MATHEMATICAL FOUNDATIONS FOR ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Code: CS33112CS	Course Type: Core	Semester: I
Evolution Scheme (TA-MSE-ESE): 20-30-100	Total Marks: 150	L-T-P (Credits): 3-0-0 (3)

Pre-Requisites: Engineering Mathematics, Linear Algebra, Probability and Statistics.

To provide students with the mathematical tools and theoretical foundations required for designing, analyzing, and optimizing AI and machine learning models.

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

CO-1	Apply linear algebra and matrix operations in AI and ML models.
CO-2	Apply probability theory and statistics for data analysis and intelligent decision making.
CO-3	Apply optimization and calculus concepts for learning algorithms.
CO-4	Analyze mathematical models used in deep learning and intelligent systems.

Course Articulation Matrix:

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

1 - Slightly; 2 - Moderately; 3 – Substantially

Syllabus:

Unit-1: Linear Algebra for AI

Vectors and vector spaces, matrices and matrix operations, eigenvalues and eigenvectors, singular value decomposition (SVD), orthogonality, rank and nullity, positive definite matrices, matrix factorization, applications in dimensionality reduction and PCA.

Unit-2: Probability and Statistics

Random variables, probability distributions, conditional probability, Bayes theorem, expectation, variance, covariance, correlation, Gaussian distribution, multivariate normal distribution, maximum likelihood estimation, hypothesis testing, confidence intervals.

Unit-3: Calculus and Optimization

Partial derivatives, gradients, Jacobian, Hessian matrix, chain rule, Taylor series, convex functions,

constrained and unconstrained optimization, gradient descent, stochastic gradient descent, momentum, Adam optimizer.

Unit-4: Mathematical Modeling for AI
Loss functions, regularization, optimization landscapes, information theory, entropy, KL divergence, probabilistic graphical models, Markov chains, mathematical basis of neural networks and deep learning.

Learning Resources:

Text Books:

1. Christopher M. Bishop, Pattern Recognition and Machine Learning, Springer, 2006.
2. Kevin P. Murphy, Machine Learning: A Probabilistic Perspective, MIT Press, 2012.

Reference Books:

1. Trevor Hastie, Robert Tibshirani, Jerome Friedman, The Elements of Statistical Learning, Springer, 2009. 2. Ian Goodfellow et al., Deep Learning, MIT Press, 2016.