**Lab 07**

**IT21312694 | SANDEEPTHA P.K.T**

Task 01

* Linear Autoencoders without activation functions and PCA both perform dimensionality reduction by finding lower-dimensional representations of the data that minimize reconstruction error.
* PCA explicitly finds orthogonal principal components that capture the most variance, while Linear AEs implicitly find similar directions through optimization.
* Under specific conditions, a Linear Autoencoder learns the same subspace as PCA, and its encoding weights correspond to the principal components.

Task 02

* **Model Trained for 10 Epochs:** The model may not be fully trained and can exhibit underfitting, as seen by higher validation loss and lower quality in the reconstructed images.
* **Model Trained for 30 Epochs:** The model generally shows improved performance in terms of lower loss values and higher-quality reconstructions because it has had more time to converge. However, it’s important to monitor the validation loss after a certain number of epochs to ensure the model doesn’t overfit.

Task 03

Q1)

* **De-noising Autoencoder** performs significantly better in scenarios where noisy data is provided, as it is trained to handle such data. Its ability to generalize and remove noise leads to better reconstruction performance in noisy environments.
* **Vanilla CNN Autoencoder** works well on clean data but performs worse on noisy data because it has not learned how to deal with noise during training.

Q2)

* **AEs** are great for tasks where you only need dimensionality reduction and reconstruction, but they lack the ability to generate new, diverse data samples.
* **VAEs** are more powerful for generative tasks, as they impose structure on the latent space, enabling the model to generate new data points by sampling from the learned latent distribution. The added KL divergence regularizes the latent space and ensures that sampling from it will yield coherent data point