**ML - Assignment : CAP – 1**

**Dataset selected : *Telco-Customer Churn Database***

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**Submitted By:  *Shashwat Srivastava***

**Code:**

#importing the libraries  
import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt

#read the dataset  
data = pd.read\_csv('/content/WA\_Fn-UseC\_-Telco-Customer-Churn.csv')

data.head()

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]

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

data.describe()

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

#printing all the unique values of the columns  
for columns in data.columns:  
 print("Columns : {} Unique Values: {}" .format(columns, data[columns].unique()))

Columns : customerID Unique Values: ['7590-VHVEG' '5575-GNVDE' '3668-QPYBK' ... '4801-JZAZL' '8361-LTMKD'  
 '3186-AJIEK']  
Columns : gender Unique Values: ['Female' 'Male']  
Columns : SeniorCitizen Unique Values: [0 1]  
Columns : Partner Unique Values: ['Yes' 'No']  
Columns : Dependents Unique Values: ['No' 'Yes']  
Columns : tenure Unique Values: [ 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 0  
 39]  
Columns : PhoneService Unique Values: ['No' 'Yes']  
Columns : MultipleLines Unique Values: ['No phone service' 'No' 'Yes']  
Columns : InternetService Unique Values: ['DSL' 'Fiber optic' 'No']  
Columns : OnlineSecurity Unique Values: ['No' 'Yes' 'No internet service']  
Columns : OnlineBackup Unique Values: ['Yes' 'No' 'No internet service']  
Columns : DeviceProtection Unique Values: ['No' 'Yes' 'No internet service']  
Columns : TechSupport Unique Values: ['No' 'Yes' 'No internet service']  
Columns : StreamingTV Unique Values: ['No' 'Yes' 'No internet service']  
Columns : StreamingMovies Unique Values: ['No' 'Yes' 'No internet service']  
Columns : Contract Unique Values: ['Month-to-month' 'One year' 'Two year']  
Columns : PaperlessBilling Unique Values: ['Yes' 'No']  
Columns : PaymentMethod Unique Values: ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'  
 'Credit card (automatic)']  
Columns : MonthlyCharges Unique Values: [29.85 56.95 53.85 ... 63.1 44.2 78.7 ]  
Columns : TotalCharges Unique Values: ['29.85' '1889.5' '108.15' ... '346.45' '306.6' '6844.5']  
Columns : Churn Unique Values: ['No' 'Yes']

#we found that Customer ID is of no use so we drop it  
data.drop(columns = "customerID", inplace = True)

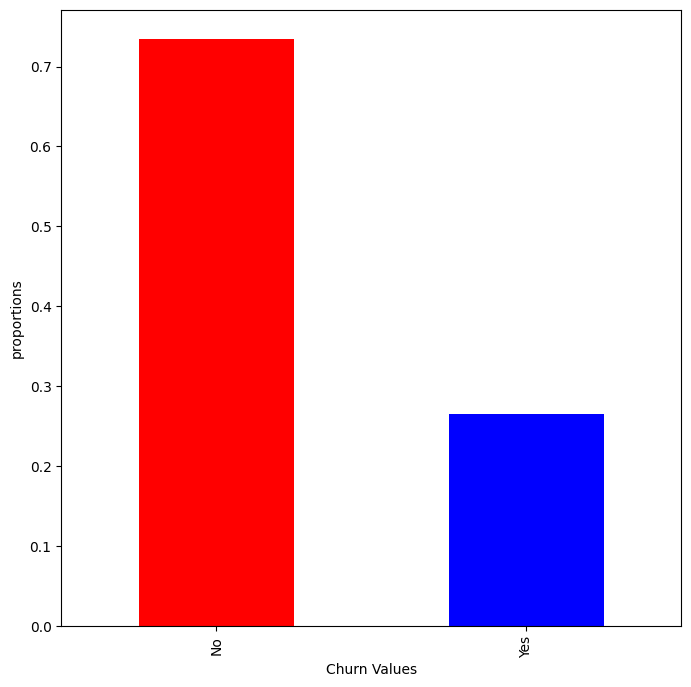
data.head()

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   
  
 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   
  
 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   
  
 PaperlessBilling PaymentMethod MonthlyCharges TotalCharges \  
0 Yes Electronic check 29.85 29.85   
1 No Mailed check 56.95 1889.5   
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   
  
 Churn   
0 No   
1 No   
2 Yes   
3 No   
4 Yes

Data Visualisation

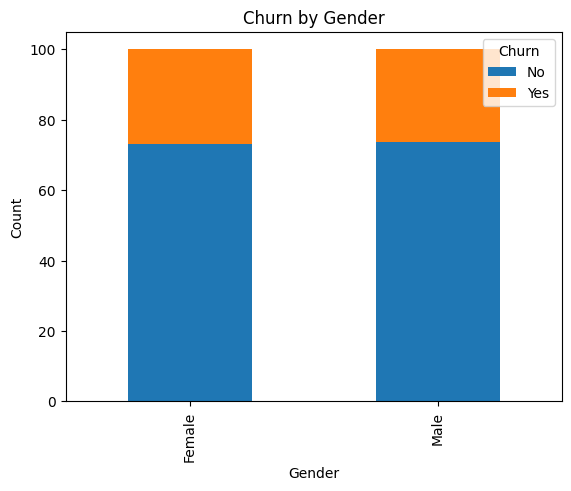
#creating a plot between churn and observation  
fig = plt.figure(figsize = (8,8))  
ax = fig.add\_subplot(111)  
  
proportion = data['Churn'].value\_counts(normalize = True)  
  
proportion.plot(kind = 'bar', ax=ax,color = ['red',"blue"])  
ax.set\_xlabel('Churn Values')  
ax.set\_ylabel('proportions')

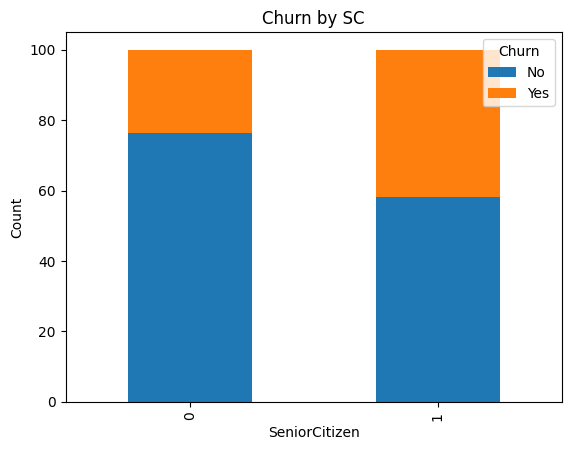
Text(0, 0.5, 'proportions')

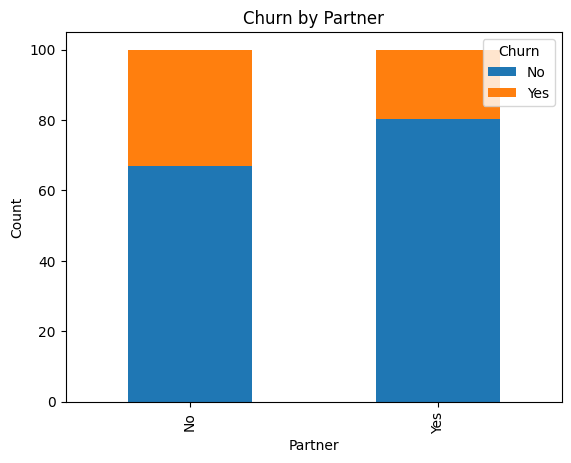


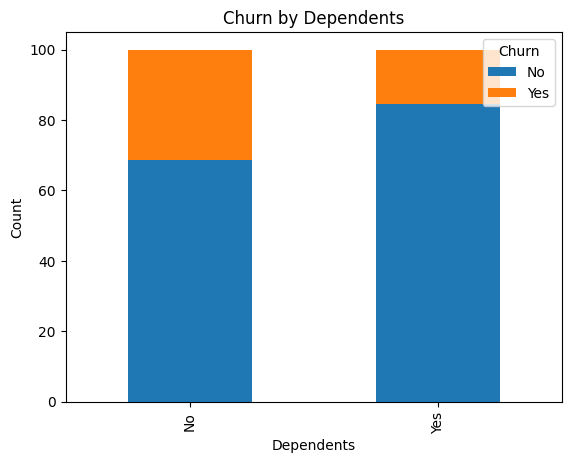
**Data Visualization for Demographic Attributes**

# Plot of Gender vs Churn  
grouped\_data = pd.crosstab(data['gender'], data['Churn']).apply(lambda x: x/x.sum()\*100, axis=1)  
  
# Plotting the stacked bar chart  
fig, ax = plt.subplots()  
grouped\_data.plot(kind='bar', stacked=True, ax=ax)  
  
# Customizing the chart labels and title  
ax.set\_xlabel('Gender')  
ax.set\_ylabel('Count')  
ax.set\_title('Churn by Gender')  
  
# Adding a legend  
ax.legend(title='Churn', loc='upper right')  
  
# Displaying the chart  
plt.show()  
  
  
# Plot SeniorCitizen vs Churn  
  
grouped\_data = pd.crosstab(data['SeniorCitizen'], data['Churn']).apply(lambda x: x/x.sum()\*100, axis=1)  
  
# Plotting the stacked bar chart  
fig, ax = plt.subplots()  
grouped\_data.plot(kind='bar', stacked=True, ax=ax)  
  
# Customizing the chart labels and title  
ax.set\_xlabel('SeniorCitizen')  
ax.set\_ylabel('Count')  
ax.set\_title('Churn by SC')  
  
# Adding a legend  
ax.legend(title='Churn', loc='upper right')  
  
# Displaying the chart  
plt.show()  
  
  
# Plot Partner vs Churn  
  
grouped\_data = pd.crosstab(data['Partner'], data['Churn']).apply(lambda x: x/x.sum()\*100, axis=1)  
  
# Plotting the stacked bar chart  
fig, ax = plt.subplots()  
grouped\_data.plot(kind='bar', stacked=True, ax=ax)  
  
# Customizing the chart labels and title  
ax.set\_xlabel('Partner')  
ax.set\_ylabel('Count')  
ax.set\_title('Churn by Partner')  
  
# Adding a legend  
ax.legend(title='Churn', loc='upper right')  
  
# Displaying the chart  
plt.show()  
  
  
# Plot Dependent vs Churn  
  
grouped\_data = pd.crosstab(data['Dependents'], data['Churn']).apply(lambda x: x/x.sum()\*100, axis=1)  
  
# Plotting the stacked bar chart  
fig, ax = plt.subplots()  
grouped\_data.plot(kind='bar', stacked=True, ax=ax)  
  
# Customizing the chart labels and title  
ax.set\_xlabel('Dependents')  
ax.set\_ylabel('Count')  
ax.set\_title('Churn by Dependents')  
  
# Adding a legend  
ax.legend(title='Churn', loc='upper right')  
  
# Displaying the chart  
plt.show()



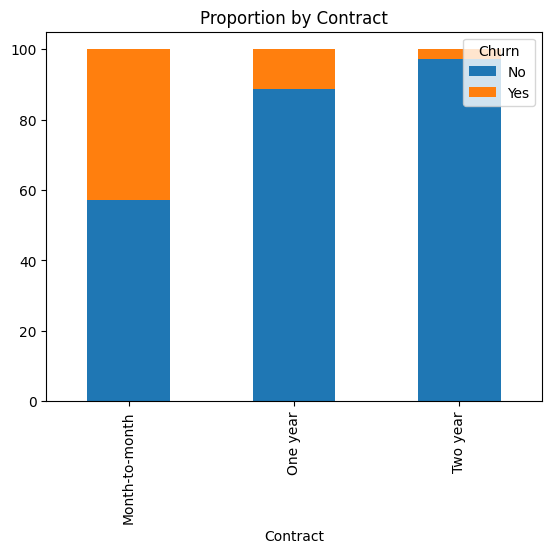


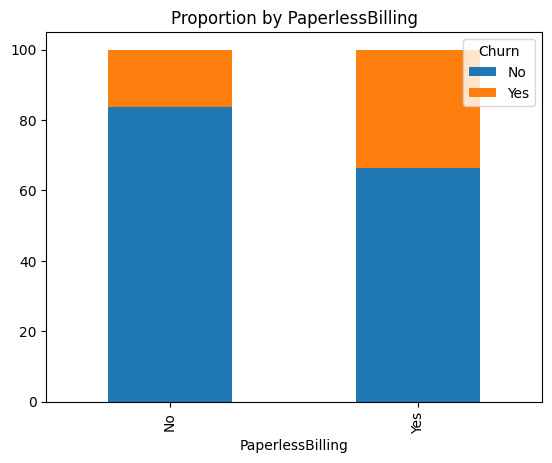


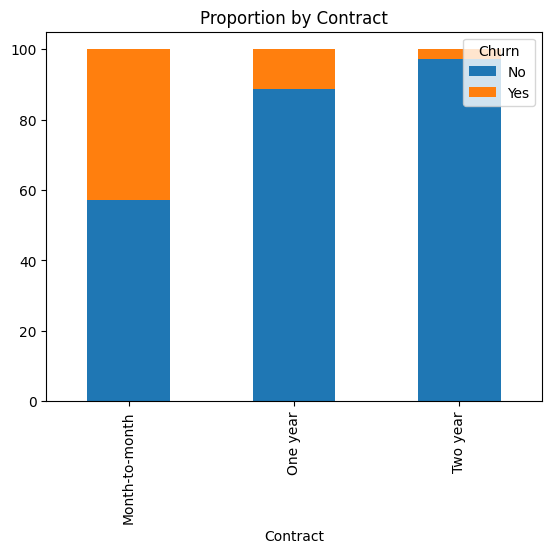


**Data Visualisation for categorical variable : using stacked bar charts**

#for Contract  
grouped\_data = pd.crosstab(data['Contract'], data['Churn']).apply(lambda x: x/x.sum()\*100, axis=1)  
  
# Plotting the stacked bar chart  
fig, ax = plt.subplots()  
grouped\_data.plot(kind='bar', stacked=True, ax=ax)  
  
# Customizing the chart labels and title  
ax.set\_title('Proportion by Contract')  
  
# Adding a legend  
ax.legend(title='Churn', loc='upper right')  
  
# Displaying the chart  
plt.show()  
  
#for PaperlessBilling  
grouped\_data = pd.crosstab(data['PaperlessBilling'], data['Churn']).apply(lambda x: x/x.sum()\*100, axis=1)  
  
# Plotting the stacked bar chart  
fig, ax = plt.subplots()  
grouped\_data.plot(kind='bar', stacked=True, ax=ax)  
  
# Customizing the chart labels and title  
ax.set\_title('Proportion by PaperlessBilling')  
  
# Adding a legend  
ax.legend(title='Churn', loc='upper right')  
  
# Displaying the chart  
plt.show()  
  
#for PaymentMethod  
grouped\_data = pd.crosstab(data['Contract'], data['Churn']).apply(lambda x: x/x.sum()\*100, axis=1)  
  
# Plotting the stacked bar chart  
fig, ax = plt.subplots()  
grouped\_data.plot(kind='bar', stacked=True, ax=ax)  
  
# Customizing the chart labels and title  
ax.set\_title('Proportion by Contract')  
  
# Adding a legend  
ax.legend(title='Churn', loc='upper right')  
  
# Displaying the chart  
plt.show()

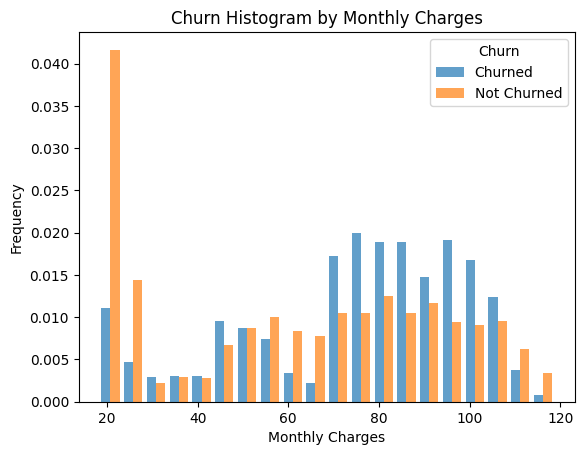


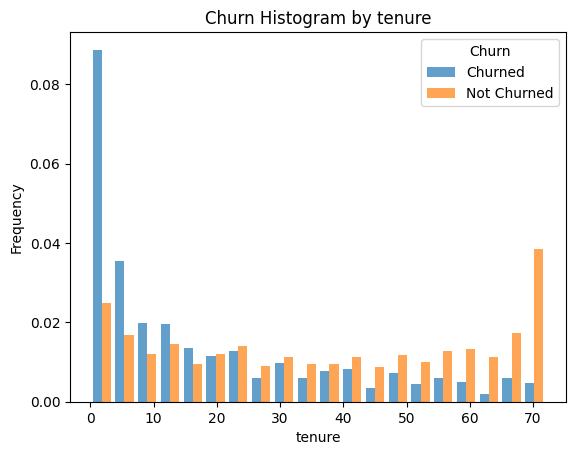


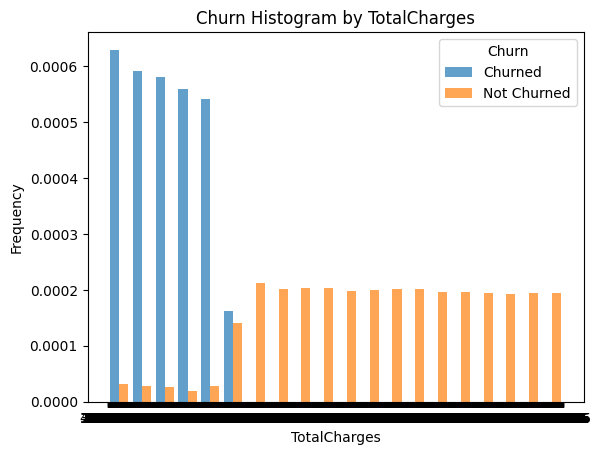


**Data Visualisation for Continuous Variables : using Histograms**

#for MonthlyCharges  
churned = data[data['Churn'] == 'Yes']['MonthlyCharges']  
not\_churned = data[data['Churn'] == 'No']['MonthlyCharges']  
  
# Plotting the histograms  
fig, ax = plt.subplots()  
  
ax.hist([churned, not\_churned],density = True, bins=20, alpha=0.7, label=['Churned', 'Not Churned'])  
  
# Customizing the chart labels and title  
ax.set\_xlabel('Monthly Charges')  
ax.set\_ylabel('Frequency')  
ax.set\_title('Churn Histogram by Monthly Charges')  
  
# Adding a legend  
ax.legend(title='Churn')  
  
# Displaying the chart  
plt.show()  
  
  
  
#for Tenure  
churned = data[data['Churn'] == 'Yes']['tenure']  
not\_churned = data[data['Churn'] == 'No']['tenure']  
  
# Plotting the histograms  
fig, ax = plt.subplots()  
  
ax.hist([churned, not\_churned],density = True, bins=20, alpha=0.7, label=['Churned', 'Not Churned'])  
  
# Customizing the chart labels and title  
ax.set\_xlabel('tenure')  
ax.set\_ylabel('Frequency')  
ax.set\_title('Churn Histogram by tenure')  
  
# Adding a legend  
ax.legend(title='Churn')  
  
# Displaying the chart  
plt.show()  
  
  
  
#for TotalCharges  
churned = data[data['Churn'] == 'Yes']['TotalCharges']  
not\_churned = data[data['Churn'] == 'No']['TotalCharges']  
  
# Plotting the histograms  
fig, ax = plt.subplots()  
  
ax.hist([churned, not\_churned],density = True, bins=20, alpha=0.7, label=['Churned', 'Not Churned'])  
  
# Customizing the chart labels and title  
ax.set\_xlabel('TotalCharges')  
ax.set\_ylabel('Frequency')  
ax.set\_title('Churn Histogram by TotalCharges')  
  
# Adding a legend  
ax.legend(title='Churn')  
  
# Displaying the chart  
plt.show()







**Encoding**

# label Encoding for all the Binary Categoricals  
df= data.copy()  
  
# label encoding (binary variables)  
labels = ['gender', 'Partner', 'Dependents', 'PaperlessBilling', 'PhoneService', 'Churn']  
  
# encode categorical binary features using label encoding  
for column in labels:  
 if column == 'gender':  
 df[column] = df[column].map({'Female': 1, 'Male': 0})  
 else:  
 df[column] = df[column].map({'Yes': 1, 'No': 0})

#One Hot Encoding for all other categoricals  
others = ['MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',  
 'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract', 'PaymentMethod']  
  
df = pd.get\_dummies(df, columns = others)

**Normalization**

normalize = ['tenure', 'MonthlyCharges']  
for column in normalize:  
 # minimum value of the column  
 min\_column = df[column].min()  
 # maximum value of the column  
 max\_column = df[column].max()  
 # min max scaler  
 df[column] = (df[column] - min\_column) / (max\_column - min\_column)

#finding Correlation among the features  
cor = df.corr()  
cor

<ipython-input-17-84f308fa91b0>:2: FutureWarning: The default value of numeric\_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric\_only to silence this warning.  
 cor = df.corr()

gender SeniorCitizen Partner \  
gender 1.000000 0.001874 0.001808   
SeniorCitizen 0.001874 1.000000 0.016479   
Partner 0.001808 0.016479 1.000000   
Dependents -0.010517 -0.211185 0.452676   
tenure -0.005106 0.016567 0.379697   
PhoneService 0.006488 0.008576 0.017706   
PaperlessBilling 0.011754 0.156530 -0.014877   
MonthlyCharges 0.014569 0.220173 0.096848   
Churn 0.008612 0.150889 -0.150448   
MultipleLines\_No -0.004476 -0.136213 -0.129929   
MultipleLines\_No phone service -0.006488 -0.008576 -0.017706   
MultipleLines\_Yes 0.008414 0.142948 0.142057   
InternetService\_DSL -0.006568 -0.108322 -0.000851   
InternetService\_Fiber optic 0.011286 0.255338 0.000304   
InternetService\_No -0.006026 -0.182742 0.000615   
OnlineSecurity\_No -0.010429 0.185532 -0.129936   
OnlineSecurity\_No internet service -0.006026 -0.182742 0.000615   
OnlineSecurity\_Yes 0.017021 -0.038653 0.143106   
OnlineBackup\_No -0.008191 0.087952 -0.136058   
OnlineBackup\_No internet service -0.006026 -0.182742 0.000615   
OnlineBackup\_Yes 0.013773 0.066572 0.141498   
DeviceProtection\_No 0.002988 0.094810 -0.147692   
DeviceProtection\_No internet service -0.006026 -0.182742 0.000615   
DeviceProtection\_Yes 0.002105 0.059428 0.153786   
TechSupport\_No -0.003397 0.205620 -0.109443   
TechSupport\_No internet service -0.006026 -0.182742 0.000615   
TechSupport\_Yes 0.009212 -0.060625 0.119999   
StreamingTV\_No -0.003267 0.049062 -0.124357   
StreamingTV\_No internet service -0.006026 -0.182742 0.000615   
StreamingTV\_Yes 0.008393 0.105378 0.124666   
StreamingMovies\_No -0.005374 0.034210 -0.117529   
StreamingMovies\_No internet service -0.006026 -0.182742 0.000615   
StreamingMovies\_Yes 0.010487 0.120176 0.117412   
Contract\_Month-to-month 0.003386 0.138360 -0.280865   
Contract\_One year -0.008026 -0.046262 0.082783   
Contract\_Two year 0.003695 -0.117000 0.248091   
PaymentMethod\_Bank transfer (automatic) 0.016024 -0.016159 0.110706   
PaymentMethod\_Credit card (automatic) -0.001215 -0.024135 0.082029   
PaymentMethod\_Electronic check -0.000752 0.171718 -0.083852   
PaymentMethod\_Mailed check -0.013744 -0.153477 -0.095125   
  
 Dependents tenure PhoneService \  
gender -0.010517 -0.005106 0.006488   
SeniorCitizen -0.211185 0.016567 0.008576   
Partner 0.452676 0.379697 0.017706   
Dependents 1.000000 0.159712 -0.001762   
tenure 0.159712 1.000000 0.008448   
PhoneService -0.001762 0.008448 1.000000   
PaperlessBilling -0.111377 0.006152 0.016505   
MonthlyCharges -0.113890 0.247900 0.247398   
Churn -0.164221 -0.352229 0.011942   
MultipleLines\_No 0.023198 -0.323088 0.315431   
MultipleLines\_No phone service 0.001762 -0.008448 -1.000000   
MultipleLines\_Yes -0.024526 0.331941 0.279690   
InternetService\_DSL 0.052010 0.013274 -0.452425   
InternetService\_Fiber optic -0.165818 0.019720 0.289999   
InternetService\_No 0.139812 -0.039062 0.172209   
OnlineSecurity\_No -0.188434 -0.263746 -0.057880   
OnlineSecurity\_No internet service 0.139812 -0.039062 0.172209   
OnlineSecurity\_Yes 0.080972 0.327203 -0.092893   
OnlineBackup\_No -0.138756 -0.312694 -0.092867   
OnlineBackup\_No internet service 0.139812 -0.039062 0.172209   
OnlineBackup\_Yes 0.023671 0.360277 -0.052312   
DeviceProtection\_No -0.129415 -0.312740 -0.074776   
DeviceProtection\_No internet service 0.139812 -0.039062 0.172209   
DeviceProtection\_Yes 0.013963 0.360653 -0.071227   
TechSupport\_No -0.172645 -0.262143 -0.054447   
TechSupport\_No internet service 0.139812 -0.039062 0.172209   
TechSupport\_Yes 0.063268 0.324221 -0.096340   
StreamingTV\_No -0.101176 -0.245039 -0.122455   
StreamingTV\_No internet service 0.139812 -0.039062 0.172209   
StreamingTV\_Yes -0.016558 0.279756 -0.022574   
StreamingMovies\_No -0.078198 -0.252220 -0.112254   
StreamingMovies\_No internet service 0.139812 -0.039062 0.172209   
StreamingMovies\_Yes -0.039741 0.286111 -0.032959   
Contract\_Month-to-month -0.231720 -0.645561 -0.000742   
Contract\_One year 0.068368 0.202570 -0.002791   
Contract\_Two year 0.204613 0.558533 0.003519   
PaymentMethod\_Bank transfer (automatic) 0.052021 0.243510 0.007556   
PaymentMethod\_Credit card (automatic) 0.060267 0.233006 -0.007721   
PaymentMethod\_Electronic check -0.150642 -0.208363 0.003062   
PaymentMethod\_Mailed check 0.059071 -0.233852 -0.003319   
  
 PaperlessBilling MonthlyCharges \  
gender 0.011754 0.014569   
SeniorCitizen 0.156530 0.220173   
Partner -0.014877 0.096848   
Dependents -0.111377 -0.113890   
tenure 0.006152 0.247900   
PhoneService 0.016505 0.247398   
PaperlessBilling 1.000000 0.352150   
MonthlyCharges 0.352150 1.000000   
Churn 0.191825 0.193356   
MultipleLines\_No -0.151864 -0.338314   
MultipleLines\_No phone service -0.016505 -0.247398   
MultipleLines\_Yes 0.163530 0.490434   
InternetService\_DSL -0.063121 -0.160189   
InternetService\_Fiber optic 0.326853 0.787066   
InternetService\_No -0.321013 -0.763557   
OnlineSecurity\_No 0.267793 0.360898   
OnlineSecurity\_No internet service -0.321013 -0.763557   
OnlineSecurity\_Yes -0.003636 0.296594   
OnlineBackup\_No 0.145120 0.210753   
OnlineBackup\_No internet service -0.321013 -0.763557   
OnlineBackup\_Yes 0.126735 0.441780   
DeviceProtection\_No 0.167121 0.171836   
DeviceProtection\_No internet service -0.321013 -0.763557   
DeviceProtection\_Yes 0.103797 0.482692   
TechSupport\_No 0.230136 0.322076   
TechSupport\_No internet service -0.321013 -0.763557   
TechSupport\_Yes 0.037880 0.338304   
StreamingTV\_No 0.047712 0.016951   
StreamingTV\_No internet service -0.321013 -0.763557   
StreamingTV\_Yes 0.223841 0.629603   
StreamingMovies\_No 0.059488 0.018075   
StreamingMovies\_No internet service -0.321013 -0.763557   
StreamingMovies\_Yes 0.211716 0.627429   
Contract\_Month-to-month 0.169096 0.060165   
Contract\_One year -0.051391 0.004904   
Contract\_Two year -0.147889 -0.074681   
PaymentMethod\_Bank transfer (automatic) -0.016332 0.042812   
PaymentMethod\_Credit card (automatic) -0.013589 0.030550   
PaymentMethod\_Electronic check 0.208865 0.271625   
PaymentMethod\_Mailed check -0.205398 -0.377437   
  
 Churn MultipleLines\_No ... \  
gender 0.008612 -0.004476 ...   
SeniorCitizen 0.150889 -0.136213 ...   
Partner -0.150448 -0.129929 ...   
Dependents -0.164221 0.023198 ...   
tenure -0.352229 -0.323088 ...   
PhoneService 0.011942 0.315431 ...   
PaperlessBilling 0.191825 -0.151864 ...   
MonthlyCharges 0.193356 -0.338314 ...   
Churn 1.000000 -0.032569 ...   
MultipleLines\_No -0.032569 1.000000 ...   
MultipleLines\_No phone service -0.011942 -0.315431 ...   
MultipleLines\_Yes 0.040102 -0.822853 ...   
InternetService\_DSL -0.124214 -0.070179 ...   
InternetService\_Fiber optic 0.308020 -0.190192 ...   
InternetService\_No -0.227890 0.310046 ...   
OnlineSecurity\_No 0.342637 -0.118040 ...   
OnlineSecurity\_No internet service -0.227890 0.310046 ...   
OnlineSecurity\_Yes -0.171226 -0.151950 ...   
OnlineBackup\_No 0.268005 -0.036277 ...   
OnlineBackup\_No internet service -0.227890 0.310046 ...   
OnlineBackup\_Yes -0.082255 -0.230852 ...   
DeviceProtection\_No 0.252481 -0.026746 ...   
DeviceProtection\_No internet service -0.227890 0.310046 ...   
DeviceProtection\_Yes -0.066160 -0.240960 ...   
TechSupport\_No 0.337281 -0.113482 ...   
TechSupport\_No internet service -0.227890 0.310046 ...   
TechSupport\_Yes -0.164674 -0.156425 ...   
StreamingTV\_No 0.128916 0.004913 ...   
StreamingTV\_No internet service -0.227890 0.310046 ...   
StreamingTV\_Yes 0.063228 -0.267528 ...   
StreamingMovies\_No 0.130845 0.013076 ...   
StreamingMovies\_No internet service -0.227890 0.310046 ...   
StreamingMovies\_Yes 0.061382 -0.275256 ...   
Contract\_Month-to-month 0.405103 0.086740 ...   
Contract\_One year -0.177820 0.002098 ...   
Contract\_Two year -0.302253 -0.102937 ...   
PaymentMethod\_Bank transfer (automatic) -0.117937 -0.070178 ...   
PaymentMethod\_Credit card (automatic) -0.134302 -0.063921 ...   
PaymentMethod\_Electronic check 0.301919 -0.080836 ...   
PaymentMethod\_Mailed check -0.091683 0.222605 ...   
  
 StreamingMovies\_No \  
gender -0.005374   
SeniorCitizen 0.034210   
Partner -0.117529   
Dependents -0.078198   
tenure -0.252220   
PhoneService -0.112254   
PaperlessBilling 0.059488   
MonthlyCharges 0.018075   
Churn 0.130845   
MultipleLines\_No 0.013076   
MultipleLines\_No phone service 0.112254   
MultipleLines\_Yes -0.080450   
InternetService\_DSL 0.295107   
InternetService\_Fiber optic 0.070650   
InternetService\_No -0.425339   
OnlineSecurity\_No 0.265304   
OnlineSecurity\_No internet service -0.425339   
OnlineSecurity\_Yes 0.094162   
OnlineBackup\_No 0.307200   
OnlineBackup\_No internet service -0.425339   
OnlineBackup\_Yes 0.047961   
DeviceProtection\_No 0.429545   
DeviceProtection\_No internet service -0.425339   
DeviceProtection\_Yes -0.079919   
TechSupport\_No 0.345993   
TechSupport\_No internet service -0.425339   
TechSupport\_Yes 0.004955   
StreamingTV\_No 0.537773   
StreamingTV\_No internet service -0.425339   
StreamingTV\_Yes -0.181135   
StreamingMovies\_No 1.000000   
StreamingMovies\_No internet service -0.425339   
StreamingMovies\_Yes -0.643815   
Contract\_Month-to-month 0.300457   
Contract\_One year -0.096726   
Contract\_Two year -0.257625   
PaymentMethod\_Bank transfer (automatic) -0.046705   
PaymentMethod\_Credit card (automatic) -0.049277   
PaymentMethod\_Electronic check 0.102571   
PaymentMethod\_Mailed check -0.021034   
  
 StreamingMovies\_No internet service \  
gender -0.006026   
SeniorCitizen -0.182742   
Partner 0.000615   
Dependents 0.139812   
tenure -0.039062   
PhoneService 0.172209   
PaperlessBilling -0.321013   
MonthlyCharges -0.763557   
Churn -0.227890   
MultipleLines\_No 0.310046   
MultipleLines\_No phone service -0.172209   
MultipleLines\_Yes -0.210564   
InternetService\_DSL -0.380635   
InternetService\_Fiber optic -0.465793   
InternetService\_No 1.000000   
OnlineSecurity\_No -0.522429   
OnlineSecurity\_No internet service 1.000000   
OnlineSecurity\_Yes -0.333403   
OnlineBackup\_No -0.464720   
OnlineBackup\_No internet service 1.000000   
OnlineBackup\_Yes -0.381593   
DeviceProtection\_No -0.465658   
DeviceProtection\_No internet service 1.000000   
DeviceProtection\_Yes -0.380754   
TechSupport\_No -0.518733   
TechSupport\_No internet service 1.000000   
TechSupport\_Yes -0.336298   
StreamingTV\_No -0.428504   
StreamingTV\_No internet service 1.000000   
StreamingTV\_Yes -0.415552   
StreamingMovies\_No -0.425339   
StreamingMovies\_No internet service 1.000000   
StreamingMovies\_Yes -0.418675   
Contract\_Month-to-month -0.218639   
Contract\_One year 0.038004   
Contract\_Two year 0.218278   
PaymentMethod\_Bank transfer (automatic) -0.002113   
PaymentMethod\_Credit card (automatic) 0.001030   
PaymentMethod\_Electronic check -0.284917   
PaymentMethod\_Mailed check 0.321361   
  
 StreamingMovies\_Yes \  
gender 0.010487   
SeniorCitizen 0.120176   
Partner 0.117412   
Dependents -0.039741   
tenure 0.286111   
PhoneService -0.032959   
PaperlessBilling 0.211716   
MonthlyCharges 0.627429   
Churn 0.061382   
MultipleLines\_No -0.275256   
MultipleLines\_No phone service 0.032959   
MultipleLines\_Yes 0.258751   
InternetService\_DSL 0.025698   
InternetService\_Fiber optic 0.322923   
InternetService\_No -0.418675   
OnlineSecurity\_No 0.175487   
OnlineSecurity\_No internet service -0.418675   
OnlineSecurity\_Yes 0.187398   
OnlineBackup\_No 0.084654   
OnlineBackup\_No internet service -0.418675   
OnlineBackup\_Yes 0.274501   
DeviceProtection\_No -0.037316   
DeviceProtection\_No internet service -0.418675   
DeviceProtection\_Yes 0.402111   
TechSupport\_No 0.091395   
TechSupport\_No internet service -0.418675   
TechSupport\_Yes 0.279358   
StreamingTV\_No -0.177328   
StreamingTV\_No internet service -0.418675   
StreamingTV\_Yes 0.533094   
StreamingMovies\_No -0.643815   
StreamingMovies\_No internet service -0.418675   
StreamingMovies\_Yes 1.000000   
Contract\_Month-to-month -0.116633   
Contract\_One year 0.064926   
Contract\_Two year 0.073960   
PaymentMethod\_Bank transfer (automatic) 0.048652   
PaymentMethod\_Credit card (automatic) 0.048575   
PaymentMethod\_Electronic check 0.137966   
PaymentMethod\_Mailed check -0.250595   
  
 Contract\_Month-to-month \  
gender 0.003386   
SeniorCitizen 0.138360   
Partner -0.280865   
Dependents -0.231720   
tenure -0.645561   
PhoneService -0.000742   
PaperlessBilling 0.169096   
MonthlyCharges 0.060165   
Churn 0.405103   
MultipleLines\_No 0.086740   
MultipleLines\_No phone service 0.000742   
MultipleLines\_Yes -0.088203   
InternetService\_DSL -0.065509   
InternetService\_Fiber optic 0.244164   
InternetService\_No -0.218639   
OnlineSecurity\_No 0.403255   
OnlineSecurity\_No internet service -0.218639   
OnlineSecurity\_Yes -0.246679   
OnlineBackup\_No 0.338796   
OnlineBackup\_No internet service -0.218639   
OnlineBackup\_Yes -0.164172   
DeviceProtection\_No 0.397454   
DeviceProtection\_No internet service -0.218639   
DeviceProtection\_Yes -0.225662   
TechSupport\_No 0.439110   
TechSupport\_No internet service -0.218639   
TechSupport\_Yes -0.285241   
StreamingTV\_No 0.295479   
StreamingTV\_No internet service -0.218639   
StreamingTV\_Yes -0.112282   
StreamingMovies\_No 0.300457   
StreamingMovies\_No internet service -0.218639   
StreamingMovies\_Yes -0.116633   
Contract\_Month-to-month 1.000000   
Contract\_One year -0.568744   
Contract\_Two year -0.622633   
PaymentMethod\_Bank transfer (automatic) -0.179707   
PaymentMethod\_Credit card (automatic) -0.204145   
PaymentMethod\_Electronic check 0.331661   
PaymentMethod\_Mailed check 0.004138   
  
 Contract\_One year Contract\_Two year \  
gender -0.008026 0.003695   
SeniorCitizen -0.046262 -0.117000   
Partner 0.082783 0.248091   
Dependents 0.068368 0.204613   
tenure 0.202570 0.558533   
PhoneService -0.002791 0.003519   
PaperlessBilling -0.051391 -0.147889   
MonthlyCharges 0.004904 -0.074681   
Churn -0.177820 -0.302253   
MultipleLines\_No 0.002098 -0.102937   
MultipleLines\_No phone service 0.002791 -0.003519   
MultipleLines\_Yes -0.003794 0.106253   
InternetService\_DSL 0.046795 0.031714   
InternetService\_Fiber optic -0.076324 -0.211526   
InternetService\_No 0.038004 0.218278   
OnlineSecurity\_No -0.121904 -0.353300   
OnlineSecurity\_No internet service 0.038004 0.218278   
OnlineSecurity\_Yes 0.100162 0.191773   
OnlineBackup\_No -0.111755 -0.287944   
OnlineBackup\_No internet service 0.038004 0.218278   
OnlineBackup\_Yes 0.083722 0.111400   
DeviceProtection\_No -0.129639 -0.339190   
DeviceProtection\_No internet service 0.038004 0.218278   
DeviceProtection\_Yes 0.102495 0.165096   
TechSupport\_No -0.118262 -0.398490   
TechSupport\_No internet service 0.038004 0.218278   
TechSupport\_Yes 0.095775 0.240824   
StreamingTV\_No -0.093177 -0.255209   
StreamingTV\_No internet service 0.038004 0.218278   
StreamingTV\_Yes 0.061612 0.072049   
StreamingMovies\_No -0.096726 -0.257625   
StreamingMovies\_No internet service 0.038004 0.218278   
StreamingMovies\_Yes 0.064926 0.073960   
Contract\_Month-to-month -0.568744 -0.622633   
Contract\_One year 1.000000 -0.289510   
Contract\_Two year -0.289510 1.000000   
PaymentMethod\_Bank transfer (automatic) 0.057451 0.154471   
PaymentMethod\_Credit card (automatic) 0.067589 0.173265   
PaymentMethod\_Electronic check -0.109130 -0.282138   
PaymentMethod\_Mailed check -0.000116 -0.004705   
  
 PaymentMethod\_Bank transfer (automatic) \  
gender 0.016024   
SeniorCitizen -0.016159   
Partner 0.110706   
Dependents 0.052021   
tenure 0.243510   
PhoneService 0.007556   
PaperlessBilling -0.016332   
MonthlyCharges 0.042812   
Churn -0.117937   
MultipleLines\_No -0.070178   
MultipleLines\_No phone service -0.007556   
MultipleLines\_Yes 0.075527   
InternetService\_DSL 0.025476   
InternetService\_Fiber optic -0.022624   
InternetService\_No -0.002113   
OnlineSecurity\_No -0.084322   
OnlineSecurity\_No internet service -0.002113   
OnlineSecurity\_Yes 0.095158   
OnlineBackup\_No -0.081590   
OnlineBackup\_No internet service -0.002113   
OnlineBackup\_Yes 0.087004   
DeviceProtection\_No -0.077791   
DeviceProtection\_No internet service -0.002113   
DeviceProtection\_Yes 0.083115   
TechSupport\_No -0.090177   
TechSupport\_No internet service -0.002113   
TechSupport\_Yes 0.101252   
StreamingTV\_No -0.044168   
StreamingTV\_No internet service -0.002113   
StreamingTV\_Yes 0.046252   
StreamingMovies\_No -0.046705   
StreamingMovies\_No internet service -0.002113   
StreamingMovies\_Yes 0.048652   
Contract\_Month-to-month -0.179707   
Contract\_One year 0.057451   
Contract\_Two year 0.154471   
PaymentMethod\_Bank transfer (automatic) 1.000000   
PaymentMethod\_Credit card (automatic) -0.278215   
PaymentMethod\_Electronic check -0.376762   
PaymentMethod\_Mailed check -0.288685   
  
 PaymentMethod\_Credit card (automatic) \  
gender -0.001215   
SeniorCitizen -0.024135   
Partner 0.082029   
Dependents 0.060267   
tenure 0.233006   
PhoneService -0.007721   
PaperlessBilling -0.013589   
MonthlyCharges 0.030550   
Churn -0.134302   
MultipleLines\_No -0.063921   
MultipleLines\_No phone service 0.007721   
MultipleLines\_Yes 0.060048   
InternetService\_DSL 0.051438   
InternetService\_Fiber optic -0.050077   
InternetService\_No 0.001030   
OnlineSecurity\_No -0.105510   
OnlineSecurity\_No internet service 0.001030   
OnlineSecurity\_Yes 0.115721   
OnlineBackup\_No -0.087822   
OnlineBackup\_No internet service 0.001030   
OnlineBackup\_Yes 0.090785   
DeviceProtection\_No -0.107618   
DeviceProtection\_No internet service 0.001030   
DeviceProtection\_Yes 0.111554   
TechSupport\_No -0.107310   
TechSupport\_No internet service 0.001030   
TechSupport\_Yes 0.117272   
StreamingTV\_No -0.041031   
StreamingTV\_No internet service 0.001030   
StreamingTV\_Yes 0.040433   
StreamingMovies\_No -0.049277   
StreamingMovies\_No internet service 0.001030   
StreamingMovies\_Yes 0.048575   
Contract\_Month-to-month -0.204145   
Contract\_One year 0.067589   
Contract\_Two year 0.173265   
PaymentMethod\_Bank transfer (automatic) -0.278215   
PaymentMethod\_Credit card (automatic) 1.000000   
PaymentMethod\_Electronic check -0.373322   
PaymentMethod\_Mailed check -0.286049   
  
 PaymentMethod\_Electronic check \  
gender -0.000752   
SeniorCitizen 0.171718   
Partner -0.083852   
Dependents -0.150642   
tenure -0.208363   
PhoneService 0.003062   
PaperlessBilling 0.208865   
MonthlyCharges 0.271625   
Churn 0.301919   
MultipleLines\_No -0.080836   
MultipleLines\_No phone service -0.003062   
MultipleLines\_Yes 0.083618   
InternetService\_DSL -0.104418   
InternetService\_Fiber optic 0.336410   
InternetService\_No -0.284917   
OnlineSecurity\_No 0.336364   
OnlineSecurity\_No internet service -0.284917   
OnlineSecurity\_Yes -0.112338   
OnlineBackup\_No 0.236947   
OnlineBackup\_No internet service -0.284917   
OnlineBackup\_Yes -0.000408   
DeviceProtection\_No 0.239705   
DeviceProtection\_No internet service -0.284917   
DeviceProtection\_Yes -0.003351   
TechSupport\_No 0.339031   
TechSupport\_No internet service -0.284917   
TechSupport\_Yes -0.114839   
StreamingTV\_No 0.096033   
StreamingTV\_No internet service -0.284917   
StreamingTV\_Yes 0.144626   
StreamingMovies\_No 0.102571   
StreamingMovies\_No internet service -0.284917   
StreamingMovies\_Yes 0.137966   
Contract\_Month-to-month 0.331661   
Contract\_One year -0.109130   
Contract\_Two year -0.282138   
PaymentMethod\_Bank transfer (automatic) -0.376762   
PaymentMethod\_Credit card (automatic) -0.373322   
PaymentMethod\_Electronic check 1.000000   
PaymentMethod\_Mailed check -0.387372   
  
 PaymentMethod\_Mailed check   
gender -0.013744   
SeniorCitizen -0.153477   
Partner -0.095125   
Dependents 0.059071   
tenure -0.233852   
PhoneService -0.003319   
PaperlessBilling -0.205398   
MonthlyCharges -0.377437   
Churn -0.091683   
MultipleLines\_No 0.222605   
MultipleLines\_No phone service 0.003319   
MultipleLines\_Yes -0.227206   
InternetService\_DSL 0.041899   
InternetService\_Fiber optic -0.306834   
InternetService\_No 0.321361   
OnlineSecurity\_No -0.191715   
OnlineSecurity\_No internet service 0.321361   
OnlineSecurity\_Yes -0.080798   
OnlineBackup\_No -0.099975   
OnlineBackup\_No internet service 0.321361   
OnlineBackup\_Yes -0.174164   
DeviceProtection\_No -0.087422   
DeviceProtection\_No internet service 0.321361   
DeviceProtection\_Yes -0.187373   
TechSupport\_No -0.187185   
TechSupport\_No internet service 0.321361   
TechSupport\_Yes -0.085509   
StreamingTV\_No -0.024261   
StreamingTV\_No internet service 0.321361   
StreamingTV\_Yes -0.247742   
StreamingMovies\_No -0.021034   
StreamingMovies\_No internet service 0.321361   
StreamingMovies\_Yes -0.250595   
Contract\_Month-to-month 0.004138   
Contract\_One year -0.000116   
Contract\_Two year -0.004705   
PaymentMethod\_Bank transfer (automatic) -0.288685   
PaymentMethod\_Credit card (automatic) -0.286049   
PaymentMethod\_Electronic check -0.387372   
PaymentMethod\_Mailed check 1.000000   
  
[40 rows x 40 columns]

df.drop(columns = 'TotalCharges' , inplace = True)

**Split the data in training and test splits**

# Selecting independent variables  
X = df.drop(columns = 'Churn')  
  
# Selecting Dependent Variables  
Y = df.loc[:,'Churn']

from sklearn.model\_selection import train\_test\_split  
X\_train, X\_test, Y\_train, Y\_test = train\_test\_split(X,Y,test\_size = 0.3, random\_state= 20)

print("Train\n",X\_train.shape)  
print("Test\n",X\_test.shape)

Train  
 (4930, 39)  
Test  
 (2113, 39)

df.head()

gender SeniorCitizen Partner Dependents tenure PhoneService \  
0 1 0 1 0 0.013889 0   
1 0 0 0 0 0.472222 1   
2 0 0 0 0 0.027778 1   
3 0 0 0 0 0.625000 0   
4 1 0 0 0 0.027778 1   
  
 PaperlessBilling MonthlyCharges Churn MultipleLines\_No ... \  
0 1 0.115423 0 0 ...   
1 0 0.385075 0 1 ...   
2 1 0.354229 1 1 ...   
3 0 0.239303 0 0 ...   
4 1 0.521891 1 1 ...   
  
 StreamingMovies\_No StreamingMovies\_No internet service \  
0 1 0   
1 1 0   
2 1 0   
3 1 0   
4 1 0   
  
 StreamingMovies\_Yes Contract\_Month-to-month Contract\_One year \  
0 0 1 0   
1 0 0 1   
2 0 1 0   
3 0 0 1   
4 0 1 0   
  
 Contract\_Two year PaymentMethod\_Bank transfer (automatic) \  
0 0 0   
1 0 0   
2 0 0   
3 0 1   
4 0 0   
  
 PaymentMethod\_Credit card (automatic) PaymentMethod\_Electronic check \  
0 0 1   
1 0 0   
2 0 0   
3 0 0   
4 0 1   
  
 PaymentMethod\_Mailed check   
0 0   
1 1   
2 1   
3 0   
4 0   
  
[5 rows x 40 columns]

df.info()

<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 7043 entries, 0 to 7042  
Data columns (total 40 columns):  
 # Column Non-Null Count Dtype   
--- ------ -------------- -----   
 0 gender 7043 non-null int64   
 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 PaperlessBilling 7043 non-null int64   
 7 MonthlyCharges 7043 non-null float64  
 8 Churn 7043 non-null int64   
 9 MultipleLines\_No 7043 non-null uint8   
 10 MultipleLines\_No phone service 7043 non-null uint8   
 11 MultipleLines\_Yes 7043 non-null uint8   
 12 InternetService\_DSL 7043 non-null uint8   
 13 InternetService\_Fiber optic 7043 non-null uint8   
 14 InternetService\_No 7043 non-null uint8   
 15 OnlineSecurity\_No 7043 non-null uint8   
 16 OnlineSecurity\_No internet service 7043 non-null uint8   
 17 OnlineSecurity\_Yes 7043 non-null uint8   
 18 OnlineBackup\_No 7043 non-null uint8   
 19 OnlineBackup\_No internet service 7043 non-null uint8   
 20 OnlineBackup\_Yes 7043 non-null uint8   
 21 DeviceProtection\_No 7043 non-null uint8   
 22 DeviceProtection\_No internet service 7043 non-null uint8   
 23 DeviceProtection\_Yes 7043 non-null uint8   
 24 TechSupport\_No 7043 non-null uint8   
 25 TechSupport\_No internet service 7043 non-null uint8   
 26 TechSupport\_Yes 7043 non-null uint8   
 27 StreamingTV\_No 7043 non-null uint8   
 28 StreamingTV\_No internet service 7043 non-null uint8   
 29 StreamingTV\_Yes 7043 non-null uint8   
 30 StreamingMovies\_No 7043 non-null uint8   
 31 StreamingMovies\_No internet service 7043 non-null uint8   
 32 StreamingMovies\_Yes 7043 non-null uint8   
 33 Contract\_Month-to-month 7043 non-null uint8   
 34 Contract\_One year 7043 non-null uint8   
 35 Contract\_Two year 7043 non-null uint8   
 36 PaymentMethod\_Bank transfer (automatic) 7043 non-null uint8   
 37 PaymentMethod\_Credit card (automatic) 7043 non-null uint8   
 38 PaymentMethod\_Electronic check 7043 non-null uint8   
 39 PaymentMethod\_Mailed check 7043 non-null uint8   
dtypes: float64(2), int64(7), uint8(31)  
memory usage: 708.6 KB

**Linear Regression**

from numpy.random import seed  
from pandas.core.common import random\_state  
from sklearn.linear\_model import LinearRegression  
from sklearn.metrics import r2\_score  
  
model = LinearRegression()  
model.fit(X\_train, Y\_train).predict(X\_test)  
  
prediction = model.predict(X\_test)  
  
accuracy = r2\_score(Y\_test, prediction)  
  
print(accuracy)

0.24553386829017543

**Polynomial** **Regression**

from sklearn.preprocessing import PolynomialFeatures  
from sklearn.linear\_model import LinearRegression  
from sklearn.metrics import r2\_score  
  
poly = PolynomialFeatures(degree = 2)  
X\_train\_poly = poly.fit\_transform(X\_train)  
X\_test\_poly = poly.transform(X\_test)  
  
model = LinearRegression()  
model.fit(X\_train\_poly, Y\_train)  
y\_pred = model.predict(X\_test\_poly)  
  
accuracy = r2\_score(Y\_test,y\_pred)  
print(accuracy)

0.29109051800604013

**Logistic** **Regression**

from sklearn.linear\_model import LogisticRegression  
from sklearn.metrics import accuracy\_score  
model = LogisticRegression()  
model.fit(X\_train, Y\_train).predict(X\_test)  
predictions = model.predict(X\_test)  
accuracy = accuracy\_score(Y\_test, predictions)  
print(accuracy)

0.8163748225272125

***ANN Model*** : 3 layer model

import tensorflow as tf  
from tensorflow.keras import Sequential  
from tensorflow.keras.layers import Dense

model = Sequential([  
 Dense(units = 12, input\_shape=(39,), activation = 'relu'),  
 Dense(units = 8, activation = 'relu'),  
 Dense(units = 1, activation = 'sigmoid')  
])

model.compile(optimizer = 'adam', loss = 'binary\_crossentropy', metrics = ['accuracy'])  
model.fit(X\_train, Y\_train, epochs = 150)

Epoch 1/150  
155/155 [==============================] - 2s 2ms/step - loss: 0.5257 - accuracy: 0.7268  
Epoch 2/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4516 - accuracy: 0.7763  
Epoch 3/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4374 - accuracy: 0.7872  
Epoch 4/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4318 - accuracy: 0.7927  
Epoch 5/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.4283 - accuracy: 0.7917  
Epoch 6/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4257 - accuracy: 0.7921  
Epoch 7/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4246 - accuracy: 0.7915  
Epoch 8/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4231 - accuracy: 0.7968  
Epoch 9/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4221 - accuracy: 0.7949  
Epoch 10/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4197 - accuracy: 0.7959  
Epoch 11/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4198 - accuracy: 0.7976  
Epoch 12/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4190 - accuracy: 0.8004  
Epoch 13/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4191 - accuracy: 0.7986  
Epoch 14/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4174 - accuracy: 0.7984  
Epoch 15/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4178 - accuracy: 0.7992  
Epoch 16/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4155 - accuracy: 0.7984  
Epoch 17/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4162 - accuracy: 0.7986  
Epoch 18/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4152 - accuracy: 0.8041  
Epoch 19/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4146 - accuracy: 0.7986  
Epoch 20/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4149 - accuracy: 0.8032  
Epoch 21/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4139 - accuracy: 0.8008  
Epoch 22/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4127 - accuracy: 0.8020  
Epoch 23/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4127 - accuracy: 0.8049  
Epoch 24/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4130 - accuracy: 0.8024  
Epoch 25/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4128 - accuracy: 0.8020  
Epoch 26/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4118 - accuracy: 0.8034  
Epoch 27/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4110 - accuracy: 0.8028  
Epoch 28/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4105 - accuracy: 0.8045  
Epoch 29/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4104 - accuracy: 0.8067  
Epoch 30/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4093 - accuracy: 0.8041  
Epoch 31/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4101 - accuracy: 0.8055  
Epoch 32/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4102 - accuracy: 0.8071  
Epoch 33/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4095 - accuracy: 0.8073  
Epoch 34/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4084 - accuracy: 0.8053  
Epoch 35/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4091 - accuracy: 0.8051  
Epoch 36/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4099 - accuracy: 0.8063  
Epoch 37/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4087 - accuracy: 0.8055  
Epoch 38/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4079 - accuracy: 0.8053  
Epoch 39/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4074 - accuracy: 0.8069  
Epoch 40/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4085 - accuracy: 0.8059  
Epoch 41/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4063 - accuracy: 0.8093  
Epoch 42/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4073 - accuracy: 0.8065  
Epoch 43/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.4068 - accuracy: 0.8081  
Epoch 44/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.4062 - accuracy: 0.8077  
Epoch 45/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4067 - accuracy: 0.8049  
Epoch 46/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4063 - accuracy: 0.8085  
Epoch 47/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4063 - accuracy: 0.8077  
Epoch 48/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4060 - accuracy: 0.8049  
Epoch 49/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.4061 - accuracy: 0.8085  
Epoch 50/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.4048 - accuracy: 0.8067  
Epoch 51/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4053 - accuracy: 0.8053  
Epoch 52/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4057 - accuracy: 0.8097  
Epoch 53/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4047 - accuracy: 0.8067  
Epoch 54/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4053 - accuracy: 0.8093  
Epoch 55/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4038 - accuracy: 0.8071  
Epoch 56/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4036 - accuracy: 0.8073  
Epoch 57/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4032 - accuracy: 0.8073  
Epoch 58/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4032 - accuracy: 0.8071  
Epoch 59/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4041 - accuracy: 0.8043  
Epoch 60/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4029 - accuracy: 0.8081  
Epoch 61/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4026 - accuracy: 0.8103  
Epoch 62/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4036 - accuracy: 0.8065  
Epoch 63/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4025 - accuracy: 0.8089  
Epoch 64/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4025 - accuracy: 0.8093  
Epoch 65/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4019 - accuracy: 0.8077  
Epoch 66/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4020 - accuracy: 0.8089  
Epoch 67/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4015 - accuracy: 0.8067  
Epoch 68/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4015 - accuracy: 0.8097  
Epoch 69/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4010 - accuracy: 0.8099  
Epoch 70/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4009 - accuracy: 0.8081  
Epoch 71/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4010 - accuracy: 0.8085  
Epoch 72/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4011 - accuracy: 0.8073  
Epoch 73/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4007 - accuracy: 0.8073  
Epoch 74/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4001 - accuracy: 0.8105  
Epoch 75/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4006 - accuracy: 0.8077  
Epoch 76/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4005 - accuracy: 0.8057  
Epoch 77/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3990 - accuracy: 0.8105  
Epoch 78/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4010 - accuracy: 0.8093  
Epoch 79/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3990 - accuracy: 0.8063  
Epoch 80/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3988 - accuracy: 0.8069  
Epoch 81/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3992 - accuracy: 0.8099  
Epoch 82/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4003 - accuracy: 0.8091  
Epoch 83/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3984 - accuracy: 0.8075  
Epoch 84/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3989 - accuracy: 0.8087  
Epoch 85/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3983 - accuracy: 0.8085  
Epoch 86/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3985 - accuracy: 0.8081  
Epoch 87/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3983 - accuracy: 0.8083  
Epoch 88/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3983 - accuracy: 0.8083  
Epoch 89/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3983 - accuracy: 0.8103  
Epoch 90/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3974 - accuracy: 0.8091  
Epoch 91/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3992 - accuracy: 0.8057  
Epoch 92/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3970 - accuracy: 0.8112  
Epoch 93/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3975 - accuracy: 0.8110  
Epoch 94/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3965 - accuracy: 0.8108  
Epoch 95/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3970 - accuracy: 0.8110  
Epoch 96/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3965 - accuracy: 0.8081  
Epoch 97/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3966 - accuracy: 0.8105  
Epoch 98/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3968 - accuracy: 0.8114  
Epoch 99/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3958 - accuracy: 0.8089  
Epoch 100/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3959 - accuracy: 0.8091  
Epoch 101/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3957 - accuracy: 0.8110  
Epoch 102/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3949 - accuracy: 0.8091  
Epoch 103/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3945 - accuracy: 0.8122  
Epoch 104/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3956 - accuracy: 0.8071  
Epoch 105/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3957 - accuracy: 0.8069  
Epoch 106/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3964 - accuracy: 0.8041  
Epoch 107/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3948 - accuracy: 0.8073  
Epoch 108/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3955 - accuracy: 0.8105  
Epoch 109/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3945 - accuracy: 0.8077  
Epoch 110/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3938 - accuracy: 0.8097  
Epoch 111/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3939 - accuracy: 0.8083  
Epoch 112/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3943 - accuracy: 0.8081  
Epoch 113/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3952 - accuracy: 0.8095  
Epoch 114/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3939 - accuracy: 0.8112  
Epoch 115/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3948 - accuracy: 0.8077  
Epoch 116/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3935 - accuracy: 0.8112  
Epoch 117/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3940 - accuracy: 0.8110  
Epoch 118/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3935 - accuracy: 0.8097  
Epoch 119/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3927 - accuracy: 0.8132  
Epoch 120/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3935 - accuracy: 0.8091  
Epoch 121/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3930 - accuracy: 0.8112  
Epoch 122/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3935 - accuracy: 0.8114  
Epoch 123/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3919 - accuracy: 0.8122  
Epoch 124/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3931 - accuracy: 0.8097  
Epoch 125/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3925 - accuracy: 0.8081  
Epoch 126/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3934 - accuracy: 0.8087  
Epoch 127/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3925 - accuracy: 0.8136  
Epoch 128/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3935 - accuracy: 0.8085  
Epoch 129/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3922 - accuracy: 0.8089  
Epoch 130/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3917 - accuracy: 0.8118  
Epoch 131/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3925 - accuracy: 0.8091  
Epoch 132/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3913 - accuracy: 0.8110  
Epoch 133/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3911 - accuracy: 0.8091  
Epoch 134/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3912 - accuracy: 0.8091  
Epoch 135/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3922 - accuracy: 0.8124  
Epoch 136/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3905 - accuracy: 0.8120  
Epoch 137/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3905 - accuracy: 0.8093  
Epoch 138/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3911 - accuracy: 0.8083  
Epoch 139/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3907 - accuracy: 0.8095  
Epoch 140/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3908 - accuracy: 0.8069  
Epoch 141/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3902 - accuracy: 0.8112  
Epoch 142/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3897 - accuracy: 0.8122  
Epoch 143/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3902 - accuracy: 0.8103  
Epoch 144/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3921 - accuracy: 0.8108  
Epoch 145/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3913 - accuracy: 0.8118  
Epoch 146/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3897 - accuracy: 0.8116  
Epoch 147/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3907 - accuracy: 0.8097  
Epoch 148/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3900 - accuracy: 0.8118  
Epoch 149/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3900 - accuracy: 0.8097  
Epoch 150/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3906 - accuracy: 0.8085

<keras.callbacks.History at 0x7f545018c4f0>

model.evaluate(X\_test, Y\_test)

67/67 [==============================] - 3s 10ms/step - loss: 0.4210 - accuracy: 0.8050

[0.42095714807510376, 0.8050165772438049]

\_, accuracy = model.evaluate(X\_test,Y\_test)  
print('Accuracy : %.2f'%(accuracy\*100))

67/67 [==============================] - 0s 1ms/step - loss: 0.4210 - accuracy: 0.8050  
Accuracy : 80.50

**ANN Model** : 4 layer model

model2 = Sequential([  
 Dense(units = 19, input\_shape=(39,), activation = 'relu'),  
 Dense(units = 15, activation = 'relu'),  
 Dense(units = 10, activation = 'relu'),  
 Dense(units = 1, activation = 'sigmoid')  
])

model2.compile(optimizer = 'adam', loss = 'binary\_crossentropy', metrics = ['accuracy'])  
model2.fit(X\_train, Y\_train, epochs = 150)

Epoch 1/150  
155/155 [==============================] - 3s 2ms/step - loss: 0.6849 - accuracy: 0.6394  
Epoch 2/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.6437 - accuracy: 0.7696  
Epoch 3/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.6085 - accuracy: 0.7838  
Epoch 4/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.5816 - accuracy: 0.7915  
Epoch 5/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.5594 - accuracy: 0.7909  
Epoch 6/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.5416 - accuracy: 0.7927  
Epoch 7/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.5258 - accuracy: 0.7961  
Epoch 8/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.5125 - accuracy: 0.7953  
Epoch 9/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.5011 - accuracy: 0.7966  
Epoch 10/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4924 - accuracy: 0.7957  
Epoch 11/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4854 - accuracy: 0.7976  
Epoch 12/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4772 - accuracy: 0.7980  
Epoch 13/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4720 - accuracy: 0.8004  
Epoch 14/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4667 - accuracy: 0.8018  
Epoch 15/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4612 - accuracy: 0.8002  
Epoch 16/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4553 - accuracy: 0.8051  
Epoch 17/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4521 - accuracy: 0.8051  
Epoch 18/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4496 - accuracy: 0.8069  
Epoch 19/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4446 - accuracy: 0.8103  
Epoch 20/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4413 - accuracy: 0.8108  
Epoch 21/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4380 - accuracy: 0.8089  
Epoch 22/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4331 - accuracy: 0.8142  
Epoch 23/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4309 - accuracy: 0.8122  
Epoch 24/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4263 - accuracy: 0.8183  
Epoch 25/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4220 - accuracy: 0.8207  
Epoch 26/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4218 - accuracy: 0.8154  
Epoch 27/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4172 - accuracy: 0.8199  
Epoch 28/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4166 - accuracy: 0.8178  
Epoch 29/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4124 - accuracy: 0.8207  
Epoch 30/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4112 - accuracy: 0.8181  
Epoch 31/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4087 - accuracy: 0.8191  
Epoch 32/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4079 - accuracy: 0.8195  
Epoch 33/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4052 - accuracy: 0.8213  
Epoch 34/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4028 - accuracy: 0.8199  
Epoch 35/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.4006 - accuracy: 0.8262  
Epoch 36/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3999 - accuracy: 0.8211  
Epoch 37/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3969 - accuracy: 0.8213  
Epoch 38/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3945 - accuracy: 0.8276  
Epoch 39/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3931 - accuracy: 0.8231  
Epoch 40/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3930 - accuracy: 0.8227  
Epoch 41/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3945 - accuracy: 0.8211  
Epoch 42/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3891 - accuracy: 0.8256  
Epoch 43/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3897 - accuracy: 0.8233  
Epoch 44/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3875 - accuracy: 0.8284  
Epoch 45/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3876 - accuracy: 0.8288  
Epoch 46/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3873 - accuracy: 0.8276  
Epoch 47/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3834 - accuracy: 0.8254  
Epoch 48/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3840 - accuracy: 0.8298  
Epoch 49/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3808 - accuracy: 0.8320  
Epoch 50/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3796 - accuracy: 0.8286  
Epoch 51/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3796 - accuracy: 0.8282  
Epoch 52/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3780 - accuracy: 0.8314  
Epoch 53/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3792 - accuracy: 0.8266  
Epoch 54/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3759 - accuracy: 0.8331  
Epoch 55/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3745 - accuracy: 0.8349  
Epoch 56/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3751 - accuracy: 0.8327  
Epoch 57/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3727 - accuracy: 0.8381  
Epoch 58/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3747 - accuracy: 0.8325  
Epoch 59/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3720 - accuracy: 0.8357  
Epoch 60/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3748 - accuracy: 0.8310  
Epoch 61/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3699 - accuracy: 0.8349  
Epoch 62/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3709 - accuracy: 0.8353  
Epoch 63/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3700 - accuracy: 0.8353  
Epoch 64/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3674 - accuracy: 0.8373  
Epoch 65/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3681 - accuracy: 0.8375  
Epoch 66/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3671 - accuracy: 0.8355  
Epoch 67/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3643 - accuracy: 0.8355  
Epoch 68/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3642 - accuracy: 0.8383  
Epoch 69/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3606 - accuracy: 0.8377  
Epoch 70/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3600 - accuracy: 0.8404  
Epoch 71/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3616 - accuracy: 0.8383  
Epoch 72/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3607 - accuracy: 0.8359  
Epoch 73/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3597 - accuracy: 0.8389  
Epoch 74/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3582 - accuracy: 0.8371  
Epoch 75/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3580 - accuracy: 0.8387  
Epoch 76/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3560 - accuracy: 0.8389  
Epoch 77/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3559 - accuracy: 0.8389  
Epoch 78/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3569 - accuracy: 0.8389  
Epoch 79/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3552 - accuracy: 0.8385  
Epoch 80/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3537 - accuracy: 0.8444  
Epoch 81/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3590 - accuracy: 0.8367  
Epoch 82/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3552 - accuracy: 0.8387  
Epoch 83/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3543 - accuracy: 0.8408  
Epoch 84/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3525 - accuracy: 0.8416  
Epoch 85/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3508 - accuracy: 0.8424  
Epoch 86/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3509 - accuracy: 0.8400  
Epoch 87/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3493 - accuracy: 0.8428  
Epoch 88/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3487 - accuracy: 0.8462  
Epoch 89/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3496 - accuracy: 0.8426  
Epoch 90/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3471 - accuracy: 0.8477  
Epoch 91/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3504 - accuracy: 0.8414  
Epoch 92/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3465 - accuracy: 0.8467  
Epoch 93/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3457 - accuracy: 0.8444  
Epoch 94/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3460 - accuracy: 0.8446  
Epoch 95/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3466 - accuracy: 0.8448  
Epoch 96/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3466 - accuracy: 0.8444  
Epoch 97/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3458 - accuracy: 0.8430  
Epoch 98/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3444 - accuracy: 0.8473  
Epoch 99/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3450 - accuracy: 0.8473  
Epoch 100/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3431 - accuracy: 0.8483  
Epoch 101/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3463 - accuracy: 0.8432  
Epoch 102/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3418 - accuracy: 0.8456  
Epoch 103/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3420 - accuracy: 0.8458  
Epoch 104/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3410 - accuracy: 0.8450  
Epoch 105/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3421 - accuracy: 0.8458  
Epoch 106/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3415 - accuracy: 0.8485  
Epoch 107/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3412 - accuracy: 0.8460  
Epoch 108/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3413 - accuracy: 0.8444  
Epoch 109/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3386 - accuracy: 0.8501  
Epoch 110/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3412 - accuracy: 0.8471  
Epoch 111/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3404 - accuracy: 0.8481  
Epoch 112/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3385 - accuracy: 0.8465  
Epoch 113/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3380 - accuracy: 0.8462  
Epoch 114/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3390 - accuracy: 0.8485  
Epoch 115/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3369 - accuracy: 0.8521  
Epoch 116/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3381 - accuracy: 0.8497  
Epoch 117/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3375 - accuracy: 0.8462  
Epoch 118/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3368 - accuracy: 0.8497  
Epoch 119/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3357 - accuracy: 0.8481  
Epoch 120/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3342 - accuracy: 0.8513  
Epoch 121/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3343 - accuracy: 0.8505  
Epoch 122/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3342 - accuracy: 0.8469  
Epoch 123/150  
155/155 [==============================] - 0s 3ms/step - loss: 0.3365 - accuracy: 0.8465  
Epoch 124/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3335 - accuracy: 0.8509  
Epoch 125/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3323 - accuracy: 0.8519  
Epoch 126/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3336 - accuracy: 0.8497  
Epoch 127/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3318 - accuracy: 0.8521  
Epoch 128/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3319 - accuracy: 0.8509  
Epoch 129/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3312 - accuracy: 0.8511  
Epoch 130/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3357 - accuracy: 0.8477  
Epoch 131/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3316 - accuracy: 0.8548  
Epoch 132/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3334 - accuracy: 0.8509  
Epoch 133/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3323 - accuracy: 0.8511  
Epoch 134/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3308 - accuracy: 0.8515  
Epoch 135/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3324 - accuracy: 0.8491  
Epoch 136/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3313 - accuracy: 0.8513  
Epoch 137/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3287 - accuracy: 0.8497  
Epoch 138/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3325 - accuracy: 0.8499  
Epoch 139/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3300 - accuracy: 0.8540  
Epoch 140/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3303 - accuracy: 0.8517  
Epoch 141/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3293 - accuracy: 0.8519  
Epoch 142/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3301 - accuracy: 0.8544  
Epoch 143/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3272 - accuracy: 0.8521  
Epoch 144/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3263 - accuracy: 0.8535  
Epoch 145/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3278 - accuracy: 0.8556  
Epoch 146/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3273 - accuracy: 0.8527  
Epoch 147/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3273 - accuracy: 0.8517  
Epoch 148/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3267 - accuracy: 0.8533  
Epoch 149/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3266 - accuracy: 0.8568  
Epoch 150/150  
155/155 [==============================] - 0s 2ms/step - loss: 0.3289 - accuracy: 0.8535

<keras.callbacks.History at 0x7f5440f45b40>

\_, accuracy = model.evaluate(X\_test,Y\_test)  
print('Accuracy : %.2f'%(accuracy\*100))

67/67 [==============================] - 0s 1ms/step - loss: 0.4280 - accuracy: 0.7979  
Accuracy : 79.79

**Gradient Boosting**

from sklearn.ensemble import GradientBoostingClassifier  
model = GradientBoostingClassifier()  
model.fit(X\_train, Y\_train)  
Y\_pred = model.predict(X\_test)  
accuracy = accuracy\_score(Y\_test, Y\_pred)  
print(accuracy)

0.8135352579271179

**Prediction Scores for all the methods**

1. Linear Regression : 0.2455
2. Polynomial Regression (Degree = 2): 0.2910
3. Logistic Regression : 0.8163
4. 3 Layered ANN Model : 0.8050
5. 4 Layered ANN Model : 0.7979
6. Gradient Boosting : 0.8135

After all the analysis and visualization of the data, the Logistic Regression and Gradient Boosting Algorithms fit well on the modified dataset.

**Therefore the best model for this dataset :** *Logistic Regression*

*Gradient Boosting is also of almost same accuracy*