**MACHINE LEARNING MAJOR PROJECT**

## Digit classification using the SVM algorithm

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Problem statement:

Design a project from the MNIST dataset to identify digit classification using the SVM alg orithm

```
# import all necessary libraries
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

from sklearn.preprocessing import scale
from sklearn.model_selection import train_test_split

from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.svm import SVC

from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
```

**DATA IMPORT:**

```
#import file and reading few lines
numbers = pd.read_csv('digit_svm.csv')
numbers.head(10)
```

```
   label  pixel0  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  \
0     1       0       0       0       0       0       0       0       0
1     0       0       0       0       0       0       0       0       0
2     1       0       0       0       0       0       0       0       0
3     4       0       0       0       0       0       0       0       0
4     0       0       0       0       0       0       0       0       0
5     0       0       0       0       0       0       0       0       0
```

```
6      7      0      0      0      0      0      0      0      0
7      3      0      0      0      0      0      0      0      0
8      5      0      0      0      0      0      0      0      0
9      3      0      0      0      0      0      0      0      0

   pixel8  ...  pixel774  pixel775  pixel776  pixel777  pixel778  pixel779  \
0       0  ...         0         0         0         0         0         0
1       0  ...         0         0         0         0         0         0
2       0  ...         0         0         0         0         0         0
3       0  ...         0         0         0         0         0         0
4       0  ...         0         0         0         0         0         0
5       0  ...         0         0         0         0         0         0
6       0  ...         0         0         0         0         0         0
7       0  ...         0         0         0         0         0         0
8       0  ...         0         0         0         0         0         0
9       0  ...         0         0         0         0         0         0

   pixel780  pixel781  pixel782  pixel783
0         0         0         0         0
1         0         0         0         0
2         0         0         0         0
3         0         0         0         0
4         0         0         0         0
5         0         0         0         0
6         0         0         0         0
7         0         0         0         0
8         0         0         0         0
9         0         0         0         0

[10 rows x 785 columns]
```

```
numbers.shape
```

```
(42000, 785)
```

```
#checking datatype
numbers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42000 entries, 0 to 41999
Columns: 785 entries, label to pixel783
dtypes: int64(785)
memory usage: 251.5 MB
```

```
numbers.describe(percentiles = [0.05,0.10,0.25,0.50,0.75,0.90,0.99])
```

```
              label   pixel0   pixel1   pixel2   pixel3   pixel4   pixel5  \
count  42000.000000  42000.0  42000.0  42000.0  42000.0  42000.0  42000.0
mean       4.456643      0.0      0.0      0.0      0.0      0.0      0.0
std        2.887730      0.0      0.0      0.0      0.0      0.0      0.0
min        0.000000      0.0      0.0      0.0      0.0      0.0      0.0
5%         0.000000      0.0      0.0      0.0      0.0      0.0      0.0
```

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 10% | 1.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 25% | 2.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 50% | 4.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 75% | 7.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 90% | 8.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 99% | 9.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| max | 9.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

| | pixel6 | pixel7 | pixel8 | ... | pixel774 | pixel775 \ |
|---|---|---|---|---|---|---|
| count | 42000.0 | 42000.0 | 42000.0 | ... | 42000.000000 | 42000.000000 |
| mean | 0.0 | 0.0 | 0.0 | ... | 0.219286 | 0.117095 |
| std | 0.0 | 0.0 | 0.0 | ... | 6.312890 | 4.633819 |
| min | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 |
| 5% | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 |
| 10% | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 |
| 25% | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 |
| 50% | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 |
| 75% | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 |
| 90% | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 |
| 99% | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 |
| max | 0.0 | 0.0 | 0.0 | ... | 254.000000 | 254.000000 |

| | pixel776 | pixel777 | pixel778 | pixel779 | pixel780 \ |
|---|---|---|---|---|---|
| count | 42000.000000 | 42000.00000 | 42000.000000 | 42000.000000 | 42000.0 |
| mean | 0.059024 | 0.02019 | 0.017238 | 0.002857 | 0.0 |
| std | 3.274488 | 1.75987 | 1.894498 | 0.414264 | 0.0 |
| min | 0.000000 | 0.00000 | 0.000000 | 0.000000 | 0.0 |
| 5% | 0.000000 | 0.00000 | 0.000000 | 0.000000 | 0.0 |
| 10% | 0.000000 | 0.00000 | 0.000000 | 0.000000 | 0.0 |
| 25% | 0.000000 | 0.00000 | 0.000000 | 0.000000 | 0.0 |
| 50% | 0.000000 | 0.00000 | 0.000000 | 0.000000 | 0.0 |
| 75% | 0.000000 | 0.00000 | 0.000000 | 0.000000 | 0.0 |
| 90% | 0.000000 | 0.00000 | 0.000000 | 0.000000 | 0.0 |
| 99% | 0.000000 | 0.00000 | 0.000000 | 0.000000 | 0.0 |
| max | 253.000000 | 253.00000 | 254.000000 | 62.000000 | 0.0 |

| | pixel781 | pixel782 | pixel783 |
|---|---|---|---|
| count | 42000.0 | 42000.0 | 42000.0 |
| mean | 0.0 | 0.0 | 0.0 |
| std | 0.0 | 0.0 | 0.0 |
| min | 0.0 | 0.0 | 0.0 |
| 5% | 0.0 | 0.0 | 0.0 |
| 10% | 0.0 | 0.0 | 0.0 |
| 25% | 0.0 | 0.0 | 0.0 |
| 50% | 0.0 | 0.0 | 0.0 |
| 75% | 0.0 | 0.0 | 0.0 |
| 90% | 0.0 | 0.0 | 0.0 |
| 99% | 0.0 | 0.0 | 0.0 |
| max | 0.0 | 0.0 | 0.0 |

[12 rows x 785 columns]

```
#checking for null values
round(100*(numbers.isnull().sum()/(len(numbers.index))),2).sort_values(ascending = False)
```

```
pixel783    0.0
pixel267    0.0
pixel265    0.0
pixel264    0.0
pixel263    0.0
pixel262    0.0
pixel261    0.0
pixel260    0.0
pixel259    0.0
pixel258    0.0
pixel257    0.0
pixel256    0.0
pixel255    0.0
pixel254    0.0
pixel253    0.0
pixel252    0.0
pixel251    0.0
pixel250    0.0
pixel249    0.0
pixel248    0.0
pixel247    0.0
pixel246    0.0
pixel245    0.0
pixel266    0.0
pixel268    0.0
pixel390    0.0
pixel269    0.0
pixel290    0.0
pixel289    0.0
pixel288    0.0
           ...
pixel495    0.0
pixel494    0.0
pixel493    0.0
pixel492    0.0
pixel491    0.0
pixel512    0.0
pixel513    0.0
pixel514    0.0
pixel526    0.0
pixel535    0.0
pixel534    0.0
pixel533    0.0
pixel532    0.0
pixel531    0.0
```

```
pixel530    0.0
pixel529    0.0
pixel528    0.0
pixel527    0.0
pixel525    0.0
pixel515    0.0
pixel524    0.0
pixel523    0.0
pixel522    0.0
pixel521    0.0
pixel520    0.0
pixel519    0.0
pixel518    0.0
pixel517    0.0
pixel516    0.0
label       0.0
Length: 785, dtype: float64
```

```
# let us check unique entries of label column
np.unique(numbers['label'])
```

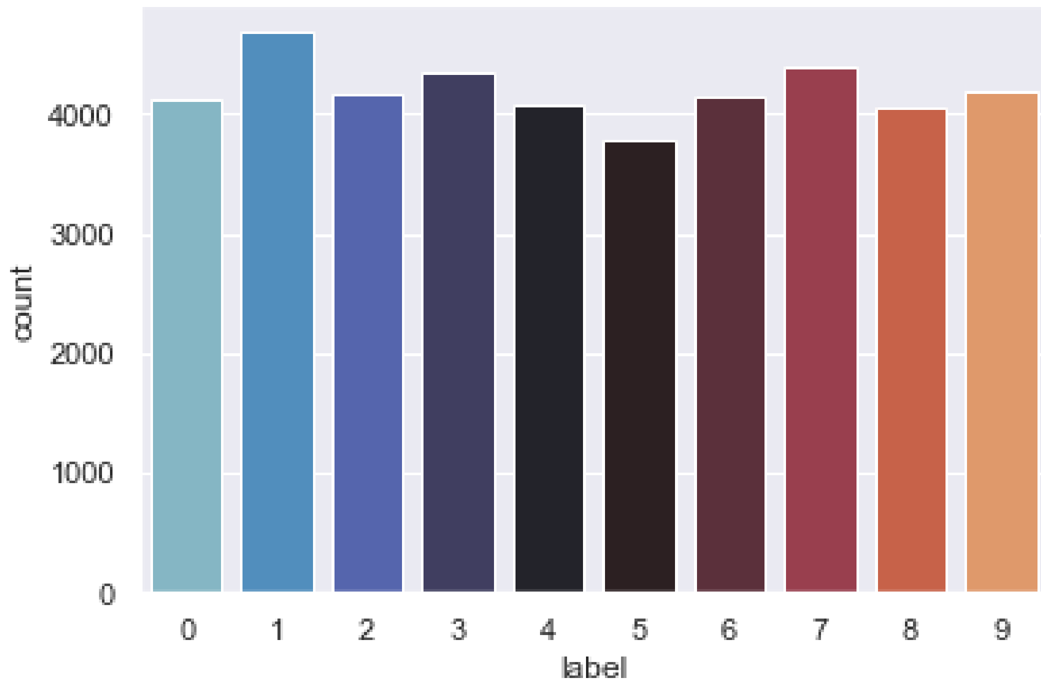
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=int64)
```

```
numbers['label'].value_counts()
```

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

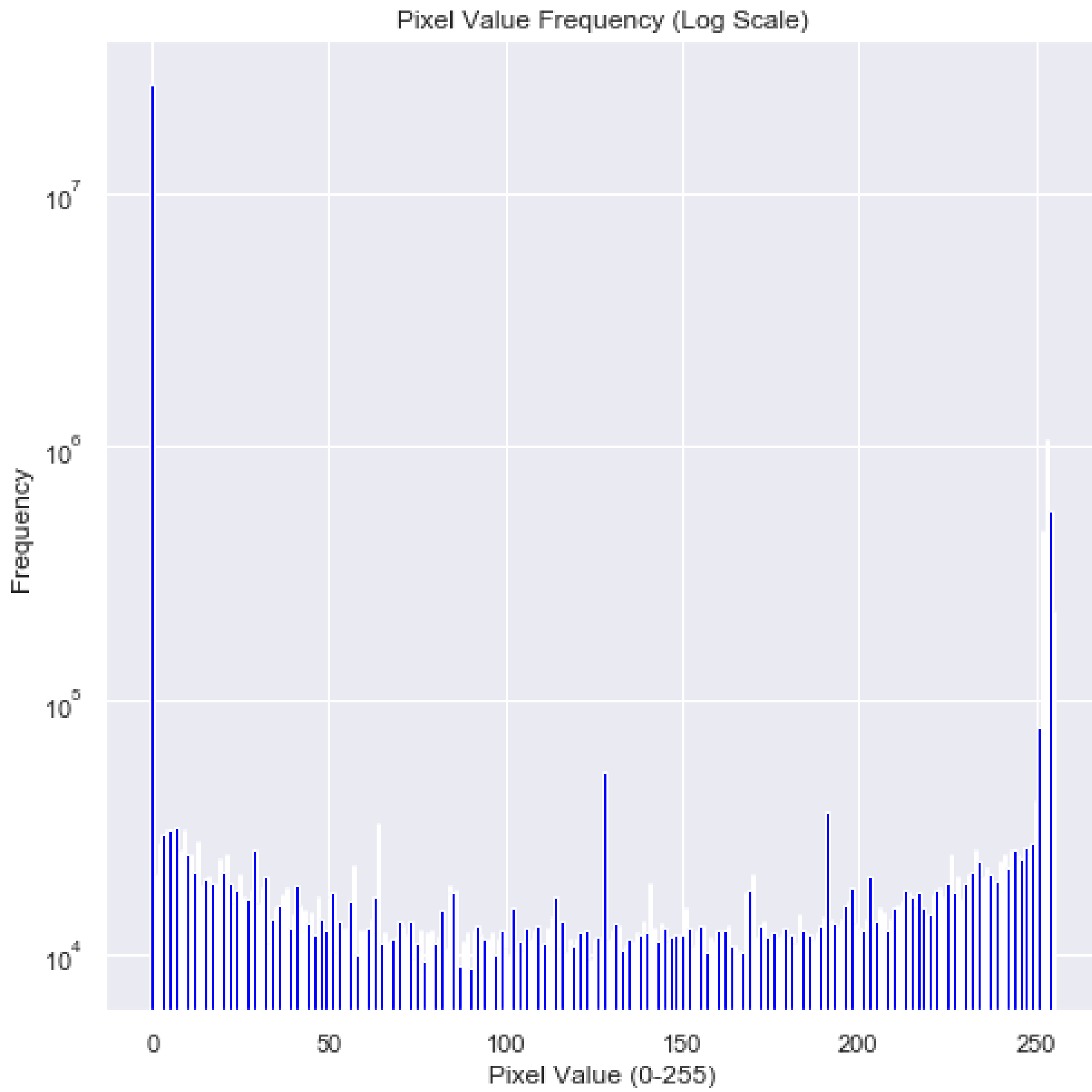
```
#visualising the column - label
sns.countplot(numbers['label'],palette = 'icefire')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2cb8f69b6a0>
```

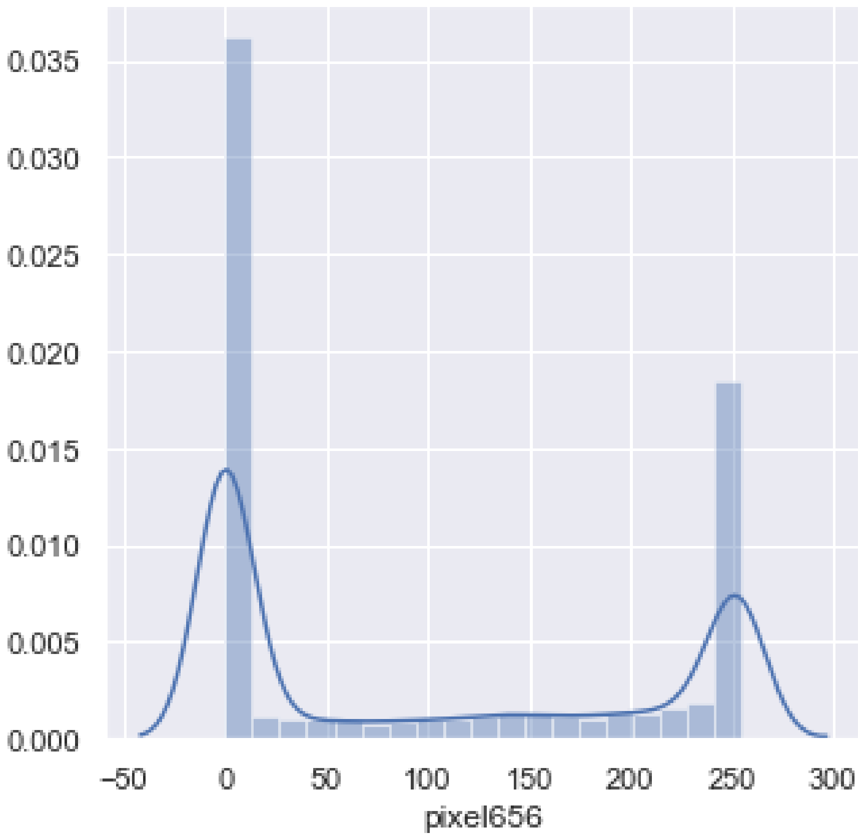



```
y = pd.value_counts(numbers.values.ravel()).sort_index()
N = len(y)
x = range(N)
width =0.9
plt.figure(figsize=[8,8])
plt.bar(x, y, width, color="blue")
plt.title('Pixel Value Frequency (Log Scale)')
plt.yscale('log')
plt.xlabel('Pixel Value (0-255)')
plt.ylabel('Frequency')
```

```
Text(0, 0.5, 'Frequency')
```

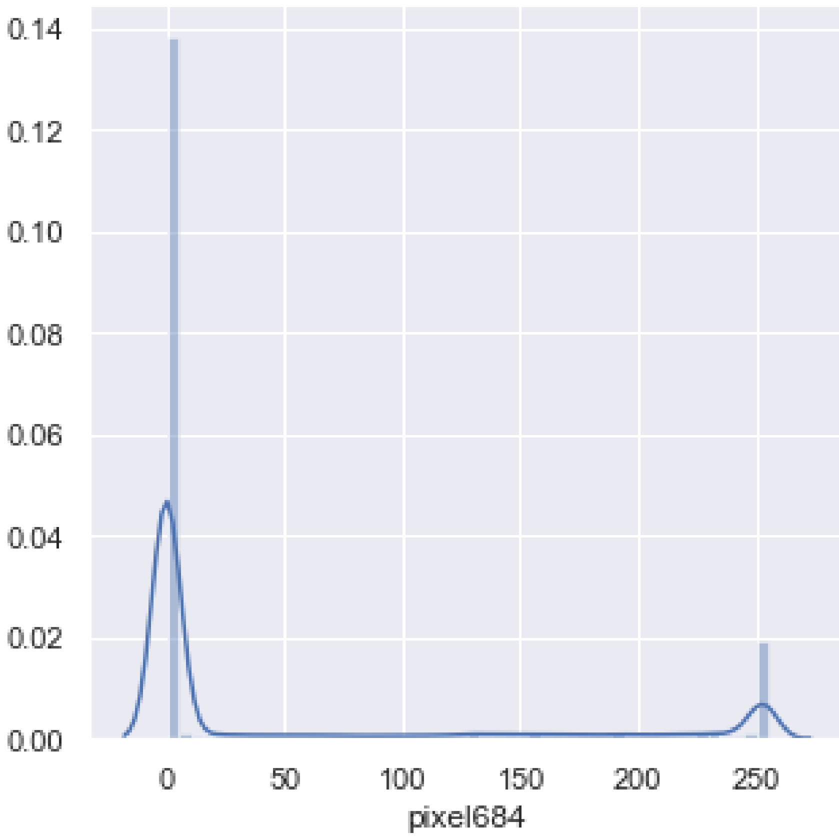



```
plt.figure(figsize=(5,5))
sns.distplot(numbers['pixel656'])
plt.show()
```



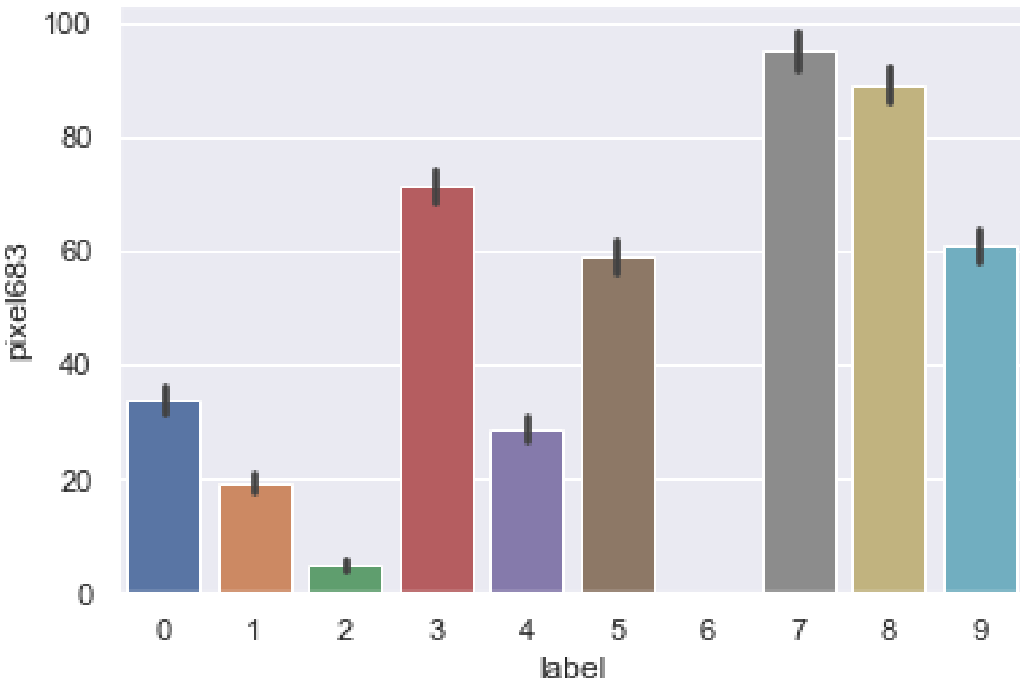

```
plt.figure(figsize=(5,5))
sns.distplot(numbers['pixel684'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x2cb900f9978>



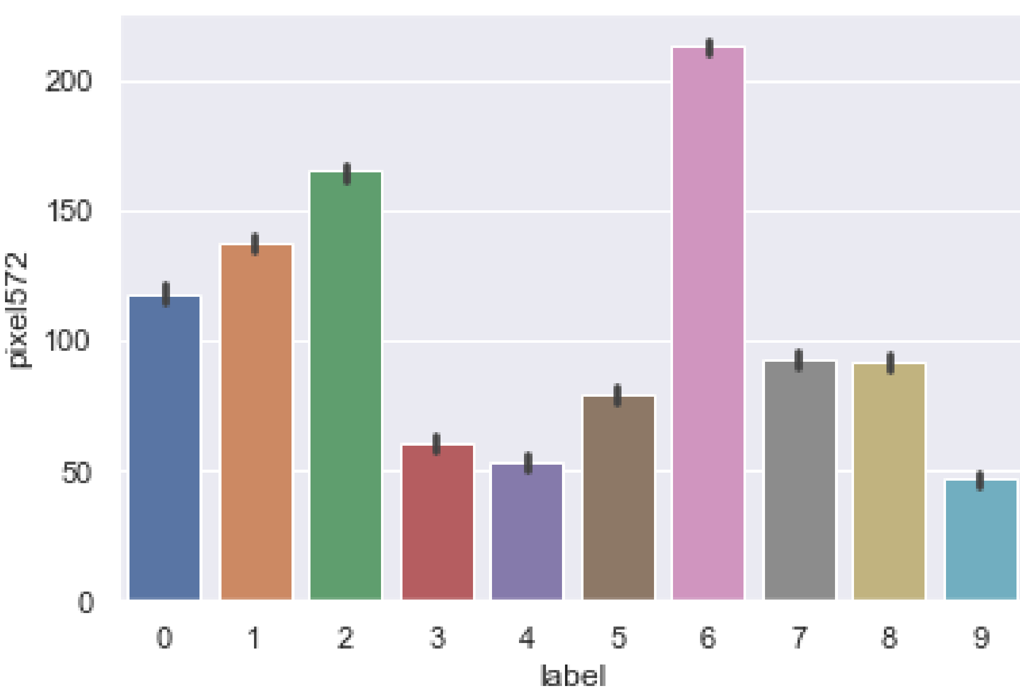

```
#label vs pixel
sns.barplot(x='label', y='pixel683', data=numbers)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2cb9019b940>
```




```
sns.barplot(x='label', y='pixel572', data=numbers)
```

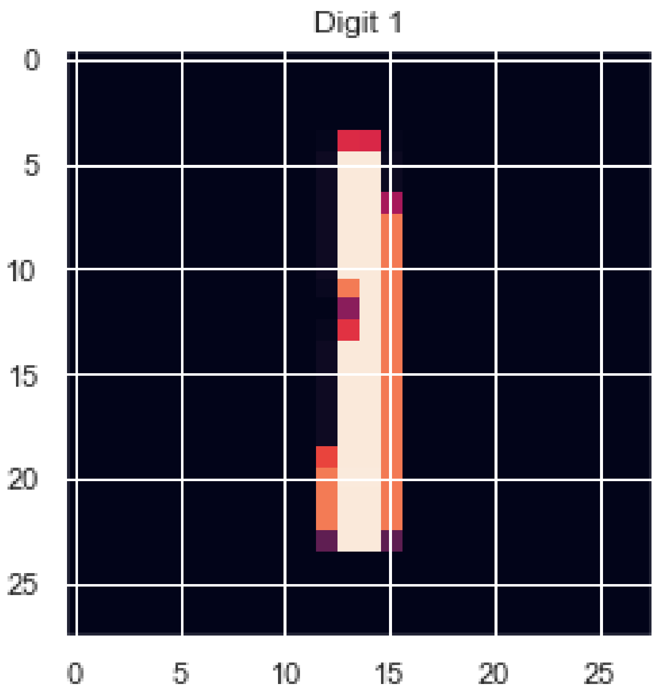
<matplotlib.axes._subplots.AxesSubplot at 0x2cb90226b38>




```
#visualize numbers
one = numbers.iloc[2, 1:]
one = one.values.reshape(28,28)
```

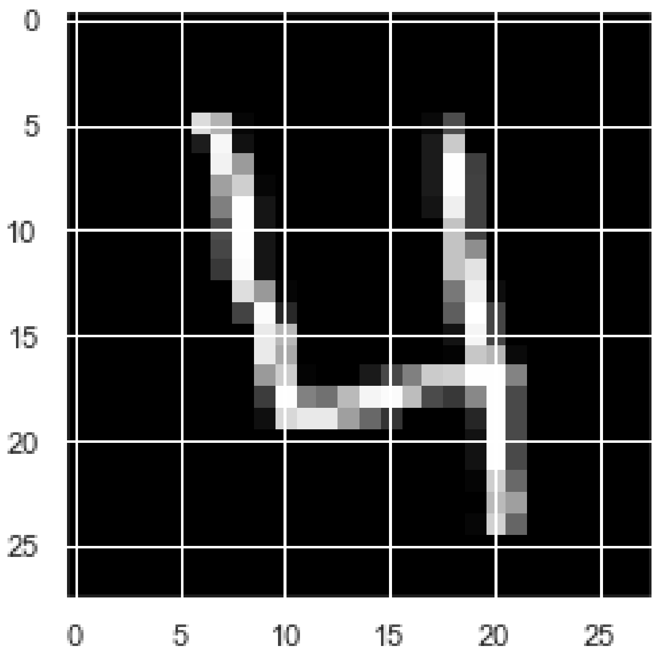
```
plt.imshow(one)
plt.title("Digit 1")
```

Text(0.5, 1.0, 'Digit 1')




```
four = numbers.iloc[3, 1:]
four.shape
four = four.values.reshape(28, 28)
plt.imshow(four, cmap='gray')
```

<matplotlib.image.AxesImage at 0x2cb900c4a20>



```python
# visualise the array
print(four[5:-5, 5:-5])
```

```
[[  0 220 179   6   0   0   0   0   0   0   0   0   9  77   0   0   0   0]
 [  0  28 247  17   0   0   0   0   0   0   0   0  27 202   0   0   0   0]
 [  0   0 242 155   0   0   0   0   0   0   0   0  27 254  63   0   0   0]
 [  0   0 160 207   6   0   0   0   0   0   0   0  27 254  65   0   0   0]
 [  0   0 127 254  21   0   0   0   0   0   0   0  20 239  65   0   0   0]
 [  0   0  77 254  21   0   0   0   0   0   0   0   0 195  65   0   0   0]
 [  0   0  70 254  21   0   0   0   0   0   0   0   0 195 142   0   0   0]
 [  0   0  56 251  21   0   0   0   0   0   0   0   0 195 227   0   0   0]
 [  0   0   0 222 153   5   0   0   0   0   0   0   0 120 240  13   0   0]
 [  0   0   0  67 251  40   0   0   0   0   0   0   0  94 255  69   0   0]
 [  0   0   0   0 234 184   0   0   0   0   0   0   0  19 245  69   0   0]
 [  0   0   0   0 234 169   0   0   0   0   0   0   0   3 199 182  10   0]
 [  0   0   0   0 154 205   4   0   0  26  72 128 203 208 254 254 131   0]
 [  0   0   0   0  61 254 129 113 186 245 251 189  75  56 136 254  73   0]
 [  0   0   0   0  15 216 233 233 159 104  52   0   0   0  38 254  73   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0  18 254  73   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0  18 254  73   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   5 206 106   0]]
```

```python
# missing values - there are none
numbers.isnull().sum()
```

```
label     0
pixel0    0
pixel1    0
pixel2    0
pixel3    0
pixel4    0
```

| | |
|---|---|
| pixel5 | 0 |
| pixel6 | 0 |
| pixel7 | 0 |
| pixel8 | 0 |
| pixel9 | 0 |
| pixel10 | 0 |
| pixel11 | 0 |
| pixel12 | 0 |
| pixel13 | 0 |
| pixel14 | 0 |
| pixel15 | 0 |
| pixel16 | 0 |
| pixel17 | 0 |
| pixel18 | 0 |
| pixel19 | 0 |
| pixel20 | 0 |
| pixel21 | 0 |
| pixel22 | 0 |
| pixel23 | 0 |
| pixel24 | 0 |
| pixel25 | 0 |
| pixel26 | 0 |
| pixel27 | 0 |
| pixel28 | 0 |
| .. | |
| pixel754 | 0 |
| pixel755 | 0 |
| pixel756 | 0 |
| pixel757 | 0 |
| pixel758 | 0 |
| pixel759 | 0 |
| pixel760 | 0 |
| pixel761 | 0 |
| pixel762 | 0 |
| pixel763 | 0 |
| pixel764 | 0 |
| pixel765 | 0 |
| pixel766 | 0 |
| pixel767 | 0 |
| pixel768 | 0 |
| pixel769 | 0 |
| pixel770 | 0 |
| pixel771 | 0 |
| pixel772 | 0 |
| pixel773 | 0 |
| pixel774 | 0 |
| pixel775 | 0 |
| pixel776 | 0 |
| pixel777 | 0 |
| pixel778 | 0 |
| pixel779 | 0 |

```
pixel780    0
pixel781    0
pixel782    0
pixel783    0
Length: 785, dtype: int64
```

```
# average values/distributions of features
description = numbers.describe()
description
```

```
             label   pixel0   pixel1   pixel2   pixel3   pixel4   pixel5  \
count  42000.000000  42000.0  42000.0  42000.0  42000.0  42000.0  42000.0
mean       4.456643      0.0      0.0      0.0      0.0      0.0      0.0
std        2.887730      0.0      0.0      0.0      0.0      0.0      0.0
min        0.000000      0.0      0.0      0.0      0.0      0.0      0.0
25%        2.000000      0.0      0.0      0.0      0.0      0.0      0.0
50%        4.000000      0.0      0.0      0.0      0.0      0.0      0.0
75%        7.000000      0.0      0.0      0.0      0.0      0.0      0.0
max        9.000000      0.0      0.0      0.0      0.0      0.0      0.0

        pixel6   pixel7   pixel8  ...      pixel774      pixel775  \
count  42000.0  42000.0  42000.0  ...  42000.000000  42000.000000
mean       0.0      0.0      0.0  ...      0.219286      0.117095
std        0.0      0.0      0.0  ...      6.312890      4.633819
min        0.0      0.0      0.0  ...      0.000000      0.000000
25%        0.0      0.0      0.0  ...      0.000000      0.000000
50%        0.0      0.0      0.0  ...      0.000000      0.000000
75%        0.0      0.0      0.0  ...      0.000000      0.000000
max        0.0      0.0      0.0  ...    254.000000    254.000000

           pixel776     pixel777      pixel778      pixel779  pixel780  \
count  42000.000000  42000.00000  42000.000000  42000.000000   42000.0
mean       0.059024      0.02019      0.017238      0.002857       0.0
std        3.274488      1.75987      1.894498      0.414264       0.0
min        0.000000      0.00000      0.000000      0.000000       0.0
25%        0.000000      0.00000      0.000000      0.000000       0.0
50%        0.000000      0.00000      0.000000      0.000000       0.0
75%        0.000000      0.00000      0.000000      0.000000       0.0
max      253.000000    253.00000    254.000000     62.000000       0.0

       pixel781  pixel782  pixel783
count   42000.0   42000.0   42000.0
mean        0.0       0.0       0.0
std         0.0       0.0       0.0
min         0.0       0.0       0.0
25%         0.0       0.0       0.0
50%         0.0       0.0       0.0
75%         0.0       0.0       0.0
max         0.0       0.0       0.0

[8 rows x 785 columns]
```

```python
# average feature values
pd.set_option('display.max_rows', 999)
round(numbers.drop('label', axis=1).mean(), 2).sort_values(ascending = False)
```

```
pixel407    139.83
pixel435    139.07
pixel408    137.42
pixel434    135.52
pixel211    135.49
pixel210    133.59
pixel602    132.98
pixel212    132.90
pixel436    132.00
pixel601    130.81
pixel380    130.66
pixel406    130.14
pixel409    128.65
pixel381    127.50
pixel463    127.45
pixel575    126.73
pixel603    126.34
pixel209    126.26
pixel629    126.03
pixel462    126.01
pixel213    126.00
pixel574    125.56
pixel183    124.89
pixel379    124.51
pixel237    123.89
pixel238    123.23
pixel433    123.10
pixel628    122.65
pixel600    122.59
pixel240    122.22
pixel239    121.98
pixel184    121.90
pixel630    121.89
pixel241    121.77
pixel437    121.70
pixel464    121.32
pixel236    120.60
pixel182    119.70
pixel576    119.67
pixel547    118.65
pixel353    118.46
pixel548    117.19
pixel573    116.96
pixel242    116.12
pixel491    115.44
pixel461    115.36
pixel405    114.96
```

| | |
|---|---|
| pixel352 | 113.93 |
| pixel627 | 113.00 |
| pixel208 | 112.99 |
| pixel214 | 112.65 |
| pixel492 | 112.60 |
| pixel519 | 112.59 |
| pixel546 | 112.43 |
| pixel599 | 112.37 |
| pixel520 | 112.15 |
| pixel490 | 112.10 |
| pixel263 | 111.90 |
| pixel185 | 111.65 |
| pixel604 | 111.62 |
| pixel378 | 111.46 |
| pixel465 | 111.36 |
| pixel270 | 111.29 |
| pixel264 | 111.12 |
| pixel269 | 110.75 |
| pixel235 | 110.21 |
| pixel382 | 109.51 |
| pixel549 | 108.68 |
| pixel631 | 108.46 |
| pixel325 | 108.00 |
| pixel354 | 107.83 |
| pixel410 | 107.68 |
| pixel181 | 107.54 |
| pixel298 | 106.52 |
| pixel572 | 106.25 |
| pixel518 | 106.08 |
| pixel521 | 105.99 |
| pixel326 | 105.68 |
| pixel577 | 105.26 |
| pixel493 | 105.24 |
| pixel432 | 104.61 |
| pixel297 | 104.54 |
| pixel265 | 104.09 |
| pixel268 | 103.87 |
| pixel291 | 103.60 |
| pixel351 | 102.12 |
| pixel438 | 101.92 |
| pixel290 | 101.85 |
| pixel489 | 101.21 |
| pixel598 | 101.02 |
| pixel262 | 101.01 |
| pixel460 | 100.51 |
| pixel545 | 100.33 |
| pixel243 | 100.19 |
| pixel318 | 99.96 |
| pixel656 | 99.90 |
| pixel657 | 99.82 |
| pixel271 | 99.14 |

| | |
|---|---|
| pixel626 | 98.92 |
| pixel346 | 98.91 |
| pixel267 | 98.87 |
| pixel266 | 98.53 |
| pixel324 | 97.82 |
| pixel571 | 97.62 |
| pixel404 | 97.16 |
| pixel374 | 97.15 |
| pixel377 | 96.88 |
| pixel466 | 95.93 |
| pixel186 | 95.59 |
| pixel207 | 95.42 |
| pixel319 | 94.94 |
| pixel522 | 94.60 |
| pixel402 | 94.56 |
| pixel517 | 94.35 |
| pixel299 | 94.19 |
| pixel296 | 93.76 |
| pixel431 | 93.73 |
| pixel494 | 93.53 |
| pixel550 | 93.43 |
| pixel292 | 93.18 |
| pixel215 | 92.73 |
| pixel403 | 92.68 |
| pixel234 | 92.12 |
| pixel373 | 91.76 |
| pixel655 | 91.62 |
| pixel155 | 91.59 |
| pixel658 | 91.57 |
| pixel347 | 91.42 |
| pixel375 | 91.12 |
| pixel345 | 91.09 |
| pixel605 | 90.95 |
| pixel430 | 90.78 |
| pixel180 | 90.47 |
| pixel570 | 90.21 |
| pixel401 | 89.73 |
| pixel350 | 89.51 |
| pixel156 | 89.45 |
| pixel544 | 89.26 |
| pixel632 | 89.06 |
| pixel488 | 88.92 |
| pixel459 | 88.88 |
| pixel327 | 88.70 |
| pixel317 | 88.65 |
| pixel597 | 87.45 |
| pixel376 | 86.84 |
| pixel154 | 86.30 |
| pixel323 | 85.60 |
| pixel289 | 85.24 |
| pixel429 | 85.14 |

| | |
|---|---|
| pixel578 | 85.09 |
| pixel355 | 84.27 |
| pixel295 | 83.99 |
| pixel458 | 83.55 |
| pixel516 | 82.62 |
| pixel543 | 82.16 |
| pixel293 | 82.03 |
| pixel569 | 81.35 |
| pixel383 | 81.27 |
| pixel320 | 81.14 |
| pixel625 | 80.79 |
| pixel157 | 80.30 |
| pixel487 | 80.26 |
| pixel261 | 79.87 |
| pixel348 | 79.76 |
| pixel411 | 79.75 |
| pixel349 | 79.70 |
| pixel294 | 78.92 |
| pixel439 | 78.86 |
| pixel495 | 78.66 |
| pixel467 | 78.36 |
| pixel523 | 78.10 |
| pixel457 | 77.70 |
| pixel542 | 77.61 |
| pixel272 | 76.66 |
| pixel244 | 76.63 |
| pixel654 | 76.57 |
| pixel659 | 76.47 |
| pixel515 | 76.27 |
| pixel322 | 76.01 |
| pixel153 | 75.01 |
| pixel206 | 74.79 |
| pixel187 | 74.60 |
| pixel486 | 74.59 |
| pixel400 | 73.58 |
| pixel551 | 73.22 |
| pixel321 | 72.99 |
| pixel372 | 72.83 |
| pixel179 | 72.00 |
| pixel514 | 71.46 |
| pixel300 | 71.39 |
| pixel541 | 71.28 |
| pixel428 | 71.10 |
| pixel596 | 70.45 |
| pixel344 | 69.60 |
| pixel485 | 69.40 |
| pixel233 | 69.18 |
| pixel568 | 68.99 |
| pixel216 | 68.90 |
| pixel606 | 67.71 |
| pixel633 | 66.84 |

| | |
|---|---|
| pixel456 | 66.20 |
| pixel513 | 65.86 |
| pixel158 | 65.76 |
| pixel316 | 65.19 |
| pixel328 | 64.59 |
| pixel540 | 62.61 |
| pixel579 | 62.30 |
| pixel288 | 60.88 |
| pixel624 | 60.69 |
| pixel484 | 60.62 |
| pixel468 | 60.52 |
| pixel496 | 60.41 |
| pixel152 | 60.18 |
| pixel440 | 58.85 |
| pixel512 | 58.56 |
| pixel356 | 58.37 |
| pixel653 | 58.29 |
| pixel660 | 58.16 |
| pixel524 | 57.81 |
| pixel412 | 56.31 |
| pixel260 | 55.56 |
| pixel384 | 55.37 |
| pixel205 | 54.74 |
| pixel178 | 54.01 |
| pixel188 | 53.74 |
| pixel567 | 53.74 |
| pixel273 | 52.10 |
| pixel245 | 52.02 |
| pixel552 | 51.85 |
| pixel595 | 51.39 |
| pixel684 | 51.24 |
| pixel539 | 51.12 |
| pixel685 | 51.04 |
| pixel427 | 51.02 |
| pixel399 | 50.57 |
| pixel455 | 49.76 |
| pixel159 | 49.65 |
| pixel511 | 48.30 |
| pixel483 | 48.02 |
| pixel371 | 47.93 |
| pixel301 | 47.89 |
| pixel232 | 47.38 |
| pixel217 | 46.21 |
| pixel683 | 46.20 |
| pixel607 | 46.19 |
| pixel127 | 46.09 |
| pixel686 | 45.93 |
| pixel634 | 45.73 |
| pixel151 | 45.36 |
| pixel128 | 44.54 |
| pixel343 | 44.02 |

| | |
|---|---|
| pixel126 | 42.71 |
| pixel469 | 42.63 |
| pixel329 | 42.46 |
| pixel441 | 41.73 |
| pixel497 | 41.52 |
| pixel580 | 41.47 |
| pixel661 | 40.59 |
| pixel623 | 40.24 |
| pixel315 | 40.07 |
| pixel652 | 39.84 |
| pixel413 | 39.24 |
| pixel129 | 38.95 |
| pixel525 | 38.40 |
| pixel357 | 38.36 |
| pixel177 | 37.88 |
| pixel385 | 37.48 |
| pixel287 | 37.33 |
| pixel687 | 37.29 |
| pixel682 | 37.14 |
| pixel566 | 36.90 |
| pixel538 | 36.88 |
| pixel204 | 36.60 |
| pixel125 | 36.08 |
| pixel189 | 34.96 |
| pixel510 | 34.72 |
| pixel259 | 34.52 |
| pixel160 | 34.39 |
| pixel553 | 33.29 |
| pixel482 | 33.28 |
| pixel594 | 32.56 |
| pixel454 | 32.25 |
| pixel150 | 32.22 |
| pixel246 | 31.16 |
| pixel130 | 30.96 |
| pixel274 | 30.89 |
| pixel426 | 30.78 |
| pixel231 | 29.64 |
| pixel635 | 28.86 |
| pixel608 | 28.82 |
| pixel398 | 28.52 |
| pixel302 | 28.21 |
| pixel124 | 28.04 |
| pixel688 | 28.02 |
| pixel218 | 27.63 |
| pixel442 | 27.17 |
| pixel470 | 27.05 |
| pixel681 | 26.40 |
| pixel414 | 25.75 |
| pixel370 | 25.70 |
| pixel662 | 25.69 |
| pixel330 | 25.37 |

| | |
|---|---|
| pixel498 | 25.25 |
| pixel581 | 25.23 |
| pixel386 | 24.29 |
| pixel176 | 24.13 |
| pixel358 | 23.99 |
| pixel651 | 23.71 |
| pixel622 | 23.26 |
| pixel131 | 22.91 |
| pixel342 | 22.85 |
| pixel526 | 22.68 |
| pixel203 | 22.36 |
| pixel537 | 21.59 |
| pixel161 | 21.46 |
| pixel149 | 21.42 |
| pixel314 | 21.09 |
| pixel190 | 20.70 |
| pixel565 | 20.66 |
| pixel286 | 20.48 |
| pixel123 | 20.33 |
| pixel509 | 20.15 |
| pixel258 | 19.54 |
| pixel689 | 19.44 |
| pixel554 | 18.95 |
| pixel481 | 18.16 |
| pixel712 | 18.13 |
| pixel713 | 17.90 |
| pixel593 | 16.95 |
| pixel230 | 16.91 |
| pixel636 | 16.69 |
| pixel711 | 16.56 |
| pixel680 | 16.42 |
| pixel453 | 16.35 |
| pixel609 | 16.23 |
| pixel714 | 16.11 |
| pixel247 | 15.89 |
| pixel663 | 15.21 |
| pixel443 | 15.10 |
| pixel275 | 15.04 |
| pixel132 | 14.87 |
| pixel415 | 14.86 |
| pixel219 | 14.79 |
| pixel471 | 14.34 |
| pixel425 | 14.31 |
| pixel175 | 14.11 |
| pixel387 | 13.90 |
| pixel122 | 13.80 |
| pixel582 | 13.66 |
| pixel715 | 13.64 |
| pixel303 | 13.50 |
| pixel710 | 13.48 |
| pixel99 | 13.40 |

| | |
|---|---|
| pixel100 | 13.07 |
| pixel359 | 12.95 |
| pixel148 | 12.93 |
| pixel499 | 12.82 |
| pixel331 | 12.66 |
| pixel202 | 12.39 |
| pixel397 | 12.36 |
| pixel162 | 12.23 |
| pixel690 | 12.16 |
| pixel98 | 12.07 |
| pixel650 | 12.01 |
| pixel101 | 11.57 |
| pixel527 | 11.29 |
| pixel191 | 11.12 |
| pixel621 | 10.91 |
| pixel716 | 10.89 |
| pixel369 | 10.70 |
| pixel97 | 10.05 |
| pixel257 | 9.88 |
| pixel285 | 9.81 |
| pixel341 | 9.56 |
| pixel709 | 9.44 |
| pixel313 | 9.44 |
| pixel102 | 9.30 |
| pixel555 | 9.13 |
| pixel679 | 8.93 |
| pixel637 | 8.91 |
| pixel229 | 8.70 |
| pixel133 | 8.69 |
| pixel121 | 8.68 |
| pixel536 | 8.62 |
| pixel564 | 8.58 |
| pixel664 | 8.41 |
| pixel610 | 8.40 |
| pixel717 | 8.06 |
| pixel96 | 7.75 |
| pixel508 | 7.52 |
| pixel174 | 7.37 |
| pixel691 | 7.31 |
| pixel147 | 7.15 |
| pixel248 | 6.91 |
| pixel220 | 6.78 |
| pixel592 | 6.76 |
| pixel103 | 6.71 |
| pixel740 | 6.61 |
| pixel583 | 6.50 |
| pixel741 | 6.44 |
| pixel163 | 6.37 |
| pixel201 | 5.98 |
| pixel739 | 5.98 |
| pixel480 | 5.89 |

| | |
|---|---|
| pixel444 | 5.89 |
| pixel276 | 5.85 |
| pixel416 | 5.84 |
| pixel708 | 5.84 |
| pixel95 | 5.71 |
| pixel742 | 5.68 |
| pixel472 | 5.59 |
| pixel718 | 5.33 |
| pixel388 | 5.26 |
| pixel192 | 5.25 |
| pixel500 | 5.05 |
| pixel649 | 5.03 |
| pixel120 | 4.95 |
| pixel743 | 4.66 |
| pixel256 | 4.65 |
| pixel738 | 4.64 |
| pixel304 | 4.63 |
| pixel134 | 4.55 |
| pixel638 | 4.55 |
| pixel360 | 4.46 |
| pixel452 | 4.45 |
| pixel528 | 4.45 |
| pixel284 | 4.31 |
| pixel665 | 4.27 |
| pixel678 | 4.15 |
| pixel104 | 4.14 |
| pixel332 | 4.13 |
| pixel611 | 4.12 |
| pixel620 | 4.03 |
| pixel692 | 4.00 |
| pixel228 | 3.97 |
| pixel71 | 3.80 |
| pixel744 | 3.77 |
| pixel94 | 3.77 |
| pixel72 | 3.74 |
| pixel312 | 3.57 |
| pixel146 | 3.56 |
| pixel556 | 3.54 |
| pixel424 | 3.48 |
| pixel70 | 3.39 |
| pixel73 | 3.33 |
| pixel173 | 3.27 |
| pixel737 | 3.24 |
| pixel719 | 3.19 |
| pixel707 | 2.99 |
| pixel340 | 2.98 |
| pixel396 | 2.94 |
| pixel164 | 2.91 |
| pixel368 | 2.81 |
| pixel745 | 2.75 |
| pixel69 | 2.70 |

| | |
|---|---|
| pixel74 | 2.68 |
| pixel584 | 2.63 |
| pixel249 | 2.48 |
| pixel200 | 2.45 |
| pixel119 | 2.45 |
| pixel221 | 2.38 |
| pixel563 | 2.29 |
| pixel93 | 2.29 |
| pixel105 | 2.27 |
| pixel736 | 2.16 |
| pixel666 | 2.11 |
| pixel135 | 2.10 |
| pixel639 | 2.10 |
| pixel535 | 2.04 |
| pixel693 | 1.99 |
| pixel75 | 1.99 |
| pixel68 | 1.98 |
| pixel591 | 1.91 |
| pixel277 | 1.84 |
| pixel648 | 1.81 |
| pixel746 | 1.80 |
| pixel255 | 1.80 |
| pixel193 | 1.77 |
| pixel720 | 1.72 |
| pixel283 | 1.71 |
| pixel677 | 1.64 |
| pixel612 | 1.63 |
| pixel507 | 1.51 |
| pixel145 | 1.44 |
| pixel227 | 1.40 |
| pixel67 | 1.35 |
| pixel501 | 1.33 |
| pixel706 | 1.31 |
| pixel311 | 1.29 |
| pixel529 | 1.25 |
| pixel473 | 1.24 |
| pixel76 | 1.20 |
| pixel92 | 1.19 |
| pixel305 | 1.16 |
| pixel619 | 1.16 |
| pixel735 | 1.15 |
| pixel172 | 1.15 |
| pixel106 | 1.09 |
| pixel747 | 1.09 |
| pixel445 | 1.06 |
| pixel557 | 1.03 |
| pixel118 | 1.03 |
| pixel479 | 0.97 |
| pixel667 | 0.95 |
| pixel694 | 0.93 |
| pixel339 | 0.90 |

| | |
|---|---|
| pixel66 | 0.87 |
| pixel136 | 0.84 |
| pixel721 | 0.84 |
| pixel417 | 0.83 |
| pixel640 | 0.80 |
| pixel165 | 0.79 |
| pixel585 | 0.75 |
| pixel770 | 0.68 |
| pixel333 | 0.65 |
| pixel451 | 0.65 |
| pixel199 | 0.62 |
| pixel389 | 0.62 |
| pixel367 | 0.61 |
| pixel77 | 0.60 |
| pixel771 | 0.60 |
| pixel769 | 0.56 |
| pixel676 | 0.56 |
| pixel748 | 0.56 |
| pixel254 | 0.55 |
| pixel282 | 0.54 |
| pixel91 | 0.54 |
| pixel65 | 0.53 |
| pixel768 | 0.51 |
| pixel734 | 0.50 |
| pixel772 | 0.49 |
| pixel222 | 0.49 |
| pixel361 | 0.48 |
| pixel423 | 0.48 |
| pixel250 | 0.48 |
| pixel705 | 0.47 |
| pixel647 | 0.47 |
| pixel310 | 0.44 |
| pixel395 | 0.43 |
| pixel613 | 0.43 |
| pixel107 | 0.42 |
| pixel144 | 0.41 |
| pixel767 | 0.41 |
| pixel695 | 0.40 |
| pixel117 | 0.39 |
| pixel226 | 0.38 |
| pixel722 | 0.38 |
| pixel194 | 0.35 |
| pixel773 | 0.34 |
| pixel278 | 0.33 |
| pixel562 | 0.32 |
| pixel668 | 0.31 |
| pixel64 | 0.30 |
| pixel766 | 0.30 |
| pixel78 | 0.29 |
| pixel534 | 0.28 |
| pixel590 | 0.27 |

| | |
|---|---|
| pixel338 | 0.27 |
| pixel90 | 0.24 |
| pixel749 | 0.24 |
| pixel171 | 0.23 |
| pixel306 | 0.22 |
| pixel774 | 0.22 |
| pixel137 | 0.20 |
| pixel502 | 0.20 |
| pixel42 | 0.20 |
| pixel641 | 0.20 |
| pixel40 | 0.19 |
| pixel474 | 0.19 |
| pixel41 | 0.19 |
| pixel765 | 0.18 |
| pixel43 | 0.17 |
| pixel108 | 0.17 |
| pixel39 | 0.17 |
| pixel506 | 0.17 |
| pixel618 | 0.17 |
| pixel530 | 0.16 |
| pixel44 | 0.16 |
| pixel558 | 0.16 |
| pixel723 | 0.15 |
| pixel63 | 0.15 |
| pixel45 | 0.15 |
| pixel704 | 0.15 |
| pixel675 | 0.14 |
| pixel446 | 0.14 |
| pixel334 | 0.14 |
| pixel733 | 0.14 |
| pixel166 | 0.13 |
| pixel38 | 0.13 |
| pixel366 | 0.13 |
| pixel775 | 0.12 |
| pixel478 | 0.11 |
| pixel46 | 0.11 |
| pixel198 | 0.11 |
| pixel764 | 0.11 |
| pixel79 | 0.10 |
| pixel281 | 0.10 |
| pixel696 | 0.10 |
| pixel253 | 0.10 |
| pixel586 | 0.10 |
| pixel750 | 0.09 |
| pixel89 | 0.09 |
| pixel116 | 0.09 |
| pixel763 | 0.08 |
| pixel418 | 0.07 |
| pixel309 | 0.07 |
| pixel37 | 0.07 |
| pixel614 | 0.07 |

| | |
|---|---|
| pixel362 | 0.07 |
| pixel450 | 0.07 |
| pixel225 | 0.07 |
| pixel390 | 0.07 |
| pixel646 | 0.06 |
| pixel62 | 0.06 |
| pixel47 | 0.06 |
| pixel669 | 0.06 |
| pixel776 | 0.06 |
| pixel36 | 0.05 |
| pixel143 | 0.05 |
| pixel394 | 0.05 |
| pixel48 | 0.05 |
| pixel337 | 0.04 |
| pixel732 | 0.04 |
| pixel422 | 0.04 |
| pixel762 | 0.04 |
| pixel138 | 0.04 |
| pixel279 | 0.03 |
| pixel80 | 0.03 |
| pixel35 | 0.03 |
| pixel195 | 0.03 |
| pixel307 | 0.03 |
| pixel115 | 0.02 |
| pixel642 | 0.02 |
| pixel49 | 0.02 |
| pixel88 | 0.02 |
| pixel697 | 0.02 |
| pixel197 | 0.02 |
| pixel777 | 0.02 |
| pixel109 | 0.02 |
| pixel724 | 0.02 |
| pixel778 | 0.02 |
| pixel674 | 0.02 |
| pixel170 | 0.02 |
| pixel503 | 0.02 |
| pixel223 | 0.02 |
| pixel703 | 0.02 |
| pixel475 | 0.02 |
| pixel251 | 0.02 |
| pixel751 | 0.02 |
| pixel363 | 0.01 |
| pixel335 | 0.01 |
| pixel365 | 0.01 |
| pixel81 | 0.01 |
| pixel308 | 0.01 |
| pixel60 | 0.01 |
| pixel61 | 0.01 |
| pixel391 | 0.01 |
| pixel761 | 0.01 |
| pixel13 | 0.01 |

| | |
|---|---|
| pixel589 | 0.01 |
| pixel50 | 0.01 |
| pixel34 | 0.01 |
| pixel252 | 0.01 |
| pixel670 | 0.01 |
| pixel561 | 0.01 |
| pixel559 | 0.01 |
| pixel51 | 0.01 |
| pixel533 | 0.01 |
| pixel531 | 0.01 |
| pixel505 | 0.01 |
| pixel280 | 0.01 |
| pixel14 | 0.01 |
| pixel725 | 0.01 |
| pixel447 | 0.01 |
| pixel142 | 0.01 |
| pixel12 | 0.00 |
| pixel33 | 0.00 |
| pixel10 | 0.00 |
| pixel24 | 0.00 |
| pixel25 | 0.00 |
| pixel26 | 0.00 |
| pixel9 | 0.00 |
| pixel8 | 0.00 |
| pixel7 | 0.00 |
| pixel6 | 0.00 |
| pixel57 | 0.00 |
| pixel5 | 0.00 |
| pixel27 | 0.00 |
| pixel28 | 0.00 |
| pixel29 | 0.00 |
| pixel32 | 0.00 |
| pixel2 | 0.00 |
| pixel1 | 0.00 |
| pixel23 | 0.00 |
| pixel56 | 0.00 |
| pixel30 | 0.00 |
| pixel17 | 0.00 |
| pixel11 | 0.00 |
| pixel15 | 0.00 |
| pixel59 | 0.00 |
| pixel54 | 0.00 |
| pixel53 | 0.00 |
| pixel52 | 0.00 |
| pixel16 | 0.00 |
| pixel18 | 0.00 |
| pixel22 | 0.00 |
| pixel4 | 0.00 |
| pixel58 | 0.00 |
| pixel55 | 0.00 |
| pixel19 | 0.00 |

| | |
|---|---|
| pixel3 | 0.00 |
| pixel20 | 0.00 |
| pixel21 | 0.00 |
| pixel31 | 0.00 |
| pixel783 | 0.00 |
| pixel82 | 0.00 |
| pixel673 | 0.00 |
| pixel726 | 0.00 |
| pixel702 | 0.00 |
| pixel701 | 0.00 |
| pixel700 | 0.00 |
| pixel699 | 0.00 |
| pixel698 | 0.00 |
| pixel672 | 0.00 |
| pixel588 | 0.00 |
| pixel671 | 0.00 |
| pixel645 | 0.00 |
| pixel644 | 0.00 |
| pixel643 | 0.00 |
| pixel617 | 0.00 |
| pixel616 | 0.00 |
| pixel727 | 0.00 |
| pixel728 | 0.00 |
| pixel729 | 0.00 |
| pixel730 | 0.00 |
| pixel731 | 0.00 |
| pixel752 | 0.00 |
| pixel753 | 0.00 |
| pixel754 | 0.00 |
| pixel755 | 0.00 |
| pixel756 | 0.00 |
| pixel757 | 0.00 |
| pixel758 | 0.00 |
| pixel759 | 0.00 |
| pixel760 | 0.00 |
| pixel779 | 0.00 |
| pixel780 | 0.00 |
| pixel781 | 0.00 |
| pixel615 | 0.00 |
| pixel587 | 0.00 |
| pixel83 | 0.00 |
| pixel113 | 0.00 |
| pixel168 | 0.00 |
| pixel167 | 0.00 |
| pixel141 | 0.00 |
| pixel140 | 0.00 |
| pixel139 | 0.00 |
| pixel114 | 0.00 |
| pixel112 | 0.00 |
| pixel560 | 0.00 |
| pixel111 | 0.00 |

```
pixel110     0.00
pixel87      0.00
pixel86      0.00
pixel85      0.00
pixel84      0.00
pixel169     0.00
pixel196     0.00
pixel224     0.00
pixel336     0.00
pixel364     0.00
pixel782     0.00
pixel392     0.00
pixel393     0.00
pixel419     0.00
pixel420     0.00
pixel421     0.00
pixel448     0.00
pixel449     0.00
pixel476     0.00
pixel477     0.00
pixel504     0.00
pixel532     0.00
pixel0       0.00
dtype: float64
```

```
# splitting into X and y
X = numbers.drop("label", axis = 1)
y = numbers['label']

# scaling the features
X_scaled = scale(X)

# train test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, train_size=0.2,test_size = 0.8, random_state
 = 101)

print('X_train shape:',X_train.shape)
print('y_train shape:',y_train.shape)
print('X_test shape:',X_test.shape)
print('y_test shape:',y_test.shape)
```

```
X_train shape: (8400, 784)
y_train shape: (8400,)
X_test shape: (33600, 784)
y_test shape: (33600,)
```

```
# linear model
model_linear = SVC(kernel='linear')
model_linear.fit(X_train, y_train)

# predict
y_pred = model_linear.predict(X_test)
```

```
# confusion matrix and accuracy, precision, recall

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

# cm
print(metrics.confusion_matrix(y_true=y_test, y_pred=y_pred))
```

```
accuracy: 0.913125

[[3188    0   10    5   11   20   32    3   15    1]
 [   0 3677   14   11    5    7    4    8   30    4]
 [  36   29 3027   54   55   10   30   42   48   12]
 [  13   12  104 3051    9  181    5   21   54   25]
 [   8   14   33    2 3057    4   25   31    6  110]
 [  30   23   29  136   44 2622   44   12   72   27]
 [  26   11   44    4   28   33 3113    0   18    0]
 [   7   24   36   19   59    9    2 3210    4  134]
 [  13   46   50  120   21  110   30   18 2843   21]
 [  19   17   21   22  172   20    4  161   26 2893]]
```

```
#precision, recall and f1-score
scores=metrics.classification_report(y_test, y_pred, labels=[0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
print(scores)
```

```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96      3285
           1       0.95      0.98      0.97      3760
           2       0.90      0.91      0.90      3343
           3       0.89      0.88      0.88      3475
           4       0.88      0.93      0.91      3290
           5       0.87      0.86      0.87      3039
           6       0.95      0.95      0.95      3277
           7       0.92      0.92      0.92      3504
           8       0.91      0.87      0.89      3272
           9       0.90      0.86      0.88      3355

    accuracy                           0.91     33600
   macro avg       0.91      0.91      0.91     33600
weighted avg       0.91      0.91      0.91     33600
```

```
# non-linear model
# using poly kernel, C=1, default value of gamma

# model
non_linear_model_poly = SVC(kernel='poly')

# fit
non_linear_model_poly.fit(X_train, y_train)
```

```
# predict
y_pred = non_linear_model_poly.predict(X_test)

#confusion matrix and accuracy, precision, recall

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

# cm
print(metrics.confusion_matrix(y_true=y_test, y_pred=y_pred))
```

```
accuracy: 0.87125

[[2893    0    8    3   38   13   28    0  299    3]
 [   1 3684   11    1   12    0    6    0   43    2]
 [  14   18 2489   37  153    1   11   19  588   13]
 [   0   16   24 2846   27   36    3   13  464   46]
 [   3    8   15    0 3080    8    3    5   17  151]
 [   6    1    5   72   73 2358   30    7  442   45]
 [  16    9   10    0  108   43 2901    2  188    0]
 [   1   41    7    7  138    1    0 2862  105  342]
 [   2   16    6   30   20   40    1    4 3131   22]
 [   6   14    1   13  153    8    0   42   88 3030]]
```

```
# non-linear model
# using rbf kernel, C=1, default value of gamma

# model
non_linear_model = SVC(kernel='rbf')

# fit
non_linear_model.fit(X_train, y_train)

# predict
y_pred = non_linear_model.predict(X_test)

# confusion matrix and accuracy, precision, recall

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

# cm
print(metrics.confusion_matrix(y_true=y_test, y_pred=y_pred))
```

```
accuracy: 0.9396428571428571

[[3195    0   19    5    4   11   32    4   14    1]
 [   0 3689   23   12    8    3    7    6    8    4]
 [  15   15 3144   29   31    5   18   37   43    6]
 [   5    8   92 3191    5   73    6   31   43   21]
```

```
 [   3    7   57    1 3099    9   19   21    7   67]
 [  15   10   37   66   16 2776   53   15   32   19]
 [  19    5   46    1   12   31 3149    2   12    0]
 [   6   21   66   11   25    3    0 3285    3   84]
 [  14   24   40   63   14   62   22   19 2996   18]
 [  12   10   38   40   80    6    0   97   24 3048]]
```

```
#precision, recall and f1-score
scores=metrics.classification_report(y_test, y_pred, labels=[0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
print(scores)
```

```
              precision    recall  f1-score   support

           0       0.97      0.97      0.97      3285
           1       0.97      0.98      0.98      3760
           2       0.88      0.94      0.91      3343
           3       0.93      0.92      0.93      3475
           4       0.94      0.94      0.94      3290
           5       0.93      0.91      0.92      3039
           6       0.95      0.96      0.96      3277
           7       0.93      0.94      0.94      3504
           8       0.94      0.92      0.93      3272
           9       0.93      0.91      0.92      3355

    accuracy                           0.94     33600
   macro avg       0.94      0.94      0.94     33600
weighted avg       0.94      0.94      0.94     33600
```

```
# creating a KFold object with 5 splits
folds = KFold(n_splits = 5, shuffle = True, random_state = 101)

# specify range of hyperparameters
# Set the parameters by cross-validation
hyper_params = [ {'gamma': [0.01, 0.001,0.0001],
                  'C': [1, 10, 100]}]



# specify model
model = SVC(kernel="rbf")

# set up GridSearchCV()
model_cv = GridSearchCV(estimator = model,
                        param_grid = hyper_params,
                        scoring= 'accuracy',
                        cv = folds,
                        verbose = 1,
                        return_train_score=True,n_jobs = -1)

# fit the model
model_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  45 out of  45 | elapsed: 22.6min finished

GridSearchCV(cv=KFold(n_splits=5, random_state=101, shuffle=True),
       error_score='raise-deprecating',
       estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
                decision_function_shape='ovr', degree=3,
                gamma='auto_deprecated', kernel='rbf', max_iter=-1,
                probability=False, random_state=None, shrinking=True,
                tol=0.001, verbose=False),
       iid='warn', n_jobs=-1,
       param_grid=[{'C': [1, 10, 100], 'gamma': [0.01, 0.001, 0.0001]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='accuracy', verbose=1)
```

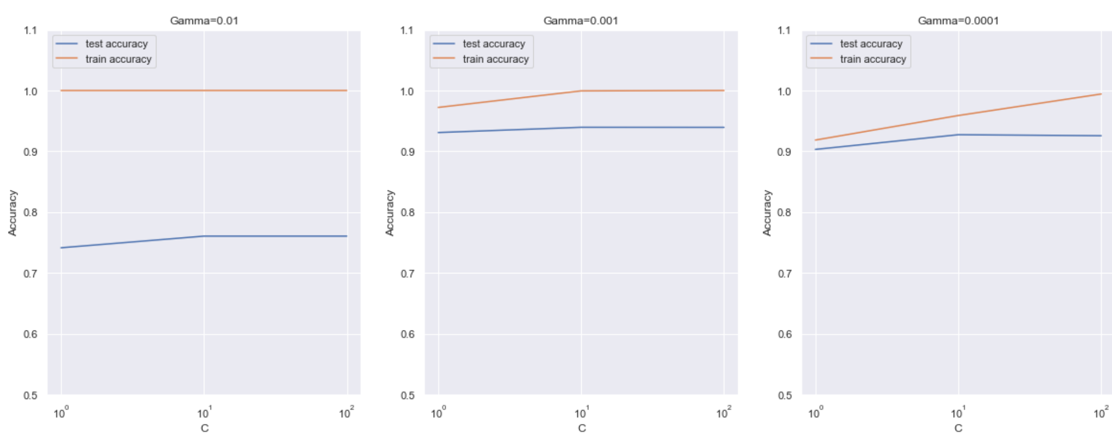
```
# cv results
cv_results = pd.DataFrame(model_cv.cv_results_)
cv_results
```

```
   mean_fit_time  std_fit_time  mean_score_time  std_score_time param_C  \
0     130.659739      1.989133        14.666499        0.081432       1
1      32.536529      0.142300         8.515690        0.093374       1
2      49.312719      1.380140        12.081309        0.709100       1
3     155.832136     12.587659        16.657551        2.226980      10
4      27.124150      0.316659         7.750964        0.016862      10
5      20.726886      0.232504         7.159922        0.099636      10
6     133.620725      1.723362        14.977487        0.186436     100
7      27.370743      0.306953         7.755510        0.118800     100
8      15.408296      0.850696         5.484372        0.774388     100

  param_gamma                          params  split0_test_score  \
0        0.01     {'C': 1, 'gamma': 0.01}           0.752381
1       0.001     {'C': 1, 'gamma': 0.001}          0.935119
2      0.0001     {'C': 1, 'gamma': 0.0001}         0.910119
3        0.01     {'C': 10, 'gamma': 0.01}          0.766071
4       0.001     {'C': 10, 'gamma': 0.001}         0.941071
5      0.0001     {'C': 10, 'gamma': 0.0001}        0.933929
6        0.01     {'C': 100, 'gamma': 0.01}         0.766071
7       0.001     {'C': 100, 'gamma': 0.001}        0.939881
8      0.0001     {'C': 100, 'gamma': 0.0001}       0.929762

   split1_test_score  split2_test_score  ...  mean_test_score  std_test_score  \
0           0.750595           0.747024  ...         0.741310        0.010784
1           0.926786           0.935119  ...         0.930833        0.004216
2           0.905952           0.907738  ...         0.903095        0.006075
3           0.772619           0.765476  ...         0.760476        0.009705
4           0.938690           0.945833  ...         0.939405        0.003865
5           0.923214           0.931548  ...         0.927262        0.004678
6           0.772619           0.765476  ...         0.760476        0.009705
```

```
7        0.936905        0.946429  ...        0.939286       0.003783
8        0.923810        0.925595  ...        0.925595       0.003409

   rank_test_score  split0_train_score  split1_train_score  \
0              9           1.000000            0.999851
1              3           0.972321            0.971429
2              6           0.916518            0.917708
3              7           1.000000            1.000000
4              1           0.999405            0.999554
5              4           0.957887            0.959970
6              7           1.000000            1.000000
7              2           1.000000            1.000000
8              5           0.994345            0.994494

   split2_train_score  split3_train_score  split4_train_score  \
0           0.999851            1.000000            1.000000
1           0.971429            0.972173            0.973214
2           0.916518            0.921577            0.919940
3           1.000000            1.000000            1.000000
4           0.999405            0.999107            0.999256
5           0.959375            0.957738            0.959077
6           1.000000            1.000000            1.000000
7           1.000000            1.000000            1.000000
8           0.994940            0.993006            0.994196

   mean_train_score  std_train_score
0          0.999940         0.000073
1          0.972113         0.000663
2          0.918452         0.002001
3          1.000000         0.000000
4          0.999345         0.000152
5          0.958810         0.000865
6          1.000000         0.000000
7          1.000000         0.000000
8          0.994196         0.000645

[9 rows x 22 columns]
```

```
# converting C to numeric type for plotting on x-axis
cv_results['param_C'] = cv_results['param_C'].astype('int')

# # plotting
plt.figure(figsize=(20,7))

# subplot 1/3
plt.subplot(131)
gamma_01 = cv_results[cv_results['param_gamma']==0.01]

plt.plot(gamma_01["param_C"], gamma_01["mean_test_score"])
plt.plot(gamma_01["param_C"], gamma_01["mean_train_score"])
```

```
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title("Gamma=0.01")
plt.ylim([0.50, 1.1])
plt.legend(['test accuracy', 'train accuracy'], loc='upper left')
plt.xscale('log')

# subplot 2/3
plt.subplot(132)
gamma_001 = cv_results[cv_results['param_gamma']==0.001]

plt.plot(gamma_001["param_C"], gamma_001["mean_test_score"])
plt.plot(gamma_001["param_C"], gamma_001["mean_train_score"])
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title("Gamma=0.001")
plt.ylim([0.50, 1.1])
plt.legend(['test accuracy', 'train accuracy'], loc='upper left')
plt.xscale('log')


# subplot 3/3
plt.subplot(133)
gamma_0001 = cv_results[cv_results['param_gamma']==0.0001]

plt.plot(gamma_0001["param_C"], gamma_0001["mean_test_score"])
plt.plot(gamma_0001["param_C"], gamma_0001["mean_train_score"])
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title("Gamma=0.0001")
plt.ylim([0.50, 1.1])
plt.legend(['test accuracy', 'train accuracy'], loc='upper left')
plt.xscale('log')
```




```
# printing the optimal accuracy score and hyperparameters
best_score = model_cv.best_score_
best_hyperparams = model_cv.best_params_
```

```
print("The best test score is {0} corresponding to hyperparameters {1}".format(best_score, best_hyperparams))
```

The best test score is 0.9394047619047619 corresponding to hyperparameters {'C': 10, 'gamma': 0.001}

```
#BUILDING AND EVALUATING THE FINAL MODEL
# model with optimal hyperparameters

# model
model = SVC(C=10, gamma=0.001, kernel="rbf")

model.fit(X_train, y_train)
y_pred = model.predict(X_test)

# metrics
print("accuracy", metrics.accuracy_score(y_test, y_pred), "\n")
print(metrics.confusion_matrix(y_test, y_pred), "\n")
```

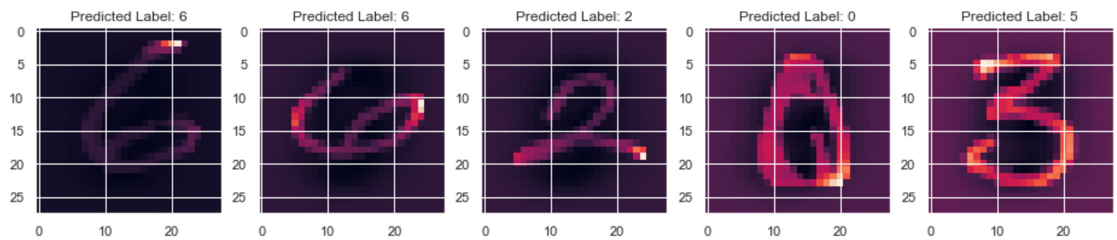
```
accuracy 0.9477083333333334

[[3211    0   19    2    2   12   26    3    8    2]
 [   0 3692   26    9    6    3    5    9    7    3]
 [  13   12 3165   29   29    6   20   40   21    8]
 [   4    5   77 3232    4   79    1   23   31   19]
 [   5    8   42    1 3117    5   20   19    9   64]
 [  15    8   33   61   15 2815   35   11   31   15]
 [  19    5   44    1   12   18 3167    1   10    0]
 [   5   17   52   12   29    4    1 3322    4   58]
 [   7   16   42   53   15   51   18   16 3044   10]
 [   9    9   33   20   81   10    0   94   21 3078]]
```

```
# different class-wise accuracy - #precision, recall and f1-score
scores=metrics.classification_report(y_test, y_pred, labels=[0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
print(scores)
```

```
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      3285
           1       0.98      0.98      0.98      3760
           2       0.90      0.95      0.92      3343
           3       0.95      0.93      0.94      3475
           4       0.94      0.95      0.94      3290
           5       0.94      0.93      0.93      3039
           6       0.96      0.97      0.96      3277
           7       0.94      0.95      0.94      3504
           8       0.96      0.93      0.94      3272
           9       0.95      0.92      0.93      3355

    accuracy                           0.95     33600
```

| | | | | |
|---|---|---|---|---|
| macro avg | 0.95 | 0.95 | 0.95 | 33600 |
| weighted avg | 0.95 | 0.95 | 0.95 | 33600 |

```python
# Let us visualize our final model on unseen training dataset

df = np.random.randint(1,y_pred.shape[0]+1,5)

plt.figure(figsize=(16,4))
for i,j in enumerate(df):
    plt.subplot(150+i+1)
    d = X_test[j].reshape(28,28)
    plt.title(f'Predicted Label: {y_pred[j]}')
    plt.imshow(d)
plt.show()
```




Conclusion:

The final accuracy of the given data set is 0.9394047619047619 corresponding to Hyper parameters which is approximately 93%.