digitdata

February 4, 2023

[31]:
```
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection  import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.datasets import load_digits
import pandas as pd
```

[32]:
```
digit_data=load_digits()
```

1 Data Description

[33]:
```
print(digit_data.DESCR)
```

```
.. _digits_dataset:

Optical recognition of handwritten digits dataset
--------------------------------------------------

**Data Set Characteristics:**

    :Number of Instances: 1797
    :Number of Attributes: 64
    :Attribute Information: 8x8 image of integer pixels in the range 0..16.
    :Missing Attribute Values: None
    :Creator: E. Alpaydin (alpaydin '@' boun.edu.tr)
    :Date: July; 1998

This is a copy of the test set of the UCI ML hand-written digits datasets
https://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digit
s

The data set contains images of hand-written digits: 10 classes where
each class refers to a digit.
```

```
Preprocessing programs made available by NIST were used to extract
normalized bitmaps of handwritten digits from a preprinted form. From a
total of 43 people, 30 contributed to the training set and different 13
to the test set. 32x32 bitmaps are divided into nonoverlapping blocks of
4x4 and the number of on pixels are counted in each block. This generates
an input matrix of 8x8 where each element is an integer in the range
0..16. This reduces dimensionality and gives invariance to small
distortions.

For info on NIST preprocessing routines, see M. D. Garris, J. L. Blue, G.
T. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, and C.
L. Wilson, NIST Form-Based Handprint Recognition System, NISTIR 5469,
1994.

.. topic:: References

  - C. Kaynak (1995) Methods of Combining Multiple Classifiers and Their
    Applications to Handwritten Digit Recognition, MSc Thesis, Institute of
    Graduate Studies in Science and Engineering, Bogazici University.
  - E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kybernetika.
  - Ken Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qin.
    Linear dimensionalityreduction using relevance weighted LDA. School of
    Electrical and Electronic Engineering Nanyang Technological University.
    2005.
  - Claudio Gentile. A New Approximate Maximal Margin Classification
    Algorithm. NIPS. 2000.
```

2 Attributes in Digit Dataset

[34]:
```python
dir(digit_data)
```

[34]:
```
['DESCR', 'data', 'feature_names', 'frame', 'images', 'target', 'target_names']
```

3 Image Data

[35]:
```python
digit_data.data
```

[35]:
```
array([[ 0.,  0.,  5., …,  0.,  0.,  0.],
       [ 0.,  0.,  0., …, 10.,  0.,  0.],
       [ 0.,  0.,  0., …, 16.,  9.,  0.],
       …,
       [ 0.,  0.,  1., …,  6.,  0.,  0.],
       [ 0.,  0.,  2., …, 12.,  0.,  0.],
       [ 0.,  0., 10., …, 12.,  1.,  0.]])
```

[36]:
```
digit_data.data.shape
```

[36]:
```
(1797, 64)
```

[37]:
```
digit_data.images.shape # Iamge are of 8x8 shape
```

[37]:
```
(1797, 8, 8)
```

4 Target Data

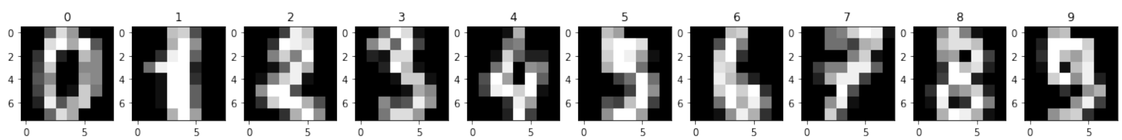
[38]:
```
digit_data.target_names
```

[38]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

5 Target Images

[39]:
```
import matplotlib.pyplot as plt
print("Target Images")
fig,ax = plt.subplots(1,10,figsize = (20,20))
ax = ax.ravel()
for i in range(10):
  image = digit_data.images[i]
  ax[i].imshow(image,cmap = 'gray')
  ax[i].set_title(digit_data.target[i])
plt.show()
```

```
Target Images
```



6 Preprocessing Data with MinMaxScaler

[40]:
```
from sklearn.preprocessing import MinMaxScaler
mn=MinMaxScaler()
X=mn.fit_transform(digit_data.data)
X
```

[40]:
```
array([[0.    , 0.    , 0.3125, …, 0.    , 0.    , 0.    ],
       [0.    , 0.    , 0.    , …, 0.625 , 0.    , 0.    ],
```

```
       [0.    , 0.    , 0.    , …, 1.    , 0.5625, 0.    ],
       …,
       [0.    , 0.    , 0.0625, …, 0.375 , 0.    , 0.    ],
       [0.    , 0.    , 0.125 , …, 0.75  , 0.    , 0.    ],
       [0.    , 0.    , 0.625 , …, 0.75  , 0.0625, 0.    ]])
```

7 Train Test Split

[78]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,digit_data.target,test_size=0.
↪3,random_state=10)
```

[42]:
```
X_train.shape
```

[42]:
```
(1257, 64)
```

[43]:
```
y_train.shape
```

[43]:
```
(1257,)
```

8 Model And Parameters Dictoniary To Select From

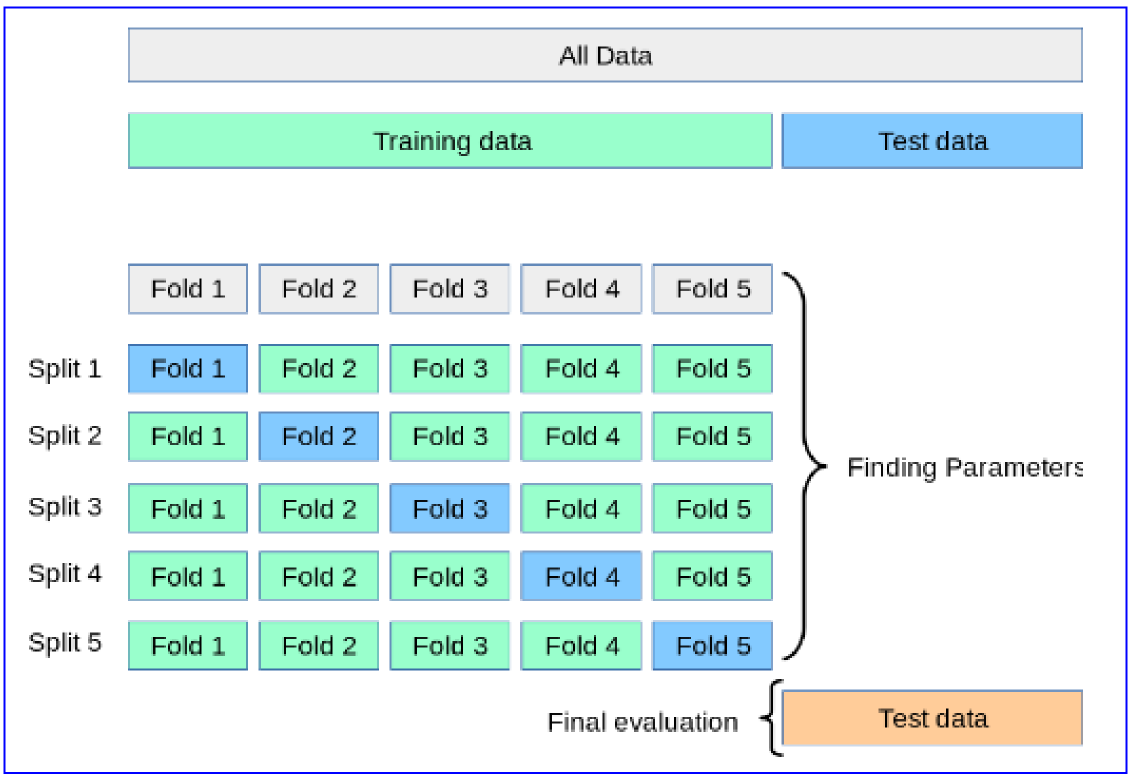
[44]:
```
model_params={
    'svm':{
        'model':SVC(gamma='auto'),
        'params':{
            'C':list(range(1,30,5)),
            'kernel':['linear','rbf']
        }
    },
    'random_forest':{
        'model':RandomForestClassifier(),
        'params':{
            'n_estimators':list(range(1,100,5))
        }
    },
    'logistic_regression':{
        'model':LogisticRegression(solver='liblinear',multi_class='auto'),
        'params':{
            'C':list(range(1,30,5))
        }
    },
    'GaussianNB':{
        'model':GaussianNB(),
        'params':{}
```

```
    },
    'MultinomialNB':{
        'model':MultinomialNB(),
        'params':{}
    },
    'DecisionTree':{
        'model':DecisionTreeClassifier(),
        'params':{
            'criterion' : ["gini", "entropy", "log_loss"],
        }
    }
}
```

- Cross Validation On Each Step in GridSearchCV is shown below

[86]:
```
from IPython import display
display.Image("D:\\Machile Learning Practise\\15) HyperParametert␣
↪Tunning\\Exercise\\image.png",width=400,height=400)
```

[86]:



9 GridSearchCV

[46]:
```
score=[]
for model,mp in model_params.items():
    clf=GridSearchCV(mp['model'],mp['params'],cv=6,return_train_score=False)
    clf.fit(X,digit_data.target)
    score.append({
        'mobel':model,
        'best_score':clf.best_score_,
        'best_pramas':clf.best_params_
    }
    )
```

10 GridSearchCV Report

[47]:
```
result=pd.DataFrame(score)
result
```

[47]:

	mobel	best_score	best_pramas
0	svm	0.963276	{'C': 6, 'kernel': 'rbf'}
1	random_forest	0.951039	{'n_estimators': 61}
2	logistic_regression	0.937679	{'C': 16}
3	GaussianNB	0.804705	{}
4	MultinomialNB	0.874812	{}
5	DecisionTree	0.822467	{'criterion': 'entropy'}

11 RandomizedSearchCV

[60]:
```
score_rand=[]
for model,mp in model_params.items():
   ␣
 ↪clf=RandomizedSearchCV(mp['model'],mp['params'],cv=6,return_train_score=False,n_iter=1)
    clf.fit(X,digit_data.target)
    score_rand.append({
        'mobel':model,
        'best_score':clf.best_score_,
        'best_pramas':clf.best_params_
    }
    )
```

12 RandomizedSearchCV Report

[61]:
```
result_rand=pd.DataFrame(score_rand)
result_rand
```

[61]:

	mobel	best_score	best_pramas
0	svm	0.963276	{'kernel': 'rbf', 'C': 6}
1	random_forest	0.724539	{'n_estimators': 1}
2	logistic_regression	0.937672	{'C': 1}
3	GaussianNB	0.804705	{}
4	MultinomialNB	0.874812	{}
5	DecisionTree	0.821355	{'criterion': 'log_loss'}

13 Now Using SVC

- which is selected as best model from both above results

[79]:
```
model=SVC(C=6,kernel='rbf')
model.fit(X_train,y_train)
```

[79]:
```
SVC(C=6)
```

14 Checkin For Overfitting

[80]:
```
from sklearn.metrics import␣
↪confusion_matrix,classification_report,accuracy_score
print("Training accuracy: ",accuracy_score(y_train,model.predict(X_train)))
print("Testing accuracy: ",accuracy_score(y_test,model.predict(X_test)))
```

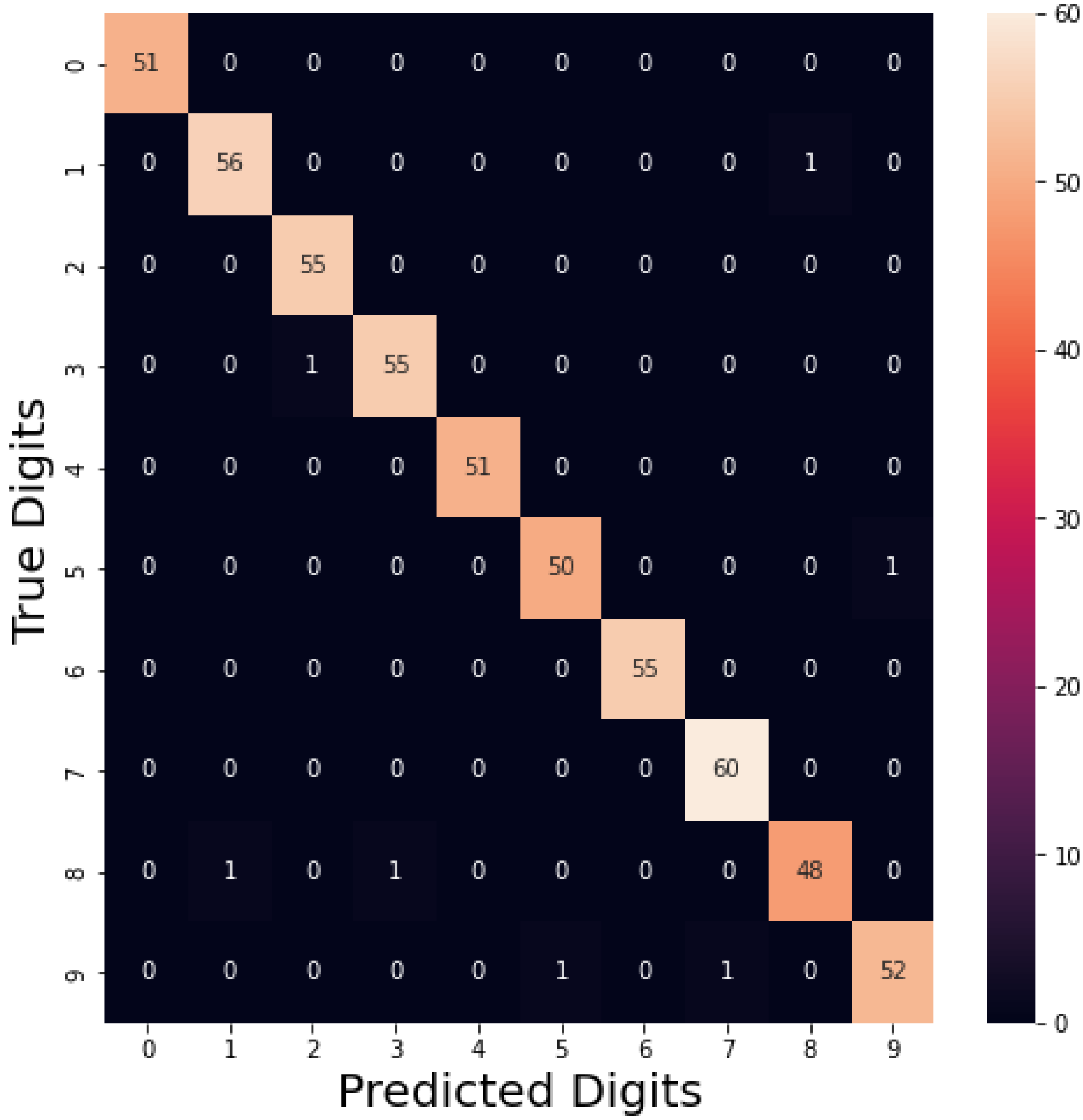
```
Training accuracy:  1.0
Testing accuracy:  0.987037037037037
```

15 Classification Visulization Using Confusion Matrix

[82]:
```
import seaborn as sns

plt.figure(figsize=(8,8))
sns.heatmap(confusion_matrix(y_test,model.predict(X_test)),annot=True)
plt.xlabel("Predicted Digits",fontdict={"size":20})
plt.ylabel("True Digits",fontdict={"size":20})
```

[82]:
```
Text(51.0, 0.5, 'True Digits')
```


True Digits
Predicted Digits
0 1 2 3 4 5 6 7 8 9
51 0 0 0 0 0 0 0 0 0
0 56 0 0 0 0 0 0 1 0
0 0 55 0 0 0 0 0 0 0
0 0 1 55 0 0 0 0 0 0
0 0 0 0 51 0 0 0 0 0
0 0 0 0 0 50 0 0 0 1
0 0 0 0 0 0 55 0 0 0
0 0 0 0 0 0 0 60 0 0
0 1 0 1 0 0 0 0 48 0
0 0 0 0 0 1 0 1 0 52
0 10 20 30 40 50 60