

----- HR AND GSR -----

In [1]:

```
import pydot
import pandas as pd
import numpy as np
import seaborn as sns
sns.set()
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
# Ignore warnings
import warnings
warnings.filterwarnings('ignore')
import sklearn
from sklearn import metrics
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import export_graphviz, DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.exceptions import NotFittedError
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras import optimizers
from keras.wrappers.scikit_learn import KerasClassifier
from IPython.display import display
```

```
In [2]: # Some useful functions we'll use in this notebook
def display_confusion_matrix(target, prediction, score=None):
    cm = metrics.confusion_matrix(target, prediction)
    plt.figure(figsize=(6,6))
    sns.heatmap(cm, annot=True, fmt=".4f", linewidths=.5, square=True, cmap='Blues')
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    if score:
        score_title = 'Accuracy Score: {}'.format(round(score, 5))
        plt.title(score_title, size = 25)

def visualize_tree(tree, feature_names):
    with open("dt.dot", 'w') as f:
        export_graphviz(tree, out_file=f, feature_names=feature_names)
    try:
        subprocess.check_call(["dot", "-Tpng", "dt.dot", "-o", "dt.png"])
    except:
        exit("Could not run dot, ie graphviz, to produce visualization")

def draw_missing_data_table(df):
    total = df.isnull().sum().sort_values(ascending=False)
    percent = (df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)
    missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
    return missing_data
```

```
In [3]: # Create dataframe for training dataset and print five first rows as preview
train_df_raw = pd.read_csv('hr_gsr.csv')
train_df_raw.head()
```

Out[3]:

	Condition	HR	RMSD	SCL
0	0.0	61.0	0.061420	80.239727
1	0.0	61.0	0.061420	77.365127
2	0.0	64.0	0.049663	77.359559
3	0.0	60.0	0.052487	76.728772
4	0.0	61.0	0.051189	76.512877

```
In [4]: train_df_raw=train_df_raw.dropna()
```

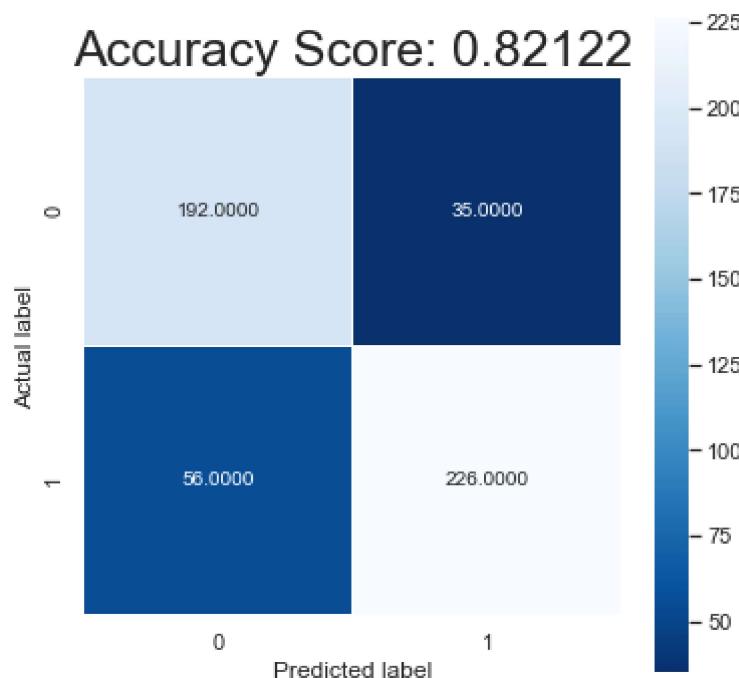
```
In [5]: # Let's divide the train dataset in two datasets to evaluate performance of the model
train_df = train_df_raw.copy()
X = train_df.drop(['Condition'], 1)
Y = train_df['Condition']
# We scale our data, it is essential for a smooth working of the models
# Scaling means that each columns has a 0 mean and a 1 variance
sc = StandardScaler()
X = pd.DataFrame(sc.fit_transform(X.values), index=X.index, columns=X.columns)
# Split dataset for model testing
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
X_train.head()
```

Out[5]:

	HR	RMSSD	SCL
1653	1.315831	-0.950608	-0.511494
1782	-0.749653	-0.466227	0.049264
2752	-1.241434	-0.194360	-0.729176
814	0.233911	-0.721839	-0.387177
886	-1.241434	0.075152	0.470411

RANDOM FOREST

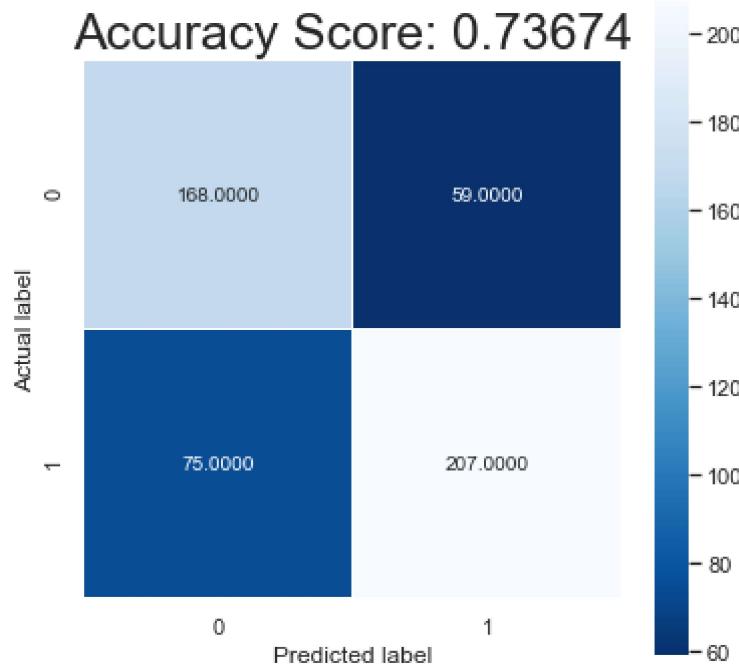
```
In [6]: rf = RandomForestClassifier(n_estimators=200, random_state=42)
rf.fit(X_train, Y_train)
rf_prediction = rf.predict(X_test)
score = metrics.accuracy_score(Y_test, rf_prediction)
display_confusion_matrix(Y_test, rf_prediction, score=score)
rf_score=rf_prediction
```



DECISION TREE

```
In [7]: dt = DecisionTreeClassifier(min_samples_split=15, min_samples_leaf=20, random_state=42)
dt.fit(X_train, Y_train)
dt_prediction = dt.predict(X_test)

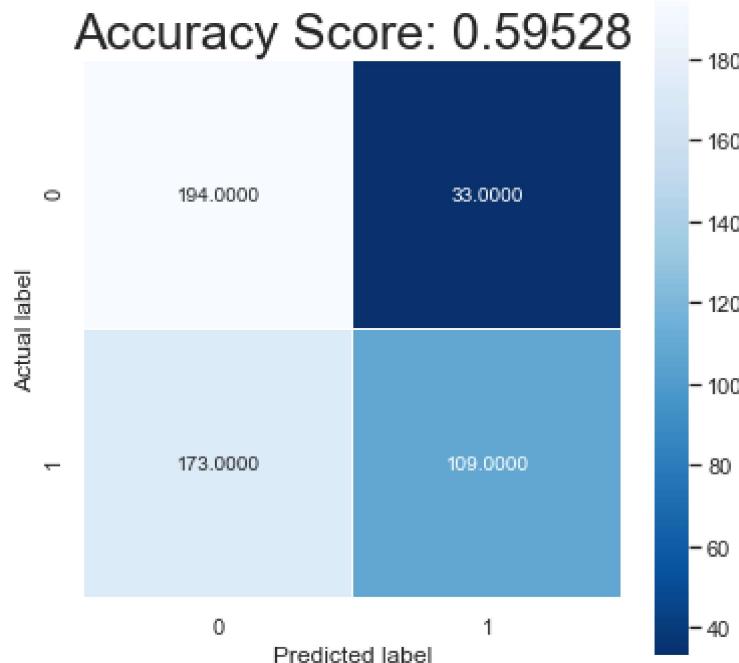
score = metrics.accuracy_score(Y_test, dt_prediction)
display_confusion_matrix(Y_test, dt_prediction, score=score)
```



SVM

```
In [8]: svm = SVC(gamma='auto', random_state=42)
svm.fit(X_train, Y_train)
svm_prediction = svm.predict(X_test)

score = metrics.accuracy_score(Y_test, svm_prediction)
display_confusion_matrix(Y_test, svm_prediction, score=score)
```



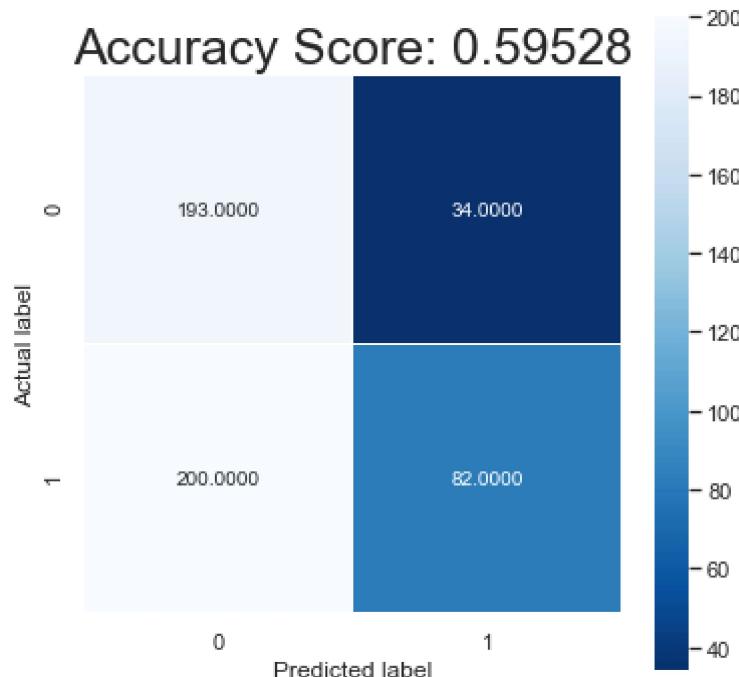
NAIVE BAYES

```
In [9]: #train a Gaussian Naive Bayes classifier on the training set
from sklearn.naive_bayes import GaussianNB
# instantiate the model
gnb = GaussianNB()
# fit the model
gnb.fit(X_train, Y_train)
NB_y_pred = gnb.predict(X_test)
from sklearn.metrics import accuracy_score
y_pred_train = gnb.predict(X_train)
y_pred_train
# print the scores on training and test set
print('Training set score: {:.4f}'.format(gnb.score(X_train, Y_train)))
print('Test set score: {:.4f}'.format(gnb.score(X_test, Y_test)))
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(Y_test, NB_y_pred)
display_confusion_matrix(Y_test, NB_y_pred, score=score)
```

Training set score: 0.6024

Test set score: 0.5403



K NEAREST NEIGHBORS

```
In [10]: from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=3)
classifier.fit(X_train, Y_train)
KNN_y_pred = classifier.predict(X_test)
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(Y_test, KNN_y_pred))
print(classification_report(Y_test, KNN_y_pred))
```

```
[[172  55]
 [ 65 217]]
```

	precision	recall	f1-score	support
0.0	0.73	0.76	0.74	227
1.0	0.80	0.77	0.78	282
accuracy			0.76	509
macro avg	0.76	0.76	0.76	509
weighted avg	0.77	0.76	0.76	509

```
In [11]: print('***** HR + GSR *****')
print('SVM ---->',metrics.accuracy_score(Y_test, svm_prediction))
print('RF ---->',metrics.accuracy_score(Y_test, rf_prediction))
print('DT ---->',metrics.accuracy_score(Y_test, dt_prediction))
print('NB ---->',metrics.accuracy_score(Y_test, NB_y_pred))
print('KNN ---->',metrics.accuracy_score(Y_test, KNN_y_pred))
```

```
***** HR + GSR *****

```

```
SVM ----> 0.5952848722986247
```

```
RF ----> 0.8212180746561886
```

```
DT ----> 0.7367387033398821
```

```
NB ----> 0.5402750491159135
```

```
KNN ----> 0.7642436149312377
```

Confusion Matrix

As we can see from the table above:

True Positive(TP) : Values that the model predicted as yes, and is actually yes.

True Negative(TN) : Values that the model predicted as not, and is actually no.

False Positive(FP): Values that the model predicted as yes, but actually no.

False Negative(FN): Values that the model predicted as no, but actually yes.

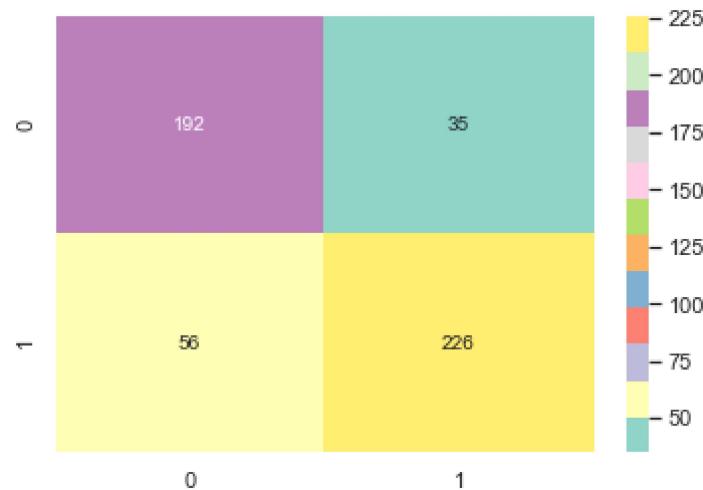
```
In [12]: from sklearn.metrics import precision_score, recall_score, confusion_matrix, precision_score
cm = np.array(confusion_matrix(Y_test, rf_prediction, labels=[0,1]))
confusion_mat = pd.DataFrame(cm, index = ['NORMAL', 'STRESSED'],
                             columns = ['NORMAL', 'STRESSED'])
confusion_mat
```

Out[12]:

	NORMAL	STRESSED
NORMAL	192	35
STRESSED	56	226

```
In [13]: sns.heatmap(cm, annot=True, fmt='g', cmap='Set3')
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x1a5821037f0>



Accuracy_Score

Accuracy_Score is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations

```
In [14]: from sklearn.metrics import accuracy_score
print(accuracy_score(Y_test, rf_prediction))
```

0.8212180746561886

Precision

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.

```
In [15]: print(precision_score(Y_test, rf_prediction))
```

```
0.8659003831417624
```

Recall

Recall also called Sensitivity, is the ratio of positive instances that are correctly detected by the classifier to the all observations in actual class

```
In [16]: print(recall_score(Y_test, rf_prediction))
```

```
0.8014184397163121
```

Classification Report

```
In [17]: from sklearn.metrics import classification_report  
print(classification_report(Y_test, rf_prediction))
```

	precision	recall	f1-score	support
0.0	0.77	0.85	0.81	227
1.0	0.87	0.80	0.83	282
accuracy			0.82	509
macro avg	0.82	0.82	0.82	509
weighted avg	0.83	0.82	0.82	509

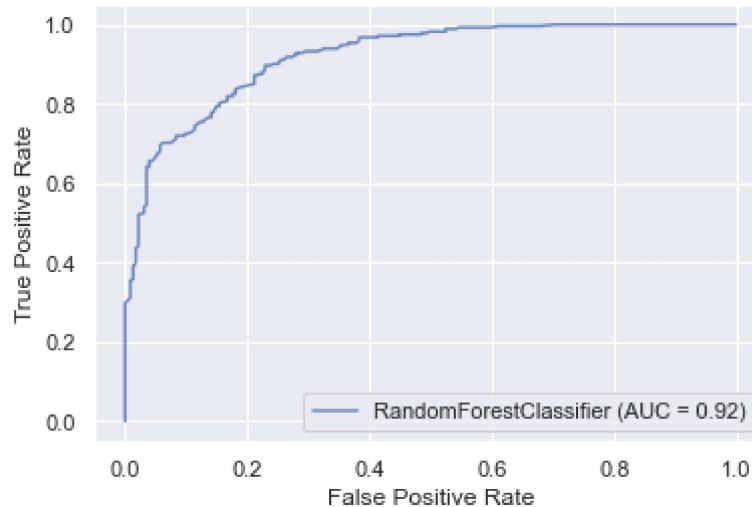
The ROC Curve

Area Under Curve

Area Under Curve is a common way to compare classifiers. A perfect classifier will have ROC AUC equal to 1

Sckit-Learn provides a function to compute the ROC AUC.

```
In [18]: from sklearn.metrics import roc_auc_score, auc, f1_score
from sklearn.metrics import plot_roc_curve
ax = plt.gca()
rfc_disp = plot_roc_curve(rf, X_test, Y_test, ax=ax, alpha=0.8)
plt.show()
```



K FOLD VALIDATION

```
In [19]: cv_score_rf1 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=5, n_jobs=-1)
cv_score_rf2 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=10, n_jobs=-1)
cv_score_rf3 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=20, n_jobs=-1)
cv_score_rf4 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=50, n_jobs=-1)
```

```
In [20]: cv_result = { 'rf5': cv_score_rf1, 'rf10': cv_score_rf2, 'rf20': cv_score_rf3, 'rf50': cv_score_rf4 }
cv_data = {model: [score.mean(), score.std()] for model, score in cv_result.items()}
cv_df = pd.DataFrame(cv_data, index=['Mean_accuracy', 'Variance'])
cv_df
```

Out[20]:

	rf5	rf10	rf20	rf50
Mean_accuracy	0.817902	0.824290	0.828194	0.819280
Variance	0.017638	0.019495	0.030666	0.061164

----- GSR AND FACIAL IMAGE -----

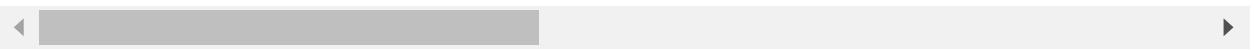
DATA-----

In [21]: `# Create dataframe for training dataset and print five first rows as preview
train_df_raw = pd.read_csv('face_gsr.csv')
train_df_raw.head()`

Out[21]:

	Condition	SCL	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unna
0	0.0	80.239727	0.968862	0.023946	-6.954147	-5.818151	-0.584952	0.0	0.00
1	0.0	77.365127	0.884570	0.076952	-10.564172	-6.567912	-3.906502	0.0	0.02
2	0.0	77.359559	0.931965	0.031468	-10.721106	-7.055848	-2.452367	0.0	0.00
3	0.0	76.728772	0.806947	0.105516	-10.782755	-5.616126	-4.669924	0.0	0.11
4	0.0	76.512877	0.951412	0.028358	-3.880091	-4.621940	-5.893645	0.0	0.03

5 rows × 24 columns



In [22]: `train_df_raw=train_df_raw.dropna()`

In [23]: `# Let's divide the train dataset in two datasets to evaluate performance of the model
train_df = train_df_raw.copy()
X = train_df.drop(['Condition'], 1)
Y = train_df['Condition']
We scale our data, it is essential for a smooth working of the models
Scaling means that each columns has a 0 mean and a 1 variance
sc = StandardScaler()
X = pd.DataFrame(sc.fit_transform(X.values), index=X.index, columns=X.columns)
Split dataset for model testing
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
X_train.head()`

Out[23]:

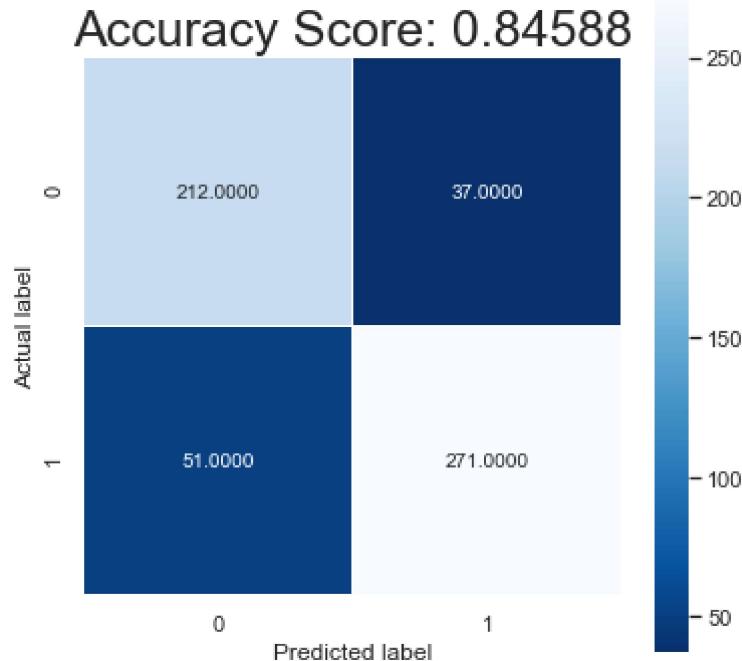
	SCL	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Un
1024	4.127854	0.913940	-0.414424	-1.725315	0.351406	0.601406	-0.627610	-0.669271	-1
673	-0.642822	-0.226861	-0.465262	-0.026317	-0.266536	-0.546780	-0.627610	-0.570223	-1
773	-0.413888	0.589678	-0.063831	1.194307	-0.388965	-1.504441	-0.047468	0.599167	-1
2357	-0.463399	-0.935954	-0.132913	-0.813533	-0.405610	-0.186839	1.172464	-0.058425	-1
868	-0.335572	0.280199	1.172927	1.388406	-1.358499	-1.317352	1.518383	-0.219520	-1

5 rows × 23 columns



RANDOM FOREST

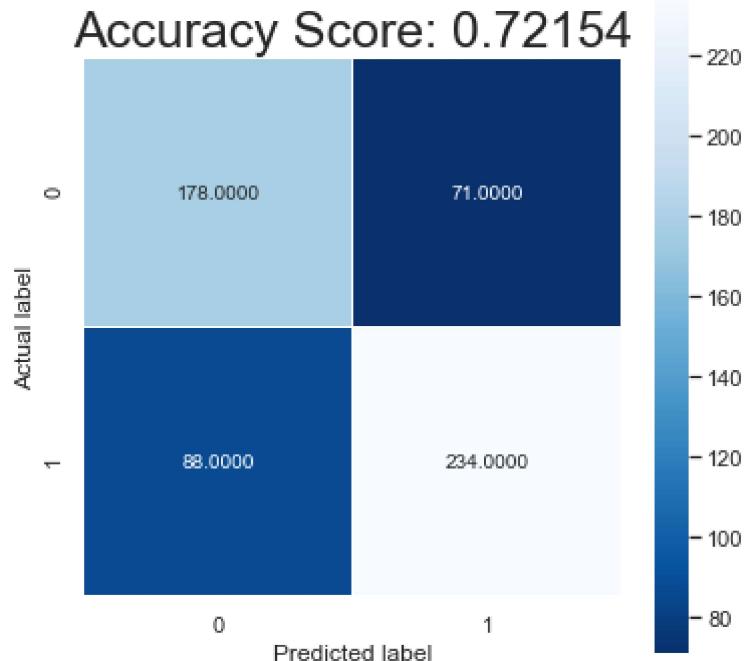
```
In [24]: rf = RandomForestClassifier(n_estimators=200, random_state=42)
rf.fit(X_train, Y_train)
rf_prediction = rf.predict(X_test)
score = metrics.accuracy_score(Y_test, rf_prediction)
display_confusion_matrix(Y_test, rf_prediction, score=score)
rf_score=rf_prediction
```



DECISION TREE

```
In [25]: dt = DecisionTreeClassifier(min_samples_split=15, min_samples_leaf=20, random_state=42)
dt.fit(X_train, Y_train)
dt_prediction = dt.predict(X_test)

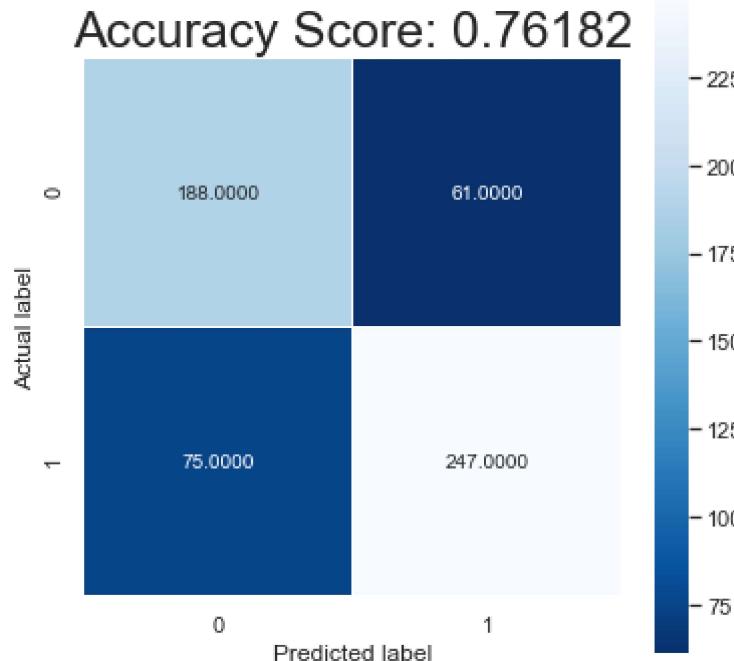
score = metrics.accuracy_score(Y_test, dt_prediction)
display_confusion_matrix(Y_test, dt_prediction, score=score)
```



SVM

```
In [26]: svm = SVC(gamma='auto', random_state=42)
svm.fit(X_train, Y_train)
svm_prediction = svm.predict(X_test)

score = metrics.accuracy_score(Y_test, svm_prediction)
display_confusion_matrix(Y_test, svm_prediction, score=score)
```



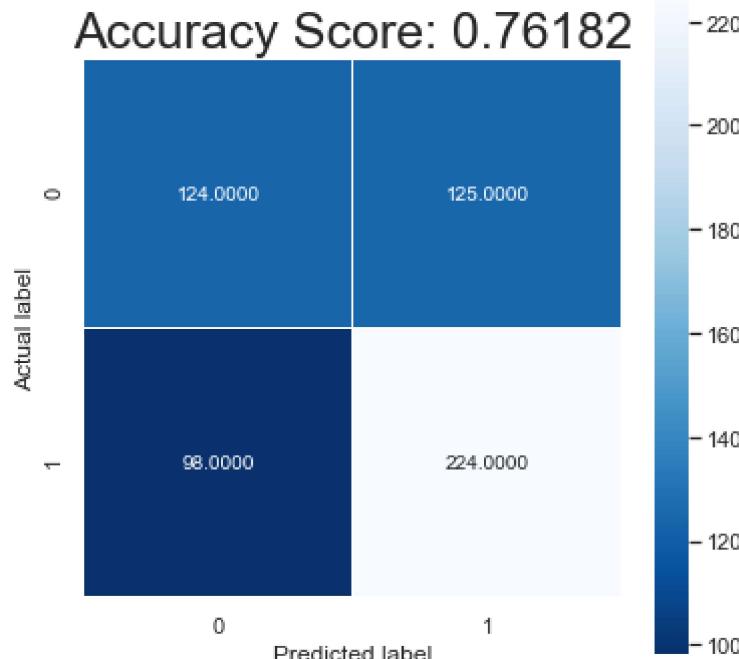
NAIVE BAYES

```
In [27]: #train a Gaussian Naive Bayes classifier on the training set
from sklearn.naive_bayes import GaussianNB
# instantiate the model
gnb = GaussianNB()
# fit the model
gnb.fit(X_train, Y_train)
NB_y_pred = gnb.predict(X_test)
from sklearn.metrics import accuracy_score
y_pred_train = gnb.predict(X_train)
y_pred_train
# print the scores on training and test set
print('Training set score: {:.4f}'.format(gnb.score(X_train, Y_train)))
print('Test set score: {:.4f}'.format(gnb.score(X_test, Y_test)))
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(Y_test, NB_y_pred)
display_confusion_matrix(Y_test, NB_y_pred, score=score)
```

Training set score: 0.6145

Test set score: 0.6095



K NEAREST NEIGHBORS

```
In [28]: from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=3)
classifier.fit(X_train, Y_train)
KNN_y_pred = classifier.predict(X_test)
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(Y_test, KNN_y_pred))
print(classification_report(Y_test, KNN_y_pred))
```

```
[[177  72]
 [ 58 264]]
          precision    recall   f1-score   support
          0.0       0.75     0.71     0.73      249
          1.0       0.79     0.82     0.80      322
          accuracy                           0.77      571
         macro avg       0.77     0.77     0.77      571
      weighted avg       0.77     0.77     0.77      571
```

```
In [29]: print('***** GSR + FACIAL IMAGE DATA *****')
print('SVM ---->',metrics.accuracy_score(Y_test, svm_prediction))
print('RF ---->',metrics.accuracy_score(Y_test, rf_prediction))
print('DT ---->',metrics.accuracy_score(Y_test, dt_prediction))
print('NB ---->',metrics.accuracy_score(Y_test, NB_y_pred))
print('KNN ---->',metrics.accuracy_score(Y_test, KNN_y_pred))
```

```
***** GSR + FACIAL IMAGE DATA *****
SVM ----> 0.7618213660245184
RF ----> 0.8458844133099825
DT ----> 0.7215411558669002
NB ----> 0.6094570928196147
KNN ----> 0.7723292469352014
```

Confusion Matrix

```
In [30]: from sklearn.metrics import precision_score, recall_score, confusion_matrix, precision_score
cm = np.array(confusion_matrix(Y_test, rf_prediction, labels=[0,1]))
confusion_mat= pd.DataFrame(cm, index = ['NORMAL', 'STRESSED'],
                             columns =['NORMAL','STRESSED'])
confusion_mat
```

Out[30]:

	NORMAL	STRESSED
NORMAL	212	37
STRESSED	51	271

```
In [31]: sns.heatmap(cm, annot=True, fmt='g', cmap='Set3')
```

```
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x1a5fff67190>
```



Accuracy_Score

```
In [32]: from sklearn.metrics import accuracy_score
print(accuracy_score(Y_test, rf_prediction))
```

```
0.8458844133099825
```

Precision

```
In [33]: print(precision_score(Y_test, rf_prediction))
```

```
0.8798701298701299
```

Recall

```
In [34]: print(recall_score(Y_test, rf_prediction))
```

```
0.8416149068322981
```

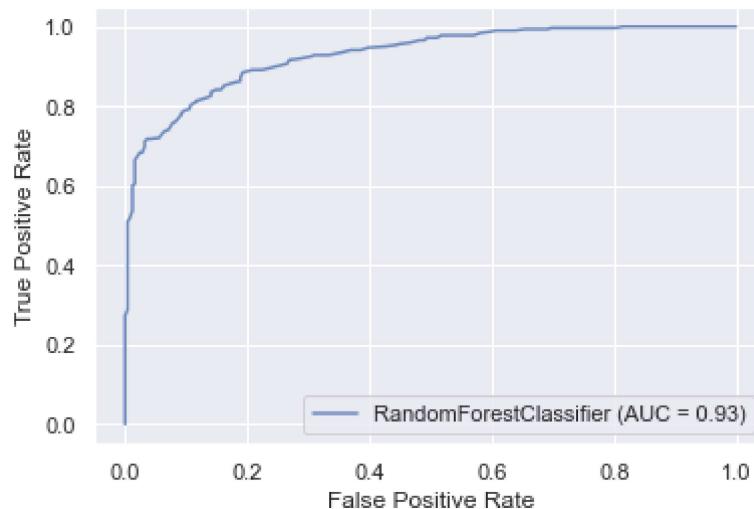
Classification Report

```
In [35]: from sklearn.metrics import classification_report
print(classification_report(Y_test, rf_prediction))
```

	precision	recall	f1-score	support
0.0	0.81	0.85	0.83	249
1.0	0.88	0.84	0.86	322
accuracy			0.85	571
macro avg	0.84	0.85	0.84	571
weighted avg	0.85	0.85	0.85	571

Area Under Curve

```
In [36]: from sklearn.metrics import roc_auc_score, auc, f1_score
from sklearn.metrics import plot_roc_curve
ax = plt.gca()
rfc_disp = plot_roc_curve(rf, X_test, Y_test, ax=ax, alpha=0.8)
plt.show()
```



K FOLD VALIDATION

```
In [37]: cv_score_rf1 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=5, n_jobs=-1)
cv_score_rf2 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=10, n_jobs=-1)
cv_score_rf3 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=20, n_jobs=-1)
cv_score_rf4 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=50, n_jobs=-1)
```

```
In [38]: cv_result = { 'rf5': cv_score_rf1, 'rf10': cv_score_rf2, 'rf20': cv_score_rf3, 'rf50': cv_score_rf4 }
cv_data = {model: [score.mean(), score.std()] for model, score in cv_result.items()}
cv_df = pd.DataFrame(cv_data, index=['Mean_accuracy', 'Variance'])
cv_df
```

Out[38]:

	rf5	rf10	rf20	rf50
Mean_accuracy	0.837719	0.842544	0.840789	0.842957
Variance	0.012862	0.020984	0.029261	0.054493

-----HR AND FACE -----

```
In [39]: # Create dataframe for training dataset and print five first rows as preview
train_df_raw = pd.read_csv('face_hr.csv')
train_df_raw.head()
```

Out[39]:

	Condition	HR	RMSSD	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8
0	0.0	61.0	0.061420	0.968862	0.023946	-6.954147	-5.818151	-0.584952	0.0
1	0.0	61.0	0.061420	0.884570	0.076952	-10.564172	-6.567912	-3.906502	0.0
2	0.0	64.0	0.049663	0.931965	0.031468	-10.721106	-7.055848	-2.452367	0.0
3	0.0	60.0	0.052487	0.806947	0.105516	-10.782755	-5.616126	-4.669924	0.0
4	0.0	61.0	0.051189	0.951412	0.028358	-3.880091	-4.621940	-5.893645	0.0

5 rows × 25 columns

```
In [40]: train_df_raw=train_df_raw.dropna()
```

```
In [41]: # Let's divide the train dataset in two datasets to evaluate performance of the model
train_df = train_df_raw.copy()
X = train_df.drop(['Condition'], 1)
Y = train_df['Condition']
# We scale our data, it is essential for a smooth working of the models
# Scaling means that each columns has a 0 mean and a 1 variance
sc = StandardScaler()
X = pd.DataFrame(sc.fit_transform(X.values), index=X.index, columns=X.columns)
# Split dataset for model testing
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
X_train.head()
```

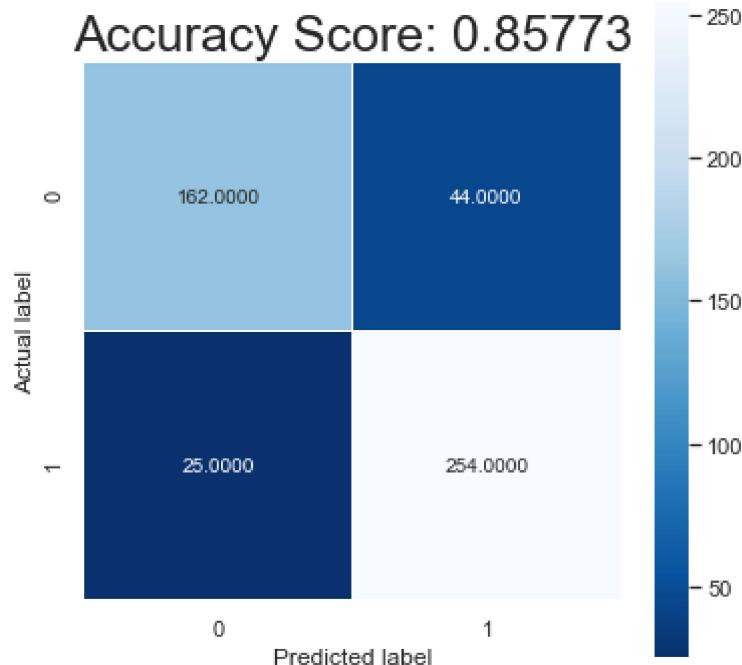
Out[41]:

	HR	RMSDD	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnamed: 9
902	-0.374209	-0.531364	0.235220	-0.446981	0.887911	0.312497	0.718565	-0.452580	-0
327	-1.155800	0.952047	-2.640218	6.057871	1.454941	-0.250884	-0.251917	-0.338512	1
1675	1.091272	-0.350915	-0.103455	-0.513293	0.764261	0.563786	0.083545	-0.593063	1
2085	-0.081113	-0.977440	-0.100863	-0.534673	-0.651750	0.520750	-0.238795	1.859607	-0
2067	0.016586	-0.806410	-0.177677	-0.147487	-1.965639	-0.074883	-0.716510	-0.593063	-0

5 rows × 24 columns

RANDOM FOREST

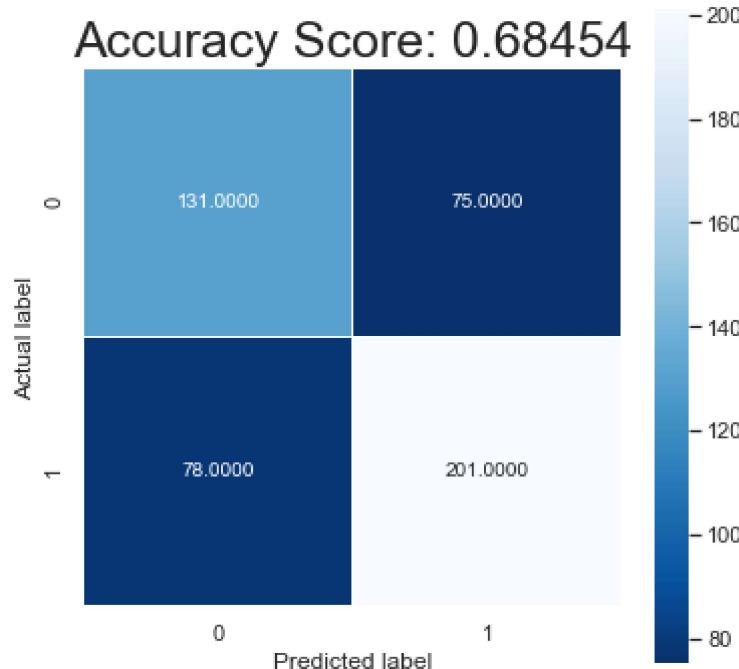
```
In [42]: rf = RandomForestClassifier(n_estimators=200, random_state=42)
rf.fit(X_train, Y_train)
rf_prediction = rf.predict(X_test)
score = metrics.accuracy_score(Y_test, rf_prediction)
display_confusion_matrix(Y_test, rf_prediction, score=score)
rf_score=rf_prediction
```



DECISION TREE

```
In [43]: dt = DecisionTreeClassifier(min_samples_split=15, min_samples_leaf=20, random_state=42)
dt.fit(X_train, Y_train)
dt_prediction = dt.predict(X_test)

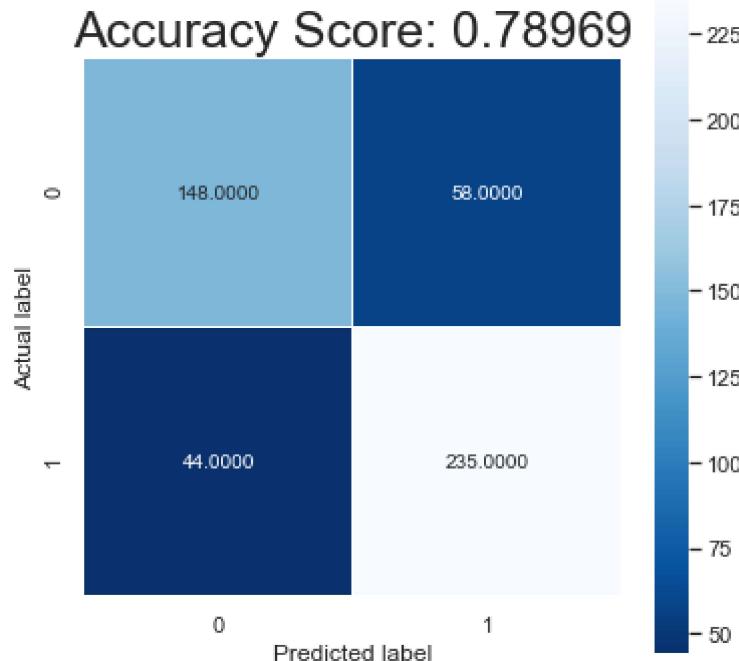
score = metrics.accuracy_score(Y_test, dt_prediction)
display_confusion_matrix(Y_test, dt_prediction, score=score)
```



SVM

```
In [44]: svm = SVC(gamma='auto', random_state=42)
svm.fit(X_train, Y_train)
svm_prediction = svm.predict(X_test)

score = metrics.accuracy_score(Y_test, svm_prediction)
display_confusion_matrix(Y_test, svm_prediction, score=score)
```



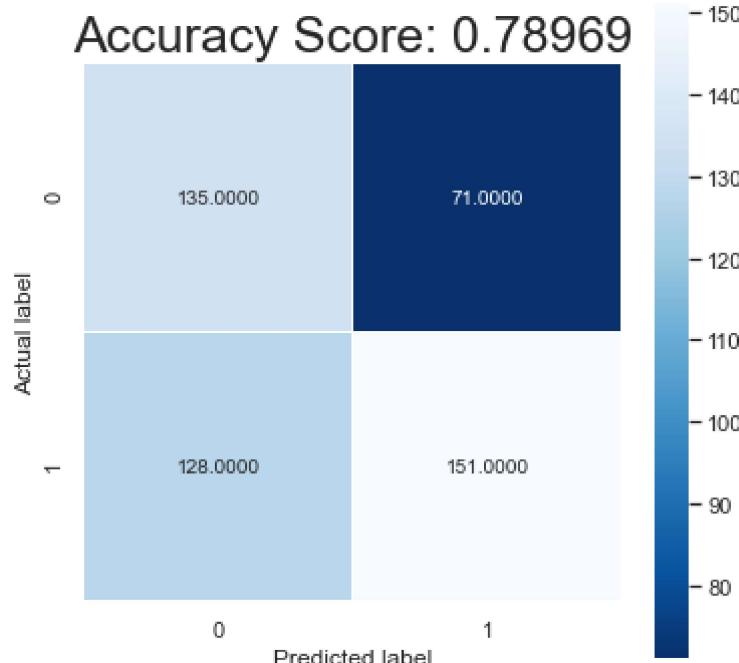
NAIVE BAYES

```
In [45]: #train a Gaussian Naive Bayes classifier on the training set
from sklearn.naive_bayes import GaussianNB
# instantiate the model
gnb = GaussianNB()
# fit the model
gnb.fit(X_train, Y_train)
NB_y_pred = gnb.predict(X_test)
from sklearn.metrics import accuracy_score
y_pred_train = gnb.predict(X_train)
y_pred_train
# print the scores on training and test set
print('Training set score: {:.4f}'.format(gnb.score(X_train, Y_train)))
print('Test set score: {:.4f}'.format(gnb.score(X_test, Y_test)))
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(Y_test, NB_y_pred)
display_confusion_matrix(Y_test, NB_y_pred, score=score)
```

Training set score: 0.6281

Test set score: 0.5897



K NEAREST NEIGHBORS

```
In [46]: from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=3)
classifier.fit(X_train, Y_train)
KNN_y_pred = classifier.predict(X_test)
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(Y_test, KNN_y_pred))
print(classification_report(Y_test, KNN_y_pred))
```

```
[[156  50]
 [ 38 241]]
          precision    recall   f1-score   support
          0.0       0.80      0.76      0.78      206
          1.0       0.83      0.86      0.85      279

      accuracy                           0.82      485
   macro avg       0.82      0.81      0.81      485
weighted avg       0.82      0.82      0.82      485
```

```
In [47]: print('***** HR + FACIAL IMAGE DATA *****')
print('SVM ---->',metrics.accuracy_score(Y_test, svm_prediction))
print('RF ---->',metrics.accuracy_score(Y_test, rf_prediction))
print('DT ---->',metrics.accuracy_score(Y_test, dt_prediction))
print('NB ---->',metrics.accuracy_score(Y_test, NB_y_pred))
print('KNN ---->',metrics.accuracy_score(Y_test, KNN_y_pred))
```

```
***** HR + FACIAL IMAGE DATA *****
SVM ----> 0.7896907216494845
RF ----> 0.8577319587628865
DT ----> 0.6845360824742268
NB ----> 0.5896907216494846
KNN ----> 0.8185567010309278
```

Confusion Matrix

```
In [48]: from sklearn.metrics import precision_score, recall_score, confusion_matrix, precision_recall_fscore_support
cm = np.array(confusion_matrix(Y_test, rf_prediction, labels=[0,1]))
confusion_mat= pd.DataFrame(cm, index = ['NORMAL', 'STRESSED'],
                             columns =['NORMAL','STRESSED'])
confusion_mat
```

Out[48]:

	NORMAL	STRESSED
NORMAL	162	44
STRESSED	25	254

In [49]: `sns.heatmap(cm, annot=True, fmt='g', cmap='Set3')`

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x1a583580b50>



Accuracy_Score

In [50]: `from sklearn.metrics import accuracy_score
print(accuracy_score(Y_test, rf_prediction))`

0.8577319587628865

Precision

In [51]: `print(precision_score(Y_test, rf_prediction))`

0.8523489932885906

Recall

In [52]: `print(recall_score(Y_test, rf_prediction))`

0.910394265232975

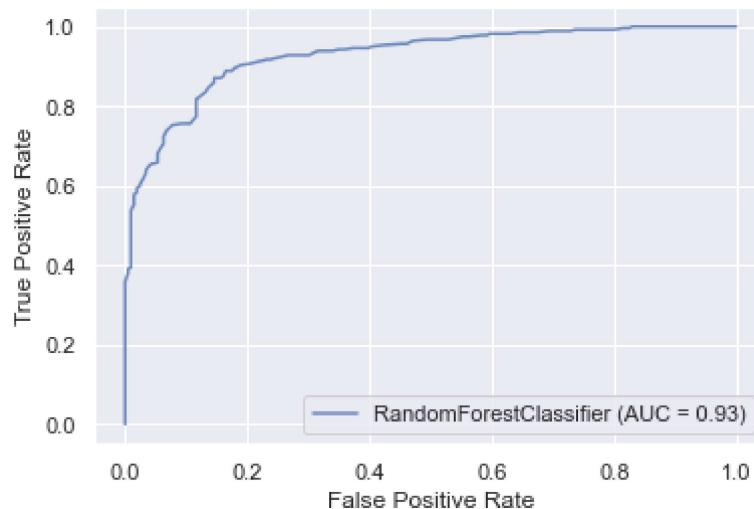
Classification Report

```
In [53]: from sklearn.metrics import classification_report
print(classification_report(Y_test, rf_prediction))
```

	precision	recall	f1-score	support
0.0	0.87	0.79	0.82	206
1.0	0.85	0.91	0.88	279
accuracy			0.86	485
macro avg	0.86	0.85	0.85	485
weighted avg	0.86	0.86	0.86	485

Area Under Curve

```
In [54]: from sklearn.metrics import roc_auc_score, auc, f1_score
from sklearn.metrics import plot_roc_curve
ax = plt.gca()
rfc_disp = plot_roc_curve(rf, X_test, Y_test, ax=ax, alpha=0.8)
plt.show()
```



K FOLD VALIDATION

```
In [55]: cv_score_rf1 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=5, n_jobs=-1)
cv_score_rf2 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=10, n_jobs=-1)
cv_score_rf3 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=20, n_jobs=-1)
cv_score_rf4 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=50, n_jobs=-1)
```

```
In [56]: cv_result = { 'rf5': cv_score_rf1, 'rf10': cv_score_rf2, 'rf20': cv_score_rf3, 'rf50': cv_score_rf4 }
cv_data = {model: [score.mean(), score.std()] for model, score in cv_result.items()}
cv_df = pd.DataFrame(cv_data, index=['Mean_accuracy', 'Variance'])
cv_df
```

Out[56]:

	rf5	rf10	rf20	rf50
Mean_accuracy	0.808872	0.832090	0.818073	0.822686
Variance	0.022793	0.022946	0.051337	0.064534

-----HR GSR AND FACIAL IMAGE DATA-----

```
In [57]: # Create dataframe for training dataset and print five first rows as preview
train_df_raw = pd.read_csv('face_phys.csv')
train_df_raw.head()
```

Out[57]:

	Condition	HR	RMSSD	SCL	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8
0	0.0	61.0	0.061420	80.239727	0.968862	0.023946	-6.954147	-5.818151	-0.584952
1	0.0	61.0	0.061420	77.365127	0.884570	0.076952	-10.564172	-6.567912	-3.906502
2	0.0	64.0	0.049663	77.359559	0.931965	0.031468	-10.721106	-7.055848	-2.452367
3	0.0	60.0	0.052487	76.728772	0.806947	0.105516	-10.782755	-5.616126	-4.669924
4	0.0	61.0	0.051189	76.512877	0.951412	0.028358	-3.880091	-4.621940	-5.893645

5 rows × 26 columns



```
In [58]: train_df_raw=train_df_raw.dropna()
```

```
In [59]: # Let's divide the train dataset in two datasets to evaluate performance of the model
train_df = train_df_raw.copy()
X = train_df.drop(['Condition'], 1)
Y = train_df['Condition']
# We scale our data, it is essential for a smooth working of the models
# Scaling means that each columns has a 0 mean and a 1 variance
sc = StandardScaler()
X = pd.DataFrame(sc.fit_transform(X.values), index=X.index, columns=X.columns)
# Split dataset for model testing
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
X_train.head()
```

Out[59]:

	HR	RMSSD	SCL	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnamed: 9
882	-0.466880	-0.514140	-0.227917	0.495755	-0.119921	1.529137	-0.578054	-1.878399	0.
2845	-0.564016	-0.373841	-0.342219	0.951577	-0.268785	-1.596594	0.285085	-0.087922	-0.
444	1.670115	0.129043	-0.411088	1.027672	0.093078	0.234768	0.893334	-1.643508	-0.
1638	0.213073	-0.805802	-0.127388	0.898400	-0.528324	-0.823113	-1.053265	-1.471973	-0.
1457	0.310209	1.367904	1.465853	-0.015720	-0.374289	0.383245	-0.948984	0.039969	0.

5 rows × 25 columns

--	--	--

```
In [60]: # Create dataframe for training dataset and print five first rows as preview
train_df_raw = pd.read_csv('face_phys.csv')
train_df_raw.head()
```

Out[60]:

	Condition	HR	RMSSD	SCL	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnamed: 9
0	0.0	61.0	0.061420	80.239727	0.968862	0.023946	-6.954147	-5.818151	-0.584952	1.0
1	0.0	61.0	0.061420	77.365127	0.884570	0.076952	-10.564172	-6.567912	-3.906502	1.0
2	0.0	64.0	0.049663	77.359559	0.931965	0.031468	-10.721106	-7.055848	-2.452367	1.0
3	0.0	60.0	0.052487	76.728772	0.806947	0.105516	-10.782755	-5.616126	-4.669924	1.0
4	0.0	61.0	0.051189	76.512877	0.951412	0.028358	-3.880091	-4.621940	-5.893645	1.0

5 rows × 26 columns

--	--	--

```
In [61]: train_df_raw=train_df_raw.dropna()
```

```
In [62]: # PRE MODELING TASK
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.neighbors import KNeighborsClassifier, NeighborhoodComponentsAnalysis
from sklearn.decomposition import PCA

X = train_df_raw.drop(['Condition'], 1)
Y = train_df_raw['Condition']

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.20, random_state = 42)
print("X_train",len(X_train))
print("X_test",len(X_test))
print("Y_train",len(Y_train))
print("Y_test",len(Y_test))
```

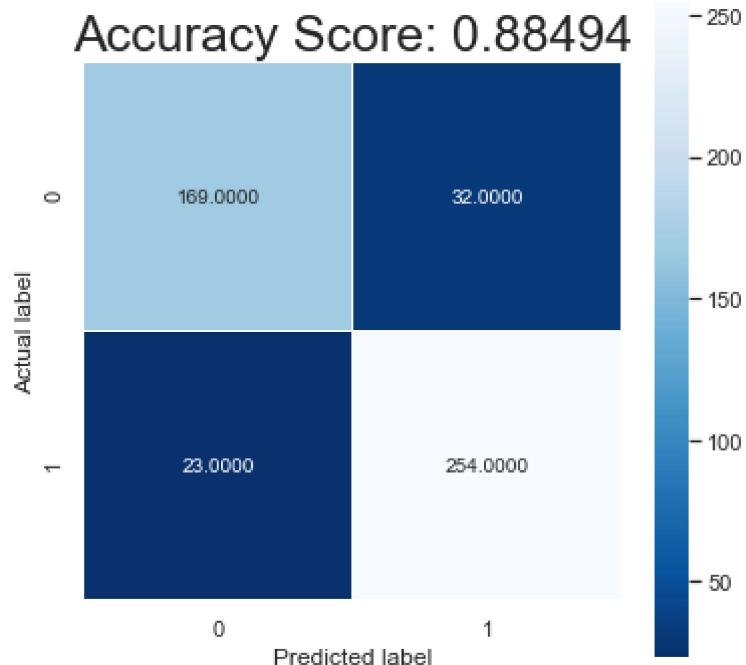
```
X_train 1909
X_test 478
Y_train 1909
Y_test 478
```

```
In [63]: # to standardize the range
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
In [ ]:
```

RANDOM FOREST

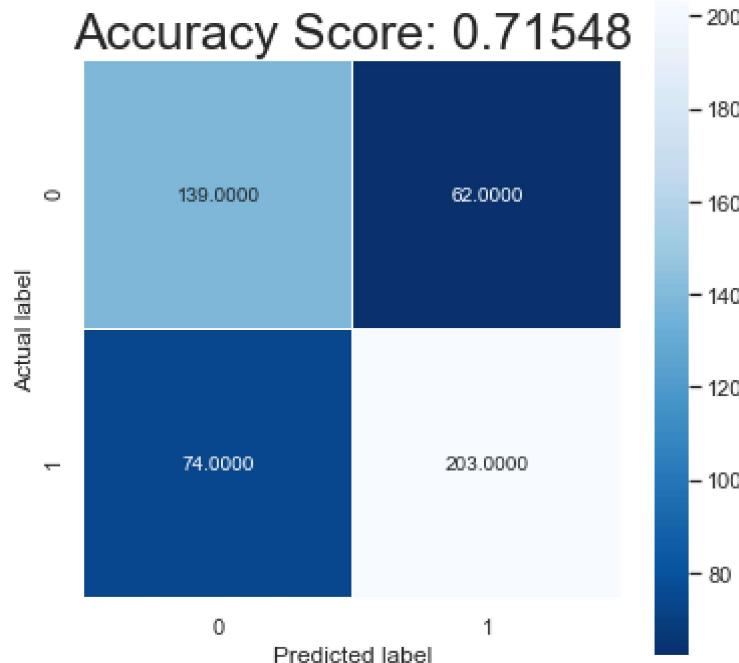
```
In [64]: rf = RandomForestClassifier(n_estimators=200, random_state=42)
rf.fit(X_train, Y_train)
rf_prediction = rf.predict(X_test)
score = metrics.accuracy_score(Y_test, rf_prediction)
display_confusion_matrix(Y_test, rf_prediction, score=score)
rf_score=rf_prediction
```



DECISION TREE

```
In [65]: dt = DecisionTreeClassifier(min_samples_split=15, min_samples_leaf=20, random_state=42)
dt.fit(X_train, Y_train)
dt_prediction = dt.predict(X_test)

score = metrics.accuracy_score(Y_test, dt_prediction)
display_confusion_matrix(Y_test, dt_prediction, score=score)
```



```
In [66]: print(precision_score(Y_test, dt_prediction))
print(recall_score(Y_test, dt_prediction))
```

0.7660377358490567
0.7328519855595668

SVM

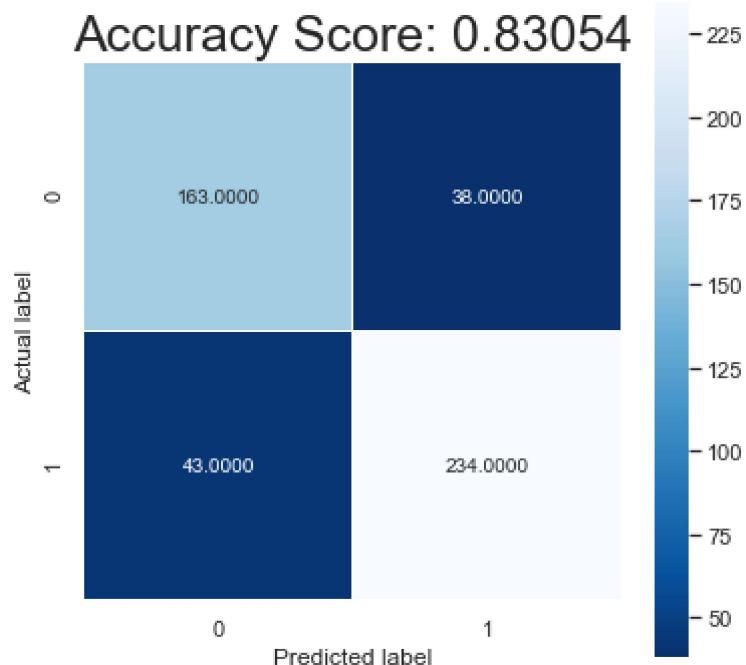
```
In [67]: svm = SVC(gamma='auto', random_state=42)
svm.fit(X_train, Y_train)
svm_prediction = svm.predict(X_test)

score = metrics.accuracy_score(Y_test, svm_prediction)
display_confusion_matrix(Y_test, svm_prediction, score=score)
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(Y_test, svm_prediction))
print(classification_report(Y_test, svm_prediction))
```

```
[[163  38]
 [ 43 234]]
          precision    recall  f1-score   support

           0.0       0.79      0.81      0.80      201
           1.0       0.86      0.84      0.85      277

    accuracy                           0.83      478
   macro avg       0.83      0.83      0.83      478
weighted avg       0.83      0.83      0.83      478
```



```
In [68]: print(precision_score(Y_test, svm_prediction))
print(recall_score(Y_test, svm_prediction))
```

```
0.8602941176470589
0.8447653429602888
```

NAIVE BAYES

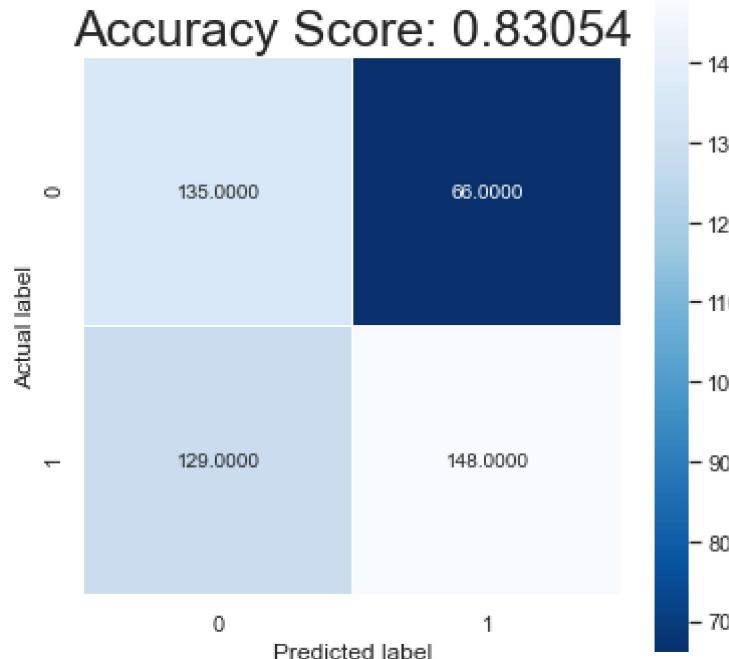
```
In [69]: #train a Gaussian Naive Bayes classifier on the training set
from sklearn.naive_bayes import GaussianNB
# instantiate the model
gnb = GaussianNB()
# fit the model
gnb.fit(X_train, Y_train)
NB_y_pred = gnb.predict(X_test)
```

```
In [70]: from sklearn.metrics import accuracy_score
y_pred_train = gnb.predict(X_train)
y_pred_train
# print the scores on training and test set
print('Training set score: {:.4f}'.format(gnb.score(X_train, Y_train)))
print('Test set score: {:.4f}'.format(gnb.score(X_test, Y_test)))
```

```
Training set score: 0.6286
Test set score: 0.5921
```

```
In [71]: from sklearn.metrics import confusion_matrix

cm = confusion_matrix(Y_test, NB_y_pred)
display_confusion_matrix(Y_test, NB_y_pred, score=score)
```



```
In [72]: print(precision_score(Y_test, NB_y_pred))
print(recall_score(Y_test, NB_y_pred))
```

0.6915887850467289
0.5342960288808665

K NEAREST NEIGHBORS

```
In [73]: from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=3)
classifier.fit(X_train, Y_train)
KNN_y_pred = classifier.predict(X_test)
```

```
In [74]: print(precision_score(Y_test, KNN_y_pred))
print(recall_score(Y_test, KNN_y_pred))
```

0.8415492957746479
0.8628158844765343

```
In [75]: print('***** HR + GSR + FACIAL IMAGE DATA *****')
print('SVM ---->',metrics.accuracy_score(Y_test, svm_prediction))
print('RF ---->',metrics.accuracy_score(Y_test, rf_prediction))
print('DT ---->',metrics.accuracy_score(Y_test, dt_prediction))
print('NB ---->',metrics.accuracy_score(Y_test, NB_y_pred))
print('KNN ---->',metrics.accuracy_score(Y_test, KNN_y_pred))
```

```
***** HR + GSR + FACIAL IMAGE DATA *****
SVM ----> 0.8305439330543933
RF ----> 0.8849372384937239
DT ----> 0.7154811715481172
NB ----> 0.5920502092050209
KNN ----> 0.8263598326359832
```

Confusion Matrix

```
In [76]: from sklearn.metrics import precision_score, recall_score, confusion_matrix, precision_score
cm = np.array(confusion_matrix(Y_test, rf_prediction, labels=[0,1]))
confusion_mat = pd.DataFrame(cm, index = ['NORMAL', 'STRESSED'],
                             columns = ['NORMAL', 'STRESSED'])
confusion_mat
```

Out[76]:

	NORMAL	STRESSED
NORMAL	169	32
STRESSED	23	254

```
In [77]: sns.heatmap(cm, annot=True, fmt='g', cmap='Set3')
```

Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x1a583878490>



Accuracy_Score

```
In [78]: from sklearn.metrics import accuracy_score
print(accuracy_score(Y_test, rf_prediction))
```

0.8849372384937239

Precision

```
In [79]: rf_pre=precision_score(Y_test, rf_prediction)
rf_pre
```

Out[79]: 0.8881118881118881

```
In [80]: # calculate score
score = f1_score(Y_test, rf_prediction, average='binary')
print('F-Measure: %.4f' % score)
```

F-Measure: 0.9023

Recall

```
In [81]: rf_recall=recall_score(Y_test, rf_prediction)
rf_recall
```

Out[81]: 0.9169675090252708

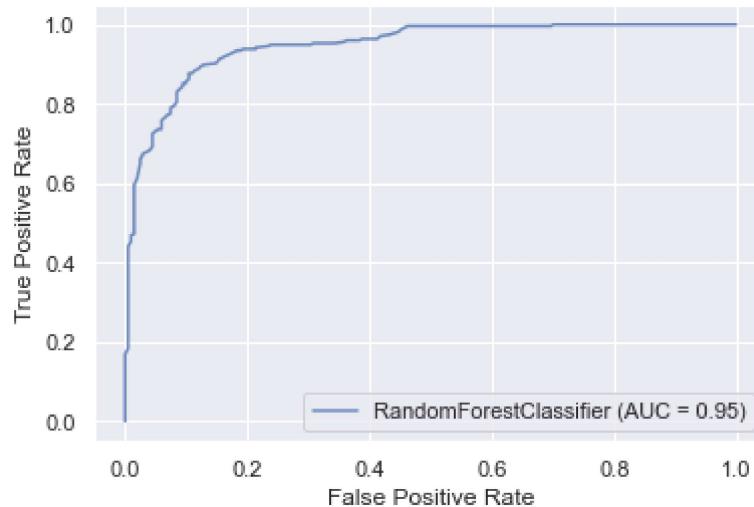
Classification Report

```
In [82]: from sklearn.metrics import classification_report
print(classification_report(Y_test, rf_prediction))
```

	precision	recall	f1-score	support
0.0	0.88	0.84	0.86	201
1.0	0.89	0.92	0.90	277
accuracy			0.88	478
macro avg	0.88	0.88	0.88	478
weighted avg	0.88	0.88	0.88	478

Area Under Curve

```
In [83]: from sklearn.metrics import roc_auc_score, auc, f1_score
from sklearn.metrics import plot_roc_curve
ax = plt.gca()
rfc_disp = plot_roc_curve(rf, X_test, Y_test, ax=ax, alpha=0.8)
plt.show()
```



K FOLD VALIDATION

```
In [84]: cv_score_rf1 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=5, n_jobs=-1)
cv_score_rf2 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=10, n_jobs=-1)
cv_score_rf3 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=20, n_jobs=-1)
cv_score_rf4 = cross_val_score(estimator=rf, X=X_train, y=Y_train, cv=50, n_jobs=-1)
```

```
In [85]: cv_result = { 'rf5': cv_score_rf1, 'rf10': cv_score_rf2, 'rf20': cv_score_rf3, 'rf50': cv_score_rf4 }
cv_data = {model: [score.mean(), score.std()] for model, score in cv_result.items()}
cv_df = pd.DataFrame(cv_data, index=['Mean_accuracy', 'Variance'])
cv_df
```

Out[85]:

	rf5	rf10	rf20	rf50
Mean_accuracy	0.871665	0.873748	0.880016	0.878516
Variance	0.012461	0.022806	0.037503	0.055084

In [86]:

```
cv_score_dt1 = cross_val_score(estimator=dt, X=X_train, y=Y_train, cv=5, n_jobs=-1)
cv_score_dt2 = cross_val_score(estimator=dt, X=X_train, y=Y_train, cv=10, n_jobs=-1)
cv_score_dt3 = cross_val_score(estimator=dt, X=X_train, y=Y_train, cv=20, n_jobs=-1)
cv_score_dt4 = cross_val_score(estimator=dt, X=X_train, y=Y_train, cv=50, n_jobs=-1)
```

In [87]:

```
cv_result = { 'rf5': cv_score_dt1, 'rf10': cv_score_dt2, 'rf20': cv_score_dt3, 'rf50': cv_score_dt4 }
cv_data = {model: [score.mean(), score.std()] for model, score in cv_result.items()}
cv_df = pd.DataFrame(cv_data, index=['Mean_accuracy', 'Variance'])
cv_df
```

Out[87]:

	rf5	rf10	rf20	rf50
Mean_accuracy	0.733373	0.722373	0.733432	0.724507
Variance	0.023499	0.020612	0.035718	0.071758

In [88]:

```
cv_score_svm1 = cross_val_score(estimator=svm, X=X_train, y=Y_train, cv=5, n_jobs=-1)
cv_score_svm2 = cross_val_score(estimator=svm, X=X_train, y=Y_train, cv=10, n_jobs=-1)
cv_score_svm3 = cross_val_score(estimator=svm, X=X_train, y=Y_train, cv=20, n_jobs=-1)
cv_score_svm4 = cross_val_score(estimator=svm, X=X_train, y=Y_train, cv=50, n_jobs=-1)
```

In [89]:

```
cv_result = { 'rf5': cv_score_svm1, 'rf10': cv_score_svm2, 'rf20': cv_score_svm3, 'rf50': cv_score_svm4 }
cv_data = {model: [score.mean(), score.std()] for model, score in cv_result.items()}
cv_df = pd.DataFrame(cv_data, index=['Mean_accuracy', 'Variance'])
cv_df
```

Out[89]:

	rf5	rf10	rf20	rf50
Mean_accuracy	0.803548	0.807746	0.811930	0.810864
Variance	0.018381	0.023710	0.036918	0.064591

In [90]:

```
cv_score_knn1 = cross_val_score(estimator=classifier, X=X_train, y=Y_train, cv=5, n_jobs=-1)
cv_score_knn2 = cross_val_score(estimator=classifier, X=X_train, y=Y_train, cv=10, n_jobs=-1)
cv_score_knn3 = cross_val_score(estimator=classifier, X=X_train, y=Y_train, cv=20, n_jobs=-1)
cv_score_knn4 = cross_val_score(estimator=classifier, X=X_train, y=Y_train, cv=50, n_jobs=-1)
```

In [91]:

```
cv_result = { 'knn5': cv_score_knn1, 'knn10': cv_score_knn2, 'knn20': cv_score_knn3, 'knn50': cv_score_knn4 }
cv_data = {model: [score.mean()] for model, score in cv_result.items()}
cv_df = pd.DataFrame(cv_data, index=['Mean_accuracy'])
cv_df
```

Out[91]:

	knn5	knn10	knn20	knn50
Mean_accuracy	0.830781	0.837071	0.840702	0.840742

```
In [92]: dictionary={"model":["KNN","SVM","DT","RF"],"score":[metrics.accuracy_score(Y_te
metrics.accuracy_score(
metrics.accuracy_score(
metrics.accuracy_score(
df1=pd.DataFrame(dictionary)
```

```
In [93]: pip install plotly==4.14.3
```

```
Requirement already satisfied: plotly==4.14.3 in c:\users\drashti\anaconda3\lib
\site-packages (4.14.3)
Requirement already satisfied: six in c:\users\drashti\anaconda3\lib\site-pac
ges (from plotly==4.14.3) (1.15.0)
Requirement already satisfied: retrying>=1.3.3 in c:\users\drashti\anaconda3\li
b\site-packages (from plotly==4.14.3) (1.3.3)
Note: you may need to restart the kernel to use updated packages.
```

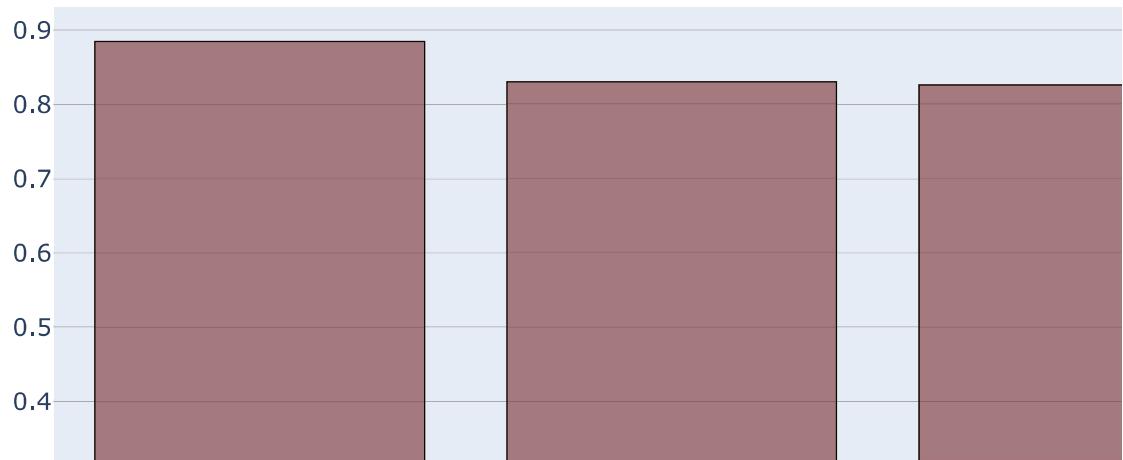
```
In [94]: import matplotlib.pyplot as plt
import plotly.graph_objs as go

#sort the values of data
import plotly
plotly.offline.init_notebook_mode()

new_index5=df1.score.sort_values(ascending=False).index.values
sorted_data5=df1.reindex(new_index5)

# create trace1
trace1 = go.Bar(
    x = sorted_data5.model,
    y = sorted_data5.score,
    name = "score",
    marker = dict(color = 'rgba(100, 10, 10, 0.5)',
                  line=dict(color='rgb(10,10,0))),
    text = sorted_data5.model)
dat = [trace1]
layout = go.Layout(barmode = "group",title= 'Scores of Classifications')
fig = go.Figure(data = dat, layout = layout)
plotly.offline.iplot(fig)
```

Scores of Classifications



In [95]:

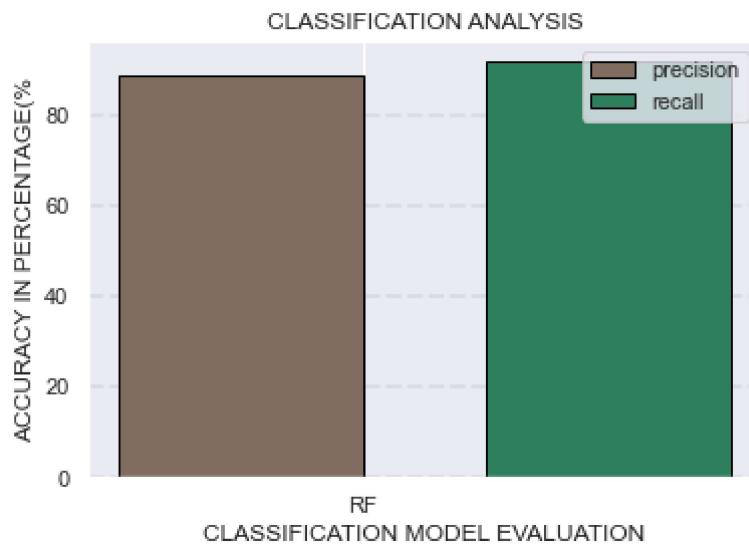
```
import numpy as np
import matplotlib.pyplot as plt

X = ['RF']
Yprecision= [88.81]
Zrecall = [91.70]

X_axis = np.arange(len(X))

plt.bar(X_axis - 0.2, Yprecision, 0.4, label = 'precision', color = '#7f6d5f', edgecolor='black')
plt.bar(X_axis + 0.4, Zrecall, 0.4, label = 'recall', color = '#2d7f5e', edgecolor='black')
plt.grid(color='#95a5a9', linestyle='--', linewidth=2, axis='y', alpha=0.2)

plt.xticks(X_axis, X)
plt.xlabel("CLASSIFICATION MODEL EVALUATION")
plt.ylabel("ACCURACY IN PERCENTAGE(%)")
plt.title("CLASSIFICATION ANALYSIS")
plt.legend()
plt.show()
```



```
In [96]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

plotdata = pd.DataFrame({
    "Accuracy": [88.48],
    "precision": [88.81],
    "recall": [91.70],
    "f-measure": [90.23]
},
index=["RF"]
)

ax=plotdata.plot(kind="bar",width=0.6)
plt.grid(color='#95a5a9', linestyle='--', linewidth=1, axis='y', alpha=0.5)

for p in ax.patches:
    ax.annotate(str(p.get_height()), (p.get_x() * 1.005, p.get_height() * 1.005))
plt.xlabel("CLASSIFICATION MODEL")
plt.ylabel("ACCURACY IN PERCENTAGE(%)")
plt.title("CLASSIFICATION ANALYSIS")
```

Out[96]: Text(0.5, 1.0, 'CLASSIFICATION ANALYSIS')



In [97]:

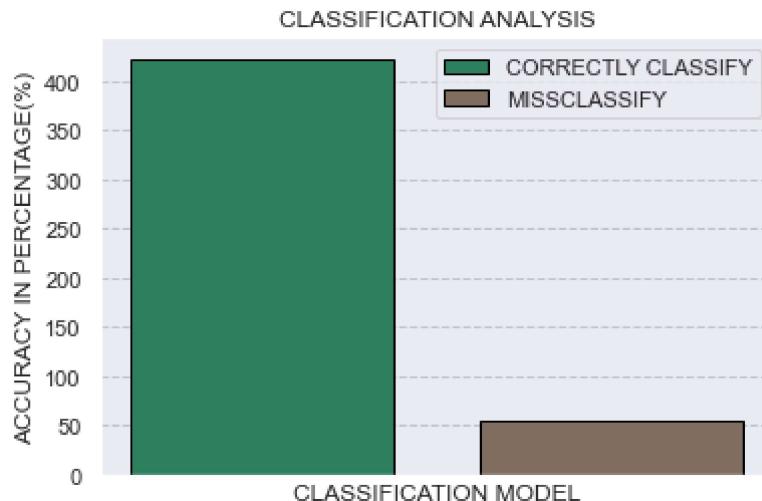
```
import numpy as np
import matplotlib.pyplot as plt

X = ['RANDOM FOREST']
correct= [423]
miss = [55]

X_axis = np.arange(len(X))#2d7f5e

plt.bar(X_axis + 0.2, correct, 0.3, label = 'CORRECTLY CLASSIFY', color = '#2d7f5e')
plt.bar(X_axis + 0.6, miss, 0.3, label = 'MISSCLASSIFY', color = '#7f6d5f', edgecolor='black')
plt.grid(color='#95a5a9', linestyle='--', linewidth=1, axis='y', alpha=0.5)

plt.xticks(X_axis, X)
plt.xlabel("CLASSIFICATION MODEL")
plt.ylabel("ACCURACY IN PERCENTAGE(%)")
plt.title("CLASSIFICATION ANALYSIS")
plt.legend()
plt.show()
```



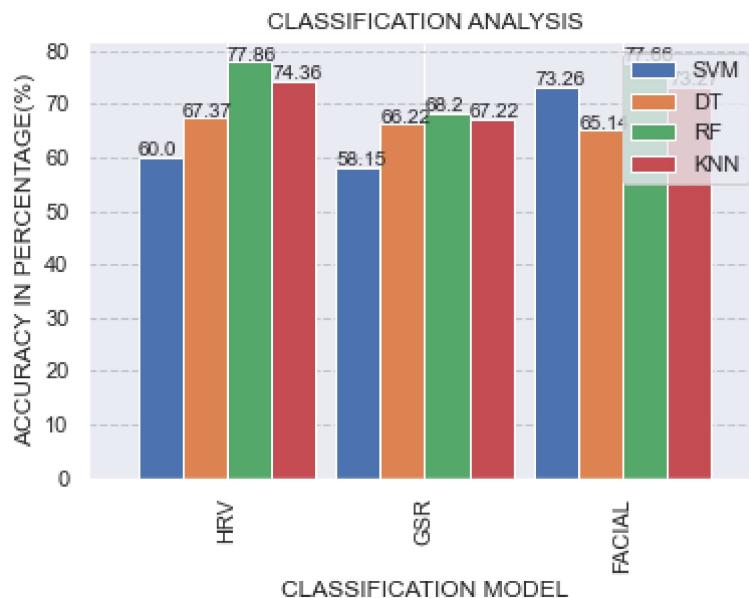
```
In [98]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

plotdata = pd.DataFrame({
    "SVM": [60, 58.15, 73.26],
    "DT": [67.37, 66.22, 65.14],
    "RF": [77.86, 68.20, 77.66],
    "KNN": [74.36, 67.22, 73.27]
},
index=['HRV', 'GSR', 'FACIAL']
)

ax=plotdata.plot(kind="bar",width=0.9)
plt.grid(color='#95a5a9', linestyle='--', linewidth=1, axis='y', alpha=0.5)

for p in ax.patches:
    ax.annotate(str(p.get_height()), (p.get_x() * 1.005, p.get_height() * 1.005))
plt.xlabel("CLASSIFICATION MODEL")
plt.ylabel("ACCURACY IN PERCENTAGE(%)")
plt.title("CLASSIFICATION ANALYSIS")
```

Out[98]: Text(0.5, 1.0, 'CLASSIFICATION ANALYSIS')



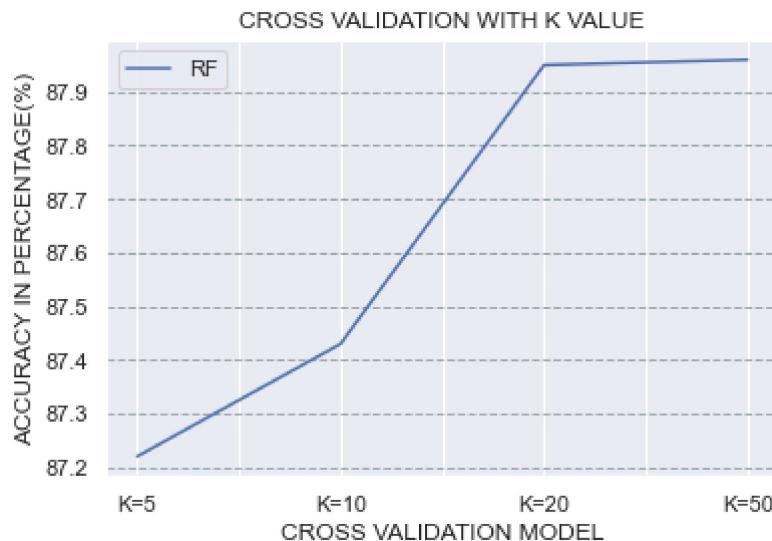
```
In [100]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plotdata = pd.DataFrame({  

    "RF": [87.22, 87.43, 87.95, 87.96],  

},  

    index=['K=5', 'K=10', 'K=20', 'K=50']
)  
  
ax=plotdata.plot(kind="line")
plt.grid(color="#95a5a9", linestyle='--', linewidth=1, axis='y', alpha=0.9)  
  
#for p in ax.patches:  
#    ax.annotate(str(p.get_height()), (p.get_x() * 1.005, p.get_height() * 1.005))  
  
plt.xlabel("CROSS VALIDATION MODEL")
plt.ylabel("ACCURACY IN PERCENTAGE(%)")
plt.title("CROSS VALIDATION WITH K VALUE")
```

Out[100]: Text(0.5, 1.0, 'CROSS VALIDATION WITH K VALUE')



In [101]:

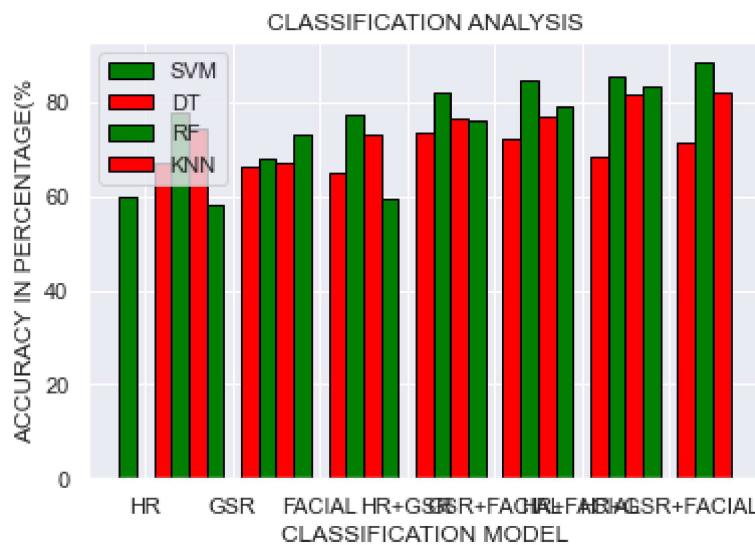
```

import numpy as np
import matplotlib.pyplot as plt

X = ['HR', 'GSR', 'FACIAL', 'HR+GSR', 'GSR+FACIAL', 'HR+FACIAL', 'HR+GSR+FACIAL']
SVM= [60, 58.15, 73.26, 59.53, 76.18, 78.97, 83.26]
DT = [67.37, 66.22, 65.14, 73.67, 72.15, 68.45, 71.54]
RF = [77.86, 68.20, 77.66, 82.21, 84.59, 85.77, 88.49]
KNN = [74.36, 67.22, 73.27, 76.42, 77.23, 81.86, 82]
X_axis = np.arange(len(X))

plt.bar(X_axis - 0.2, SVM, 0.2, label = 'SVM', color = 'green', edgecolor = 'black')
plt.bar(X_axis + 0.2, DT, 0.2, label = 'DT', color = 'red', edgecolor = 'black')
plt.bar(X_axis + 0.4, RF, 0.2, label = 'RF', color = 'green', edgecolor = 'black')
plt.bar(X_axis + 0.6, KNN, 0.2, label = 'KNN', color = 'red', edgecolor = 'black')
plt.xticks(X_axis, X)
plt.xlabel("CLASSIFICATION MODEL")
plt.ylabel("ACCURACY IN PERCENTAGE(%)")
plt.title("CLASSIFICATION ANALYSIS")
plt.legend()
plt.show()

```



In [102]:

```
import numpy as np
import matplotlib.pyplot as plt

X = ['HRV+GSR', 'GSR+FACIAL', 'HR+FACIAL', 'HR+GSR+FACIAL']

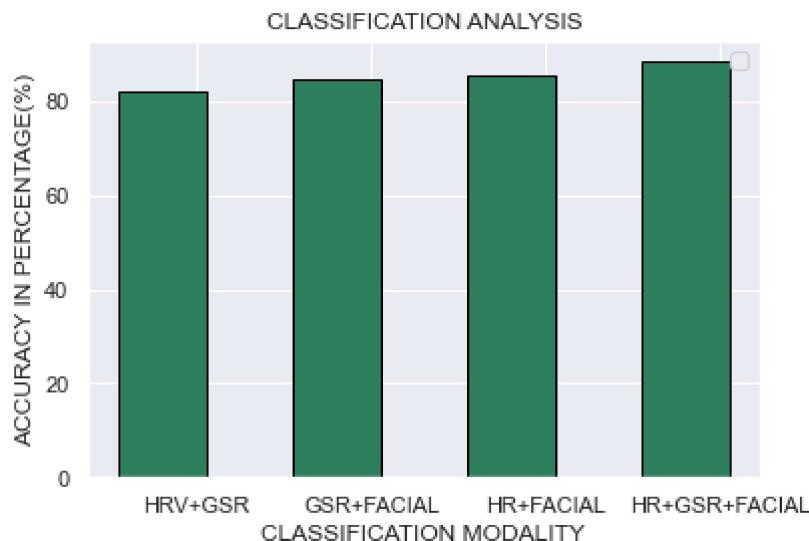
RF = [82.21, 84.59, 85.77, 88.49]

X_axis = np.arange(len(X))

plt.bar(X_axis - 0.2, RF, 0.5, color = '#2d7f5e', edgecolor = 'black')

plt.xticks(X_axis, X)
plt.xlabel("CLASSIFICATION MODALITY")
plt.ylabel("ACCURACY IN PERCENTAGE(%)")
plt.title("CLASSIFICATION ANALYSIS")
plt.legend()
plt.show()
```

No handles with labels found to put in legend.



In [103]:

```

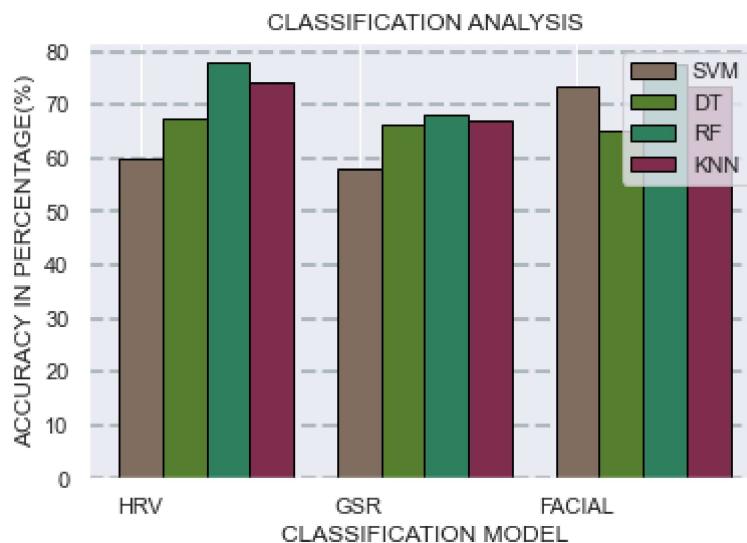
import numpy as np
import matplotlib.pyplot as plt

X = ['HRV', 'GSR', 'FACIAL']
SVM= [60,58.15,73.26]
DT = [67.37,66.22,65.14]
RF = [77.86,68.20,77.66]
KNN = [74.36,67.22,73.27]
X_axis = np.arange(len(X))

plt.bar(X_axis - 0.0, SVM, 0.2, label = 'SVM', color = '#7f6d5f', edgecolor = 'black')
plt.bar(X_axis + 0.2, DT, 0.2, label = 'DT', color = '#557f2d', edgecolor = 'black')
plt.bar(X_axis + 0.4, RF, 0.2, label = 'RF', color = '#2d7f5e', edgecolor = 'black')
plt.bar(X_axis + 0.6, KNN, 0.2, label = 'KNN', color = '#7f2d4d', edgecolor = 'black')
plt.grid(color='#95a5a6', linestyle='--', linewidth=2, axis='y', alpha=0.7)

plt.xticks(X_axis, X)
plt.xlabel("CLASSIFICATION MODEL")
plt.ylabel("ACCURACY IN PERCENTAGE(%)")
plt.title("CLASSIFICATION ANALYSIS")
plt.legend()
plt.show()

```



In [104]:

```

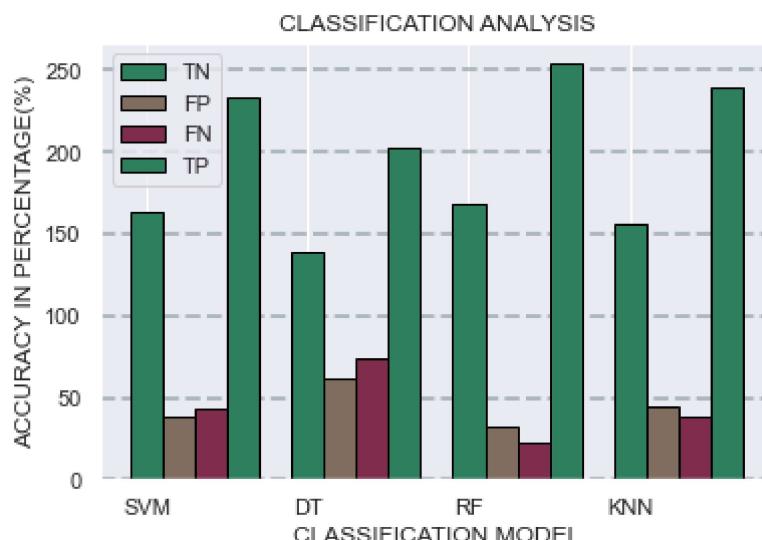
import numpy as np
import matplotlib.pyplot as plt

X = ['SVM', 'DT', 'RF', 'KNN']
TN= [163,139,169,156]
FP = [38,62,32,45]
FN = [43,74,23,38]
TP = [234,203,254,239]
X_axis = np.arange(len(X))

plt.bar(X_axis - 0.0, TN, 0.2, label = 'TN', color = '#2d7f5e', edgecolor = 'black')
plt.bar(X_axis + 0.2, FP, 0.2, label = 'FP', color = '#7f6d5f', edgecolor = 'black')
plt.bar(X_axis + 0.4, FN, 0.2, label = 'FN', color = '#7f2d4d', edgecolor = 'black')
plt.bar(X_axis + 0.6, TP, 0.2, label = 'TP', color = '#2d7f5e', edgecolor = 'black')
plt.grid(color='#95a5a6', linestyle='--', linewidth=2, axis='y', alpha=0.7)

plt.xticks(X_axis, X)
plt.xlabel("CLASSIFICATION MODEL")
plt.ylabel("ACCURACY IN PERCENTAGE(%)")
plt.title("CLASSIFICATION ANALYSIS")
plt.legend()
plt.show()

```



```
In [105]: from sklearn import metrics

print('Mean Absolute Error:', metrics.mean_absolute_error(Y_test, rf_prediction))
print('Mean Squared Error:', metrics.mean_squared_error(Y_test, rf_prediction))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(Y_test, rf_p
```

```
Mean Absolute Error: 0.11506276150627615
Mean Squared Error: 0.11506276150627615
Root Mean Squared Error: 0.3392090233267331
```

```
In [110]: from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix
print("== Confusion Matrix ==")
print(confusion_matrix(Y_test, rf_prediction))
print('\n')
print("== Classification Report ==")
print(classification_report(Y_test, rf_prediction))
print('\n')
```

```
== Confusion Matrix ==
[[169  32]
 [ 23 254]]

== Classification Report ==
      precision    recall  f1-score   support
          0.0       0.88     0.84     0.86      201
          1.0       0.89     0.92     0.90      277

      accuracy                           0.88      478
     macro avg       0.88     0.88     0.88      478
  weighted avg       0.88     0.88     0.88      478
```