Shubhnoor Gill 18BCS6061 ML Worksheet 5&6

November 5, 2020

Problem Statement A classic problem in the field of pattern recognition is that of handwritten digit recognition. Suppose that you have images of handwritten digits ranging from 0-9 written by various people in boxes of a specific size - similar to the application forms in banks and universities.

The goal is to develop a model that can correctly identify the digit (between 0-9) written in an image.

Objective You are required to develop a model using Support Vector Machine which should correctly classify the handwritten digits from 0-9 based on the pixel values given as features. Thus, this is a 10-class classification problem.

1 Load Libraries and dataset

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
import numpy as np  # To deal with arrays and matrices
import pandas as pd # To deal with dataset
```

[3]:
```
# Read the csv files using pandas
train_data = pd.read_csv("/content/drive/My Drive/Colab Notebooks/train.csv")
```

Since the training dataset is quite large (42,000 labelled images), it would take a lot of time for training an SVM on the full MNIST data, so we sub-sample the data for training (10-20% of the data, approx 8400 sample)

[4]:
```
np.random.seed = 28 # Randomly select the data
train_data_index=np.random.randint(0,train_data.shape[0],8400)
train_data = train_data.iloc[train_data_index,:]
```

2 Data Understanding

[5]:
```
print("Train data rows and columns: ",train_data.shape)
```

```
Train data rows and columns:  (8400, 785)
```

[6]:
```
train_data.head() # Display first 5 rows
```

[6]:
```
       label  pixel0  pixel1  pixel2  …  pixel780  pixel781  pixel782
pixel783
39493      4       0       0       0  …         0         0         0
0
33688      1       0       0       0  …         0         0         0
0
11326      1       0       0       0  …         0         0         0
0
8272       7       0       0       0  …         0         0         0
0
15981      2       0       0       0  …         0         0         0
0

[5 rows x 785 columns]
```

[7]:
```python
train_data.isnull().sum() # To check if null values are present in dataset
```

[7]:
```
label       0
pixel0      0
pixel1      0
pixel2      0
pixel3      0
           ..
pixel779    0
pixel780    0
pixel781    0
pixel782    0
pixel783    0
Length: 785, dtype: int64
```

The train dataset has no null values.

[8]:
```python
train_data.describe() #Display the description of dataset
```

[8]:
```
             label  pixel0  pixel1  …  pixel781  pixel782  pixel783
count  8400.000000  8400.0  8400.0  …    8400.0    8400.0    8400.0
mean      4.435476     0.0     0.0  …       0.0       0.0       0.0
std       2.889747     0.0     0.0  …       0.0       0.0       0.0
min       0.000000     0.0     0.0  …       0.0       0.0       0.0
25%       2.000000     0.0     0.0  …       0.0       0.0       0.0
50%       4.000000     0.0     0.0  …       0.0       0.0       0.0
75%       7.000000     0.0     0.0  …       0.0       0.0       0.0
max       9.000000     0.0     0.0  …       0.0       0.0       0.0

[8 rows x 785 columns]
```

[9]:
```python
# Check the unique entries of label column
np.unique(train_data['label'])
```

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

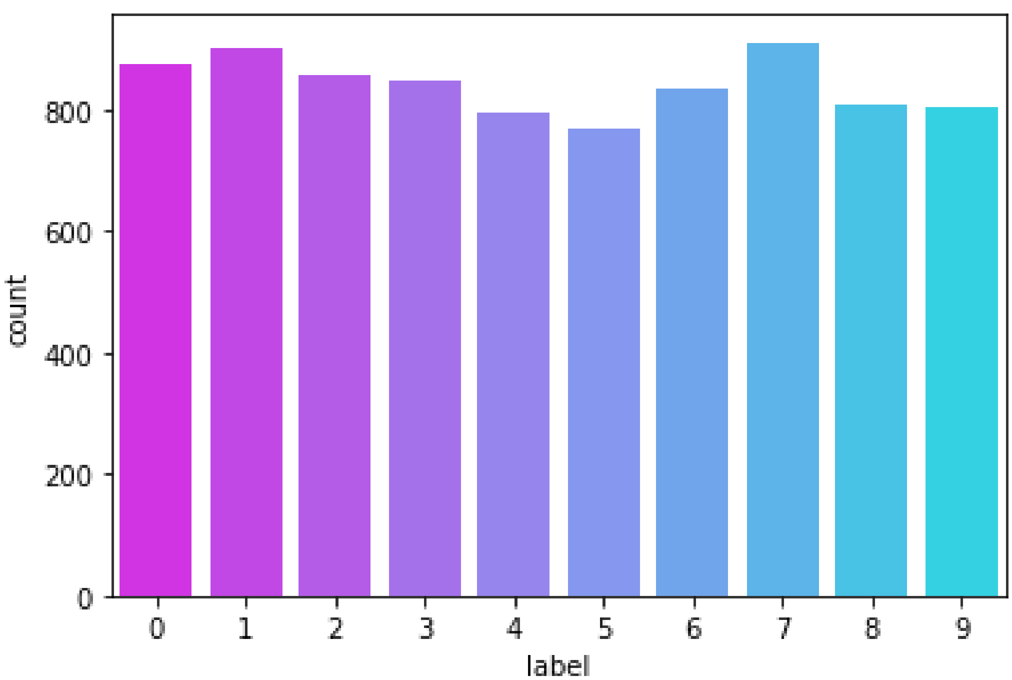
[10]:
```
train_data['label'].value_counts()
```

[10]:
```
7    911
1    902
0    875
2    855
3    849
6    835
8    807
9    805
4    794
5    767
Name: label, dtype: int64
```

3 Data Visualisation

[11]:
```
# Import data visualisation libraries
import matplotlib.pyplot as plt
import seaborn as sns
```

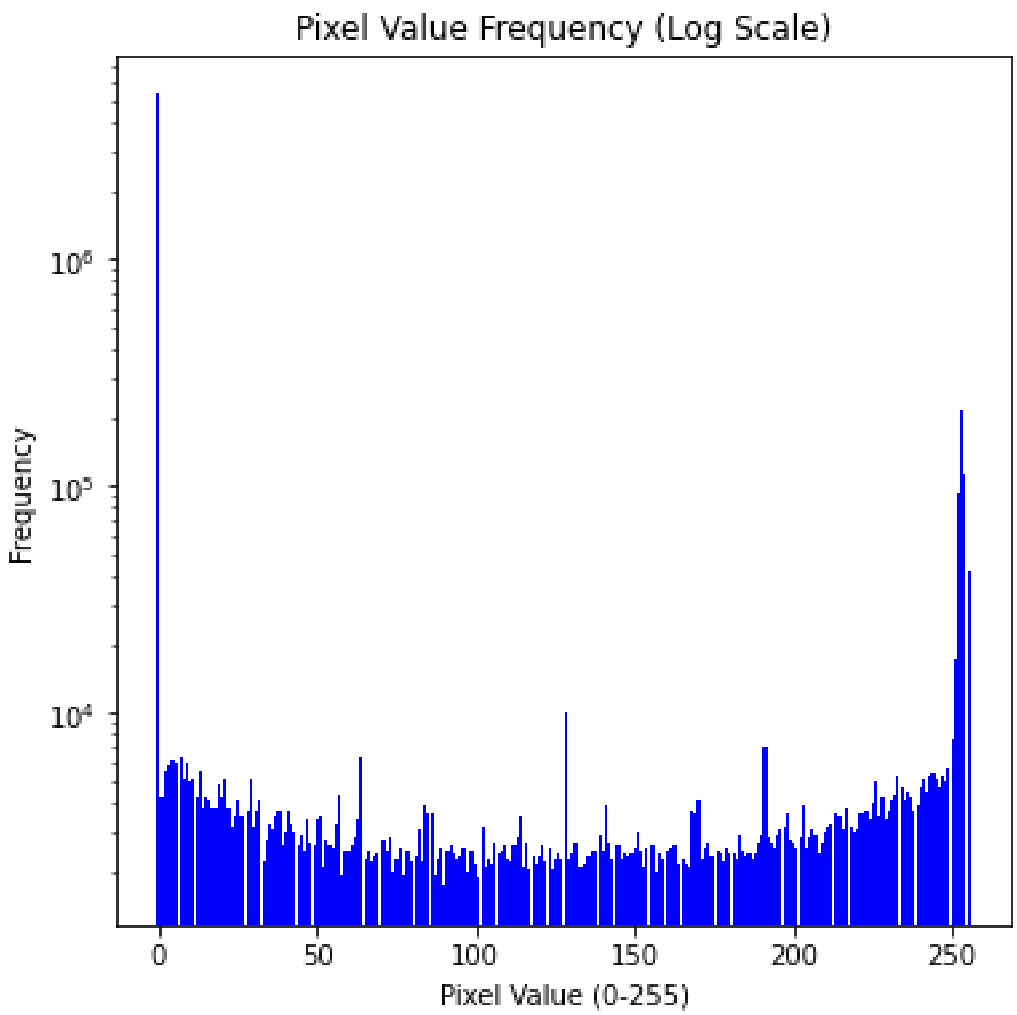
[15]:
```
# Visualizing the number of class and counts in the datasets
sns.countplot(train_data["label"],palette = 'cool_r');
```



3.0.1 Let us examine few pixels

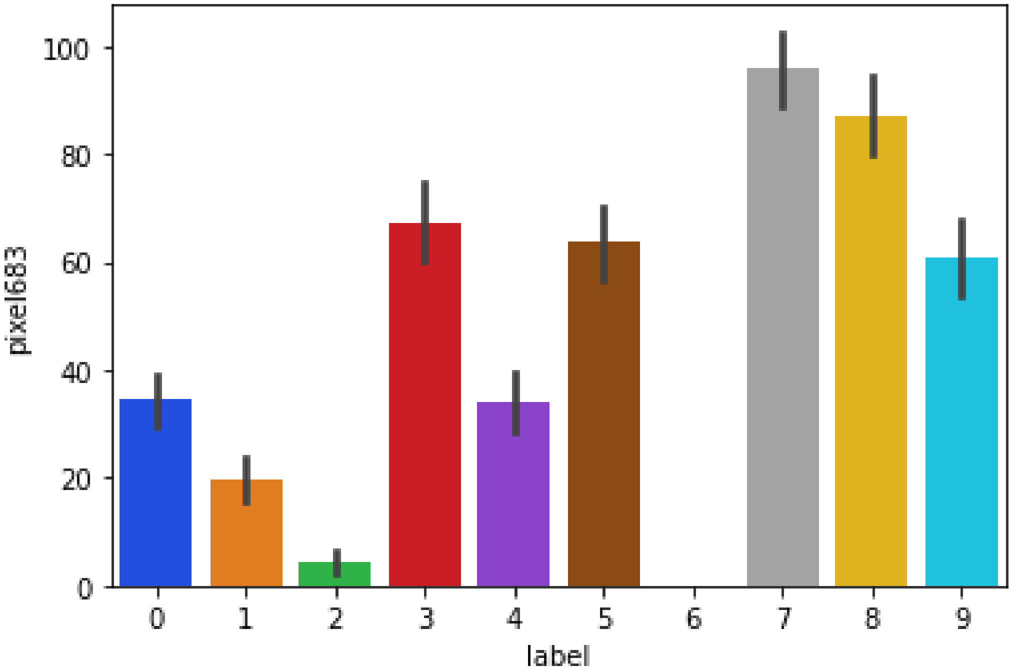
[20]:
```
y = pd.value_counts(train_data.values.ravel()).sort_index()
N = len(y)
x = range(N)
width =0.9
plt.figure(figsize=[6,6])
plt.bar(x, y, width, color="blue")
plt.title('Pixel Value Frequency (Log Scale)')
plt.yscale('log')
plt.xlabel('Pixel Value (0-255)')
plt.ylabel('Frequency')
```

[20]:
```
Text(0, 0.5, 'Frequency')
```

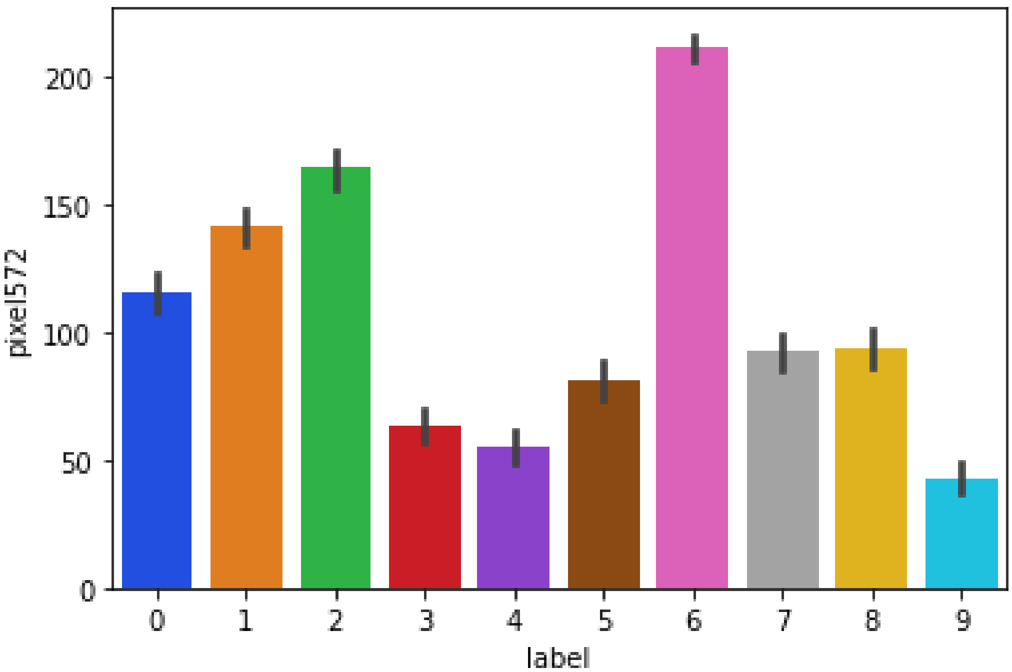


3.0.2 Label vs pixel

[32]:
```
sns.barplot(x='label', y='pixel683', data=train_data,palette='bright');
```



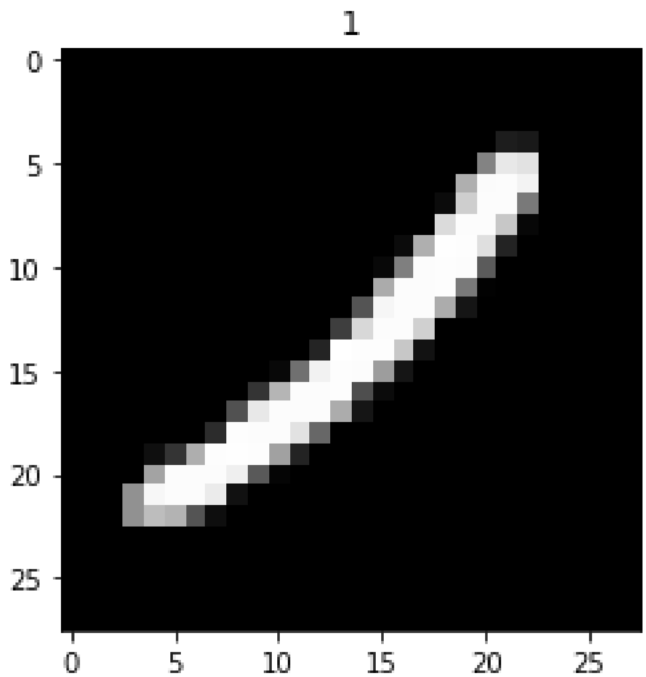
[31]:
```
sns.barplot(x='label', y='pixel572', data=train_data, palette='bright');
```



3.0.3 Let us visualise few numbers:

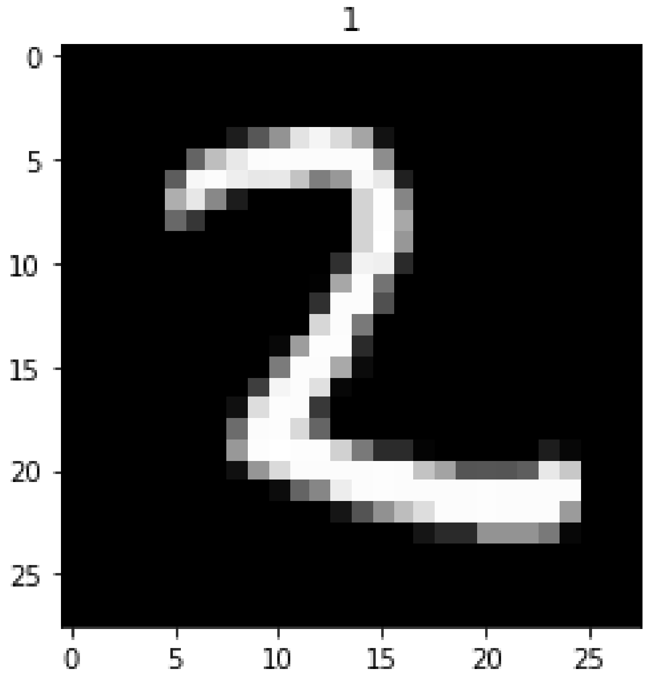
[42]:
```
x = train_data.iloc[2, 1:]
x = x.values.reshape(28,28)
plt.imshow(x,cmap='gray')
title=train_data['label'][2]
plt.title(title)
```

[42]: Text(0.5, 1.0, '1')



[43]:
```
x = train_data.iloc[6, 1:]
x = x.values.reshape(28,28)
plt.imshow(x,cmap='gray')
title=train_data['label'][6]
plt.title(title)
```

[43]: Text(0.5, 1.0, '1')



4 Data Preparation

4.0.1 Averaging the feature values

[44]:
```
# average feature values
round(train_data.drop('label', axis=1).mean(), 2)
```

[44]:
```
pixel0      0.0
pixel1      0.0
pixel2      0.0
pixel3      0.0
pixel4      0.0
           ...
pixel779    0.0
pixel780    0.0
pixel781    0.0
pixel782    0.0
pixel783    0.0
Length: 784, dtype: float64
```

4.0.2 Separating the dependent and independent variables

[45]:
```
## Separating the X and Y variable
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)
```

```
(8400, 785)
```

4.0.3 Normalize data

[46]:
```
# Normalization
X = X/255.0
print("X:", X.shape)
```

```
X: (8400, 784)
```

4.0.4 Scale data

[47]:
```
# scaling the features
from sklearn.preprocessing import scale
X_scaled = scale(X)
```

4.0.5 Split Data into train and validation

[48]:
```
from sklearn.model_selection import train_test_split
# train test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size = 0.
↪3, train_size =0.7)
```

5 Model Building

[49]:
```
# Importing the libraries to build the SVM model
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
```

5.0.1 Building a Linear SVM model

[50]:
```
# linear model
model_linear = SVC(kernel='linear')
model_linear.fit(X_train, y_train)
# predict
```

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

[51]:
```
from sklearn import metrics  # for accuracy
from sklearn.metrics import confusion_matrix # for confusion matrix
```

[52]:
```
# accuracy
print("accuracy:", metrics.accuracy_score(y_true=y_test, y_pred=y_pred), "\n")
# confusion matrix
print(metrics.confusion_matrix(y_true=y_test, y_pred=y_pred))
```

```
accuracy: 0.9119047619047619

[[255   0   0   0   1   0   3   2   0   0]
 [  0 290   1   2   2   0   0   2   0   1]
 [  0   3 198   4   6   0   2   1   0   0]
 [  2   3   4 217   0  12   2   3   4   4]
 [  0   1   2   0 221   0   0   0   0   8]
 [  2   4   5   7   2 197   5   1   3   0]
 [  4   1   3   0   3   3 225   0   1   0]
 [  1   3   5   2   2   0   0 230   0  15]
 [  4   3   3  12   3   7   3   3 217   1]
 [  1   2   0   2  11   2   0  18   0 248]]
```

[53]:
```
#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      0.98      0.96       261
           1       0.94      0.97      0.95       298
           2       0.90      0.93      0.91       214
           3       0.88      0.86      0.87       251
           4       0.88      0.95      0.92       232
           5       0.89      0.87      0.88       226
           6       0.94      0.94      0.94       240
           7       0.88      0.89      0.89       258
           8       0.96      0.85      0.90       256
           9       0.90      0.87      0.88       284

    accuracy                           0.91      2520
   macro avg       0.91      0.91      0.91      2520
weighted avg       0.91      0.91      0.91      2520
```

We have achieved an accuracy of 91% with the help of linear SVM model.

5.0.2 Building non-linear SVM model using RBF kernel

[54]:
```
# non-linear model using rbf kernel, C=1, default value of gamma
non_linear_model = SVC(kernel='rbf')
# fit model
non_linear_model.fit(X_train, y_train)
# predict model
y_pred = non_linear_model.predict(X_test)
```

[55]:
```
# Calculate accuracy
print("accuracy:", metrics.accuracy_score(y_true=y_test, y_pred=y_pred), "\n")
# Confusion Matrix
print(metrics.confusion_matrix(y_true=y_test, y_pred=y_pred))
```

```
accuracy: 0.9297619047619048

[[255   0   2   0   0   0   4   0   0   0]
 [  0 289   2   2   1   1   0   1   1   1]
 [  1   0 204   2   3   0   3   1   0   0]
 [  1   2  10 228   0   4   1   3   1   1]
 [  0   1   1   0 227   0   0   0   0   3]
 [  0   2   5   2   0 208   7   0   2   0]
 [  2   1  10   0   2   1 224   0   0   0]
 [  1   2   7   0   4   0   0 234   0  10]
 [  4   4   5   7   2   8   1   2 221   2]
 [  2   0   6   2   6   1   0  14   0 253]]
```

[56]:
```
#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       0.96      0.98      0.97       261
           1       0.96      0.97      0.96       298
           2       0.81      0.95      0.88       214
           3       0.94      0.91      0.92       251
           4       0.93      0.98      0.95       232
           5       0.93      0.92      0.93       226
           6       0.93      0.93      0.93       240
           7       0.92      0.91      0.91       258
           8       0.98      0.86      0.92       256
           9       0.94      0.89      0.91       284

    accuracy                           0.93      2520
   macro avg       0.93      0.93      0.93      2520
weighted avg       0.93      0.93      0.93      2520
```

We have achieved an accuracy of 93% approx by building a non-linear SVM model using RBF kernel.

We will now try to tune in our hyperparameters to improve the accuracy.

5.1 Grid Search: Hyperparameter Tuning:

[57]:
```
# creating a KFold object with 5 splits
folds = KFold(n_splits = 5, shuffle = True, random_state = 10)
# specify range of hyperparameters and set the parameters by cross-validation
hyper_params = [ {'gamma': [1e-2, 1e-3, 1e-4],'C': [5,10]}]
# 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)
model_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  30 out of  30 | elapsed: 21.3min finished
```

[57]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=10, shuffle=True),
             error_score=nan,
             estimator=SVC(C=1.0, break_ties=False, cache_size=200,
                           class_weight=None, coef0=0.0,
                           decision_function_shape='ovr', degree=3,
                           gamma='scale', kernel='rbf', max_iter=-1,
                           probability=False, random_state=None, shrinking=True,
                           tol=0.001, verbose=False),
             iid='deprecated', n_jobs=None,
             param_grid=[{'C': [5, 10], 'gamma': [0.01, 0.001, 0.0001]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
             scoring='accuracy', verbose=1)
```

[58]:
```
cv_results = pd.DataFrame(model_cv.cv_results_)
cv_results
```

[58]:

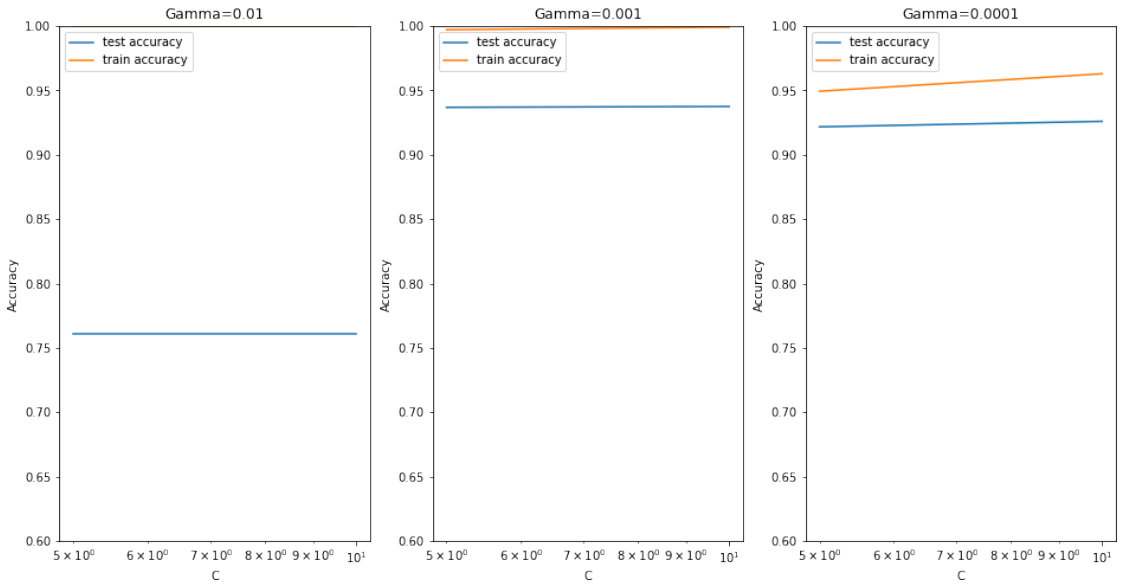
	mean_fit_time	std_fit_time	…	mean_train_score	std_train_score
0	43.183779	0.215039	…	1.000000	0.000000
1	10.425212	0.071576	…	0.997194	0.000159
2	9.929614	0.039062	…	0.949405	0.001652
3	43.339500	0.443365	…	1.000000	0.000000
4	10.331604	0.080817	…	0.999235	0.000104
5	8.132794	0.044637	…	0.963010	0.001674

```
[6 rows x 22 columns]
```

5.1.1 Plot the graphs for the Train vs Test accuracy

[60]:

```
# converting C to numeric type for plotting on x-axis
cv_results['param_C'] = cv_results['param_C'].astype('int')
# # plotting
plt.figure(figsize=(16,8))
# 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([0.60, 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([0.60, 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([0.60, 1])
plt.legend(['test accuracy', 'train accuracy'], loc='upper left')
plt.xscale('log')
```



[61]:
```
# 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 0.9375850340136054 corresponding to hyperparameters {'C':
10, 'gamma': 0.001}
```

Build the final model with the optimal hyperparameters

[62]:
```
# 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 0.9424603174603174

[[256   0   2   0   0   0   3   0   0   0]
 [  0 290   1   3   2   0   0   1   1   0]
 [  1   0 208   3   1   0   1   0   0   0]
 [  1   3   5 231   0   2   2   5   1   1]
 [  0   1   2   0 227   0   0   0   0   2]
 [  1   1   3   1   0 212   5   1   2   0]
 [  2   1  10   0   2   2 223   0   0   0]
```

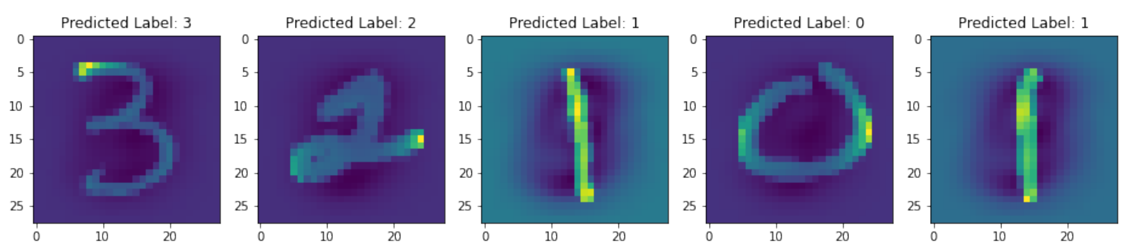
```
 [  1   3   7   0   4   0   0 238   0   5]
 [  2   3   2  10   2   7   1   1 226   2]
 [  1   0   2   2   3   1   0  11   0 264]]
```

[63]:
```python
# 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       0.97      0.98      0.97       261
           1       0.96      0.97      0.97       298
           2       0.86      0.97      0.91       214
           3       0.92      0.92      0.92       251
           4       0.94      0.98      0.96       232
           5       0.95      0.94      0.94       226
           6       0.95      0.93      0.94       240
           7       0.93      0.92      0.92       258
           8       0.98      0.88      0.93       256
           9       0.96      0.93      0.95       284

    accuracy                           0.94      2520
   macro avg       0.94      0.94      0.94      2520
weighted avg       0.94      0.94      0.94      2520
```

Finally, after tuning our hyperparameters we achieve an accuracy of 94% approx.

[64]:
```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()
```



5.2 Let us use our final model on test data

[65]:
```
#import file and reading few lines
test_df = pd.read_csv('/content/drive/My Drive/Colab Notebooks/test.csv')
test_df.head(10)
```

[65]:

	pixel0	pixel1	pixel2	pixel3	…	pixel780	pixel781	pixel782	pixel783
0	0	0	0	0	…	0	0	0	0
1	0	0	0	0	…	0	0	0	0
2	0	0	0	0	…	0	0	0	0
3	0	0	0	0	…	0	0	0	0
4	0	0	0	0	…	0	0	0	0
5	0	0	0	0	…	0	0	0	0
6	0	0	0	0	…	0	0	0	0
7	0	0	0	0	…	0	0	0	0
8	0	0	0	0	…	0	0	0	0
9	0	0	0	0	…	0	0	0	0

[10 rows x 784 columns]

[66]:
```
test_df.shape
```

[66]: (28000, 784)

[67]:
```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28000 entries, 0 to 27999
Columns: 784 entries, pixel0 to pixel783
dtypes: int64(784)
memory usage: 167.5 MB
```

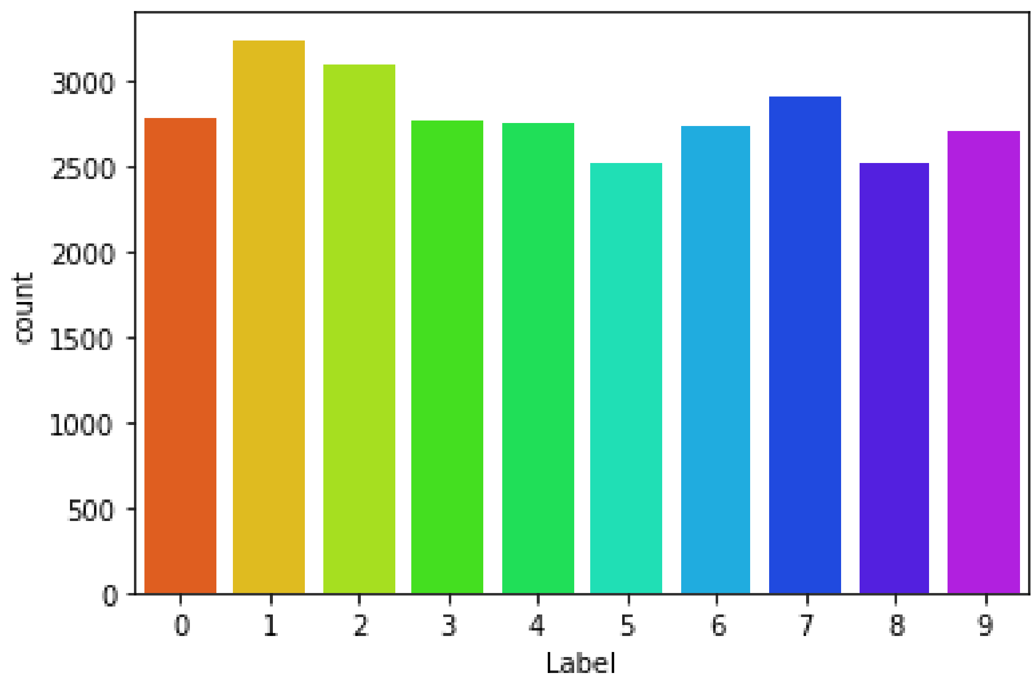
[69]:
```
test_df = test_df/255.0
print("test_data:", test_df.shape)
```

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

[70]:
```
test_scaled = scale(test_df)
```

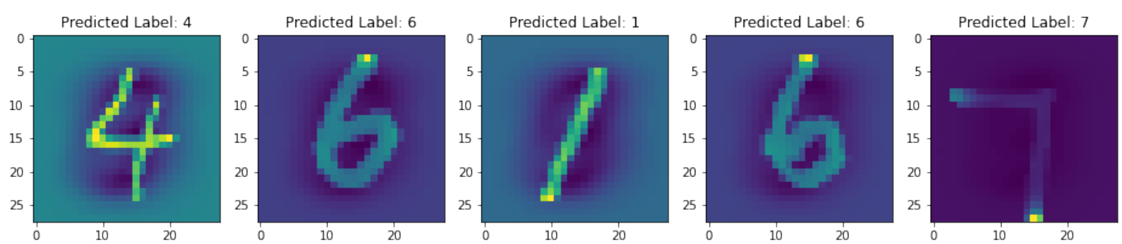
[71]:
```
test_predict = model.predict(test_scaled)
```

[75]:
```
# Plotting the distribution of prediction
a = {'ImageId': np.arange(1,test_predict.shape[0]+1), 'Label': test_predict}
data_to_export = pd.DataFrame(a)
sns.countplot(data_to_export['Label'], palette = 'gist_rainbow');
```



[73]:

```
# Let us visualize few of predicted test numbers

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

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



5.3 Conclusion

The accuracy achieved using a non-linear kernel (0.94) is a bit higher than that of a linear one (0.91). We can conclude that the problem is non-linear in nature.