EXP No: 10 :- Perform Compression on MNIST dataset Using Auto Encoder.

Aim:-

To implement an Autoencoder for compressing and reconstructing MNIST images, thereby understanding the concept of dimensionality reduction using neural network.

Objectives:-

1. To build an encoder that compresses high dimensional image data into a lower-dimensional latent space
2. To reconstruct the input image using a decoder work
3. To visualize and evaluate the performance of compression and reconstruction
4. To understand unsupervised feature learning using neural networks

Algorithm:-

1. Import MNIST dataset.
2. Normalize image data (scale pixels b/w 0 & 1)
3. Build an Autoencoder consisting of:
   - Encoder: Compresses image into latent vector
   - Decoder: Reconstructs image from latent representation
4. Compile the model with loss = 'binary_crossentropy' & optimizer = 'adam'.

5. Train the model on MNIST images.

6. Evaluate the reconstruction quality using test images.

7 Visualize input vs reconstructed images.

Pseudo Code:-

```
Load MNIST dataset

Normalize images to range [0,1]

Define encoder:
    Flatten input
    Dense (128, relu)
    Dense (64, relu)
    Dense (latent_dim, relu)

Define decoder:
    Dense (64, relu)
    Dense (128 relu)
    Dense (784, Sigmoid)
    Reshape (28, 28)

Combine encoder + decoder -> autoencoder

Compile autoencoder (adam, binary-crossentropy)
Train on MNIST data (epochs = 50, batch_size = 256)

Generate reconstructed images
Display original & reconstructed samples
```

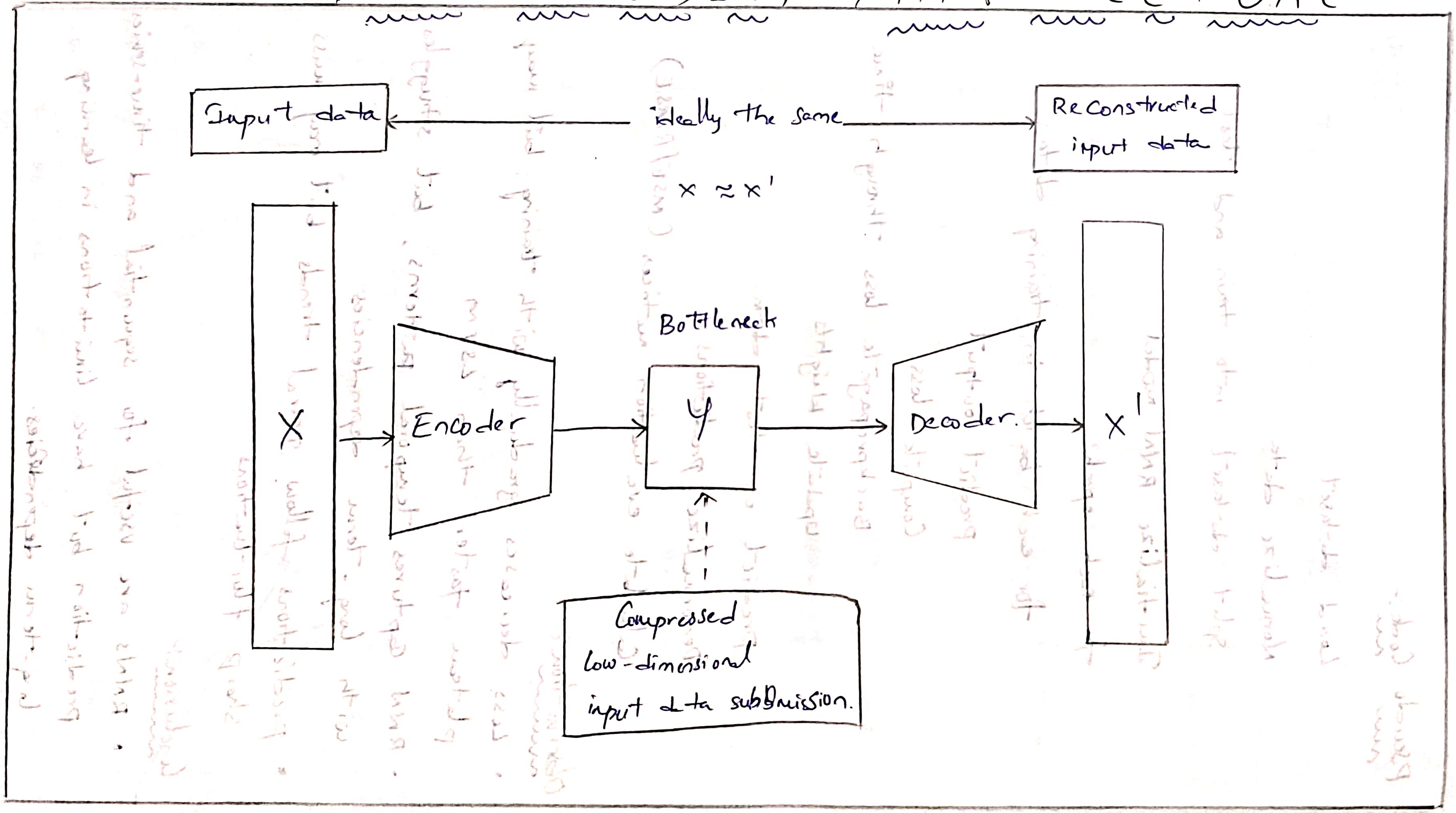
Observation:-

- The Autoencoder successfully Compresses 784 feature into a 32-dimensional talent space
- The reconstructed images closely resemble the original MNIST digits, though with slight bluring due to compression loss.
- Training loss decreases steadily with epochs, indicating good learning.

Conclusion:-

Autoencoders efficiently learn compressed feature representations of images without supervision The MNIST Autoencoder achieves dimensionality reduction while maintaining the essential structure of the digits, demonstrating effective unsupervised Compression

AUTOENCODER ARCHITECTURE.



Output

Simple AE | Epoch [1/5], Loss : 0.0501

Simple AE | Epoch [2/5], Loss : 0.0211

Simple AE | Epoch [3/5], Loss : 0.0154

Simple AE | Epoch [4/5], Loss : 0.0128

Simple AE | Epoch [5/5], Loss : 0.0114

Deep AE | Epoch[1/5], Loss: 0.0445

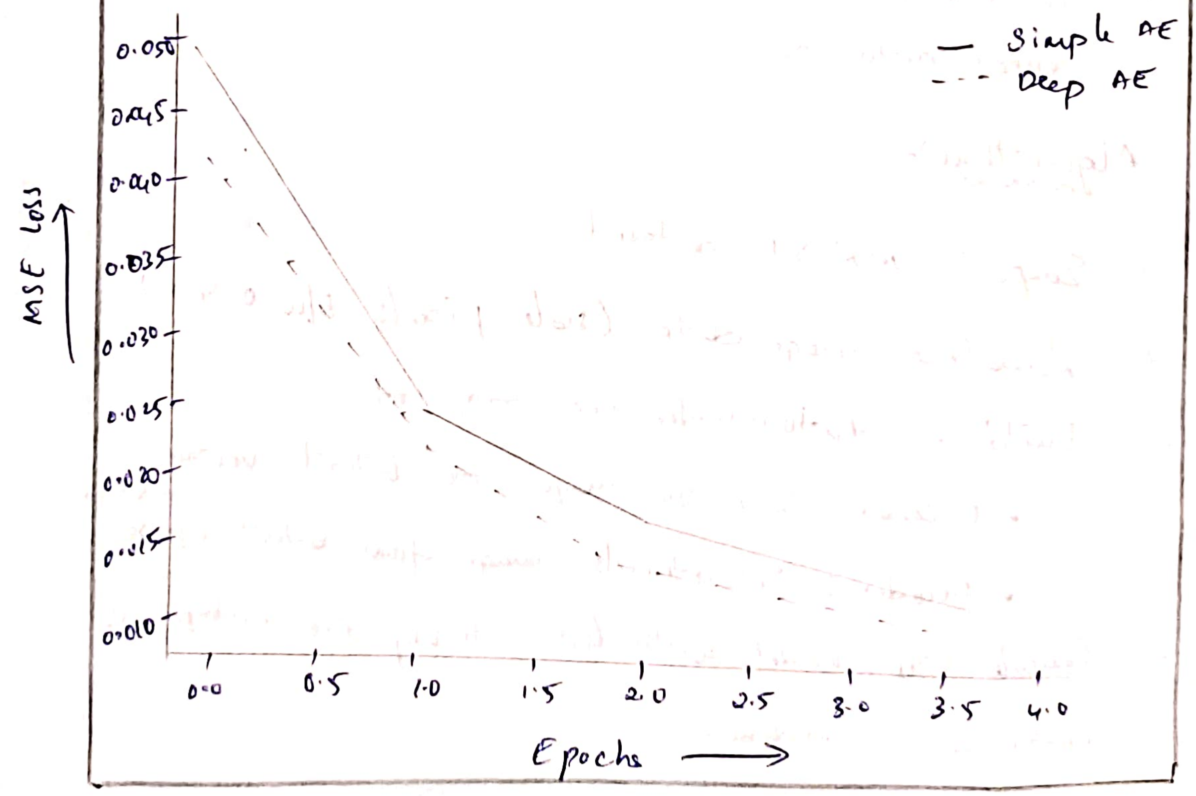
Deep AE | Epoch[2/5], Loss: 0.0199

Deep AE | Epoch[3/5], Loss : 0.0150

Deep AE | Epoch[4/5], Loss : 0.0124

Deep AE | Epoch[5/5], Loss : 0.0108

Training Loss Companision



dltlab10.ipynb

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```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
tf = transforms.Compose([transforms.ToTensor()])
train_data = datasets.MNIST(root='data', train=True, transform=tf, download=True)
train_loader = DataLoader(train_data, batch_size=128, shuffle=True)
class SimpleAE(nn.Module):
    def __init__(self):
        super(SimpleAE, self).__init__()
        self.encoder = nn.Sequential(
            nn.Linear(28*28, 128),
            nn.ReLU(),
            nn.Linear(128, 32)
        )
        self.decoder = nn.Sequential(
            nn.Linear(32, 128),
            nn.ReLU(),
            nn.Linear(128, 28*28),
            nn.Sigmoid()
        )
    def forward(self, x):
        x = x.view(-1, 28*28)
        z = self.encoder(x)
        out = self.decoder(z)
        return out.view(-1, 1, 28, 28)
class DeepAE(nn.Module):
    def __init__(self):
        super(DeepAE, self).__init__()
        self.encoder = nn.Sequential(
            nn.Linear(784, 512),
            nn.ReLU(),
            nn.Linear(512, 128),
            nn.ReLU(),
            nn.Linear(128, 32)
        )
        self.decoder = nn.Sequential(
            nn.Linear(32, 128),
            nn.ReLU(),
            nn.Linear(128, 512),
            nn.ReLU(),
            nn.Linear(512, 784),
            nn.Sigmoid()
        )
    def forward(self, x):
        x = x.view(-1, 784)
        z = self.encoder(x)
        out = self.decoder(z)
        return out.view(-1, 1, 28, 28)
```

```python
simpleAE = SimpleAE().to(device)
deepAE = DeepAE().to(device)
criterion = nn.MSELoss()
opt_simple = optim.Adam(simpleAE.parameters(), lr=1e-3)
opt_deep = optim.Adam(deepAE.parameters(), lr=1e-3)
def train_model(model, optimizer, name):
    losses = []
    for epoch in range(5):
        total_loss = 0
        for imgs, _ in train_loader:
            imgs = imgs.to(device)
            out = model(imgs)
            loss = criterion(out, imgs)
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        avg = total_loss / len(train_loader)
        losses.append(avg)
        print(f"{name} | Epoch [{epoch+1}/5], Loss: {avg:.4f}")
    return losses
loss_simple = train_model(simpleAE, opt_simple, "SimpleAE")
loss_deep = train_model(deepAE, opt_deep, "DeepAE")
plt.plot(loss_simple, label='Simple AE')
plt.plot(loss_deep, label='Deep AE')
plt.title("Training Loss Comparison")
plt.xlabel("Epochs")
plt.ylabel("MSE Loss")
plt.legend()
plt.show()
def show_reconstruction(model, name):
    model.eval()
    imgs, _ = next(iter(train_loader))
    imgs = imgs[:5].to(device)
    with torch.no_grad():
        recons = model(imgs)
    imgs, recons = imgs.cpu(), recons.cpu()
    fig, axes = plt.subplots(2, 5, figsize=(10, 4))
    for i in range(5):
        axes[0, i].imshow(imgs[i].squeeze(), cmap='gray')
        axes[0, i].axis('off')
        axes[1, i].imshow(recons[i].squeeze(), cmap='gray')
        axes[1, i].axis('off')
    plt.suptitle(f"{name} Reconstruction (Top: Original, Bottom: Reconstructed)")
    plt.show()

show_reconstruction(simpleAE, "Simple Autoencoder")
show_reconstruction(deepAE, "Deep Autoencoder")
```

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100%|██████████| 28.9k/28.9k [00:00<00:00, 483kB/s]
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100%|██████████| 4.54k/4.54k [00:00<00:00, 3.40MB/s]
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```