NATIONAL INSTITUTE OF ELECTRONICS AND INFORMATION TECHNOLOGY

DEEMED TO BE UNIVERSITY UNDER DISTINCT CATEGORY

(AN AUTONOMOUS INSTITUTION UNDER MINISTRY OF ELECTRONICS & IT, GOVT. OF INDIA)

Curriculum and Syllabi for

M.Tech - Artificial Intelligence

(2025-26 Scheme)

रा.इ.सू.प्रौ.सं

NIELIT

Deemed to be University

Main Campus at Ropar and Constituent Units at Aizawl, Agartala, Aurangabad, Calicut, Gorakhpur, Imphal, Itanagar, Kekri, Kohima, Patna and Srinagar

Vision

To position the institute as a premier destination for advanced learning in Artificial Intelligence, fostering a dynamic ecosystem of education, research, and entrepreneurship.

Mission

To provide a strong foundation in theoretical and applied aspects of Artificial Intelligence.

To cultivate a research-oriented and ethical mindset among students.

To empower learners with the skills to solve complex real-world problems using advanced AI and ML tools.

To promote industry-academia collaboration for innovation and technology transfer.

Program Education Objectives

Equip students with deep knowledge in mathematical foundations, machine learning, and optimization techniques.

Foster innovation and independent research in AI and related domains.

Instill ethical values, effective communication, and a commitment to continuous learning for sustainable development.

Program Outcomes

Solve complex machine learning problems with advanced algorithms and AI tools.

Communicate effectively and collaborate across interdisciplinary teams.

Demonstrate a commitment to lifelong learning and adaptability to emerging trends.

Contribute to innovative AI solutions with research competence and ethical responsibility.

Adhere to ethical standards, societal responsibilities, and respect for intellectual property.

Program Specific Outcomes

Apply AI models and techniques to domains such as cybersecurity, healthcare, natural language processing, and computer vision.

Design, implement, and optimize intelligent systems for real-world applications using modern AI tools.

Conduct applied research and develop scalable AI-driven solutions to emerging challenges.

CATEGORY WISE CREDIT DISTRIBUTION

Category	Category Code	Credits
Skill / Employment Enhancement Courses (Project/Internship/Seminar/Dissertation/Research)	EE	36
Audit Courses (without grade or credit)	AU	0
Open Elective Courses	OE	8
Professional Elective Courses	PE	16
Program Core Courses	PC	20
Total Credits (Common track)		**80**

EVALUATION AND ASSESSMENT

1. Performance of a student in a semester shall be evaluated through continuous Class assessment, Tutorial/Lab assessment, Mid-Semester Examination (MSE) and End-Semester Examination (ESE). Both the MSE and ESE shall be the University examination and will be conducted as notified by the Controller of Examinations (CoE) of the University.

2. The continuous assessment shall be based on assignments, tutorials, paper presentation / quizzes/ viva-voce / flipped classes, lab work / projects / fieldwork and attendance, etc.

3. The MSE/ESE shall be comprising of written papers.

4. The overall assessment of the students will be done as per the following scheme:

S. No.	Assessment Type	Marks Weightage
1.	Mid Semester Examination	20
2.	End Semester Examination	40
3.	Continuous Assessment - Practical /Lab/ Tutorial	25
4.	Continuous Assessment - Theory	15
Total		**100**

For more details, please refer the applicable ordinance for this programme and Assessment SOPs.

CURRICULUM

Semester 1

Semester Code	Course Code	Course Title	L	T	P	Cr
PC-MTECAI-101	DASH250074	Mathematical Foundations of Machine Learning	3	1	0	4
PC-MTECAI-102	DOAI250032	Machine Learning	3	0	2	4
PE-MTECAI-103	Elective	Program Elective				4
OE-MTECAI-104	Elective	Open Elective				4
PC-MTECAI-105	DASH250095	Research Methodology and IPR	3	1	0	4
AU-MTECAI-106	Elective	Audit Elective				0

Semester 2

Semester Code	Course Code	Course Title	L	T	P	Cr
PC-MTECAI-201	DOAI250042	Optimisation Techniques	3	1	0	4
PC-MTECAI-202	DOAI250006	Deep Learning Techniques	3	0	2	4
PE-MTECAI-203	Elective	Program Elective				4
PE-MTECAI-204	Elective	Program Elective				4
AU-MTECAI-205	Elective	Audit Elective				0
EE-MTECAI-206	EE	Mini project with Seminar				4

Semester 3

Semester Code	Course Code	Course Title	L	T	P	Cr
PE-MTECAI-301	Elective	Program Elective				4
OE-MTECAI-302	Elective	Open Elective				4
EE-MTECAI-303	EE	Dissertation-I/ Industrial project				12

Semester 4

Semester Code	Course Code	Course Title	L	T	P	Cr
EE-MTECAI-401	EE	Dissertation-II				20

Elective Courses

Elective Courses for PE Category						
Course Code	**Course Title**	**L**	**T**	**P**	**Cr**	**For Sem./Code**
DASH250015	Cognitive Systems	3	1	0	4	
DCSA250009	Blockchain Technology	3	1	0	4	
DCSA250020	Computer Vision	3	0	2	4	
DCSA250068	Soft Computing	3	0	2	4	
DCSE250001	Advanced Algorithms and Analysis	3	1	0	4	
DCSE250086	Health Care and Data Analytics	3	1	0	4	
DOAI250004	Artificial Intelligence	3	1	0	4	
DOAI250009	Big Data Analytics	3	0	2	4	
DOAI250019	Data Mining and Warehousing	3	0	2	4	
DOAI250028	Information Retrieval	3	1	0	4	
DOAI250031	Introduction to High Performance Computing	3	1	0	4	
DOAI250041	Natural Language Processing	3	0	2	4	
DOAI250043	Pattern Recognition	3	0	2	4	
DOAI250045	Problem Solving Methods in Artificial Intelligence	3	0	2	4	
DOAI250049	Social Media Analytics	3	1	0	4	
DOAI250052	Video Analytics using AI	3	0	2	4	

Elective Courses for OE Category
Students may opt courses under MOOC, NPTEL, SWAYAM, NSQF/NCVET aligned courses or other relevant technical subjects not included in their core curriculum. The exercise of option shall be subject to the Course Schedule of the respective Constituent Unit, the credit requirements and availability of seats. Guidelines for choosing MOOC/Online courses are given separately and shall have to be adhered to.

Elective Courses for AU (Audit) Category					
Course Code	**Course Title**	**L**	**T**	**P**	**Cr**
DASH240027	Disaster Management	2	0	0	0
DASH240047	English for Research Paper Writing	2	0	0	0
DASH240052	Environmental Science	3	0	0	0
DASH240085	Pedagogy Studies	2	0	0	0
DASH240086	Personality Development through Life Enlightenment Skills	2	0	0	0
DASH240097	Sanskrit for Technical Knowledge	2	0	0	0
DASH240103	Stress Management by Yoga	2	0	0	0
DASH240104	Technical Presentation and Report Writing	0	0	2	0
DASH240106	Value Education	2	0	0	0
DASH240124	Constitution of India - AU	2	0	0	0
DASH250023	Constitution of India	2	1	0	0
DASH250027	Disaster Management	3	0	0	0

DASH250034	Energy and Environmental Engineering	3	0	0	0
DASH250047	English for Research Paper Writing	2	0	0	0
DASH250054	Essence of Indian Knowledge and Tradition	2	0	0	0
DASH250085	Pedagogy Studies	2	0	0	0
DASH250086	Personality Development	2	0	0	0
DASH250097	Sanskrit for Technical Knowledge	3	0	0	0
DASH250103	Stress Management by Yoga	3	0	0	0
DASH250106	Value Education	2	0	0	0
DASH250117	Innovative Thinking and Entrepreneurship Skills	1	0	0	0
DASH250118	Intellectual Property Rights	2	0	0	0
DCSA240080	Training on Computer Networking	0	0	2	0
DCSA240304	Lab Based on Statistical Package	0	0	2	0
Any other Scheduled Course as per the Course Schedule of the respective Constituent Unit can also be chosen, subject to availability of seats. However, there shall be no assessment and grading for the course chosen as Audit Course.					

The choice of all type of Electives available shall be as per the Course Schedule of the respective Constituent Unit.

Guidelines for Massive Open Online Courses (MOOC) / approved Online Courses

1. Relevant Swayam, MOOC, NPTEL, NIELIT NSQF and any other online courses approved by UGC/AICTE shall also be allowed as Open Electives(OE).

2. One credit of MOOC course should be minimum of 30 hours.

3. A student can choose any approved online course as Open Elective, subject to minimum credit requirements.

4. The students willing to opt OE under MOOC in their next semester, will submit their request to the MOOC Coordinator at their respective campus.

5. Once approved, the campus shall display the list of accepted courses.

6. The student has to submit certificate issued by the institution offering the MOOCs course, along with the number of credits and grades, to get credits transferred into his/her marks certificate issued by NDU.

7. The transfer of credits shall be as adopted by NDU.

Detailed Syllabus

Course Code	Course Name	L	T	P	Cr
DASH250074	Mathematical Foundations of Machine Learning	3	1	0	4

Course Outcomes:

CO1: Apply linear algebra concepts such as matrix operations, eigenvalues, and eigenvectors to solve machine learning problems including regression and dimensionality reduction.
CO2: Analyze probabilistic models and statistical measures to interpret datasets and implement algorithms like Naïve Bayes.
CO3: Utilize optimization techniques such as gradient descent to minimize loss functions and improve machine learning model performance.
CO4: Evaluate information-theoretic measures and statistical learning bounds to assess classification, regression, and decision tree models.
CO5: Integrate mathematical tools including distance metrics, norms, and probabilistic models to design and implement machine learning algorithms for various applications

Module 1:

Linear Algebra for Machine Learning (9 Hours)
Scalars, vectors, matrices: definitions and notation; Matrix operations: addition, multiplication, transpose, inverse; Special matrices: identity, diagonal, symmetric, orthogonal; Rank, determinant, linear independence;Eigenvalues and eigenvectors (basic applications);Applications: Linear regression, Principal Component Analysis

Module 2:

Probability and Statistics (9 Hours)
Probability basics: sample space, events, conditional probability; Bayes' Theorem; Random variables: discrete and continuous; Expectation, variance, standard deviation; Covariance, correlation, joint and marginal distributions; Common distributions: Bernoulli, Binomial, Normal; Applications in ML: Naive Bayes, probabilistic modeling

Module 3:

Optimization for Learning (9 Hours)
Optimization in Machine Learning, Loss functions (MSE, Cross-Entropy – intuitive level),Convex vs non-convex functions, Basics of gradient descent and stochastic gradient descent, Learning rate and convergence, Applications: Optimization in linear models and neural networks

Module 4:

Information Theory and Learning Bounds (9 Hours)
Entropy: definition and intuition; Cross-entropy and KL-divergence; Mutual information and its significance; Maximum Likelihood Estimation (MLE) and Maximum A Posteriori (MAP); Bias-variance trade-off; Loss functions for classification and regression; Applications: Classification, decision trees, model evaluation

Module 5:

Mathematical Tools in Practice (9 Hours)
Distance metrics: Euclidean, Manhattan, cosine similarity; Norms (L1, L2), feature scaling and normalization; Linear models: least squares, logistic regression, decision theory and loss functions, perceptron algorithm, basics of kernels; Role of math in k-means clustering, SVM; Probabilistic models: Naïve Bayes

Labs / Practicals:

N/A

References:

1. Pankaj Jalote – Mathematical Foundations of Computer Science, Wiley India.
2. B. Yegnanarayana – Artificial Neural Networks, PHI Learning.
3. S. Kumaran & A. Rajesh – Mathematical Foundations for Machine Learning and AI, McGraw Hill India.
4. S. Kumaresan – Linear Algebra: A Geometric Approach, Prentice-Hall of India.
5. Veerarajan T. – Probability, Statistics and Random Processes, McGraw Hill Education India.
6. S. Venkatesh – Foundations of Machine Learning, Universities Press (India)

Course Code	Course Name	L	T	P	Cr
DOAI250032	Machine Learning	3	0	2	4

Course Outcomes:

CO1: Identify and extract relevant features from raw IoT data suitable for applying appropriate Machine Learning (ML) techniques.
CO2: Evaluate and compare the strengths and limitations of various ML algorithms across diverse application domains, particularly in IoT.
CO3: Select and implement appropriate ML models based on data characteristics and application requirements.
CO4: Mathematically formulate and analyze ML models and algorithms, including their underlying assumptions and performance metrics.
CO5: Design and validate machine learning-based solutions for real-world problems in IoT, demonstrating practical understanding and technical proficiency.

Module 1:

Module 1
Introduction: Introduction to Machine Learning: Introduction. Different types of learning, Hypothesis space and inductive bias, Evaluation. Training and test sets, cross validation, Concept of over fitting, under fitting, Bias and Variance.
Linear Regression: Introduction, Linear regression, Simple and Multiple Linear regression, Polynomial regression, evaluating regression fit.

Module 2:

Module 2
Decision tree learning: Introduction, Decision tree representation, appropriate problems for decision tree learning, the basic decision tree algorithm, hypothesis space search in decision tree learning, inductive bias in decision tree learning, issues in decision tree learning, Python exercise on Decision Tree.
Instance based Learning: K nearest neighbor, the Curse of Dimensionality, Feature Selection: forward search, backward search, univariate, multivariate feature selection approach, Feature reduction (Principal Component Analysis), Python exercise on KNN and PCA. Recommender System: Content based system, Collaborative filtering based.

Module 3:

Probability and Bayes Learning: Bayesian Learning, Naïve Bayes, Python exercise on Naïve Bayes, Logistic Regression.
Support Vector Machine: Introduction, the Dual formulation, Maximum margin with noise, nonlinear SVM and Kernel function, solution to dual problem.

Module 4:

Artificial Neural Networks: Introduction, Biological motivation, ANN representation, appropriate problem for ANN learning, Perceptron, multilayer networks and the back propagation algorithm.

Module 5:

Ensembles: Introduction, Bagging and boosting, Random forest, Discussion on some research papers.
Clustering: Introduction, K-mean clustering, agglomerative hierarchical clustering, Python exercise on k-mean clustering.

Labs / Practicals:

1 Write a Python program that imports a dataset of your choice, displays the first five rows, and prints the data type of the DataFrame as a whole. Then, generate and display the statistical summary (mean, median, standard deviation, etc.) for each column and provide complete information about the DataFrame.

2 Write a Python program to import (or create) a dataset with missing values, display the count of missing values per column, and handle them using both imputation and dropping methods. Then, compare the dataset before and after handling missing values, and display the final cleaned dataset.
3 Write a Python program to load (or create) a dataset, split it into training and testing sets, and standardize the features using StandardScaler from sklearn. preprocessing. Finally, display the dataset before and after standardization to observe the changes.
4 Write a Python program to load (or create) a dataset, separate it into predictor variables (X) and target variable (y), and then split the dataset into training and testing sets. Finally, print both the training and testing datasets.
5 Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Python ML library classes in the program.
6 Write a Python program to load (or create) a dataset with missing values, count missing values in each column, and handle them by replacing with NaN, the column mean, and the most frequent value. Finally, display the dataset before and after performing the replacements.
7 Write a Python program to load (or create) a dataset, split it into training and testing sets, and apply feature scaling to the data. Finally, display the dataset before and after scaling to observe the changes.
8 Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions. Python ML library classes can be used for this problem.
9 Implement the working principle of Artificial Neural Network with feed forward and feed backward principle.
10 Implement and demonstrate the working of SVM algorithm for classification.

References:

1. Kevin P. Murphy, “Machine Learning: A Probabilistic Perspective”, MIT Press, 2012.
2. C. M. Bishop. Pattern Recognition and Machine Learning. First Edition. Springer, 2006. (Second Indian Reprint, 2015).
3. Tom M. Mitchell, “Machine Learning”, McGraw-Hill, 2010
4. P. Flach. Machine Learning: The Art and Science of Algorithms that Make Sense of Data. First Edition, Cambridge University Press, 2012.

Course Code	Course Name	L	T	P	Cr
DASH250095	Research Methodology and IPR	3	1	0	4

Course Outcomes:

CO1: Understand the principles and process of research methodology.
CO2: Apply appropriate research design and data collection methods in computing projects.
CO3: Analyze and interpret qualitative and quantitative data using statistical tools.
CO4: Develop ethically sound, well-documented research or project reports conforming to academic and industrial standards.
CO5: Understand various forms of intellectual property and apply processes for protection and patent filing.

Module 1:

Introduction to Research and Research Ethics
Definition and objectives of research, types of research – fundamental, applied, exploratory, empirical, significance of research in computer applications, research ethics and integrity, plagiarism, citation styles (APA, IEEE), tools for plagiarism check.

Module 2:

Research Design and Data Collection
Research problem identification and formulation, hypothesis generation, literature review techniques, types of research design: experimental, descriptive, analytical, sampling techniques, primary and secondary data sources, survey design, case study design.

Module 3:

Data Analysis and Interpretation
Quantitative and qualitative data analysis, measures of central tendency and dispersion, t-test, ANOVA, correlation and regression, chi-square test, software tools: Excel, R, SPSS (demo-level), data visualization and result interpretation.

Module 4:

Technical Writing and Project Report Preparation
Structure of research papers and reports, abstract, introduction, literature review, methodology, results, and conclusions, referencing tools (Mendeley/Zotero), IEEE/ACM/SCI journal guidelines, thesis and dissertation formatting, proposal writing basics.

Module 5:

Intellectual Property Rights and Patent Process
Introduction to IPR: patents, copyrights, trademarks, industrial design, Indian and international patent systems (WIPO, TRIPS), criteria for patentability, patent filing process in India (IPINDIA portal), open-source licenses, patent drafting basics, IPR in software and AI innovations.

Labs / Practicals:

N/A

References:

1. C.R. Kothari & Gaurav Garg – Research Methodology: Methods and Techniques, New Age International.
2. Ranjit Kumar – Research Methodology – A Step-by-Step Guide, Sage Publications India.
3. P. Narayan – Intellectual Property Law, Eastern Book Company.
4. Neeraj Pandey & Khushdeep Dharni – Intellectual Property Rights, PHI Learning.
5. Yogesh Kumar Singh – Fundamentals of Research Methodology and Statistics, New Age International.
6. Bharat Bhushan – Research Methodology in Computer Science, Himalaya Publishing.
7. WIPO and IPIndia Manuals – Guidelines for Filing Patents in India.

Course Code	Course Name	L	T	P	Cr
DOAI250042	Optimisation Techniques	3	1	0	4

Course Outcomes:

CO1: Understand mathematical foundations and unconstrained optimization methods for solving optimization problems.
CO2: Apply gradient-based optimization techniques and analyze their applications in machine learning and neural networks.
CO3: Implement constrained optimization methods using Lagrange multipliers, KKT conditions, and duality theory.
CO4: Analyze and apply nature-inspired metaheuristic algorithms for AI and ML optimization tasks.
CO5: Utilize optimization techniques in supervised and unsupervised ML applications, including PCA, regression, and SVMs.

Module 1:

Mathematical Foundations and Unconstrained Optimization:
Mathematical Preliminaries: Vector Spaces and Matrices, Calculus Concepts- Gradients, Hessians, Taylor series.
Optimization Basics: Definitions, problem formulation, Necessary and sufficient conditions for local optima, Convex sets and convex functions.
One-Dimensional Optimization: Golden Section Search, Fibonacci Method, Newton’s and Secant Methods.

Module 2:

Gradient-Based Optimization and Applications in ML:
Multidimensional Optimization: Steepest Descent Method and convergence analysis, Newton’s and Quasi-Newton Methods- DFP, BFGS.
Conjugate Gradient Methods for Quadratic and Non-Quadratic functions.
Solving Systems of Equations via Optimization.
Application in Neural Networks- Backpropagation as gradient descent.

Module 3:

Constrained Optimization Techniques:
Equality and Inequality Constraints: Lagrange Multipliers, Karush-Kuhn-Tucker (KKT) conditions.
Convex Optimization: Duality Theory: Weak and Strong Duality.
Algorithms for Constrained Problems: Projected Gradient Methods, Penalty Methods

Module 4:

Nature-Inspired Metaheuristics for AI & ML:
Introduction to Metaheuristics, Simulated Annealing, Genetic Algorithms, Differential Evolution.
Swarm Intelligence: Particle Swarm Optimization, Ant Colony Optimization, Bee Colony Optimization, Firefly and Bat Algorithms, Comparison with classical methods

Module 5:

Optimization in Machine Learning Applications: Optimization in Supervised and Unsupervised ML, Feature Engineering: PCA and Linear Autoencoder, Stochastic Gradient Descent and Variants (SVRG), Regularized Linear and Logistic Regression, Support Vector Machines (SVM) and Hinge Loss, Kernel Methods and Optimization

Labs / Practicals:

NA

References:

1. Edwin K. P. Chong, Wu-Sheng Lu, Stanislaw H. Zak. – An Introduction to Optimization with Applications to

Machine Learning, 5th Ed., Wiley, 2024.
2. Xin-She Yang – Nature-Inspired Metaheuristic Algorithms, 2nd Ed., Luniver Press, 2010
3. Hamdy A. Taha, Operations Research, Prentice Hall, Pearso.
4. J. S Arora, Introduction to optimum design, 2nd edition, Elsevier India Pvt. Ltd.,
5. S. S Rao, Optimization: theory and application, Wiley Eastern Ltd., New Delhi.

Course Code	Course Name	L	T	P	Cr
DOAI250006	Deep Learning Techniques	3	0	2	4

Course Outcomes:

CO1: Understand basics of machine learning and implement regression models using TensorFlow and Keras.
CO2: Apply activation functions and perceptron models to solve linear and non-linear problems.
CO3: Design CNN architectures and address underfitting and overfitting issues.
CO4: Develop RNN, LSTM, and GRU models for sequential data processing.
CO5: Apply deep learning techniques to vision, NLP, speech, and video analytics applications.

Module 1:

Introduction: Overview of machine learning, linear classifiers, loss functions Introduction to Tensor Flow: Computational Graph, Key highlights, Creating a Graph, Regression example, Gradient Descent, Tensor Board, Modularity, Sharing Variables, Keras

Module 2:

Activation Functions: Sigmoid, ReLU, Hyperbolic Fns, Soft max Perceptrons: What is a Perceptron, XOR Gate Artificial Neural Networks: Introduction, Perceptron Training Rule, Gradient Descent Rule, vanishing gradient problem and solution

Module 3:

Convolutional Neural Networks: Introduction to CNNs, Kernel filter, Principles behind CNNs, Multiple Filters, problem and solution of under fitting and over fitting

Module 4:

Recurrent Neural Networks: Introduction to RNNs, Unfolded RNNs, Seq2Seq RNNs, LSTM, GRU, Encoder Decoder architectures

Module 5:

Deep Learning applications: Image segmentation, Object detection, Attention model for computer vision tasks, Natural Language Processing, Speech Recognition, Video Analytics

Labs / Practicals:

List of Experiment

1. Loading and Visualizing the MNIST Handwritten Digit Dataset
2. Classification of MNIST handwritten digits.
3. Developing a Binary Classification Model for Disease Risk Prediction using ANN
4. Image classification using CNN, 2 Convolutional layers on MNIST and CIFAR-10 dataset.
5. Handling and evaluating imbalance data using resampling, ensemble method and custom loss function.
6. Image data augmentation using Keras.
7. Implementation of ANN using backpropagation with different activation function.
8. Implementation of deep feed forward ANN with 4 hidden layer backpropagation.
9. Time series forecasting using deep learning network using LSTM.
10. Image data comparison using autoencoder neural network on CIFAR-10 dataset.
11. Implementation of deep CNN for multiclass image classification and comparison of CPU-vs-GPU training performance.

References:

1. Satish Kumar, Neural Networks - A Class Room Approach, Second Edition, Tata McGraw-Hill, 2013
2. Bishop, C., M., Pattern Recognition and Machine Learning, Springer, 2006.
3. Yegnanarayana, B., Artificial Neural Networks PHI Learning Pvt. Ltd, 2009.

4. Ian Goodfellow, Yoshua Bengio and Aaron Courville, Deep learning, MIT Press, Available online: http://www.deeplearningbook.org, 2016

Course Code	Course Name	L	T	P	Cr
DASH250015	Cognitive Systems	3	1	0	4

Course Outcomes:

CO1 : Demonstrate a thorough understanding of cognitive systems principles.
CO2 : Apply knowledge of cognitive science concepts to analyze and solve complex problems.
CO3 : Design and implement computational models of cognitive processes.
CO4 : Develop cognitive robotics systems capable of sensorimotor integration, spatial cognition, and human-robot interaction.
CO5 : Critically evaluate the ethical, societal, and practical implications of cognitive systems and their applications.

Module 1:

Introduction
Introduction to Cognitive Systems Overview of cognitive systems, Historical development, Interdisciplinary nature, Basic concepts in cognitive science, Cognitive architectures, Applications of cognitive systems, Cognitive system modeling approaches, Cognitive development across the lifespan, Neural correlates of cognition, Ethical considerations in cognitive systems, Future trends in cognitive science.

Module 2:

Foundations of Cognitive Psychology
Cognitive Psychology Fundamentals Human cognition and perception, Memory systems, Attention and consciousness, Language processing, Problem-solving and decision-making, Learning and adaptation, Emotion and cognition, Social cognition, Cognitive biases and heuristics, Cognitive development theories, Cognitive neuroscience methods.

Module 3:

Foundations of Cognitive Robotics
Cognitive Robotics Cognitive robotics fundamentals, Embodied cognition, Sensorimotor integration, Spatial cognition, Navigation and mapping, Human-robot interaction, Cognitive architectures for robots, Developmental robotics, Robot learning and adaptation, Multi-robot systems, Ethical considerations in cognitive robotics.

Module 4:

Professional Communication and Career Development
The role of Business Presentations, Planning and organizing presentations, Team Presentations, online Presentations. Understanding yourself, Career, Goal Setting, Preparing Resume, Resume Formats, Writing Covering Letters, and Enquiry mails, Preparing for the job interview.

Module 5:

Advanced Topics in Cognitive Computing and Applications
Applications and Advanced Topics Cognitive computing applications, Autonomous systems, Cognitive modeling and simulation, Brain-computer interfaces, Ethical considerations in cognitive systems, Future trends and challenges in cognitive science, Cognitive augmentation technologies, Cognitive rehabilitation techniques, Computational psychiatry, Neuromorphic computing, Human-centered AI design principles.

References:

1)Boden, M. A. (Ed.). "Handbook of Cognitive Science: An Embodied Approach." Elsevier.
2)Russel, S., & Norvig, P. "Artificial Intelligence: A Modern Approach." Pearson.
3)Thrun, S., Burgard, W., & Fox, D. "Probabilistic Robotics." MIT Press.
4)Luger, G. F., & Stubblefield, W. A. "Artificial Intelligence: Structures and Strategies for Complex Problem Solving." Pearson.
5)Hutto, D. D., & Myin, E."Evolutionary Robotics and the Reach of Embodiment." Frontiers in Psychology.

Course Code	Course Name	L	T	P	Cr
DCSA250009	Blockchain Technology	3	1	0	4

Course Outcomes:

Upon completion of the course, the learners will be able to:
CO1: Understand the concept of blockchain and its need.
CO2: Analyze methods of cryptography for application with blockchain.
CO3: Evaluate the working of blockchain.
CO4: Understand the underlying technology of transactions, blocks, proof-of-work, and consensus building.
CO5: Identify real world problems that blockchain can solve and analyze a use case.

Module 1:

Fundamentals of Blockchains Technology, The Structure of Blockchains, Blockchain Applications, The Blockchain Life Cycle, Distributed Ledger vs Centralized System, Merkel Root, Nonce Value, Hash Algorithm, and its applications.

Module 2:

Block Ciphers; Encryptions; Secret Keys; Elliptic Curve Cryptography; Hash cryptography; Encryption vs hashing; Digital Signature; Memory Hard Algorithm, Zero Knowledge Proof.

Module 3:

Introduction: Transactions, blocks, hashes, consensus, verify and confirm blocks, peer to peer networks, blocks of data in a chain, decentralization of networks, processes & workflows, cryptocurrencies, nodes, assets, consensus; types of blockchain; chain policy; working of blockchain; life of blockchain application; privacy, anonymity and security of blockchain.

Module 4:

Hyperledger: Introduction, where can Hyperledger be used, Hyperledger architecture, Hyperledger Fabric, features of Hyperledger; Open source blockchain platform technology; Tools & services; Cloud options in blockchains AWS; Azure workbench; Hyperledger console; Consensus: Proof of work, proof of stake, delegated proof of stake, proof of burn, BlocBox Protocol.

Module 5:

History; Distributed ledger; Smart contracts; Cryptocurrency; Bitcoin protocols; Mining strategy and rewards; Ethereum – construction; DAO; GHOST; Vulnerability; Attacks; Sidechain; Namecoin

Labs / Practicals:

NA

References:

1. D. Tapscott, A. Tapscott, Blockchain Revolution: How the Technology Behind Bitcoin Is Changing Money, Business, and the World, Portfolio Publishers.
2. A. Antonopoulos, Mastering Bitcoin: Programming the Open Blockchain, O'Reilly.
3. P. Champagne, The Book of Satoshi: The Collected Writings of Bitcoin Creator Satoshi Nakamoto, e53 Publishing, LLC.
4. M. Swan, Blockchain: Blueprint for a New Economy, O'Reilly.

5. R. Wattenhofer, The Science of the Blockchain, Inverted Forest Publishing.
6. R. Modi, Solidity Programming Essentials: A beginner's guide to build smart contracts for Ethereum and blockchain, Pack

Course Code	Course Name	L	T	P	Cr
DCSA250020	Computer Vision	3	0	2	4

Course Outcomes:

CO1: Explain the fundamentals of digital image formation, transformations, and low-level image processing techniques such as filtering, enhancement, and restoration.
CO2: Apply various feature extraction and representation methods (edges, corners, histograms, texture, SIFT, SURF, etc.) for image analysis and recognition.
CO3: Analyze depth estimation, multi-view geometry, and segmentation techniques to perform object detection and 3D reconstruction.
CO4: Evaluate motion analysis approaches including optical flow, spatio-temporal modeling, and background subtraction for dynamic scene interpretation.
CO5: Design computer vision solutions by integrating shape-from-X methods, reflectance models, and photometric techniques for real-world applications.

Module 1:

Digital Image Formation and low-level processing: Overview and State-of-the-art, Fundamentals of Image Formation, Transformation: Orthogonal, Euclidean, Affine, Projective, etc; Fourier Transform, Convolution and Filtering, Image Enhancement, Restoration, Histogram Processing, introduction to computer vision

Module 2:

Feature Extraction: Shape, histogram, color, spectral, texture, Feature analysis, feature vectors, distance /similarity measures, data preprocessing, Edges - Canny, LOG, DOG; Scale-Space Analysis-Image Pyramids and Gaussian derivative filters, Gabor Filters and DWT; Line detectors (Hough Transform), Orientation Histogram, SIFT, SURF, GLOH, Corners - Harris and Hessian Affine.

Module 3:

Depth estimation and Multi-camera views: Perspective, Homography, Rectification, DLT, RANSAC, 3-D reconstruction framework; Binocular Stereopsis: Camera and Epipolar Geometry; Auto-calibration.
Image Segmentation: Region Growing, Edge Based approaches to segmentation, Graph-Cut, Mean-Shift, MRFs, Texture Segmentation; Object detection.

Module 4:

Motion Analysis: Optical Flow, KLT, Spatio-Temporal Analysis, Background Subtraction and Modeling, Dynamic Stereo; Motion parameter estimation.

Module 5:

Shape from X: Light at Surfaces; Use of Surface Smoothness Constraint; Shape from Texture, color, motion and edges Albedo estimation; Photometric Stereo; Phong Model; Reflectance Map

Labs / Practicals:

Preparing

References:

1. Richard Szeliski, Computer Vision: Algorithms and Applications, Springer-Verlag London Limited 2011.
2. Computer Vision: A Modern Approach, D. A. Forsyth, J. Ponce, Pearson Education, 2003.
3. Richard Hartley and Andrew Zisserman, Multiple View Geometry in Computer Vision, Second Edition,

Cambridge University Press, March 2004.
4. R.C. Gonzalez and R.E. Woods, Digital Image Processing, Addison- Wesley, 1992.
5. K. Fukunaga; Introduction to Statistical Pattern Recognition, Second Edition, Academic Press, Morgan Kaufmann, 1990.

Course Code	Course Name	L	T	P	Cr
DCSA250068	Soft Computing	3	0	2	4

Course Outcomes:

After completion of course, students would be able to:
CO1: Identify and describe soft computing techniques and their roles in building intelligent machines.
CO2: Apply genetic algorithms to combinatorial optimization problems.
CO3: Explain the basic concepts, components, and paradigms of neural networks, and compare them with other information processing methods.
CO4: Apply fuzzy logic and reasoning to handle uncertainty and solve various engineering problems.
CO5: Evaluate and compare solutions by various soft computing approaches for a given problem.

Module 1:

Introduction: What is computational intelligence?- Biological basis for neural networks- Biological versus Artificial neural networks- Biological basis for evolutionary computation- Behavioral motivations for fuzzy logic, Myths about computational intelligence- Computational intelligence application areas, Evolutionary computation, computational intelligence-Adoption, Types, self-organization and evolution, Historical views of computational intelligence, Computational intelligence and Soft computing versus Artificial intelligence and Hard computing.

Module 2:

Evolutionary computation concepts and paradigms- History of evolutionary computation & overview, Genetic algorithms, Evolutionary programming &strategies, Genetic programming, Particle swarm optimization, Evolutionary computation implementations-Implementation issues, Genetic algorithm implementation, Particle swarm optimization implementation.

Module 3:

Neural Network Concepts and Paradigms- What Neural Networks are? Why they are useful, Neural network components and terminology- Topologies - Adaptation, Comparing neural networks and other information Processing methods- Stochastic- Kalman filters - Linear and Nonlinear regression - Correlation - Bayes classification -Vector quantization -Radial basis functions -Preprocessing - Post processing.

Module 4:

Fuzzy Systems concepts and paradigms - Fuzzy sets and Fuzzy logic - Approximate reasoning, Developing a fuzzy controller - Fuzzy rule system implementation.

Module 5:

Performance Metrics- General issues- Partitioning the patterns for training, testing, and validation-Cross validation - Fitness and fitness functions - Parametric and nonparametric statistics, Evolutionary algorithm effectiveness metrics, Receiver operating characteristic curves, Computational intelligence tools for explanation facilities, Case Studies for implementation of practical applications in computational intelligence.

Labs / Practicals:

preparing

References:

1. David B. Fogel and Charles J. Robinson; Computational Intelligence: The experts speak. Wiley - Intersciece 2003.
2. Neuro Fuzzy & Soft Computing - J.-S.R.Jang, C.-T.Sun, E.mizutani, Pearson Education
3. Digital Neural Network - S.Y.Kung, Prentice Hall International Inc.
4. Spiking Neural Networks - Wulfram Gerstner, Wenner Kristler, Cambridge University Press.
5. Neural Networks and Fuzzy Systems: Dynamical Systems Application to Machine Intelligence - Bart Kosko,

Prentice Hall, 1992.

Course Code	Course Name	L	T	P	Cr
DCSE250001	Advanced Algorithms and Analysis	3	1	0	4

Course Outcomes:

CO1: Learn core algorithmic techniques: greedy, dynamic programming, backtracking, and branch-and-bound.
CO2: Understand computational complexity (P, NP, NP-hard, NP-complete) and heuristic/randomized methods.
CO3: Apply analytical tools like probabilistic inequalities, amortized analysis, and competitive analysis.
CO4: Explore advanced applications in geometry, graph algorithms, network flows, and string processing.
CO5: Gain exposure to approximation and parallel algorithms, including linear programming, heuristics, and PRAMs.

Module 1:

Defining Key Terms: Algorithm complexity, Greedy method, Dynamic Programming, Backtracking, Branch-and-bound Techniques; Examples for understanding above techniques; Memory model, linked lists and basic programming skills.

Module 2:

Overview - Class P - Class NP - NP Hardness - NP Completeness - Cook Levine Theorem - Important NP Complete Problems. Heuristic and Randomized algorithms.

Module 3:

Use of probabilistic inequalities in analysis, Amortized Analysis - Aggregate Method - Accounting Method - Potential Method, competitive analysis, applications using examples.

Module 4:

Point location, Convex hulls and Voronoi diagrams, Arrangements, graph connectivity, Network Flow and Matching: Flow Algorithms - Maximum Flow – Cuts - Maximum Bipartite Matching - Graph partitioning via multi-commodity flow, Karger'r Min Cut Algorithm, String matching and document processing algorithms.

Module 5:

Approximation algorithms for known NP hard problems - Analysis of Approximation Algorithms Use of Linear programming and primal dual; local search heuristics; Parallel algorithms: Basic techniques for sorting, searching, merging, list ranking in PRAMs and Interconnection.

Labs / Practicals:

NA

References:

1. Michael T Goodric and Roberto Tamassia, “Algorithm Design: Foundations, Analysis and Internet Examples”, John Wiley and Sons, 2002.
2. Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest and Clifford Stein, “Introduction to Algorithms”, Third Edition, The MIT Press, 2009.
3. Sanjoy Dasgupta, Christos Papadimitriou and Umesh Vazirani, “Algorithms”, Tata McGraw-Hill, 2009.
4. Cormen, Leiserson, Rivest, and Stein. Introduction to Algorithms. 2nd ed. Cambridge, MA: MIT Press, 2001.David P. Williamson and David B. Shmoys, The Design of Approximation Algorithms

Course Code	Course Name	L	T	P	Cr
DCSE250086	Health Care and Data Analytics	3	1	0	4

Course Outcomes:

CO1. Describe the basics of healthcare data analytics.
CO2. Use biomedical image features and perform data analytics.
CO3. Apply natural language processing for data analytics
CO4. Use prediction models for healthcare data analytics.
CO5. Interpret genomic and clinical data for healthcare data analytics.
CO6. Explain data analytics applications for healthcare.

Module 1:

Introduction to Healthcare Data Analytics- Electronic Health Records– Components of EHR- Coding Systems- Benefits of EHR- Barrier to Adopting HER, Challenges- Phenotyping Algorithms.

Module 2:

Biomedical Image Analysis
Biomedical image modalities, Object detection, image segmentation, image registration, feature extraction
Genomic Data Analysis for Personalized Medicine
Genomic data generation, methods for data analysis, types of computational genomics studies towards personalized medicine.

Module 3:

Data Analysis using Natural language Processing for healthcare.
Natural Language Processing, Mining information from Clinical Text, challenges of processing clinical reports, applications.

Module 4:

Clinical Prediction Models and Data Mining for Healthcare data
Basic Statistical Prediction Models, Alternative Clinical Prediction Models, Survival Models. Association Analysis, Temporal Pattern Mining: Sequential Pattern Mining, Time-Interval Pattern Mining.

Module 5:

Visual Analytics and Integrating data for Healthcare
Medical data visualization, visual analytics for public health and population research, clinical workflow, clinicians, patients.

Labs / Practicals:

NA

References:

1. Chandan K. Reddy and Charu C Aggarwal, “Healthcare data analytics”, Taylor & Francis, 2015
2. Hui Yang and Eva K. Lee, “Healthcare Analytics: From Data to Knowledge to Healthcare Improvement, Wiley, 2016.
3. Tinglong Dai, Sridhar Tayur , “Handbook of Healthcare Analytics”, Wiley, 2018.
4. Anand J Kulkarni, Patrick Siarry,”Big Data Analytics in healthcare”,Springer,Studies in Big Data

Course Code	Course Name	L	T	P	Cr
DOAI250004	Artificial Intelligence	3	1	0	4

Course Outcomes:

CO1: Understand AI foundations, intelligent agents, and problem-solving formulations.
CO2: Apply uninformed and heuristic search strategies, and adversarial game-playing techniques.
CO3: Represent knowledge using logic, rules, and reasoning methods.
CO4: Analyze different learning approaches including neural networks and connectionist models.
CO5: Design and evaluate expert systems for domain-specific knowledge representation and reasoning.

Module 1:

Introduction: AI problems, foundation of AI and history of AI intelligent agents: Agents and Environments, the concept of rationality, the nature of environments, structure of agents, problem solving agents, problem formulation.

Module 2:

Searching: Searching for solutions, uniformed search strategies – Breadth first search, depth first Search. Search with partial information (Heuristic search) Greedy best first search, A* search Game Playing: Adversial search, Games, minimax, algorithm, optimal decisions in multiplayer games, Alpha-Beta pruning, Evaluation functions, cutting of search.

Module 3:

Knowledge Representation: Using Predicate logic, representing facts in logic, functions and predicates, Conversion to clause form, Resolution in propositional logic, Resolution in predicate logic, Unification.
Representing Knowledge Using Rules: Procedural Versus Declarative knowledge, Logic Programming, Forward versus Backward Reasoning

Module 4:

Learning: What is learning, Rote learning, Learning by Taking Advice, Learning in Problem-solving,
Learning from example: induction, Explanation-based learning.
Connectionist Models: Hopfield Networks, Learning in Neural Networks, Applications of Neural Networks, Recurrent Networks. Connectionist AI and Symbolic AI.

Module 5:

Expert System: Representing and using Domain Knowledge, Reasoning with knowledge, Expert System Shells, Support for explanation examples, Knowledge acquisition-examples.

Labs / Practicals:

NA

References:

1. Artificial Intelligence – A Modern Approach. Second Edition, Stuart Russel, Peter Norvig, PHI/ Pearson Education.
2. Artificial Intelligence, Kevin Knight, Elaine Rich, B. Shivashankar Nair, 3rd Edition,2008
3. Artificial Neural Networks B. Yagna Narayana, PHI.
4. Artificial Intelligence, 2nd Edition, E.Rich and K.Knight (TMH)
5. Artificial Intelligence and Expert Systems – Patterson PHI.
6. Expert Systems: Principles and Programming- Fourth Edn, Giarrantana/ Riley, Thomson.
7. PROLOG Programming for Artificial Intelligence. Ivan Bratka- Third Edition – Pearson Education.
8. Neural Networks Simon Haykin PHI.
9. Artificial Intelligence, 3rd Edition, Patrick Henry Winston., Pearson Edition.

Course Code	Course Name	L	T	P	Cr
DOAI250009	Big Data Analytics	3	0	2	4

Course Outcomes:

CO1: Describe big data characteristics, challenges, and applications across industries and domains.

CO2: Evaluate and apply NoSQL databases and distributed storage architectures for big data management.

CO3: Install, configure, and operate Hadoop and HDFS for batch-oriented big data processing.

CO4: Develop and implement data analysis workflows using Hadoop ecosystem tools including Hive, Pig, and HBase.

CO5: Design and implement real-time data processing and analytics using Spark Streaming and PySpark.

CO6: Apply visualization and regression techniques for analytical insights from large-scale data.

Module 1:

Introduction to Big Data Ecosystem

Big Data Characteristics: Volume, Variety, Velocity, Veracity, and Value, Business applications and case studies of big data analytics, Challenges in conventional systems, Big Data Analytics Lifecycle, Tools and Technologies in Big Data, Hadoop vs. Traditional Systems, NoSQL Overview (Key-Value, Document, Columnar, Graph databases), Basics of MongoDB and Cassandra for big data storage.

Module 2:

Hadoop Framework for Big Data

History and Evolution of Hadoop, Hadoop Distributed File System (HDFS): Architecture, Internals, and Operations, Block-level Storage, Fault Tolerance, MapReduce Paradigm: Concepts, Anatomy of a MapReduce Job, Failures, Scheduling, Shuffle, Sort, and Task Execution, Input / Output Formats in MapReduce, Hadoop Streaming and Integrations, Developing MapReduce Applications with Java and Python APIs.

Module 3:

Data Analysis with Hadoop Ecosystem

Hive: Data Modeling, Data Types, File Formats, HiveQL (DDL, DML, DQL), Querying Structured Data, Hive Services and Optimization.
Pig: Data Flow Language, Pig Latin Programming, Grunt Shell, Data Models, Operators, Joins, Developing and Testing Pig Scripts.
HBase: Architecture, Data Model, Integration with Hadoop, Use Cases.
Introduction to Data Lakes using Hadoop.
Hands-on with Hadoop Ecosystem for ETL pipelines.

Module 4:

Real-Time Big Data Analytics and Streaming

Stream Processing Fundamentals, Stream Data Models, Stream Architecture, Concepts of Sampling, Filtering, Counting in Streams, Real-time Sentiment Analysis, Stock Market Analysis using Streams, Introduction to Apache Kafka for Streaming Data Ingestion, Spark Basics: RDD, DataFrames, Spark SQL, In-Memory Computing, PySpark APIs, Spark Streaming for Real-Time Processing, Real-Time Analytics Applications, Case

Studies.

Module 5:

Analytical Models and Visualization for Big Data

Regression Techniques: Simple Linear Regression, Multiple Linear Regression, Model Interpretation for Large-Scale Data, Feature Engineering for Big Data, Visualization Techniques: Interactive Dashboards, Graphical Tools for Big Data (Tableau / PowerBI concepts), Visual Analytics: Trends, Patterns, Correlations, Interaction Models, Real-World Applications of Big Data Visualizations.

Labs / Practicals:

1. Setting up Hadoop, HDFS, and YARN on local and cloud-based environments (AWS / Azure / GCP).

2. Developing basic MapReduce jobs using Java and Python.

3. Implementing ETL pipelines using Hive and Pig.

4. Performing analytics with HBase and Hive.

5. Real-time data streaming with Apache Kafka and Spark Streaming (using PySpark).

6. Implementing basic ML pipelines over Spark (MLlib).

7. Visualizing Big Data using interactive tools (Matplotlib, Plotly, Tableau / PowerBI).

8. Group Project: Building and deploying an end-to-end Big Data Analytics pipeline on a real-world dataset.

References:

1. Tom White, Hadoop: The Definitive Guide, 4th Edition, O'Reilly Media, 2015.

2. Anand Rajaraman, Jeffrey David Ullman, Mining of Massive Datasets, Cambridge University Press, 3rd Edition, 2020.

3. Bill Franks, Taming the Big Data Tidal Wave: Finding Opportunities in Huge Data Streams with Advanced Analytics, John Wiley & Sons, 2012.

4. Jiawei Han, Micheline Kamber, Jian Pei, Data Mining: Concepts and Techniques, 3rd Edition, Morgan Kaufmann / Elsevier, 2011.

5. Holden Karau, Andy Konwinski, Patrick Wendell, Matei Zaharia, Learning Spark: Lightning-Fast Big Data Analysis, 2nd Edition, O'Reilly Media, 2020.

6. Paul Zikopoulos, Dirk deRoos, Krishnan Parasuraman, Thomas Deutsch, James Giles, David Corrigan, Harness the Power of Big Data – The IBM Big Data Platform, Tata McGraw Hill, 2012.

7. Michael Berthold, David J. Hand, Intelligent Data Analysis, Springer, 2007.

8. Da Ruan, Guoqing Chen, Etienne E. Kerre, Geert Wets, Intelligent Data Mining, Springer, 2007.

Official Documentation (Highly Recommended for Labs / Practical Work):

9. Official documentation for Hadoop: https://hadoop.apache.org/

10. Official documentation for Spark: https://spark.apache.org/docs/latest/

11. Official documentation for Hive: https://cwiki.apache.org/confluence/display/Hive/Home

12. Official documentation for Pig: https://pig.apache.org/

13. Official documentation for HBase: https://hbase.apache.org/

14. Official documentation for Kafka: https://kafka.apache.org/documentation/

15. Official documentation for PySpark: https://spark.apache.org/docs/latest/api/python/

Course Code	Course Name	L	T	P	Cr
DOAI250019	Data Mining and Warehousing	3	0	2	4

Course Outcomes:

CO1: Understand and apply data warehousing concepts and architectures.

CO2: Perform clustering, classification, and prediction for pattern discovery.

CO3: Address issues related to data streams and implement stream mining techniques.

CO4: Analyze and apply web mining methodologies for real-world applications.

CO5: Explore current trends and advancements in distributed warehousing and pattern mining.

Module 1:

Data warehousing components, Building a data warehouse, Data warehouse architecture, DBMS schemas for decision support, Data extraction, cleanup, and transformation tools, Metadata, Reporting, Query tools and applications, Online Analytical Processing (OLAP), OLAP and multidimensional data analysis.

Module 2:

Data mining functionalities, Data preprocessing: cleaning, integration, transformation, reduction, discretization, Concept hierarchy generation, Architecture of typical data mining systems, Classification of data mining systems, Efficient and scalable frequent itemset mining methods, Mining various kinds of association rules, From association mining to correlation analysis, Constraint-based association mining.

Module 3:

Issues in classification and prediction, Classification methods: Decision Trees, Bayesian classification, Rule-based classification, Neural networks: backpropagation, Support Vector Machines (SVM), Associative classification, Lazy learners, Other classification methods, Prediction techniques, Accuracy and error measures, Evaluating classifiers/predictors, Ensemble methods, Model selection.

Module 4:

Types of data in clustering, Categorization of major clustering methods, Partitioning methods, Hierarchical methods, Density-based methods, Grid-based methods, Model-based clustering methods, Clustering high-dimensional data, Constraint-based clustering, Outlier analysis.

Module 5:

Mining objects, Spatial data mining, Multimedia data mining, Text mining, Mining the World Wide Web, Multidimensional analysis of complex data, Descriptive mining of complex data objects.

Labs / Practicals:

1. Design a Data Warehouse Schema

Create Star Schema and Snowflake Schema for business data (sales, e-commerce, etc.).

2. ETL Process Implementation

Perform Extract, Transform, Load (ETL) operations on structured data using SQL-based tools (MySQL / PostgreSQL).

3. Association Rule Mining

Apply the Apriori Algorithm for mining frequent itemsets and generating association rules from transactional datasets.

4. Classification Using Decision Trees

Build, visualize, and evaluate Decision Tree Classifiers on datasets like Iris or Titanic.

5. Clustering Using K-Means

Apply K-Means Clustering on multi-dimensional datasets and visualize the results.

6. Data Preprocessing & Dimensionality Reduction

Handle missing values, normalize data, and apply Principal Component Analysis (PCA).

7. OLAP Operations and Cube Construction

Perform OLAP operations (Roll-up, Drill-down, Slice, Dice) using sample datasets.

8. Web Mining Basics

Analyze web log files for pattern discovery (frequent user paths, sessions).

References:

1. Jiawei Han, Micheline Kamber, Jian Pei, Data Mining Concepts and Techniques, Third Edition, Elsevier, 2011.

2. Alex Berson, Stephen J. Smith, Data Warehousing, Data Mining & OLAP, Tata McGraw-Hill, 10th Reprint, 2007.

3. K.P. Soman, Shyam Diwakar, V. Ajay, Insight into Data Mining: Theory and Practice, PHI, 2006.

4. G.K. Gupta, Introduction to Data Mining with Case Studies, PHI, 2006.

5. Pang-Ning Tan, Michael Steinbach, Vipin Kumar, Introduction to Data Mining, Pearson Education, 2007.

Course Code	Course Name	L	T	P	Cr
DOAI250028	Information Retrieval	3	1	0	4

Course Outcomes:

CO1: Understand information retrieval concepts, search engine architecture, data acquisition, and text processing techniques.
CO2: Apply ranking models, indexing, query processing, refinement, and result presentation methods.
CO3: Analyze retrieval models including Boolean, vector space, probabilistic, and machine learning-based approaches.
CO4: Evaluate search engines using test collections, effectiveness metrics, and statistical validation.
CO5: Explore advanced retrieval methods including social search, feature-based models, LSI, and multimedia retrieval.

Module 1:

Introduction: Overview of Information Retrieval, Architecture of a Search Engine,
Acquiring Data : Crawling the Web, Document Conversion, Storing the Documents, Detecting Duplicates, Noise Detection and Removal.
Processing Text: Text Statistics, Document Parsing, Tokenizing, Stopping, Stemming, Phrases, Document Structure, Link Extraction, More detail on Page Rank, Feature Extraction and Named Entity Recognition, Internationalization.

Module 2:

Ranking with Indexes Abstract Model of Ranking, Inverted indexes, Map Reduce, Query Processing: Document-at-a-time evaluation, Term-at-a-time evaluation, Optimization techniques, Structured queries, Distributed evaluation, Caching.
Queries and Interfaces: Information Needs and Queries, Query Transformation and Refinement: Stopping and Stemming Revisited, Spell Checking and Query Suggestions, Query Expansion, Relevance Feedback, Context and Personalization. Displaying the Results: Result Pages and Snippets, Advertising and Search, Clustering the Results; Translation; User Behavior Analysis.

Module 3:

Retrieval Models: Overview of Retrieval Models; Boolean Retrieval, The Vector Space Model. Probabilistic Models: Information Retrieval as Classification, The BM25 Ranking Algorithm. Ranking based on Language Models: Query Likelihood Ranking, Relevance Models and Pseudo-Relevance Feedback. Complex Queries and Combining Evidence: The Inference Network Model, The Galago Query Language. Models for Web search, Machine Learning and Information Retrieval: Learning to Rank (Le ToR), Topic Models

Module 4:

Evaluating Search Engines: Test collections, Query logs, Effectiveness Metrics: Recall and Precision, Averaging and interpolation, focusing on the top documents. Training, Testing, and Statistics: Significance tests, setting parameter values Classification and Clustering

Module 5:

Social Search: Networks of People and Search Engines: User tagging, searching within Communities, Filtering and recommending, Meta search. Beyond Bag of Words: Feature-Based Retrieval Models, Term Dependence Models, Question Answering, Pictures, Pictures of Words, etc., XML Retrieval, Dimensionality Reduction and LSI

Labs / Practicals:

NA

References:

1. Search Engines: Information Retrieval in Practice. Bruce Croft, Donald Metzler, and Trevor Strohman, Pearson Education, 2009.
2. Modern Information Retrieval. Baeza-Yates Ricardo and BerthierRibeiro-Neto. 2nd edition, Addison-Wesley, 2011.
3. Christopher D. Manning, Prabhakar Raghavan and Hinrich Schtze, Introduction to Information Retrieval, Cambridge University Press. 2008
4. Ricardo Baeza-Yates and Berthier Ribeiro-Neto, Modern Information Retrieval, Addison Wesley, 1st edition, 1999.

Course Code	Course Name	L	T	P	Cr
DOAI250031	Introduction to High Performance Computing	3	1	0	4

Course Outcomes:

CO1: Understand instruction-level parallelism, pipelining techniques, hazards, and compiler/hardware methods for ILP exploitation.
CO2: Analyze multiprocessors, thread-level parallelism, vector architectures, GPU architectures, and CUDA programming concepts.
CO3: Evaluate cache performance, virtual memory, and advanced memory optimization techniques.
CO4: Apply parallel programming platforms (OpenMP, MPI, OpenCL, OpenACC) for performance improvement in AI/ML applications.
CO5: Explain interconnection networks, clusters, SoC interconnects, and NoC architectures for parallel systems.

Module 1:

Introduction to pipelining – Types of pipelining – Hazards in pipelining - Introduction to instruction level parallelism (ILP) – Challenges in ILP - Basic Compiler Techniques for exposing ILP - Reducing Branch costs with prediction - Overcoming Data hazards with Dynamic scheduling - Hardware-based speculation - Exploiting ILP using multiple issue and static scheduling - Exploiting ILP using dynamic scheduling, multiple issue and speculation - Tomasulo’s approach, VLIW approach for multi-issue

Module 2:

Introduction to multi processors and thread level parallelism - Characteristics of application domain - Systematic shared memory architecture - Distributed shared – memory architecture – Synchronization
– Multithreading - Multithreading-fined grained and coarse grained, superscalar and super pipelining, hyper threading. Vector architectures; organizations and performance tuning; GPU architecture and internal organization, Elementary concepts in CUDA programming

Module 3:

Introduction to cache performance - Cache Optimizations - Virtual memory - Advanced optimizations of Cache performance - Memory technology and optimizations - Protection: Virtual memory and virtual machines - multi-banked caches, critical word first, early restart approaches, hardware pre-fetching, write buffer merging.

Module 4:

Introduction to parallel computing platforms; (Open MP, MPI, Open CL, Open ACC) with performance improvement analysis done using real-life AI and ML applications

Module 5:

Introduction to inter connection networks and clusters - interconnection network media - practical issues in interconnecting networks- examples - clusters - designing a cluster – System on Chip (SoC) Interconnects – Network on Chip (NOC).

Labs / Practicals:

NA

References:

1. Wang, Endong, Qing Zhang, Bo Shen, Guangyong Zhang, Xiaowei Lu, Qing Wu, and Yajuan Wang. "High-performance computing on the Intel Xeon Phi." Springer 5, 2014.
2. Sanders, Jason, and Edward Kandrot. “CUDA by example: an introduction to general-purpose GPU programming”, Addison-Wesley Professional, 2010.
3. Chandra, Rohit, Leo Dagum, David Kohr, Ramesh Menon, Dror Maydan, and Jeff McDonald. Parallel programming in Open MP. Morgan kaufmann, 2001.

4. Kaeli, David R., Perhaad Mistry, Dana Schaa, and Do

Course Code	Course Name	L	T	P	Cr
DOAI250041	Natural Language Processing	3	0	2	4

Course Outcomes:

CO1: Understand the history, stages, challenges, and applications of NLP in real-world systems.
CO2: Apply morphological analysis, finite state methods, stemming, and n-gram models for language processing.
CO3: Implement POS tagging, CFG parsing, and sentence-level syntactic analysis using statistical and ML-based methods.
CO4: Analyze word sense disambiguation techniques using machine learning and dictionary-based approaches.
CO5: Apply discourse analysis techniques including reference resolution, pronoun interpretation, and coherence modeling.

Module 1:

History of NLP; Generic NLP system; Levels of NLP; Knowledge in language processing problem; Ambiguity in natural language; Stages in NLP; Challenges of NLP; Role of machine learning; Brief history of the field; Applications of NLP: Machine translation, Question answering system, Information retrieval, Text categorization, text summarization & Sentiment analysis

Module 2:

Morphology analysis survey of English morphology, inflectional morphology & derivational morphology; Regular expressions; Finite automata; Finite state transducers (FST); Morphological parsing with FST; Lexicon free FST, Porter stemmer, N-Grams, N-gram language model, N-gram for spelling correction.

Module 3:

Part-of-Speech tagging (POS); Lexical syntax tag set for English (Penn Treebank); Rule based POS tagging; Stochastic POS tagging; Issues: Multiple tags & words, unknown words, class-based n-grams, HM Model ME, SVM, CRF; Context Free Grammar; Constituency; Context free rules & trees; Sentence level construction; Noun Phrase; Coordination; Agreement; Verb phrase & sub categorization

Module 4:

Attachment for fragment of English sentences, noun phrases, verb phrases, prepositional phrases; Relations among lexemes & their senses; Homonymy, Polysemy based disambiguation & limitations, Robust WSD; Machine learning approach and dictionary-based approach.

Module 5:

Discourse reference resolution; Reference phenomenon; Syntactic & semantic constraints on co reference; Preferences in pronoun interpretation; Algorithm for pronoun resolution; Text coherence; Discourse structure

Labs / Practicals:

Module 1: Introduction to NLP & Applications
1. Experiment 1: Demonstration of NLP Applications
o Implement basic NLP applications like sentiment analysis, text summarization, question answering, and information retrieval using pre-trained models or APIs.
2. Experiment 2: Text Preprocessing Techniques
o Perform tokenization, stop-word removal, stemming, and lemmatization on sample English texts.

Module 2: Morphology and Language Models
3. Experiment 3: Morphological Analysis using Stemming and Lemmatization
o Analyze inflectional and derivational forms of English words using stemmers and lemmatizers.
4. Experiment 4: Implementation of N-Gram Language Models

o Build unigram, bigram, and trigram models from a text corpus and compute probabilities of word sequences.
5. Experiment 5: Spelling Correction using N-Gram Probabilities
o Implement a simple spelling corrector using edit distance and N-gram based word probability estimation.

Module 3: POS Tagging and Grammar Parsing
6. Experiment 6: POS Tagging using Rule-Based and Statistical Methods
o Perform part-of-speech tagging using both rule-based and statistical approaches; evaluate accuracy on tagged corpora.
7. Experiment 7: Constituency Parsing using Context-Free Grammar (CFG)
o Define a CFG and parse given sentences to generate parse trees showing sentence structure.

Module 4: Word Sense Disambiguation
8. Experiment 8: Word Sense Disambiguation using Dictionary-Based Methods
o Use the Lesk algorithm to identify correct word senses in different sentence contexts.
9. Experiment 9: Word Sense Disambiguation using Supervised Learning
o Implement a supervised machine learning model to classify the correct sense of an ambiguous word using labeled data.

Module 5: Discourse and Reference Resolution
10. Experiment 10: Co-reference Resolution and Discourse Analysis
• Resolve pronouns and noun phrase references in a passage and analyze coherence and discourse structure.

References:

1. James Allen. Natural Language Understanding. The Benajmins/Cummings Publishing Company Inc. 1994. ISBN 0-8053-0334-0.
2. Tom Mitchell. Machine Learning. McGraw Hill, 1997. ISBN 0070428077.
3. Cover, T. M. and J. A. Thomas: Elements of Information Theory. Wiley. 1991. ISBN 0-471-06259-6.

Course Code	Course Name	L	T	P	Cr
DOAI250043	Pattern Recognition	3	0	2	4

Course Outcomes:

CO1: Understand the fundamentals of pattern recognition, probability, discriminant functions, and supervised learning methods.
CO2: Apply clustering techniques for unsupervised learning and validate cluster quality.
CO3: Perform feature extraction and selection using statistical, transform-based, and dimensionality reduction methods.
CO4: Implement classification techniques using HMMs, SVMs, and feature selection methods.
CO5: Apply fuzzy logic and genetic algorithms for pattern classification in real-world case studies.

Module 1:

Overview of Pattern recognition – Basics of Probability and Statistics, Linear Algebra, Linear Transformations, Components of Pattern Recognition System, Learning and adaptation Discriminant functions – Supervised learning – Parametric estimation – Maximum Likelihood Estimation – Bayesian parameter Estimation – Problems with Bayes approach– Pattern classification by distance functions – Minimum distance pattern classifier.

Module 2:

Clustering for unsupervised learning and classification–Clustering concept – C Means algorithm – Hierarchical clustering – Graph theoretic approach to pattern Clustering – Validity of Clusters.

Module 3:

Feature Extraction and Feature Selection: Feature extraction – discrete cosine and sine transform, Discrete Fourier transform, Principal Component analysis, Kernel Principal Component Analysis. Feature selection – class separability measures, Feature Selection Algorithms - Branch and bound algorithm, sequential forward / backward selection algorithms. Principle component analysis, Independent component analysis, Linear discriminant analysis, Feature selection through functional approximation – Elements of formal grammars.

Module 4:

State Machines – Hidden Markov Models – Training – Classification – Support vector Machine – Feature Selection.

Module 5:

Fuzzy logic – Fuzzy Pattern Classifiers – Pattern Classification using Genetic Algorithms – Case Study Using Fuzzy Pattern Classifiers and Perception

Labs / Practicals:

1. Implementation of Minimum Distance Classifier
   - o Classify patterns using Euclidean distance-based decision rules.
2. Supervised Learning using Bayesian Classifier with Gaussian Assumptions
   - o Implement Bayesian classification with maximum likelihood parameter estimation.
3. Unsupervised Learning using C-Means Clustering Algorithm
   - o Perform clustering on multivariate data using the C-Means algorithm.
4. Hierarchical Clustering and Dendrogram Visualization
   - o Apply hierarchical clustering and plot dendrograms for visual analysis.
5. Feature Extraction using PCA and Kernel PCA
   - o Extract features and reduce dimensionality using PCA and Kernel PCA.
6. Sequential Forward Feature Selection Algorithm
   - o Implement and evaluate sequential forward feature selection technique.
7. Design and Training of Hidden Markov Model (HMM)
   - o Train an HMM and use it for classification of sequential data.

8. Support Vector Machine Classification using scikit-learn
o Train an SVM with linear and nonlinear kernels for binary/multi-class classification.
9. Pattern Classification using Fuzzy Inference Systems
o Implement a fuzzy rule-based classifier using membership functions.
10. Feature Selection using Genetic Algorithms
• Apply genetic algorithm for optimal feature subset selection in classification problems.

References:

1. Andrew Webb, “Statistical Pattern Recognition”, Arnold publishers, London,1999.
2. C.M.Bishop, “Pattern Recognition and Machine Learning”, Springer, 2006.
3. M. Narasimha Murthy and V. Susheela Devi, “Pattern Recognition”, Springer 2011.
4. Menahem Friedman, Abraham Kandel, “Introduction to Pattern Recognition Statistical, Structural, Neural and Fuzzy Logic Approaches”, World Scientific publishing Co. Ltd, 2000.
5. Robe

Course Code	Course Name	L	T	P	Cr
DOAI250045	Problem Solving Methods in Artificial Intelligence	3	0	2	4

Course Outcomes:

CO1: Understand problem-solving concepts, representations, and logic-based approaches in AI.
CO2: Apply uninformed and informed search strategies, including A* and heuristic methods, to solve problems.
CO3: Model and solve Constraint Satisfaction Problems (CSPs) using backtracking, arc consistency, and related algorithms.
CO4: Analyze combinatorial optimization problems and apply exact, heuristic, and approximation techniques.
CO5: Implement metaheuristic approaches such as Genetic Algorithms, Ant Colony Optimization, Particle Swarm, and other evolutionary algorithms for optimization.

Module 1:

Problem solving and artificial intelligence; Puzzles and games; What is a solution? Problem states and operators; Reducing problems into sub problems; Problem representation; The use of logic in problem solving; Representation and search problems.

Module 2:

State descriptions; Operators; Goal states; Graph notation; Problem reduction; Problem Solving as Search; Uninformed or blind search; Informed search; Graph searching process: Breadth-first methods, Depth first methods, Optimal search algorithms, A* search - admissibility, optimality; heuristics

Module 3:

Constraint Satisfaction Problems (CSPs); Constraints as relations; Constraint modelling and solving; Map-Coloring Problem; Constraint Graph; Methods to solve CSPs - backtracking, Forward checking, Look ahead, Arc consistency algorithms; Implementation issues of CSP algorithms.

Module 4:

Combinatorial Optimization Problems; Discrete optimization techniques: exact algorithms (linear programming), approximation algorithms heuristic algorithms. Identifying various instances of problems such as Resource allocation, Knapsack, travelling salesman etc

Module 5:

Local search and met heuristics; Single-solution based algorithms vs population based algorithms; Simulated Annealing; Tabu search; Genetic Algorithms; Scatter Search; Ant Colony Optimization; Adaptive Memory Procedures; Variable Neighborhood Search; Evolutionary Algorithms; Memetic Algorithms; Particle Swarm, The Harmony Method etc

Labs / Practicals:

NA

References:

1. Problem Solving Methods in Artificial Intelligence - Nils Nilson (McGraw-Hill).
2. How to solve it by computer - R. G. Dromey.
3. Artificial Intelligence for Humans Volume-1,2,3 - Jeff Heaton.

Course Code	Course Name	L	T	P	Cr
DOAI250049	Social Media Analytics	3	1	0	4

Course Outcomes:

CO1: Understand foundations of analytics, social media data sources, and methods of data gathering.
CO2: Apply visualization and data mining techniques in social media analytics.
CO3: Implement keyword search, classification, clustering, and transfer learning methods for social media data.
CO4: Analyze network centrality, similarity, and structural measures in social media networks.
CO5: Model and predict individual and collective behavior using social media data.

Module 1:

The foundation for analytics, Social media data sources, Defining social media data, data sources in social media channels, Estimated Data sources and Factual Data Sources, Public and Private data, data gathering in social media analytics.

Module 2:

Introduction, A Taxonomy of Visualization, The convergence of Visualization, Interaction and Analytics. Data mining in Social Media: Introduction, Motivations for Data mining in Social Media, Data mining methods for Social Media, Related Efforts

Module 3:

Introduction, Keyword search, Classification Algorithms, Clustering Algorithms Greedy Clustering, Hierarchical clustering, k-means clustering, Transfer Learning in heterogeneous Networks, Sampling of online social networks, Comparison of different algorithms used for mining, tools for text mining.

Module 4:

Centrality: Degree Centrality , Eigenvector Centrality, Katz Centrality , Page Rank, Betweenness Centrality, Closeness Centrality ,Group Centrality ,Transitivity and Reciprocity, Balance and Status, Similarity: Structural Equivalence, Regular Equivalence

Module 5:

Individual Behavior: Individual Behavior Analysis, Individual Behavior Modeling, Individual Behavior Prediction Collective Behavior: Collective Behavior Analysis, Collective Behavior Modeling, Collective Behavior Prediction

Labs / Practicals:

NA

References:

1. Reza Zafarani Mohammad Ali Abbasi Huan Liu, Social Media Mining, Cambridge University Press,ISBN: 10: 1107018854.
2. Charu C. Aggarwal, Social Network Data Analytics, Springer, ISBN: 978-1-4419-8461-6.
3. Marshall Sponder, Social Media Analytics: Effective Tools for Building, Interpreting, and Using Metrics, McGraw Hill Education, 978-0-07-176829-0.
4. Matthew A. Russell, Mining the Social Web, O'Reilly, 2nd Edition, ISBN:10: 1449367615.
5. Jiawei Han University of Illinois at Urbana-Champaign Micheline Kamber, Data Mining: Concepts and Techniques, Morgan Kaufmann, 2nd Edition, ISBN: 13: 978-1-55860-901-3 ISBN: 10: 1-55860- 901-6.
6. Bing Liu, Web Data Mining : Exploring Hyperlinks, Contents and Usage Data, Springer, 2nd Editio

Course Code	Course Name	L	T	P	Cr
DOAI250052	Video Analytics using AI	3	0	2	4

Course Outcomes:

CO1: Understand fundamentals of video formation, perception, and sampling techniques.
CO2: Apply digital video processing, compression, and coding standards for video analytics.
CO3: Implement vector quantization, fractal compression, and subband coding methods.
CO4: Analyze AI-based video analytics techniques for detection, tracking, and recognition.
CO5: Apply video analytics in real-world domains such as industry, retail, transportation, and business intelligence.

Module 1:

Video Formation, Perception, and Representation
Color Perception and Specification. Video Capture and Display. Analog Video Raster. Analog Color Television Systems. Digital Video. Video Sampling- Basics of the Lattice Theory. Sampling over Lattices. Sampling of Video Signals. Filtering Operations in Cameras and Display Devices

Module 2:

Video Analytics
Analog Video signal, Analog video standards, Analog video equipment, Digital Video Signal, Digital video Standards, digital Video Processing. Video Compression: Basic Concepts and Techniques of Video Coding and the H.264 Standard, MPEG1and MPEG-2Video Standards.

Module 3:

Vector Quantization, Subband Coding
Structure of vector quantizer, VC Codebook Design, Practical VQ Examples, Fractal Compression, Subband Coding: sub band decomposition, coding of subbands

Module 4:

AI Based Application of Video Analytics
Object Tracking , object detection, Loitering detection, People counting, Automatic number plate detection, motion detection, Automatic number plate recognition , crowd detection, Facial detection and recognition, optical character recognition

Module 5:

Object Detection and Recognition in Video
Texture models Image and Video classification models- Object tracking in Video. Applications and Case studies- Industrial- Retail-Transportation& Travel Remote sensing. Video Analytics for business Intelligence using AI.

Labs / Practicals:

NA

References:

1. R.G.Gupta, Audio and Video Systems, McGraw Hill l Education (India), 2nd Edition,2010.
2. Kelthjack, Video Demystified: A Handbook for the Digital Engineer,5th Edition, Newnes, 2007.
3. Intelligent Video Surveillance Systems Jean-Yves Dufour
4. Akramullah, S. (2014). Video Coding Standards. In: Digital Video Concepts, Methods, and Metrics. Apress, Berkeley, CA. https://doi.org/10.1007/978-1-4302-6713-3_3
5. Maheshkumar H Kolekar , Intelligent Video Surveillance Systems An Algorithmic Approach , Chapmanand Hall/CRC208 Pages 94 B/W Illustrations, ISBN 9781498767118, 2018

6. Video Processing and Communications, Yao Wang, J. Osternann and QinZhang, Pearson Education
7. A.M. Dhake, Televisi