CS6910: Programming Assignment 2

Team 37

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1 TASK 1 - DIMENSION REDUCTION

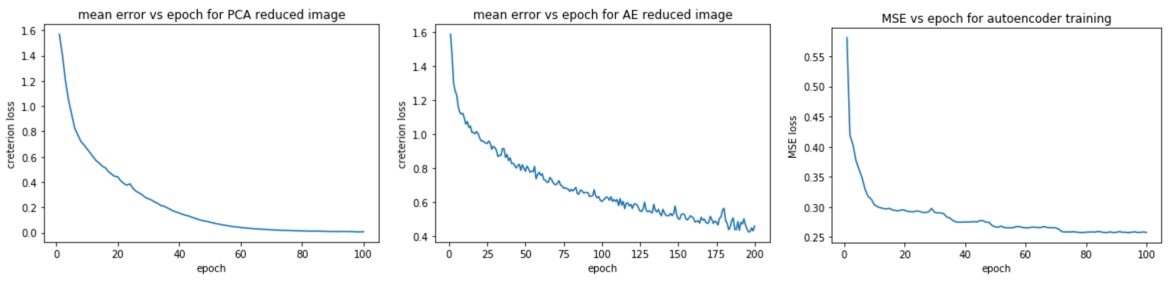
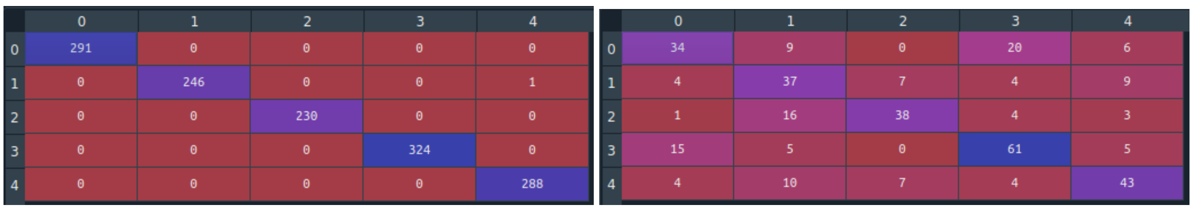


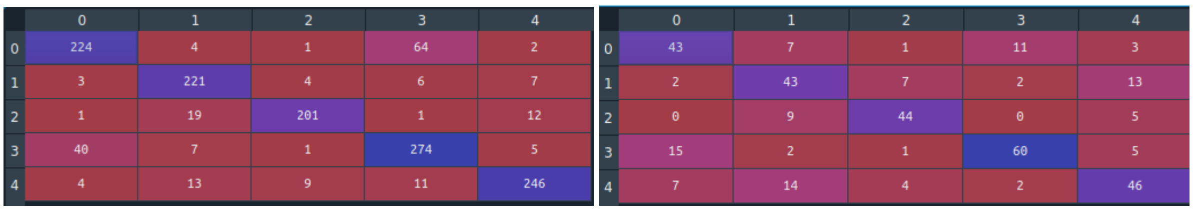
Figure 1.1: Training error curves vs epoch number



	0	1	2	3	4
0	291	0	0	0	0
1	0	246	0	0	1
2	0	0	230	0	0
3	0	0	0	324	0
4	0	0	0	0	288

	0	1	2	3	4
0	34	9	0	20	6
1	4	37	7	4	9
2	1	16	38	4	3
3	15	5	0	61	5
4	4	10	7	4	43

Figure 1.2: Confusion Matrices for the model with dimensionality reduction using PCA followed by MLFFNN for training and validation data respectively. Accuracy's are **99.93%** and **61.56%** respectively.



	0	1	2	3	4
0	224	4	1	64	2
1	3	221	4	6	7
2	1	19	201	1	12
3	40	7	1	274	5
4	4	13	9	11	246

	0	1	2	3	4
0	43	7	1	11	3
1	2	43	7	2	13
2	0	9	44	0	5
3	15	2	1	60	5
4	7	14	4	2	46

Figure 1.3: Confusion Matrices for the model with dimensionality reduction using AANN followed by MLFFNN for training and validation data respectively. Accuracy's are **84.49%** and **68.2%** respectively.

Configuration and Observations:

- From 828 dimension vector, we brought it down to 64 dimensions using PCA and AANN. Then we feed this vector as input to a MLFFNN to classify Data-set 1 with hidden layer sizes 32 and 16 using ReLU as activation function for the neurons, followed by output layer of size 5 (number of classes). Moreover, we split the data randomly in ratio 80:20 for training and validation.

- Used learning rate of 0.001 for classifier network training in case of PCA and 0.003 for the same after AANN, both having batch size of 32. Also, trained the dimension reducing Autoencoder with learning rate of 0.004 and batch size 32. For all cases we have used the Adam optimizer with default hyper-parameters.

- Despite having lower train accuracy for AANN, results on validation data are better for AANN than PCA (both having similar classifier network structure), this reflects that Auto-encoder learns better features than the transformation done by PCA.

- Even after training the second network for 200 epochs, we see the overall error going down slowly, unlike first case, where error almost saturates around 80 epochs. If we train the second network for more epochs, we observed the training accuracy to increase, but the validation accuracy took a hit in that case. Also, increasing the learning rate causes more jumps in the tail of the error v epoch graph, which is already very unstable.

2 Task 2 - Stacked Auto-encoder Dataset 1

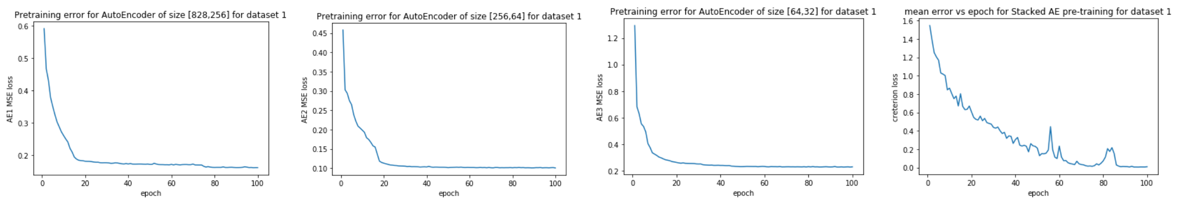
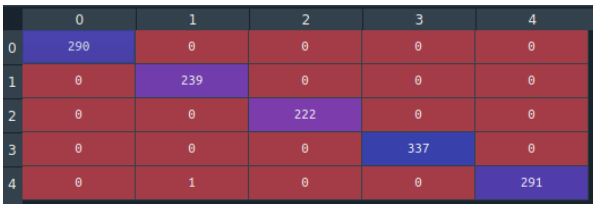
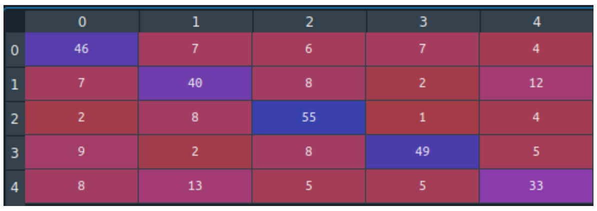


Figure 2.1: Loss v Epoch plots for training three autoencoders and fine-tuning the pre-trained network over Dataset 1.



	0	1	2	3	4
0	290	0	0	0	0
1	0	239	0	0	0
2	0	0	222	0	0
3	0	0	0	337	0
4	0	1	0	0	291



	0	1	2	3	4
0	46	7	6	7	4
1	7	40	8	2	12
2	2	8	55	1	4
3	9	2	8	49	5
4	8	13	5	5	33

Figure 2.2: Confusion Matrices for the Stacked Autoencoder model on Dataset 1. Accuracy's are **99.93%** and **64.45%** respectively.

Configuration and Observations:

- Stacked 3 Auto-Encoders, of size (828,256), (256,64), (63,32) in-order. Then recursively copied the individual AE parameters into the layers of a Multi-layer feed forward neural network, followed by the output layer of dimension 5. The input vector was of dimension 828.

- Used learning rate of 0.002 for Auto-encoder training, and 0.001 for fine tuning the neural network. Batch size is kept 32 everywhere. We can see that graphs of error vs epoch of all three auto-encoders are very smooth, signifying that learning rate is not too high, but high enough to steeply reduce the error within a few epochs.

- While fine-tuning the stacked Auto-encoder parameters, it is very important to maintain a very low learning rate otherwise the pre-trained weights will be changed drastically and the representation learned will be forgotten. Even with a slower learning rate, we can see that the Neural Network takes way more epochs than Auto-encoders for errors to saturate, yet having plenty of spikes in the plot.

- Using stacked Autoencoder resulted in very high training accuracy, and not so significant improvement on the validation accuracy. Data-set 1 having less number of examples, and also having to split that into train and validation sets, might have lead to over-fitting on train examples.

- Also experimented by training a simple MLFFNN (having same number of layers and nodes) for Dataset 1 to compare results, achieved training and validation accuracy of **99.23%** and **67.34%** respectively. Clearly, we have a case of over-fitting on train data on either case.

3 Task 3 - Stacked Autoencoder Dataset 2

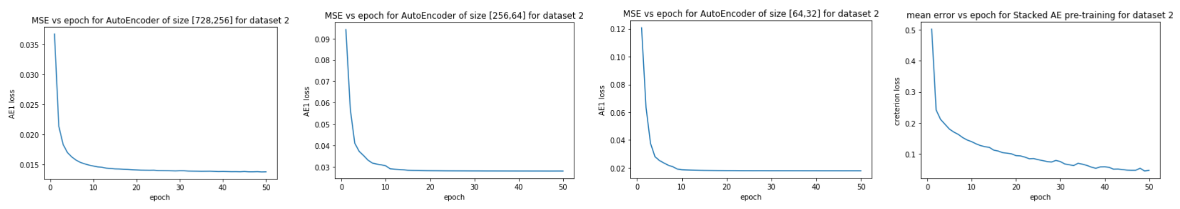
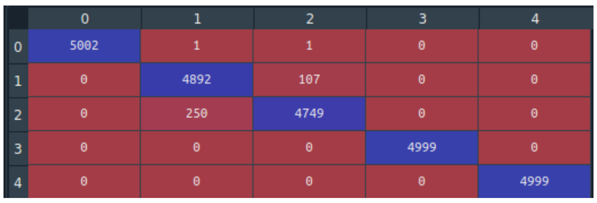
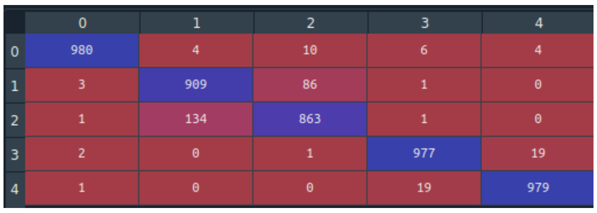


Figure 3.1: Loss v Epoch plots for training three autoencoders and fine-tuning the pre-trained network over Dataset 2.



	0	1	2	3	4
0	5002	1	1	0	0
1	0	4892	107	0	0
2	0	250	4749	0	0
3	0	0	0	4999	0
4	0	0	0	0	4999



	0	1	2	3	4
0	980	4	10	6	4
1	3	909	86	1	0
2	1	134	863	1	0
3	2	0	1	977	19
4	1	0	0	19	979

Figure 3.2: Confusion Matrices for the Stacked Autoencoder model on Dataset 2. Accuracy's are **98.56%** and **94.16%** respectively.

Configuration and Observations:

- Stacked 3 Auto-Encoders, of size (784,256), (256,64), (64,32) respectively. Then recursively copied the individual AE parameters into the layers of a Multi-layer feed forward neural network, followed by the output layer of dimension 5 (similar to task 2).

- Data-set 2 had exactly 6000 examples for each of the 5 classes, so we split classes individually into 5000 examples for training and 1000 validation examples for each class. The input vector is of dimension 784 (28x28). Used batch size of 100 for training both auto-encoders and final neural network.

- Used learning rate of 0.001 for Auto-encoder training, and 0.0005 for fine tuning the neural network. We can see that graphs of error vs epoch of all three autoencoders are very smooth. Also having so many examples leads to error minimization in very less number of epochs (in comparison to data-set 1).

- Similar to task 2, we keep learning rate lower during fine tuning of the final classifier network. Despite having a bigger batch size (100 vs 32), we see faster convergence for the network. As expected, from having abundant training examples, we get very high training and validation accuracy.

- Also experimented by training a simple MLFFNN (having same number of layers and nodes) for Dataset 2 to compare results, achieved training and validation accuracy of **98.21%** and **93.7%**

respectively. Clearly, we are getting a slight improvement when pre-training using autoencoders, for both training and validation.