Exp 10.

Perform Compression on MNIST Dataset using Autoencoder.

Aim:

To develop an Autoencoder to compress and reconstruct images from the MNIST dataset

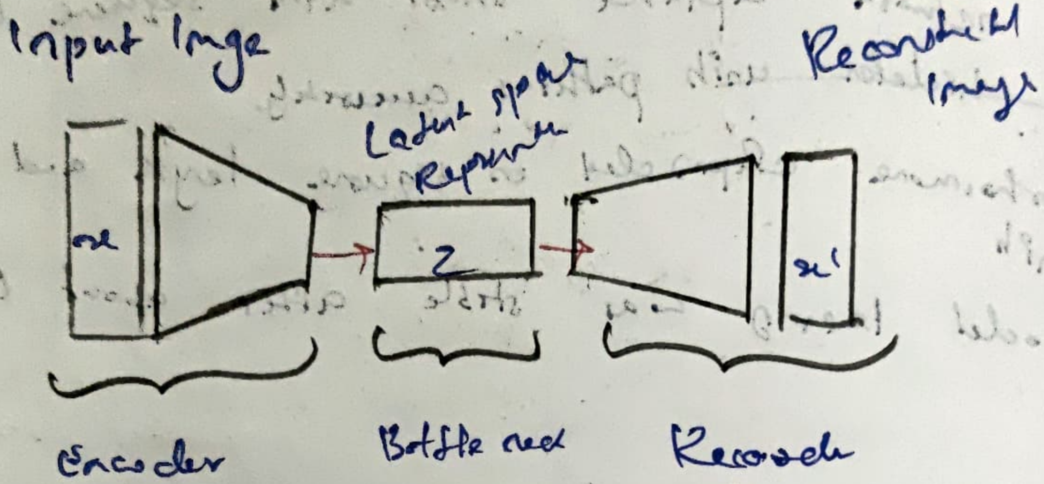
Objectives:

1. To understand the concept of unsupervised feature learning
2. To perform image compression using a bottleneck architecture
3. To reconstruct input images from compressed representation.
4. To minimize ~~[illegible]~~ reconstruction loss.
5. To visualize original and reconstructed images.

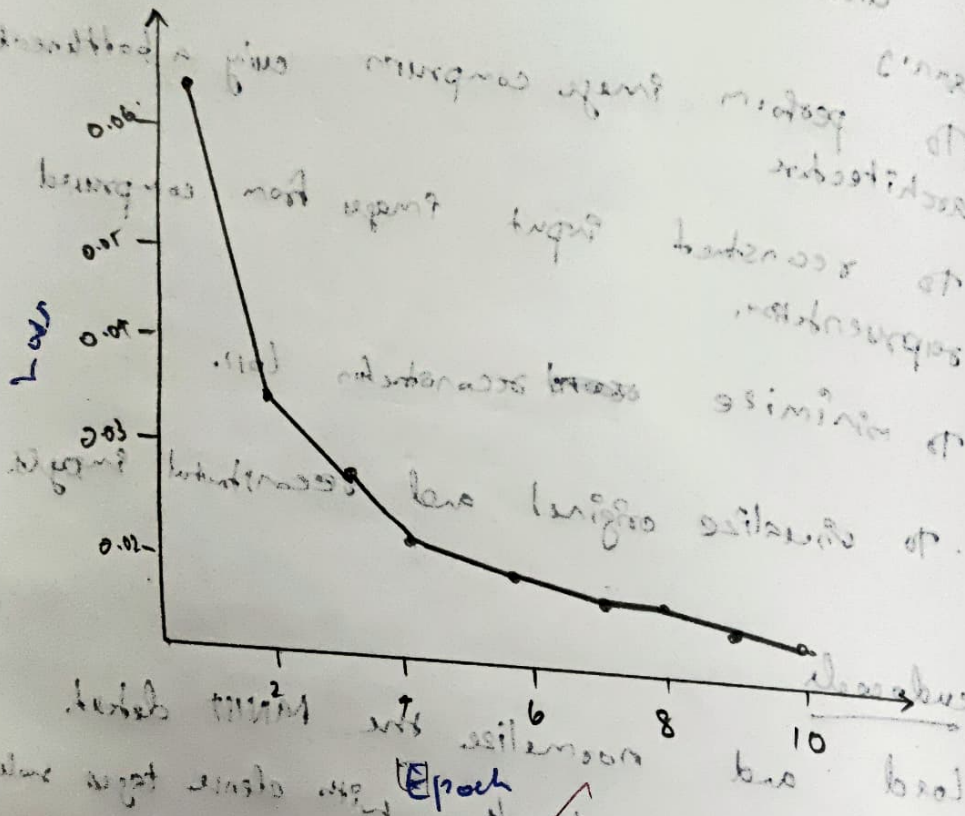
Pseudocode

1. Load and normalize the MNIST dataset.
2. Define encoder network with dense layers reducing dimensionality
3. Define decoder network for image reconstruction
4. Compile autoencoder using Adam optimizer and mean squared error
5. Train model and display reconstructed output

Autoencoder



Epoch	Training loss	Validation loss
1	0.125	0.108
5	0.075	0.071
10	0.050	0.048
20	0.030	0.024
30	0.025	0.026



Observation

1. Loss decreases as training progresses
2. Encoded features retain digit identity
3. Reconstructed digits appear slightly blurred
4. Compression ratio depends on bottleneck size
5. Model generalizes well for unseen digits

Result

Autoencoder successfully compressed and reconstructed MNIST digits, demonstrating efficient feature representation

Exp 11.

Experiment using Variational Autoencoder (VAE)

Aim:

To implement a Variational Autoencoder to generate new images similar to MNIST digits

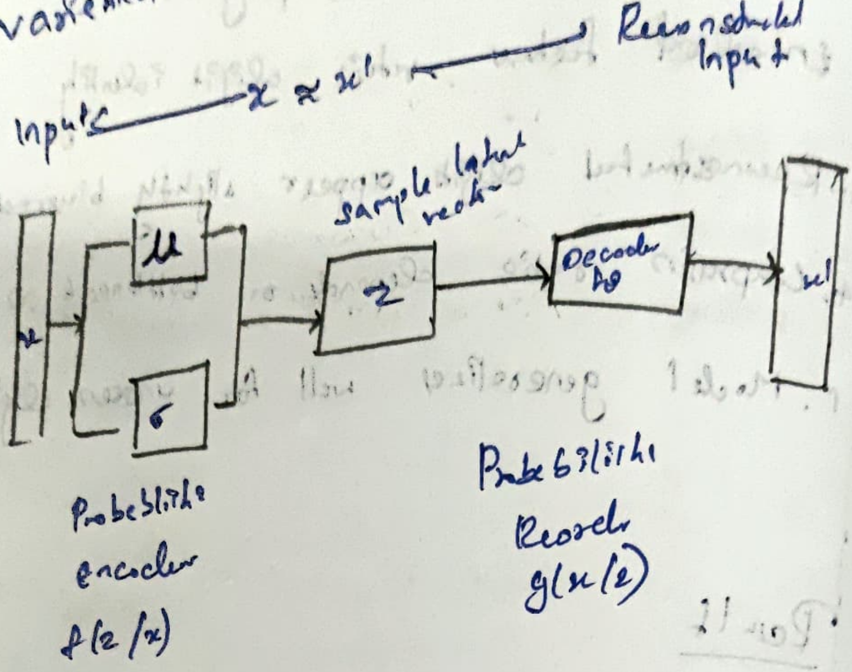
Objectives:

1. To learn probabilistic latent representation
2. To apply the reparameterization trick for sampling
3. To generate synthetic data from learned latent space
4. To balance ~~reconstruction~~ reconstruction and KL divergence loss.
5. To visualize new digit generation.

Pseudocode

1. Load MNIST and normalize images.
2. Build encoder to output mean and log variance
3. Use reparameterization to sample latent vector
4. Decode latent vector to reconstruct ~~imp~~ images
5. Train and generate new samples.

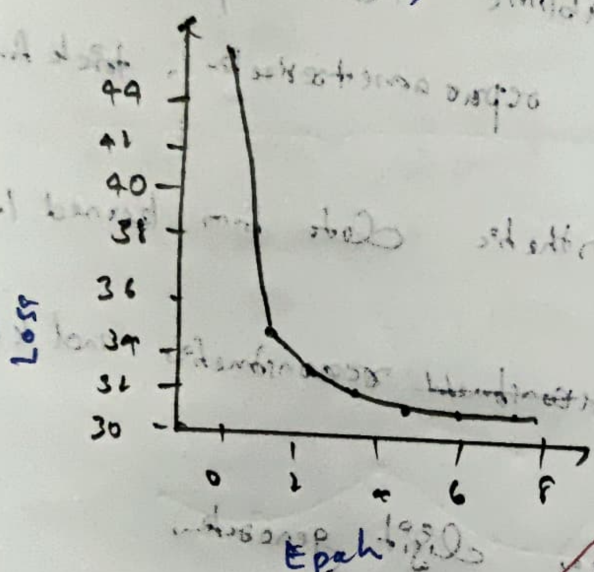
Variational Autoencoder Architecture



2 (i) the compressed low dimensional representation of input x.

Epoch	Reconstruction Loss	KL Divergence	Total Loss
1	120.4	3.5	123.9
5	92.6	2.8	95.4
10	70.2	2.2	72.4
20	55.8	1.7	57.5

Training Loss



Observation:

1. VAE produces smoother reconstruction the AE
2. Latent space is continuous and structured.
3. Generated digits are similar to real ones.
4. KL divergence regularizes latent distribution
5. Model performance improves with increasing epoch

Result:

VAE successfully generated realistic digit images by learning continuous latent representation