PATTERN RECOGNITION(CS-669)

ASSIGNMENT-1

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SPEECH ACTIVITY DETECTION

MAXIMUM LIKELIHOOD FOR GAUSSIAN DISTRIBUTION

The likelihood function is given by:

$$L(\mu, \sigma \mid x) = \frac{1}{\sqrt{2\pi\sigma}}\, e^{-(x-\mu)^2/2\sigma^2}$$

Calculation of mean μ:

Sample mean of data points is given by:

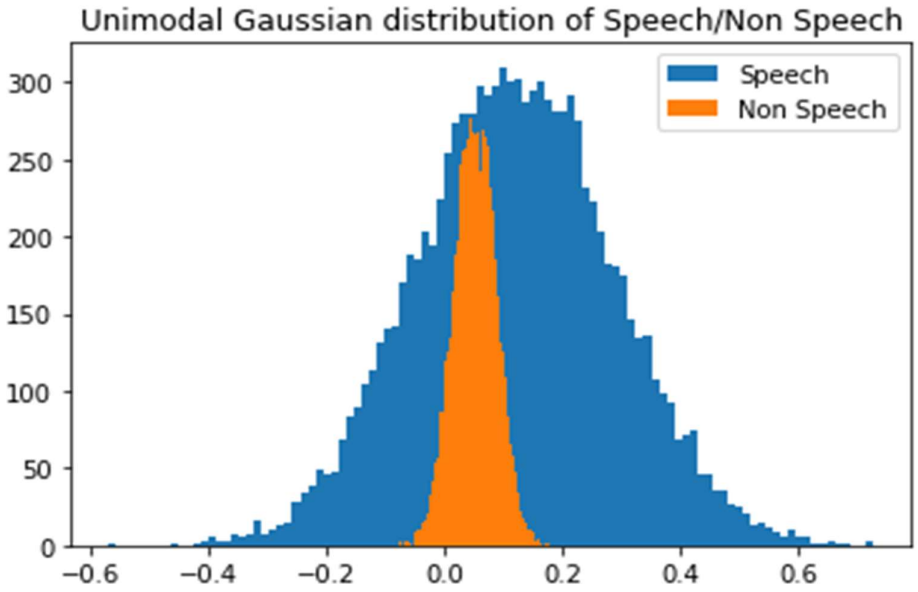
$$\mu = \frac{x_1+x_2+x_3+\cdots+x_n}{n}$$

Calculation of Variance σ^2:

Sample variance of data points:

$$\sigma^2 = \frac{(x_1-\mu)^2 + (x_2-\mu)^2 + \cdots + (x_n-u)^2}{n}$$

STE Features



POSTERIOR FOR CLASSIFICATION:

The classification of speech or Non-speech is based on posteriori is given by :

$$P(s|x_i) = \frac{P(x_i|s)P(s)}{P(x_i|s)P(s) + P(x_i|ns)P(ns)}$$

RECEIVER OPERATING CHARACTERISTICS (ROC):

The ROC curve tells us the which feature gives us the better model by calculating the TPR (True Positive Rate) and FPR (False Positive Rate). Assume some threshold x*,

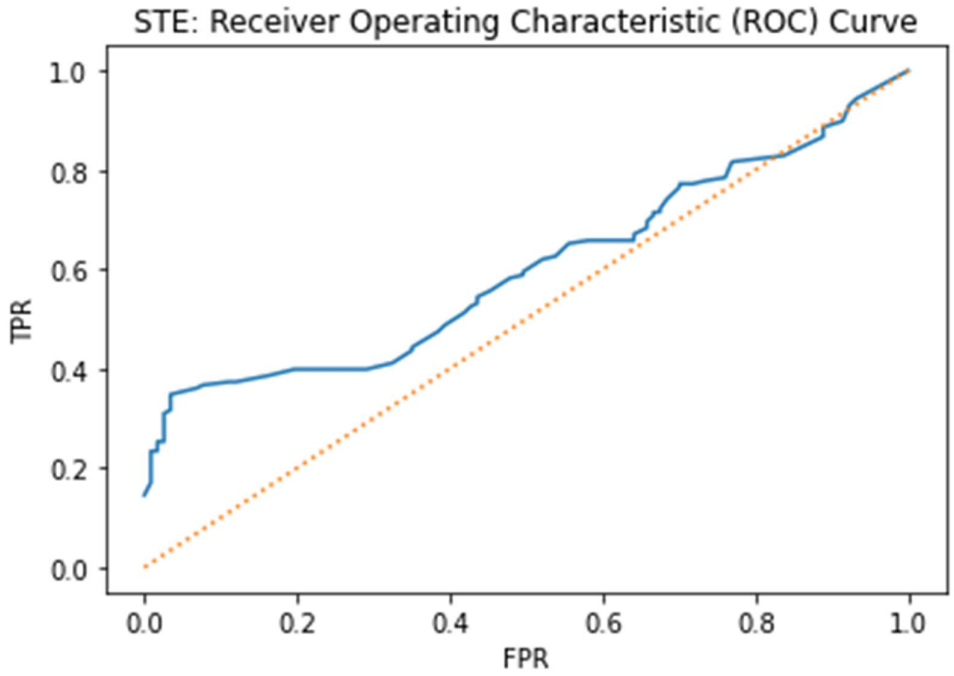
- $P(x > x^*|x \in \omega_2)$: a *hit* — the probability that the internal signal is above x^* given that the external signal is present
- $P(x > x^*|x \in \omega_1)$: a *false alarm* — the probability that the internal signal is above x^* despite there being no external signal is present
- $P(x < x^*|x \in \omega_2)$: a *miss* — the probability that the internal signal is below x^* given that the external signal is present
- $P(x < x^*|x \in \omega_1)$: a *correct rejection* — the probability that the internal signal is below x^* given that the external signal is not present.

FORMULAS USED:

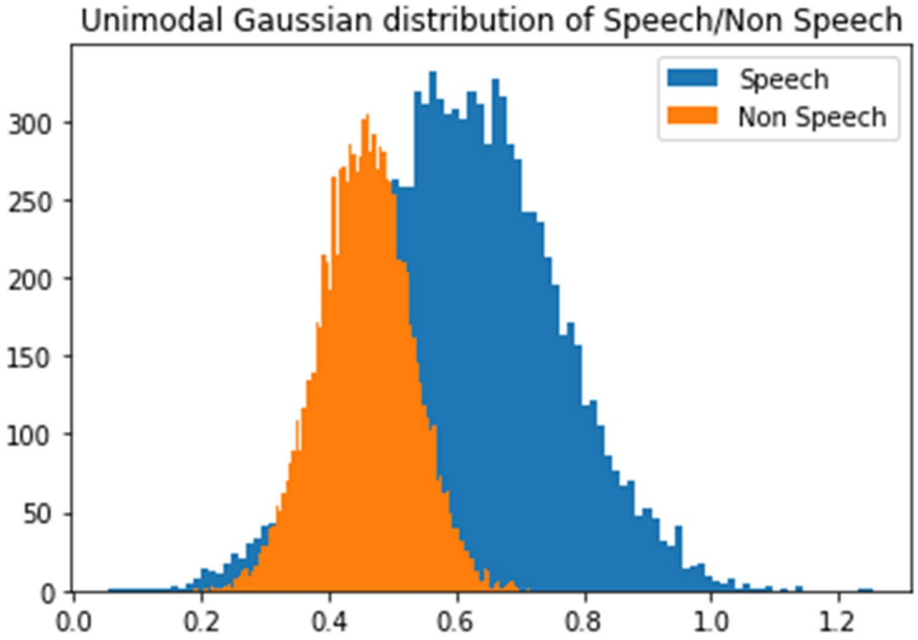
$$TPR\ (True\ positive\ rate) = \frac{TP}{TP+FN}$$

$$FPR\ (False\ positive\ rate) = \frac{TP}{TP+FN}$$

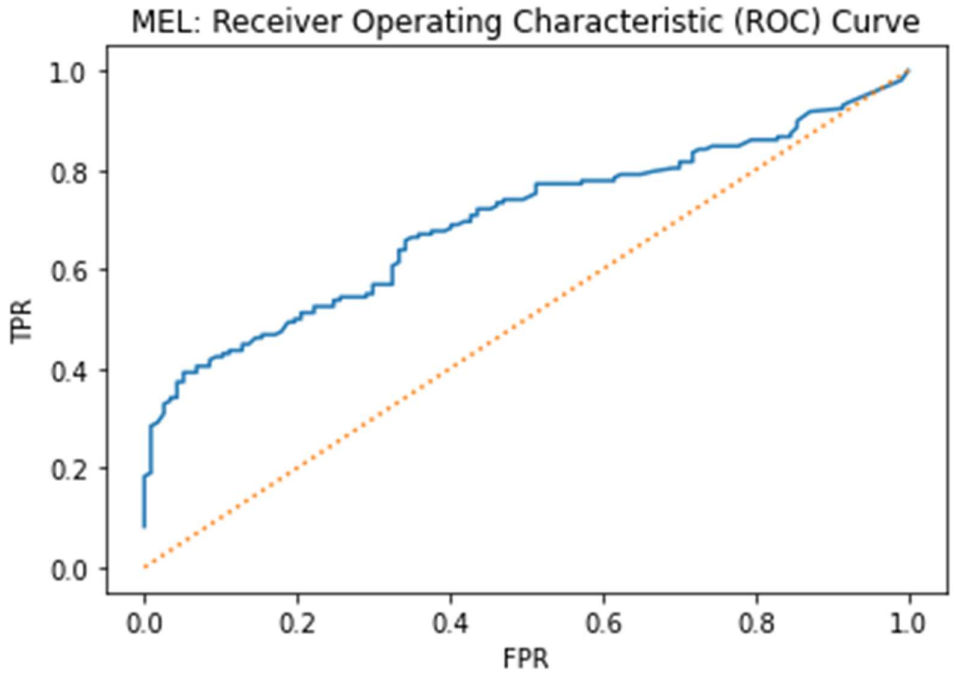
ROC Curve (STE Feature):



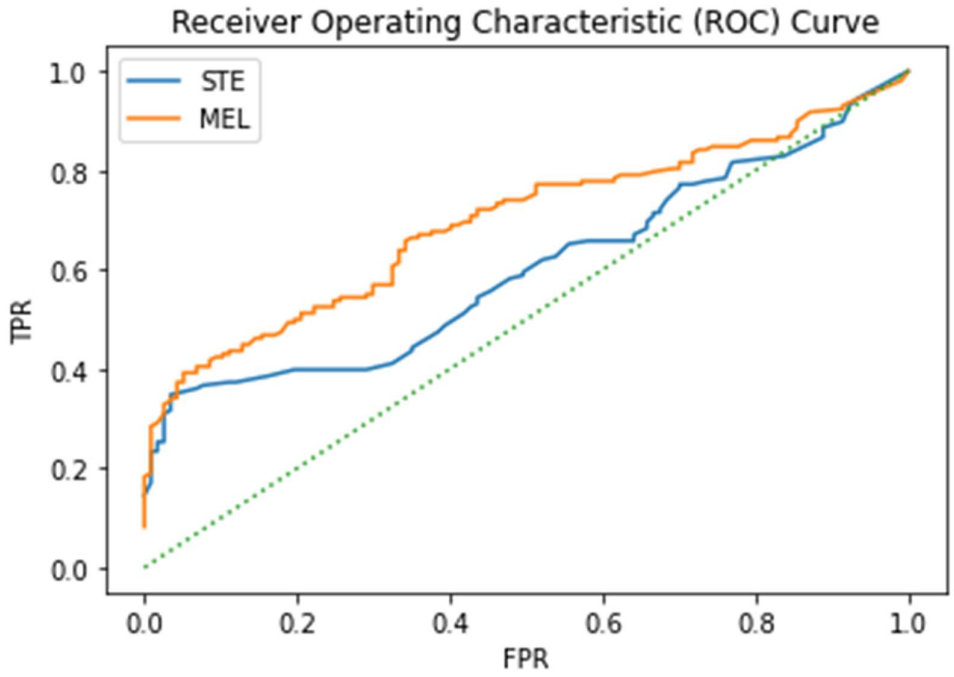
MEL Feautures



ROC Curve(MEL Feature):



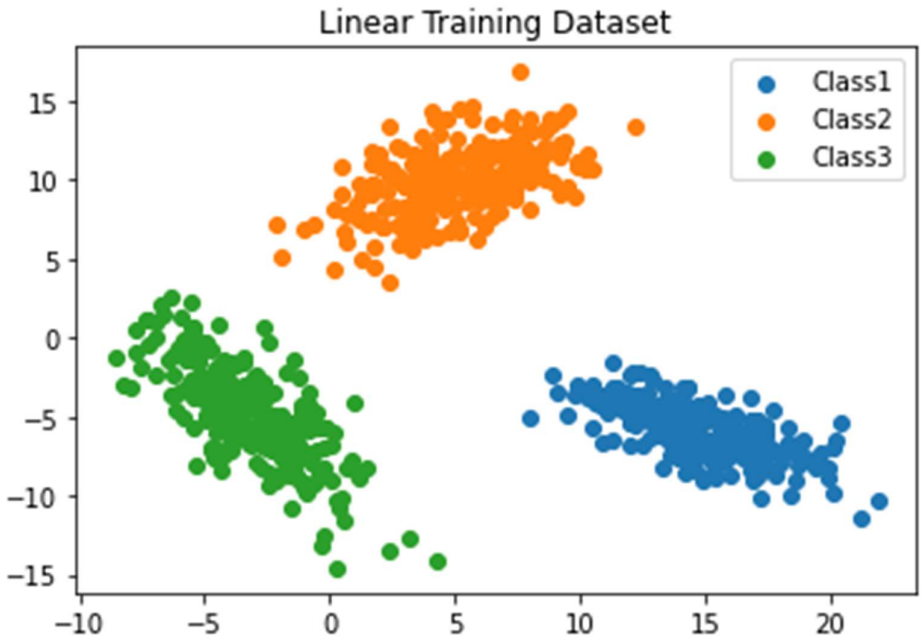
Comparison of STE and MEL Feature:

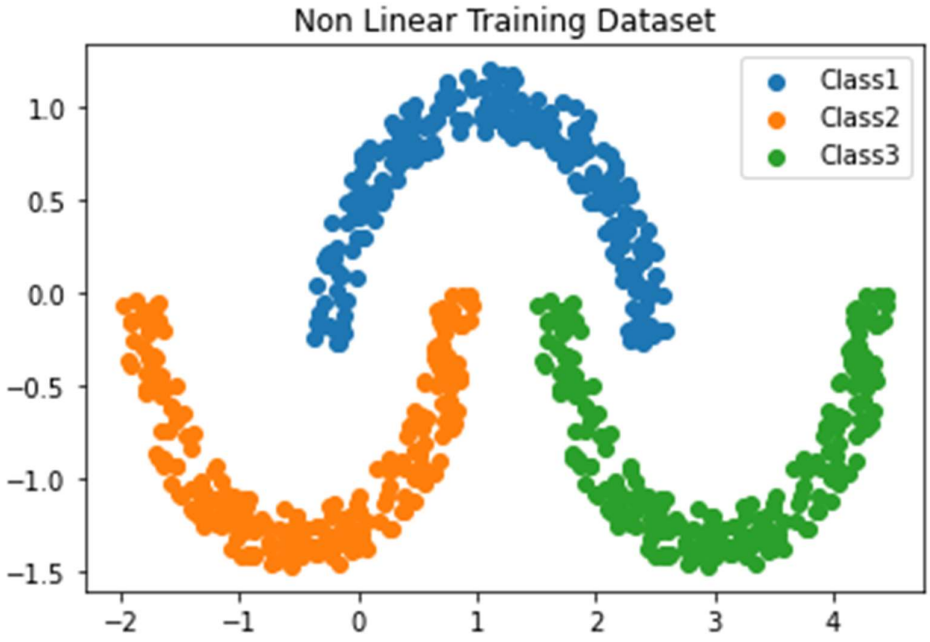


From the above ROC curve it is observed that **MEL feature performs better than STE feature** for classification of audio into speech or Non-speech.

BAYES CLASSIFIER (THREE CLASS CLASSIFICATION)

Given two datasets of three classes each. 50% training and 50% testing separated. One is linearly separable data and the other is non linearly separable data.





Bayes Classifier

The likelihood of the multimodal gaussian distribution is given by,

$$L(\mu, \sigma \mid x) = \frac{1}{\sqrt{2\pi|\sum|}} e^{-\frac{1}{2}(x-\mu)\sum^{-1}(x-\mu)^T}$$

Where μ is the mean of the samples and $\sum$ is the covariance of the training samples.

CLASSIFIER 1

Covariance for all classes is $I\sigma^2$. Using the average of the sample variances for all dimensions, for all classes, from the training data as σ^2 .

$$\sum = I\sigma^2 \text{ for all classes.}$$

CLASSIFIER 2

Full but equal covariance for all classes$\sum$. Use the average of the sample covariance matrix from all classes in the train data as $\sum$.

$$\sum = \frac{\sum_1 + \sum_2 + \sum_3}{3}$$

CLASSIFIER 3

Diagonal covariance matrix, distinct for each class. Use variances from the sample covariance matrix for each class

$$\sum_1 = diagonal(\sigma_1^2)$$

$$\sum_2 = diagonal(\sigma_2^2)$$

$$\sum_3 = diagonal(\sigma_3^2)$$

CLASSIFIER 4

Full covariance matrix, distinct for each class. Use the sample covariance matrix for each class.

$$\sum_1, \sum_2, \sum_3$$

Confusion Matrix

Actual Class				
Predicted Class		Class 1	Class 2	Class 3
	Class 1	C11	C12	C13
	Class 2	C21	C22	C23
	Class 3	C31	C32	C33

- C11: 98 test samples predicted as class 1 & actually belongs to class 1
- C12: 0 test samples predicted as class 1 & actually belongs to class 2
- C13: 2 test samples predicted as class 1 & actually belongs to class 3
- C21: 0 test samples predicted as class 2 & actually belongs to class 1
- C22: 100 test samples predicted as class 2 & actually belongs to class 2
- C23: 0 test samples predicted as class 2 & actually belongs to class 3
- C31: 0 test samples predicted as class 3 & actually belongs to class 1
- C32: 0 test samples predicted as class 3 & actually belongs to class 2
- C33: 100 test samples predicted as class 3 & actually belongs to class 3

ACCURACY

$$\text{Accuracy} = \frac{\text{Number of samples correctly classified (C11+C22+C33)}}{\text{Total number of samples used for testing}} * 100$$

MEAN PRECISION

$$\text{Class 1 Precision} = \frac{\text{TP for Class 1}}{\text{TP for Class 1 + FP for class 1}}$$

$$\text{Class 2 Precision} = \frac{\text{TP for Class 2}}{\text{TP for Class 2 + FP for class 2}}$$

$$\text{Class 3 Precision} = \frac{\text{TP for Class 3}}{\text{TP for Class 3 + FP for class 3}}$$

Mean precision = $\frac{1}{3}\sum_{i=1}^{3} precision_i$

Recall

Class 1 Recall = $\frac{\text{TP for Class 1}}{\text{TP for Class 1 + FN for class 1}}$

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Mean recall = $\frac{1}{3}\sum_{i=1}^{3} recall_i$

F-MEASURE

"Harmonic mean of precision and recall"

Class1 F measure = $2\frac{Precision_1 * Recall_1}{Precision_1 + Recall_1}$

Class2 F measure = $2\frac{Precision_2 * Recall_2}{Precision_2 + Recall_2}$

Class3 F measure = $2\frac{Precision_3 * Recall_3}{Precision_3 + Recall_3}$

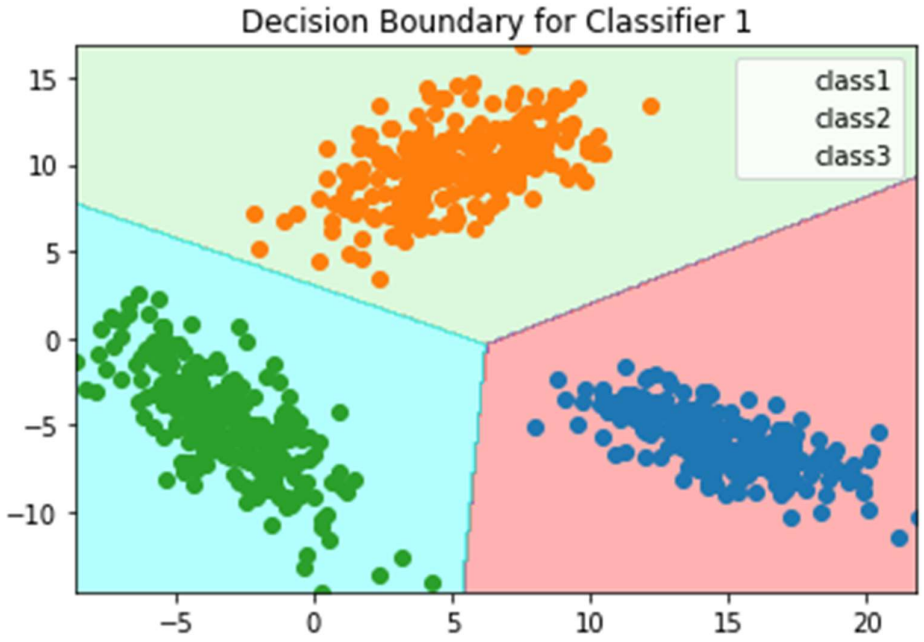
Mean Fmeasure = $\frac{1}{3}\sum_{i=1}^{3} Fmeasure_i$

Linearly Separable Data Samples

Classifier 1 Result

Actual Class				
Predicted Class		Class 1	Class 2	Class 3
	Class 1	250	0	0
	Class 2	0	250	0
	Class 3	0	0	250

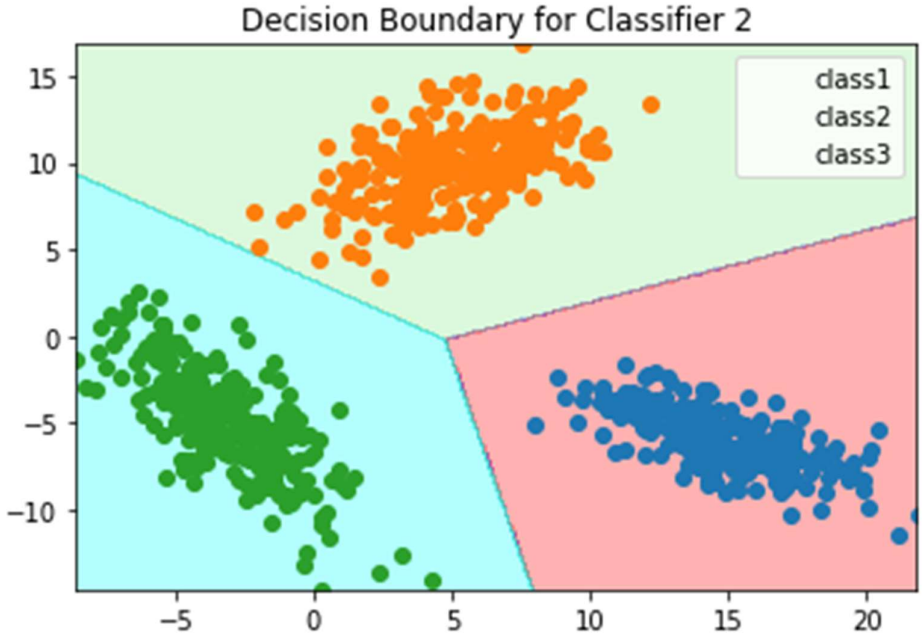
Accuracy	1.0
Precision	1.0
Recall	1.0
F score	1.0



Classifier 2 Result

Actual Class				
Predicted Class		Class 1	Class 2	Class 3
	Class 1	250	0	0
	Class 2	0	250	0
	Class 3	0	0	250

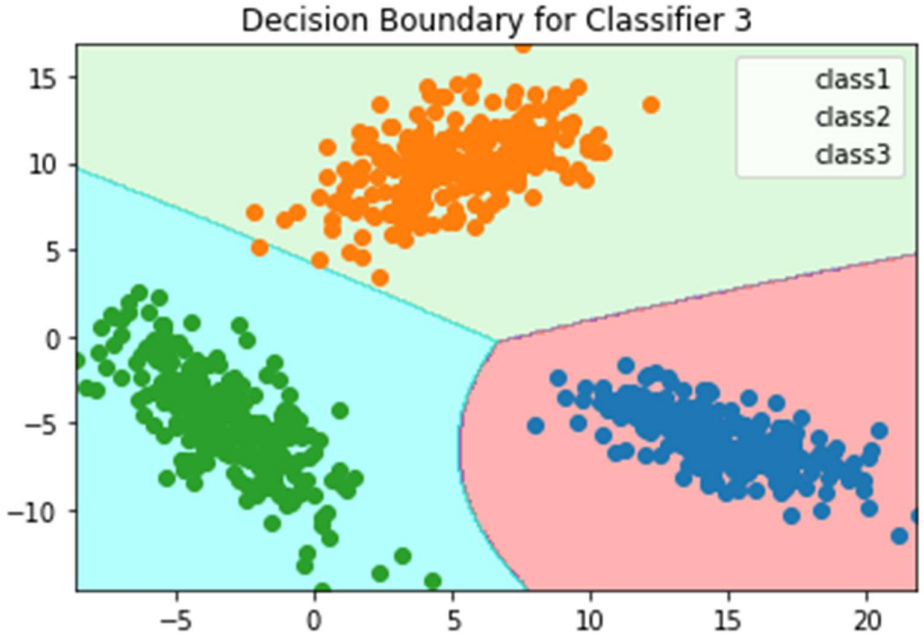
Accuracy	1.0
Precision	1.0
Recall	1.0
F score	1.0



Classifier 3 Result

Actual Class				
Predicted Class		Class 1	Class 2	Class 3
	Class 1	250	0	0
	Class 2	0	250	0
	Class 3	0	0	250

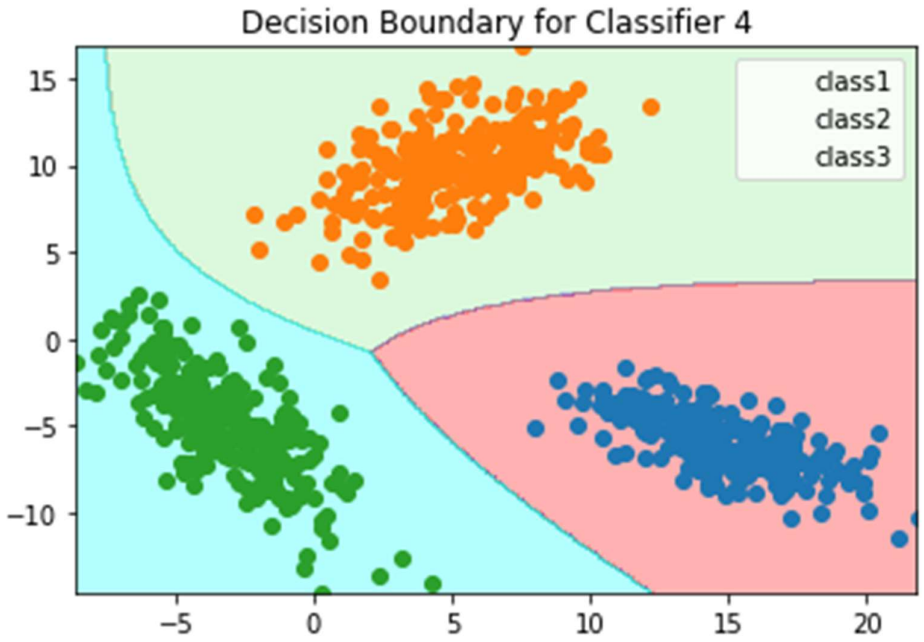
Accuracy	1.0
Precision	1.0
Recall	1.0
F score	1.0



Classifier 4 Result

Actual Class				
Predicted Class		Class 1	Class 2	Class 3
	Class 1	250	0	0
	Class 2	0	250	0
	Class 3	0	0	250

Accuracy	1.0
Precision	1.0
Recall	1.0
F score	1.0



CONCLUSION

	Classifier 1	Classifier 2	Classifier 3	Classifier 4
Accuracy	1.0	1.0	1.0	1.0
Precision	1.0	1.0	1.0	1.0
Recall	1.0	1.0	1.0	1.0
F measure	1.0	1.0	1.0	1.0

For this dataset all the classifier models gives same result and performing well. The differences we can note in the decision

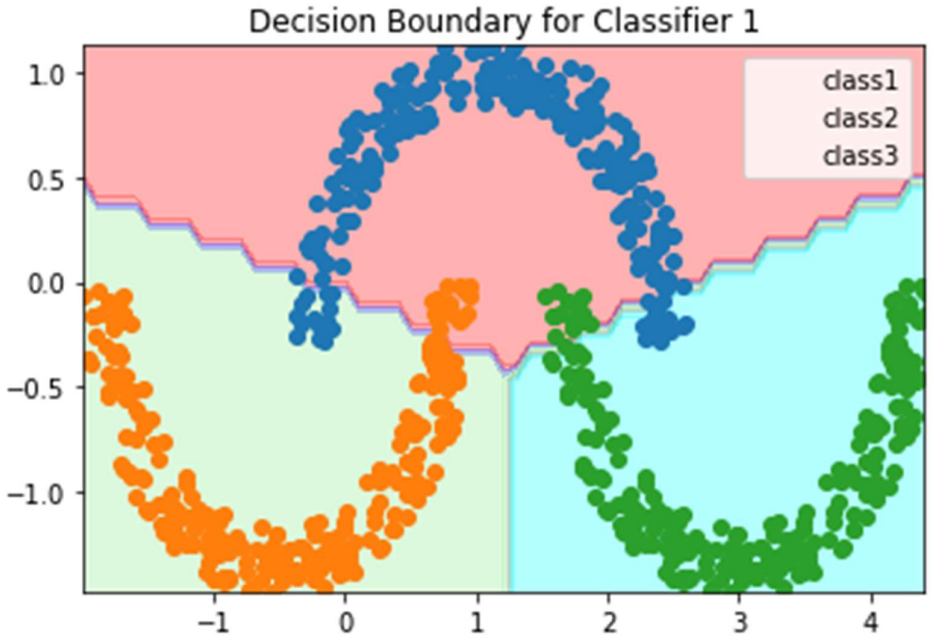
boundaries of each classifier. As the covariance matrix becomes distinct and full, the boundary becomes much more accurate and exhibits non-linear characteristics.

Non-Linearly Separable Data Samples

Classifier 1 Results

Actual Class				
Predicted Class		Class 1	Class 2	Class 3
	Class 1	222	16	22
	Class 2	0	234	0
	Class 3	0	0	228

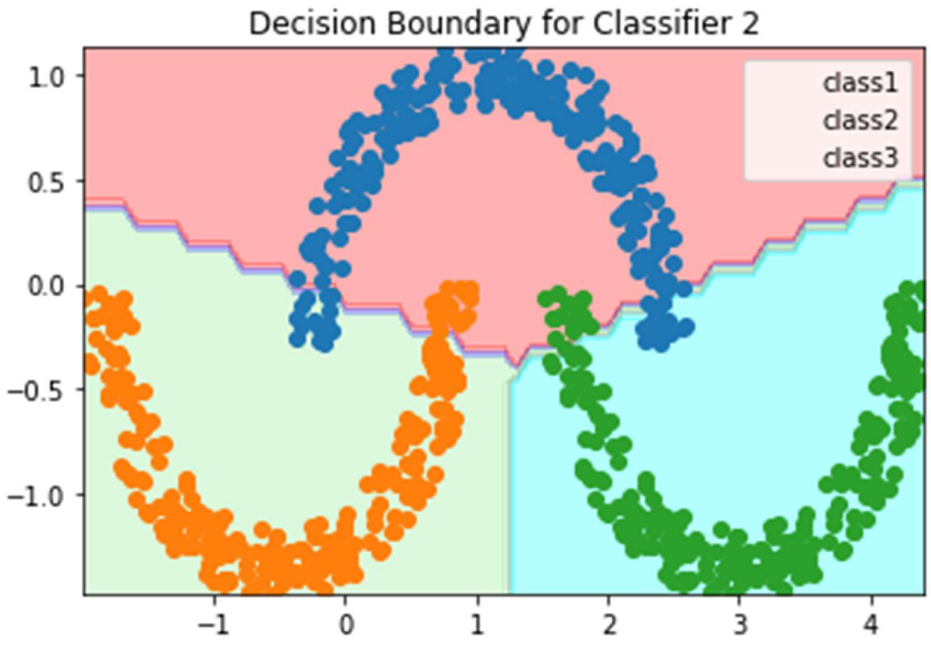
Accuracy	0.912
Precision	0.951
Recall	0.949
F score	0.947



Classifier 2 Results

Actual Class				
Predicted Class		Class 1	Class 2	Class 3
	Class 1	222	16	22
	Class 2	0	234	0
	Class 3	0	0	228

Accuracy	0.912
Precision	0.951
Recall	0.949
F score	0.947

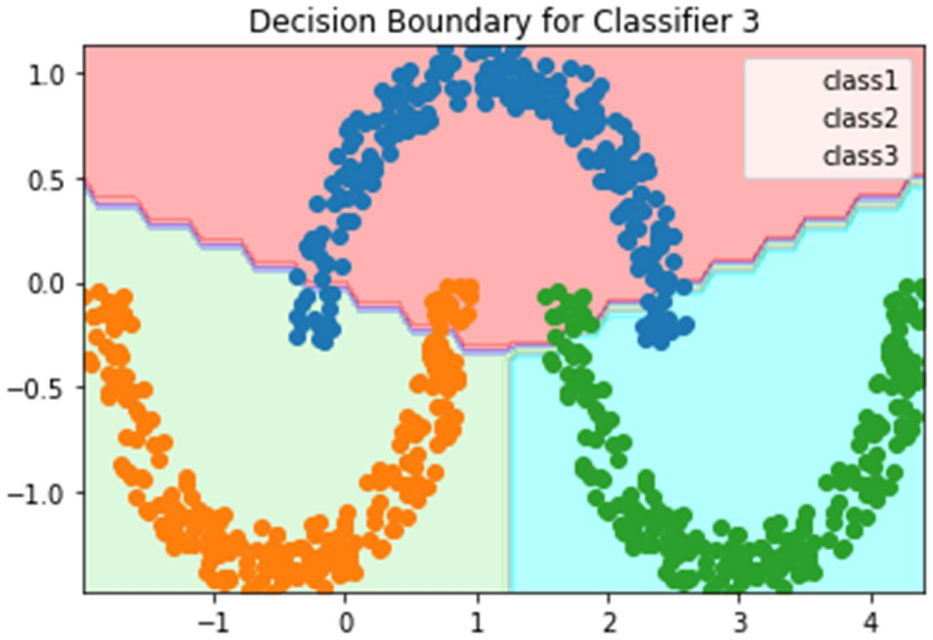


Classifier 3 Results

Actual Class				
Predicted		Class 1	Class 2	Class 3
	Class 1	220	12	21

Class	Class 2	0	238	0
	Class 3	0	0	229

Accuracy	0.916
Precision	0.956
Recall	0.956
F score	0.953

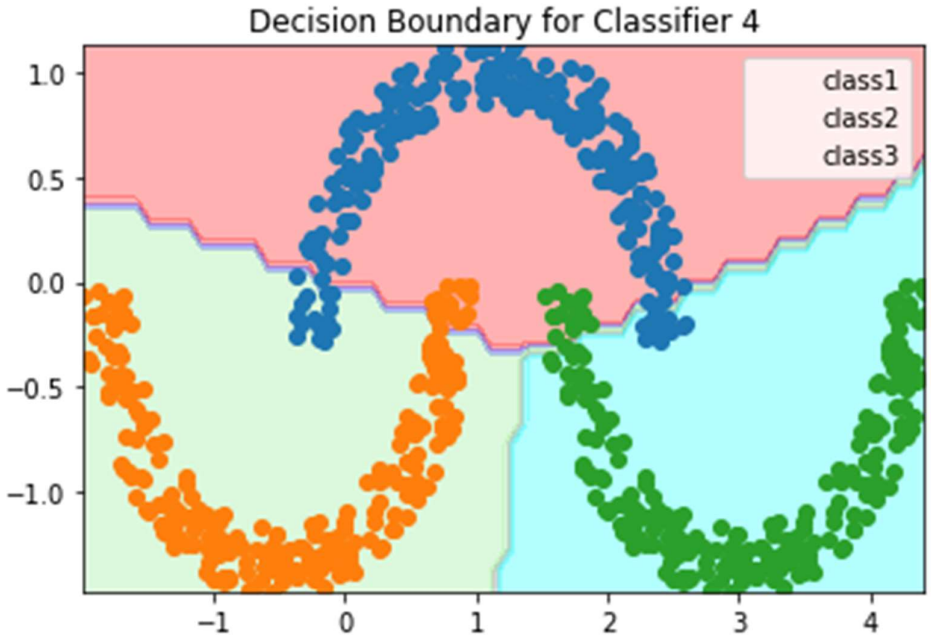


Classifier 4 Results

Actual Class				
Predicted Class		Class 1	Class 2	Class 3
	Class 1	221	9	22
	Class 2	0	241	0
	Class 3	0	0	228

Accuracy	0.920
Precision	0.958

Recall	0.958
F score	0.956



CONCLUSION

	Classifier 1	Classifier 2	Classifier 3	Classifier 4
Accuracy	**0.912**	**0.916**	**0.916**	**0.920**
Precision	**0.951**	**0.951**	**0.956**	**0.958**
Recall	**0.949**	**0.949**	**0.956**	**0.958**
F measure	**0.947**	**0.947**	**0.953**	**0.956**

For this non- linear dataset all the classifier models does not performs very well, but gives some reasonable result. The differences we can note in the decision boundaries of each classifier also in the scores of the classifiers. As the covariance matrix becomes distinct and full, the boundary becomes much more accurate and the accuracy, precision, recall, and the F-measure also improves.

Colab Ques-1	**https://colab.research.google.com/drive/1eIzw15komeH8AhljJ7_iWs9uMaWGx-Fi?usp=sharing**
Colab Ques-2	**https://colab.research.google.com/drive/1YOZb_rqxEcPKL2jMX8WPH5mkih1Sp-zM?usp=sharing**