Final

January 17, 2023

[1]:
```
import os
import numpy as np
import pandas as pd
import pymatreader as pymat
from sklearn.svm import SVC
from termcolor import colored
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.model_selection import GridSearchCV, cross_val_score,␣
 ↪train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪ConfusionMatrixDisplay, cohen_kappa_score
```

[2]:
```
path_str = os.getcwd() + '/'
```

[5]:
```
data_file_name = 'Majazi1.mat'
gt_file_name = 'Majazi1_gt.mat'
```

[7]:
```
data = pymat.read_mat(path_str + data_file_name)['Botswana']
data_gt = pymat.read_mat(path_str + gt_file_name)['Botswana_gt']
```

[8]:
```
print(f'\nShape of Data: {data.shape}\n')
print(f'\nShape of GT: {data_gt.shape}\n')
```

```

Shape of Data: (1476, 256, 145)


Shape of GT: (1476, 256)

```

[9]:
```
def BG_removal(data_3D: np.ndarray, data_gt_2D: np.ndarray) -> (np.ndarray, np.
 ↪ndarray):
    data_copy = data_3D.copy()
    gt_copy = data_gt_2D.copy()
```

```
    data_reshaped = data_copy.reshape((data_copy.shape[0] * data_copy.shape[1],
 ↪data_copy.shape[2]))
    gt_reshaped = gt_copy.ravel()
    classes_unique = np.unique(gt_reshaped)
    new_data = data_reshaped[gt_reshaped != 0]
    new_gt = gt_reshaped[gt_reshaped != 0]

    return new_data, new_gt
```

[10]:
```
data_without_BG, gt_without_BG = BG_removal(data_3D=data, data_gt_2D=data_gt)
```

[11]:
```
print(f'\nShape of the BG_removed Data: {colored(data_without_BG.shape,
 ↪"blue")}\n')
print(f' ... and its {colored("Data Type", "blue")}: {colored(data_without_BG.
 ↪dtype, "green")}\n\n')
print(f'\nShape of the BG_removed GT: {colored(gt_without_BG.shape, "blue")}\n')
print(f' ... and its {colored("Data Type", "blue")}: {colored(gt_without_BG.
 ↪dtype, "green")}\n')
```

```
Shape of the BG_removed Data: (3248, 145)

 … and its Data Type: uint16



Shape of the BG_removed GT: (3248,)

 … and its Data Type: uint8
```

[12]:
```
def class_separator(X: np.ndarray, y: np.ndarray) -> dict:

    unique_labels = np.unique(y)
    total_data = {}
    for class_name in unique_labels:
        total_data[str(class_name)], total_data[str(class_name) + '_label'] = \
        X[y == class_name], y[y == class_name]


    return total_data



def train_test_for_each_class(X: np.ndarray, y: np.ndarray, train_size_float:
 ↪float) -> (dict, dict):
```

```
    splitter = train_test_split
    data = class_separator(X, y)
    num_classes = int(len(data) / 2)
    train_data, test_data = {}, {}
    for class_name in range(1, num_classes + 1):
        train_data[str(class_name)], test_data[str(class_name)],␣
 ↪train_data[str(class_name) + '_label'], \
        test_data[str(class_name) + '_label'] = splitter(data[str(class_name)],␣
 ↪\
                                            data[str(class_name) + '_label'],␣
 ↪train_size=train_size_float, \
                                                        shuffle=True,␣
 ↪random_state=0)

    return train_data, test_data


def train_test_splitter(X: np.ndarray, y: np.ndarray, train_size_floatt: float)␣
 ↪-> \
(np.ndarray, np.ndarray, np.ndarray, np.ndarray):

    data_train, data_test = train_test_for_each_class(X, y, train_size_floatt)
    keys = list(data_train.keys())
    X_train, X_test, y_train, y_test = data_train[keys[0]], \
    data_test[keys[0]], data_train[keys[1]], data_test[keys[1]]

    re_keys = keys[2:]
    n = int(len(re_keys) / 2)
    for i in range(n):
        X_train, X_test, y_train, y_test = np.concatenate((X_train,␣
 ↪data_train[re_keys[2*i]]), axis=0), \
        np.concatenate((X_test, data_test[re_keys[2*i]]), axis=0), \
        np.concatenate((y_train, data_train[re_keys[2*i + 1]])), \
        np.concatenate((y_test, data_test[re_keys[2*i + 1]]))


    return X_train, X_test, y_train, y_test
```

[25]:
```
standard_scaler = StandardScaler()
```

[15]:
```
data_without_BG.shape
```

[15]: (3248, 145)

[16]:
```
input_data = data_without_BG
input_gt = gt_without_BG
```

[17]:
```
pca = PCA(n_components=3)
```

[18]:
```
data_reduced = pca.fit_transform(input_data)
```

[19]:
```
data_reduced.shape
```

[19]: (3248, 3)

[20]:
```
data_tensor = data_reduced.reshape((116, 28, 3))
```

[21]:
```
data_tensor.shape
```

[21]: (116, 28, 3)

[22]:
```
band1 = data_tensor[:, :, [0]].reshape((116, 28))
band2 = data_tensor[:, :, [1]].reshape((116, 28))
band3 = data_tensor[:, :, [2]].reshape((116, 28))
```

[23]:
```
band1.shape
```

[23]: (116, 28)

0.0.1 Morphology:

[26]:
```
import cv2 as cv
```

- **Opening**
- - **band 1**

[27]:
```
data_morph = band1
```

[28]:
```
kernel = np.ones((1, 1), np.uint8)
data_opening_1 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_1.shape
data_opening_1_tensor = data_opening_1.reshape((m, n, 1))
```

[29]:
```
kernel = np.ones((2, 2), np.uint8)
data_opening_2 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_2.shape
data_opening_2_tensor = data_opening_2.reshape((m, n, 1))
```

[30]:
```
kernel = np.ones((3, 3), np.uint8)
data_opening_3 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_3.shape
data_opening_3_tensor = data_opening_3.reshape((m, n, 1))
```

[31]:
```
kernel = np.ones((4, 4), np.uint8)
data_opening_4 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_4.shape
data_opening_4_tensor = data_opening_4.reshape((m, n, 1))
```

[32]:
```
band1_opening_1234 = np.concatenate((data_opening_1_tensor,␣
↪data_opening_2_tensor, data_opening_3_tensor, \
                                    data_opening_4_tensor), \
                                    axis=2)
```

- – **band 2**

[33]:
```
data_morph = band2
```

[34]:
```
kernel = np.ones((1, 1), np.uint8)
data_opening_1 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_1.shape
data_opening_1_tensor = data_opening_1.reshape((m, n, 1))
```

[35]:
```
kernel = np.ones((2, 2), np.uint8)
data_opening_2 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_2.shape
data_opening_2_tensor = data_opening_2.reshape((m, n, 1))
```

[36]:
```
kernel = np.ones((3, 3), np.uint8)
data_opening_3 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_3.shape
data_opening_3_tensor = data_opening_3.reshape((m, n, 1))
```

[37]:
```
kernel = np.ones((4, 4), np.uint8)
data_opening_4 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_4.shape
data_opening_4_tensor = data_opening_4.reshape((m, n, 1))
```

[38]:
```
band2_opening_1234 = np.concatenate((data_opening_1_tensor,␣
↪data_opening_2_tensor, data_opening_3_tensor, \
```

```
                                                   data_opening_4_tensor), \
                                                   axis=2)
```

- – **band 3**

[39]:
```
data_morph = band3
```

[40]:
```
kernel = np.ones((1, 1), np.uint8)
data_opening_1 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_1.shape
data_opening_1_tensor = data_opening_1.reshape((m, n, 1))
```

[41]:
```
kernel = np.ones((2, 2), np.uint8)
data_opening_2 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_2.shape
data_opening_2_tensor = data_opening_2.reshape((m, n, 1))
```

[42]:
```
kernel = np.ones((3, 3), np.uint8)
data_opening_3 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_3.shape
data_opening_3_tensor = data_opening_3.reshape((m, n, 1))
```

[43]:
```
kernel = np.ones((4, 4), np.uint8)
data_opening_4 = cv.morphologyEx(data_morph, cv.MORPH_OPEN, kernel)

m, n = data_opening_4.shape
data_opening_4_tensor = data_opening_4.reshape((m, n, 1))
```

[44]:
```
band3_opening_1234 = np.concatenate((data_opening_1_tensor,␣
↪data_opening_2_tensor, data_opening_3_tensor, \
                                                   data_opening_4_tensor), \
                                                   axis=2)
```

[45]:
```
data_total_opening = np.concatenate((band1_opening_1234, band2_opening_1234,␣
↪band3_opening_1234), axis=2)
data_total_opening.shape
```

[45]: (116, 28, 12)

- **Closing**
- – **band 1**

[46]:
```
data_morph = band1
```

[47]:
```
kernel = np.ones((1, 1), np.uint8)
data_closing_1 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_1.shape
data_closing_1_tensor = data_closing_1.reshape((m, n, 1))
```

[48]:
```
kernel = np.ones((2, 2), np.uint8)
data_closing_2 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_2.shape
data_closing_2_tensor = data_closing_2.reshape((m, n, 1))
```

[49]:
```
kernel = np.ones((3, 3), np.uint8)
data_closing_3 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_3.shape
data_closing_3_tensor = data_closing_3.reshape((m, n, 1))
```

[50]:
```
kernel = np.ones((4, 4), np.uint8)
data_closing_4 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_4.shape
data_closing_4_tensor = data_closing_4.reshape((m, n, 1))
```

[51]:
```
band1_closing_1234 = np.concatenate((data_closing_1_tensor,␣
 ↪data_closing_2_tensor, data_closing_3_tensor, \
                                     data_closing_4_tensor), \
                                     axis=2)
```

- – **band 2**

[52]:
```
data_morph = band2
```

[53]:
```
kernel = np.ones((1, 1), np.uint8)
data_closing_1 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_1.shape
data_closing_1_tensor = data_closing_1.reshape((m, n, 1))
```

[54]:
```
kernel = np.ones((2, 2), np.uint8)
data_closing_2 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_2.shape
data_closing_2_tensor = data_closing_2.reshape((m, n, 1))
```

[55]:
```
kernel = np.ones((3, 3), np.uint8)
data_closing_3 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)
```

```
m, n = data_closing_3.shape
data_closing_3_tensor = data_closing_3.reshape((m, n, 1))
```

[56]:
```
kernel = np.ones((4, 4), np.uint8)
data_closing_4 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_4.shape
data_closing_4_tensor = data_closing_4.reshape((m, n, 1))
```

[57]:
```
band2_closing_1234 = np.concatenate((data_closing_1_tensor,␣
↪data_closing_2_tensor, data_closing_3_tensor, \
                                    data_closing_4_tensor), \
                                    axis=2)
```

- – **band 3**

[58]:
```
data_morph = band3
```

[59]:
```
kernel = np.ones((1, 1), np.uint8)
data_closing_1 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_1.shape
data_closing_1_tensor = data_closing_1.reshape((m, n, 1))
```

[61]:
```
kernel = np.ones((2, 2), np.uint8)
data_closing_2 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_2.shape
data_closing_2_tensor = data_closing_2.reshape((m, n, 1))
```

[62]:
```
kernel = np.ones((3, 3), np.uint8)
data_closing_3 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_3.shape
data_closing_3_tensor = data_closing_3.reshape((m, n, 1))
```

[63]:
```
kernel = np.ones((4, 4), np.uint8)
data_closing_4 = cv.morphologyEx(data_morph, cv.MORPH_CLOSE, kernel)

m, n = data_closing_4.shape
data_closing_4_tensor = data_closing_4.reshape((m, n, 1))
```

[64]:
```
band3_closing_1234 = np.concatenate((data_closing_1_tensor,␣
↪data_closing_2_tensor, data_closing_3_tensor, \
                                    data_closing_4_tensor), \
                                    axis=2)
```

[65]:
```
data_total_closing = np.concatenate((band1_closing_1234, band2_closing_1234,␣
↪band3_closing_1234), axis=2)
data_total_closing.shape
```

[65]: (116, 28, 12)

[66]:
```
principal_band = data_tensor[:, :, 0].reshape((116, 28, 1))
input_data_opening = data_total_opening
input_data_closing = data_total_closing
```

0.0.2 Data after Feature Extraction

[67]:
```
input_data_25 = np.concatenate((principal_band, input_data_opening,␣
↪input_data_closing), axis=2)
input_data_25.shape
```

[67]: (116, 28, 25)

[68]:
```
data_reshaped = input_data_25.reshape((116 * 28, 25))
```

[69]:
```
data_scaled = standard_scaler.fit_transform(data_reshaped)
data_scaled.var()
```

[69]: 1.0000000000000007

- **Data Separating**

[70]:
```
train_size_list = [0.05]
data = {}
for train_size_float in train_size_list: data['X_train_' +␣
↪str(train_size_float)], \
    data['X_test_' + \
    str(train_size_float)], data['y_train_' + str(train_size_float)], \
    data['y_test_' + str(train_size_float)] =\
            train_test_splitter(data_without_BG, gt_without_BG,␣
↪train_size_floatt=train_size_float)
```

[71]:
```
train_size_list = [0.05]
data_scaled = {}

for train_size in train_size_list:
    data_scaled['X_train_' + str(train_size)] = \
    standard_scaler.fit_transform(data['X_train_' + str(train_size)])
    data_scaled['X_test_' + str(train_size)] = standard_scaler.
↪fit_transform(data['X_test_' + str(train_size)])
    data_scaled['y_train_' + str(train_size)] = data['y_train_' +␣
↪str(train_size)]
```

```
    data_scaled['y_test_' + str(train_size)] = data['y_test_' + str(train_size)]
```

[72]:

```
train_size_tuple = (0.05, )
k_fold_tuple = range(2, 16)

parameters_for_k_fold_dict = {'train_size': train_size_tuple, 'k_fold':␣
 ↪k_fold_tuple}
total_length = 1
for key_name_str in parameters_for_k_fold_dict.keys():
    total_length *= len(parameters_for_k_fold_dict[key_name_str])


train_size_stored_values = np.zeros(total_length)
acc_mean_stored_values = np.zeros(total_length)
k_fold_stored_values = np.zeros(total_length)


clf_without_pca = SVC()
count = 0
for train_size in parameters_for_k_fold_dict['train_size']:
    X_train, y_train, X_test, y_test = data_scaled['X_train_' +␣
 ↪str(train_size)], \
    data_scaled['y_train_' + str(train_size)], data_scaled['X_test_' +␣
 ↪str(train_size)], \
    data_scaled['y_test_' + str(train_size)]
    clf_without_pca.fit(X_train, y_train)
    for k_fold in parameters_for_k_fold_dict['k_fold']:
        count += 1
        scores = cross_val_score(clf_without_pca, X_train, y_train, cv=k_fold)
        acc_mean = scores.mean()
        train_size_stored_values[count - 1] = train_size
        acc_mean_stored_values[count - 1] = acc_mean
        k_fold_stored_values[count - 1] = k_fold

df_for_k_fold = pd.DataFrame({'Train Size': train_size_stored_values,␣
 ↪'K-fold(CV)': k_fold_stored_values,\
'Mean of Accuracy': acc_mean_stored_values})
```

```
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=6.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
```

```
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=7.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=8.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=9.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=10.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=11.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=12.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=13.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=14.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=15.
  warnings.warn(
```

[73]:
```
df_for_k_fold
```

[73]:

	Train Size	K-fold(CV)	Mean of Accuracy
0	0.05	2.0	0.576923
1	0.05	3.0	0.673077
2	0.05	4.0	0.698718
3	0.05	5.0	0.711492
4	0.05	6.0	0.724359
5	0.05	7.0	0.697911
6	0.05	8.0	0.705263
7	0.05	9.0	0.749092

```
8          0.05        10.0          0.765000
9          0.05        11.0          0.742424
10         0.05        12.0          0.782051
11         0.05        13.0          0.775641
12         0.05        14.0          0.768939
13         0.05        15.0          0.758788
```

[74]:
```python
df1 = df_for_k_fold[df_for_k_fold['Train Size'] == 0.05]
df1
```

[74]:

	Train Size	K-fold(CV)	Mean of Accuracy
0	0.05	2.0	0.576923
1	0.05	3.0	0.673077
2	0.05	4.0	0.698718
3	0.05	5.0	0.711492
4	0.05	6.0	0.724359
5	0.05	7.0	0.697911
6	0.05	8.0	0.705263
7	0.05	9.0	0.749092
8	0.05	10.0	0.765000
9	0.05	11.0	0.742424
10	0.05	12.0	0.782051
11	0.05	13.0	0.775641
12	0.05	14.0	0.768939
13	0.05	15.0	0.758788

[75]:
```python
df1_result = df1[df1['Mean of Accuracy'] == (df1['Mean of Accuracy']).max()]
df1_result
```

[75]:

	Train Size	K-fold(CV)	Mean of Accuracy
10	0.05	12.0	0.782051

[76]:
```python
svc = SVC(kernel='rbf', random_state=0)
```

[77]:
```python
pipe = Pipeline(steps=[("svc", svc)])
```

[79]:
```python
param_grid = {'svc__gamma': np.linspace(0, 1, 11)}
```

[80]:
```python
input_data_dict = data_scaled
```

[81]:
```python
train_size = 0.05
best_k_fold = 12
X_train, y_train = input_data_dict['X_train_' + str(train_size)],␣
↪input_data_dict['y_train_' + str(train_size)]
search = GridSearchCV(pipe, param_grid, cv=best_k_fold)
search.fit(X_train, y_train)
```

```
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_split.py:684: UserWarning: The least populated
class in y has only 4 members, which is less than n_splits=12.
  warnings.warn(
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_validation.py:378: FitFailedWarning:
12 fits failed out of a total of 132.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
12 fits failed with the following error:
Traceback (most recent call last):
  File "/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_validation.py", line 686, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/home/shahin/.local/lib/python3.10/site-packages/sklearn/pipeline.py",
line 382, in fit
    self._final_estimator.fit(Xt, y, **fit_params_last_step)
  File "/home/shahin/.local/lib/python3.10/site-packages/sklearn/svm/_base.py",
line 237, in fit
    raise ValueError(msg)
ValueError: gamma value must be > 0; 0.0 is invalid. Use a positive number or
use 'auto' to set gamma to a value of 1 / n_features.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/home/shahin/.local/lib/python3.10/site-
packages/sklearn/model_selection/_search.py:953: UserWarning: One or more of the
test scores are non-finite: [       nan 0.83333333 0.79487179 0.75
0.73076923 0.69871795
 0.60897436 0.51923077 0.44230769 0.38461538 0.33974359]
  warnings.warn(
```

[81]:
```
GridSearchCV(cv=12, estimator=Pipeline(steps=[('svc', SVC(random_state=0))]),
             param_grid={'svc__gamma': array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6,
0.7, 0.8, 0.9, 1. ])})
```

[82]:
```
from termcolor import colored
```

[83]:
```
best_params = search.best_params_
best_gamma = best_params['svc__gamma']
print(f'\n\n\u03B3 = {colored(best_gamma, "blue")}\n')
```

= 0.1

[84]:
```
best_score = search.best_score_
print(f'\nBest Accuracy is: {colored(best_score, "blue")}\n')
```

Best Accuracy is: 0.8333333333333335

[85]:
```
train_size = 0.05
clf = SVC(kernel='rbf', gamma=best_gamma)
X_train, y_train, X_test, y_test = input_data_dict['X_train_' +␣
 ↪str(train_size)], \
input_data_dict['y_train_' + str(train_size)], input_data_dict['X_test_' +␣
 ↪str(train_size)], \
input_data_dict['y_test_' + str(train_size)]
clf.fit(X_train, y_train)
```

[85]: SVC(gamma=0.1)

[86]:
```
y_pred = clf.predict(X_test)
ov_acc = accuracy_score(y_test, y_pred)
conf_mat = confusion_matrix(y_test, y_pred)
kappa = cohen_kappa_score(y_test, y_pred)
acc_for_each_class = conf_mat.diagonal()/conf_mat.sum(axis=1)
df_result1 = pd.DataFrame({'Class': range(1, 15), 'Accuracy':␣
 ↪acc_for_each_class})
df_result1
```

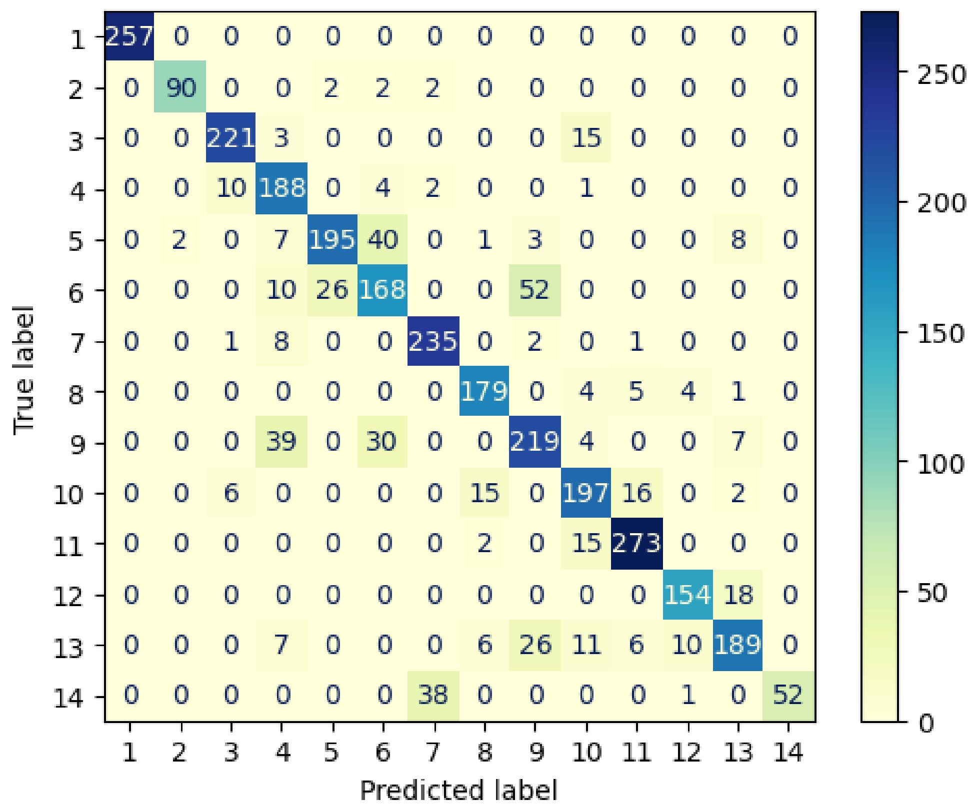
[86]:

	Class	Accuracy
0	1	1.000000
1	2	0.937500
2	3	0.924686
3	4	0.917073
4	5	0.761719
5	6	0.656250
6	7	0.951417
7	8	0.927461
8	9	0.732441
9	10	0.834746
10	11	0.941379
11	12	0.895349
12	13	0.741176
13	14	0.571429

[87]:

```
cmap_list = ['Greys', 'Purples', 'Blues', 'Greens', 'Oranges', 'Reds', \
                      'YlOrBr', 'YlOrRd', 'OrRd', 'PuRd', 'RdPu', 'BuPu',\
                      'GnBu', 'PuBu', 'YlGnBu', 'PuBuGn', 'BuGn', 'YlGn']

disp = ConfusionMatrixDisplay(confusion_matrix=conf_mat, display_labels=clf.
 ↪classes_)
disp.plot(cmap=cmap_list[14])
plt.show()
```



[88]:

```
print(f'\nOverall Accuracy: {colored(ov_acc, "green")}\n\n\u03BA =␣
 ↪{colored(kappa, "green")}\n')
```

```
Overall Accuracy: 0.8463777490297542

 = 0.833495563774022
```

Classification Map

[118]:
```
X_3d = pymat.read_mat(path_str + data_file_name)['Botswana']
y_2d = pymat.read_mat(path_str + gt_file_name)['Botswana_gt']
```

[119]:
```
X_test = X_3d.reshape((X_3d.shape[0]*X_3d.shape[1], 145))
y_test = y_2d.ravel()
```

[120]:
```
y_pred = clf.predict(X_test)
```

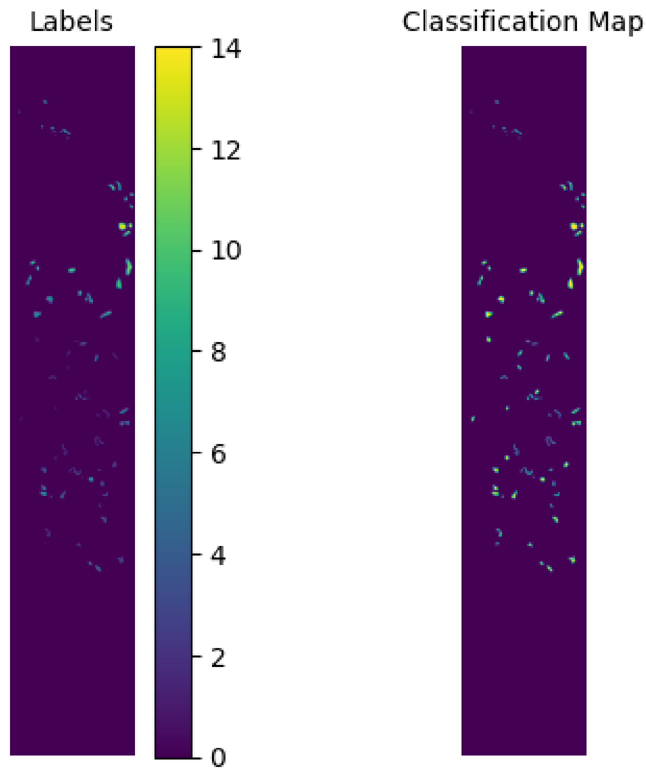
[124]:
```
y_pred[y_test == 0] = 0
```

[125]:
```
y_pred_plot = y_pred.reshape((1476, 256))
y_test_plot = y_test.reshape((1476, 256))
```

[126]:
```
y_test_plot.dtype
```

[126]:
```
dtype('uint8')
```

[132]:
```
plt.figure(1)
plt.subplot(1, 2, 1), plt.imshow(y_test_plot), plt.axis('off'), plt.
 ↪title('Labels', fontsize=10)
plt.colorbar()
plt.subplot(1, 2, 2), plt.imshow(y_pred_plot), plt.axis('off'), plt.
 ↪title('Classification Map', fontsize=10)
plt.show()
```



End Classification Map

Classification Map for Test Data

[90]:
```
plt.figure(1)
plt.subplot(1, 2, 1), plt.imshow(selected_y_pred_reshaped), \
plt.axis('off'), plt.title('Class. Map for Test Data')

plt.subplot(1, 2, 2), plt.imshow(selected_y_test_reshaped), \
plt.axis('off'), plt.title('Class. Map for Labels')
plt.show()
```

End of Classification Map for Test Data

```
[91]: my_ov_acc = len(y_pred[y_pred == y_test]) / len(y_pred)
      print(f'\n{colored("Ov. Accuracy:", "green")} {my_ov_acc: 0.3f}\n')
```

```
Ov. Accuracy:  0.846
```

```
[92]: AA = df_result1['Accuracy'].mean()
      AA
```

```
[92]: 0.8423304772142849
```

```
[93]: gt = gt_without_BG.flatten()
```

```
[94]: num_class_1 = len(data_without_BG[gt == 1])
      num_class_1
```

```
[94]: 270
```

```
[95]: num_class_14 = len(data_without_BG[gt == 14])
      num_class_14
```

```
[95]: 95
```