

Machine Learning Lab Assignment 3

Name – Rishav Kundu

Roll – 001811001039

Semester – 7

PART 1

1) Wine Dataset

1.1) GaussianHMM Without Tuning

↳ Confusion Matrix:

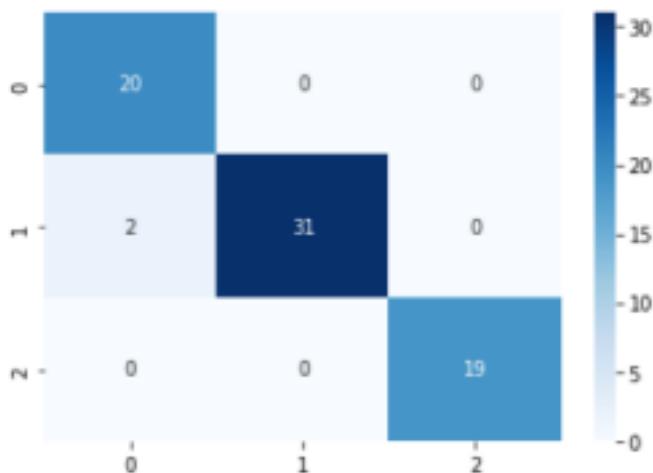
```
[[20  0  0]
 [ 2 31  0]
 [ 0  0 19]]
```

Performance Evaluation

	precision	recall	f1-score	support
1	0.91	1.00	0.95	20
2	1.00	0.94	0.97	33
3	1.00	1.00	1.00	19
accuracy			0.97	72
macro avg	0.97	0.98	0.97	72
weighted avg	0.97	0.97	0.97	72

Accuracy:

0.9722222222222222



1.2) GaussianHMM With Tuning

▷ Confusion Matrix:

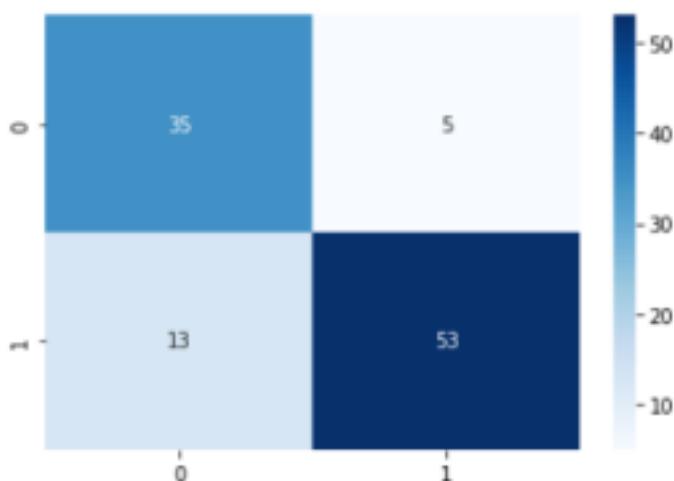
```
[[35  5]
 [13 53]]
```

Performance Evaluation

	precision	recall	f1-score	support
b	0.73	0.88	0.80	40
g	0.91	0.80	0.85	66
accuracy			0.83	106
macro avg	0.82	0.84	0.83	106
weighted avg	0.84	0.83	0.83	106

Accuracy:

0.8301886792452831



1.3) GMMHMM Without Tuning

Confusion Matrix:

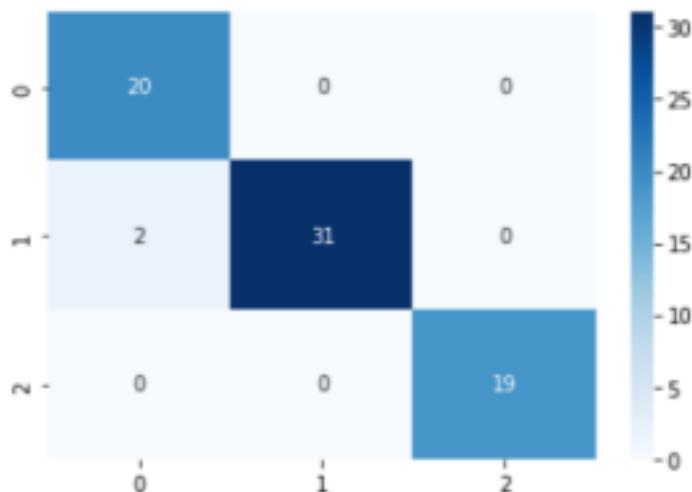
```
[[20  0  0]
 [ 2 31  0]
 [ 0  0 19]]
```

Performance Evaluation

	precision	recall	f1-score	support
1	0.91	1.00	0.95	20
2	1.00	0.94	0.97	33
3	1.00	1.00	1.00	19
accuracy			0.97	72
macro avg	0.97	0.98	0.97	72
weighted avg	0.97	0.97	0.97	72

Accuracy:

0.9722222222222222



1.4) GMMHMM With Tuning

➡ Confusion Matrix:

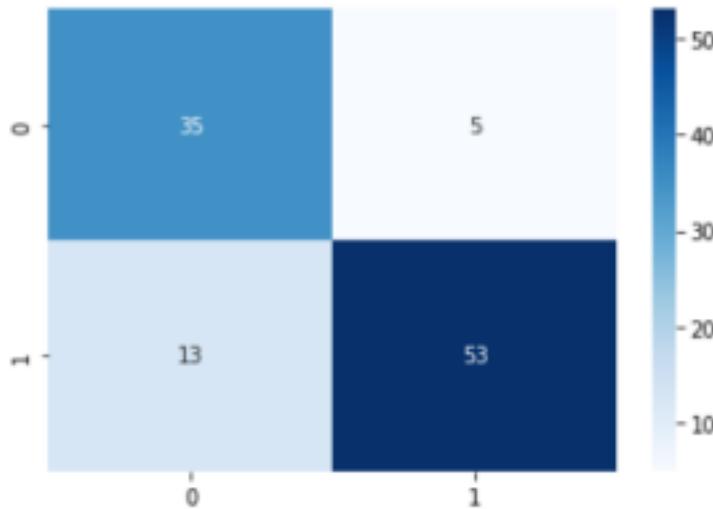
```
[[35  5]
 [13 53]]
```


Performance Evaluation

	precision	recall	f1-score	support
b	0.73	0.88	0.80	40
g	0.91	0.80	0.85	66
accuracy			0.83	106
macro avg	0.82	0.84	0.83	106
weighted avg	0.84	0.83	0.83	106

Accuracy:

0.8301886792452831



1.5) MultinomialHMM Without Tuning

➡ Confusion Matrix:

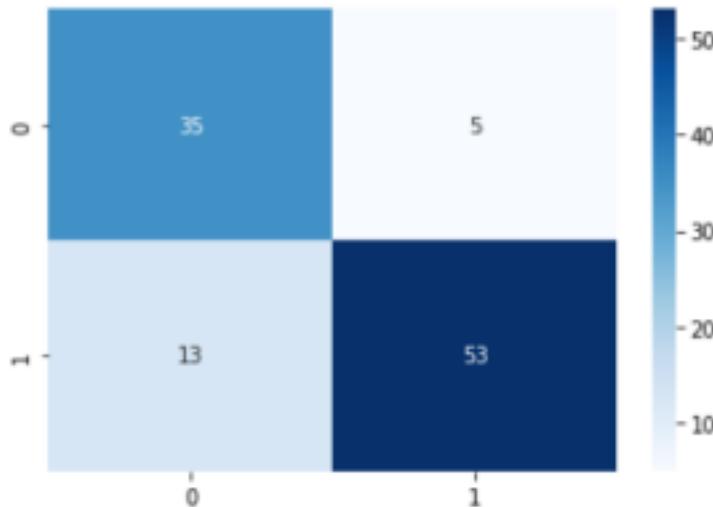
```
[[35  5]
 [13 53]]
```


Performance Evaluation

	precision	recall	f1-score	support
b	0.73	0.88	0.80	40
g	0.91	0.80	0.85	66
accuracy			0.83	106
macro avg	0.82	0.84	0.83	106
weighted avg	0.84	0.83	0.83	106

Accuracy:

0.8301886792452831



1.6) MultinomialHMM Without Tuning

↳ Confusion Matrix:

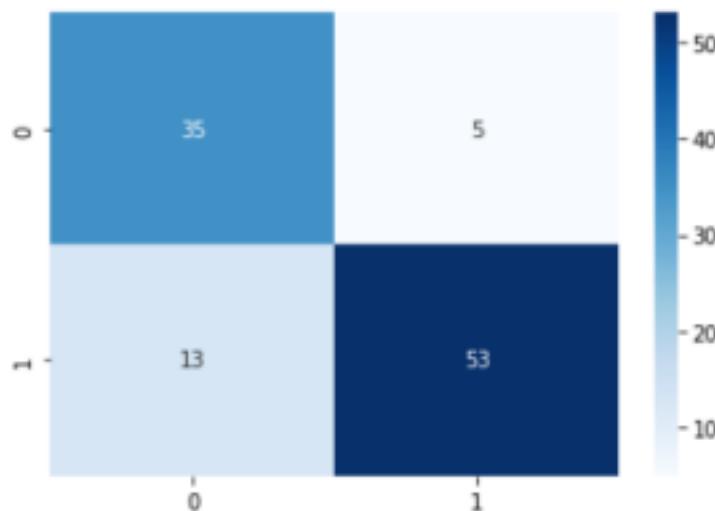
```
[[35  5]
 [13 53]]
```

Performance Evaluation

	precision	recall	f1-score	support
b	0.73	0.88	0.80	40
g	0.91	0.80	0.85	66
accuracy			0.83	106
macro avg	0.82	0.84	0.83	106
weighted avg	0.84	0.83	0.83	106

Accuracy:

```
0.8301886792452831
```



The maximum accuracy was achieved when the Train-Test split ratio was 70:30, which was achieved by using the Gaussian Model. The maximum range of accuracies was achieved by the Gaussian Model, followed by the GMMHMM model, which is followed by the MultinomialHMM model.

2) Ionosphere Dataset

2.1) GaussianHMM Without Tuning

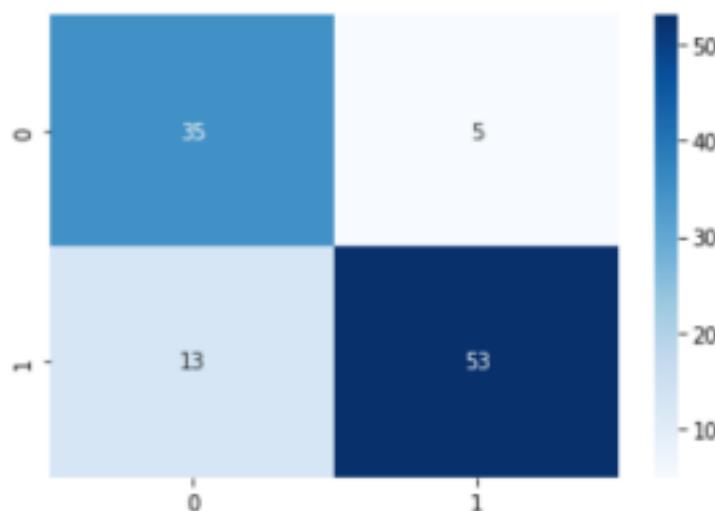
↳ Confusion Matrix:

```
[[35  5]
 [13 53]]
```

Performance Evaluation		precision	recall	f1-score	support
b	g	0.73	0.88	0.80	40
		0.91	0.80	0.85	66
accuracy				0.83	106
macro avg		0.82	0.84	0.83	106
weighted avg		0.84	0.83	0.83	106

Accuracy:

0.8301886792452831



2.2) GaussianHMM With Tuning

▷ Confusion Matrix:

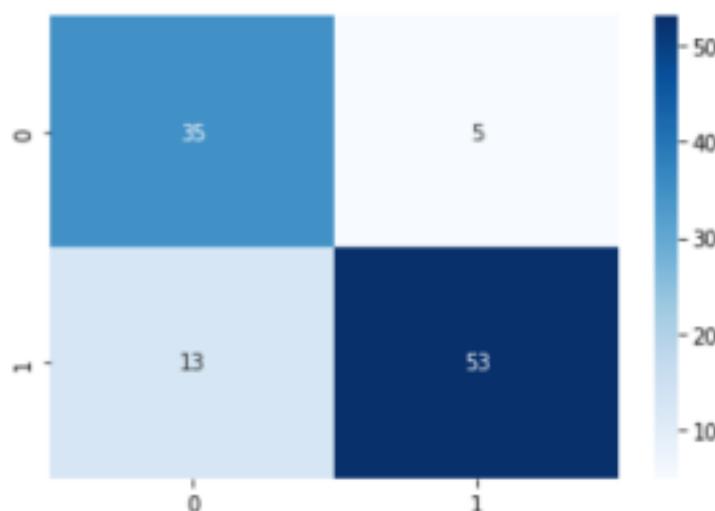
```
[[35  5]
 [13 53]]
```

Performance Evaluation

	precision	recall	f1-score	support
b	0.73	0.88	0.80	40
g	0.91	0.80	0.85	66
accuracy			0.83	106
macro avg	0.82	0.84	0.83	106
weighted avg	0.84	0.83	0.83	106

Accuracy:

0.8301886792452831



2.3) GMMHMM Without Tuning

▷ Confusion Matrix:

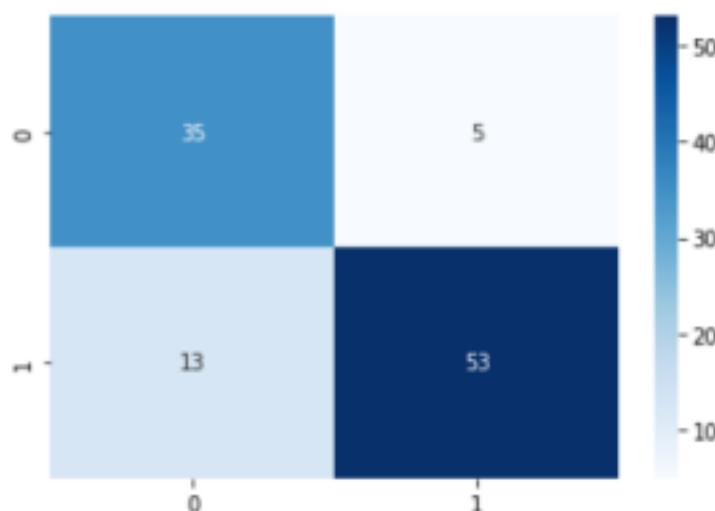
```
[[35  5]
 [13 53]]
```

Performance Evaluation

	precision	recall	f1-score	support
b	0.73	0.88	0.80	40
g	0.91	0.80	0.85	66
accuracy			0.83	106
macro avg	0.82	0.84	0.83	106
weighted avg	0.84	0.83	0.83	106

Accuracy:

0.8301886792452831



2.4) GMMHMM With Tuning

▷ Confusion Matrix:

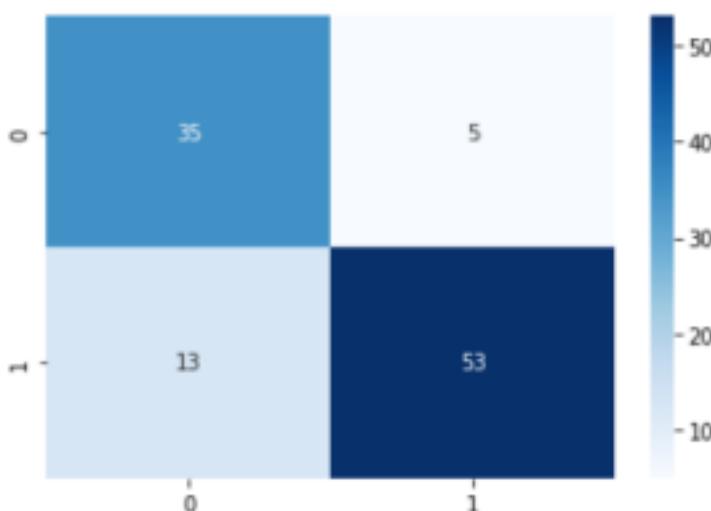
```
[[35  5]
 [13 53]]
```

Performance Evaluation

	precision	recall	f1-score	support
b	0.73	0.88	0.80	40
g	0.91	0.80	0.85	66
accuracy			0.83	106
macro avg	0.82	0.84	0.83	106
weighted avg	0.84	0.83	0.83	106

Accuracy:

0.8301886792452831



2.5) MultinomialHMM Without Tuning

↳ Confusion Matrix:

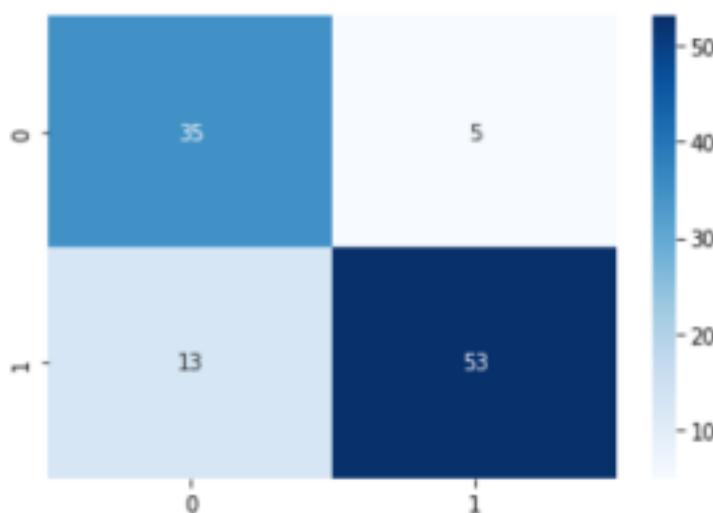
```
[[35  5]
 [13 53]]
```

Performance Evaluation

	precision	recall	f1-score	support
b	0.73	0.88	0.80	40
g	0.91	0.80	0.85	66
accuracy			0.83	106
macro avg	0.82	0.84	0.83	106
weighted avg	0.84	0.83	0.83	106

Accuracy:

0.8301886792452831



2.6) MultinomialHMM Without Tuning

The maximum accuracy was achieved when the Train-Test split ratio was 70:30, which was achieved by using the Gaussian Model. The maximum range of accuracies was achieved by the Gaussian Model, followed by the GMMHMM model, which is

followed by the MultinomialHMM model.

3) Breast Cancer Dataset

3.1) GaussianHMM Without Tuning

↳ Confusion Matrix:

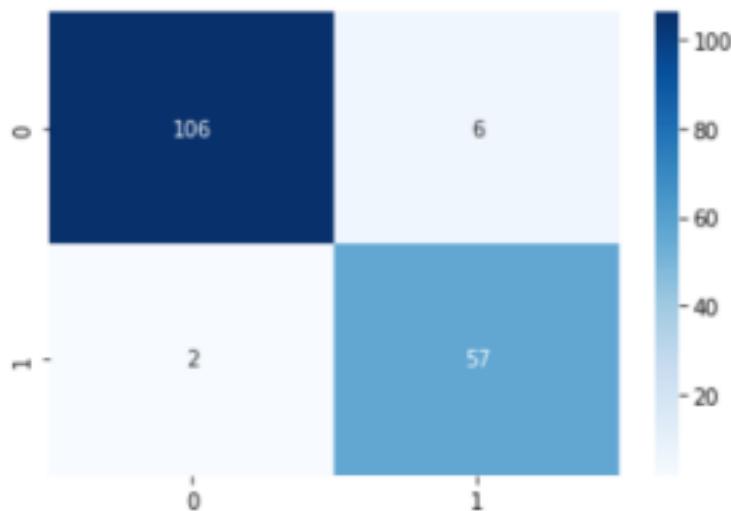
```
[[106  6]
 [ 2  57]]
```

Performance Evaluation

	precision	recall	f1-score	support
B	0.98	0.95	0.96	112
M	0.90	0.97	0.93	59
accuracy			0.95	171
macro avg	0.94	0.96	0.95	171
weighted avg	0.96	0.95	0.95	171

Accuracy:

0.9532163742690059



3.2) GaussianHMM With Tuning

▷ Confusion Matrix:

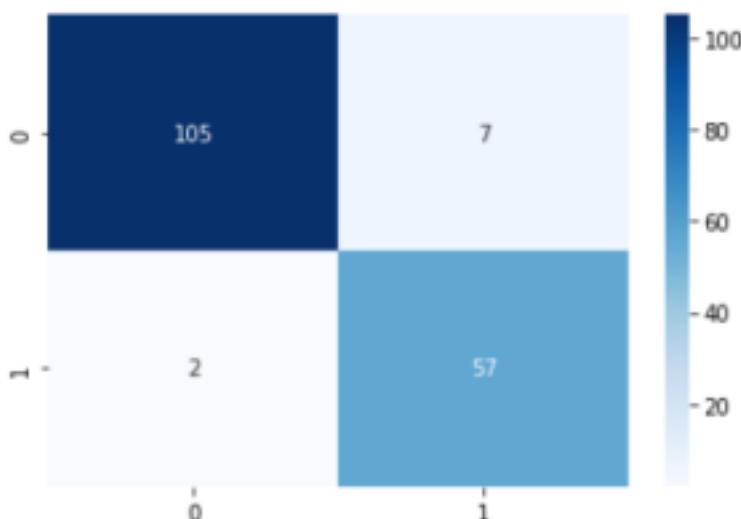
```
[[105  7]
 [ 2  57]]
```

Performance Evaluation

	precision	recall	f1-score	support
B	0.98	0.94	0.96	112
M	0.89	0.97	0.93	59
accuracy			0.95	171
macro avg	0.94	0.95	0.94	171
weighted avg	0.95	0.95	0.95	171

Accuracy:

0.9473684210526315



3.3) GMMHMM Without Tuning

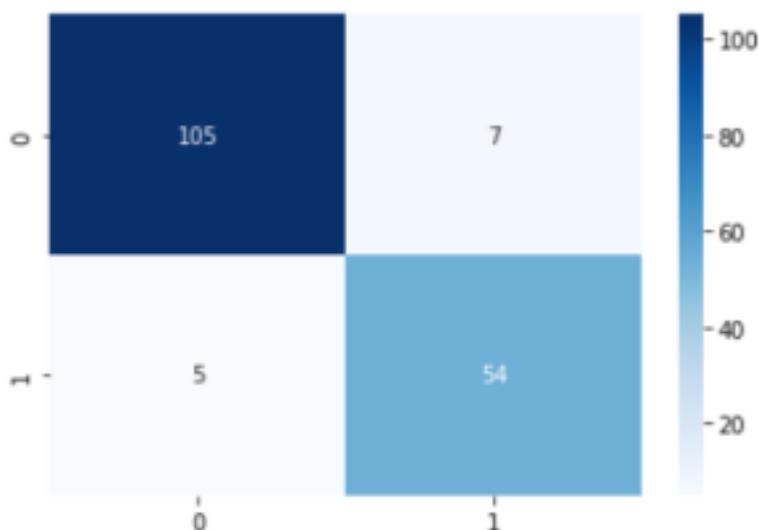
↳ Confusion Matrix:

```
[[105  7]
 [ 5  54]]
```

Performance Evaluation		precision	recall	f1-score	support
	B	0.95	0.94	0.95	112
	M	0.89	0.92	0.90	59
accuracy				0.93	171
macro avg		0.92	0.93	0.92	171
weighted avg		0.93	0.93	0.93	171

Accuracy:

0.9298245614035088



3.4) GMMHMM With Tuning



3.5) MultinomialHMM Without Tuning



3.6) MultinomialHMM Without Tuning



The maximum accuracy was achieved when the Train-Test split ratio was 70:30, which was achieved by using the Gaussian Model. The maximum range of accuracies was achieved by the Gaussian Model, followed by the GMMHMM model, which is followed by the MultinomialHMM model.

PART 2

1) CIFAR-10





2) MNIST



3) SAVEE





4) EmoDB





It was observed that the more layers we add the higher accuracy we can achieve. At the same time, if we keep on adding more layers, the final accuracy will saturate. Also, the number of convolution and the pooling layers play an important role in training the model.

PART 3

1) VGG-16

1.1) CIFAR-10



1.2) MNIST



1.3) SAVEE



1.4) EmoDB



The entire model can be broken down into 5 blocks, where each block contains 3 convolution and 1 max-pooling layers.

Looking at the complexity of the model and the limitations of google colab, I have reduced the input size for the model,i.e., i have taken 2000 training data points and 2000 testing data points.

2) ResNet-50

2.1) CIFAR-10



2.2) MNIST



2.3) SAVEE



2.4) EmoDB



Looking at the complexity of the model and the limitations of google colab, I have reduced the input size for the model,i.e., I have taken 2000 training data points and 2000 testing data points.

3) Recurrent Neural Networks (RNN)

3.1) CIFAR-10



3.2) MNIST



3.3) SAVEE



3.4) EmoDB



Looking at the complexity of the model and the limitations of google colab, I have reduced the input size for the model,i.e., I have taken 2000 training data points and 2000 testing data points.

4) AlexNet

4.1) CIFAR-10



4.2) MNIST



4.3) SAVEE



4.4) EmoDB



Looking at the complexity of the model and the limitations of google colab, I have reduced the input size for the model,i.e., I have taken 2000 training data points and 2000 testing data points.

5) GoogleNet

5.1) CIFAR-10



5.2) MNIST



5.3) SAVEE



5.4) EmoDB

Looking at the complexity of the model and the limitations of google colab, I have reduced the input size for the model ,i.e., I have taken 2000 training data points and 2000 testing data points.