1 X_SVM_Center

April 1, 2023

PAVIA Random Forest 10 2022

[ ]:
```
import plotly.express as px
import matplotlib.pyplot as plt
import numpy as np
#sns.axes_style('whitegrid');
#fig = plt.figure(figsize = (12, 6))
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
import seaborn as sn
#########################################################################################



 ␣
 ↪#########################################################################################
```

[ ]:
```
#  Read the Data #
```

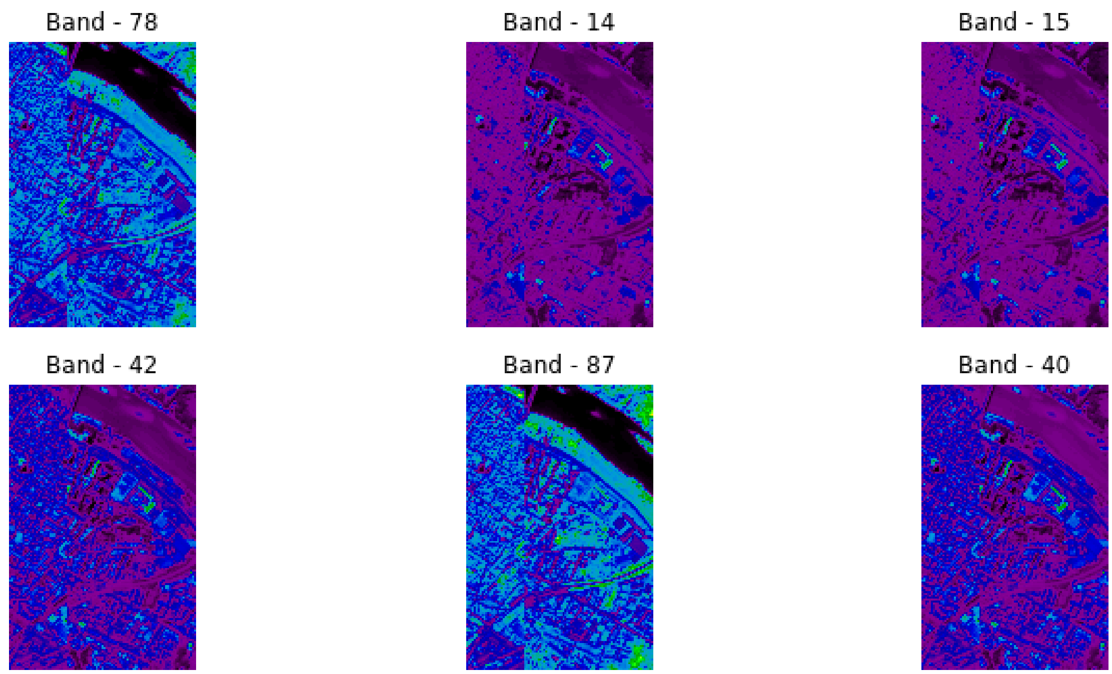
[ ]:
```
from scipy.io import loadmat

def read_HSI():
  X = loadmat('Pavia.mat')['pavia']
  y = loadmat('Pavia_gt.mat')['pavia_gt']
  print(f"X shape: {X.shape}\ny shape: {y.shape}")
  return X, y

X, y = read_HSI()
```

```
X shape: (1096, 715, 102)
y shape: (1096, 715)
```

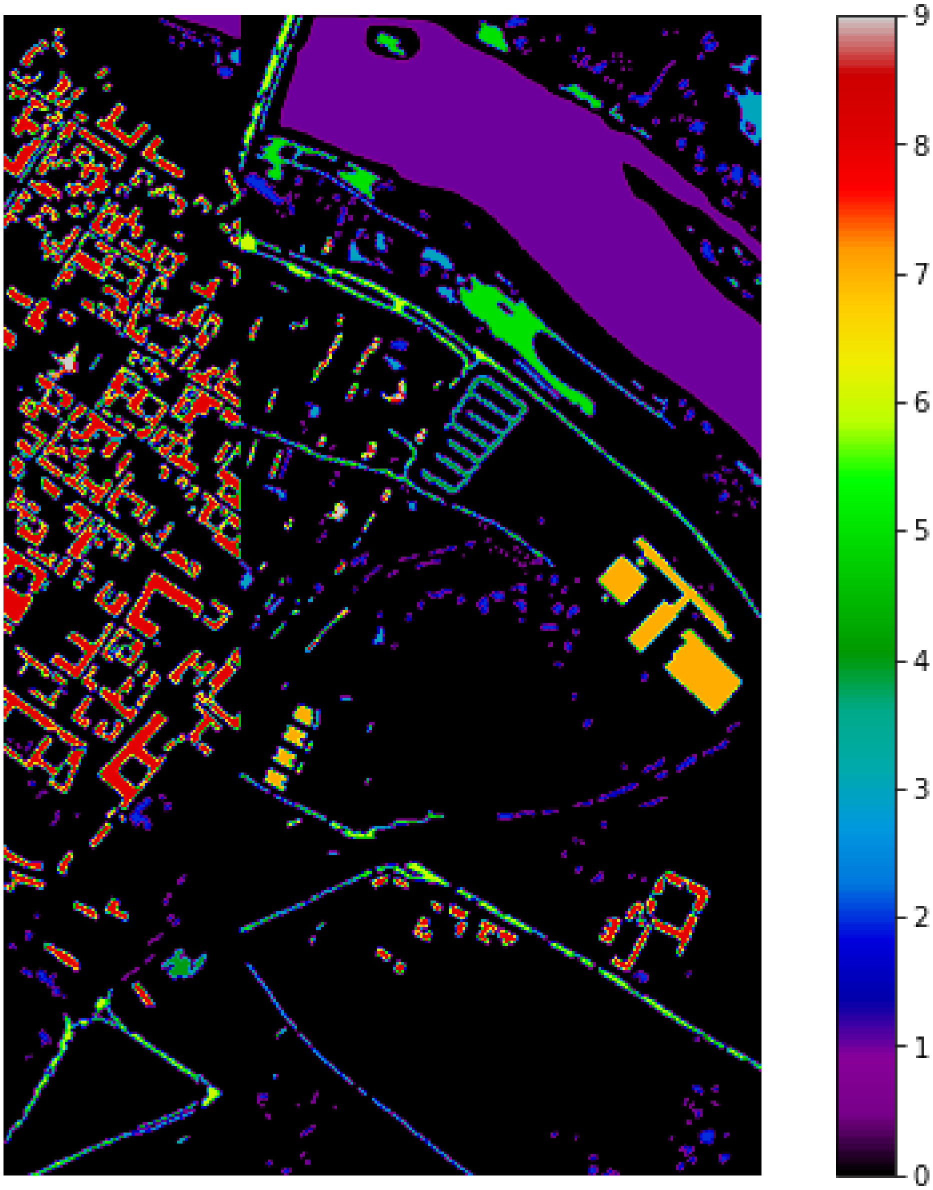
[ ]:
```
 # Visualize Bands #
import matplotlib.pyplot as plt
import numpy as np
```

```
import seaborn as sns
sns.axes_style('whitegrid')
fig = plt.figure(figsize = (12, 6))
for i in range(1, 1+6):
    fig.add_subplot(2,3, i)
    q = np.random.randint(X.shape[2])
    plt.imshow(X[:,:,q], cmap='nipy_spectral')
    plt.axis('off')
    plt.title(f'Band - {q}')
    plt.savefig('IP_Bands.png')

X, y = read_HSI()
```

```
X shape: (1096, 715, 102)
y shape: (1096, 715)
```




```
[ ]: plt.figure(figsize=(10, 8))
     plt.imshow(y, cmap='nipy_spectral')
     plt.colorbar()
     plt.axis('off')
     plt.savefig('IP_GT.png')
     plt.show()
```



[ ]:
```
## Convert the dataset into csv

import pandas as pd
import numpy as np

def extract_pixels(X, y):
  q = X.reshape(-1, X.shape[2])
  df = pd.DataFrame(data = q)
  df = pd.concat([df, pd.DataFrame(data = y.ravel())], axis=1)
  df.columns= [f'band{i}' for i in range(1, 1+X.shape[2])]+['class']
```

```python
    df.to_csv('Dataset.csv')
    return df

df = extract_pixels(X, y)
```

[ ]:
```python
df.head()
```

[ ]:

	band1	band2	band3	band4	band5	band6	band7	band8	band9	band10	...
0	854	601	350	266	138	118	178	194	257	269	...
1	527	642	575	294	123	168	207	154	209	299	...
2	374	322	179	87	169	268	360	339	286	309	...
3	706	520	560	572	425	243	271	272	258	276	...
4	1120	1027	592	414	407	463	417	365	332	334	...

	band94	band95	band96	band97	band98	band99	band100	band101	band102
0	3759	3773	3779	3752	3690	3671	3664	3636	3643
1	3873	3902	3921	3861	3854	3882	3834	3725	3768
2	4443	4472	4428	4353	4306	4284	4318	4311	4321
3	3972	4006	4032	3975	3946	3954	3944	3936	3939
4	4502	4485	4479	4445	4364	4290	4268	4235	4272

	class
0	0
1	0
2	0
3	0
4	0

[5 rows x 103 columns]

[ ]:
```python
df.iloc[:, :-1].describe()
```

[ ]:

	band1	band2	band3	band4
count	783640.000000	783640.000000	783640.000000	783640.000000
mean	756.377920	690.307315	643.929436	650.127791
std	396.311133	395.274284	403.694296	427.116754
min	0.000000	0.000000	0.000000	0.000000
25%	496.000000	428.000000	368.000000	348.000000
50%	730.000000	647.000000	589.000000	595.000000
75%	974.000000	893.000000	846.000000	863.000000
max	8000.000000	8000.000000	8000.000000	8000.000000

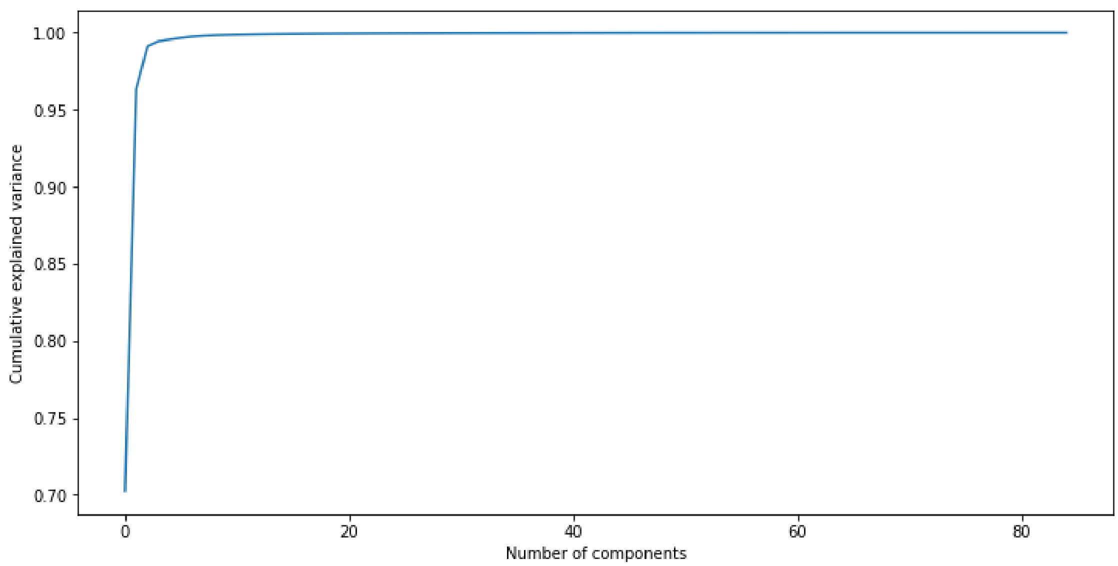
	band5	band6	band7	band8
count	783640.000000	783640.000000	783640.000000	783640.000000
mean	666.007831	671.834180	675.212941	672.903627
std	449.411658	462.099314	469.061070	471.706490
min	0.000000	0.000000	0.000000	0.000000

```
25%       345.000000     342.000000     339.000000     332.000000
50%       613.000000     617.000000     614.000000     606.000000
75%       884.000000     888.000000     890.000000     884.000000
max      8000.000000    8000.000000    8000.000000    8000.000000

               band9         band10  …         band93         band94  \
count  783640.000000  783640.000000  …  783640.000000  783640.000000
mean      674.686433     680.781220  …    1697.386833    1699.732885
std       478.086505     488.054049  …    1101.857332    1101.298899
min         0.000000       0.000000  …       0.000000       0.000000
25%       327.000000     324.000000  …     883.000000     886.000000
50%       604.000000     607.000000  …    1683.000000    1686.000000
75%       885.000000     894.000000  …    2410.000000    2412.000000
max      8000.000000    8000.000000  …    8000.000000    8000.000000

              band95         band96         band97         band98  \
count  783640.000000  783640.000000  783640.000000  783640.000000
mean     1703.646257    1699.515219    1692.456623    1682.842181
std      1101.531161    1094.214808    1080.862130    1066.634222
min         0.000000       0.000000       0.000000       0.000000
25%       890.000000     891.000000     897.000000     902.000000
50%      1689.000000    1686.000000    1680.000000    1672.000000
75%      2417.000000    2411.000000    2395.000000    2374.000000
max      8000.000000    8000.000000    8000.000000    8000.000000

              band99        band100        band101        band102
count  783640.000000  783640.000000  783640.000000  783640.000000
mean     1671.153438    1658.587115    1638.005885    1643.461353
std      1058.692782    1054.097477    1044.365696    1051.107124
min         0.000000       0.000000       0.000000       0.000000
25%       898.000000     889.000000     874.000000     874.000000
50%      1661.000000    1648.000000    1627.000000    1634.000000
75%      2356.000000    2341.000000    2316.000000    2328.000000
max      8000.000000    8000.000000    8000.000000    8000.000000

[8 rows x 102 columns]
```

[ ]:

```python
## Principal Component Analysis(PCA)

from sklearn.decomposition import PCA

pca = PCA(n_components = 85)

principalComponents = pca.fit_transform(df.iloc[:, :-1].values)

ev=pca.explained_variance_ratio_
```

```
plt.figure(figsize=(12, 6))
plt.plot(np.cumsum(ev))
plt.xlabel('Number of components')
plt.ylabel('Cumulative explained variance')


plt.show()
```

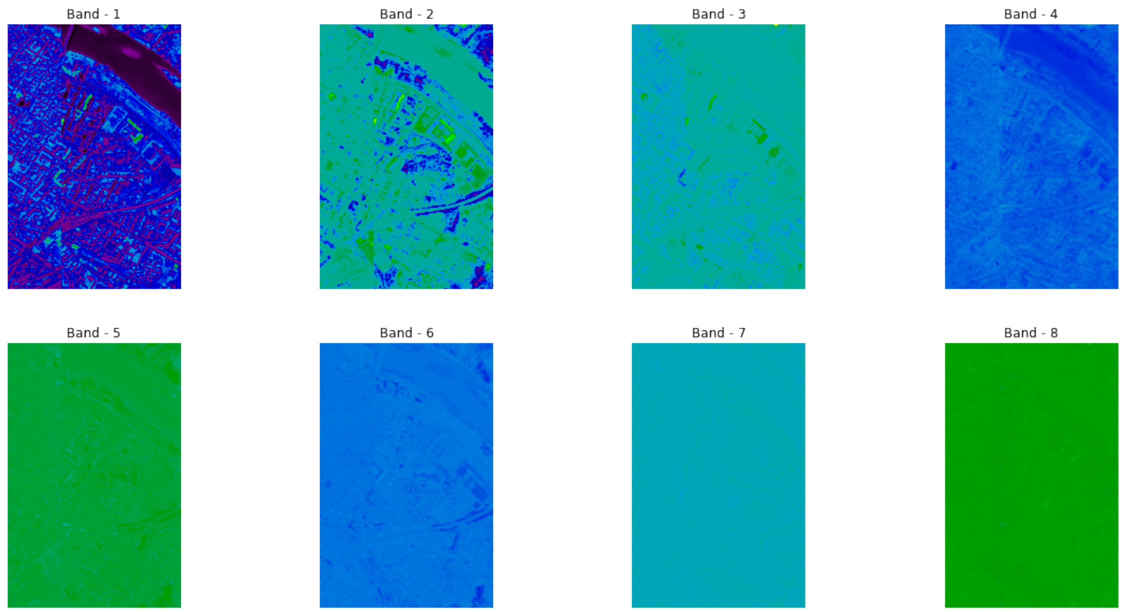


[ ]:
```
## Select 40 as the no.of components for PCA
pca = PCA(n_components = 40)
dt = pca.fit_transform(df.iloc[:, :-1].values)
q = pd.concat([pd.DataFrame(data = dt), pd.DataFrame(data = y.ravel())], axis =
↪1)
q.columns = [f'PC-{i}' for i in range(1,41)]+['class']
q.head()
```

[ ]:
```
          PC-1          PC-2         PC-3        PC-4        PC-5        PC-6  \
0  3903.296351 -10579.424391   969.223926  133.981938  -60.165558 -419.585371
1  4489.219702 -10495.362304  1200.288715 -120.391541   82.721431 -314.886175
2  7537.525472 -11984.664882  1063.019707 -516.632363  -82.281712  181.350808
3  5856.807574 -10092.589084  1308.820550 -202.800970   67.710994 -354.438385
4  7812.803615 -11935.049725  1544.780731  307.047887 -579.237495 -340.076493

         PC-7        PC-8        PC-9       PC-10  …      PC-32      PC-33  \
0  -26.111761  230.439417  130.689057   -9.264859  … -22.567974 -34.159705
1  213.728724 -168.935354  235.476246 -110.077835  … -16.046955  28.165469
2  -84.127048  176.169867  -14.801842 -139.918927  …  15.444590  16.771598
3  154.679932 -236.993154   28.490321  139.822899  …   0.794270 -26.930473
```

```
4   -2.565575  126.552586   28.922063   10.033348  …   3.051910 -22.535434

       PC-34      PC-35      PC-36      PC-37      PC-38      PC-39  \
0  26.669711 -55.005859 -44.071105 -19.261431   2.716232   8.160080
1   4.812089 -12.943369 -23.978494  17.704949  54.060669  -0.699653
2 -54.367347 -28.077307  34.793647 -27.934291  26.160026  -8.710876
3   5.761637  46.462322  11.700253  47.131453 -37.957915  12.828978
4  17.081050  17.559010 -11.547039  -8.279827 -25.725183  21.448004

       PC-40  class
0  -1.501953      0
1  39.507699      0
2  10.561863      0
3 -23.262363      0
4  99.140224      0

[5 rows x 41 columns]
```

[ ]:
```
########### Display the bands after PCA #############

fig = plt.figure(figsize = (20, 10))

for i in range(1, 1+8):
    fig.add_subplot(2,4, i)
    plt.imshow(q.loc[:, f'PC-{i}'].values.reshape(1096, 715),␣
 ↪cmap='nipy_spectral') # 1096
    plt.axis('off')
    plt.title(f'Band - {i}')

plt.savefig('IP_PCA_Bands.png')
```



Random forest modal

[ ]:
```python
from sklearn.ensemble import RandomForestClassifier

x = q[q['class'] != 0]

X = x.iloc[:, :-1].values

y = x.loc[:, 'class'].values

names = ['1. Water', '2. Trees', '3. Asphalt', '4. Self-Blocking Bricks',
                 '5. Bitumen','6. Tiles', '7. Shadows',
                 '8. Meadows', '9. Bare Soil']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=11, stratify=y)
```

[ ]:
```python
# RF
#model = RandomForestClassifier(n_estimators=1000)

#model.fit(X_train, y_train)
#ypred = model.predict(X_test)
```

[ ]:
```python
import matplotlib.pyplot as plt



def plot_hist(hist):
```

```
    plt.plot(hist.history["accuracy"])
    plt.plot(hist.history["val_accuracy"])
    plt.title("model accuracy")
    plt.ylabel("accuracy")
    plt.xlabel("epoch")
    plt.legend(["train", "validation"], loc="upper left")
    plt.show()
```

[ ]:
```
#history=model.fit(X_train, y_train)
```

[ ]:
```

```

[ ]:
```
from sklearn.metrics import accuracy_score, f1_score, precision_score,␣
 ↪confusion_matrix

def my_metrics(y_true, y_pred):
    accuracy=accuracy_score(y_true, y_pred)
    precision=precision_score(y_true, y_pred,average='weighted')
    f1Score=f1_score(y_true, y_pred, average='weighted')
    print("Accuracy  : {}".format(accuracy))
    print("Precision : {}".format(precision))
    print("f1Score : {}".format(f1Score))
    cm=confusion_matrix(y_true, y_pred)
    print(cm)
    return accuracy, precision, f1Score
```

[ ]:
```
from tensorflow.keras.losses import sparse_categorical_crossentropy
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import KFold
from tensorflow.keras import layers

import numpy as np
from sklearn.metrics import confusion_matrix, accuracy_score,␣
 ↪classification_report, cohen_kappa_score
import matplotlib.pyplot as plt
from keras.applications.inception_resnet_v2 import InceptionResNetV2,␣
 ↪preprocess_input
from keras.layers import Dense, GlobalAveragePooling2D, Dropout, Flatten
from keras.models import Model

import tensorflow as tf

# configuration
confmat = 0
batch_size = 50
loss_function = sparse_categorical_crossentropy
no_classes = 9
```

```python
no_epochs = 20
optimizer = Adam()
verbosity = 1
num_folds = 5

Xtrain=X_train
Xtest=X_test
ytrain=y_train
ytest=y_test

NN=len(Xtrain)
#NN=500

input_train=Xtrain[0:NN]
target_train=ytrain[0:NN]

input_test=Xtest[0:NN]
target_test=ytest[0:NN]

# Determine shape of the data
#input_shape = (img_width, img_height, img_num_channels)

# Parse numbers as floats
#input_train = input_train.astype('float32')
#input_test = input_test.astype('float32')

# Normalize data
#input_train = input_train / 255
#input_test = input_test / 255

# Define per-fold score containers
acc_per_fold = []
loss_per_fold = []

Y_pred=[]
y_pred=[]
# Merge inputs and targets
inputs = np.concatenate((input_train, input_test), axis=0)
targets = np.concatenate((target_train, target_test), axis=0)

# Define the K-fold Cross Validator
kfold = KFold(n_splits=num_folds, shuffle=True)

# K-fold Cross Validation model evaluation
fold_no = 1
for train, test in kfold.split(inputs, targets):
```

```
 #  model architecture

 # Compile the model
 #model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])

  # Compile the model
# model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])

 #model = build_model(num_classes=9)
# model = RandomForestClassifier(n_estimators=1000)
 model =  SVC(C = 100, kernel = 'rbf', cache_size = 10*1024)



 #model.compile(loss=loss_function, optimizer='rmsprop',metrics=['accuracy'])

 #model.summary()

 #unfreeze_model(model)
 #model.compile(loss=loss_function, optimizer='rmsprop',metrics=['accuracy'])



 # Generate a print
 print('------------------------------------------------------------------------')
 print(f'Training for fold {fold_no} ...')

 # Fit data to model
 #model.summary()

# history = model.fit(inputs[train], targets[train],
   #          validation_data = (inputs[test],targets[test]),
   #          epochs=no_epochs,verbose=2 )
 history=model.fit(X_train, y_train)

 #plt.figure()
 #plot_hist(history)
# hist = model.fit(inputs[train], targets[train],
  #                 steps_per_epoch=(29943/batch_size),
  #                 epochs=5,
  #                 validation_data=(inputs[test],targets[test]),
  #                 validation_steps=(8000/batch_size),
  #                 initial_epoch=20,
  #                 verbose=1 )
```

```
  plt.figure()



  # Generate generalization metrics
  #scores = model.predict(inputs[test], targets[test])
  #print(f'Score for fold {fold_no}: {model.metrics_names[0]} of {scores[0]};␣
↪{model.metrics_names[1]} of {scores[1]*100}%')
  #acc_per_fold.append(scores[1] * 100)
  #loss_per_fold.append(scores[0])



  # confusion_matrix
  y_pred = model.predict(inputs[test])

  #ypred = model.predict(X_test)

  #y_pred = np.argmax(Y_pred, axis=1)
  #target_test=targets[test]

  valAcc, valPrec, valFScore = my_metrics(targets[test], y_pred)


  confusion = confusion_matrix(targets[test], y_pred)
  print(classification_report(targets[test], y_pred, target_names = names))


  df_cm = pd.DataFrame(confusion, columns=np.unique(names), index = np.
↪unique(names))
  df_cm.index.name = 'Actual'
  df_cm.columns.name = 'Predicted'
  plt.figure(figsize = (9,9))
  sn.set(font_scale=1.4)#for label size
  sn.heatmap(df_cm, cmap="Reds", annot=True,annot_kws={"size": 16}, fmt='d')
  plt.savefig('cmap.png', dpi=300)
  print(confusion_matrix(targets[test], y_pred))

  confmat    = confmat + confusion;


  # Increase fold number
  fold_no = fold_no + 1

# == average scores ==
print('------------------------------------------------------------------------')
print('Score per fold')
```

```
for i in range(0, len(acc_per_fold)):
  ␣
  ↪print('------------------------------------------------------------------------')
  print(f'> Fold {i+1} - Loss: {loss_per_fold[i]} - Accuracy:␣
  ↪{acc_per_fold[i]}%')
print('------------------------------------------------------------------------')
print('Average scores for all folds:')
print(f'> Accuracy: {np.mean(acc_per_fold)} (+- {np.std(acc_per_fold)})')
print(f'> Loss: {np.mean(loss_per_fold)}')
print('------------------------------------------------------------------------')

Overall_Conf = pd.DataFrame(confmat, columns=np.unique(names), index = np.
 ↪unique(names))
Overall_Conf.index.name = 'Actual Overall'
Overall_Conf.columns.name = 'Predicted Overall'
plt.figure(figsize = (10,8))
sn.set(font_scale=1.4)#for label size
sn.heatmap(Overall_Conf, cmap="Reds", annot=True,annot_kws={"size": 16},␣
 ↪fmt='d')
plt.savefig('cmap.png', dpi=300)
print(Overall_Conf)
```

```
------------------------------------------------------------------------
Training for fold 1 …
Accuracy  : 0.9932165637339273
Precision : 0.9932680793301017
f1Score : 0.9932268979862107
[[13081     0     0     0     0     0     0     0     0]
 [    0  1529    29     0     0     0     0     0     0]
 [    0    20   603     0     2     0     0     0     0]
 [    0     0     0   512    14     1    18     0     0]
 [    0     0     3    14  1340     0     0     3     0]
 [    0     0     0     8     1  1833     8     0     0]
 [    0     0     0    17     1    42  1348     1     0]
 [    0     0     0     4     1    11     3  8613     0]
 [    0     0     0     0     0     0     0     0   571]]
                         precision    recall  f1-score   support

               1. Water       1.00      1.00      1.00     13081
               2. Trees       0.99      0.98      0.98      1558
             3. Asphalt       0.95      0.96      0.96       625
4. Self-Blocking Bricks       0.92      0.94      0.93       545
             5. Bitumen       0.99      0.99      0.99      1360
               6. Tiles       0.97      0.99      0.98      1850
             7. Shadows       0.98      0.96      0.97      1409
             8. Meadows       1.00      1.00      1.00      8632
           9. Bare Soil       1.00      1.00      1.00       571
```

```
              accuracy                           0.99     29631
             macro avg       0.98      0.98      0.98     29631
          weighted avg       0.99      0.99      0.99     29631

[[13081     0     0     0     0     0     0     0     0]
 [    0  1529    29     0     0     0     0     0     0]
 [    0    20   603     0     2     0     0     0     0]
 [    0     0     0   512    14     1    18     0     0]
 [    0     0     3    14  1340     0     0     3     0]
 [    0     0     0     8     1  1833     8     0     0]
 [    0     0     0    17     1    42  1348     1     0]
 [    0     0     0     4     1    11     3  8613     0]
 [    0     0     0     0     0     0     0     0   571]]
------------------------------------------------------------------------
Training for fold 2 …
Accuracy  : 0.9938240356383518
Precision : 0.9938634845611976
f1Score : 0.9938190133287623
[[13293     0     0     0     0     0     0     0     0]
 [    0  1522    27     0     0     0     0     0     0]
 [    0    21   595     0     2     0     0     0     0]
 [    0     0     0   506    11     2    13     2     0]
 [    0     0     1    10  1302     0     0     1     0]
 [    0     0     0     3     0  1817     5     2     0]
 [    0     0     0    12     3    46  1404     5     0]
 [    0     0     0     3     3    11     0  8444     0]
 [    0     0     0     0     0     0     0     0   565]]
                         precision    recall  f1-score   support

              1. Water       1.00      1.00      1.00     13293
              2. Trees       0.99      0.98      0.98      1549
            3. Asphalt       0.96      0.96      0.96       618
4. Self-Blocking Bricks       0.95      0.95      0.95       534
            5. Bitumen       0.99      0.99      0.99      1314
              6. Tiles       0.97      0.99      0.98      1827
            7. Shadows       0.99      0.96      0.97      1470
            8. Meadows       1.00      1.00      1.00      8461
          9. Bare Soil       1.00      1.00      1.00       565

              accuracy                           0.99     29631
             macro avg       0.98      0.98      0.98     29631
          weighted avg       0.99      0.99      0.99     29631

[[13293     0     0     0     0     0     0     0     0]
 [    0  1522    27     0     0     0     0     0     0]
 [    0    21   595     0     2     0     0     0     0]
 [    0     0     0   506    11     2    13     2     0]
```

```
 [    0     0     1    10  1302     0     0     1     0]
 [    0     0     0     3     0  1817     5     2     0]
 [    0     0     0    12     3    46  1404     5     0]
 [    0     0     0     3     3    11     0  8444     0]
 [    0     0     0     0     0     0     0     0   565]]
--------------------------------------------------------------------------
Training for fold 3 …
Accuracy  : 0.9932163347958151
Precision : 0.9932437416582498
f1Score : 0.9932018161845584
[[13255     0     0     0     0     0     0     0     0]
 [    0  1488    20     0     0     0     0     0     0]
 [    0    20   611     0     2     0     0     0     0]
 [    0     0     0   504    12     4    19     2     0]
 [    0     0     3    12  1316     0     0     1     0]
 [    0     0     0     6     1  1798     6     1     0]
 [    0     0     0    11     6    57  1368     3     0]
 [    0     0     0     2     5     6     2  8518     0]
 [    0     0     0     0     0     0     0     0   571]]
                         precision    recall  f1-score   support

             1. Water       1.00      1.00      1.00     13255
             2. Trees       0.99      0.99      0.99      1508
           3. Asphalt       0.96      0.97      0.96       633
4. Self-Blocking Bricks       0.94      0.93      0.94       541
           5. Bitumen       0.98      0.99      0.98      1332
             6. Tiles       0.96      0.99      0.98      1812
           7. Shadows       0.98      0.95      0.96      1445
           8. Meadows       1.00      1.00      1.00      8533
         9. Bare Soil       1.00      1.00      1.00       571

             accuracy                           0.99     29630
            macro avg       0.98      0.98      0.98     29630
         weighted avg       0.99      0.99      0.99     29630
```


```
[[13255     0     0     0     0     0     0     0     0]
 [    0  1488    20     0     0     0     0     0     0]
 [    0    20   611     0     2     0     0     0     0]
 [    0     0     0   504    12     4    19     2     0]
 [    0     0     3    12  1316     0     0     1     0]
 [    0     0     0     6     1  1798     6     1     0]
 [    0     0     0    11     6    57  1368     3     0]
 [    0     0     0     2     5     6     2  8518     0]
 [    0     0     0     0     0     0     0     0   571]]
```


```
--------------------------------------------------------------------------
Training for fold 4 …
Accuracy  : 0.9928113398582518
Precision : 0.9928668058680381
```

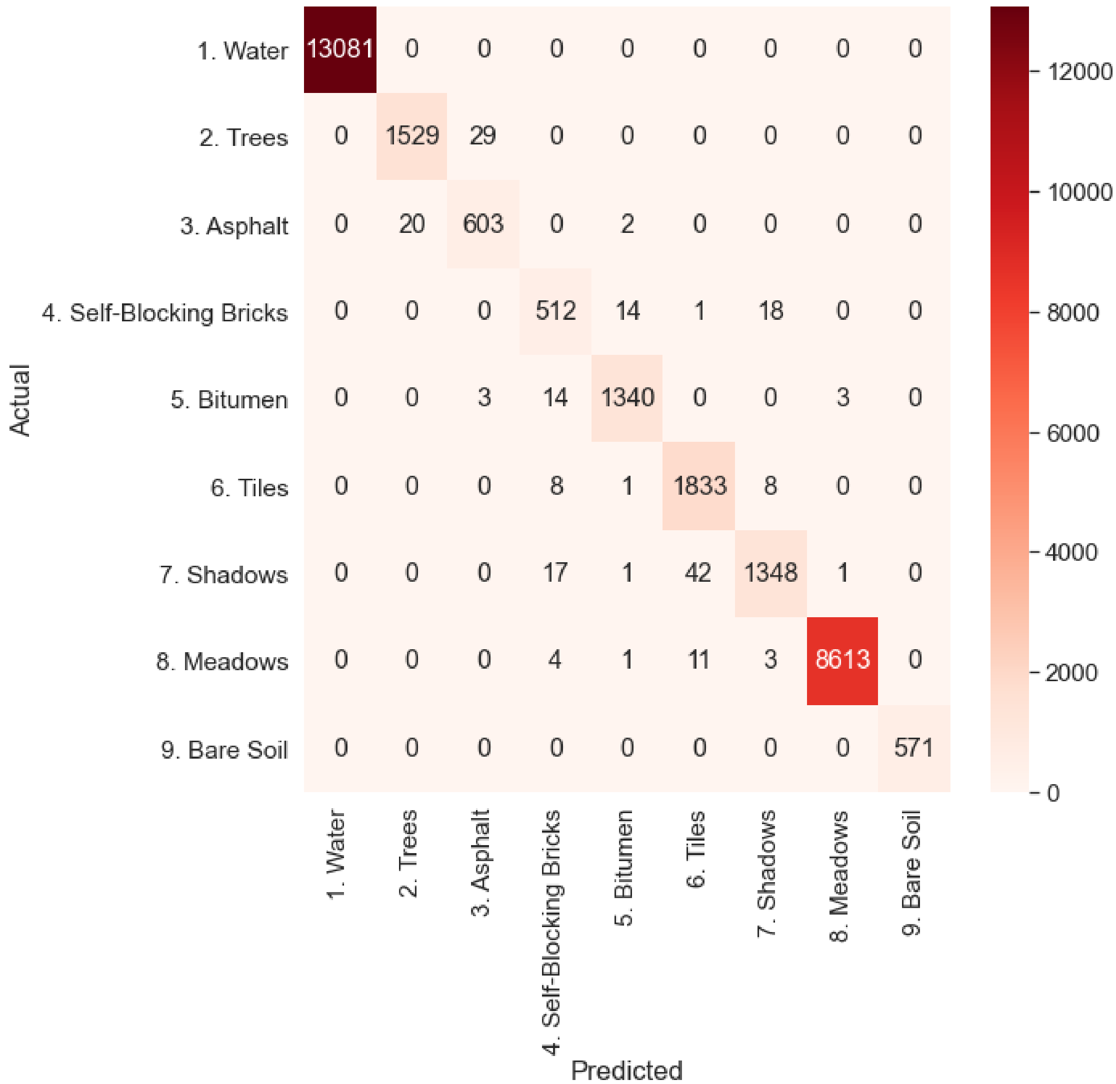
```
f1Score : 0.9928141612491863
[[13205     0     0     0     0     0     0     0     0]
 [    0  1410    24     0     0     0     0     0     0]
 [    0    28   579     0     2     0     0     0     0]
 [    0     0     0   499    14     3     8     0     0]
 [    0     0     3    22  1294     0     0     1     0]
 [    0     0     0     7     1  1854    12     3     0]
 [    0     0     0     6     5    53  1406     6     0]
 [    0     0     0     4     0    10     1  8615     0]
 [    0     0     0     0     0     0     0     0   555]]
                         precision    recall  f1-score   support

             1. Water       1.00      1.00      1.00     13205
             2. Trees       0.98      0.98      0.98      1434
           3. Asphalt       0.96      0.95      0.95       609
4. Self-Blocking Bricks       0.93      0.95      0.94       524
           5. Bitumen       0.98      0.98      0.98      1320
             6. Tiles       0.97      0.99      0.98      1877
           7. Shadows       0.99      0.95      0.97      1476
           8. Meadows       1.00      1.00      1.00      8630
         9. Bare Soil       1.00      1.00      1.00       555

             accuracy                           0.99     29630
            macro avg       0.98      0.98      0.98     29630
         weighted avg       0.99      0.99      0.99     29630
```


```
[[13205     0     0     0     0     0     0     0     0]
 [    0  1410    24     0     0     0     0     0     0]
 [    0    28   579     0     2     0     0     0     0]
 [    0     0     0   499    14     3     8     0     0]
 [    0     0     3    22  1294     0     0     1     0]
 [    0     0     0     7     1  1854    12     3     0]
 [    0     0     0     6     5    53  1406     6     0]
 [    0     0     0     4     0    10     1  8615     0]
 [    0     0     0     0     0     0     0     0   555]]
```

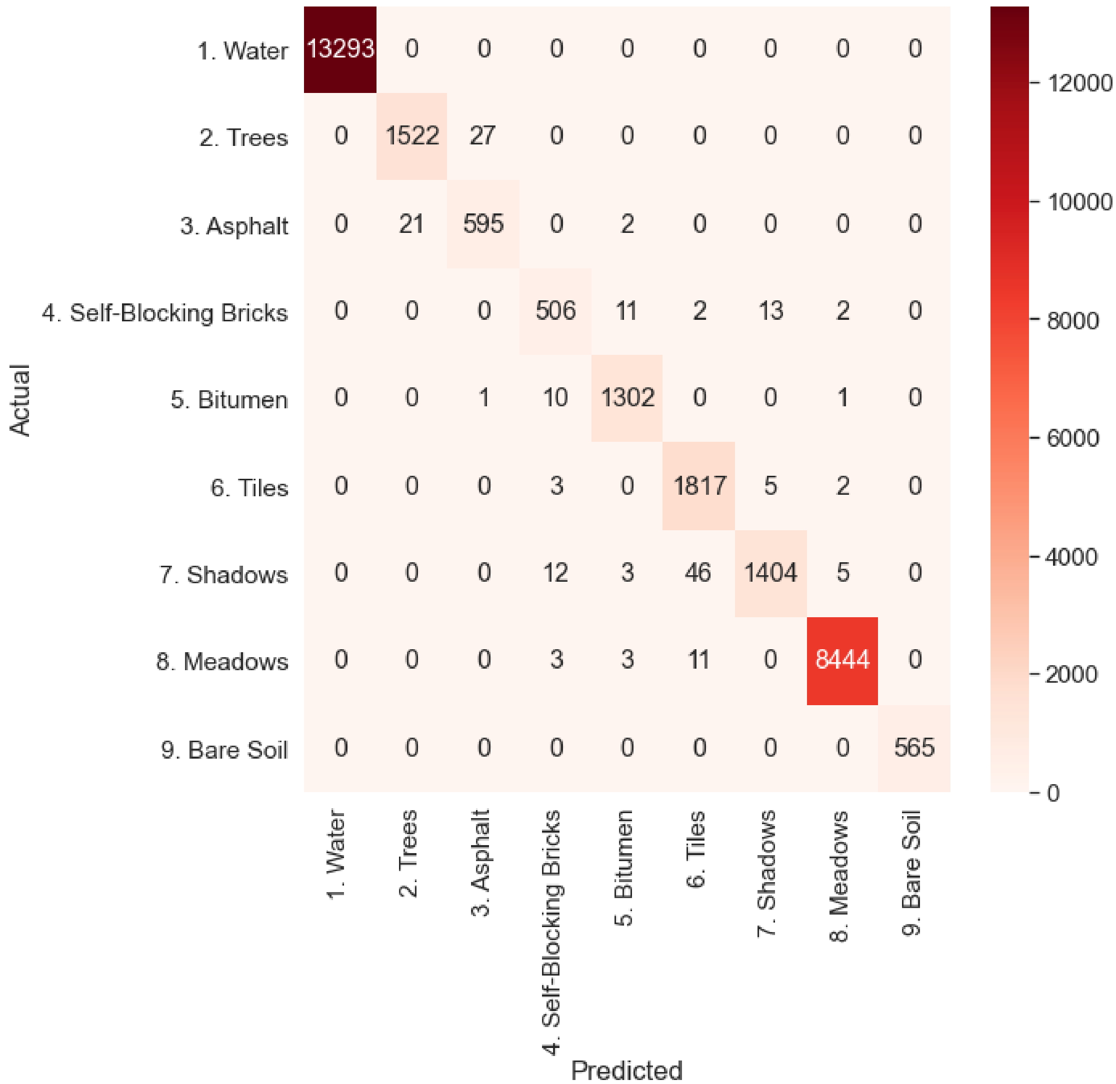

```
------------------------------------------------------------------------
Training for fold 5 …
Accuracy  : 0.9936550793115086
Precision : 0.9937305845775855
f1Score : 0.9936655112657454
[[13137     0     0     0     0     0     0     0     0]
 [    0  1524    25     0     0     0     0     0     0]
 [    0    13   590     0     2     0     0     0     0]
 [    0     0     0   513    13     3    11     1     0]
 [    0     0     3    15  1238     0     1     1     0]
 [    0     0     0     8     1  1866     6     1     0]
 [    0     0     0    11     4    51  1421     0     0]
 [    0     0     0     5     5     8     0  8552     0]
```

```
 [    0     0     0     0     0     0     0     0   601]]
                       precision    recall  f1-score   support

            1. Water       1.00      1.00      1.00     13137
            2. Trees       0.99      0.98      0.99      1549
          3. Asphalt       0.95      0.98      0.96       605
4. Self-Blocking Bricks       0.93      0.95      0.94       541
          5. Bitumen       0.98      0.98      0.98      1258
            6. Tiles       0.97      0.99      0.98      1882
          7. Shadows       0.99      0.96      0.97      1487
          8. Meadows       1.00      1.00      1.00      8570
        9. Bare Soil       1.00      1.00      1.00       601

            accuracy                           0.99     29630
           macro avg       0.98      0.98      0.98     29630
        weighted avg       0.99      0.99      0.99     29630

[[13137     0     0     0     0     0     0     0     0]
 [    0  1524    25     0     0     0     0     0     0]
 [    0    13   590     0     2     0     0     0     0]
 [    0     0     0   513    13     3    11     1     0]
 [    0     0     3    15  1238     0     1     1     0]
 [    0     0     0     8     1  1866     6     1     0]
 [    0     0     0    11     4    51  1421     0     0]
 [    0     0     0     5     5     8     0  8552     0]
 [    0     0     0     0     0     0     0     0   601]]
------------------------------------------------------------------------
Score per fold
------------------------------------------------------------------------
Average scores for all folds:
> Accuracy: nan (+- nan)
> Loss: nan
------------------------------------------------------------------------

c:\Users\kifah\anaconda3\lib\site-packages\numpy\core\fromnumeric.py:3419:
RuntimeWarning: Mean of empty slice.
  return _methods._mean(a, axis=axis, dtype=dtype,
c:\Users\kifah\anaconda3\lib\site-packages\numpy\core\_methods.py:188:
RuntimeWarning: invalid value encountered in double_scalars
  ret = ret.dtype.type(ret / rcount)
c:\Users\kifah\anaconda3\lib\site-packages\numpy\core\_methods.py:261:
RuntimeWarning: Degrees of freedom <= 0 for slice
  ret = _var(a, axis=axis, dtype=dtype, out=out, ddof=ddof,
c:\Users\kifah\anaconda3\lib\site-packages\numpy\core\_methods.py:221:
RuntimeWarning: invalid value encountered in true_divide
  arrmean = um.true_divide(arrmean, div, out=arrmean, casting='unsafe',
c:\Users\kifah\anaconda3\lib\site-packages\numpy\core\_methods.py:253:
RuntimeWarning: invalid value encountered in double_scalars
```

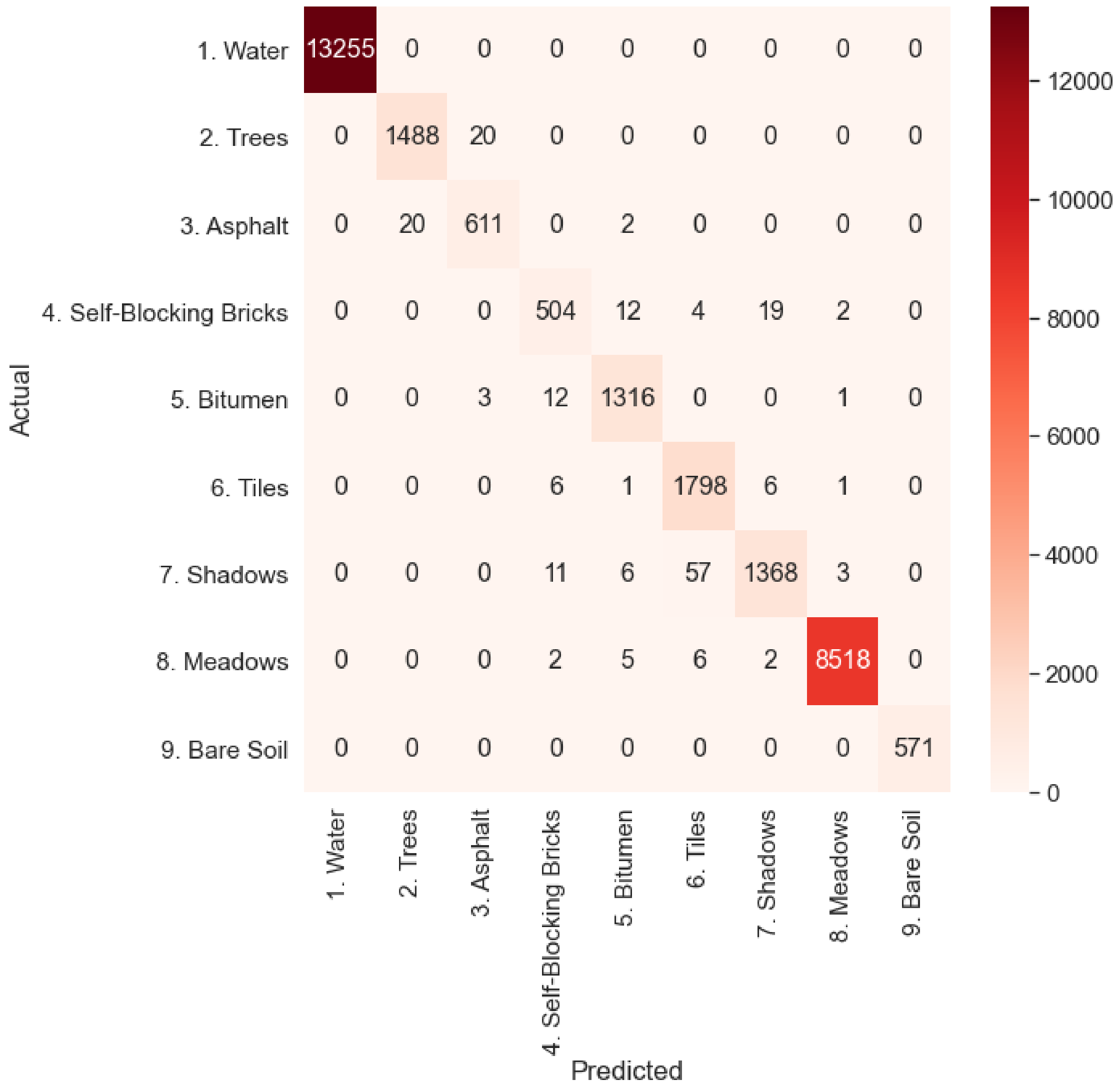
```
  ret = ret.dtype.type(ret / rcount)

Predicted Overall        1. Water  2. Trees  3. Asphalt  \
Actual Overall
1. Water                    65971         0           0
2. Trees                        0      7473         125
3. Asphalt                      0       102        2978
4. Self-Blocking Bricks         0         0           0
5. Bitumen                      0         0          13
6. Tiles                        0         0           0
7. Shadows                      0         0           0
8. Meadows                      0         0           0
9. Bare Soil                    0         0           0

Predicted Overall        4. Self-Blocking Bricks  5. Bitumen  6. Tiles  \
Actual Overall
1. Water                                       0           0         0
2. Trees                                       0           0         0
3. Asphalt                                     0          10         0
4. Self-Blocking Bricks                     2534          64        13
5. Bitumen                                    73        6490         0
6. Tiles                                      32           4      9168
7. Shadows                                    57          19       249
8. Meadows                                    18          14        46
9. Bare Soil                                   0           0         0

Predicted Overall        7. Shadows  8. Meadows  9. Bare Soil
Actual Overall
1. Water                          0           0             0
2. Trees                          0           0             0
3. Asphalt                        0           0             0
4. Self-Blocking Bricks          69           5             0
5. Bitumen                        1           7             0
6. Tiles                         37           7             0
7. Shadows                     6947          15             0
8. Meadows                        6       42742             0
9. Bare Soil                      0           0          2863

<Figure size 432x288 with 0 Axes>
```



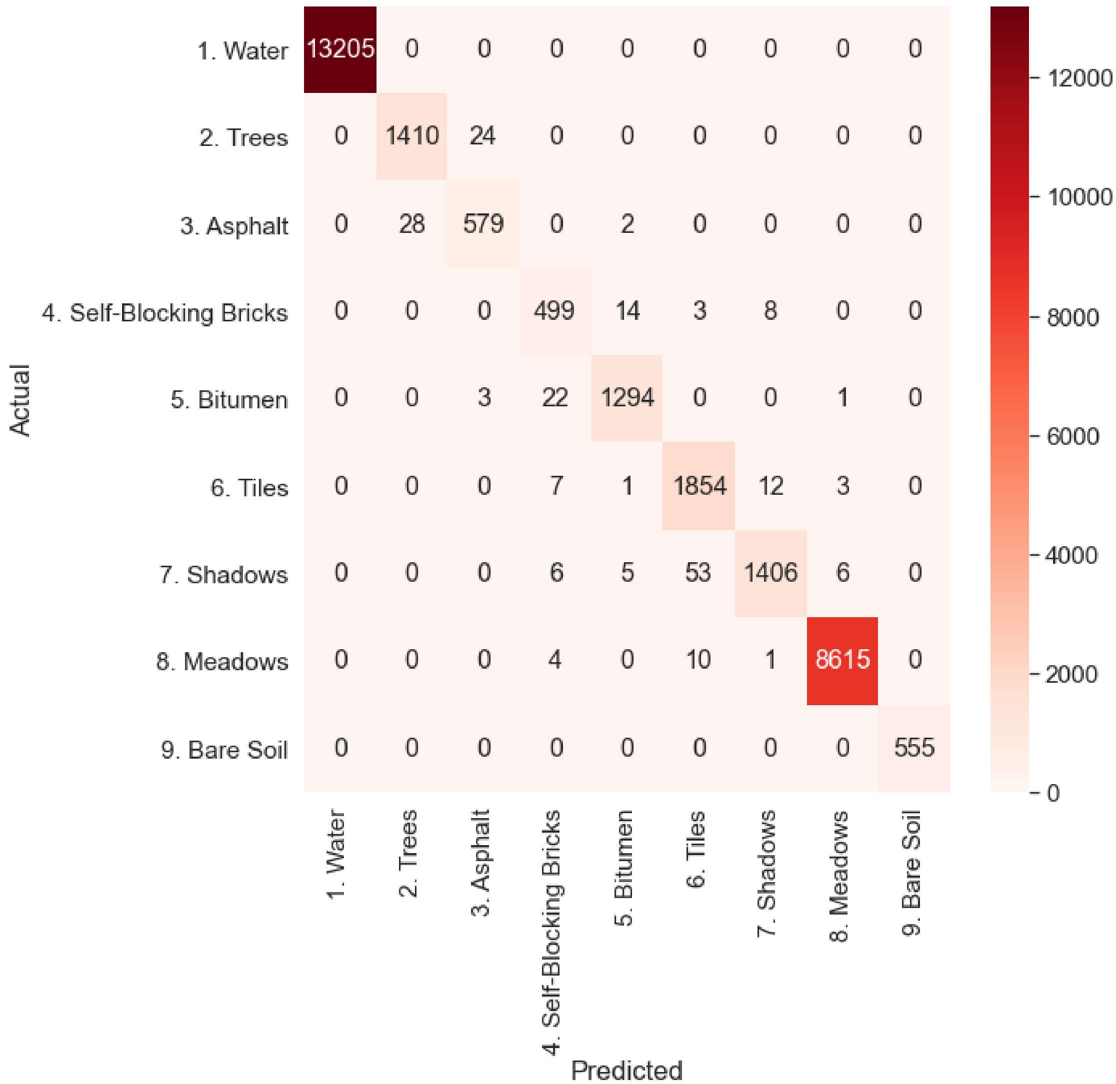

```
&lt;Figure size 432x288 with 0 Axes&gt;
```



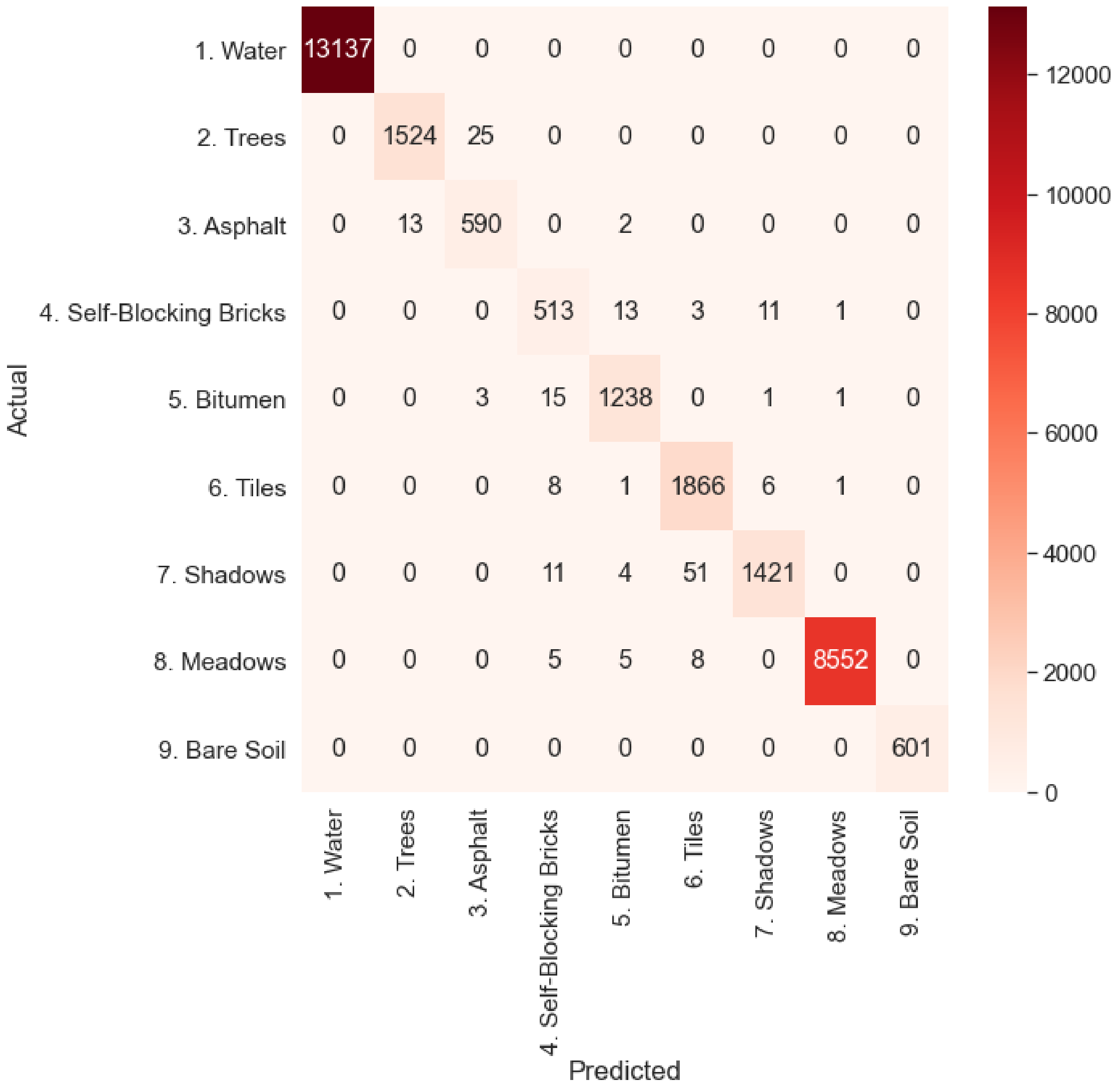
<Figure size 432x288 with 0 Axes>

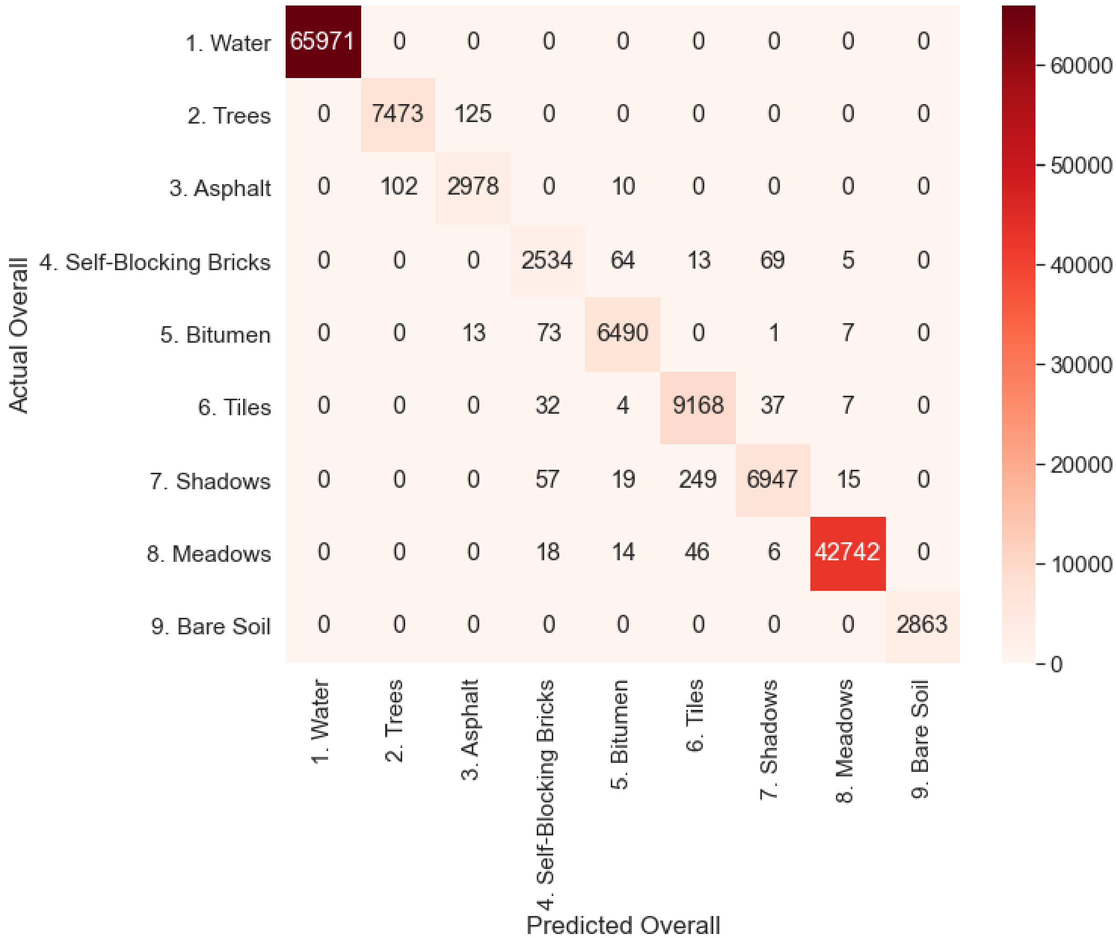


<Figure size 432x288 with 0 Axes>




```
<Figure size 432x288 with 0 Axes>
```


1. Water
2. Trees
3. Asphalt
4. Self-Blocking Bricks
5. Bitumen
6. Tiles
7. Shadows
8. Meadows
9. Bare Soil
Actual
Predicted
13137 0 0 0 0 0 0 0 0
0 1524 25 0 0 0 0 0 0
0 13 590 0 2 0 0 0 0
0 0 0 513 13 3 11 1 0
0 0 3 15 1238 0 1 1 0
0 0 0 8 1 1866 6 1 0
0 0 0 11 4 51 1421 0 0
0 0 0 5 5 8 0 8552 0
0 0 0 0 0 0 0 0 601
12000
10000
8000
6000
4000
2000
0



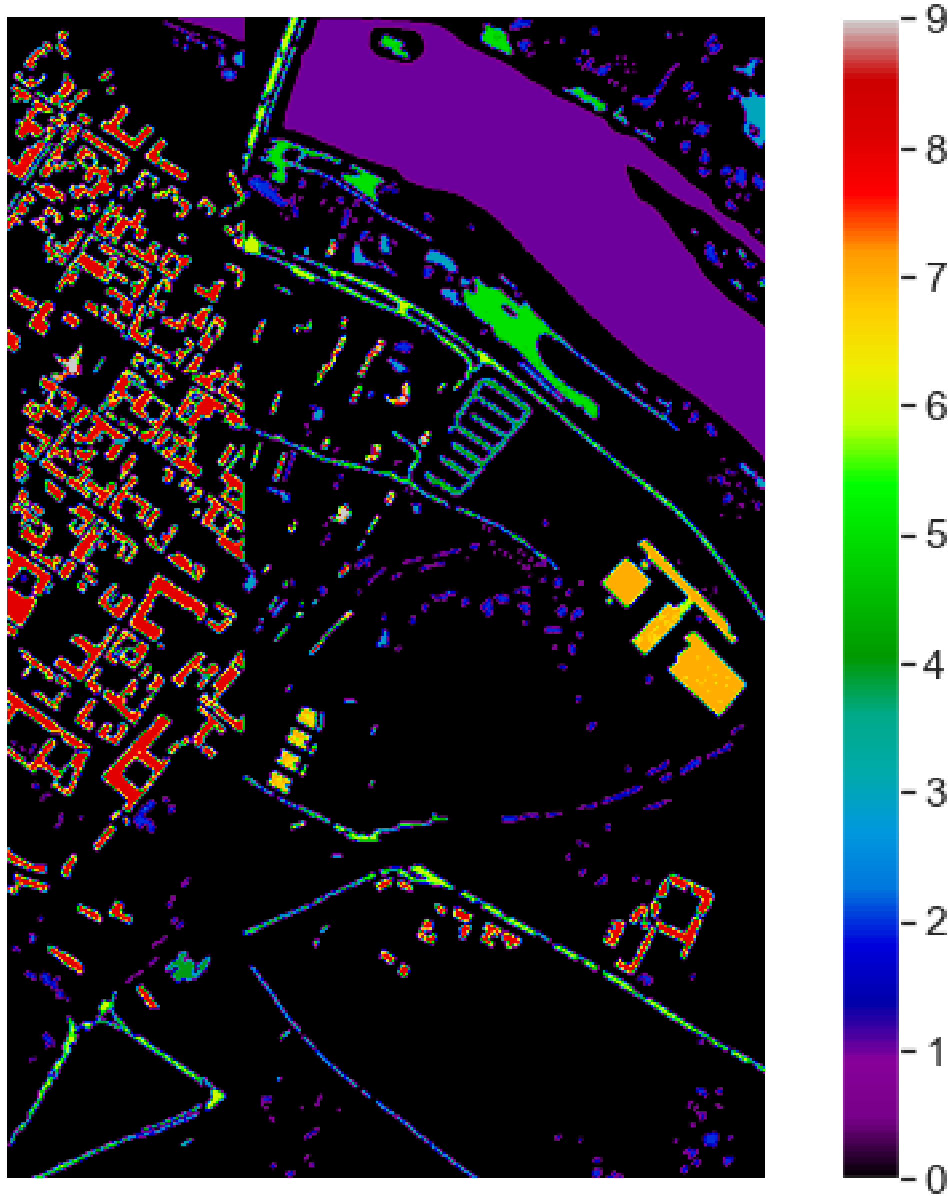
[ ]:
```python
print(classification_report(targets[test], y_pred, target_names = names))
```

```
                      precision    recall  f1-score   support

            1. Water       1.00      1.00      1.00     13137
            2. Trees       0.99      0.98      0.99      1549
          3. Asphalt       0.95      0.98      0.96       605
4. Self-Blocking Bricks    0.93      0.95      0.94       541
          5. Bitumen       0.98      0.98      0.98      1258
            6. Tiles       0.97      0.99      0.98      1882
          7. Shadows       0.99      0.96      0.97      1487
          8. Meadows       1.00      1.00      1.00      8570
        9. Bare Soil       1.00      1.00      1.00       601

            accuracy                           0.99     29630
           macro avg       0.98      0.98      0.98     29630
        weighted avg       0.99      0.99      0.99     29630
```

[ ]:
```python
##############  Classification Map  ###################
l=[]
for i in range(q.shape[0]):
  if q.iloc[i, -1] == 0:
    l.append(0)
  else:
    l.append(model.predict(q.iloc[i, :-1].values.reshape(1, -1)))
```

[ ]:
```python
clmap = np.array(l).reshape(1096, 715).astype('float')
plt.figure(figsize=(10, 8))
plt.imshow(clmap, cmap='nipy_spectral')
plt.colorbar()
plt.axis('off')
plt.savefig('IP_cmap.png')
plt.show()
```

```
C:\Users\kifah\AppData\Local\Temp\ipykernel_6864\616001129.py:1:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray.
  clmap = np.array(l).reshape(1096, 715).astype('float')
```


9
8
7
6
5
4
3
2
1
0