```
import pandas as pd
import numpy as np
import pickle
from  google.colab import files
import io
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
```

```
data=files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving WA_Fn-UseC_-Telco-Customer-Churn.csv to WA_Fn-UseC_-Telco-Customer-Churn.csv

```
data=pd.read_csv("/content/WA_Fn-UseC_-Telco-Customer-Churn.csv")
df=data
data
```

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

7043 rows × 21 columns

```
data = data.iloc[:,1:]
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
```

```
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
```

```
data.TotalCharges.fillna(data.TotalCharges.mean(), 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
```

```
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.head()
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	Devi
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	

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

```
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
```

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

```
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)
```

```
x
```

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

```
y
```

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

```
from imblearn.over_sampling import SMOTE
sm = SMOTE()
x_resampled, y_resampled = sm.fit_resample(x, y)
```

```
x_resampled
```

```
array([[0.00000000e+00, 1.00000000e+00, 0.00000000e+00, ...,
        1.00000000e+00, 2.98500000e+01, 2.98500000e+01],
       [1.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
        0.00000000e+00, 5.69500000e+01, 1.88950000e+03],
       [1.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
        1.00000000e+00, 5.38500000e+01, 1.08150000e+02],
       ...,
       [0.00000000e+00, 0.00000000e+00, 1.00000000e+00, ...,
        1.00000000e+00, 1.01372937e+02, 2.48954129e+03],
       [0.00000000e+00, 0.00000000e+00, 1.00000000e+00, ...,
        1.00000000e+00, 1.07716086e+02, 5.53516561e+03],
       [4.85936934e-01, 0.00000000e+00, 5.14063066e-01, ...,
        5.14063066e-01, 9.20199927e+01, 1.71654212e+03]])
```

```
y_resampled
```

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

```
x.shape,x_resampled.shape
```

```
((7043, 40), (10348, 40))
```

```
y.shape,y_resampled.shape
```

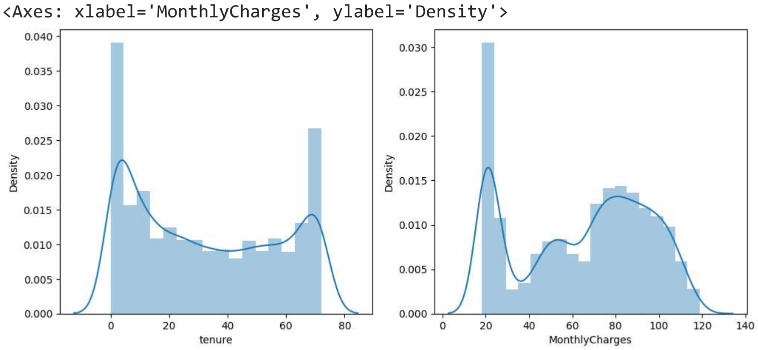
```
((7043, 1), (10348,))
```

```
data.describe()
```

	gender	SeniorCitizen	Partner	Dependents	tenure	Pl
count	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	
mean	0.504756	0.162147	0.483033	0.299588	32.371149	
std	0.500013	0.368612	0.499748	0.458110	24.559481	
min	0.000000	0.000000	0.000000	0.000000	0.000000	

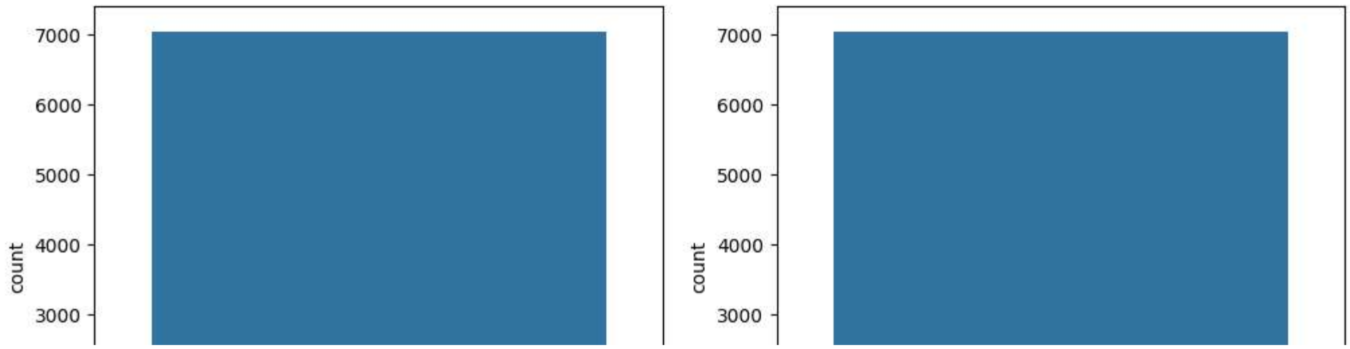
```
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.distplot(data["tenure"])
plt.subplot(1,2,2)
sns.distplot(data["MonthlyCharges"])
```

```
<ipython-input-22-3bd718de5fe4>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.(

Please adapt your code to use either `displot` (a figure-level function wi
similar flexibility) or `histplot` (an axes-level function for histograms)

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data["tenure"])
<ipython-input-22-3bd718de5fe4>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.(

Please adapt your code to use either `displot` (a figure-level function wi
similar flexibility) or `histplot` (an axes-level function for histograms)

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data["MonthlyCharges"])
<Axes: xlabel='MonthlyCharges', ylabel='Density'>
```



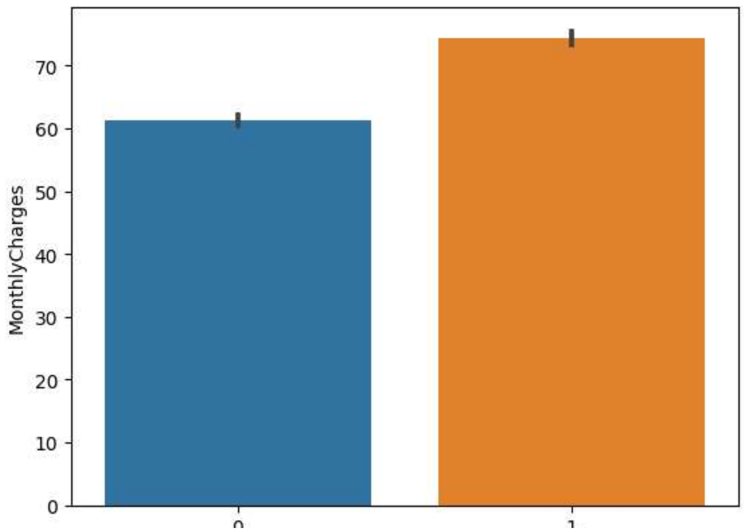

```
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.countplot(data["gender"])
plt.subplot(1,2,2)
sns.countplot(data["Dependents"])
```

```
<Axes: ylabel='count'>
```




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

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

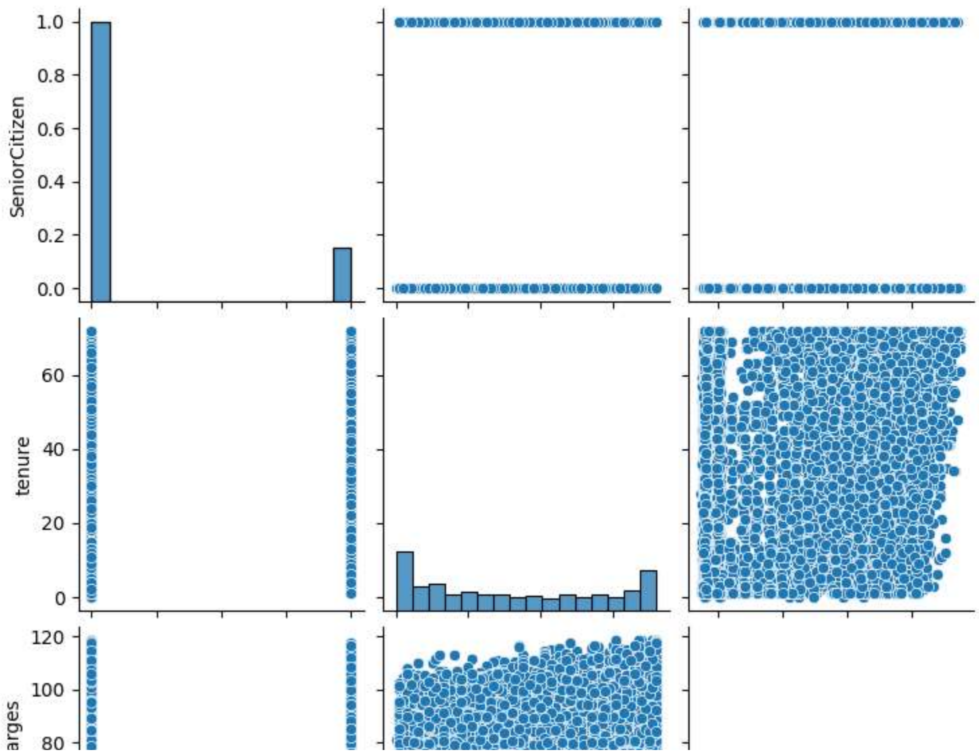



```
sns.heatmap(df.corr(),annot=True)
```

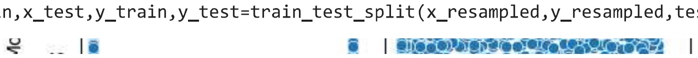
```
<Axes: >
```


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

```
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1507: UserWarning: Ignoring `palette` because no `hue` variable has been as
  func(x=vector, **plot_kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1507: UserWarning: Ignoring `palette` because no `hue` variable has been as
  func(x=vector, **plot_kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1507: UserWarning: Ignoring `palette` because no `hue` variable has been as
  func(x=vector, **plot_kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` because no `hue` variable has been as
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` because no `hue` variable has been as
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` because no `hue` variable has been as
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` because no `hue` variable has been as
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` because no `hue` variable has been as
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` because no `hue` variable has been as
  func(x=x, y=y, **kwargs)
<seaborn.axisgrid.PairGrid at 0x7fcc01cad640>
```




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



```
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, 40)
```

```
def logreg(x_train,x_test,y_train,y_test):
  lr=LogisticRegression(random_state=0)
  lr.fit(x_train,y_train)
  ylt=lr.predict(x_train)
  print("Accuracy Score :",accuracy_score(ylt,y_train))
  yPred_lr=lr.predict(x_test)
  print("Accuracy Test :",accuracy_score(yPred_lr,y_test))
  print("Logistic Regression")
  print("Confusion Matrix")
  print(confusion_matrix(y_test, yPred_lr))
  print("Classification Reprot")
  print(classification_report(y_test, yPred_lr))

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

```
Accuracy Score : 0.7726503986470162
Accuracy Test : 0.7801932367149759
Logistic Regression
Confusion Matrix
[[762 271]
 [184 853]]
Classification Reprot
              precision    recall  f1-score   support

           0       0.81      0.74      0.77      1033
           1       0.76      0.82      0.79      1037

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

```
def dTree(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 :",accuracy_score(y_dt_tr,y_train))
  yPred_dt=dtc.predict(x_test)
  print("Accuracy Test :",accuracy_score(yPred_dt,y_test))
  print("Decsion Tree")
  print("Confusion Matrix")
  print(confusion_matrix(y_test, yPred_dt))
  print("Classification Reprot")
  print(classification_report(y_test, yPred_dt))

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

```
Accuracy Score : 0.9981879681082387
Accuracy Test : 0.7888888888888889
Decsion Tree
Confusion Matrix
[[685 348]
 [ 89 948]]
Classification Reprot
              precision    recall  f1-score   support

           0       0.89      0.66      0.76      1033
           1       0.73      0.91      0.81      1037

    accuracy                           0.79      2070
   macro avg       0.81      0.79      0.79      2070
weighted avg       0.81      0.79      0.79      2070
```

```
def RandomForest(x_train,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 :",accuracy_score(y_rf_tr,y_train))
  yPred_rf=rf.predict(x_test)
  print("Accuracy Test :",accuracy_score(yPred_rf,y_test))
  print("Random Forest")
  print("Confusion Matrix")
  print(confusion_matrix(y_test, yPred_rf))
  print("Classification Reprot")
  print(classification_report(y_test, yPred_rf))

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

```
Accuracy Score : 0.9890070065233149
Accuracy Test : 0.7922705314009661
Random Forest
Confusion Matrix
[[701 332]
 [ 98 939]]
Classification Reprot
              precision    recall  f1-score   support

           0       0.88      0.68      0.77      1033
           1       0.74      0.91      0.81      1037

    accuracy                           0.79      2070
   macro avg       0.81      0.79      0.79      2070
```

```
    weighted avg       0.81      0.79      0.79      2070
```

```
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 :",accuracy_score(y_knn_tr,y_train))
  yPred_knn=knn.predict(x_test)
  print("Accuracy Test :",accuracy_score(yPred_knn,y_test))
  print("KNN")
  print("Confusion Matrix")
  print(confusion_matrix(y_test, yPred_knn))
  print("Classification Reprot")
  print(classification_report(y_test, yPred_knn))

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

```
    Accuracy Score : 0.851171780623339
    Accuracy Test : 0.7956521739130434
    KNN
    Confusion Matrix
    [[720 313]
     [110 927]]
    Classification Reprot
                  precision    recall  f1-score   support

               0       0.87      0.70      0.77      1033
               1       0.75      0.89      0.81      1037

        accuracy                           0.80      2070
       macro avg       0.81      0.80      0.79      2070
    weighted avg       0.81      0.80      0.79      2070
```

```
def SVM(x_train,x_test,y_train,y_test):
  svm=KNeighborsClassifier()
  svm.fit(x_train,y_train)
  y_svm_tr=svm.predict(x_train)
  print("Accuracy Score :",accuracy_score(y_svm_tr,y_train))
  yPred_svm=svm.predict(x_test)
  print("Accuracy Test :",accuracy_score(yPred_svm,y_test))
  print("SVM")
  print("Confusion Matrix")
  print(confusion_matrix(y_test, yPred_svm))
  print("Classification Reprot")
  print(classification_report(y_test, yPred_svm))

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

```
    Accuracy Score : 0.851171780623339
    Accuracy Test : 0.7956521739130434
    SVM
    Confusion Matrix
    [[720 313]
     [110 927]]
    Classification Reprot
                  precision    recall  f1-score   support

               0       0.87      0.70      0.77      1033
               1       0.75      0.89      0.81      1037

        accuracy                           0.80      2070
       macro avg       0.81      0.80      0.79      2070
    weighted avg       0.81      0.80      0.79      2070
```

```
import keras
from keras.models import Sequential
from keras.layers import Dense
classifier=Sequential()
classifier.add(Dense(units=30, activation="relu",input_dim=40))
classifier.add(Dense(units=30, activation="relu"))
classifier.add(Dense(units=1, activation="sigmoid"))
classifier.compile(optimizer="adam",loss="binary_crossentropy",metrics=['accuracy'])
```

```
model_histroty=classifier.fit(x_train,y_train, batch_size=10, validation_split=0.33,epochs=200)
```

```
Epoch 1/200
555/555 [==============================] - 3s 3ms/step - loss: 0.5095 - accuracy: 0.7413 - val_loss: 0.4750 - val_accuracy: 0.7687
Epoch 2/200
555/555 [==============================] - 2s 3ms/step - loss: 0.4637 - accuracy: 0.7773 - val_loss: 0.4680 - val_accuracy: 0.7731
Epoch 3/200
555/555 [==============================] - 2s 3ms/step - loss: 0.4493 - accuracy: 0.7908 - val_loss: 0.4627 - val_accuracy: 0.7723
Epoch 4/200
555/555 [==============================] - 1s 3ms/step - loss: 0.4365 - accuracy: 0.7981 - val_loss: 0.4537 - val_accuracy: 0.7782
Epoch 5/200
555/555 [==============================] - 2s 3ms/step - loss: 0.4248 - accuracy: 0.8035 - val_loss: 0.4470 - val_accuracy: 0.7796
Epoch 6/200
555/555 [==============================] - 2s 3ms/step - loss: 0.4170 - accuracy: 0.8103 - val_loss: 0.4580 - val_accuracy: 0.7840
Epoch 7/200
555/555 [==============================] - 1s 2ms/step - loss: 0.4063 - accuracy: 0.8152 - val_loss: 0.4507 - val_accuracy: 0.7778
Epoch 8/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3970 - accuracy: 0.8190 - val_loss: 0.4605 - val_accuracy: 0.7796
Epoch 9/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3912 - accuracy: 0.8238 - val_loss: 0.4395 - val_accuracy: 0.7925
Epoch 10/200
555/555 [==============================] - 2s 4ms/step - loss: 0.3813 - accuracy: 0.8298 - val_loss: 0.4345 - val_accuracy: 0.7939
Epoch 11/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3773 - accuracy: 0.8329 - val_loss: 0.4342 - val_accuracy: 0.7961
Epoch 12/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3715 - accuracy: 0.8336 - val_loss: 0.4352 - val_accuracy: 0.8020
Epoch 13/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3621 - accuracy: 0.8375 - val_loss: 0.4271 - val_accuracy: 0.8031
Epoch 14/200
555/555 [==============================] - 1s 2ms/step - loss: 0.3583 - accuracy: 0.8390 - val_loss: 0.4306 - val_accuracy: 0.7990
Epoch 15/200
555/555 [==============================] - 1s 2ms/step - loss: 0.3517 - accuracy: 0.8404 - val_loss: 0.4386 - val_accuracy: 0.8005
Epoch 16/200
555/555 [==============================] - 1s 2ms/step - loss: 0.3476 - accuracy: 0.8460 - val_loss: 0.4380 - val_accuracy: 0.8038
Epoch 17/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3412 - accuracy: 0.8489 - val_loss: 0.4250 - val_accuracy: 0.8067
Epoch 18/200
555/555 [==============================] - 2s 4ms/step - loss: 0.3364 - accuracy: 0.8507 - val_loss: 0.4340 - val_accuracy: 0.8097
Epoch 19/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3318 - accuracy: 0.8502 - val_loss: 0.4359 - val_accuracy: 0.7932
Epoch 20/200
555/555 [==============================] - 1s 2ms/step - loss: 0.3295 - accuracy: 0.8541 - val_loss: 0.4287 - val_accuracy: 0.8005
Epoch 21/200
555/555 [==============================] - 1s 2ms/step - loss: 0.3261 - accuracy: 0.8556 - val_loss: 0.4440 - val_accuracy: 0.7943
Epoch 22/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3200 - accuracy: 0.8585 - val_loss: 0.4282 - val_accuracy: 0.8067
Epoch 23/200
555/555 [==============================] - 1s 2ms/step - loss: 0.3189 - accuracy: 0.8577 - val_loss: 0.4323 - val_accuracy: 0.8042
Epoch 24/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3138 - accuracy: 0.8608 - val_loss: 0.4284 - val_accuracy: 0.8056
Epoch 25/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3063 - accuracy: 0.8646 - val_loss: 0.4564 - val_accuracy: 0.7950
Epoch 26/200
555/555 [==============================] - 3s 6ms/step - loss: 0.3080 - accuracy: 0.8657 - val_loss: 0.4347 - val_accuracy: 0.8089
Epoch 27/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3006 - accuracy: 0.8687 - val_loss: 0.4352 - val_accuracy: 0.8078
Epoch 28/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3016 - accuracy: 0.8677 - val_loss: 0.4310 - val_accuracy: 0.8133
Epoch 29/200
555/555 [==============================] - 2s 3ms/step - loss: 0.2982 - accuracy: 0.8678 - val_loss: 0.4464 - val_accuracy: 0.8075
```

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

```
65/65 [==============================] - 0s 1ms/step
array([[ True],
       [False],
       [ True],
       ...,
       [ True],
       [ True],
       [ True]])
```

```
print("Accuracy Test :",accuracy_score(ann_pred,y_test))
print("ANN model")
print("Confusion Matrix")
print(confusion_matrix(y_test, ann_pred))
```

```
print("Classification Reprot")
print(classification_report(y_test, ann_pred))
```

```
Accuracy Test : 0.808695652173913
ANN model
Confusion Matrix
[[759 274]
 [122 915]]
Classification Reprot
              precision    recall  f1-score   support

           0       0.86      0.73      0.79      1033
           1       0.77      0.88      0.82      1037

    accuracy                           0.81      2070
   macro avg       0.82      0.81      0.81      2070
weighted avg       0.82      0.81      0.81      2070
```

```
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]
```

Double-click (or enter) to edit

```
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 : [1]
```

```
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]
```

```
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]]))
ann_pred_own=(ann_pred_own>0.5)
print("output is :", ann_pred_own)
```

```
Predicting on random input
1/1 [==============================] - 0s 23ms/step
output is : [[ True]]
```

```
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]
```

```
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]
```

```
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 43ms/step
[[1.]]
output is : [[ True]]
```

```
def comp_mod(x_train,x_test,y_train,y_test):
  logreg(x_train,x_test,y_train,y_test)
  print("-"*100)
  dTree(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)
```

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

```
Accuracy Score : 0.7726503986470162
Accuracy Test : 0.7801932367149759
Logistic Regression
Confusion Matrix
[[762 271]
 [184 853]]
Classification Reprot
              precision    recall  f1-score   support

           0       0.81      0.74      0.77      1033
           1       0.76      0.82      0.79      1037

    accuracy                           0.78      2070
   macro avg       0.78      0.78      0.78      2070
weighted avg       0.78      0.78      0.78      2070

----------------------------------------------------------------------------------------------------
Accuracy Score : 0.9981879681082387
Accuracy Test : 0.7888888888888889
Decsion Tree
Confusion Matrix
[[685 348]
 [ 89 948]]
Classification Reprot
              precision    recall  f1-score   support

           0       0.89      0.66      0.76      1033
           1       0.73      0.91      0.81      1037

    accuracy                           0.79      2070
   macro avg       0.81      0.79      0.79      2070
weighted avg       0.81      0.79      0.79      2070

----------------------------------------------------------------------------------------------------
Accuracy Score : 0.9890070065233149
Accuracy Test : 0.7922705314009661
Random Forest
Confusion Matrix
[[701 332]
 [ 98 939]]
Classification Reprot
              precision    recall  f1-score   support

           0       0.88      0.68      0.77      1033
           1       0.74      0.91      0.81      1037

    accuracy                           0.79      2070
   macro avg       0.81      0.79      0.79      2070
weighted avg       0.81      0.79      0.79      2070
```

```
-----------------------------------------------------------------------------------------------------
Accuracy Score : 0.851171780623339
Accuracy Test : 0.7956521739130434
SVM
Confusion Matrix
[[720 313]
 [110 927]]
Classification Reprot
```

```
model = RandomForestClassifier()
model.fit(x_train, y_train)
y_rf=model.predict(x_train)
print(accuracy_score(y_rf,y_train))
y_pred_rcv=model.predict(x_test)
print(accuracy_score(y_pred_rcv,y_test))
print("**Random Forest after Hyperparameter tuning**")
print("Confusion Matrix")
print(confusion_matrix(y_test, y_pred_rcv))
print("Classification Reprot")
print(classification_report(y_test, y_pred_rcv))
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)
```

```
0.9981879681082387
0.7990338164251207
**Random Forest after Hyperparameter tuning**
Confusion Matrix
[[678 355]
 [ 61 976]]
Classification Reprot
              precision    recall  f1-score   support

           0       0.92      0.66      0.77      1033
           1       0.73      0.94      0.82      1037

    accuracy                           0.80      2070
   macro avg       0.83      0.80      0.79      2070
weighted avg       0.83      0.80      0.79      2070

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

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