

# **Machine Learning for Image Processing**

# **Programming Assignment 2**

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### 1. Brief Description:

To present brief details of the datasets provided

Table:

Name of Dataset	Feature vector dimension	No. of classes	Prior Prob. of each class	Mean vector dimension	Covariance matrix dimension
Image segmentation dataset1	19 X 1	7	1/7 for all classes	19 X 1	19 X 19
Iris Dataset 3	4 X 1	3	1/3 for all classes	4 X 1	4 X 4
Letter Recognition dataset 4	26 X 1	26	variable	26 X 1	26 X 26
Solar Flare dataset 6	10 X 1	3	variable	30 X 1	30 X 30
Wisconsin prognostic breast cancer					
dataset	30 X 1	2	variable	30 X 1	30 X 30
Wisconsin diagnostic breast cancer					
dataset	32 X 1	22	variable	32 X 1	32 X 32

#### 2. Aim:

To plot 1-D and 2-D histograms on one of the datasets provided and apply Bayesian classification **Short Theory:** 

If  $P(X/W_1)$  and  $P(X/W_2)$  are the likelihoods of the classes  $W_1$  and  $W_2$  respectively, the decision boundary obtained from,

$$P(X/W_1) = P(X/W_2)$$

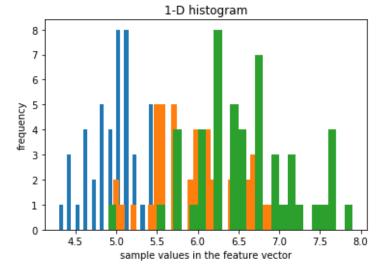
$$P\left(\frac{X}{W}\right) = \left[\frac{1}{(2\pi)^{0.5}}\right] * e^{-0.5*\frac{(x-\mu)^2}{(\sigma)^2}}$$

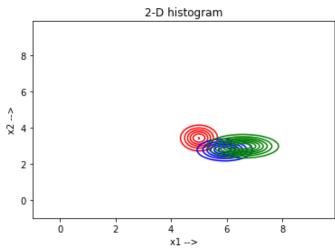
The decision boundary is where the probability curves of two classes meet.

I have worked on the iris dataset

#### **Procedure:**

- → After importing the dataset, split the samples into each class
- → Define one\_d and two\_d functions, with parameters stating which feature to use for the plots, to plot the 1-D and 2-D histograms
- $\rightarrow$  Input the feature index you wish to use to plot the histograms. By default, for the one\_d, 0<sup>th</sup> feature is used and for the two d, 0<sup>th</sup> and 1<sup>st</sup> features are used.





#### Interferences:

The edges where the plots belonging to two different classes, denoted by different colours, meet are the decision boundaries

#### 3. Aim:

To perform Bayesian classification on the dataset, que3.xlxs, for the given conditions

- i) Same covariance matrices for all the classes
- ii) Different covariance matrices
- iii) Diagonal covariance matrices

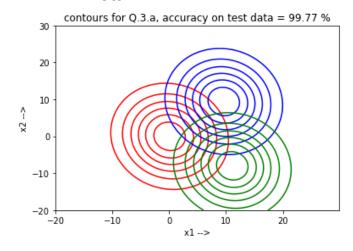
### **Short Description:**

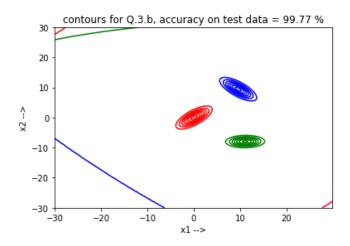
If we have three classes,  $W_1$ ,  $W_2$ , and  $W_3$  respectively, a test case X will belong to that class which has the highest value among  $P(X/W_1)$ ,  $P(X/W_2)$  and  $P(X/W_3)$ . The Bayesian classification done here is only using the likelihood functions and I have not used the prior probabilities.

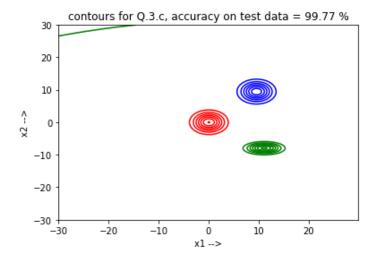
#### **Procedure:**

- → Import the dataset and split them into three classes and in each class, split it into 70% and 30% for training and test data respectively.
- → Define a custom function, gauss, to calculate probability and assign respective class
- → Calculate mean and sigma matrices for each case, calculate accuracy on test data using the cusom gauss function and plot their respective contours individually for each case

#### **Plots:**







# Inferences:

In the  $\mathbf{1}^{\text{st}}$  case, when all the classes have the same sigma matrices, the decision boundary is a perpendicular bisector between the mean points of every class.