Name of Faculty	:	Faculty of Engineering & Technology
Name of Program	:	Master of Technology (M. Tech)
Course Code	:	2MSE03
Course Title	:	Machine Learning (PE - II)
Type of Course	:	PE
Year of Introduction	:	2023-24

Prerequisite	:	Mathematics and Programming
Course Objective	:	The course objectives of a machine learning course may vary depending on the institution or specific program. However, here are some common objectives you might find in a machine learning course: Understanding the Fundamentals, Knowledge of Algorithms and Techniques, Practical Implementation Skills etc.
Course Outcomes	:	At the end of this course, students will be able to:
	CO1	Apply basic concepts of Machine Learning and Understanding of standard learning algorithms
	CO2	Analyse mathematical modelling of various Machine Learning algorithms
	CO3	Understanding challenges of machine learning like data characteristics, model selection, and model complexity
	CO4	Identify strengths and weaknesses of machine learning techniques suitable for a given problem domain and data set
	CO5	Design and implement of various machine learning algorithms in a range of real-world applications.
	CO6	Evaluate and interpret the results of learning algorithms

Teaching and Examination Scheme

Teaching Scheme (Contact Hours)			Credits	Examination Marks				
				Theory Marks		Practical Marks		Total Marks
L	**T**	**P**	**C**	**SEE**	**CIA**	**SEE**	**CIA**	
4	0	2	5	70	30	30	20	150

*Legends: **L**-Lecture; **T**–Tutorial/Teacher Guided Theory Practice; **P** – Practical, **C** – Credit, **SEE** – Semester End Examination, **CIA** - Continuous Internal Assessment (It consists of Assignments/Seminars/Presentations/MCQ Tests, etc.))*

Course Content

Unit No.	Topics	Teaching Hours	Weightage	Mapping of CO
1	**Introduction** Definition of learning systems. Goals and applications of machine learning. Aspects of developing a learning system: training data, concept representation, function approximation.	04	07%	CO1
2	**Inductive Classification** The concept learning task. Concept learning as search through a hypothesis space. General-to-specific ordering of hypotheses. Finding maximally specific hypotheses. Version spaces and the candidate elimination algorithm. Learning conjunctive concepts. The importance of inductive bias.	04	09%	CO2
3	**Ensemble Learning** Using committees of multiple hypotheses. Bagging, boosting, and DECORATE. Active learning with ensembles.	05	11%	CO2
4	**Experimental Evaluation of Learning Algorithms** Measuring the accuracy of learned hypotheses. Comparing learning algorithms: cross-validation, learning curves, and statistical hypothesis testing	04	09%	CO3
5	**Computational Learning Theory** Models of learnability: learning in the limit; probably approximately correct (PAC) learning. Sample complexity: quantifying the number of examples needed to PAC learn. Computational complexity of training. Sample complexity for finite hypothesis spaces. PAC results for learning conjunctions, kDNF, and kCNF. Sample complexity for infinite hypothesis spaces, Vapnik-Chervonenkis dimension.	05	11%	CO3
6	**Rule Learning:** Propositional and First-Order Translating decision trees into rules. Heuristic rule induction using separate and conquer and information gain. First-order Horn-clause induction (Inductive Logic Programming) and Foil. Learning recursive rules. Inverse resolution, Golem, and Progol.	05	11%	CO4
7	**Artificial Neural Networks** Neurons and biological motivation. Linear threshold units. Perceptions: representational limitation and gradient descent training. Multilayer networks and back propagation.	04	09%	CO5

	Hidden layers and constructing intermediate, distributed representations. Over fitting, learning network structure, recurrent networks.			
8	**Support Vector Machines** Maximum margin linear separators. Quadratic programming solution to finding maximum margin separators. Kernels for learning non-linear functions	06	09%	CO5
9	**Bayesian Learning** Probability theory and Bayes rule. Naive Bayes learning algorithm. Parameter smoothing. Generative vs. discriminative training. Logistic regression. Bayes nets and Markov nets for representing dependencies	05	04%	CO6
10	**Instance-Based Learning** Constructing explicit generalizations versus comparing to past specific examples. K-Nearest-neighbour algorithm. Case-based learning.	05	04%	CO5
11	**Introduction to G A, N N and Fuzzy logic** Introduction to Genetic Algorithms - Definition of GA - Description of Terminology/Vocabulary of GA - Importance and Goal of Traditional Optimization Methods - Classification of Search Techniques - Introduction to Hill climbing - Simulated annealing – Decision Tree - Difference between Genetic Algorithms and Traditional Methods - Fuzzy logic - Introduction – Definition and Terminology - Set Theoretic Operations-MF Formulation and Parameterization-Extension Principal and Fuzzy Relations-Fuzzy Rules-Fuzzy Reasoning - Mamdani Fuzzy Model, Neural Network- Basic Concept of Neural Network - Human Brain, Model of An Artificial Neuron-Neural. Network Architecture - Characteristic of Neural Network	07	09%	CO5
12	**Hybrid Systems** Introduction to Hybrid System – Types of Hybrid Systems – Neuro Fuzzy Hybrids – Neuro Genetic Hybrid – Fuzzy Genetic Hybrids – Neuro Fuzzy Modelling – Application.	06	07%	CO6

Suggested Distribution of Theory Marks Using Bloom's Taxonomy						
Level	Remembrance	Understanding	Application	Analyse	Evaluate	Create
Weightage	**40**	**20**	**20**	**10**	**-**	**10**

NOTE: This specification table shall be treated as a general guideline for the students and the teachers. The actual distribution of marks in the question paper may vary slightly from above table.

Suggested List of Experiments/Tutorials

Sr. No.	Name of Experiment/Tutorial	Teaching Hours
1	Minimum 10 experiments based on the contents.	10
2	Mini Project in a group of max. 3 students.	10
3	Writing a research paper on selected topic from content with latest research issues in that topic.	04

Reference Books

Sr. No.	Name of Reference Books
1	Christopher M. Bishop, "Pattern Recognition and Machine Learning", Springer, 2006.
2	Richard O. Duda, Peter E. Hart & David G. Stork, "Pattern Classification. Second Edition", Wiley & Sons, 2001.
3	Trevor Hastie, Robert Tibshirani and Jerome Friedman, "The elements of statistical learning", Springer, 2001.
4	Richard S. Sutton and Andrew G. Barto, "Reinforcement learning: An introduction", MIT.