ELECTIVE: III

BEIT803T4 **MACHINE LEARNING**

(Theory Credit: 05)

Teaching Scheme:	**Examination Scheme:**
Lecture: 4 Hours/week	**Theory: T (U): 80 Marks T (I): 20 Marks**
Tutorial: 1 Hour/week	**Duration of University Exam. : 03 Hours**

==

UNIT I:

Introduction:

Machine Learning, Machine Learning Foundations, Overview, applications, Types of machine learning, basic concepts in machine learning, Examples of Machine Learning , Applications, Linear Models for Regression, Linear Basis Function Models, The Bias, Variance Decomposition, Bayesian Linear Regression, Bayesian Model Comparison

UNIT II:

Supervised Learning:

Linear Models for Classification, Discriminate Functions, Single layer neural network, linear reparability, general gradient descent, perception learning algorithm, multi-Layer perception: two-layers universal approximations, back propagation learning, important parameters, Margin of a classifier, dual perception algorithm, learning non-linear hypotheses with perception.

UNIT III:

Unsupervised Learning: Clustering, K-means, EM, Mixtures of Gaussians, The EM Algorithm in General, Model selection for latent variable models, high-dimensional spaces, The Curse of Dimensionality, Dimensionality Reduction, Factor analysis, Principal Component Analysis, Probabilistic PCA, Independent components analysis. Neural Networks, Feed-forward Network Functions, Error Back, propagation, Regularization , Mixture Density and Bayesian Neural Networks, Kernel Methods, Dual Representations , Radial Basis Function Networks. Ensemble methods, Bagging, Boosting

UNIT IV:

Instance-Based Learning:

Nearest neighbor classification, k-nearest neighbor, nearest neighbor error probability Machine, Machine learning concepts and limitations: Learning theory, formal model of the learnable, sample complexity, learning in zero-bayes and realizable case, VC-dimension, fundamental algorithm independent concepts, hypothesis class, target class, inductive bias, Occam's razor, empirical risk, limitations of inference machines, approximation and estimation errors, Tradeoff.

UNIT V:

Support Vector Machine (SVM): Kernel functions, implicit non-linear feature space, theory, zero-Bayes, realizable infinite hypothesis class, finite covering, margin-based bounds on risk, maximal margin classifier. Machine learning assessment and Improvement: Statistical model selection, structural risk minimization, bootstrapping, bagging, boosting.

UNIT VI:

Advanced Learning:

Sampling, Basic sampling methods, Monte Carlo, Reinforcement Learning, K-Armed Bandit-Elements, Model-Based Learning, Value Iteration, Policy Iteration. Temporal Difference Learning, Exploration Strategies, Deterministic and Non-deterministic Rewards and Actions, Eligibility Traces, Generalization, Partially Observable States, the Setting-Example, Semi - Supervised Learning. Computational Learning Theory: Mistake bound analysis, sample complexity analysis, VC dimension. Occam learning, accuracy and confidence boosting

Text Books:

1. Machine Learning – Tom M. Mitchell, - MGH
2. Ethem Alpaydin, "Introduction to Machine Learning", Prentice Hall of India, 2005

Reference Books:

1. Christopher Bishop, "Pattern Recognition and Machine Learning" Springer, 2006
2. Kevin P. Murphy, "Machine Learning: A Probabilistic Perspective", MIT Press, 2012
3. Stephen Marsland, "Machine Learning –An Algorithmic Perspective", CRC Press, 2009

******