

PA4_EE21S056

November 4, 2022

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EE5179: Deep Learning for Imaging

1 Comparing PCA and Autoencoders

1.1 Importing packages

```
[1]: import torch
from torch.utils.data import Dataset
from torch.utils.data import DataLoader
from torchvision import datasets
from torchvision.transforms import ToTensor, Lambda
from torch import nn
from torchvision.utils import make_grid
import matplotlib.pyplot as plt
import numpy as np
```

1.2 Loading MNIST dataset

```
[2]: training_data = datasets.MNIST(root="data", train=True, download =
    ↳True, transform = ToTensor())
test_data = datasets.MNIST(root="data", train = False, download =
    ↳True, transform = ToTensor())

batch_size = 64

train_loader = DataLoader(dataset=training_data, batch_size=batch_size,
    ↳shuffle=True)
test_loader = DataLoader(dataset=test_data, batch_size=batch_size,
    ↳shuffle=False)
```

Downloading <http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz>
Downloading <http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz> to
data/MNIST/raw/train-images-idx3-ubyte.gz

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```

Extracting data/MNIST/raw/train-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to
data/MNIST/raw/train-labels-idx1-ubyte.gz

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Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to
data/MNIST/raw/t10k-images-idx3-ubyte.gz

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Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to
data/MNIST/raw/t10k-labels-idx1-ubyte.gz

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Extracting data/MNIST/raw/t10k-labels-idx1-ubyte.gz to data/MNIST/raw

```

1.3 MNIST Image Reconstruction using PCA

Reference used: <https://analyticsindiamag.com/guide-to-image-reconstruction-using-principal-component-analysis/>

[3]: *# Extracting just images from the dataset for PCA*

```

images = training_data.data
print(images.shape)

```

```
torch.Size([60000, 28, 28])
```

1.3.1 Finding indices representing each class

[4]: *# 114-0, 102-1, 117-2, 111-3, 115-4, 145-5, 106-6, 103-7, 125-8, 110-9*

```

idx_PCA = [114, 102, 117, 111, 115, 145, 106, 103, 125, 110]

i=1 #just an iterator variable

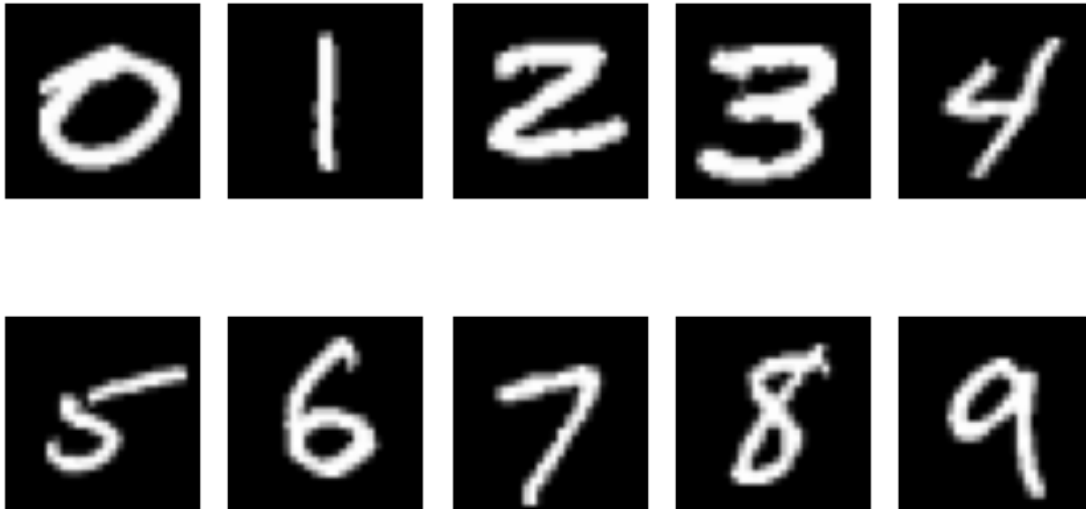
for idx in idx_PCA:
    plt.subplot(2,5,i)
    plt.imshow(images[idx].reshape(28,28), cmap='gray')
    plt.axis('off')

```

```

    i+=1
plt.tight_layout()
plt.show()

```



1.3.2 Flattening PCA input images

```

[5]: data = np.zeros((60000, 784))
    k=0
    for img in images:
        data[k] = img.squeeze().flatten()
        data[k] = data[k]/255
        k+=1
    print(data.shape)

```

(60000, 784)

1.3.3 Performing PCA and checking reconstruction error

```

[6]: from sklearn.decomposition import PCA
    from sklearn.metrics import mean_squared_error
    pca = PCA(n_components=30)
    reconst_data = pca.inverse_transform(pca.fit_transform(data))

    i = 1

    for idx in idx_PCA:
        plt.subplot(2,5,i)
        plt.imshow(reconst_data[idx].reshape(28,28), cmap='gray')
        plt.axis('off')

```

```

i+=1

plt.tight_layout()
plt.show()

print('Reconstruction error for PCA is ', mean_squared_error(data,
↪reconst_data))

```



Reconstruction error for PCA is 0.018121815941217218

1.4 Using an Autoencoder on MNIST dataset

1.4.1 Defining stacked autoencoder class

```

[7]: class stack_AE(nn.Module):
    def __init__(self):
        super(stack_AE, self).__init__()
        self.flatten = nn.Flatten()
        self.encoder = nn.Sequential(
            nn.Linear(784,512),
            nn.ReLU(),
            nn.Linear(512,256),
            nn.ReLU(),
            nn.Linear(256,128),
            nn.ReLU(),
            nn.Linear(128,30),
            nn.ReLU())
        self.decoder =nn.Sequential(
            nn.Linear(30,128),

```

```

        nn.ReLU(),
        nn.Linear(128,256),
        nn.ReLU(),
        nn.Linear(256,784),
        nn.ReLU())

def forward(self, x):
    x = self.flatten(x)
    encoded = self.encoder(x)
    decoded = self.decoder(encoded)
    return decoded, encoded

```

1.4.2 Autoencoder Training

```

[8]: device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

learning_rate = 0.001
epochs = 10

criterion = nn.MSELoss() # Reconstruction error is defined as the MSE Loss

model_stackAE = stack_AE().to(device)
optimizer = torch.optim.Adam(model_stackAE.parameters(), learning_rate)

train_batch_loss = []
train_epoch_loss = []
val_loss = []

```

```

[9]: for epoch in range(epochs):
    for batch_idx, (data, target) in enumerate(train_loader):
        data = data.to(device)
        target = target.to(device)

        model_stackAE.train()
        decoded, encoded = model_stackAE(data)
        loss = criterion(decoded, torch.flatten(data,1))
        train_batch_loss.append(loss.item())

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    train_epoch_loss.append(train_batch_loss[-1])

    model_stackAE.eval()
    with torch.no_grad():
        for (data, target) in test_loader:

```

```

        data = data.to(device)
        target = target.to(device)
        decoded, encoded = model_stackAE(data)
        val_iter_loss = criterion(decoded, torch.flatten(data,1))

    val_loss.append(val_iter_loss.item())
    print('Epoch Number: ',epoch+1)
    print('Training loss: ', train_epoch_loss[-1])
    print('Validation loss: ', val_loss[-1])
    print('-----')

print('Training done!')

```

```

Epoch Number:  1
Training loss:  0.025514619424939156
Validation loss:  0.025768259540200233
-----

```

```

Epoch Number:  2
Training loss:  0.018792742863297462
Validation loss:  0.01956520602107048
-----

```

```

Epoch Number:  3
Training loss:  0.018027035519480705
Validation loss:  0.017227349802851677
-----

```

```

Epoch Number:  4
Training loss:  0.016422612592577934
Validation loss:  0.015180998481810093
-----

```

```

Epoch Number:  5
Training loss:  0.013217149302363396
Validation loss:  0.015349737368524075
-----

```

```

Epoch Number:  6
Training loss:  0.01580682583153248
Validation loss:  0.014463952742516994
-----

```

```

Epoch Number:  7
Training loss:  0.016053110361099243
Validation loss:  0.01427979115396738
-----

```

```

Epoch Number:  8
Training loss:  0.015601414255797863
Validation loss:  0.013991869054734707
-----

```

```

Epoch Number:  9
Training loss:  0.01586502604186535
Validation loss:  0.013657165691256523

```

```
-----  
Epoch Number: 10  
Training loss: 0.012922598049044609  
Validation loss: 0.014202686958014965  
-----
```

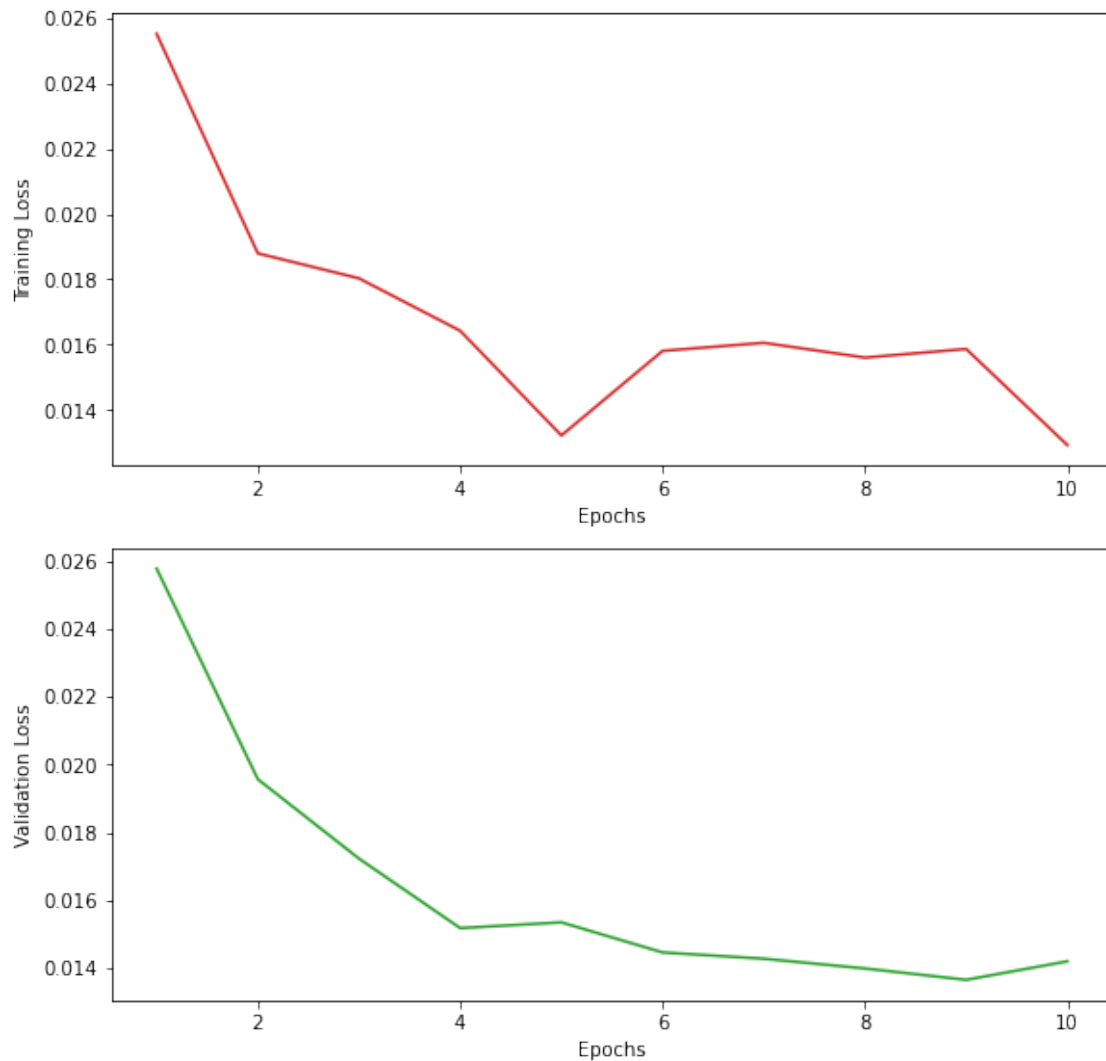
Training done!

1.4.3 Visualizing training and validation loss for autoencoder

```
[10]: fig, axs = plt.subplots(2, constrained_layout= True, figsize=(8,8))  
fig.suptitle('Plots for Stacked Autoencoder')  
axs[0].set(ylabel='Training Loss', xlabel='Epochs')  
axs[0].plot(range(1,epochs+1),train_epoch_loss, 'tab:red')  
axs[1].set(ylabel='Validation Loss', xlabel='Epochs')  
axs[1].plot(range(1,epochs+1),val_loss, 'tab:green')
```

```
[10]: [<matplotlib.lines.Line2D at 0x7fbd686d7a50>]
```

Plots for Stacked Autoencoder

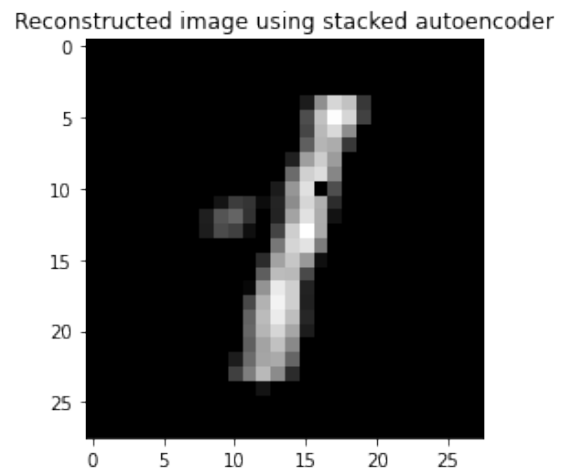
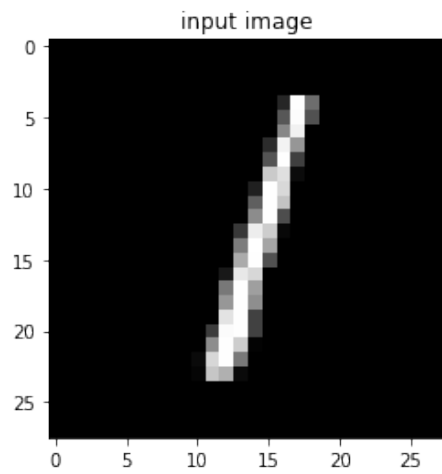
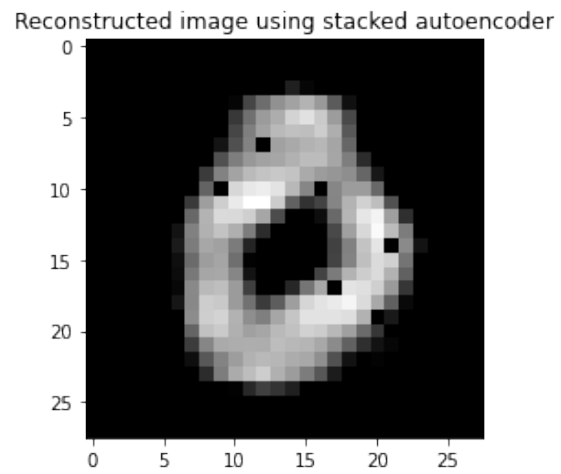
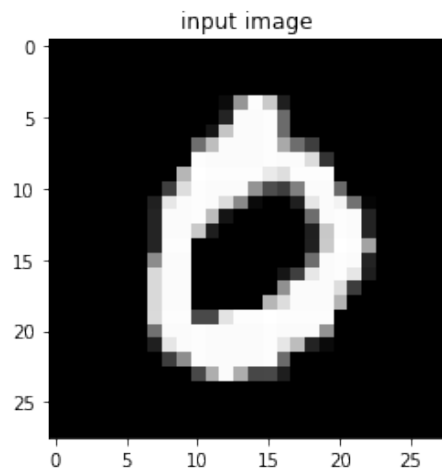


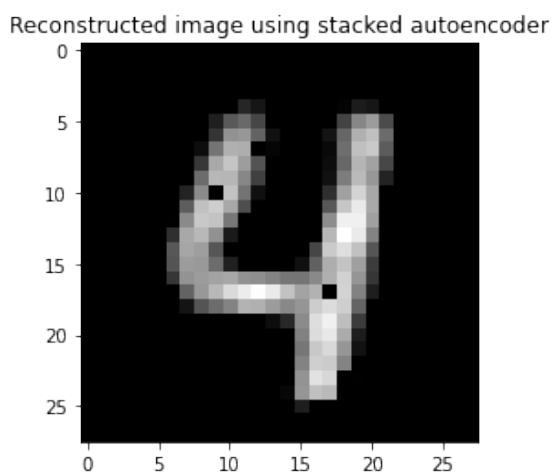
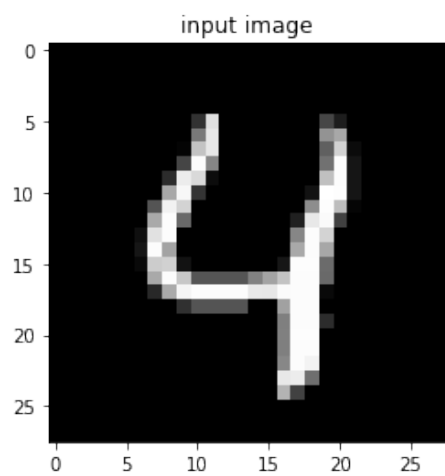
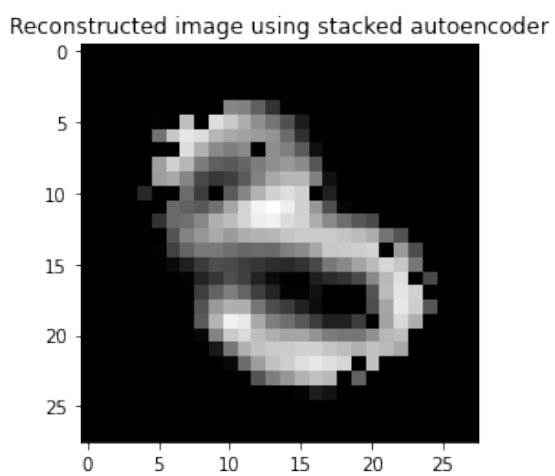
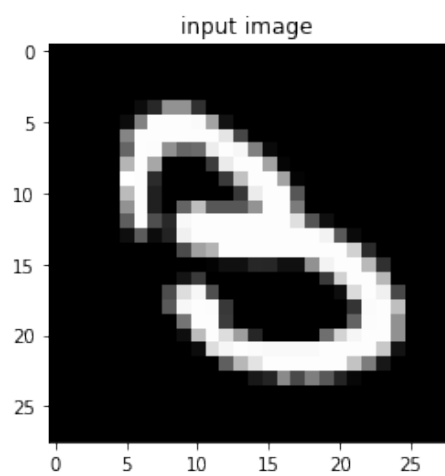
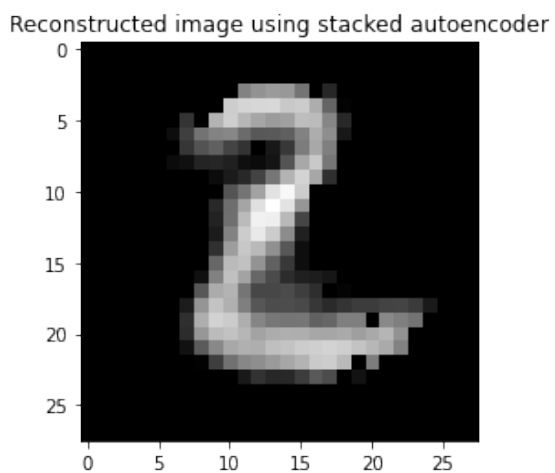
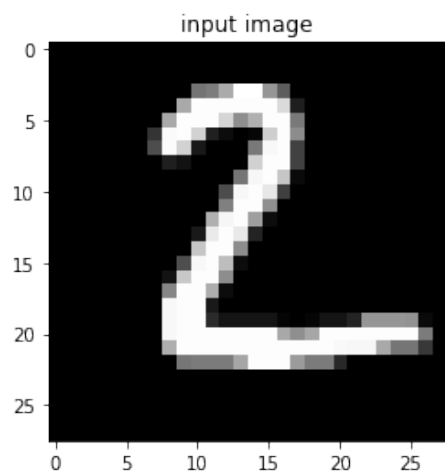
```
[11]: idx_test=[3,2,1,18,4,8,11,0,84,7]

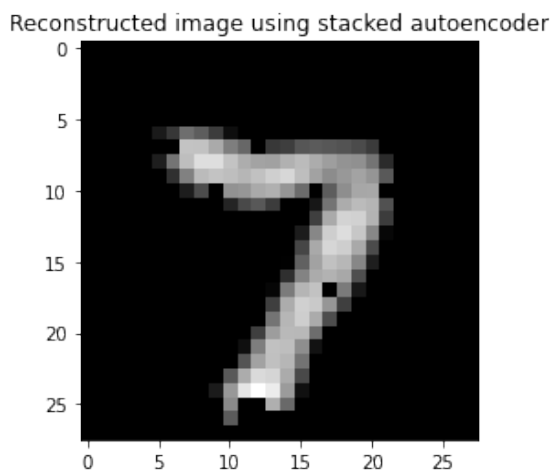
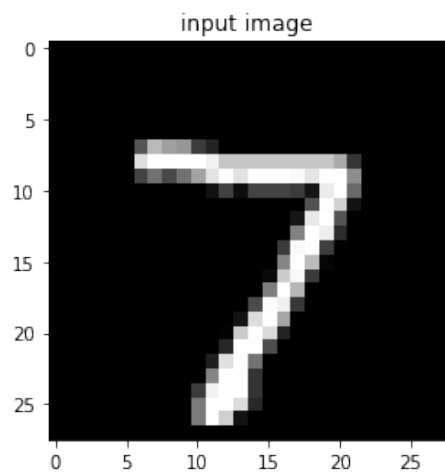
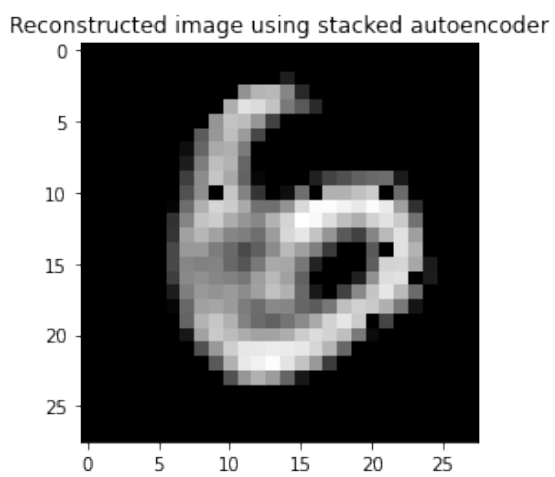
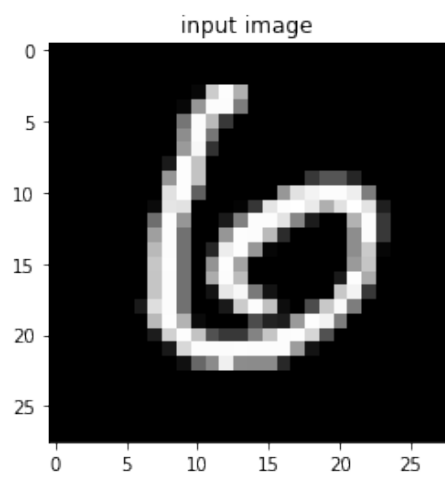
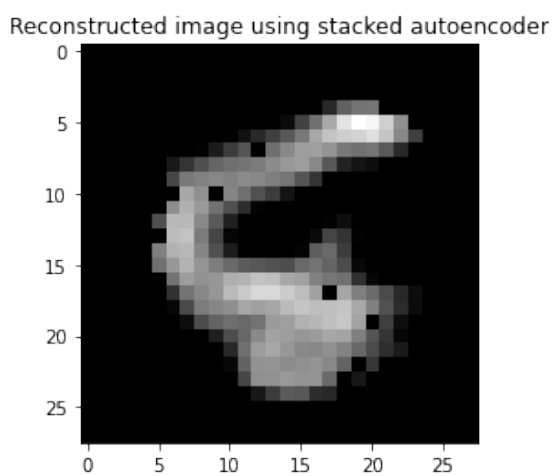
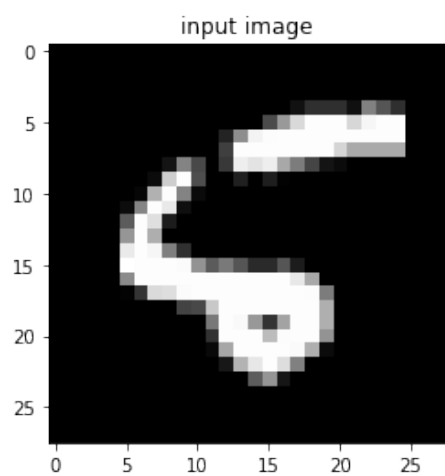
for idx in idx_test:
    image = test_loader.dataset.data[idx, :, :].clone()
    with torch.no_grad():
        image = image.view(-1,28,28).to(device=device).float()
        decoded, encoded = model_stackAE.forward(image)
        decoded = decoded.detach().cpu().numpy()
        image = image.reshape(28,28).detach().cpu().numpy()
        plt.subplot(1,2,1)
        plt.imshow(image , cmap='gray')
        plt.title('input image')
        plt.subplots_adjust(right=1.5)
```

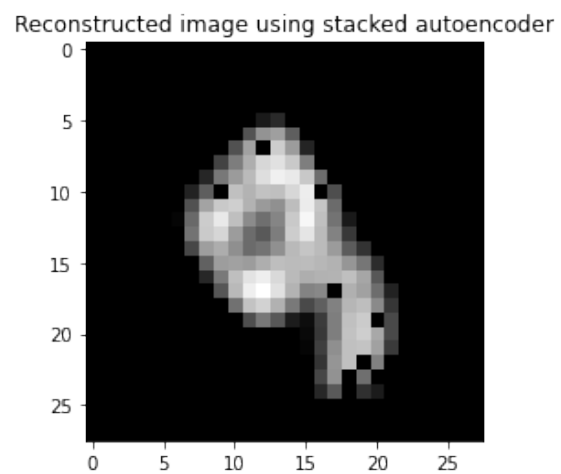
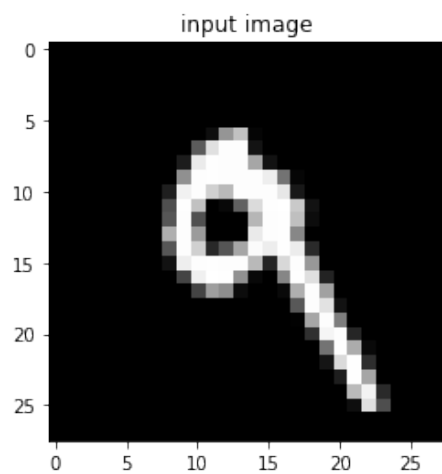
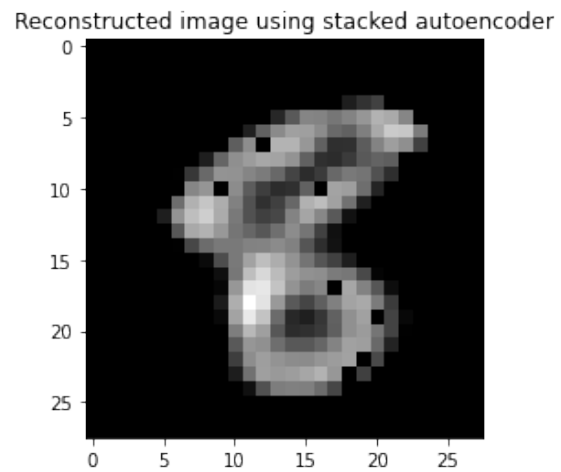
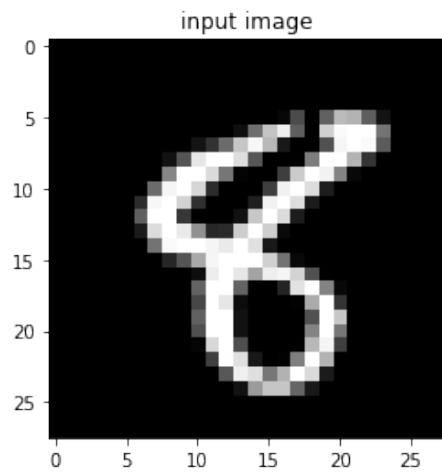


```
plt.subplot(1,2,2)
plt.imshow(decoded.reshape(28,28),cmap = 'gray')
plt.title("Reconstructed image using stacked autoencoder")
plt.show()
```









```
[12]: model_stackAE.eval()
test_loss = 0
with torch.no_grad():
    for (data, target) in test_loader:
        data = data.to(device)
        target = target.to(device)
        decoded, encoded = model_stackAE(data)
        val_iter_loss = criterion(decoded, torch.flatten(data,1))
        test_loss += val_iter_loss/len(test_loader)
```

```
print('Reconstruction accuracy with the given autoencoder configuration is ',  
      ↪test_loss.item())
```

Reconstruction accuracy with the given autoencoder configuration is
0.014440055005252361

2 Experimenting with hidden units of varying sizes

2.1 Defining standard autoencoder class

The following model takes the size of hidden layer as input as required by the experiment.

```
[13]: class standard_AE(nn.Module):  
    def __init__(self,hidden_layer):  
        super(standard_AE, self).__init__()  
        self.flatten = nn.Flatten()  
        self.encoder = nn.Sequential(  
            nn.Linear(784,hidden_layer),  
            nn.ReLU())  
        self.decoder =nn.Sequential(  
            nn.Linear(hidden_layer,784),  
            nn.ReLU())  
  
    def forward(self,x):  
        x = self.flatten(x)  
        encoded=self.encoder(x)  
        decoded =self.decoder(encoded)  
        return decoded, encoded
```

2.2 Loading Fashion MNIST for experiment

```
[14]: fash_test_data = datasets.FashionMNIST(root="data", train = False, download =  
      ↪True,transform = ToTensor())  
fash_test_loader = DataLoader(dataset=fash_test_data, batch_size=batch_size,  
      ↪shuffle=False)
```

Downloading <http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz>

Downloading <http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz> to data/FashionMNIST/raw/train-images-idx3-ubyte.gz

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data/FashionMNIST/raw

Downloading <http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1-ubyte.gz>

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1-ubyte.gz to data/FashionMNIST/raw/train-labels-idx1-ubyte.gz

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Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx3-ubyte.gz

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx3-ubyte.gz to data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz

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Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz to data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz

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2.3 Training and experiment results

```
[15]: hid_size = [64, 128, 256]

for size in hid_size:
    model_standardAE = standard_AE(size).to(device)
    optimizer = torch.optim.Adam(model_standardAE.parameters(), learning_rate)

    train_batch_loss = []
    train_epoch_loss = []
    val_loss = []
    print('Training begins for hidden unit size ', size, '!!')
    print('-----')
    for epoch in range(epochs):
        for batch_idx, (data, target) in enumerate(train_loader):
            data = data.to(device=device)
            target = target.to(device=device)

            model_standardAE.train()
```

```

        decoded, encoded = model_standardAE(data)
        loss = criterion(decoded, torch.flatten(data,1))
        train_batch_loss.append(loss.item())

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

train_epoch_loss.append(train_batch_loss[-1])

model_standardAE.eval()
with torch.no_grad():
    for (data, target) in test_loader:
        data = data.to(device)
        target = target.to(device)
        decoded, encoded = model_standardAE(data)
        val_iter_loss = criterion(decoded, torch.flatten(data,1))

val_loss.append(val_iter_loss.item())
print('Epoch Number: ',epoch+1)
print('Training loss: ', train_epoch_loss[-1])
print('Validation loss: ', val_loss[-1])
print('-----')

fig, axs = plt.subplots(2, constrained_layout= True, figsize=(8,8))
fig.suptitle('Plots for Standard Autoencoder')
axs[0].set(ylabel='Training Loss', xlabel='Epochs')
axs[0].plot(range(1,epochs+1),train_epoch_loss, 'tab:red')
axs[1].set(ylabel='Validation Loss', xlabel='Epochs')
axs[1].plot(range(1,epochs+1),val_loss, 'tab:green')
plt.show()
print('Training done for hidden unit size ', size, '!')
print('-----')
image = test_loader.dataset.data[1, :, :].clone() #take one image from test_
↪ set
with torch.no_grad():
    image = image.view(-1,28,28).to(device=device).float()
    decoded, encoded = model_standardAE.forward(image)
    decoded = decoded.detach().cpu().numpy()
    image = image.reshape(28,28).detach().cpu().numpy()
    plt.subplot(1,2,1)
    plt.imshow(image , cmap='gray')
    plt.title('input image')
    plt.subplots_adjust(right=1.5)
    plt.subplot(1,2,2)
    plt.imshow(decoded.reshape(28,28),cmap = 'gray')

```

```

plt.title("Reconstructed image using standard AE hidden unit size_
↪"+str(size))
plt.show()

fash_image = fash_test_loader.dataset.data[12, :, :].clone()
fash_image = fash_image.view(-1,28,28).to(device=device).float()
decoded, encoded = model_standardAE.forward(fash_image)
decoded = decoded.detach().cpu().numpy()
fash_image = fash_image.reshape(28,28).detach().cpu().numpy()
plt.subplot(1,2,1)
plt.imshow(fash_image , cmap='gray')
plt.title('input image')
plt.subplots_adjust(right=1.5)
plt.subplot(1,2,2)
plt.imshow(decoded.reshape(28,28),cmap = 'gray')
plt.title("Reconstructed image using standard AE hidden unit size_
↪"+str(size))
plt.show()

noisy_img = np.random.normal(loc=128,scale=10,size=(28,28))
noisy_img = torch.from_numpy(noisy_img).reshape(1,1,28,28).
↪to(device=device).float()
decoded, encoded = model_standardAE.forward(noisy_img)
decoded = decoded.detach().cpu().numpy()
noisy_img = noisy_img.reshape(28,28).detach().cpu().numpy()
plt.subplot(1,2,1)
plt.imshow(noisy_img , cmap='gray')
plt.title('input image')
plt.subplots_adjust(right=1.5)
plt.subplot(1,2,2)
plt.imshow(decoded.reshape(28,28),cmap = 'gray')
plt.title("Reconstructed image using standard AE hidden unit size_
↪"+str(size))
plt.show()
print('-----')
print('-----')

```

Training begins for hidden unit size 64 !

```

-----
Epoch Number: 1
Training loss: 0.015205412171781063
Validation loss: 0.014379788190126419
-----

```

```

Epoch Number: 2
Training loss: 0.013814076781272888
Validation loss: 0.013476143591105938

```

Epoch Number: 3
Training loss: 0.013716896064579487
Validation loss: 0.013173110783100128

Epoch Number: 4
Training loss: 0.012501811608672142
Validation loss: 0.013136602006852627

Epoch Number: 5
Training loss: 0.013467206619679928
Validation loss: 0.012923912145197392

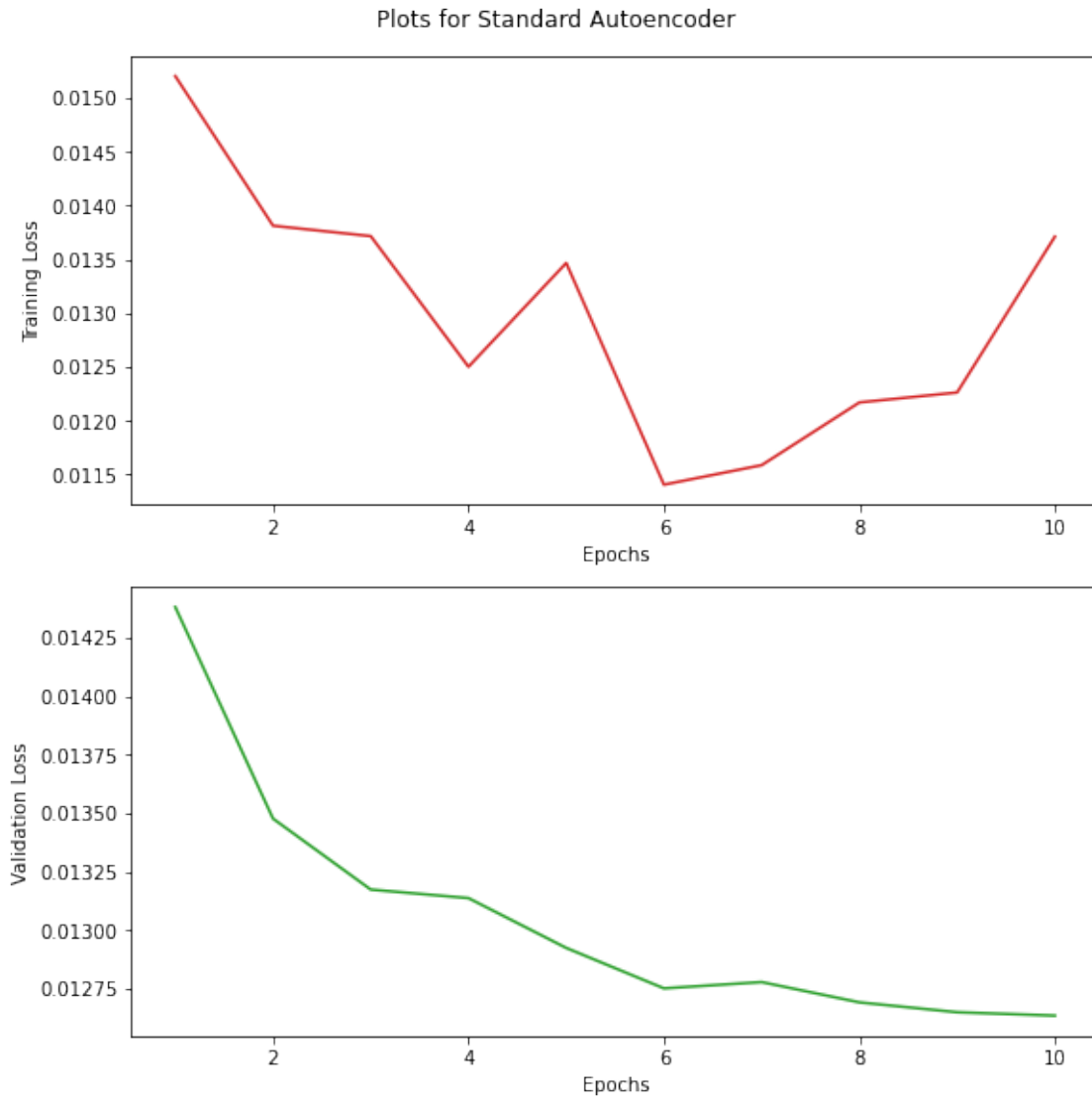
Epoch Number: 6
Training loss: 0.011405030265450478
Validation loss: 0.012751072645187378

Epoch Number: 7
Training loss: 0.011586284264922142
Validation loss: 0.012777873314917088

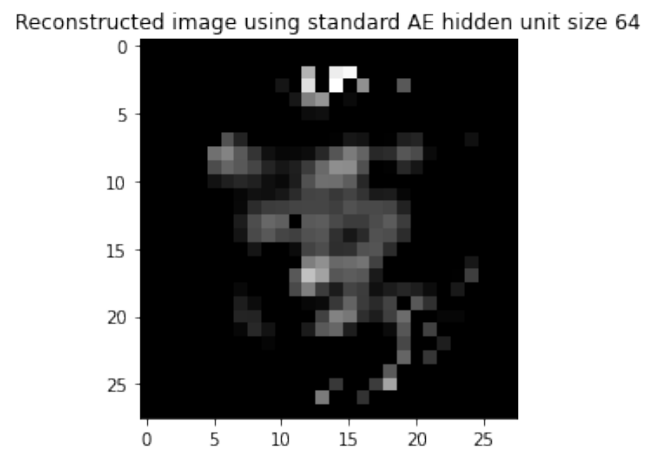
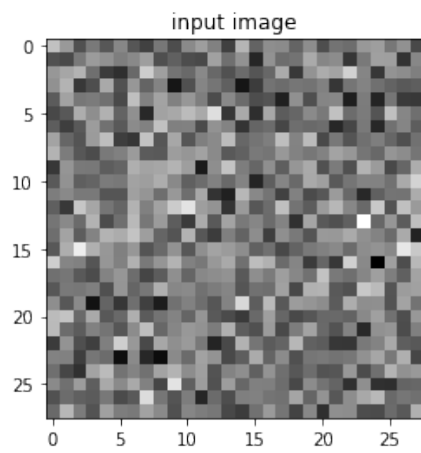
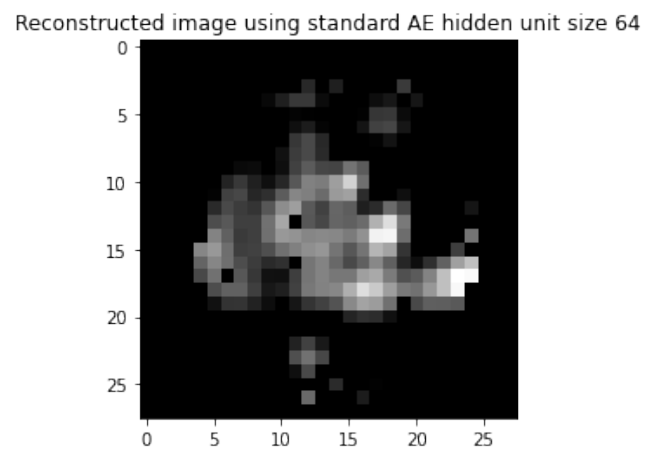
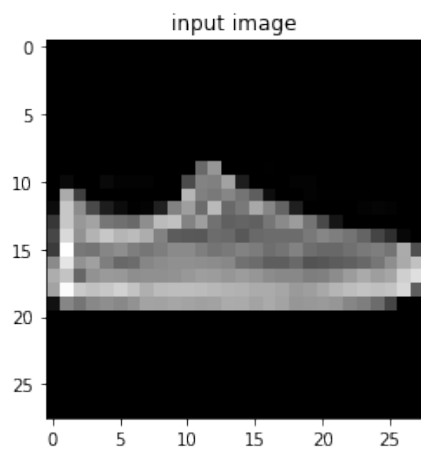
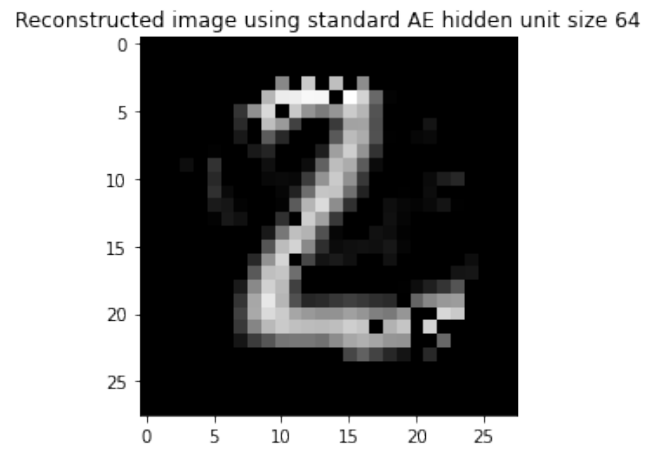
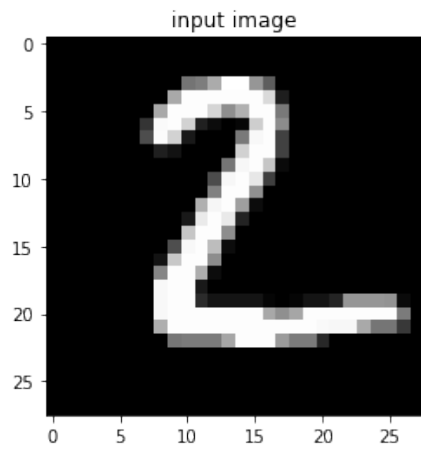
Epoch Number: 8
Training loss: 0.012170090340077877
Validation loss: 0.012691356241703033

Epoch Number: 9
Training loss: 0.012262396514415741
Validation loss: 0.012649083510041237

Epoch Number: 10
Training loss: 0.013712306506931782
Validation loss: 0.012634700164198875



Training done for hidden unit size 64 !



Training begins for hidden unit size 128 !

Epoch Number: 1
Training loss: 0.009362838231027126
Validation loss: 0.010682893916964531

Epoch Number: 2
Training loss: 0.009639010764658451
Validation loss: 0.009487487375736237

Epoch Number: 3
Training loss: 0.008285951800644398
Validation loss: 0.009182061068713665

Epoch Number: 4
Training loss: 0.010454070754349232
Validation loss: 0.009161614812910557

Epoch Number: 5
Training loss: 0.00843499694019556
Validation loss: 0.00904966238886118

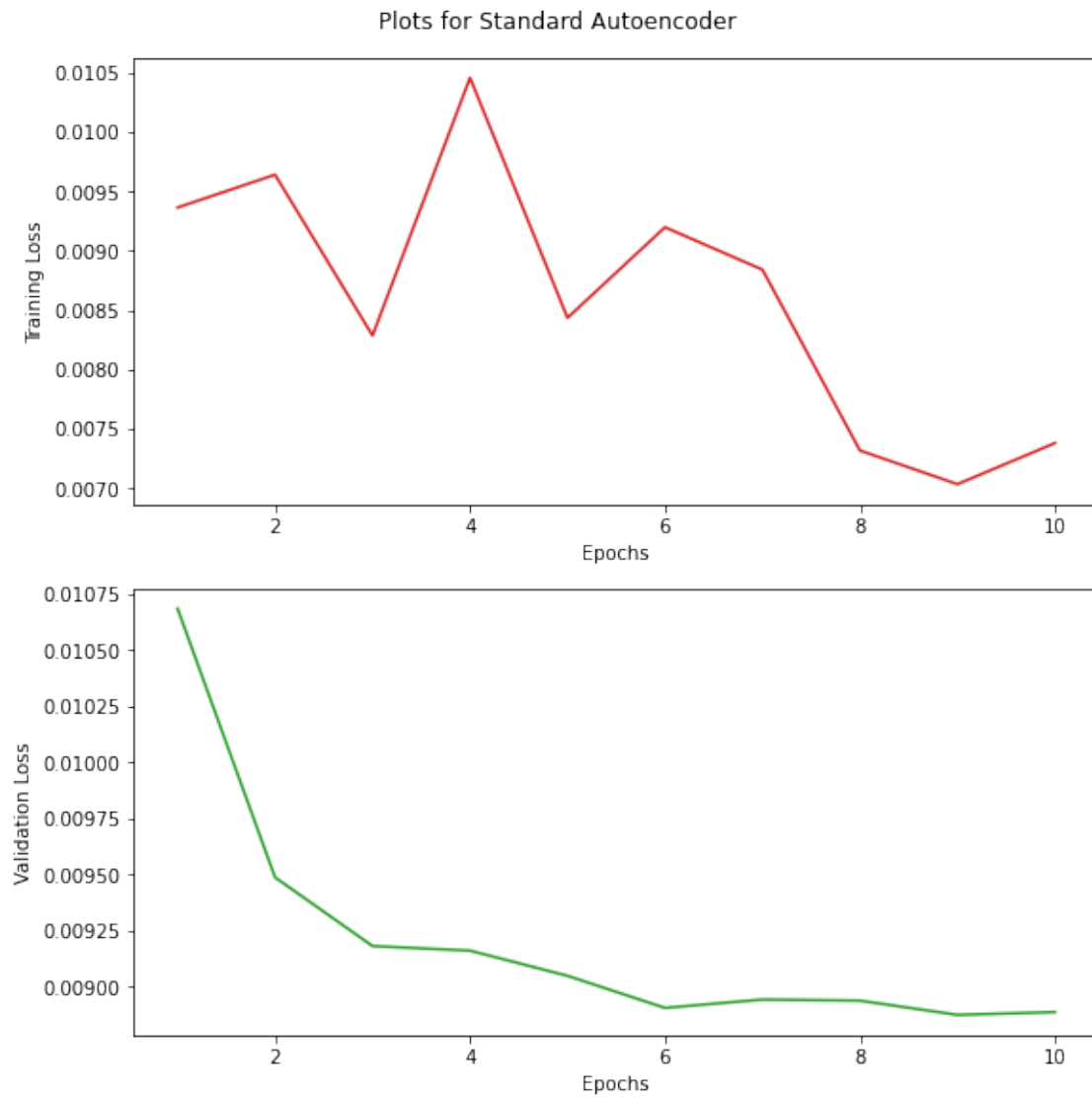
Epoch Number: 6
Training loss: 0.009196995757520199
Validation loss: 0.008906994014978409

Epoch Number: 7
Training loss: 0.008840101771056652
Validation loss: 0.00894408393651247

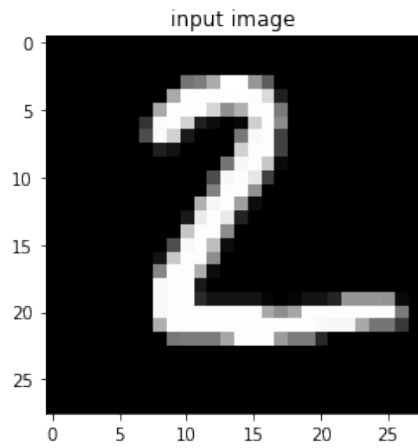
Epoch Number: 8
Training loss: 0.0073185451328754425
Validation loss: 0.00893931183964014

Epoch Number: 9
Training loss: 0.0070354267954826355
Validation loss: 0.008875870145857334

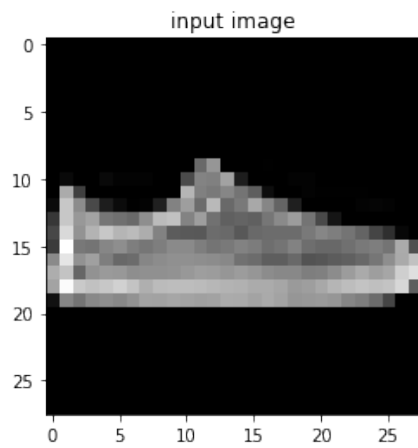
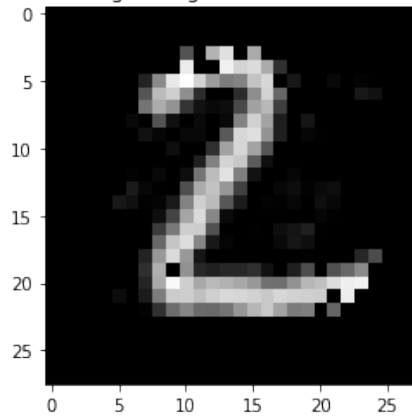
Epoch Number: 10
Training loss: 0.007381132338196039
Validation loss: 0.008888255804777145



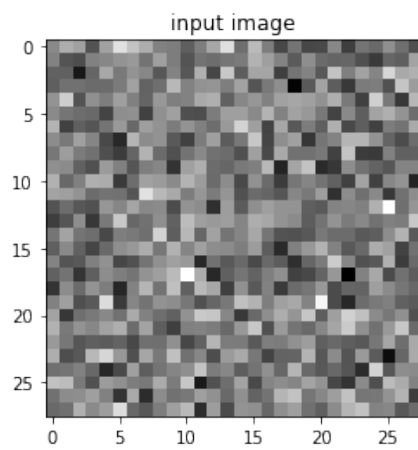
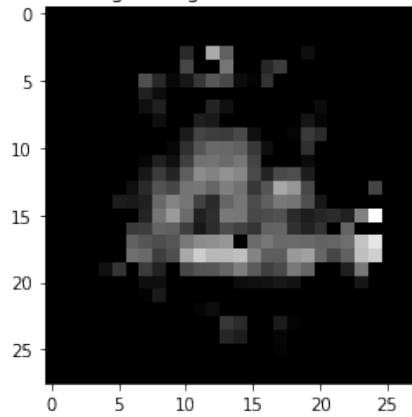
Training done for hidden unit size 128 !



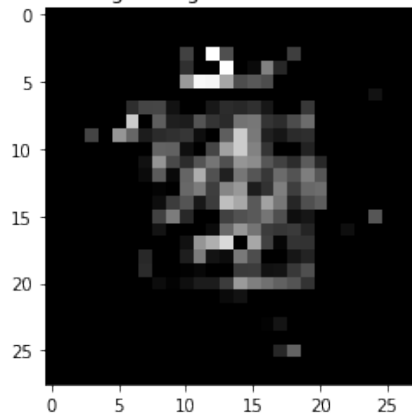
Reconstructed image using standard AE hidden unit size 128



Reconstructed image using standard AE hidden unit size 128



Reconstructed image using standard AE hidden unit size 128



Training begins for hidden unit size 256 !

Epoch Number: 1
Training loss: 0.010379760526120663
Validation loss: 0.009749290533363819

Epoch Number: 2
Training loss: 0.008854160085320473
Validation loss: 0.008706873282790184

Epoch Number: 3
Training loss: 0.007910887710750103
Validation loss: 0.008333210833370686

Epoch Number: 4
Training loss: 0.008666816167533398
Validation loss: 0.008095543831586838

Epoch Number: 5
Training loss: 0.00818319246172905
Validation loss: 0.008007722906768322

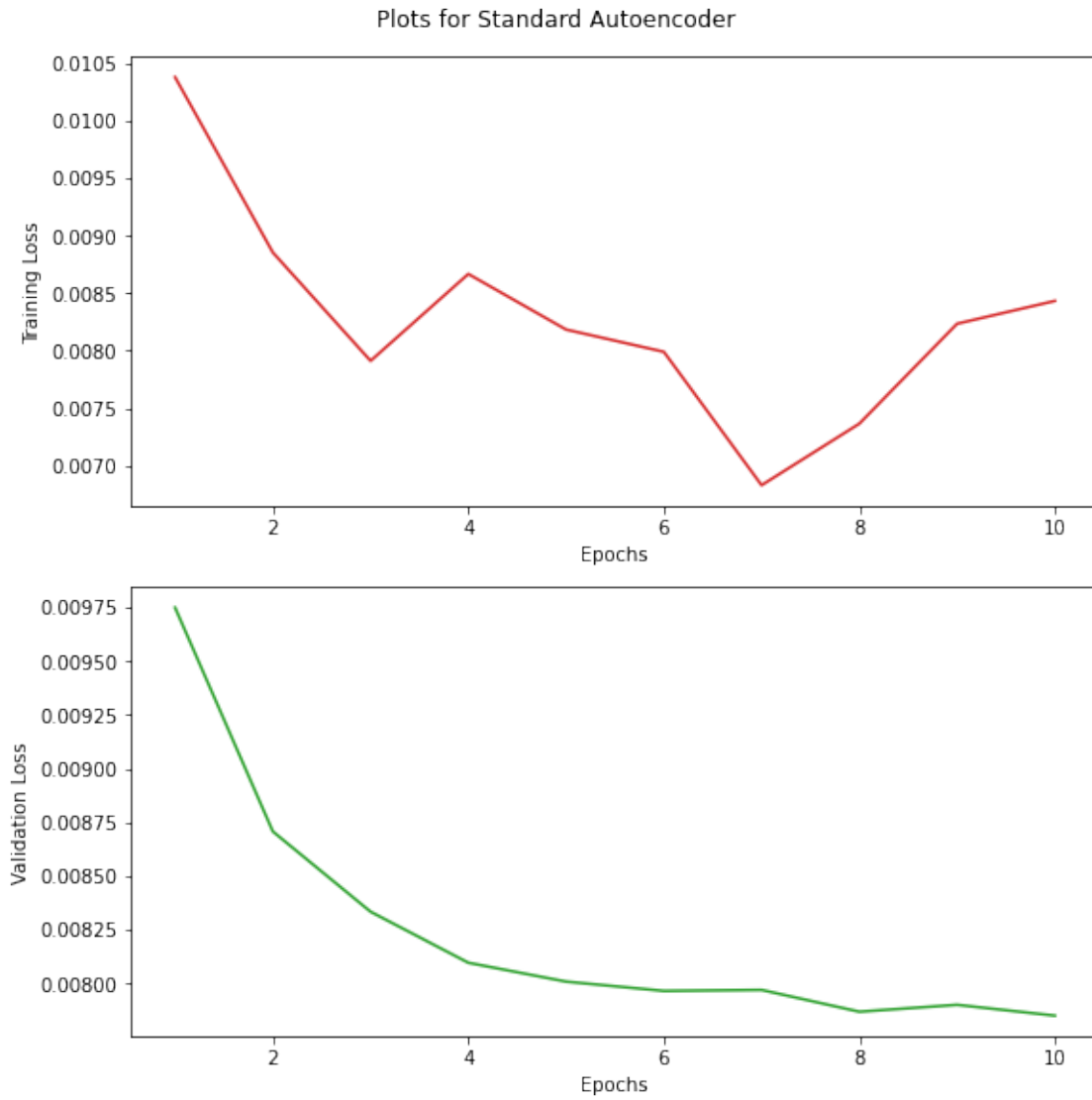
Epoch Number: 6
Training loss: 0.007989658042788506
Validation loss: 0.007964433170855045

Epoch Number: 7
Training loss: 0.006828519515693188
Validation loss: 0.007969017140567303

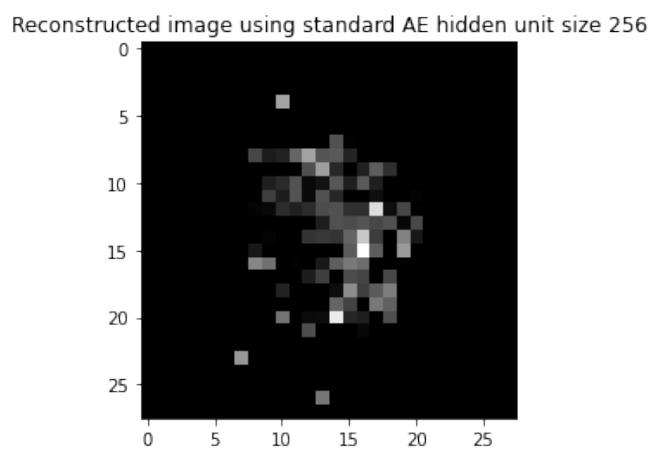
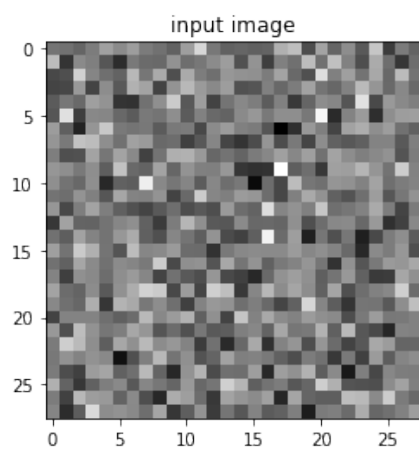
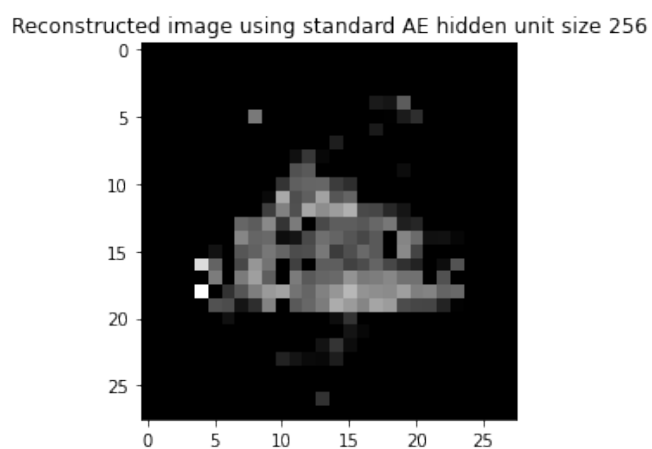
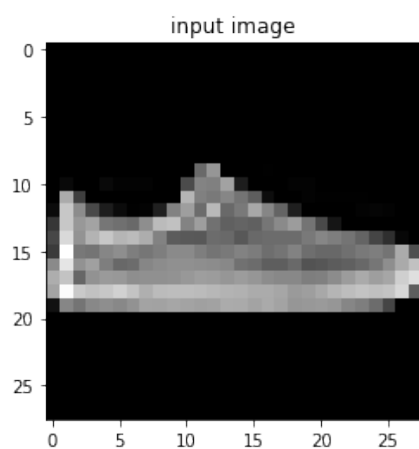
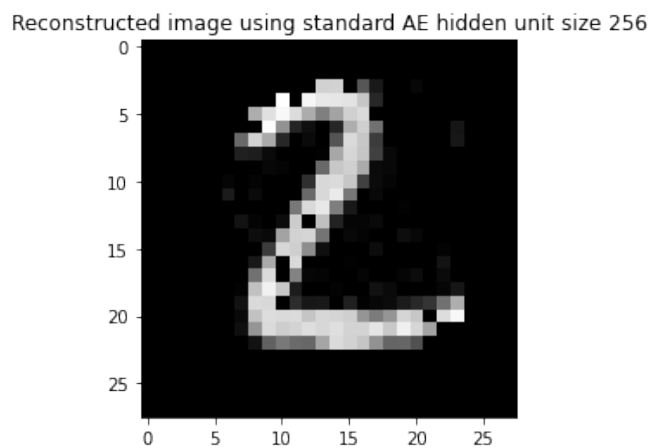
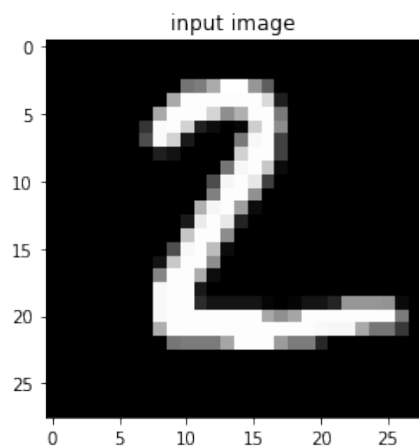
Epoch Number: 8
Training loss: 0.007364301010966301
Validation loss: 0.007867636159062386

Epoch Number: 9
Training loss: 0.008234119042754173
Validation loss: 0.007899788208305836

Epoch Number: 10
Training loss: 0.008432411588728428
Validation loss: 0.007849331013858318



Training done for hidden unit size 256 !



3 Sparse Autoencoders

3.1 Defining sparse autoencoder class

```
[16]: class overcomp_sparse_AE(nn.Module):
    def __init__(self):
        super(overcomp_sparse_AE, self).__init__()
        self.flatten = nn.Flatten()
        self.encoder = nn.Sequential(
            nn.Linear(784,1521),
            nn.ReLU())
        self.decoder =nn.Sequential(
            nn.Linear(1521,784),
            nn.ReLU())

    def forward(self,x):
        x = self.flatten(x)
        encoded=self.encoder(x)
        decoded =self.decoder(encoded)
        return decoded, encoded
```

3.2 Defining experimentation functions

- Average hidden layer activation avg_hl_activations
- Visualize activations visualize_activations
- Visualize learned filters encoder_decoder_filters_plots

```
[17]: def avg_hl_activations(model,test_dataloader,model_name):
    model.eval()
    avg_act_val = 0
    with torch.no_grad():
        for (data,label) in test_dataloader:
            (data,label) = (data.to(device),label.to(device))
            decoded,encoded = model(data) #our prediction
            avg_act_val += float(torch.mean(encoded))
    avg_act_val /= len(test_dataloader)
    print("The average activation of " + str(model_name)+" is",avg_act_val)

def encoder_decoder_filters_plots(model,model_name,device):
    with torch.no_grad():
        encoder_filters = model.encoder[0].weight.detach().cpu().numpy()
        decoder_filters = model.decoder[0].weight.detach().cpu().numpy()
        #plot the encoder and decoder weights as an image for 0th neuron
```

```

plt.imshow(encoder_filters[0].reshape(28,28), cmap='gray')
plt.colorbar()
plt.title('Encoder Filters for '+str(0)+'th neuron of '+
↳str(model_name))
plt.show()

plt.imshow(decoder_filters[:,0].reshape(28,28), cmap='gray')
plt.colorbar()
plt.title('Decoder Filters for '+str(0)+'th neuron of '+
↳str(model_name))
plt.show()

def visualize_activations(model, test_dataloader, model_name, device, hidden_layer):
    ↳ #visualize the activations
    for i, ind in enumerate(idx_test):
        test_image = test_dataloader.dataset.data[ind].clone()
        test_label = test_dataloader.dataset.targets[ind].clone()
        with torch.no_grad():
            test_image = test_image.reshape(1,1,28,28).to(device=device).float()
            decoded, encoded = model.forward(test_image)
            encoded = encoded.detach().cpu().numpy()
            plt.imshow(encoded.reshape(int(np.sqrt(hidden_layer)),int(np.
↳sqrt(hidden_layer))), cmap='gray')
            str_title = "Activation for digit "+str(test_label.item())
            plt.title(str_title)
            plt.show()

```

```

[18]: sparsity_values = [0.0001, 0.001, 0.005, 0.1]

for lam in sparsity_values:
    model_over_sparseAE = overcomp_sparse_AE().to(device)
    optimizer = torch.optim.Adam(model_over_sparseAE.parameters(), learning_rate)

    train_batch_loss = []
    train_epoch_loss = []
    val_loss = []
    print('Training begins for regularization lambda value ', lam, '!!')
    print('-----')
    for epoch in range(epochs):
        for batch_idx, (data, target) in enumerate(train_loader):
            data = data.to(device=device)
            target = target.to(device=device)

            model_over_sparseAE.train()
            decoded, encoded = model_over_sparseAE(data)
            loss = criterion(decoded, torch.flatten(data,1))
            loss+= lam*torch.linalg.norm(encoded, 1)

```

```

train_batch_loss.append(loss.item())

optimizer.zero_grad()
loss.backward()
optimizer.step()

train_epoch_loss.append(train_batch_loss[-1])

model_over_sparseAE.eval()
with torch.no_grad():
    for (data, target) in test_loader:
        data = data.to(device)
        target = target.to(device)

        decoded, encoded = model_over_sparseAE(data)
        val_iter_loss = criterion(decoded, torch.flatten(data,1))
        val_iter_loss += lam*torch.linalg.norm(encoded, 1)

val_loss.append(val_iter_loss.item())
print('Epoch Number: ', epoch+1)
print('Training loss: ', train_epoch_loss[-1])
print('Validation loss: ', val_loss[-1])
print('-----')

fig, axs = plt.subplots(2, constrained_layout= True, figsize=(8,8))
fig.suptitle('Plots for Standard Autoencoder')
axs[0].set(ylabel='Training Loss', xlabel='Epochs')
axs[0].plot(range(1, epochs+1), train_epoch_loss, 'tab:red')
axs[1].set(ylabel='Validation Loss', xlabel='Epochs')
axs[1].plot(range(1, epochs+1), val_loss, 'tab:green')
plt.show()
print('Training done for regularization lambda value ', lam, '!')
print('-----')
image = test_loader.dataset.data[1, :, :].clone() #take one image from test_
↪set
with torch.no_grad():
    image = image.view(-1,28,28).to(device=device).float()
    decoded, encoded = model_over_sparseAE.forward(image)
    decoded = decoded.detach().cpu().numpy()
    image = image.reshape(28,28).detach().cpu().numpy()
    plt.subplot(1,2,1)
    plt.imshow(image, cmap='gray')
    plt.title('input image')
    plt.subplots_adjust(right=1.5)
    plt.subplot(1,2,2)
    plt.imshow(decoded.reshape(28,28), cmap = 'gray')
    plt.title("Reconstructed image using Sparse AE with lambda value "+str(lam))

```

```

plt.show()
avg_hl_activations(model_over_sparseAE,test_loader,"Sparse AE with lambda_
↪value "+str(lam))
encoder_decoder_filters_plots(model_over_sparseAE,"Sparse AE with lambda_
↪value"+str(lam),device)
visualize_activations(model_over_sparseAE,test_loader,"Sparse AE with_
↪lambda value"+str(lam),device,1521)
print('-----')
print('-----')

```

Training begins for regularization lambda value 0.0001 !

```

-----
Epoch Number: 1
Training loss: 0.015572241507470608
Validation loss: 0.015071733854711056
-----

```

```

Epoch Number: 2
Training loss: 0.014412588439881802
Validation loss: 0.015841398388147354
-----

```

```

Epoch Number: 3
Training loss: 0.015103071928024292
Validation loss: 0.01383668091148138
-----

```

```

Epoch Number: 4
Training loss: 0.01100159715861082
Validation loss: 0.013298295438289642
-----

```

```

Epoch Number: 5
Training loss: 0.012901985086500645
Validation loss: 0.012650098651647568
-----

```

```

Epoch Number: 6
Training loss: 0.013376357965171337
Validation loss: 0.012648377567529678
-----

```

```

Epoch Number: 7
Training loss: 0.009877783246338367
Validation loss: 0.012382451444864273
-----

```

```

Epoch Number: 8
Training loss: 0.010951398871839046
Validation loss: 0.012081769295036793
-----

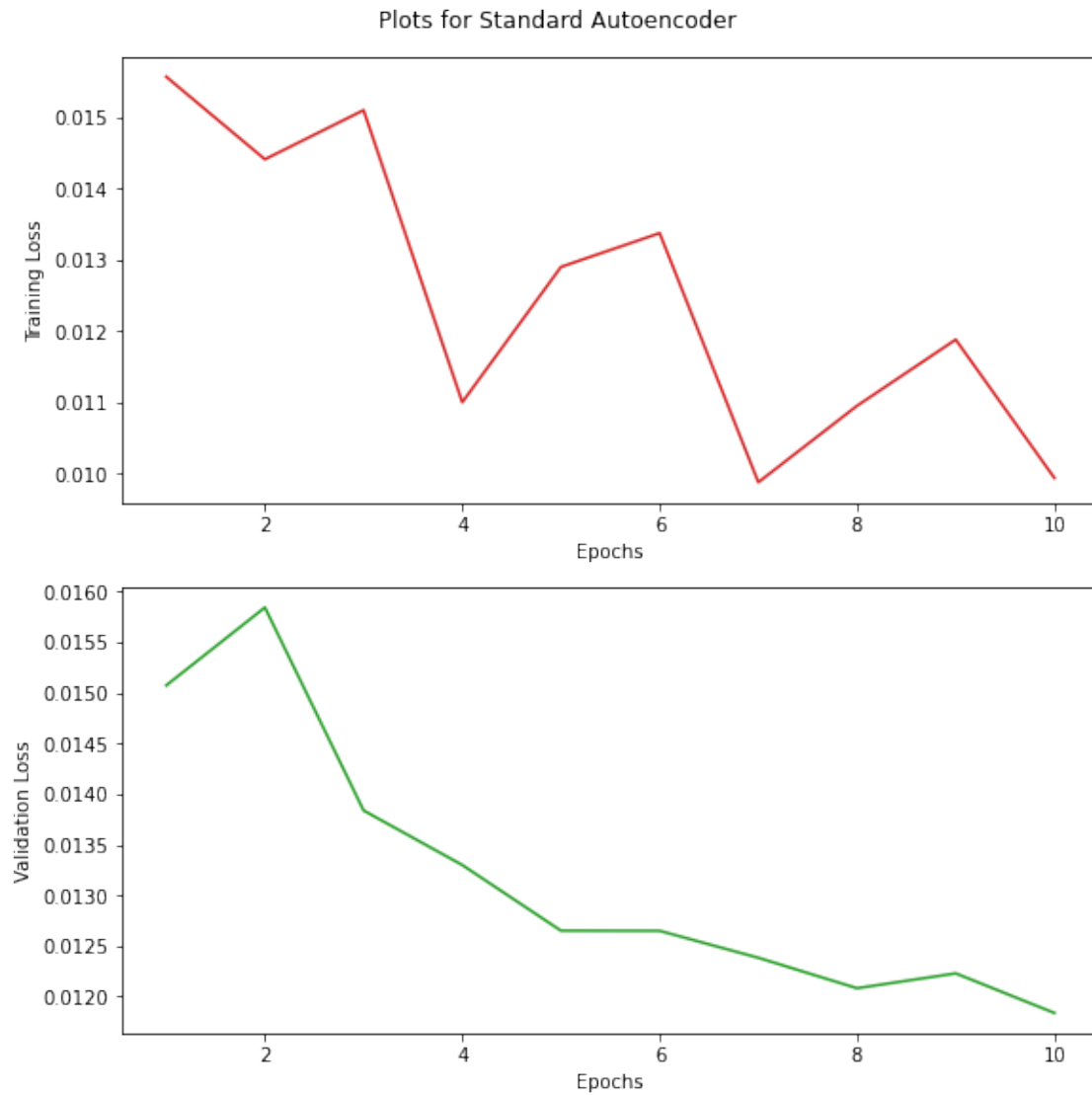
```

```

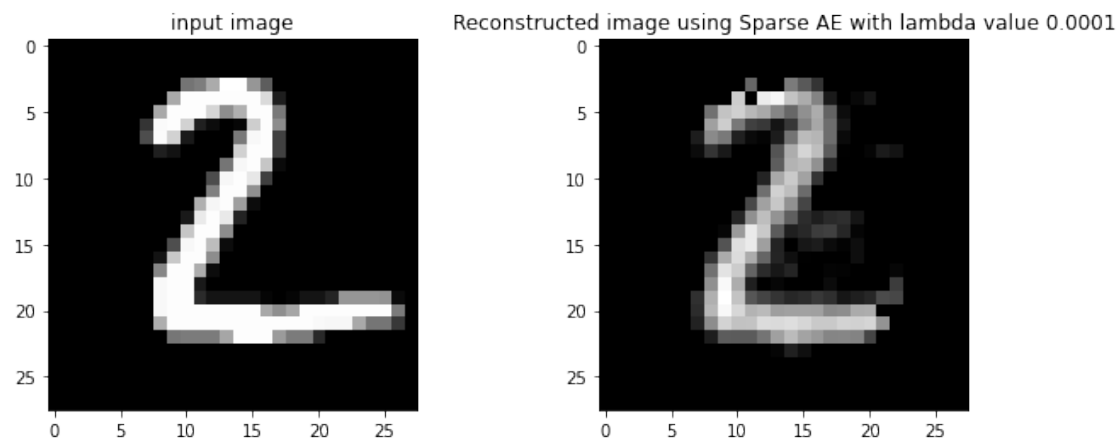
Epoch Number: 9
Training loss: 0.011881495825946331
Validation loss: 0.012228610925376415
-----

```

Epoch Number: 10
Training loss: 0.009938022121787071
Validation loss: 0.011837400496006012

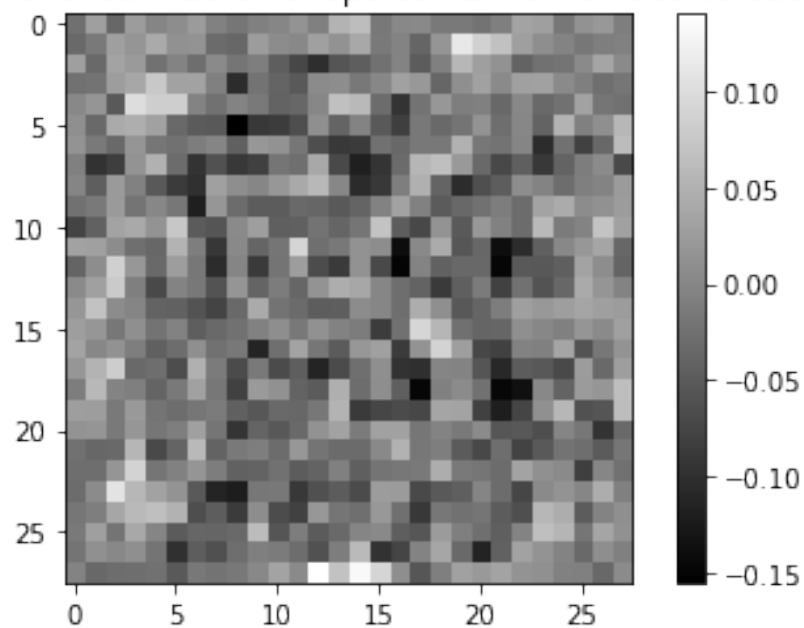


Training done for regularization lambda value 0.0001 !

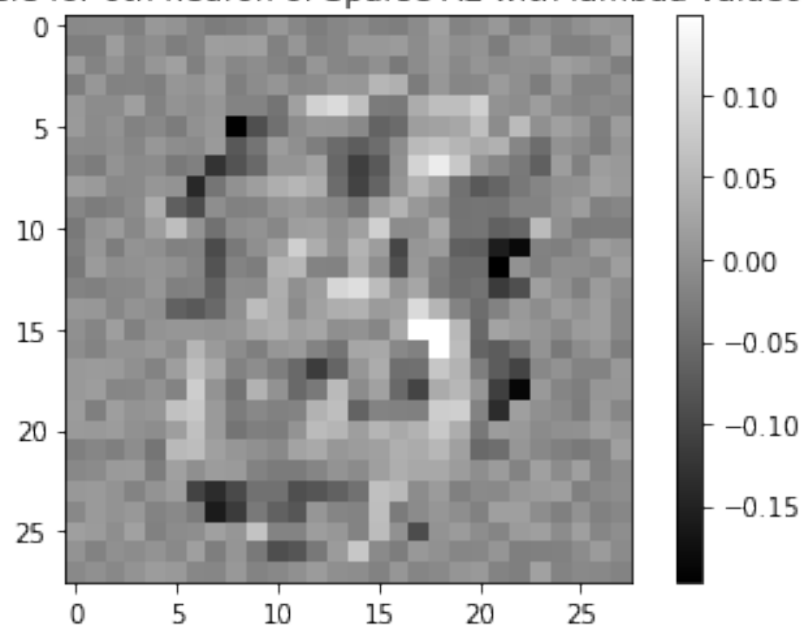


The average activation of Sparse AE with lambda value 0.0001 is
0.024317094676528768

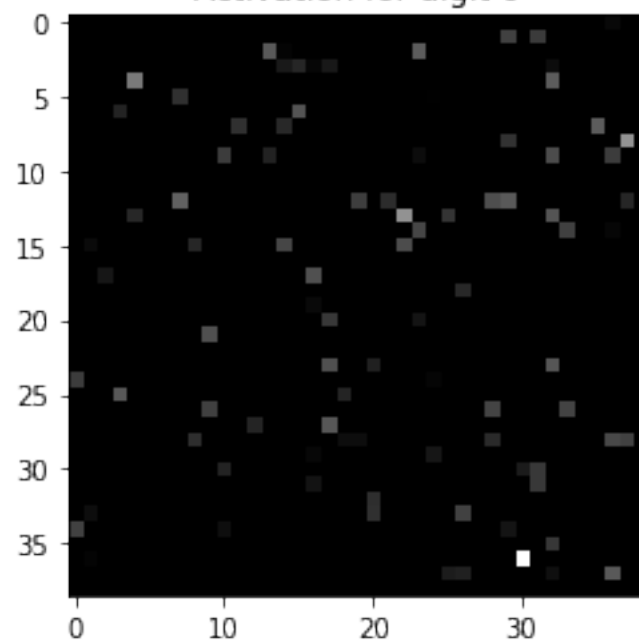
Encoder Filters for 0th neuron of Sparse AE with lambda value 0.0001

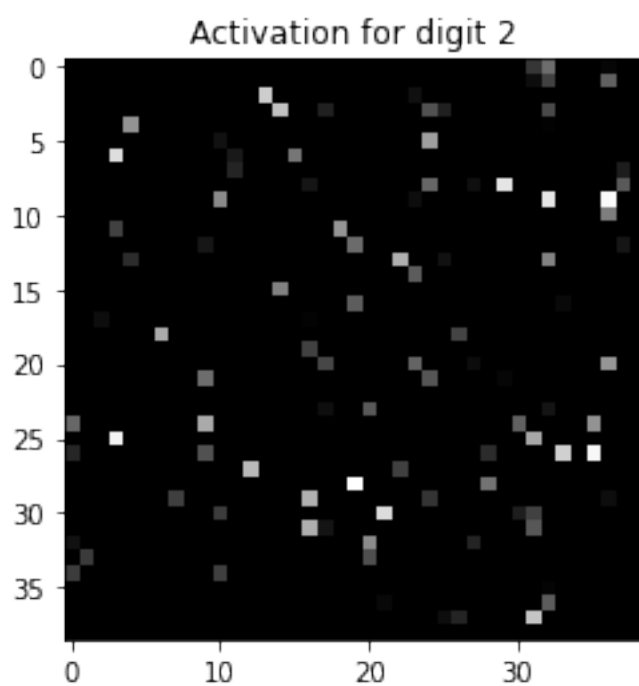
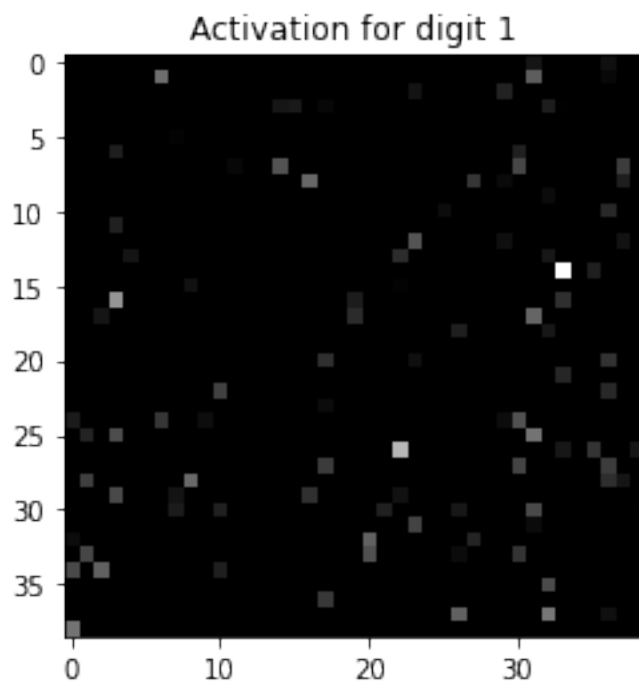


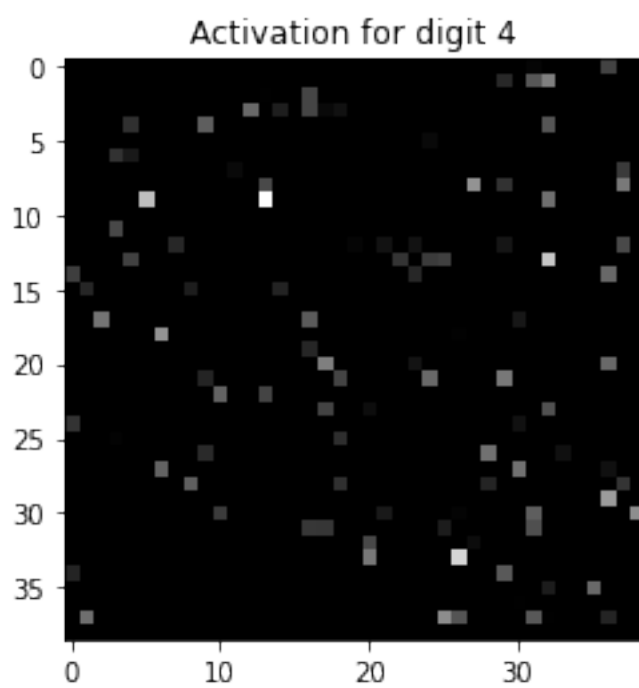
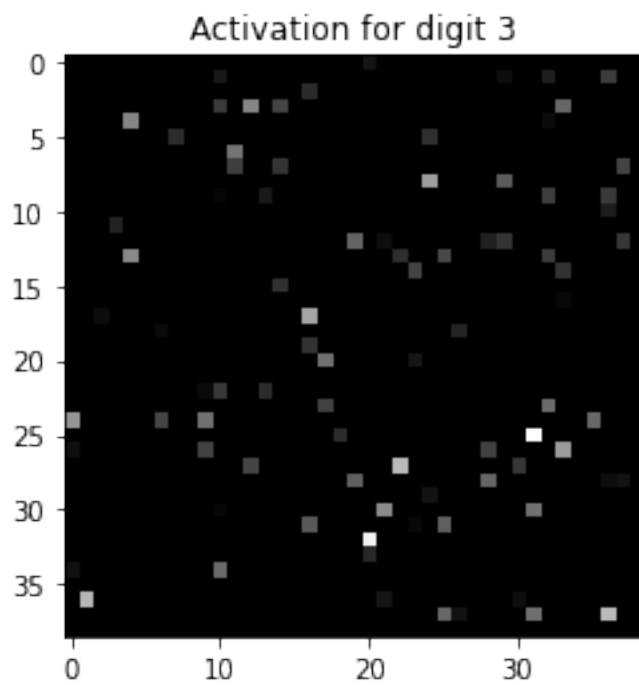
Decoder Filters for 0th neuron of Sparse AE with lambda value 0.0001

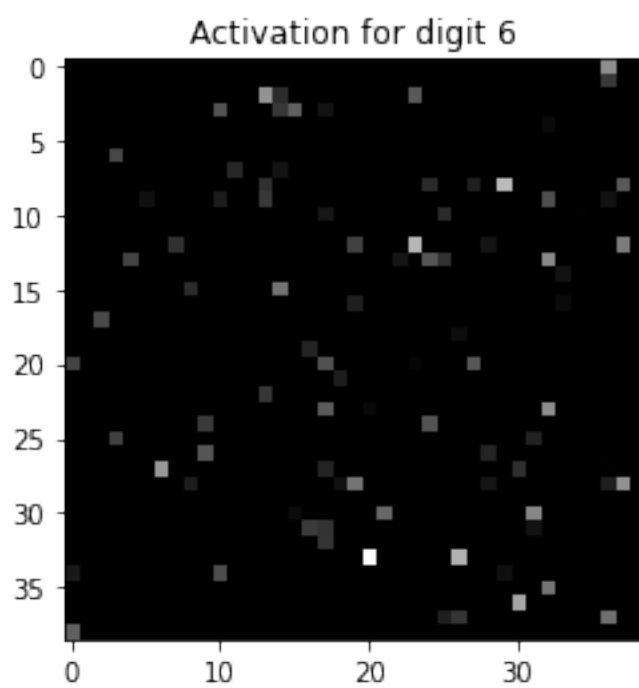
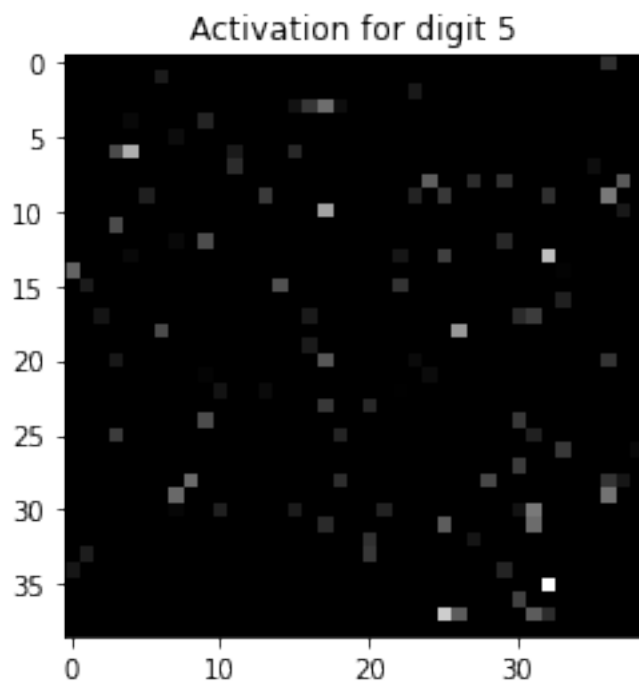


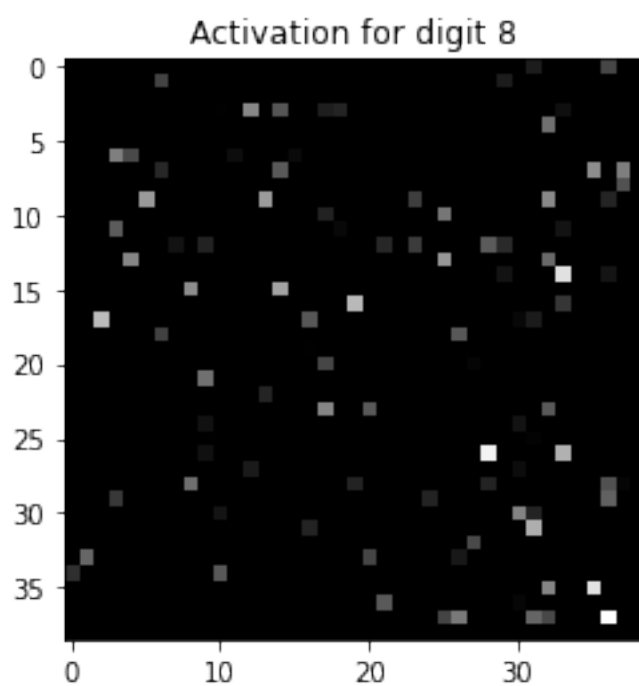
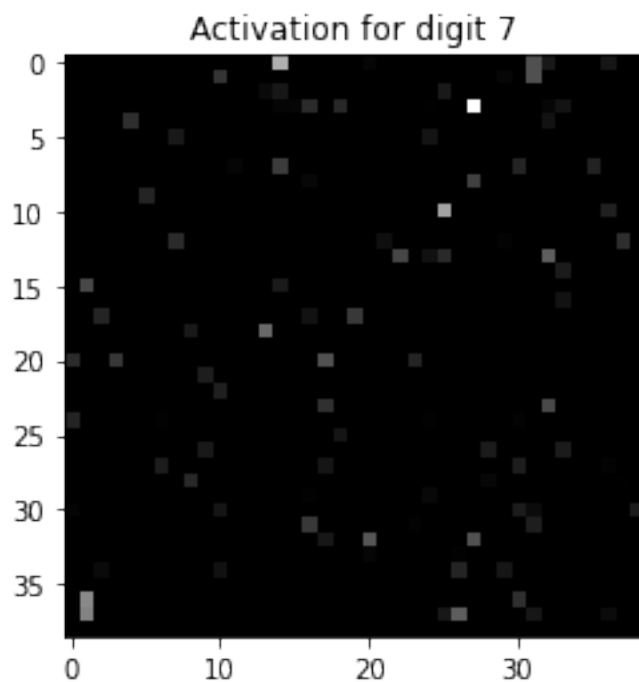
Activation for digit 0

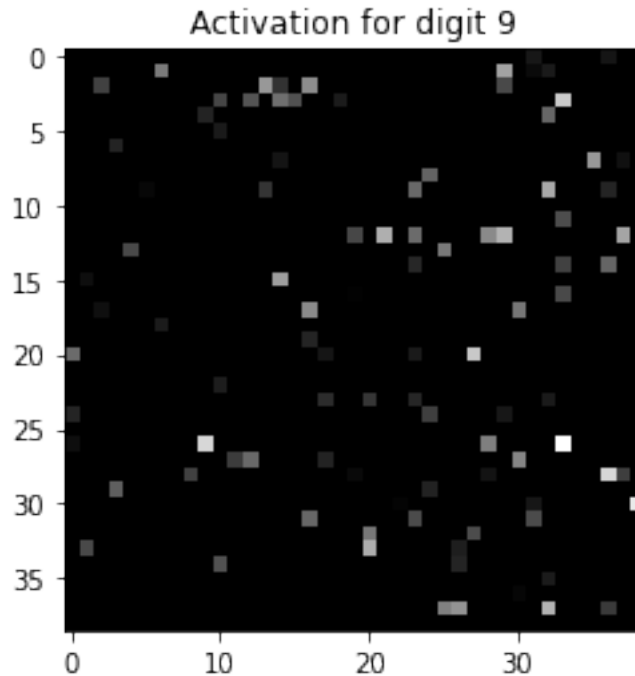












Training begins for regularization lambda value 0.001 !

Epoch Number: 1
Training loss: 0.03657766059041023
Validation loss: 0.02819947898387909

Epoch Number: 2
Training loss: 0.03130034729838371
Validation loss: 0.030439140275120735

Epoch Number: 3
Training loss: 0.03125472366809845
Validation loss: 0.027336187660694122

Epoch Number: 4
Training loss: 0.026766687631607056
Validation loss: 0.02722999081015587

Epoch Number: 5
Training loss: 0.023902306333184242
Validation loss: 0.0263354554772377

Epoch Number: 6

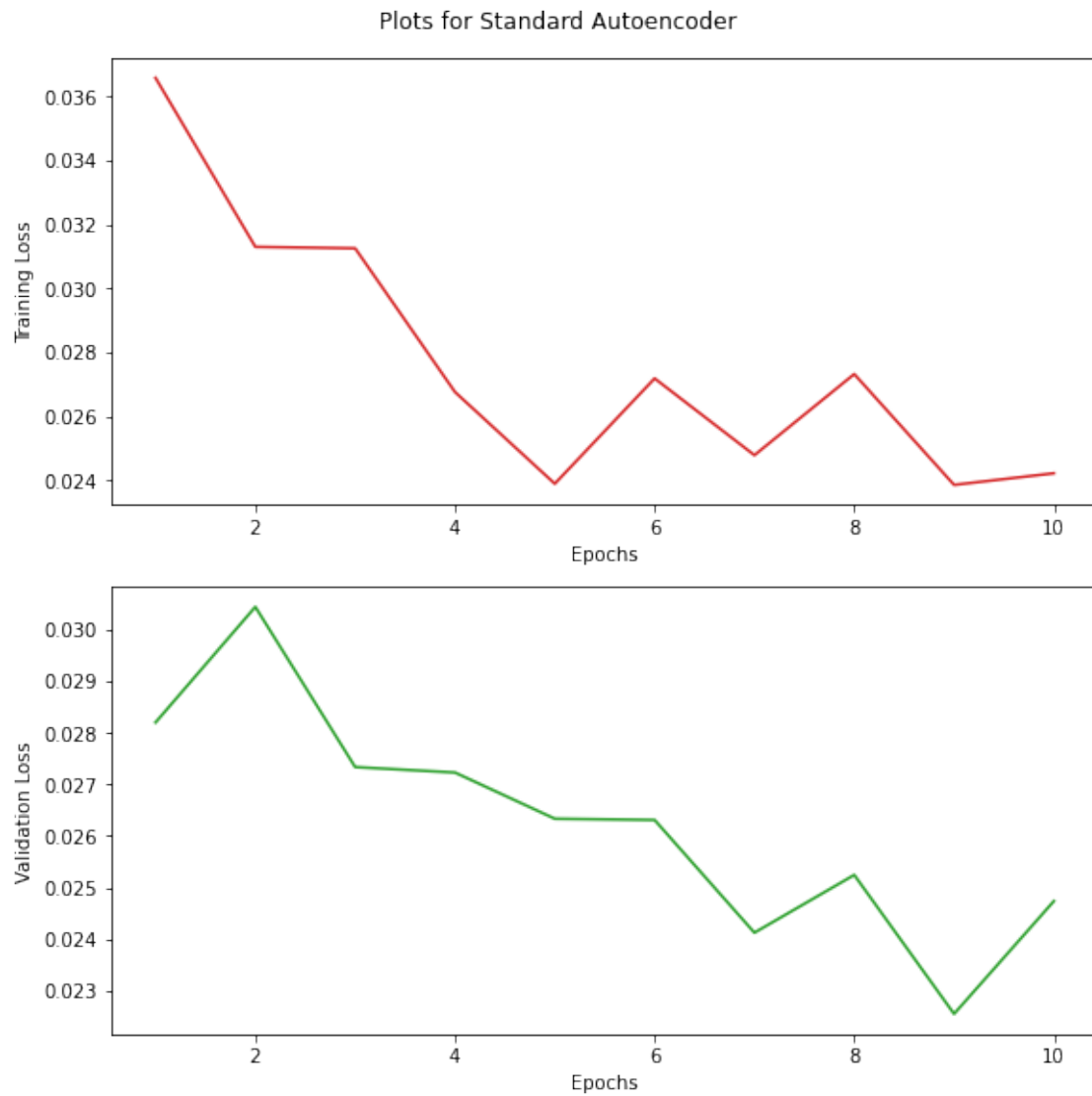
Training loss: 0.02719135954976082
Validation loss: 0.026311347261071205

Epoch Number: 7
Training loss: 0.02479413151741028
Validation loss: 0.024127982556819916

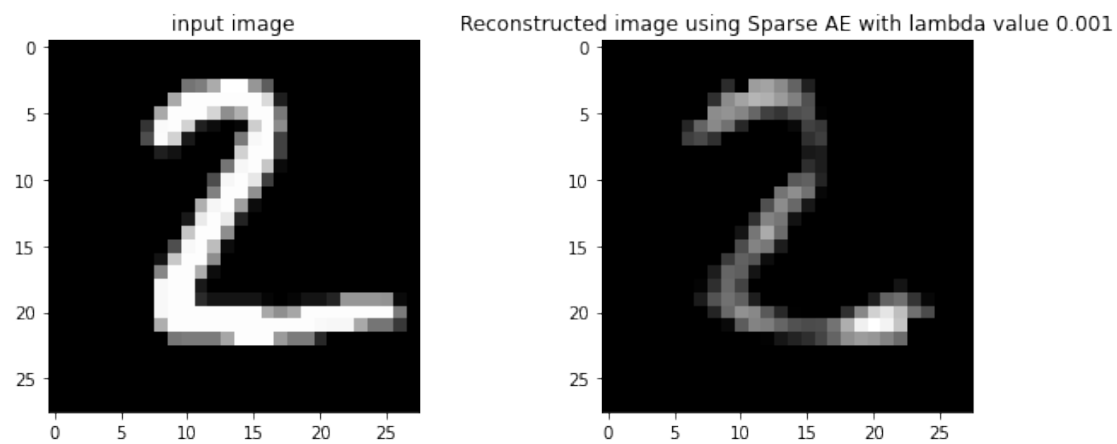
Epoch Number: 8
Training loss: 0.027327170595526695
Validation loss: 0.02524668537080288

Epoch Number: 9
Training loss: 0.023866549134254456
Validation loss: 0.022555096074938774

Epoch Number: 10
Training loss: 0.024228475987911224
Validation loss: 0.024739695712924004

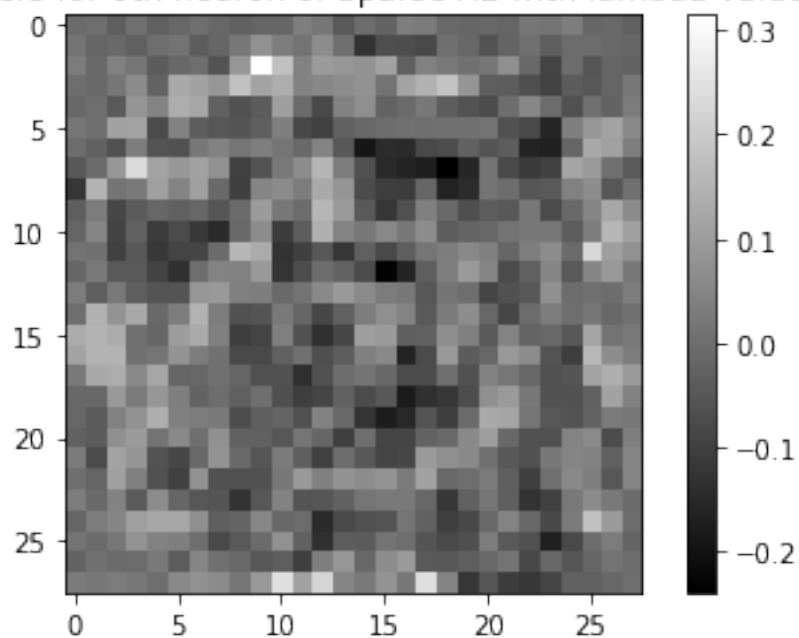


Training done for regularization lambda value 0.001 !

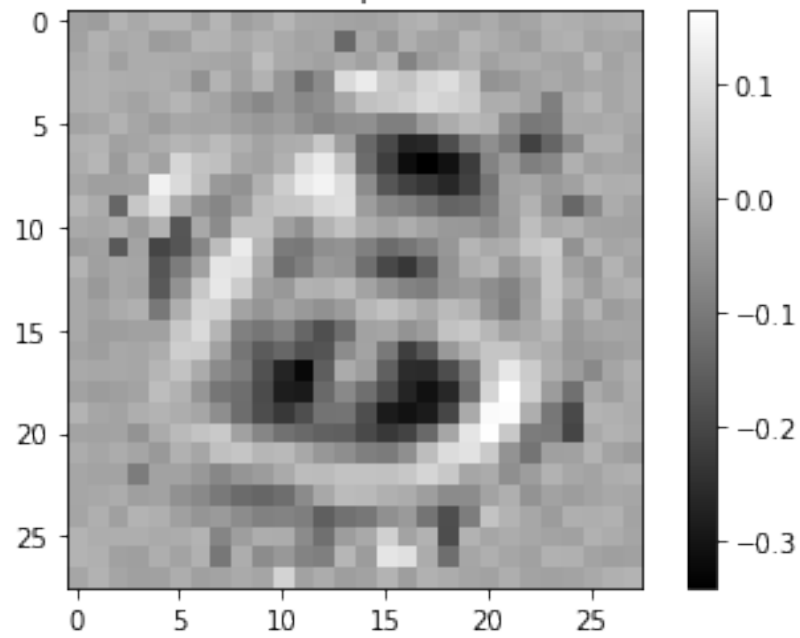


The average activation of Sparse AE with lambda value 0.001 is
0.005339490537454558

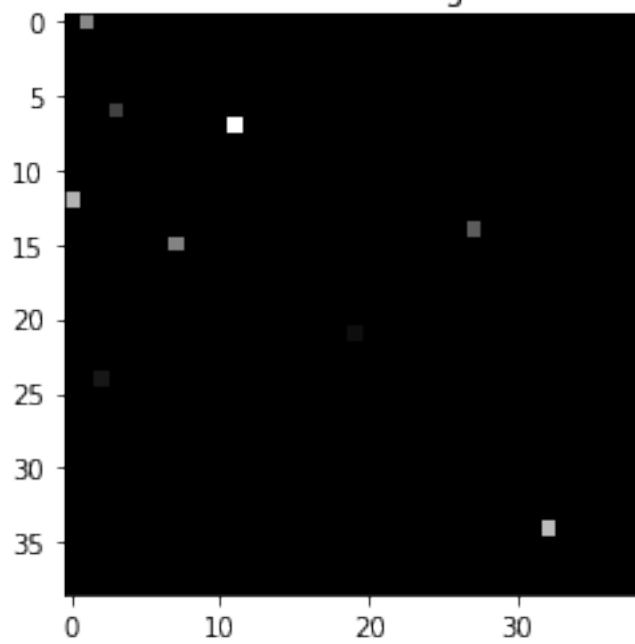
Encoder Filters for 0th neuron of Sparse AE with lambda value 0.001

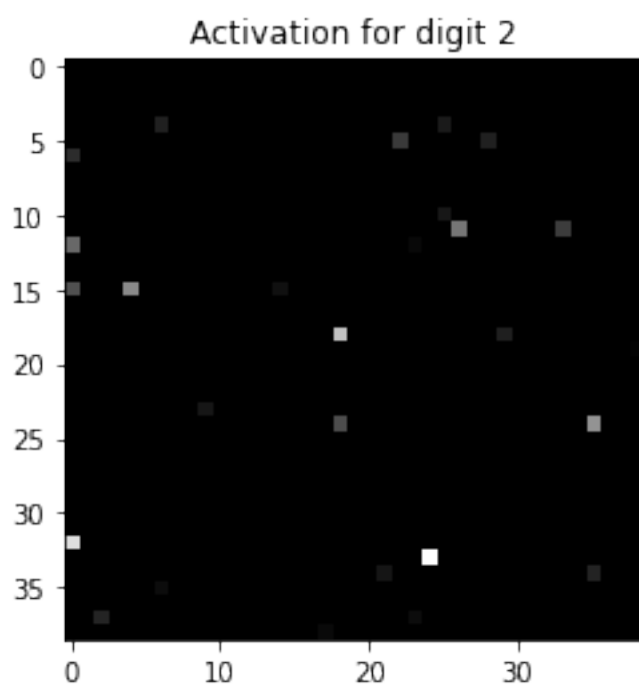
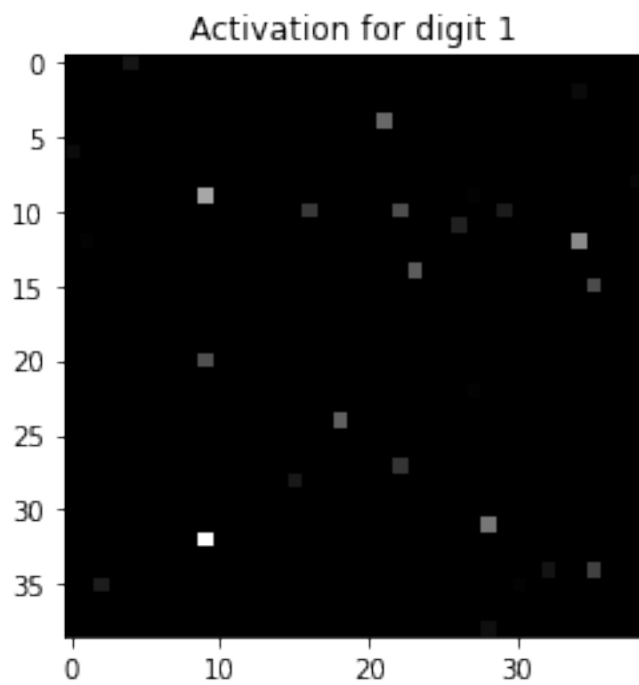


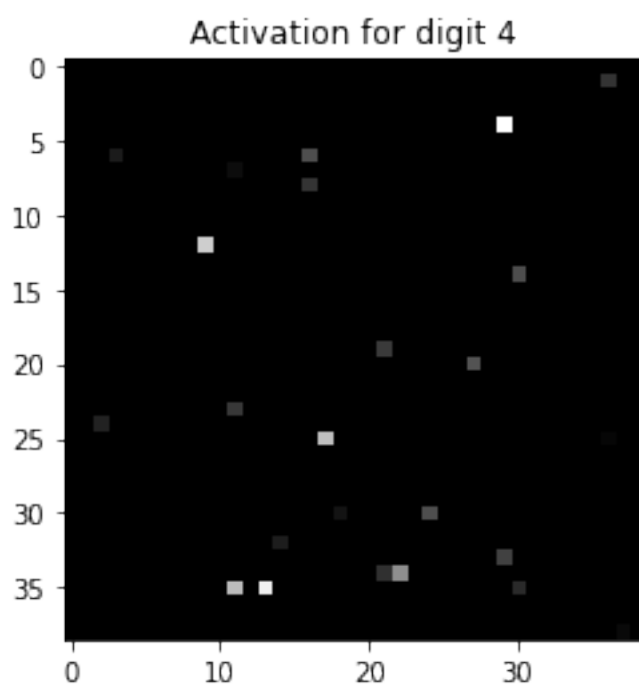
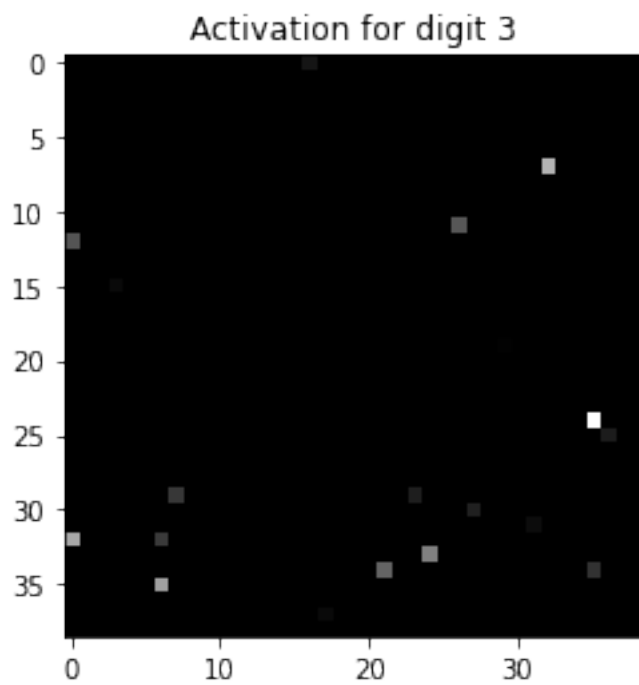
Decoder Filters for 0th neuron of Sparse AE with lambda value 0.001

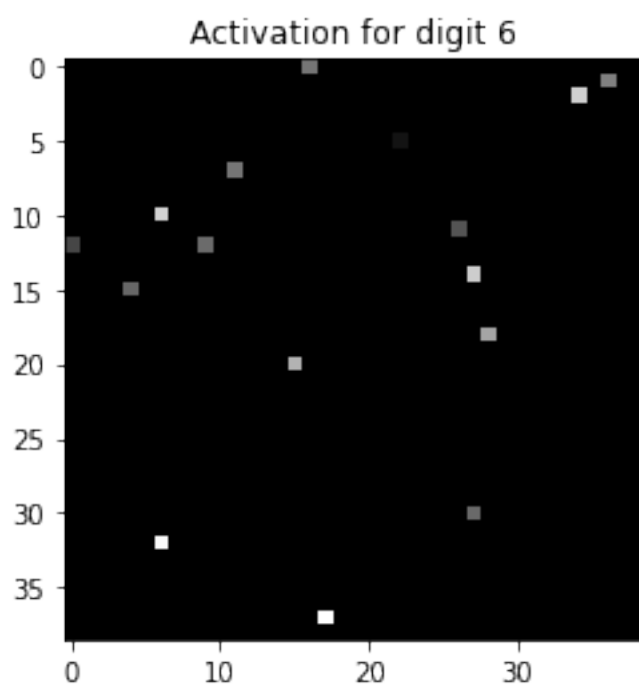
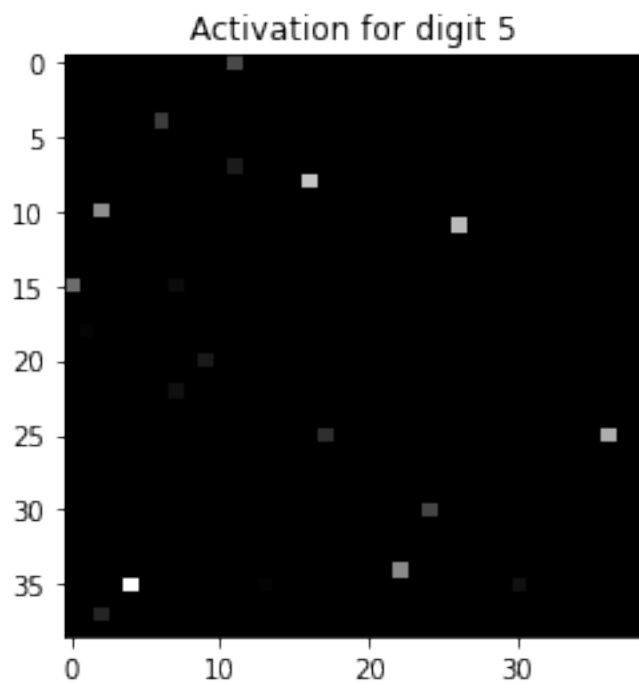


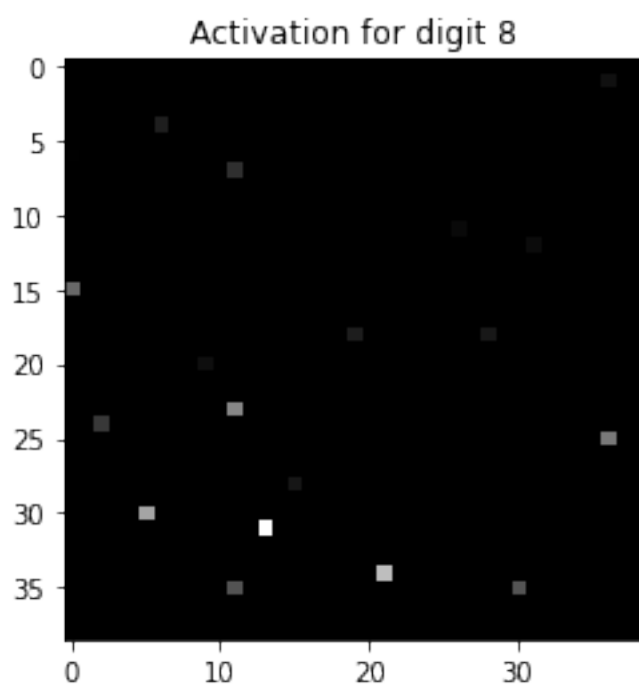
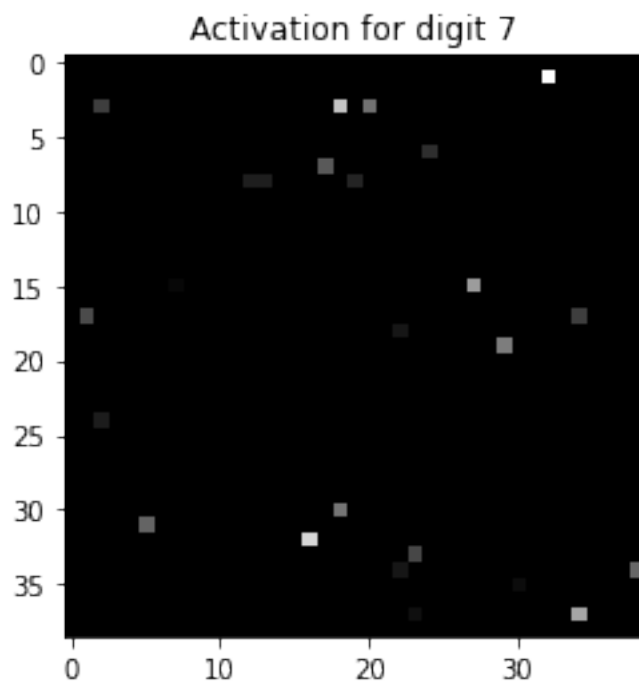
Activation for digit 0

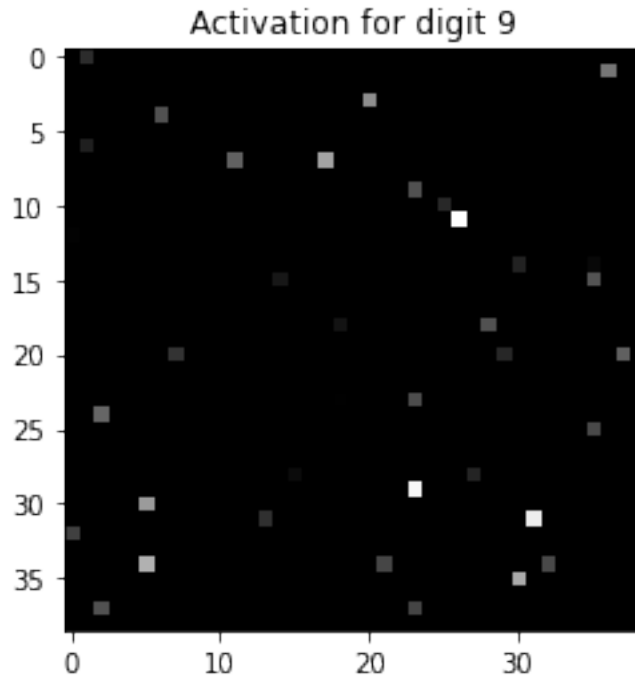












Training begins for regularization lambda value 0.005 !

Epoch Number: 1
Training loss: 0.14927056431770325
Validation loss: 0.09885752201080322

Epoch Number: 2
Training loss: 0.05682261288166046
Validation loss: 0.06706684827804565

Epoch Number: 3
Training loss: 0.05783994868397713
Validation loss: 0.0616452656686306

Epoch Number: 4
Training loss: 0.04894670844078064
Validation loss: 0.05445782095193863

Epoch Number: 5
Training loss: 0.0468580424785614
Validation loss: 0.053544532507658005

Epoch Number: 6

Training loss: 0.056293077766895294
Validation loss: 0.056057292968034744

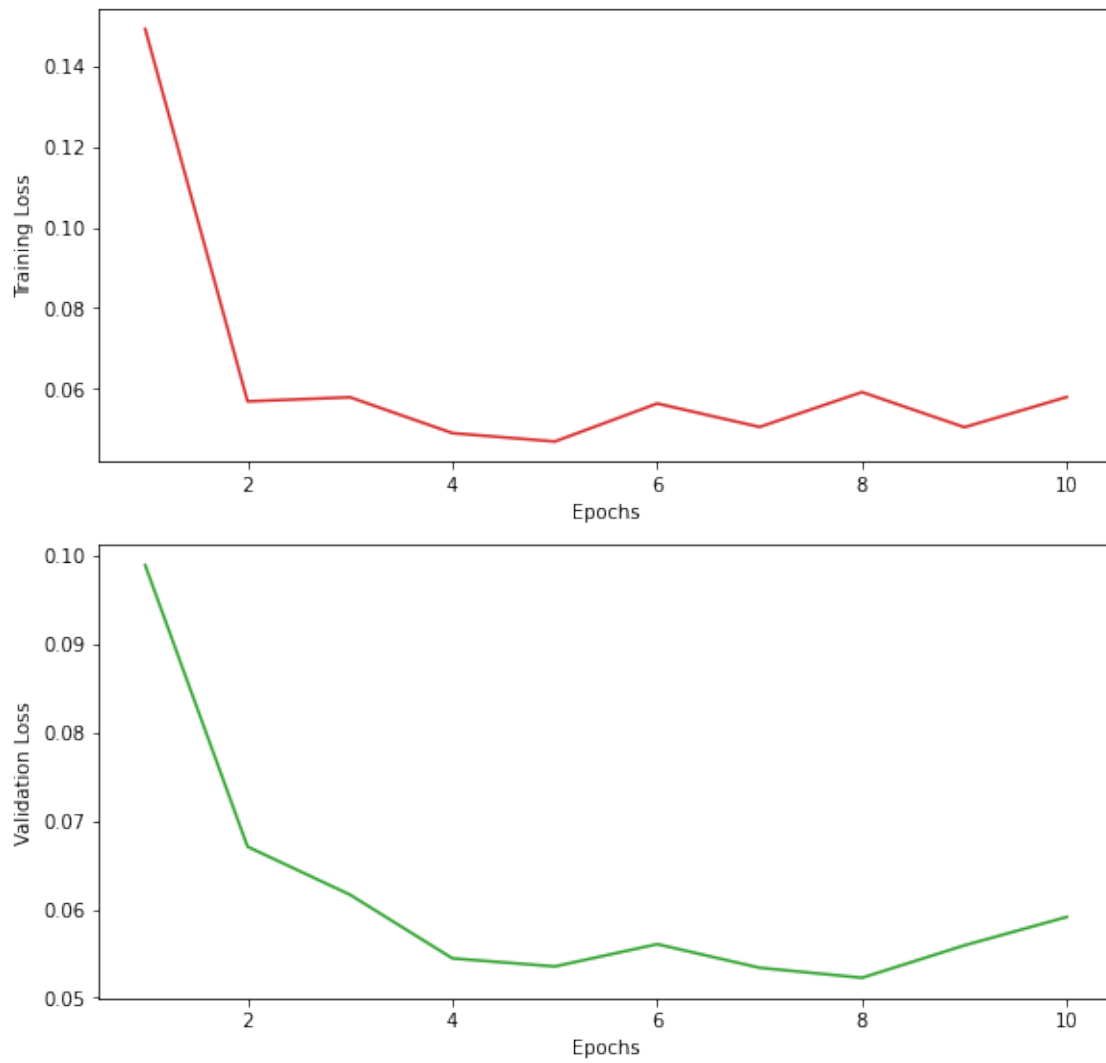
Epoch Number: 7
Training loss: 0.05046890303492546
Validation loss: 0.053395211696624756

Epoch Number: 8
Training loss: 0.05911600589752197
Validation loss: 0.05226348713040352

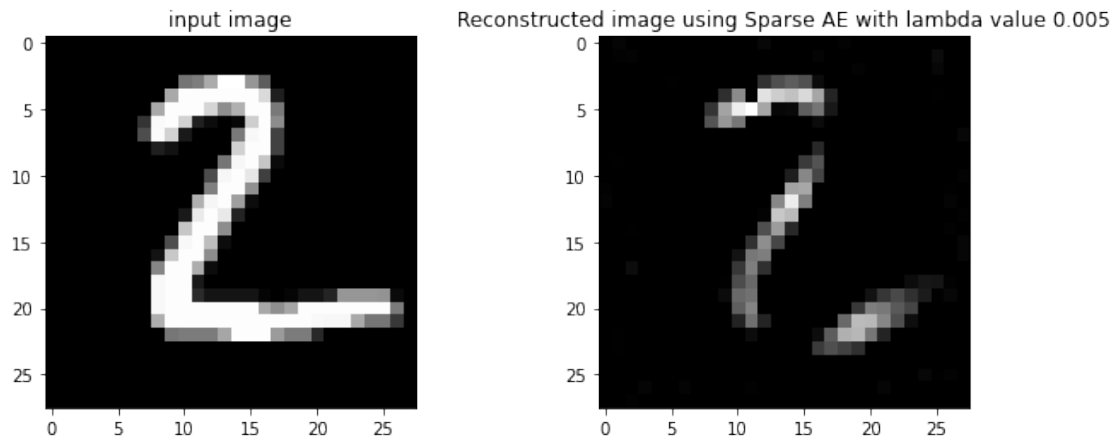
Epoch Number: 9
Training loss: 0.050400275737047195
Validation loss: 0.05592313036322594

Epoch Number: 10
Training loss: 0.05790144205093384
Validation loss: 0.05912882089614868

Plots for Standard Autoencoder

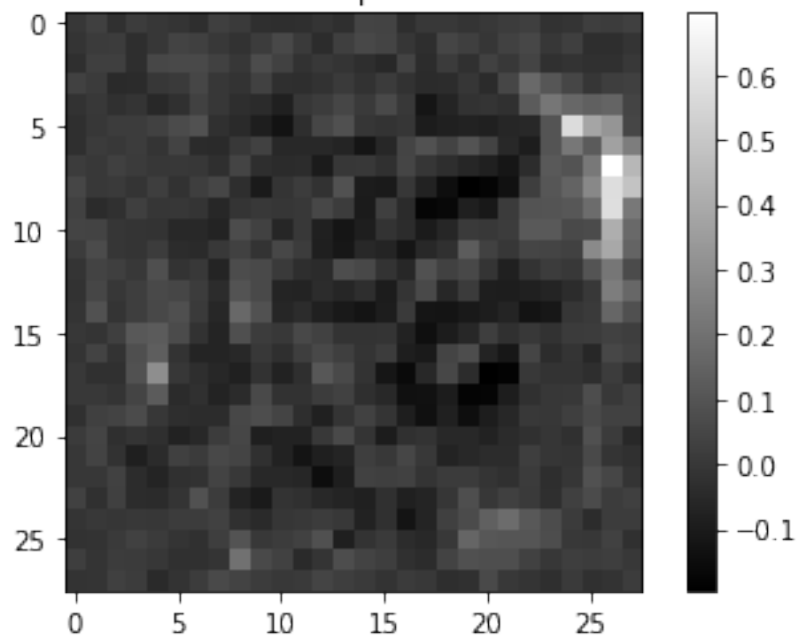


Training done for regularization lambda value 0.005 !

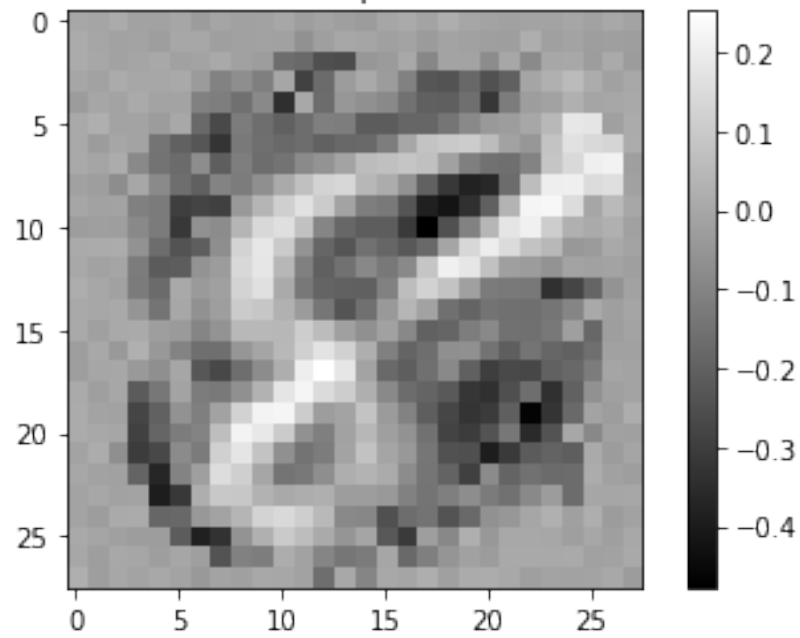


The average activation of Sparse AE with lambda value 0.005 is
0.0010910846091284874

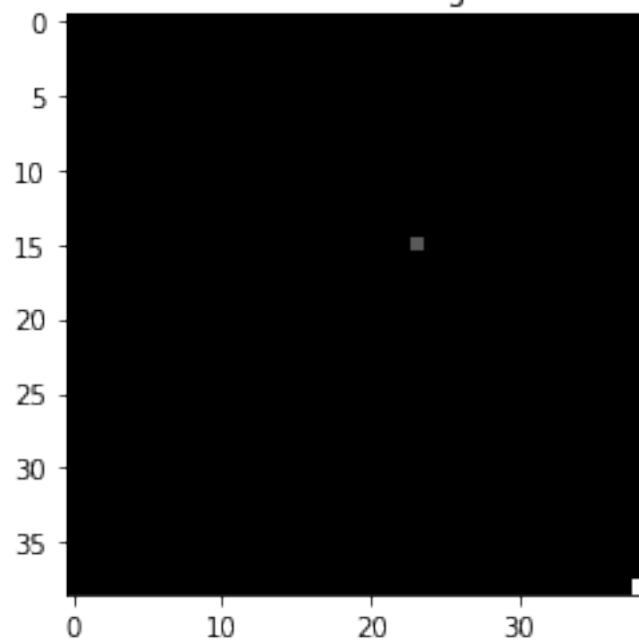
Encoder Filters for 0th neuron of Sparse AE with lambda value 0.005

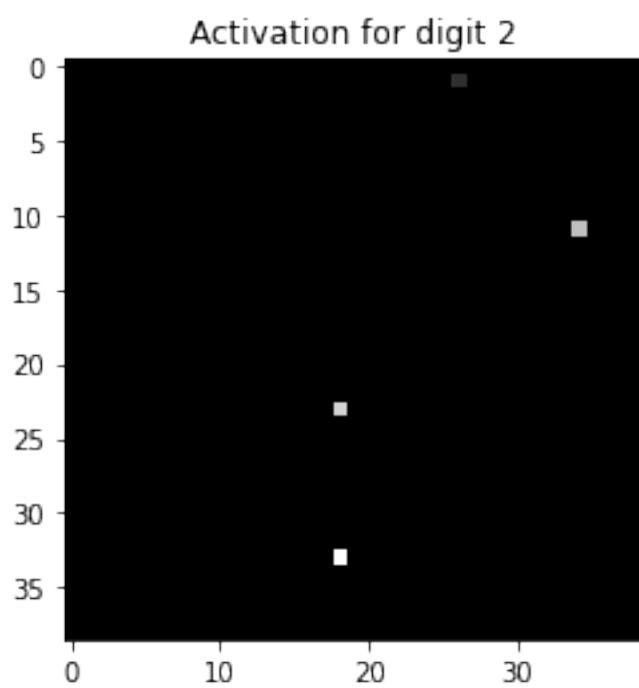
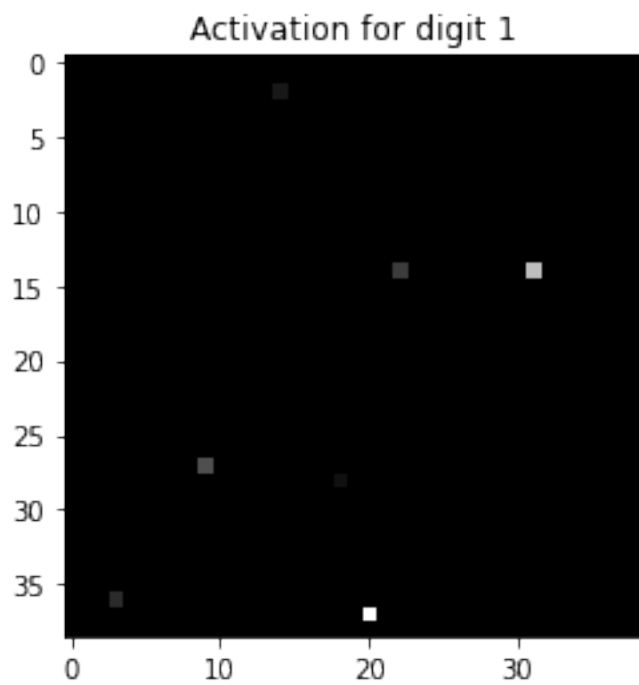


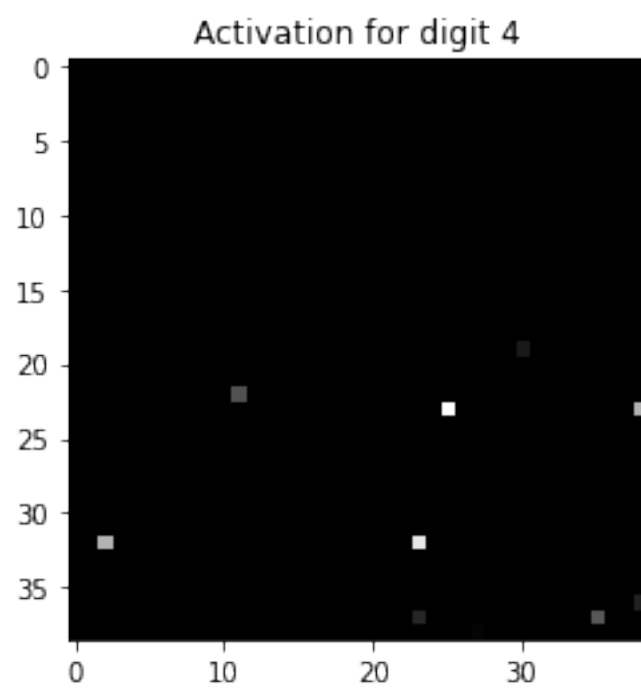
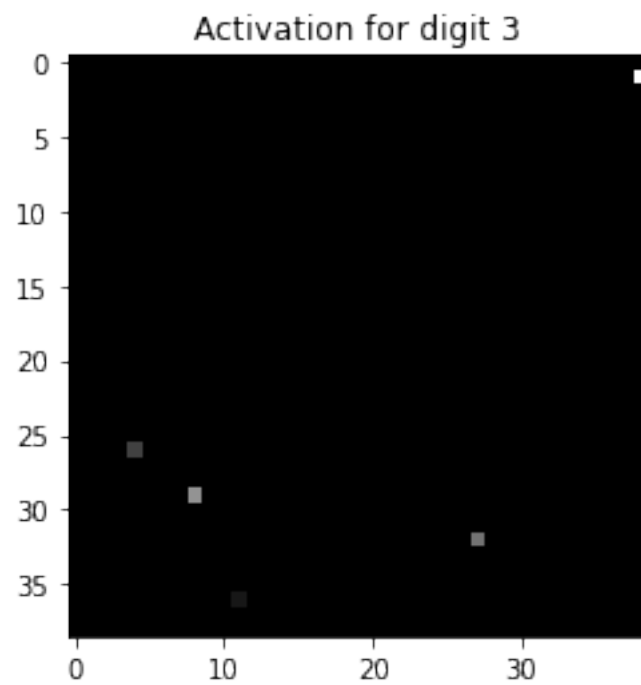
Decoder Filters for 0th neuron of Sparse AE with lambda value 0.005

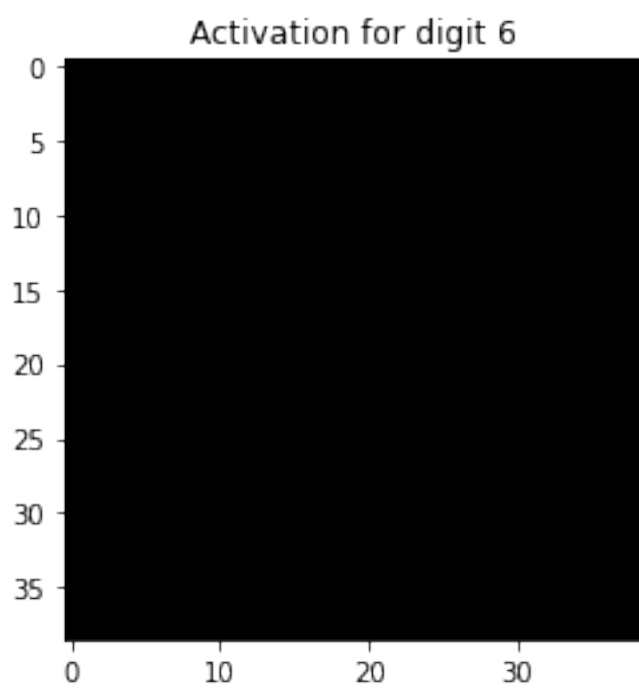
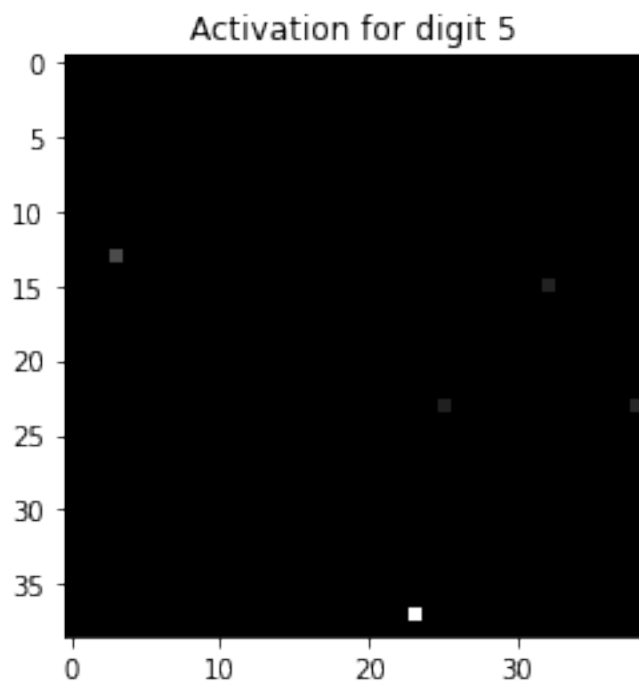


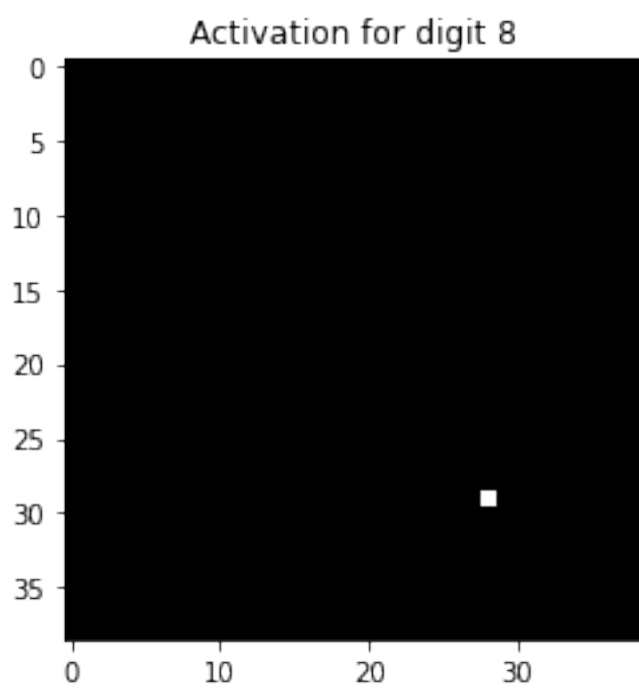
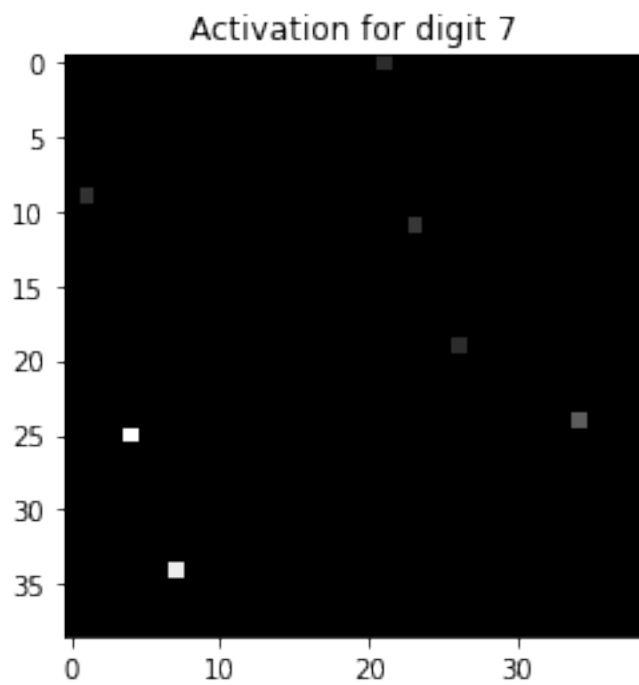
Activation for digit 0

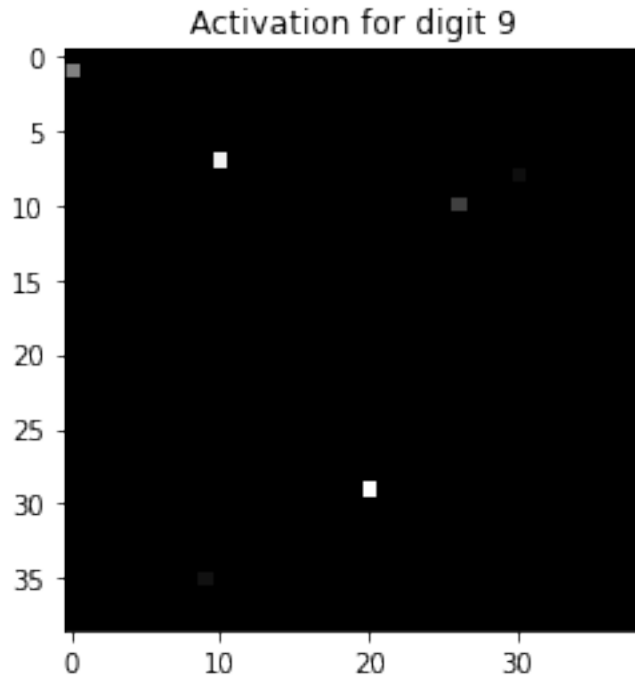












 Training begins for regularization lambda value 0.1 !

Epoch Number: 1
 Training loss: 2.71380352973938
 Validation loss: 1.5620596408843994

Epoch Number: 2
 Training loss: 0.14296624064445496
 Validation loss: 0.1392284780740738

Epoch Number: 3
 Training loss: 0.11376488953828812
 Validation loss: 0.1082632914185524

Epoch Number: 4
 Training loss: 0.07981755584478378
 Validation loss: 0.09571825712919235

Epoch Number: 5
 Training loss: 0.0655784159898758
 Validation loss: 0.07309792935848236

Epoch Number: 6

Training loss: 0.06599514186382294
Validation loss: 0.07321781665086746

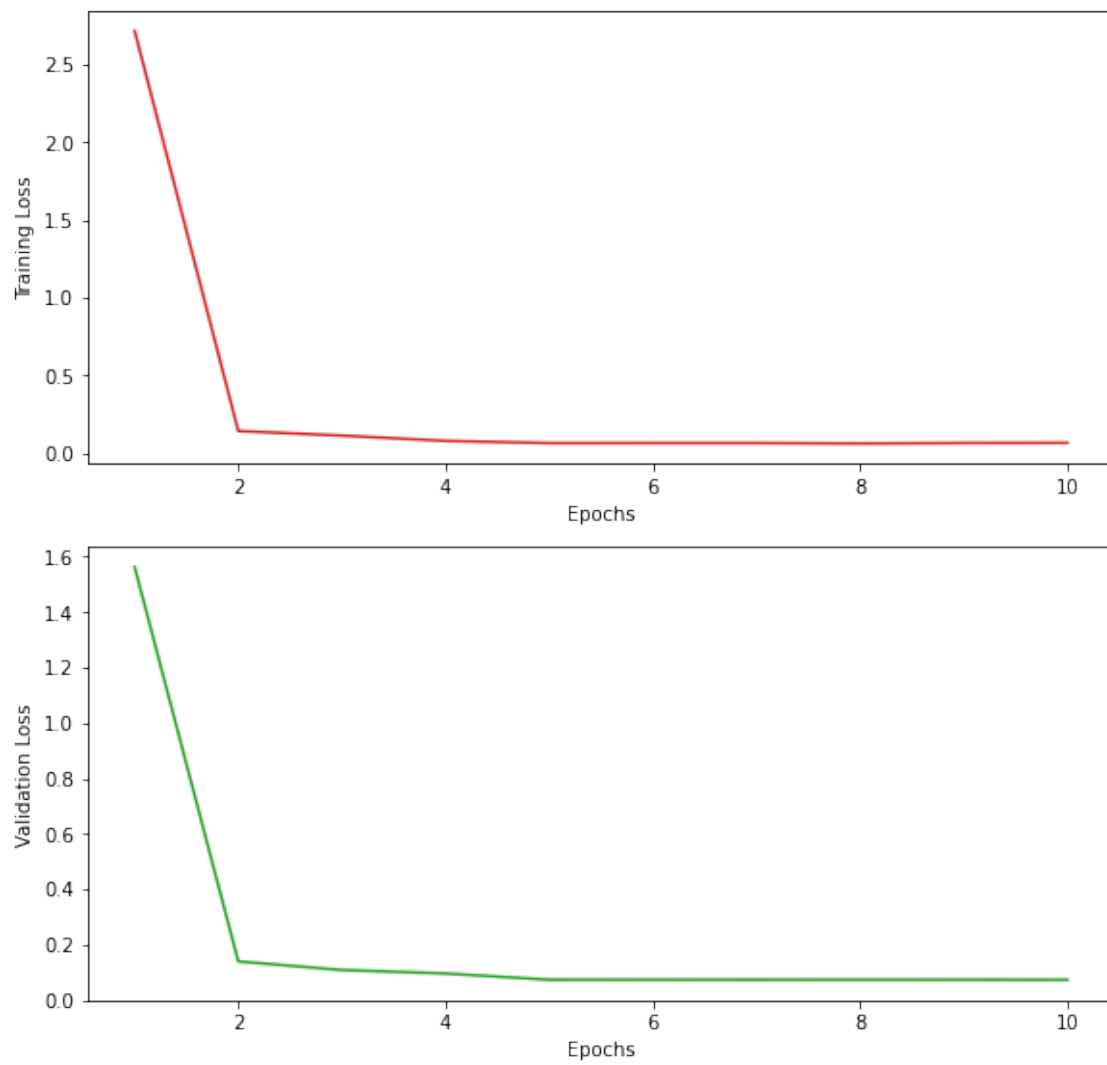
Epoch Number: 7
Training loss: 0.06614267081022263
Validation loss: 0.07310178875923157

Epoch Number: 8
Training loss: 0.06285998225212097
Validation loss: 0.07327315956354141

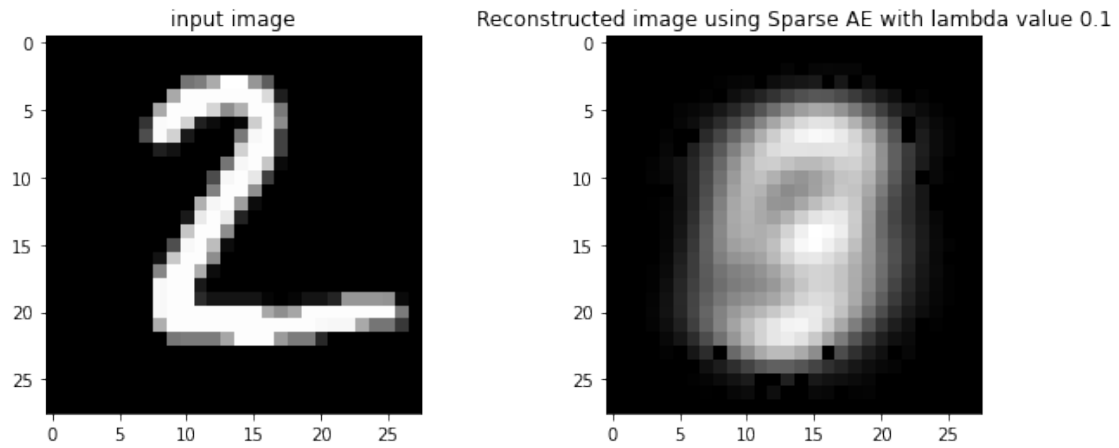
Epoch Number: 9
Training loss: 0.06616947799921036
Validation loss: 0.07315822690725327

Epoch Number: 10
Training loss: 0.06715003401041031
Validation loss: 0.07301023602485657

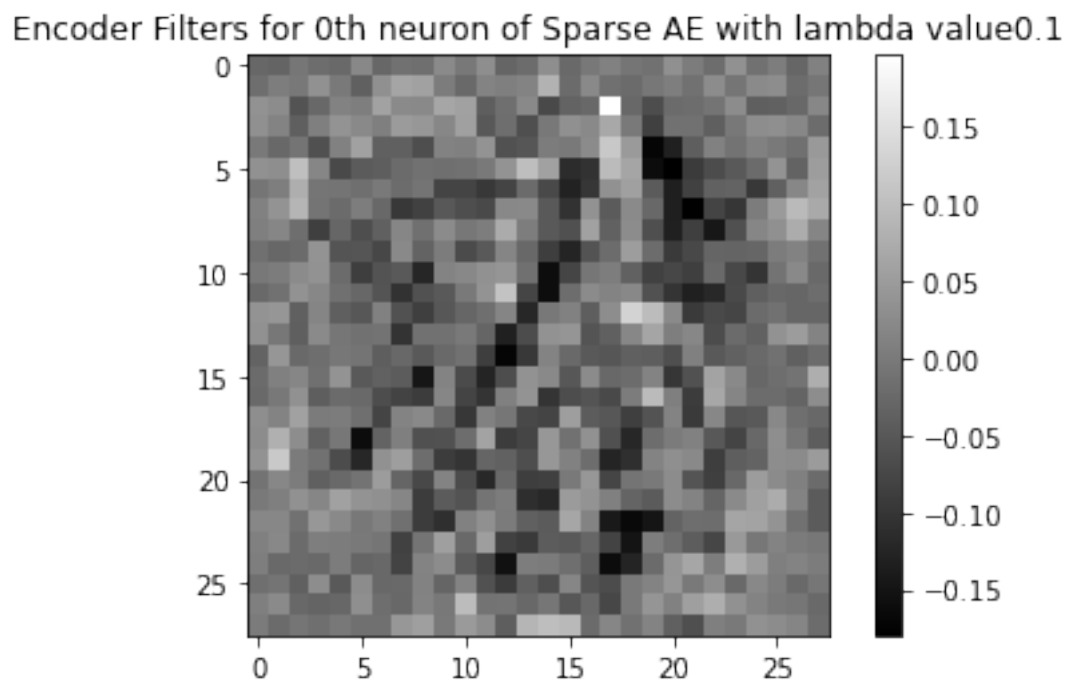
Plots for Standard Autoencoder



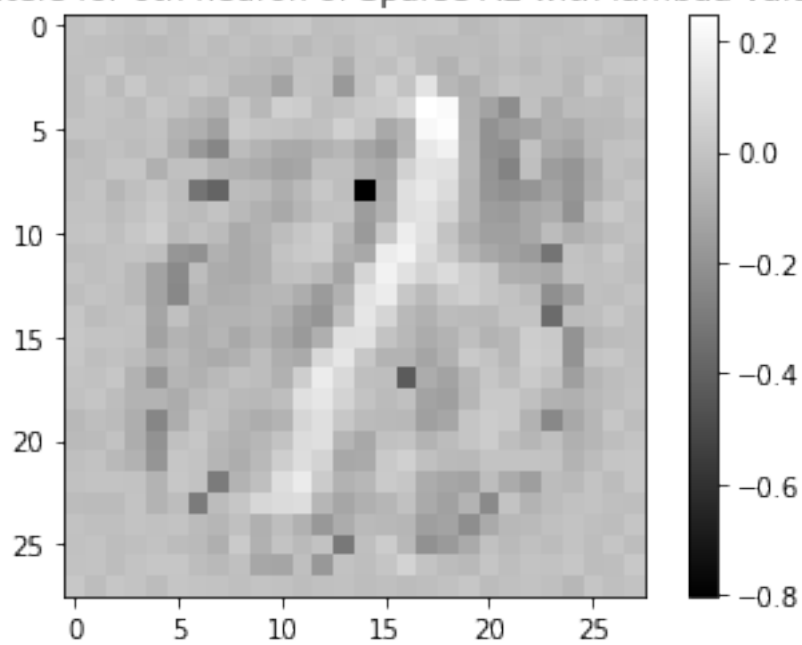
Training done for regularization lambda value 0.1 !



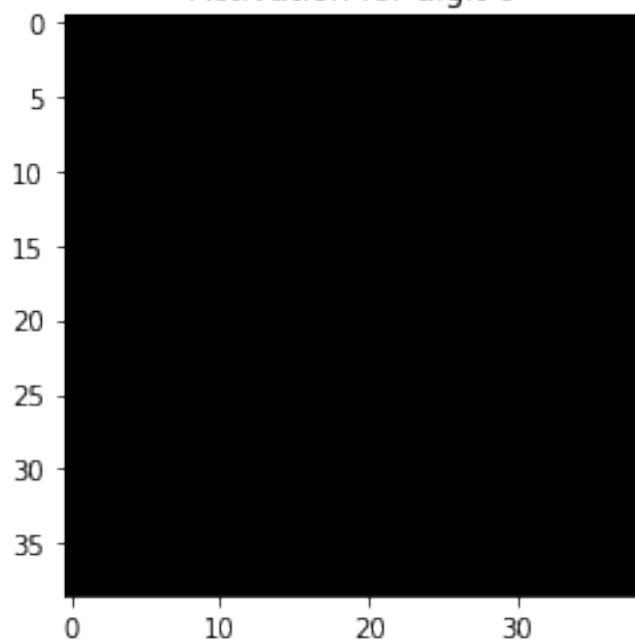
The average activation of Sparse AE with lambda value 0.1 is
4.6114608687622034e-07

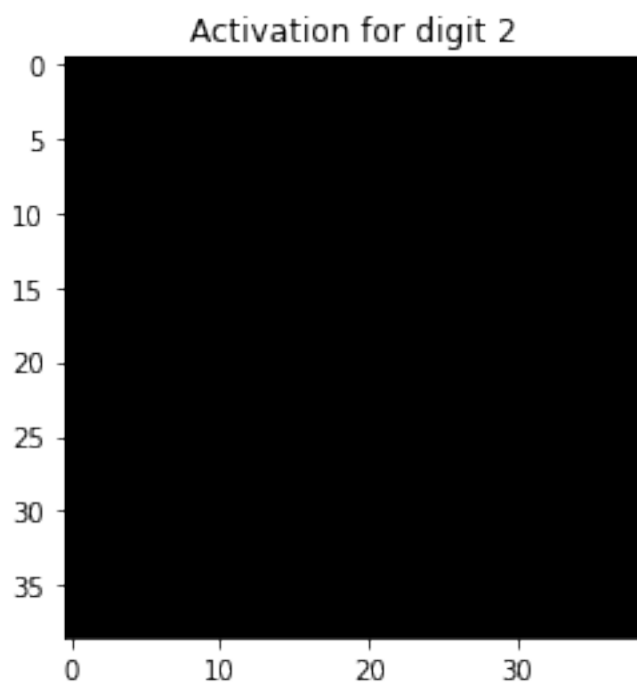
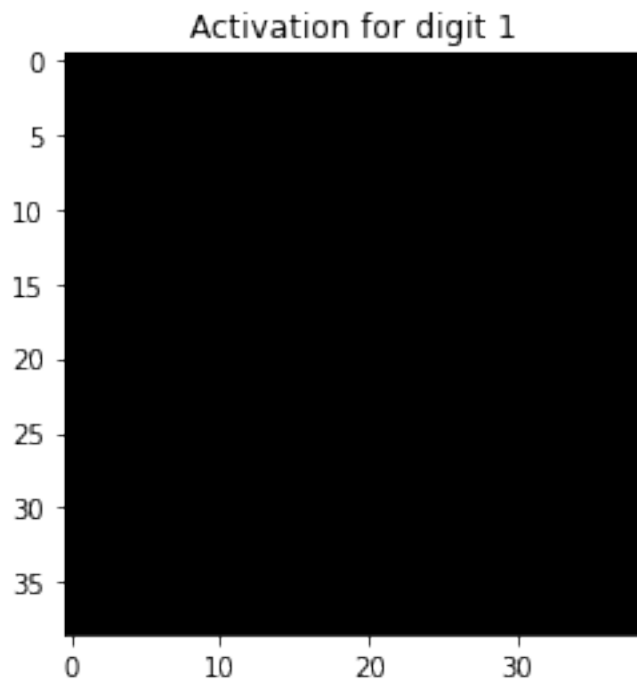


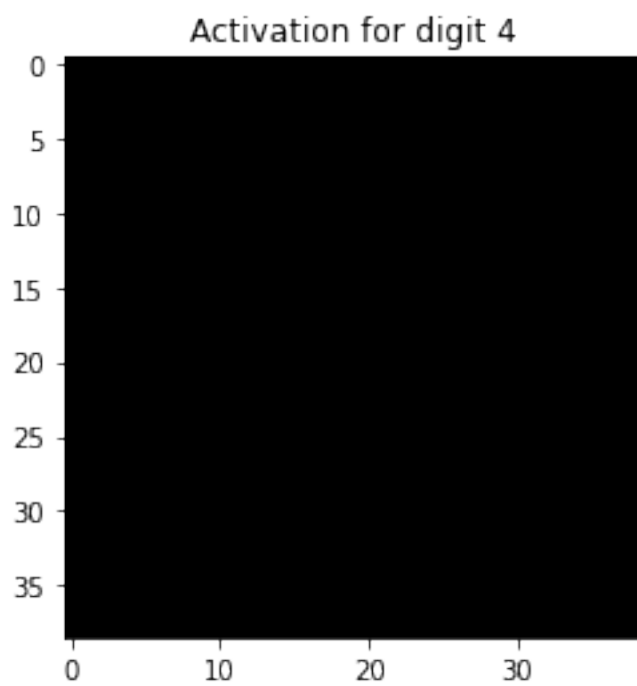
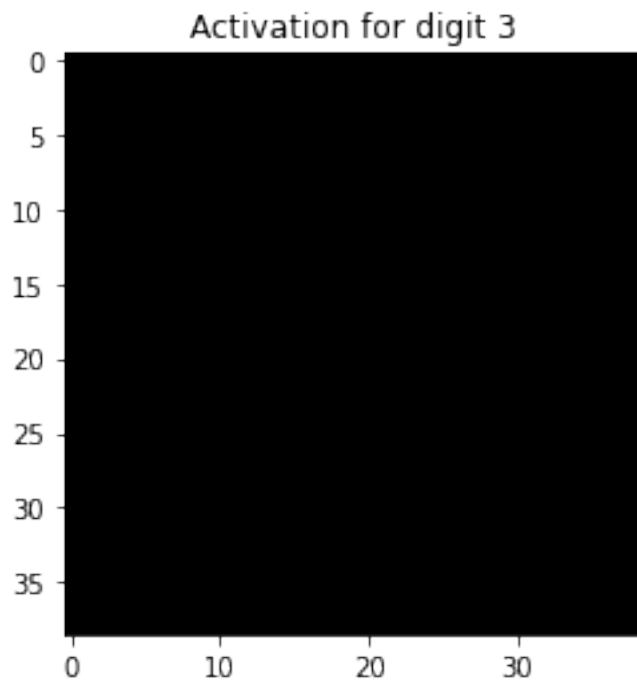
Decoder Filters for 0th neuron of Sparse AE with lambda value 0.1

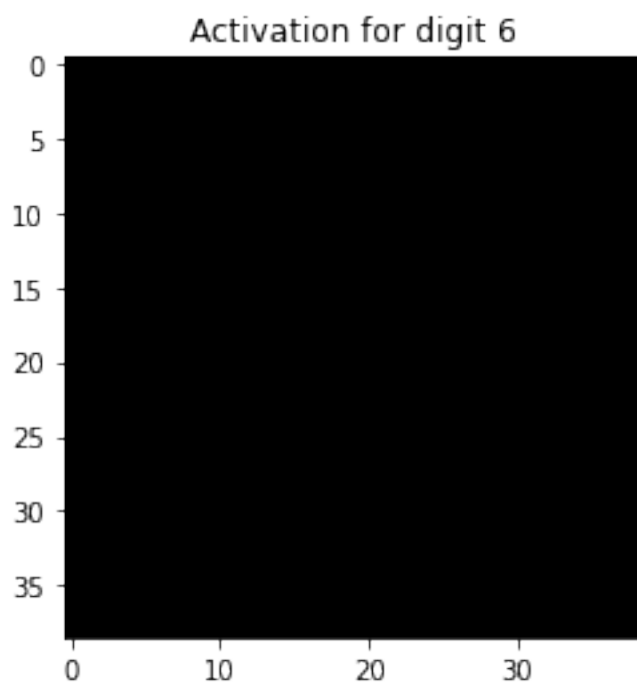
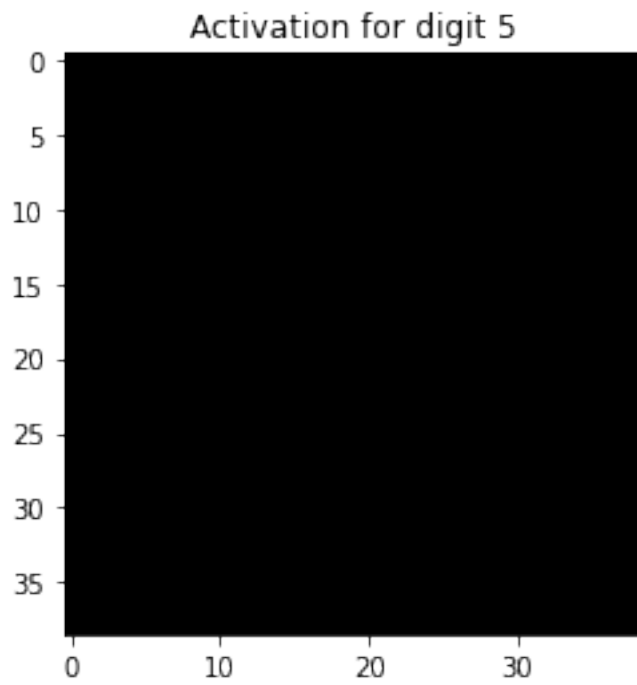


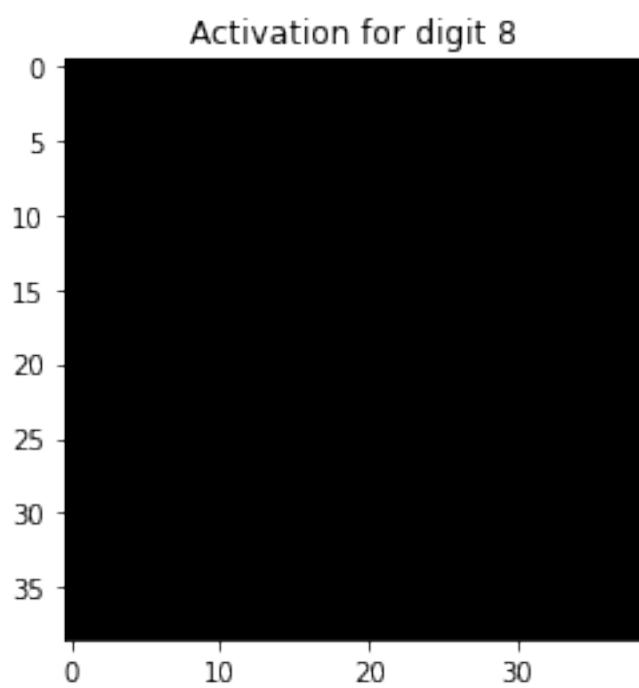
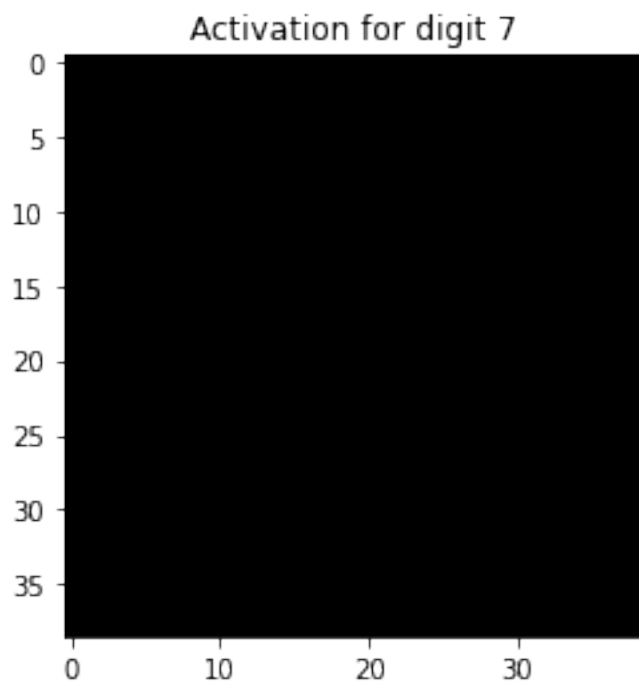
Activation for digit 0

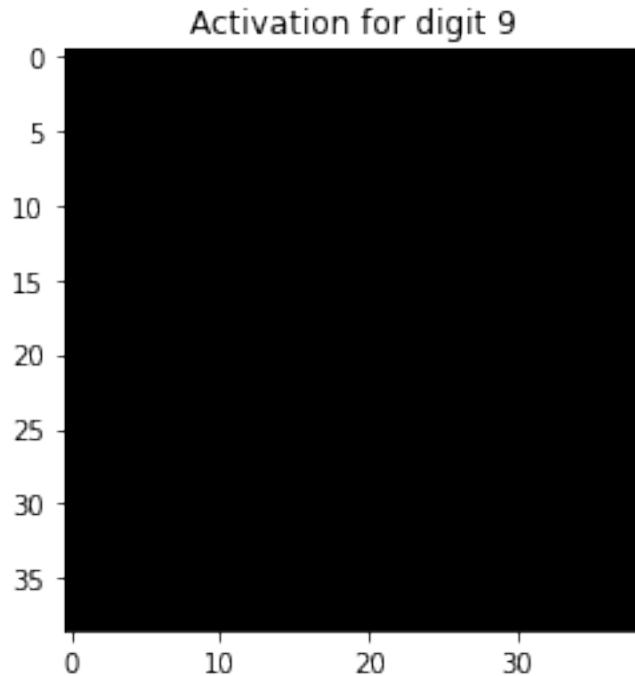












Observations

- For different sparsity values, it can be noted that for higher sparsity values the reconstruction is recognizable but not perfect in the sense that the strokes of digits are not continuous. However, for lower sparsity values, the reconstruction includes more pixels as part of the reconstructions making it more noisy.
- This can also be interpreted using the activation filters shown above, as the sparsity value is increased, the activation for each digit also becomes sparse.
- For the highest sparsity value (`lambda` value) chosen, it can be noticed that the activation for any digit is almost blank, it also reflects in the reconstructed image as it does not resemble the chosen digit at all.

4 Denoising Autoencoders

4.1 Experimentation with different noise values

```
[21]: noise_values = [0.3, 0.5, 0.8, 0.9]

for noise_val in noise_values:
    model_denoiseAE = standard_AE(256).to(device)
    optimizer = torch.optim.Adam(model_denoiseAE.parameters(), learning_rate)
```



```

train_batch_loss = []
train_epoch_loss = []
val_loss = []
print('Training begins for noise value ', noise_val, '!')
print('-----')
for epoch in range(epochs):
    for batch_idx, (data, target) in enumerate(train_loader):

        noise = torch.randn(data.size())*noise_val
        data = data + noise
        data = data.to(device=device)
        target = target.to(device=device)

        model_denoiseAE.train()
        decoded, encoded = model_denoiseAE(data)
        loss = criterion(decoded, torch.flatten(data,1))
        train_batch_loss.append(loss.item())

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    train_epoch_loss.append(train_batch_loss[-1])

    model_denoiseAE.eval()
    with torch.no_grad():
        for (data, target) in test_loader:
            noise = torch.randn(data.size())*noise_val
            data = data + noise
            data = data.to(device=device)
            target = target.to(device)
            decoded, encoded = model_denoiseAE(data)
            val_iter_loss = criterion(decoded, torch.flatten(data,1))

    val_loss.append(val_iter_loss.item())
    print('Epoch Number: ', epoch+1)
    print('Training loss: ', train_epoch_loss[-1])
    print('Validation loss: ', val_loss[-1])
    print('-----')

fig, axs = plt.subplots(2, constrained_layout= True, figsize=(8,8))
fig.suptitle('Plots for Standard Autoencoder')
axs[0].set(ylabel='Training Loss', xlabel='Epochs')
axs[0].plot(range(1, epochs+1), train_epoch_loss, 'tab:red')
axs[1].set(ylabel='Validation Loss', xlabel='Epochs')

```

```

axs[1].plot(range(1,epochs+1),val_loss, 'tab:green')
plt.show()
print('Training done for denoising AE with noise value',noise_val,'!')
print('-----')
test_image = test_loader.dataset.data[5, :, :].clone() #RANDOM TEST IMAGE
noise = torch.randn(test_image.size())*noise_val
image = test_image + noise
with torch.no_grad():
    image = image.view(-1,28,28).to(device=device).float()
    decoded, encoded = model_denoiseAE.forward(image)
    decoded = decoded.detach().cpu().numpy()
    image = image.reshape(28,28).detach().cpu().numpy()
    plt.subplot(1,2,1)
    plt.imshow(image , cmap='gray')
    plt.title('input image')
    plt.subplots_adjust(right=1.5)
    plt.subplot(1,2,2)
    plt.imshow(decoded.reshape(28,28),cmap = 'gray')
    plt.title("Reconstructed image using Denoising AE with noise value_
↪"+str(noise_val))
    plt.show()
    encoder_decoder_filters_plots( model_denoiseAE,"Denoising AE with noise_
↪value"+str(noise_val),device)
print('-----')
print('-----')

```

Training begins for noise value 0.3 !

```

-----
Epoch Number: 1
Training loss: 0.07919100672006607
Validation loss: 0.07763116806745529
-----
Epoch Number: 2
Training loss: 0.07891659438610077
Validation loss: 0.07751056551933289
-----
Epoch Number: 3
Training loss: 0.07668483257293701
Validation loss: 0.07605963945388794
-----
Epoch Number: 4
Training loss: 0.07608699053525925
Validation loss: 0.0766594409942627
-----
Epoch Number: 5
Training loss: 0.07629714161157608
Validation loss: 0.07491587102413177

```

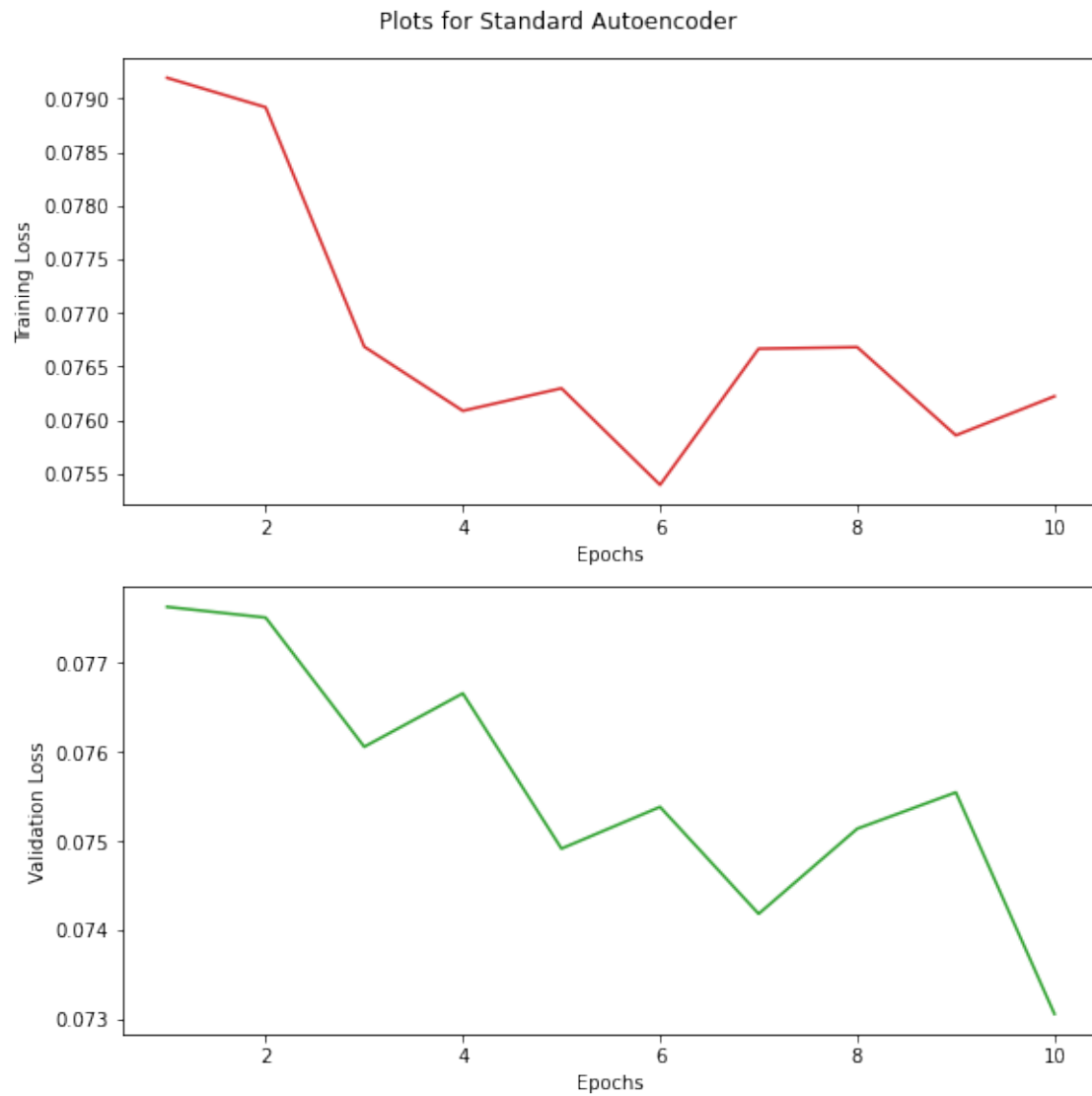
Epoch Number: 6
Training loss: 0.07539673149585724
Validation loss: 0.0753844678401947

Epoch Number: 7
Training loss: 0.07666618376970291
Validation loss: 0.07418350130319595

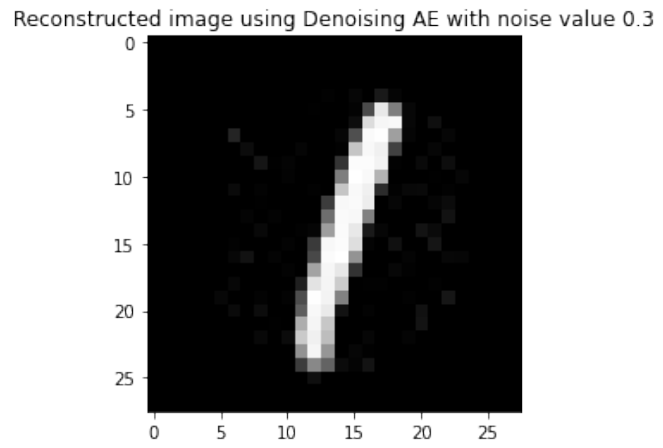
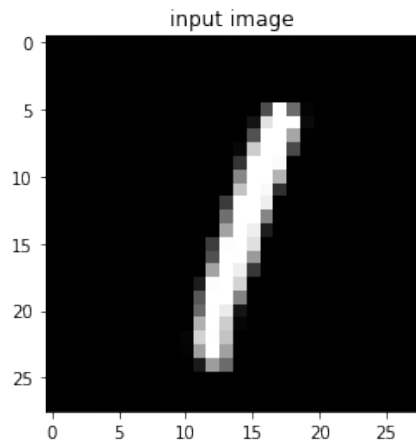
Epoch Number: 8
Training loss: 0.07668063789606094
Validation loss: 0.0751395970582962

Epoch Number: 9
Training loss: 0.07585837692022324
Validation loss: 0.07554743438959122

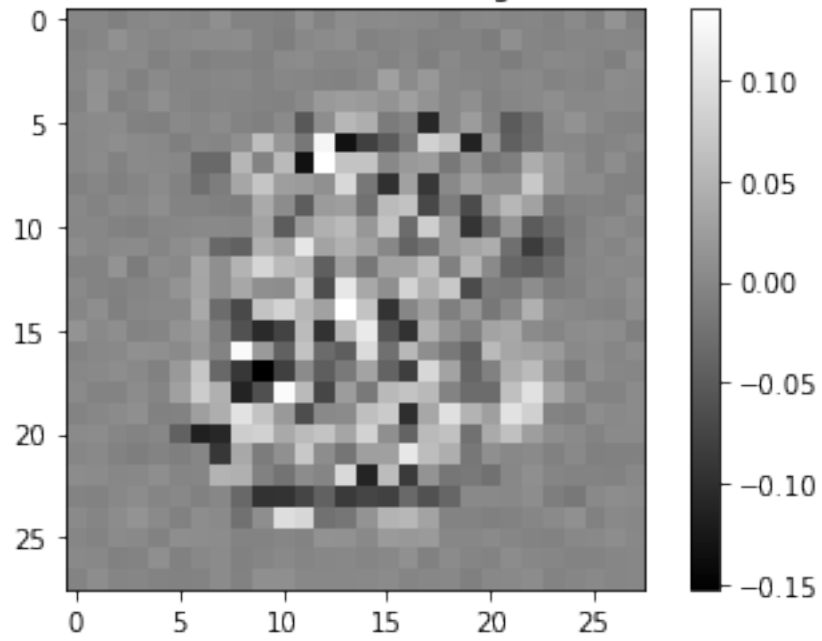
Epoch Number: 10
Training loss: 0.07622240483760834
Validation loss: 0.07305971533060074



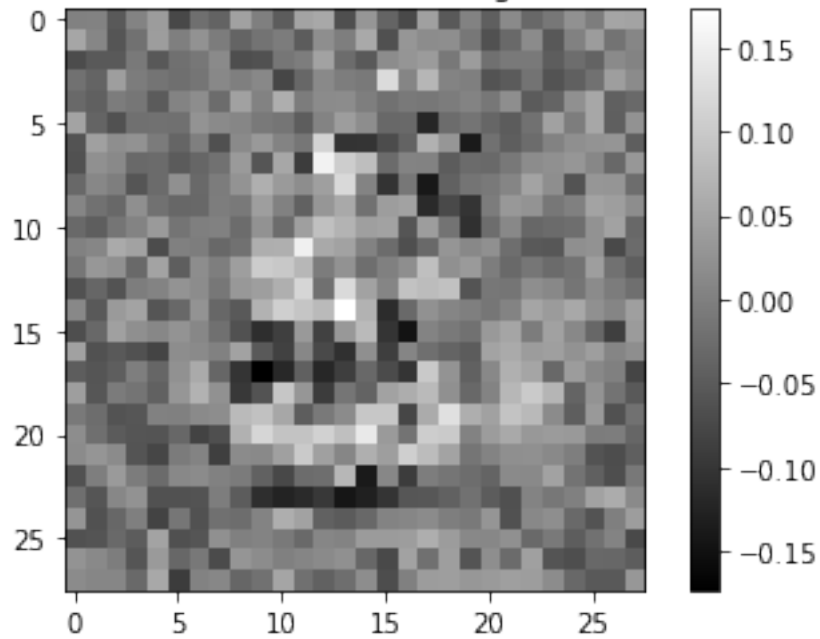
Training done for denoising AE with noise value 0.3 !



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



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



```
-----
-----
Training begins for noise value  0.5 !
-----
```

```
Epoch Number:  1
Training loss:  0.2066396325826645
Validation loss: 0.20023320615291595
-----
```

```
Epoch Number:  2
Training loss:  0.19966499507427216
Validation loss: 0.19900991022586823
-----
```

```
Epoch Number:  3
Training loss:  0.2001471221446991
Validation loss: 0.1935756355524063
-----
```

```
Epoch Number:  4
Training loss:  0.20333196222782135
Validation loss: 0.19886252284049988
-----
```

```
Epoch Number:  5
Training loss:  0.1990119367837906
Validation loss: 0.1963425874710083
-----
```

```
Epoch Number:  6
```

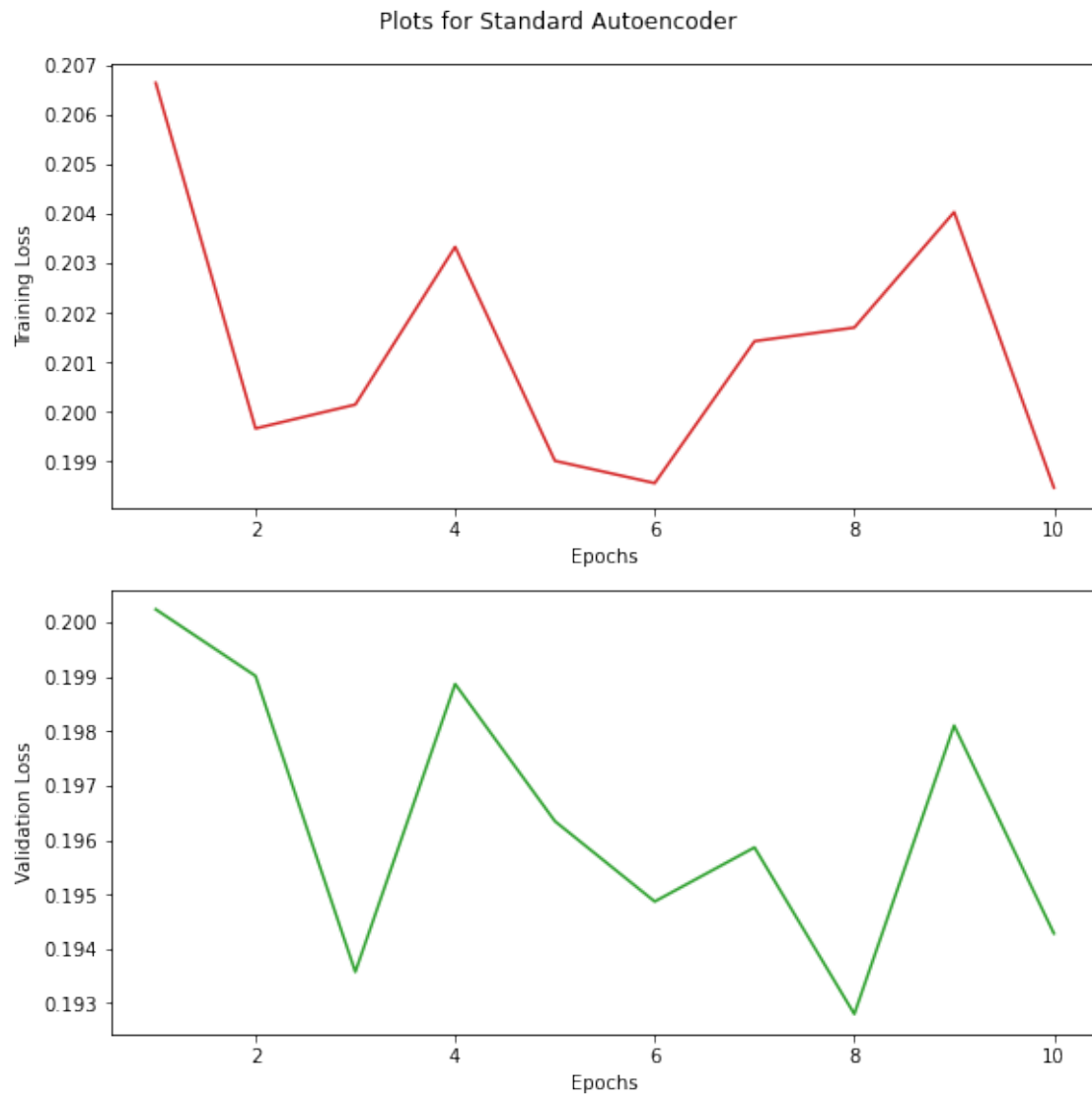
Training loss: 0.19856153428554535
Validation loss: 0.19486773014068604

Epoch Number: 7
Training loss: 0.2014264464378357
Validation loss: 0.19586099684238434

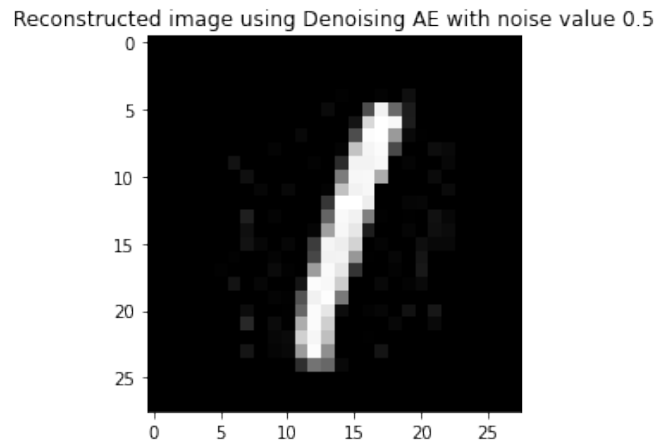
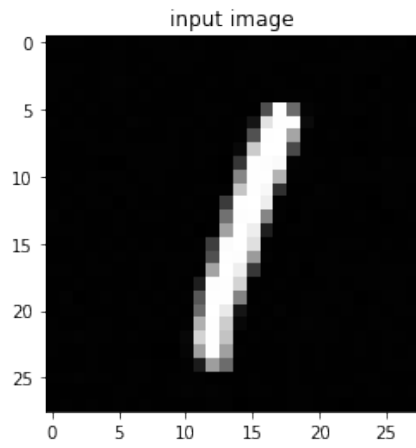
Epoch Number: 8
Training loss: 0.20170161128044128
Validation loss: 0.1928018033504486

Epoch Number: 9
Training loss: 0.20403216779232025
Validation loss: 0.1980990767478943

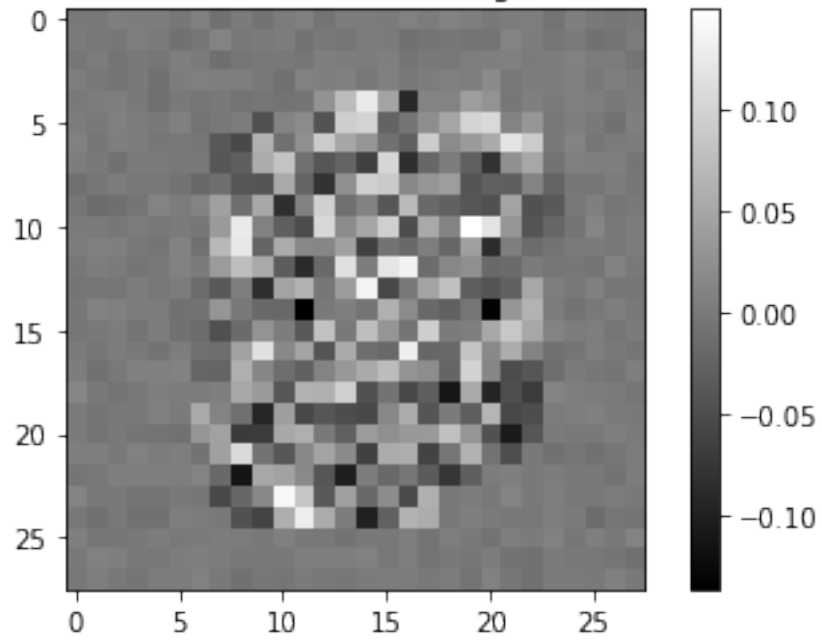
Epoch Number: 10
Training loss: 0.19847135245800018
Validation loss: 0.19428159296512604



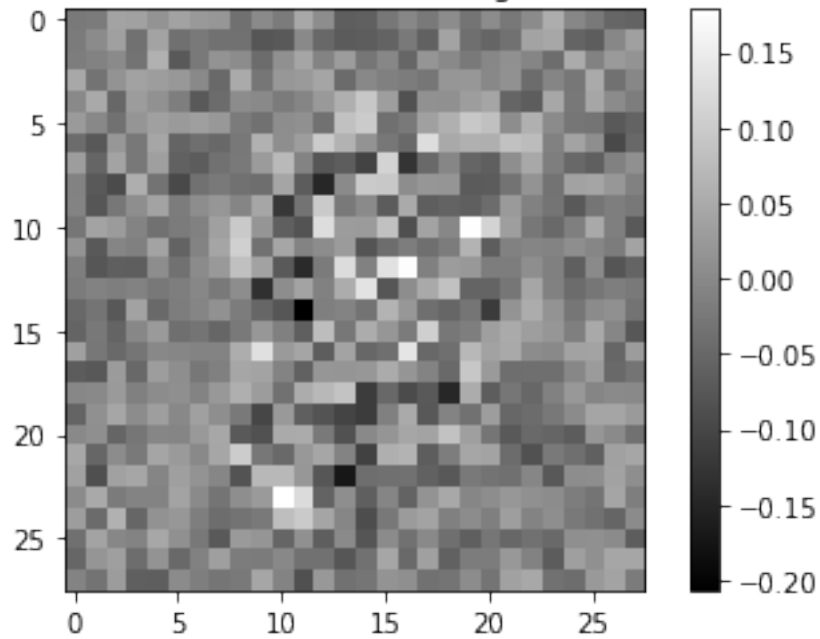
Training done for denoising AE with noise value 0.5 !



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



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



Training begins for noise value 0.8 !

Epoch Number: 1
Training loss: 0.5117299556732178
Validation loss: 0.5008126497268677

Epoch Number: 2
Training loss: 0.516144871711731
Validation loss: 0.5109405517578125

Epoch Number: 3
Training loss: 0.5085366368293762
Validation loss: 0.5050548315048218

Epoch Number: 4
Training loss: 0.5145164132118225
Validation loss: 0.5008255839347839

Epoch Number: 5
Training loss: 0.5108858942985535
Validation loss: 0.4850398302078247

Epoch Number: 6

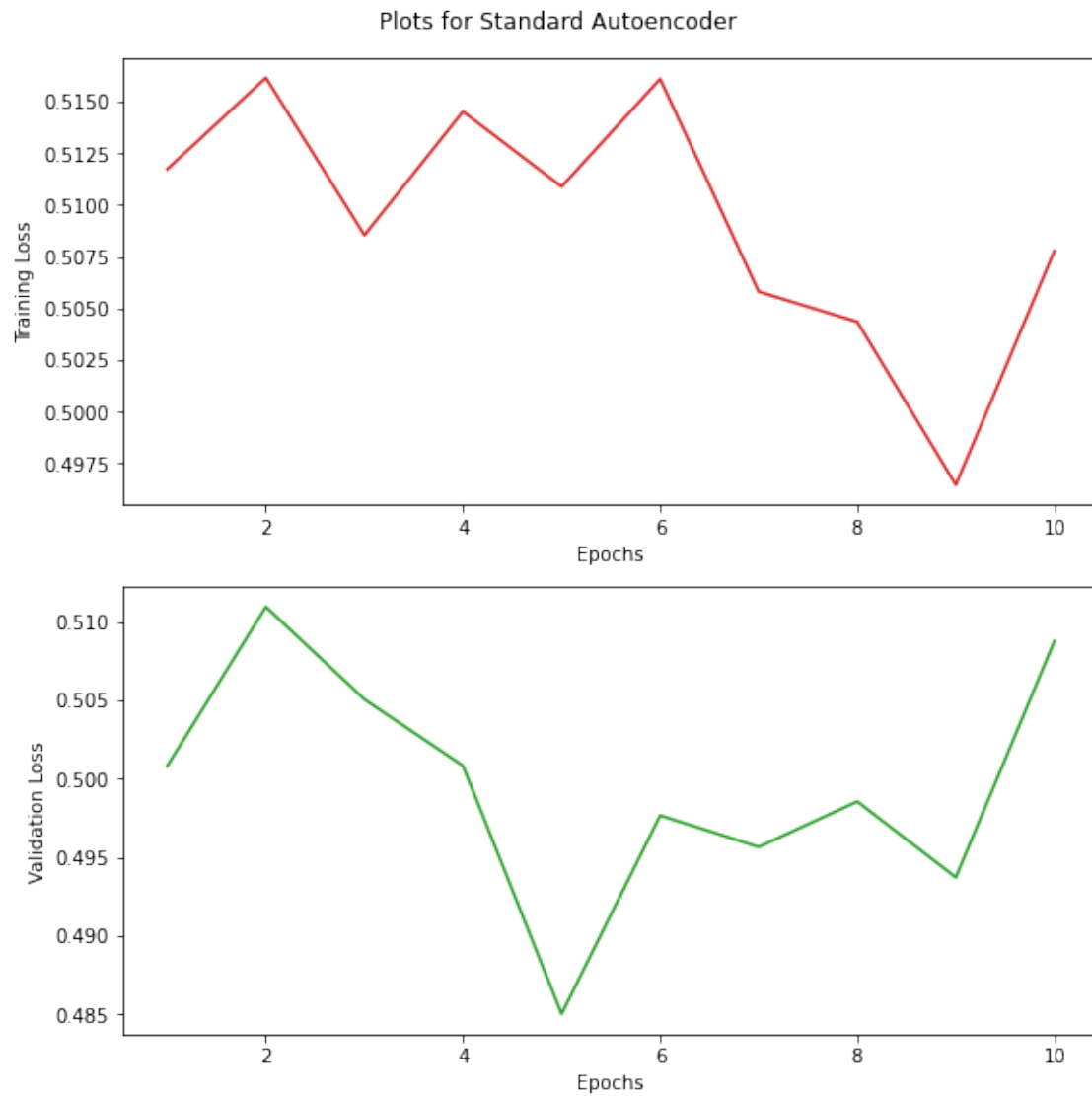
Training loss: 0.516089677810669
Validation loss: 0.49766290187835693

Epoch Number: 7
Training loss: 0.505807101726532
Validation loss: 0.49566373229026794

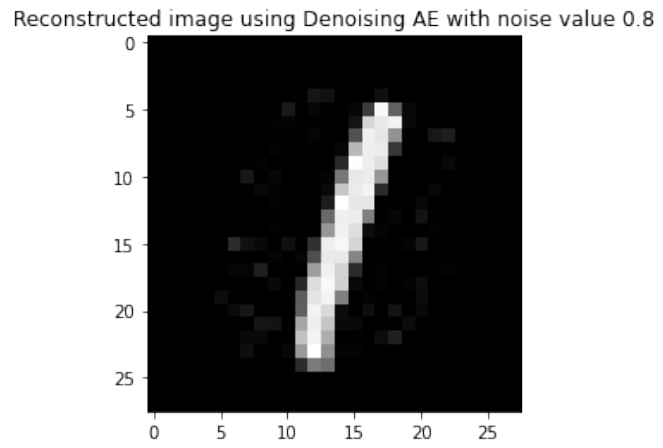
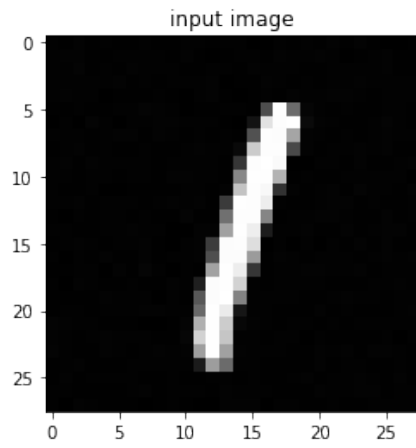
Epoch Number: 8
Training loss: 0.5043478012084961
Validation loss: 0.49855220317840576

Epoch Number: 9
Training loss: 0.496466726064682
Validation loss: 0.4937262535095215

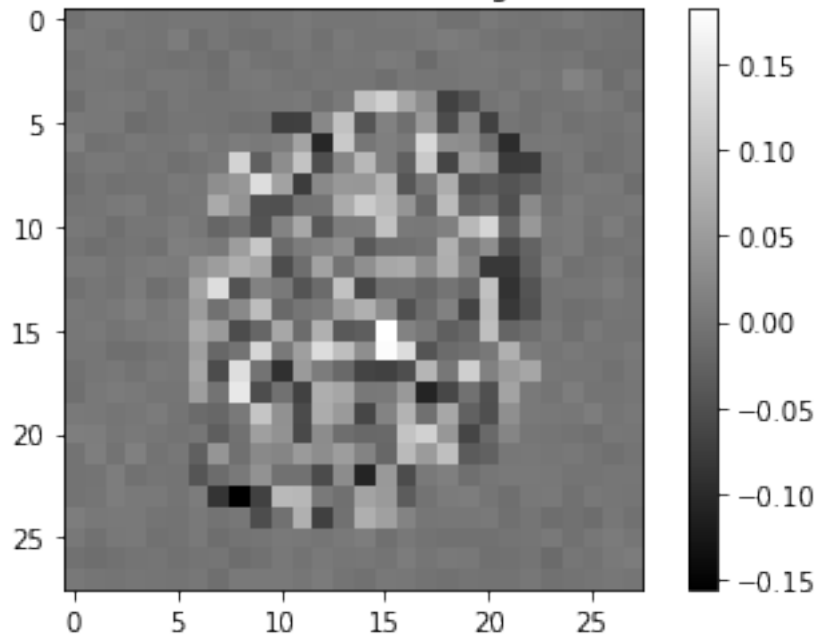
Epoch Number: 10
Training loss: 0.507779598236084
Validation loss: 0.5087576508522034



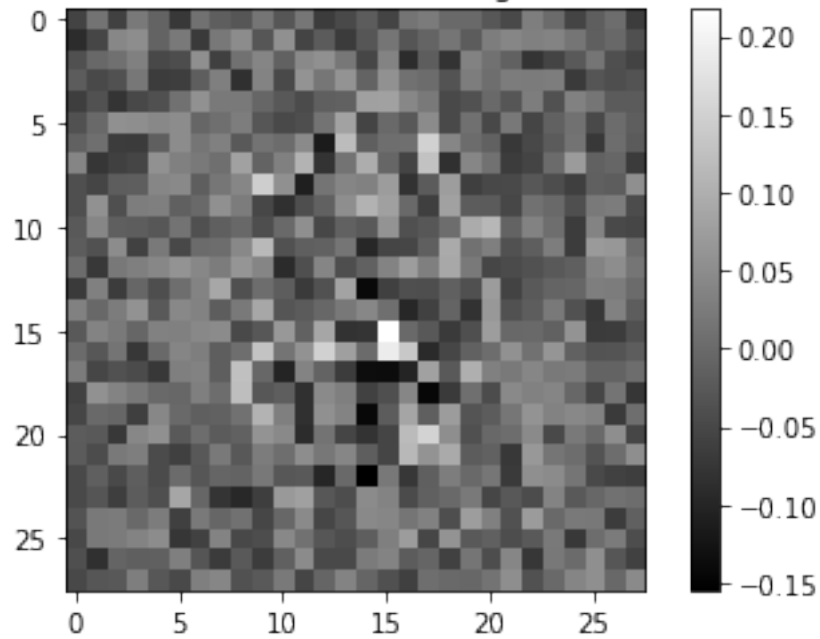
Training done for denoising AE with noise value 0.8 !



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



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



Training begins for noise value 0.9 !

Epoch Number: 1
Training loss: 0.6532461047172546
Validation loss: 0.6429724097251892

Epoch Number: 2
Training loss: 0.6543552279472351
Validation loss: 0.6423315405845642

Epoch Number: 3
Training loss: 0.6487111449241638
Validation loss: 0.6369641423225403

Epoch Number: 4
Training loss: 0.657607913017273
Validation loss: 0.6441336274147034

Epoch Number: 5
Training loss: 0.6530838012695312
Validation loss: 0.625943124294281

Epoch Number: 6

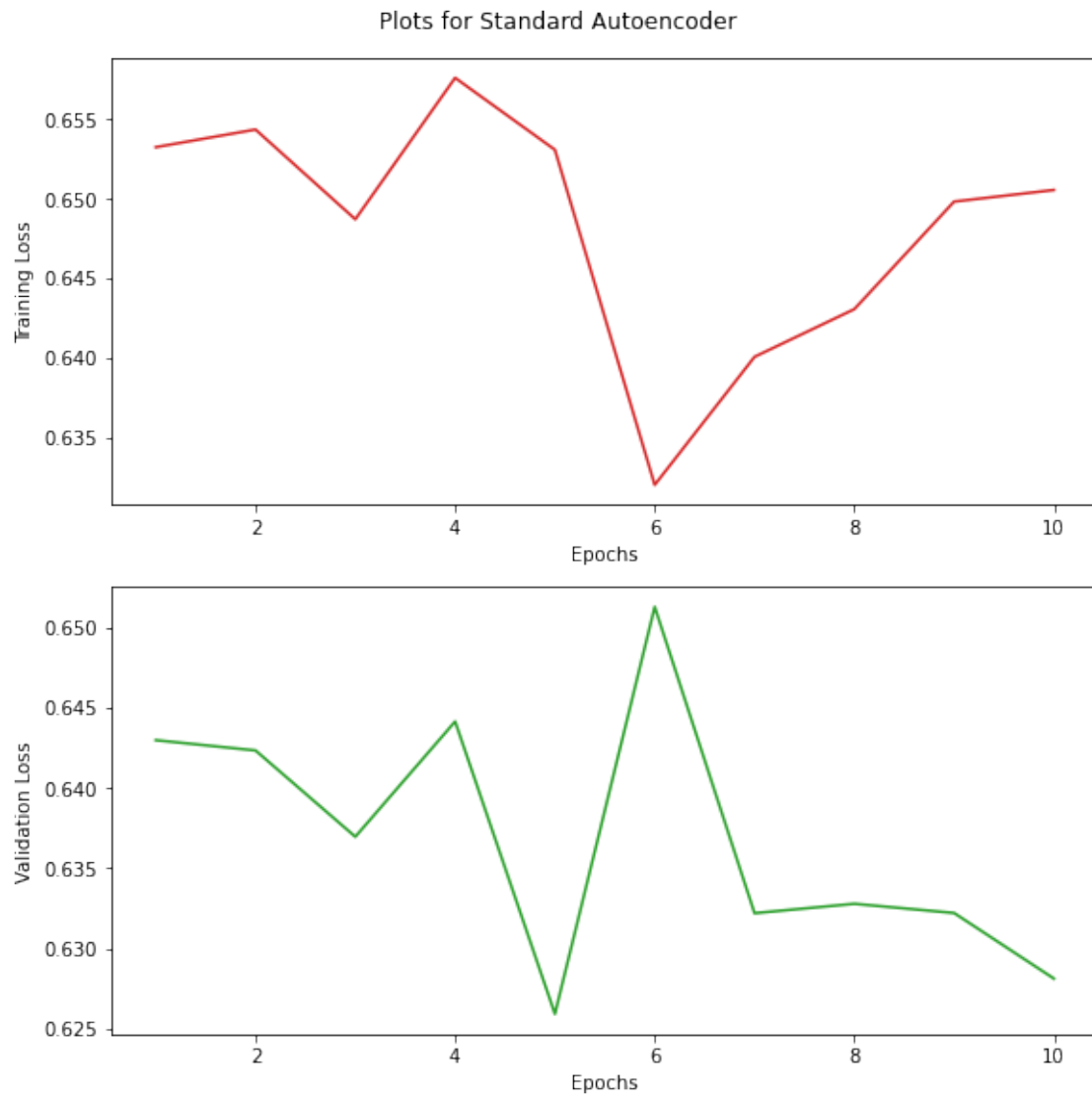
Training loss: 0.6320071816444397
Validation loss: 0.6512637138366699

Epoch Number: 7
Training loss: 0.640059232711792
Validation loss: 0.6322088241577148

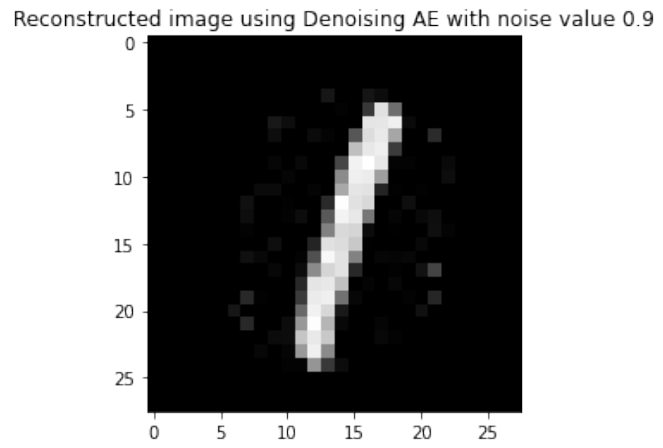
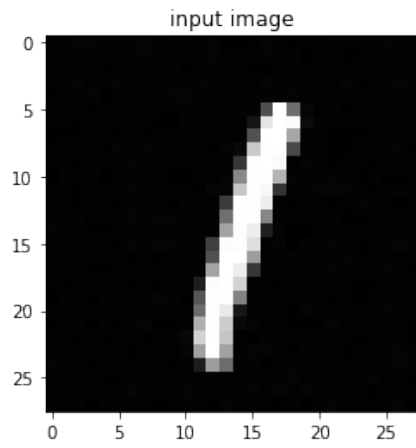
Epoch Number: 8
Training loss: 0.6430586576461792
Validation loss: 0.6327941417694092

Epoch Number: 9
Training loss: 0.6498229503631592
Validation loss: 0.6322207450866699

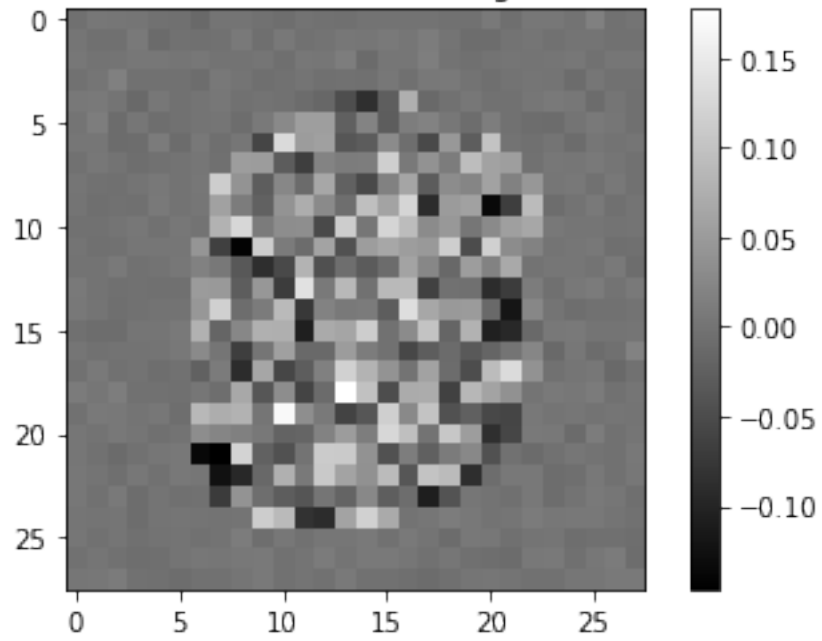
Epoch Number: 10
Training loss: 0.650553286075592
Validation loss: 0.6281419992446899



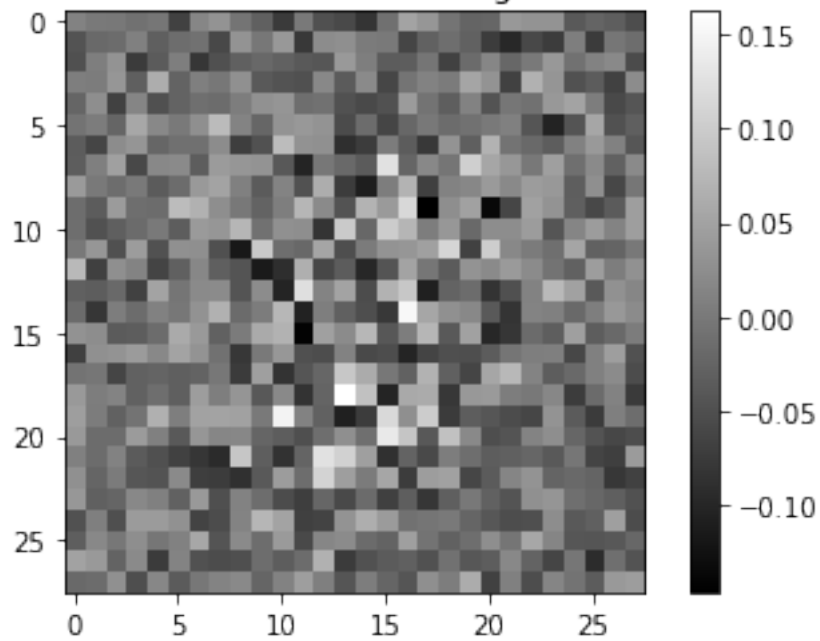
Training done for denoising AE with noise value 0.9 !



Encoder Filters for 0th neuron of Denoising AE with noise value 0.9



Decoder Filters for 0th neuron of Denoising AE with noise value 0.9



Observations

- As the noise value is increased, the reconstruction becomes worse but the shape of the digits are still recognizable.
- The learned filters are more focused and have higher variation in pixel values as the noise value increases.