driving_behavior_brf_v3

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
                                                     VelX
                                                               VelY
          0.000000 0.000000 0.101938
    0
                                         NORMAL
                                                0.000000 0.000000
    1
         -1.624864 -1.082492 0.135536
                                         NORMAL -0.812432 -0.541246
    2
         -0.594660 -0.122410 0.087888
                                         NORMAL -0.297330 -0.061205
    3
           0.738478 -0.228456 0.054902
                                         NORMAL 0.369239 -0.114228
    4
           0.101741 0.777568 0.054902
                                        NORMAL
                                                0.050871 0.388784
    3639 0.915688 -2.017489 -1.236468
                                          SLOW 0.457844 -1.008745
    3640 -1.934203 0.914925 -0.477162
                                          SLOW -0.967102 0.457462
    3641 -0.222845 0.747304 0.054291
                                          SLOW -0.111422 0.373652
    3642 -0.349423 0.067261 -0.004963
                                          SLOW -0.174712 0.033630
    3643 -0.402428 0.406218 0.001145
                                          SLOW -0.201214 0.203109
     [3644 rows x 6 columns]
[]: df_train.isna().sum()
[ ]: AccX
             0
    AccY
             0
    GyroZ
             0
    Class
             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
                                                  VelX
                                                            VelY
          0.000000 0.000000 0.101938
                                           0 0.000000 0.000000
    0
    1
         -1.624864 -1.082492 0.135536
                                           0 -0.812432 -0.541246
         -0.594660 -0.122410 0.087888
                                            0 -0.297330 -0.061205
    3
          0.738478 -0.228456 0.054902
                                           0 0.369239 -0.114228
          0.101741 0.777568 0.054902
                                           0 0.050871 0.388784
    3639 0.915688 -2.017489 -1.236468
                                          1 0.457844 -1.008745
    3640 -1.934203 0.914925 -0.477162
                                           1 -0.967102 0.457462
    3641 -0.222845 0.747304 0.054291
                                           1 -0.111422 0.373652
    3642 -0.349423  0.067261 -0.004963
                                           1 -0.174712 0.033630
    3643 -0.402428 0.406218 0.001145
                                       1 -0.201214 0.203109
    [3644 rows x 6 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
                                                  VelX
                                                            VelY
    0
          0.000000 0.000000 0.101938
                                           0 0.000000 0.000000
    1
         -1.624864 -1.082492 0.135536
                                           0 -0.812432 -0.541246
    2
         -0.594660 -0.122410 0.087888
                                           0 -0.297330 -0.061205
    3
          0.738478 -0.228456 0.054902
                                           0 0.369239 -0.114228
          0.101741 0.777568 0.054902
                                           0 0.050871 0.388784
                                           2 0.269435 -0.822992
    2308 0.538870 -1.645984 0.662712
    2309 1.678918 -1.392127 -0.168675
                                           2 0.839459 -0.696064
    2310 0.323433 0.589311 0.639500
                                           2 0.161716 0.294656
```

```
      2311
      2.497311
      -0.606175
      -0.240757
      2
      1.248655
      -0.303088

      2312
      0.482297
      -0.090277
      -0.383700
      2
      0.241148
      -0.045139
```

[2313 rows x 6 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
                                                   VelX
                                                               VelY
                            AccY
                                      GyroZ
    0
           -3.509345
                        9.776257
                                  74.896498
                                              -3.509345
                                                           9.776257
         -157.992905 -99.985349 102.351035 -157.992905 -99.985349
    1
    2
          -60.046498
                                 63.415515 -60.046498
                      -2.635757
                                                         -2.635757
    3
           66.701299 -13.388488
                                  36.460154
                                              66.701299 -13.388488
                                               6.163664
                                                          88.619412
    4
            6.163664
                       88.619412
                                  36.460154
    2308
           47.723614 -157.121833 533.137616 47.723614 -157.121833
    2309 156.113434 -131.381523 -146.237282 156.113434 -131.381523
    2310
           27.240939
                       69.530762 514.169013
                                              27.240939
                                                          69.530762
    2311 233.921883 -51.688213 -205.139734 233.921883 -51.688213
    2312
           42.344893
                        0.622405 -321.946292 42.344893
                                                           0.622405
```

[2313 rows x 5 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
```

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

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

[]: 0.8698659749243407

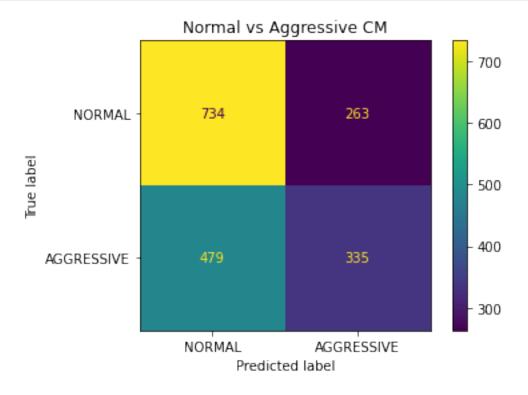
[]: rfc.score(X_test, y_test)

[]: 0.590281612368857

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

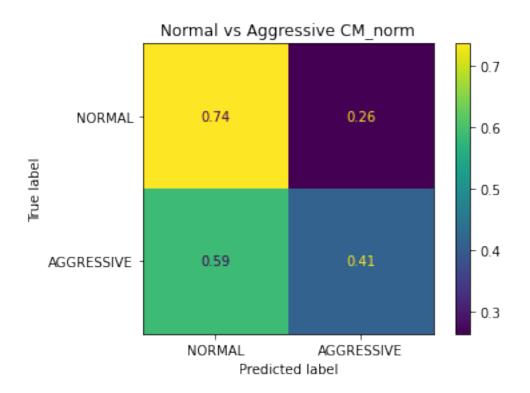
[]: y_pred = rfc.predict(X_test)

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)
[]: 0.590281612368857
[]: 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
            20.707617
    AccY
            18.978936
    GyroZ
            19.055211
    VelX
            19.951624
    VelY
            21.306612
[]: rfc_imp.sort_values(by='importance', ascending=False)
[]:
            importance
            21.306612
    VelY
     AccX
            20.707617
    VelX
            19.951624
```

```
GyroZ 19.055211
AccY 18.978936
```

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': 128,
      'min_samples_split': 4,
      'min_samples_leaf': 1,
      'max_features': None,
      'max_depth': 20,
      'bootstrap': True}
[]: random_gscv.best_score_
[]: 0.5602965788710929
[]: random_gscv.score(X_train, y_train)
[]: 0.9818417639429312
```

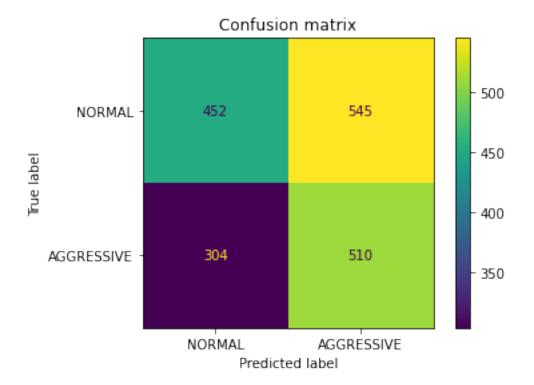
```
[]: random_gscv.score(X_test, y_test)

[]: 0.5311982330204307

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

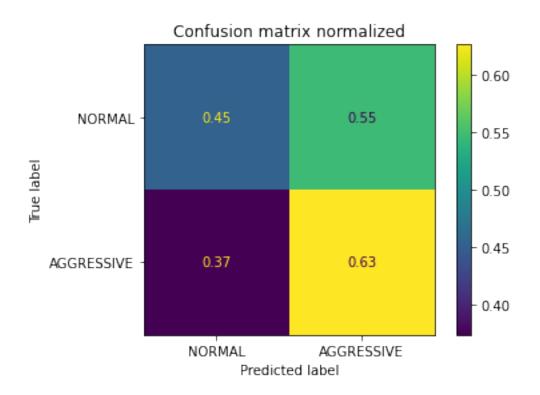
[]: y_pred = random_gscv.predict(X_test)

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()
```

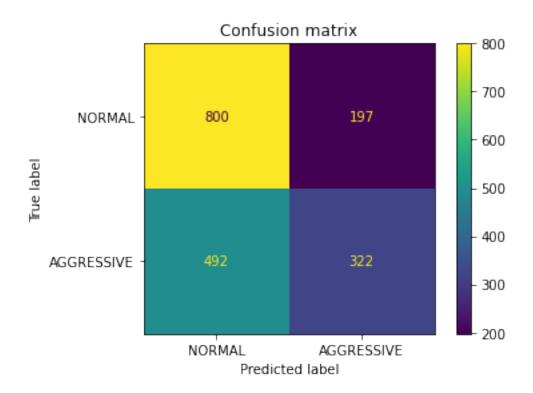


Evaluate improvment

Model Performance Accuracy = 0.568%. Model Performance Accuracy = 0.531%. Improvement of -6.511%.

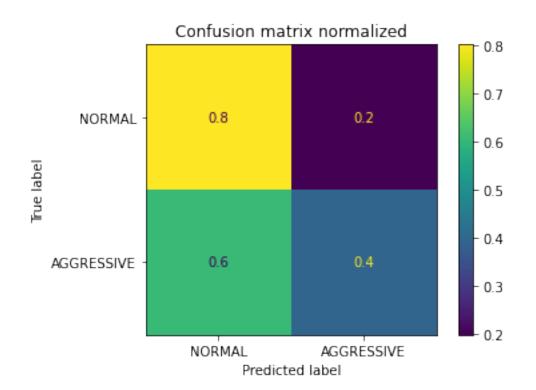
0.2.3 KNN

```
[]: 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': 86}
[]: knn_gscv.best_score_
[]: 0.6143614484867184
[]: knn_gscv.score(X_train, y_train)
[]: 0.6191093817552962
[]: knn_gscv.score(X_test, y_test)
[]: 0.6195472114853672
[]: 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()
```



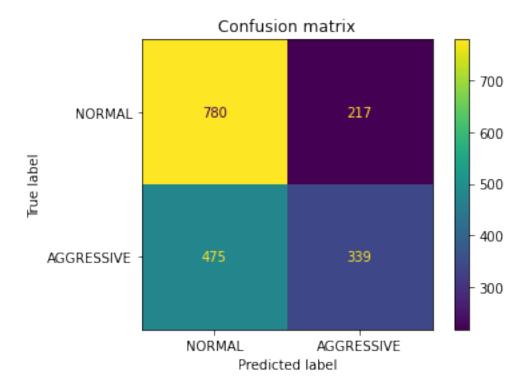
```
[]: CM_norm = confusion_matrix(y_test, y_pred, normalize="true")

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



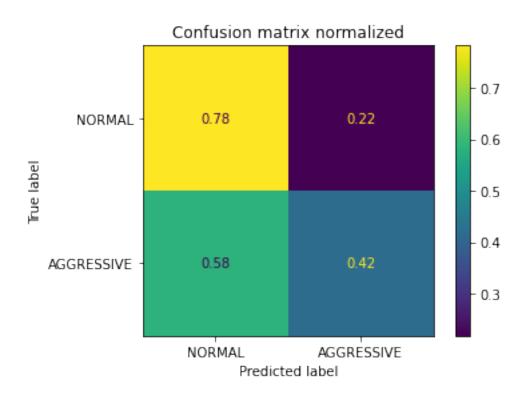
Knn with Bagging classifier

```
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 = 0.618%.
    Model Performance
    Accuracy = 0.620\%.
    Improvement of -0.267%.
[]:
```