```
# 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
data = pd.read_csv(r"/content/Churn_Modelling[1].csv")
data
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMe
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	
...	...	...	...	...	...	...	...	...	...	...	...	
9995	9996	15606229	Obijiaku	771	France	Male	39	5	0.00	2	1	
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	

10000 rows × 14 columns

```
data.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	

```
import warnings
warnings.filterwarnings("ignore")
from sklearn import metrics
from sklearn.metrics import accuracy_score
```

```
# importing .csv files using Pandas
train = pd.read_csv('/content/Churn_Modelling[1].csv')
test = pd.read_csv('/content/Churn_Modelling[1].csv')
```

```
train['Balance'] = train['Balance'].apply(lambda x: 1 if x == 'male' else 2)
```

```
train.drop(columns=['RowNumber','CustomerId','Surname','Gender','Age'], inplace=True)
```

```
X = train.drop(["Balance"], axis=1)
y = train.Balance
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
```

```
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=21)
```

```
#importing and building the Decision tree model
def logreg(x_train,x_test,y_train,y_test):
  Ir = LogisticRegression(random_state=0)
  Ir.fit(x_train,y_train)
  y_Ir_tr = Ir.predict(x_train)
  print(accuracy_score(y_Ir_tr,y_train))
  ypred_Ir = Ir.predict(x_test)
  print(accuracy_score(ypred_tr,y_train))
  print("***LogisticRegression***")
  print("Confusion_Matrix")
  print(Confusion_Matrix(y_test,ypred_Ir))
  print("Classification Report")
  print(classification_report(y_test,ypred_Ir))
```

```
!pip install matplotlib-venn
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: matplotlib-venn in /usr/local/lib/python3.9/dist-packages (0.11.9)
Requirement already satisfied: numpy in /usr/local/lib/python3.9/dist-packages (from matplotlib-venn) (1.22.4)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.9/dist-packages (from matplotlib-venn) (3.7.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.9/dist-packages (from matplotlib-venn) (1.10.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.9/dist-packages (from matplotlib->matplotlib-venn) (1.0
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.9/dist-packages (from matplotlib->matplotlib-venn) (
Requirement already satisfied: importlib-resources>=3.2.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib->matplotlib-v
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib->matplotlib-venn) (4.3
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.9/dist-packages (from matplotlib->matplotlib-venn) (1.4
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.9/dist-packages (from matplotlib->matplotlib-venn) (3.0
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib->matplotlib-venn) (23.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.9/dist-packages (from matplotlib->matplotlib-venn) (0.11.0)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib->matplotlib-venn) (8.4.0)
Requirement already satisfied: zipp>=3.1.0 in /usr/local/lib/python3.9/dist-packages (from importlib-resources>=3.2.0->matplotlib-
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.9/dist-packages (from python-dateutil>=2.7->matplotlib->matplotl
```

```
!apt-get -qq install -y libfluidsynth1
```

```
E: Package 'libfluidsynth1' has no installation candidate
```

```
# https://pypi.python.org/pypi/libarchive
!apt-get -qq install -y libarchive-dev && pip install -U libarchive
import libarchive
```

```
Selecting previously unselected package libarchive-dev:amd64.
(Reading database ... 122349 files and directories currently installed.)
Preparing to unpack .../libarchive-dev_3.4.0-2ubuntu1.2_amd64.deb ...
Unpacking libarchive-dev:amd64 (3.4.0-2ubuntu1.2) ...
Setting up libarchive-dev:amd64 (3.4.0-2ubuntu1.2) ...
Processing triggers for man-db (2.9.1-1) ...
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting libarchive
  Downloading libarchive-0.4.7.tar.gz (23 kB)
  Preparing metadata (setup.py) ... done
Collecting nose
  Downloading nose-1.3.7-py3-none-any.whl (154 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 154.7/154.7 kB 5.3 MB/s eta 0:00:00
Building wheels for collected packages: libarchive
  Building wheel for libarchive (setup.py) ... done
  Created wheel for libarchive: filename=libarchive-0.4.7-py3-none-any.whl size=31644 sha256=c4b4a7dbf9b52924689d8407a2aa36e903d1b
  Stored in directory: /root/.cache/pip/wheels/c9/a5/cc/cb20f1314d4cdec0001fd72baa1efe93e1542a81bdea2fc639
Successfully built libarchive
Installing collected packages: nose, libarchive
Successfully installed libarchive-0.4.7 nose-1.3.7
```

```
pip install lazypredict
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: lazypredict in /usr/local/lib/python3.9/dist-packages (0.2.12)
```

```
Requirement already satisfied: lightgbm in /usr/local/lib/python3.9/dist-packages (from lazypredict) (3.3.5)
Requirement already satisfied: tqdm in /usr/local/lib/python3.9/dist-packages (from lazypredict) (4.65.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.9/dist-packages (from lazypredict) (1.2.2)
Requirement already satisfied: click in /usr/local/lib/python3.9/dist-packages (from lazypredict) (8.1.3)
Requirement already satisfied: xgboost in /usr/local/lib/python3.9/dist-packages (from lazypredict) (1.7.5)
Requirement already satisfied: pandas in /usr/local/lib/python3.9/dist-packages (from lazypredict) (1.5.3)
Requirement already satisfied: joblib in /usr/local/lib/python3.9/dist-packages (from lazypredict) (1.2.0)
Requirement already satisfied: wheel in /usr/local/lib/python3.9/dist-packages (from lightgbm->lazypredict) (0.40.0)
Requirement already satisfied: scipy in /usr/local/lib/python3.9/dist-packages (from lightgbm->lazypredict) (1.10.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.9/dist-packages (from lightgbm->lazypredict) (1.22.4)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.9/dist-packages (from scikit-learn->lazypredict) (3
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-packages (from pandas->lazypredict) (2022.7.1)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.9/dist-packages (from pandas->lazypredict) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.9/dist-packages (from python-dateutil>=2.8.1->pandas->lazypredic
```

```
### importing lazypredict library
import lazypredict
### importing LazyClassifier for classification problem
from lazypredict.Supervised import LazyClassifier
### importing LazyClassifier for classification problem because here we are solving Classification use case.
from lazypredict.Supervised import LazyClassifier
### importing breast Cancer Dataset from sklearn
from sklearn.datasets import load_breast_cancer
### spliting dataset into training and testing part
from sklearn.model_selection import train_test_split
```

```
import lazypredict
from lazypredict.Supervised import LazyClassifier
```

```
clf = LazyClassifier(verbose=0,ignore_warnings=True)
models, predictions = clf.fit(X_train, X_test, y_train, y_test)
models
```

```
100%|██████████| 29/29 [00:11<00:00,  2.45it/s]
```

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score	Time Taken
AdaBoostClassifier	1.00	1.00	None	1.00	0.10
BaggingClassifier	1.00	1.00	None	1.00	0.13
BernoulliNB	1.00	1.00	None	1.00	0.08
DecisionTreeClassifier	1.00	1.00	None	1.00	0.05
DummyClassifier	1.00	1.00	None	1.00	0.05
ExtraTreeClassifier	1.00	1.00	None	1.00	0.05
ExtraTreesClassifier	1.00	1.00	None	1.00	0.43
GaussianNB	1.00	1.00	None	1.00	0.07
KNeighborsClassifier	1.00	1.00	None	1.00	0.39
LabelPropagation	1.00	1.00	None	1.00	3.17
LabelSpreading	1.00	1.00	None	1.00	4.76
LinearDiscriminantAnalysis	1.00	1.00	None	1.00	0.31
RandomForestClassifier	1.00	1.00	None	1.00	0.82
RidgeClassifier	1.00	1.00	None	1.00	0.10
RidgeClassifierCV	1.00	1.00	None	1.00	0.11
LGBMClassifier	1.00	1.00	None	1.00	0.23

```
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.models import load_model
```

```
#empty model
classifier = Sequential()
```

```
from tensorflow.keras.models import Model
import numpy as np
import pandas as pd
import tensorflow
```

```
import keras
import tensorflow.keras
```

```
veri=pd.read_csv("/content/Churn_Modelling[1].csv")
```

```
data=veri.copy()
```

```
data.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Bal
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	838(
2	3	15619304	Onio	502	France	Female	42	8	1596(
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	1255

```
len(data.columns)
```

```
14
```

```
data.columns
```

```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

```
data.isnull()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	E
0	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	
9995	False	False	False	False	False	False	False	False	
9996	False	False	False	False	False	False	False	False	
9997	False	False	False	False	False	False	False	False	
9998	False	False	False	False	False	False	False	False	
9999	False	False	False	False	False	False	False	False	

10000 rows × 14 columns

```
data.isnull().sum()
```

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

```
x=data.iloc[:,3:-1].values
y=data.Exited.values
```

```
x
```

```
array([[619, 'France', 'Female', ..., 1, 1, 101348.88],
       [608, 'Spain', 'Female', ..., 0, 1, 112542.58],
       [502, 'France', 'Female', ..., 1, 0, 113931.57],
       ...,
       [709, 'France', 'Female', ..., 0, 1, 42085.58],
       [772, 'Germany', 'Male', ..., 1, 0, 92888.52],
       [792, 'France', 'Female', ..., 1, 0, 38190.78]], dtype=object)
```

```
y
```

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

```
from sklearn.preprocessing import LabelEncoder
le= LabelEncoder()
x[:,2]=le.fit_transform(x[:,2])
```

```
x
```

```
array([[619, 'France', 0, ..., 1, 1, 101348.88],
       [608, 'Spain', 0, ..., 0, 1, 112542.58],
       [502, 'France', 0, ..., 1, 0, 113931.57],
       ...,
       [709, 'France', 0, ..., 0, 1, 42085.58],
       [772, 'Germany', 1, ..., 1, 0, 92888.52],
       [792, 'France', 0, ..., 1, 0, 38190.78]], dtype=object)
```

```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct=ColumnTransformer(transformers=[("encoder",OneHotEncoder(),[1])],remainder="passthrough")
x=np.array(ct.fit_transform(x))
```

```
x
```

```
array([[1.0, 0.0, 0.0, ..., 1, 1, 101348.88],
       [0.0, 0.0, 1.0, ..., 0, 1, 112542.58],
       [1.0, 0.0, 0.0, ..., 1, 0, 113931.57],
       ...,
       [1.0, 0.0, 0.0, ..., 0, 1, 42085.58],
       [0.0, 1.0, 0.0, ..., 1, 0, 92888.52],
       [1.0, 0.0, 0.0, ..., 1, 0, 38190.78]], dtype=object)
```

```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2,random_state=43)
```

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
xtrain1=sc.fit_transform(xtrain)
xtest1=sc.transform(xtest)
```

```
ann=tensorflow.keras.models.Sequential()
```

```
ann.add(tensorflow.keras.layers.Dense(units=6,activation="relu"))
ann.add(tensorflow.keras.layers.Dense(units=6,activation="relu"))
ann.add(tensorflow.keras.layers.Dense(units=1,activation="sigmoid"))
```

```
ann.compile(optimizer="adam",loss="binary_crossentropy",metrics=["accuracy"])
```

```
ann.fit(xtrain1,ytrain,epochs=100)
```

```
250/250 [==============================] - 1s 3ms/step - loss: 0.3265 - accuracy: 0.8659
Epoch 80/100
250/250 [==============================] - 1s 3ms/step - loss: 0.3263 - accuracy: 0.8656
Epoch 81/100
250/250 [==============================] - 1s 3ms/step - loss: 0.3261 - accuracy: 0.8661
Epoch 82/100
250/250 [==============================] - 1s 3ms/step - loss: 0.3257 - accuracy: 0.8669
Epoch 83/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3258 - accuracy: 0.8659
Epoch 84/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3256 - accuracy: 0.8660
Epoch 85/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3258 - accuracy: 0.8656
Epoch 86/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3261 - accuracy: 0.8658
Epoch 87/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3254 - accuracy: 0.8673
Epoch 88/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3254 - accuracy: 0.8659
Epoch 89/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3255 - accuracy: 0.8664
Epoch 90/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3255 - accuracy: 0.8659
Epoch 91/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3260 - accuracy: 0.8670
Epoch 92/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3255 - accuracy: 0.8651
Epoch 93/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3251 - accuracy: 0.8664
Epoch 94/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3254 - accuracy: 0.8666
Epoch 95/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3255 - accuracy: 0.8648
Epoch 96/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3256 - accuracy: 0.8664
Epoch 97/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3252 - accuracy: 0.8661
Epoch 98/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3251 - accuracy: 0.8652
Epoch 99/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3255 - accuracy: 0.8646
Epoch 100/100
250/250 [==============================] - 0s 2ms/step - loss: 0.3246 - accuracy: 0.8668
<keras.callbacks.History at 0x7feed8dab5e0>
```

```
ypred=ann.predict(xtest1)
ypred=(ypred>0.5)
```

```
from sklearn.metrics import accuracy_score
accuracy_score(ytest,ypred)
```

```
#Let's Import the Packages...
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
import warnings
warnings.filterwarnings('ignore')
```

```
from sklearn.linear_model import LogisticRegression # for Logistic Regression Algorithm
from sklearn.model_selection import train_test_split # to split the dataset for training and testing
from sklearn import metrics # for checking the model accuracy
```

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
```

```
print(classification_report(ytest, ypred))
```

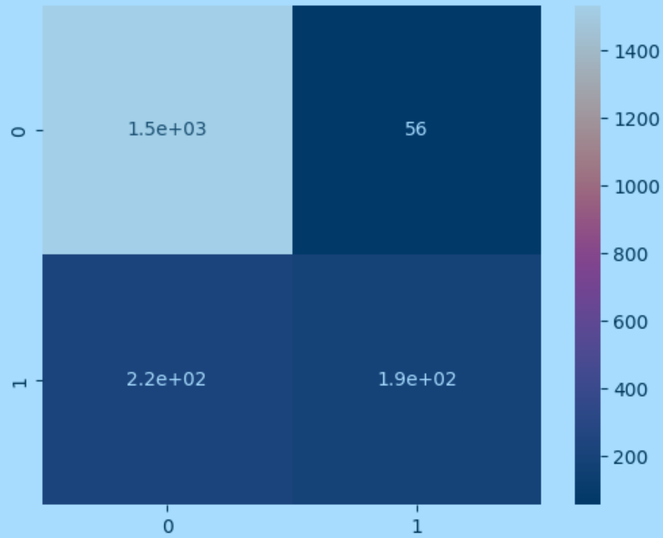
```
              precision    recall  f1-score   support

           0       0.87      0.96      0.92      1588
           1       0.77      0.46      0.57       412

    accuracy                           0.86      2000
   macro avg       0.82      0.71      0.74      2000
weighted avg       0.85      0.86      0.85      2000
```

```
cm =confusion_matrix(ytest, ypred)
sns.heatmap(cm, square=True , annot=True)
```

<Axes: >




```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=5)
print(xtrain.shape)
print(ytrain.shape)
print(xtest.shape)
print(ytest.shape)
```

```
(8000, 12)
(8000,)
(2000, 12)
(2000,)
```

```
from sklearn.tree import DecisionTreeClassifier
classifier_Decicsion = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
classifier_Decicsion.fit(xtrain, ytrain)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=0)
```

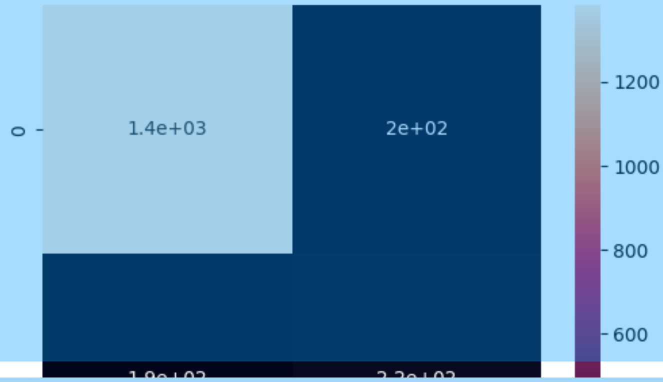
```
ypred_Decision = classifier_Decicsion.predict(xtest)
```

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(ytest, ypred_Decision)
print(cm)
accuracy_score(ytest,ypred_Decision)
```

```
[[1383  205]
 [ 194  218]]
0.8005
```

```
sns.heatmap(cm, square=True , annot=True)
```

<Axes: >




```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size =0.25, random_state = 4)
print(xtrain.shape)
print(ytrain.shape)
print(xtest.shape)
print(ytest.shape)
```

```
(8000, 12)
(8000,)
(2000, 12)
(2000,)
```

```
# Building  Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(criterion = 'entropy', random_state = 42)
rfc.fit(xtrain, ytrain)
```

```
RandomForestClassifier
RandomForestClassifier(criterion='entropy', random_state=42)
```

```
from sklearn.metrics import f1_score
rfc_pred_test = rfc.predict(xtest)
print('Testing Set Evaluation F1-Score=>',f1_score(ytest,rfc_pred_test))
```

```
Testing Set Evaluation F1-Score=> 0.5805471124620062
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=5)
print(xtrain.shape)
print(ytrain.shape)
print(xtest.shape)
print(ytest.shape)
```

```
(8000, 12)
(8000,)
(2000, 12)
(2000,)
```

```
from sklearn.svm import SVC
svclassifier = SVC(kernel='linear')
svclassifier.fit(xtrain, ytrain)
```

```
SVC
SVC(kernel='linear')
```

```
ypred_svm = svclassifier.predict(xtest)
```

```
ypred_svm
```

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

```
accuracy = accuracy_score(ytest, ypred_svm) * 100
print("Accuracy of the Logistic Regression Model: ",accuracy)
```

```
Accuracy of the Logistic Regression Model:  77.8
```

```
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(ytest,ypred_svm))
print(classification_report(ytest,ypred_svm))
```

```
[[1544   44]
 [ 400   12]]
              precision    recall  f1-score   support

           0       0.79      0.97      0.87      1588
           1       0.21      0.03      0.05       412

    accuracy                           0.78      2000
   macro avg       0.50      0.50      0.46      2000
weighted avg       0.67      0.78      0.70      2000
```

```
cm =confusion_matrix(ytest,ypred_svm)
sns.heatmap(cm, square=True , annot=True)
```

```
<Axes: >
```