

Exp 10:

Perform compression on mnist dataset using auto encoder.

Aim:

To implement an Autoencoder that compresses and reconstruct MNIST handwritten digit image using PyTorch.

Pseudo code:

1. Import libraries & load MNIST dataset
2. Normalize & flatten the images
3. Define Autoencoder:
 - Encoder: compresses input to latent vector
 - Decoder: Reconstructs the image from latent vectors
4. Define loss (MSE) & optimizer (Adam)
5. Train model:
 - Forward pass
 - ~~Backward pass~~
 - compute loss
 - Backpropagate
 - update weights.
6. Evaluate on test data
7. Visualize:
 - Original vs Reconstructed images
 - Latent space (compressed features)

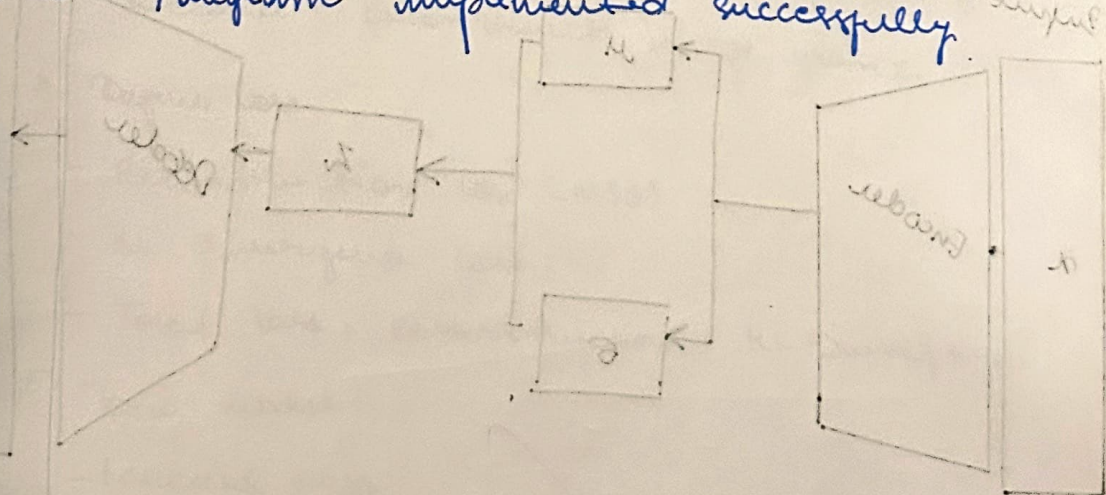
Justification:

An autoencoder is an unsupervised neural network that learns to compress (encode) input data into a smaller representative (latent space) and then reconstruct (decode) it back to the original form.

It helps in:

- Data compression.
- Noise reduction
- feature extraction
- Dimensionality reduction.

Result: Program implemented successfully.



$$30 + 10 = 40$$
$$(1, 0) \text{ is } 3$$

Output :

Epoch 1, loss: 0.0257

Epoch 2, loss: 0.0163

Epoch 3, loss: 0.0141

Epoch 4, loss: 0.0121

Epoch 5, loss: 0.0098.

Accuracy: 0.9689

Recall: 0.8528

f1: 0.8876

original

7

recon.

7

original

2

recon.

2

original

1

recon.

1

original

0

recon.

0

original

4

recon.

4

(masks) reinitgo & (32) oval initgo

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[1] ▶ import torch, torch.nn as nn, torch.optim as optim
    from torchvision import datasets, transforms
    from torch.utils.data import DataLoader
    import matplotlib.pyplot as plt
    from sklearn.metrics import accuracy_score, recall_score, f1_score
    transform = transforms.ToTensor()
    train = datasets.MNIST(root='./data', train=True, download=True, transform=transform)
    test = datasets.MNIST(root='./data', train=False, download=True, transform=transform)
    train_loader = DataLoader(train, batch_size=128, shuffle=True)
    test_loader = DataLoader(test, batch_size=128, shuffle=False)
    class AE(nn.Module):
        def __init__(self):
            super().__init__()
            self.enc = nn.Sequential(nn.Linear(784,128), nn.ReLU(), nn.Linear(128,32))
            self.dec = nn.Sequential(nn.Linear(32,128), nn.ReLU(), nn.Linear(128,784), nn.Sigmoid())
        def forward(self,x):
            x = x.view(-1,784)
            return self.dec(self.enc(x))

    device = 'cuda' if torch.cuda.is_available() else 'cpu'
    model = AE().to(device)
    opt = optim.Adam(model.parameters(), lr=1e-3)
    loss_fn = nn.MSELoss()
    for epoch in range(5):
        for imgs, _ in train_loader:
    
```



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[1] for epoch in range(5):
    for imgs, _ in train_loader:
        imgs = imgs.to(device)
        out = model(imgs)
        loss = loss_fn(out, imgs.view(-1,784))
        opt.zero_grad(); loss.backward(); opt.step()
    print(f"Epoch {epoch+1}, Loss: {loss.item():.4f}")
model.eval()
imgs, _ = next(iter(test_loader))
imgs = imgs.to(device)
recon = model(imgs).cpu().detach().view(-1,1,28,28)
orig = imgs.cpu().view(-1,784).numpy() > 0.5
recon_bin = recon.view(-1,784).numpy() > 0.5
acc = accuracy_score(orig.flatten(), recon_bin.flatten())
rec = recall_score(orig.flatten(), recon_bin.flatten())
f1 = f1_score(orig.flatten(), recon_bin.flatten())
print(f"Accuracy: {acc:.4f}, Recall: {rec:.4f}, F1: {f1:.4f}")
fig, ax = plt.subplots(2,5, figsize=(10,4))
for i in range(5):
    ax[0,i].imshow(imgs[i].cpu().view(28,28), cmap='gray'); ax[0,i].set_title("Original")
    ax[1,i].imshow(recon[i].view(28,28), cmap='gray'); ax[1,i].set_title("Reconstructed")
    ax[0,i].axis('off'); ax[1,i].axis('off')
plt.show()
```

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Epoch 1, Loss: 0.0257

Epoch 2, Loss: 0.0163

Epoch 3, Loss: 0.0141

Epoch 4, Loss: 0.0121

Epoch 5, Loss: 0.0098

Accuracy: 0.9689, Recall: 0.8528, F1: 0.8676

Original

Original

Original

Original

Original

Reconstructed

Reconstructed

Reconstructed

Reconstructed

Reconstructed

VariablesTerminal

8:37 AMPython 3