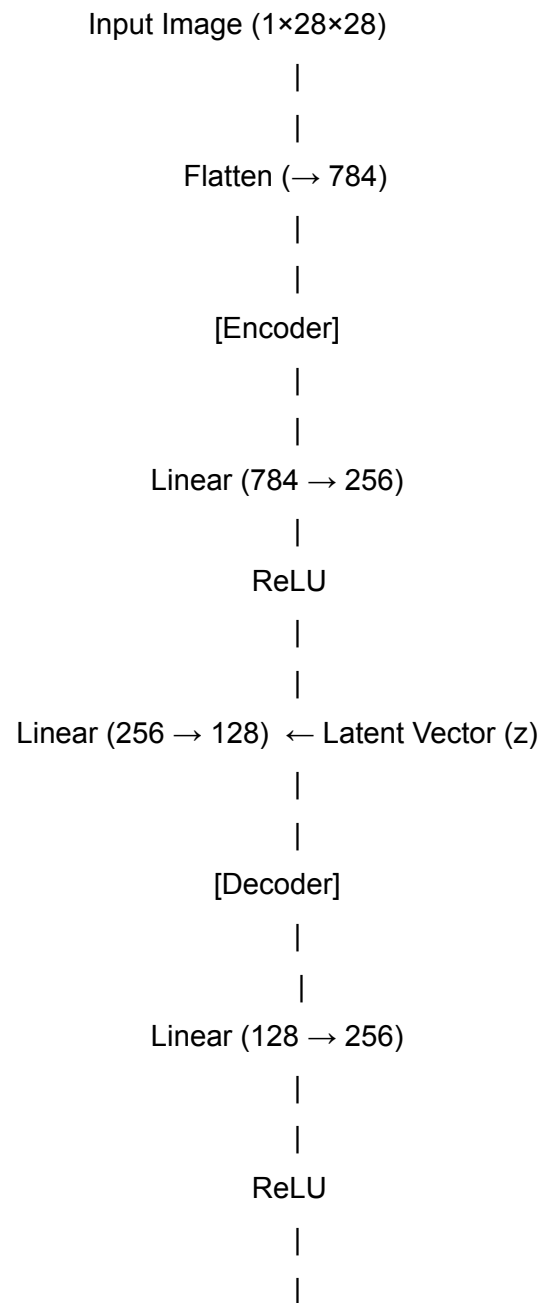
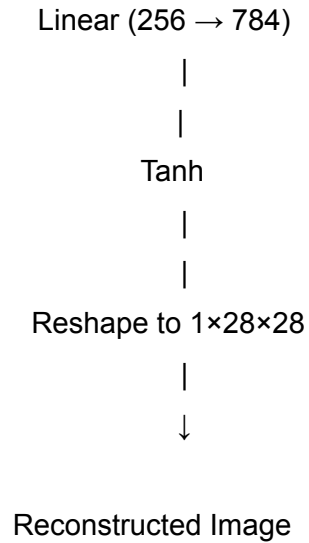


REPORT

1. Block Diagram of the architecture -





2. **Dataset analysis :** **MNIST** (loaded via Hugging Face).

Size: Training: 60,000 images

Image Dimensions: 28×28 grayscale.

Preprocessing: Normalized from $[0, 255] \rightarrow [0.0, 1.0] \rightarrow [-1.0, 1.0]$ using:
 $\text{images} = (\text{images} - 0.5) / 0.5$

3. **Hyperparameters—** Not used

4. **Model parameter counting—** Learning rate, Depth size, Latent dimension

5. **If batch normalization , dropout , regularizations used how have you used it—** Not used

6. **Existing clustering comparison—** Silhouette Score: 0.044 , Davies-Bouldin Index: 2.808

7. How to decide your clustering accuracy labeling of unsupervised

learning— In unsupervised learning like K-Means clustering, we don't have access to class labels during training, but we do have them in the MNIST dataset after training, which allows us to evaluate clustering performance.

- I trained an autoencoder to get embeddings (z).
- Then I applied K-Means clustering on those embeddings.
- Then I used two unsupervised evaluation metrics:
 - Silhouette Score – measures intra-cluster tightness vs inter-cluster separation.
 - Davies-Bouldin Index (DBI) – lower is better, measures average similarity between clusters.

These two metrics do *not* need true labels (y) and are appropriate for unsupervised evaluation.

8. Limitations and obstacles, and how you overcome them—

- The encoding can be improved
- The transformer model is better to use
- PCA visualization includes decomposition, so some features don't work accurately.

Overcoming obstacles:

- Used **autoencoder latent space** to effectively compress and structure data for better clustering.
- Used **PCA** to reduce dimensions for visualization.
- Used **unsupervised metrics** (Silhouette, DBI) for valid evaluation without labels.