notebook

April 13, 2024

[1]:
```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report,confusion_matrix
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import seaborn as sns
import numpy as np
from sklearn.inspection import DecisionBoundaryDisplay
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
```

[2]:
```
data = pd.read_csv("framingham.csv")
data
```

[2]:
```
      male  age  education  currentSmoker  cigsPerDay  BPMeds  \
0        1   39        4.0              0         0.0     0.0
1        0   46        2.0              0         0.0     0.0
2        1   48        1.0              1        20.0     0.0
3        0   61        3.0              1        30.0     0.0
4        0   46        3.0              1        23.0     0.0
…     …    …          …              …           …       …
4235     0   48        2.0              1        20.0     NaN
4236     0   44        1.0              1        15.0     0.0
4237     0   52        2.0              0         0.0     0.0
4238     1   40        3.0              0         0.0     0.0
4239     0   39        3.0              1        30.0     0.0

      prevalentStroke  prevalentHyp  diabetes  totChol  sysBP  diaBP    BMI  \
0                   0             0         0    195.0  106.0   70.0  26.97
1                   0             0         0    250.0  121.0   81.0  28.73
2                   0             0         0    245.0  127.5   80.0  25.34
3                   0             1         0    225.0  150.0   95.0  28.58
4                   0             0         0    285.0  130.0   84.0  23.10
…                 …             …         …        …      …      …      …
4235                0             0         0    248.0  131.0   72.0  22.00
4236                0             0         0    210.0  126.5   87.0  19.16
```

```
4237                0             0          0    269.0  133.5    83.0   21.47
4238                0             1          0    185.0  141.0    98.0   25.60
4239                0             0          0    196.0  133.0    86.0   20.91

      heartRate  glucose  TenYearCHD
0          80.0     77.0           0
1          95.0     76.0           0
2          75.0     70.0           0
3          65.0    103.0           1
4          85.0     85.0           0
…           …        …          …
4235       84.0     86.0           0
4236       86.0      NaN           0
4237       80.0    107.0           0
4238       67.0     72.0           0
4239       85.0     80.0           0

[4240 rows x 16 columns]
```

[3]:
```python
# check for any null values
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4240 entries, 0 to 4239
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   male             4240 non-null   int64
 1   age              4240 non-null   int64
 2   education        4135 non-null   float64
 3   currentSmoker    4240 non-null   int64
 4   cigsPerDay       4211 non-null   float64
 5   BPMeds           4187 non-null   float64
 6   prevalentStroke  4240 non-null   int64
 7   prevalentHyp     4240 non-null   int64
 8   diabetes         4240 non-null   int64
 9   totChol          4190 non-null   float64
 10  sysBP            4240 non-null   float64
 11  diaBP            4240 non-null   float64
 12  BMI              4221 non-null   float64
 13  heartRate        4239 non-null   float64
 14  glucose          3852 non-null   float64
 15  TenYearCHD       4240 non-null   int64
dtypes: float64(9), int64(7)
memory usage: 530.1 KB
```

[4]:
```python
data.describe()
```

[4]:

	male	age	education	currentSmoker	cigsPerDay
count	4240.000000	4240.000000	4135.000000	4240.000000	4211.000000
mean	0.429245	49.580189	1.979444	0.494104	9.005937
std	0.495027	8.572942	1.019791	0.500024	11.922462
min	0.000000	32.000000	1.000000	0.000000	0.000000
25%	0.000000	42.000000	1.000000	0.000000	0.000000
50%	0.000000	49.000000	2.000000	0.000000	0.000000
75%	1.000000	56.000000	3.000000	1.000000	20.000000
max	1.000000	70.000000	4.000000	1.000000	70.000000

	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol
count	4187.000000	4240.000000	4240.000000	4240.000000	4190.000000
mean	0.029615	0.005896	0.310613	0.025708	236.699523
std	0.169544	0.076569	0.462799	0.158280	44.591284
min	0.000000	0.000000	0.000000	0.000000	107.000000
25%	0.000000	0.000000	0.000000	0.000000	206.000000
50%	0.000000	0.000000	0.000000	0.000000	234.000000
75%	0.000000	0.000000	1.000000	0.000000	263.000000
max	1.000000	1.000000	1.000000	1.000000	696.000000

	sysBP	diaBP	BMI	heartRate	glucose
count	4240.000000	4240.000000	4221.000000	4239.000000	3852.000000
mean	132.354599	82.897759	25.800801	75.878981	81.963655
std	22.033300	11.910394	4.079840	12.025348	23.954335
min	83.500000	48.000000	15.540000	44.000000	40.000000
25%	117.000000	75.000000	23.070000	68.000000	71.000000
50%	128.000000	82.000000	25.400000	75.000000	78.000000
75%	144.000000	90.000000	28.040000	83.000000	87.000000
max	295.000000	142.500000	56.800000	143.000000	394.000000

	TenYearCHD
count	4240.000000
mean	0.151887
std	0.358953
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

[5]:

```
# Let's fill all the null values by their mean value
data["education"] = data["education"].fillna(data["education"].mean())
data["cigsPerDay"] = data["cigsPerDay"].fillna(data["cigsPerDay"].mean())
data["BPMeds"] = data["BPMeds"].fillna(data["BPMeds"].mean())
data["totChol"] = data["totChol"].fillna(data["totChol"].mean())
data["BMI"] = data["BMI"].fillna(data["BMI"].mean())
data["heartRate"] = data["heartRate"].fillna(data["heartRate"].mean())
```

```
data["glucose"] = data["glucose"].fillna(data["glucose"].mean())
data.info()
```

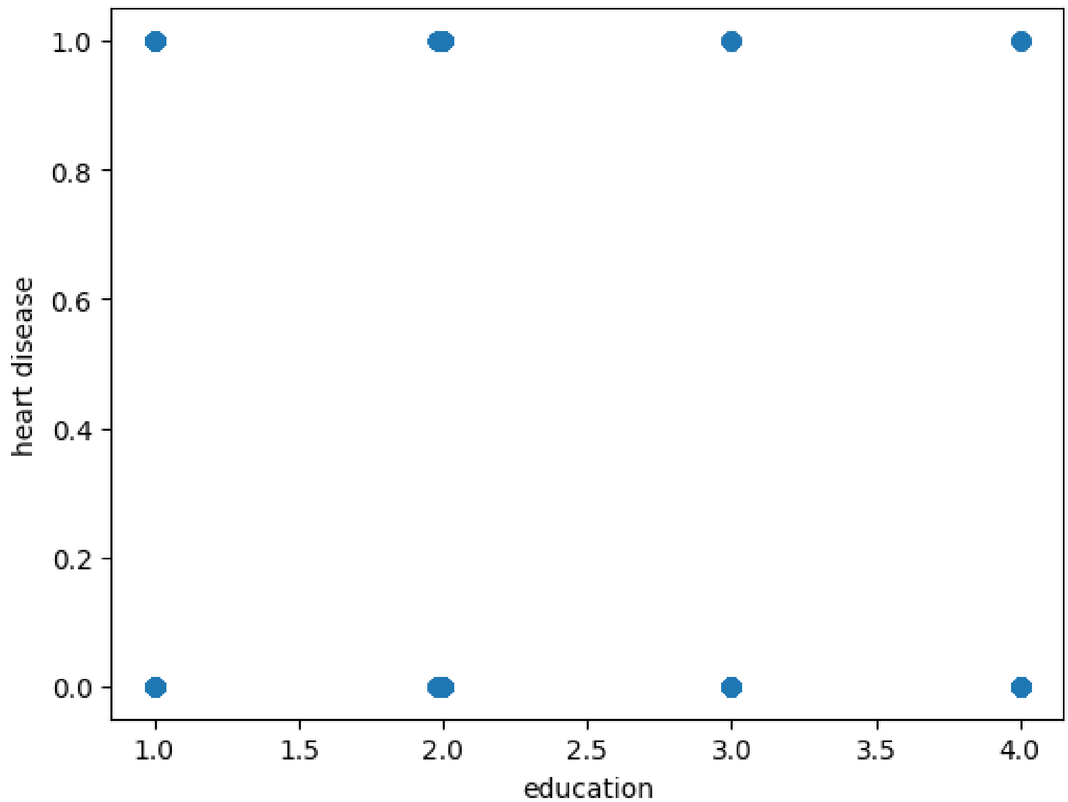
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4240 entries, 0 to 4239
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   male             4240 non-null   int64
 1   age              4240 non-null   int64
 2   education        4240 non-null   float64
 3   currentSmoker    4240 non-null   int64
 4   cigsPerDay       4240 non-null   float64
 5   BPMeds           4240 non-null   float64
 6   prevalentStroke  4240 non-null   int64
 7   prevalentHyp     4240 non-null   int64
 8   diabetes         4240 non-null   int64
 9   totChol          4240 non-null   float64
 10  sysBP            4240 non-null   float64
 11  diaBP            4240 non-null   float64
 12  BMI              4240 non-null   float64
 13  heartRate        4240 non-null   float64
 14  glucose          4240 non-null   float64
 15  TenYearCHD       4240 non-null   int64
dtypes: float64(9), int64(7)
memory usage: 530.1 KB
```

[6]:
```
# By using scaler , scale the data so that it can be easily analyzed
scaler = StandardScaler()
model = scaler.fit(data)
scaled_data = model.transform(data)
data
```

[6]:
```
      male  age  education  currentSmoker  cigsPerDay    BPMeds  \
0        1   39        4.0              0         0.0  0.000000
1        0   46        2.0              0         0.0  0.000000
2        1   48        1.0              1        20.0  0.000000
3        0   61        3.0              1        30.0  0.000000
4        0   46        3.0              1        23.0  0.000000
…     …   …          …              …         …        …
4235     0   48        2.0              1        20.0  0.029615
4236     0   44        1.0              1        15.0  0.000000
4237     0   52        2.0              0         0.0  0.000000
4238     1   40        3.0              0         0.0  0.000000
4239     0   39        3.0              1        30.0  0.000000

      prevalentStroke  prevalentHyp  diabetes  totChol  sysBP  diaBP    BMI  \
0                   0             0         0    195.0  106.0   70.0  26.97
```

```
1                      0             0          0    250.0  121.0   81.0  28.73
2                      0             0          0    245.0  127.5   80.0  25.34
3                      0             1          0    225.0  150.0   95.0  28.58
4                      0             0          0    285.0  130.0   84.0  23.10
…                …            …        …       …     …     …     …
4235                   0             0          0    248.0  131.0   72.0  22.00
4236                   0             0          0    210.0  126.5   87.0  19.16
4237                   0             0          0    269.0  133.5   83.0  21.47
4238                   0             1          0    185.0  141.0   98.0  25.60
4239                   0             0          0    196.0  133.0   86.0  20.91

      heartRate     glucose  TenYearCHD
0          80.0   77.000000           0
1          95.0   76.000000           0
2          75.0   70.000000           0
3          65.0  103.000000           1
4          85.0   85.000000           0
…          …          …          …
4235       84.0   86.000000           0
4236       86.0   81.963655           0
4237       80.0  107.000000           0
4238       67.0   72.000000           0
4239       85.0   80.000000           0

[4240 rows x 16 columns]
```

[7]:
```
# let's check if education affects heart disease
plt.scatter(data["education"],data["TenYearCHD"])
plt.xlabel("education")
plt.ylabel("heart disease")
plt.show()
```



[8]:
```
# as seen in the graph, education doesn't show any direct relation to having
↪heart disease. So we can delete that column.
data.drop(["education"] , axis=1)
```

[8]:
```
      male  age  currentSmoker  cigsPerDay    BPMeds  prevalentStroke  \
0        1   39              0         0.0  0.000000                0
1        0   46              0         0.0  0.000000                0
2        1   48              1        20.0  0.000000                0
3        0   61              1        30.0  0.000000                0
4        0   46              1        23.0  0.000000                0
…     …    …              …           …         …                …
4235     0   48              1        20.0  0.029615                0
4236     0   44              1        15.0  0.000000                0
4237     0   52              0         0.0  0.000000                0
4238     1   40              0         0.0  0.000000                0
4239     0   39              1        30.0  0.000000                0

      prevalentHyp  diabetes  totChol  sysBP  diaBP    BMI  heartRate  \
0                0         0    195.0  106.0   70.0  26.97       80.0
1                0         0    250.0  121.0   81.0  28.73       95.0
2                0         0    245.0  127.5   80.0  25.34       75.0
```

```
3              1        0    225.0  150.0   95.0  28.58       65.0
4              0        0    285.0  130.0   84.0  23.10       85.0
…            …       …      …     …     …     …          …
4235           0        0    248.0  131.0   72.0  22.00       84.0
4236           0        0    210.0  126.5   87.0  19.16       86.0
4237           0        0    269.0  133.5   83.0  21.47       80.0
4238           1        0    185.0  141.0   98.0  25.60       67.0
4239           0        0    196.0  133.0   86.0  20.91       85.0

         glucose  TenYearCHD
0      77.000000           0
1      76.000000           0
2      70.000000           0
3     103.000000           1
4      85.000000           0
…           …          …
4235   86.000000           0
4236   81.963655           0
4237  107.000000           0
4238   72.000000           0
4239   80.000000           0

[4240 rows x 15 columns]
```

[9]:

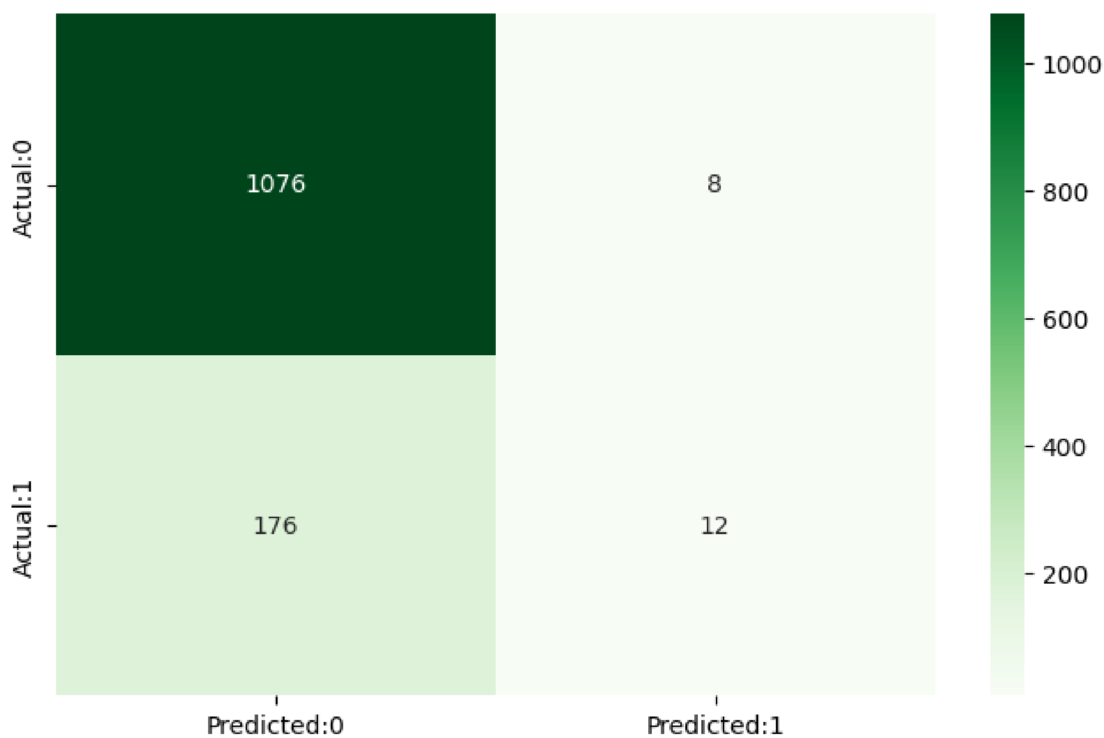
```
X = np.
 ↪asarray(data[["male","age","currentSmoker","cigsPerDay","BPMeds","prevalentStroke","prevale
y = np.asarray(data['TenYearCHD'])
# split the data in two parts as train data and test data in 80% and 20% ratio
X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size = 0.3, random_state = 4)

# LogisticRegression
model = LogisticRegression(max_iter=3000)
model.fit(X_train, y_train)

# Prediction
y_pred = model.predict(X_test)


# check for the accuracy
print(accuracy_score(y_pred,y_test))
print(classification_report(y_pred,y_test))
```

```
0.8553459119496856
              precision    recall  f1-score   support

           0       0.99      0.86      0.92      1252
           1       0.06      0.60      0.12        20
```

```
    accuracy                           0.86      1272
   macro avg       0.53      0.73      0.52      1272
weighted avg       0.98      0.86      0.91      1272
```

[10]:

```
# confusion matrix
cm = confusion_matrix(y_test, y_pred)
conf_matrix = pd.DataFrame(data = cm,
                           columns = ['Predicted:0', 'Predicted:1'],
                           index =['Actual:0', 'Actual:1'])

plt.figure(figsize = (8, 5))
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cmap = "Greens")

plt.show()
print('The details for confusion matrix is =')
print (classification_report(y_test, y_pred))
```




```
The details for confusion matrix is =
              precision    recall  f1-score   support

           0       0.86      0.99      0.92      1084
           1       0.60      0.06      0.12       188
```

```
    accuracy                           0.86      1272
   macro avg       0.73      0.53      0.52      1272
weighted avg       0.82      0.86      0.80      1272
```

The above model which uses a logistic regression model has around 85-86% accuracy. So this model is pretty accurate to make predictions.

Let's try and implement SVM model and check for accuracy.

[11]:
```
#Build the model
svm = SVC(kernel="rbf")
# Trained the model
svm.fit(X_train, y_train)
predict_y = svm.predict(X_test)
print(classification_report(predict_y,y_test))
```

```
              precision    recall  f1-score   support

           0       1.00      0.85      0.92      1270
           1       0.01      0.50      0.01         2

    accuracy                           0.85      1272
   macro avg       0.50      0.68      0.47      1272
weighted avg       1.00      0.85      0.92      1272
```

This SVM model also has 85% accuracy same as logistic regression. So both models can be used for making accurate predictions.

Both the models have high accuracy but the f1-score in predicting 1 is very low meaning that both the models are not accurate in predicting the patients who have cardiac disease. However in predicting the patients who do not have cardiac disease, both models are almost 100% accurate.

Let's implement and check accuracy by using Random Forest Algorithm.

[18]:
```
rfc = RandomForestClassifier(n_estimators = 500)

rfc.fit(X_train, y_train)

# performing predictions on the test dataset
y_pred = rfc.predict(X_test)

print(accuracy_score(y_pred,y_test))
print(classification_report(y_pred,y_test))
```

```
0.8482704402515723
              precision    recall  f1-score   support

           0       0.99      0.85      0.92      1255
```

```
           1       0.03      0.35      0.06        17

    accuracy                           0.85      1272
   macro avg       0.51      0.60      0.49      1272
weighted avg       0.98      0.85      0.91      1272
```

Random Forest Classifier also shows around the same results meaning that there is not any significant difference between the accuracy of these three models. And maybe using Logistic Regression for this problem might be a better choice to get more accurate results.