```
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	MultipleLines	Inte
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	
...	...	...	...	...	...	...	...	...	
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes	
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	

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	On
0	0	0	1	0	1	0	1	0	
1	1	0	0	0	34	1	0	0	
2	1	0	0	0	2	1	0	0	
3	1	0	0	0	45	0	1	0	
4	0	0	0	0	2	1	0	1	

```
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
```

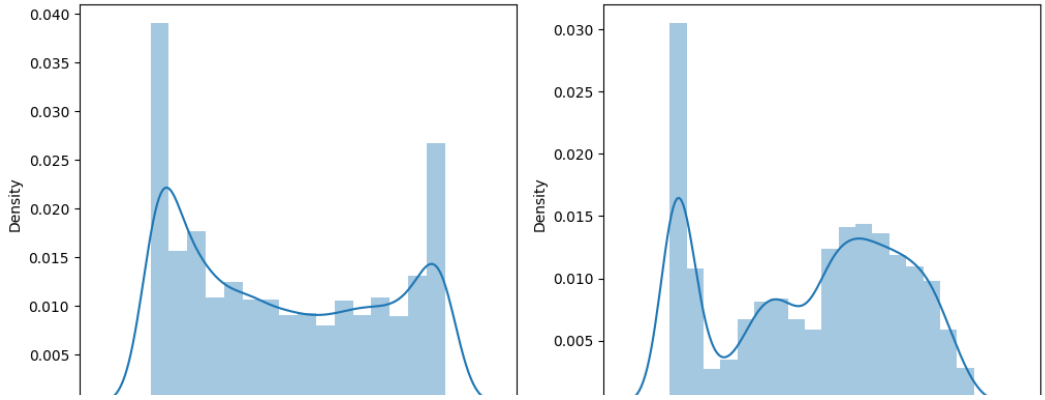
```
((7043, 1), (10348,))
```

```
data.describe()
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	In
count	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	
mean	0.504756	0.162147	0.483033	0.299588	32.371149	0.903166	0.940508	
std	0.500013	0.368612	0.499748	0.458110	24.559481	0.295752	0.948554	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	9.000000	1.000000	0.000000	
50%	1.000000	0.000000	0.000000	0.000000	29.000000	1.000000	1.000000	
75%	1.000000	0.000000	1.000000	1.000000	55.000000	1.000000	2.000000	
max	1.000000	1.000000	1.000000	1.000000	72.000000	1.000000	2.000000	

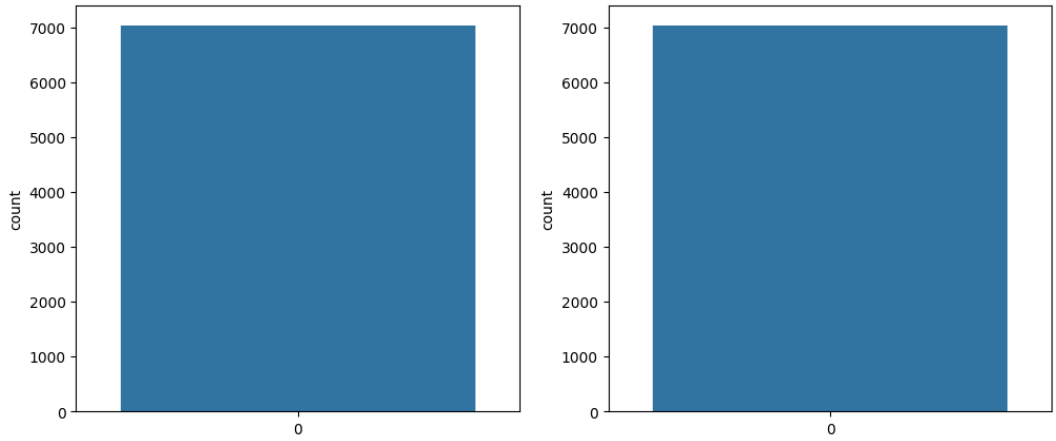
```
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.distplot(data["tenure"])
plt.subplot(1,2,2)
sns.distplot(data["MonthlyCharges"])
```

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

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
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 v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
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'>
```



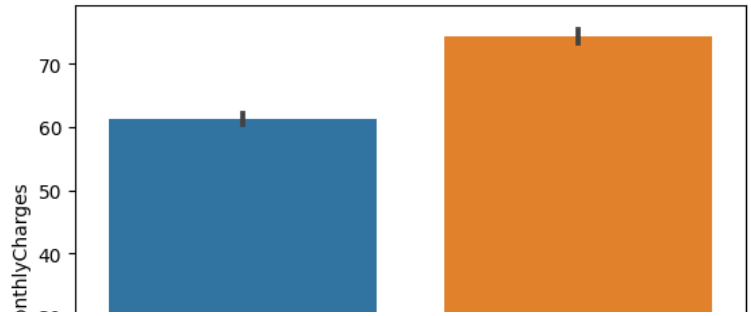

```
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.countplot(data["gender"])
plt.subplot(1,2,2)
sns.countplot(data["Dependents"])
```

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



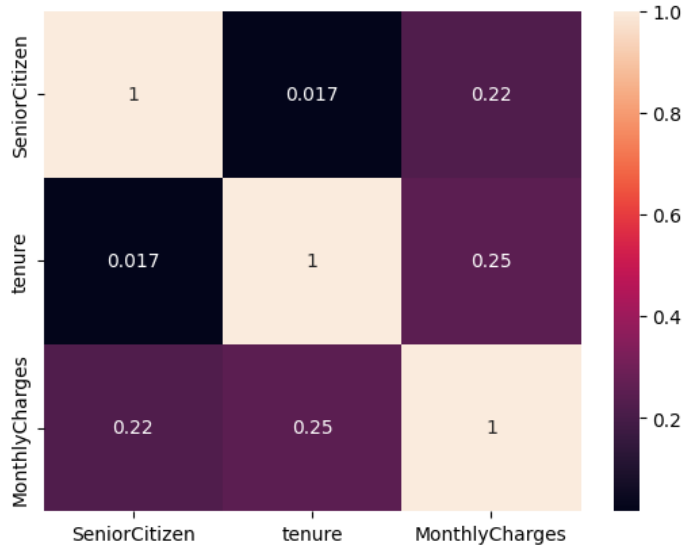

```
sns.barplot(x="Churn",y="MonthlyCharges",data=data)
```

```
<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` becau
  func(x=vector, **plot_kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1507: UserWarning: Ignoring `palette` becau
  func(x=vector, **plot_kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1507: UserWarning: Ignoring `palette` becau
  func(x=vector, **plot_kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` becau
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` becau
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` becau
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` becau
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` becau
  func(x=x, y=y, **kwargs)
/usr/local/lib/python3.9/dist-packages/seaborn/axisgrid.py:1609: UserWarning: Ignoring `palette` becau
  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.
    Epoch 2/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.4637 - accuracy: 0.7773 - val_loss: 0.4680 - val_accuracy: 0.
    Epoch 3/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.4493 - accuracy: 0.7908 - val_loss: 0.4627 - val_accuracy: 0.
    Epoch 4/200
    555/555 [==============================] - 1s 3ms/step - loss: 0.4365 - accuracy: 0.7981 - val_loss: 0.4537 - val_accuracy: 0.
    Epoch 5/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.4248 - accuracy: 0.8035 - val_loss: 0.4470 - val_accuracy: 0.
    Epoch 6/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.4170 - accuracy: 0.8103 - val_loss: 0.4580 - val_accuracy: 0.
    Epoch 7/200
    555/555 [==============================] - 1s 2ms/step - loss: 0.4063 - accuracy: 0.8152 - val_loss: 0.4507 - val_accuracy: 0.
    Epoch 8/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.3970 - accuracy: 0.8190 - val_loss: 0.4605 - val_accuracy: 0.
    Epoch 9/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.3912 - accuracy: 0.8238 - val_loss: 0.4395 - val_accuracy: 0.
    Epoch 10/200
    555/555 [==============================] - 2s 4ms/step - loss: 0.3813 - accuracy: 0.8298 - val_loss: 0.4345 - val_accuracy: 0.
    Epoch 11/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.3773 - accuracy: 0.8329 - val_loss: 0.4342 - val_accuracy: 0.
    Epoch 12/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.3715 - accuracy: 0.8336 - val_loss: 0.4352 - val_accuracy: 0.
    Epoch 13/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.3621 - accuracy: 0.8375 - val_loss: 0.4271 - val_accuracy: 0.
    Epoch 14/200
    555/555 [==============================] - 1s 2ms/step - loss: 0.3583 - accuracy: 0.8390 - val_loss: 0.4306 - val_accuracy: 0.
    Epoch 15/200
    555/555 [==============================] - 1s 2ms/step - loss: 0.3517 - accuracy: 0.8404 - val_loss: 0.4386 - val_accuracy: 0.
    Epoch 16/200
    555/555 [==============================] - 1s 2ms/step - loss: 0.3476 - accuracy: 0.8460 - val_loss: 0.4380 - val_accuracy: 0.
    Epoch 17/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.3412 - accuracy: 0.8489 - val_loss: 0.4250 - val_accuracy: 0.
    Epoch 18/200
    555/555 [==============================] - 2s 4ms/step - loss: 0.3364 - accuracy: 0.8507 - val_loss: 0.4340 - val_accuracy: 0.
    Epoch 19/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.3318 - accuracy: 0.8502 - val_loss: 0.4359 - val_accuracy: 0.
    Epoch 20/200
    555/555 [==============================] - 1s 2ms/step - loss: 0.3295 - accuracy: 0.8541 - val_loss: 0.4287 - val_accuracy: 0.
    Epoch 21/200
    555/555 [==============================] - 1s 2ms/step - loss: 0.3261 - accuracy: 0.8556 - val_loss: 0.4440 - val_accuracy: 0.
    Epoch 22/200
    555/555 [==============================] - 2s 3ms/step - loss: 0.3200 - accuracy: 0.8585 - val_loss: 0.4282 - val_accuracy: 0.
```

```
Epoch 23/200
555/555 [==============================] - 1s 2ms/step - loss: 0.3189 - accuracy: 0.8577 - val_loss: 0.4323 - val_accuracy: 0.
Epoch 24/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3138 - accuracy: 0.8608 - val_loss: 0.4284 - val_accuracy: 0.
Epoch 25/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3063 - accuracy: 0.8646 - val_loss: 0.4564 - val_accuracy: 0.
Epoch 26/200
555/555 [==============================] - 3s 6ms/step - loss: 0.3080 - accuracy: 0.8657 - val_loss: 0.4347 - val_accuracy: 0.
Epoch 27/200
555/555 [==============================] - 2s 3ms/step - loss: 0.3006 - accuracy: 0.8687 - val_loss: 0.4352 - val_accuracy: 0.
Epoch 28/200
```

```
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([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,456,1,0,3245,4567]]))
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([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,456,1,0,3245,4567]]))
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([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,456,1,0,3245,4567]]))
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([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
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([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
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([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
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([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
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)
```

```
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

--------------------------------------------------------------------------------------------------------
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

--------------------------------------------------------------------------------------------------------
```

```
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([[0,0,1,1,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,1,0,0,1,1,0,0,456,1,0,3245,4567]]))
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")
```

```
!pip install nbconvert
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: nbconvert in /usr/local/lib/python3.9/dist-packages (6.5.4)
Requirement already satisfied: tinycss2 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (1.2.1)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (2.1.2)
Requirement already satisfied: jinja2>=3.0 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (3.1.2)
Requirement already satisfied: jupyterlab-pygments in /usr/local/lib/python3.9/dist-packages (from nbconvert) (0.2.2)
Requirement already satisfied: traitlets>=5.0 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (5.7.1)
Requirement already satisfied: lxml in /usr/local/lib/python3.9/dist-packages (from nbconvert) (4.9.2)
Requirement already satisfied: defusedxml in /usr/local/lib/python3.9/dist-packages (from nbconvert) (0.7.1)
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (4.11.2)
Requirement already satisfied: jupyter-core>=4.7 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (5.3.0)
Requirement already satisfied: entrypoints>=0.2.2 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (0.4)
Requirement already satisfied: pygments>=2.4.1 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (2.14.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.9/dist-packages (from nbconvert) (23.1)
Requirement already satisfied: pandocfilters>=1.4.1 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (1.5.0)
```

```
Requirement already satisfied: nbformat>=5.1 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (5.8.0)
Requirement already satisfied: bleach in /usr/local/lib/python3.9/dist-packages (from nbconvert) (6.0.0)
Requirement already satisfied: mistune<2,>=0.8.1 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (0.8.4)
Requirement already satisfied: nbclient>=0.5.0 in /usr/local/lib/python3.9/dist-packages (from nbconvert) (0.7.3)
Requirement already satisfied: platformdirs>=2.5 in /usr/local/lib/python3.9/dist-packages (from jupyter-core>=4.7->nbconvert) (3
Requirement already satisfied: jupyter-client>=6.1.12 in /usr/local/lib/python3.9/dist-packages (from nbclient>=0.5.0->nbconvert)
Requirement already satisfied: jsonschema>=2.6 in /usr/local/lib/python3.9/dist-packages (from nbformat>=5.1->nbconvert) (4.3.3)
Requirement already satisfied: fastjsonschema in /usr/local/lib/python3.9/dist-packages (from nbformat>=5.1->nbconvert) (2.16.3)
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.9/dist-packages (from beautifulsoup4->nbconvert) (2.4.1)
Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.9/dist-packages (from bleach->nbconvert) (1.16.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.9/dist-packages (from bleach->nbconvert) (0.5.1)
Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0 in /usr/local/lib/python3.9/dist-packages (from json
Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.9/dist-packages (from jsonschema>=2.6->nbformat>=5.1->nbco
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.9/dist-packages (from jupyter-client>=6.1.12->nbcli
Requirement already satisfied: tornado>=4.1 in /usr/local/lib/python3.9/dist-packages (from jupyter-client>=6.1.12->nbclient>=0.5
Requirement already satisfied: pyzmq>=13 in /usr/local/lib/python3.9/dist-packages (from jupyter-client>=6.1.12->nbclient>=0.5.0-
```

```
! jupyter nbconvert --to html Telephone_churn_checkpoint.ipynb
```

```
[NbConvertApp] Converting notebook Telephone_churn_checkpoint.ipynb to html
[NbConvertApp] Writing 1099260 bytes to Telephone_churn_checkpoint.html
```

✓ 2s completed at 10:52 AM