# CS612: Statistical Pattern Recognition Laboratory
# Programming Assignment 2


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# Chapter 1

# Dataset 1: Non-linearly separable classes

## 1.1 Dataset description

**No. of classes** : 3

**Class 1 and Class 2** :

- No. of data points: 500
- No. of features of each data-point: 2
- Size of train data: 350
- Size of test data: 150

**Class 3** :

- No. of data points: 1000
- No. of features of each data-point: 2
- Size of train data: 700
- Size of test data: 300

## 1.2 Result

### 1.2.1 Performance metrics

Table 1.1 shows the performance metrics (Accuracy, precision, recall and f-measure) for dataset 1 with 1, 2, 4, 8, 16 and 32 GMM mixtures.

### 1.2.2 Confusion matrices

Table 1.2a to Table 1.2f shows the confusion matrices for dataset 1 with 1, 2, 4, 8, 16 and 32 GMM mixtures respectively.

Table 1.1: Performance metrics for dataset 1 with 1, 2, 4, 8, 16 and 32 GMM mixtures

| **No. of mixtures** | **Accuracy** | | **Precision** | **Recall** | **F-measure** |
|---|---|---|---|---|---|
| 1 | 0.97 | **Class 1** | 0.92 | 0.96 | 0.94 |
| | | **Class 2** | 0.96 | 0.95 | 0.95 |
| | | **Class 3** | 1.00 | 0.98 | 0.99 |
| | | **Mean** | 0.96 | 0.96 | 0.96 |
| 2 | 0.99 | **Class 1** | 0.97 | 1.00 | 0.99 |
| | | **Class 2** | 1.00 | 1.00 | 1.00 |
| | | **Class 3** | 1.00 | 0.99 | 0.99 |
| | | **Mean** | 1.00 | 1.00 | 0.99 |
| 4 | 1.00 | **Class 1** | 1.00 | 1.00 | 1.00 |
| | | **Class 2** | 1.00 | 1.00 | 1.00 |
| | | **Class 3** | 1.00 | 1.00 | 1.00 |
| | | **Mean** | 1.00 | 1.00 | 1.00 |
| 8 | 1.00 | **Class 1** | 1.00 | 1.00 | 1.00 |
| | | **Class 2** | 1.00 | 1.00 | 1.00 |
| | | **Class 3** | 1.00 | 1.00 | 1.00 |
| | | **Mean** | 1.00 | 1.00 | 1.00 |
| 16 | 1.00 | **Class 1** | 1.00 | 1.00 | 1.00 |
| | | **Class 2** | 1.00 | 1.00 | 1.00 |
| | | **Class 3** | 1.00 | 1.00 | 1.00 |
| | | **Mean** | 1.00 | 1.00 | 1.00 |
| 32 | 1.00 | **Class 1** | 1.00 | 1.00 | 1.00 |
| | | **Class 2** | 1.00 | 1.00 | 1.00 |
| | | **Class 3** | 1.00 | 1.00 | 1.00 |
| | | **Mean** | 1.00 | 1.00 | 1.00 |

Table 1.2: Confusion matrices for dataset 1 with 1, 2, 4, 8, 16 and 32 GMM mixtures

(a) 1 Mixture

| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 144 | 6 | 0 |
| **Class 2** | 7 | 142 | 1 |
| **Class 3** | 5 | 0 | 295 |

(b) 2 Mixtures

| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 150 | 0 | 0 |
| **Class 2** | 0 | 150 | 0 |
| **Class 3** | 4 | 0 | 296 |

(c) 4 Mixtures

| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 150 | 0 | 0 |
| **Class 2** | 0 | 150 | 0 |
| **Class 3** | 0 | 0 | 300 |

(d) 8 Mixtures

| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 150 | 0 | 0 |
| **Class 2** | 0 | 150 | 0 |
| **Class 3** | 0 | 0 | 300 |

(e) 16 Mixtures

| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 150 | 0 | 0 |
| **Class 2** | 0 | 150 | 0 |
| **Class 3** | 0 | 0 | 300 |

(f) 32 Mixtures

| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 150 | 0 | 0 |
| **Class 2** | 0 | 150 | 0 |
| **Class 3** | 0 | 0 | 300 |

Table 1.3: Performance metrics comparison between the unimodal Gaussian model and the multimodal Gaussian model (4 GMM mixtures) for dataset 1

| | **Unimodel Gaussian** | | | | **Multimodal Gaussian (4 GMM Mixtures)** | | | |
|---|---|---|---|---|---|---|---|---|
| **Accuracy** | 0.96 | | | | 1.00 | | | |
| | Class1 | Class2 | Class3 | Mean | Class1 | Class2 | Class3 | Mean |
| **Precision** | 0.93 | 0.92 | 0.99 | 0.95 | 1.00 | 1.00 | 1.00 | 1.00 |
| **Recall** | 0.92 | 0.93 | 0.99 | 0.95 | 1.00 | 1.00 | 1.00 | 1.00 |
| **F-measure** | 0.92 | 0.93 | 0.99 | 0.95 | 1.00 | 1.00 | 1.00 | 1.00 |

### 1.2.3 Constant density contour plot for all the classes with the training data superposed

Figure 1.1 shows the constant density contour plot for all the classes with the training data superposed for dataset 1 with 1, 2, 4, 8, 16, and 32 GMM mixtures.

### 1.2.4 Decision regions plot for all the classes with the training data superposed

Figure 1.2 shows the decision regions plots for all the classes with the training data superposed for dataset 1 with 1, 2, 4, 8, 16, and 32 GMM mixtures.

### 1.2.5 Graph of iterations vs log likelihood

Figure 1.3 shows the graph of iterations vs log likelihood for dataset 1 with different number of components.

## 1.3 Comparison with the results from the Assignment 1

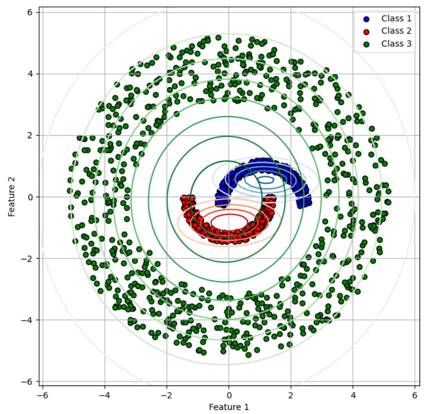
### 1.3.1 Performance Metrics comparison

Table 1.3 shows the performance metrics comparison between the unimodal Gaussian model and the multimodal Gaussian model (4 GMM mixtures) for dataset 1.

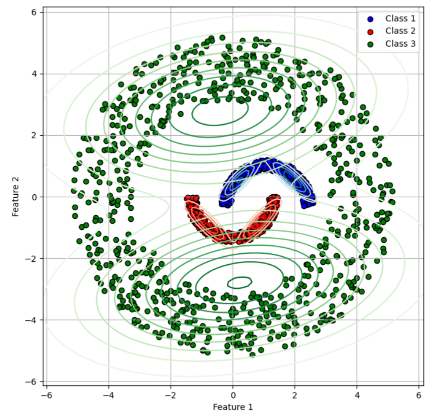
This comparison show a clear advantage of Multimodal Gaussian as compared to Unimodal. It has higher accuracy as well as higher precision, recall and f-measure.

### 1.3.2 Confusion Matrix comparison

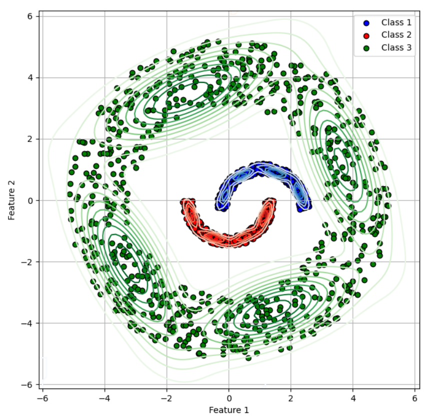
Table 2.4 shows the confusion matrix comparison between the unimodal Gaussian model and the multimodal Gaussian model (4 GMM mixtures) for dataset 1.



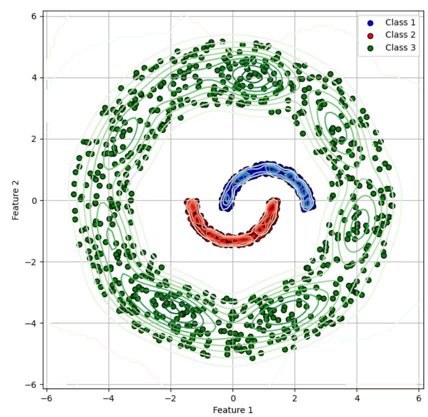

(a) 1 Mixture



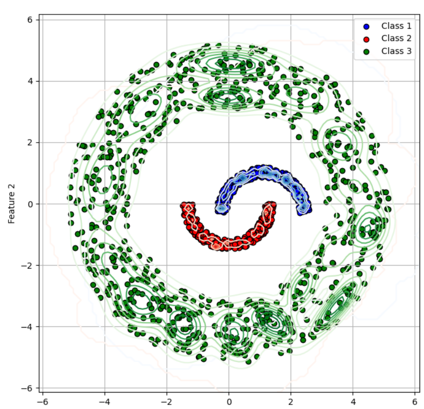

(b) 2 Mixtures



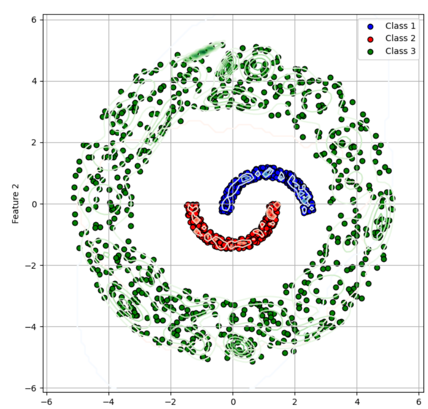

(c) 4 Mixtures




(d) 8 Mixtures

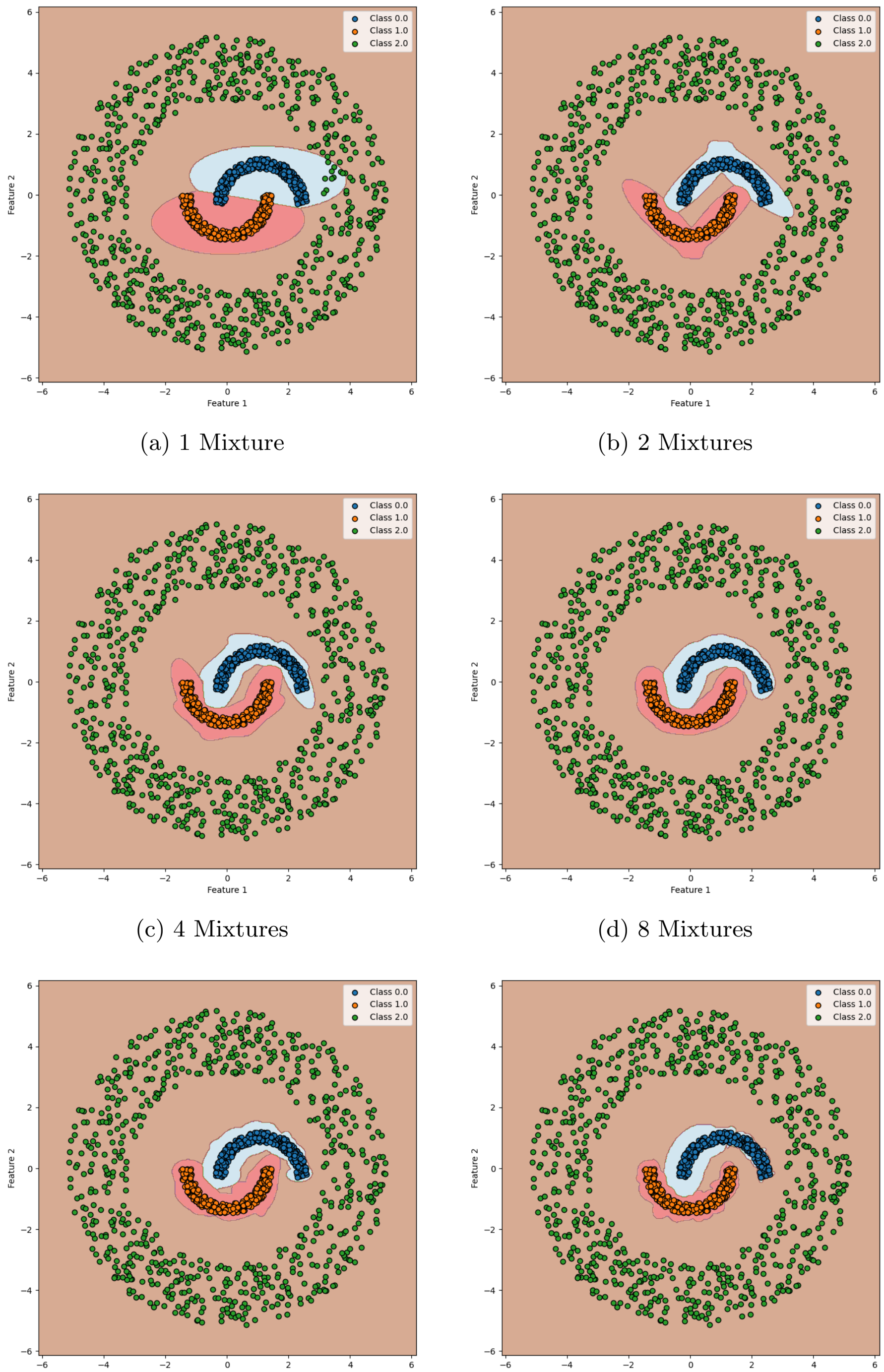



(e) 16 Mixtures




(f) 32 Mixtures

Figure 1.1: Constant Density Plots for dataset 1 with 1, 2, 4, 8, 16, and 32 GMM mixtures




(a) 1 Mixture

(b) 2 Mixtures

(c) 4 Mixtures

(d) 8 Mixtures

(e) 16 Mixtures

(f) 32 Mixtures

Figure 1.2: Decision Regions Plots for dataset 1 with 1, 2, 4, 8, 16, and 32 Mixtures.

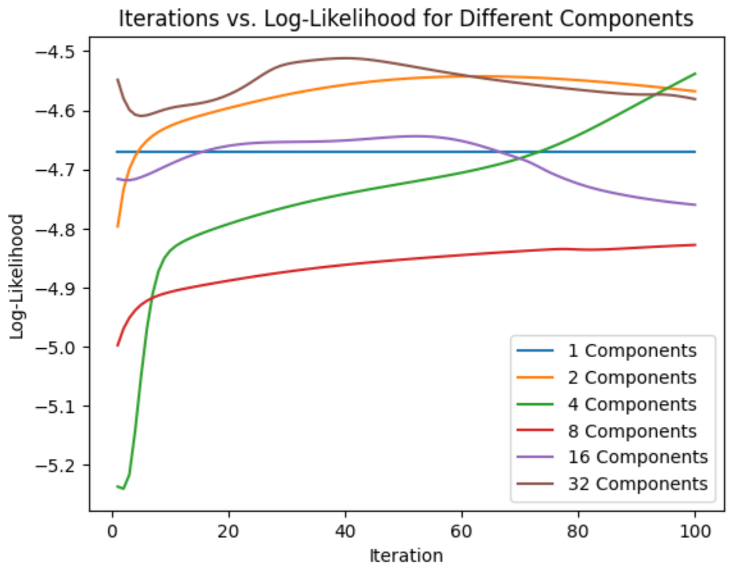



Figure 1.3: Iteration vs log likelihood graph for dataset 1

Table 1.4: Confusion matrix comparison between the unimodal Gaussian model and the multimodal Gaussian model (4 GMM mixtures) for dataset 1

(a) Unimodal

| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 138 | 8 | 3 |
| **Class 2** | 12 | 140 | 0 |
| **Class 3** | 0 | 2 | 297 |

(b) Multimodal

| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 150 | 0 | 0 |
| **Class 2** | 0 | 150 | 0 |
| **Class 3** | 0 | 0 | 300 |

The confusion matrix also shows the superiority of Multimodal Gaussian modal. We see a perfect confusion matrix in case of Multimodal Gaussian.

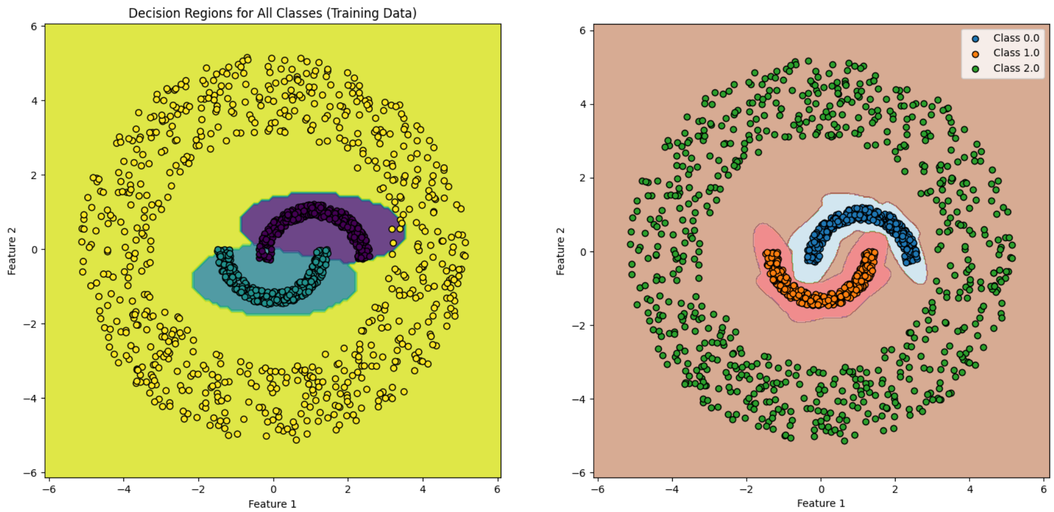
### 1.3.3 Decision Region Plot comparison

Figure 1.4 shows the decision region plot comparison comparison between the unimodal Gaussian model and the multimodal Gaussian model (4 GMM mixtures) for dataset 1.

## 1.4 Inference

We see that the assuming multimodal Guassian generally improves the classification accuracy.

We see that we get 100% accuracy from 4 GMM mixtures onwards. The reason of accuracy improvement is clear from the decision region plots (Figure 1.2). We see that in




(a) Uni-modal

(b) Multi-modal

Figure 1.4: decision region plot comparison comparison between the unimodal Gaussian model and the multimodal Gaussian model (4 GMM mixtures) for dataset 1

the decision region plots 1.2a and 1.2b, there are some points of class 3 which enters the decision region of class 1, which creates this classification inaccuracies, but from figure 1.2c to 1.2f, the decision regions formed are proper and they separate the classes properly.

For The case of 64 GMM mixtures, we get singular matrix error for covariance matrix, making it impossible to find the inverse of the matrix, hence the results including performance matrices, confusion matrix and the plots could not be generated.

From the figure 1.3 that is of iteration vs. log likelihood, it can be observed that GMM has converged within 20 iterations for all the components (1 - 32). There are some variation for higher values of K (16 and 32).

If we compare the results from the previous model, the table 1.3 shows that this time, GMM has achieved 100% accuracy which was not achieved in previous model. Above inference is also validated by the confusion matrix comparison shown in table 2.4 and decision region plot comparison shown in figure 1.4.

# Chapter 2

# Dataset 2a: Two-dimensional speech dataset

## 2.1 Dataset description

**No. of classes** : 3

**Class 1** :

- No. of data points: 2454
- No. of features of each data-point: 2
- Size of train data: 1717
- Size of test data: 737

**Class 2** :

- No. of data points: 2488
- No. of features of each data-point: 2
- Size of train data: 1741
- Size of test data: 747

**Class 3** :

- No. of data points: 2291
- No. of features of each data-point: 2
- Size of train data: 1603
- Size of test data: 688

## 2.2 Result

### 2.2.1 Performance metrics for Dataset 2a

Table 2.1 shows the performance metrics (Accuracy, precision, recall, and f-measure) for Dataset 2a with 1, 2, 4, 8 and 16 GMM mixtures.

Table 2.1: Performance metrics for Dataset 2a with 1, 2, 4, 8, and 16 GMM mixtures

| **No. of mixtures** | **Accuracy** | | **Precision** | **Recall** | **F-measure** |
|---|---|---|---|---|---|
| 1 | 0.91 | **Class 1** | 0.89 | 0.83 | 0.86 |
| | | **Class 2** | 0.84 | 0.90 | 0.87 |
| | | **Class 3** | 1.00 | 0.99 | 0.99 |
| | | **Mean** | 0.91 | 0.91 | 0.91 |
| 2 | 0.92 | **Class 1** | 0.91 | 0.86 | 0.88 |
| | | **Class 2** | 0.86 | 0.91 | 0.89 |
| | | **Class 3** | 1.00 | 0.99 | 0.99 |
| | | **Mean** | 0.92 | 0.92 | 0.92 |
| 4 | 0.93 | **Class 1** | 0.91 | 0.91 | 0.91 |
| | | **Class 2** | 0.90 | 0.91 | 0.91 |
| | | **Class 3** | 1.00 | 0.99 | 0.99 |
| | | **Mean** | 0.94 | 0.94 | 0.94 |
| 8 | 0.93 | **Class 1** | 0.92 | 0.89 | 0.90 |
| | | **Class 2** | 0.89 | 0.93 | 0.91 |
| | | **Class 3** | 1.00 | 0.99 | 0.99 |
| | | **Mean** | 0.94 | 0.94 | 0.94 |
| 16 | 0.94 | **Class 1** | 0.92 | 0.90 | 0.91 |
| | | **Class 2** | 0.90 | 0.93 | 0.91 |
| | | **Class 3** | 1.00 | 0.99 | 0.99 |
| | | **Mean** | 0.94 | 0.94 | 0.94 |

Table 2.2: Confusion matrices for Dataset 2a with 1, 2, 4, 8, and 16 GMM mixtures

(a) 1 Mixture

| | **Class 1** | **Class 2** | **Class 3** |
|---|---|---|---|
| **Class 1** | 613 | 121 | 3 |
| **Class 2** | 73 | 674 | 0 |
| **Class 3** | 5 | 3 | 680 |

(b) 2 Mixtures

| | **Class 1** | **Class 2** | **Class 3** |
|---|---|---|---|
| **Class 1** | 632 | 103 | 2 |
| **Class 2** | 64 | 682 | 1 |
| **Class 3** | 1 | 6 | 681 |

(c) 4 Mixtures

| | **Class 1** | **Class 2** | **Class 3** |
|---|---|---|---|
| **Class 1** | 668 | 68 | 1 |
| **Class 2** | 66 | 680 | 1 |
| **Class 3** | 3 | 4 | 681 |

(d) 8 Mixtures

| | **Class 1** | **Class 2** | **Class 3** |
|---|---|---|---|
| **Class 1** | 653 | 83 | 1 |
| **Class 2** | 50 | 696 | 1 |
| **Class 3** | 4 | 4 | 680 |

(e) 16 Mixtures

| | **Class 1** | **Class 2** | **Class 3** |
|---|---|---|---|
| **Class 1** | 663 | 74 | 0 |
| **Class 2** | 52 | 694 | 1 |
| **Class 3** | 3 | 4 | 681 |

### 2.2.2 Confusion matrices for Dataset 2a

Table 2.2 shows the confusion matrices for Dataset 2a with 1, 2, 4, 8 and 16 GMM mixtures.

### 2.2.3 Constant density contour plot for all the classes with the training data superposed

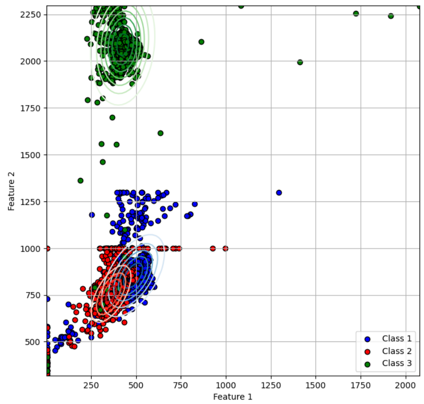
Figure 2.1 shows the Constant density contour plot for all the classes with the training data superposed for dataset 2a with 1, 2, 4, 8, and 16 GMM mixtures.

### 2.2.4 Decision regions plot for all the classes with the training data superposed

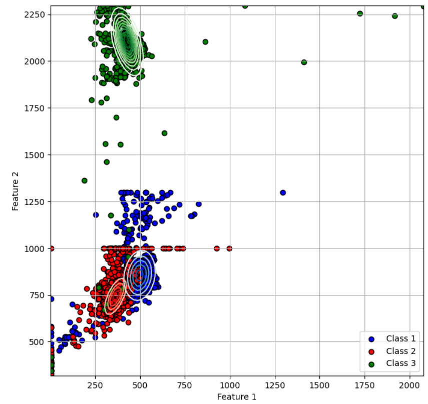
Figure 2.2 shows the decision regions plots for all the classes with the training data superposed for dataset 2a with 1, 2, 4, 8, and 16 GMM mixtures.

### 2.2.5 Graph of iterations vs log likelihood

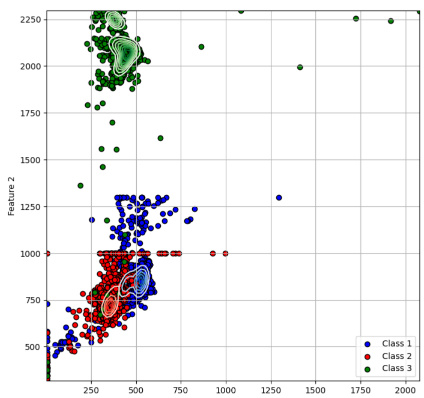
Figure 2.3 shows the graph of iterations vs log likelihood for dataset 2a with different number of components.



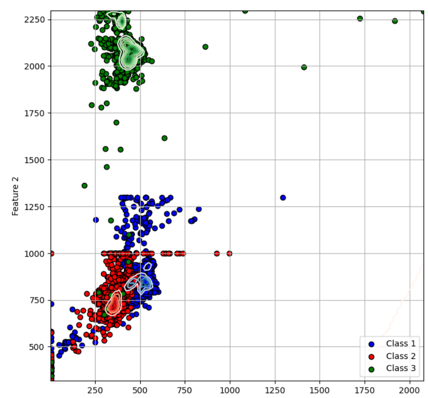

(a) 1 Mixture



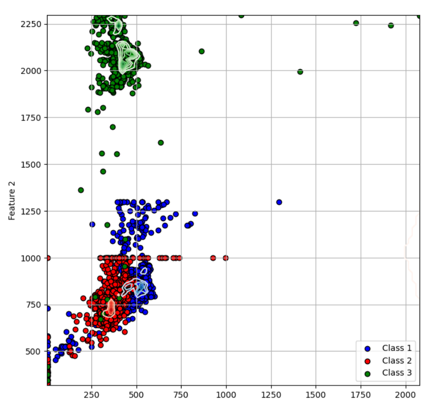

(b) 2 Mixtures




(c) 4 Mixtures

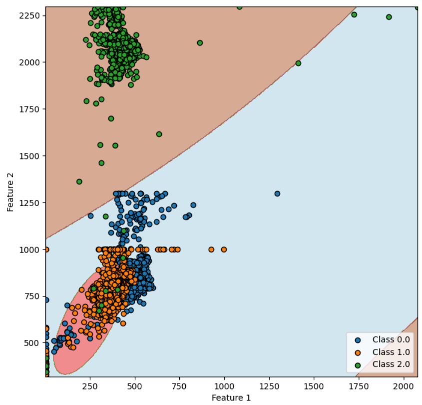



(d) 8 Mixtures

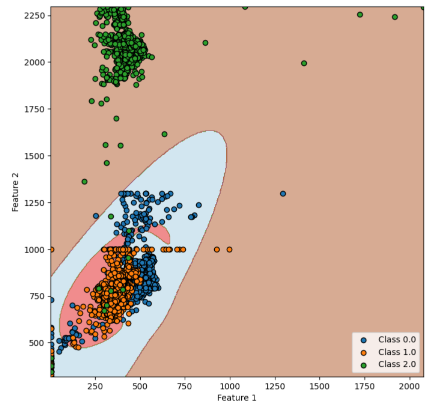



(e) 16 Mixtures

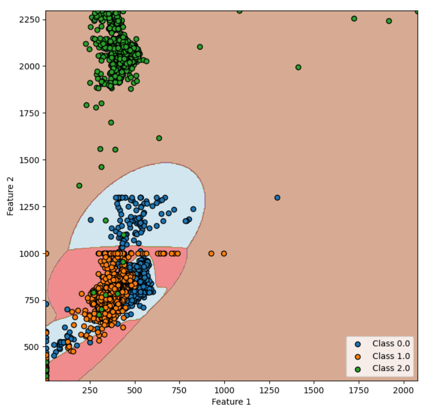
Figure 2.1: Constant Density Plots for dataset 2a with 1, 2, 4, 8, and 16 mixtures



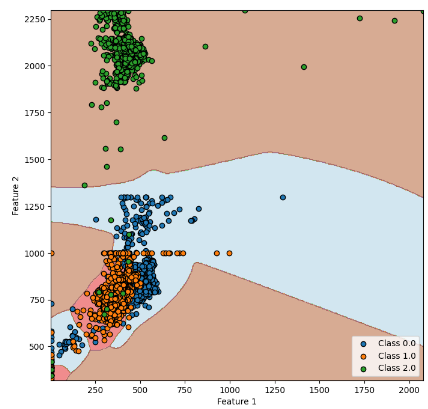

(a) 1 Mixture



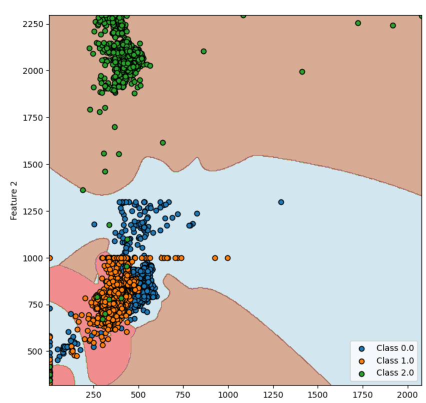

(b) 2 Mixtures




(c) 4 Mixtures




(d) 8 Mixtures




(e) 16 Mixtures

Figure 2.2: Decision Regions Plots for dataset 2a with 1, 2, 4, 8, and 16 mixtures

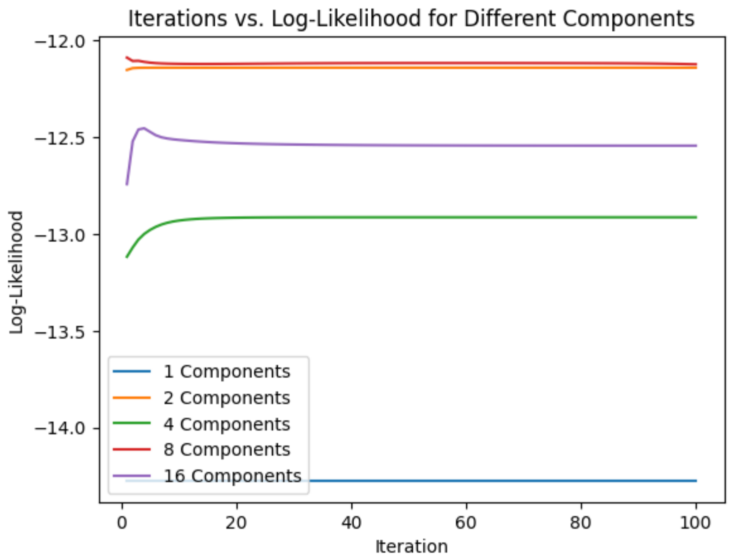



Figure 2.3: Iteration vs log likelihood graph for dataset 2a

## 2.3 Comparison with the results from the Assignment 1

### 2.3.1 Performance Metrics comparison

Table 2.3 shows the performance metrics comparison between the unimodal Gaussian model and the multimodal Gaussian model (16 GMM mixtures) for dataset 1.

Table 2.3: Performance metrics comparison between the unimodal Gaussian model and the multimodal Gaussian model (16 GMM mixtures) for dataset 1

| | **Unimodal Gaussian** | | | | **Multimodal Gaussian (16 GMM Mixtures)** | | | |
|---|---|---|---|---|---|---|---|---|
| **Accuracy** | 0.91 | | | | 0.94 | | | |
| | Class1 | Class2 | Class3 | Mean | Class1 | Class2 | Class3 | Mean |
| **Precision** | 0.89 | 0.84 | 1.00 | 0.91 | 0.92 | 0.90 | 1.00 | 0.94 |
| **Recall** | 0.83 | 0.90 | 0.99 | 0.91 | 0.90 | 0.93 | 0.99 | 0.94 |
| **F-measure** | 0.86 | 0.87 | 0.99 | 0.91 | 0.91 | 0.91 | 0.99 | 0.94 |

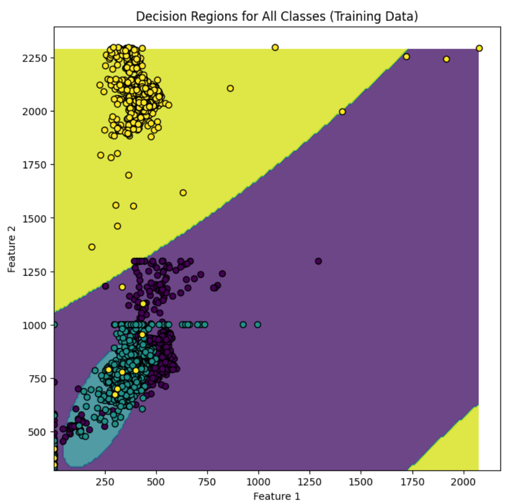
Table 2.4: Confusion matrix comparison between the unimodal Gaussian model and the multimodal Gaussian model (4 GMM mixtures) for dataset 1

(a) Unimodal

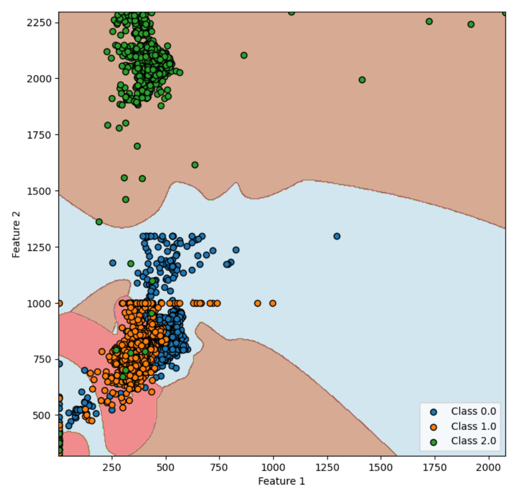
| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 138 | 8 | 3 |
| **Class 2** | 12 | 140 | 0 |
| **Class 3** | 0 | 2 | 297 |

(b) Multimodal

| | **Class1** | **Class2** | **Class3** |
|---|---|---|---|
| **Class 1** | 150 | 0 | 0 |
| **Class 2** | 0 | 150 | 0 |
| **Class 3** | 0 | 0 | 300 |




(a) Uni-modal




(b) Multi-modal

Figure 2.4: decision region plot comparison comparison between the unimodal Gaussian model and the multimodal Gaussian model (16 GMM mixtures) for dataset 2a

### 2.3.2 Confusion Matrix comparison

Table 2.4 shows the confusion matrix comparison between the unimodal Gaussian model and the multimodal Gaussian model (4 GMM mixtures) for dataset 1.

The confusion matrix also shows the superiority of Multimodal Gaussian modal. We see a perfect confusion matrix in case of Multimodal Gaussian.

### 2.3.3 Decision Region Plot comparison

Figure 2.4 shows the decision region plot comparison comparison between the unimodal Gaussian model and the multimodal Gaussian model (16 GMM mixtures) for dataset 2a.

## 2.4 Inference

We again see that the assuming multimodal Gaussian generally improves the classification accuracy.

According to Table 1.3, we see a slight improvement in the performance metrics, like accuracy increases from 0.91 to 0.94 etc.

The constant density plots shown in figure 2.1 shows that datapoints are very cluttered making the contours less evident. There are lots of overlapping between the data points of different classes.

From the plots of figure 2.2, we see the decision regions becomes increasingly complicated to include as many points as possible in the respective class.

Here also, we got singular matrix error from K=32 onwards.

From the figure 2.3 it can be observed that the GMM has converged quite early in even less than 10 mixtures.

# Chapter 3

# Dataset 2b: 3 class scene image dataset

## 3.1 Dataset description

**No. of classes** : 3

**For all classes** :

- Total number of images: 100
- No. of images in train set: 50
- No. of images in test set: 50

## 3.2 Results of experiment using set of 24-dimensional colour histogram feature vectors

### 3.2.1 Performance metrics

Table 3.1 shows the performance metrics (Accuracy, precision, recall and f-measure) for dataset 2b with 1, 2, 4, 8, and 16 GMM mixtures and using 24-dimensional color histogram feature vectors.

### 3.2.2 Confusion matrices

Table 3.2a to Table 3.2e respectively shows the confusion matrices for dataset 2b with 1, 2, 4, 8, and 16 GMM mixtures using the 24-dimensional color histogram feature vectors.

Table 3.1: Performance metrics for dataset 2b with 1, 2, 4, 8, and 16 GMM mixtures using 24-dimensional color histogram feature vectors

| **No. of mixtures** | **Accuracy** | | **Precision** | **Recall** | **F-measure** |
|---|---|---|---|---|---|
| 1 | 0.66 | **Class 0** | 0.53 | 0.46 | 0.49 |
| | | **Class 1** | 0.77 | 0.94 | 0.85 |
| | | **Class 2** | 0.63 | 0.58 | 0.60 |
| | | **Mean** | 0.65 | 0.66 | 0.65 |
| 2 | 0.70 | **Class 0** | 0.57 | 0.62 | 0.60 |
| | | **Class 1** | 0.73 | 0.96 | 0.83 |
| | | **Class 2** | 0.87 | 0.52 | 0.65 |
| | | **Mean** | 0.72 | 0.70 | 0.69 |
| 4 | 0.69 | **Class 0** | 0.58 | 0.62 | 0.60 |
| | | **Class 1** | 0.72 | 0.94 | 0.82 |
| | | **Class 2** | 0.81 | 0.52 | 0.63 |
| | | **Mean** | 0.71 | 0.69 | 0.68 |
| 8 | 0.67 | **Class 0** | 0.56 | 0.56 | 0.56 |
| | | **Class 1** | 0.73 | 0.94 | 0.82 |
| | | **Class 2** | 0.72 | 0.52 | 0.60 |
| | | **Mean** | 0.67 | 0.67 | 0.66 |
| 16 | 0.63 | **Class 0** | 0.00 | 0.00 | 0.00 |
| | | **Class 1** | 0.67 | 0.98 | 0.80 |
| | | **Class 2** | 0.60 | 0.92 | 0.72 |
| | | **Mean** | 0.42 | 0.63 | 0.51 |

Table 3.2: Confusion matrices for dataset 2b with 1, 2, 4, 8, and 16 GMM mixtures using 24-dimensional color histogram feature vectors are shown respectively in tables (a) to (e)

(a) 1 Mixture

| | **Class 0** | **Class 1** | **Class 2** |
|---|---|---|---|
| **Class 0** | 23 | 11 | 16 |
| **Class 1** | 2 | 47 | 1 |
| **Class 2** | 18 | 3 | 29 |

(b) 2 Mixtures

| | **Class 0** | **Class 1** | **Class 2** |
|---|---|---|---|
| **Class 0** | 31 | 15 | 4 |
| **Class 1** | 2 | 48 | 0 |
| **Class 2** | 21 | 3 | 26 |

(c) 4 Mixtures

| | **Class 0** | **Class 1** | **Class 2** |
|---|---|---|---|
| **Class 0** | 31 | 14 | 5 |
| **Class 1** | 2 | 47 | 1 |
| **Class 2** | 20 | 4 | 26 |

(d) 8 Mixtures

| | **Class 0** | **Class 1** | **Class 2** |
|---|---|---|---|
| **Class 0** | 28 | 13 | 9 |
| **Class 1** | 2 | 47 | 1 |
| **Class 2** | 20 | 4 | 26 |

(e) 16 Mixtures

| | **Class 0** | **Class 1** | **Class 2** |
|---|---|---|---|
| **Class 0** | 0 | 20 | 30 |
| **Class 1** | 0 | 49 | 1 |
| **Class 2** | 0 | 4 | 46 |

Table 3.3: Performance metrics for dataset 2b with 1, 2, and 4 GMM mixtures using 32-dimensional Bag-of-Visual-Words feature vectors

| No. of mixtures | Accuracy | | Precision | Recall | F-measure |
|---|---|---|---|---|---|
| 1 | 0.2867 | **Class 0** | 0.30 | 0.56 | 0.39 |
| | | **Class 1** | 0.35 | 0.14 | 0.20 |
| | | **Class 2** | 0.22 | 0.16 | 0.18 |
| | | **Mean** | 0.29 | 0.29 | 0.26 |
| 2 | 0.3267 | **Class 0** | 0.33 | 0.76 | 0.46 |
| | | **Class 1** | 0.47 | 0.16 | 0.24 |
| | | **Class 2** | 0.17 | 0.06 | 0.09 |
| | | **Mean** | 0.32 | 0.33 | 0.26 |
| 4 | 0.2733 | **Class 0** | 0.27 | 0.36 | 0.31 |
| | | **Class 1** | 0.33 | 0.14 | 0.20 |
| | | **Class 2** | 0.26 | 0.32 | 0.29 |
| | | **Mean** | 0.29 | 0.27 | 0.26 |

## 3.3 Results of experiment using 32-dimentional bag-of-visual-words (BoVW)

### 3.3.1 Performance metrics

Table 3.3 shows the performance metrics (Accuracy, precision, recall, and F-measure) for dataset 2b with 1, 2, and 4 GMM mixtures using 32-dimensional Bag-of-Visual-Words feature vectors.

### 3.3.2 Confusion matrices

Table 3.4a to Table 3.4c respectively show the confusion matrices for dataset 2b with 1, 2, and 4 GMM mixtures using the 32-dimensional Bag-of-Visual-Words feature vectors.

## 3.4 Inference

Table 3.1 shows that the highest accuracy acheived for histogram feature vectors is 70% that is for 2 GMM mixtures. Increasing or decreasing the no. of mixtures leads to lesser accuracy.

GMM could not be properly built for BoVW features because of singular matrix error. This error is then removed by adding regularization in Gaussian density and EM but it led to very poor accuracy which in show in table 3.3.

Table 3.4: Confusion matrices for dataset 2b with 1, 2, and 4 GMM mixtures using 32-dimensional Bag-of-Visual-Words feature vectors are shown respectively in tables (a) to (c)

(a) 1 Mixture

| | **Class 0** | **Class 1** | **Class 2** |
|---|---|---|---|
| **Class 0** | 28 | 7 | 15 |
| **Class 1** | 29 | 7 | 14 |
| **Class 2** | 36 | 6 | 8 |

(b) 2 Mixtures

| | **Class 0** | **Class 1** | **Class 2** |
|---|---|---|---|
| **Class 0** | 38 | 6 | 6 |
| **Class 1** | 33 | 8 | 9 |
| **Class 2** | 44 | 3 | 3 |

(c) 4 Mixtures

| | **Class 0** | **Class 1** | **Class 2** |
|---|---|---|---|
| **Class 0** | 18 | 6 | 26 |
| **Class 1** | 23 | 7 | 20 |
| **Class 2** | 26 | 8 | 16 |

# Chapter 4

# Dataset 2c: Cervical Cytology (Cell) Image Dataset

## 4.1 Dataset Description

Size of train set: 60 images
Size of test set: 3 images

## 4.2 Results

### 4.2.1 Plot of 3 Clusters on Training Images

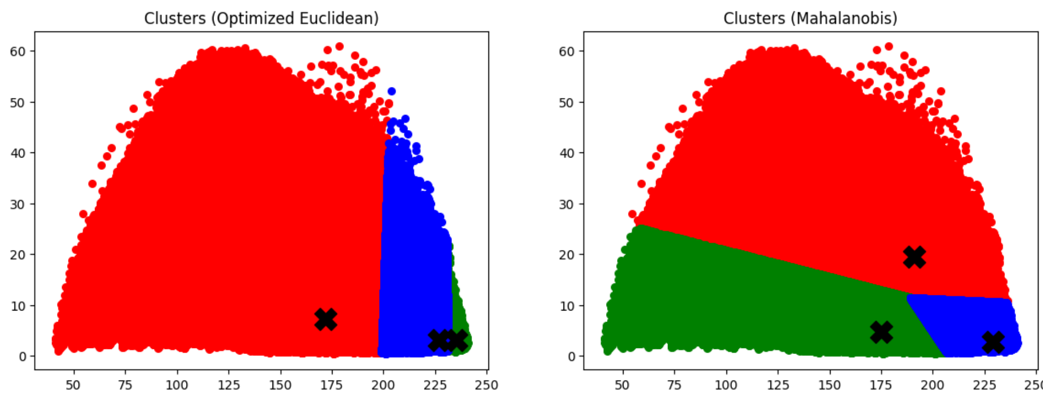
Figure 4.1 shows the plot of 3 clusters on training images.

### 4.2.2 Result of Cluster Projected on Test Images

Figure 4.2, 4.3 and 4.4 shows the result of cluster projected on image 11.png, 46.png and 51.png respectively.

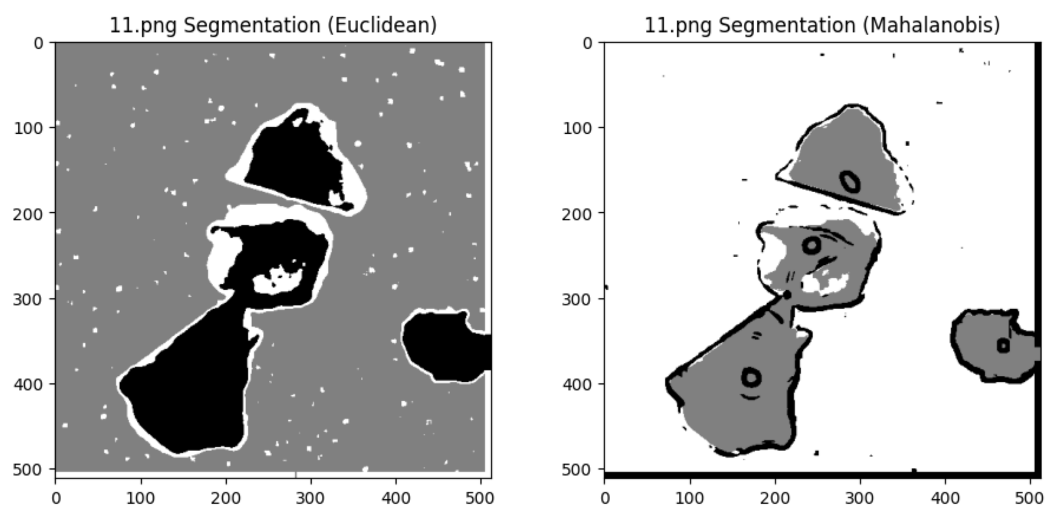
## 4.3 Inference

From figures 4.2, 4.3 and 4.4, it can be observed that the segmented images using modified K-means show better separation of distinct regions. Finer details and textures are captured more precisely if we use Mahalanobis distance instead of Euclidian distance. The separation between the nucleus and remaining cell is visible in modified K-means but not in K-means. This is because Mahalanobis distance considers features co-relation which is not considered in Euclidian distance. It also handles outliers quite effectively and not let them affect the segmentation leading to a better segmented image.



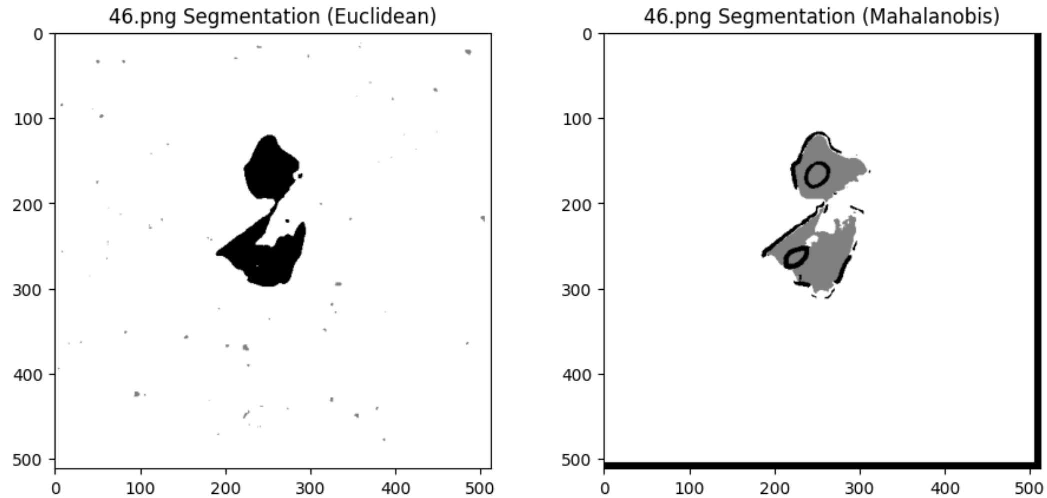

(a) K-means (b) Modified K-means

Figure 4.1: Plot of 3 clusters on training images. The left shows results from the standard K-means, and the right shows results from the modified K-means algorithm.




(a) K-means (b) Modified K-means

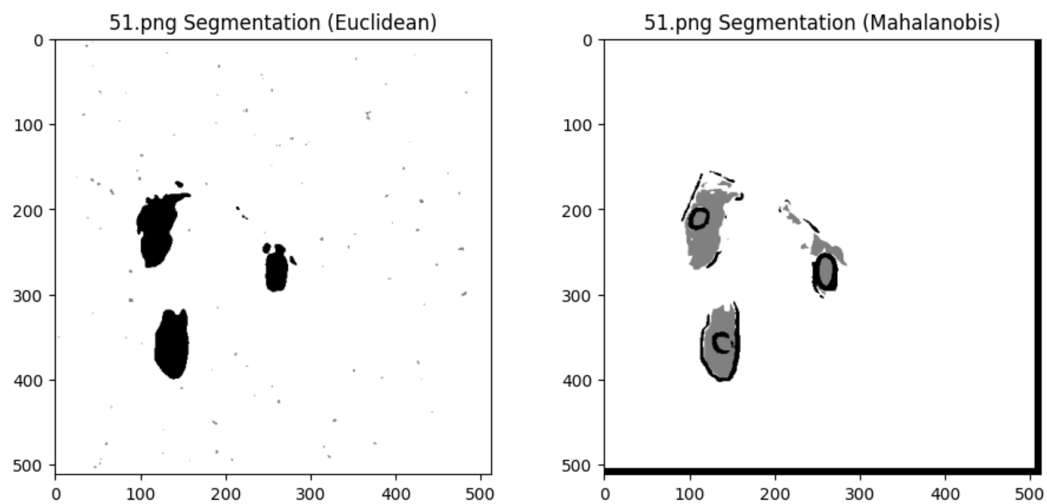
Figure 4.2: Clustering results on test image 11. The left image shows the K-means results, while the right image shows the modified K-means results.




(a) K-means

(b) Modified K-means

Figure 4.3: Clustering results on test image 46. The left image shows the K-means results, while the right image shows the modified K-means results.




(a) K-means

(b) Modified K-means

Figure 4.4: Clustering results on test image 51. The left image shows the K-means results, while the right image shows the modified K-means results.