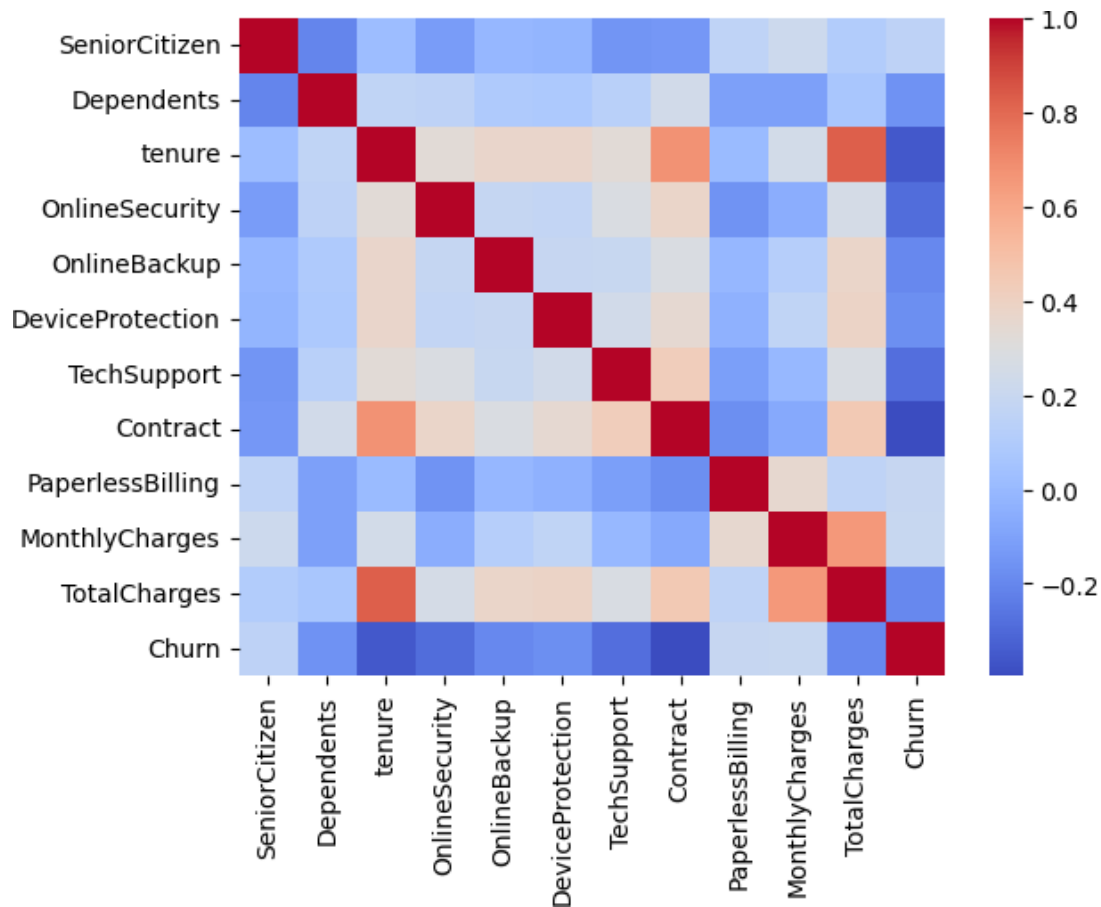
```
Data columns (total 12 columns):
```

#	Column	Non-Null Count	Dtype
0	SeniorCitizen	7032 non-null	int64
1	Dependents	7032 non-null	int32
2	tenure	7032 non-null	int64
3	OnlineSecurity	7032 non-null	int32
4	OnlineBackup	7032 non-null	int32
5	DeviceProtection	7032 non-null	int32
6	TechSupport	7032 non-null	int32
7	Contract	7032 non-null	int32
8	PaperlessBilling	7032 non-null	int32
9	MonthlyCharges	7032 non-null	float64
10	TotalCharges	7032 non-null	float64
11	Churn	7032 non-null	int32

```
dtypes: float64(2), int32(8), int64(2)
```

```
memory usage: 494.4 KB
```

```
[346]: import matplotlib.pyplot as plt
import seaborn as sns
corr=telco_data.corr()
heatmap=sns.heatmap(corr,cmap="coolwarm")
plt.show()
```



```
[347]: X=telco_data.drop("Churn",axis=1)
Y=telco_data["Churn"]
df=telco_data.copy()
```

```
[348]: from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.
↳2,random_state=42)
```

```
[349]: from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier(criterion='gini',random_state=100,max_depth=6,min_samples_leaf=8)
dt.fit(X_train,Y_train)
Y_predict=dt.predict(X_test)
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
print(classification_report(Y_test,Y_predict))
print(confusion_matrix(Y_test,Y_predict))
```

precision    recall    f1-score    support

0	0.81	0.90	0.86	1033
1	0.62	0.43	0.51	374
accuracy			0.78	1407
macro avg	0.72	0.67	0.68	1407
weighted avg	0.76	0.78	0.76	1407

```
[[934  99]
 [213 161]]
```

```
[350]: from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=100)
rf.fit(X_train,Y_train) Y_rf_pred=rf.predict(X_test)
print(classification_report(Y_test,Y_rf_pred))
print(confusion_matrix(Y_test,Y_rf_pred))
```

	precision	recall	f1-score	support
0	0.83	0.90	0.86	1033
1	0.63	0.49	0.55	374
accuracy			0.79	1407
macro avg	0.73	0.69	0.71	1407
weighted avg	0.78	0.79	0.78	1407

```
[[925 108]
 [191 183]]
```

```
[351]: from imblearn.combine import SMOTEENN
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
sm=SMOTEENN()
X_resampled,Y_resampled=sm.fit_resample(X,Y)
Xr_train,Xr_test,Yr_train,Yr_test=train_test_split(X_resampled,Y_resampled,test_size=0.
↪2,random_state=42)
X_train_scaled = scaler.fit_transform(Xr_train)
X_test_scaled = scaler.transform(Xr_test)
print(Y_resampled.value_counts())
print(Y.value_counts())
```

```
1    3130
0    2679
Name: Churn, dtype: int64
0    5163
1    1869
Name: Churn, dtype: int64
```

```
[352]: from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier(criterion="gini",random_state=100,max_depth=6,min_samples_leaf=8)
dt.fit(X_train_scaled,Yr_train)
Yr_predict=dt.predict(X_test_scaled)
print(classification_report(Yr_test,Yr_predict))
print(confusion_matrix(Yr_test,Yr_predict))
```

	precision	recall	f1-score	support
0	0.92	0.91	0.92	544
1	0.92	0.93	0.93	618
accuracy			0.92	1162
macro avg	0.92	0.92	0.92	1162
weighted avg	0.92	0.92	0.92	1162

```
[[495  49]
 [ 41 577]]
```

```
[353]: from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=100)
rf.fit(X_train_scaled,Yr_train)
Yr_rf_pred=rf.predict(X_test_scaled)
print(classification_report(Yr_test,Yr_rf_pred))
print(confusion_matrix(Yr_test,Yr_rf_pred))
```

	precision	recall	f1-score	support
0	0.95	0.93	0.94	544
1	0.94	0.96	0.95	618
accuracy			0.95	1162
macro avg	0.95	0.95	0.95	1162
weighted avg	0.95	0.95	0.95	1162

```
[[508  36]
 [ 24 594]]
```

```
[354]: from sklearn.neural_network import MLPClassifier

# Model 6: Neural Network Classifier
print("\nModel 6: Neural Network Classifier")
model_nn = MLPClassifier(hidden_layer_sizes=(100,), max_iter=1000)
model_nn.fit(X_train_scaled, Yr_train)
yr_pred_nn = model_nn.predict(X_test_scaled)
print("Classification Report:")
print(classification_report(Yr_test, yr_pred_nn))
```

```
print("Confusion Matrix:")
print(confusion_matrix(Yr_test, yr_pred_nn))
```

Model 6: Neural Network Classifier

Classification Report:

	precision	recall	f1-score	support
0	0.93	0.93	0.93	544
1	0.94	0.94	0.94	618
accuracy			0.93	1162
macro avg	0.93	0.93	0.93	1162
weighted avg	0.93	0.93	0.93	1162

Confusion Matrix:

```
[[504  40]
 [ 40 578]]
```

```
[355]: from sklearn.model_selection import RandomizedSearchCV
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix

# Define pipeline
pipe_dt = Pipeline([
    ('clf', DecisionTreeClassifier())
])

# Define parameter grid
param_grid_dt = {
    'clf__criterion': ['gini', 'entropy'],
    'clf__max_depth': [None, 10, 20, 30, 40, 50],
    'clf__min_samples_split': [2, 5, 10],
    'clf__min_samples_leaf': [1, 2, 4],
    'clf__max_features': ['sqrt', 'log2', None]
}

# Perform GridSearchCV
grid_dt = RandomizedSearchCV(pipe_dt, param_grid_dt, cv=5)
grid_dt.fit(X_train_scaled, Yr_train)

# Print best parameters
print("Best Parameters (GridSearchCV):", grid_dt.best_params_)

# Predict on the testing set using the best model
best_classifier_dt = grid_dt.best_estimator_
```

```
yrr_pred_dt = best_classifier_dt.predict(X_test_scaled)
```

```
# Evaluate the model
```

```
print("\nClassification Report:")
```

```
print(classification_report(Yr_test, yrr_pred_dt))
```

```
print("\nConfusion Matrix:")
```

```
print(confusion_matrix(Yr_test, yrr_pred_dt))
```

Best Parameters (GridSearchCV): {'clf\_min\_samples\_split': 2, 'clf\_min\_samples\_leaf': 1, 'clf\_max\_features': None, 'clf\_max\_depth': 30, 'clf\_criterion': 'gini'}

Classification Report:

	precision	recall	f1-score	support
0	0.95	0.92	0.93	544
1	0.93	0.96	0.94	618
accuracy			0.94	1162
macro avg	0.94	0.94	0.94	1162
weighted avg	0.94	0.94	0.94	1162

Confusion Matrix:

```
[[501  43]
 [ 27 591]]
```

```
[356]: from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn.model_selection import RandomizedSearchCV
```

```
# Initialize and train Random Forest classifier
```

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

```
param_grid = {
```

```
    'n_estimators': [50, 100, 200],
```

```
    'max_depth': [None, 5, 10],
```

```
    'min_samples_split': [2, 5, 10],
```

```
    'min_samples_leaf': [1, 2, 4]
```

```
}
```

```
grid_search = RandomizedSearchCV(rf_clf, param_grid, cv=5, scoring='accuracy')
```

```
grid_search.fit(X_train_scaled, Yr_train)
```

```
# Get the best estimator
```

```
best_rf_clf = grid_search.best_estimator_

# Evaluate on test data
Yrgd_pred = best_rf_clf.predict(X_test_scaled)
print(classification_report(Yr_test, Yrgd_pred))
```

	precision	recall	f1-score	support
0	0.96	0.94	0.95	544
1	0.94	0.96	0.95	618
accuracy			0.95	1162
macro avg	0.95	0.95	0.95	1162
weighted avg	0.95	0.95	0.95	1162

```
[357]: from xgboost import XGBClassifier

# Model 7: XGBoost Classifier
print("\nModel 7: XGBoost Classifier")
model_xgb = XGBClassifier()
model_xgb.fit(X_train_scaled, Yr_train)
yr_pred_xgb = model_xgb.predict(X_test_scaled)
print("Classification Report:")
print(classification_report(Yr_test, yr_pred_xgb))
print("Confusion Matrix:")
print(confusion_matrix(Yr_test, yr_pred_xgb))
```

Model 7: XGBoost Classifier

Classification Report:

	precision	recall	f1-score	support
0	0.97	0.94	0.95	544
1	0.95	0.97	0.96	618
accuracy			0.96	1162
macro avg	0.96	0.96	0.96	1162
weighted avg	0.96	0.96	0.96	1162

Confusion Matrix:

```
[[511  33]
 [ 18 600]]
```

```
[358]: telco_data
```

```
[358]: SeniorCitizen  Dependents  tenure  OnlineSecurity  OnlineBackup \
0          0          0          1          0          2
1          0          0          34          2          0
2          0          0          2          2          2
3          0          0          45          2          0
4          0          0          2          0          0
...
7038      ...          ...          24          2          0
7039      ...          ...          72          0          2
7040      ...          ...          11          2          0
7041      ...          ...          4          0          0
7042      ...          ...          66          2          0
```

```
DeviceProtection  TechSupport  Contract  PaperlessBilling \
0          0          0          0          1
1          2          0          1          0
2          0          0          0          1
3          2          2          1          0
4          0          0          0          1
...
7038      ...          ...          1          1
7039      ...          ...          1          1
7040      ...          ...          0          1
7041      ...          ...          0          1
7042      ...          ...          2          1
```

```
MonthlyCharges  TotalCharges  Churn
0          29.85          29.85    0
1          56.95         1889.50    0
2          53.85          108.15    1
3          42.30         1840.75    0
4          70.70          151.65    1
...
7038      ...          ...          0
7039      ...          ...          0
7040      ...          ...          0
7041      ...          ...          1
7042      ...          ...          0
```

[7032 rows x 12 columns]

```
[359]: for i in telco_data.columns:
        print(i)
        print(telco_data[i].unique())
```

```
SeniorCitizen
[0 1]
```



Dependents

[0 1]

tenure

[ 1 34 2 45 8 22 10 28 62 13 16 58 49 25 69 52 71 21 12 30 47 72 17 27  
5 46 11 70 63 43 15 60 18 66 9 3 31 50 64 56 7 42 35 48 29 65 38 68  
32 55 37 36 41 6 4 33 67 23 57 61 14 20 53 40 59 24 44 19 54 51 26 39]

OnlineSecurity

[0 2 1]

OnlineBackup

[2 0 1]

DeviceProtection

[0 2 1]

TechSupport

[0 2 1]

Contract

[0 1 2]

PaperlessBilling

[1 0]

MonthlyCharges

[29.85 56.95 53.85 ... 63.1 44.2 78.7 ]

TotalCharges

[ 29.85 1889.5 108.15 ... 346.45 306.6 6844.5 ]

Churn

[0 1]

[360]: `for i in Data.columns:`

`print(i)`

`print(Data[i].unique())`

gender

['Female' 'Male']

SeniorCitizen

[0 1]

Partner

['Yes' 'No']

Dependents

['No' 'Yes']

tenure

[ 1 34 2 45 8 22 10 28 62 13 16 58 49 25 69 52 71 21 12 30 47 72 17 27  
5 46 11 70 63 43 15 60 18 66 9 3 31 50 64 56 7 42 35 48 29 65 38 68  
32 55 37 36 41 6 4 33 67 23 57 61 14 20 53 40 59 24 44 19 54 51 26 39]

PhoneService

['No' 'Yes']

MultipleLines

['No phone service' 'No' 'Yes']

InternetService

['DSL' 'Fiber optic' 'No']

OnlineSecurity

```

['No' 'Yes' 'No internet service']
OnlineBackup
['Yes' 'No' 'No internet service']
DeviceProtection
['No' 'Yes' 'No internet service']
TechSupport
['No' 'Yes' 'No internet service']
StreamingTV
['No' 'Yes' 'No internet service']
StreamingMovies
['No' 'Yes' 'No internet service']
Contract
['Month-to-month' 'One year' 'Two year']
PaperlessBilling
['Yes' 'No']
PaymentMethod
['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
MonthlyCharges
[29.85 56.95 53.85 ... 63.1 44.2 78.7 ]
TotalCharges
[ 29.85 1889.5 108.15 ... 346.45 306.6 6844.5 ]
Churn
['No' 'Yes']

```

```

[361]: # Taking user input:
sen=input("Enter Yes If Customer is Senior Citizen else Enter No: ")
if sen.lower()=="yes":
    senior=1
elif sen.lower()=="no":
    senior=0
else:
    senior=0
dep=input("Enter Customer's Dependency (Yes or No): ")
if dep.lower()=="yes":
    depend=1
elif dep.lower()=="no":
    depend=0
else:
    depend=0

tenure=int(input("Number of Months the customer has Stayed: "))
ois=input("Whether Customer has Online Security or not (Yes, No or No internet_
↪service): ")
if ois.lower()=="yes":
    OnlineSecurity=2
elif ois.lower()=="no":

```

```

OnlineSecurity=0
else:
    OnlineSecurity=1

oib=input("Whether the customer has Online Backup or Not (Yes, No or No_
↳internet Service): ")
if oib.lower()=="yes":
    OnlineBackup=2
elif oib.lower()=="no":
    OnlineBackup=0
else:
    OnlineBackup=1

dvp=input("Whether Custom has Device Protection or not (Yes, No or No internet_
↳service): ")
if dvp.lower()=="yes":
    DeviceP=2
elif dvp.lower()=="no":
    DeviceP=0
else:
    DeviceP=1

ts=input("Whether Custom has Tech Support or not (Yes, No or No internet_
↳service): ")
if ts.lower()=="yes":
    TechS=2
elif ts.lower()=="no":
    TechS=0
else:
    TechS=1

con=input("Contract Term of the Customer (Month-to-Month, One Year or Two Year):
↳ ")
if con.lower()=="month-to-month":
    Contract=0
elif con.lower()=="one year":
    Contract=1
elif con.lower()=="two year":
    Contract=2

plb=input("Whether the customer has Paperless Billing or Not (Yes or No): ")
if plb.lower()=="yes":
    Bill=1
elif plb.lower()=="two year":
    Bill=0
else:
    Bill=1

month=float(input("The amount charged to the Customer Monthly: "))

```

```
total=float(input("Total Amount charged to the customer: "))
```

```
X_input=[senior,depend,tenure,OnlineSecurity,OnlineBackup,DeviceP,TechS,Contract,Bill,month,to
```

```
X_input_df=pd.DataFrame([X_input])
```

```
X_input_df
```

```
[361]:
```

0	1	2	3	4	5	6	7	8	9	10
0	0	0	2	2	2	0	0	1	1	53.85 108.15

```
[362]: X_input_df.  
↳columns=["SeniorCitizen","Dependents","tenure","OnlineSecurity","OnlineBackup","DeviceProte  
X_input_df
```

```
[362]:
```

SeniorCitizen	Dependents	tenure	OnlineSecurity	OnlineBackup \
0	0	0	2	2
DeviceProtection	TechSupport	Contract	PaperlessBilling	MonthlyCharges \
0	0	0	1	1
TotalCharges				53.85
0				108.15

```
[363]: X_input_scaled=scaler.transform(X_input_df)  
X_input_scaled  
  
Y_input_pred=model_xgb.predict(X_input_scaled)  
if Y_input_pred[0]==0:  
    predicted="No"  
else:  
    predicted="Yes"  
print("Churn Prediction: ",predicted)
```

Churn Prediction: No

```
[364]: telco_data.head()
```

```
[364]:
```

SeniorCitizen	Dependents	tenure	OnlineSecurity	OnlineBackup \
0	0	0	1	0
1	0	0	34	2
2	0	0	2	2
3	0	0	45	2
4	0	0	2	0
DeviceProtection	TechSupport	Contract	PaperlessBilling	MonthlyCharges \
0	0	0	0	1
1	2	0	1	0
				29.85
				56.95

2	0	0	0	1	53.85
3	2	2	1	0	42.30
4	0	0	0	1	70.70

	TotalCharges	Churn
0	29.85	0
1	1889.50	0
2	108.15	1
3	1840.75	0
4	151.65	1