LAB 11

Try SVM classifier on MNIST dataset, compare the preformance of linear, polynomial and RBF kernels.

In [1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os
```

In [2]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.model_selection import validation_curve
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:
```
train_data = pd.read_csv("/home/nihar/Desktop/SEM 7/ML/Lab/Lab11/train.csv")
#reading the csv files using pandas
test_data = pd.read_csv("/home/nihar/Desktop/SEM 7/ML/Lab/Lab11/test.csv")
```

In [4]:
```
train_data.shape
```

Out[4]:
```
(42000, 785)
```

In [5]:
```
test_data.shape
```

Out[5]:
```
(28000, 784)
```

In [6]:
```
train_data.head()
```

Out[6]:

	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	...	pixel774	pixel775	pixe
0	1	0	0	0	0	0	0	0	0	0	...	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	
2	1	0	0	0	0	0	0	0	0	0	...	0	0	
3	4	0	0	0	0	0	0	0	0	0	...	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	

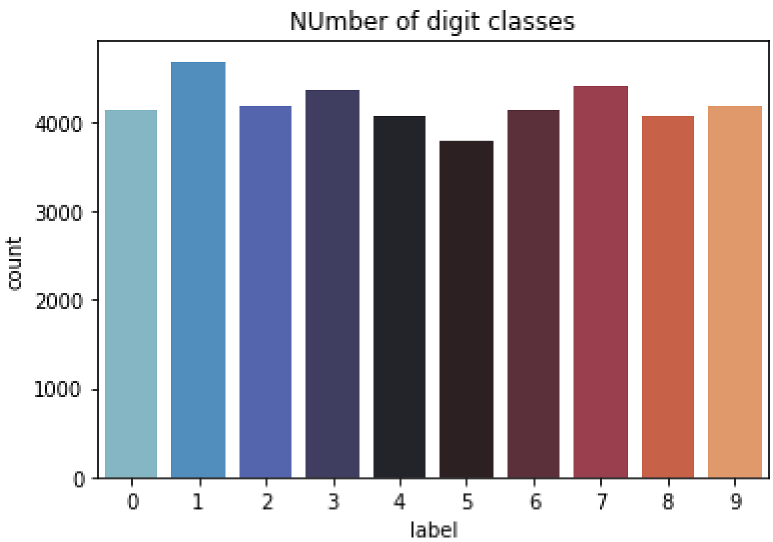
5 rows × 785 columns

In [7]:
```
order = list(np.sort(train_data['label'].unique()))
print(order)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

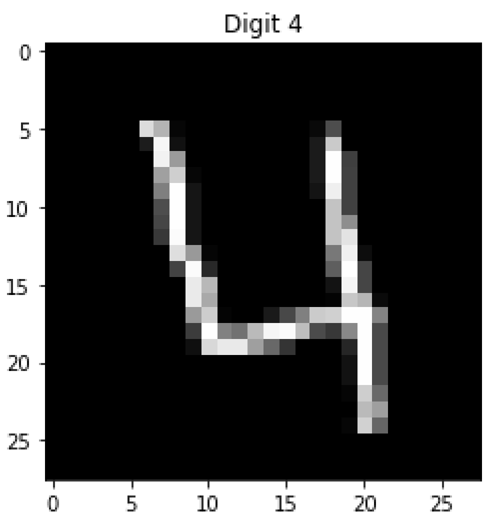
In [8]:
```
## Visualizing the number of class and counts in the datasets
plt.plot(figure = (16,10))
g = sns.countplot( train_data["label"], palette = 'icefire')
plt.title('NUmber of digit classes')
train_data.label.astype('category').value_counts()
```

Out[8]:
```
1    4684
7    4401
3    4351
9    4188
2    4177
6    4137
0    4132
4    4072
8    4063
5    3795
Name: label, dtype: int64
```



In [9]:
```
four = train_data.iloc[3, 1:]
four.shape
four = four.values.reshape(28,28)
plt.imshow(four, cmap='gray')
plt.title("Digit 4")
```

Out[9]:
```
Text(0.5, 1.0, 'Digit 4')
```



In [10]:
```
y = train_data['label']
## Dropping the variable 'label' from X variable
X = train_data.drop(columns = 'label')
## Printing the size of data
print(train_data.shape)
```

```
(42000, 785)
```

In [11]:
```
## Normalization
X = X/255.0
test_data = test_data/255.0
print("X:", X.shape)
print("test_data:", test_data.shape)
```

```
X: (42000, 784)
test_data: (28000, 784)
```

In [12]:
```
# train test split
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size = 0.3, tr
ain_size = 0.2 ,random_state = 129)
```

In [13]:
```
# linear model
model_linear = SVC(kernel='linear')
model_linear.fit(X_train, y_train)
# predict
y_pred_linear = model_linear.predict(X_test)
```

In [14]:
```
from sklearn import metrics
# accuracy
print("accuracy:", metrics.accuracy_score(y_true=y_test, y_pred=y_pred_linea
r), "\n")
```

```
accuracy: 0.9115873015873016
```

In [15]:
```
#RBF model
rbf_model = SVC(kernel='rbf')
# fit
rbf_model.fit(X_train, y_train)
# predict
y_pred_rbf = rbf_model.predict(X_test)
```

In [16]:
```
# accuracy
print("accuracy:", metrics.accuracy_score(y_true=y_test, y_pred=y_pred_rbf),
"\n")
```

```
accuracy: 0.9597619047619048
```

In [17]:
```
#Polinomial model
polinomial_model = SVC(kernel='poly')
# fit
polinomial_model.fit(X_train, y_train)
# predict
y_pred_poli = polinomial_model.predict(X_test)
```

In [18]:

```python
# accuracy
print("accuracy:", metrics.accuracy_score(y_true=y_test, y_pred=y_pred_poli), "\n")
```

```
accuracy: 0.9515079365079365
```

From above result we can say that rbf is better than polinomial and linear

RBF > Poli > Linear