In [1]:

```
import numpy as np
import torch
import matplotlib.pyplot as plt
import torchvision
import torchvision.transforms as transforms
from torch import nn
```

In [20]:

```
#HYPERPARAMETERS
learning_rate=0.001
epochs=10
batch_size= 300
number_of_pc=30 #number of principal components (for PCA)
```

In [3]:

```
train_data = torchvision.datasets.MNIST(root="./",train=True,transform=transform
s.ToTensor(),download=True)
test_data = torchvision.datasets.MNIST(root="./",train=False,transform=transform
s.ToTensor(),download=True)
```

In [4]:

```
train_loader = torch.utils.data.DataLoader(dataset=train_data,batch_size=batch_s
ize,shuffle=True)
test_loader = torch.utils.data.DataLoader(dataset=test_data,batch_size=len(test_
data),shuffle=False)
```

In [5]:

```
test_sample_loader = torch.utils.data.DataLoader(dataset=test_data.data[9705:971
5],shuffle=False,batch_size=10)
```

In [6]:

```
train_dataset=train_data.data.reshape(train_data.data.shape[0],train_data.data.s
hape[1]*train_data.data.shape[2])
test_dataset = test_data.data.reshape(test_data.data.shape[0],test_data.data.sha
pe[1]*test_data.data.shape[2])
test_dataset_sampled= test_dataset[np.arange(9705,9715),:]
```

Question 1

In [9]:

```
def PCA(input_data,top_k_ev):
  '''
  function: This function performs pca.
  Input: input_data = (torch matrix) = of shape num_datapts,784pixels
         top_k_ev = (integer) = how many principal components to be taken

  Output: top_k_eigen_vectors= shape(784,top_k_ev) top k eigen vectors in column
s
          centered_ip_data= shape(num_datapts,784) = centered ip data (used for
 reconstruction from principal components)

  '''


  input_mean = torch.mean(input_data,0)
  centered_ip_data = input_data-input_mean
  cov_matrix = torch.matmul(centered_ip_data.T,centered_ip_data)
  eigen_values, eigen_vectors = torch.linalg.eigh(cov_matrix)
  eigen_values_descending,indices = torch.sort(eigen_values,descending=True)
  top_k_eigen_values,top_k_indices = eigen_values_descending[:top_k_ev],indices
[:top_k_ev]
  top_k_eigen_vectors = eigen_vectors[:,top_k_indices]


  assert top_k_eigen_vectors.shape == (784,top_k_ev)
  assert centered_ip_data.shape == input_data.shape
  assert input_mean.shape == torch.Size([784])

  return top_k_eigen_vectors
```

In [10]:

```
pc=PCA(train_dataset.float(),number_of_pc)
```

In [11]:

```
def reconstruct_data(principal_components,dataset):
  '''
  function: This function reconstructs the datapoints in lower dimension (i.e. t
op k eigen_vector components).

  Input: principal_components= shape(784,top_k_ev) top k eigen vectors in column
s
          centered_ip_data= shape(num_datapts,784) = centered ip data (used for
 reconstruction from principal components)

  Output: projected_data = (torch matrix) = of shape num_datapts , top_k_ev

  '''
  projection_matrix = torch.matmul(principal_components,principal_components.T)
  projected_data = torch.matmul(dataset,projection_matrix)

  assert projected_data.shape == (dataset.shape[0],principal_components.shape[0
])

  return projected_data
```

In [12]:

```
reconstructed_test_data_sampled=reconstruct_data(pc,test_dataset_sampled.float
())
```

In [13]:

```
class AE1(nn.Module):
  def __init__(self):
    super(AE1, self).__init__()
    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.encoder(x)
    encoded_output=x
    x=self.decoder(x)
    return x,encoded_output
```

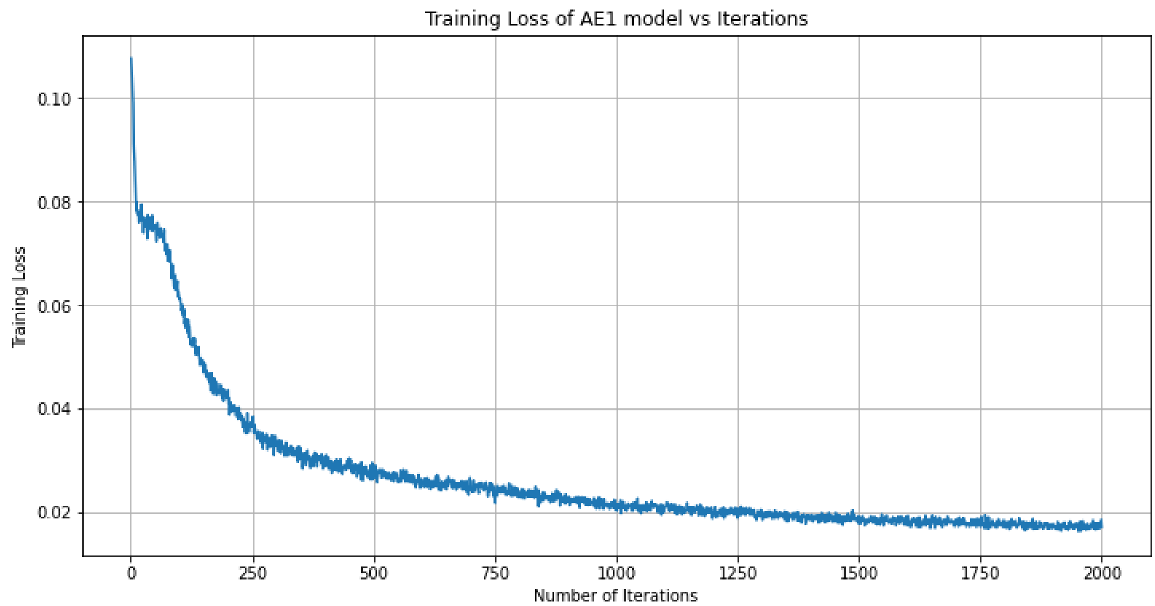
In [14]:

```
model1=AE1()
criterion1=nn.MSELoss()
optimizer1 = torch.optim.Adam(model1.parameters(),lr=learning_rate)

training_loss=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    outputs,_=model1(images)
    loss=criterion1(outputs,images)
    training_loss.append(loss.item())

    optimizer1.zero_grad()
    loss.backward()
    optimizer1.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [15]:

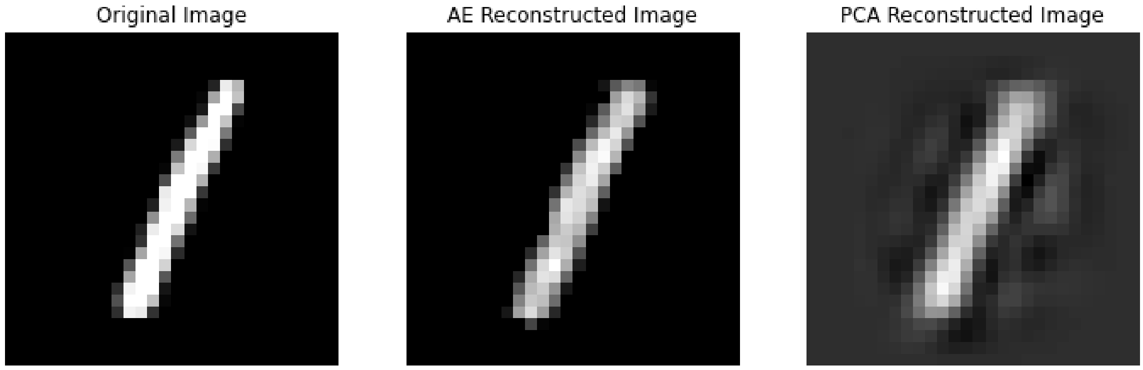
```
plt.figure(figsize=(12,6))
plt.plot(range(1,len(training_loss)+1),training_loss)
plt.title("Training Loss of AE1 model vs Iterations")
plt.xlabel("Number of Iterations")
plt.ylabel("Training Loss")
plt.grid()
```



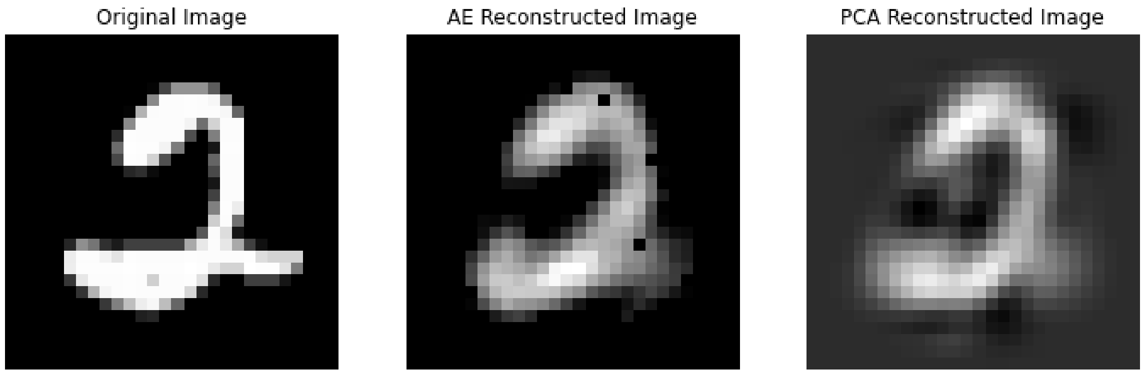
In [16]:

```
#MODEL EVALUATION AND RESULT PLOTTING
model1.eval()
with torch.no_grad():
  for images in test_sample_loader:
    # print(images.shape)
    images = images.reshape(10,28*28)
    outputs,_ = model1(images.float())

plt.rcParams["figure.figsize"] = (12,6)
for i in range (10):
  fig, (ax1, ax2, ax3) = plt.subplots(1,3)

  ax1.imshow(images[i].detach().numpy().reshape(28,28),cmap='gray')
  ax1.set_title('Original Image')
  ax1.axis("off")

  ax2.imshow(outputs[i].detach().numpy().reshape(28,28),cmap='gray')
  ax2.set_title('AE Reconstructed Image')
  ax2.axis("off")

  ax3.imshow(reconstructed_test_data_sampled[i].reshape(28,28),cmap='gray')
  ax3.set_title('PCA Reconstructed Image')
  ax3.axis("off")
  print("______________________________________________________________________________________")
  print("Reconstruction Error in AE:",np.dot(((images[i].detach().numpy()/255)-(outputs[i].detach().numpy()/255)),((images[i].detach().numpy()/255)-(outputs[i].detach().numpy()/255)).T))
  print("Reconstruction Error in PCA:",np.dot(((images[i].detach().numpy()/255)-(reconstructed_test_data_sampled[i].detach().numpy()/255)),((images[i].detach().numpy()/255)-(reconstructed_test_data_sampled[i].detach().numpy()/255)).T))
  plt.show()
```

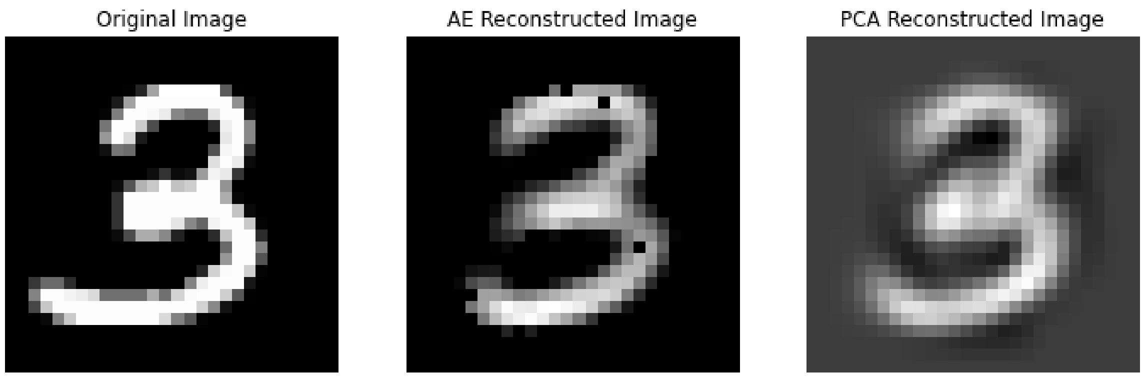
```
Reconstruction Error in AE: 2.7472248430821784
Reconstruction Error in PCA: 4.90691098406753
```



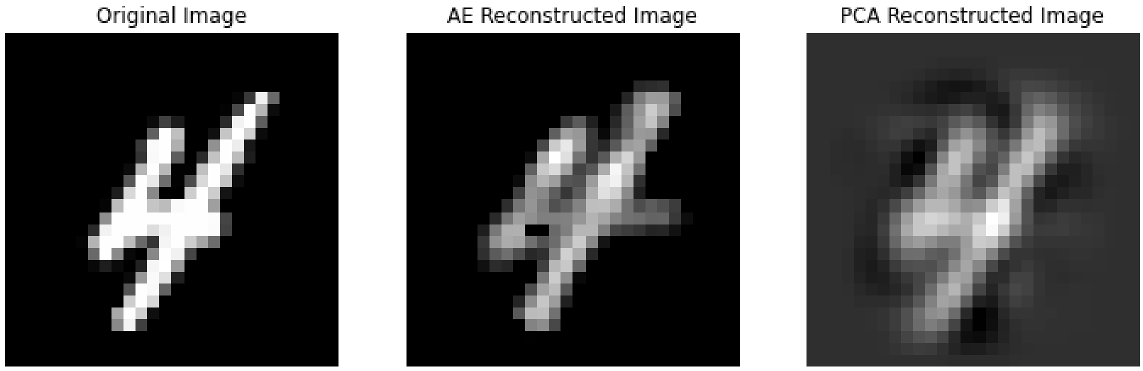

```
Reconstruction Error in AE: 21.762326668644867
Reconstruction Error in PCA: 16.86237506274601
```



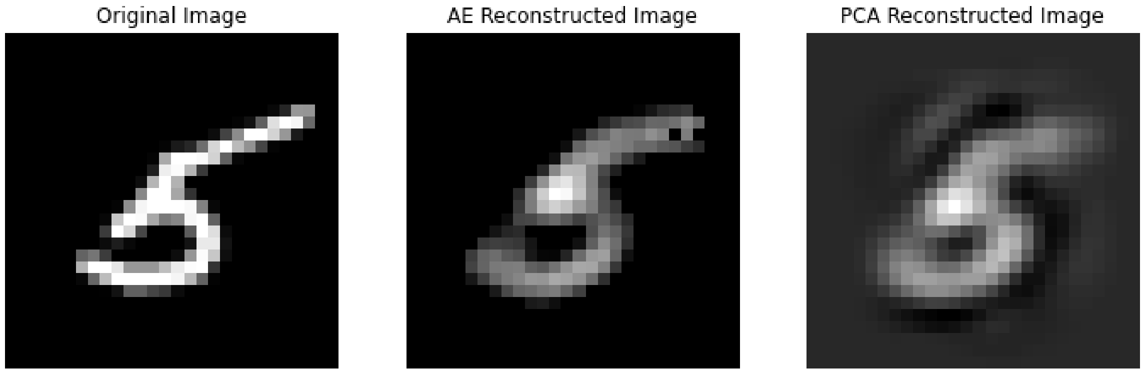

```
Reconstruction Error in AE: 21.333864113817814
Reconstruction Error in PCA: 16.045755599921307
```



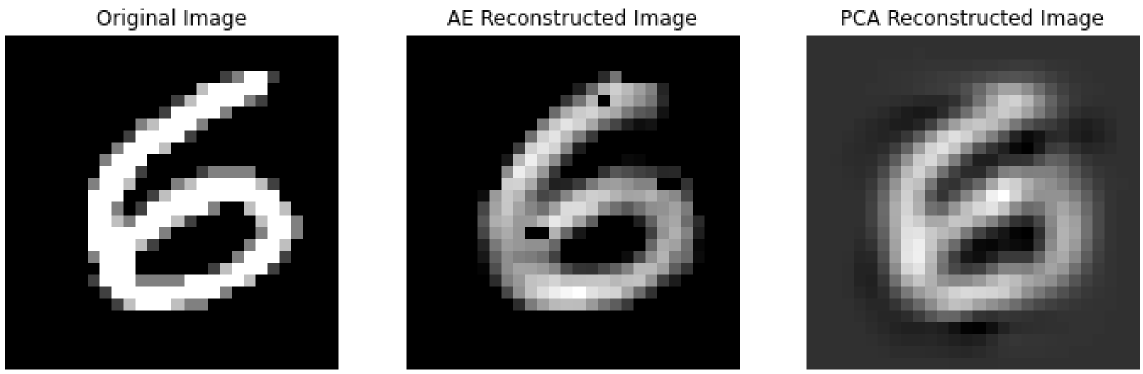

```
Reconstruction Error in AE: 14.849075947558745
Reconstruction Error in PCA: 10.714795712809165
```



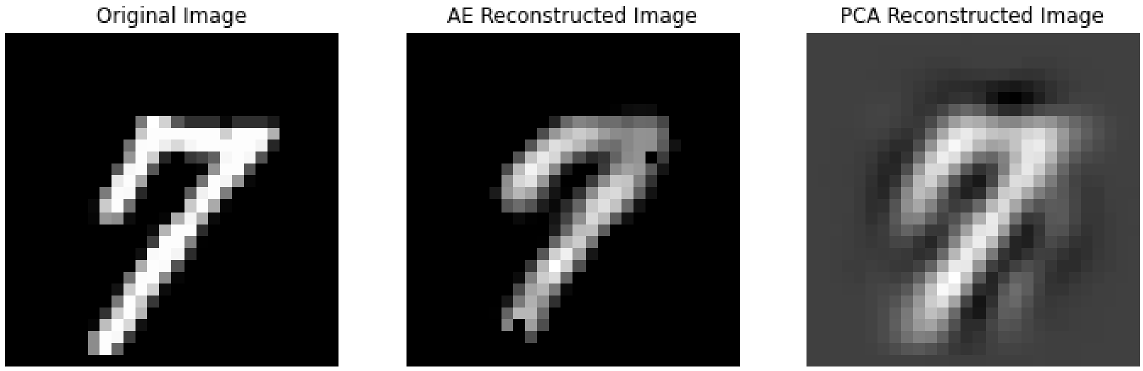

```
Reconstruction Error in AE: 15.122479463273889
Reconstruction Error in PCA: 14.848193698340676
```



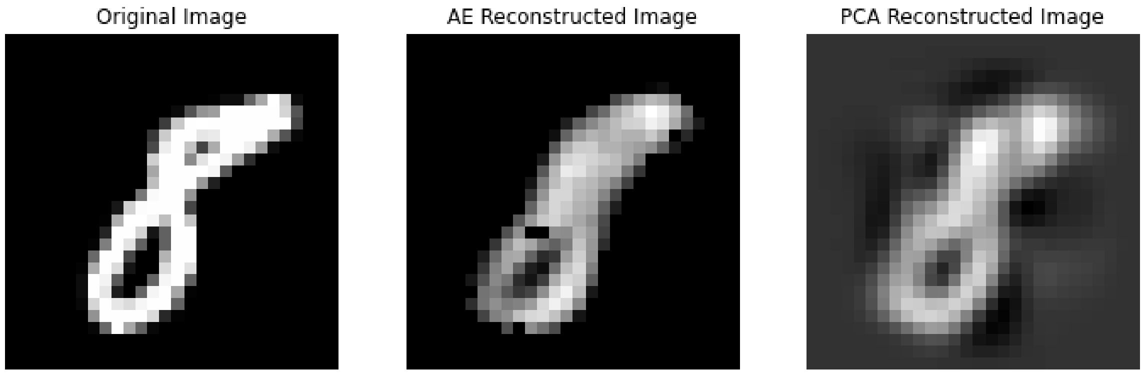

```
Reconstruction Error in AE: 22.65667615807221
Reconstruction Error in PCA: 20.390818940836983
```



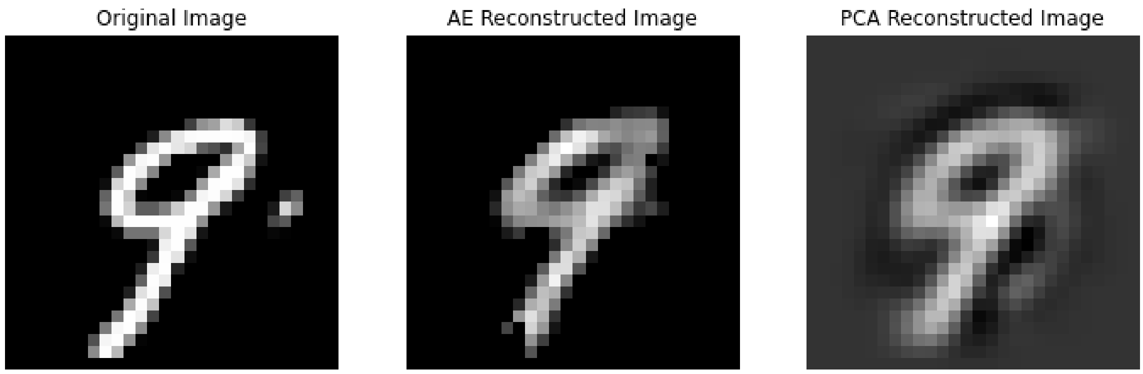

```
Reconstruction Error in AE: 16.34095082586718
Reconstruction Error in PCA: 11.735863192062858
```



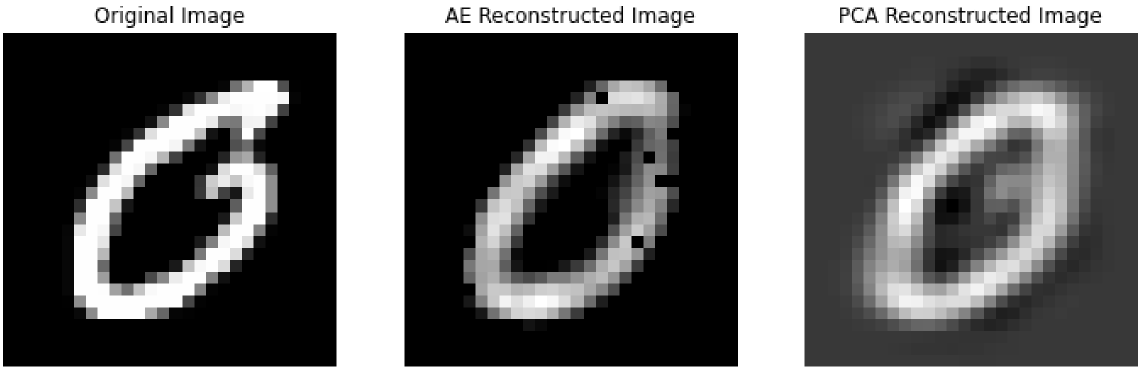

```
Reconstruction Error in AE: 15.306385477625026
Reconstruction Error in PCA: 14.35657074432876
```




```
Reconstruction Error in AE: 14.786297900784824
Reconstruction Error in PCA: 13.215489962853521
```




```
Reconstruction Error in AE: 19.088079263514267
Reconstruction Error in PCA: 16.605796880360153
```



Observations:

- Visually, Reconstructed Autoencoder images look appealing as they have better contrast.
- Reconstruction error-wise, Reconstructed PCA images are found to have lesser error (doesnot have much difference though), however they lack the contrast.

Question 2

In [21]:

```
class AE2(nn.Module):
  def __init__(self,hid):
    super(AE2, self).__init__()
    self.hid=hid
    self.encoder = nn.Sequential(
        nn.Linear(784,self.hid),
        nn.ReLU()
        )
    self.decoder =nn.Sequential(
        nn.Linear(self.hid,784),
        nn.ReLU()
        )

  def forward(self,x):
    x=self.encoder(x)
    encoded_output=x
    x=self.decoder(x)
    return x,encoded_output
```

In [18]:

```
#HIDDEN_SIZE=64
model_hid64=AE2(64)
criterion_hid64=nn.MSELoss()
optimizer_hid64 = torch.optim.Adam(model_hid64.parameters(),lr=learning_rate)

training_loss_hid64=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    outputs,_=model_hid64(images)
    loss=criterion_hid64(outputs,images)
    training_loss_hid64.append(loss.item())

    optimizer_hid64.zero_grad()
    loss.backward()
    optimizer_hid64.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [19]:

```
#HIDDEN_SIZE=128
model_hid128=AE2(128)
criterion_hid128=nn.MSELoss()
optimizer_hid128 = torch.optim.Adam(model_hid128.parameters(),lr=learning_rate)

training_loss_hid128=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    outputs,_=model_hid128(images)
    loss=criterion_hid128(outputs,images)
    training_loss_hid128.append(loss.item())

    optimizer_hid128.zero_grad()
    loss.backward()
    optimizer_hid128.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

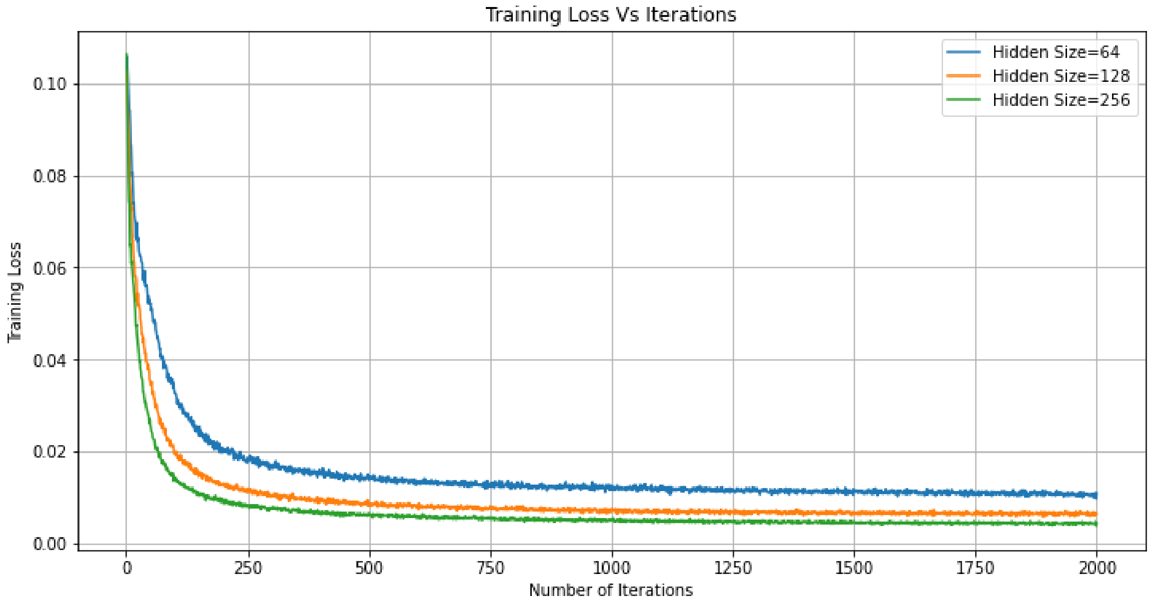
In [22]:

```
#HIDDEN_SIZE=256
model_hid256=AE2(256)
criterion_hid256=nn.MSELoss()
optimizer_hid256 = torch.optim.Adam(model_hid256.parameters(),lr=learning_rate)

training_loss_hid256=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    outputs,_=model_hid256(images)
    loss=criterion_hid256(outputs,images)
    training_loss_hid256.append(loss.item())

    optimizer_hid256.zero_grad()
    loss.backward()
    optimizer_hid256.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [21]:

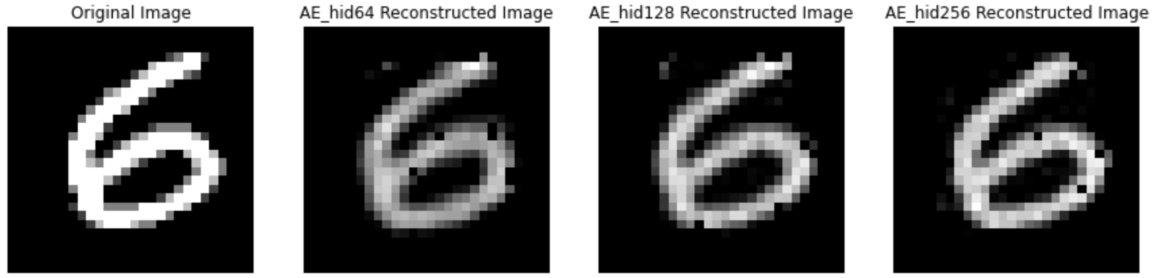
```
plt.plot(range(1,len(training_loss_hid64)+1),training_loss_hid64,label="Hidden Size=64")
plt.plot(range(1,len(training_loss_hid64)+1),training_loss_hid128,label="Hidden Size=128")
plt.plot(range(1,len(training_loss_hid64)+1),training_loss_hid256,label="Hidden Size=256")
plt.legend()
plt.grid()
plt.title("Training Loss Vs Iterations")
plt.xlabel("Number of Iterations")
plt.ylabel("Training Loss")
plt.show()
```



In [22]:

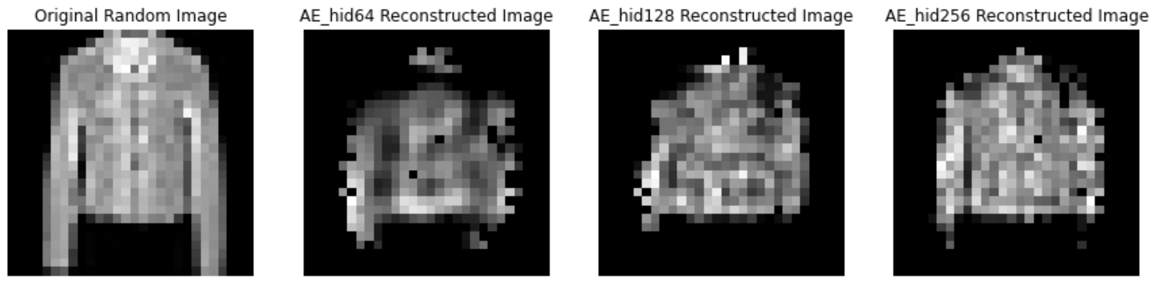
```
model_hid64.eval()
with torch.no_grad():
  for images in test_sample_loader:
    # print(images.shape)
    images = images.reshape(10,28*28)
    outputs_hid64,_ = model_hid64(images.float())

model_hid128.eval()
with torch.no_grad():
  for images in test_sample_loader:
    # print(images.shape)
    images = images.reshape(10,28*28)
    outputs_hid128,_ = model_hid128(images.float())


model_hid256.eval()
with torch.no_grad():
  for images in test_sample_loader:
    # print(images.shape)
    images = images.reshape(10,28*28)
    outputs_hid256,activations_hid256 = model_hid256(images.float())


plt.rcParams["figure.figsize"] = (15,6)
i=5
if i==5:
  fig, (ax1, ax2, ax3, ax4) = plt.subplots(1,4)

  ax1.imshow(images[i].detach().numpy().reshape(28,28),cmap='gray')
  ax1.set_title('Original Image')
  ax1.axis("off")

  ax2.imshow(outputs_hid64[i].detach().numpy().reshape(28,28),cmap='gray')
  ax2.set_title('AE_hid64 Reconstructed Image')
  ax2.axis("off")

  ax3.imshow(outputs_hid128[i].detach().numpy().reshape(28,28),cmap='gray')
  ax3.set_title('AE_hid128 Reconstructed Image')
  ax3.axis("off")

  ax4.imshow(outputs_hid256[i].detach().numpy().reshape(28,28),cmap='gray')
  ax4.set_title('AE_hid256 Reconstructed Image')
  ax4.axis("off")

  print("Reconstruction Error in AE_hid64:",np.dot(((images[i].detach().numpy()/
255)-(outputs_hid64[i].detach().numpy()/255)),((images[i].detach().numpy()/255)-
(outputs_hid64[i].detach().numpy()/255)).T))
  print("Reconstruction Error in AE_hid128:",np.dot(((images[i].detach().numpy()
/255)-(outputs_hid128[i].detach().numpy()/255)),((images[i].detach().numpy()/255
)-(outputs_hid128[i].detach().numpy()/255)).T))
  print("Reconstruction Error in AE_hid256:",np.dot(((images[i].detach().numpy()
/255)-(outputs_hid256[i].detach().numpy()/255)),((images[i].detach().numpy()/255
)-(outputs_hid256[i].detach().numpy()/255)).T))
```

```
Reconstruction Error in AE_hid64: 17.168603545148102
Reconstruction Error in AE_hid128: 10.844266659450152
Reconstruction Error in AE_hid256: 9.580246903034212
```



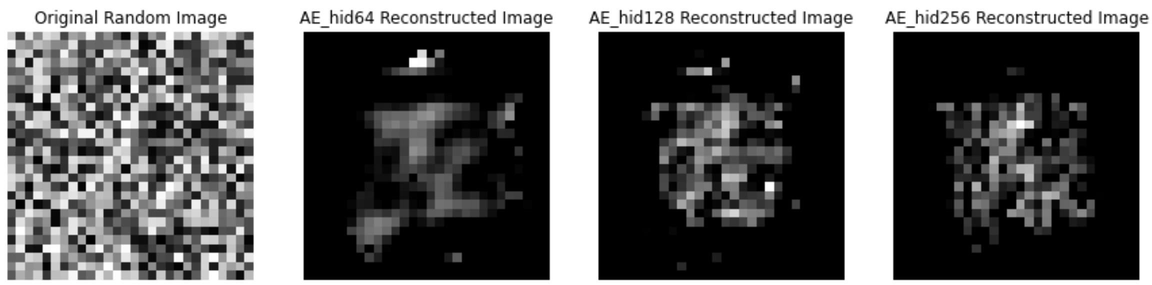
In [23]:

```
#FASHION MNIST OUTPUT
test_data_fashion = torchvision.datasets.FashionMNIST(root="./",train=False,tran
sform=transforms.ToTensor(),download=True)
fashion_image_sample=test_data_fashion.data[10]

model_hid64.eval()
with torch.no_grad():
    images = fashion_image_sample.reshape(1,28*28)
    outputs_hid64,_ = model_hid64(images.float())

model_hid128.eval()
with torch.no_grad():
  images = fashion_image_sample.reshape(1,28*28)
  outputs_hid128,_ = model_hid128(images.float())

model_hid256.eval()
with torch.no_grad():
  images = fashion_image_sample.reshape(1,28*28)
  outputs_hid256,_ = model_hid256(images.float())


plt.rcParams["figure.figsize"] = (15,6)

fig, (ax1, ax2, ax3, ax4) = plt.subplots(1,4)

ax1.imshow(fashion_image_sample.detach().numpy().reshape(28,28),cmap='gray')
ax1.set_title('Original Random Image')
ax1.axis("off")

ax2.imshow(outputs_hid64.detach().numpy().reshape(28,28),cmap='gray')
ax2.set_title('AE_hid64 Reconstructed Image')
ax2.axis("off")

ax3.imshow(outputs_hid128.detach().numpy().reshape(28,28),cmap='gray')
ax3.set_title('AE_hid128 Reconstructed Image')
ax3.axis("off")

ax4.imshow(outputs_hid256.detach().numpy().reshape(28,28),cmap='gray')
ax4.set_title('AE_hid256 Reconstructed Image')
ax4.axis("off")
plt.show()
```



In [24]:

```
#OUTPUTS FOR RANDOM IMAGE
torch.manual_seed(0)
random_image=torch.randint(low=0, high=255,size=(1,28,28))

model_hid64.eval()
with torch.no_grad():
    images = random_image.reshape(1,28*28)
    outputs_hid64,_ = model_hid64(images.float())

model_hid128.eval()
with torch.no_grad():
  images = random_image.reshape(1,28*28)
  outputs_hid128,_ = model_hid128(images.float())

model_hid256.eval()
with torch.no_grad():
  images = random_image.reshape(1,28*28)
  outputs_hid256,_ = model_hid256(images.float())

plt.rcParams["figure.figsize"] = (15,6)

fig, (ax1, ax2, ax3, ax4) = plt.subplots(1,4)

ax1.imshow(random_image.numpy().reshape(28,28),cmap='gray')
ax1.set_title('Original Random Image')
ax1.axis("off")

ax2.imshow(outputs_hid64.detach().numpy().reshape(28,28),cmap='gray')
ax2.set_title('AE_hid64 Reconstructed Image')
ax2.axis("off")

ax3.imshow(outputs_hid128.detach().numpy().reshape(28,28),cmap='gray')
ax3.set_title('AE_hid128 Reconstructed Image')
ax3.axis("off")

ax4.imshow(outputs_hid256.detach().numpy().reshape(28,28),cmap='gray')
ax4.set_title('AE_hid256 Reconstructed Image')
ax4.axis("off")
plt.show()
```



Observations:

- For an image sample from MNIST dataset, AE with hidden size 256 seems to reconstruct the image in a better manner. This was expected as more components would able to reproduce the image in a better manner by capturing the minor details of the input image. This is also proved by the lesser reconstruction error by this model.
- For an image from Fashion MNIST dataset, the models try to reconstruct the image but the models with 64 and 128 hidden size could not reconstruct properly. On the other hand, 256 hidden size model does better job than them but also seems to struggle in the reconstruction, though if the model was trained on fashion mnist dataset, it would've performed better.
- For a random image, the models perform as if they were trying to find out the digits, so the center pixels have some noisy output and the outer/edge pixels seem to be off (similar to the MNIST digit dataset, as our model has been trained on them.)

Question 3

In [25]:

```
class AE3_SparseAutoencoder(nn.Module):
  def __init__(self):
    super(AE3_SparseAutoencoder, self).__init__()
    self.encoder = nn.Sequential(
        nn.Linear(784,1156),
        nn.ReLU())
    self.decoder =nn.Sequential(
        nn.Linear(1156,784),
        nn.ReLU())

  def forward(self,x):
    x=self.encoder(x)
    encoded_output=x
    l1_norm=torch.norm(x,p=1)
    x=self.decoder(x)
    return x,l1_norm,encoded_output
```

In [26]:

```
lambda_ = 3*1e-6
model_3_a=AE3_SparseAutoencoder()
criterion_3_a=nn.MSELoss()
optimizer_3_a = torch.optim.Adam(model_3_a.parameters(),lr=learning_rate)

training_loss_3_a=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    outputs,l1_norm,_=model_3_a(images)
    loss=criterion_3_a(outputs,images)+lambda_*l1_norm
    training_loss_3_a.append(loss.item())

    optimizer_3_a.zero_grad()
    loss.backward()
    optimizer_3_a.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [27]:

```
lambda_ = 1.5*1e-6
model_3_b=AE3_SparseAutoencoder()
criterion_3_b=nn.MSELoss()
optimizer_3_b = torch.optim.Adam(model_3_b.parameters(),lr=learning_rate)

training_loss_3_b=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    outputs,l1_norm,_=model_3_b(images)
    loss=criterion_3_b(outputs,images)+lambda_*l1_norm
    training_loss_3_b.append(loss.item())

    optimizer_3_b.zero_grad()
    loss.backward()
    optimizer_3_b.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [28]:

```
lambda_ = 0.6*1e-6
model_3_c=AE3_SparseAutoencoder()
criterion_3_c=nn.MSELoss()
optimizer_3_c = torch.optim.Adam(model_3_c.parameters(),lr=learning_rate)

training_loss_3_c=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    outputs,l1_norm,_=model_3_c(images)
    loss=criterion_3_c(outputs,images)+lambda_*l1_norm
    training_loss_3_c.append(loss.item())

    optimizer_3_c.zero_grad()
    loss.backward()
    optimizer_3_c.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

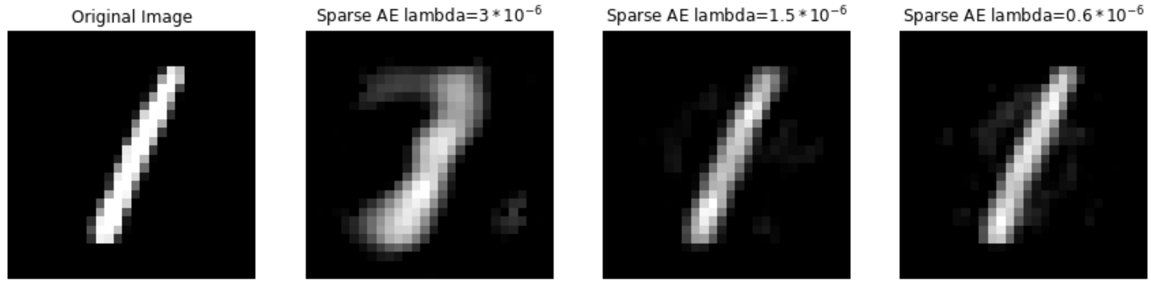
```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [29]:

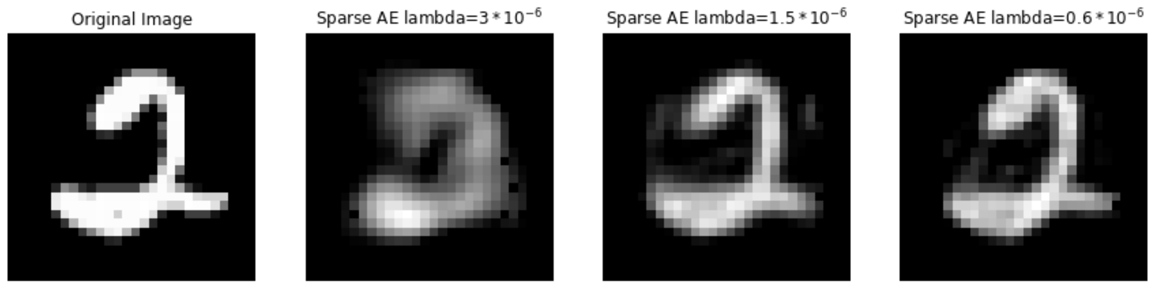
```
plt.plot(range(1,len(training_loss_3_a)+1),training_loss_3_a,label="lambda=$3*10
^{-6}$")
plt.plot(range(1,len(training_loss_3_a)+1),training_loss_3_b,label="lambda=$1.5*
10^{-6}$")
plt.plot(range(1,len(training_loss_3_a)+1),training_loss_3_c,label="lambda=$0.6*
10^{-6}$")
plt.legend()
plt.grid()
plt.title("Training Loss Vs Iterations")
plt.xlabel("Number of Iterations")
plt.ylabel("Training Loss")
plt.show()
```

In [30]:

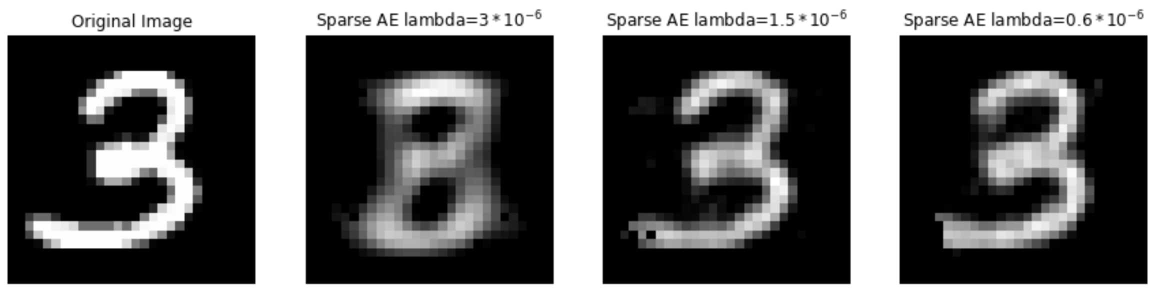
```
model_3_a.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    outputs_3_a,_,activation_3_a = model_3_a(images.float())


model_3_b.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    outputs_3_b,_,activation_3_b = model_3_b(images.float())


model_3_c.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    outputs_3_c,_ ,activation_3_c= model_3_c(images.float())


plt.rcParams["figure.figsize"] = (15,6)

for i in range(10):
  fig, (ax1, ax2,ax3,ax4) = plt.subplots(1,4)

  ax1.imshow(images[i].detach().numpy().reshape(28,28),cmap='gray')
  ax1.set_title('Original Image')
  ax1.axis("off")

  ax2.imshow(outputs_3_a[i].detach().numpy().reshape(28,28),cmap='gray')
  ax2.set_title('Sparse AE lambda=$3*10^{-6}$')
  ax2.axis("off")

  ax3.imshow(outputs_3_b[i].detach().numpy().reshape(28,28),cmap='gray')
  ax3.set_title('Sparse AE lambda=$1.5*10^{-6}$')
  ax3.axis("off")

  ax4.imshow(outputs_3_c[i].detach().numpy().reshape(28,28),cmap='gray')
  ax4.set_title('Sparse AE lambda=$0.6*10^{-6}$')
  ax4.axis("off")

  plt.show()

  print("Reconstruction Error in SparseAE lambda = 3*1e-6:",np.dot(((images[i].d
etach().numpy()/255)-(outputs_3_a[i].detach().numpy()/255)),((images[i].detach()
.numpy()/255)-(outputs_3_a[i].detach().numpy()/255)).T))
  print("Reconstruction Error in SparseAE lambda = 1.5*1e-6:",np.dot(((images[i]
.detach().numpy()/255)-(outputs_3_b[i].detach().numpy()/255)),((images[i].detach
().numpy()/255)-(outputs_3_b[i].detach().numpy()/255)).T))
  print("Reconstruction Error in SparseAE lambda = 0.6*1e-6:",np.dot(((images[i]
.detach().numpy()/255)-(outputs_3_c[i].detach().numpy()/255)),((images[i].detach
().numpy()/255)-(outputs_3_c[i].detach().numpy()/255)).T))
  print("_______________________________________________________________________________________________________________")
```



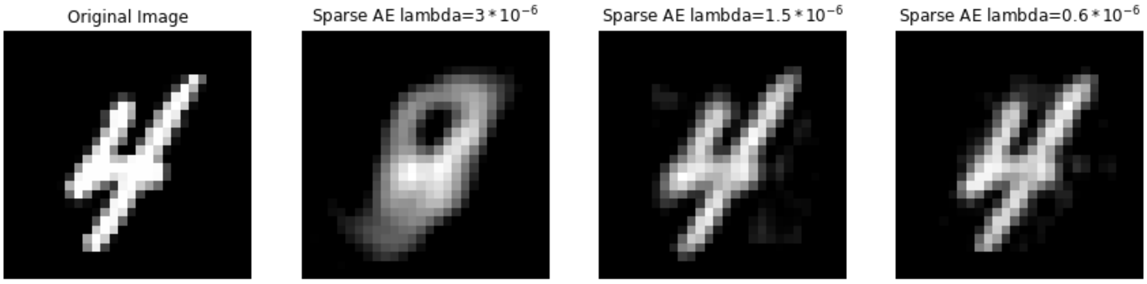

```
Reconstruction Error in SparseAE lambda = 3*1e-6: 14.973617678392557
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 2.61367661274686
03
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 3.24840965436654
15
```



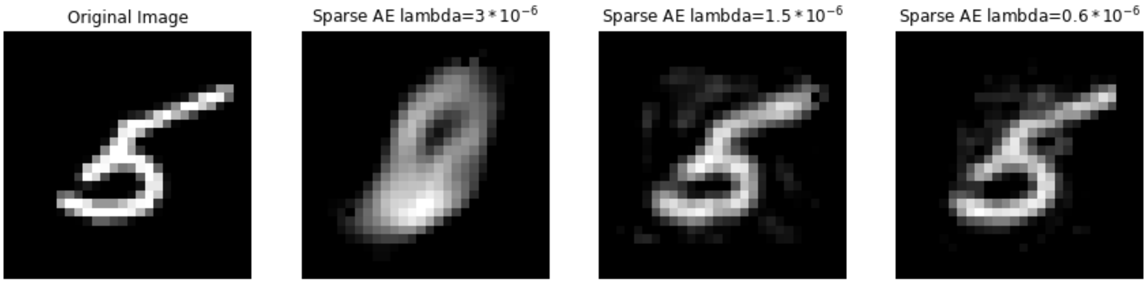

```
Reconstruction Error in SparseAE lambda = 3*1e-6: 31.45378367254754
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 10.7902274525253
57
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 10.5296989239763
87
```



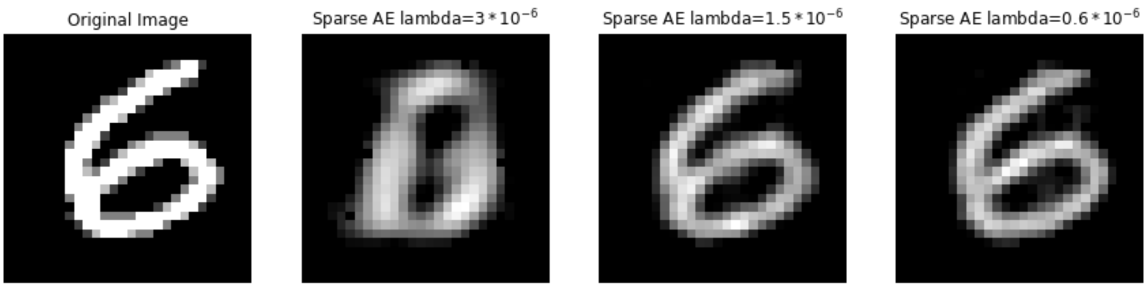

```
Reconstruction Error in SparseAE lambda = 3*1e-6: 35.407050044721316
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 8.96031820622504
3
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 13.3052458512635
57
```



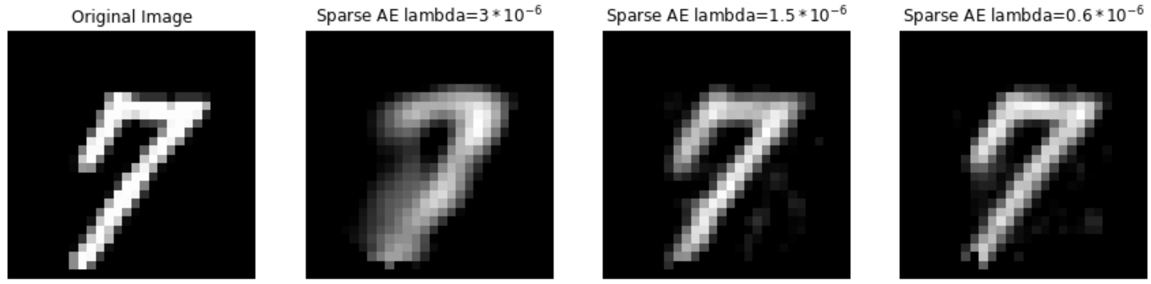

```
Reconstruction Error in SparseAE lambda = 3*1e-6: 28.65200092778902
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 5.53092973497781
6
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 5.76904392243360
2
```



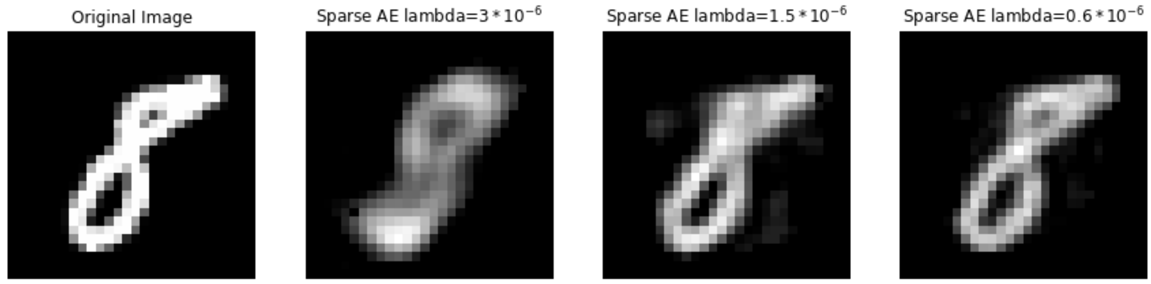

```
Reconstruction Error in SparseAE lambda = 3*1e-6: 35.12167571625308
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 8.69297798002163
3
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 7.52081489900155
9
```



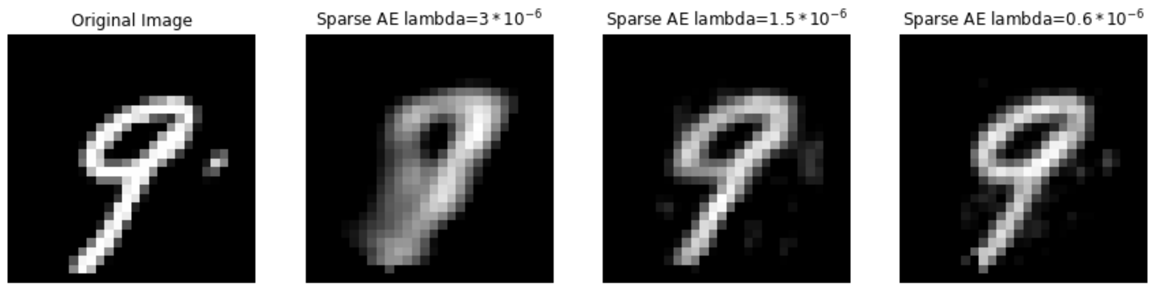

```
Reconstruction Error in SparseAE lambda = 3*1e-6: 60.559072609549965
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 12.4697726663372
5
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 14.4455125669140
54
```



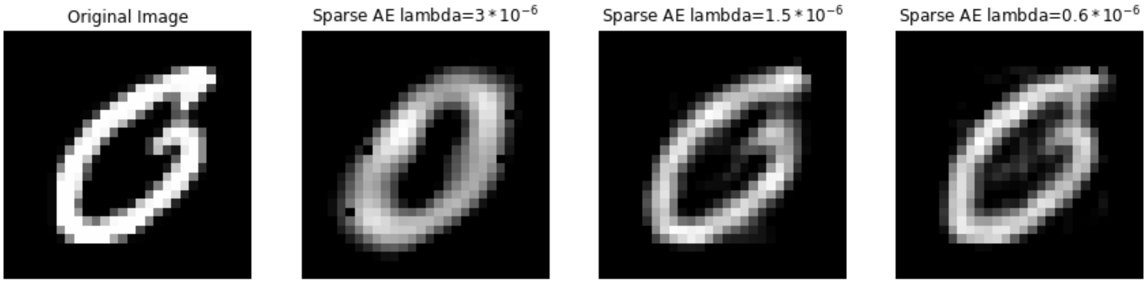

```
Reconstruction Error in SparseAE lambda = 3*1e-6: 29.60746996381112
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 6.78235910911763
4
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 8.19118042354352
```




```
Reconstruction Error in SparseAE lambda = 3*1e-6: 34.148959339821836
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 8.82763069986666
5
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 8.81962174996091
4
```



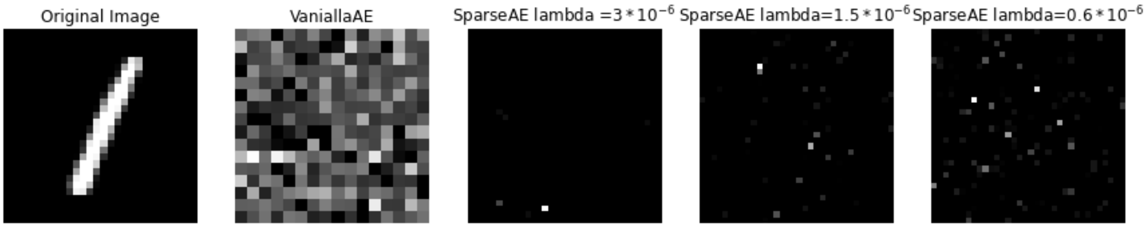

```
Reconstruction Error in SparseAE lambda = 3*1e-6: 29.96832909700308
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 9.05938606700964
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 8.93139726212009
```

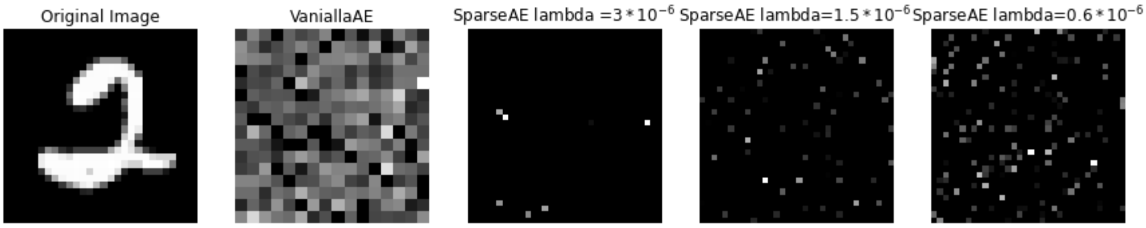


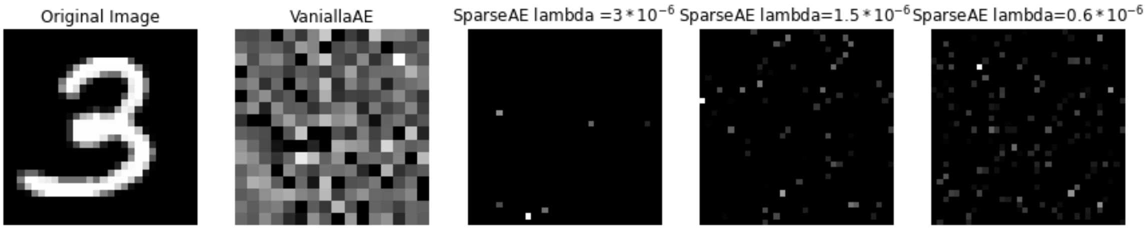

```
Reconstruction Error in SparseAE lambda = 3*1e-6: 30.037623122081364
Reconstruction Error in SparseAE lambda = 1.5*1e-6: 7.42948966445585
95
Reconstruction Error in SparseAE lambda = 0.6*1e-6: 11.4139420554862
81
```

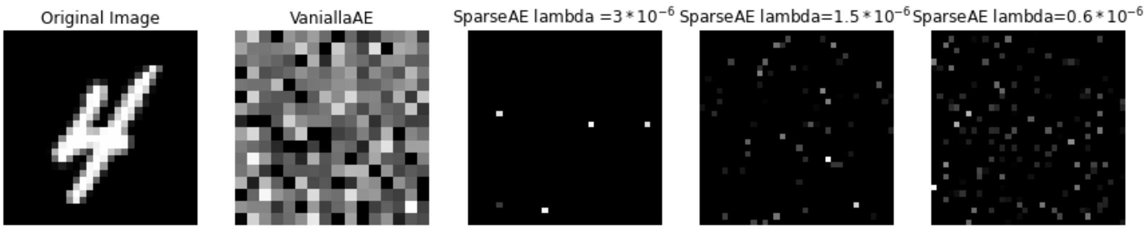
In [31]:

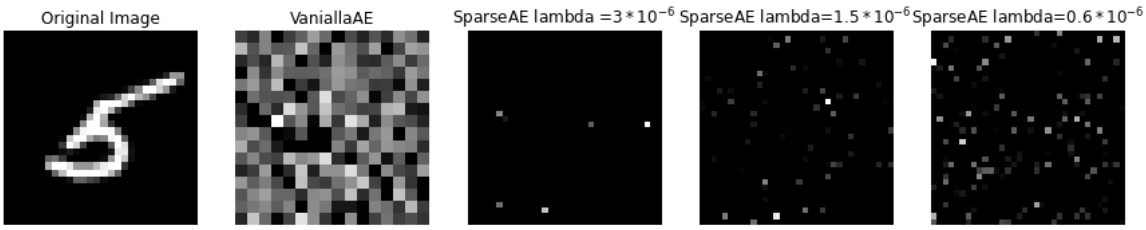
```
##VISUALISING ACTIVATIONS

plt.rcParams["figure.figsize"] = (15,6)
for i in range(10):
  fig, (ax1, ax2,ax3,ax4,ax5) = plt.subplots(1,5)
  ax1.imshow(images[i].detach().numpy().reshape(28,28),cmap='gray')
  ax1.set_title('Original Image')
  ax1.axis("off")

  ax2.imshow(np.array(activations_hid256.detach().numpy())[i].reshape(int(np.sqr
t(256)),int(np.sqrt(256))),cmap='gray')
  ax2.set_title('VaniallaAE')
  ax2.axis("off")

  ax3.imshow(np.array(activation_3_a.detach().numpy())[i].reshape(int(np.sqrt(11
56)),int(np.sqrt(1156))),cmap='gray')
  ax3.set_title('SparseAE lambda =$3*10^{-6}$')
  ax3.axis("off")

  ax4.imshow(np.array(activation_3_b.detach().numpy())[i].reshape(int(np.sqrt(11
56)),int(np.sqrt(1156))),cmap='gray')
  ax4.set_title('SparseAE lambda=$1.5*10^{-6}$')
  ax4.axis("off")

  ax5.imshow(np.array(activation_3_c.detach().numpy())[i].reshape(int(np.sqrt(11
56)),int(np.sqrt(1156))),cmap='gray')
  ax5.set_title('SparseAE lambda=$0.6*10^{-6}$')
  ax5.axis("off")

plt.show()
```

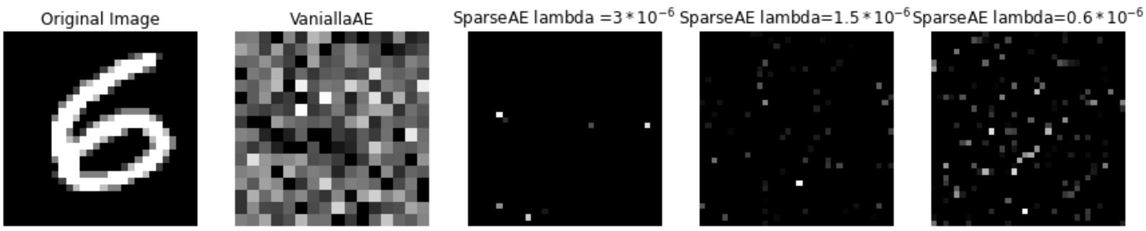

Original Image
VaniallaAE
SparseAE lambda =$3*10^{-6}$
SparseAE lambda=$1.5*10^{-6}$
SparseAE lambda=$0.6*10^{-6}$

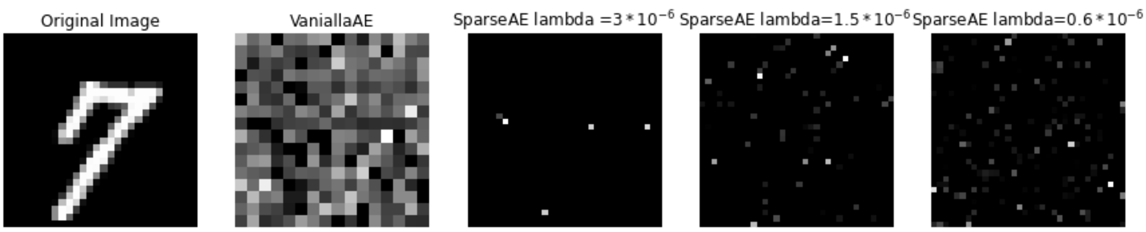

Original Image
VaniallaAE
SparseAE lambda =$3*10^{-6}$
SparseAE lambda=$1.5*10^{-6}$
SparseAE lambda=$0.6*10^{-6}$

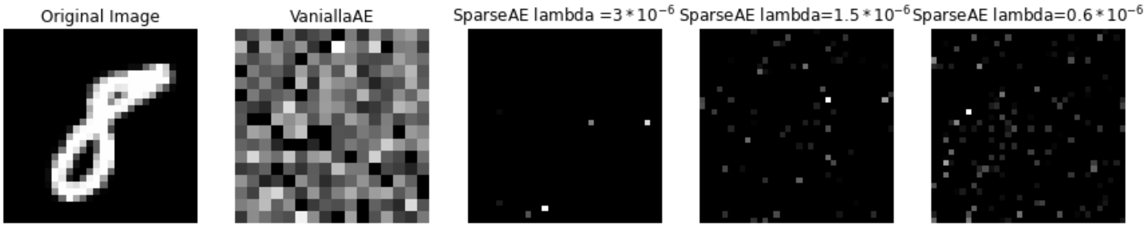

Original Image
VaniallaAE
SparseAE lambda =$3*10^{-6}$
SparseAE lambda=$1.5*10^{-6}$
SparseAE lambda=$0.6*10^{-6}$

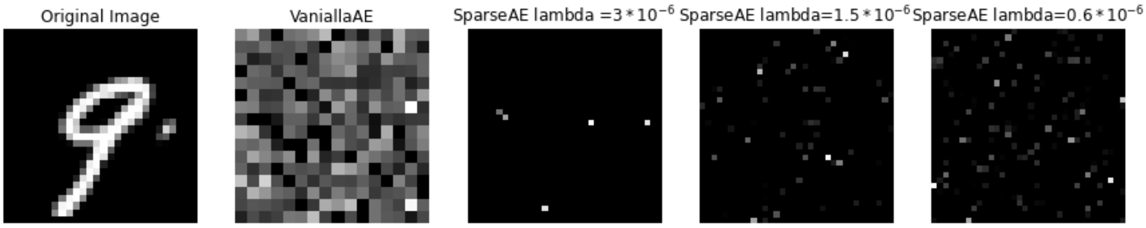

Original Image
VaniallaAE
SparseAE lambda =$3*10^{-6}$
SparseAE lambda=$1.5*10^{-6}$
SparseAE lambda=$0.6*10^{-6}$

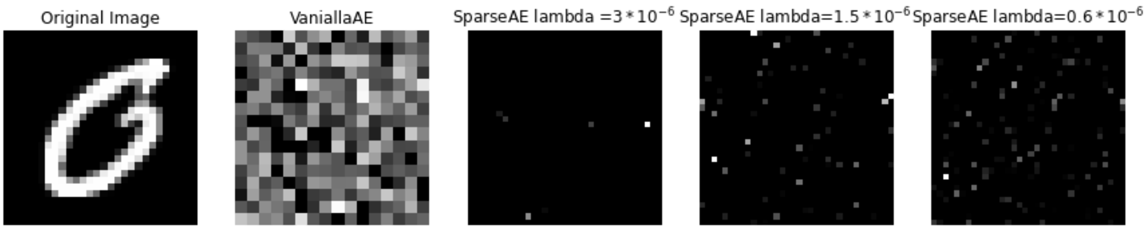

Original Image
VaniallaAE
SparseAE lambda =$3*10^{-6}$
SparseAE lambda=$1.5*10^{-6}$
SparseAE lambda=$0.6*10^{-6}$


Original Image
VaniallaAE
SparseAE lambda =$3*10^{-6}$
SparseAE lambda=$1.5*10^{-6}$
SparseAE lambda=$0.6*10^{-6}$


Original Image
VaniallaAE
SparseAE lambda =$3*10^{-6}$
SparseAE lambda=$1.5*10^{-6}$
SparseAE lambda=$0.6*10^{-6}$

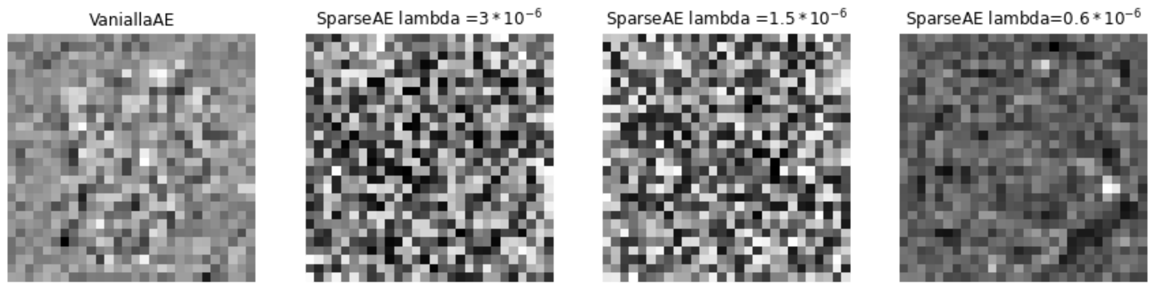

Original Image
VaniallaAE
SparseAE lambda =$3 * 10^{-6}$
SparseAE lambda=$1.5 * 10^{-6}$
SparseAE lambda=$0.6 * 10^{-6}$


Original Image
VaniallaAE
SparseAE lambda =$3 * 10^{-6}$
SparseAE lambda=$1.5 * 10^{-6}$
SparseAE lambda=$0.6 * 10^{-6}$


Original Image
VaniallaAE
SparseAE lambda =$3 * 10^{-6}$
SparseAE lambda=$1.5 * 10^{-6}$
SparseAE lambda=$0.6 * 10^{-6}$

In [33]:

```
##VISUALISING ENCODER WEIGHTS

plt.rcParams["figure.figsize"] = (15,6)

fig, (ax1, ax2,ax3,ax4) = plt.subplots(1,4)
ax1.imshow(model_hid256.encoder[0].weight.detach().numpy()[0].reshape(28,28),cma
p='gray')
ax1.set_title('VaniallaAE')
ax1.axis("off")

ax2.imshow(model_3_a.encoder[0].weight.detach().numpy()[0].reshape(28,28),cmap=
'gray')
ax2.set_title('SparseAE lambda =$3*10^{-6}$')
ax2.axis("off")

ax3.imshow(model_3_b.encoder[0].weight.detach().numpy()[0].reshape(28,28),cmap=
'gray')
ax3.set_title('SparseAE lambda =$1.5*10^{-6}$')
ax3.axis("off")

ax4.imshow(model_3_c.encoder[0].weight.detach().numpy()[0].reshape(28,28),cmap=
'gray')
ax4.set_title('SparseAE lambda=$0.6*10^{-6}$')
ax4.axis("off")

plt.show()
```



Observations:

- As lambda(sparsity factor) is decreased, reconstruction error goes down.
- If the lambda is continually decreased beyond a point then the model starts to overfit data. since the model is overcomplete, we need to iterate over the optimal lambda parameter to get desired output.
- as we decrease lambda(sparcity parameter) more neurons get activated. As can be observed from activation visualisations. However, in vanilla AE all the neurons are activated.
- Visualisation of encoder weights is difficult as nothing could be inferred from the images.

Question 4

In [7]:

```
class AE4_DenoisingAutoencoder(nn.Module):
  def __init__(self):
    super(AE4_DenoisingAutoencoder, self).__init__()
    self.encoder = nn.Sequential(
        nn.Linear(784,256),
        nn.ReLU())
    self.decoder =nn.Sequential(
        nn.Linear(256,784),
        nn.ReLU())

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

In [8]:

```
def add_noise(img, noise_val):
    noise = torch.randn(img.size())*noise_val
    noisy_img = img + noise
    return noisy_img
```

In [18]:

```
#HYPERPARAMETERS
learning_rate=0.00008
epochs=10
batch_size= 300
```

In [10]:

```
model_4_a=AE4_DenoisingAutoencoder()
criterion_4_a=nn.MSELoss()
optimizer_4_a = torch.optim.Adam(model_4_a.parameters(),lr=learning_rate)

training_loss_4_a=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    noisy_images=add_noise(images,0.3)
    outputs=model_4_a(noisy_images)
    loss=criterion_4_a(outputs,images)
    training_loss_4_a.append(loss.item())

    optimizer_4_a.zero_grad()
    loss.backward()
    optimizer_4_a.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [12]:

```
model_4_b=AE4_DenoisingAutoencoder()
criterion_4_b=nn.MSELoss()
optimizer_4_b = torch.optim.Adam(model_4_b.parameters(),lr=learning_rate)

training_loss_4_b=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    noisy_images=add_noise(images,0.5)
    outputs=model_4_b(noisy_images)
    loss=criterion_4_b(outputs,images)
    training_loss_4_b.append(loss.item())

    optimizer_4_b.zero_grad()
    loss.backward()
    optimizer_4_b.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [13]:

```
model_4_c=AE4_DenoisingAutoencoder()
criterion_4_c=nn.MSELoss()
optimizer_4_c = torch.optim.Adam(model_4_c.parameters(),lr=learning_rate)

training_loss_4_c=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    noisy_images=add_noise(images,0.8)
    outputs=model_4_c(noisy_images)
    loss=criterion_4_c(outputs,images)
    training_loss_4_c.append(loss.item())

    optimizer_4_c.zero_grad()
    loss.backward()
    optimizer_4_c.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

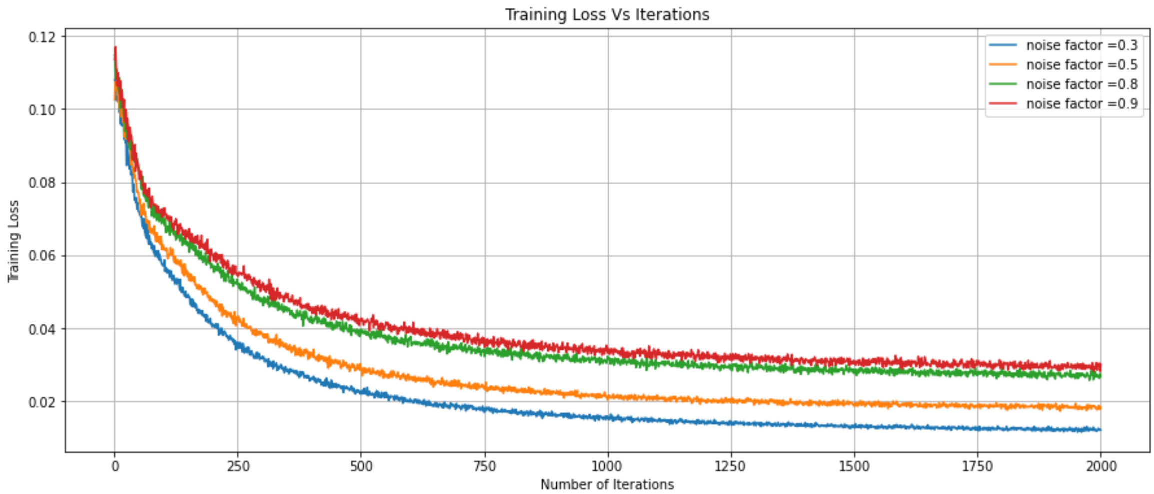
In [14]:

```
model_4_d=AE4_DenoisingAutoencoder()
criterion_4_d=nn.MSELoss()
optimizer_4_d = torch.optim.Adam(model_4_d.parameters(),lr=learning_rate)

training_loss_4_d=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    images=images.reshape(images.shape[0],-1)
    noisy_images=add_noise(images,0.9)
    outputs=model_4_d(noisy_images)
    loss=criterion_4_d(outputs,images)
    training_loss_4_d.append(loss.item())

    optimizer_4_d.zero_grad()
    loss.backward()
    optimizer_4_d.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [15]:

```
plt.rcParams["figure.figsize"] = (15,6)

plt.plot(range(1,len(training_loss_4_a)+1),training_loss_4_a,label="noise factor
=0.3")
plt.plot(range(1,len(training_loss_4_a)+1),training_loss_4_b,label="noise factor
=0.5")
plt.plot(range(1,len(training_loss_4_a)+1),training_loss_4_c,label="noise factor
=0.8")
plt.plot(range(1,len(training_loss_4_a)+1),training_loss_4_d,label="noise factor
=0.9")
plt.legend()
plt.grid()
plt.title("Training Loss Vs Iterations")
plt.xlabel("Number of Iterations")
plt.ylabel("Training Loss")
plt.show()
```



In [24]:

```
#INPUT WITH NOISE FACTOR=0.3,0.5,0.8,0.9 GIVEN TO VANILLA AE HIDLAYER=256
model_hid256.eval()
with torch.no_grad():
  for images in test_sample_loader:
    # print(images.shape)
    images = images.reshape(10,28*28)
    noisy_images=add_noise(images,0.3)
    outputs_hid256_03,activations_hid256 = model_hid256(noisy_images.float())

model_hid256.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    noisy_images=add_noise(images,0.5)
    outputs_hid256_05,activations_hid256 = model_hid256(noisy_images.float())

model_hid256.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    noisy_images=add_noise(images,0.8)
    outputs_hid256_08,activations_hid256 = model_hid256(noisy_images.float())

model_hid256.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    noisy_images=add_noise(images,0.9)
    outputs_hid256_09,activations_hid256 = model_hid256(noisy_images.float())

plt.rcParams["figure.figsize"] = (15,6)
i=5
fig, (ax1, ax2,ax3,ax4,ax5) = plt.subplots(1,5)

ax1.imshow(images[i].detach().numpy().reshape(28,28),cmap='gray')
ax1.set_title('Original Image')
ax1.axis("off")

ax2.imshow(outputs_hid256_03[i].detach().numpy().reshape(28,28),cmap='gray')
ax2.set_title('AE_Reconst.Image_nf=0.3')
ax2.axis("off")

ax3.imshow(outputs_hid256_05[i].detach().numpy().reshape(28,28),cmap='gray')
ax3.set_title('AE_Reconst.Image_nf=0.5')
ax3.axis("off")

ax4.imshow(outputs_hid256_08[i].detach().numpy().reshape(28,28),cmap='gray')
ax4.set_title('AE_Reconst.Image_nf=0.8')
ax4.axis("off")

ax5.imshow(outputs_hid256_09[i].detach().numpy().reshape(28,28),cmap='gray')
ax5.set_title('AE_Reconst.Image_nf=0.9')
ax5.axis("off")

print("Reconstruction Error in VanillaAE with noise factor = 0.3 :",np.dot(((ima
ges[i].detach().numpy()/255.)-(outputs_hid256_03[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_hid256_03[i].detach().numpy()/255.)).T))
print("Reconstruction Error in VanillaAE with noise factor = 0.5 :",np.dot(((ima
ges[i].detach().numpy()/255.)-(outputs_hid256_05[i].detach().numpy()/255.)),((im
```

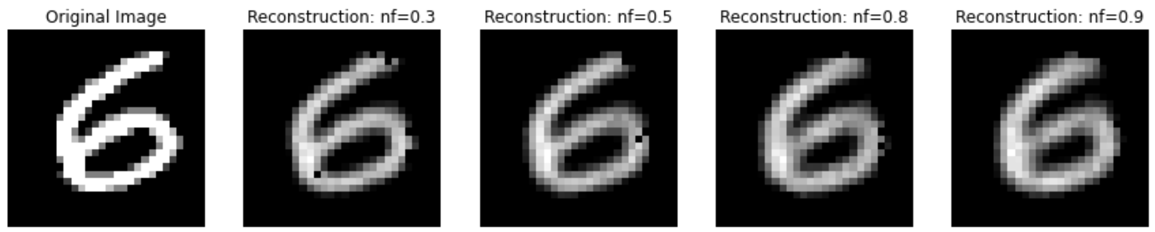
```
ages[i].detach().numpy()/255.)-(outputs_hid256_05[i].detach().numpy()/255.)).T))
print("Reconstruction Error in VanillaAE with noise factor = 0.8 :",np.dot(((ima
ges[i].detach().numpy()/255.)-(outputs_hid256_08[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_hid256_08[i].detach().numpy()/255.)).T))
print("Reconstruction Error in VanillaAE with noise factor = 0.9 :",np.dot(((ima
ges[i].detach().numpy()/255.)-(outputs_hid256_09[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_hid256_09[i].detach().numpy()/255.)).T))
```

```
Reconstruction Error in VanillaAE with noise factor = 0.3 : 12.29054
5043085082
Reconstruction Error in VanillaAE with noise factor = 0.5 : 12.28854
7516879056
Reconstruction Error in VanillaAE with noise factor = 0.8 : 12.31252
712926534
Reconstruction Error in VanillaAE with noise factor = 0.9 : 12.32003
4453259053
```

In [16]:

```
model_4_a.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    noisy_images = add_noise(images,0.3)
    outputs_4_a = model_4_a(noisy_images.float())

model_4_b.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    noisy_images = add_noise(images,0.5)
    outputs_4_b = model_4_b(noisy_images.float())

model_4_c.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    noisy_images = add_noise(images,0.8)
    outputs_4_c = model_4_c(noisy_images.float())

model_4_d.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    noisy_images = add_noise(images,0.9)
    outputs_4_d = model_4_d(noisy_images.float())

plt.rcParams["figure.figsize"] = (15,6)
i=5
if i==5:
  fig, (ax1, ax2,ax3,ax4,ax5) = plt.subplots(1,5)

  ax1.imshow(images[i].detach().numpy().reshape(28,28),cmap='gray')
  ax1.set_title('Original Image')
  ax1.axis("off")

  ax2.imshow(outputs_4_a[i].detach().numpy().reshape(28,28),cmap='gray')
  ax2.set_title('Reconstruction: nf=0.3')
  ax2.axis("off")

  ax3.imshow(outputs_4_b[i].detach().numpy().reshape(28,28),cmap='gray')
  ax3.set_title('Reconstruction: nf=0.5')
  ax3.axis("off")

  ax4.imshow(outputs_4_c[i].detach().numpy().reshape(28,28),cmap='gray')
  ax4.set_title('Reconstruction: nf=0.8')
  ax4.axis("off")

  ax5.imshow(outputs_4_d[i].detach().numpy().reshape(28,28),cmap='gray')
  ax5.set_title('Reconstruction: nf=0.9')
  ax5.axis("off")

  plt.show()

  print("Reconstruction Error in DenoisingAE with noise factor = 0.3 :",np.dot
(((images[i].detach().numpy()/255.)-(outputs_4_a[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_4_a[i].detach().numpy()/255.)).T))
  print("Reconstruction Error in DenoisingAE with noise factor = 0.5 :",np.dot
```

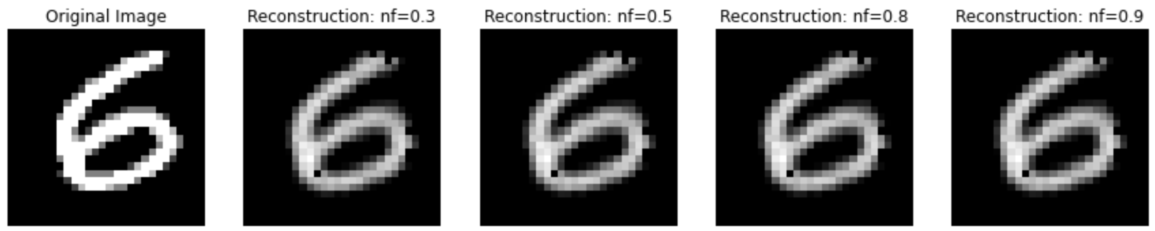
```
(((images[i].detach().numpy()/255.)-(outputs_4_b[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_4_b[i].detach().numpy()/255.)).T))
  print("Reconstruction Error in DenoisingAE with noise factor = 0.8 :",np.dot
(((images[i].detach().numpy()/255.)-(outputs_4_c[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_4_c[i].detach().numpy()/255.)).T))
  print("Reconstruction Error in DenoisingAE with noise factor = 0.9 :",np.dot
(((images[i].detach().numpy()/255.)-(outputs_4_d[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_4_d[i].detach().numpy()/255.)).T))
  print("_______________________________________________________________________
______________________")
```




```
Reconstruction Error in DenoisingAE with noise factor = 0.3 : 11.504
991739148307
Reconstruction Error in DenoisingAE with noise factor = 0.5 : 14.426
701488962669
Reconstruction Error in DenoisingAE with noise factor = 0.8 : 19.260
798583259362
Reconstruction Error in DenoisingAE with noise factor = 0.9 : 21.399
583871015913
____________________________________________________________________
__________________________
```

In [25]:

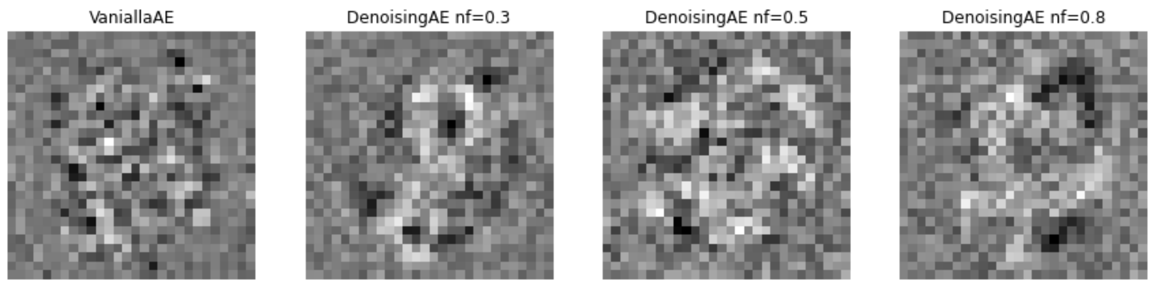
```
#DENOISING ENCODER TRAINED ON NOISE LEVEL=0.3 AND TESTED RECONSTRUCTION FOR NOIS
E LEVEL 0.3,0.5,0.8,0.9
model_4_a.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images = images.reshape(10,28*28)
    noisy_images = add_noise(images,0.3)
    outputs_4_a = model_4_a(noisy_images.float())
    noisy_images = add_noise(images,0.5)
    outputs_4_b = model_4_a(noisy_images.float())
    noisy_images = add_noise(images,0.8)
    outputs_4_c = model_4_a(noisy_images.float())
    noisy_images = add_noise(images,0.9)
    outputs_4_d = model_4_a(noisy_images.float())
i=5
if i==5:
  fig, (ax1, ax2,ax3,ax4,ax5) = plt.subplots(1,5)

  ax1.imshow(images[i].detach().numpy().reshape(28,28),cmap='gray')
  ax1.set_title('Original Image')
  ax1.axis("off")

  ax2.imshow(outputs_4_a[i].detach().numpy().reshape(28,28),cmap='gray')
  ax2.set_title('Reconstruction: nf=0.3')
  ax2.axis("off")

  ax3.imshow(outputs_4_b[i].detach().numpy().reshape(28,28),cmap='gray')
  ax3.set_title('Reconstruction: nf=0.5')
  ax3.axis("off")

  ax4.imshow(outputs_4_c[i].detach().numpy().reshape(28,28),cmap='gray')
  ax4.set_title('Reconstruction: nf=0.8')
  ax4.axis("off")

  ax5.imshow(outputs_4_d[i].detach().numpy().reshape(28,28),cmap='gray')
  ax5.set_title('Reconstruction: nf=0.9')
  ax5.axis("off")

  plt.show()

  print("Reconstruction Error in DenoisingAE with noise factor = 0.3 :",np.dot
(((images[i].detach().numpy()/255.)-(outputs_4_a[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_4_a[i].detach().numpy()/255.)).T))
  print("Reconstruction Error in DenoisingAE with noise factor = 0.5 :",np.dot
(((images[i].detach().numpy()/255.)-(outputs_4_b[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_4_b[i].detach().numpy()/255.)).T))
  print("Reconstruction Error in DenoisingAE with noise factor = 0.8 :",np.dot
(((images[i].detach().numpy()/255.)-(outputs_4_c[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_4_c[i].detach().numpy()/255.)).T))
  print("Reconstruction Error in DenoisingAE with noise factor = 0.9 :",np.dot
(((images[i].detach().numpy()/255.)-(outputs_4_d[i].detach().numpy()/255.)),((im
ages[i].detach().numpy()/255.)-(outputs_4_d[i].detach().numpy()/255.)).T))
  print("____________________________________________________________________________________________________________")
```




```
Reconstruction Error in DenoisingAE with noise factor = 0.3 : 11.504
407994823417
Reconstruction Error in DenoisingAE with noise factor = 0.5 : 11.499
836309490743
Reconstruction Error in DenoisingAE with noise factor = 0.8 : 11.495
695934586088
Reconstruction Error in DenoisingAE with noise factor = 0.9 : 11.509
95439903982
```

In [23]:

```
##VISUALISING ENCODER WEIGHTS

plt.rcParams["figure.figsize"] = (15,6)

fig, (ax1, ax2,ax3,ax4) = plt.subplots(1,4)
ax1.imshow(model_hid256.encoder[0].weight.detach().numpy()[0].reshape(28,28),cma
p='gray')
ax1.set_title('VaniallaAE')
ax1.axis("off")

ax2.imshow(model_4_a.encoder[0].weight.detach().numpy()[0].reshape(28,28),cmap=
'gray')
ax2.set_title('DenoisingAE nf=0.3')
ax2.axis("off")

ax3.imshow(model_4_b.encoder[0].weight.detach().numpy()[0].reshape(28,28),cmap=
'gray')
ax3.set_title('DenoisingAE nf=0.5')
ax3.axis("off")

ax4.imshow(model_4_c.encoder[0].weight.detach().numpy()[0].reshape(28,28),cmap=
'gray')
ax4.set_title('DenoisingAE nf=0.8')
ax4.axis("off")

plt.show()
```



Observations:

- Vanilla autoencoder when given corrupted input has reconstruction error more than Denoising Autoencoder trained on noise level 0.3.
- Though not very clearly visible but encoder weights of denoising AE have some penstroke detector type visualisation.

Question 5

In [26]:

```
class AE5_ConvAE_with_unpooling(nn.Module): #define unpooling outside the decode
r and separately in forward nn.Sequential just takes one input

    def __init__(self): #class constructor
        super(AE5_ConvAE_with_unpooling,self).__init__() #calls the parent const
ructor

        #initializing the encoder module
        self.encoder_conv1 = nn.Sequential(
            nn.Conv2d(1,8, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2),return_indices = True)
        ) # 28x28x1 to 14x14x8
        self.encoder_conv2 = nn.Sequential(
            nn.Conv2d(8,16, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2),return_indices = True)
        ) #14x14x8 to 7x7x16
        self.encoder_conv3 = nn.Sequential(
            nn.Conv2d(16,16, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2),return_indices = True)
        ) #7x7x16 to 3x3x16

        #initializing the decoder module
        self.decoder_conv1 = nn.Sequential(nn.Identity()) #7x7x16 to 7x7x16
        self.decoder_conv2 = nn.Sequential(
            nn.Conv2d(16,8, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU()
        ) #14x14x16 to 14x14x8
        self.decoder_conv3 = nn.Sequential(
            nn.Conv2d(8,1, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU()
        ) #28x28x8 to 28x28x1

        #defining the unpooling operation
        self.unpool = nn.MaxUnpool2d(kernel_size = (2,2))


    def forward(self,x): #defines the forward pass and also the structure of the
network thus helping backprop

        encoded_input,indices1  = self.encoder_conv1(x.float())  # 28x28x1 to 14
x14x8
        encoded_input,indices2  = self.encoder_conv2(encoded_input) #14x14x8 to
 7x7x16
        encoded_input,indices3  = self.encoder_conv3(encoded_input) #7x7x16 to 3
x3x16

        reconstructed_input     = self.unpool(encoded_input,indices3,output_size
=torch.Size([batch_size, 16, 7, 7])) #3x3x16 to 7x7x16
        reconstructed_input     = self.decoder_conv1(reconstructed_input) #7x7x1
6 to 7x7x16
        reconstructed_input     = self.unpool(reconstructed_input,indices2) #7x7
x16 to 14x14x16
        reconstructed_input     = self.decoder_conv2(reconstructed_input)#14x14x
16 to 14x14x8
        reconstructed_input     = self.unpool(reconstructed_input,indices1)#14x1
4x8 to 28x28x8
```

```
        reconstructed_input     = self.decoder_conv3(reconstructed_input)#28x28x
8 to 28x28x1

        return reconstructed_input,encoded_input
```

In [27]:

```
model_5_a = AE5_ConvAE_with_unpooling()
criterion_5_a = nn.MSELoss()
optimizer_5_a = torch.optim.Adam(model_5_a.parameters(),lr=0.001)

training_loss_5_a=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    outputs,_=model_5_a(images)
    loss=criterion_5_a(outputs,images)
    training_loss_5_a.append(loss.item())

    optimizer_5_a.zero_grad()
    loss.backward()
    optimizer_5_a.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [28]:

```
class AE5_ConvAE_with_deconv(nn.Module):
    def __init__(self):
        super(AE5_ConvAE_with_deconv,self).__init__()

        #encoder
        self.encoder_conv1 = nn.Sequential(
            nn.Conv2d(1,8, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2))
        )
        self.encoder_conv2 = nn.Sequential(
            nn.Conv2d(8,16, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2))
        )
        self.encoder_conv3 = nn.Sequential(
            nn.Conv2d(16,16, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2))
        )

        #decoder module
        self.decoder_conv1 = nn.Sequential(
            nn.ConvTranspose2d(16,16, kernel_size = 3, stride = 2),
            nn.ReLU()
        )
        self.decoder_conv2 = nn.Sequential(
            nn.ConvTranspose2d(16,8, kernel_size = 4, stride = 2, padding = 1),
            nn.ReLU()
        )
        self.decoder_conv3 = nn.Sequential(
            nn.ConvTranspose2d(8,1, kernel_size = 4, stride = 2, padding = 1),
            nn.ReLU()
        )

    def forward(self,x):

        encoded_input  = self.encoder_conv1(x.float())
        encoded_input  = self.encoder_conv2(encoded_input)
        encoded_input  = self.encoder_conv3(encoded_input)

        reconstructed_input = self.decoder_conv1(encoded_input)
        reconstructed_input = self.decoder_conv2(reconstructed_input)
        reconstructed_input = self.decoder_conv3(reconstructed_input)

        return reconstructed_input,encoded_input
```

In [29]:

```
model_5_b = AE5_ConvAE_with_deconv()
criterion_5_b = nn.MSELoss()
optimizer_5_b = torch.optim.Adam(model_5_b.parameters(),lr=0.001)

training_loss_5_b=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    outputs,_=model_5_b(images)
    loss=criterion_5_b(outputs,images)
    training_loss_5_b.append(loss.item())

    optimizer_5_b.zero_grad()
    loss.backward()
    optimizer_5_b.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

In [30]:

```
class AE5_ConvAE_with_deconv_unpool(nn.Module):
    def __init__(self):
        super(AE5_ConvAE_with_deconv_unpool,self).__init__()

         #encoder
        self.encoder_conv1 = nn.Sequential(
            nn.Conv2d(1,8, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2),return_indices = True)
        )
        self.encoder_conv2 = nn.Sequential(
            nn.Conv2d(8,16, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = (2,2),return_indices = True)
        )
        self.encoder_conv3 = nn.Sequential(
            nn.Conv2d(16,16, kernel_size = 3, stride = 1,padding= 1),
            nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2),return_indices = True)
        )

        #initializing the decoder module
        self.decoder_conv1 = nn.Sequential(
            nn.ConvTranspose2d(16,16, kernel_size = 3, stride = 1, padding = 1),
            nn.ReLU()
        )
        self.decoder_conv2 = nn.Sequential(
            nn.ConvTranspose2d(16,8, kernel_size = 3, stride = 1, padding = 1),
            nn.ReLU()
        )
        self.decoder_conv3 = nn.Sequential(
            nn.ConvTranspose2d(8,1, kernel_size = 3, stride = 1, padding = 1),
            nn.ReLU()
        )

        #unpooling
        self.unpool = nn.MaxUnpool2d(kernel_size = (2,2))

    def forward(self,x): #defines the forward pass and also the structure of the
network thus helping backprop

        encoded_input,indices1  = self.encoder_conv1(x.float())
        encoded_input,indices2  = self.encoder_conv2(encoded_input)
        encoded_input,indices3  = self.encoder_conv3(encoded_input)

        reconstructed_input = self.unpool(encoded_input,indices3,output_size=tor
ch.Size([batch_size, 16, 7, 7]))
        reconstructed_input = self.decoder_conv1(reconstructed_input)
        reconstructed_input = self.unpool(reconstructed_input,indices2)
        reconstructed_input = self.decoder_conv2(reconstructed_input)
        reconstructed_input = self.unpool(reconstructed_input,indices1)
        reconstructed_input = self.decoder_conv3(reconstructed_input)

        return reconstructed_input,encoded_input
```

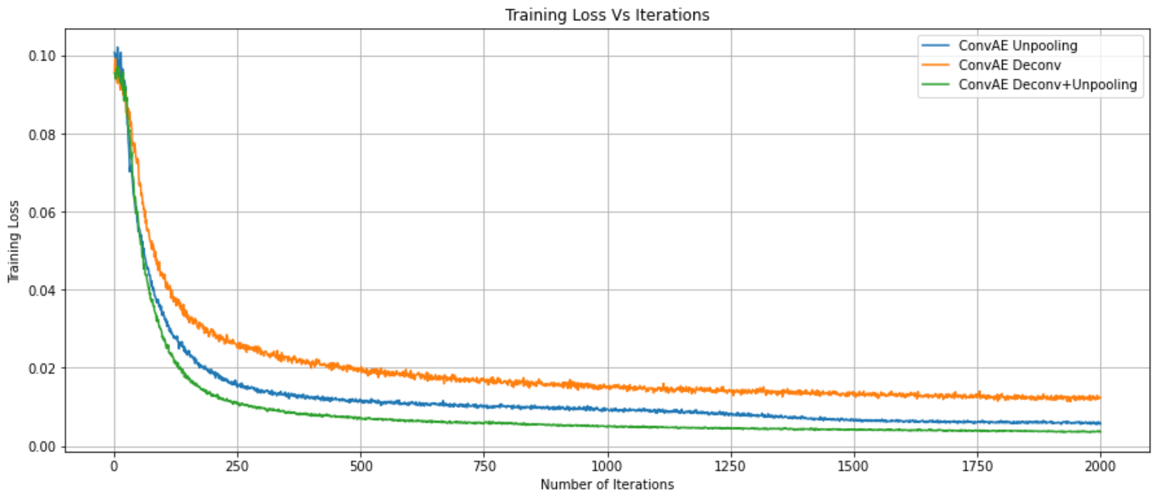
In [31]:

```
model_5_c = AE5_ConvAE_with_deconv_unpool()
criterion_5_c = nn.MSELoss()
optimizer_5_c = torch.optim.Adam(model_5_c.parameters(),lr=0.001)

training_loss_5_c=[]

for epoch in range(epochs):
  for images,labels in train_loader:
    outputs,_=model_5_c(images)
    loss=criterion_5_c(outputs,images)
    training_loss_5_c.append(loss.item())

    optimizer_5_c.zero_grad()
    loss.backward()
    optimizer_5_c.step()

  print("Epoch","[",epoch+1,"/",epochs,"]", ": completed")
```

```
Epoch [ 1 / 10 ] : completed
Epoch [ 2 / 10 ] : completed
Epoch [ 3 / 10 ] : completed
Epoch [ 4 / 10 ] : completed
Epoch [ 5 / 10 ] : completed
Epoch [ 6 / 10 ] : completed
Epoch [ 7 / 10 ] : completed
Epoch [ 8 / 10 ] : completed
Epoch [ 9 / 10 ] : completed
Epoch [ 10 / 10 ] : completed
```

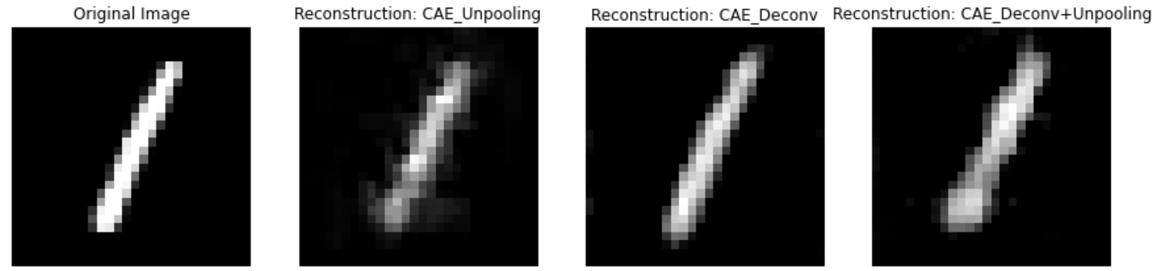
In [32]:

```
plt.plot(range(1,len(training_loss_5_a)+1),training_loss_5_a,label="ConvAE Unpoo
ling")
plt.plot(range(1,len(training_loss_5_a)+1),training_loss_5_b,label="ConvAE Decon
v")
plt.plot(range(1,len(training_loss_5_a)+1),training_loss_5_c,label="ConvAE Decon
v+Unpooling")
plt.legend()
plt.grid()
plt.title("Training Loss Vs Iterations")
plt.xlabel("Number of Iterations")
plt.ylabel("Training Loss")
plt.show()
```

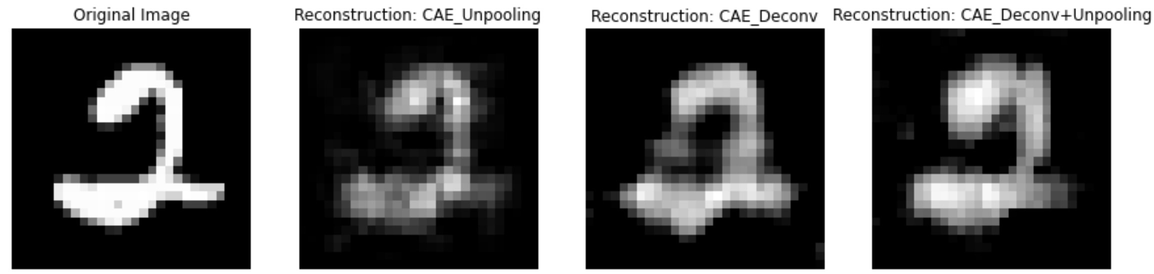


In [33]:

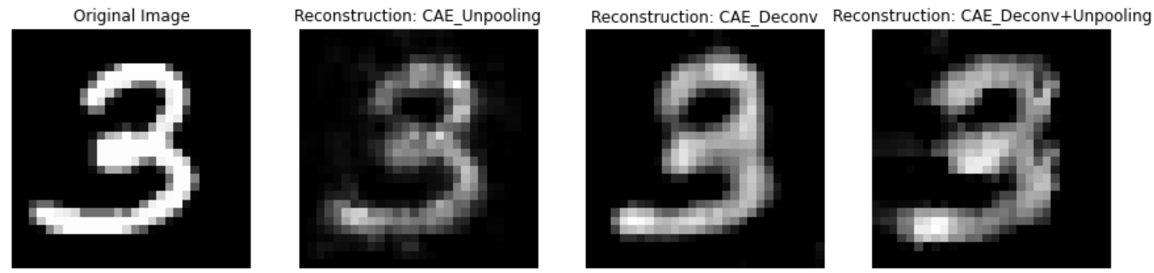
```
model_5_a.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images=images.reshape(10,1,28,28)
    outputs_5_a,_ = model_5_a(images.float())


model_5_b.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images=images.reshape(10,1,28,28)
    outputs_5_b,_ = model_5_b(images.float())


activation_5_c=[]
model_5_c.eval()
with torch.no_grad():
  for images in test_sample_loader:
    images=images.reshape(10,1,28,28)
    outputs_5_c,_= model_5_c(images.float())


plt.rcParams["figure.figsize"] = (15,6)

for i in range(10):
  fig, (ax1, ax2,ax3,ax4) = plt.subplots(1,4)

  ax1.imshow(images[i].detach().numpy().reshape(28,28),cmap='gray')
  ax1.set_title('Original Image')
  ax1.axis("off")

  ax2.imshow(outputs_5_a[i].detach().numpy().reshape(28,28),cmap='gray')
  ax2.set_title('Reconstruction: CAE_Unpooling')
  ax2.axis("off")

  ax3.imshow(outputs_5_b[i].detach().numpy().reshape(28,28),cmap='gray')
  ax3.set_title('Reconstruction: CAE_Deconv')
  ax3.axis("off")

  ax4.imshow(outputs_5_c[i].detach().numpy().reshape(28,28),cmap='gray')
  ax4.set_title('Reconstruction: CAE_Deconv+Unpooling')
  ax4.axis("off")

  plt.show()

  print("Reconstruction Error in ConvAE Unpooling:",np.sum(np.dot(((images[i].de
tach().numpy()/255)-(outputs_5_a[i].detach().numpy()/255)),((images[i].detach().
numpy()/255)-(outputs_5_a[i].detach().numpy()/255)).T)))
  print("Reconstruction Error in ConvAE Deconv:",np.sum(np.dot(((images[i].detac
h().numpy()/255)-(outputs_5_b[i].detach().numpy()/255)),((images[i].detach().num
py()/255)-(outputs_5_b[i].detach().numpy()/255)).T)))
  print("Reconstruction Error in ConvAE Deconv+Unpooling:",np.sum(np.dot(((image
s[i].detach().numpy()/255)-(outputs_5_c[i].detach().numpy()/255)),((images[i].de
tach().numpy()/255)-(outputs_5_c[i].detach().numpy()/255)).T)))
  print("________________________________________________________________________
_______________________")
```



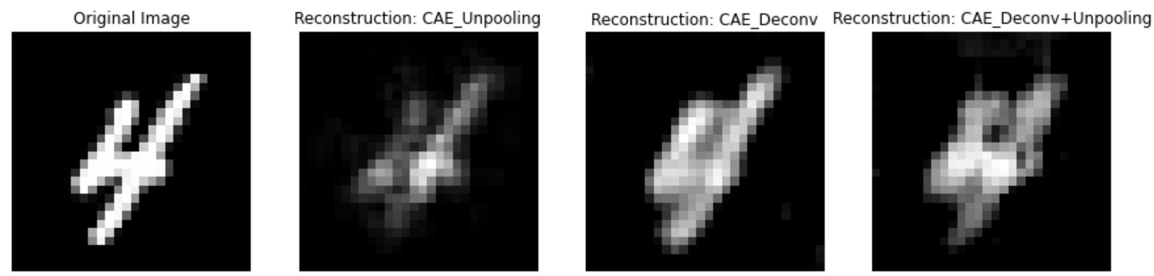

```
Reconstruction Error in ConvAE Unpooling: 1.7310008604428355
Reconstruction Error in ConvAE Deconv: 26.001679380843555
Reconstruction Error in ConvAE Deconv+Unpooling: 11.89297063287778
```



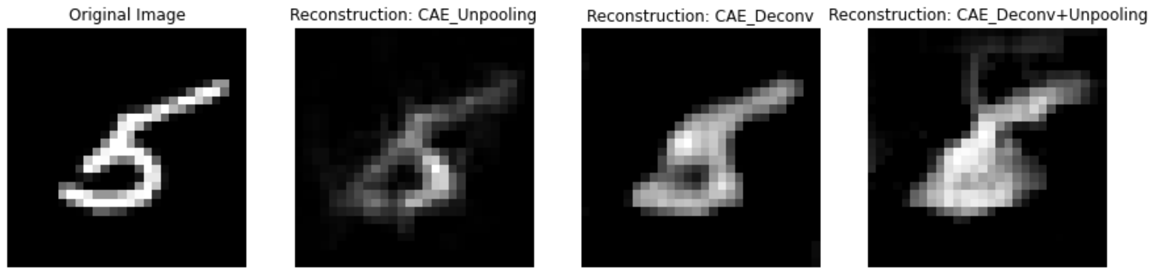

```
Reconstruction Error in ConvAE Unpooling: 36.132811210593644
Reconstruction Error in ConvAE Deconv: 118.04138416590519
Reconstruction Error in ConvAE Deconv+Unpooling: 93.50976356860426
```



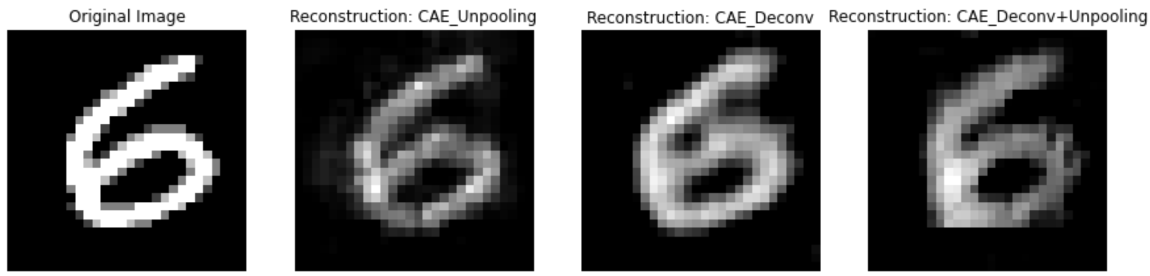

```
Reconstruction Error in ConvAE Unpooling: 0.2794066287723087
Reconstruction Error in ConvAE Deconv: 130.92309175297225
Reconstruction Error in ConvAE Deconv+Unpooling: 56.26377338926373
```



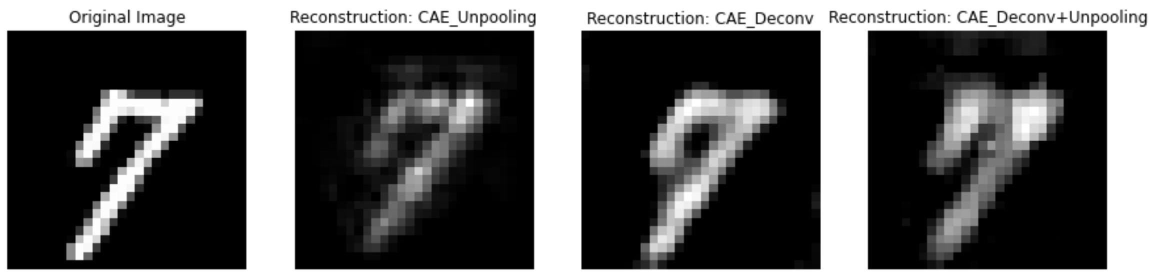
```
Reconstruction Error in ConvAE Unpooling: 21.321372713953124
Reconstruction Error in ConvAE Deconv: 95.42958725539685
Reconstruction Error in ConvAE Deconv+Unpooling: 38.815502513706875
```



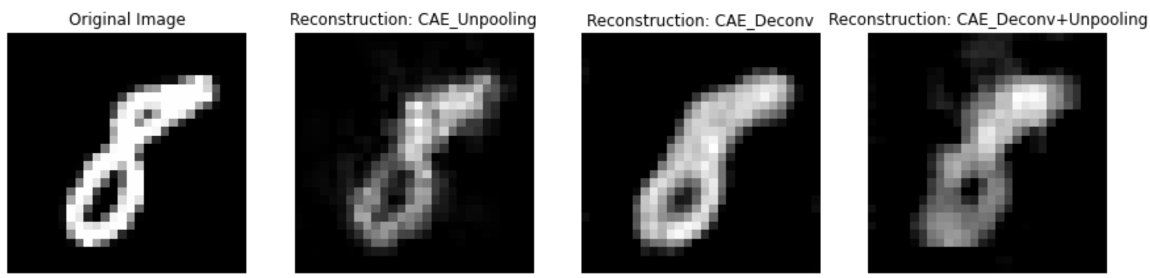

```
Reconstruction Error in ConvAE Unpooling: 6.22126437500681
Reconstruction Error in ConvAE Deconv: 61.48894311018323
Reconstruction Error in ConvAE Deconv+Unpooling: 9.12990892796395
```



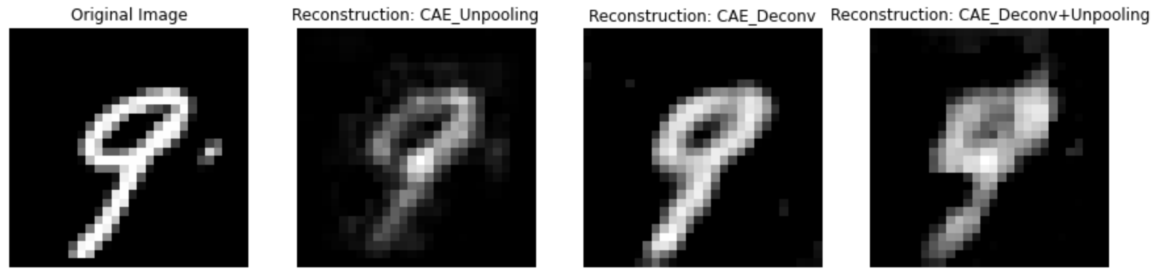

```
Reconstruction Error in ConvAE Unpooling: 71.43498495324837
Reconstruction Error in ConvAE Deconv: 212.74946483973974
Reconstruction Error in ConvAE Deconv+Unpooling: 168.52247765694244
```



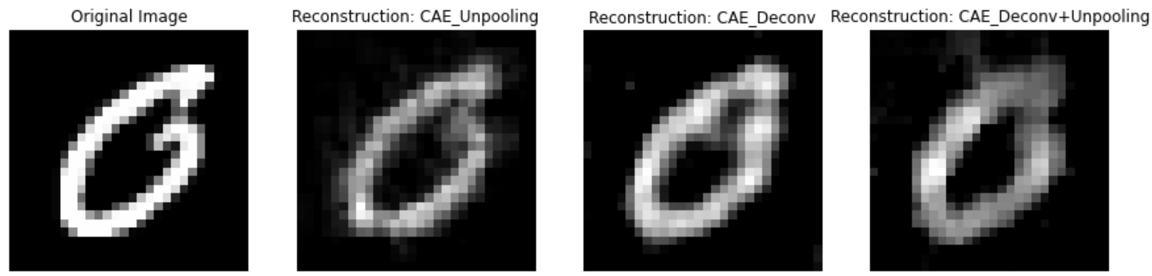

```
Reconstruction Error in ConvAE Unpooling: 25.535638771069415
Reconstruction Error in ConvAE Deconv: 95.00550731184873
Reconstruction Error in ConvAE Deconv+Unpooling: 35.801245134441594
```



```
Reconstruction Error in ConvAE Unpooling: 29.760346086314858
Reconstruction Error in ConvAE Deconv: 101.14872994906563
Reconstruction Error in ConvAE Deconv+Unpooling: 53.518502795113626
```




```
Reconstruction Error in ConvAE Unpooling: 24.24100375371164
Reconstruction Error in ConvAE Deconv: 86.583618580179
Reconstruction Error in ConvAE Deconv+Unpooling: 41.803233553557405
```




```
Reconstruction Error in ConvAE Unpooling: 41.52189672531831
Reconstruction Error in ConvAE Deconv: 205.93324026718437
Reconstruction Error in ConvAE Deconv+Unpooling: 80.49537718296492
```

In [34]:

```
model_5_a.encoder_conv1[0].weight.detach().numpy().squeeze().shape
```

Out[34]:

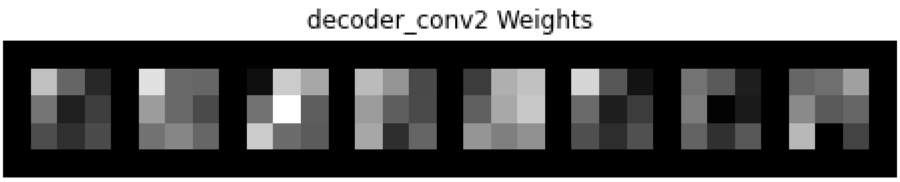
```
(8, 3, 3)
```

In [35]:

```
#Function for visualisation of weights
from torchvision import utils

def visTensor(tensor, ch=0, allkernels=False, nrow=8, padding=1):
  n,c,w,h = tensor.shape

  if allkernels: tensor = tensor.view(n*c, -1, w, h)
  elif c != 3: tensor = tensor[:,ch,:,:].unsqueeze(dim=1)

  rows = np.min((tensor.shape[0] // nrow + 1, 64))
  grid = utils.make_grid(tensor, nrow=nrow, normalize=True, padding=padding)
  plt.figure( figsize=(nrow,rows) )
  plt.imshow(grid.numpy().transpose((1, 2, 0)))
```

In [36]:

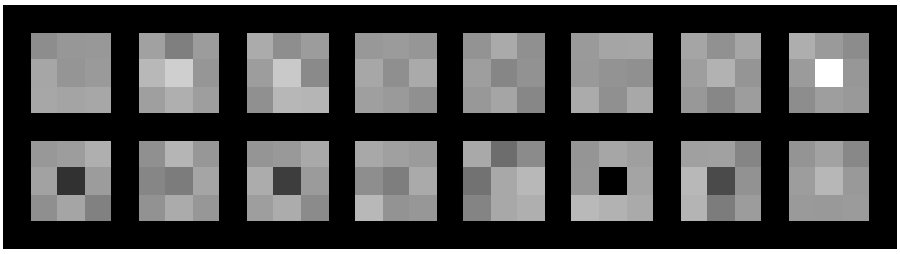
```
#VISUALISING DECODER WEIGHTS FOR CONVOLUTION AUTOENCODER WITH UNPOOLING

filter = model_5_a.decoder_conv2[0].weight.data.clone()
visTensor(filter, ch=0, allkernels=False)

plt.axis('off')
plt.ioff()
plt.title('decoder_conv2 Weights')
plt.show()

filter = model_5_a.decoder_conv3[0].weight.data.clone()
visTensor(filter, ch=0, allkernels=False)

plt.axis('off')
plt.ioff()
plt.title('decoder_conv3 Weights')
plt.show()
```



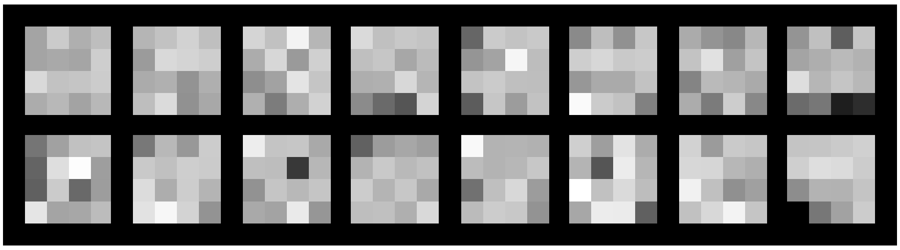
In [37]:

```
#VISUALISING DECODER WEIGHTS FOR CONVOLUTION AUTOENCODER WITH DECONVOLUTION

filter = model_5_b.decoder_conv1[0].weight.data.clone()
visTensor(filter, ch=0, allkernels=False)

plt.axis('off')
plt.ioff()
plt.title('decoder_conv1 Weights')
plt.show()

filter = model_5_b.decoder_conv2[0].weight.data.clone()
visTensor(filter, ch=0, allkernels=False)

plt.axis('off')
plt.ioff()
plt.title('decoder_conv2 Weights')
plt.show()

filter = model_5_b.decoder_conv3[0].weight.data.clone()
visTensor(filter, ch=0, allkernels=False)

plt.axis('off')
plt.ioff()
plt.title('decoder_conv3 Weights')
plt.show()
```

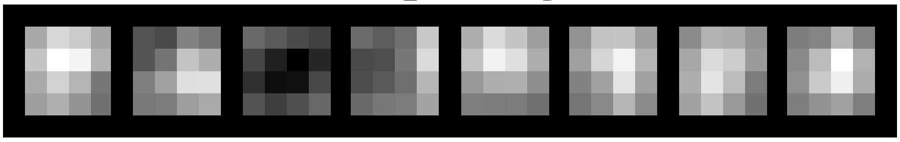
decoder_conv1 Weights



decoder_conv2 Weights



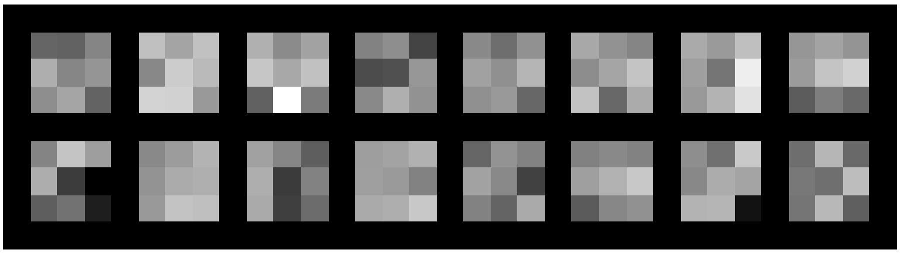
decoder_conv3 Weights



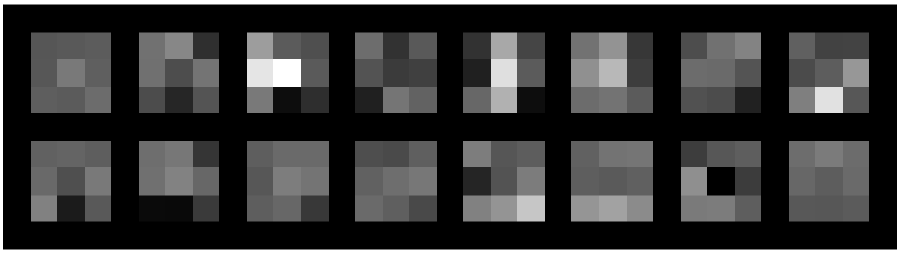
In [38]:

```
#VISUALISING DECODER WEIGHTS FOR CONVOLUTION AUTOENCODER WITH DECONVOLUTION+UNPO
OLING

filter = model_5_c.decoder_conv1[0].weight.data.clone()
visTensor(filter, ch=0, allkernels=False)

plt.axis('off')
plt.ioff()
plt.title('decoder_conv1 Weights')
plt.show()

filter = model_5_c.decoder_conv2[0].weight.data.clone()
visTensor(filter, ch=0, allkernels=False)

plt.axis('off')
plt.ioff()
plt.title('decoder_conv2 Weights')
plt.show()

filter = model_5_c.decoder_conv3[0].weight.data.clone()
visTensor(filter, ch=0, allkernels=False)

plt.axis('off')
plt.ioff()
plt.title('decoder_conv3 Weights')
plt.show()
```

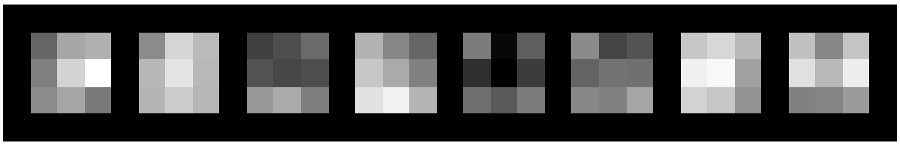
decoder_conv1 Weights



decoder_conv2 Weights



decoder_conv3 Weights



Observations:

- Decoder weights of Deconvolution with Unpooling and Unpooling are smaller than the only Deconvolution one.
- By looking at reconstruction error, it looks like unpooling and deconv+ unpooling does better on reconstruction of images.
- Visually, reconstructed images using Deconvolution are appealing.