driving_behavior_brf_v4

September 1, 2022

0.1 Binary Random Forest / KNN

[ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

[ ]:
```
df_train = pd.read_csv("../data_mod/train_motion_data.csv")
df_test = pd.read_csv("../data_mod/test_motion_data.csv")

df_train
```

[ ]:
```
          AccX      AccY     GyroZ   Class  DiffAccX  DiffAccY      VelX  \
0     0.000000  0.000000  0.101938  NORMAL  0.000000  0.000000  0.000000
1     0.101741  0.777568  0.054902  NORMAL -0.636737  1.006023  0.050871
2     0.158470  0.345891  0.014584  NORMAL  0.056728 -0.431676  0.079235
3     0.308851  0.239022 -0.072769  NORMAL -0.543828  0.655800  0.154425
4     0.163595  0.475107 -0.061163  NORMAL  0.768208 -0.365124  0.081798
..         …         …        …       …         …         …         …
965   0.872744  0.801287 -0.139964    SLOW -0.857083  0.085469  0.436372
966   1.464669  0.226299 -0.170508    SLOW  0.591925 -0.574988  0.732334
967   1.587379  0.583067 -0.196164    SLOW  0.122710  0.356769  0.793690
968   0.319258  0.272088 -0.062385    SLOW -0.383045  1.202910  0.159629
969   0.402702  0.432955  0.362167    SLOW  0.083444  0.160867  0.201351

          VelY
0     0.000000
1     0.388784
2     0.172946
3     0.119511
4     0.237554
..         …
965   0.400644
966   0.113149
967   0.291534
968   0.136044
969   0.216477
```

```
[970 rows x 8 columns]
```

[ ]:
```
df_train.isna().sum()
```

[ ]:
```
AccX        0
AccY        0
GyroZ       0
Class       0
DiffAccX    0
DiffAccY    0
VelX        0
VelY        0
dtype: int64
```

0.1.1 Change categories to numbers

[ ]:
```
df_train = df_train.replace(
    {"Class": {"NORMAL": 0, "SLOW": 1, "AGGRESSIVE": 2}})
df_test = df_test.replace(
    {"Class": {"NORMAL": 0, "SLOW": 1, "AGGRESSIVE": 2}})
df_train
```

[ ]:

	AccX	AccY	GyroZ	Class	DiffAccX	DiffAccY	VelX	VelY
0	0.000000	0.000000	0.101938	0	0.000000	0.000000	0.000000	0.000000
1	0.101741	0.777568	0.054902	0	-0.636737	1.006023	0.050871	0.388784
2	0.158470	0.345891	0.014584	0	0.056728	-0.431676	0.079235	0.172946
3	0.308851	0.239022	-0.072769	0	-0.543828	0.655800	0.154425	0.119511
4	0.163595	0.475107	-0.061163	0	0.768208	-0.365124	0.081798	0.237554
..	…	…	…	…	…	…	…	…
965	0.872744	0.801287	-0.139964	1	-0.857083	0.085469	0.436372	0.400644
966	1.464669	0.226299	-0.170508	1	0.591925	-0.574988	0.732334	0.113149
967	1.587379	0.583067	-0.196164	1	0.122710	0.356769	0.793690	0.291534
968	0.319258	0.272088	-0.062385	1	-0.383045	1.202910	0.159629	0.136044
969	0.402702	0.432955	0.362167	1	0.083444	0.160867	0.201351	0.216477

[970 rows x 8 columns]

0.1.2 Remove unnecessary columns

[ ]:
```
# df_train.drop(['AccZ', 'GyroX', 'GyroY', 'Timestamp'], axis=1, inplace=True)
# df_test.drop(['AccZ', 'GyroX', 'GyroY', 'Timestamp'], axis=1, inplace=True)

# df_train
```

0.1.3 Only select normal and aggressive values

[ ]:
```
df_train = df_train.loc[df_train['Class'] != 1]
df_test = df_test.loc[df_test['Class'] != 1]

df_train
```

[ ]:

	AccX	AccY	GyroZ	Class	DiffAccX	DiffAccY	VelX	VelY
0	0.000000	0.000000	0.101938	0	0.000000	0.000000	0.000000	0.000000
1	0.101741	0.777568	0.054902	0	-0.636737	1.006023	0.050871	0.388784
2	0.158470	0.345891	0.014584	0	0.056728	-0.431676	0.079235	0.172946
3	0.308851	0.239022	-0.072769	0	-0.543828	0.655800	0.154425	0.119511
4	0.163595	0.475107	-0.061163	0	0.768208	-0.365124	0.081798	0.237554
..	…	…	…	…	…	…		…
590	2.251131	1.144779	-0.157069	2	2.343684	1.371086	1.125565	0.572390
591	0.835830	0.448533	-0.243812	2	-1.415301	-0.696246	0.417915	0.224266
592	1.737348	0.775190	-0.179060	2	0.798653	1.006152	0.868674	0.387595
593	0.893512	1.587903	-0.058719	2	0.817109	1.925164	0.446756	0.793952
594	0.323433	0.589311	0.639500	2	-1.355486	1.981439	0.161716	0.294656

[595 rows x 8 columns]

[ ]:
```
X_train = df_train.drop(columns=["Class"])
y_train = df_train['Class']

X_test = df_test.drop(columns=["Class"])
y_test = df_test['Class']
```

0.1.4 Normalize data

[ ]:
```
X_train = (X_train - X_train.mean()) / X_train.std() * 100
X_test = (X_test - X_test.mean()) / X_test.std() * 100

X_train
```

[ ]:
```
           AccX        AccY       GyroZ    DiffAccX    DiffAccY        VelX  \
0   -112.259505 -113.126599  114.530826  -53.626286  -61.735289 -112.259505
1    -98.990521    1.736333   69.974799 -118.009186   36.103370  -98.990521
2    -91.592040  -62.031275   31.783917  -47.890255 -103.717074  -91.592040
3    -71.979452  -77.818022  -50.962992 -108.614796    2.043186  -71.979452
4    -90.923528  -42.943388  -39.968647   24.050135  -97.244611  -90.923528
..          …           …           …           …           …           …
590  181.331076   55.981150 -130.816660  183.352460   71.606804  181.331076
591   -3.251245  -46.868949 -212.984917 -196.732705 -129.447266   -3.251245
592  114.323949    1.385121 -151.648052   27.128507   36.115876  114.323949
593    4.271540  121.439825  -37.654052   28.994734  125.492451    4.271540
594  -70.077695  -26.073035  623.742585 -190.684579  130.965359  -70.077695

           VelY
0   -113.126599
1      1.736333
2    -62.031275
3    -77.818022
4    -42.943388
..          …
590   55.981150
591  -46.868949
592    1.385121
593  121.439825
594  -26.073035

[595 rows x 7 columns]
```

0.2 Train model

0.2.1 Random Forest

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

[ ]:
```
rfc = RandomForestClassifier(n_estimators=30, max_depth=15, random_state=5,␣
↪criterion="entropy")
rfc.fit(X_train, y_train)
```

[ ]:
```
RandomForestClassifier(criterion='entropy', max_depth=15, n_estimators=30,
                       random_state=5)
```

[ ]:
```
rfc.score(X_train, y_train)
```

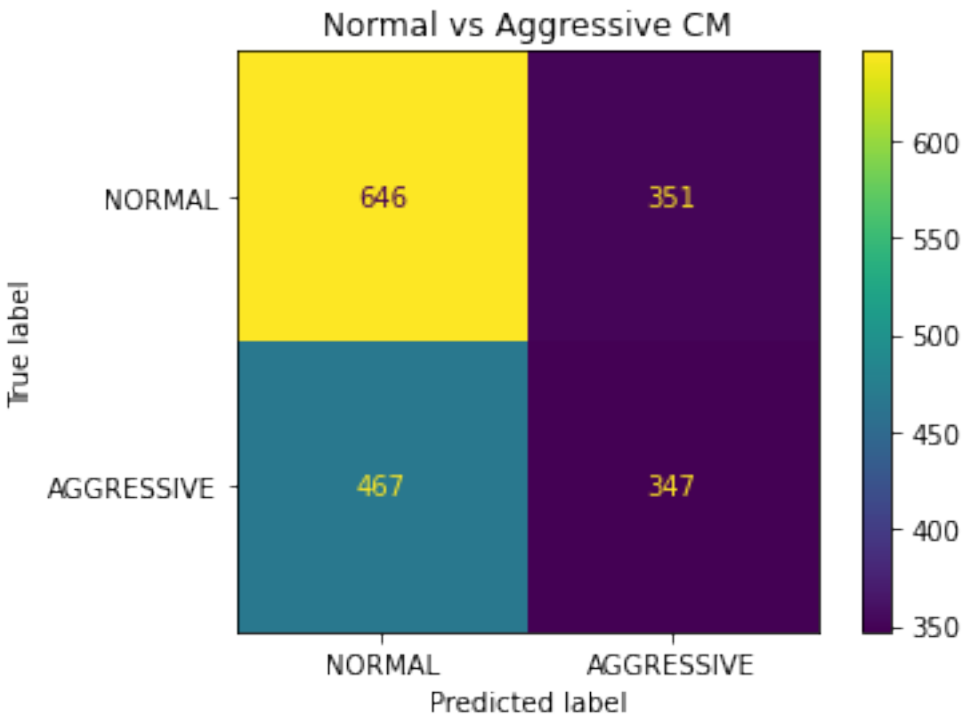
[ ]:
```
0.9899159663865547
```

[ ]:
```
rfc.score(X_test, y_test)
```

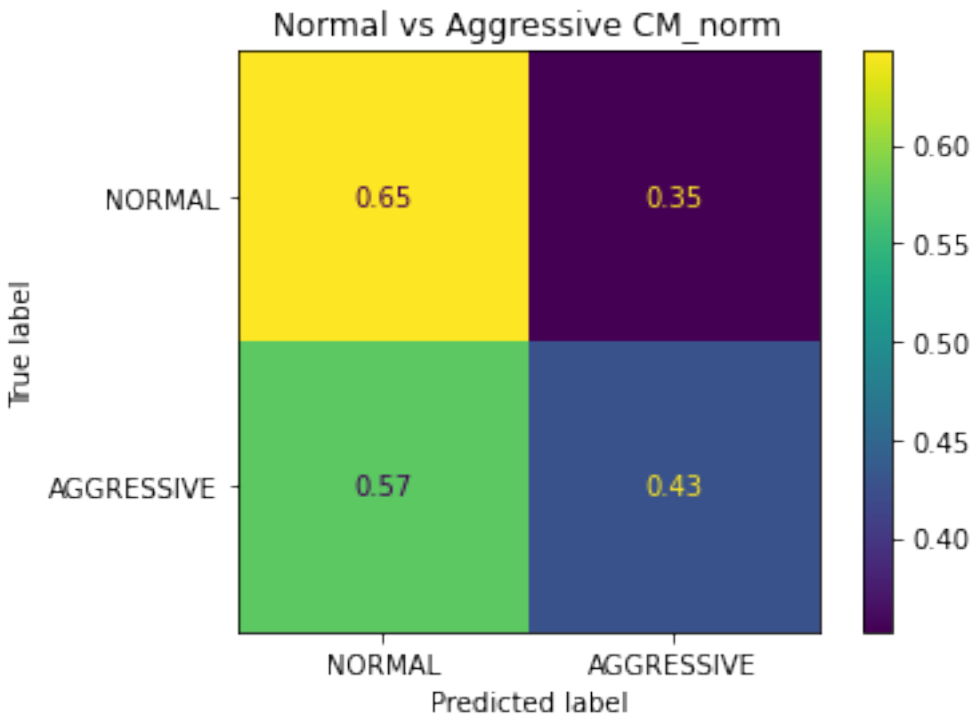
[ ]:
```
0.5483158475980121
```

[ ]:
```
classes=['NORMAL', 'AGGRESSIVE']
```

[ ]:
```
y_pred = rfc.predict(X_test)

CM = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(confusion_matrix=CM, display_labels=classes).plot()
plt.title('Normal vs Aggressive CM')
plt.show()
```



[ ]:
```
CM_norm = confusion_matrix(y_test, y_pred, normalize="true")

ConfusionMatrixDisplay(confusion_matrix=CM_norm, display_labels=classes).plot()
plt.title('Normal vs Aggressive CM_norm')
plt.show()
```



[ ]:
```
rfc.score(X_test, y_test)
```

[ ]:
```
0.5483158475980121
```

[ ]:
```
rfc_imp = pd.DataFrame(rfc.feature_importances_, columns=['importance'])
```

[ ]:
```
rfc_imp['importance'] = rfc_imp['importance'] * 100
rfc_imp = rfc_imp.set_index(X_train.columns)
rfc_imp
```

[ ]:
```
           importance
AccX        14.120372
AccY        13.518680
GyroZ       14.965620
DiffAccX    13.346155
DiffAccY    15.941248
VelX        15.490976
VelY        12.616949
```

[ ]:
```
rfc_imp.sort_values(by='importance', ascending=False)
```

[ ]:
```
           importance
DiffAccY    15.941248
```

```
VelX        15.490976
GyroZ       14.965620
AccX        14.120372
AccY        13.518680
DiffAccX    13.346155
VelY        12.616949
```

0.2.2 Train model with RandomSearchCV

[ ]:
```
n_estimators = np.arange(2, 200, 2)

max_features = ['sqrt', None]

max_depth = [int(x) for x in np.linspace(5, 20, num = 20)]

min_samples_split = np.arange(2, 10)

min_samples_leaf = np.arange(1, 4)

bootstrap = [True, False]
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
```

[ ]:
```
weights = {0:1, 2:2.8}
random_forest = RandomForestClassifier(random_state=0, criterion="entropy",␣
 ↪min_impurity_decrease=0, class_weight=weights)

random_gscv = RandomizedSearchCV(random_forest, random_grid, n_iter=1000, cv=5,␣
 ↪verbose=10, n_jobs=10, random_state=0)
random_gscv.fit(X_train, y_train)
```

[ ]:
```
random_gscv.best_params_
```

[ ]:
```
{'n_estimators': 68,
 'min_samples_split': 5,
 'min_samples_leaf': 2,
 'max_features': 'sqrt',
 'max_depth': 14,
 'bootstrap': True}
```

[ ]:
```
random_gscv.best_score_
```

[ ]:
```
0.5966386554621848
```

[ ]:
```
random_gscv.score(X_train, y_train)
```

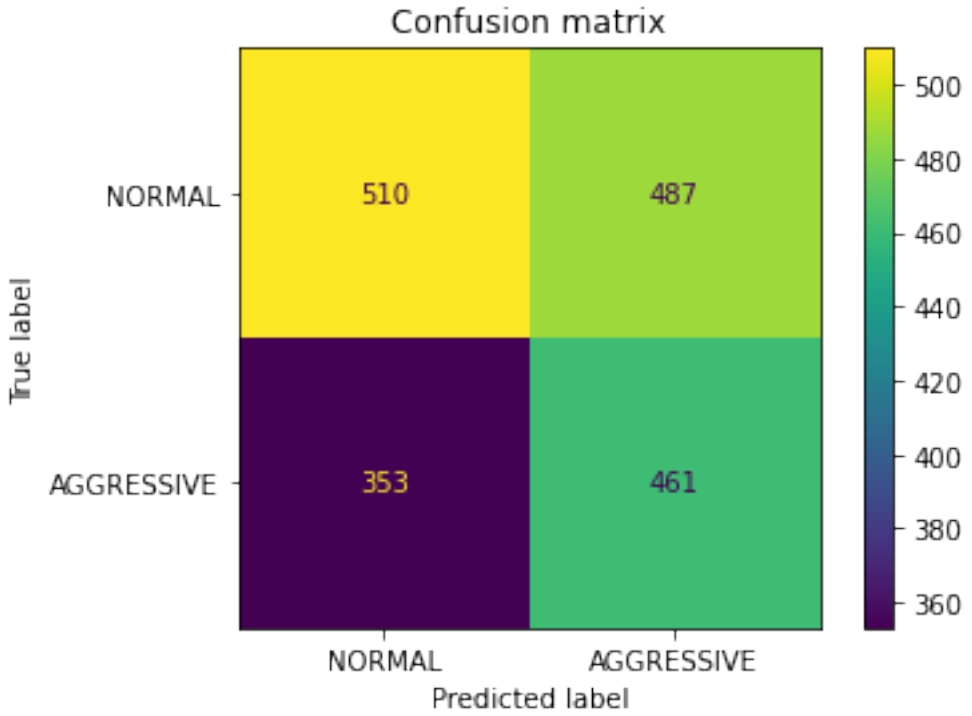
[ ]: 0.9781512605042016

[ ]:
```
random_gscv.score(X_test, y_test)
```

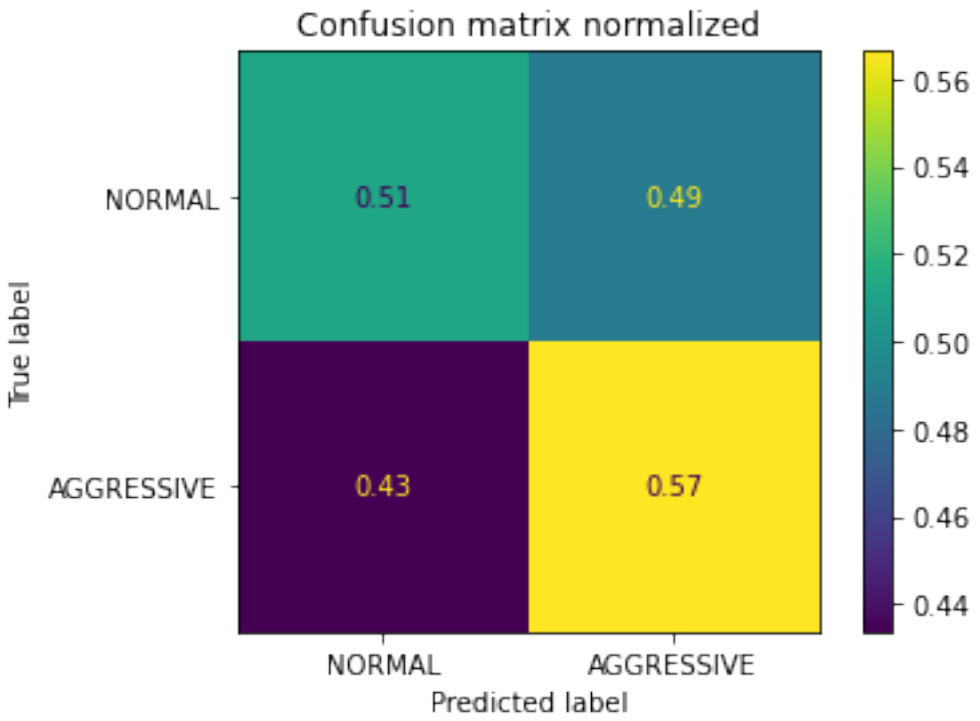
[ ]: 0.5361678630590834

[ ]:
```
classes = ["NORMAL", "AGGRESSIVE"]
```

[ ]:
```
y_pred = random_gscv.predict(X_test)

CM = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(confusion_matrix=CM, display_labels=classes).plot()
plt.title('Confusion matrix')
plt.show()
```



[ ]:
```
CM_norm = confusion_matrix(y_test, y_pred, normalize="true")

ConfusionMatrixDisplay(confusion_matrix=CM_norm, display_labels=classes).plot()
plt.title('Confusion matrix normalized')
plt.show()
```



Evaluate improvment

[ ]:
```
def evaluate(model, test_features, test_labels):
    accuracy = model.score(test_features, test_labels)
    print('Model Performance')
    print('Accuracy = {:0.3f}%.'.format(accuracy))

    return accuracy

base_model = RandomForestClassifier(n_estimators = 10, random_state=0,␣
 ↪criterion="entropy", min_impurity_decrease=0, class_weight=weights)
base_model.fit(X_train, y_train)
base_accuracy = evaluate(base_model, X_test, y_test)

best_random = random_gscv.best_estimator_
random_accuracy = evaluate(best_random, X_test, y_test)

print(f'Improvement of {100 * (random_accuracy - base_accuracy) / base_accuracy:
 ↪.3f}%.')
```

```
Model Performance
Accuracy = 0.552%.
Model Performance
Accuracy = 0.536%.
```

Improvement of -2.900%.

0.2.3 KNN

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
```

[ ]:
```
Kneigh = KNeighborsClassifier(weights="uniform")

param_grid = {'n_neighbors': np.arange(1, 100), 'leaf_size': np.arange(20, 40)}

knn_gscv = GridSearchCV(Kneigh, param_grid, cv=5, verbose=10, n_jobs=10)
knn_gscv.fit(X_train, y_train)
```

[ ]:
```
best_params = knn_gscv.best_params_
best_params
```

[ ]:
```
{'leaf_size': 20, 'n_neighbors': 35}
```

[ ]:
```
knn_gscv.best_score_
```

[ ]:
```
0.6201680672268909
```

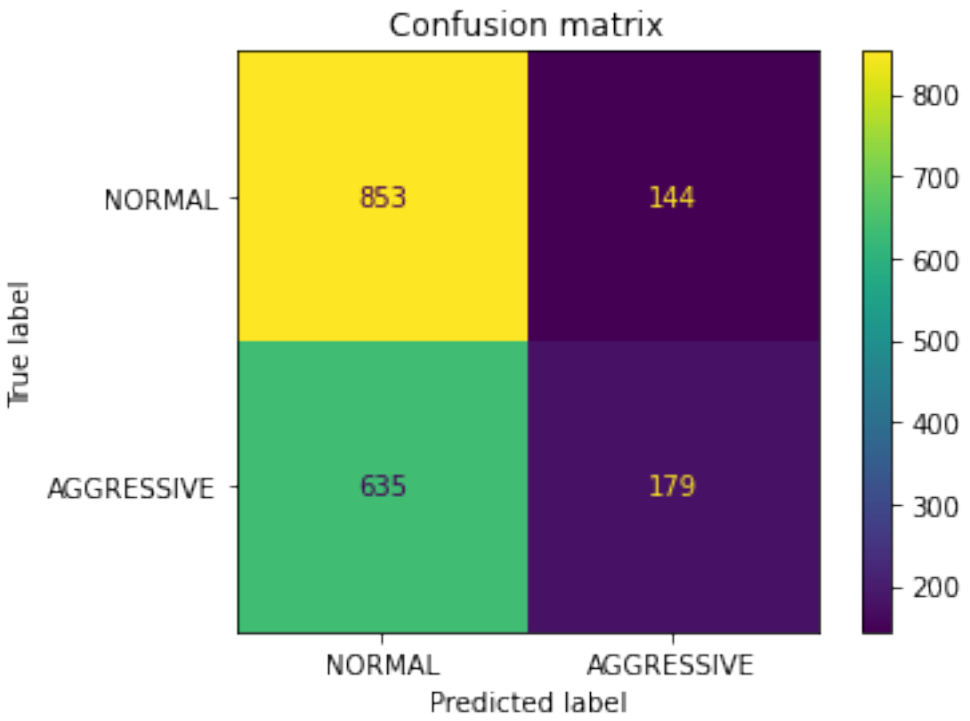
[ ]:
```
knn_gscv.score(X_train, y_train)
```

[ ]:
```
0.6487394957983194
```

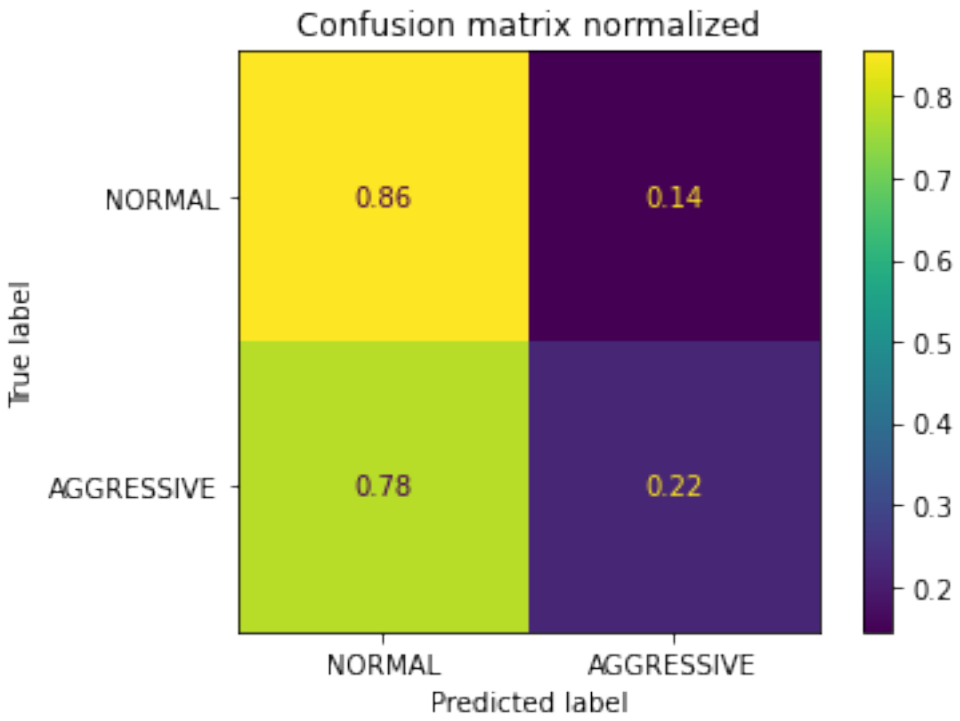
[ ]:
```
knn_gscv.score(X_test, y_test)
```

[ ]:
```
0.5698509110988405
```

[ ]:
```
y_pred = knn_gscv.predict(X_test)

CM = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(confusion_matrix=CM, display_labels=classes).plot()
plt.title('Confusion matrix')
plt.show()
```



[ ]:
```
CM_norm = confusion_matrix(y_test, y_pred, normalize="true")

ConfusionMatrixDisplay(confusion_matrix=CM_norm, display_labels=classes).plot()
plt.title('Confusion matrix normalized')
plt.show()
```



Knn with Bagging classifier

[ ]:
```
from sklearn.ensemble import BaggingClassifier

knn_bagging = BaggingClassifier(KNeighborsClassifier(**knn_gscv.best_params_),␣
↪max_samples=0.9, max_features=0.8, random_state=0)
knn_bagging.fit(X_train, y_train)
```

[ ]:
```
BaggingClassifier(base_estimator=KNeighborsClassifier(leaf_size=20,
                                                      n_neighbors=35),
                  max_features=0.8, max_samples=0.9, random_state=0)
```

[ ]:
```
knn_bagging.score(X_train, y_train)
```

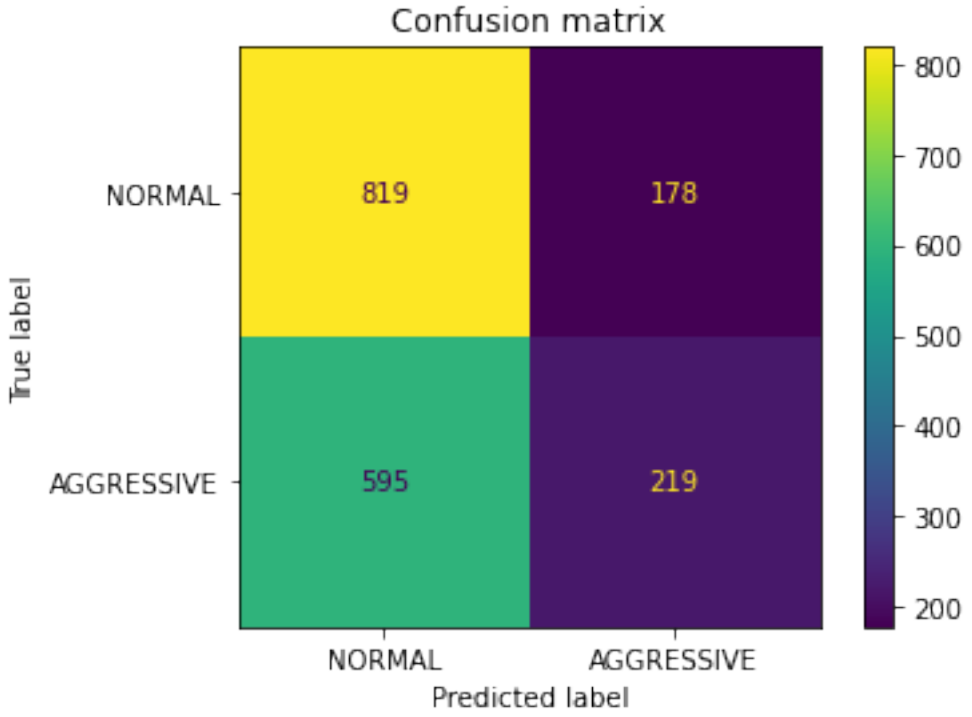
[ ]:
```
0.6420168067226891
```

[ ]:
```
knn_bagging.score(X_test, y_test)
```

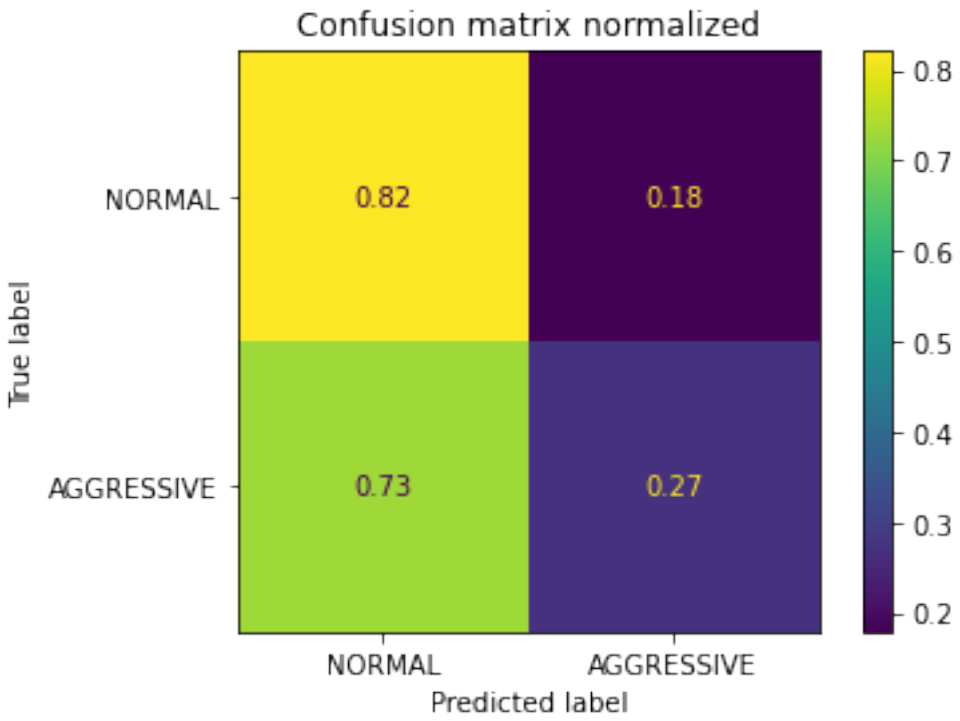
[ ]:
```
0.5731639977912756
```

[ ]:
```
y_pred = knn_bagging.predict(X_test)

CM = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(confusion_matrix=CM, display_labels=classes).plot()
```

```
plt.title('Confusion matrix')
plt.show()
```



[ ]:
```
CM_norm = confusion_matrix(y_test, y_pred, normalize="true")

ConfusionMatrixDisplay(confusion_matrix=CM_norm, display_labels=classes).plot()
plt.title('Confusion matrix normalized')
plt.show()
```



[ ]:
```
def evaluate(model, test_features, test_labels):
    accuracy = model.score(test_features, test_labels)
    print('Model Performance')
    print('Accuracy = {:0.3f}%.'.format(accuracy))

    return accuracy

bagging_accuracy = evaluate(knn_bagging, X_test, y_test)

best_random = knn_gscv.best_estimator_
random_accuracy = evaluate(best_random, X_test, y_test)

print(f'Improvement of {100 * (bagging_accuracy - random_accuracy) /␣
 ↪random_accuracy:.3f}%.')
```

```
Model Performance
Accuracy = 0.573%.
Model Performance
Accuracy = 0.570%.
Improvement of 0.581%.
```

[ ]:
```

```