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මගේ ව්‍යාපෘතිය

Superior
Note Books

Index

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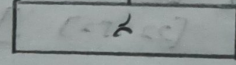
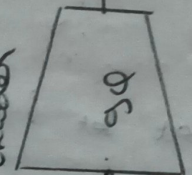
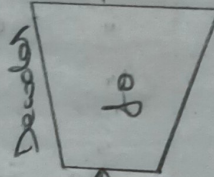
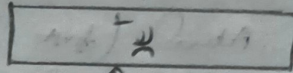
Subject : DL

Std. : 10 Sec. : 1 Roll No. 10040

School :

No.	Date	Title	Marks	Signature
1	24/7/25	Exploring the DL platforms.		<u>[Signature]</u>
2	31/7/25	Implement a classifier using open source dataset		
3	7/8/25	Study the classifier with respect to statistical parameters.		<u>[Signature]</u>
4	14/8/25	Build a simple feed forward neural network to recognize handwritten characters.		<u>[Signature]</u>
5	22/8/25	Study of Activation functions & their role.		<u>[Signature]</u>
6	9/9/25	Implement Gradient Descent & Backpropagation in Deep neural network.		<u>[Signature]</u>
7	16/9/25	Build a CNN model to classify cat & dog image.		<u>[Signature]</u>
8	30/9/25	Build a RNN network.		<u>[Signature]</u>
9	9/10/25	Experiment using LSTM		<u>[Signature]</u>
10	9/10/25	Autoencoder		<u>[Signature]</u>
11	9/10/25	Variational Autoencoder		<u>[Signature]</u>
12	17/10/25	Deep convolutional GAN		<u>[Signature]</u>

Reconstructed
Input



Architecture of Autoencoder

9/10/21

Lab 10: Perform compression on MNIST Dataset using Autoencoder

Aim:

To implement an Autoencoder for compressing & reconstructing MNIST images, demonstrating dimensionality reduction & unsupervised learning.

Objectives

- 1) To understand the architecture & working of Autoencoder.
- 2) To perform image compression using the encoder network.
- 3) To reconstruct compressed images using the decoder network.
- 4) To visualize the quality of compression & reconstruction.

Observation

- * Autoencoders learn compressed latent representations of input data without supervision.
- * The encoder reduces images dimensions, while the decoder reconstructs it back to near-original form.
- * As training progresses, reconstruction error decreases significantly.
- * Compressed features occupy fewer dimensions, demonstrating the model's ability to capture essential information.

Pseudocode:

BEGIN

Step 1: Import libraries (TensorFlow, Keras, Numpy, Matplotlib)

Step 2: Load MNIST dataset and normalize images (values between 0 and 1)

Step 3: Flatten images for input to the autoencoder.

Step 4: Define encoder model

- Input layer (784 neurons)
- Dense hidden layers with decreasing dimensions

Step 5: Define decoder model

- Dense hidden layers with increasing dimensions.

- Output layer (784 neurons, sigmoid activation)

Step 6: compile the autoencoder with optimizer

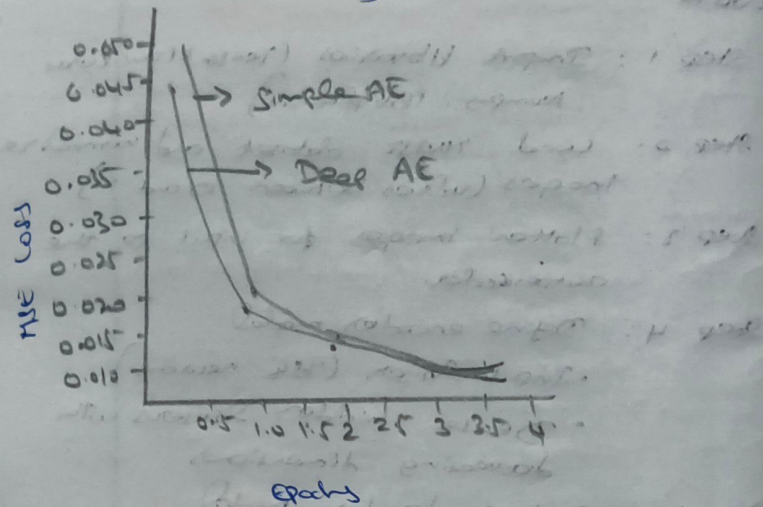
Step 7: Train the model using training data for N epochs.

Step 8: Encode and decode test images

Step 9: visualize original vs reconstructed images

END

Training Loss Comparison.



Simple AE Reconstruction (Top: original, Bottom: Reconstructed)

8 6 3 5 8

8 6 3 5 8

Deep AE Reconstruction (Top: original, Bottom: Reconstructed)

1 4 1 7 9

1 4 1 7 9

Output:

Simple AE

Epoch	1	Loss	: 0.0501
Epoch	2	Loss	: 0.0211
Epoch	3	Loss	: 0.0154
Epoch	4	Loss	: 0.0128
Epoch	5	Loss	: 0.0114

Deep AE

Epoch	1	Loss	: 0.0445
Epoch	2	Loss	: 0.0199
Epoch	3	Loss	: 0.0150
Epoch	4	Loss	: 0.0124
Epoch	5	Loss	: 0.0128

Result:

✓ Successfully Implemented the Autoencoder for MNIST Dataset.

```
pip install torch torchvision matplotlib
```

```
Requirement already satisfied: torch in /usr/local/lib/python3.12/dist-packages (2.8.0+cu126)
Requirement already satisfied: torchvision in /usr/local/lib/python3.12/dist-packages (0.23.0+cu126)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.12/dist-packages (3.10.0)
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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
```



```

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")
    
```

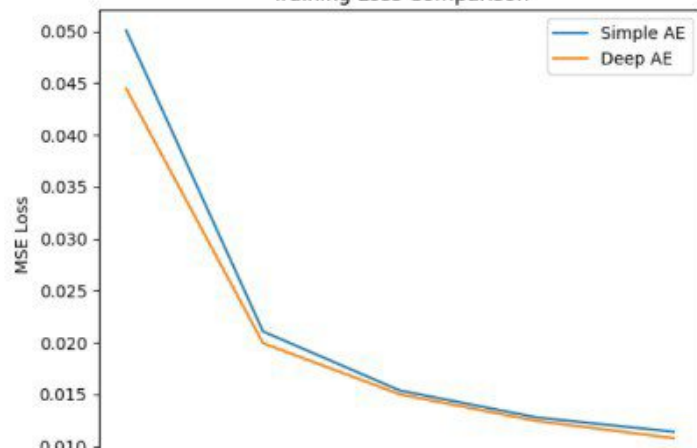
```
( )
class SimpleAE(nn.Module):
    def __init__(self):
        super(SimpleAE, self).__init__()
        self.encoder = nn.Sequential(
            nn.Linear(28*28, 128),
            nn.ReLU(),
            nn.Linear(128, 32)
        )
        self.decoder = nn.Sequential(
            nn.Linear(32, 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)
simpleAE = SimpleAE().to(device)
deepAE = DeepAE().to(device)
criterion = nn.MSELoss()
```

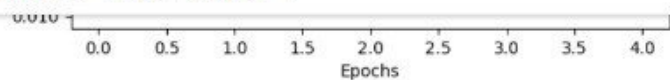


```
( )  
fig, axes = plt.subplots(2, 5, figsize=(10, 4))  
for i in range(5):  
    axes[0, i].imshow(imgs[i].squeeze(), cmap='gray')  
    axes[0, i].axis('off')  
    axes[1, i].imshow(recons[i].squeeze(), cmap='gray')  
    axes[1, i].axis('off')  
plt.suptitle(f"{name} Reconstruction (Top: Original, Bottom: Reconstructed)")  
plt.show()  
  
show_reconstruction(simpleAE, "Simple Autoencoder")  
show_reconstruction(deepAE, "Deep Autoencoder")
```

```
(4)  
100%|██████████| 28.9k/28.9k [00:00<00:00, 483kB/s]  
100%|██████████| 1.65M/1.65M [00:00<00:00, 4.51MB/s]  
100%|██████████| 4.54k/4.54k [00:00<00:00, 3.40MB/s]  
SimpleAE | Epoch [1/5], Loss: 0.0501  
SimpleAE | Epoch [2/5], Loss: 0.0211  
SimpleAE | Epoch [3/5], Loss: 0.0154  
SimpleAE | Epoch [4/5], Loss: 0.0128  
SimpleAE | Epoch [5/5], Loss: 0.0114  
DeepAE | Epoch [1/5], Loss: 0.0445  
DeepAE | Epoch [2/5], Loss: 0.0199  
DeepAE | Epoch [3/5], Loss: 0.0150  
DeepAE | Epoch [4/5], Loss: 0.0124  
DeepAE | Epoch [5/5], Loss: 0.0108
```

Training Loss Comparison





Simple Autoencoder Reconstruction (Top: Original, Bottom: Reconstructed)



Deep Autoencoder Reconstruction (Top: Original, Bottom: Reconstructed)

