## COURSE CONTENT

| INTRODUCTION TO DEEP LEARNING | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| I Semester: CE / CSD / CSE / CSM / ECE / EEE / ME | | | | | | | | |
| Course Code | Category | Hours / Week | | | Credits | Maximum Marks | | |
| 24X6610 | Foundation | L | T | P | C | CIA | SEE | Total |
| | | 2 | 0 | 0 | 2 | 40 | 60 | 100 |
| Contact Classes: 48 | Tutorial Classes: Nil | Practical Classes: Nil | | | | Total Classes: 48 | | |
| Prerequisites: Machine Learning | | | | | | | | |

### Course Overview:

This course provides a solid foundation in Machine Learning and Deep Learning, covering core concepts such as learning algorithms, overfitting/underfitting, bias–variance tradeoff, and supervised/unsupervised learning. Students learn deep feedforward networks, CNNs, and RNNs, including architectures, backpropagation, and optimization techniques. The course also covers regularization, data augmentation, ensemble methods, and advanced optimization strategies. Practical methodology, performance evaluation, and real-world applications in computer vision, speech recognition, and NLP are included, enabling students to design, train, and deploy deep learning models effectively.

### Course Objectives:

1. To understand basics of machine learning and deep feed forward networks.
2. To learn regularization and optimization methods for deep models.
3. To study convolutional networks and their applications.
4. To explore recurrent and recursive networks for sequence data.
5. To apply deep learning techniques to real-world problems in vision, speech, and NLP.

### Course Outcomes: After Completion of the Course, Students should be able to

1. Implement and train deep feedforward neural networks using gradient-based learning.
2. Apply regularization and optimization techniques to improve model performance.
3. Design and implement convolutional neural networks for image and structured data tasks.
4. Develop recurrent and recursive neural networks for sequence modeling and long-term dependencies.
5. Evaluate and apply deep learning models to real-world applications in computer vision, speech, and NLP.

### UNIT - I:

Machine Learning Basics: Learning Algorithms, Capacity, Overfitting and Underfitting, Hyperparameters and Validation Sets, Estimators, Bias and Variance, Maximum Likelihood Estimation, Bayesian Statistics, Supervised Learning Algorithms, Unsupervised Learning Algorithms, Stochastic Gradient Descent, Building a Machine Learning Algorithm, Challenges Motivating Deep Learning

Deep Feedforward Networks Learning XOR, Gradient-Based Learning, Hidden Units, Architecture Design, Back-Propagation and Other Differentiation Algorithms

**UNIT – II**

Regularization for Deep Learning: Noise Robustness,Early Stopping, Dropout,Bagging and Other Ensemble Methods,Semi-Supervised Learning, Multi- Task Learning, Parameter Tying and Parameter Sharing, Sparse Representations, Adversarial Training, Tangent Distance, Tangent Prop, and Manifold Tangent Classifier, Optimization for Training Deep Models, Learning vs Pure Optimization, Challenges in Neural Network Optimization, Basic Algorithms, Parameter Initialization Strategies, Algorithms with Adaptive Learning Rates

**UNIT – III**

Convolutional Networks: The Convolution Operation, Motivation, Pooling, Convolution and Pooling as an Infinitely Strong Prior, Variants of the Basic Convolution Function, Structured Outputs, Data Types, Efficient Convolution Algorithms, Random or Unsupervised Features,Parameter Norm Penalties, Norm Penalties as Constrained Optimization, Regularization and Under- Constrained Problems, Dataset Augmentation,

**UNIT – IV**

Recurrent and Recursive Nets: Unfolding Computational Graphs, Recurrent Neural Networks, Bidirectional RNNs, Encoder-Decoder Sequence-to-Sequence Architectures, Deep Recurrent Networks, Recursive Neural Networks, The Challenge of Long-Term Dependencies, Echo State Networks, Leaky Units and Other Strategies for Multiple Time Scales.

**UNIT – V**

The Long Short-Term Memory and Other Gated RNNs, Optimization for Long- Term Dependencies, Explicit Memory

Practical Methodology: Performance Metrics, Default Baseline Models, Determining Whether to Gather More Data, Selecting Hyperparameters, Debugging Strategies, Example: Multi-Digit Number Recognition

Applications: Large-Scale Deep Learning, Computer Vision, Speech Recognition, Natural Language Processing, Other Applications.

**TEXT BOOKS:**


1. Deep Learning by Ian Goodfellow, Yoshua Bengio and Aaron Courville, MIT Press.


**REFERENCE BOOKS:**


1. The Elements of Statistical Learning. Hastie, R. Tibshirani, and J. Friedman, Springer.
2. Probabilistic Graphical Models. Koller, and N. Friedman, MIT Press.
3. Bishop. C.M., Pattern Recognition and Machine Learning, Springer, 2006.
4. Yegnanarayana, B., Artificial Neural Networks PHI Learning Pvt. Ltd, 2009.
5. Golub, G.,H., and Van Loan, C.,F., Matrix Computations, JHU Press, 2013.
6. Satish Kumar, Neural Networks: A Classroom Approach, Tata McGraw-Hill Education, 2004.


**ELECTRONIC RESOURCES:**


1. https://www.geeksforgeeks.org/introduction-deep-learning/
2. https://training.deepneuron.in/a-guide-on-deep-learning-from-basics-to-advanced-concepts/
3. https://en.wikipedia.org/wiki/Convolutional_neural_network

## MATERIALS ONLINE:

1. Course template
2. Tutorial question bank
3. Tech talk and Concept Video topics
4. Open-ended experiments
5. Definitions and terminology
6. Assignments
7. Model question paper – I
8. Model question paper – II
9. Lecture notes
10. E-Learning Readiness Videos (ELRV)