Pattern Recognition

Code: CS32221CS	Course Type: Elective	Semester: II
Evolution Scheme (TA-MSE-ESE): 20-30-100	Total Marks: 150	L-T-P (Credits): 3-0-0 (3)

Pre-Requisites:

- Linear Algebra (Vector spaces, Eigen decomposition, Orthogonality)
- Probability Theory and Statistics (Distributions, Bayes Theorem, Expectations)
- Multivariate Calculus
- Proficiency in a programming language (Python/MATLAB/C++).

Course Objectives:

1. To build a strong mathematical foundation in classical statistical decision theory and continuous/discrete density estimation.
2. To design linear and non-linear discriminant functions and understand the theoretical guarantees of margin-based classifiers.
3. To analyze the ”dimensionality” and apply optimal feature selection and unsupervised extraction methodologies.
4. To explore advanced pattern recognition paradigms, including sequential data modelling and structural/syntactic pattern recognition.

Course Outcomes: At the end of the course, the student will be able to

CO-1	Formulate pattern classification tasks using Bayesian decision theory and analyze probabilistic density estimation methods.
CO-2	Design and optimize linear and kernel-based discriminant functions for binary and multiclass pattern classification.
CO-3	Evaluate feature extraction, dimensionality reduction, and clustering techniques to effectively manage high-dimensional data spaces.
CO-4	Model sequential data and complex relational patterns using Hidden Markov Models and syntactic/structural recognition paradigms.

Course Articulation Matrix:

PO	PEO-1	PEO-2	PEO-3	PEO-4	PEO-5
CO-1	3	3	1	1	2
CO-2	3	3	2	1	3
CO-3	3	2	2	2	3
CO-4	3	3	2	2	3

1 - Slightly; 2 - Moderately; 3 – Substantially

Syllabus:

Unit-1: Foundations of Statistical Decision Theory and Density Estimation:

Introduction to pattern recognition systems and design cycles. Bayesian Decision Theory: Continuous and discrete features, minimum-error-rate classification, and minimum-risk Bayes classifiers. Discriminant functions and decision surfaces for the normal density. Error evaluation, ROC analysis, and Bayes error bounds. Parametric estimation: Maximum Likelihood Estimation (MLE) and Bayesian parameter estimation paradigms. Expectation-

Maximization (EM) algorithm and its application to Gaussian Mixture Models (GMM). Non-parametric estimation: Density estimation theory, Parzen-window, and k-Nearest Neighbor (k-NN) rule.

Unit-2: Discriminant Functions and Margin-Based Classifiers:

Linear discriminant functions and decision geometry. Perceptron criteria, relaxation procedures, and gradient descent optimization. Fisher's Linear Discriminant. Support Vector Machines (SVM): Geometric margin maximization, hard and soft margin formulations, and Lagrangian duality. The Kernel trick, Mercer's condition, and non-linear SVMs. Multi-class classification extensions (One-vs-Rest, One-vs-One).

Unit-3: Dimensionality Reduction and Unsupervised Clustering:

The curse of dimensionality and dataset geometry. Feature extraction paradigms: Principal Component Analysis (PCA) and Independent Component Analysis (ICA). Feature selection methodologies: Search strategies, filter, and wrapper methods. Unsupervised learning and clustering algorithms: K-Means formulation, hierarchical clustering methods, spectral clustering concepts, and Gaussian mixture-based clustering. Cluster validity indices and evaluation

Unit-4: Sequential Data and Structural Pattern Recognition:

TModeling sequential and temporal data. Discrete Hidden Markov Models (HMM): The evaluation, decoding (Viterbi), and learning (Baum-Welch) problems. Continuous observation HMMs. Introduction to Syntactic and Structural Pattern Recognition: Elements of formal grammars, relational descriptions, string matching architectures, and graph-theoretic pattern matching.

Learning Resources:

Text Books:

1. Pattern Recognition Theodoridis S., Koutroumbas K. Academic Press 2008 (4th Ed.).
2. Pattern Recognition and Machine Learning Bishop C.M. Springer 2006.
3. Pattern Classification Duda R.O., Hart P.E., Stork D.G. John Wiley & Sons 2001 (2nd Ed.)

Reference Books:

1. The Elements of Statistical Learning Hastie T., Tibshirani R., Friedman J. Springer 2017 (2nd Ed.)
2. Machine Learning: A Probabilistic Perspective Murphy K.P. MIT Press 2012