## Linear SVM over diabetic dataset

```
In [1]: # importing required libraries
import numpy as np #nd-arrays
import pandas as pd #read data from datasources
from sklearn.preprocessing import LabelEncoder #Encode numerical varible into categorical variables
from sklearn.preprocessing import StandardScaler #Standardize the data using mean and std
from sklearn.model_selection import train_test_split #split the data into train and test
from sklearn.metrics import accuracy_score,confusion_matrix #evaluate a model
from sklearn.svm import LinearSVC, SVC #develop svm based clssification models
from sklearn.model_selection import GridSearchCV #tune the hyperparamters
from sklearn.metrics import average_precision_score, make_scorer, recall_score #design custom scoring functions
In [2]: #Reading the data into dataframe
diabetes_df=pd.read_excel('data_file.xlsx')
diabetes_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2703 entries, 0 to 2702
Data columns (total 9 columns):
GENDER
            2703 non-null int64
AGE
            2703 non-null int64
Height
            2703 non-null int64
            2703 non-null float64
Weight
            2703 non-null float64
BMI
BAI
            2703 non-null float64
HBA1C1
            2703 non-null float64
OGTT1FBS
            2703 non-null int64
NDD
            2703 non-null int64
dtypes: float64(4), int64(5)
memory usage: 190.2 KB
```

```
In [3]: #work on the copy of the dataset
        clean df=diabetes df.copy()
        #Pruning the data
        clean df.drop duplicates(keep = 'first',inplace=True)
        print(clean df.shape)
        (1065, 9)
        clean df.head(1)
In [4]:
Out[4]:
           GENDER AGE Height Weight
                                           BMI
                                                 BAI HBA1C1 OGTT1FBS NDD
         0
                 1
                      37
                            156
                                  88.0 36.160421 41.53
                                                          5.1
                                                                   102
                                                                          0
        #Assigning labels with appropriate numerics
In [5]:
        nondia=0
        diabetic=1
        #create a dataframe and assign a column to indicate the diabetic status
        Ynew = pd.DataFrame(nondia, index=clean df.index, columns=['diabetic'])
In [6]: #Identify the diabetic status of each record using the blood test results of FBS or HBA1C1
        Ynew.iloc[list(np.where((clean df.OGTT1FBS>=126) | (clean df.HBA1C1>=6.5))[0])]=diabetic
        #Concatenate the diabetic status with the anthroprometric features of the dataset
        data df=pd.concat([clean df.iloc[:,:6],Ynew],axis=1)
In [7]:
        data df.head(1)
Out[7]:
           GENDER AGE Height Weight
                                           BMI
                                                 BAI diabetic
         0
                                  88.0 36.160421 41.53
                                                           0
                 1
                      37
                            156
In [8]: #Find the diabetic and non-diabetic patients
        diabetic yes=data df.iloc[list(np.where(data df.diabetic==diabetic)[0])]
        diabetic_no=data_df.iloc[list(np.where(data_df.diabetic==nondia)[0])]
```

In [9]: diabetic\_yes.describe()

Out[9]:

	GENDER	AGE	Height	Weight	ВМІ	BAI	diabetic
count	528.000000	528.000000	528.000000	528.000000	528.000000	528.000000	528.0
mean	0.571970	51.812500	160.280303	68.404356	26.640045	29.618864	1.0
std	0.495262	10.921528	7.562330	12.759664	4.809005	7.753363	0.0
min	0.000000	25.000000	138.000000	36.500000	15.390454	8.300000	1.0
25%	0.000000	43.750000	156.000000	59.000000	23.290154	24.790000	1.0
50%	1.000000	50.000000	159.500000	68.000000	26.527004	28.145000	1.0
75%	1.000000	59.000000	165.000000	76.000000	29.585799	33.847500	1.0
max	1.000000	80.000000	186.000000	102.000000	41.207076	58.250000	1.0

In [10]: diabetic\_no.describe()

Out[10]:

	GENDER	AGE	Height	Weight	ВМІ	BAI	diabetic
count	537.000000	537.000000	537.000000	537.000000	537.000000	537.000000	537.0
mean	0.450652	44.463687	158.217877	68.325885	27.261189	31.687058	0.0
std	0.498023	11.890164	7.930377	13.118822	4.770046	8.276824	0.0
min	0.000000	20.000000	139.000000	33.500000	13.671875	14.080000	0.0
25%	0.000000	35.000000	153.000000	61.000000	24.508946	25.650000	0.0
50%	0.000000	44.000000	158.000000	68.000000	26.959840	30.140000	0.0
75%	1.000000	52.000000	162.000000	76.000000	29.757785	38.260000	0.0
max	1.000000	84.000000	186.000000	110.000000	50.219138	59.760000	0.0

Label encoding for Y column

```
In [11]: # Encode the categorical columns with labels
         le=LabelEncoder()
         data df.diabetic=le.fit transform(data df.diabetic)
         data df.GENDER=le.fit transform(data df.GENDER)
         Data split into training and test data
In [12]: train x, test x, train y, test y = train test split(data df.iloc[:,:6],
                                                              data df.diabetic,test_size=0.3,
                                                              random state=43)
         Normalizing the data using StandardScaler
In [13]: sc=StandardScaler() # creating an instance for StandardScaler class
         train x=sc.fit transform(train x) # estimate mu and sigma for train set and transform
         test x=sc.transform(test x) # transform the test set
In [14]: # fetch the diabetic records from train set
         diabetic_yes_train=train_x[list(np.where(train y==diabetic)[0])]
         # fetch the non-diabetic records from train set
         diabetic no train=train x[list(np.where(train y==nondia)[0])]
         # display the counts for each class
         print('non-diabetic=',diabetic no train.shape,'diabetic=',diabetic yes train.shape)
```

non-diabetic= (369, 6) diabetic= (376, 6)

```
In [15]: # fetch the diabetic records from test set
         diabetic yes test=test x[list(np.where(test y==diabetic)[0])]
         # fetch the non-diabetic records from test set
         diabetic no test=test x[list(np.where(test y==nondia)[0])]
         # display the counts for each class from test set
         print('non-diabetic=',diabetic no test.shape,'diabetic=',diabetic yes test.shape)
         non-diabetic= (168, 6) diabetic= (152, 6)
         Evaluation metrics
In [16]: #evaluate a model using confusion matrix and accuracy score between true and actual
```

```
def evaluate(vt,vp):
   cf=confusion matrix(yt,yp) #estimate confusion matrix
```

acc=accuracy score(yt,yp) # estimate accuracy of the model return cf,acc

```
In [17]: # Display metrics
         def display(yt,yp,model):
             cf,acc = evaluate(yt,yp)
             print('Model=',model,'\ncf=',cf,'\n')#,'\nacc=',acc,'\n')
```

## Linear SVM

```
In [18]: #Perform Classification using Linear SVM
         lsvc = LinearSVC(random state=0,C=10,max iter=100000) # create a LinearSVC instance
         lsvc.fit(train x, train y) # fit the model for trainset
         train yp=lsvc.predict(train x) # predict the y for train set
         test yp=lsvc.predict(test x) # predict the y for test set
```

```
In [19]: # display the results
         display(train_y, train_yp, 'Linear SVC: Validation')
         display(test y, test yp, 'Linear SVC: Testing')
         Model= Linear SVC: Validation
         cf= [[232 137]
          [140 236]]
         Model= Linear SVC: Testing
         cf= [[106 62]
          [ 61 91]]
In [20]: # coefficients corresponding to each feature of X in scaled X
         lsvc.coef
Out[20]: array([[ 0.03429241, 0.30614179, 0.47751593, -0.81867076, 0.75756964,
                 -0.04616905]])
In [21]: # intercept of the classifier at the scaled X
         lsvc.intercept
Out[21]: array([0.009402])
In [22]: # rescaling the coefficients to original scale of the features of X
         rescaled coef=lsvc.coef /np.sqrt(sc.var )
         rescaled coef
Out[22]: array([[ 0.06864427, 0.02514219, 0.06038546, -0.06373275, 0.1595825,
                 -0.00584295]])
In [23]: # the intercept in the original feature space
         rescaled intercept=rescaled coef.dot(sc.mean .T)+lsvc.intercept
         rescaled intercept
Out[23]: array([10.64537545])
```

```
In [24]: # display the counts for each class
         print('non-diabetic=',diabetic no train.shape,'diabetic=',diabetic yes train.shape)
         display(train y, train yp, 'Linear SVC: Validation')
         non-diabetic= (369, 6) diabetic= (376, 6)
         Model= Linear SVC: Validation
         cf= [[232 137]
          [140 236]]
In [25]: # identifiv the slacks for each class
         non dia slacks=(lsvc.coef .dot(diabetic yes train.T)+lsvc.intercept )
         np.sum(non dia slacks<0)</pre>
Out[25]: 140
In [26]: dia slacks=(lsvc.coef .dot(diabetic no train.T)+lsvc.intercept )
         np.sum(dia slacks>0)
Out[26]: 137
         Hyperparamter tuning using Gridsearchcv
In [27]: # recall = tp / (tp + fn) = Sensitivity or True Positive Rate / True Negative Rate
         # precision = tp / (tp + fp) = Positive predictive value
         custom scorer = {'recall':make scorer(recall score, pos label=diabetic),
                           'precision':make_scorer(average_precision_score, pos label=diabetic)}
In [28]: gscv = GridSearchCV(LinearSVC(max iter=1e7), {'C':[1e-5,1e-4,1e-3,1e-2,1e-1,1,10,100,1000]},
                              cv=5,verbose=False,scoring=custom scorer,refit='recall')
         gscv.fit(train x,train y)
         gscv.best params
Out[28]: {'C': 1e-05}
```

```
In [29]: # display the results
display(train_y, train_yp, 'For C=10: Training')
#display(test_y, test_yp, 'For C=10: Testing')
#Perform Classification using Linear SVM
lsvc = LinearSVC(random_state=0,C=0.001,max_iter=100000) # create a LinearSVC instance
lsvc.fit(train_x, train_y) # fit the model for trainset
train_yp=lsvc.predict(train_x) # predict the y for train set
test_yp=lsvc.predict(test_x) # predict the y for test set
# display the results
display(train_y, train_yp, 'For C=0.001: Training')
#display(test_y, test_yp, 'For C=0.001: Testing')
Model= For C=10: Training
cf= [[232 137]
[140 236]]
```

**END OF SCRIPT** 

cf= [[229 140] [133 243]]

Model= For C=0.001: Training