Intelligent Customer Retention using Machine Learning

Overview:

Project Description:

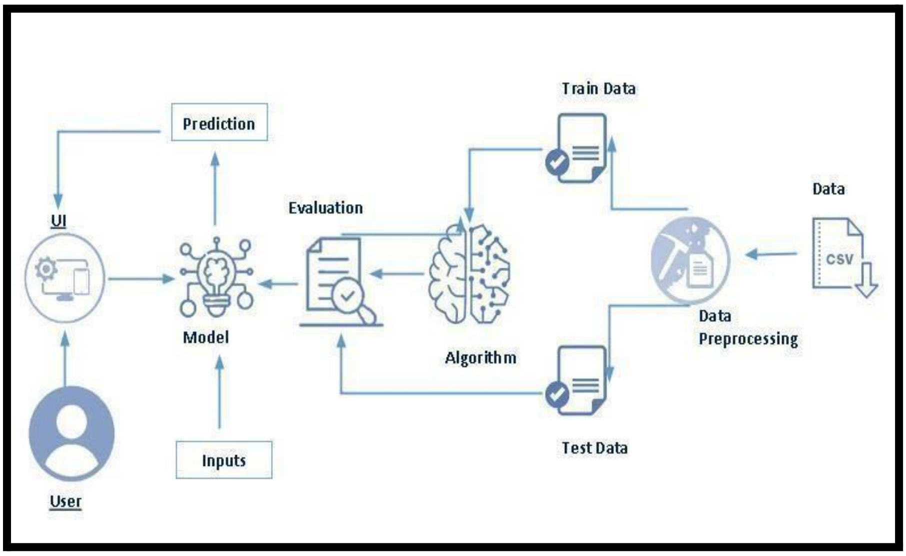
Customer churn is often referred to as customer attrition, or customer defection which is the rate at which the customers are lost. Customer churn is a major problem and one of the most important concerns for large companies. Due to the direct effect on the revenues of the companies, especially in the telecom field, companies are seeking to develop means to predict potential customer to churn. Looking at churn, different reasons trigger customers to terminate their contracts, for example better price offers, more interesting packages, bad service experiences or change of customers' personal situations.

Customer churn has become highly important for companies because of increasing competition among companies, increased importance of marketing strategies and conscious behaviour of customers in the recent years. Customers can easily trend toward alternative services. Companies must develop various strategies to prevent these possible trends, depending on the services they provide. During the estimation of possible churns, data from the previous churns might be used. An efficient churn predictive model benefits companies in many ways. Early identification of customers likely to leave may help to build cost effective ways in marketing strategies. Customer retention campaigns might be limited to selected customers but it should cover most of the customer. Incorrect predictions could result in a company losing profits because of the discounts offered to continuous subscribers.

Telecommunication industry always suffers from a very high churn rates when one industry offers a better plan than the previous there is a high possibility of the customer churning from the present due to a better plan in such a scenario it is very difficult to avoid losses but through prediction we can keep it to a minimal level.

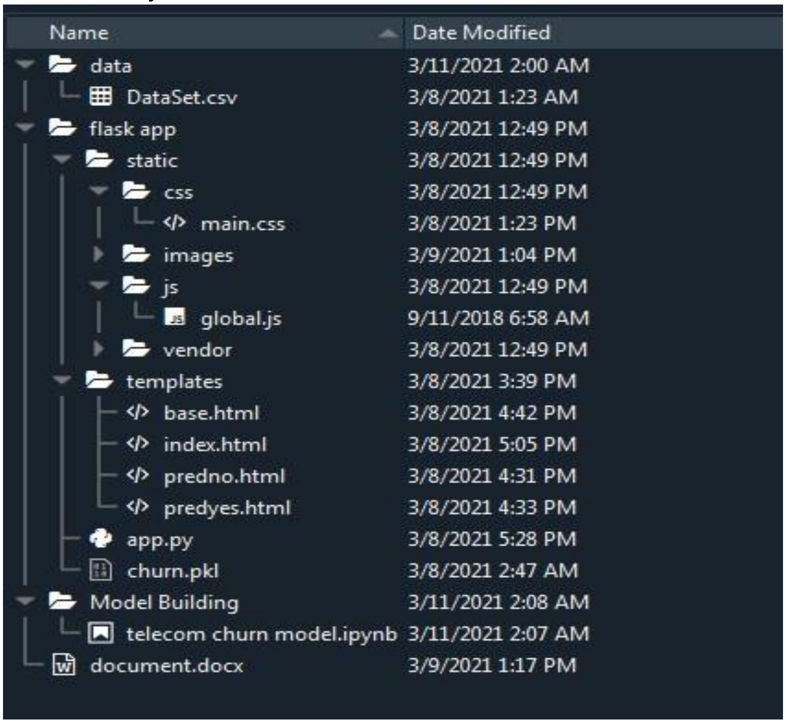
Telecom companies often use customer churn as a key business metrics to predict the number of customers that will leave a telecom service provider. A machine learning model can be used to identity the probable churn customers and then makes the necessary business decisions.

Technical Architecture:

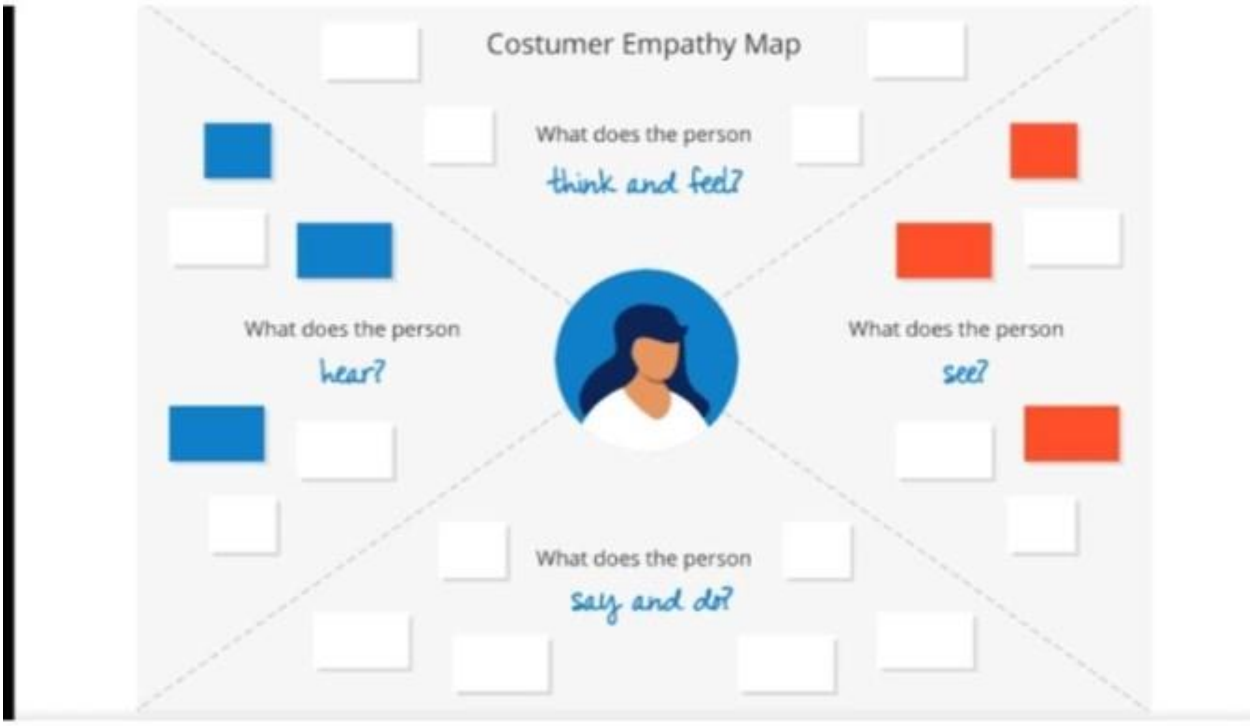


Project Structure:

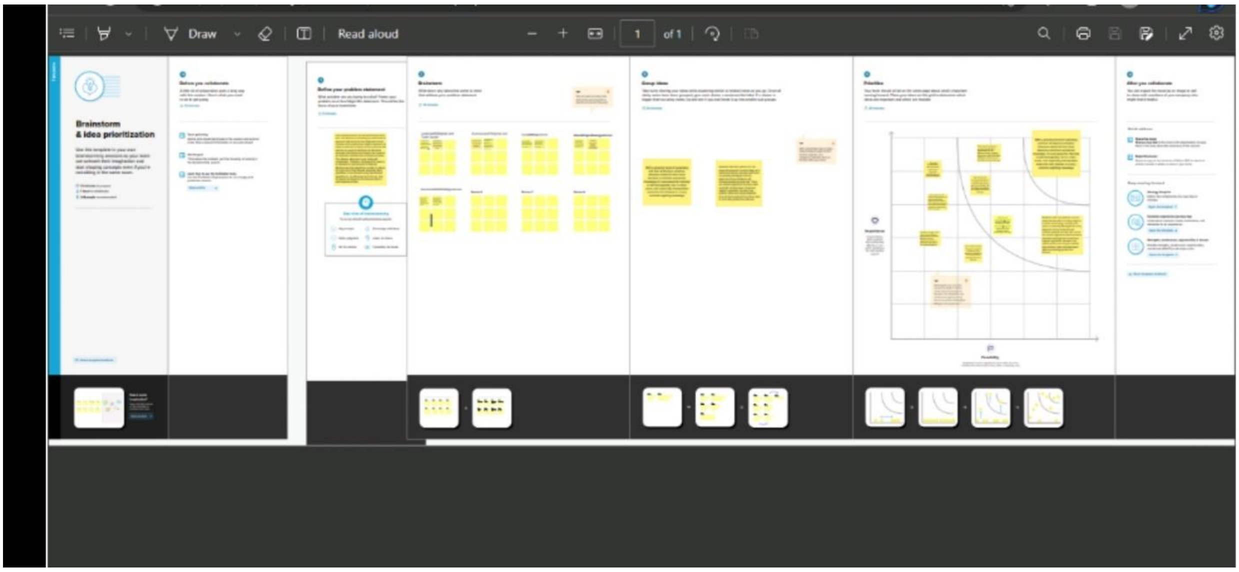
Create a Project folder which contains files as shown below



Empathy Map:



Brainstorm Map:



Activity 1.1: Importing the libraries Import

the necessary libraries as shown in the image.

```
#import necessary libraries
import pandas as pd
import numpy as np
import pickle
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import sklearn
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import  RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.model_selection import RandomizedSearchCV
import imblearn
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, f1_score
```

Activity 1.2: Read the Dataset

Our dataset format might be in .csv, excel files, .txt, .json, etc. We can read the dataset with the help of pandas.

In pandas we have a function called read_csv() to read the dataset. As a parameter we have to give the directory of the csv file.

```
#import dataset
data = pd.read_csv(r"C:\Users\Shivani_SB\OneDrive\Desktop\Telecom churn modelling-updated\data\DataSet.csv")
data
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupport	StreamingTV
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	No	No	No
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	Yes	No	No
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	No	No	No
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	Yes	Yes	No
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	No	No	No
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	DSL	Yes	...	Yes	Yes	Yes
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	No	...	Yes	No	Yes
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	DSL	Yes	...	No	No	No

Activity 2: Data Preparation

As we have understood how the data is, let's pre-process the collected data.

The download data set is not suitable for training the machine learning model as it might have so much randomness so we need to clean the dataset properly in order to fetch good results. This activity includes the following steps.

- Handling missing values
- Handling categorical data
- Handling Imbalance Data

Note: These are the general steps of pre-processing the data before using it for machine learning. Depending on the condition of your dataset, you may or may not have to go through all these steps.

Activity 2.1: Handling missing values

- Let's find the shape of our dataset first. To find the shape of our data, the df.shape method is used. To find the data type, df.info() function is used.

```
data.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   object
 1   SeniorCitizen     7043 non-null   int64
 2   Partner           7043 non-null   object
 3   Dependents        7043 non-null   object
 4   tenure            7043 non-null   int64
 5   PhoneService      7043 non-null   object
 6   MultipleLines     7043 non-null   object
 7   InternetService   7043 non-null   object
 8   OnlineSecurity    7043 non-null   object
 9   OnlineBackup      7043 non-null   object
 10  DeviceProtection  7043 non-null   object
 11  TechSupport       7043 non-null   object
 12  StreamingTV       7043 non-null   object
 13  StreamingMovies   7043 non-null   object
 14  Contract          7043 non-null   object
 15  PaperlessBilling  7043 non-null   object
 16  PaymentMethod     7043 non-null   object
 17  MonthlyCharges    7043 non-null   float64
 18  TotalCharges      7043 non-null   object
 19  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(17)
memory usage: 1.1+ MB
```

- For checking the null values, df.isnull() function is used. To sum those null values we use .sum() function. From the below image we found that there are no null values present in our dataset. So we can skip handling the missing values step.

```
#checking for null values
data.TotalCharges = pd.to_numeric(data.TotalCharges, errors='coerce')
data.isnull().any()

gender              False
SeniorCitizen       False
Partner             False
Dependents          False
tenure              False
PhoneService        False
MultipleLines       False
InternetService     False
OnlineSecurity      False
OnlineBackup        False
DeviceProtection    False
TechSupport         False
StreamingTV         False
StreamingMovies     False
Contract            False
PaperlessBilling    False
PaymentMethod       False
MonthlyCharges      False
TotalCharges         True
Churn               False
dtype: bool
```

- From the above code of analysis, we can infer that column TotalCharges is having the missing values, we need to treat them in a required way.

```
data["TotalCharges"].fillna(data["TotalCharges"].median() , inplace =True)

data.isnull().sum()

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
```

- We will fill in the missing values in the TotalCharges column by median as it's a numercal column and then again we checked for null values to see if there is any null value left.

Activity 2.2: Handling Categorical Values

As we can see our dataset has categorical data we must convert the categorical data to integer encoding or binary encoding.

To convert the categorical features into numerical features we use encoding techniques. There are several techniques but in our project we are using manual encoding with the help of list comprehension.

Label Encoding.

Label Encoding refers to converting the labels into numeric form so as to convert it into the machine-readable form. Machine learning algorithms can then decide in a better way on how those labels must be operated. It is an important pre-processing step for the structured dataset in supervised learning.

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data["gender"] = le.fit_transform(data["gender"])
data["Partner"] = le.fit_transform(data["Partner"])
data["Dependents"] = le.fit_transform(data["Dependents"])
data["PhoneService"] = le.fit_transform(data["PhoneService"])
data["MultipleLines"] = le.fit_transform(data["MultipleLines"])
data["InternetService"] = le.fit_transform(data["InternetService"])
data["OnlineSecurity"] = le.fit_transform(data["OnlineSecurity"])
data["OnlineBackup"] = le.fit_transform(data["OnlineBackup"])
data["DeviceProtection"] = le.fit_transform(data["DeviceProtection"])
data["TechSupport"] = le.fit_transform(data["TechSupport"])
data["StreamingTV"] = le.fit_transform(data["StreamingTV"])
data["StreamingMovies"] = le.fit_transform(data["StreamingMovies"])
data["Contract"] = le.fit_transform(data["Contract"])
data["PaperlessBilling"] = le.fit_transform(data["PaperlessBilling"])
data["PaymentMethod"] = le.fit_transform(data["PaymentMethod"])
data["Churn"] = le.fit_transform(data["Churn"])
```

Data after label encoding

```
data.head()
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBa
0	0	0	1	0	1	0	1	0	0	2
1	1	0	0	0	34	1	0	0	2	0
2	1	0	0	0	2	1	0	0	2	2
3	1	0	0	0	45	0	1	0	2	0
4	0	0	0	0	2	1	0	1	0	0

All the data is converted into numerical values.

Splitting the Dataset into Dependent and Independent variable

Let's split our dataset into independent and dependent variables.

1. The independent variable in the dataset would be considered as 'x' and gender,SeniorCitizen,Partner,Dependents,tenure,PhoneService,MultipleLines,InternetService,OnlineSecurity,OnlineBackup,DeviceProtection,TechSupport,StreamingTV,StreamingMovies,Contract,PaperlessBilling,PaymentMethod,MonthlyCharges,TotalCharges columns would be considered as independent variable.
2. The dependent variable in the dataset would be considered as 'y' and the 'Churn' column is considered as dependent variable.

Now we will split the data of independent variables,

```
x= data.iloc[:,0:19].values
y= data.iloc[:,19:20].values
```

From the above code **“:”** indicates that you are considering all the rows in the dataset and **“0:18”** indicates that you are considering columns 0 to 8 such as sex, job and purpose as input values and assigning them to variable x. In the same way in second line **“:”** indicates you are considering all the rows and **“18:19”** indicates that you are considering only last column as output value and assigning them to variable y.

After splitting we see the data as below x

```
x

array([[0.0000e+00, 0.0000e+00, 1.0000e+00, ..., 2.0000e+00, 2.9850e+01,
        2.9850e+01],
       [1.0000e+00, 0.0000e+00, 0.0000e+00, ..., 3.0000e+00, 5.6950e+01,
        1.8895e+03],
       [1.0000e+00, 0.0000e+00, 0.0000e+00, ..., 3.0000e+00, 5.3850e+01,
        1.0815e+02],
       ...,
       [0.0000e+00, 0.0000e+00, 1.0000e+00, ..., 2.0000e+00, 2.9600e+01,
        3.4645e+02],
       [1.0000e+00, 1.0000e+00, 1.0000e+00, ..., 3.0000e+00, 7.4400e+01,
        3.0660e+02],
       [1.0000e+00, 0.0000e+00, 0.0000e+00, ..., 0.0000e+00, 1.0565e+02,
        6.8445e+03]])
```

Y

```
y

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

OneHot Encoding

Sometimes in datasets, we encounter columns that contain numbers of no specific order of preference. The data in the column usually denotes a category or value of the category and also when the data in the column is label encoded. This confuses the machine learning model, to avoid this, the data in the column should be One Hot encoded. One Hot Encoding –

It refers to splitting the column which contains numerical categorical data to many columns depending on the number of categories present in that column. Each column contains “0” or “1” corresponding to which column it has been placed.

```
from sklearn.preprocessing import OneHotEncoder
one = OneHotEncoder()
a= one.fit_transform(x[:,6:7]).toarray()
b= one.fit_transform(x[:,7:8]).toarray()
c= one.fit_transform(x[:,8:9]).toarray()
d= one.fit_transform(x[:,9:10]).toarray()
e= one.fit_transform(x[:,10:11]).toarray()
f= one.fit_transform(x[:,11:12]).toarray()
g= one.fit_transform(x[:,12:13]).toarray()
h= one.fit_transform(x[:,13:14]).toarray()
i= one.fit_transform(x[:,14:15]).toarray()
j= one.fit_transform(x[:,16:17]).toarray()
x=np.delete(x,[6,7,8,9,10,11,12,13,14,16],axis=1)
x=np.concatenate((a,b,c,d,e,f,g,h,i,j,x),axis=1)
```

Activity 2.3: Handling Imbalance Data

Data Balancing is one of the most important step, which need to be performed for classification models, because when we train our model on imbalanced dataset ,we will get biassed results, which means our model is able to predict only one class element For Balancing the data we are using the SMOTE Method.

SMOTE: Synthetic minority over sampling technique, which will create new synthetic data points for under class as per the requirements given by us using KNN method.

```
from imblearn.over_sampling import SMOTE
```

```
smt = SMOTE()

x_resample, y_resample = smt.fit_resample(x,y)
```

```
x_resample
```

```
array([[0.00000000e+00, 0.00000000e+00, 1.00000000e+00, ...,
        2.00000000e+00, 2.98500000e+01, 2.98500000e+01],
       [1.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
        3.00000000e+00, 5.69500000e+01, 1.88950000e+03],
       [1.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
        3.00000000e+00, 5.38500000e+01, 1.08150000e+02],
       ...,
       [0.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
        3.00000000e+00, 2.02307905e+01, 2.02307905e+01],
       [1.00000000e+00, 0.00000000e+00, 6.76069757e-01, ...,
        3.23930243e-01, 9.00059277e+01, 3.69766940e+03],
       [0.00000000e+00, 3.89455378e-01, 1.00000000e+00, ...,
        2.00000000e+00, 9.63258517e+01, 3.21144455e+03]])
```

```
y_resample
```

```
array([0, 0, 1, ..., 1, 1, 1])
```

```
x.shape, x_resample.shape
```

```
((7043, 19), (10348, 19))
```

```
y.shape, y_resample.shape
```

```
((7043, 1), (10348,))
```

From the above picture, we can infer that ,previously our dataset had 492 class 1, and 192 class items, after applying smote technique on the dataset the size has been changed for minority class.

Milestone 3: Exploratory Data Analysis

Activity 1: Descriptive statistical

Descriptive analysis is to study the basic features of data with the statistical process. Here pandas has a worthy function called describe. With this describe function we can understand the unique, top and frequent values of categorical features. And we can find mean, std, min, max and percentile values of continuous features.

```
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

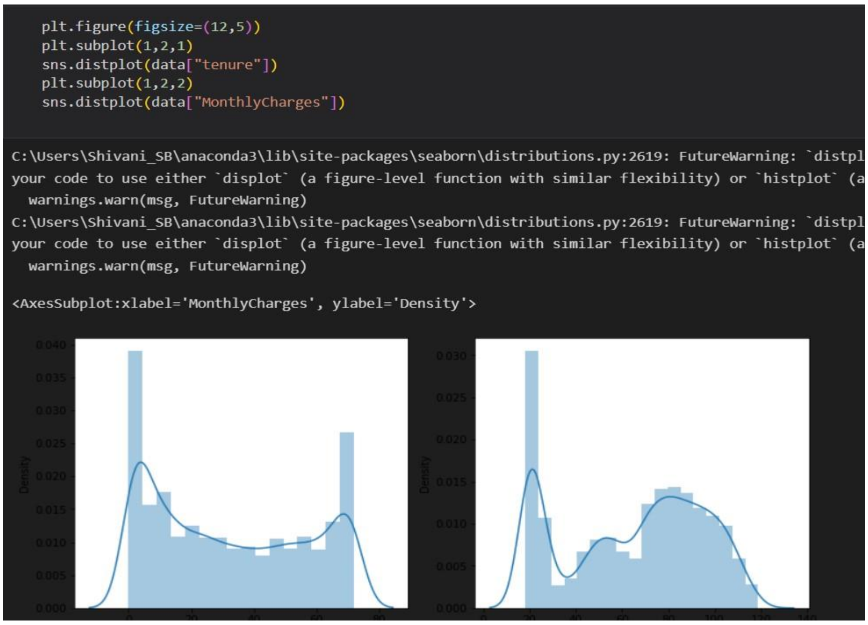
Activity 2: Visual analysis

Visual analysis is the process of using visual representations, such as charts, plots, and graphs, to explore and understand data. It is a way to quickly identify patterns, trends, and outliers in the data, which can help to gain insights and make informed decisions.

Activity 2.1: Univariate analysis

In simple words, univariate analysis is understanding the data with a single feature. Here we have displayed two different graphs such as distplot and countplot.

- The Seaborn package provides a wonderful function distplot. With the help of distplot, we can find the distribution of the feature. To make multiple graphs in a single plot, we use subplot.



- In our dataset we have some categorical features. With the count plot function, we are going to count the unique category in those features. We have created a dummy data frame with categorical features. With for loop and subplot we have plotted this below graph.
- From the plot we came to know, Applicants income is skewed towards left side, where as credit history is categorical with 1.0 and 0.0

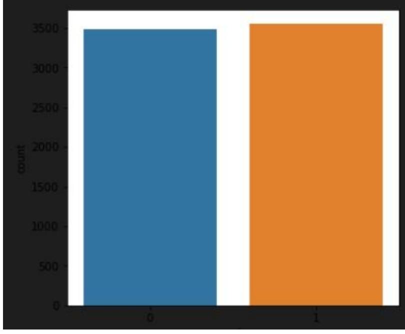
Countplot :-
A count plot can be thought of as a histogram across a categorical, instead of quantitative, variable. The basic API and options are identical to those for barplot() , so you can compare counts across nested variables.

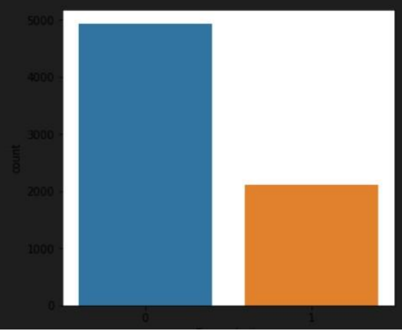
From the graph we can infer that , gender and education is a categorical variables with 2 categories , from gender column we can infer that 0-category is having more weightage than category-1,while education with 0,it means no education is a underclass when compared with category -1, which means educated .

```python
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.countplot(data["gender"])
plt.subplot(1,2,2)
sns.countplot(data["Dependents"])
```

```
C:\Users\Shivani_SB\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fo
argument will be `data`, and passing other arguments without an explicit keyword will result in an er
  warnings.warn(
C:\Users\Shivani_SB\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fo
argument will be `data`, and passing other arguments without an explicit keyword will result in an er
  warnings.warn(

<AxesSubplot:xlabel='Dependents', ylabel='count'>
```

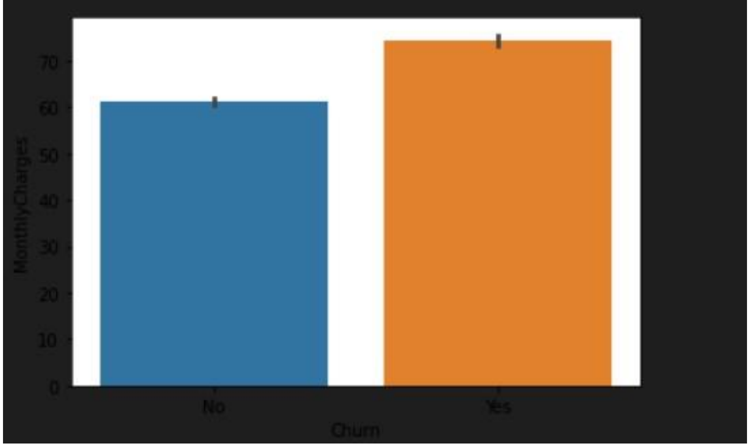




Activity 2.2: Bivariate analysis

```python
sns.barplot(x="Churn", y="MonthlyCharges",data=data)
```

```
<AxesSubplot:xlabel='Churn', ylabel='MonthlyCharges'>
```



From the above graph we can infer the analysis such as

- Segmenting the gender column and married column based on bar graphs
- Segmenting the Education and Self-employed based on bar graphs ,for drawing insights such as educated people are employed.
- Loan amount term based on the property area of a person holding

Activity 2.3: Multivariate analysis

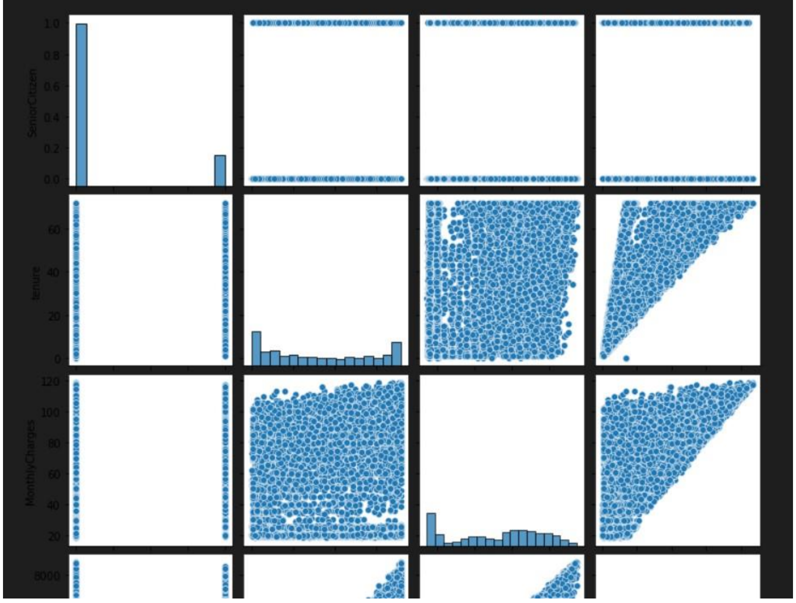
In simple words, multivariate analysis is to find the relation between multiple features. Here we have used a swarm plot from the seaborn package.

```
sns.heatmap(data.corr(), annot=True)
```

```
<AxesSubplot:>
```


```
sns.pairplot(data=data, markers=["^","v"], palette="inferno")
```

```
<seaborn.axisgrid.PairGrid at 0x160fe479f70>
```



From the above graph we are plotting the relationship between the Gender, applicants income and loan status of the person.

Now, the code would be normalising the data by scaling it to have a similar range of values, and then splitting that data into a training set and a test set for training the model and testing its performance, respectively.

Splitting data into train and test
Now let's split the Dataset into train and test sets

Changes: first split the dataset into x and y and then split the data set

Here x and y variables are created. On x variable, df is passed with dropping the target variable. And on y target variable is passed. For splitting training and testing data we are using the train_test_split() function from sklearn. As parameters, we are passing x, y, test_size, random_state.

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x_resample,y_resample,test_size = 0.2, random_state = 0)
```

Scaling the Data

Scaling is one the important process, we have to perform on the dataset, because of data measures in different ranges can leads to mislead in prediction

Models such as KNN, Logistic regression need scaled data, as they follow distance based method and Gradient Descent concept.

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.fit_transform(x_test)
```

```
x_train.shape
```

```
(8278, 19)
```

We will perform scaling only on the input values.Once the dataset is scaled, it will be converted into an array and we need to convert it back to a dataframe.

Milestone 4: Model Building

Activity 1: Training the model in multiple algorithms

Now our data is cleaned and it's time to build the model. We can train our data on different algorithms. For this project we are applying four classification algorithms. The best model is saved based on its performance.

Activity 1.2: Logistic Regression Model

Logistic regression estimates the probability of an event occurring, such as voted or didn't vote, based on a given dataset of independent variables. Since the outcome is a probability, the dependent variable is bounded between 0 and 1. In logistic regression, a logit transformation is applied on the odds—that is, the probability of success divided by the probability of failure.

```
#importing and building the Decision tree model
def logreg(x_train,x_test,y_train,y_test):
    lr = LogisticRegression(random_state=0)
    lr.fit(x_train,y_train)
    y_lr_tr = lr.predict(x_train)
    print(accuracy_score(y_lr_tr,y_train))
    yPred_lr = lr.predict(x_test)
    print(accuracy_score(yPred_lr,y_test))
    print("***Logistic Regression***")
    print("Confusion_Matrix")
    print(confusion_matrix(y_test,yPred_lr))
    print("Classification Report")
    print(classification_report(y_test,yPred_lr))
```

```
#printing the train accuracy and test accuracy respectively
logreg(x_train,x_test,y_train,y_test)
```

```
0.7734960135298381
0.7734299516908213
***Logistic Regression***
Confusion_Matrix
[[754 279]
 [190 847]]
Classification Report
              precision    recall  f1-score   support

           0       0.80      0.73      0.76      1033
           1       0.75      0.82      0.78      1037

    accuracy                           0.77      2070
   macro avg       0.78      0.77      0.77      2070
weighted avg       0.78      0.77      0.77      2070
```

Activity 1.2: Decision tree model

A function named decisionTree is created and train and test data are passed as the parameters. Inside the function, DecisionTreeClassifier algorithm is initialised and training data is passed to the model with the .fit() function. Test data is predicted with .predict() function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

```python
#importing and building the Decision tree model
def decisionTree(x_train,x_test,y_train,y_test):
    dtc = DecisionTreeClassifier(criterion="entropy",random_state=0)
    dtc.fit(x_train,y_train)
    y_dt_tr = dtc.predict(x_train)
    print(accuracy_score(y_dt_tr,y_train))
    yPred_dt = dtc.predict(x_test)
    print(accuracy_score(yPred_dt,y_test))
    print("***Decision Tree***")
    print("Confusion_Matrix")
    print(confusion_matrix(y_test,yPred_dt))
    print("Classification Report")
    print(classification_report(y_test,yPred_dt))
```

```python
#printing the train accuracy and test accuracy respectively
decisionTree(x_train,x_test,y_train,y_test)
```

```
0.9981879681082387
0.6067632850241546
***Decision Tree***
Confusion_Matrix
[[ 242  791]
 [  23 1014]]
Classification Report
              precision    recall  f1-score   support

           0       0.91      0.23      0.37      1033
           1       0.56      0.98      0.71      1037

    accuracy                           0.61      2070
   macro avg       0.74      0.61      0.54      2070
```

Activity 1.3: Random forest model

A function named randomForest is created and train and test data are passed as the parameters. Inside the function, RandomForestClassifier algorithm is initialised and training data is passed to the model with .fit() function. Test data is predicted with .predict() function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

```python
#importing and building the random forest model
def RandomForest(x_tarin,x_test,y_train,y_test):
    rf = RandomForestClassifier(criterion="entropy",n_estimators=10,random_state=0)
    rf.fit(x_train,y_train)
    y_rf_tr = rf.predict(x_train)
    print(accuracy_score(y_rf_tr,y_train))
    yPred_rf = rf.predict(x_test)
    print(accuracy_score(yPred_rf,y_test))
    print("***Random Forest***")
    print("Confusion_Matrix")
    print(confusion_matrix(y_test,yPred_rf))
    print("Classification Report")
    print(classification_report(y_test,yPred_rf))
```

```python
#printing the train accuracy and test accuracy respectively
RandomForest(x_train,x_test,y_train,y_test)
```

```
0.9886446001449626
0.7536231884057971
***Random Forest***
Confusion_Matrix
[[563 470]
 [ 40 997]]
Classification Report
              precision    recall  f1-score   support

           0       0.93      0.55      0.69      1033
           1       0.68      0.96      0.80      1037

    accuracy                           0.75      2070
   macro avg       0.81      0.75      0.74      2070
weighted avg       0.81      0.75      0.74      2070
```

Activity 1.3: KNN model

A function named KNN is created and train and test data are passed as the parameters. Inside the function, KNeighborsClassifier algorithm is initialised and training data is passed to the model with .fit() function. Test data is predicted with .predict() function and saved in new variable. For evaluating the model, confusion matrix and classification report is done.

```
#importing and building the KNN model
def KNN(x_train,x_test,y_train,y_test):
    knn = KNeighborsClassifier()
    knn.fit(x_train,y_train)
    y_knn_tr = knn.predict(x_train)
    print(accuracy_score(y_knn_tr,y_train))
    yPred_knn = knn.predict(x_test)
    print(accuracy_score(yPred_knn,y_test))
    print("***KNN***")
    print("Confusion_Matrix")
    print(confusion_matrix(y_test,yPred_knn))
    print("Classification Report")
    print(classification_report(y_test,yPred_knn))
```

```
#printing the train accuracy and test accuracy respectively
KNN(x_train,x_test,y_train,y_test)
```

```
0.8570910848030925
0.7913043478260869
***KNN***
Confusion_Matrix
[[730 303]
 [129 908]]
Classification Report
              precision    recall  f1-score   support

           0       0.85      0.71      0.77      1033
           1       0.75      0.88      0.81      1037

    accuracy                           0.79      2070
   macro avg       0.80      0.79      0.79      2070
weighted avg       0.80      0.79      0.79      2070
```

Activity 1.4: SVM model

“Support Vector Machine” (SVM) is a supervised machine learning algorithm that can be used for both classification or regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is a number of features you have) with the value of each feature being the value of a particular coordinate.

```
#importing and building the random forest model
def svm(x_tarin,x_test,y_train,y_test):
    svm = SVC(kernel = "linear")
    svm.fit(x_train,y_train)
    y_svm_tr = svm.predict(x_train)
    print(accuracy_score(y_svm_tr,y_train))
    yPred_svm = svm.predict(x_test)
    print(accuracy_score(yPred_svm,y_test))
    print("***Support Vector Machine***")
    print("Confusion_Matrix")
    print(confusion_matrix(y_test,yPred_svm))
    print("Classification Report")
    print(classification_report(y_test,yPred_svm))
```

```
#printing the train accuracy and test accuracy respectively
svm(x_train,x_test,y_train,y_test)
```

```
0.7628654264315052
0.7555555555555555
***Support Vector Machine***
Confusion_Matrix
[[719 314]
 [192 845]]
Classification Report
              precision    recall  f1-score   support

           0       0.79      0.70      0.74      1033
           1       0.73      0.81      0.77      1037

    accuracy                           0.76      2070
   macro avg       0.76      0.76      0.75      2070
weighted avg       0.76      0.76      0.75      2070
```

Activity 1.5: ANN model

Building and training an Artificial Neural Network (ANN) using the Keras library with TensorFlow as the backend. The ANN is initialised as an instance of the Sequential class, which is a linear stack of layers. Then, the input layer and two hidden layers are added to the model using the Dense class, where the number of units and activation function are specified. The output layer is also added using the Dense class with a sigmoid activation function. The model is then compiled with the Adam optimizer, binary cross-entropy loss function, and accuracy metric. Finally, the model is fit to the training data with a batch size of 100, 20% validation split, and 100 epochs.

ANN Model

```
# Importing the Keras libraries and packages
import keras
from keras.models import Sequential
from keras.layers import Dense
```

```
# Initialising the ANN
classifier = Sequential()
```

```
# Adding the input layer and the first hidden layer
classifier.add(Dense(units=30, activation='relu', input_dim=40))
```

```
# Adding the second hidden layer
classifier.add(Dense(units=30, activation='relu'))
```

```
# Adding the output layer
classifier.add(Dense(units=1, activation='sigmoid'))
```

```
# Compiling the ANN
classifier.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

```
# Fitting the ANN to the Training set
model_history = classifier.fit(x_train, y_train, batch_size=10, validation_split=0.33, epochs=200)
```

```
Epoch 1/200
555/555 [==============================] - 4s 3ms/step - loss: 0.5017 - accuracy: 0.7494 - val_loss: 0.4688 - val_accuracy: 0.7756
Epoch 2/200
555/555 [==============================] - 2s 3ms/step - loss: 0.4535 - accuracy: 0.7815 - val_loss: 0.4627 - val_accuracy: 0.7782
Epoch 3/200
555/555 [==============================] - 1s 3ms/step - loss: 0.4424 - accuracy: 0.7865 - val_loss: 0.4691 - val_accuracy: 0.7778
Epoch 4/200
555/555 [==============================] - 1s 2ms/step - loss: 0.4325 - accuracy: 0.7950 - val_loss: 0.4541 - val_accuracy: 0.7917
Epoch 5/200
555/555 [==============================] - 1s 2ms/step - loss: 0.4239 - accuracy: 0.8002 - val_loss: 0.4536 - val_accuracy: 0.7892
Epoch 6/200
555/555 [==============================] - 1s 3ms/step - loss: 0.4146 - accuracy: 0.8078 - val_loss: 0.4564 - val_accuracy: 0.7936
Epoch 7/200
555/555 [==============================] - 1s 2ms/step - loss: 0.4058 - accuracy: 0.8100 - val_loss: 0.4551 - val_accuracy: 0.7921
Epoch 8/200
555/555 [==============================] - 1s 2ms/step - loss: 0.3999 - accuracy: 0.8150 - val_loss: 0.4510 - val_accuracy: 0.7943
```

```
Epoch 195/200
555/555 [==============================] - 2s 3ms/step - loss: 0.1564 - accuracy: 0.9335 - val_loss: 0.7783 - val_accuracy: 0.8093
Epoch 196/200
555/555 [==============================] - 2s 3ms/step - loss: 0.1514 - accuracy: 0.9347 - val_loss: 0.7982 - val_accuracy: 0.7994
Epoch 197/200
555/555 [==============================] - 2s 3ms/step - loss: 0.1549 - accuracy: 0.9327 - val_loss: 0.8319 - val_accuracy: 0.7917
Epoch 198/200
555/555 [==============================] - 2s 3ms/step - loss: 0.1593 - accuracy: 0.9320 - val_loss: 0.7693 - val_accuracy: 0.8130
Epoch 199/200
555/555 [==============================] - 2s 3ms/step - loss: 0.1535 - accuracy: 0.9362 - val_loss: 0.7646 - val_accuracy: 0.8089
Epoch 200/200
555/555 [==============================] - 1s 3ms/step - loss: 0.1544 - accuracy: 0.9356 - val_loss: 0.7744 - val_accuracy: 0.8115
```

```
ann_pred = classifier.predict(x_test)
ann_pred = (ann_pred>0.5)
ann_pred
```

```
65/65 [==============================] - 0s 2ms/step
array([[False],
       [False],
       [ True],
       ...,
       [False],
       [False],
       [False]])
```

```
print(accuracy_score(ann_pred,y_test))
print("***ANN Model***")
print("Confusion_Matrix")
print(confusion_matrix(y_test,ann_pred))
print("Classification Report")
print(classification_report(y_test,ann_pred))
```

```
0.8067632850241546
***ANN Model***
Confusion_Matrix
[[840 193]
 [207 830]]
Classification Report
              precision    recall  f1-score   support

           0       0.80      0.81      0.81      1033
           1       0.81      0.80      0.81      1037

    accuracy                           0.81      2070
   macro avg       0.81      0.81      0.81      2070
```

Activity 2: Testing the model

```
#testing on random input values
lr = LogisticRegression(random_state=0)
lr.fit(x_train,y_train)
print("Predicting on random input")
lr_pred_own = lr.predict(sc.transform([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
print("output is: ",lr_pred_own)
```

```
Predicting on random input
output is:  [0]
```

```
#testing on random input values
dtc = DecisionTreeClassifier(criterion="entropy",random_state=0)
dtc.fit(x_train,y_train)
print("Predicting on random input")
dtc_pred_own = dtc.predict(sc.transform([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
print("output is: ",dtc_pred_own)
```

```
Predicting on random input
output is:  [0]
```

For ANN

```
#testing on random input values
rf = RandomForestClassifier(criterion="entropy",n_estimators=10,random_state=0)
rf.fit(x_train,y_train)
print("Predicting on random input")
rf_pred_own = rf.predict(sc.transform([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
print("output is: ",rf_pred_own)
```

```
Predicting on random input
output is:  [0]
```

```
#testing on random input values
svc = SVC(kernel = "linear")
svc.fit(x_train,y_train)
print("Predicting on random input")
svm_pred_own = svc.predict(sc.transform([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
print("output is: ",svm_pred_own)
```

```
Predicting on random input
output is:  [0]
```

```
#testing on random input values
knn = KNeighborsClassifier()
knn.fit(x_train,y_train)
print("Predicting on random input")
knn_pred_own = knn.predict(sc.transform([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
print("output is: ",knn_pred_own)
```

```
Predicting on random input
output is:  [0]
```

```
#testing on random input values
print("Predicting on random input")
ann_pred_own = classifier.predict(sc.transform([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
print(ann_pred_own)
ann_pred_own = (ann_pred_own>0.5)
print("output is: ",ann_pred_own)
```

```
Predicting on random input
1/1 [==============================] - 0s 24ms/step
[[1.]]
output is:  [[ True]]
```

Milestone 5: Performance Testing & Hyperparameter Tuning

Activity 1: Testing model with multiple evaluation metrics

Multiple evaluation metrics means evaluating the model's performance on a test set using different performance measures. This can provide a more comprehensive understanding of the model's strengths and weaknesses. We are using evaluation metrics for classification tasks including accuracy, precision, recall, support and F1-score.

Activity 1.1: Compare the model

For comparing the above four models, the compareModel function is defined.

```
def compareModel(X_train,X_test,y_train,y_test):
    logreg(x_train,x_test,y_train,y_test)
    print('-'*100)
    decisionTree(X_train,X_test,y_train,y_test)
    print('-'*100)
    RandomForest(X_train,X_test,y_train,y_test)
    print('-'*100)
    svm(X_train,X_test,y_train,y_test)
    print('-'*100)
    KNN(X_train,X_test,y_train,y_test)
    print('-'*100)
```

```
compareModel(x_train,x_test,y_train,y_test)
```

```
0.7734960135298381
0.7734299516908213
***Logistic Regression***
Confusion_Matrix
[[754 279]
 [190 847]]
Classification Report
              precision    recall  f1-score   support

           0       0.80      0.73      0.76      1033
           1       0.75      0.82      0.78      1037

    accuracy                           0.77      2070
   macro avg       0.78      0.77      0.77      2070
weighted avg       0.78      0.77      0.77      2070
```

```
0.9981879681082387
0.6067632850241546
***Decision Tree***
Confusion_Matrix
[[ 242  791]
 [  23 1014]]
Classification Report
              precision    recall  f1-score   support

           0       0.91      0.23      0.37      1033
           1       0.56      0.98      0.71      1037

    accuracy                           0.61      2070
   macro avg       0.74      0.61      0.54      2070
weighted avg       0.74      0.61      0.54      2070
```

```
0.9886446001449626
0.7536231884057971
***Random Forest***
Confusion_Matrix
[[563 470]
 [ 40 997]]
Classification Report
              precision    recall  f1-score   support

           0       0.93      0.55      0.69      1033
           1       0.68      0.96      0.80      1037

    accuracy                           0.75      2070
   macro avg       0.81      0.75      0.74      2070
weighted avg       0.81      0.75      0.74      2070
```

```
0.7628654264315052
0.7555555555555555
***Support Vector Machine***
Confusion_Matrix
[[719 314]
 [192 845]]
Classification Report
              precision    recall  f1-score   support

           0       0.79      0.70      0.74      1033
           1       0.73      0.81      0.77      1037

    accuracy                           0.76      2070
   macro avg       0.76      0.76      0.75      2070
weighted avg       0.76      0.76      0.75      2070
```

```
0.8570910848030925
0.7913043478260869
***KNN***
Confusion_Matrix
[[730 303]
 [129 908]]
Classification Report
              precision    recall  f1-score   support

           0       0.85      0.71      0.77      1033
           1       0.75      0.88      0.81      1037

    accuracy                           0.79      2070
   macro avg       0.80      0.79      0.79      2070
weighted avg       0.80      0.79      0.79      2070
```

```
print(accuracy_score(ann_pred,y_test))
print("***ANN Model***")
print("Confusion_Matrix")
print(confusion_matrix(y_test,ann_pred))
print("Classification Report")
print(classification_report(y_test,ann_pred))
```

```
0.8067632850241546
***ANN Model***
Confusion_Matrix
[[840 193]
 [207 830]]
Classification Report
              precision    recall  f1-score   support

           0       0.80      0.81      0.81      1033
           1       0.81      0.80      0.81      1037

    accuracy                           0.81      2070
   macro avg       0.81      0.81      0.81      2070
weighted avg       0.81      0.81      0.81      2070
```

After calling the function, the results of models are displayed as output. From the five models Xgboost is performing well. From the below image, We can see the accuracy of the model. Xgboost is giving the accuracy of 93.39% with training data , 82.2% accuracy for the testing data.

Activity 2: Comparing model accuracy before & after applying hyperparameter tuning

Evaluating performance of the model From sklearn, cross_val_score is used to evaluate the score of the model. On the parameters, we have given rf (model name), x, y, cv (as 5 folds).

Note: To understand cross validation, refer to this [link]

```
y_rf = model.predict(x_train)
print(accuracy_score(y_rf,y_train))
yPred_rfcv = model.predict(x_test)
print(accuracy_score(yPred_rfcv,y_test))
print("***Random Forest after Hyperparameter tuning***")
print("Confusion_Matrix")
print(confusion_matrix(y_test,yPred_rfcv))
print("Classification Report")
print(classification_report(y_test,yPred_rfcv))
print("Predicting on random input")
rfcv_pred_own = model.predict(sc.transform([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
print("output is: ",rfcv_pred_own)
```

```
0.8859627929451558
0.7454106280193237
***Random Forest after Hyperparameter tuning***
Confusion_Matrix
[[553 480]
 [ 47 990]]
Classification Report
              precision    recall  f1-score   support

           0       0.92      0.54      0.68      1033
           1       0.67      0.95      0.79      1037

    accuracy                           0.75      2070
   macro avg       0.80      0.75      0.73      2070
weighted avg       0.80      0.75      0.73      2070
```

Milestone 6: Model Deployment

Activity 1:Save the best model

Saving the best model after comparing its performance using different evaluation metrics means selecting the model with the highest performance and saving its weights and configuration. This can be useful in avoiding the need to retrain the model every time it is needed and also to be able to use it in the future.

```
classifier.save("telcom_churn.h5")
```

Activity 2: Integrate with Web Framework

In this section, we will be building a web application that is integrated to the model we built. A UI is provided for the uses where he has to enter the values for predictions. The enter values are given to the saved model and prediction is showcased on the UI.

This section has the following tasks

- Building HTML Pages
- Building server side script
- Run the web application

Activity 2.1: Building Html Pages:

For this project create two HTML files namely

- base.html
- index.html
- predyes.html ● predno.html

and save them in the templates folder.

Activity 2.2: Build Python code:

Import the libraries

```
from flask import Flask, render_template, request
import keras
from keras.models import  load_model
```

Load the saved model. Importing the flask module in the project is mandatory. An object of Flask class is our WSGI application. Flask constructor takes the name of the current module (__name__) as argument.

```
app = Flask(__name__)
model = load_model("telcom_churn.h5")
```

Render HTML page:

```
@app.route('/') # rendering the html template
def home():
    return render_template('home.html')
```

Here we will be using a declared constructor to route to the HTML page which we have created earlier.

In the above example, ‘/’ URL is bound with the home.html function. Hence, when the home page of the web server is opened in the browser, the html page will be rendered. Whenever you enter the values from the html page the values can be retrieved using POST Method.

Retrieves the value from UI:

Here we are routing our app to predict() function. This function retrieves all the values from the HTML page using Post request. That is stored in an array. This array is passed to the model.predict() function. This function returns the prediction. And this prediction value will be rendered to the text that we have mentioned in the submit.html page earlier.

Main Function:

```python
@app.route('/')
def helloworld():
    return render_template("base.html")
@app.route('/assesment')
def prediction():
    return render_template("index.html")

@app.route('/predict', methods = ['POST'])
def admin():
    a= request.form["gender"]
    if (a == 'f'):
        a=0
    if (a == 'm'):
        a=1
    b= request.form["srcitizen"]
    if (b == 'n'):
        b=0
    if (b == 'y'):
        b=1
    c= request.form["partner"]
    if (c == 'n'):
        c=0
    if (c == 'y'):
        c=1
    d= request.form["dependents"]
    if (d == 'n'):
        d=0
    if (d == 'y'):
        d=1
    e= request.form["tenure"]
    f= request.form["phservices"]
    if (f == 'n'):
        f=0
    if (f == 'y'):
        f=1
    g= request.form["multi"]
    if (g == 'n'):
```

```python
if (g == 'n'):
    g1,g2,g3=1,0,0
if (g == 'nps'):
    g1,g2,g3=0,1,0
if (g == 'y'):
    g1,g2,g3=0,0,1
h= request.form["is"]
if (h == 'dsl'):
    h1,h2,h3=1,0,0
if (h == 'fo'):
    h1,h2,h3=0,1,0
if (h == 'n'):
    h1,h2,h3=0,0,1
i= request.form["os"]
if (i == 'n'):
    i1,i2,i3=1,0,0
if (i == 'nis'):
    i1,i2,i3=0,1,0
if (i == 'y'):
    i1,i2,i3=0,0,1
j= request.form["ob"]
if (j == 'n'):
    j1,j2,j3=1,0,0
if (j == 'nis'):
    j1,j2,j3=0,1,0
if (j == 'y'):
    j1,j2,j3=0,0,1
k= request.form["dp"]
if (k == 'n'):
    k1,k2,k3=1,0,0
if (k == 'nis'):
    k1,k2,k3=0,1,0
if (k == 'y'):
    k1,k2,k3=0,0,1
l= request.form["ts"]
if (l == 'n'):
    l1,l2,l3=1,0,0
```

```python
    l1,l2,l3=1,0,0
if (l == 'nis'):
    l1,l2,l3=0,1,0
if (l == 'y'):
    l1,l2,l3=0,0,1
m= request.form["stv"]
if (m == 'n'):
    m1,m2,m3=1,0,0
if (m == 'nis'):
    m1,m2,m3=0,1,0
if (m == 'y'):
    m1,m2,m3=0,0,1
n= request.form["smv"]
if (n == 'n'):
    n1,n2,n3=1,0,0
if (n == 'nis'):
    n1,n2,n3=0,1,0
if (n == 'y'):
    n1,n2,n3=0,0,1
o= request.form["contract"]
if (o == 'mtm'):
    o1,o2,o3=1,0,0
if (o == 'oyr'):
    o1,o2,o3=0,1,0
if (o == 'tyrs'):
    o1,o2,o3=0,0,1
p= request.form["pmt"]
if (p == 'ec'):
    p1,p2,p3,p4=1,0,0,0
if (p == 'mail'):
    p1,p2,p3,p4=0,1,0,0
if (p == 'bt'):
    p1,p2,p3,p4=0,0,1,0
if (p == 'cc'):
    p1,p2,p3,p4=0,0,0,1
q= request.form["plb"]
if (q == 'n'):
```

```
q= request.form["plb"]
if (q == 'n'):
    q=0
if (q == 'y'):
    q=1
r= request.form["mcharges"]
s= request.form["tcharges"]

t=[[int(g1),int(g2),int(g3),int(h1),int(h2),int(h3),int(i1),int(i2),int(i3),int(j1
print(t)
x = model.predict(t)
print(x[0])
if (x[[0]] <=0.5):
    y ="No"
    return render_template("predno.html", z = y)

if (x[[0]] >= 0.5):
    y ="Yes"
    return render_template("predyes.html", z = y)
```

Activity 2.3: Run the web application

- Open anaconda prompt from the start menu
- Navigate to the folder where your python script is.
- Now type “python app.py” command
- Navigate to the localhost where you can view your web page.
- Click on the predict button from the top left corner, enter the inputs, click on the submit button, and see the result/prediction on the web.

```
(base) C:\Users\Shivani_SB\OneDrive\Desktop\Telecom churn modelling-updated\flask app>python
2023-01-26 00:46:27.532503: I tensorflow/core/platform/cpu_feature_guard.cc:193] This Tensor
h oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in perfo
 AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
 * Serving Flask app "app" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deployment.
   Use a production WSGI server instead.
 * Debug mode: on
 * Restarting with watchdog (windowsapi)
2023-01-26 00:46:34.072445: I tensorflow/core/platform/cpu_feature_guard.cc:193] This Tensor
h oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in perfo
 AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
 * Debugger is active!
 * Debugger PIN: 109-979-709
 * Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
```

Now,Go the web browser and write the localhost url (http://127.0.0.1:5000) to get the below result

TELECOM CUSTOMER CHURN PREDICTION

Customer churn has become highly important for companies because of increasing competition among companies, increased importance of marketing strategies and conscious behaviour of customers in the recent years. Customers can easily trend toward alternative services. Companies must develop various strategies to prevent these possible trends, depending on the services they provide. During the estimation of possible churns, data from the previous churns might be used. An efficient churn predictive model benefits companies in many ways. Early identification of customers likely to leave may help to build cost effective ways in marketing strategies. Customer retention campaigns might be limited to selected customers but it should cover most of the customer. Incorrect predictions could result in a company losing profits because of the discounts offered to continuous subscribers.

Click me to continue with prediction

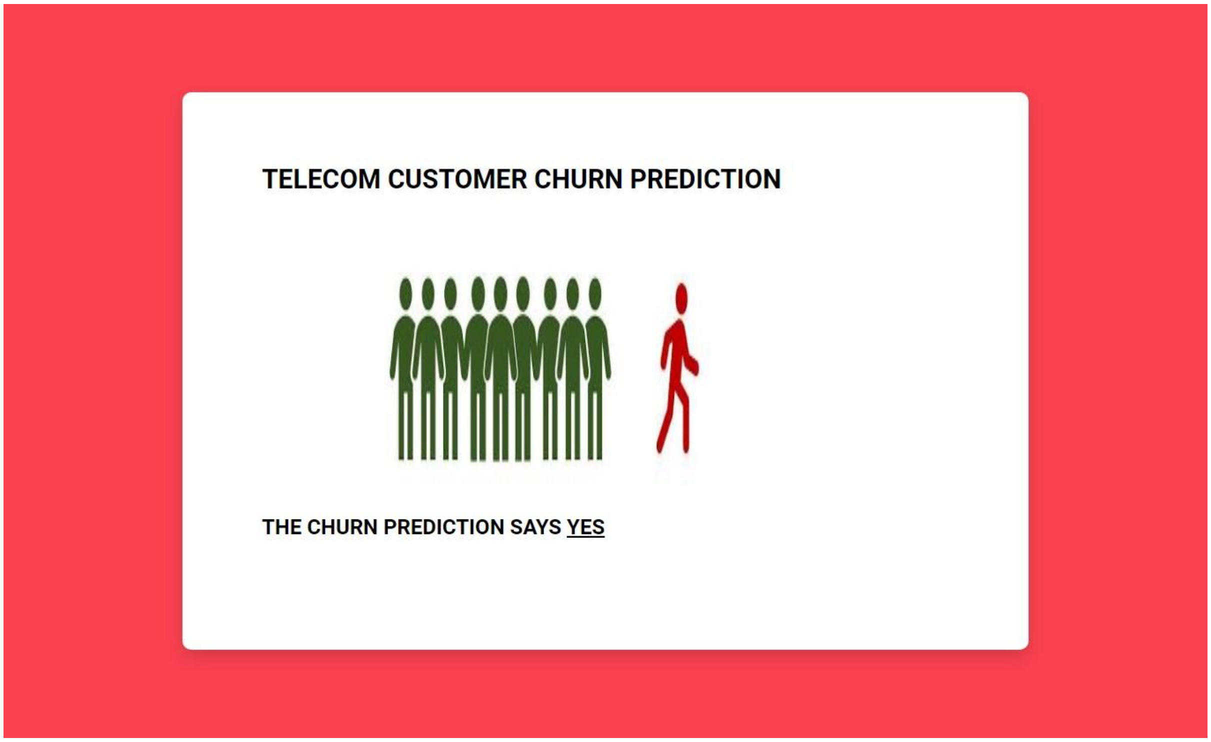
PREDICTION FORM

Gender	Yes
Yes	Yes
3	Yes
No Phone service	DSL
No	Yes
No	No
Yes	Yes
Month to Month	Yes
Bank Transfer(Automatic)	39.5
39.5	

Submit

TELECOM CUSTOMER CHURN PREDICTION

THE CHURN PREDICTION SAYS NO



Milestone 7: Project Demonstration & Documentation

Below mentioned deliverables to be submitted along with other deliverables

Activity 1:- Record explanation Video for project end to end solution

Activity 2:- Project Documentation-Step by step project development procedure

Create document as per the template provided