Customer Churn Prediction

In [1]:
```
import pandas as pd
from matplotlib import pyplot as plt
import numpy as np
%matplotlib inline
```

In [2]:
```
df = pd.read_csv(r"C:\Users\Lenovo\Downloads\archive (11)\data.csv")
df.sample(5)
```

Out[2]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLin
1011	6614-YOLAC	Female	0	Yes	Yes	71	No	No phor servi
525	0750-EBAIU	Male	0	No	No	52	Yes	N
6249	7823-JSOAG	Male	0	No	No	3	Yes	Y
3380	5178-LMXOP	Male	1	Yes	No	1	Yes	Y
3228	3567-PQTSO	Male	0	Yes	Yes	53	Yes	Y

5 rows × 21 columns

In [3]:
```
df.drop('customerID',axis='columns',inplace=True)
df.dtypes
```

Out[3]:
```
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
```

In [4]:
```
df.TotalCharges.values
```

Out[4]:
```
array(['29.85', '1889.5', '108.15', ..., '346.45', '306.6', '6844.5'],
      dtype=object)
```

In [6]:
```
pd.to_numeric(df.TotalCharges,errors='coerce').isnull()
```

Out[6]:
```
0       False
1       False
2       False
3       False
4       False
        ...
7038    False
7039    False
7040    False
7041    False
7042    False
Name: TotalCharges, Length: 7043, dtype: bool
```

In [7]:
```
df[pd.to_numeric(df.TotalCharges,errors='coerce').isnull()]
```

Out[7]:

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

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

Out[8]:
```
(7043, 20)
```

In [9]:
```
df.iloc[488].TotalCharges
```

Out[9]:
```
' '
```

In [10]:
```
df[df.TotalCharges!=' '].shape
```

Out[10]:
```
(7032, 20)
```

In [11]:
```
df1 = df[df.TotalCharges!=' ']
df1.shape
```

Out[11]:
```
(7032, 20)
```

In [12]:
```
df1.dtypes
```

Out[12]:
```
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
```

In [13]:
```
df1.TotalCharges = pd.to_numeric(df1.TotalCharges)
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_13684\973151263.py:1: SettingWithCopyW
arning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
user_guide/indexing.html#returning-a-view-versus-a-copy
  df1.TotalCharges = pd.to_numeric(df1.TotalCharges)
```

In [14]:
```
df1.TotalCharges.values
```

Out[14]:
```
array([  29.85, 1889.5 ,  108.15, ...,  346.45,  306.6 , 6844.5 ])
```

In [15]:
```
df1[df1.Churn=='No']
```

Out[15]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetSe
0	Female	0	Yes	No	1	No	No phone service	
1	Male	0	No	No	34	Yes	No	
3	Male	0	No	No	45	No	No phone service	
6	Male	0	No	Yes	22	Yes	Yes	Fiber
7	Female	0	No	No	10	No	No phone service	
...	...	...	...	...	...	...	...	
7037	Female	0	No	No	72	Yes	No	
7038	Male	0	Yes	Yes	24	Yes	Yes	
7039	Female	0	Yes	Yes	72	Yes	Yes	Fiber
7040	Female	0	Yes	Yes	11	No	No phone service	
7042	Male	0	No	No	66	Yes	No	Fiber

5163 rows × 20 columns

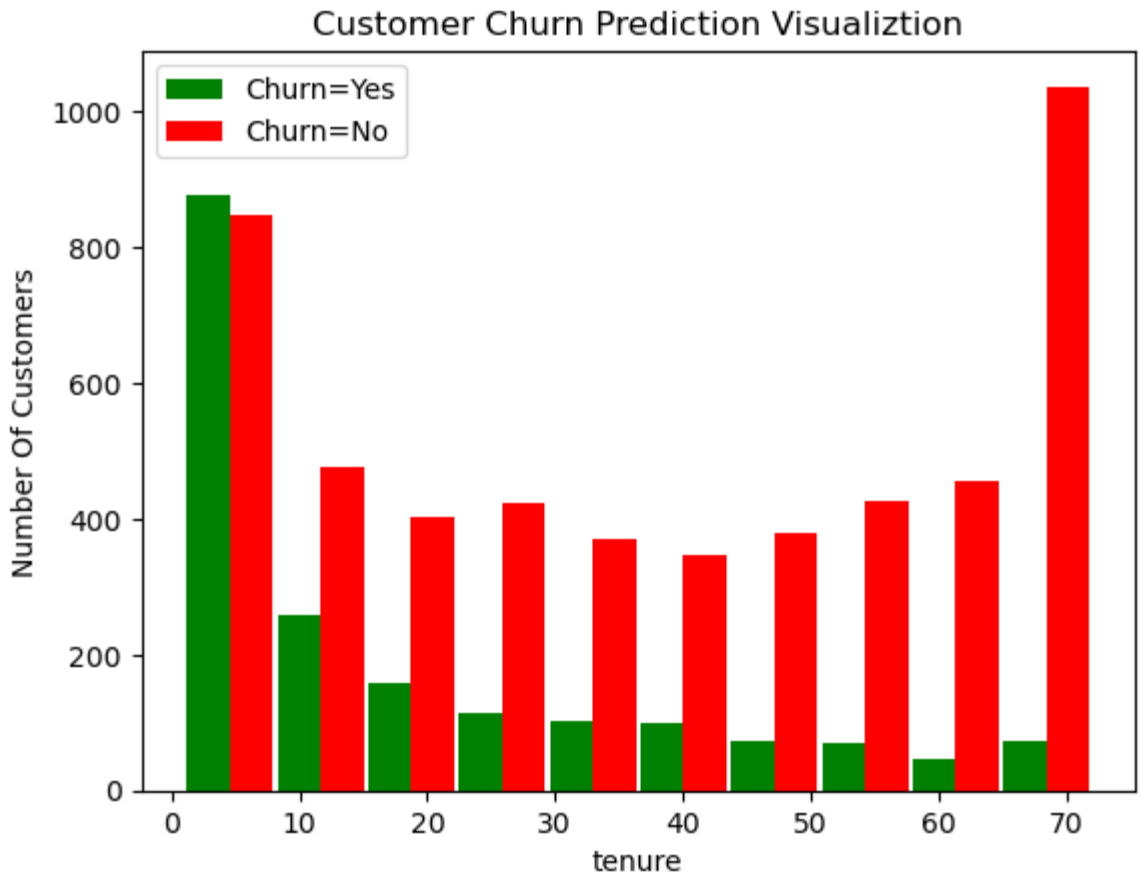
Data Visualization

In [16]:

```
tenure_churn_no = df1[df1.Churn=='No'].tenure
tenure_churn_yes = df1[df1.Churn=='Yes'].tenure

plt.xlabel("tenure")
plt.ylabel("Number Of Customers")
plt.title("Customer Churn Prediction Visualiztion")

blood_sugar_men = [113, 85, 90, 150, 149, 88, 93, 115, 135, 80, 77, 82, 129]
blood_sugar_women = [67, 98, 89, 120, 133, 150, 84, 69, 89, 79, 120, 112, 100]

plt.hist([tenure_churn_yes, tenure_churn_no], rwidth=0.95, color=['green','red'],la
plt.legend()
```

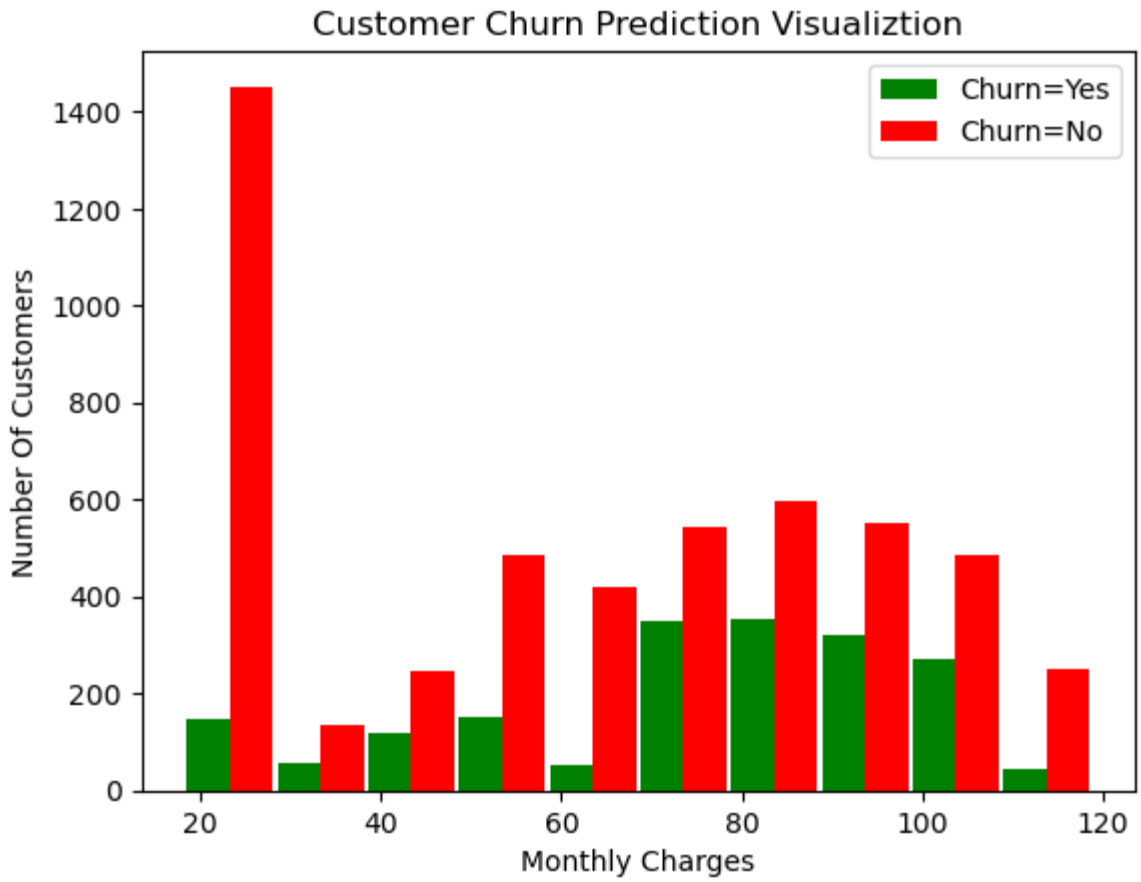
Out[16]:

```
<matplotlib.legend.Legend at 0x20827610750>
```



In [17]:
```
mc_churn_no = df1[df1.Churn=='No'].MonthlyCharges
mc_churn_yes = df1[df1.Churn=='Yes'].MonthlyCharges

plt.xlabel("Monthly Charges")
plt.ylabel("Number Of Customers")
plt.title("Customer Churn Prediction Visualiztion")

blood_sugar_men = [113, 85, 90, 150, 149, 88, 93, 115, 135, 80, 77, 82, 129]
blood_sugar_women = [67, 98, 89, 120, 133, 150, 84, 69, 89, 79, 120, 112, 100]

plt.hist([mc_churn_yes, mc_churn_no], rwidth=0.95, color=['green','red'],label=['Ch
plt.legend()
```

Out[17]:
```
<matplotlib.legend.Legend at 0x20827622f10>
```



In [18]:
```
def print_unique_col_values(df):
       for column in df:
            if df[column].dtypes=='object':
                print(f'{column}: {df[column].unique()}')
```

In [19]:
```
print_unique_col_values(df1)
```

```
gender: ['Female' 'Male']
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 [20]:
```
df1.replace('No internet service','No',inplace=True)
df1.replace('No phone service','No',inplace=True)
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_13684\2045096646.py:1: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
user_guide/indexing.html#returning-a-view-versus-a-copy
  df1.replace('No internet service','No',inplace=True)
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_13684\2045096646.py:2: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
user_guide/indexing.html#returning-a-view-versus-a-copy
  df1.replace('No phone service','No',inplace=True)
```

In [21]:
```
print_unique_col_values(df1)
```

```
gender: ['Female' 'Male']
Partner: ['Yes' 'No']
Dependents: ['No' 'Yes']
PhoneService: ['No' 'Yes']
MultipleLines: ['No' 'Yes']
InternetService: ['DSL' 'Fiber optic' 'No']
OnlineSecurity: ['No' 'Yes']
OnlineBackup: ['Yes' 'No']
DeviceProtection: ['No' 'Yes']
TechSupport: ['No' 'Yes']
StreamingTV: ['No' 'Yes']
StreamingMovies: ['No' 'Yes']
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 [22]:
```
yes_no_columns = ['Partner','Dependents','PhoneService','MultipleLines','OnlineSecu
                  'DeviceProtection','TechSupport','StreamingTV','StreamingMovies',
for col in yes_no_columns:
    df1[col].replace({'Yes': 1,'No': 0},inplace=True)
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_13684\1648037665.py:4: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
user_guide/indexing.html#returning-a-view-versus-a-copy
  df1[col].replace({'Yes': 1,'No': 0},inplace=True)
```

In [23]:
```
for col in df1:
    print(f'{col}: {df1[col].unique()}')
```

```
gender: ['Female' 'Male']
SeniorCitizen: [0 1]
Partner: [1 0]
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]
PhoneService: [0 1]
MultipleLines: [0 1]
InternetService: ['DSL' 'Fiber optic' 'No']
OnlineSecurity: [0 1]
OnlineBackup: [1 0]
DeviceProtection: [0 1]
TechSupport: [0 1]
StreamingTV: [0 1]
StreamingMovies: [0 1]
Contract: ['Month-to-month' 'One year' 'Two year']
PaperlessBilling: [1 0]
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: [0 1]
```

In [24]:
```
df1['gender'].replace({'Female':1,'Male':0},inplace=True)
df1.gender.unique()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_13684\2321097074.py:1: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
user_guide/indexing.html#returning-a-view-versus-a-copy
  df1['gender'].replace({'Female':1,'Male':0},inplace=True)
```

Out[24]:
```
array([1, 0], dtype=int64)
```

One hot encoding for categorical data

In [25]:
```
df2 = pd.get_dummies(data=df1, columns=['InternetService','Contract','PaymentMethod
df2.columns
```

Out[25]:
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'OnlineSecurity', 'OnlineBackup',
       'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
       'PaperlessBilling', 'MonthlyCharges', 'TotalCharges', 'Churn',
       'InternetService_DSL', 'InternetService_Fiber optic',
       'InternetService_No', 'Contract_Month-to-month', 'Contract_One year',
       'Contract_Two year', 'PaymentMethod_Bank transfer (automatic)',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check'],
      dtype='object')
```

In [26]:
```
df2.sample(5)
```

Out[26]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	OnlineSec
4891	0	0	1	0	4	1	1	
1255	1	0	0	0	2	0	0	
5682	1	0	1	0	1	0	0	
2058	0	0	0	0	72	1	1	
2820	0	0	0	0	53	1	1	

5 rows × 27 columns

In [27]:

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

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df2[cols_to_scale] = scaler.fit_transform(df2[cols_to_scale])
for col in df2:
    print(f'{col}: {df2[col].unique()}')
```

```
gender: [1 0]
SeniorCitizen: [0 1]
Partner: [1 0]
Dependents: [0 1]
tenure: [0.         0.46478873 0.01408451 0.61971831 0.09859155 0.29577465
 0.12676056 0.38028169 0.85915493 0.16901408 0.21126761 0.8028169
 0.67605634 0.33802817 0.95774648 0.71830986 0.98591549 0.28169014
 0.15492958 0.4084507  0.64788732 1.         0.22535211 0.36619718
 0.05633803 0.63380282 0.14084507 0.97183099 0.87323944 0.5915493
 0.1971831  0.83098592 0.23943662 0.91549296 0.11267606 0.02816901
 0.42253521 0.69014085 0.88732394 0.77464789 0.08450704 0.57746479
 0.47887324 0.66197183 0.3943662  0.90140845 0.52112676 0.94366197
 0.43661972 0.76056338 0.50704225 0.49295775 0.56338028 0.07042254
 0.04225352 0.45070423 0.92957746 0.30985915 0.78873239 0.84507042
 0.18309859 0.26760563 0.73239437 0.54929577 0.81690141 0.32394366
 0.6056338  0.25352113 0.74647887 0.70422535 0.35211268 0.53521127]
PhoneService: [0 1]
MultipleLines: [0 1]
OnlineSecurity: [0 1]
OnlineBackup: [1 0]
DeviceProtection: [0 1]
TechSupport: [0 1]
StreamingTV: [0 1]
StreamingMovies: [0 1]
PaperlessBilling: [1 0]
MonthlyCharges: [0.11542289 0.38507463 0.35422886 ... 0.44626866 0.25820896 0.60149
254]
TotalCharges: [0.0012751  0.21586661 0.01031041 ... 0.03780868 0.03321025 0.7876413
6]
Churn: [0 1]
InternetService_DSL: [1 0]
InternetService_Fiber optic: [0 1]
InternetService_No: [0 1]
Contract_Month-to-month: [1 0]
Contract_One year: [0 1]
Contract_Two year: [0 1]
PaymentMethod_Bank transfer (automatic): [0 1]
PaymentMethod_Credit card (automatic): [0 1]
PaymentMethod_Electronic check: [1 0]
PaymentMethod_Mailed check: [0 1]
```

train test split

In [28]:
```
X = df2.drop('Churn',axis='columns')
y = df2['Churn']

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=
```

In [31]:
```
X_train.shape
```

Out[31]:
```
(5625, 26)
```

In [32]:
```
X_test.shape
```

Out[32]: (1407, 26)

In [33]:
```
X_train[:10]
```

Out[33]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	OnlineS
5664	1	1	0	0	0.126761	1	0	
101	1	0	1	1	0.000000	1	0	
2621	0	0	1	0	0.985915	1	0	
392	1	1	0	0	0.014085	1	0	
1327	0	0	1	0	0.816901	1	1	
3607	1	0	0	0	0.169014	1	0	
2773	0	0	1	0	0.323944	0	0	
1936	1	0	1	0	0.704225	1	0	
5387	0	0	0	0	0.042254	0	0	
4331	0	0	0	0	0.985915	1	1	

10 rows × 26 columns

In [34]:
```
len(X_train.columns)
```

Out[34]: 26

Tensorflow/keras

In [37]:
```
import tensorflow as tf
from tensorflow import keras


model = keras.Sequential([
    keras.layers.Dense(26, input_shape=(26,), activation='relu'),
    keras.layers.Dense(15, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])

# opt = keras.optimizers.Adam(learning_rate=0.01)

model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])

model.fit(X_train, y_train, epochs=100)
```

```
C:\Users\Lenovo\AppData\Roaming\Python\Python311\site-packages\keras\src\layers\cor
e\dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a
layer. When using Sequential models, prefer using an `Input(shape)` object as the f
irst layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Epoch 1/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.7441 - loss: 0.5267
Epoch 2/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7961 - loss: 0.4331
Epoch 3/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8006 - loss: 0.4176
Epoch 4/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8003 - loss: 0.4147
Epoch 5/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8028 - loss: 0.4107
Epoch 6/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7992 - loss: 0.4224
Epoch 7/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8080 - loss: 0.4069
Epoch 8/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8089 - loss: 0.4108
Epoch 9/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8152 - loss: 0.3981
Epoch 10/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8164 - loss: 0.4033
Epoch 11/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8159 - loss: 0.3907
Epoch 12/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8085 - loss: 0.4105
Epoch 13/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8228 - loss: 0.3953
Epoch 14/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8205 - loss: 0.3949
Epoch 15/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8177 - loss: 0.3991
Epoch 16/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8178 - loss: 0.3944
Epoch 17/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8138 - loss: 0.3991
Epoch 18/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8244 - loss: 0.3941
Epoch 19/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8196 - loss: 0.3903
Epoch 20/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8125 - loss: 0.3941
Epoch 21/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8201 - loss: 0.3983
Epoch 22/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8133 - loss: 0.3946
Epoch 23/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8175 - loss: 0.3970
Epoch 24/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8162 - loss: 0.3977
Epoch 25/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8225 - loss: 0.3858
Epoch 26/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8121 - loss: 0.4076
Epoch 27/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8235 - loss: 0.3802
Epoch 28/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8263 - loss: 0.3765
Epoch 29/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8268 - loss: 0.3825
Epoch 30/100
```

```
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8283 - loss: 0.3735
Epoch 31/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8229 - loss: 0.3806
Epoch 32/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8253 - loss: 0.3770
Epoch 33/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8217 - loss: 0.3804
Epoch 34/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8216 - loss: 0.3840
Epoch 35/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8294 - loss: 0.3724
Epoch 36/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8310 - loss: 0.3717
Epoch 37/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8309 - loss: 0.3771
Epoch 38/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8342 - loss: 0.3669
Epoch 39/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8228 - loss: 0.3770
Epoch 40/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8101 - loss: 0.3915
Epoch 41/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8233 - loss: 0.3759
Epoch 42/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8231 - loss: 0.3721
Epoch 43/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8246 - loss: 0.3770
Epoch 44/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8269 - loss: 0.3741
Epoch 45/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8295 - loss: 0.3680
Epoch 46/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8311 - loss: 0.3737
Epoch 47/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8273 - loss: 0.3676
Epoch 48/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8263 - loss: 0.3687
Epoch 49/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8242 - loss: 0.3783
Epoch 50/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8307 - loss: 0.3738
Epoch 51/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8334 - loss: 0.3571
Epoch 52/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8222 - loss: 0.3757
Epoch 53/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8352 - loss: 0.3507
Epoch 54/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8262 - loss: 0.3684
Epoch 55/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8280 - loss: 0.3717
Epoch 56/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8327 - loss: 0.3614
Epoch 57/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8303 - loss: 0.3689
Epoch 58/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8305 - loss: 0.3713
Epoch 59/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8308 - loss: 0.3622
```

```
Epoch 60/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8274 - loss: 0.3722
Epoch 61/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8385 - loss: 0.3453
Epoch 62/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8321 - loss: 0.3588
Epoch 63/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8290 - loss: 0.3678
Epoch 64/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8340 - loss: 0.3547
Epoch 65/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8373 - loss: 0.3590
Epoch 66/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8299 - loss: 0.3615
Epoch 67/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8333 - loss: 0.3569
Epoch 68/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8286 - loss: 0.3714
Epoch 69/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8340 - loss: 0.3672
Epoch 70/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8330 - loss: 0.3617
Epoch 71/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8388 - loss: 0.3519
Epoch 72/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8312 - loss: 0.3624
Epoch 73/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8353 - loss: 0.3707
Epoch 74/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8349 - loss: 0.3525
Epoch 75/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8262 - loss: 0.3698
Epoch 76/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8387 - loss: 0.3601
Epoch 77/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8351 - loss: 0.3518
Epoch 78/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8351 - loss: 0.3457
Epoch 79/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8313 - loss: 0.3609
Epoch 80/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8413 - loss: 0.3411
Epoch 81/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8327 - loss: 0.3479
Epoch 82/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8444 - loss: 0.3421
Epoch 83/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8394 - loss: 0.3482
Epoch 84/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8341 - loss: 0.3567
Epoch 85/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8374 - loss: 0.3499
Epoch 86/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8336 - loss: 0.3489
Epoch 87/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8318 - loss: 0.3455
Epoch 88/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8366 - loss: 0.3510
Epoch 89/100
```

```
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8345 - loss: 0.3499
Epoch 90/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8350 - loss: 0.3523
Epoch 91/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8357 - loss: 0.3462
Epoch 92/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8272 - loss: 0.3597
Epoch 93/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8376 - loss: 0.3506
Epoch 94/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8397 - loss: 0.3476
Epoch 95/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8454 - loss: 0.3415
Epoch 96/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8445 - loss: 0.3382
Epoch 97/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8360 - loss: 0.3455
Epoch 98/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8455 - loss: 0.3433
Epoch 99/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8371 - loss: 0.3402
Epoch 100/100
176/176 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8268 - loss: 0.3594
```

Out[37]:
```
<keras.src.callbacks.history.History at 0x20833233c10>
```

In [38]:
```
model.evaluate(X_test, y_test)
```

Out[38]:
```
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7781 - loss: 0.4787
[0.48671993613243103, 0.7711442708969116]
```

In [39]:
```
yp = model.predict(X_test)
yp[:5]
```

Out[39]:
```
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
array([[0.17012183],
       [0.5717167 ],
       [0.00540317],
       [0.7973403 ],
       [0.54782796]], dtype=float32)
```

In [40]:
```
y_pred = []
for element in yp:
    if element > 0.5:
        y_pred.append(1)
    else:
        y_pred.append(0)
```

In [41]:
```
y_pred[:10]
```

Out[41]:
```
[0, 1, 0, 1, 1, 1, 0, 1, 0, 0]
```

In [42]:
```
y_test[:10]
```

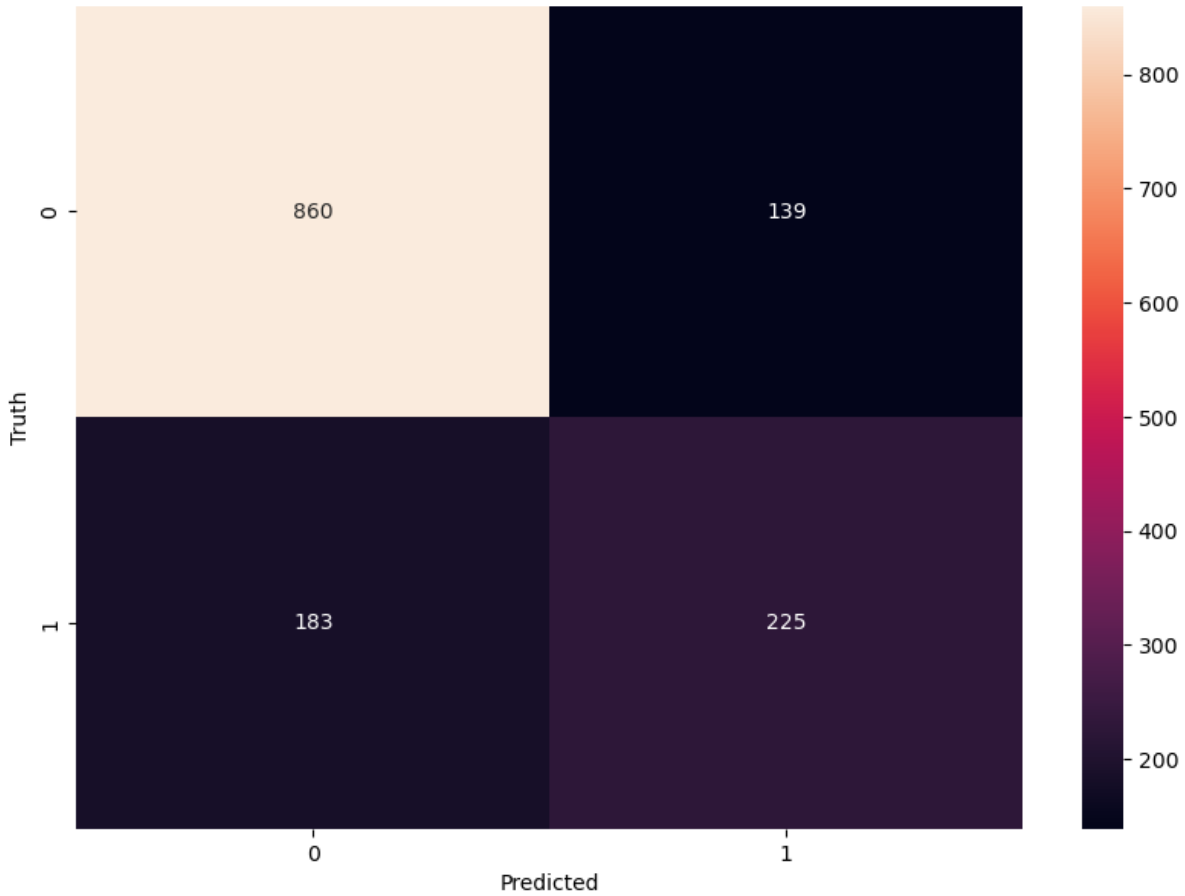
Out[42]:
```
2660    0
744     0
5579    1
64      1
3287    1
816     1
2670    0
5920    0
1023    0
6087    0
Name: Churn, dtype: int64
```

In [43]:
```
from sklearn.metrics import confusion_matrix , classification_report

print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.86      0.84       999
           1       0.62      0.55      0.58       408

    accuracy                           0.77      1407
   macro avg       0.72      0.71      0.71      1407
weighted avg       0.76      0.77      0.77      1407
```

In [44]:
```
import seaborn as sn
cm = tf.math.confusion_matrix(labels=y_test,predictions=y_pred)

plt.figure(figsize = (10,7))
sn.heatmap(cm, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[44]:
```
Text(95.72222222222221, 0.5, 'Truth')
```



In [45]:
```
#Accuracy
round((862+229)/(862+229+137+179),2)
```

Out[45]: 0.78

In [46]:
```
#precision for 0 class
round(862/(862+179),2)
```

Out[46]: 0.83

In [47]:
```
#precision for 1 class
round(229/(229+137),2)
```

Out[47]: 0.63

In [48]:
```
#recall for 0 class
round(862/(862+137),2)
```

Out[48]: 0.86

In [49]:
```
#recall for 1 class
round(229/(229+179),2)
```

Out[49]: 0.56

In [ ]: