

## Programming Assignment - 4

EE5179

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### A. Hyperparameters

- a. Number of epochs = 10
- b. Batch Size = 64
- c. Learning Rate =  $1e-3$
- d. Optimizer - Adam

### B. Models

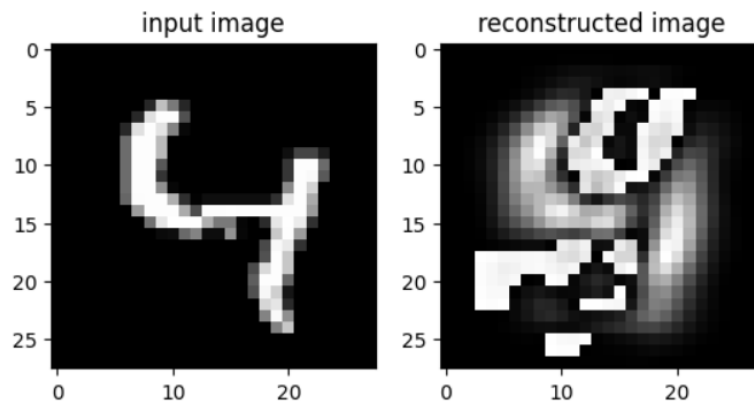
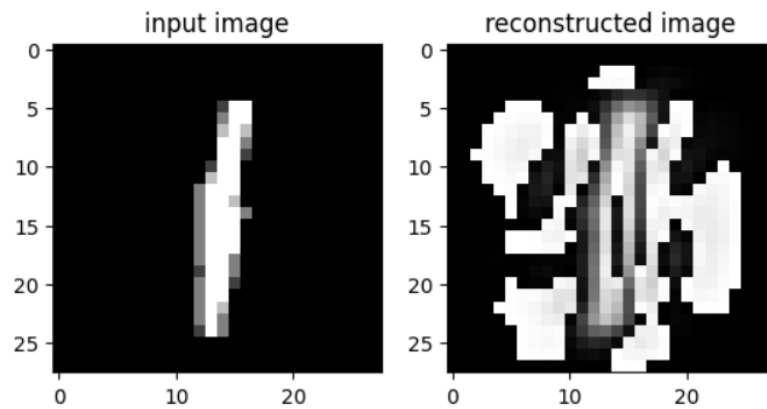
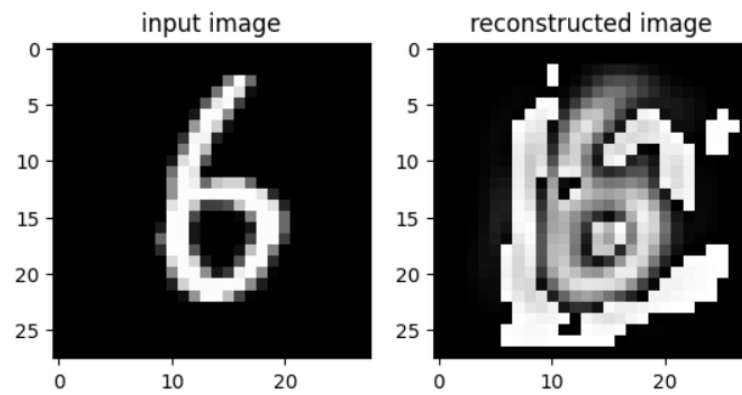
- a. PCA
- b. Vanilla Autoencoder
- c. Autoencoder with one hidden layer
  - i. Hidden\_layer size - 64, 128, 256
- d. Covolutional Autoencoders:
  - i. Convolutional Autoencoder with Unpooling
  - ii. Convolutional Autoencoder with deconvolution
  - iii. Convolutional Autoencoder with both deconvolution and Unpooling

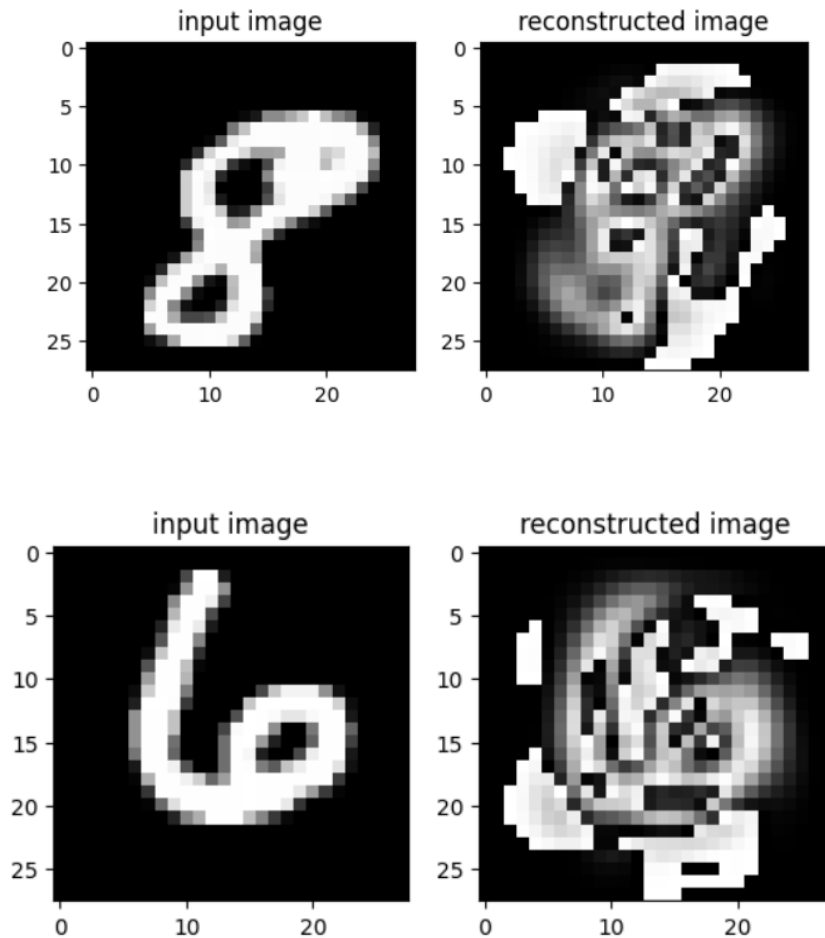
### C. Functions : Following are the functions defined for this assignment

- a. *pca\_reconstructed\_images* : function to plot the reconstructed images obtained using PCA
- b. *train*: function to train different models
- c. *test*: function to test different models
- d. *train\_test*: Generalized function to train and test models for the given number of epochs.
- e. *plot\_reconstructed-image*: function to plot the reconstructed image obtained using different models
- f. *plot\_losses*; function to plot training and test losses obtained using different models.
- g. *encoder\_decoder\_filters\_plots*: function to visualize the encoder and decoder learned filter weights
- h. *avg\_hl\_activations*: function to calculate the average activation of neurons
- i. *visualize\_activations*: function to visualize the output of activations
- j. *add\_noise*: function to add random noise of different noise levels to a given input image

## 1. Comparing PCA and Autoencoders

- a. **PCA** : PCA is performed on MNIST dataset using the first 30 principal components and following are some of the reconstructed images obtained for randomly selected input images.





PCA MSE reconstruction error : 0.018121636925097294

**b. Autoencoder :** Architecture used for Autoencoder is as follows

- Encoder

- input (784)

- fc (512)

- fc (256)

- fc (128)

- fc (30)

- Decoder

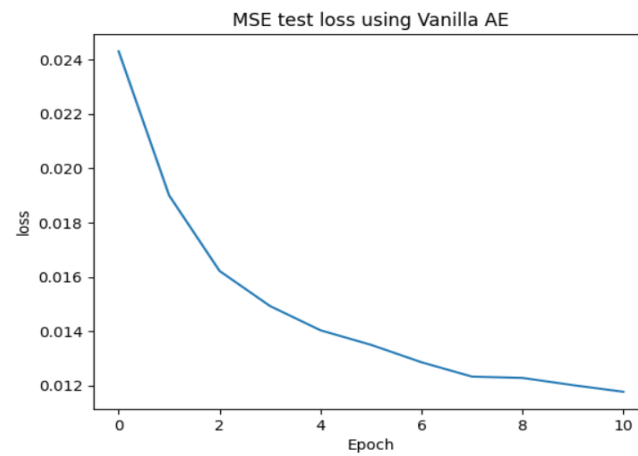
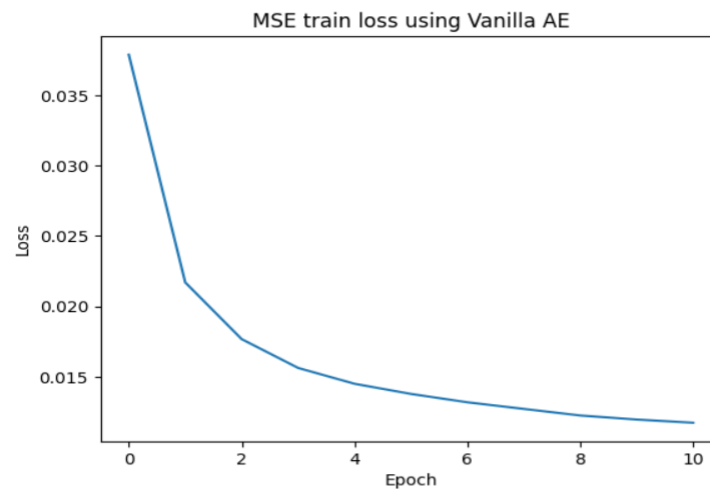
- fc (128)

- fc (256)

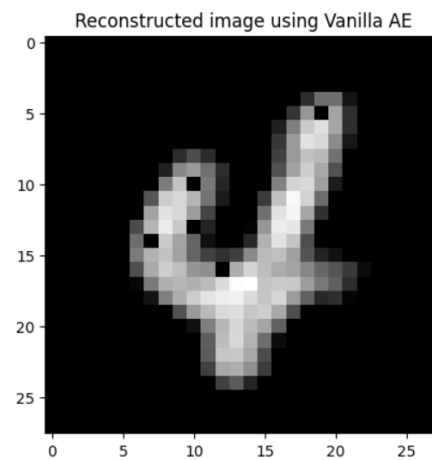
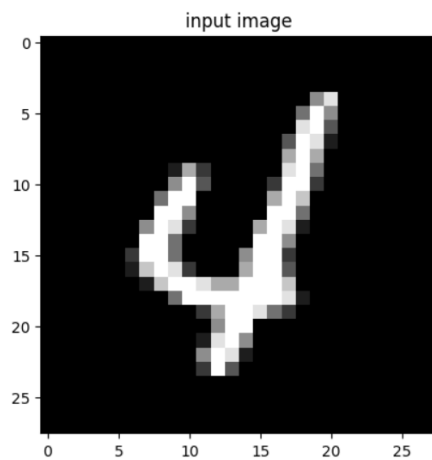
- fc (784)

ReLU is used as the activation function

## I. Training and Test loss plots :



## II. Reconstructed image using this autoencoder for a random MNIST input :



III. MSE Reconstruction error for Vanilla AE is 0.011768510565161705

**Observations:**

1. As PCA is reconstructing the image after projecting the data into a 30 dimensional space having high variance from a 784 dimensional space, the reconstructed images are not so smooth but we can visually still make out the digit.
2. Reconstructed images using Autoencoder are much better compared to PCA as the contours of the input image are almost there.
3. The reconstruction error of PCA is more than that of the Autoencoder
4. As Autoencoder uses nonlinear activations the performance of Autoencoder is much better than PCA

**2. Experimenting with hidden units of varying sizes**

**Architecture:**

**Encoder:**

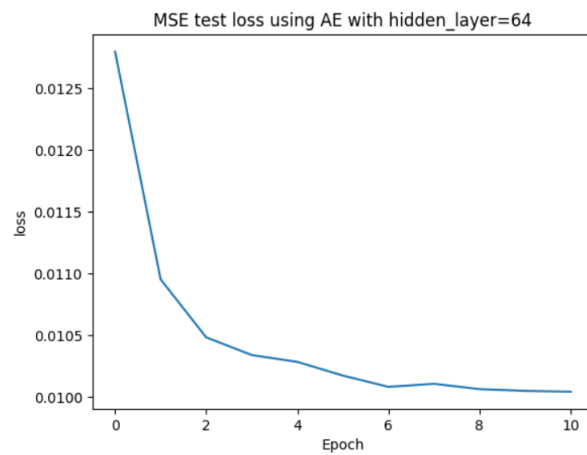
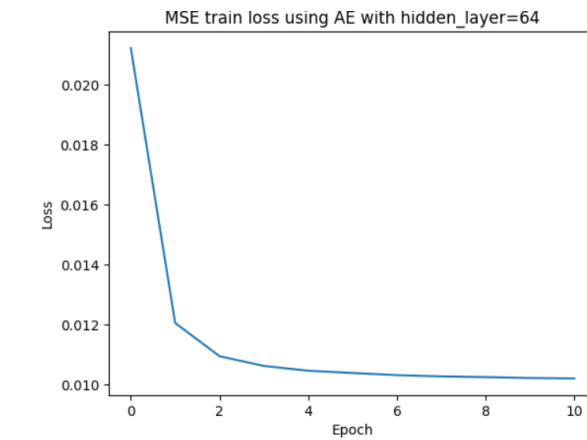
input (784)  
fc (hidden\_dimension)  
ReLU  
encoded

**Decoder:**

encoded  
fc(hidden\_dimension)  
ReLU  
decoded(784)  
ReLU  
reconstructed\_image(784)

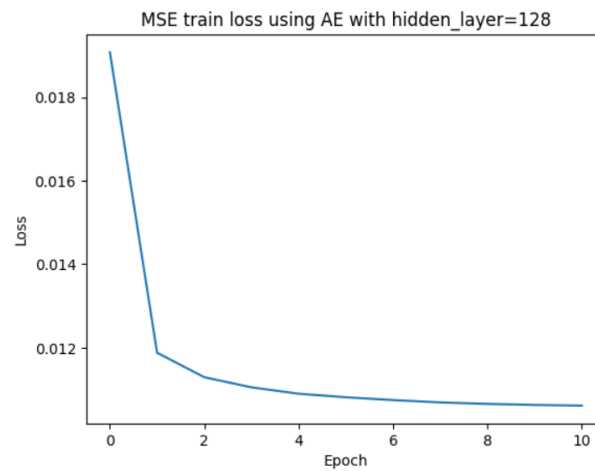
## I. Training and Test loss plots for different hidden layer size

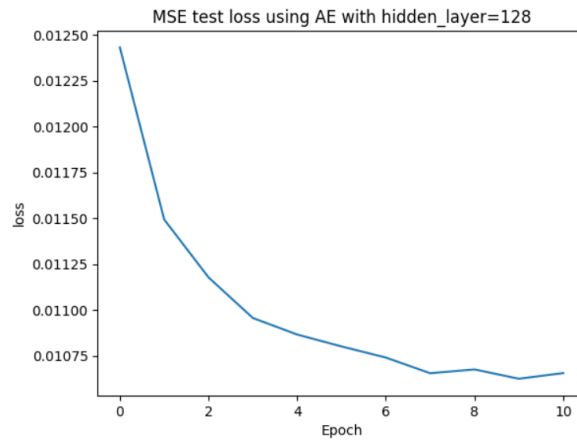
### A. $h=64$



MSE Reconstruction error for AE with hidden layer size 64 is 0.10811023414134979

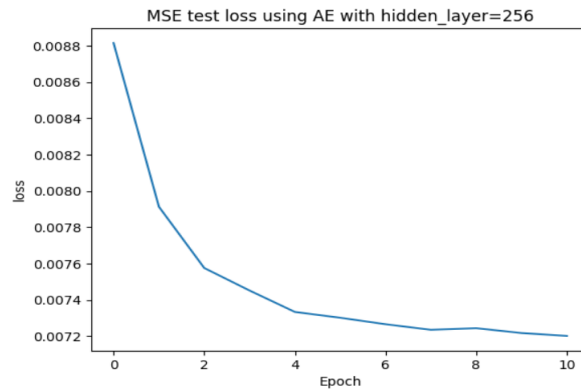
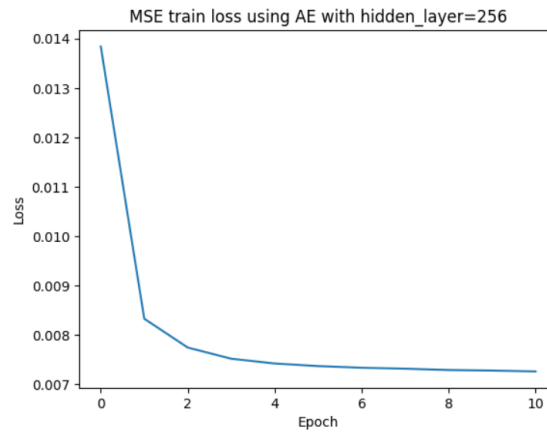
### B. $h=128$





MSE Reconstruction error for AE with hidden layer size 128 is 0.1090042516589164

C. h=256

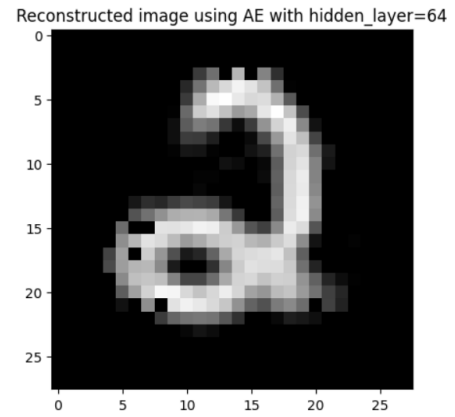
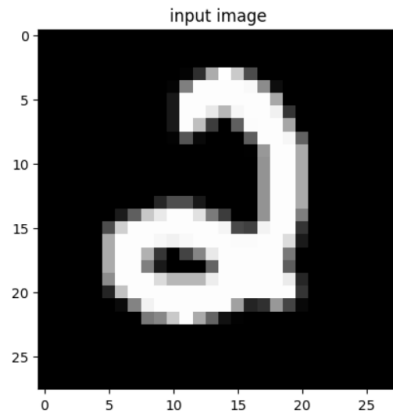


MSE Reconstruction error for AE with hidden layer size 256 is 0.10745961964130402

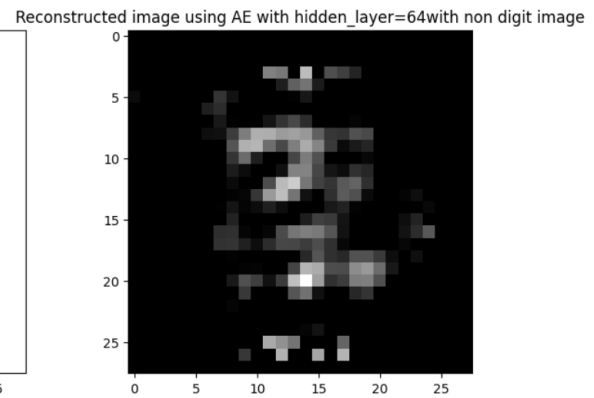
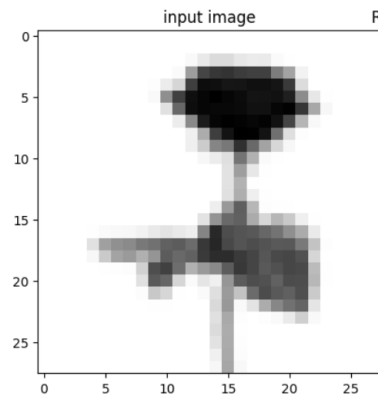
## II. Reconstructed Images:

a.  $h=64$

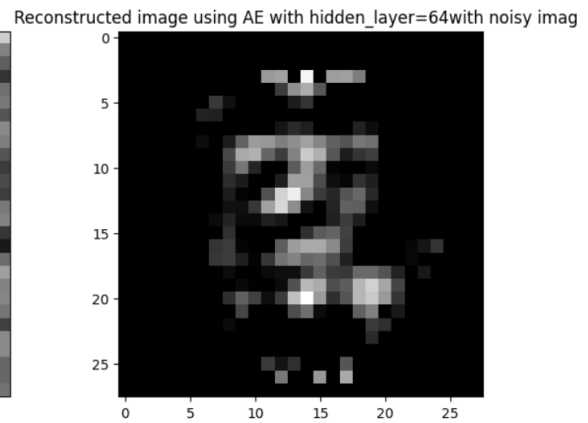
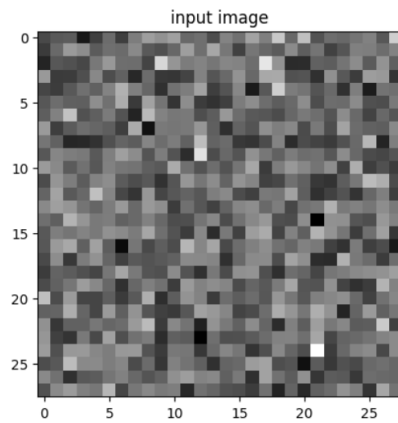
i. MNIST digit image



ii. Non-digit image



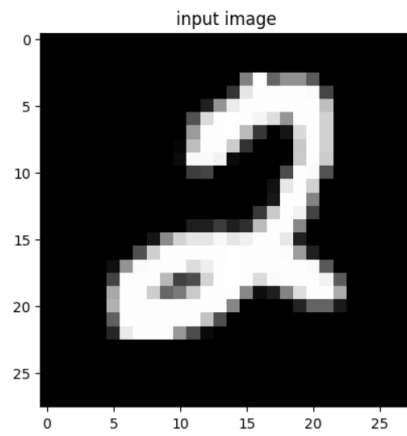
iii. Noisy image



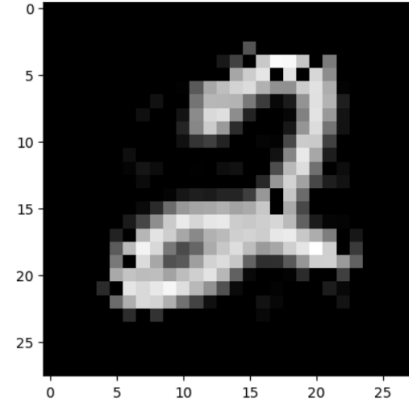


b.  $h=128$

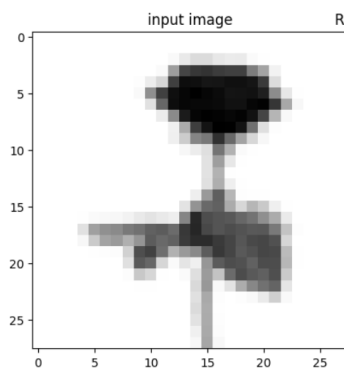
i. MNIST digit image



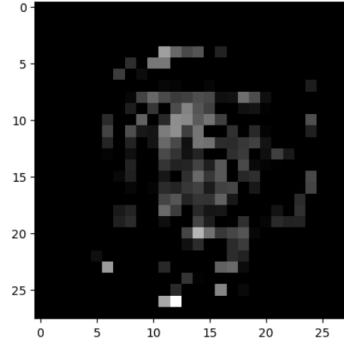
Reconstructed image using AE with hidden\_layer=128



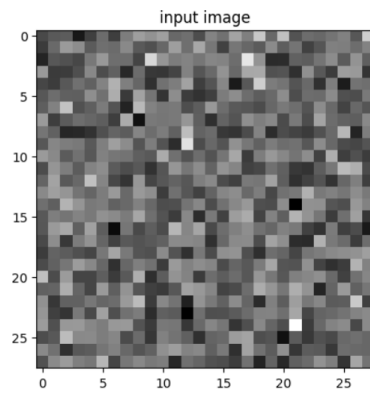
ii. Non-digit image



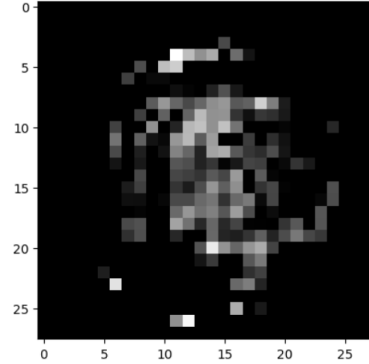
Reconstructed image using AE with hidden\_layer=128with non digit image



iii. Noisy image

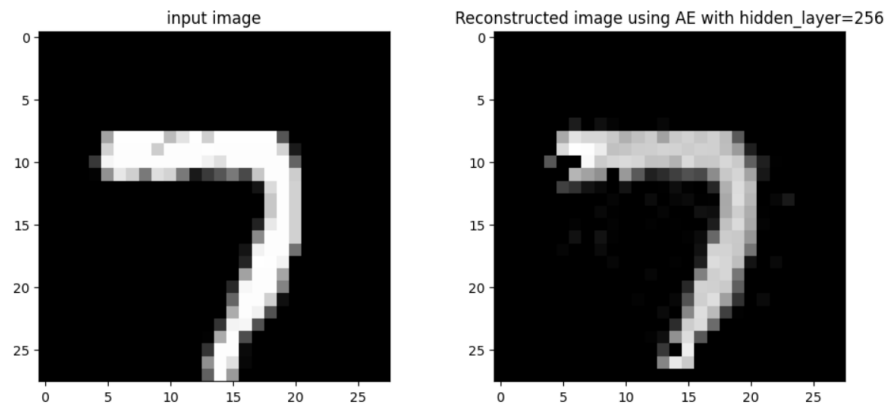


Reconstructed image using AE with hidden\_layer=128with noisy image

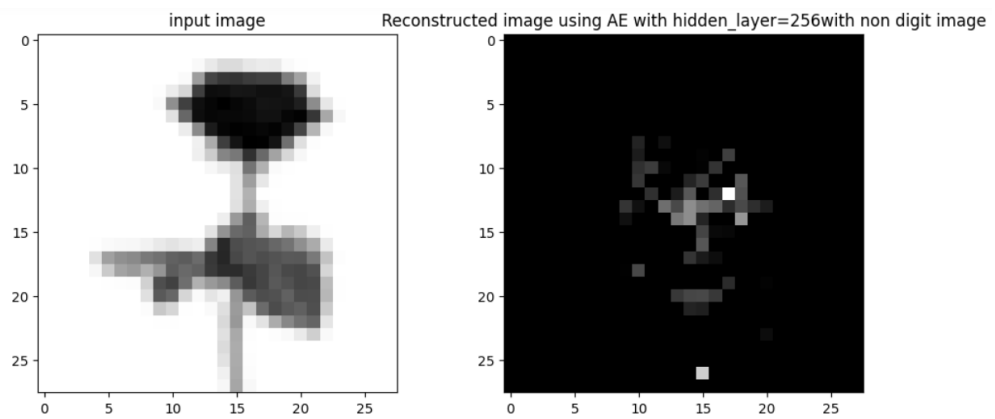


c.  $h=256$

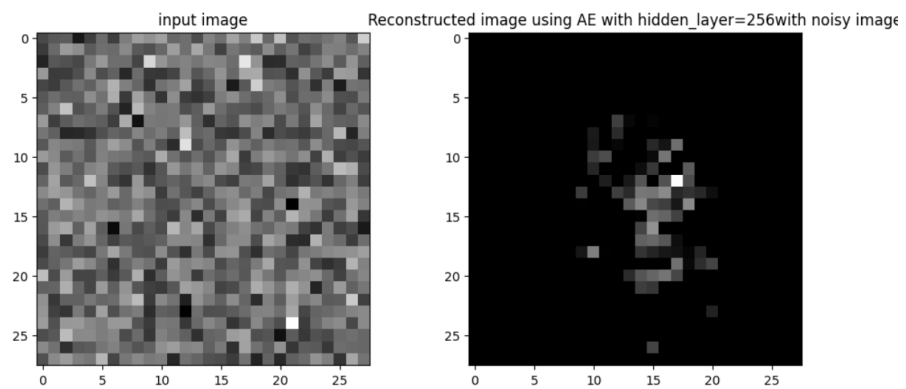
i. MNIST digit image



ii. Non-digit image



iii. Noisy image



## Observations:

1. As the size of the hidden layer increases the AE performs better, which can be observed from the reconstructed image for the input MNIST digit images for all three models.
2. For both the non digit image and noisy image as input the model output is just noise as the model is trained on the MNIST dataset but not on any random images.
3. The MSE reconstruction error has not been improved much as the size of hidden layer increases but visually the reconstructed image of AE with hidden size = 256 produced better results.

## 3. Sparse Autoencoders:

### Architecture:

#### Encoder:

Linear(784,961)

ReLU()

#### Decoder:

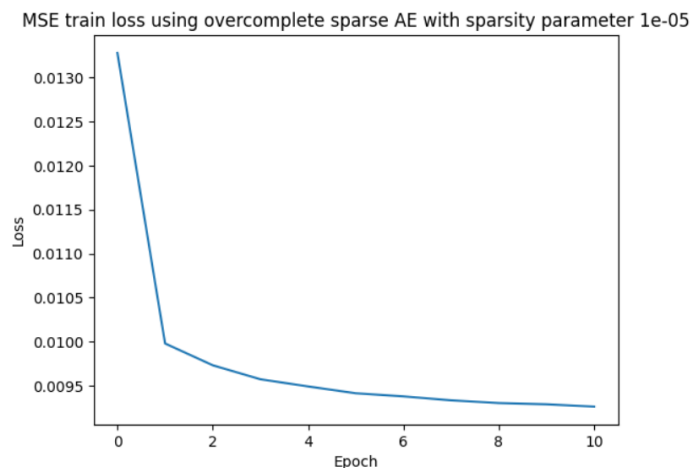
Linear(961,784)

ReLU()

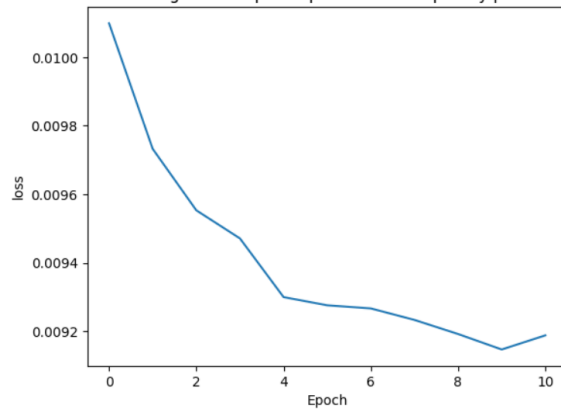
The hidden layer size is chosen as 961 so that the designed AE is an overcomplete AE. An L1 regularization with different regularization parameters has been added to the loss.

## I. Training and Test loss plots:

- a.  $\text{Lambda\_reg} = 1e-5$

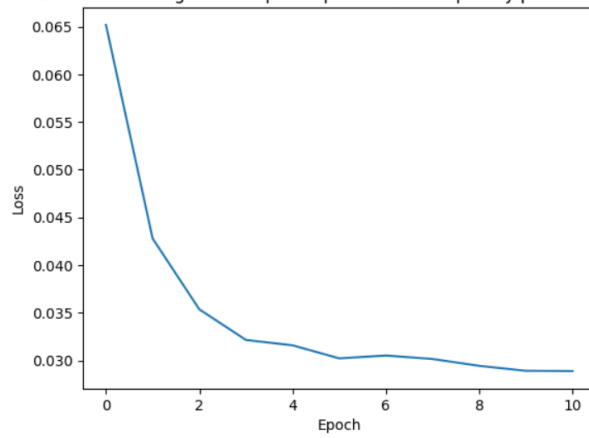


MSE test loss using overcomplete sparse AE with sparsity parameter 1e-05

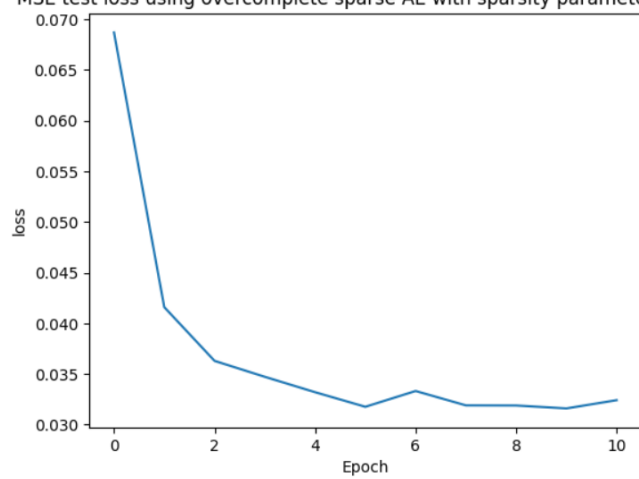


b.  $\text{Lambda\_reg} = 1\text{e-}3$

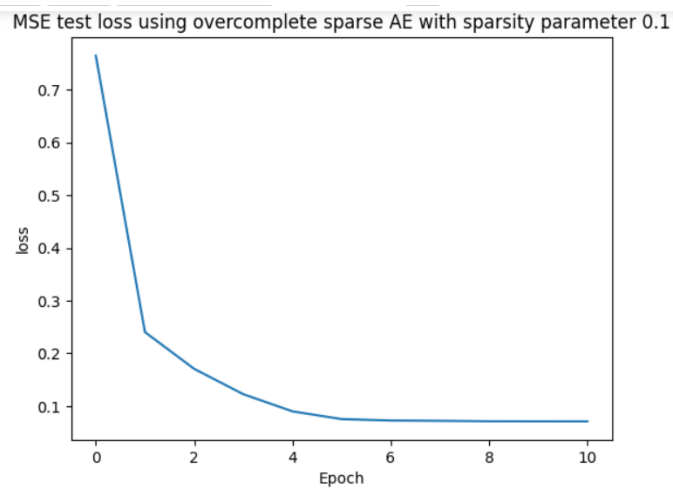
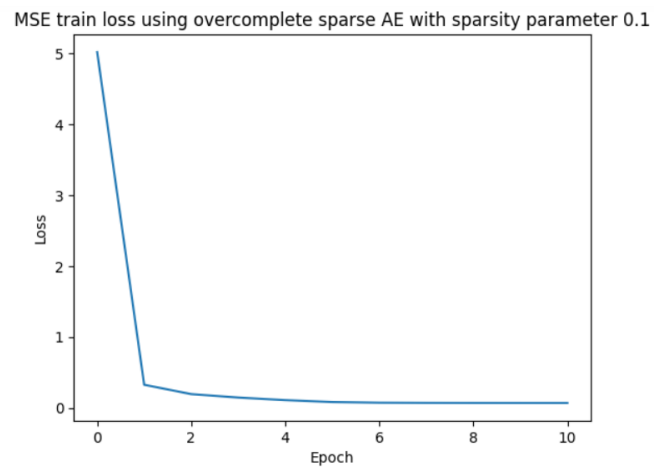
MSE train loss using overcomplete sparse AE with sparsity parameter 0.001



MSE test loss using overcomplete sparse AE with sparsity parameter 0.001



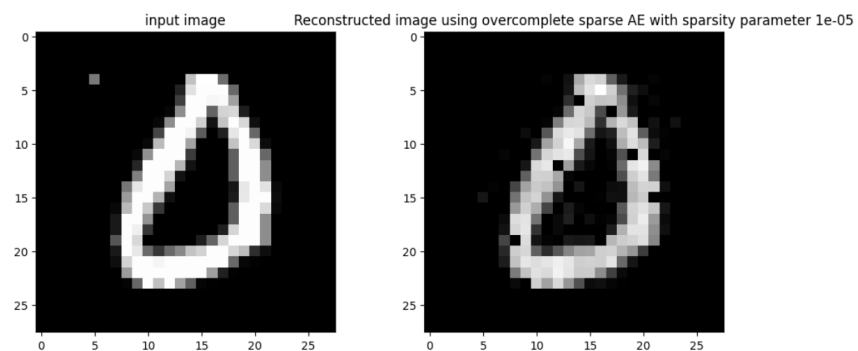
c.  $\text{Lambda\_reg} = 1\text{e-}1$



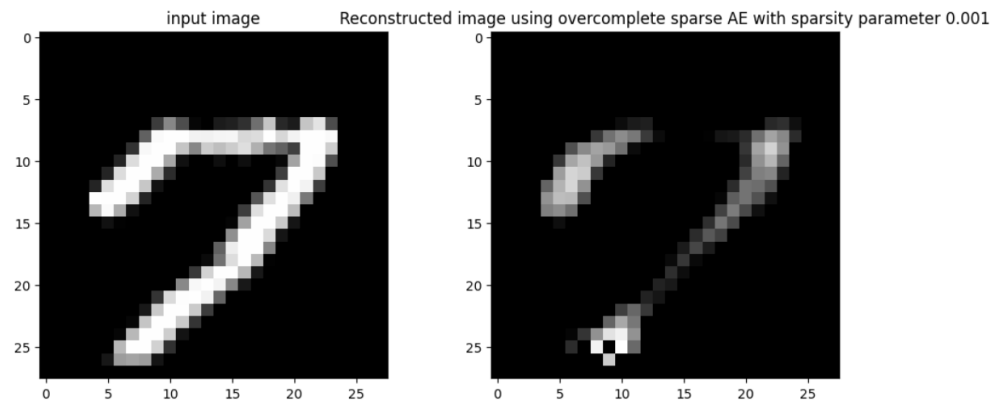
## II. Reconstructed images:

Reconstructed images for a random MNIST digit input using sparse AE with different sparsity parameters.

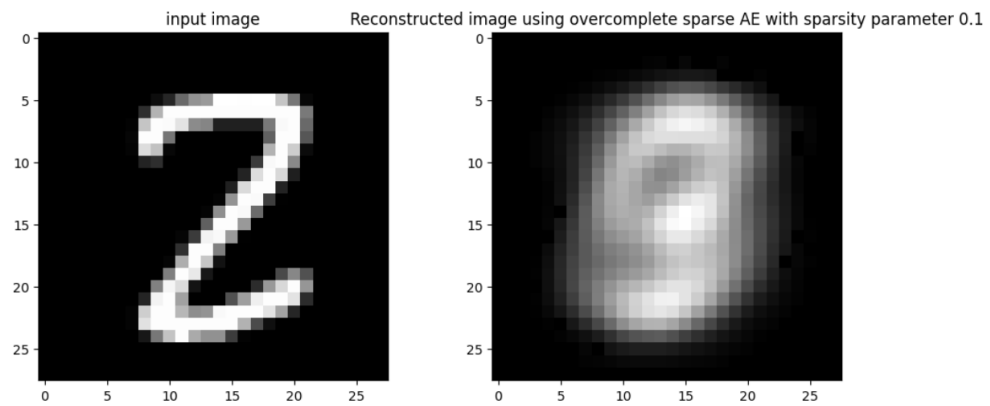
a.  $\text{Lambda\_reg} = 1\text{e-}5$



b.  $\text{Lambda\_reg} = 1\text{e-}3$

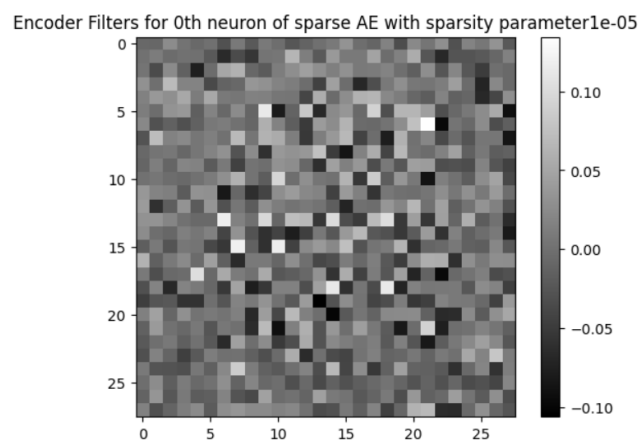


c.  $\text{Lambda\_reg} = 1\text{e-}1$

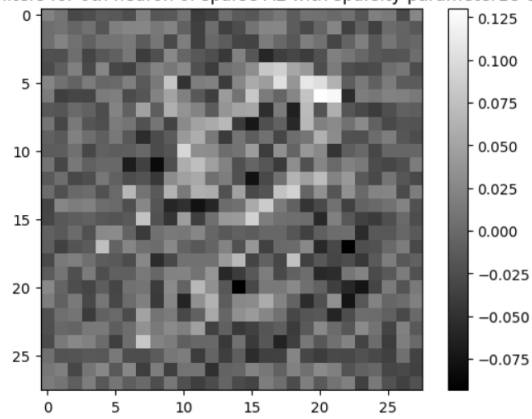


### III. Visual Representation of learned filters of 0th neuron

a.  $\text{Lambda\_reg} = 1\text{e-}5$

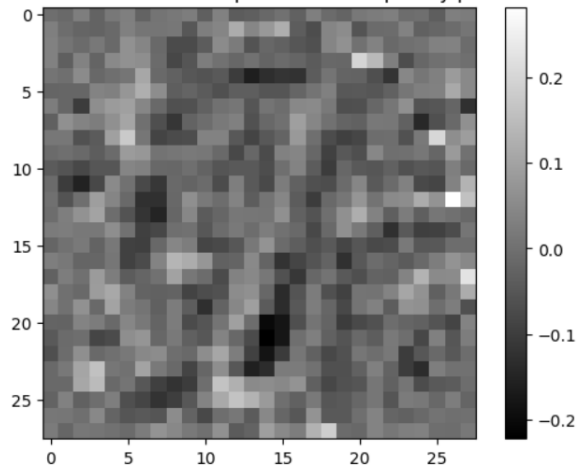


Decoder Filters for 0th neuron of sparse AE with sparsity parameter  $1e-05$

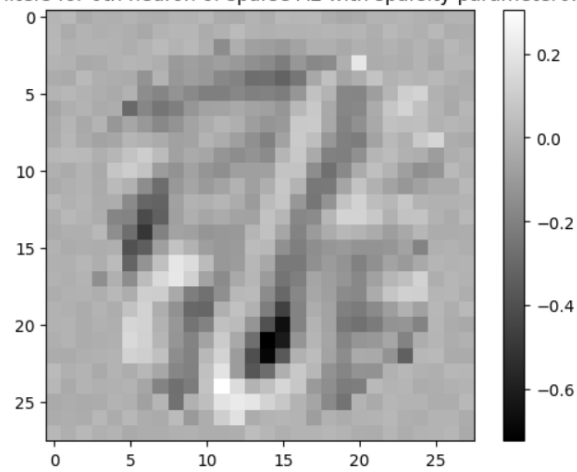


b.  $\text{Lambda\_reg} = 1e-3$

Encoder Filters for 0th neuron of sparse AE with sparsity parameter 0.001

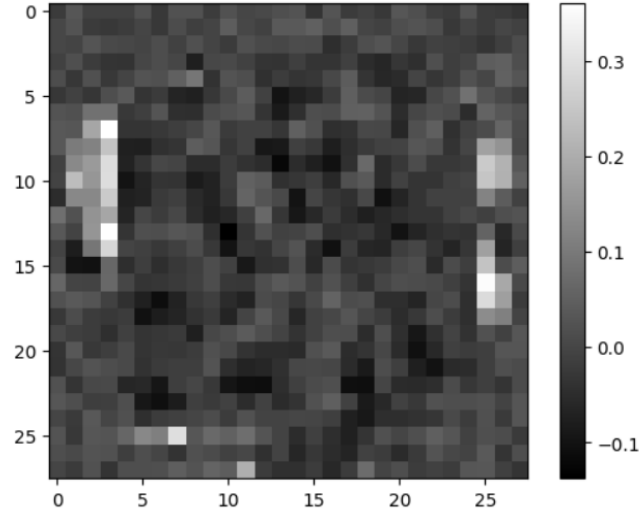


Decoder Filters for 0th neuron of sparse AE with sparsity parameter 0.001

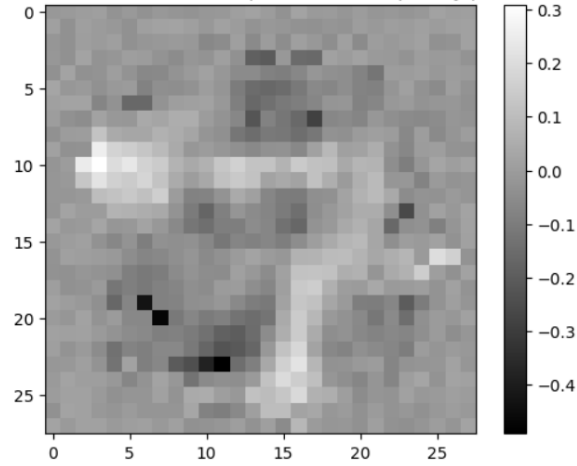


c.  $\text{Lambda\_reg} = 1\text{e-}1$

Encoder Filters for 0th neuron of sparse AE with sparsity parameter 0.1



Decoder Filters for 0th neuron of sparse AE with sparsity parameter 0.1



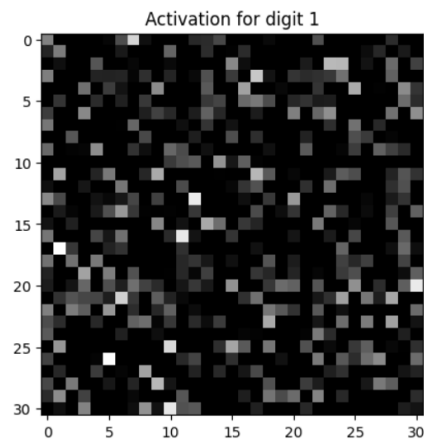
#### IV. Average Activation

- The average activation of overcomplete sparse AE with sparsity parameter  $1\text{e-}05$  is 0.17650093831074465
- The average activation of overcomplete sparse AE with sparsity parameter 0.001 is 0.008566434456593101
- The average activation of overcomplete sparse AE with sparsity parameter 0.1 is  $1.1660724150623433\text{e-}06$

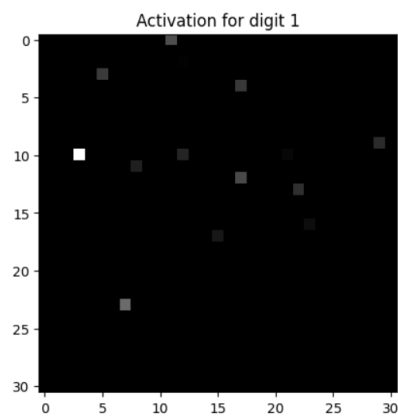


## V. Activations of neurons for a digit with different sparsity parameters:

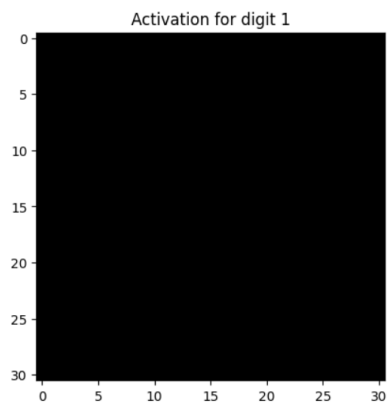
a.  $\text{Lambda\_reg} = 1\text{e-}5$



b.  $\text{Lambda\_reg} = 1\text{e-}3$

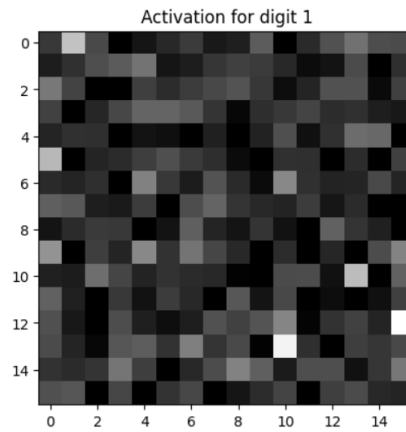


c.  $\text{Lambda\_reg} = 1\text{e-}1$



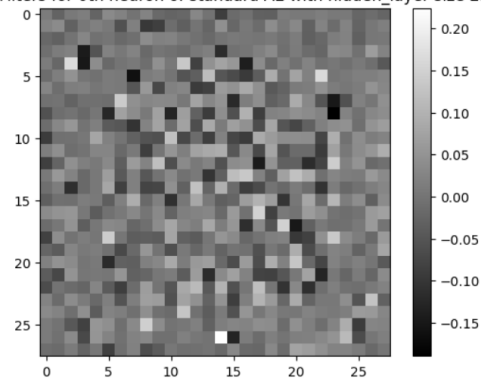
## VI. Standard AE with hidden size = 256

### a. Activations of neurons for a digit

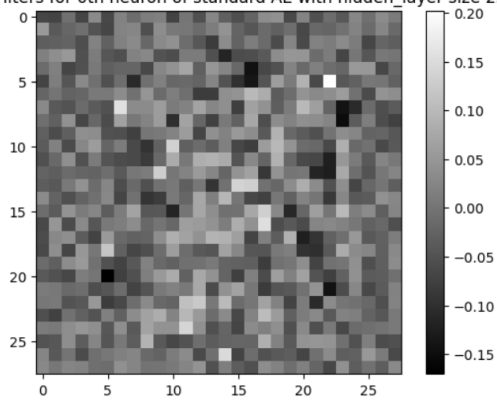


### b. Visual Representation of learned filters of 0th neuron

Encoder Filters for 0th neuron of standard AE with hidden\_layer size 256



Decoder Filters for 0th neuron of standard AE with hidden\_layer size 256



The average activation of Standard AE with hidden\_layer=256 is 0.07100810338357452

**Observations:**

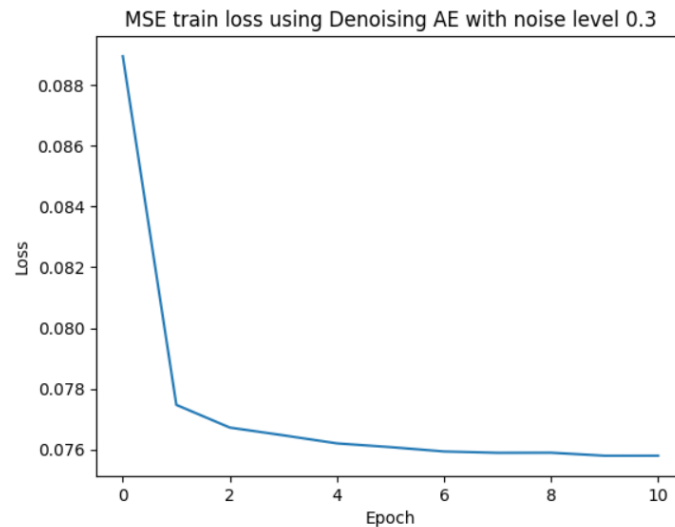
1. As the regularization increases the performance decreases i.e. images are not reconstructed properly
2. Reconstruction is better using standard AE with hidden layer size 256 compared to sparse autoencoders.
3. Losses of regularized sparse AE are more than that of standard AE
4. As the regularization increases fewer number of neurons fire
5. Average activation of neurons of standard AE is more than that of regularized sparse AE
6. Encoder and decoder filters plots look similar to digits which implies that each neuron is looking for features of some digits and they fire when that digit is provided as input whereas for standard AE encoder and decoder filters plots don't give any specific implication.

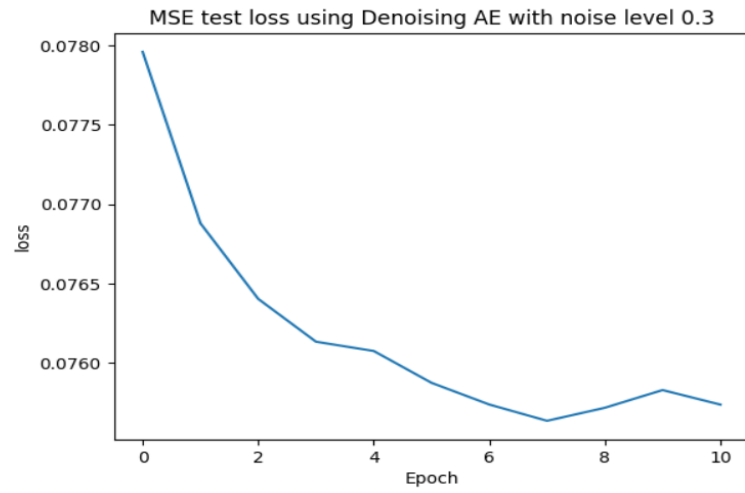
**4. Denoising Autoencoders**

For the denoising Autoencoder the architecture used is the standard AE with hidden layer size = 256 but the inputs to the encoder are noisy i.e noise is added to the MNIST digit input

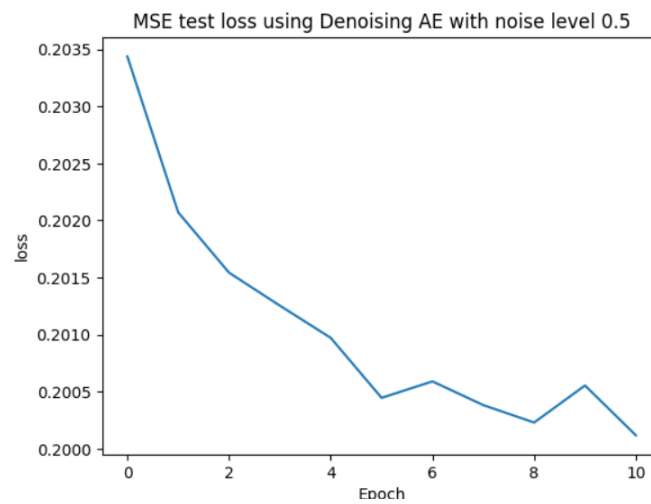
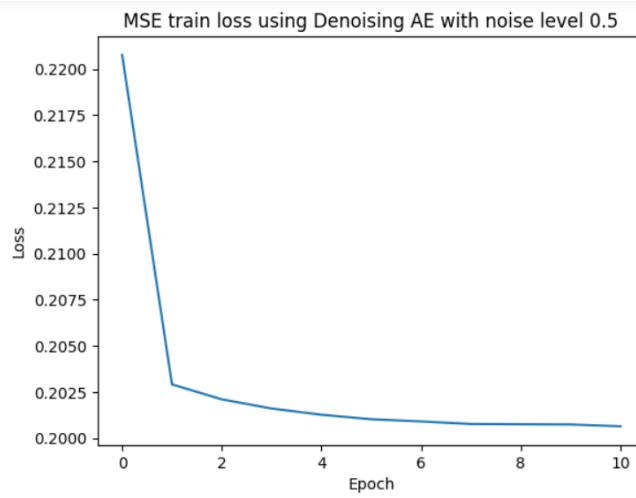
**I. Training and Test loss plots for different noise levels**

- a. Noise level = 0.3

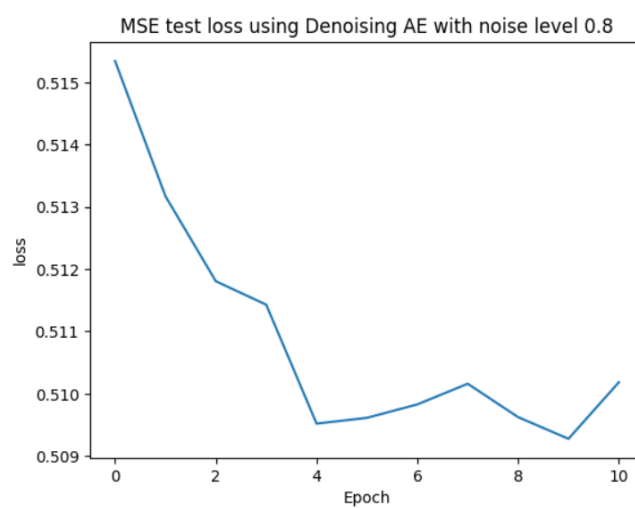
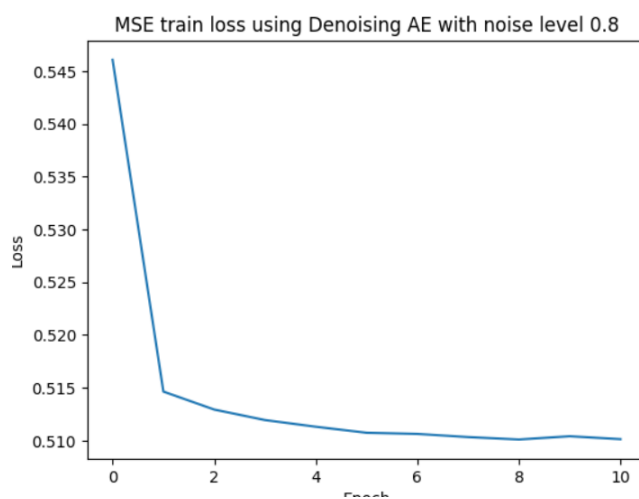




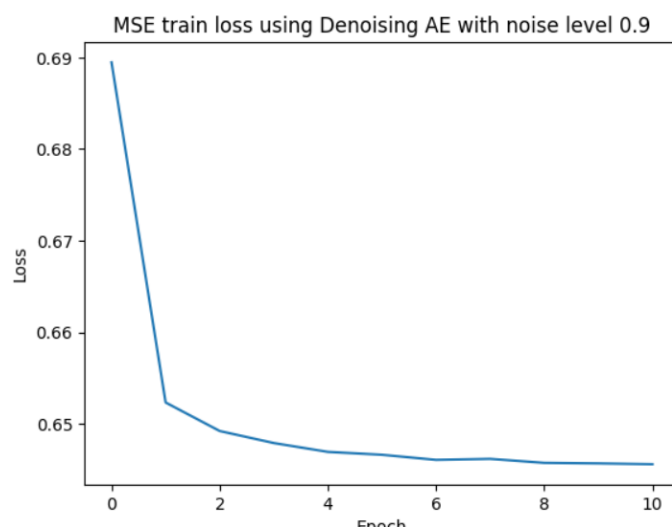
b. Noise level = 0.5

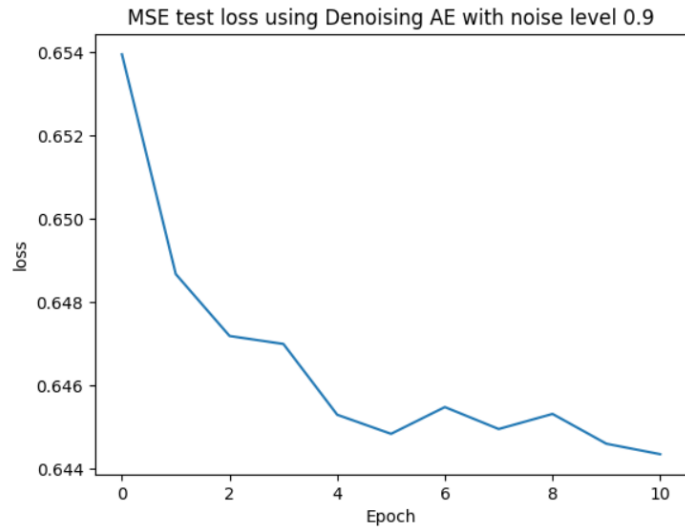


c. Noise level = 0.8



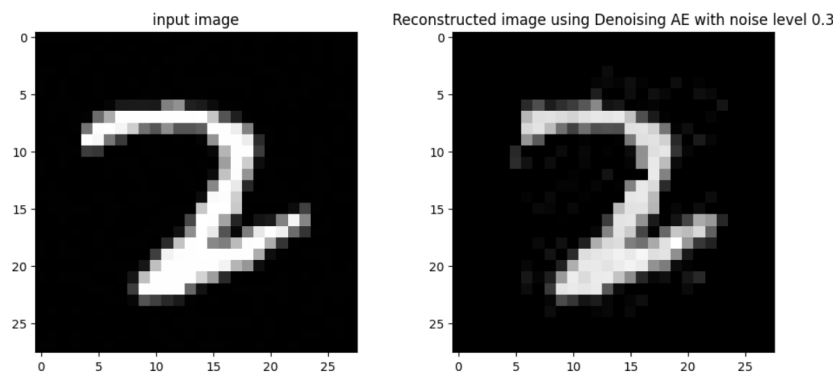
d. Noise level = 0.9



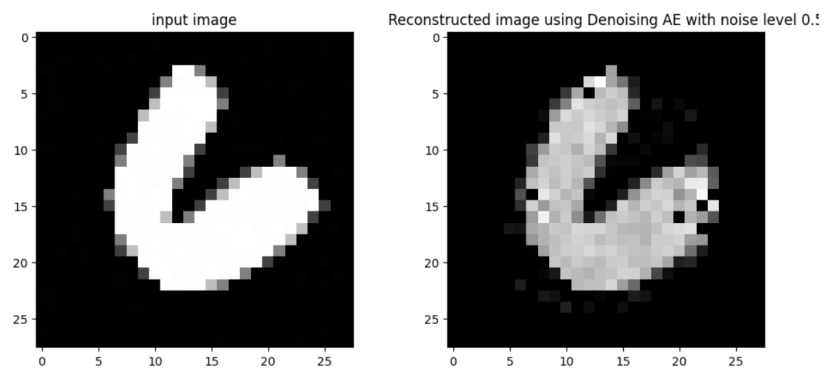


## II. Reconstructed images for different noise levels

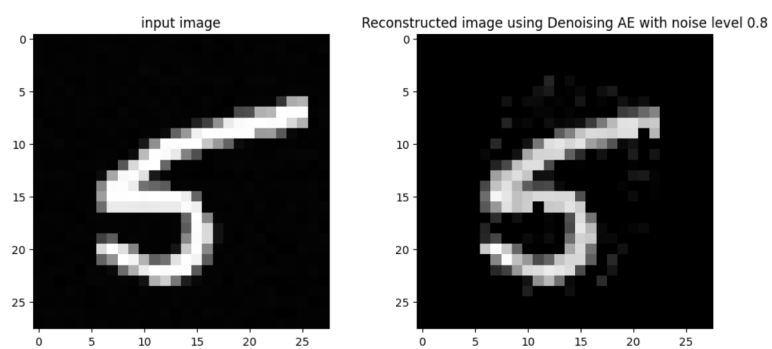
a. Noise level = 0.3



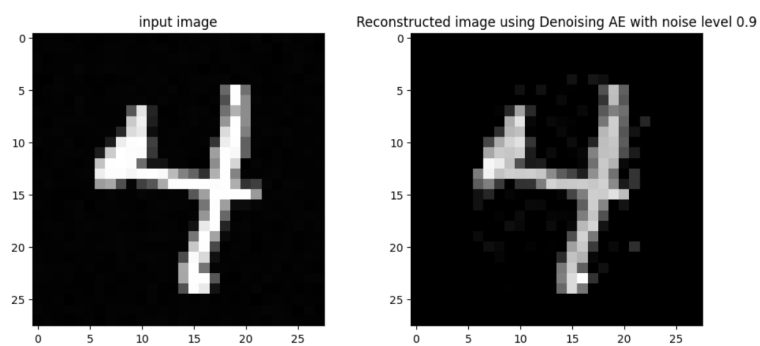
b. Noise level = 0.5



c. Noise level = 0.8



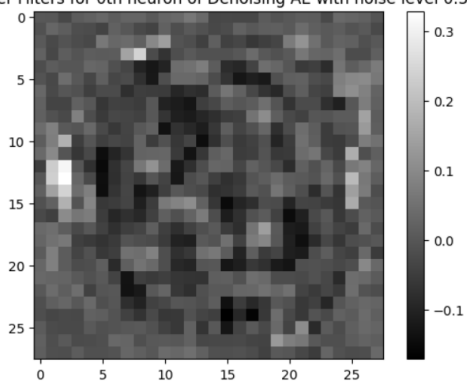
d. Noise level = 0.9



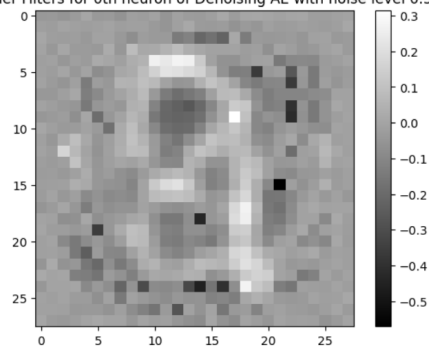
### III. Visual Representation of learned filters of 0th neuron

a. Noise level = 0.3

Encoder Filters for 0th neuron of Denoising AE with noise level 0.3

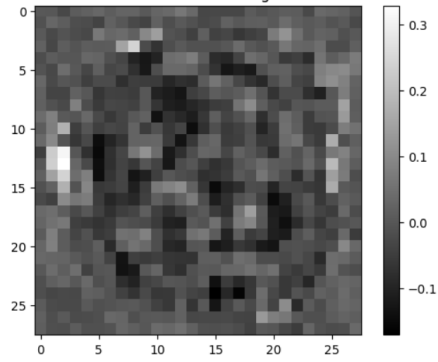


Decoder Filters for 0th neuron of Denoising AE with noise level 0.3

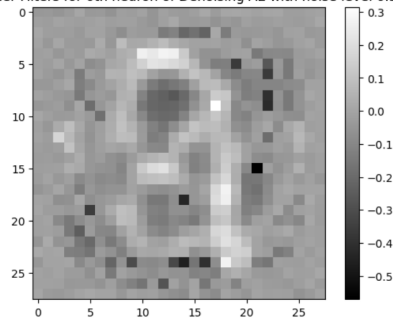


b. Noise level = 0.5

Encoder Filters for 0th neuron of Denoising AE with noise level 0.5

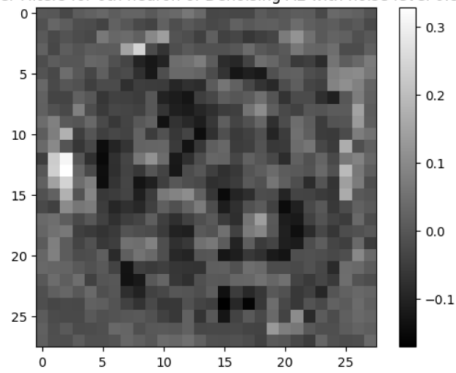


Decoder Filters for 0th neuron of Denoising AE with noise level 0.5

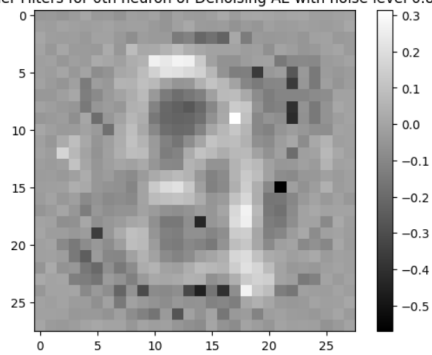


c. Noise level = 0.8

Encoder Filters for 0th neuron of Denoising AE with noise level 0.8

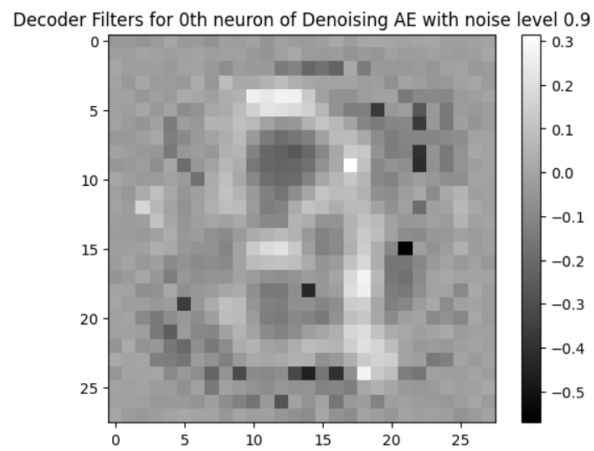
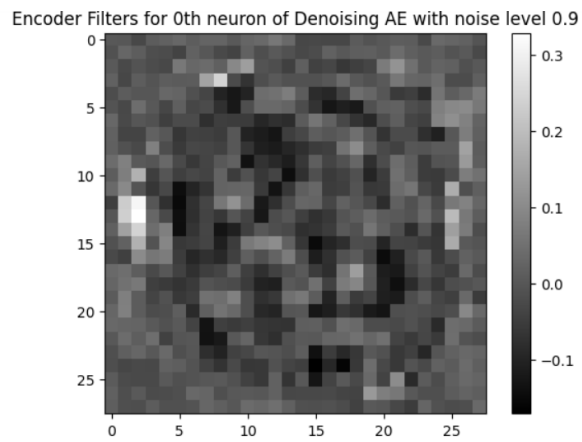


Decoder Filters for 0th neuron of Denoising AE with noise level 0.8





d. Noise level = 0.9



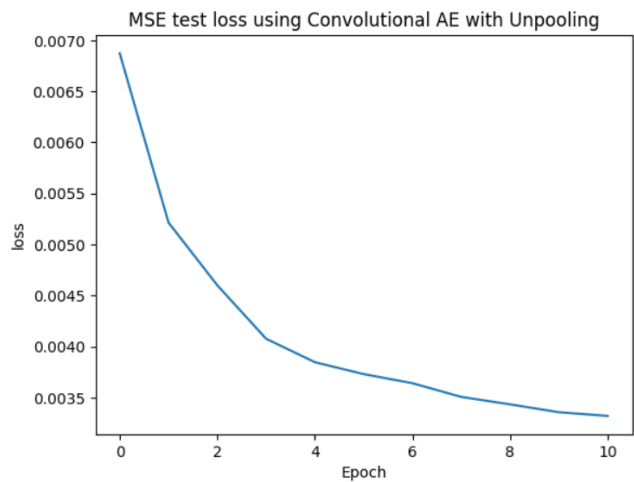
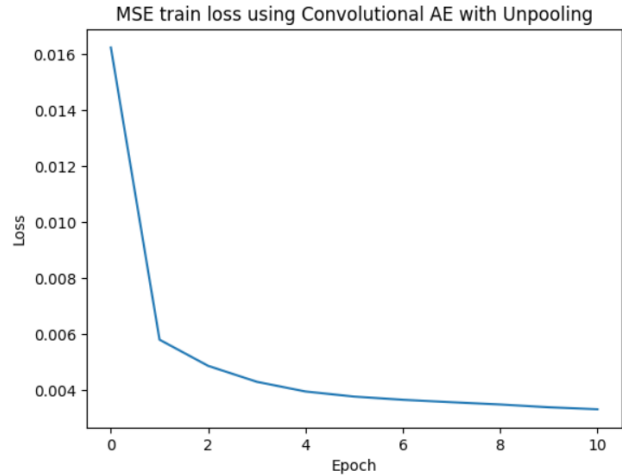
**Observations:**

1. As noise level increases reconstruction error increases
2. Encoder and decoder filters resembles digits
3. Denoising AEs are more prone to noise compared to standard AE

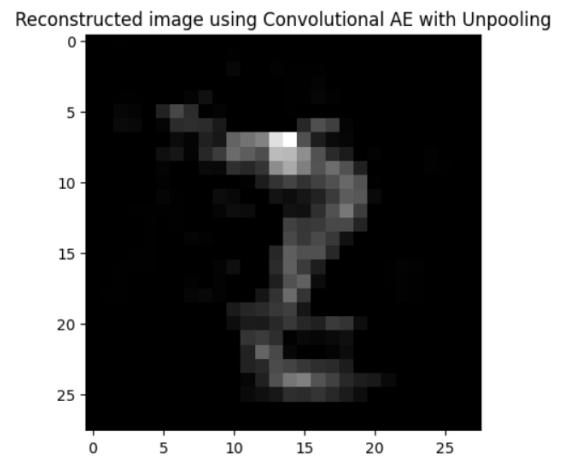
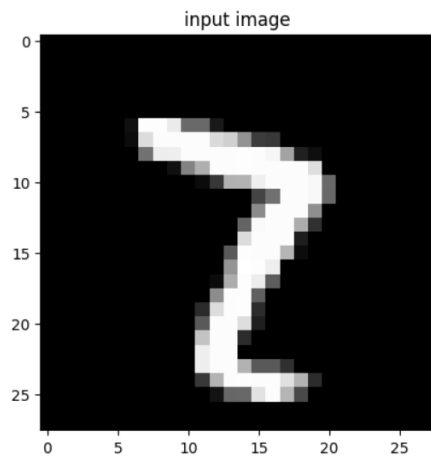
## 5. Convolutional Autoencoders

### I. Convolutional Autoencoders with Unpooling

#### a. Training and Test loss plots



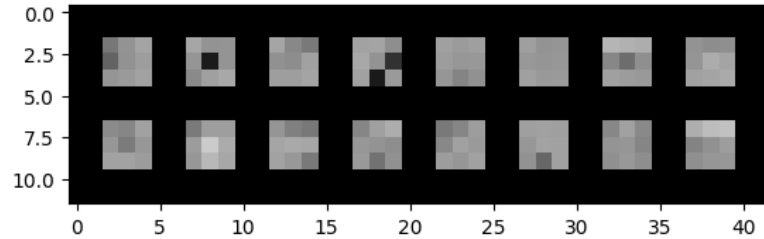
#### b. Reconstructed image for a given random MNIST input image



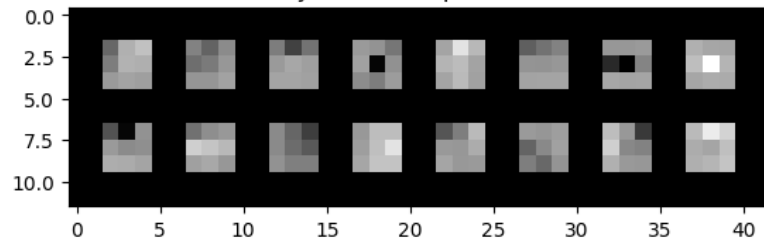
**c. Visualizing the decoder weights**

Second convolution layer has 8 -  $16 \times 3 \times 3$  filters, following are three randomly selected filter outputs out of the 8 filters

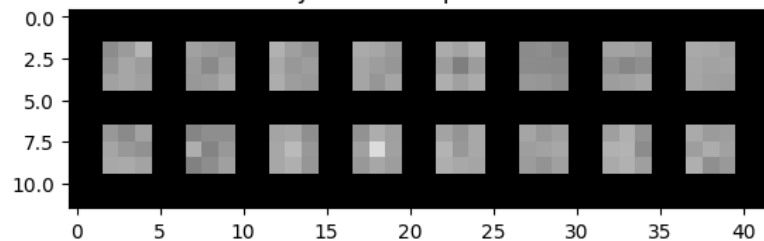
Decoder second Convolutional layer filter outputs for filter no. 4 of CAE with unpooling



Decoder second Convolutional layer filter outputs for filter no. 1 of CAE with unpooling

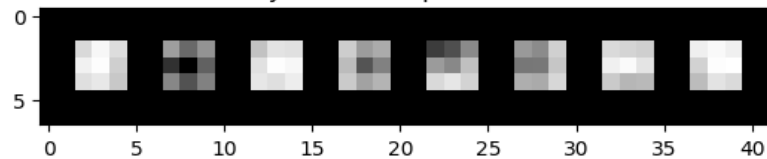


Decoder second Convolutional layer filter outputs for filter no. 5 of CAE with unpooling



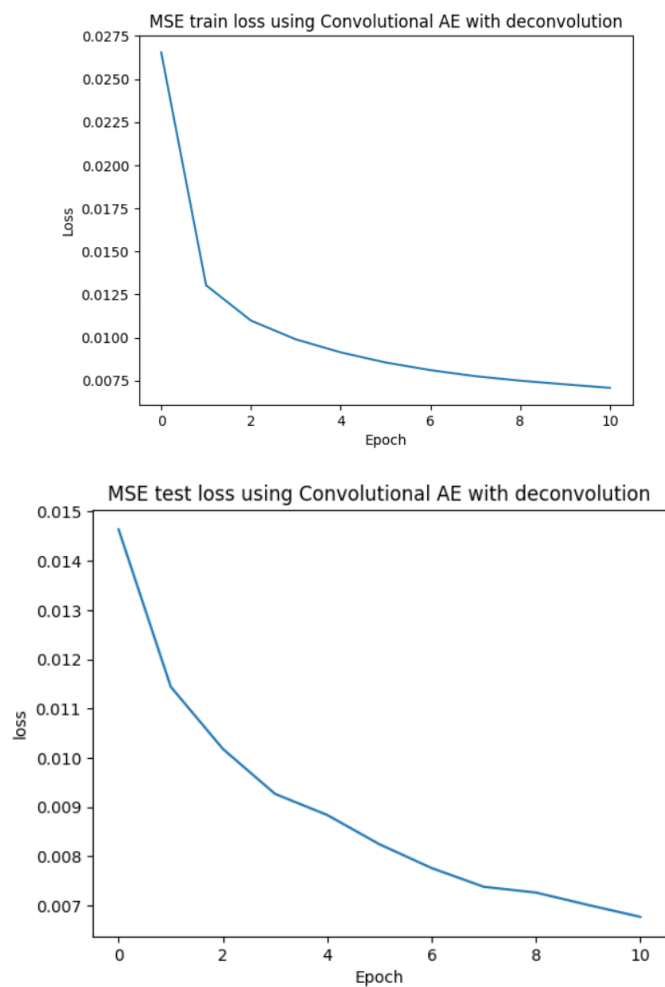
The third convolutional layer has 8- $3 \times 3 \times 1$  filters, following are those 8 filter outputs.

Decoder Third Convolutional layer filter outputs for filter no. 0 of CAE with unpooling

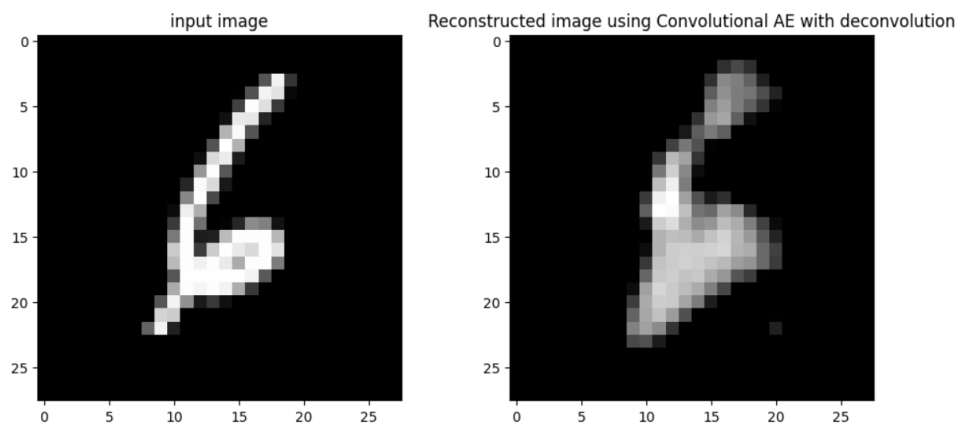


## II. Convolutional Autoencoders with deconvolution

### a. Training and Test loss plots



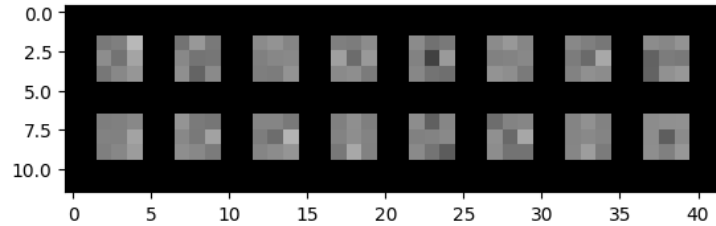
### b. Reconstructed image for a given random MNIST input image



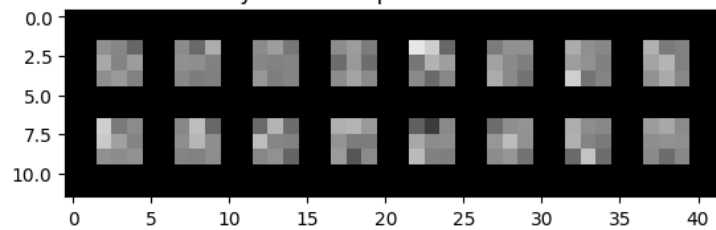
### c. Visualizing the decoder weights

First convolutional layer has 8 -  $16 \times 3 \times 3$  filters, following are three randomly selected filter outputs out of the 8 filters

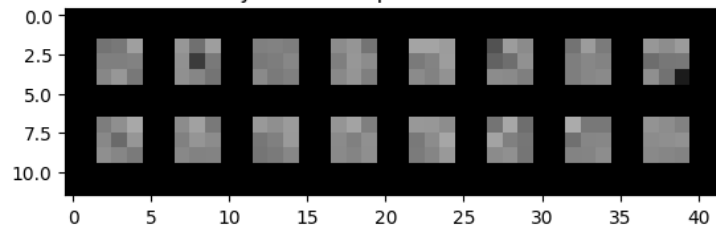
Decoder First Convolutional layer filter outputs for filter no. 4 of CAE with deconvolution



Decoder First Convolutional layer filter outputs for filter no. 8 of CAE with deconvolution

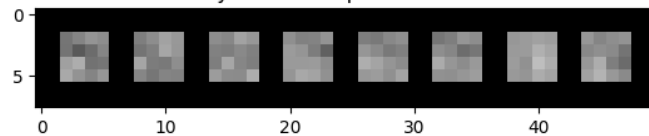


Decoder First Convolutional layer filter outputs for filter no. 2 of CAE with deconvolution

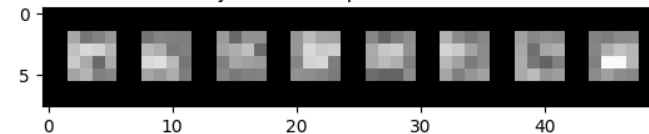


Second convolutional layer has 16 -  $8 \times 4 \times 4$  filters, following are three randomly selected filter outputs

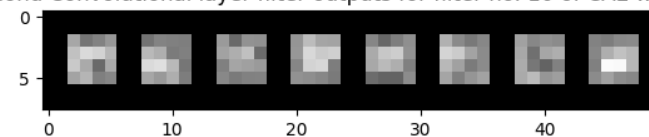
Decoder Second Convolutional layer filter outputs for filter no. 3 of CAE with deconvolution



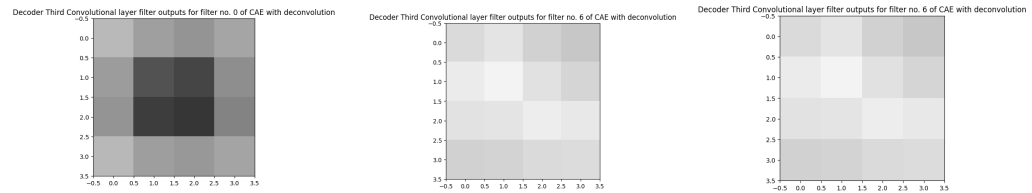
Decoder Second Convolutional layer filter outputs for filter no. 10 of CAE with deconvolution



Decoder Second Convolutional layer filter outputs for filter no. 10 of CAE with deconvolution



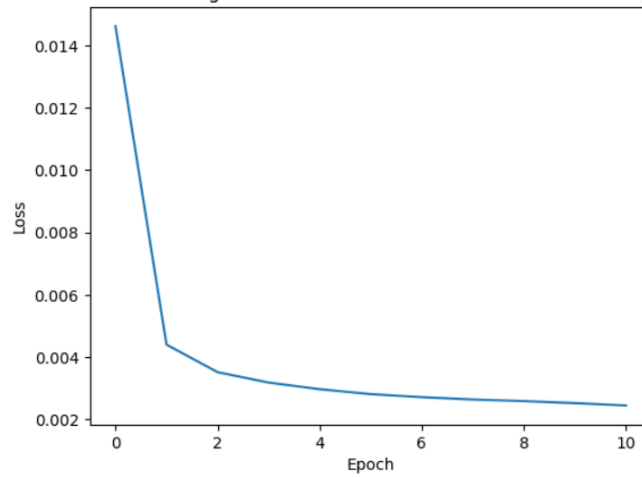
Third convolutional layer has 8- 1x4x4 filters following are three randomly plotted filter outputs.



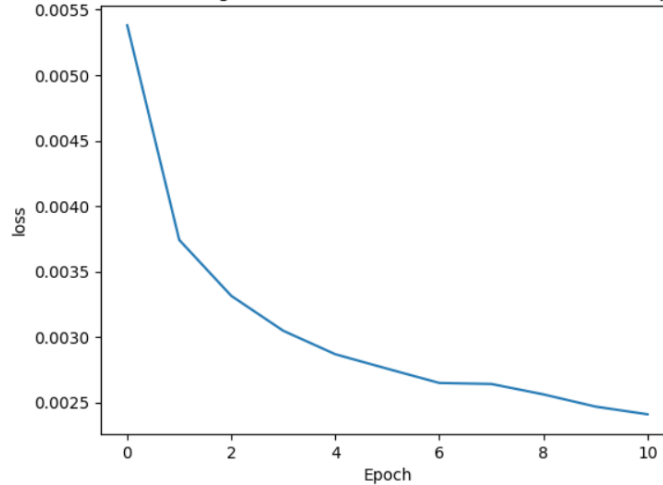
### III. Convolutional Autoencoders with deconvolution and Unpooling

#### a. Training and Test loss plots

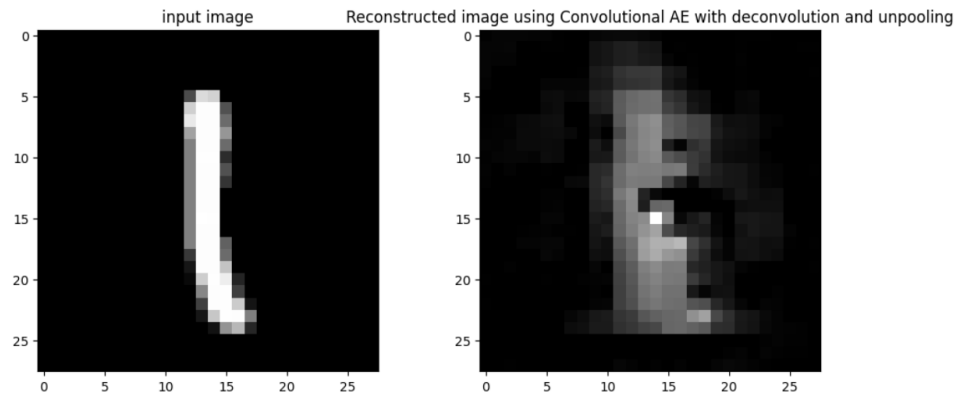
MSE train loss using Convolutional AE with deconvolution and unpooling



MSE test loss using Convolutional AE with deconvolution and unpooling



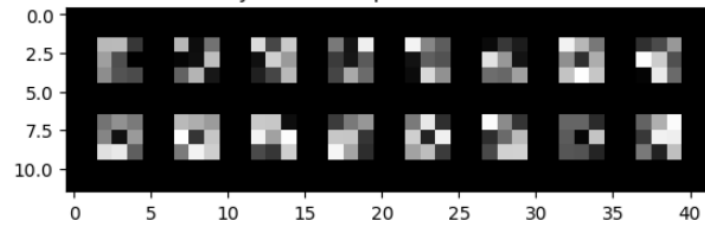
**b. Reconstructed image for a given random MNIST input image**



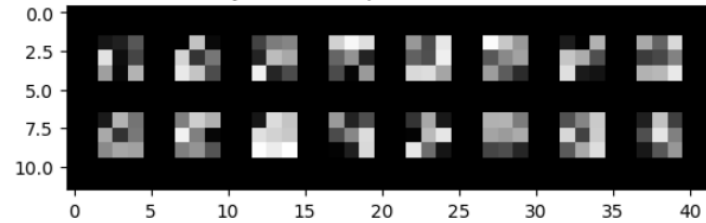
**c. Visualizing the decoder weights**

First convolutional layer has 16 -  $8 \times 3 \times 3$  filters following are three randomly selected filter outputs.

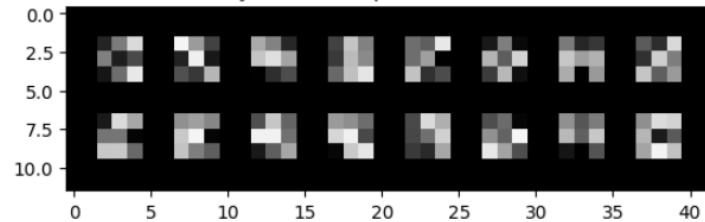
Decoder First Convolutional layer filter outputs for filter no. 5 of CAE with deconvolution



Decoder First Convolutional layer filter outputs for filter no. 13 of CAE with deconvolution

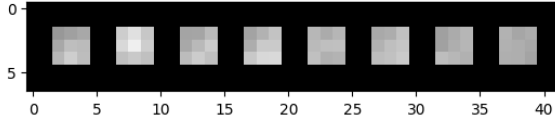


Decoder First Convolutional layer filter outputs for filter no. 8 of CAE with deconvolution

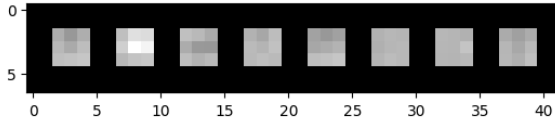


Second convolutional layer has 8 - 1x4x4 filters following are three randomly selected filter outputs.

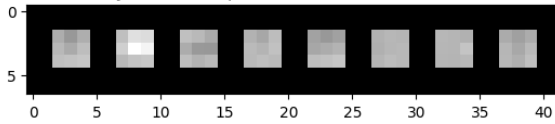
Decoder second Convolutional layer filter outputs for filter no. 1 of CAE with deconvolution and unpooling



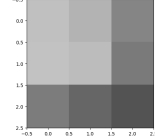
Decoder second Convolutional layer filter outputs for filter no. 8 of CAE with deconvolution and unpooling



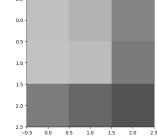
Decoder second Convolutional layer filter outputs for filter no. 8 of CAE with deconvolution and unpooling



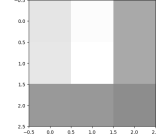
Decoder Third Convolutional layer filter outputs for filter no. 6 of CAE with deconvolution and unpooling



Decoder Third Convolutional layer filter outputs for filter no. 6 of CAE with deconvolution and unpooling



Decoder Third Convolutional layer filter outputs for filter no. 1 of CAE with deconvolution and unpooling



### Observations:

1. Performance wise Convolutional AE with unpooling and deconvolution perform much better than the one with only unpooling and one with only deconvolution which can be observed from the reconstruction images.