Date - 17/10/2023

Team ID - 721

Project Title - Customer Churn Prediction

1.Import Libraries required to create the Customer Churn Model

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

2. Load Churn Prediction Dataset

In [2]:
```
data = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
```

3.Exploring Dataset

1. Displaying the top 5 rows

In [3]:
```
data.head()
```

Out[3]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service
1	5575-GNVDE	Male	0	No	No	34	Yes	No
2	3668-QPYBK	Male	0	No	No	2	Yes	No
3	7795-CFOCW	Male	0	No	No	45	No	No phone service
4	9237-HQITU	Female	0	No	No	2	Yes	No

5 rows × 21 columns

2. Displaying the bottom 5 rows

In [4]:
```
data.tail()
```

Out[4]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLin
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Y
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Y
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phor servi
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Y
7042	3186-AJIEK	Male	0	No	No	66	Yes	N

5 rows × 21 columns

3. Displaying the colomns

In [5]:
```
data.columns
```

Out[5]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

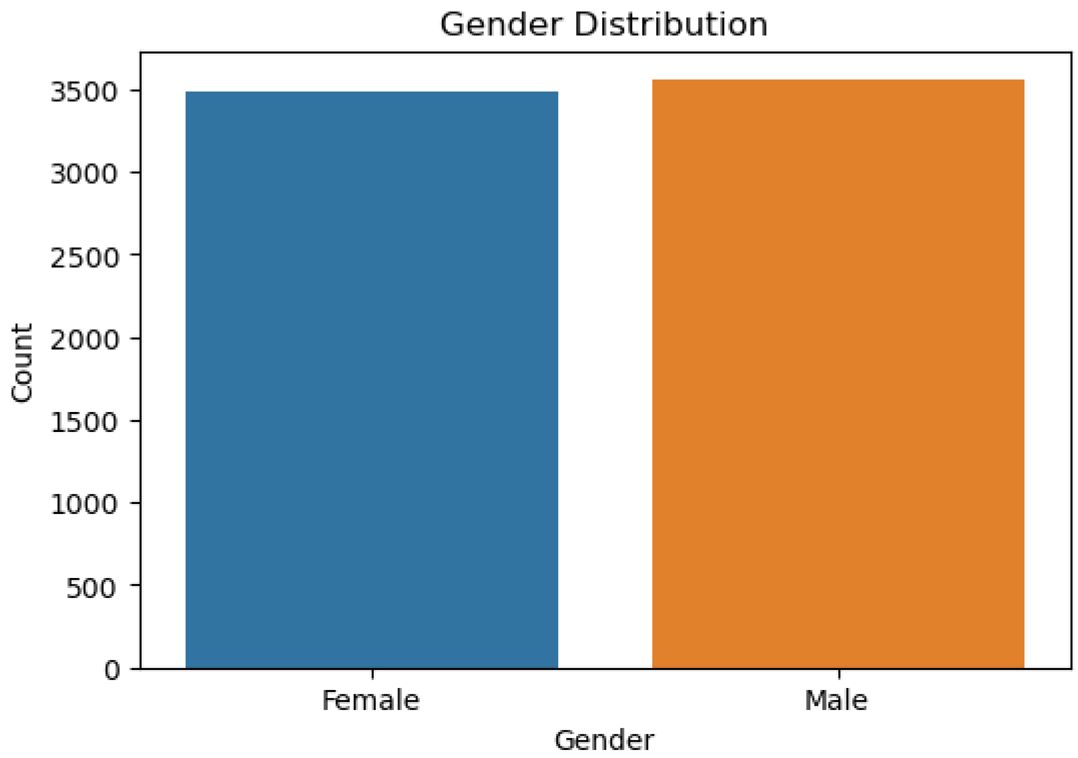
4. Finding the shape

In [6]:
```
data.shape
```

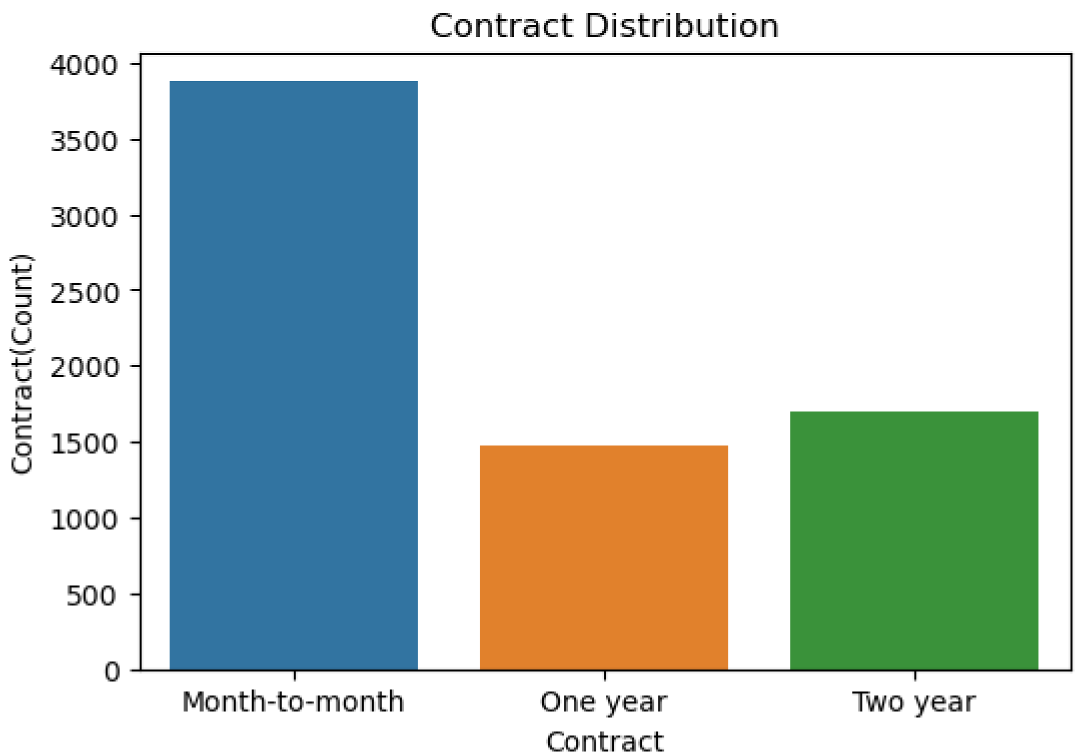
Out[6]:
```
(7043, 21)
```

4.Data Visualization

In [7]:
```
plt.figure(figsize=(6, 4))
sns.countplot(data=data, x='gender')
plt.title('Gender Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```



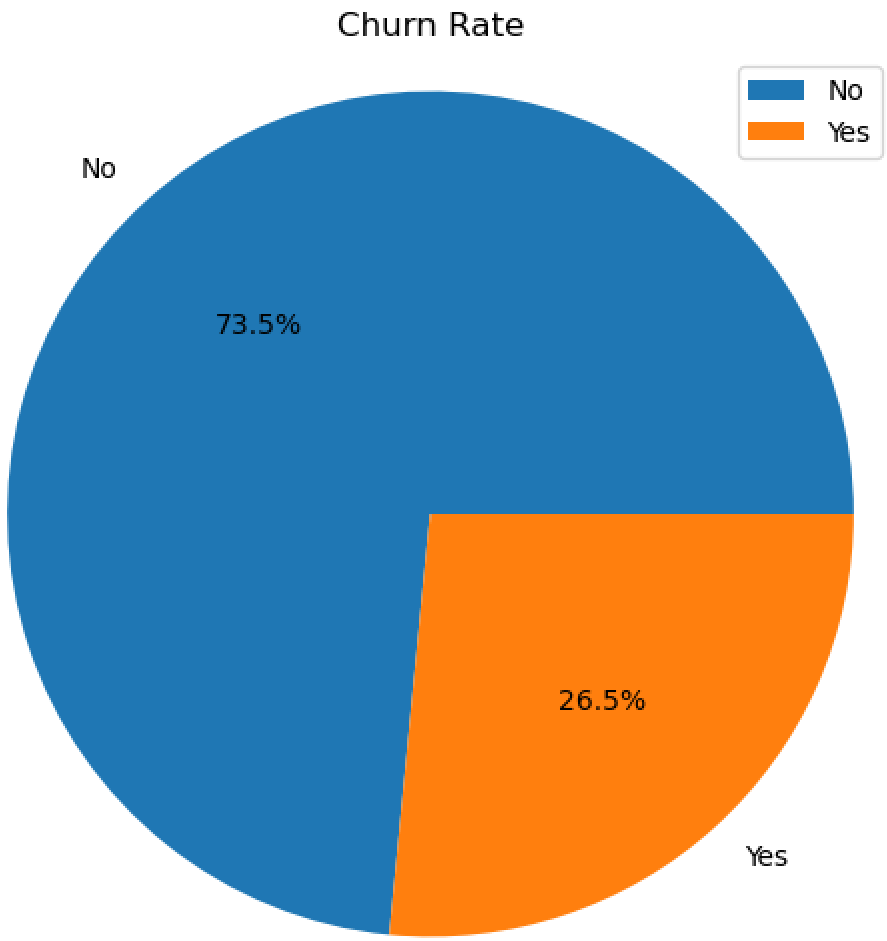
In [8]:
```
plt.figure(figsize=(6, 4))
sns.countplot(data=data, x='Contract')
plt.title('Contract Distribution')
plt.xlabel('Contract')
plt.ylabel('Contract(Count)')
plt.show()
```



In [9]:
```
# Count the number of customers for each churn category
churn_counts = data['Churn'].value_counts()
```

In [10]:
```
# Create a pie chart
plt.figure(figsize=(6, 6))
plt.pie(churn_counts, labels=churn_counts.index, autopct='%1.1f%%')
```

```
plt.title('Churn Rate')
plt.axis('equal')  # Equal aspect ratio ensures that the pie chart is circular.
plt.legend()
plt.show()
```



5.Preprocess Dataset

In [11]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

In [12]:
```
missing_values = data.isnull().sum()
```

In [13]:
```
print("Missing Values:\n", missing_values)
```

```
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
```

In [14]:
```
data = data.dropna()
```

In [15]:
```
data.describe()
```

Out[15]:

	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

In [16]:

```
df = data.drop('customerID',axis=1)
```

In [17]:

```
df
```

Out[17]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetS
0	Female	0	Yes	No	1	No	No phone service	
1	Male	0	No	No	34	Yes	No	
2	Male	0	No	No	2	Yes	No	
3	Male	0	No	No	45	No	No phone service	
4	Female	0	No	No	2	Yes	No	Fiber
...	...	...	...	...	...	...	...	
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	
7041	Male	1	Yes	No	4	Yes	Yes	Fiber
7042	Male	0	No	No	66	Yes	No	Fiber

7043 rows × 20 columns

In [18]:

```
#count of string value into the column.
count=0
for i in df.TotalCharges:
    if i==' ':
```

```
        count+=1
print('count of empty string:- ',count)
#we will replace this empty string to nan values
df['TotalCharges'] = df['TotalCharges'].replace(" ",np.nan)
# typecasting of the TotalCharges column
df['TotalCharges'] = df['TotalCharges'].astype(float)
```

```
count of empty string:-  11
```

6. Checking Null Values in Customer Churn Data

In [19]:
```
df.isnull().sum()
```

Out[19]:
```
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
```

In [20]:
```
# fill null values with mean
df['TotalCharges'] = df['TotalCharges'].fillna(df['TotalCharges'].mean())
```

In [21]:
```
#numerical variables

num = list(df.select_dtypes(include=['int64','float64']).keys())

#categorical variables

cat = list(df.select_dtypes(include='O').keys())

print(cat)

print(num)
```

```
['gender', 'Partner', 'Dependents', 'PhoneService', 'MultipleLines', 'InternetServ
ice', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'Stream
ingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod', 'Chur
n']
['SeniorCitizen', 'tenure', 'MonthlyCharges', 'TotalCharges']
```

In [22]:
```
# value_counts of the categorical columns
for i in cat:
    print(df[i].value_counts())
# as we see that there is extra categories which we have to convert it into No.
df.MultipleLines = df.MultipleLines.replace('No phone service','No')
df.OnlineSecurity = df.OnlineSecurity.replace('No internet service','No')
df.OnlineBackup = df.OnlineBackup.replace('No internet service','No')
```

```
df.DeviceProtection = df.DeviceProtection.replace('No internet service','No')
df.TechSupport = df.TechSupport.replace('No internet service','No')
df.StreamingTV = df.StreamingTV.replace('No internet service','No')
df.StreamingMovies = df.StreamingMovies.replace('No internet service','No')
```

```
gender
Male      3555
Female    3488
Name: count, dtype: int64
Partner
No     3641
Yes    3402
Name: count, dtype: int64
Dependents
No     4933
Yes    2110
Name: count, dtype: int64
PhoneService
Yes    6361
No      682
Name: count, dtype: int64
MultipleLines
No                  3390
Yes                 2971
No phone service     682
Name: count, dtype: int64
InternetService
Fiber optic    3096
DSL            2421
No             1526
Name: count, dtype: int64
OnlineSecurity
No                     3498
Yes                    2019
No internet service    1526
Name: count, dtype: int64
OnlineBackup
No                     3088
Yes                    2429
No internet service    1526
Name: count, dtype: int64
DeviceProtection
No                     3095
Yes                    2422
No internet service    1526
Name: count, dtype: int64
TechSupport
No                     3473
Yes                    2044
No internet service    1526
Name: count, dtype: int64
StreamingTV
No                     2810
Yes                    2707
No internet service    1526
Name: count, dtype: int64
StreamingMovies
No                     2785
Yes                    2732
No internet service    1526
Name: count, dtype: int64
Contract
Month-to-month    3875
Two year          1695
One year          1473
Name: count, dtype: int64
PaperlessBilling
Yes    4171
No     2872
```

```
Name: count, dtype: int64
PaymentMethod
Electronic check             2365
Mailed check                 1612
Bank transfer (automatic)    1544
Credit card (automatic)      1522
Name: count, dtype: int64
Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

7.Handling categorical Variables in Customer Churn Data

In [23]:
```
# we have to handel this all categorical variables
# there are mainly Yes/No features in most of the columns
# we will convert Yes = 1 and No = 0
for i in cat:
    df[i] = df[i].replace('Yes',1)
    df[i] = df[i].replace('No',0)
```

In [24]:
```
df
```

Out[24]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetS
0	Female	0	1	0	1	0	0	
1	Male	0	0	0	34	1	0	
2	Male	0	0	0	2	1	0	
3	Male	0	0	0	45	0	0	
4	Female	0	0	0	2	1	0	Fiber
...	...	...	...	...	...	...	...	
7038	Male	0	1	1	24	1	1	
7039	Female	0	1	1	72	1	1	Fiber
7040	Female	0	1	1	11	0	0	
7041	Male	1	1	0	4	1	1	Fiber
7042	Male	0	0	0	66	1	0	Fiber

7043 rows × 20 columns

In [25]:
```
from sklearn.preprocessing import OrdinalEncoder
oe = OrdinalEncoder()
#from sklearn.preprocessing import OrdinalEncoder

# Convert all values in 'InternetService' to strings
df['InternetService'] = df['InternetService'].astype(str)

# Create and fit the OrdinalEncoder
oe = OrdinalEncoder()
df['InternetService'] = oe.fit_transform(df[['InternetService']])

df['Contract'] = oe.fit_transform(df[['Contract']])
df['PaymentMethod'] = oe.fit_transform(df[['PaymentMethod']])
# df['Gender'] = oe.fit_transform(df['Gender'])
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df['gender'] = label_encoder.fit_transform(df['gender'])
df
```

Out[25]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetS
0	0	0	1	0	1	0	0	
1	1	0	0	0	34	1	0	
2	1	0	0	0	2	1	0	
3	1	0	0	0	45	0	0	
4	0	0	0	0	2	1	0	
...	...	...	...	...	...	...	...	
7038	1	0	1	1	24	1	1	
7039	0	0	1	1	72	1	1	
7040	0	0	1	1	11	0	0	
7041	1	1	1	0	4	1	1	
7042	1	0	0	0	66	1	0	

7043 rows × 20 columns

In [26]:
```
scale_cols = ['tenure','MonthlyCharges','TotalCharges']
# now we scling all the data
from sklearn.preprocessing import MinMaxScaler
scale = MinMaxScaler()
df[scale_cols] = scale.fit_transform(df[scale_cols])
df
```

Out[26]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Internet
0	0	0	1	0	0.013889	0	0	
1	1	0	0	0	0.472222	1	0	
2	1	0	0	0	0.027778	1	0	
3	1	0	0	0	0.625000	0	0	
4	0	0	0	0	0.027778	1	0	
...	...	...	...	...	...	...	...	
7038	1	0	1	1	0.333333	1	1	
7039	0	0	1	1	1.000000	1	1	
7040	0	0	1	1	0.152778	0	0	
7041	1	1	1	0	0.055556	1	1	
7042	1	0	0	0	0.916667	1	0	

7043 rows × 20 columns

In [27]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   gender            7043 non-null   int32  
 1   SeniorCitizen     7043 non-null   int64  
 2   Partner           7043 non-null   int64  
 3   Dependents        7043 non-null   int64  
 4   tenure            7043 non-null   float64
 5   PhoneService      7043 non-null   int64  
 6   MultipleLines     7043 non-null   int64  
 7   InternetService   7043 non-null   float64
 8   OnlineSecurity    7043 non-null   int64  
 9   OnlineBackup      7043 non-null   int64  
 10  DeviceProtection  7043 non-null   int64  
 11  TechSupport       7043 non-null   int64  
 12  StreamingTV       7043 non-null   int64  
 13  StreamingMovies   7043 non-null   int64  
 14  Contract          7043 non-null   float64
 15  PaperlessBilling  7043 non-null   int64  
 16  PaymentMethod     7043 non-null   float64
 17  MonthlyCharges    7043 non-null   float64
 18  TotalCharges      7043 non-null   float64
 19  Churn             7043 non-null   int64  
dtypes: float64(6), int32(1), int64(13)
memory usage: 1.0 MB
```

Independent and Dependent variables

In [28]:

```
# independent and dependent variables
x = df.drop('Churn',axis=1)
y = df['Churn']
```

Splitting data

In [29]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.2,random_state=10)
print(xtrain.shape)
print(xtest.shape)
```

```
(5634, 19)
(1409, 19)
```

1. Building Neural Network for Customer Churn Data

In [30]:
```
# import tensorflow
import tensorflow as tf
#import keras
from tensorflow import keras
```

Define Model

In [31]:
```
# define se`quential model
model = keras.Sequential([
    # input layer
    keras.layers.Dense(19, input_shape=(19,), activation='relu'),
    keras.layers.Dense(15, activation='relu'),
    keras.layers.Dense(10,activation = 'relu'),
    # we use sigmoid for binary output
    # output layer
    keras.layers.Dense(1, activation='sigmoid')
]
)
```

In [32]:
```
# xtrain = np.array(xtrain, dtype=np.float32)  # Example: Convert xtrain to float32
# ytrain = np.array(ytrain, dtype=np.float32)  # Example: Convert ytrain to float32
```

Compile the Customer Churn Model

In [33]:
```
# time for compilation of neural net.
model.compile(optimizer = 'adam',
             loss = 'binary_crossentropy',
             metrics = ['accuracy'])
# now we fit our model to training data
model.fit(xtrain,ytrain,epochs=100)
```

```
Epoch 1/100
177/177 [==============================] - 3s 4ms/step - loss: 0.5090 - accuracy: 
0.7428
Epoch 2/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4403 - accuracy: 
0.7836
Epoch 3/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4340 - accuracy: 
0.7943
Epoch 4/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4296 - accuracy: 
0.7962
Epoch 5/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4287 - accuracy: 
0.7962
Epoch 6/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4251 - accuracy: 
0.8016
Epoch 7/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4240 - accuracy: 
0.7985
Epoch 8/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4233 - accuracy: 
0.8012
Epoch 9/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4199 - accuracy: 
0.8055
Epoch 10/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4198 - accuracy: 
0.8037
Epoch 11/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4195 - accuracy: 
0.8032
Epoch 12/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4181 - accuracy: 
0.8042
Epoch 13/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4175 - accuracy: 
0.8035
Epoch 14/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4176 - accuracy: 
0.8035
Epoch 15/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4155 - accuracy: 
0.8076
Epoch 16/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4148 - accuracy: 
0.8065
Epoch 17/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4136 - accuracy: 
0.8048
Epoch 18/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4152 - accuracy: 
0.8083
Epoch 19/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4156 - accuracy: 
0.8076
Epoch 20/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4131 - accuracy: 
0.8094
Epoch 21/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4128 - accuracy: 
0.8071
Epoch 22/100
```

```
177/177 [==============================] - 1s 6ms/step - loss: 0.4122 - accuracy:
0.8074
Epoch 23/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4116 - accuracy:
0.8074
Epoch 24/100
177/177 [==============================] - 1s 7ms/step - loss: 0.4101 - accuracy:
0.8072
Epoch 25/100
177/177 [==============================] - 1s 8ms/step - loss: 0.4094 - accuracy:
0.8092
Epoch 26/100
177/177 [==============================] - 1s 7ms/step - loss: 0.4109 - accuracy:
0.8094
Epoch 27/100
177/177 [==============================] - 1s 7ms/step - loss: 0.4105 - accuracy:
0.8062
Epoch 28/100
177/177 [==============================] - 1s 7ms/step - loss: 0.4085 - accuracy:
0.8101
Epoch 29/100
177/177 [==============================] - 1s 7ms/step - loss: 0.4079 - accuracy:
0.8099
Epoch 30/100
177/177 [==============================] - 1s 7ms/step - loss: 0.4072 - accuracy:
0.8094
Epoch 31/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4078 - accuracy:
0.8115
Epoch 32/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4056 - accuracy:
0.8110
Epoch 33/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4060 - accuracy:
0.8117
Epoch 34/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4062 - accuracy:
0.8101
Epoch 35/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4074 - accuracy:
0.8081
Epoch 36/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4047 - accuracy:
0.8104
Epoch 37/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4046 - accuracy:
0.8110
Epoch 38/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4041 - accuracy:
0.8094
Epoch 39/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4041 - accuracy:
0.8140
Epoch 40/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4043 - accuracy:
0.8119
Epoch 41/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4033 - accuracy:
0.8108
Epoch 42/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4021 - accuracy:
0.8104
Epoch 43/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4022 - accuracy:
```

```
0.8127
Epoch 44/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4029 - accuracy:
0.8133
Epoch 45/100
177/177 [==============================] - 1s 6ms/step - loss: 0.4004 - accuracy:
0.8149
Epoch 46/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4011 - accuracy:
0.8165
Epoch 47/100
177/177 [==============================] - 1s 4ms/step - loss: 0.4018 - accuracy:
0.8135
Epoch 48/100
177/177 [==============================] - 1s 3ms/step - loss: 0.3995 - accuracy:
0.8138
Epoch 49/100
177/177 [==============================] - 1s 3ms/step - loss: 0.4002 - accuracy:
0.8136
Epoch 50/100
177/177 [==============================] - 1s 3ms/step - loss: 0.3998 - accuracy:
0.8154
Epoch 51/100
177/177 [==============================] - 1s 3ms/step - loss: 0.3994 - accuracy:
0.8159
Epoch 52/100
177/177 [==============================] - 1s 3ms/step - loss: 0.3996 - accuracy:
0.8110
Epoch 53/100
177/177 [==============================] - 1s 3ms/step - loss: 0.3980 - accuracy:
0.8165
Epoch 54/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3975 - accuracy:
0.8143
Epoch 55/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3963 - accuracy:
0.8133
Epoch 56/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3968 - accuracy:
0.8161
Epoch 57/100
177/177 [==============================] - 1s 6ms/step - loss: 0.3962 - accuracy:
0.8166
Epoch 58/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3970 - accuracy:
0.8143
Epoch 59/100
177/177 [==============================] - 1s 6ms/step - loss: 0.3957 - accuracy:
0.8131
Epoch 60/100
177/177 [==============================] - 1s 6ms/step - loss: 0.3966 - accuracy:
0.8168
Epoch 61/100
177/177 [==============================] - 1s 6ms/step - loss: 0.3959 - accuracy:
0.8136
Epoch 62/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3937 - accuracy:
0.8177
Epoch 63/100
177/177 [==============================] - 1s 6ms/step - loss: 0.3942 - accuracy:
0.8174
Epoch 64/100
177/177 [==============================] - 1s 5ms/step - loss: 0.3938 - accuracy:
0.8147
```

```
Epoch 65/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3945 - accuracy:
0.8158
Epoch 66/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3935 - accuracy:
0.8152
Epoch 67/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3939 - accuracy:
0.8172
Epoch 68/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3923 - accuracy:
0.8166
Epoch 69/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3925 - accuracy:
0.8163
Epoch 70/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3931 - accuracy:
0.8175
Epoch 71/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3926 - accuracy:
0.8197
Epoch 72/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3912 - accuracy:
0.8198
Epoch 73/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3922 - accuracy:
0.8154
Epoch 74/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3897 - accuracy:
0.8197
Epoch 75/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3921 - accuracy:
0.8143
Epoch 76/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3901 - accuracy:
0.8154
Epoch 77/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3897 - accuracy:
0.8182
Epoch 78/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3883 - accuracy:
0.8198
Epoch 79/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3883 - accuracy:
0.8195
Epoch 80/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3888 - accuracy:
0.8213
Epoch 81/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3895 - accuracy:
0.8163
Epoch 82/100
177/177 [==============================] - 1s 4ms/step - loss: 0.3882 - accuracy:
0.8207
Epoch 83/100
177/177 [==============================] - 1s 6ms/step - loss: 0.3870 - accuracy:
0.8248
Epoch 84/100
177/177 [==============================] - 1s 6ms/step - loss: 0.3865 - accuracy:
0.8193
Epoch 85/100
177/177 [==============================] - 1s 6ms/step - loss: 0.3866 - accuracy:
0.8172
Epoch 86/100
```

```
177/177 [==============================] - 1s 8ms/step - loss: 0.3866 - accuracy: 
0.8182
Epoch 87/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3869 - accuracy: 
0.8204
Epoch 88/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3860 - accuracy: 
0.8186
Epoch 89/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3865 - accuracy: 
0.8166
Epoch 90/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3870 - accuracy: 
0.8191
Epoch 91/100
177/177 [==============================] - 1s 8ms/step - loss: 0.3844 - accuracy: 
0.8202
Epoch 92/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3844 - accuracy: 
0.8223
Epoch 93/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3849 - accuracy: 
0.8227
Epoch 94/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3861 - accuracy: 
0.8207
Epoch 95/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3840 - accuracy: 
0.8232
Epoch 96/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3829 - accuracy: 
0.8220
Epoch 97/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3839 - accuracy: 
0.8220
Epoch 98/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3828 - accuracy: 
0.8222
Epoch 99/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3821 - accuracy: 
0.8248
Epoch 100/100
177/177 [==============================] - 1s 7ms/step - loss: 0.3815 - accuracy: 
0.8216
```

Out[33]:

```
<keras.src.callbacks.History at 0x14ef7380790>
```

evalute the model

In [34]:

```
model.evaluate(xtest,ytest)
```

```
45/45 [==============================] - 1s 3ms/step - loss: 0.4320 - accuracy: 0.
7800
```

Out[34]:

```
[0.4320320785045624, 0.779985785484314]
```

predict the churn values

In [35]:

```
# predict the churn values
ypred = model.predict(xtest)
print(ypred)
# unscaling the ypred values
ypred_lis = []
```

```
for i in ypred:
    if i>0.5:
        ypred_lis.append(1)
    else:
        ypred_lis.append(0)
print(ypred_lis)
```

```
45/45 [==============================] - 0s 5ms/step
[[0.30121344]
 [0.96312666]
 [0.22262603]
 ...
 [0.2961771 ]
 [0.11197827]
 [0.9920137 ]]
[0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0,
0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1,
0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0,
0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0,
1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0,
1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
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1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0,
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1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
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1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0,
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0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0,
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0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0,
0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
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1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0,
0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1,
1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0,
0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0,
1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1,
0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0,
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1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0,
0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1,
0, 0, 0, 0, 1]
```

In [36]:
```
#make dataframe for comparing the orignal and predict values
data = {'orignal_churn':ytest, 'predicted_churn':ypred_lis}
```

```
df_check = pd.DataFrame(data)
df_check.head(10)
```

Out[36]:

	orignal_churn	predicted_churn
6418	0	0
1948	1	1
4497	0	0
66	0	0
1705	0	0
924	0	0
1051	0	0
7012	0	0
3723	0	0
4590	0	0

Performance Matrices

In [37]:

```
# checking for performance metrices
#importing classification_report and confusion metrics
from sklearn.metrics import confusion_matrix, classification_report
#print classification_report
print(classification_report(ytest,ypred_lis))
```

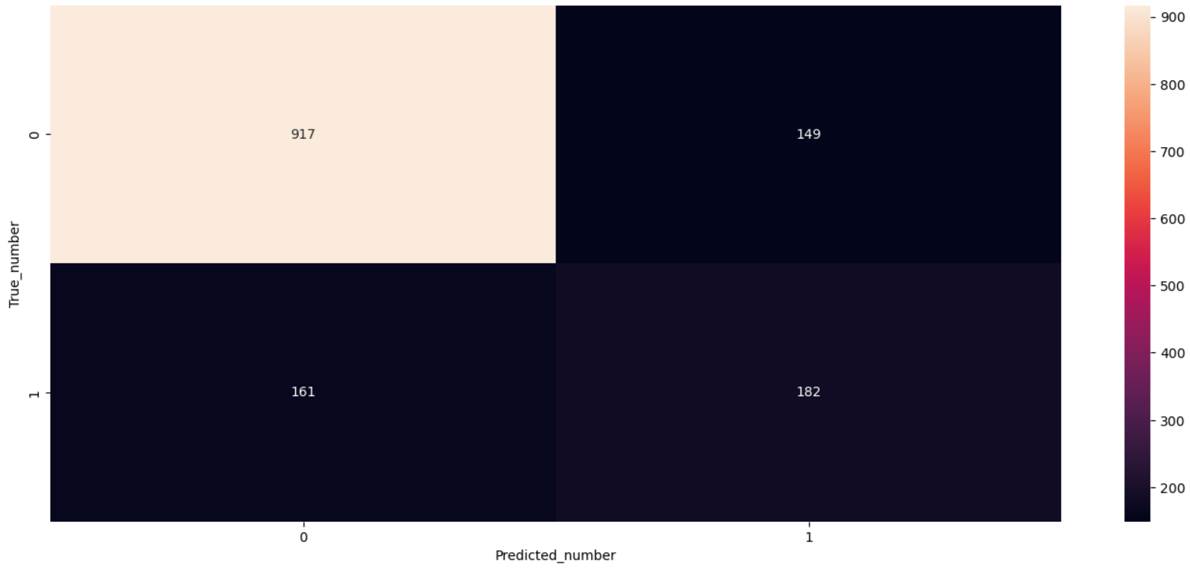
```
              precision    recall  f1-score   support

           0       0.85      0.86      0.86      1066
           1       0.55      0.53      0.54       343

    accuracy                           0.78      1409
   macro avg       0.70      0.70      0.70      1409
weighted avg       0.78      0.78      0.78      1409
```

In [38]:

```
# ploting the confusion metrix plot
conf_mat = confusion_matrix(ytest, ypred_lis)
# conf_mat = df.confusion_matrix(labels=ytest,predictions=ypred_lis)
plt.figure(figsize = (17,7))
sns.heatmap(conf_mat, annot=True,fmt='d')
plt.xlabel('Predicted_number')
plt.ylabel('True_number')
```

Out[38]:

```
Text(183.22222222222223, 0.5, 'True_number')
```



Independent and Dependent

In [39]:
```
x=df.drop(columns=['Churn'],axis=1)
y=df['Churn']
```

In [40]:
```
y.value_counts()# imbalance
```

Out[40]:
```
Churn
0    5174
1    1869
Name: count, dtype: int64
```

In [41]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=44)

print(f"the shape of x_train is : {x_train.shape}")
print(f'the shape of x_test is : {x_test.shape}')
print(f'the shape of y_tain is : {y_train.shape}')
print(f'the shape of y_test is {y_test.shape}')
```

```
the shape of x_train is : (5282, 19)
the shape of x_test is : (1761, 19)
the shape of y_tain is : (5282,)
the shape of y_test is (1761,)
```

2.Decision Tree Classifier

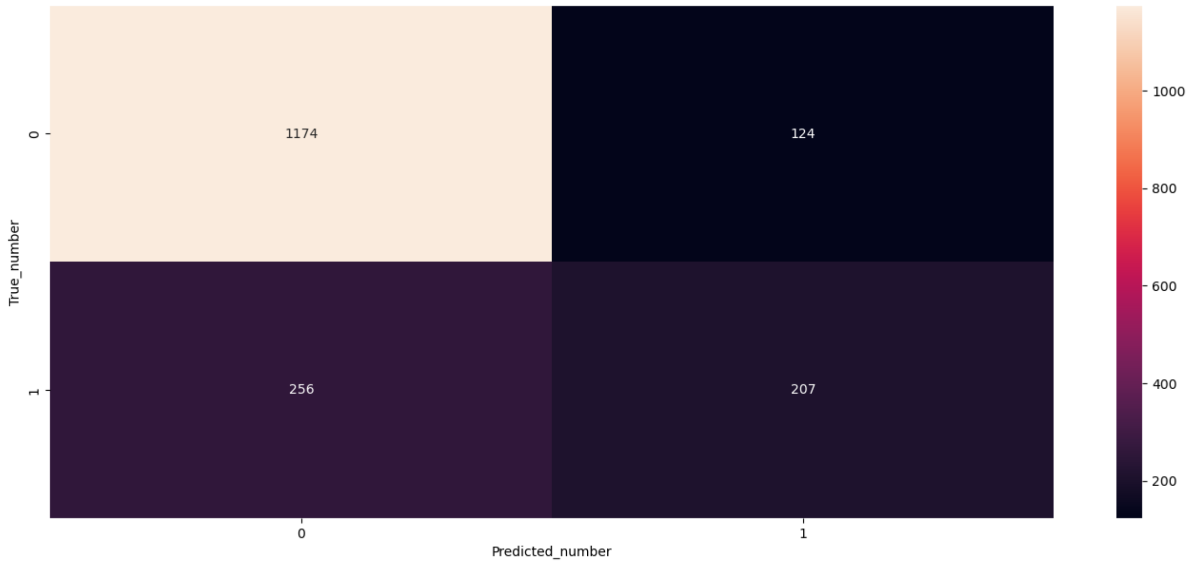
In [42]:
```
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier(criterion="entropy", max_depth = 4)
model2=dt.fit(x_train,y_train)
```

In [43]:
```
y_pred=model2.predict(x_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.90      0.86      1298
           1       0.63      0.45      0.52       463

    accuracy                           0.78      1761
   macro avg       0.72      0.68      0.69      1761
weighted avg       0.77      0.78      0.77      1761
```

In [44]:
```
# ploting the confusion metrix plot
conf_mat = confusion_matrix(y_test, y_pred)
# conf_mat = df.confusion_matrix(labels=ytest,predictions=ypred_lis)
plt.figure(figsize = (17,7))
sns.heatmap(conf_mat, annot=True,fmt='d')
plt.xlabel('Predicted_number')
plt.ylabel('True_number')
```

Out[44]:
```
Text(183.22222222222223, 0.5, 'True_number')
```



3.Logistics Regression

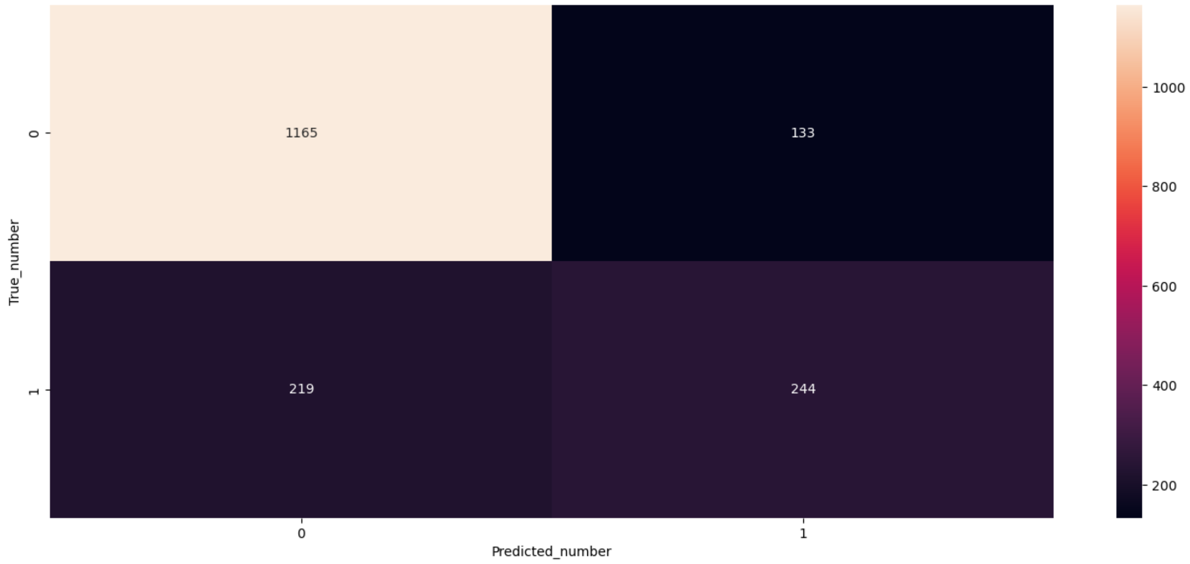
In [45]:
```
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()
model3=lr.fit(x_train,y_train)
```

In [46]:
```
y_pred=model3.predict(x_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1298
           1       0.65      0.53      0.58       463

    accuracy                           0.80      1761
   macro avg       0.74      0.71      0.72      1761
weighted avg       0.79      0.80      0.79      1761
```

In [47]:
```
# ploting the confusion metrix plot
conf_mat = confusion_matrix(y_test, y_pred)
# conf_mat = df.confusion_matrix(labels=ytest,predictions=ypred_lis)
plt.figure(figsize = (17,7))
sns.heatmap(conf_mat, annot=True,fmt='d')
plt.xlabel('Predicted_number')
plt.ylabel('True_number')
```

Out[47]:
```
Text(183.22222222222223, 0.5, 'True_number')
```



4.Random Forest Classifier

In [48]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=44)
```

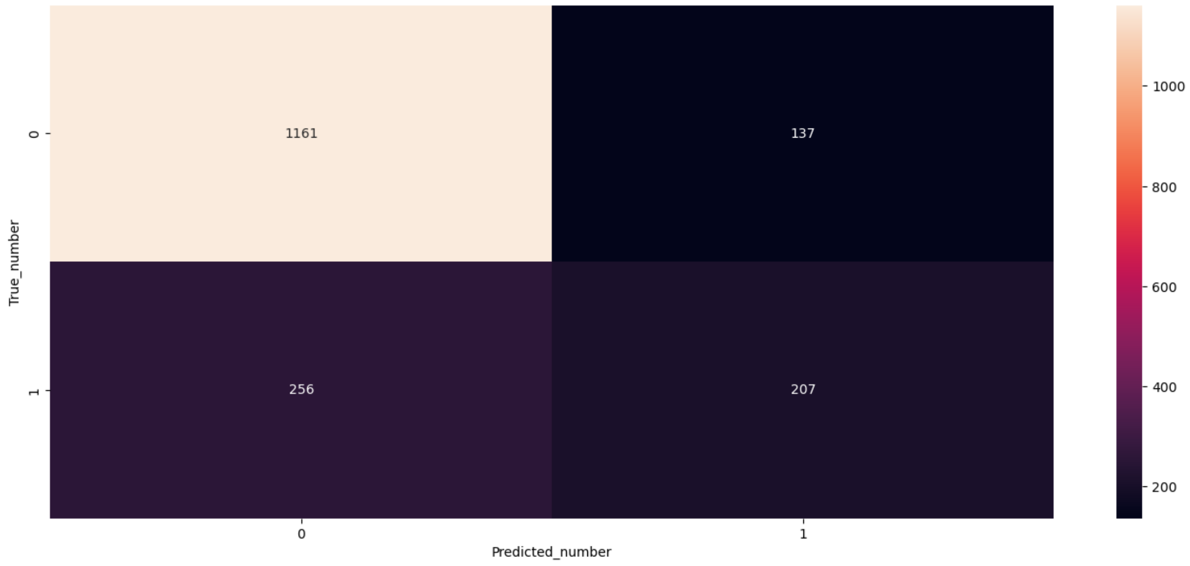
In [49]:
```
# Create a Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

# Fit the model to the resampled training data
rf_classifier.fit(x_train, y_train)

# Make predictions on the test data
y_pred = rf_classifier.predict(x_test)
```

In [50]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.89      0.86      1298
           1       0.60      0.45      0.51       463

    accuracy                           0.78      1761
   macro avg       0.71      0.67      0.68      1761
weighted avg       0.76      0.78      0.77      1761
```

In [51]:
```
# ploting the confusion metrix plot
conf_mat = confusion_matrix(y_test, y_pred)
# conf_mat = df.confusion_matrix(labels=ytest,predictions=ypred_lis)
plt.figure(figsize = (17,7))
sns.heatmap(conf_mat, annot=True,fmt='d')
plt.xlabel('Predicted_number')
plt.ylabel('True_number')
```

Out[51]:
```
Text(183.22222222222223, 0.5, 'True_number')
```



5. SVM

In [52]:
```
from sklearn.svm import SVC
from sklearn.metrics import classification_report
```

In [53]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=44)
# Create an SVM classifier
svm_classifier = SVC(kernel='linear', C=1, random_state=42)

# Fit the SVM model to the training data
svm_classifier.fit(x_train, y_train)
```

Out[53]:
```
SVC
SVC(C=1, kernel='linear', random_state=42)
```

In [54]:
```
# Make predictions on the test data
y_pred_svm = svm_classifier.predict(x_test)

# Generate a classification report for the SVM model
svm_classification_report = classification_report(y_test, y_pred_svm)
```

In [55]:
```
# Print the classification report for the SVM model
print("SVM Classifier Classification Report:")
print(svm_classification_report)
```

```
SVM Classifier Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.89      0.87      1298
           1       0.65      0.55      0.59       463

    accuracy                           0.80      1761
   macro avg       0.75      0.72      0.73      1761
weighted avg       0.80      0.80      0.80      1761
```

In [56]:
```
# ploting the confusion metrix plot
conf_mat = confusion_matrix(y_test, y_pred)
# conf_mat = df.confusion_matrix(labels=ytest,predictions=ypred_lis)
plt.figure(figsize = (17,7))
sns.heatmap(conf_mat, annot=True,fmt='d')
```

```
plt.xlabel('Predicted_number')
plt.ylabel('True_number')
```

Out[56]: Text(183.22222222222223, 0.5, 'True_number')