transfer-3-1

September 27, 2021

```
[1]: base_transfer_set = ['01', '02', '04', '05', '08', '09', '12', '13', '16', __
     →'17', '18', '20']
    target_transfer_set = ['03', '06', '07', '10', '11', '14', '15', '19']
    import random
    def random combination(iterable, r):
         "Random selection from itertools.combinations(iterable, r)"
        pool = tuple(iterable)
        n = len(pool)
        indices = sorted(random.sample(range(n), r))
        return tuple(pool[i] for i in indices)
    transfers_size_6 = []
    for i in range(4):
        transfers_size_6.append(random_combination(target_transfer_set, 6))
    print(transfers_size_6)
    transfers_size_6 = [('03', '06', '07', '10', '11', '14'), ('03', '06', '07', \_
     \rightarrow '10', '14', '15'), ('03', '06', '07', '10', '14', '15'), ('03', '07', '10', \Box
     →'14', '15', '19')]
    for i, tmp in enumerate(transfers_size_6):
        transfers_size_6[i] = list(transfers_size_6[i])
    print(transfers_size_6)
    transfers_size_4 = []
    for i in range(4):
        transfers_size_4.append(random_combination(target_transfer_set, 4))
    print(transfers size 4)
    transfers_size_4 = [('06', '10', '14', '15'), ('03', '10', '14', '19'), ('03', )]
     for i, tmp in enumerate(transfers_size_4):
        transfers_size_4[i] = list(transfers_size_4[i])
    print(transfers_size_4)
    transfers_size_3 = []
    for i in range(4):
        transfers_size_3.append(random_combination(target_transfer_set, 3))
    print(transfers size 3)
```

```
transfers_size_3 = [('07', '11', '14'), ('06', '07', '10'), ('03', '15', '19'),
     for i, tmp in enumerate(transfers_size_3):
         transfers size 3[i] = list(transfers size 3[i])
     print(transfers_size_3)
     transfers size 2 = []
     for i in range(4):
        transfers_size_2.append(random_combination(target_transfer_set, 2))
     print(transfers_size_2)
     transfers_size_2 = [('06', '10'), ('07', '11'), ('06', '15'), ('14', '15')]
     for i, tmp in enumerate(transfers_size_2):
         transfers_size_2[i] = list(transfers_size_2[i])
     print(transfers_size_2)
    [('03', '06', '10', '11', '14', '19'), ('03', '07', '10', '11', '14', '19'),
    ('03', '06', '11', '14', '15', '19'), ('06', '07', '11', '14', '15', '19')]
    [['03', '06', '07', '10', '11', '14'], ['03', '06', '07', '10', '14', '15'],
    ['03', '06', '07', '10', '14', '15'], ['03', '07', '10', '14', '15', '19']]
    [('03', '06', '10', '19'), ('03', '06', '11', '19'), ('03', '06', '14', '19'),
    ('03', '06', '07', '10')]
    [['06', '10', '14', '15'], ['03', '10', '14', '19'], ['03', '06', '10', '15'],
    ['03', '07', '10', '15']]
    [('03', '10', '11'), ('10', '11', '19'), ('03', '10', '14'), ('03', '10', '11')]
    [['07', '11', '14'], ['06', '07', '10'], ['03', '15', '19'], ['06', '14', '19']]
    [('14', '19'), ('14', '19'), ('14', '15'), ('06', '15')]
    [['06', '10'], ['07', '11'], ['06', '15'], ['14', '15']]
[2]: import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     def make confusion matrix(cf,
                               group_names=None,
                               categories='auto',
                               count=True,
                               percent=True,
                               cbar=True,
                               xyticks=True,
                               xyplotlabels=True,
                               sum_stats=True,
                               figsize=None,
                               cmap='Blues',
                               title=None):
         This function will make a pretty plot of an sklearn Confusion Matrix cm_{\sqcup}
      →using a Seaborn heatmap visualization.
```

```
Arguments
   cf:
                   confusion matrix to be passed in
   group names: List of strings that represent the labels row by row to be ...
\hookrightarrowshown in each square.
   categories:
                   List of strings containing the categories to be displayed on
\hookrightarrow the x,y axis. Default is 'auto'
   count:
                    If True, show the raw number in the confusion matrix.
\hookrightarrow Default is True.
   normalize: If True, show the proportions for each category. Default is \sqcup
\hookrightarrow True.
                   If True, show the color bar. The cbar values are based of f_{\perp}
   cbar:
\hookrightarrow the values in the confusion matrix.
                    Default is True.
                    If True, show x and y ticks. Default is True.
   xyticks:
   xyplotlabels: If True, show 'True Label' and 'Predicted Label' on the \sqcup
\hookrightarrow figure. Default is True.
                   If True, display summary statistics below the figure.
   sum_stats:
\hookrightarrow Default is True.
                    Tuple representing the figure size. Default will be the
   fiqsize:
\rightarrow matplotlib rcParams value.
                    Colormap of the values displayed from matplotlib.pyplot.cm.
\hookrightarrow Default is 'Blues'
                    See http://matplotlib.org/examples/color/colormaps_reference.
\hookrightarrow h.t.ml.
   title:
                   Title for the heatmap. Default is None.
   111
   # CODE TO GENERATE TEXT INSIDE EACH SQUARE
   blanks = ['' for i in range(cf.size)]
   if group_names and len(group_names) == cf.size:
       group_labels = ["{}\n".format(value) for value in group_names]
   else:
       group_labels = blanks
   if count:
       group_counts = ["{0:0.0f}\n".format(value) for value in cf.flatten()]
   else:
       group_counts = blanks
   if percent:
       group_percentages = ["{0:.2%}".format(value) for value in cf.flatten()/
\rightarrownp.sum(cf)]
```

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else:
       group_percentages = blanks
   box_labels = [f''\{v1\}\{v2\}\{v3\}''.strip() for v1, v2, v3 in_{\square}]
→zip(group_labels,group_counts,group_percentages)]
   box labels = np.asarray(box labels).reshape(cf.shape[0],cf.shape[1])
   # CODE TO GENERATE SUMMARY STATISTICS & TEXT FOR SUMMARY STATS
   if sum_stats:
       #Accuracy is sum of diagonal divided by total observations
       accuracy = np.trace(cf) / float(np.sum(cf))
       #if it is a binary confusion matrix, show some more stats
       if len(cf)==2:
           #Metrics for Binary Confusion Matrices
           precision = cf[1,1] / sum(cf[:,1])
           recall = cf[1,1] / sum(cf[1,:])
           f1_score = 2*precision*recall / (precision + recall)
           stats_text = "\n\nAccuracy={:0.3f}\nPrecision={:0.3f}\nRecall={:0.
\rightarrow3f}\nF1 Score={:0.3f}".format(
               accuracy, precision, recall, f1_score)
       else:
           stats_text = "\n\nAccuracy={:0.3f}".format(accuracy)
   else:
       stats_text = ""
   # SET FIGURE PARAMETERS ACCORDING TO OTHER ARGUMENTS
   if figsize==None:
       #Get default figure size if not set
       figsize = plt.rcParams.get('figure.figsize')
   if xyticks==False:
       #Do not show categories if xyticks is False
       categories=False
   # MAKE THE HEATMAP VISUALIZATION
   plt.figure(figsize=figsize)
→heatmap(cf,annot=box_labels,fmt="",cmap=cmap,cbar=cbar,xticklabels=categories,yticklabels=c
   if xyplotlabels:
       plt.ylabel('True label')
       plt.xlabel('Predicted label' + stats_text)
   else:
```

```
plt.xlabel(stats_text)

if title:
    plt.title(title)
plt.show()
```

```
RuntimeError Traceback (most recent call last)
RuntimeError: module compiled against API version Oxe but this version of numpy
is Oxd
```

```
RuntimeError Traceback (most recent call last)
RuntimeError: module compiled against API version 0xe but this version of numpy

→is 0xd
```

```
[3]: import os
     import pandas as pd
     import warnings
     warnings.filterwarnings("ignore")
     def create_transfer_models(baseset, gesture_subset):
         print("Processing tranfers models at 10%, 20%, 25%, 50% and 80% data for ⊔
     →gestures: ", gesture_subset)
         print("Baseset: ", baseset)
         print("Loadind Dataset: ", gesture_subset)
         path = 'gestures-dataset'
         dataset = None
         samples = 0
         for subject in os.listdir(path):
             if os.path.isfile(os.path.join(path, subject)):
                 continue
             if subject in ('U01', 'U02', 'U03', 'U04', 'U05', 'U06', 'U07', 'U08'):
                 for gesture in os.listdir(os.path.join(path, subject)):
                     if os.path.isfile(os.path.join(path, subject, gesture)):
                         continue
                     gesture = str(gesture)
                     if gesture not in gesture_subset:
                         continue
                     for samplefile in os.listdir(os.path.join(path, subject,
      →gesture)):
```

```
if os.path.isfile(os.path.join(path, subject, gesture, __
→samplefile)):
                       df = pd.read_csv(os.path.join(path, subject, gesture,__
→samplefile), \
                           sep = ' ', \
                           names = ['System.currentTimeMillis()', \
                           'System.nanoTime()', \
                           'sample.timestamp', \
                           'X', \
                           'Y', \
                           'Z' \
                           ])
                       df = df[["sample.timestamp", "X", "Y", "Z"]]
                       start = df["sample.timestamp"][0]
                       df["sample.timestamp"] -= start
                       df["sample.timestamp"] /= 10000000
                       df["subject"] = subject
                       df["gesture"] = gesture
                       df["sample"] = str(samplefile[:-4])
                       samples += 1
                       #print(df)
                       if dataset is None:
                           dataset = df.copy()
                       else:
                           dataset = pd.concat([dataset, df])
   dataset = dataset.sort_values(by=['gesture','subject','sample','sample.
→timestamp'])
   data = dataset
   print(str(samples) + " samples loaded")
   print("Scaling Dataset: ", gesture_subset)
   from sklearn.preprocessing import StandardScaler
   scaler = StandardScaler()
   dataset_scaled = None
   samples = 0
   for i, gesture in enumerate(gesture_subset):
       df_gesture=data[data['gesture']==gesture]
       for j, subject in enumerate(df_gesture['subject'].unique()):
           df_subject=df_gesture[df_gesture['subject']==subject]
           for k, sample in enumerate(df_subject['sample'].unique()):
               df_sample=df_subject[df_subject['sample'] == sample].copy()
               df_sample.sort_values(by=['sample.timestamp'])
```

```
sc = scaler
              sc = sc.fit_transform(df_sample[["X", "Y", "Z"]])
              sc = pd.DataFrame(data=sc, columns=["X", "Y", "Z"])
              df_sample['X'] = sc['X']
              df_sample['Y'] = sc['Y']
              df_{sample['Z']} = sc['Z']
              if dataset_scaled is None:
                 dataset_scaled = df_sample.copy()
              else:
                 dataset_scaled = pd.concat([dataset_scaled, df_sample])
              samples += 1
  print(str(samples) + " samples scaled")
  data = dataset_scaled
  print("Cleaning Dataset: ", gesture_subset)
  dataset_outliers = None
  dataset_cleaned = None
  samples = 0
  outliers = 0
  for i, gesture in enumerate(gesture_subset):
      df_gesture = data[data['gesture']==gesture]
      for j, subject in enumerate(df_gesture['subject'].unique()):
          df_subject = df_gesture[df_gesture['subject']==subject]
          time_mean = df_subject.groupby(["gesture", "subject", "sample"]).
time_std = df_subject.groupby(["gesture", "subject", "sample"]).
time_max = time_mean['sample.timestamp'].iloc[0]['mean'] + 1.0 *__
→time_std['sample.timestamp'].iloc[0]['std']
          time_min = time_mean['sample.timestamp'].iloc[0]['mean'] - 1.0 *__
→time_std['sample.timestamp'].iloc[0]['std']
          for k, sample in enumerate(df_subject['sample'].unique()):
              df sample=df subject[df subject['sample']==sample]
              df_sample_count = df_sample.count()['sample.timestamp']
              if df_sample_count < time_min or df_sample_count > time_max:
                 if dataset_outliers is None:
                     dataset_outliers = df_sample.copy()
                 else:
                     dataset_outliers = pd.concat([dataset_outliers,__
→df_sample])
                 outliers += 1
              else:
                 if dataset_cleaned is None:
                     dataset_cleaned = df_sample.copy()
                 else:
```

```
dataset_cleaned = pd.concat([dataset_cleaned,__

→df_sample])
                   samples += 1
   print(str(samples) + " samples cleaned")
   print(str(outliers) + " samples outliers")
   data = dataset cleaned
   print("Time slicing Cleaned Dataset: ", gesture_subset)
   dataset_timecut = None
   samples = 0
   damaged = 0
   for i, gesture in enumerate(data['gesture'].unique()):
       df_gesture = data[data['gesture'] == gesture]
       for j, subject in enumerate(df_gesture['subject'].unique()):
           df_subject = df_gesture[df_gesture['subject']==subject]
           time_max = 19 # 18 * 11 = 198
           for i, sample in enumerate(df_subject['sample'].unique()):
               df_sample = df_subject[df_subject['sample'] == sample]
               df_sample_count = df_sample.count()['sample.timestamp']
               #print(df_sample_count)
               if df sample count >= time max:
                   df_sample = df_sample[df_sample['sample.timestamp'] <= (11__
\rightarrow* (time_max-1))]
                   df_sample_count = df_sample.count()['sample.timestamp']
                   #print(df_sample_count)
               elif df_sample_count < time_max:</pre>
                   for tmp in range(df sample count * 11, (time max) * 11, 11):
                       df = pd.DataFrame([[tmp, 0.0, 0.0, 0.0, gesture,_
→subject, sample]], columns=['sample.timestamp', 'X', 'Y', 'Z', 'gesture', __
df_sample = df_sample.append(df, ignore_index=True)
               #print(df_sample)
               df_sample_count = df_sample.count()['sample.timestamp']
               #print(df_sample_count)
               if df_sample_count != time_max:
                   damaged += 1
                   continue
               if dataset timecut is None:
                   dataset_timecut = df_sample.copy()
               else:
                   dataset_timecut = pd.concat([dataset_timecut, df_sample])
               samples += 1
   dataset_cleaned = dataset_timecut
   print(str(samples) + " cleaned samples sliced")
   print(str(damaged) + " cleaned samples damaged")
```

```
data = dataset_outliers
   print("Time slicing Outliers Dataset: ", gesture_subset)
   dataset_timecut = None
   samples = 0
   damaged = 0
   for i, gesture in enumerate(data['gesture'].unique()):
       df_gesture = data[data['gesture']==gesture]
       for j, subject in enumerate(df_gesture['subject'].unique()):
           df_subject = df_gesture[df_gesture['subject']==subject]
           time max = 19 \# 18 * 11 = 198
           for i, sample in enumerate(df_subject['sample'].unique()):
               df_sample = df_subject[df_subject['sample'] == sample]
               df_sample_count = df_sample.count()['sample.timestamp']
               #print(df_sample_count)
               if df_sample_count >= time_max:
                   df_sample = df_sample[df_sample['sample.timestamp'] <= (11__
\rightarrow* (time_max-1))]
                   df_sample_count = df_sample.count()['sample.timestamp']
                   #print(df_sample_count)
               elif df_sample_count < time_max:</pre>
                   for tmp in range(df_sample_count * 11, (time_max) * 11, 11):
                       df = pd.DataFrame([[tmp, 0.0, 0.0, 0.0, gesture,_
→subject, sample]], columns=['sample.timestamp', 'X', 'Y', 'Z', 'gesture', __
df_sample = df_sample.append(df, ignore_index=True)
               #print(df_sample)
               df sample count = df sample.count()['sample.timestamp']
               #print(df_sample_count)
               if df_sample_count != time_max:
                   damaged += 1
                   continue
               if dataset timecut is None:
                   dataset_timecut = df_sample.copy()
               else:
                   dataset_timecut = pd.concat([dataset_timecut, df_sample])
               samples += 1
   dataset_outliers = dataset_timecut
   print(str(samples) + " outliers samples sliced")
   print(str(damaged) + " outliers samples damaged")
   from keras import backend as K
   data = dataset_cleaned
   from keras.models import Sequential
   from keras.layers import Bidirectional
   from keras.layers import LSTM
   from keras.layers import Dense
```

```
from keras.layers import Dropout
  from keras.optimizers import adam_v2
  from keras.wrappers.scikit_learn import KerasClassifier
  from sklearn.model_selection import StratifiedGroupKFold
  from sklearn.model_selection import cross_validate
  from sklearn.model_selection import GridSearchCV
  from keras.utils import np_utils
  from sklearn.preprocessing import LabelEncoder
  from sklearn.pipeline import Pipeline
  from sklearn.metrics import accuracy_score
   import numpy as np
   import tensorflow as tf
   # fix random seed for reproducibility
   seed = 1000
  np.random.seed(seed)
   # create the dataset
  def get_dataset(data, index=[]):
      X_train = []
      Y_train = []
      groups = []
       samples idx=0
       for i, gesture in enumerate(data['gesture'].unique()):
           df gesture = data[data['gesture'] == gesture]
           for j, subject in enumerate(df_gesture['subject'].unique()):
               df_subject = df_gesture[df_gesture['subject'] == subject]
               for k, sample in enumerate(df_subject['sample'].unique()):
                   df_sample = df_subject[df_subject['sample'] == sample]
                   accel vector = []
                   for idx, row in df_sample.sort_values(by='sample.
→timestamp').iterrows():
                       accel vector.append([row['X'],row['Y'],row['Z']])
                   accel_vector = np.asarray(accel_vector)
                   if len(index)==0:
                       X_train.append(accel_vector)
                       Y_train.append(gesture)
                       groups.append(subject)
                   else:
                       if samples_idx in index:
                           X_train.append(accel_vector)
                           Y_train.append(gesture)
                           groups.append(subject)
                   samples_idx+=1
       X_train = np.asarray(X_train)
       Y_train = LabelEncoder().fit_transform(Y_train)
       #print(Y_train)
       return X_train, Y_train, groups
```

```
def build_model(baseset, gesture_subset):
       baseset.sort()
       basename = '-'.join(baseset)
       basemodel = tf.keras.models.load_model(basename + '_lstm')
       model = tf.keras.Sequential()
       for layer in basemodel.layers[:-1]: # go through until last layer
           layer.trainable= True
           model.add(layer)
       model.add(tf.keras.layers.Dense(len(gesture subset),
→activation='softmax', name="transfer_adjust"))
       model.build([None, 19, 3])
       #print(model.summary())
       model.compile(loss='sparse_categorical_crossentropy', optimizer=adam_v2.
→Adam(learning_rate=0.001), metrics=['accuracy'])
       return model
   # Function to create model, required for KerasClassifier
   import pickle
   def load_classifier(baseset, gesture_subset):
       gesture_subset.sort()
       name = '-'.join(gesture_subset)
       classifier = KerasClassifier(build_fn=build_model, baseset=baseset,_
⇒gesture_subset=gesture_subset, epochs=128, batch_size=19, verbose=0)
       classifier.classes_ = pickle.load(open(name + '_model_classes.
→pkl','rb'))
       classifier.model = build_model(baseset,gesture_subset)
       return classifier
   #print(model.model.summary())
   #print(model.classes_)
   from sklearn.metrics import classification report
   from sklearn.metrics import confusion_matrix
   for n_splits in [10, 5, 4, 2]:
       for epoch in [[8], [16], [32], [64], [128]]:
           cv = StratifiedGroupKFold(n_splits=n_splits, shuffle=True,_
→random_state=(1000+epoch[0]))
           X, y, g = get_dataset(dataset_cleaned)
           # Initialize the accuracy of the models to blank list. The accuracy
→of each model will be appended to this list
           accuracy_model = []
           best estimator = None
           # Initialize the array to zero which will store the confusion matrix
```

```
array = None
           outliers = None
           report_cleaned = None
           report_outliers = None
           print("Processing started for split estimator: " + str(n_splits) +

→", epochs: " + str(epoch))
           # Iterate over each train-test split
           fold = 1
           for train_index, test_index in cv.split(X, y, g):
               #print(test_index)
               if len(test_index) == 0:
                    continue
               print("Processing ", fold, "-fold")
               fold += 1
               classifier = load_classifier(baseset, gesture_subset)
               # Split train-test (Inverted)
               X_train, y_train, group_train = get_dataset(dataset_cleaned,__
→test index)
               X_test, y_test, group_test = get_dataset(dataset_cleaned,__
→train_index)
               X_{outliers}, y_{outliers}, group_test =
→get_dataset(dataset_outliers)
               # Train the model
               History = classifier.fit(X_train, y_train, epochs=epoch[0])
               # Append to accuracy_model the accuracy of the model
               accuracy_model.append(accuracy_score(y_test, classifier.
→predict(X_test), normalize=True))
               if accuracy_model[-1] == max(accuracy_model):
                   best_estimator = classifier
               # Calculate the confusion matrix
               c = confusion_matrix(y_test, classifier.predict(X_test))
               # Add the score to the previous confusion matrix of previous_{\sqcup}
\rightarrow model
               if isinstance(array, np.ndarray) == False:
                   array = c.copy()
               else:
                   array = array + c
               # Calculate the confusion matrix
               c = confusion_matrix(y_outliers, classifier.predict(X_outliers))
               # Add the score to the previous confusion matrix of previous \Box
\rightarrow model
               if isinstance(outliers, np.ndarray) == False:
```

```
outliers = c.copy()
               else:
                   outliers = outliers + c
               #Accumulate for classification report
               if isinstance(report_cleaned, list) == False:
                   report_cleaned = [y_test, classifier.predict(X_test)]
               else:
                   report_cleaned[0] = np.append(report_cleaned[0],y_test)
                   report_cleaned[1] = np.append(report_cleaned[1],classifier.
→predict(X_test))
               #Accumulate for classification report
               if isinstance(report_outliers, list) == False:
                   report_outliers = [y_outliers, classifier.
→predict(X_outliers)]
               else:
                   report_outliers[0] = np.
→append(report_outliers[0],y_outliers)
                   report_outliers[1] = np.
→append(report_outliers[1],classifier.predict(X_outliers))
           # Print the accuracy
           print("At split estimator: " + str(n_splits) + ", epochs: " +__

str(epoch))
           print("Accurace mean(std): " + str(np.mean(accuracy_model)) + "(" +__

str(np.std(accuracy model)) + ")")
           # To calculate the classification reports
           print("Classification report for all valid cross_validations⊔
→against their tests sets")
           print(classification_report(report_cleaned[0], report_cleaned[1],__
→target_names=gesture_subset))
           print("Classification report for all valid cross_validations⊔
→against outliers")
           print(classification_report(report_outliers[0], report_outliers[1],__
→target_names=gesture_subset))
           # To calculate the confusion matrix
           print("Confusion Matrix for all valid cross_validations against⊔
→their tests sets")
           make_confusion_matrix(array, categories=gesture_subset)
```

```
print("Confusion Matrix for all valid cross_validations against⊔
\hookrightarrowoutliers")
           make_confusion_matrix(outliers, categories=gesture_subset)
   for n_splits in [5]:
       for epoch in [[8], [16], [32], [64], [128]]:
           cv = StratifiedGroupKFold(n_splits=n_splits, shuffle=True,_
→random state=(1000+epoch[0]))
           X, y, g = get_dataset(dataset_cleaned)
           # Initialize the accuracy of the models to blank list. The accuracy
→of each model will be appended to this list
           accuracy_model = []
           best_estimator = None
           # Initialize the array to zero which will store the confusion matrix
           array = None
           outliers = None
           report_cleaned = None
           report_outliers = None
           print("Processing started for real split: " + str(n_splits) + ",__
→epochs: " + str(epoch))
           # Iterate over each train-test split
           fold = 1
           for train_index, test_index in cv.split(X, y, g):
               #print(test_index)
               if len(test_index) == 0:
                   continue
               print("Processing ", fold, "-fold")
               fold += 1
               classifier = load_classifier(baseset, gesture_subset)
               # Split train-test (Inverted)
               X train, y train, group train = get dataset(dataset cleaned,
→train index)
               X_test, y_test, group_test = get_dataset(dataset_cleaned,__
→test_index)
               X_outliers, y_outliers, group_test =
→get_dataset(dataset_outliers)
               # Train the model
               History = classifier.fit(X_train, y_train, epochs=epoch[0])
               # Append to accuracy_model the accuracy of the model
               accuracy_model.append(accuracy_score(y_test, classifier.
→predict(X_test), normalize=True))
               if accuracy_model[-1] == max(accuracy_model):
```

```
best_estimator = classifier
               # Calculate the confusion matrix
               c = confusion_matrix(y_test, classifier.predict(X_test))
               # Add the score to the previous confusion matrix of previous
\rightarrow model
               if isinstance(array, np.ndarray) == False:
                   array = c.copy()
               else:
                   array = array + c
               # Calculate the confusion matrix
               c = confusion_matrix(y_outliers, classifier.predict(X_outliers))
               # Add the score to the previous confusion matrix of previous
\rightarrowmodel
               if isinstance(outliers, np.ndarray) == False:
                   outliers = c.copy()
               else:
                   outliers = outliers + c
               #Accumulate for classification report
               if isinstance(report_cleaned, list) == False:
                   report_cleaned = [y_test, classifier.predict(X_test)]
               else:
                   report_cleaned[0] = np.append(report_cleaned[0],y_test)
                   report_cleaned[1] = np.append(report_cleaned[1], classifier.
→predict(X_test))
               #Accumulate for classification report
               if isinstance(report_outliers, list) == False:
                   report_outliers = [y_outliers, classifier.
→predict(X_outliers)]
               else:
                   report_outliers[0] = np.
→append(report_outliers[0],y_outliers)
                   report_outliers[1] = np.
→append(report_outliers[1], classifier.predict(X_outliers))
           # Print the accuracy
           print("At split estimator: " + str(n_splits) + ", epochs: " +__
→str(epoch))
           print("Accurace mean(std): " + str(np.mean(accuracy_model)) + "(" +__
⇒str(np.std(accuracy_model)) + ")")
           # To calculate the classification reports
           print("Classification report for all valid cross_validations⊔
→against their tests sets")
```

```
print(classification_report(report_cleaned[0], report_cleaned[1], u
 →target_names=gesture_subset))
            print("Classification report for all valid cross_validations_
 →against outliers")
            print(classification_report(report_outliers[0], report_outliers[1],
 →target_names=gesture_subset))
            # To calculate the confusion matrix
            print("Confusion Matrix for all valid cross_validations against_
 make_confusion_matrix(array, categories=gesture_subset)
            print("Confusion Matrix for all valid cross_validations against⊔
 ⇔outliers")
            make_confusion_matrix(outliers, categories=gesture_subset)
baseset = base_transfer_set
dataset = transfers_size_3[1]
model = create_transfer_models(baseset, dataset)
Processing tranfers models at 10%, 20%, 25%, 50% and 80% data for gestures:
['06', '07', '10']
Baseset: ['01', '02', '04', '05', '08', '09', '12', '13', '16', '17', '18',
Loadind Dataset: ['06', '07', '10']
489 samples loaded
Scaling Dataset: ['06', '07', '10']
489 samples scaled
Cleaning Dataset: ['06', '07', '10']
365 samples cleaned
124 samples outliers
Time slicing Cleaned Dataset: ['06', '07', '10']
364 cleaned samples sliced
1 cleaned samples damaged
Time slicing Outliers Dataset: ['06', '07', '10']
124 outliers samples sliced
O outliers samples damaged
Processing started for split estimator: 10, epochs: [8]
Processing 1 -fold
2021-09-27 15:42:56.892129: I tensorflow/core/platform/cpu_feature_guard.cc:142]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
```

operations: AVX2 AVX512F FMA

To enable them in other operations, rebuild ${\tt TensorFlow}$ with the appropriate

compiler flags.

2021-09-27 15:44:14.009234: I

tensorflow/compiler/mlir_graph_optimization_pass.cc:185] None of the MLIR Optimization Passes are enabled (registered 2)

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

Processing 6 -fold

Processing 7 -fold

Processing 8 -fold

At split estimator: 10, epochs: [8]

Accurace mean(std): 0.8219608752989542(0.08169040156520169)

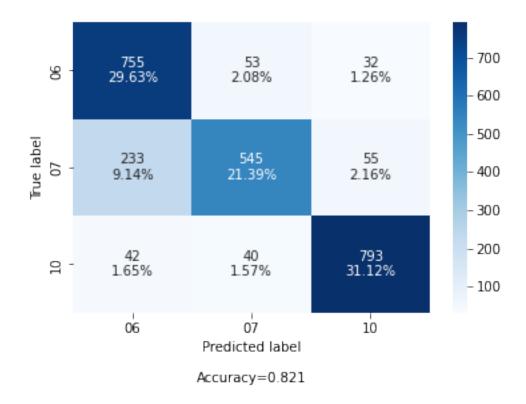
Classification report for all valid cross_validations against their tests sets precision recall f1-score support

	06	0.73	0.90	0.81	840
	07	0.85	0.65	0.74	833
	10	0.90	0.91	0.90	875
accur	cacy			0.82	2548
macro	avg	0.83	0.82	0.82	2548
weighted	avg	0.83	0.82	0.82	2548

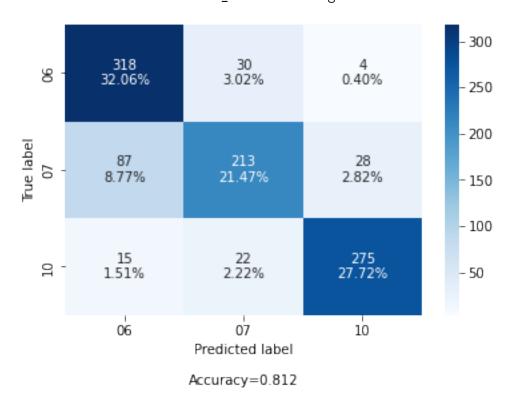
Classification report for all valid cross_validations against outliers

precision recall f1-score support

		brecipion	recarr	II SCOLE	Support
	06	0.76	0.90	0.82	352
	07	0.80	0.65	0.72	328
	10	0.90	0.88	0.89	312
accur	acy			0.81	992
macro	avg	0.82	0.81	0.81	992
weighted	avg	0.82	0.81	0.81	992



Confusion Matrix for all valid cross_validations against outliers



```
Processing 1 -fold
Processing 2 -fold
Processing 3 -fold
Processing 4 -fold
Processing 5 -fold
Processing 6 -fold
Processing 7 -fold
Processing 8 -fold
```

At split estimator: 10, epochs: [16]

Accurace mean(std): 0.8361728301321958(0.05568026090440531)

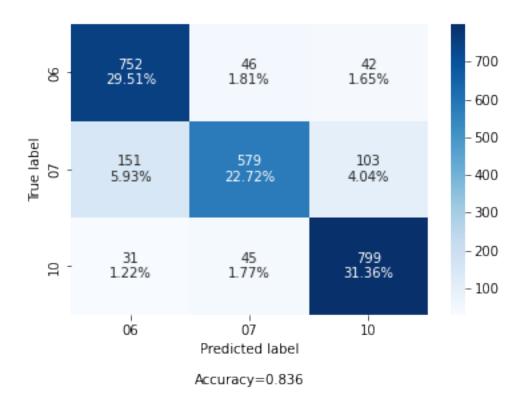
Processing started for split estimator: 10, epochs: [16]

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ their\ tests\ sets}$

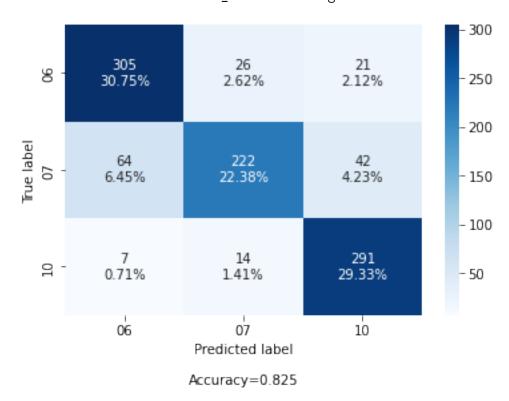
	precision	recall	f1-score	support
06 07 10	0.81 0.86 0.85	0.90 0.70 0.91	0.85 0.77 0.88	840 833 875
accuracy macro avg weighted avg	0.84	0.83	0.84 0.83 0.83	2548 2548 2548

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

	precision	recall	f1-score	support
06 07	0.81 0.85	0.87 0.68	0.84 0.75	352 328
10	0.82	0.93	0.87	312
accuracy			0.82	992
macro avg	0.83	0.83	0.82	992
weighted avg	0.83	0.82	0.82	992



Confusion Matrix for all valid cross_validations against outliers



```
Processing 1 -fold
Processing 2 -fold
Processing 3 -fold
Processing 4 -fold
```

Processing started for split estimator: 10, epochs: [32]

Processing 4 -fold Processing 5 -fold Processing 6 -fold

Processing 7 -fold

Processing 8 -fold

At split estimator: 10, epochs: [32]

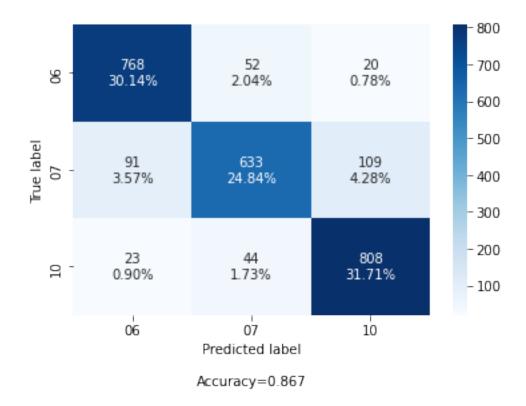
Accurace mean(std): 0.8673393803883194(0.07580711655202127)

Classification report for all valid cross_validations against their tests sets

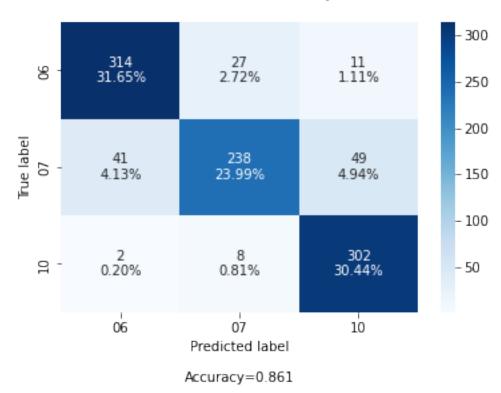
	precision	recall	f1-score	support	
	-				
06	0.87	0.91	0.89	840	
07	0.87	0.76	0.81	833	
10	0.86	0.92	0.89	875	
accuracy			0.87	2548	
macro avg	0.87	0.87	0.86	2548	
weighted avg	0.87	0.87	0.87	2548	

 ${\tt Classification}\ {\tt report}\ {\tt for\ all\ valid\ cross_validations\ against\ outliers\\$

	precision	recall	f1-score	support
06	0.88	0.89	0.89	352
07	0.87	0.73	0.79	328
10	0.83	0.97	0.90	312
accuracy			0.86	992
macro avg	0.86	0.86	0.86	992
weighted avg	0.86	0.86	0.86	992



Confusion Matrix for all valid cross_validations against outliers



```
Processing 1 -fold
Processing 2 -fold
Processing 3 -fold
Processing 4 -fold
```

Processing started for split estimator: 10, epochs: [64]

Processing 4 -fold Processing 5 -fold Processing 6 -fold

Processing 7 -fold Processing 8 -fold

At split estimator: 10, epochs: [64]

Accurace mean(std): 0.8805398656779134(0.08852610238067796)

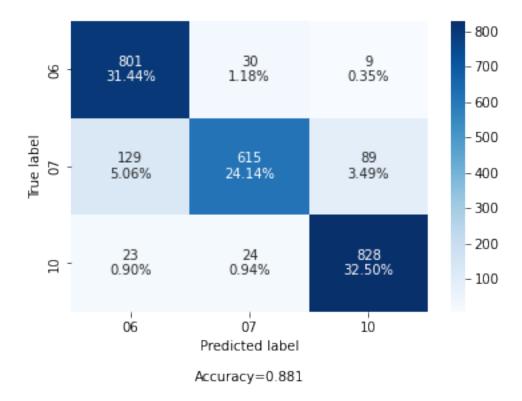
 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ their\ tests\ sets}$

	precision	recall	f1-score	support	_
06	0.84	0.95	0.89	840	
07	0.92	0.74	0.82	833	
10	0.89	0.95	0.92	875	
accuracy			0.88	2548	
macro avg	0.88	0.88	0.88	2548	
weighted avg	0.88	0.88	0.88	2548	

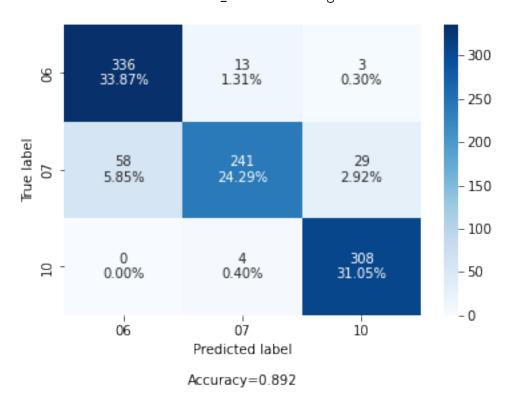
Classification report for all valid cross_validations against outliers

precision recall f1-score support

		precision	recall	Il-score	support
	06	0.85	0.95	0.90	352
	07	0.93	0.73	0.82	328
	10	0.91	0.99	0.94	312
accur	acy			0.89	992
macro	avg	0.90	0.89	0.89	992
weighted	avg	0.90	0.89	0.89	992



Confusion Matrix for all valid cross_validations against outliers



```
Processing 1 -fold
Processing 2 -fold
Processing 3 -fold
Processing 4 -fold
Processing 5 -fold
Processing 6 -fold
Processing 7 -fold
Processing 8 -fold
```

At split estimator: 10, epochs: [128]

Accurace mean(std): 0.8601337629512167(0.058383395680229835)

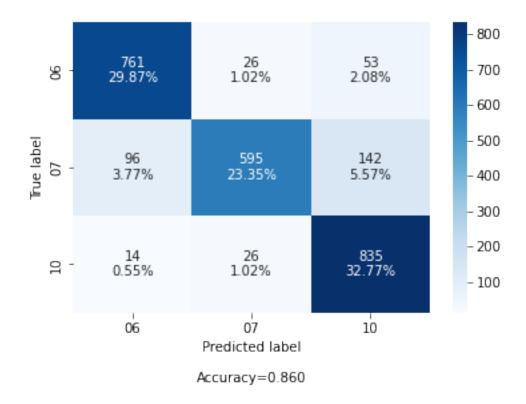
Processing started for split estimator: 10, epochs: [128]

Classification report for all valid cross_validations against their tests sets precision recall f1-score support

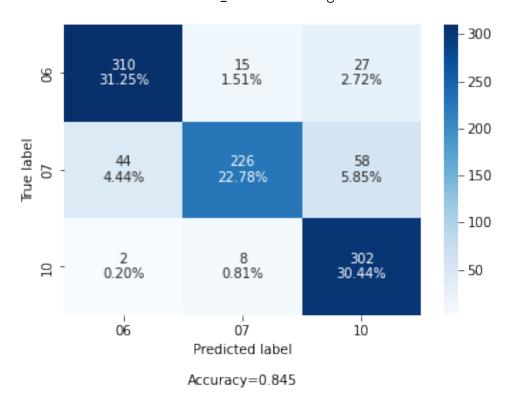
	1			11
06	0.87	0.91	0.89	840
07	0.92	0.71	0.80	833
10	0.81	0.95	0.88	875
accuracy			0.86	2548
macro avg	0.87	0.86	0.86	2548
weighted avg	0.87	0.86	0.86	2548

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

	precision	recall	f1-score	support
06	0.87	0.88	0.88	352
07 10	0.91 0.78	0.69 0.97	0.78 0.86	328 312
accuracy			0.84	992
macro avg	0.85	0.85	0.84	992
weighted avg	0.85	0.84	0.84	992



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 5, epochs: [8]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [8]

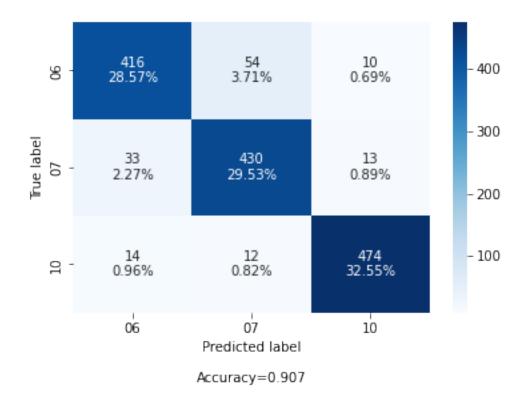
Accurace mean(std): 0.9093527824039764(0.04527621212933132)

Classification report for all valid cross_validations against their tests sets

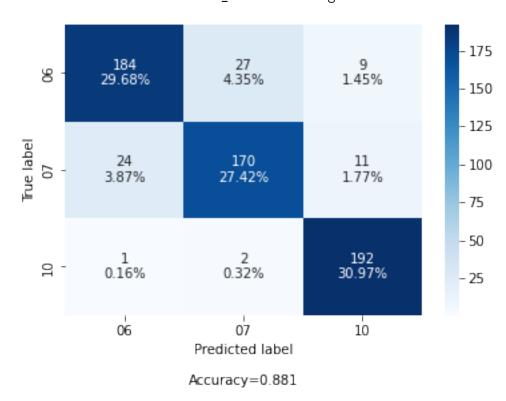
	precision	recall	f1-score	support	
06 07	0.90 0.87	0.87 0.90	0.88	480 476	
10	0.95	0.95	0.95	500	
accuracy			0.91	1456	
macro avg	0.91	0.91	0.91	1456	
weighted avg	0.91	0.91	0.91	1456	

 ${\tt Classification}\ {\tt report}\ {\tt for\ all\ valid\ cross_validations\ against\ outliers\\$

	precision	recall	f1-score	support	
06 07	0.88	0.84	0.86	220 205	
10	0.91	0.63	0.64	195	
accuracy			0.88	620	
macro avg weighted avg	0.88 0.88	0.88 0.88	0.88 0.88	620 620	



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 5, epochs: [16]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [16]

Accurace mean(std): 0.9052357581380907(0.03809085622670242)

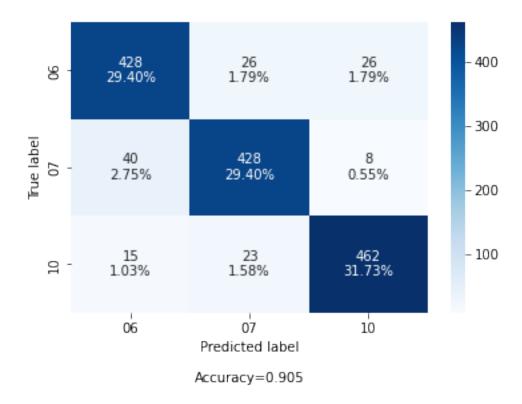
 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ their\ tests\ sets}$

	precision	recall	f1-score	support	Ü
06	0.89	0.89	0.89	480	
07	0.90	0.90	0.90	476	
10	0.93	0.92	0.93	500	
accuracy			0.91	1456	
macro avg	0.90	0.90	0.90	1456	
weighted avg	0.91	0.91	0.91	1456	

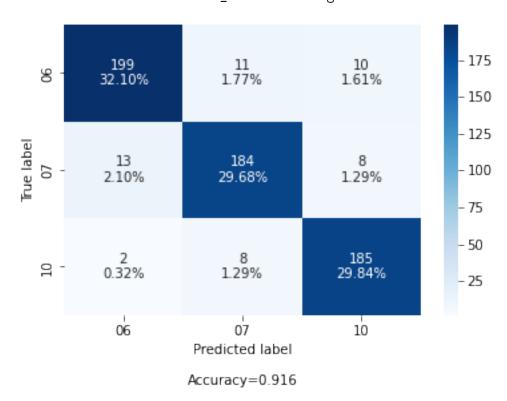
Classification report for all valid cross_validations against outliers

precision recall f1-score support

	precision	recarr	II-SCOLE	support
06	0.93	0.90	0.92	220
07	0.91	0.90	0.90	205
10	0.91	0.95	0.93	195
accuracy			0.92	620
macro avg	0.92	0.92	0.92	620
weighted avg	0.92	0.92	0.92	620



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 5, epochs: [32]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [32]

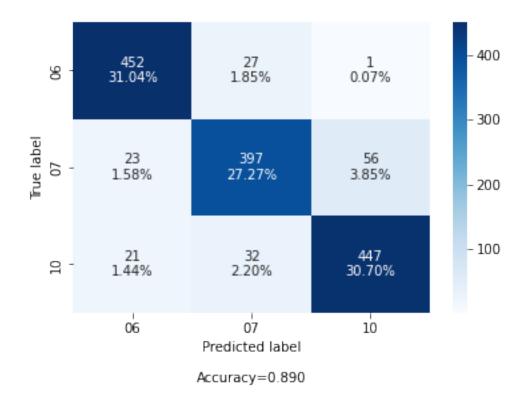
Accurace mean(std): 0.8967534719466557(0.09079323481435025)

Classification report for all valid cross_validations against their tests sets

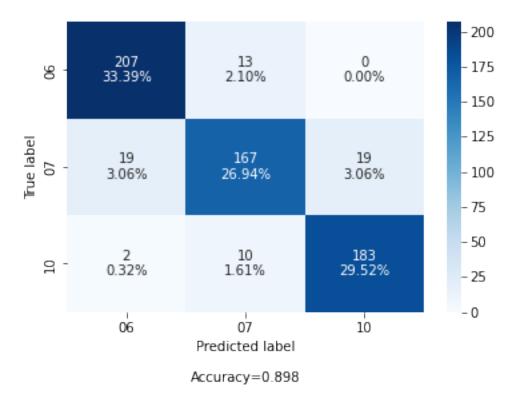
	precision	recall	f1-score	support	
06	0.91	0.94	0.93	480	
07	0.87	0.83	0.85	476	
10	0.89	0.89	0.89	500	
accuracy			0.89	1456	
macro avg	0.89	0.89	0.89	1456	
weighted avg	0.89	0.89	0.89	1456	

 ${\tt Classification}\ \ {\tt report}\ \ {\tt for\ all\ valid\ cross_validations\ against\ outliers\\$

	precision	recall	f1-score	support
06	0.91	0.94	0.92	220
07	0.88	0.81	0.85	205
10	0.91	0.94	0.92	195
accuracy	0.31	0.01	0.90	620
macro avg	0.90	0.90	0.90	620
weighted avg	0.90	0.90		620



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 5, epochs: [64]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [64]

Accurace mean(std): 0.925507911227962(0.05748524536828443)

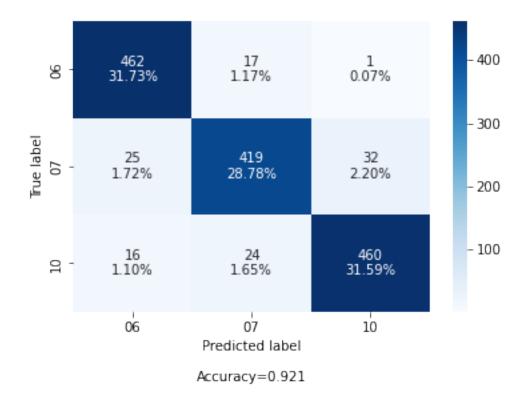
 ${\tt Classification}\ {\tt report}\ {\tt for\ all\ valid\ cross_validations\ against\ their\ tests\ sets$

	precision	recall	il-score	support	
	_				
06	0.92	0.96	0.94	480	
07	0.91	0.88	0.90	476	
10	0.93	0.92	0.93	500	
accuracy			0.92	1456	
macro avg	0.92	0.92	0.92	1456	
weighted avg	0.92	0.92	0.92	1456	

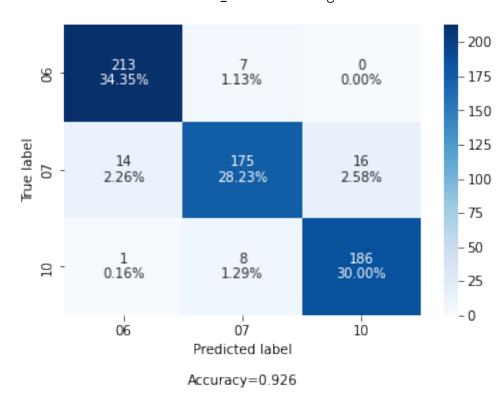
Classification report for all valid cross_validations against outliers

precision recall f1-score support

	precision	recall	II-score	support	
06	0.93	0.97	0.95	220	
07	0.92	0.85	0.89	205	
10	0.92	0.95	0.94	195	
accuracy			0.93	620	
macro avg	0.93	0.93	0.92	620	
weighted avg	0.93	0.93	0.93	620	



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 5, epochs: [128]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [128]

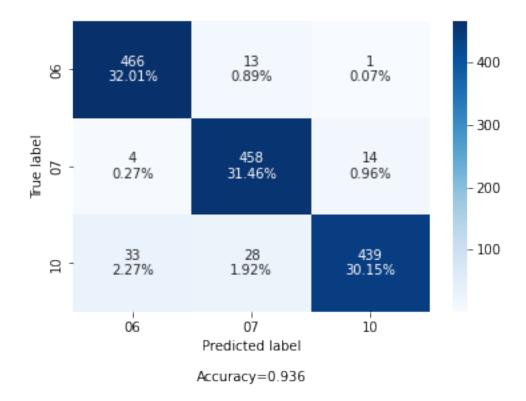
Accurace mean(std): 0.9399948145964947(0.05251755466475419)

Classification report for all valid cross_validations against their tests sets

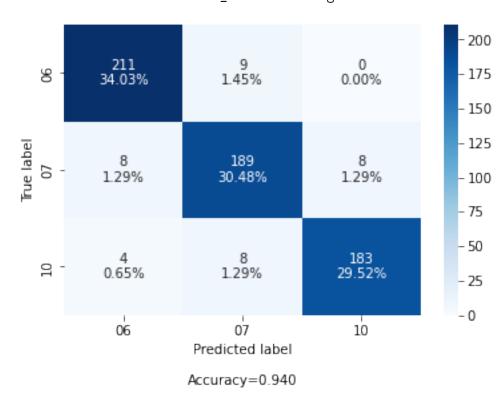
	precision	recall	f1-score	support
06 07	0.93 0.92	0.97 0.96	0.95 0.94	480 476
10	0.97	0.88	0.92	500
accuracy			0.94	1456
macro avg	0.94	0.94	0.94	1456
weighted avg	0.94	0.94	0.94	1456

 ${\tt Classification}\ \ {\tt report}\ \ {\tt for\ all\ valid\ cross_validations\ against\ outliers$

	precision	recall	f1-score	support
06 07	0.95 0.92	0.96 0.92	0.95 0.92	220 205
10	0.96	0.94	0.95	195
accuracy			0.94	620
macro avg	0.94	0.94	0.94	620
weighted avg	0.94	0.94	0.94	620



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 4, epochs: [8]

Processing 1 -fold Processing 2 -fold Processing 3 -fold Processing 4 -fold

At split estimator: 4, epochs: [8]

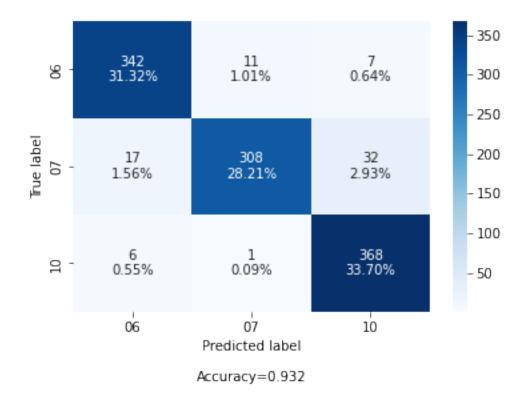
Accurace mean(std): 0.9308400563239159(0.056307167411356586)

Classification report for all valid cross_validations against their tests sets

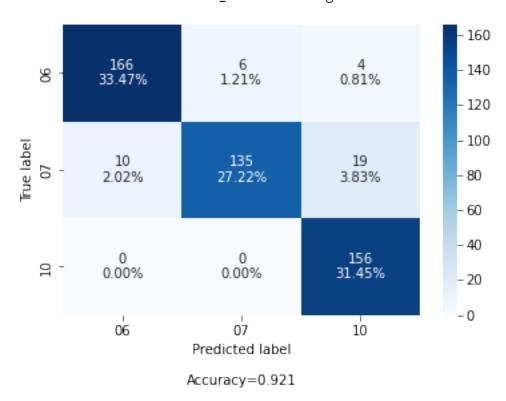
	precision	recall	f1-score	support
06	0.94	0.95	0.94	360
07	0.96	0.86	0.91	357
10	0.90	0.98	0.94	375
accuracy			0.93	1092
macro avg	0.93	0.93	0.93	1092
weighted avg	0.93	0.93	0.93	1092

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

	precision	recall	il-score	support
06	0.94	0.94	0.94	176
07	0.96	0.82	0.89	164
10	0.87	1.00	0.93	156
accuracy			0.92	496
macro avg	0.92	0.92	0.92	496
weighted avg	0.93	0.92	0.92	496



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 4, epochs: [16]

Processing 1 -fold Processing 2 -fold Processing 3 -fold Processing 4 -fold

At split estimator: 4, epochs: [16]

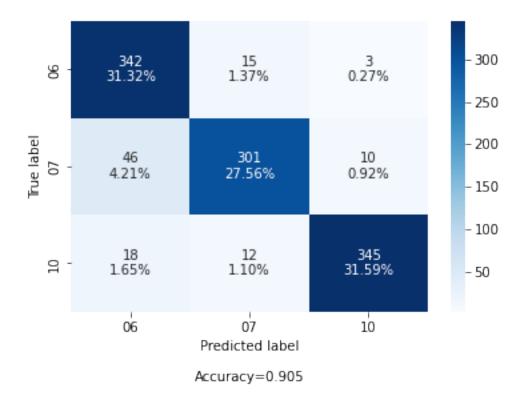
Accurace mean(std): 0.904731258986398(0.0457618863789857)

Classification report for all valid cross_validations against their tests sets

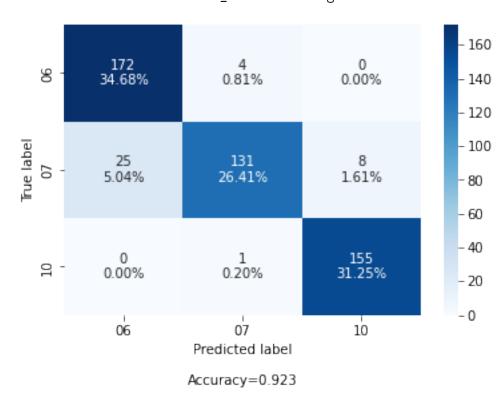
	precision	recall	f1-score	support
06	0.84	0.95	0.89	360
07	0.92	0.84	0.88	357
10	0.96	0.92	0.94	375
accuracy			0.90	1092
macro avg	0.91	0.90	0.90	1092
weighted avg	0.91	0.90	0.90	1092

Classification report for all valid cross_validations against outliers precision recall f1-score support

	brecipion	recarr	II SCOLE	Support
06	0.87	0.98	0.92	176
07	0.96	0.80	0.87	164
10	0.95	0.99	0.97	156
accuracy			0.92	496
macro avg	0.93	0.92	0.92	496
weighted avg	0.93	0.92	0.92	496



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 4, epochs: [32]

Processing 1 -fold Processing 2 -fold Processing 3 -fold Processing 4 -fold

At split estimator: 4, epochs: [32]

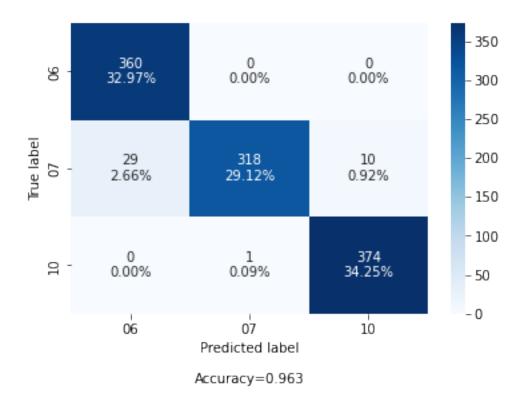
Accurace mean(std): 0.9626520549487648(0.0377527173082539)

Classification report for all valid cross_validations against their tests sets

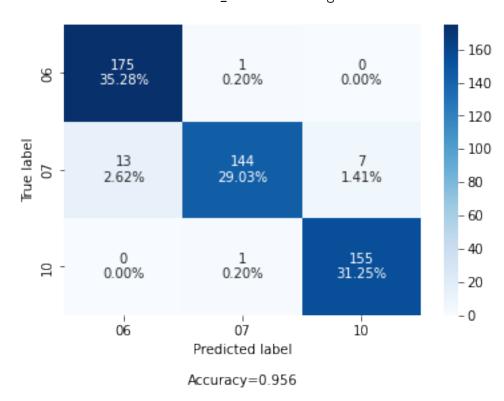
	precision	recall	il-score	support
06	0.93	1.00	0.96	360
07	1.00	0.89	0.94	357
10	0.97	1.00	0.99	375
accuracy	•		0.96	1092
macro avg	0.97	0.96	0.96	1092
weighted ave	0.97	0.96	0.96	1092

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

		precision	recall	f1-score	support	
	06	0.93	0.99	0.96	176	
	07	0.99	0.88	0.93	164	
	10	0.96	0.99	0.97	156	
accur	acy			0.96	496	
macro	avg	0.96	0.96	0.96	496	
weighted	avg	0.96	0.96	0.95	496	



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 4, epochs: [64]

Processing 1 -fold Processing 2 -fold Processing 3 -fold Processing 4 -fold

At split estimator: 4, epochs: [64]

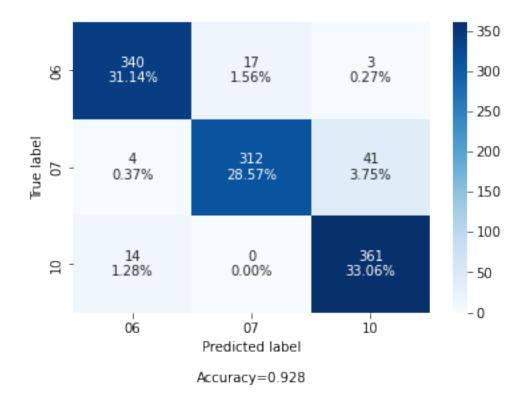
Accurace mean(std): 0.9275311615571034(0.021375149770970357)

Classification report for all valid cross_validations against their tests sets

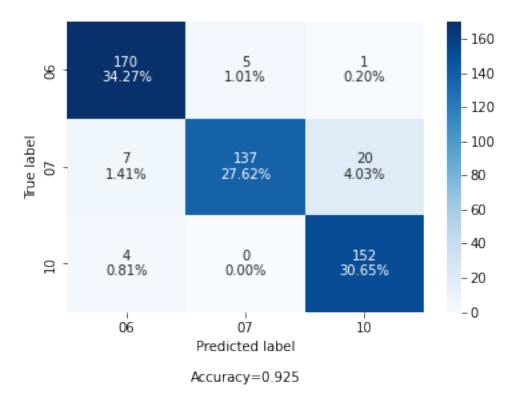
	precision	recall	f1-score	support
06	0.95	0.94	0.95	360
07	0.95	0.87	0.91	357
10	0.89	0.96	0.93	375
accuracy			0.93	1092
macro avg	0.93	0.93	0.93	1092
weighted avg	0.93	0.93	0.93	1092

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

		precision	recall	f1-score	${ t support}$	
	06	0.94	0.97	0.95	176	
	07	0.96	0.84	0.90	164	
	10	0.88	0.97	0.92	156	
accur	acy			0.93	496	
macro	avg	0.93	0.93	0.92	496	
weighted	avg	0.93	0.93	0.92	496	



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 4, epochs: [128]

Processing 1 -fold Processing 2 -fold Processing 3 -fold Processing 4 -fold

At split estimator: 4, epochs: [128]

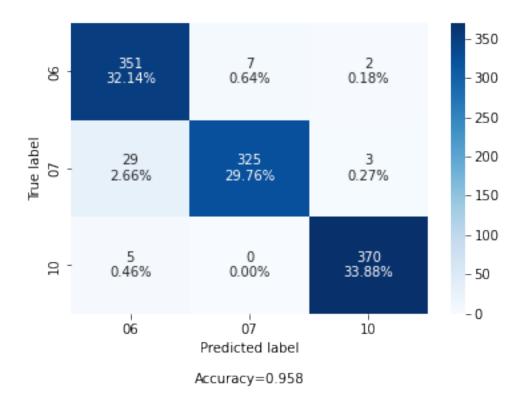
Accurace mean(std): 0.9580947067205126(0.042841354849541304)

Classification report for all valid cross_validations against their tests sets

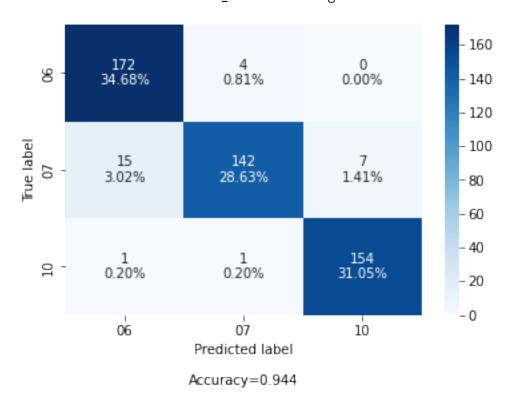
	precision	recall	il-score	support
06	0.91	0.97	0.94	360
07	0.98	0.91	0.94	357
10	0.99	0.99	0.99	375
accuracy			0.96	1092
macro avg	0.96	0.96	0.96	1092
weighted avg	0.96	0.96	0.96	1092

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

	precision	recall	f1-score	${ t support}$
06	0.91	0.98	0.95	176
07	0.97	0.87	0.91	164
10	0.96	0.99	0.97	156
accuracy			0.94	496
macro avg	0.95	0.94	0.94	496
weighted avg	0.94	0.94	0.94	496



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 2, epochs: [8]

Processing 1 -fold Processing 2 -fold

At split estimator: 2, epochs: [8]

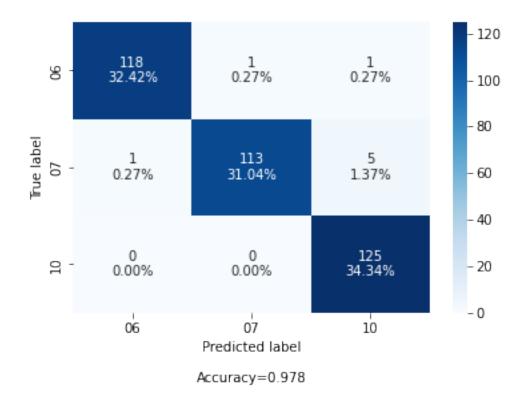
Accurace mean(std): 0.9783607350096712(0.010275628626692457)

Classification report for all valid cross_validations against their tests sets

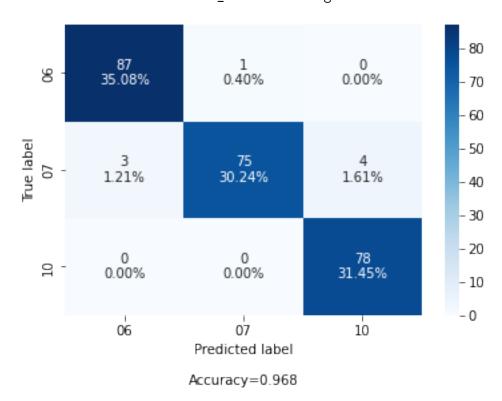
	precision	recall	f1-score	support
06 07	0.99 0.99	0.98 0.95	0.99 0.97	120 119
10	0.95	1.00	0.98	125
accuracy			0.98	364
macro avg	0.98	0.98	0.98	364
weighted avg	0.98	0.98	0.98	364

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

	precision	recall	f1-score	support	
	•			••	
06	0.97	0.99	0.98	88	
07	0.99	0.91	0.95	82	
10	0.95	1.00	0.97	78	
accuracy			0.97	248	
macro avg	0.97	0.97	0.97	248	
weighted avg	0.97	0.97	0.97	248	



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 2, epochs: [16]

Processing 1 -fold Processing 2 -fold

At split estimator: 2, epochs: [16]

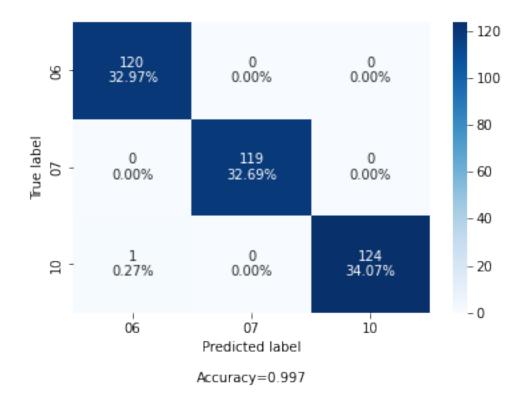
Accurace mean(std): 0.997395833333333(0.00260416666666685)

Classification report for all valid cross_validations against their tests sets

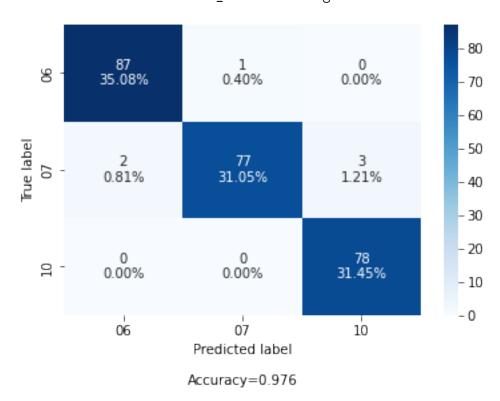
	precision	recall	f1-score	support
06 07	0.99 1.00	1.00	1.00	120 119
10	1.00	0.99	1.00	125
accuracy			1.00	364
macro avg	1.00	1.00	1.00	364
weighted avg	1.00	1.00	1.00	364

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

	precision	recall	f1-score	support	
	•				
06	0.98	0.99	0.98	88	
07	0.99	0.94	0.96	82	
10	0.96	1.00	0.98	78	
accuracy			0.98	248	
macro avg	0.98	0.98	0.98	248	
weighted avg	0.98	0.98	0.98	248	



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 2, epochs: [32]

Processing 1 -fold Processing 2 -fold

At split estimator: 2, epochs: [32]

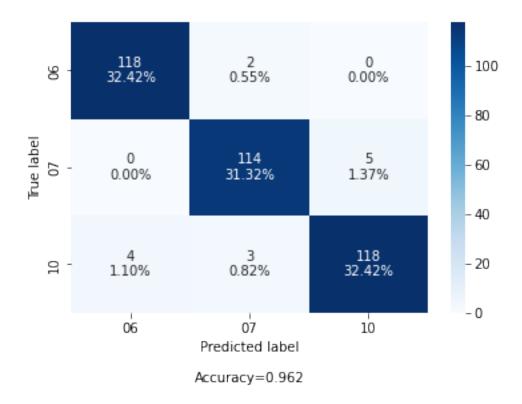
Accurace mean(std): 0.9616779497098646(0.004231141199226296)

Classification report for all valid cross_validations against their tests sets

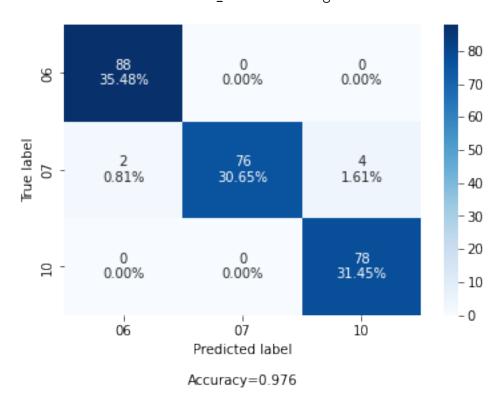
	precision	recall	f1-score	support
06	0.97	0.98	0.98	120
07	0.96	0.96	0.96	119
10	0.96	0.94	0.95	125
accuracy			0.96	364
macro avg	0.96	0.96	0.96	364
weighted avg	0.96	0.96	0.96	364

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

06 0.98 1.00 0.99 88	
07 1.00 0.93 0.96 82	
10 0.95 1.00 0.97 78	
accuracy 0.98 248	
macro avg 0.98 0.98 0.98 248	
weighted avg 0.98 0.98 0.98 248	



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 2, epochs: [64]

Processing 1 -fold Processing 2 -fold

At split estimator: 2, epochs: [64]

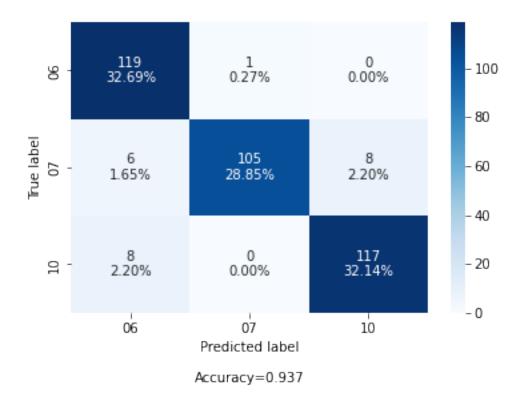
Accurace mean(std): 0.9369169459288108(0.018884159043564885)

Classification report for all valid cross_validations against their tests sets

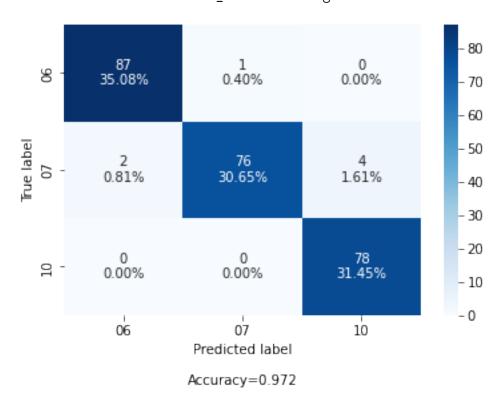
	precision	recall	f1-score	support
06	0.89	0.99	0.94	120
07 10	0.99 0.94	0.88 0.94	0.93 0.94	119 125
accuracy			0.94	364
macro avg	0.94	0.94	0.94	364
weighted avg	0.94	0.94	0.94	364

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

	precision	recall	f1-score	support	
	•			• •	
06	0.98	0.99	0.98	88	
07	0.99	0.93	0.96	82	
10	0.95	1.00	0.97	78	
accuracy			0.97	248	
macro avg	0.97	0.97	0.97	248	
weighted avg	0.97	0.97	0.97	248	



Confusion Matrix for all valid cross_validations against outliers



Processing started for split estimator: 2, epochs: [128]

Processing 1 -fold Processing 2 -fold

At split estimator: 2, epochs: [128]

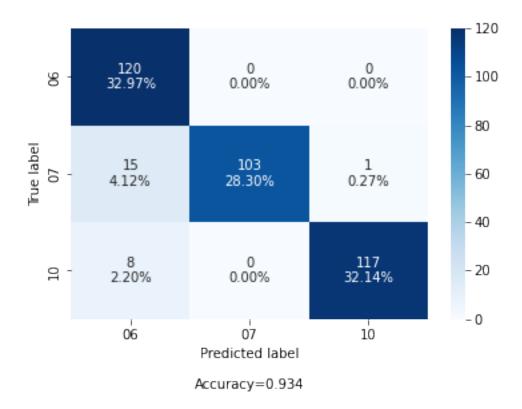
Accurace mean(std): 0.9337318479606316(0.060803671165051476)

Classification report for all valid cross_validations against their tests sets

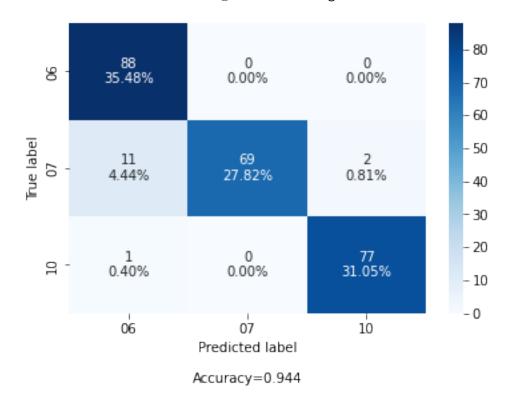
	precision	recall	f1-score	support
06 07	0.84 1.00	1.00	0.91 0.93	120 119
10	0.99	0.87	0.96	125
accuracy			0.93	364
macro avg	0.94	0.93	0.93	364
weighted avg	0.94	0.93	0.93	364

 ${\tt Classification\ report\ for\ all\ valid\ cross_validations\ against\ outliers}$

	precision	recall	f1-score	support	
	•			11	
06	0.88	1.00	0.94	88	
07	1.00	0.84	0.91	82	
10	0.97	0.99	0.98	78	
accuracy			0.94	248	
macro avg	0.95	0.94	0.94	248	
weighted avg	0.95	0.94	0.94	248	



Confusion Matrix for all valid cross_validations against outliers



Processing started for real split: 5, epochs: [8]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [8]

Accurace mean(std): 0.9814736842105264(0.02303892887630226)

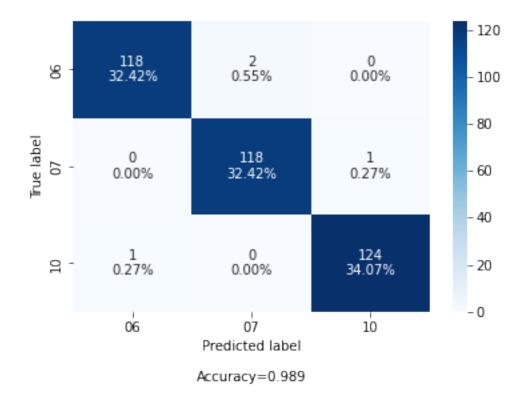
Classification report for all valid cross_validations against their tests sets

	precision	recall	f1-score	support	
	_				
06	0.99	0.98	0.99	120	
07	0.98	0.99	0.99	119	
10	0.99	0.99	0.99	125	
accuracy			0.99	364	
macro avg	0.99	0.99	0.99	364	
weighted avg	0.99	0.99	0.99	364	

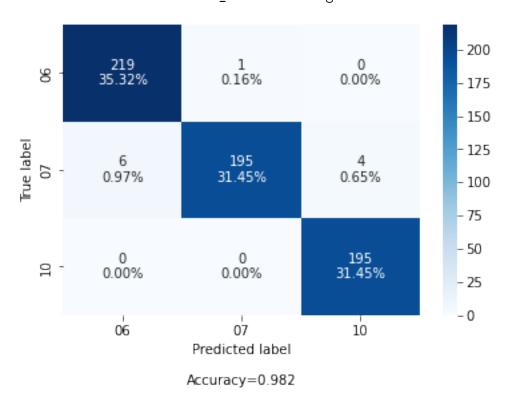
Classification report for all valid cross_validations against outliers

precision recall f1-score support

	precision	recall	II-score	support	
06	0.97	1.00	0.98	220	
07	0.99	0.95	0.97	205	
10	0.98	1.00	0.99	195	
accuracy			0.98	620	
macro avg	0.98	0.98	0.98	620	
weighted avg	0.98	0.98	0.98	620	



Confusion Matrix for all valid cross_validations against outliers



Processing started for real split: 5, epochs: [16]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [16]

Accurace mean(std): 0.9879999999999(0.024000000000000)

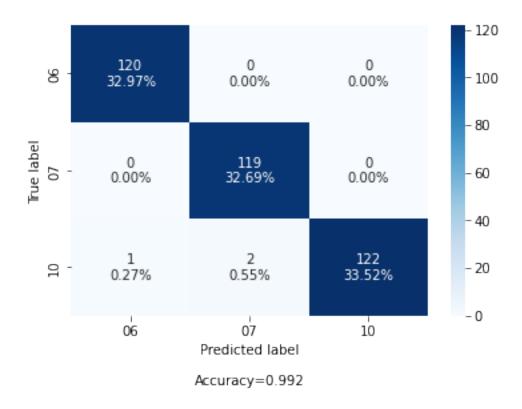
 ${\tt Classification}\ {\tt report}\ {\tt for\ all\ valid\ cross_validations\ against\ their\ tests\ sets\\$

		precision	recall	il-score	support	
(06	0.99	1.00	1.00	120	
(07	0.98	1.00	0.99	119	
:	10	1.00	0.98	0.99	125	
accura	су			0.99	364	
macro a	vg	0.99	0.99	0.99	364	
weighted av	vg	0.99	0.99	0.99	364	

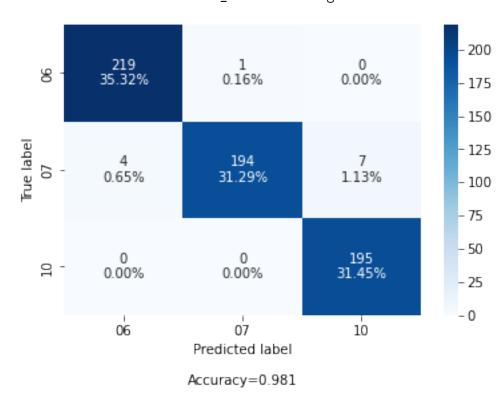
Classification report for all valid cross_validations against outliers

precision recall f1-score support

	pr	recision	recall	II-score	support	
0	6	0.98	1.00	0.99	220	
0	7	0.99	0.95	0.97	205	
1	0	0.97	1.00	0.98	195	
accurac	У			0.98	620	
macro av	g	0.98	0.98	0.98	620	
weighted av	g	0.98	0.98	0.98	620	



Confusion Matrix for all valid cross_validations against outliers



Processing started for real split: 5, epochs: [32]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [32]

Accurace mean(std): 0.9881162887455794(0.010845550545698447)

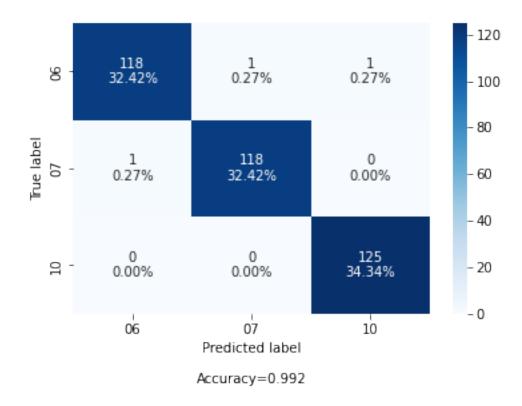
 ${\tt Classification}\ {\tt report}\ {\tt for\ all\ valid\ cross_validations\ against\ their\ tests\ sets$

	precision	recall	il-score	support	
	_				
06	0.99	0.98	0.99	120	
07	0.99	0.99	0.99	119	
10	0.99	1.00	1.00	125	
accuracy			0.99	364	
macro avg	0.99	0.99	0.99	364	
weighted avg	0.99	0.99	0.99	364	

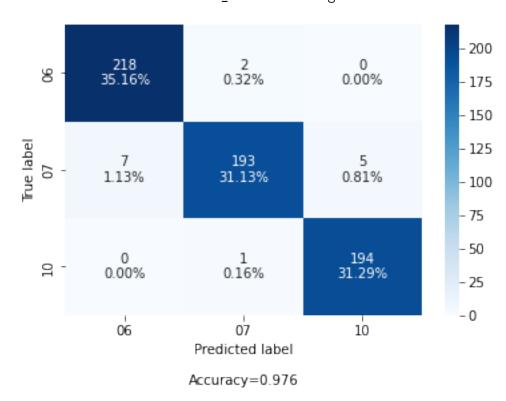
Classification report for all valid cross_validations against outliers

precision recall f1-score support

	brecision	recarr	II-SCOIE	support
06	0.97	0.99	0.98	220
07	0.98	0.94	0.96	205
10	0.97	0.99	0.98	195
accuracy			0.98	620
macro avg	0.98	0.98	0.98	620
weighted avg	0.98	0.98	0.98	620



Confusion Matrix for all valid cross_validations against outliers



Processing started for real split: 5, epochs: [64]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [64]

Accurace mean(std): 0.9520783564261827(0.07580169832277567)

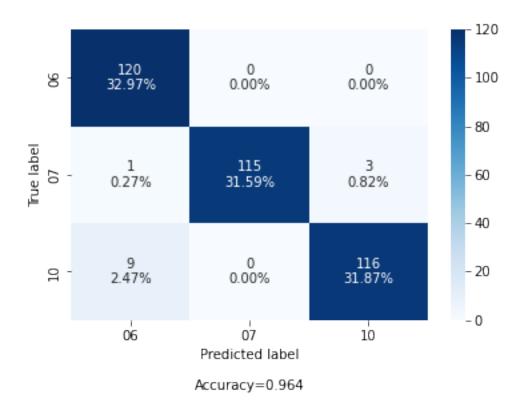
Classification report for all valid cross_validations against their tests sets

	precision	recall	f1-score	support	
06	0.92	1.00	0.96	120	
07	1.00	0.97	0.98	119	
10	0.97	0.93	0.95	125	
accuracy			0.96	364	
macro avg	0.97	0.96	0.96	364	
weighted avg	0.97	0.96	0.96	364	

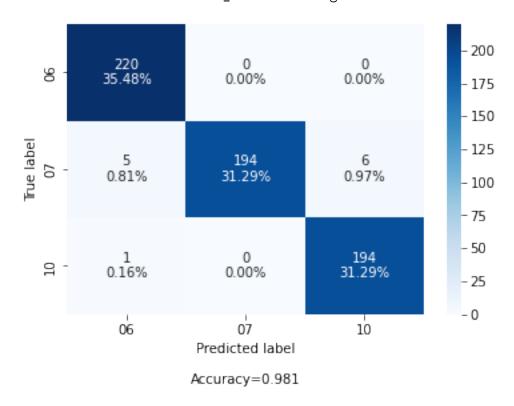
Classification report for all valid cross_validations against outliers

precision recall f1-score support

	precision	recall	il-score	support	
06	0.97	1.00	0.99	220	
07	1.00	0.95	0.97	205	
10	0.97	0.99	0.98	195	
accuracy			0.98	620	
macro avg	0.98	0.98	0.98	620	
weighted avg	0.98	0.98	0.98	620	



Confusion Matrix for all valid cross_validations against outliers



Processing started for real split: 5, epochs: [128]

Processing 1 -fold

Processing 2 -fold

Processing 3 -fold

Processing 4 -fold

Processing 5 -fold

At split estimator: 5, epochs: [128]

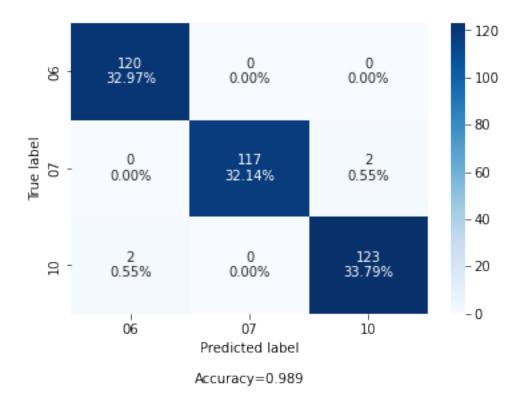
Accurace mean(std): 0.9908568443051202(0.011198337749875479)

Classification report for all valid cross_validations against their tests sets

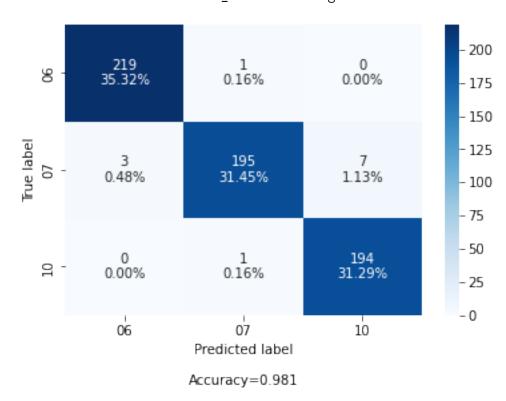
	precision	recall	f1-score	support	Ü
06	0.98	1.00	0.99	120	
07	1.00	0.98	0.99	119	
10	0.98	0.98	0.98	125	
accuracy			0.99	364	
macro avg	0.99	0.99	0.99	364	
weighted avg	0.99	0.99	0.99	364	

 ${\tt Classification}\ \ {\tt report}\ \ {\tt for\ all\ valid\ cross_validations\ against\ outliers\\$

		precision	recall	f1-score	support	
		-				
	06	0.99	1.00	0.99	220	
	07	0.99	0.95	0.97	205	
	10	0.97	0.99	0.98	195	
accur	acy			0.98	620	
macro	avg	0.98	0.98	0.98	620	
weighted	avg	0.98	0.98	0.98	620	



Confusion Matrix for all valid cross_validations against outliers



[]:[