Tresserct - BE17B011&BS17B011

November 12, 2020

1 Importing libraries

[19]:
```
#Importing Required libraries
import numpy as np
import pandas as pd
import sklearn as skl
import seaborn as sns
import matplotlib.pyplot as plt
import PIL
from IPython.display import display,IFrame
import os
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.impute import KNNImputer, SimpleImputer
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
import pickle
from sklearn.neighbors import KNeighborsClassifier
from scipy.stats import mode
np.random.seed(25)
```

2 Imputation by averaging surrounding values

[2]:
```
# Imputation
def averaging_nans(data_matrix):

    """
    This function performs imputation of NaN values by taking the average of␣
↪all the immediate non-nan neighbors surrounding pixels in the same image. In␣
↪case if all neighbours are nans, the value of the pixel is set to 0.
    """
    def pixel_average(data_matrix, i, j):
        l = []
        for c1 in range(3):
```

```
            for c2 in range(3):

                if (0<i-1+c1 < len(data_matrix) and␣
↪0<j-1+c2<len(data_matrix[0])):
                    if not np.isnan(data_matrix[i-1+c1][j-1+c2]):
                        l.append(data_matrix[i-1+c1][j-1+c2])
        if len(l)>0:
            return np.mean(l)
        else:
            return 0.0


    for i in range(len(data_matrix)):
        for j in range(len(data_matrix[i])):
            if np.isnan(data_matrix[i][j]):
                data_matrix[i][j] = pixel_average(data_matrix,i,j)


    return data_matrix
```

3 Loading Training and Test Data and Performing Imputation

[3]:
```
##Change this code to make it work it in Jupyter
N_TRAIN = 10000
dim = 28
data_original = np.zeros((dim,dim,N_TRAIN))
labels = np.zeros((N_TRAIN,1))

data_flattened = np.zeros((N_TRAIN,dim**2))
im = 0

# Importing from kaggle
for dirname, _, filenames in os.walk('/kaggle/input/iitmee4708/'):
    for filename in filenames:

        if filename == "public_test.csv":
            test_data = np.loadtxt(open(os.path.join(dirname, filename), "rb"),␣
↪delimiter=",")
        else:
            if filename =="SVM_rbfC1000_pred.csv":
                break
            # imputing nans and storing the images in the appropriate position␣
↪in the matrix
            data_original[:,:,im] = averaging_nans((np.loadtxt(open(os.path.
↪join(dirname, filename), "rb"), delimiter=",")))
```

```
            labels[im] = dirname[-1]
            # 28x28 data is flattened to 784 data point
            data_flattened[im,:] = data_original[:,:,im].T.reshape(1,dim**2)
            im += 1

labels = labels.astype(int)
```

4 Addition of small Gaussian Noise and Normalization

[4]:
```
# Normalize the data
X = (data_flattened.copy())/255.0
y = labels.copy()
X_test = test_data.copy()/255.0
X_test = np.transpose(X_test)

# Adding white noise to create another dataset
X_noise = data_flattened + np.random.normal(0,1e-4,(data_flattened.
 ↪shape[0],data_flattened.shape[1]))
X_noise /= 255

# Joining the given dataset and noisy dataset
X = np.append(X,X_noise,axis=0)
y = np.append(y,y,axis = 0)
X.shape, y.shape
```

[4]:
```
((20000, 784), (20000, 1))
```

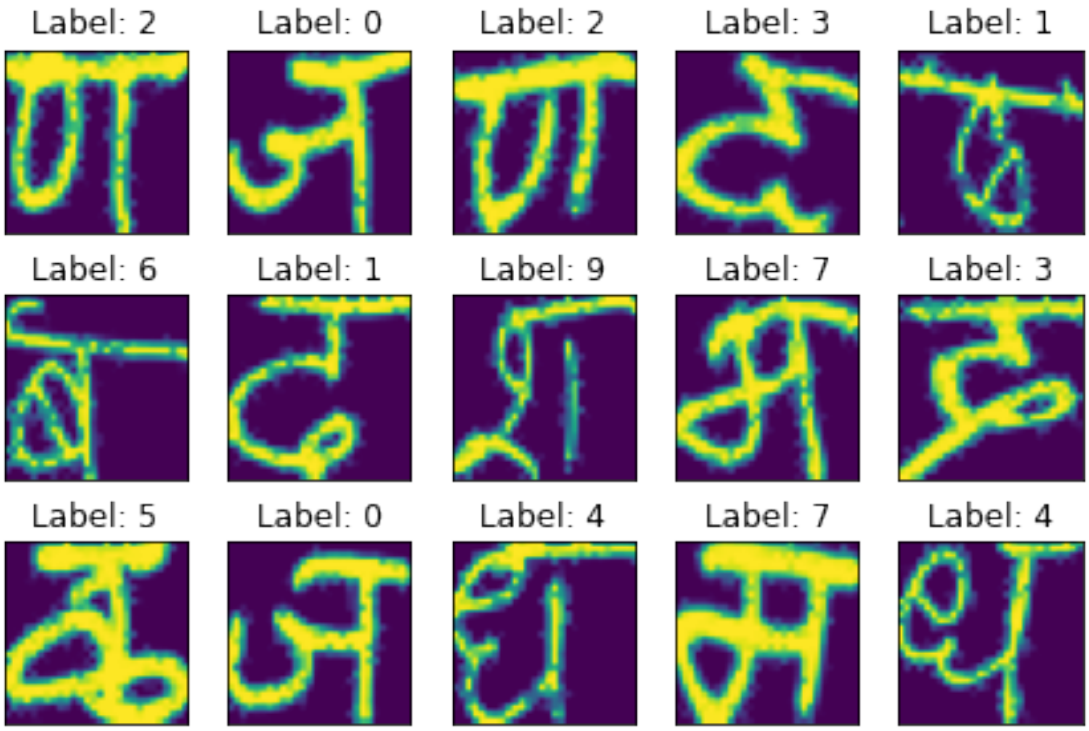
5 Shuffling the training data

[5]:
```
# Suffling the dataset to remove class bias during the traininig
X_y = np.append(X,y,axis = 1)
np.random.shuffle(X_y)
X = X_y[:,:-1]
y = X_y[:,-1]
```

6 Training Data Visualization

[6]:
```
ind_display = np.random.randint(0,N_TRAIN,15)
fig,ax = plt.subplots(3,5)
for ind in range(len(ind_display)):
    ax[ind//5,ind%5].imshow(PIL.Image.fromarray(X_noise[ind_display[ind],:].
 ↪reshape(dim,dim).T*255).convert("L"))
    ax[ind//5,ind%5].set_xticks([])
    ax[ind//5,ind%5].set_yticks([])
```

```
    ax[ind//5,ind%5].set_title("Label: "+str(labels[ind_display[ind]][0]))
fig.tight_layout(pad=1)
```



7 Dimensionality reduction using PCA

[7]:
```
pca = PCA(n_components=45)
pca.fit(X)
X_1 = pca.fit_transform(X)
```

8 Ensembling with SVM - RBF Kernel

[8]:
```
from tqdm import tqdm
def bagging_SVM_rbf_same(sample_size,X,y):
    models = []

    for i in tqdm(range(200)):
        ## Bootstrap samples
        ind = np.random.choice(np.arange(X.shape[0]),sample_size,replace =␣
 ↪False)
        X_sample = X[ind]
        y_sample = y[ind]
```

```
        #Train-validation Split
        Xs_train,Xs_val,ys_train,ys_val =␣
↪train_test_split(X_sample,y_sample,test_size  = 1000/sample_size)
        #SVC Model - RBF Kernel with regularization parameter C = 1000
        svm_model = SVC(kernel = "rbf",C = 1000)
        svm_model.fit(Xs_train,ys_train.ravel())
        train_acc = svm_model.score(Xs_train,ys_train)
        #Only store model if training accuracy is greater than 90%
        if train_acc>0.9:
            val_acc = svm_model.score(Xs_val,ys_val)
            models.append((svm_model,(train_acc,val_acc)))

    return models
```

[1]:
```
bagging_ensemble_rbf_same_new = bagging_SVM_rbf_same(20000,X_1,y)
```

9 Evaluating all models on the test data and taking the mode (consensus prediction)

[10]:
```
y_mat_comb = np.zeros((1000,1))
#PCA transformation of Test Data
X_test_pca = pca.transform(X_test)

for model in bagging_ensemble_rbf_same_new:
    y_mat_comb = np.append(y_mat_comb,model[0].predict(X_test_pca).
↪reshape(-1,1),axis = 1)

y_mat_comb = y_mat_comb[:,1:]
y_test_pred = mode(y_mat_comb,axis = 1)[0].astype(int).ravel()
```

[10]:
```
(1000, 15)
```

10 Saving the models

[11]:
```
import csv
l = [['Id', 'Expected']]

with open("SVM_ENSEMBLE_RBF1000_2X_Norm_NOISE.csv",'w') as f:
    w = csv.writer(f)
    w.writerow(l[0])
    for i in range(1000):
        l.append(['Sample_'+str(i+1), y_test_pred[i]])
        w.writerow(['Sample_'+str(i+1), y_test_pred[i]])
import os
```

```
os.chdir(r'/kaggle/working')
from IPython.display import FileLink
FileLink(r'SVM_ENSEMBLE_RBF1000_2X_Norm_NOISE.csv')
```

[11]: /kaggle/working/SVM_ENSEMBLE_RBF1000_2X_Norm_NOISE.csv

[12]:
```
import pickle
import os
os.chdir(r'/kaggle/working')
from IPython.display import FileLink
final_model = [pca,bagging_ensemble_rbf_same_new]
with open('SVM_ENSEMBLE_RBF1000_2X_Norm_NOISE.pkl', 'wb') as f:
    pickle.dump(final_model, f)
FileLink(r'./SVM_ENSEMBLE_RBF1000_2X_Norm_NOISE.pkl')
```

[12]: /kaggle/working/SVM_ENSEMBLE_RBF1000_2X_Norm_NOISE.pkl

11 Function to load model and predict on the given test datasets

[2]:
```
def predict_private_dataset():

    # Data Pre-processing
    test_data = np.loadtxt(open('private_test.csv', "rb"), delimiter=",")
    test_data = test_data.copy()/255.0
    test_data = np.transpose(test_data)

    # Loading the models
    pca, ensemble_svm = pickle.load(open('SVM_ENSEMBLE_RBF1000_2X_Norm_NOISE.
↪pkl', 'rb'))
    y_mat_comb = np.zeros((len(test_data),1))

    #PCA transformation of Test Data
    X_test_pca = pca.transform(test_data)
    for model in ensemble_svm:
        y_mat_comb = np.append(y_mat_comb,model[0].predict(X_test_pca).
↪reshape(-1,1),axis = 1) # Predict from each model

    y_mat_comb = y_mat_comb[:,1:]

    # Taking the consensus
    y_test_pred = mode(y_mat_comb,axis = 1)[0].astype(int).ravel()

    predicted_class = y_test_pred.reshape(-1,1);

    return predicted_class
```

```
# predict_private_dataset()
```