Pattern Recognition and Machine Learning : Assignment 1

- The assignment is **due** on **February 12**.
- The assignments are meant to enhance your learning, so that you master the basics by the close of this semester. You may work in groups for discussion, but it is **mandatory** that you attempt to write your own code and get the results.
- You are expected to upload a soft copy of the code and a report highlighting your inferences on the moodle page. You may also submit a hard copy of the same to speed up the grading process.
- The deadline date for submission is **rigid**. Any deviations from the same will result in a **penalization** of marks in the grading process.
- You will be graded for both the effort taken in the implementation of your code as well as the knowledge gained in the process. There will be a **viva voce** scheduled after the due date of submission.
- **Plagiarism of any kind will result in a failing grade in the course. This also includes downloading codes that are freely available from the Internet and using it**.

1(a)

(15 points) In this assignment, I expect you to build a rudimentary pattern recognizer by making use of the Bayesian decision theory concepts discussed in class. To this goal, you are given training images of 3 characters in a folder named **TrainCharacters.zip**. There are 200 training images of size 128×128 for each character class. For evaluating the classifiers, you are provided 300 test images of size 128×128 in a separate folder **TestCharacters.zip**.

Assume the samples to be generated from a multi dimensional Gaussian distribution, having class specific mean vectors $\boldsymbol{\mu_i}$. Consider each of the modelling schemes for computing the covariance matrix.

(i) The samples of a given character class are modelled by a separate covariance matrix $\boldsymbol{\Sigma_i}$.

(ii) The samples across all the character classes are pooled together to generate a common non diagonal covariance matrix $\mathbf{\Sigma}$.

(iii) The samples of a given character class are separately modelled by a diagonal covariance matrix $\mathbf{\Sigma_i}$. The diagonal entries of the matrix correspond to the variances of the individual features. The features are assumed to be independent- hence their cross variances are forced to zero.

(iv) The samples across all the character classes are pooled to generate a common diagonal covariance matrix $\mathbf{\Sigma}$. The diagonal entries correspond to the variances of the individual features, that are considered to be independent.

(v) The covariance matrix of each class is forced to be **spherical**.

For each scenario, build a generative Bayesian classifier using the training images and categorize the 300 character samples contained in the test folder. The mean and the covariance matrices are to be estimated from the training data using the Maximum Likelihood techniques. Report the individual character accuracies as well as the averaged accuracy for each of the models.

Employ the 128×128 pixel intensity values as features (after appropriate normalization). If you encounter memory storage issues during simulation, you may consider resizing the images to a more manageable size (say 32×32) for the feature computation. However, note that in order to beat the curse of dimensionality, you have to add a regularization term of the form $\lambda\mathbf{I}$ in the computation of the covariance matrix.

1(b)

(5 points) Give 4 examples of images from the test set that are misclassified by each of the classifiers designed in Task 1(a). Display both the state of nature (true label) and the predicted class for each image.

1(c)

(BONUS) (10 points) Try implementing better features to enhance the performance of the recognition system. Do delve into the literature if you wish to. However, you are free to be creative in coming up with new features and gain the bonus points!