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| **Satyug Darshan Institute of Technology,Faridabad** | | |
| | **Programme: B.Tech** | **Year:/Semester: 7th** |
| | **Subject Name : Neural Network and deep Learning** | **Subject Code: PEC-CS-D-703** |
| | **Department:CSE** | **AY:2025-2026** |
| **Prepared By: Ms.Deepika Khurana** | | |
| **Unit -1** | | |
| **Short Questions** | | |
| **S. No.** | **Questions** | **Bloom Taxonomy (KL)** |
| 1 | Define Artificial Intelligence. | BTL–1 |
| 2 | Define Artificial Neural Network (ANN). | BTL–1 |
| 3 | List the characteristics of neural networks. | BTL–1 |
| 4 | Identify the basic elements of an artificial neuron. | BTL–1 |
| 5 | Explain the function of synaptic weights. | BTL–2 |
| 6 | Explain the significance of bias in neural networks. | BTL–2 |
| 7 | Classify neural networks based on architecture. | BTL–2 |
| 8 | Distinguish between hard limit and soft limit activation functions. | BTL–2 |
| 9 | Give examples of real-world problems suitable for neural networks. | BTL–2 |

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| 10 | Interpret the role of threshold in neuron firing. | BTL–2 |
| | **Long Questions** | |
| 1 | Explain how the choice of activation function affects the convergence and performance of a neural network. | BTL–4 |
| 2 | Derive the mathematical model of an artificial neuron and discuss the significance of bias and weights in determining the neuron’s decision boundary. | BTL–3 |
| 3 | Compare and contrast feedforward and feedback network architectures in terms of stability, computational complexity, and applications. | BTL–4 |
| 4 | Analyze how learning paradigms (supervised, unsupervised, reinforcement) differ in their approach to minimizing the cost function. | BTL–4 |
| 5 | Derive the gradient descent weight update rule for minimizing mean squared error in a single-layer network. | BTL–3 |
| 6 | Discuss the limitations of the single-layer perceptron in solving non-linearly separable problems and how multi-layer perceptrons overcome these limitations. | BTL–4 |
| 7 | Examine how Hebbian learning can lead to both stable and unstable weight configurations depending on input correlations. | BTL–4 |
| 8 | Compare Boltzmann learning with gradient descent in terms of energy minimization and probabilistic weight updates. | BTL–4 |
| 9 | Evaluate the role of learning rate in convergence — what are the trade-offs between small and large learning rates. | BTL–5 |
| 10 | Formulate the decision boundary equation for a single-layer perceptron given a specific input pattern and weight vector. | BTL–6 |
| 11 | Discuss how network capacity, overfitting, and generalization are related in multilayer networks. | BTL–4 |
| 12 | Analyze the effect of initial weight selection on the convergence speed and accuracy of learning in neural networks. | BTL-4 |

# Unit -2

## Short Questions

| S. No. | Questions | Bloom Taxonomy |
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| 1 | Define supervised learning. | BTL–1 |
| 2 | Define unsupervised learning. | BTL–1 |
| 3 | Identify the purpose of the learning rate parameter. | BTL–2 |
| 4 | State the difference between batch learning and online learning. | BTL–2 |
| 5 | Name any two learning rules used in neural networks. | BTL–1 |
| 6 | Explain the concept of attractor neural networks. | BTL–2 |
| 7 | Define associative learning and associative memory. | BTL–1 |
| 8 | Describe the working principle of a discrete Hopfield network. | BTL–2 |
| 9 | Explain the concept of perfect recall in associative memory. | BTL–2 |
| 10 | Differentiate between auto-associative and hetero-associative memories. | BTL-4 |

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| 11 | Describe the structure and function of Bidirectional Associative Memory (BAM). | BTL–2 |
| 12 | Discuss the energy functions in Hopfield and Boltzmann machines. | BTL–3 |
| 13 | Explain the architecture and learning process of a Boltzmann machine. | BTL–2 |
| 14 | Define Adaptive Resonance Theory (ART) networks. | BTL–1 |
| 15 | Compare Hopfield and Boltzmann networks. | BTL-2 |
| | **Long Questions** | |
| 1 | Derive the energy function for a discrete Hopfield network and explain how it guarantees convergence to a stable state. | BTL-3 |
| 2 | Explain the working principle of a discrete Hopfield network and its use as an associative memory model. How many patterns can it store without errors? | BTL-2 |
| 3 | Compare the recall mechanisms in Hopfield networks, Bidirectional Associative Memories (BAM), and differentiate between auto-associative and hetero-associative memories. | BTL-4 |
| 4 | Discuss the conditions necessary for perfect recall in associative memory and how these conditions are affected in noisy environments. | BTL-4 |
| 5 | Examine the stability conditions for a Hopfield network and explain the concept of attractor states in recurrent networks. | BTL-4 |
| 6 | Analyze how feedback connections in recurrent networks contribute to pattern completion and temporal sequence learning. | BTL–4 |
| 7 | Compare deterministic and stochastic recurrent networks in terms of learning stability, computational efficiency, and | BTL–4 |
| 8 | Explain the concept of attractor neural networks and their role in memory representation. | BTL–3 |
| 9 | Discuss how Boltzmann machines use stochastic processes for optimization, including the effect of temperature on convergence. | BTL–5 |
| 10 | Derive the weight update rule in a Boltzmann machine and explain its relationship to the energy landscape. | BTL–4 |
| 11 | Explain the architecture and learning process of a Boltzmann machine and compare it with Hopfield networks. | BTL-4 |
| 12 | Analyze the mechanism of resonance and vigilance in Adaptive Resonance Theory (ART) networks and discuss the stability–plasticity dilemma. | BTL-4 |
| 13 | Explain how can recurrent networks be used to model dynamic time-dependent data such as speech or EEG signals. | BTL-2 |
| 14 | Define associative learning and associative memory, highlighting the differences between various recurrent network models. | BTL-4 |
| 15 | Compare Hopfield, Boltzmann, and ART networks in terms of architecture, learning, stability, and memory recall capabilities. | BTL-4 |
| | **Unit -3** | |
| | **Short Questions** | |

| S. No. | Questions | Bloom Taxonomy |
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| 1 | Define gradient descent algorithm? Derive the weight update rule. | BTL–3 |
| 2 | Explain the Least Mean Squares (LMS) algorithm. | BTL–2 |
| 3 | Describe the backpropagation algorithm for multilayer perceptrons. | BTL–2 |
| 4 | Discuss the different types of errors in backpropagation training. | BTL–2 |
| 5 | Explain the concept of overfitting and how it can be reduced. | BTL–2 |
| 6 | How can a multi-layer perceptron be used for multi-class classification? | BTL–2 |
| 7 | Differentiate between batch and stochastic gradient descent. | BTL–4 |
| 8 | Explain the working of a Support Vector Machine (SVM). | BTL–2 |
| 9 | Discuss is the role of kernel functions in SVM? | BTL–2 |
| 10 | Explain how SVM separates linearly and non-linearly separable data. | BTL–2 |
| 11 | Explain the Radial Basis Function (RBF) network? | BTL–2 |
| 12 | Explain Cover's Theorem and its importance in RBF networks. | BTL–2 |
| 13 | Describe the learning mechanisms in RBF networks. | BTL–2 |
| **Long Questions** | | |
| 1 | Derive the backpropagation algorithm starting from the error function and chain rule. Explain how gradient descent optimizes network weights. | BTL–3 |
| 2 | Compare the efficiency and convergence properties of batch gradient descent, stochastic gradient descent, and mini-batch approaches. | BTL–4 |
| 3 | Explain how vanishing and exploding gradients affect deep feedforward networks, and suggest modern techniques to mitigate these issues. | BTL–4 |
| 4 | Discuss the differences between local minima and saddle points in the error surface of multi-layer neural networks. | BTL-4 |
| 5 | Evaluate how the choice of activation function influences the learning dynamics in a multilayer perceptron. | BTL-5 |
| 6 | Describe how SVMs handle linearly non-separable patterns using kernel trick. Derive the dual form of the SVM optimization problem. | BTL-4 |
| 7 | Compare SVM and MLP in terms of their learning mechanisms, interpretability, and computational complexity. | BTL–4 |
| 8 | Derive the expression for the weight update in the Least Mean Square (LMS) algorithm and discuss its convergence conditions. | BTL–4 |
| 9 | Analyze how Cover's theorem supports the use of Radial Basis Function (RBF) networks for complex classification problems. | BTL–4 |

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| 10 | Explain the architecture and training mechanism of RBF networks. Compare them with MLPs in terms of decision boundaries. | BTL–4 |
| 11 | How can overfitting in feedforward networks be controlled using regularization and early stopping. | BTL–4 |
| 12 | Evaluate the role of hyperparameters (learning rate, momentum, epochs, and hidden layers) in determining the performance of feedforward networks. | BTL–5 |

# Unit -4

## Short Questions

| S. No. | Questions | Bloom Taxonomy |
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| 1 | Discuss Principal Component Analysis (PCA). | BTL–2 |
| 2 | Explain the need for dimensionality reduction in machine learning. | BTL–2 |
| 3 | Derive the mathematical formulation for PCA. | BTL–3 |
| 4 | Explain how eigenvalues and eigenvectors are used in PCA. | BTL–2 |
| 5 | Describe the steps involved in implementing PCA. | BTL–2 |
| 6 | Define the applications of PCA in neural networks. | BTL–2 |
| 7 | Explain Hebbian-based principal component analysis. | BTL–2 |
| 8 | Describe the concept of self-organizing maps (SOM). | BTL–2 |
| 9 | Define the cooperative and adaptive processes in SOM | BTL–1 |
| 10 | Explain the training algorithm of SOM. | BTL–2 |
| 11 | Define vector quantization.How is it related to SOM. | BTL–2 |
| 12 | Discuss the topology preservation property in SOM. | BTL–2 |
| 13 | Compare PCA and SOM in terms of learning and functionality. | BTL–4 |
| 14 | Discuss the advantages and limitations of PCA | BTL–2 |

## Long Questions

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| 1 | Derive the mathematical formulation of Principal Component Analysis (PCA) and show how eigenvalues and eigenvectors correspond to data variance. | BTL–3 |
| 2 | Explain how PCA performs dimensionality reduction while preserving maximum variance. Provide a geometric interpretation. | BTL–3 |
| 3 | Compare PCA and Linear Discriminant Analysis (LDA) in terms of objective functions and data separability. | BTL–4 |
| 4 | Derive the Hebbian learning rule used for computing principal components. | BTL–3 |
| 5 | Discuss the advantages and drawbacks of using PCA as a preprocessing step for neural network models. | BTL–5 |

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| 6 | Explain the concept of competitive learning and how it is implemented in Self-Organizing Maps (SOM). | BTL–3 |
| 7 | Analyze the role of neighborhood function and learning rate in the convergence of SOM. | BTL–4 |
| 8 | Describe how SOM preserves topological properties of the input data. | BTL–4 |
| 9 | Compare vector quantization using SOM with K-means clustering. | BTL–4 |
| 10 | Discuss how dimensionality reduction in PCA complements visualization using SOM. | BTL–5 |
| 11 | Examine the trade-off between data compression and information loss in PCA. | BTL–4 |
| 12 | How does the cooperative and adaptive learning mechanism in SOM ensure convergence to stable clusters. | BTL–4 |
| 13 | Propose how hybrid PCA–SOM systems can be used for high-dimensional data visualization and clustering. | BTL–6 |
| 14 | Derive the weight update rule for a neuron trained using Hebbian PCA. | BTL–3 |