Vidyavardhini's College of Engineering and Technology

Department of Artificial Intelligence & Data Science

AY: 2025-26

Class:	AI	Semester:	VII
Course Code:		Course Name:	DL

Name of Student:	BARI ANKIT VINOD
Roll No. :	61
Assignment No.:	3
Title of Assignment:	
Date of Submission:	
Date of Correction:	

Evaluation

Performance Indicator	Max. Marks	Marks Obtained
Completeness	5	
Demonstrated Knowledge	3	
Legibility	2	
Total	10	

Performance Indicator	Exceed Expectations (EE)	Meet Expectations (ME)	Below Expectations (BE)
Completeness	5	3-4	1-2
Demonstrated Knowledge	3	2	1
Legibility	2	1	0

Checked by

Name of Faculty : Raunak Joshi

Signature :

Date :

Assignment No.- 3

DL

Q. 1) Compare undercomplete and overcomplete autoencoders in terms of their: architecture, learning objective, risk of identity mapping, suitability for dimensional reduction. support your answer with a labeled diagram of each architecture.

→

	Undercomplete Autoencoder	Overcomplete Autoencoder
Arch^n	- latent space	- latent space diamention.
	- forces the model to compress information	- Allows the model to expand and possibly memorize input.
	- encoder → small bottelneck → decoder	- encoder → large bottelneck → decoder.
learning obj^n	- learn concept	- learn redundant representation.
	- Typically MSE	- Not specified.
Risk of Id^n mapping	- low risk	- high risk
	- Network must compress and reconstruct key features	- large latent space can trivially map input to output.
Suitability	- Ideal for dimentiality reduction.	- Not suitable for regularized.
	- Compact and meaningfuless.	- possibly redundant or noisy.
	- Eg. feature extraction	- Eg. anomaly detection

Q. 2) A researcher is experimenting with three types of regularized autoencoders. denoising autoencoders, sparse autoencoders, contractive autoencoders. Analyze how each regularization technique modifies the learning process of the autoencoder. Illustrative the role of noice addition, sparsity constraints and jacobian penalty in each case.

→ (i) Denoising Autoencoder (DAE) -

- Idea - Instead of learning to reconstruct the input directly, the autoencoder learns to reconstruct the original input from a corrupted version.

- learning process modification - Random noise is added to the input. The network tries to reconstruct the clean original input.

$$\tilde{x} = x + \text{noice}.$$

$$L = ||x - f(\tilde{x})||^2$$

(ii) Sparse Autoencoder (SAE) -

- Idea - enforces sparsity in the activations of the hidden units. most hidden neurons should be inactive for any given input.

- learning process modification - Adds the sparsity penalty to the loss function, typically using Kullback-leibler divergence to match the average activation $\hat{\rho}$ to a small target ρ. forces the autoencoder to learn a distributed, compact representation, even if the input.

$$L = ||x - \tilde{x}||^2 + \beta \sum KL(\rho || \hat{\rho}_j)$$

(iii) Contractive autoencoder (CAE) -

$$L = ||x - \hat{x}||^2 + \lambda \sum_i \left|\left| \frac{\partial h(x)}{\partial (x_i)} \right|\right|^2$$