Marathwada Shikshan Prasarak Mandal's
DEOGIRI INSTITUTE OF ENGINEERING AND MANAGEMENT STUDIES
(An Autonomous Institute)
Affiliated to Dr. Babasaheb Ambedkar Technological University, Lonere, Raigad |B.Tech | M. Tech
Affiliated to Dr. Babasaheb Ambedkar Marathwada University, CSN| MBA
Approved by AICTE/UGC- Govt. of India & DTE- Govt. of Maharashtra
Deogiri College Campus, Railway Station Road, Chhatrapati Sambhajinagar-431005 (MS)
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Department of Computer Science and Engineering
(Artificial Intelligence & Machine Learning)
MTech CSE(AI&ML) PROGRAM STRUCTURE (2026-28)

Course Category			I	II	III	IV	Total Credits
Program Courses	Program Core Course (PCC)	-	12	04	04		24
		MOOC		04			
	Program Elective Course (PEC)		06	06			12
Vocational and Skill Enhancement Courses (VSE)	Seminar		01				02
	PG Lab		01				
Humanities Social Science and Management (HSSM)	Indian Knowledge System (IKS)			02			02
Experiential Learning Courses (EL)	Research Methodology			03			
	Mini Project			01			34
	Project				10	20	
Open Elective Courses (OE)	Open Elective (OE)				03		03
Multi-Disciplinary Minor Courses (MDM)	Multi-Disciplinary Minor (MDM)				03		03
Liberal Learning Courses (LLC)	Co-Curricular Courses (CC)		-		-	AU	AU
Total Credits			**20**	**20**	**20**	**20**	**80**

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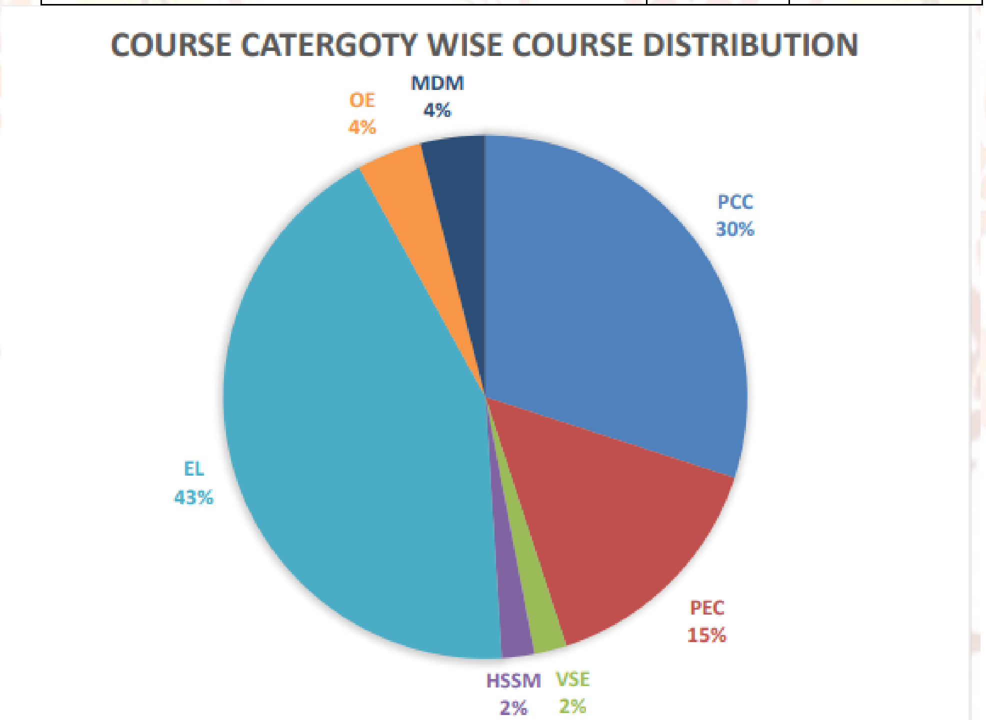
M Tech in CSE(AI&ML)		
Course Category	**Credits**	**% Credits**
Program Core Courses **(PCC)**	24	30
Program Elective Courses **(PEC)**	12	15
Vocational & Skill Enhancement **(VSE)**	02	2
Humanity, Social Science & Management (AEC, EM, IKS, VEC) **HSSM**	02	2
Experiential Learning **(EL)**	34	43
Open Electives **(OE)**	03	4
Multi-Disciplinary Minor (MDM)	03	4
Total Credits	**80**	



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SEMESTER I

Category	Course Code	Name of the Course	Teaching Scheme				Evaluation Scheme					Credits
			L	T	PR	Total	CA-I	CA-II	MSE	ESE	Total	
PCC	PL261001	Mathematics for Machine Learning Algorithms	4			4	10	10	20	60	100	4
PCC	PL261002	Deep Learning for Computer Vision	4			4	10	10	20	60	100	4
PCC	PL261003	Advanced Algorithms	4			4	10	10	20	60	100	4
PEC	PL261101-102	Program Elective I	3			3	10	10	20	60	100	3
PEC	PL261103-104	Program Elective II	3			3	10	10	20	60	100	3
SC-SEC	PL261401	Seminar			2	2	15	15		20	50	1
SC-SEC	PL261402	PG Lab			2	2	15	15		20	50	1
Total			**18**		**4**	**22**					**600**	**20**

SEMESTER II

Category	Course Code	Name of the Course	Teaching Scheme				Evaluation Scheme					
			L	T	PR	Total	CA-I	CA-II	MSE	ESE	Total	Credits
PCC	PL262004	Autonomous Intelligent Systems	4			4	10	10	20	60	100	4
PCC	PL262005	MOOC/SWAYAM	4			4	10	10	20	60	100	4
PEC	PL262105-106	Program Elective III	3			3	10	10	20	60	100	3
PEC	PL262107-108	Program Elective IV	3			3	10	10	20	60	100	3
#HSSM-IKS	PG262501	Interdisciplinary Perspective on Indian Science and Technology	2			2	10	10	20	60#	100	2
ELC	PG262601	Research Methodology	3			3	10	10	20	60	100	3
ELC	PL262602	Mini Project			2	2	15	15		20	50	1
Total			**19**		**2**	**21**					**650**	**20**

SEMESTER III

Category	Course Code	Name of the Course	Teaching Scheme				Evaluation Scheme					Credits
			L	T	PR	Total	CA-I	CA-II	MSE	ESE	Total	
PCC	PL263006	Distributed Systems	4			4	10	10	20	60	100	4
OE	PL263301	Open Elective	3			3	10	10	20	60	100	3
MDM	PL263201	Multi- Disciplinary Minor	3			3	10	10	20	60	100	3
ELC	PL263603	Dissertation Part I			10	10	25	25		50	100	10
Total			**10**		**10**	**20**					**400**	**20**

SEMESTER IV

Category	Course Code	Name of the Course	Teaching Scheme				Evaluation Scheme					Credits
			L	T	PR	Total	CA-I	CA-II	MSE	ESE	Total	
ELC	PL264604	Dissertation Part II			20	20	50	50		100	200	20
CC	PL264701	Communication Skills and Technical Writing	2			2	25	25			AU	AU
Total			**2**		**20**	**22**					**200**	**20**

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Note : # End semester Evaluation will be done at department level

OE and MDM courses

Note: OE and MDM Minor courses shall be offered through the SWAYAM/NPTEL online learning platform. The Board of Studies (BoS) shall identify, approve, and recommend the course based on its relevance to the program curriculum, academic quality, and prevailing industry standards.

Program Elective Courses (PEC)

Semester	Course Category	No. of Credits		Computer Science & Engineering	
SEM I	Program Elective I	3	**Course Code**	PL261101	PL261102
			Course	Data Mining & Analysis	Time Series Analysis
	Program Elective II	3	**Course Code**	PL261103	PL261104
			Course	Artificial Intelligence & Data Science	Large Language Model
SEM II	Program Elective III	3	**Course Code**	PL262105	PL262106
			Course	Soft Computing	Reinforcement Learning
	Program Elective IV	3	**Course Code**	PL262107	PL262108
			Course	Speech Modelling & Recognition	Generative AI

Course Title: Mathematics for Machine Learning Algorithms

Course Code: PL261001 **Course Category: PCC**

Teaching Scheme	Examination Scheme	
Lectures: 04 hrs. / week	CA-1	10 Marks
Tutorial: ---	CA-2	10 Marks
Credits: 04	MSE	20 Marks
Semester: First Year (Semester I)	ESE	60 Marks

Course Prerequisite:
Fundamental of computer science, discrete mathematics and probability theory and statistics.

Course Description:
This course integrates essential mathematical concepts with machine learning algorithms. It focuses on how linear algebra, optimization, geometry, and probability are used in real-world ML models such as regression, classification, clustering, and dimensionality reduction. Students will gain the ability to mathematically interpret and implement machine learning algorithms.

Course Objectives:
1.Develop a strong foundation in linear algebra concepts such as vectors, matrices, vector spaces, eigenvalues, eigenvectors, and SVD for representing and processing machine learning data.
2. Apply geometric and dimensionality-reduction concepts including norms, inner products, distance measures, orthogonality, projections, and PCA to solve machine learning problems.
3. Understand mathematical optimization techniques such as loss functions, partial differentiation, gradients, gradient descent, learning rate, and convergence used in training machine learning models.
4. Develop knowledge of probability and statistics including conditional probability, Bayes' theorem, random variables, probability distributions, expectation, variance, covariance, and correlation for handling uncertainty and analysing data.
5.Apply mathematical foundations to machine learning algorithms and model evaluation, including Linear Regression, Logistic Regression, KNN, K-Means, Naive Bayes, and basic Neural Networks, while understanding overfitting, underfitting, and bias-variance trade-offs

Course Outcomes:

COs	After completion of the course Students will be able to	Bloom's Level
CO1	**Recall** fundamental concepts of linear algebra, analytic geometry, vector calculus, and probability used in AI systems	Remember L1
CO2	**Explain** properties of vector spaces, mappings, norms, inner products, and probability distributions	Understand L2
CO3	**Apply** matrix operations, gradients, and probability rules in ML problems	Apply L3
CO4	**Analyze** decomposition methods, projections, and optimization techniques in ML	Analyze L4

CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	1	1
CO2	3	2	–	–	–	–	–	–	1	–	1	2	1
CO3	3	3	1	1	2	–	–	–	1	–	1	3	3
CO4	3	3	2	2	2	–	–	–	1	–	2	3	2

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Assessment	
CA-1 (a) (10M)	Subjective Test / Assignment/ MCQ Test etc.
CA-2 (b) (10M)	Subjective Test / Assignment/ MCQ Test etc.
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	**Linear Algebra for Data Representation** Systems of Linear Equations, Matrices and Matrix Operations, Rank, Linear Independence, Basis, Vector Spaces **ML Algorithms:** Dataset representation as matrices, Feature vectors in supervised learning, solving linear regression using matrix form	8 Hrs.
Unit 2	**Linear Transformations & Dimensionality Reduction** Linear Transformations and Mappings, Eigenvalues and Eigenvectors, Diagonalization, Singular Value Decomposition (SVD) **ML Algorithms:** Principal Component Analysis (PCA), Feature extraction and dimensionality reduction, Data compression	8 Hrs.
Unit 3	**Geometry, Distance & Similarity Measures** Norms (L1, L2), Inner Products, Angles and Orthogonality, Orthogonal Projections, Distance Metrics **ML Algorithms:** K-Nearest Neighbors (KNN), Clustering (K-Means), Cosine similarity in recommendation systems	8 Hrs.
Unit 4	**Optimization Techniques for Machine Learning** Functions and Loss Functions (MSE, Log Loss), Partial Differentiation, Gradient and Jacobian, Gradient Descent Algorithm, Learning Rate and Convergence, Convex vs Non-convex Optimization **ML Algorithms:** Linear Regression optimization, Logistic Regression training, Neural network training basics	8 Hrs.
Unit 5	**Probability Theory in Machine Learning** Probability Spaces and Events, Conditional Probability and Independence, Bayes Theorem, Random Variables (Discrete & Continuous), Probability Distributions (Normal, Bernoulli) **ML Algorithms:** Naive Bayes Classifier, Probabilistic modelling, Handling uncertainty in predictions	8 Hrs.
Unit 6	**Statistics & Model Evaluation** Expectation, Variance, Covariance, Correlation, Bias-Variance Tradeoff, Sampling and Estimation, Central Limit Theorem (basic idea) **ML Algorithms:** Model evaluation metrics, Overfitting and underfitting, Performance analysis of ML models	8 Hrs.

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Sr. No.	Textbooks
1.	Marc Peter Deisenroth et al., Mathematics for Machine Learning, Cambridge University Press.
	Reference Books
1.	Christopher Bishop - *Pattern Recognition and Machine Learning*
2.	Kevin Murphy - *Machine Learning: A Probabilistic Perspective*
3.	Sheldon Ross - *A First Course in Probability*
	Web Resources
1.	Mathematics for Computer Science (Lehman, Leighton, Meyer) https://ocw.mit.edu/courses/6-042j-mathematics-for-computer-science-fall-2010/pages/readings/
2.	Linear Algebra (18.06): https://ocw.mit.edu/courses/18-06-linear-algebra-spring-2010/
3.	Essential Mathematics for Machine Learning https://nptel.ac.in/courses/111107137

Course Title:	**Deep Learning for Computer Vision**		
Course Code:PL261002		**Course Category: PCC**	
Teaching Scheme		**Examination Scheme**	
Lectures: 04 hrs / week		CA-1	10 Marks
Tutorial: ---		CA-2	10 Marks
Credits: 04		MSE	20 Marks
Semester: First Year (Semester I)		ESE	60 Marks

Course Prerequisite:
Linear Algebra and Probability, Machine Learning, Basic Deep Learning, Python Programming

Course Description: This course provides an in-depth understanding of deep learning techniques applied to computer vision problems. It covers foundational image processing concepts, convolutional neural networks, advanced architecture, object detection, segmentation, vision transformers, generative models, and self-supervised learning. The course emphasizes both theoretical foundations and practical implementation of state-of-the-art vision systems, preparing students for research and industry-level AI applications.

Course Objectives:
1. Understand fundamental principles of computer vision and deep learning.
2. Analyze and design convolutional neural network architectures for image classification.
3. Apply deep learning techniques for object detection and image segmentation.
4. Explore transformer-based vision models and generative models.
5. Develop practical skills to implement state-of-the-art computer vision systems.

Course Outcomes:

COs	After completion of the course: Students will be able to	Bloom's Level
CO1	**Recall** the fundamental concepts of computer vision, image representation, convolution operations, neural networks, and deep learning architectures used in vision tasks.	Remember L1
CO2	**Explain** the working principles of convolutional neural networks, pooling and normalization techniques, feature visualization methods, and interpretability techniques used in deep vision models.	Understand L2
CO3	**Apply** deep learning models such as CNNs, object detection frameworks, segmentation networks, and sequence models to solve computer vision problems.	Apply L3
CO4	**Analyze** the performance of deep learning architectures, attention mechanisms, generative models, and modern vision systems for recognition, detection, and image generation.	Analyze L4

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CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	1	1
CO2	3	2	–	1	1	–	–	–	1	–	1	2	1
CO3	3	3	3	2	3	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	–	–	–	1	–	2	3	2

Assessment	
CA-1 (a) (10M)	Assignment
CA-2 (b) (10M)	Assignment
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	**Foundations of Computer Vision and Deep Learning** Introduction to computer vision, image representation and basic image processing concepts, review of neural networks and backpropagation, convolution operation, padding and stride, pooling layers, activation functions, loss functions used in vision tasks, optimization techniques including SGD and Adam, regularization methods such as dropout and batch normalization, overfitting and generalization in deep networks	8 Hrs.
Unit 2	**Deep Learning Foundations and CNN Architectures** Review of neural networks and backpropagation, convolutional neural networks and hierarchical feature learning, pooling and normalization techniques, evolution of CNN architectures including AlexNet, VGGNet, GoogLeNet and ResNet, residual learning and vanishing gradient problem, training strategies for deep networks.	8 Hrs.
Unit 3	**Understanding and Visualizing Deep Networks** Feature visualization techniques, deconvolution and backpropagation to image, saliency maps and class activation mapping, Grad-CAM methods, interpretability in deep learning models, analysis of learned representations, robustness and generalization issues in deep vision networks.	8 Hrs.
Unit 4	**Deep Learning for Recognition, Detection and Segmentation** Image classification using deep networks, object detection frameworks including Faster R-CNN and YOLO, semantic segmentation and fully convolutional networks, U-Net and Mask R-CNN, evaluation metrics including IoU and mean Average Precision.	8 Hrs.
Unit 5	**Sequence Models and Attention in Vision** Recurrent neural networks and their role in video understanding, temporal modeling for vision tasks, attention mechanisms and self-attention, transformer architecture fundamentals, Vision Transformer for image classification, comparison of CNN and transformer based vision models.	8 Hrs.

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Unit 6	**Generative Models and Recent Trends in Vision** Autoencoders and Variational Autoencoders, Generative Adversarial Networks and their variants, image generation and image-to-image translation, self-supervised learning methods, few-shot and zero-shot learning approaches, recent trends and research directions in computer vision.	8 Hrs.

Sr. No.	Textbooks
1.	Ian Goodfellow, Yoshua Bengio, Aaron Courville, *Deep Learning*, MIT Press, 2016.
2.	Richard Szeliski, *Computer Vision: Algorithms and Applications*, Springer, 2nd Edition, 2022.
	Reference Books
1.	Simon J. D. Prince, *Computer Vision: Models, Learning and Inference*, Cambridge University Press, 2012.
2.	Christopher M. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006.
3.	Dive into Deep Learning, Aston Zhang, Zachary C. Lipton, Mu Li, Alexander J. Smola, Cambridge University Press, 2023.
	Web Resources
1.	Deep Learning for Computer Vision, NPTEL Course by Vineeth N. Balasubramanian, Indian Institute of Technology Hyderabad – https://nptel.ac.in
2.	CS231n: Convolutional Neural Networks for Visual Recognition, Stanford University – https://cs231n.stanford.edu
3.	Deep Learning Specialization, DeepLearning.AI – https://www.deeplearning.ai

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Course Title: Advanced Algorithm **Course Code: PL261003**		**Course Category: PCC**
Teaching Scheme	**Examination Scheme**	
Lectures: 04 hrs / week	CA-1	10 Marks
Tutorial: –	CA-2	10 Marks
Credits: 04	MSE	20 Marks
	ESE	60 Marks

Course Prerequisite:
Strong understanding of DSA (sorting, searching, hashing, graphs, trees), Familiarity with Mathematics for Computer Science (DM, Probability, Linear algebra), Basic knowledge of Computational Complexity (Big-O notation, recursion), Exposure to Programming in C/C++/Java/Python for algorithm implementation

Course Description: This course introduces advanced techniques in the design and analysis of algorithms. Topics include asymptotic analysis, recurrence solving, amortized analysis, number-theoretic algorithms, string matching, advanced sorting, graph algorithms, and specialized data structures. It also covers matrix computations, Fast Fourier Transform (FFT), linear programming, and probabilistic algorithms. Emphasis is on applying these methods to efficiently solve complex computational problems.

Course Objectives:

1. Introduce advanced algorithm design and analysis techniques including recurrence solving, amortized analysis, and asymptotic growth of functions.
2. Develop competence in applying mathematical foundations such as number theory, linear algebra, and Fourier transforms to solve computational problems.
3. Expose students to advanced data structures and graph algorithms for efficient handling of complex networks, searching, and optimization tasks.
4. Familiarize students with modern algorithmic paradigms including linear programming, probabilistic and randomized algorithms, and their applications in real-world problem solving.
5. Encourage problem-solving and research orientation by applying advanced techniques to analyze, design and implement efficient algorithms for computationally hard problems.

Course Outcomes:

COs	**After completion of the course: Students will be able to**	**Bloom's Level**
CO1	**Recall** the fundamental concepts of algorithm analysis, asymptotic notations, recurrence relations, number representation, and basic string-matching techniques.	Remember L1
CO2	**Explain** the principles of advanced data structures, graph algorithms, recurrence solving methods, and number theoretic algorithms used in computational problems.	Understand L2
CO3	**Apply** string matching algorithms, graph algorithms, matrix computation techniques, and FFT-based methods to solve algorithmic and computational problems.	Apply L3
CO4	**Analyze** the performance and complexity of linear programming methods, probabilistic algorithms, randomized algorithms, and NP-complete problems.	Analyze L4

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CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	1	1
CO2	3	2	–	1	1	–	–	–	1	–	1	2	1
CO3	3	3	2	2	2	–	–	–	1	–	1	3	3
CO4	3	3	2	3	1	–	–	–	1	–	2	3	2

Assessment	
CA-1 (a) (10M)	Subjective Test
CA-2 (b) (10M)	Problem Solving using Programming
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	**Fundamentals of Analysis Techniques and Recurrences and Solution of Recurrence equations** Growth of Functions: Asymptotic notations, Standard notations and common functions. The substitution method, The recurrence tree method, The master method, Amortized Analysis: Aggregate, Accounting and Potential Methods.	8 Hrs.
Unit 2	**Representation of integers and String-Matching Algorithms** Chinese Remainder Theorem, Conversion between base-representation and modulo-representation, Powers of an element, RSA cryptosystem, Primality testing, Integer factorization. Naïve string Matching, Rabin-Karp algorithm, Knuth-Morris-Pratt algorithm, Boyer – Moore algorithms. Sorting: Review of various sorting algorithms, topological sorting	8 Hrs.
Unit 3	**Graph Algorithms** Johnson's Algorithm for sparse graphs, Maxflow-mincut theorem, Flow networks and Ford-Fulkerson method, Maximum bipartite matching. **Trees:** Red Black Trees, B Trees, Fibonacci Heaps, van Emde Boas Trees	8 Hrs.
Unit 4	**Matrix Computations** Strassen's algorithm and introduction to divide and conquer paradigm, inverse of a triangular matrix, relation between the time complexities of basic matrix operations, LUP-decomposition.	8 Hrs.
Unit 5	**Polynomials and the FFT and Discrete Fourier Transform (DFT)** Representation of polynomials; The DFT and FFT, Efficient implementation of FFT, Edmond's Blossom algorithm to compute augmenting path. In complex field, DFT in modulo ring, Fast Fourier Transform algorithm, Schönhage -Strassen Integer Multiplication algorithm.	8 Hrs.
Unit 6	**Linear Programming and Probabilistic and Randomized Algorithms** Formulation of Problems as Linear Programs, Duality, Simplex, Interior Point, and Ellipsoid Algorithm, proof of NP-hardness and NP-completeness. Probabilistic alg alg	8 Hrs.

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Sr. No.	Textbooks
1.	Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest, Clifford Stein, “Introduction to Algorithms”, 3rd Edition, PHI, 2014.
2.	Aho, Hopcroft, Ullman "The Design and Analysis of Computer Algorithms".
	Reference Books
1.	Kenneth A. Berman. Algorithms. Cengage Learning. 2002
2.	Kleinberg and Tardos. "Algorithm Design"
	Web Resources
1.	https://nptel.ac.in/courses/106/101/106101060/

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Course Title: Data Mining & Analysis
Course Code: PL261101 **Course Category: PEC-I**

Teaching Scheme	Examination Scheme	
Lectures: 03 hrs./ week	CA-1	10 Marks
Tutorial: -----	CA-2	10 Marks
Credits: 03	MSE	20 Marks
Semester: First Year (Semester I)	ESE	60 Marks

Course Prerequisite:
Linear algebra, probability, statistics, and calculus. Proficiency in Python programming with libraries such as NumPy and scikit-learn is required, Basic knowledge of machine learning concepts, optimization methods, and prior exposure to data science or related courses is recommended.

Course Description: This course introduces fundamental and advanced techniques in data mining and data analytics for extracting meaningful patterns from large datasets. It covers data preprocessing, frequent pattern mining, clustering, classification, and predictive modeling. The course also explores high-dimensional data analysis, text mining, and big data frameworks. Emphasis is given to real-world applications and domain-specific case studies to bridge theory and practice.

Course Objectives:
1. Understand fundamental concepts of data analysis and data representation.
2. Apply data preprocessing and feature engineering techniques to prepare datasets.
3. Analyze and implement pattern mining and association rule techniques.
4. Apply clustering and classification algorithms for predictive modeling.
5. Evaluate models using appropriate performance metrics.
6. Explore advanced analytics techniques and domain-specific applications

Course Outcomes

COs	After completion of the course: Student will be able to	Bloom's Level
CO 1	**Recall** the fundamental concepts of data types, data representation, similarity measures, and basic principles of data analysis and visualization.	Remember L1
CO 2	**Explain** the techniques of data preprocessing, feature engineering, dimensionality reduction, and handling data quality issues for effective data analysis.	Understand L2
CO 3	**Apply** pattern mining, clustering, and classification algorithms to discover patterns and build predictive models from data.	Apply L3
CO4	**Analyze** the performance of data mining models, evaluation metrics, and AI applications, including ethical considerations in intelligent data-driven systems.	Analyze L4

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CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO 2
CO1	3	1	–	–	–	–	–	–	–	–	1	1	2
CO2	3	2	1	1	2	–	–	–	1	–	1	2	2
CO3	3	3	3	2	3	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	1	1	1	1	–	2	3	3

Assessment	
CA-1 (a) (10M)	Subjective Test / Open book test / etc.
CA-2 (b) (10M)	Model Making / Assignment / Presentation / etc.
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	**Data Analysis Foundations** Types of Data: Structured, Semi-structured, Unstructured, Data Objects and Attributes, Numeric and Categorical Attributes, Matrix Representation of Data, Similarity and Distance Measures, Graph and Network Data, High-Dimensional Data, Kernel Methods, Data Visualization Basics	6 Hrs.
Unit 2	**Data Preprocessing** Data Cleaning (Missing values, Noise, Outliers), Data Integration, Data Reduction (Dimensionality Reduction, Feature Selection), Data Transformation (Normalization, Aggregation), Data Discretization, Feature Engineering, Handling Imbalanced Data	6 Hrs.
Unit 3	**Frequent Pattern Mining** Introduction to Pattern Mining, Frequent Itemset Mining, Apriori Algorithm, FP-Growth Algorithm, Association Rule Mining, Rule Evaluation (Support, Confidence, Lift), Sequence Mining, Graph Pattern Mining, Pattern and Rule Assessment	6 Hrs.
Unit 4	**Clustering Techniques** Representative-based Clustering (K-Means, K-Medoids), Hierarchical Clustering, Density-based Clustering (DBSCAN), Spectral Clustering, Graph-based Clustering, Clustering Validation (Silhouette, Davies-Bouldin Index)	6 Hrs.

Unit 5	**Classification and Predictive Modeling** Supervised Learning Basics, Decision Trees, Naïve Bayes, k-Nearest Neighbors, Support Vector Machines, Ensemble Methods (Bagging, Boosting – Introduction), Model Evaluation (Accuracy, Precision, Recall, F1-score, ROC), Cross-Validation, Overfitting and Underfitting	6 Hrs.
Unit 6	**Applications, Ethics** Applications of ANN in computer vision, natural language processing, bioinformatics, and speech recognition, Explainable AI (XAI) and interpretability of neural networks, Ethical issues in AI: Bias, fairness, accountability	6 Hrs.

Sr.No.	Textbooks
1.	Data Mining: Concepts and Techniques – Jiawei Han, Micheline Kamber, Jian Pei, Morgan Kaufmann.
2	Introduction to Data Mining – Pang-Ning Tan, Michael Steinbach, Vipin Kumar, Pearson.
	Reference Books
1.	Pattern Recognition and Machine Learning – Christopher M. Bishop, Springer.
2.	The Elements of Statistical Learning – Trevor Hastie, Robert Tibshirani, Jerome Friedman, Springer.
3.	Mining of Massive Datasets – Jure Leskovec, Anand Rajaraman, Jeffrey D. Ullman, Cambridge University Press.
	Web Resources
1	https://onlinecourses.nptel.ac.in/noc26_cs58/preview
2	https://www.coursera.org/browse/data-science

Course Title: Time Series Analysis Course Code: PL261102		Course Category: PEC-I
Teaching Scheme	**Examination Scheme**	
Lectures: 03 hrs. / week	CA-1	10 Marks
Tutorial: ---	CA-2	10 Marks
Credits: 03	MSE	20 Marks
Semester: First Year (Semester I)	ESE	60 Marks

Course Prerequisite:
Basic knowledge of Linear Algebra, Calculus, and Probability & Statistics.
Familiarity with signals, programming (Python/MATLAB), and data analysis concepts is recommended.

Course Description: This course introduces the fundamentals of Probability, Statistics, and Random Processes with applications in signal processing and time-series analysis. Students will learn to model and analyze stationary and non-stationary processes, compute correlation functions, and perform spectral analysis using Fourier methods. The course also covers SARIMA modeling, estimation theory, and various estimators for forecasting and signal property evaluation. Practical applications in real-world datasets and simulations are emphasized throughout.

Course Objectives:
This course will enable students to:
1. Understand the fundamental concepts of Probability, Statistics, Random Variables, and Random Processes and their applications in signal processing and machine learning.
2. Analyze stationary, non-stationary, and ergodic processes, and compute correlation functions to characterize random signals.
3. Model and simulate linear random processes and basic time-series models (AR, MA, ARMA, SARIMA) for forecasting and signal analysis.
4. Apply Fourier analysis, spectral density estimation, and harmonic process theory to study the frequency domain properties of signals.
5. Implement estimation techniques (LS, WLS, MLE, Bayesian) to estimate signal properties, forecast future data, and evaluate estimator performance in terms of bias, variance, efficiency, and consistency

Course Outcomes:

COs	After completion of the course: Students will be able to	Bloom's Level
CO1	**Recall** the fundamental concepts of probability theory, random variables, and random processes used in signal processing and machine learning applications.	Remember L1
CO2	**Explain** the properties of stationary and non-stationary processes, ergodicity, correlation functions, and time-series components such as trend, seasonality, and noise.	Understand L2
CO3	**Apply** time-series models including AR, MA, ARMA, and SARIMA, as well as spectral analysis techniques, for modeling and forecasting real-world data.	Apply L3
CO4	**Analyze** the performance of statistical estimators and estimation techniques such as least squares, maximum likelihood, and Bayesian estimation for signal and data analysis.	Analyze L4

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CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	1	2
CO2	3	2	–	1	1	–	–	–	1	–	1	2	2
CO3	3	3	2	2	2	–	–	–	1	–	1	3	3
CO4	3	3	2	3	1	–	–	–	1	–	2	3	3

Assessment	
CA-1 (a) (10M)	Subjective Test / Assignment/ MCQ Test etc.
CA-2 (b) (10M)	Subjective Test / Assignment/ MCQ Test etc.
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	**Introduction to Probability & Random Processes** Probability and Statistics (basic concepts), Random Variables and Random Processes, Classification of Random Processes, Applications in Signal Processing & ML.	6 Hrs.
Unit 2	**Stationarity, Ergodicity & Correlation Cleaning** Stationary and Non-stationary Processes, Ergodicity, Autocorrelation and Cross-correlation functions, Partial Correlation Functions (PACF), Practical examples.	6 Hrs.
Unit 3	**Linear Models of Random Processes** Linear Stationary Processes, Linear Non-Stationary Processes, Introduction to Time Series Models, Trend, Seasonality, Noise, Basics of AR, MA, ARMA models).	6 Hrs.
Unit 4	**Spectral Analysis & Fourier Methods** Fourier Analysis of Signals, Power Spectral Density (PSD), Spectral Representation of Random Processes, Wiener–Khinchin Theorem, Harmonic Processes.	6 Hrs.
Unit 5	**SARIMA & Time-Series Modeling** Seasonal ARIMA (SARIMA) Models, Model Identification, Parameter Estimation, Forecasting, Applications in real-world data.	6 Hrs.
Unit 6	**Estimation Theory & Estimators** Introduction to Estimation Theor, Goodness of Estimators, Fisher's Information, Properties: Bias, Variance, Efficiency, Consistency, Cramér–Rao Bound, Estimators: Least Squares (LS), Weighted Least Squares (WLS), Non-linear LS, Maximum Likelihood (MLE), Bayesian Estimation. Estimation of Signal Properties.	6 Hrs.

Sr. No.	Textbooks
1.	Terence C. Mills. Applied Time Series Analysis. Academic Press, 2019
Sr. No	**Reference Books**
1.	Chris Chatfield. The Analysis of Time Series. CRC Press, 2003.
Sr. No	**Web Resources**
1.	https://userpilot.com/blog/resources-for-data-analyst/
2.	https://onlinecourses.nptel.ac.in/noc21_cs45/preview
3.	https://nptel.ac.in/courses/106107220

Course Title: Artificial Intelligence & Data Science
Course Code: PL261103 **Course Category: PEC-II**

Teaching Scheme	Examination Scheme	
Lectures: 03 hrs./ week	CA-1	10 Marks
Tutorial: ---	CA-2	10 Marks
Credits: 03	MSE	20 Marks
Semester: First-year (Semester I)	ESE	60 Marks

Course Prerequisite:
Prior knowledge of programming (preferably Python), data structures and algorithms, discrete mathematics, linear algebra, and basic probability & statistics. Familiarity with fundamental machine learning concepts is desirable.

Course Description: This course introduces the fundamental concepts of Artificial Intelligence and Data Science. It covers intelligent search, knowledge representation, statistical foundations, and data preprocessing techniques. Students learn supervised and unsupervised learning methods for building predictive models. The course also explores advanced topics such as optimization, ensemble learning, and ethical AI, with practical implementation using real-world datasets.

Course Objectives:
1. To provide foundational knowledge of Artificial Intelligence concepts including search, knowledge representation and reasoning.
2. To develop understanding of statistical methods and their application in data analysis.
3. To equip students with techniques for data preprocessing, exploratory data analysis, and feature engineering.
   To enable students to design and implement supervised and unsupervised learning models.
4. To introduce advanced AI concepts such as optimization, ensemble learning, reinforcement learning, and ethical considerations in AI systems

Course Outcomes:

COs	After completion of the course Student will be able to	Bloom's Level
CO1	**Recall** the fundamental concepts of artificial intelligence, intelligent agents, search techniques, probability theory, and statistical foundations used in data science.	Remember L1
CO2	**Explain** the principles of data preprocessing, exploratory data analysis, feature engineering, and statistical methods used for data-driven decision making.	Understand L2
CO3	**Apply** supervised and unsupervised machine learning algorithms such as regression, decision trees, clustering, and association rule mining to solve data analysis problems.	Apply L3
CO4	**Analyze** the performance of AI models, optimization techniques, ensemble learning methods, and advanced AI applications, considering ethical aspects of AI systems.	Analyze L4

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CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	2	1
CO2	3	2	1	1	2	–	–	–	1	–	1	2	2
CO3	3	3	3	2	3	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	1	1	1	1	–	2	3	3

Assessment	
CA-1 (a) (10M)	Subjective Test / Assignment/ MCQ Test etc.
CA-2 (b) (10M)	Model Making / Assignment / Presentation / etc.
MSE (c) (20M)	Subjective Test

	Course Contents	
Unit 1	**Introduction to AI:** History & Applications, Intelligent Agents & Rationality, State Space Representation, Uninformed Search (BFS, DFS, UCS), Informed Search (Greedy, A*), Knowledge Representation (Propositional Logic, FOL), Inference Mechanisms.	6 Hrs.
Unit 2	**Statistical Foundations for Data Science:** Probability Theory & Random Variables, Probability Distributions (Binomial, Poisson, Normal), Bayes Theorem, Estimation & Confidence Intervals, Hypothesis Testing (t-test, Chi-square, ANOVA), Correlation & Regression Basics.	6 Hrs.
Unit 3	**Data Preprocessing & Exploratory Data Analysis:** Data Cleaning & Missing Value Handling, Data Transformation & Scaling, Feature Engineering, Feature Selection, Outlier Detection, Exploratory Data Analysis (EDA), Data Visualization Techniques.	6 Hrs.
Unit 4	**Supervised Learning Methods:** Linear & Logistic Regression, k-NN and Naïve Bayes, Support Vector Machines, Decision Trees and Random Forest, Model Evaluation Metrics (Accuracy, Precision, Recall, F1, ROC), Cross Validation and Bias-Variance Tradeoff.	6 Hrs.
Unit 5	**Unsupervised Learning & Data Mining**: K-Means and Hierarchical Clustering, DBSCAN, Association Rule Mining (Apriori Algorithm), PCA (Dimensionality Reduction),LDA, Introduction to Recommender Systems.	6 Hrs.
Unit 6	**Advanced Topics in AI & Data Science**: Optimization Techniques (Gradient Descent Variants), Ensemble Learning (Bagging, Boosting, AdaBoost) , Introduction to Reinforcement Learning, Time Series Analysis, Ethical AI	6 Hrs.

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Sr. No.	Textbooks
1.	**Stuart Russell & Peter Norvig**, Artificial Intelligence: A Modern Approach, 3rd Edition, Pearson.
2.	**Gareth James, Daniela Witten, Trevor Hastie & Robert Tibshirani**, An Introduction to Statistical Learning with Applications in R, Springer.
	Reference Books
1.	**Christopher M. Bishop**, Pattern Recognition and Machine Learning, Springer.
2.	**Tom Mitchell**, Machine Learning, McGraw Hill.
3.	**Trevor Hastie, Robert Tibshirani & Jerome Friedman**, The Elements of Statistical Learning, Springer.
	Web Resources
1.	NPTEL – Artificial Intelligence & Data Science Courses https://nptel.ac.in
2.	Coursera – AI & Machine Learning Specializations https://www.coursera.org
3.	Scikit-Learn Official Documentation https://scikit-learn.org

Course Title: Large Language Models **Course Code: PL261104**			**Course Category: PEC-II**
Teaching Scheme	**Examination Scheme**		
Lectures: 03 hrs./ week	CA-1	10 Marks	
Tutorial: -	CA-2	10 Marks	
Credits: 03	MSE	20 Marks	
Semester: First Year (Semester I)	ESE	60 Marks	

Course Prerequisite:
Fundamental knowledge of Machine Learning and Deep Learning. Basic understanding of Natural Language Processing concepts. Proficiency in Python programming and use of ML libraries. Knowledge of Linear Algebra, Probability, and Statistics. Familiarity with neural networks and training workflows

Course Description: This course introduces the concepts and architectures behind Large Language Models (LLMs) used in modern generative AI. It covers transformers, pretraining, prompt engineering, and fine-tuning techniques. Students gain hands-on experience in building and deploying LLM-based applications such as chatbots and question answering systems. The course also examines evaluation methods, ethical issues, bias, and safety concerns. By the end, learners will be able to design efficient and responsible LLM-powered solutions.

Course Objectives:
1. Understand fundamentals of NLP and transformer architectures
2. Analyze design and training of large language models
3. Apply LLMs for downstream NLP tasks
4. Evaluate ethical, safety, and deployment challenges
5. Design and implement LLM-based applications.

Course Outcomes:

COs	After completion of the course: Student will be able to	Bloom's Level
CO 1	**Recall** the fundamental concepts of natural language processing, text preprocessing techniques, statistical language models, and word embeddings used in NLP systems.	Remember L1
CO 2	**Explain** the working principles of neural language models, recurrent neural networks, attention mechanisms, and sequence modeling techniques for language processing tasks.	Understand L2
CO 3	**Apply** transformer-based architectures and pretrained language models for tasks such as text generation, summarization, question answering, and conversational AI.	Apply L3
CO 4	**Analyze** the performance and limitations of large language models, evaluation metrics, deployment strategies, and ethical considerations in NLP systems.	Analyze L4

CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	2	1
CO2	3	2	1	1	2	–	–	–	1	–	1	2	2
CO3	3	3	3	2	3	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	1	1	1	1	–	2	3	3

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Assessment	
CA-1 (a) (10M)	Subjective Test / Open book test / etc.
CA-2 (b) (10M)	Model Making / Assignment / Presentation / etc.
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	Evolution of Natural Language Processing, Text preprocessing techniques, N-gram language models, Statistical language modeling, Word embeddings: Word2Vec, GloVe, FastText, Limitations of traditional NLP	6 Hrs.
Unit 2	Neural language models, RNN, LSTM, GRU architectures, Sequence-to-sequence models, Attention mechanism, Limitations of RNN-based models, Introduction to self-attention	6 Hrs.
Unit 3	Transformer architecture overview, Self-attention and multi-head attention, Positional encoding, Encoder–decoder architecture, pre-training vs fine-tuning paradigm, Scaling laws in LLMs	6 Hrs.
Unit 4	Pretrained language models, BERT, GPT family, T5, PaLM overview, Tokenization methods (BPE, WordPiece, SentencePiece), Prompt engineering fundamentals, Instruction tuning, Reinforcement Learning from Human Feedback (RLHF), Parameter-efficient fine-tuning (LoRA, adapters)	6 Hrs.
Unit 5	Text generation and summarization, Question answering systems, Chatbots and conversational AI, Retrieval-Augmented Generation (RAG), Multimodal LLMs (text + image), LLM evaluation metrics (BLEU, ROUGE, perplexity), Model compression and optimization, Deployment using APIs and local models	6 Hrs.
Unit 6	Bias and fairness in LLMs, Hallucination problem, Privacy and security, Responsible AI guidelines, Regulatory landscape, Open-source vs proprietary LLMs, Future trends in foundation models	6 Hrs.

Sr. No.	Textbooks
1.	Speech and Language Processing — Daniel Jurafsky & James H. Martin
2	Natural Language Processing with Transformers — Lewis Tunstall, Leandro von Werra, Thomas Wolf
3	Deep Learning — Ian Goodfellow, Yoshua Bengio, Aaron Courville
	Reference Books
1.	Natural Language Processing with Python — Steven Bird, Ewan Klein, Edward Loper
2	Transformers for Natural Language Processing — Denis Rothman
3	Build a Large Language Model (From Scratch) — Sebastian Raschka
	Web Resources
1.	Hugging Face Transformers Documentation: https://huggingface.co/docs/transformers
2	OpenAI Developer Documentation https://platform.openai.com/docs
3	

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Course Title: Seminar Course Code: PL261401 Course Category: SE-SEC		
Teaching Scheme	**Examination Scheme (As Applicable)**	
Practical's/Sessions: 02 Hours/Week	CA-I	15 Marks
Credit: 01	CA-II	15 Marks
Semester: First Year (Semester-I)	ESE	20 Marks

Course Prerequisite:
Basic understanding of core subjects in specialization, Ability access, and interpret scientific literature, Exposure to technical report writing and presentation.

Course Description:
The M. Tech Seminar course is designed to enhance student ability to identify, analyze and present research-oriented or industry-relevant topics related to their field of specialization. It provides a platform to review recent literature, critically analyze methodologies, and effectively communicate technical concepts written and oral forms. The course emphasizes independent learning analytical thinking presentation and interaction with peers and faculty to prepare students for research and professional careers.

Course Objectives:

1. To enhance the ability to conduct a comprehensive literature review on a selected research/technical topic.
2. To develop skills in critical analysis, organization, and synthesis of technical information.
3. To improve proficiency in technical report writing and formatting.
4. To strengthen communication skills through oral presentation and discussion.
5. To build confidence in defending technical ideas and responding to queries effectively.

Course Outcomes:

COs	After completion of the course: Students should be able to	Bloom's Level
CO1	**Recall** basic concepts and background of the selected AI & Computer Science topic.	Remember L1
CO2	**Explain** the chosen research problem and recent developments.	Understand L2
CO3	**Apply** knowledge to organize and prepare a structured seminar report.	Apply L3
CO4	**Analyze** research papers, techniques, and methodologies related to the topic.	Analyze L4
CO5	**Evaluate** different approaches and present findings effectively	Evaluate L5

CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	2	1	–	–	–	–	–	–	–	–	2	1	1
CO2	2	2	–	1	–	–	–	–	2	–	2	2	1
CO3	2	2	1	1	1	–	–	–	3	1	2	2	2
CO4	2	3	2	3	1	–	–	–	2	–	3	3	2
CO5	2	3	2	2	1	–	–	–	3	1	3	3	2

Assessment	
Evaluation and Examination The seminar will be evaluated out of a total of 50 marks, with 30 marks for internal assessment and 20 marks for the semester-end examination. The semester-end examination will be conducted by a committee of three faculty members. Students must submit their completed reports, which should be authenticated by both their guide and the Head of the Department. Each student will individually present their work to the committee, who will then evaluate them and award marks.	
CA-I (a) (15M)	Review-I: 15 Marks (Concept/knowledge in the topic:10 marks, Literature: 05 marks)
CA-II (b) (15M)	Review-II: 15 Marks (Report writing & Presentation: 15 Marks)
ESE (Practical/viva voce (c))(20M)	20 Marks (Individual evaluation through viva voce/test:20 marks)
Total (d)	50 Marks

Course Content

The seminar requires each candidate to prepare a report on a topic that they and their supervisor have mutually agreed upon. This topic must be a current problem in the field of A.I. & Computer Science. Problem should have strong research orientation. The candidate is expected to demonstrate a thorough understanding of the recent developments related to their chosen topic. Once the report is complete, the candidate will present it to an examining committee, as well as to other faculty members from the department. The PG coordinator and the Head of the Computer Science and Engineering Department will form this committee to evaluate the seminar.

Course Title: PG Lab **Course Code: PL261402**		**Course Category: SE-SEC**
Teaching Scheme	**Examination Scheme**	
Practical's /Sessions: 02 Hours/Week	CA-I	15 Marks
Credit: 01	CA-II	15 Marks
Semester: First Year (Semester I)	ESE	20 Marks
Course Prerequisite: Artificial Intelligence & Data Science		
Course Description: This course introduces the fundamental concepts of Artificial Intelligence and Data Science. It covers intelligent search, knowledge representation, statistical foundations, and data preprocessing techniques. Students learn supervised and unsupervised learning methods for building predictive models. The course also explores advanced topics such as optimization, ensemble learning, and ethical AI, with practical implementation using real-world datasets.		
Course Objective: 1. To provide hands-on experience in implementing AI search algorithms such as BFS, DFS, and A. 2. To develop practical skills in statistical analysis, data preprocessing, and exploratory data analysis using Python tools. 3. To enable students to implement and evaluate supervised learning algorithms. 4. To provide exposure to unsupervised learning, dimensionality reduction, and data mining techniques. 5. To encourage students to solve real-world problems through a mini project using real datasets.		

Course Outcomes:		
COs	**After completion of the course: Students will be able to**	**Bloom's Level**
CO1	**Recall** fundamental concepts of search algorithms, statistical analysis, and machine learning techniques.	Remember L1
CO2	**Explain** the working principles of BFS, DFS, A*, regression, classification, clustering, and data preprocessing methods.	Understand L2
CO3	**Apply** Python tools and libraries to implement algorithms, perform data preprocessing, and build machine learning models.	Apply L3
CO4	**Analyze** results of models and evaluate performance using statistical measures and visualization techniques.	Analyze L4
CO5	**Evaluate** the effectiveness and accuracy of machine learning models and select appropriate techniques for given problems	Evaluate L5

CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	2	1
CO2	3	2	1	1	2	–	–	–	1	–	1	2	2
CO3	3	3	3	2	3	–	–	–	2	–	1	3	3
CO4	3	3	2	3	3	–	–	–	2	–	2	3	3
CO5	3	3	3	3	2	1	1	1	2	1	3	3	3

Assessment	
CA-I (a) (15M)	Practical implementation of concept/ Laboratory Performance and Attendance Lab Records and Technical Report
CA-II (b) (15M)	Practical implementation of concept/ Experiment Conduction, Observation and Data Collection Marks Viva voce (during lab session)

Sr. No.	List of Experiments/Activities
1.	Implementation of BFS & DFS
2.	Implementation of A* Algorithm
3.	Statistical analysis using Python
4.	Data preprocessing using Pandas
5.	EDA & Visualization
6.	Linear & Logistic Regression
7.	K-NN & Naïve Bayes
8.	K-Means & Hierarchical Clustering

Course Title: Autonomous Intelligent System Course Code: PL262004		Course Category: PCC	
Teaching Scheme	**Examination Scheme**		
Lectures: 04 hrs / week	CA-1	10 Marks	
Tutorial: ---	CA-2	10 Marks	
Credits: 04	MSE	20 Marks	
Semester: First Year (Semester II)	ESE	60 Marks	
Course Prerequisite: Basic knowledge of AI, Data Structures, Probability, and Python/C++ programming.			
Course Description: This course covers the design and development of intelligent autonomous systems. It includes agent architectures, knowledge representation, perception and state estimation, planning, multi-agent systems, reinforcement learning, and adaptive autonomy. The course also addresses real-world applications and ethical, safety, and security considerations in autonomous systems.			

Course Outcomes:

COs	After completion of the course: Students should be able to	Bloom's Level
CO1	**Recall** the fundamental concepts of intelligent agents, agent architectures, environment classifications, and agent communication frameworks used in autonomous systems**.**	Remember L1
CO2	**Explain** the principles of knowledge representation, logical reasoning, probabilistic models, and decision-theoretic approaches used in intelligent agents.	Understand L2
CO3	**Apply** perception, planning, and learning techniques including reinforcement learning and multi-agent system concepts to solve problems in autonomous systems.	Apply L3
CO4	**Analyze** the performance and behavior of autonomous agents in real-world applications, considering safety, ethical, and trustworthiness issues.	Analyze L4

CO- PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	2	1
CO2	3	2	1	1	1	–	–	–	1	–	1	2	2
CO3	3	3	3	2	2	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	2	1	2	1	–	2	3	3

Assessment	
CA-1 (a) (10M)	Subjective Test
CA-2 (b) (10M)	Database Modelling/ Query Simulation and optimization / Assignment
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	**Intelligent Agents and Architectures** Definition and characteristics of intelligent agents, Agent types: Simple reflex, Model-based, Goal-based, Utility-based agents, Rationality and performance measures, Environment classification, Reactive, Deliberative and Hybrid architectures, BDI and Subsumption architecture, Cognitive architectures overview, Agent communication languages (ACL, KQML), Agent development frameworks (JADE, ROS agents)	8 Hrs.
Unit 2	**Knowledge Representation and Reasoning** Logical agents and propositional logic, First-order logic, Rule-based systems, Ontologies and semantic reasoning, Bayesian networks, Hidden Markov Models, MDP and POMDP, Decision-theoretic agents, Utility theory	8 Hrs.
Unit 3	**Perception and World Modeling** Sensor modeling (Camera, LiDAR, Radar, IMU), Kalman Filter, EKF, Particle Filter, Computer vision basics, Object detection and tracking, SLAM techniques, Occupancy grids, State estimation methods	8 Hrs.
Unit 4	**Planning and Multi-Agent Systems** Classical and heuristic search algorithms, Planning algorithms (STRIPS, GraphPlan), Path planning (RRT, PRM, D*), Multi-agent systems fundamentals, Distributed AI, Consensus algorithms, Swarm intelligence, Game theory fundamentals	8 Hrs.
Unit 5	**Learning Agents and Adaptive Autonomy** Learning agent architecture, Supervised and Unsupervised learning, Reinforcement Learning (Q-learning, SARSA), Deep Reinforcement Learning, Policy gradients, Multi-agent RL, Imitation and Transfer learning, Self-supervised learning	8 Hrs.
Unit 6	**Applications and Ethics** Autonomous vehicles, UAVs and robotic systems, Industrial automation, Human-agent interaction, Explainable AI, Ethical and legal issues, Safety-critical systems, Trustworthy AI, Cybersecurity in autonomous systems	8 Hrs.

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Sr. No.	Textbooks
1.	Artificial Intelligence: A Modern Approach – Stuart Russell and Peter Norvig, 4th Edition, Pearson Education.
2.	Probabilistic Robotics – Sebastian Thrun, Wolfram Burgard, and Dieter Fox, MIT Press.
	Reference Books
1.	Reinforcement Learning: An Introduction – Richard S. Sutton and Andrew G. Barto, MIT Press.
2.	Planning Algorithms – Steven M. LaValle, Cambridge University Press.
	Web Resources
1.	MIT OpenCourseWare – Artificial Intelligence course materials: https://ocw.mit.edu Stanford University – Artificial Intelligence and Machine Learning lectures https://ai.stanford.edu ROS.org – Robot Operating System documentation and tutorials: https://www.ros.org

Course Title: MOOC/SWAYAM Course Code: PL262005		Course Category: PCC
Teaching Scheme	**Examination Scheme**	
Lectures: 04 hrs./ week	CA-1	10 Marks
Tutorial: -----	CA-2	10 Marks
Credits: 04	MSE	20 Marks
Semester: First Year (Semester II)	ESE	60 Marks

Course Description:

This course is part of a curated set of MOOCs offered, with the specific courses selected and approved by the Board of Studies (BoS) to ensure alignment with current academic and industry standards.

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Course Title: Soft computing Course Code: PL262105		Course Category: PEC-III
Teaching Scheme	**Examination Scheme**	
Lectures: 03 hrs. / week	CA-1	10 Marks
Tutorial: ----	CA-2	10 Marks
Credits: 03	MSE	20 Marks
Semester: First Year (Semester II)	ESE	60 Marks

Course Prerequisite:
Students should have a strong foundation in Engineering Mathematics including Linear Algebra, Probability & Statistics, and Multivariable Calculus. Basic programming skills (Python/MATLAB/C++) and understanding of Data Structures are required. Prior knowledge of Machine Learning concepts such as supervised and unsupervised learning, along with fundamentals of Artificial Neural Network and Fuzzy Logic is expected. Familiarity with numerical methods and basic optimization techniques will be helpful for better understanding of advanced soft computing models.

Course Description: This course focuses on advanced soft computing techniques for solving complex and uncertain real-world problems. It covers concepts of Artificial Neural Network, Fuzzy Logic, and Evolutionary Computation. The course emphasizes mathematical foundations, algorithm design, and hybrid intelligent systems. Applications in optimization, control, and machine learning are discussed. It prepares students for research and advanced development in intelligent systems.

Course Objectives:
To understand advanced concepts of Artificial Neural Network and deep learning models.
To apply Fuzzy Logic techniques for uncertainty modeling and control systems.
To explore optimization methods in Evolutionary Computation.
To design hybrid soft computing models for real-world applications.

Course Outcomes:

COs	After completion of the course: Students will be able to	Bloom's Level
CO1	**Recall** the fundamental concepts of artificial neural networks, neuron models, learning paradigms, activation functions, and basic optimization techniques used in soft computing**.**	Remember L1
CO2	**Explain** the working principles of advanced neural network architectures, fuzzy set theory, fuzzy inference systems, and uncertainty modeling techniques.	Understand L2
CO3	**Apply** neural network models, fuzzy logic systems, and evolutionary computation algorithms to solve complex optimization and decision-making problems.	Apply L3
CO4	**Analyze** the performance of hybrid intelligent systems, swarm intelligence techniques, and soft computing models, considering emerging trends and real-world applications.	Analyze L4

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CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	2	1
CO2	3	2	1	1	1	–	–	–	1	–	1	2	2
CO3	3	3	3	2	2	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	1	1	1	1	–	2	3	3

Assessment	
CA-1 (a) (10M)	Subjective Test / Assignment/ MCQ Test etc.
CA-2 (b) (10M)	Subjective Test / Assignment/ MCQ Test etc.
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	**Foundations of Neural Networks:** Introduction to Artificial Neural Network, Biological neuron vs Artificial neuron, Artificial neuron model, Bias, Threshold concept, McCulloch-Pitts Neuron, Logical implementation: AND, OR, XOR, Linear neuron mode, Learning paradigms: Supervised, Unsupervised, Reinforcement, Gradient Descent & Stochastic Gradient Descent, Loss functions (MSE, Cross-Entropy),Activation functions (Binary, Sigmoid, Tanh, ReLU), Hebbian Learning, Delta Rule, Perceptron limitations & Regularization	6 Hrs.
Unit 2	**Advanced Neural Network Architectures: Multilayer** Perceptron (MLP), Architecture design, Backpropagation Algorithm (Mathematical derivation), Applications of MLP, Vanishing & Exploding Gradient problem, Radial Basis Function (RBF) Networks, Hopfield Network, Self-Organizing Maps (SOM), Learning Vector Quantization (LVQ), Deep Neural Networks overview, CNN & RNN introduction, LSTM & Transfer Learning concepts	6 Hrs.
Unit 3	**Fuzzy Logic – Foundations:** Introduction to Fuzzy Logic, Crisp vs Fuzzy Sets, Fuzzy Set Theory & Operations, Properties of Fuzzy Sets, Alpha-cuts, Fuzzy Relations, Composition of Relations, Fuzzy to Crisp Conversion, Defuzzification basic, Type-1 & Type-2 Fuzzy Sets, Uncertainty modeling	6 Hrs.
Unit 4	**Fuzzy Systems & Controllers: Membership** Functions (Triangular, Gaussian, etc.), Fuzzy Inference Systems, Mamdani Inference System, Sugeno Fuzzy Model, Fuzzification & Defuzzification methods, Fuzzy IF–THEN Rules, Fuzzy Controllers, Industrial Applications, Neuro-Fuzzy (ANFIS concept)	6 Hrs.
Unit 5	**Evolutionary Computation: Introduction** to Evolutionary Computation, Genetic Algorithms fundament, Selection methods (Rank, Roulette Wheel), Fitness computation, Crossover, Mutation, Reproduction, Simulated Annealing, Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Differential Evolution, Multi-objective Optimization (NSGA-II overview)	6 Hrs.

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Unit 6	**Hybrid Intelligent Systems & Research Trends: Hybrid** Soft Computing Systems, Euro-Fuzzy Systems, Genetic-Neural Hybrid Models, Swarm Intelligence in Machine Learning, Explainable AI (XAI) in Soft Computing, Edge AI concepts, Research Challenges, Case Studies & Paper Discussion	6 Hrs.

Sr. No.	Textbooks
1.	Laurene Fausett, "Fundamentals of Neural Networks: Architectures, Algorithms And Applications", Pearson Education, 2008
2.	Timothy Ross, "Fuzzy Logic With Engineering Applications", 3rd Edition, John Wiley & Sons, 2010
3.	J.S. Jang, C.T. Sun, E. Mizutani, "Neuro- Fuzzy and Soft Computing", PHI Learning Private Limited

	Reference Books
1.	Statistical pattern Recognition; K. Fukunaga; Academic Press, 2000
2.	S.Theodoridis and K.Koutroumbas, Pattern Recognition, 4th Ed., Academic Press, 2009
3.	Rajjan Shinghal, Pattern Recognition: Techniques and Applications, Oxford University Press, 2015.
	Web Resources
1.	Pattern Recognition and Application, NPTEL,https://onlinecourses.nptel.ac.in/noc19_ee56/preview
2.	Pattern Recognition, NPTEL, https://nptel.ac.in/courses/117108048
3.	Principles of Pattern Recognition I, NPTEL, https://nptel.ac.in/courses/106106046

Course Title: Reinforcement Learning Course Code: PL262106		Course Category: PEC-III
Teaching Scheme	**Examination Scheme**	
Lectures: 03 hrs./ week	CA-1	10 Marks
Tutorial: -----	CA-2	10 Marks
Credits: 03	MSE	20 Marks
Semester: First Year (Semester II)	ESE	60 Marks

Course Prerequisite:

Basic knowledge of Probability and Statistics, Linear Algebra, Calculus, Optimization techniques, and Programming concepts (preferably Python). Familiarity with Machine Learning fundamentals is recommended.

Course Description:

This course introduces the fundamentals and advanced concepts of Reinforcement Learning (RL). It covers Markov Decision Processes (MDPs), dynamic programming, model-free methods such as TD learning and Q-learning, and function approximation techniques. The course also includes policy gradient methods, actor-critic architectures, and deep reinforcement learning algorithms like DQN and PPO, along with selected advanced topics and real-world applications

Course Objectives:

1. Understand the fundamental concepts of Reinforcement Learning, including agents, environments, rewards, exploration–exploitation, Multi-Armed Bandits, Markov Decision Processes, and Bellman equations.
2. Develop knowledge of Dynamic Programming and Model-Based Reinforcement Learning techniques, including Policy Iteration, Value Iteration, planning, and Monte Carlo Tree Search.
3. Apply Model-Free Reinforcement Learning algorithms such as Monte Carlo methods, Temporal Difference Learning, Q-Learning, SARSA, and Expected SARSA for solving sequential decision-making problems.
4. Explore Deep and Advanced Reinforcement Learning techniques such as DQN, DDPG, SAC, Multi-Agent RL, Safe RL, Inverse RL, and Offline RL, with applications in robotics, autonomous systems, games, and finance.

Course Outcomes:

COs	After completion of the course: Student will be able to	Bloom's Level
CO1	**Recall** the fundamental concepts of reinforcement learning, multi-armed bandits, Markov Decision Processes (MDPs), and Bellman equations used in sequential decision making.	Remember L1
CO2	**Explain** the principles of dynamic programming, model-based reinforcement learning, Monte Carlo methods, and temporal difference learning techniques.	Understand L2
CO3	**Apply** model-free reinforcement learning algorithms, function approximation methods, and policy gradient techniques to solve sequential decision-making problems.	Apply L3
CO4	**Analyze** the performance of deep reinforcement learning algorithms and advanced RL techniques for real-world applications such as robotics, autonomous systems, and intelligent agents.	Analyze L4

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	2	1
CO2	3	2	1	1	1	–	–	–	1	–	1	2	2
CO3	3	3	3	2	2	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	2	1	2	1	–	2	3	3

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Assessment	
CA-1 (a) (10M)	Subjective Test
CA-2 (b) (10M)	Subjective Test / Presentation
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	**Foundations of Reinforcement Learning** Introduction to Reinforcement Learning, Historical perspective (Atari, AlphaGo, robotics applications), RL vs Supervised and Unsupervised Learning, Multi-armed Bandits, Exploration vs Exploitation, ε-greedy, SoftMax, Upper Confidence Bound (UCB), Upper Confidence Reinforcement Learning (UCRL), Regret analysis, Markov Decision Processes (MDP), Finite and infinite horizon MDPs, Bellman equations, Policy evaluation and optimality	6 Hrs.
Unit 2	**Dynamic Programming and Model-Based RL** Policy Evaluation, Policy Iteration (PI), Value Iteration (VI), Linear Programming formulation of MDPs, Convergence analysis, Model-based Reinforcement Learning, Planning vs Learning, Monte Carlo Tree Search (MCTS) (e.g., AlphaGo style planning)	6 Hrs.
Unit 3	**Model-Free Reinforcement Learning** Monte Carlo Methods, Temporal Difference (TD) Learning, TD(0), TD(λ), Q-Learning, SARSA, Expected SARSA, On-policy vs Off-policy learning, Convergence properties	6 Hrs.
Unit 4	**Function Approximation and Approximate RL** Curse of Dimensionality, Linear Function Approximation, Approximate Value Iteration, Approximate Policy Iteration, Stochastic Approximation, Single-timescale, Multi-timescale, Gradient TD methods, Least-Squares TD (LSTD), Convergence guarantees, Bias-variance tradeoff.	6 Hrs.
Unit 5	**Policy Gradient and Actor-Critic Methods** Policy Gradient Theorem, REINFORCE Algorithm, Baselines and Variance Reduction, Natural Policy Gradient, Actor-Critic Methods, Advantage Actor-Critic (A2C), Asynchronous A3C, Deterministic Policy Gradient (DPG), Trust Region Policy Optimization (TRPO), Proximal Policy Optimization (PPO)	6 Hrs.
Unit 6	**Deep Reinforcement Learning and Advanced Topic** Deep Q-Network (DQN), Experience Replay, Target Networks, Double DQN, Dueling Networks, Deep Deterministic Policy Gradient (DDPG), Soft Actor-Critic (SAC), Exploration in Deep RL, Safe Reinforcement Learning, Multi-Agent Reinforcement Learning, Inverse Reinforcement Learning, Offline Reinforcement Learning, Applications: Robotics, Autonomous Driving, Finance, Games	6 Hrs.

Sr. No.	Textbooks
1	Reinforcement Learning: An Introduction by Richard S. Sutton and Andrew G. Barto— The foundational textbook for RL (covers MDPs, TD, Q-Learning, policy gradient, function approximation) 2nd Edition, MIT Press
2	Algorithms for Reinforcement Learning by Csaba Szepesvári — Compact and mathematically rigorous treatment of RL algorithms.
3	Deep Reinforcement Learning Hands-On by Maxim Lapan — Practical guide with PyTorch implementation of Deep RL methods
	Reference Books
1.	Deep Learning by Ian Goodfellow, Yoshua Bengio & Aaron Courville — Important for understanding the deep neural networks used within Deep RL
2	Machine Learning: A Probabilistic Perspective by Kevin P. Murphy — Good foundation on probabilistic methods often used in RL theory.
3	Optimal Control and Estimation by Robert F. Stengel— Useful for perspective on continuous control and connections to RL.
4.	Markov Decision Processes: Discrete Stochastic Dynamic Programming by Martin L. Puterman— Rigorous treatment of MDP theory and dynamic programming.
	Web Resources
1.	https://www.davidsilver.uk/teaching/
2	https://web.stanford.edu/class/cs234/lecture1.pdf
3	https://torlattimore.com/downloads/book.html

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Course Title: Speech Modelling & Recognition **Course Code: PL262107**		**Course Category: PEC-IV**
Teaching Scheme	**Examination Scheme**	
Lectures: 03 hrs. / week	CA-1	10 Marks
Tutorial: --	CA-2	10 Marks
Credits: 03	MSE	20 Marks
Semester: Second Year (Semester III)	ESE	60 Marks

Course Prerequisite:
Students should have basic knowledge of Signals & Systems, Digital Signal Processing, and Probability & Statistics. Familiarity with Python/MATLAB and Machine Learning fundamentals is recommended.

Course Description:
This course introduces the fundamentals of speech signal processing, feature extraction, statistical modeling, and modern speech recognition and synthesis systems. Students learn how human speech is produced and modeled using digital signal processing techniques and probabilistic models. The course covers Hidden Markov Models, large vocabulary continuous speech recognition, and text-to-speech systems. Practical insights into real-world speech applications are also provided.

Course Objectives:
1. Understand the fundamentals of human speech production and acoustic characteristics.
2. Apply digital signal processing techniques for speech analysis and feature extraction.
3. Implement speech modeling techniques using statistical models such as Hidden Markov Models.
4. Analyze large vocabulary continuous speech recognition systems and language modeling techniques.
5. Understand the principles and techniques used in speech synthesis and text-to-speech systems.

Course Outcomes:

COs	**After completion of the course: Students will be able to**	**Bloom's Level**
CO1	**Recall** the fundamental concepts of speech production, phonetics, acoustics properties of speech, and basic digital speech signal processing techniques.	Remember L1
CO2	**Explain** the principles of speech signal analysis, feature extraction techniques, speech distortion measures, and sequence modeling methods used in speech and language processing.	Understand L2
CO3	**Apply** speech processing and NLP techniques include feature extraction, language models, and evaluation metrics for tasks such as speech recognition, machine translation, and text analysis.	Apply L3
CO4	**Analyze** the performance and implications of speech and NLP systems, considering evaluation methods, real-world applications, and ethical issues in language technologies.	Analyze L4

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CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	2	1
CO2	3	2	1	1	2	–	–	–	1	–	1	2	2
CO3	3	3	3	2	3	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	1	1	1	1	–	2	3	3

Assessment	
CA-1 (a) (10M)	Subjective Test / Assignment/ MCQ Test etc.
CA-2 (b) (10M)	Subjective Test / Assignment/ MCQ Test etc.
MSE (c) (20M)	Subjective Test

	Course Contents	
Unit 1	**INTRODUCTION TO SPEECH & PHONETICS** **Basic Concepts:** Speech Fundamentals; Articulatory Phonetics – Production and Classification of Speech Sounds; Acoustic Phonetics – Acoustics of Speech Production.	6 Hrs.
Unit 2	**DIGITAL SPEECH SIGNAL PROCESSING** **Review of DSP Concepts:** Review of Digital Signal Processing concepts; Short-Time Fourier Transform (STFT); Filter-Bank Methods; Linear Predictive Coding (LPC) Methods.	6 Hrs.
Unit 3	**SPEECH ANALYSIS & FEATURE EXTRACTION** Speech Features, Feature Extraction and Pattern Comparison Techniques, Speech Distortion Measures – Mathematical and Perceptual, Log Spectral Distance, Cepstral Distances; Weighted Cepstral Distances and Filtering, Likelihood Distortions, Spectral Distortion using Warped Frequency Scale.	6 Hrs.
Unit 4	**Sequence Modelling and Language Models** Markov Models, Seq2Seq, Machine Translation, Text Summarization, Pretrained Language Models: BERT, GPT, T5, RoBERTa, and DistilBERT, Transfer Learning	6 Hrs.
Unit 5	**Evaluation Metrics and Applications** Precision, Recall, F1 Score, BLEU score for Machine Translation, ROUGE score for Summarization, Applications of NLP: Text Classification, Machine Translation, Speech Recognition, Information Retrieval and Search Engines	6 Hrs.
Unit 6	**Ethical Considerations in NLP** Bias in Language Models: Gender, racial, and socio-cultural biases in NLP models, Data Privacy Concerns: Ethical implications, Fairness in AI Systems	6 Hrs.

Sr. No.	Textbooks
1.	Jurafsky, Daniel and Martin, James H., Speech and Language Processing, Pearson, 2021.
2.	Bird, Steven, Klein, Ewan, and Loper, Edward, Natural Language Processing with Python, O'Reilly Media, 2009.
3.	Goldberg, Yoav, Neural Network Methods for Natural Language Processing, Morgan & Claypool, 2017.
4.	Eisenstein, Jacob, Introduction to Natural Language Processing, MIT Press, 2019.
	Reference Books
1.	Thomas F Quatieri,—Discrete-Time Speech Signal Processing–Principles and Practice‖ , Pearson Education, 2002
2.	Claudio Becchetti and Lucio Prina Ricotti, Speech Recognition‖, John Wiley and Sons, 1999
3.	Bengold and Nelson Morgan, —Speech and audio signal processing‖, processing and perception of speech and music, Wiley-India Edition, 2006.
4.	Himanshu Mohan, Megha Yadav, "Speech Recognition System and its Application‖, LAPLAMBERT Academic Publishing,2019
	Web Resources
1.	https://archive.nptel.ac.in/courses/117/105/117105145/
2.	http://onlinecourses.nptel.ac.in/noc22_ee117/preview

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Course Title: Generative AI Course Code: PL262108		Course Category: PEC-IV
Teaching Scheme	**Examination Scheme**	
Lectures: 03 hrs. / week	CA-1	10 Marks
Tutorial: ---	CA-2	10 Marks
Credits: 03	MSE	20 Marks
Semester: First Year (Semester II)	ESE	60 Marks

Course Prerequisite:
Machine Learning, Python Programming

Course Description: This course introduces the fundamental concepts, architectures, and applications of Generative Artificial Intelligence (GenAI). It covers generative models such as Autoencoders, Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and Large Language Models (LLMs). Students will learn how generative models create new data including text, images, audio, and code. The course also discusses prompt engineering, foundation models, ethical considerations, responsible AI, and real-world applications in healthcare, education, software development, and creative industries.

Course Objectives:

1. To understand the fundamentals and working principles of generative AI models.
2. To study various generative models such as Autoencoders, VAEs, GANs, and Transformers.
3. To apply prompt engineering techniques and work with Large Language Models (LLMs).
4. To implement generative AI models for text, image, and content generation.
5. To understand ethical, legal, and societal implications of generative AI.

Course Outcomes:

COs	After completion of the course Students will be able to	Bloom's Level
CO1	**Recall** fundamental concepts of Generative AI, probability theory, neural networks, and transformer architectures.	Remember L1
CO2	**Explain** deep learning foundations, sequence models, generative models (VAE, GAN, LLMs), and diffusion models.	Understand L2
CO3	**Apply** generative AI techniques, transformer models, and deep learning methods to solve real-world problems.	Apply L3
CO4	**Analyze** performance, limitations, and ethical implications of generative AI systems and models	Analyze L4

CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	2	1
CO2	3	2	1	1	2	–	–	–	1	–	1	2	2
CO3	3	3	3	2	3	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	2	1	2	1	–	2	3	3

Assessment	
CA-1 (a) (10M)	Assignment
CA-2 (b) (10M)	Assignment
MSE (c) (20M)	Subjective Test

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Course Contents		
Unit 1	**Introduction to Generative AI** Introduction to Artificial Intelligence, Machine Learning, and Deep Learning. Generative vs Discriminative models. Mathematical foundations: probability theory, joint and conditional distributions, latent variable models, Maximum Likelihood Estimation (MLE), Maximum A Posteriori (MAP), and Bayesian inference. Information theory concepts: entropy, KL divergence, cross-entropy. Neural network fundamentals: feedforward networks, activation functions, loss functions, and optimization objectives.	6 Hrs.
Unit 2	**Deep Learning Foundations for Generative Models** Backpropagation and computational graphs. Gradient descent optimization methods: SGD, Momentum, Adam, RMSProp. Training deep neural networks: convergence, generalization, bias-variance tradeoff. Regularization methods: L1, L2, dropout, batch normalization. Representation learning and feature extraction. Embedding methods and latent space representation. Introduction to probabilistic deep learning.	6 Hrs.
Unit 3	**Sequence Modeling and Transformer Architecture** Probabilistic language models: N-grams, Markov assumptions, limitations. Neural language models using RNN, LSTM, and GRU. Vanishing and exploding gradient problems and mitigation techniques. Sequence-to-Sequence learning and encoder-decoder framework. Attention mechanism and self-attention. Transformer architecture: encoder, decoder, positional encoding, multi-head attention. Pretrained transformer models: BERT, GPT, T5. Applications in text generation, machine translation, and conversational AI**.**	6 Hrs.
Unit 4	**Variational Autoencoders and Generative Adversarial Networks** Latent variable models and representation learning. Autoencoders and probabilistic interpretation. Variational Autoencoders (VAE): ELBO objective function, reparameterization trick, latent space sampling. Generative Adversarial Networks (GAN): min-max optimization, generator and discriminator architectures, loss functions. GAN variants: Conditional GAN, DCGAN, CycleGAN, StyleGAN. Training challenges: mode collapse, convergence issues, stability improvements.	6 Hrs.
Unit 5	**Large Language Models and Diffusion Models** Foundation models and scaling laws. Architecture and training of Large Language Models (LLMs). Pretraining objectives: autoregressive and masked language modeling. Fine-tuning techniques: transfer learning, instruction tuning, parameter-efficient fine-tuning (PEFT). Prompt engineering and in-context learning. Retrieval Augmented Generation (RAG). Diffusion models: forward diffusion, reverse denoising process, score-based models. Applications in image generation, multimodal systems, and AI agents.	6 Hrs.
Unit 6	**Responsible AI, Ethics, and Advanced Topics** Ethical challenges in Generative AI: bias, fairness, hallucination, misinformation, and deepfakes. Privacy-preserving generative models. Explainability and interpretability of generative systems. Safety and alignment of large language models. Regulatory frameworks and AI governance. Emerging trends: multimodal generative models, agent-based systems, and autonomous AI.	6 Hrs.

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Sr. No.	Textbooks
1.	Kevin Murphy, **Probabilistic Machine Learning**, MIT Press.
2.	Denis Rothman, **Transformers for NLP**, Packt
3.	Research Papers from NeurIPS, ICML, ACL, CVPR.

Reference Books
1. David Foster, **Generative Deep Learning: Teaching Machines to Paint, Write, Compose, and Play**, O'Reilly Media, 2023. (Practical and theoretical guide to generative models such as Autoencoders, GANs, VAEs, and Transformers.)
2. Jay Alammar, Maarten Grootendorst, **Hands-On Large Language Models**, O'Reilly Media, 2024.(Detailed explanation of LLM architecture, training, fine-tuning, embeddings, and applications.)
3. Kevin Murphy, **Probabilistic Machine Learning: An Introduction**, MIT Press, 2022. (Covers probabilistic foundations required for generative modeling and latent variable methods.)
Web Resources
1. https://openai.com/research/
2. https://ai.google/research/

Course Title: Research Methodology **Course Code: PG262601**		**Course Category: EL**
Teaching Scheme	**Examination Scheme**	
Lectures: 03 hrs./ week	CA-1	10 Marks
Tutorial: -----	CA-2	10 Marks
Credits: 03	MSE	20 Marks
Semester: First Year (Semester II)	ESE	60 Marks

Course Prerequisite: Basic knowledge of engineering fundamentals, Familiarity with undergraduate-level mathematics and statistics, Ability to use computers and standard engineering software tools

Course Description:

This course introduces postgraduate engineering students to the principles, processes, and practices of research methodology. It emphasizes problem identification, literature review, research design, data collection, analysis, and interpretation. The course also covers ethical practices, mathematical modeling, computational tools, and scientific communication through thesis, research papers, and presentations. It aims to equip students with essential skills to undertake independent research projects and contribute effectively to the advancement of science and technology.

Course Objectives:

1. To provide a clear understanding of the fundamentals and process of research in engineering.
2. To develop the ability to identify research problems through literature review and formulate hypotheses.
3. To impart knowledge of research ethics, integrity, and professional responsibility.
4. To familiarize students with research design, data collection, analysis, and interpretation techniques.
5. To introduce mathematical modelling and computational tools relevant to engineering research.
6. To develop effective academic writing and presentation skills for disseminating research outcomes.

Course Outcomes:

Cos	After completion of the course Student will be able to	Bloom's Level
CO1	**Recall** fundamental concepts of research methodology, ethics, and mathematical modeling.	Remember L1
CO2	**Explain** research processes, literature review techniques, research design, and ethical principles.	Understand L2
CO3	**Apply** research methods, data collection techniques, statistical tools, and computational software in problem-solving.	Apply L3
CO4	**Analyze** research problems, literature gaps, experimental data, and modeling techniques.	Analyze L4

Cos	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	2	1	–	–	–	1	1	2	–	–	2	1	1
CO2	2	2	–	1	–	1	1	2	2	–	2	2	1
CO3	2	3	2	2	2	1	1	1	2	1	2	2	3
CO4	2	3	2	3	1	1	1	1	2	–	3	3	2

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Assessment	
CA-1 (a)(10M)	Subjective Test / Open book test / Assignment.
CA-2 (b)(10M)	Assignment / Presentation/ Case Study
MSE (c)(20M)	Mid Sem Examination

Course Contents		
Unit 1	**Introduction to Research:** meaning, objectives, motivation, types, Research process, Criteria of good research, Importance of literature review in defining a problem, Literature review: primary and secondary sources, Critical literature review, Identifying gap areas from literature and research database, Research problem: selection, necessity and formulation, Technique Involved in Defining a Problem, Hypothesis formation, Problems Encountered by Researchers	6 Hrs.
Unit 2	**Research Ethics:** Ethical considerations in research, Plagiarism, Intellectual Property, Research Integrity, and misconduct, Ethical issues in data collection, experimentation, and analysis, Ethical considerations in publication and peer review, Case studies of ethical dilemmas in engineering research, Conflict of interest, Ethics in Emerging Technologies like AI	6Hrs
Unit 3	**Research Design, Experimentation, Analysis And Data Analysis and Interpretation:** Experimental and non-experimental research designs, Sampling techniques, and sample size determination, Data collection methods: Surveys, interviews, and observation, Instrumentation and measurement techniques, Reliability and validity in research, Design of experiments and analysis of results, Data processing and cleaning, Statistical analysis: Descriptive and inferential statistics, Advanced data analysis techniques: Regression, ANOVA, and multivariate analysis, Interpretation of results. Reporting and presenting data	6 Hrs.
Unit 4	**Mathematical Modeling in Engineering Research, Use of Computer Technology and Software:** Introduction to mathematical modeling, Types of models: Deterministic and probabilistic, Model development and validation, Applications of mathematical Modeling, Introduction to computational tool, Data analysis software: Usage and applications	6 Hrs.
Unit 5	**Writing and Presenting Research: Writing a thesis and project report:** Structure and content, Writing progress reports and project updates, Structuring a research paper, Writing research proposals and grants, Writing for journals and conferences, Incorporating references and citations: APA, MLA, IEEE styles, Managing references with citation management software (e.g., End Note, Zotero), Preparing and delivering oral presentations, Creating effective visual aids (charts, graphs, tables), Poster presentations: Design and delivery, The publication process and peer review, Communicating research to non-specialists and stakeholders	6Hrs
Unit 6	**Case Studies and Applications:** Case studies of successful engineering research, Application of research methodologies to real-life projects, Problem-solving through interdisciplinary approaches, Integration of ethical, technical, and methodological aspects, Emerging trends in engineering research.	6 Hrs.

Text Books	
1	C. R. Kothari, Research Methodology, New Age Publishers.
2	Ranjit Kumar, Research Methodology: A Step-by-Step Guide for Beginners
3	Herman Tang, Engineering Research: Design, Methods, and Analysis
4	Douglas C. Montgomery, Design and Analysis of Experiments
5	C. Neal Stewart Jr., Research Ethics for Scientists: A Companion for Students
Reference Books	
1	Cooper, D.R. & Schindler, P.S. – Business Research Methods, McGraw Hill.
2	Montgomery, D.C. – Design and Analysis of Experiments, Wiley.
3	Krishnaswamy, K.N., Sivakumar, A.I., Mathirajan, M. – Management Research Methodology, Pearson.
4	Deborah Rumsey – Statistics for Dummies, Wiley.

Web Resources	
1	MIT OpenCourseWare: Research Methods (https://ocw.mit.edu)
2	NCBI – PubMed Central (https://www.ncbi.nlm.nih.gov/pmc/)
3	https://researcheracademy.elsevier.com/
4	https://link.springer.com/

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Course Title: Interdisciplinary Perspective on Indian Science and Technology Course Code: PG262501 Course Category: HSSM-IKS		
Teaching Scheme	**Examination Scheme**	
Lectures: 02 hrs./ week	CA-1	10 Marks
Tutorial: -----	CA-2	10 Marks
Credits: 02	MSE	20 Marks
Semester: First Year (Semester II)	ESE	60 Marks
Course Prerequisite: None		

Course Description:

The course Interdisciplinary Perspective on Indian Science and Technology introduces students to India's rich contributions in mathematics, astronomy, architecture, metallurgy, textiles, and agriculture. It emphasizes the scientific principles embedded in traditional practices, tracing their historical development and global impact. Students will explore how ancient Indian innovations such as the number system, astronomical instruments, town planning, metallurgy, and sustainable farming shaped modern science and engineering. The course bridges theoretical understanding with practical relevance, enabling appreciation of indigenous knowledge systems and their applications in contemporary contexts.

Course Objectives:

1. To understand the foundational concepts and necessity of the Indian Knowledge System.
2. To identify key historical contributions of Indian scholars in mathematics, astronomy, architecture, metallurgy, textiles, and agriculture.
3. To interpret the scientific principles and techniques underlying traditional Indian practices.
4. To analyze the relevance of IKS in modern scientific and technological contexts.
5. To appreciate the global influence and sustainability of Indian innovations throughout history.

Course Outcomes:

COs	After completion of the course, students will be able to	Bloom's Level
CO1	**Recall** key concepts and contributions of Indian Knowledge System in various domains.	L1 Remember
CO2	**Explain** principles, techniques, and historical developments in Indian Knowledge System.	L2 Understand
CO3	**Apply** traditional knowledge and techniques to understand practical aspects of science and engineering.	L3 Apply
CO4	**Analyze** the scientific, technological, and cultural significance of Indian Knowledge Systems.	L4 Analyze

CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	1	1	–	–	–	2	2	2	–	–	2	1	1
CO2	1	2	–	1	–	2	2	2	1	–	2	1	1
CO3	2	2	1	1	–	2	2	2	1	–	2	2	1
CO4	2	3	1	2	–	3	2	3	1	–	3	2	1

Assessment	
CA-1 (a) (10M)	Subjective Test / Open-book test / etc.
CA-2 (b) (10M)	Model Making / Assignment / Presentation / etc.
MSE (c) (20M)	Mid Sem Examination

Course Contents		
Unit 1	**Indian Mathematics** Necessity of Indian Knowledge System, Defining Indian Knowledge System, Contributions of Indian Mathematicians, Historical Evidence and features of Indian Numerical Number System, The Idea of Zero and Infinity, Decimal System, Representation of Large Numbers, Global Spread and Adoption of Indian Numericals , Arithmetic (Square of a Number, Square Root, Series and Propagation), Geometry (Simple Constructions from Sulba-Sutras, e.g, Right Angle Triangle, The Value of Pi), Trigonometry and Algebra in IKS, Modern Indian Contributions to Mathematics	4 Hrs.
Unit 2	**Indian Astronomy** Historical Development of Indian Astronomy, Astronomy for Timekeeping, Solar and Lunar Motions, The Celestial Coordinate System, Various Regional Indian Calendar Systems, Planetary Model of Aryabhata and Nilakantha, Astronomical Instruments, Various Royal Endeavors for Astronomy (e.g., Jaisingh's Jantar Mantar), Modern Indian Contributions to Astronomy	4 Hrs.

Unit 3	**Indian Architecture and Town Planning** Sthapatya-Veda and Vastu-Shastra, Historical Features of Indian Town Planning, Water Management and Drainage Systems, Town Planning of Harappan Cities, Temple Architecture, Features and Examples of Cave, Rock Cut, Nagara, Dravida, Kalinga, Vesara, Deccan, Rajput, Mughal, Indo-Saracenic Architecture Styles, Modern Indian Contributions to Architecture and Town Planning	4 Hrs.
Unit 4	**Indian Metallurgy** Ancient Mining and Ore Extraction Technologies, Mining and Manufacture of Zinc, Copper and its Alloys, Silver, Gold, Mercury and Lead, Iron Extraction from Biotite, Steel Manufacturing, Global Influence of Wootz Steel, Wax Casting, Modern Indian Contributions to Metallurgy	4 Hrs.
Unit 5	**Indian Textile** Textile Traditions in Ancient India, The Variety and Diversity of Indian Textiles, Types of Fabrics and Materials, Cotton and Silk, Weaving Techniques and Looms, Dyeing Process and Natural Colors, Major Textile Centers, Significance of Indian Textile in Historical Global Trade, Fall of Indian Textile in Colonial Era, Modern Indian Contributions to Textile	4 Hrs.
Unit 6	**Indian Agriculture** Importance of Agriculture in Ancient India, Traditional Crops (Grains, Fruits, Vegetables Spices), Significance of Indian Agricultural Products in Historical Global Trade, Significance of Agriculture and Irrigation for the Indian Kings, The Ery System of South India, Traditional Farming Techniques (Land Preparation, Sowing Techniques, Weeding and Pest Management, Harvesting and Storage), Irrigation Techniques and Rainwater Harvesting, Modern Indian Contributions to Agriculture	4 Hrs.

Sr.No.	Textbooks
1.	D. M. Bose, S. N. Sen and B. V. Subbarayappa, Eds., A Concise History of Science in India, 2nd Ed., Universities Press, Hyderabad, 2010.
2.	B. Mahadevan, Nagendra Pavana, Vinayak Rajat Bhat, Introduction to Indian Knowledge System: Concepts and Applications, PHI Learning, 2022
3.	Kapil Kapoor, Awadhesh Kumar Singh, Indian Knowledge Systems, D.K. Print World Ltd; First Edition (15 October 2005)
4.	Bhag Chand Chauhan, IKS: The Knowledge system of Bharata, Garuda Prakashan (13 March 2023)
5.	Science in India: A Historical Perspective by B V Subbarayappa, Rupa & Co (2013)

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	Reference Books
1.	G. G. Joseph, Indian Mathematics Engaging the World from Ancient to Modern Times, World Scientific, London, 2016
2.	History of Astronomy: A Handbook, Edited by K. Ramasubramanian, Aniket Sule, and Mayank Vahia, Sandhi, IIT Bombay, and T.I.F.R. Mumbai, 2016.
3.	History of Science in India Volume-1, Part-I, Part-II, Volume VIII, by Sibaji Raha, et al. National Academy of Sciences, India and The Ramkrishna Mission Institute of Culture, Kolkata (2014).
4.	Christopher Tadgell, History of Architecture in India, Architecture Design and Technology Press (1990)
5.	Bindia Thapar, Introduction to Indian Architecture, Periplus Asian Architecture Series
	Web Resources
1.	Indian Knowledge System Division, Ministry of Education, Government of India, https://iksindia.org/lectures-and-videos.php

Course Title: Mini Project **Course Code: PL262602**		**Course Category: EL**
Teaching Scheme	**Examination Scheme (As Applicable)**	
Practical/Sessions: 02 Hours/Week	CA-I	15 Marks
Credits: 01	CA-II	15 Marks
Semester: First Year (Semester-II)	ESE	20 Marks

Course Prerequisite:
Basic understanding of core subjects in specialization, Ability to access, and interpret scientific literature, Exposure to technical report writing and presentation.

Course Description:
The Mini Project course provides students with an opportunity to apply theoretical knowledge gained during coursework to a small-scale practical problem in Artificial Intelligence & Machine Learning. It enables students to experience the process of identifying a problem, reviewing literature, formulating objectives, and developing solutions using experimental, analytical, or simulation-based approaches. The course emphasizes independent learning, teamwork, critical thinking, innovation, and technical communication.

Course Objectives:
1. Develop the ability to identify, analyze, and solve engineering problems using modern tools and techniques.
2. Encourage creativity, innovation, and research aptitude in addressing Computer Science and Engineering challenges.
3. Provide hands-on exposure to design, modeling, analysis, and/or experimental work on a defined problem.
4. Strengthen teamwork, project management, and professional ethics in executing engineering tasks.
5. Enhance technical writing and oral presentation skills through project documentation and seminars.

Course Outcomes:

COs	**After completion of the course: Students will be able to**	**Bloom's Level**
CO1	**Recall** and **identify** real-world problems in Computer Science, AI/ML, and engineering domains.	Remember L1
CO2	**Explain** problem statements, requirements, and relevant background research.	Understand L2
CO3	**Apply** appropriate tools, techniques, and methodologies to develop solutions for selected problems.	Apply L3
CO4	**Analyze** system performance, results, and limitations of the implemented solution.	Analyze L4
CO5	**Evaluate** outcomes and present the project effectively through reports and presentations.	Evaluate L5
CO6	**Design** and **develop** an innovative solution/project and present it effectively through a structured report.	Create L6

CO-PO Mapping

COs	PO1	PO2	PO 3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	2	3	–	1	–	1	1	–	–	–	2	1	2
CO2	2	3	1	2	–	1	1	1	2	–	2	2	2
CO3	3	3	3	2	3	1	1	1	2	1	2	3	3
CO4	3	3	2	3	2	1	1	1	2	–	2	3	3
CO5	2	3	2	3	2	1	1	1	3	2	3	3	3
CO6	3	3	3	3	3	2	1	1	3	3	3	3	3

Assessment	
The mini project is worth a total of 50 marks, with 30 marks for the internal assessment and 20 marks for the semester-end examination. The semester-end examination will be conducted by a committee of three faculty members. Students must bring their completed reports, which should be duly authenticated by their guide and the Head of the Department. Each student will individually present their work to the committee, who will then evaluate them and award marks accordingly.	
CA-I (a) (15M)	Review-I: 15 Marks (Concept/knowledge in the topic = 10 marks, Literature-05 marks)
CA-II (b) (15M)	Review-II: 15 Marks (Report writing & Presentation =15 Marks)
Practical / viva voce (c) (20M)	20 Marks (Individual evaluation through viva voce / test (20 marks)
Total (d)	50 Marks

Course Contents
The mini project is designed to help students identify, analyze, and solve real-world problems in Computer Science and Engineering and management. This project also aims to improve their overall skills and capabilities. Each student should choose a topic they are interested in. The project's content must be relevant to emerging areas within the field, address current issues with a research focus, or be based on industrial visits. Students can also select a practical problem from the field of Artificial Intelligence and machine Learning to work on. By the end of the semester, each student must submit a final report to the Head of the Department. The report must be authenticated by their guide.

Course Title: Distributed Systems **Course Code: PL263006**		**Course Category: PCC**
Teaching Scheme	**Examination Scheme**	
Lectures: 04 hrs / week	CA-1	10 Marks
Tutorial: -	CA-2	10 Marks
Credits: 04	MSE	20 Marks
Semester: Second Year (Semester III)	ESE	60 Marks

Course Prerequisite:
Operating Systems fundamentals (processes, threads, synchronization), Computer Networks (protocols, communication), Basic programming in C/C++/Java/Python.

Course Description: This course introduces the principles, models, and algorithms of distributed computing systems. It covers communication protocols, process coordination, synchronization, fault tolerance, and distributed applications. Students will gain both theoretical and practical understanding of distributed architectures, middleware, and real-world distributed platforms such as Hadoop, Spark, and Blockchain.

Course Objectives:

1. To understand fundamental concepts and design goals of distributed computing systems
2. To study process models, communication mechanisms, and distributed algorithms.
3. To analyze issues of coordination, synchronization, and consistency in distributed systems.
4. To explore techniques for replication, fault tolerance, and recovery
5. To introduce real-world distributed platforms and applications.

Course Outcomes:

COs	**After completion of the course: Students will be able to**	**Bloom's Level**
CO1	**Recall** the fundamental concepts, architectures, and characteristics of distributed systems including communication models, naming mechanisms, and distributed platforms.	Remember L1
CO2	**Explain** the working principles of distributed system communication mechanisms, processes, threads, and naming services used in distributed environments.	Understand L2
CO3	**Apply** distributed algorithms and coordination techniques such as logical clocks, leader election, and mutual exclusion to analyze distributed computing scenarios.	Apply L3
CO4	**Analyze** fault tolerance mechanisms, replication strategies, consistency models, and distributed system architectures used in modern cloud and big-data platforms.	Analyze L4

CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	3	1	–	–	–	–	–	–	–	–	1	2	1
CO2	3	2	1	1	2	–	–	–	1	–	1	2	2
CO3	3	3	3	2	2	–	–	–	1	–	1	3	3
CO4	3	3	2	3	2	1	1	1	1	–	2	3	3

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Assessment	
CA-1 (a) (10M)	Subjective Test / Assignment/ MCQ Test etc.
CA-2 (b) (10M)	Subjective Test / Assignment/ MCQ Test etc.
MSE (c) (20M)	Subjective Test

Course Contents		
Unit 1	**Unit 1: Fundamentals of Distributed Systems** Definition, Characteristics, and Goals of Distributed Systems: Transparency, Openness, Scalability, Architectures: Centralized, Client–Server, Peer-to-Peer, Hardware Concepts: Multiprocessors, Homogeneous & Heterogeneous Multicomputer Systems, Software Concepts: Distributed OS, Network OS, Middleware. Case Study: Client–Server in Web Applications.	8 Hrs.
Unit 2	**Unit 2: Communication in Distributed Systems** Communication Paradigms: Layered Protocols, Transport Protocols, Middleware, Remote Procedure Call (RPC): Basics, Parameter Passing, Extended Models, Remote Object Invocation: Static vs Dynamic Binding, Message-Oriented Communication: Persistence, Queues, Synchronicity, Stream-Oriented Communication: Continuous Media, QoS, Synchronization, Case Study: REST APIs & gRPC in Microservices.	8 Hrs.
Unit 3	**Unit 3: Processes, Threads, and Naming** Threads and Concurrency in Distributed Systems, Clients and Servers: Transparency Issues, Software Agents and their Role in DS, Naming: Names, Identifiers, and Addressing, Name Resolution and Name Service Implementation, Locating Mobile Entities: Home-Based & Hierarchical Approaches	8 Hrs.
Unit 4	**Unit 4: Coordination and Distributed Algorithms** Logical Clocks: Lamppost, Vector Clocks, Global State and Snapshot Algorithms, Clock Synchronization Techniques, Distributed Mutual Exclusion Algorithms, Leader Election, Deadlock Detection, Termination Detection, Case Study: Apache Zookeeper for Coordination	8 Hrs.
Unit 5	**Unit 5: Fault Tolerance, Replication, and Consistency** Fault Models and Recovery in Distributed Systems, Commit Protocols (2PC, 3PC), Voting Protocols, Replica Management: Data-Centric & Client-Centric Consistency Models, Check pointing and Recovery Methods.	8 Hrs.
Unit 6	**Unit 6: Distributed Applications and Emerging Systems** Distributed Object-Based Systems: CORBA, DCOM, Globe, Distributed File Systems: GFS, HDFS, Dropbox, Bigtable, RDDs, Distributed Multimedia Systems: Characteristics, QoS, Scheduling, Emerging Distributed Platforms: Map Reduce, Apache Spark, Cloud Architectures	8 Hrs.

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Sr. No.	Textbooks
1.	Andrew S. Tanenbaum and Maarten Van Steen, Distributed Systems: Principles and Paradigms, Pearson Education.
2.	George Coulouris, Jean Dollimore, Tim Kindberg, and Gordon Blair, Distributed Systems: Concepts and Design, Pearson Education.
3.	Pradeep K. Sinha, Distributed Operating Systems: Concepts and Design, PHI Learning.
	Reference Books
1.	Ajay D. Kshemkalyani and Mukesh Singhal, Distributed Computing: Principles, Algorithms, and Systems, Cambridge University Press.
2.	M. L. Liu, Distributed Computing: Principles and Applications, Addison-Wesley.
3.	Andrew S. Tanenbaum, Modern Operating Systems, Pearson Education.
4.	Martin Kleppmann, Designing Data-Intensive Applications, O'Reilly Media.
	Web Resources
1.	GeeksforGeeks – Distributed Systems Tutorials

Course Title: Project-I **Course Code: PL263603**		**Course Category: EL**
Teaching Scheme	**Examination Scheme (As Applicable)**	
Practical's/Sessions:10Hours/Week	CA-I	25 Marks
Credits: 10	CA-II	25 Marks
Semester: Second Year (Semester III)	ESE	50 Marks

Course Prerequisite:

- Advanced understanding of core domain subjects within the specific engineering specialization.
- Competency in scientific literature review, technical documentation, and basic research methodologies.

Course Description: Project I initiates the final MTech dissertation, transitioning students into independent, advanced engineering research. Applicable across all engineering disciplines, this course requires students to identify a substantial technical, industrial, or scientific problem. Students will progress through an exhaustive literature survey, formulate a robust methodology, and execute the initial stages of their research—such as pilot experiments, baseline simulations, algorithm development, or software proofs-of-concept. The course emphasizes professional research practices, culminating in the drafting of a formal review article and a scalable project plan to be fully executed in Project II.

Course Objectives:

1. To develop the ability to identify and formulate a complex, real-world engineering problem relevant to the student's specialization.
2. To conduct an exhaustive literature survey to establish a clear research gap and synthesize findings into a comprehensive review article.
3. To design a preliminary methodology to validate the feasibility of the proposed solution through pilot experiments, baseline simulations, or architectural proof-of-concepts.
4. To strengthen professional project management skills, emphasizing ethical research practices and structured milestone planning.
5. To enhance high-level technical communication through the defence of a project proposal, documented validation results, and formal report writing.

Course Outcomes:		
COs	**After Successful Completion of Project-I Students will be able to**	**Bloom's Level**
CO1	**Summarize** the current state-of-the-art and contextualize the specific engineering research problem using relevant scientific literature.	Understand L2
CO2	**Implement** professional project management principles and ethical standards to construct a structured, actionable research execution plan.	Apply L3
CO3	**Investigate** synthesized literature to pinpoint precise research gaps and systematically structure a comprehensive review article.	Analyze L4
CO4	**Validate** the feasibility of the proposed methodology by conducting and assessing initial pilot experiments, baseline numerical simulations, or algorithmic proof-of-concepts.	Evaluate L5
CO5	**Design** a detailed research methodology and engineer the experimental, computational, or software architecture required for full-scale execution.	Create L6
CO6	**Compile** a formal technical report and logically defend the research proposal and preliminary validation data before an expert review committee.	Create L6

CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	2	3	–	1	–	1	1	–	–	–	2	1	2
CO2	2	3	1	2	–	1	1	1	2	–	2	2	2
CO3	3	3	3	2	3	1	1	1	2	2	2	3	3
CO4	3	3	2	3	2	1	1	1	2	–	2	3	3
CO5	2	3	2	3	2	1	1	1	3	2	3	3	3
CO6	3	3	3	3	3	2	1	1	3	3	3	3	3

Course Contents

Project I is dedicated to rigorous problem formulation, literature synthesis, and the critical initial stages of methodology validation. Students must select a research topic with significant academic or industrial relevance within their branch of engineering.

During this phase, students are required to:

1. Finalize their problem statement and complete a thorough literature review.
2. Write and submit at least one review article based on their literature survey, intended for publication in a peer-reviewed journal or presentation at a conference.
3. Advance their research to the initial stages of experimentation, computational modeling, or system development. This includes completing pilot experiments, proof-of-concept software testing, baseline

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<tr><td colspan="2">model setups, algorithm optimization checks, or preliminary analytical validation to prove their proposed solution is viable.
By the end of Semester-III, each student must submit a formal Project I Report (inclusive of the review article draft and preliminary validation data) to the Head of the Department, authenticated by their designated faculty guide.</td></tr>
<tr><td colspan="2">Assessment</td></tr>
<tr><td colspan="2">The Project Phase I course is worth a total of 100 marks, distributed as 50 marks for continuous internal assessment and 50 marks for the semester-end examination. Evaluation will be conducted by a committee consisting of the project guide and relevant faculty/industry experts.</td></tr>
<tr><td>CA-I (a)</td><td>Review-I: 25 Marks (Problem Identification (05), Literature Survey (10), & Proposed Methodology & Execution Plan (10))</td></tr>
<tr><td>CA-II (b)</td><td>Review-II: 25 Marks (Pilot Experiments / Baseline Validation for Numerical Work (25))</td></tr>
<tr><td>ESE (c)</td><td>50 Marks (Final Project I Report (15), Review Article Draft (15), & Technical Presentation/Defense (20))</td></tr>
<tr><td>Total</td><td>100 Marks</td></tr>
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Course Title: Project-II **CourseCode:PL264604** **Course Category: EL**		
Teaching Scheme	**Examination Scheme(As Applicable)**	
Practical's/Sessions:20Hours/Week	CA-I	50 Marks
Credits: 20	CA-II	50 Marks
Semester: Second Year(Semester-II)	ESE	100 Marks

Course Prerequisite:

Successful completion of Project I

Academic Clearance: To appear for the End Semester Examination (ESE), a student must be "all-Clear". No active backlogs from previous semesters are permitted.

Course Description:

Project II represents the culmination of the MTech dissertation, focusing on the full-scale execution, comprehensive analysis, and dissemination of the independent engineering research initiated in Project I. This course requires students to fully implement their validated methodology, whether experimental, computational, analytical, algorithmic, or architectural. The primary focus is on the rigorous extraction of data, statistical or error validation, logical interpretation of results, and the synthesis of these findings into a substantial master's thesis. Furthermore, students must navigate the academic publication process and defend their work before departmental committees to ensure their research meets established industrial and academic standards.

Course Objectives:

1. To guide the complete execution of the proposed research methodology to gather extensive, high-quality data.
2. To ensure rigorous analytical processing and interpretation of the collected experimental, computational, or algorithmic results.
3. To foster the ability to benchmark and validate final findings against existing literature or theoretical models.
4. To develop advanced technical writing skills for the synthesis of a comprehensive master's dissertation.
5. To emphasize the academic publication process by requiring the formulation of complete research manuscripts for journals or conferences.
6. To enhance professional oral defense capabilities through presentations to the departmental committee and external reviewers.

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Course Outcomes:		
COs	**After Successful Completion of Project-II**	**Bloom's Level**
CO1	**Execute** the comprehensive experimental, analytical, or computational plan while adhering strictly to ethical and safety protocols.	Apply L3
CO2	**Analyze** the raw research data systematically to extract meaningful trends, correlations, and engineering conclusions.	Analyze L4
CO3	**Validate** the overall research outcomes by benchmarking the findings against standard theoretical models, contemporary literature, or baseline systems.	Evaluate L5
CO4	**Compose** a rigorously formatted final master's dissertation detailing the complete research methodology, findings, and conclusions.	Create L6
CO5	**Defend** the entirety of the research methodology, data analysis, and final conclusions confidently before the expert evaluation panel.	Create L6
CO6	**Author** and **publish** a review article and at least one original research paper in a department-approved peer-reviewed journal or high-impact conference.	Create L6

CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2
CO1	2		3	3	3	2	3	2		2	1		
CO2	3	3		3	3			1	1		1		
CO3	3	3	1	3	2			1	2		2		
CO4	1	1		1			1	2	3		2		
CO5							1	2	3		2		
CO6	1	2		2			3	1	3		3		

Course Contents

Project II is entirely dedicated to data generation, final analysis, formal academic documentation, and dissemination.

During this final phase, students are required to:

. Full-Scale Execution: Complete the entirety of the physical experiments, field studies, numerical simulations, or system/software developments outlined in Project I.
. Results & Discussion: Perform a rigorous scientific analysis of the acquired data, including necessary error analyses, optimization, and comparative studies.
. Publication Mandate: It is compulsory to publish a review article (originating from Project I) and at least one original research paper based on Project II findings in a department-approved peer-reviewed journal or high-impact conference.

Note: If a student fails to publish the review article during Project I, the publication of two original research papers based on their dissertation work is compulsory to fulfill this requirement.

Dissertation Compilation: Draft the final M.Tech thesis document, adhering to the institutional formatting guidelines, covering all aspects from the introduction and literature review to the methodology, results, and final conclusions.

Assessment

The Project II course is worth a Total of 200 Marks. The evaluation incorporates continuous assessment by the guide, a mandatory departmental screening, and a rigorous final defence.
Pre-ESE Requirement (DPAC Approval): Before appearing for the End Semester Examination (final defence), students must deliver a comprehensive presentation before the Departmental Postgraduate Academic Committee (DPAC). Approval from the DPAC is mandatory to be eligible for the ESE.

CA-I (a)	Review-I: 50 Marks (Execution of Full-Scale Methodology (25) & Initial Data Collection/Simulation Runs (25))
CA-II (b)	Review-II: 50 Marks (Comprehensive Data Analysis & Validation (25) & Draft of Dissertation/Manuscripts (25))
ESE (c)	100 Marks (Final Plagiarism-Free Dissertation (30), Proof of Required Publications (30), & Final Oral Defense/Presentation (40))
Total	200 Marks

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Course Title: Communication skill and Technical writing Course Code: PL264701		Course Category: CC
Teaching Scheme	**Examination Scheme**	
Lectures:02hrs/week	**CA-1**	**25 Marks**
Tutorial: -----	**CA-2**	**25 Marks**
Credits: AU	MSE	-
Semester: PG Second year (Semester IV)	ESE	-
Course Prerequisite: Basic English Communication		

Course Description: This course equips students with advanced communication and technical writing skills essential for both academic research and professional industry roles. The curriculum spans fundamental communication principles, professional business correspondence, and strategic job-seeking methods. Emphasizing rigorous scholarly standards, the course provides focused training in drafting research proposals, authoring journal papers, structuring theses, and compiling technical reports. Furthermore, students will develop practical proficiency in delivering formal academic presentations, utilizing visual aids, and participating in professional group discussions, ensuring a seamless transition from the academic environment into high-level engineering workplaces.

Course Objectives:

1. To introduce foundational business correspondence and interpersonal communication methods, establishing a baseline for effective workplace dynamics and professional collaboration.
2. To explain the principles of academic and technical writing, focusing on the structured composition of research proposals, theses, and industry-standard reports.
3. To impart practical techniques for technical presentations and job-seeking processes, preparing postgraduates for advanced engineering roles and seamless industry integration.

Course Outcomes:

COs	After completion of the course: Students will be able to	Bloom's Level
CO1	**Identify** the fundamental principles, standard formats, and structural components of interpersonal communication, business correspondence, employment documentation, academic research papers, and technical presentations.	Remember (Level1)
CO2	**Discuss** the audience expectations, contextual barriers, and theoretical frameworks necessary for effective general workplace communication, business correspondence, career development, academic research, and technical presentations.	Understand (Level 2)
CO3	**Demonstrate** professional linguistic styles, drafting conventions, and delivery techniques to execute effective general workplace communication, business correspondence, career development, academic research, and technical presentations.	Apply (Level 3)
CO4	**Examine** diverse contextual scenarios, target audiences, and objective requirements to determine the most appropriate strategies for general workplace communication, business correspondence, career development, academic research, and technical presentations.	Analyze (Level 4)

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CO-PO Mapping

COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO 1	PSO 2
CO1									3				
CO2									3				
CO3					1		1		3		1		
CO4					1		1		3		1		

Assessment	
CA-1(a)	Résumé Writiing/Subjective Test / Assignment/ MCQ Test, etc.
CA-2(b)	Literature Review/ Subjective Test / Assignment/ MCQ Test, etc.

Course Contents		
Unit 1	**General Communication** Basics of Communication, Process of Communication: Levels of Communication; Flow of Communication, Barriers to Communication: Physical Barriers; Psychological Barriers; Cultural Barriers, Non-Verbal Communication: Kinesics; Proxemics, Listening and Speaking: Active Listening; Effective Speaking	6 Hrs.
Unit 2	**Business Communication** Formats of Written Correspondence: Formal Letters; Memos; Email, Business Letters: Credit Letters; Collection Letters; Sales Letters, Business Memos: Structure; Layout; Writing Strategies, Electronic Mail: Style; Structure; Email Etiquette	4 Hrs.
Unit 3	**Job Getting Processes** Employment Communication: Importance; Interview Preparation Techniques, Interview Stages: Face-To-Face Interviews; Online/Telephonic Interviews, Interview Conduct: Answering Strategies; Projecting A Positive Image, Résumé Design: Structure; Types of Résumés, Cover Letters: Structure; Writing Effective Job Application Letters	4 Hrs.
Unit 4	**Research Communication I (Proposals & Papers)** Research Proposals: Structure of Formal Proposals; Body of The Proposal, Research Papers: Characteristics; Components of A Journal Paper, Drafting The Manuscript: Developing Productive Drafting Habits; Integrating Quotations Into Your Text; Interpreting Complex Or Detailed Evidence, Elements of Effective Writing: Using Concrete And Specific Words; Avoiding Excessive Use of Jargons, Revising And Finalizing: Checking For Blind Spots In Your Argument; Revising Sentences; Proofreading	6 Hrs.

Unit 5	**Research Communication II (Thesis, Reports, & Citations)** Thesis Structuring: The Core Chapter; Writing A Literature Review, Technical Reports: Informative Reports; Analytical Reports, Drafting Reports: Writing the Draft; Guarding Against Inadvertent Plagiarism, Referencing Methods: Notes-Bibliography Style; Author-Date Style, Visual Evidence: Designing Tables; Designing Figures	2 Hrs
Unit 6	**Presentation Skills** Formal Presentations: Planning; Outlining; Structuring, Delivery Techniques: Controlling Nervousness; Using Visual Aids Like Ms PowerPoint, Group Discussions: Promoting Optimal Participation; Handling Conflict, Alternative Forums: Poster Presentations; Conference Proposals, Seminars: Seminar Presentation; Conference Presentation	2 Hrs

Sr. No.	Textbooks
1.	Meenakshi Raman and Sangeeta Sharma, Technical Communication: Principles and Practice, Oxford University Press.
2.	M. Ashraf Rizvi, Effective Technical Communication, McGraw-Hill Education.
3.	Heather Silyn-Roberts, Writing for Science and Engineering: Papers, Presentations and Reports, Elsevier.
	Reference Books
1.	Kate L. Turabian, A Manual for Writers of Research Papers, Theses, and Dissertations, University of Chicago Press.
2.	Wayne C. Booth, Gregory G. Colomb, and Joseph M. Williams, The Craft of Research, University of Chicago Press.
3.	Michael Alley, The Craft of Scientific Presentations, Springer.
	Web Resources
1.	Purdue Online Writing Lab (OWL) (https://owl.purdue.edu/owl/index.html)

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