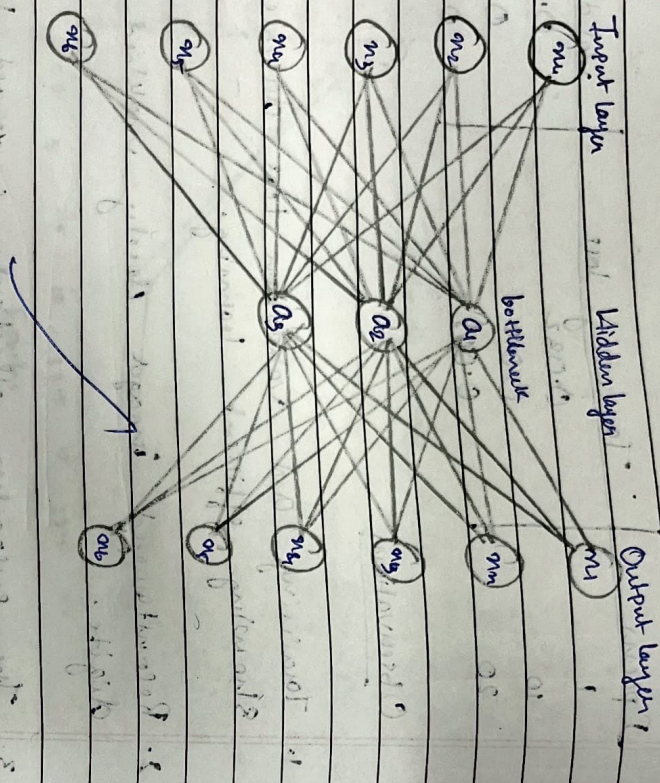


## VAE Architecture:



17.10.25

Lab

## Emil: Empiriment Using Variations CVAE

Aim: To implement a Variational Autoencoder (VAE) and Study its generative ability to reconstruct.

### Objective:

- To understand the concept and working of Variational Autoencoder.

- To perform unsupervised feature learning using probabilistic latent space representation.

- To train a VAE model that learn better encoding and decoding.

- To visualize the latent space and generate new images by sampling from it.

### PSEUDOCODE:

#### BEFORE:

Import torch, torchvision.

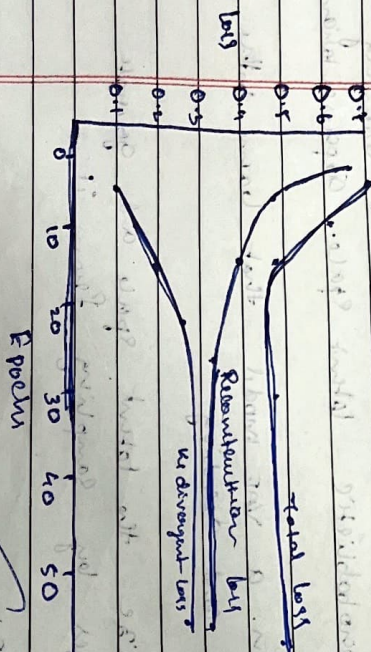
Load MNIST dataset and normalize

Class VAE:



Epoch	Reconstruction	KL Divergence	Total loss
1	0.65	0.00	0.35
5	0.45	0.15	0.60
10	0.35	0.20	0.55
20	0.20	0.15	0.55
50	0.25	0.28	0.53

### VAE training loss Over Epoch



decode(z)  $\rightarrow$  generate(m)

$z = \text{superparameterize}(mu, log-va)$

return decode(z); mu, log-va

loss = BCE(given\_m, n) + KL divergence(mu, log-va)

Train: Optimize loss over epochs.

Generate: Sample  $z \sim \text{NCEID}$  output decode(z)

### Observations:

- Learns smooth latent space.
- Balances reconstruction and regularization.
- Generate new samples by decoding random latent

~~Epochs~~

Epoch	Reconstruction loss	KL Divergence loss	Total loss
1	0.65	0.10	0.35
5	0.45	0.15	0.60
10	0.35	0.20	0.55
20	0.30	0.25	0.55
50	0.25	0.28	0.53

Result:

$\therefore$  The VAE experiment is successfully implemented.