# MADANAPALLE INSTITUTE OF TECHNOLOGY & SCIENCE
## (Deemed to be University)
## MADANAPALLE
## www.mits.ac.in

Estd 1998

# MASTER OF TECHNOLOGY
## Computer Science and Engineering
## (Artificial Intelligence and Machine Learning)
## Course Structure
## &
## Detailed Syllabi

**For the students admitted to**

**Master of Technology in Computer Science and Engineering (Artificial Intelligence and Machine Learning) from the Academic Year 2026 – 27 Batch onwards**

## M.Tech Regular Two Year P.G. Degree Course

# MADANAPALLE INSTITUTE OF TECHNOLOGY & SCIENCE
## (Deemed to be University)
## MADANAPALLE
# M. Tech Two Year Curriculum Structure
## Branch: Computer Science and Engineering (Artificial Intelligence and Machine Learning)

| | |
|---|---|
| **Total Credits** | 80 Credits for 2026 Admitted Batch onwards |

**M. Tech Computer Science and Engineering (Artificial Intelligence and Machine Learning)**

# R25 - Curriculum Structure
## I Year I Semester

| S. No. | Category | Course Code | Course Title | Hours Per Week | | | | Credits |
|---|---|---|---|---|---|---|---|---|
| | | | | L | T | P | Total | |
| 1 | PC | 25MBCAMTC01 | Advanced Data Structures and Algorithms | 3 | 0 | 0 | 3 | 3 |
| 2 | PC | 25MBCAMTC02 | Programming for Artificial Intelligence | 3 | 0 | 0 | 3 | 3 |
| 3 | DE | | **Discipline Elective-I** *(Refer ANNEXURE - I)* | 3 | 0 | 0 | 3 | 3 |
| 4 | DE | | **Discipline Elective-II** *(Refer ANNEXURE - I)* | 3 | 0 | 0 | 3 | 3 |
| 5 | ESC | 25MBCOMTC01 | Research Methodology and IPR | 2 | 0 | 0 | 2 | 2 |
| 6 | PC | 25MBCAMLC01 | Advanced Data Structures and Algorithms Laboratory | 0 | 0 | 4 | 4 | 2 |
| 7 | PC | 25MBCAMLC02 | Programming for Artificial Intelligence Laboratory | 0 | 0 | 4 | 4 | 2 |
| 8 | SEC | 25MBCAMSC01 | Data Science Using Python | 1 | 0 | 2 | 3 | 2 |
| 9 | MC | 25MBCIVMC01 | Disaster Management | 2 | 0 | 0 | 2 | 0 |
| 10 | EEC | | **NSDC - Certification Course – I** *(Refer ANNEXURE – III)* | 0 | 0 | 2 | 2 | 0 |
| **Total** | | | | **17** | **0** | **10** | **27** | **20** |

## I Year II Semester

| S. No. | Category | Course Code | Course Title | Hours Per Week | | | | Credits |
|---|---|---|---|---|---|---|---|---|
| | | | | L | T | P | Total | |
| 1 | PC | 25MBCAMTC03 | Machine Learning for Intelligent Systems | 3 | 0 | 0 | 3 | 3 |
| 2 | PC | 25MBCAMTC04 | Data Management for Machine Learning | 3 | 0 | 0 | 3 | 3 |
| 3 | DE | | **Discipline Elective-III** *(Refer ANNEXURE - I)* | 3 | 0 | 0 | 3 | 3 |
| 4 | DE | | **Discipline Elective-IV** *(Refer ANNEXURE - I)* | 3 | 0 | 0 | 3 | 3 |
| 5 | OE | | **Open Elective-I** *(Refer ANNEXURE – II)* | 2 | 0 | 0 | 2 | 2 |
| 6 | PC | 25MBCAMLC03 | Machine Learning for Intelligent Systems Laboratory | 0 | 0 | 4 | 4 | 2 |
| 7 | PC | 25MBCAMLC04 | Data Management for Machine Learning Laboratory | 0 | 0 | 4 | 4 | 2 |
| 8 | SEC | 25MBCAMSC02 | Generative AI Techniques | 1 | 0 | 2 | 3 | 2 |
| 9 | EEC | | **NSDC - Certification Course – II** *(Refer ANNEXURE – III)* | 0 | 0 | 2 | 2 | 0 |
| **Total** | | | | **15** | **0** | **10** | **25** | **20** |

(L = Lecture, T = Tutorial, P = Practical, C = Credit

## Tentative R25 - Curriculum Structure
## II Year I Semester

| S. No. | Category | Course Code | Course Title | Hours Per Week | | | | Credits |
|---|---|---|---|---|---|---|---|---|
| | | | | L | T | P | Total | |
| 1 | PC | 25MBCAMTC05 | Cloud Infrastructure and Services | 3 | 0 | 0 | 3 | 3 |
| 2 | DE | | **Discipline Elective – V** *(Refer ANNEXURE - I)* | 3 | 0 | 0 | 3 | 3 |
| 3 | OE | | **Open Elective- II** *(Refer ANNEXURE - II)* | 3 | 0 | 0 | 3 | 3 |
| 4 | SEC | 25MBCAMSC03 | Data warehousing and Pattern Mining | 1 | 0 | 2 | 3 | 2 |
| 5 | PR | 25MBCAMIC01 | Summer Internship* | 0 | 0 | 6 | 6 | 3 |
| 6 | PR | 25MBCAMPC01 | Capstone Project Phase I | 0 | 0 | 20 | 20 | 10 |
| 7 | EEC | | **NSDC - Certification Course – III** *(Refer ANNEXURE – III)* | 0 | 0 | 2 | 2 | 0 |
| **Total** | | | | **10** | **0** | **28** | **38** | **24** |

* 6 Weeks Internship during I Year II Semester Summer Break and to be evaluated in II Year I Semester

## II Year II Semester

| S. No. | Category | Course Code | Course Title | Hours Per Week | | | | Credits |
|---|---|---|---|---|---|---|---|---|
| | | | | L | T | P | Total | |
| 1 | PR | 25MBCAMPC02 | Capstone Project Phase II | 0 | 0 | 32 | 32 | 16 |
| **Total** | | | | **0** | **0** | **32** | **32** | **16** |

(L = Lecture, T = Tutorial, P = Practical, C = Credit

**ANNEXURE - I**

## LIST OF DISCIPLINE ELECTIVE COURSES

| Discipline Elective – I | | |
|---|---|---|
| **Sl. No.** | **Course Code** | **Course Title** |
| 1. | 25MBCAMDC01 | Mathematical foundations for Machine Learning |
| 2. | 25MBCAMDC02 | DevOps |
| 3. | 25MBCAMDC03 | Explainable AI |
| 4. | 25MBCAMDC04 | Deep Neural Networks |
| Any advanced courses can be appended in future. | | |

| Discipline Elective – II | | |
|---|---|---|
| **Sl. No.** | **Course Code** | **Course Title** |
| 1. | 25MBCAMDC05 | Stochastic Models and Applications |
| 2. | 25MBCAMDC06 | Agentic AI |
| 3. | 25MBCAMDC07 | Statistical Natural Language Processing |
| 4. | 25MBCAMDC08 | Machine Learning for Image Processing |
| Any advanced courses can be appended in future. | | |

| Discipline Elective – III | | |
|---|---|---|
| **Sl. No.** | **Course Code** | **Course Title** |
| 1. | 25MBCAMDC09 | Statistical Data Analytics for Artificial Intelligence |
| 2. | 25MBCAMDC10 | Advances in System and Network Security |
| 3. | 25MBCAMDC11 | Remote Sensing and GIS |
| 4. | 25MBCAMDC12 | Human AI Interaction |
| Any advanced courses can be appended in future. | | |

**M. Tech Computer Science and Engineering (Artificial Intelligence and Machine Learning)**

| **Discipline Elective – IV** | | |
|---|---|---|
| **Sl. No.** | **Course Code** | **Course Title** |
| 1. | 25MBCAMDC13 | MLOps |
| 2. | 25MBCAMDC14 | Recommender Systems |
| 3. | 25MBCAMDC15 | Video Analysis |
| 4. | 25MBCAMDC16 | Multimodal Information Retrieval |
| Any advanced courses can be appended in future. | | |

| **Discipline Elective – V**<br>(To be offered under MOOC's Category from SWAYAM – NPTEL) | | |
|---|---|---|
| **Sl. No.** | **Course Code** | **Course Title** |
| 1. | 25MBCAMDM01 | Responsible & Safe AI Systems |
| 2. | 25MBCAMDM02 | Mobile Virtual Reality and Artificial Intelligence |
| 3. | 25MBCAMDM03 | Machine Learning for Earth System Sciences |
| 4. | 25MBCAMDM04 | GPU Architectures and Programming |
| Any other new Disciplinary Course which doesn't exist in the Curriculum can be appended in future. | | |

**ANNEXURE - II**

## LIST OF OPEN ELECTIVE COURSES

| **Open Elective - I**<br>(To be offered under MOOC's Category from SWAYAM – NPTEL) | | |
|---|---|---|
| **Sl. No.** | **Course Code** | **Course Title** |
| 1. | 25MBMECOM01 | Product Engineering and Design Thinking |
| 2. | 25MBMBAOM01 | Innovation, Business Models and Entrepreneurship |
| 3. | 25MBMBAOM02 | AI in Human Resource Management |
| 4. | 25MBCIVOM02 | Sustainable Engineering Concepts and Life Cycle Analysis |
| Any other new Inter-Disciplinary Course offered by SWAYAM NPTEL which doesn't exist in the Curriculum can be appended in future. | | |

| **Open Elective - II**<br>(To be offered under Conventional Mode) | | |
|---|---|---|
| **Sl. No.** | **Course Code** | **Course Title** |
| 1. | 25MBMECOC01 | Automation and Robotics |
| 2. | 25MBECEOC01 | Community Radio Technology |
| Any new Interdisciplinary Course can be appended in future. | | |

# I Year I Semester

**M. Tech I Year I Semester**

## 25MBCAMTC01 ADVANCED DATA STRUCTURES AND ALGORITHMS

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Data Structures & Algorithms**

**Course Description:**

This course introduces the fundamentals of algorithm design and analysis. It covers algorithm efficiency, asymptotic notations, searching, sorting, graph algorithms, and major design techniques such as brute force, divide and conquer, dynamic programming, greedy method, backtracking, and branch and bound. Students learn to design and analyze efficient algorithms for computational problems.

**Course Objectives:**

1. To understand the fundamentals of algorithms and different types of algorithmic problems.
2. To analyze the working and complexity of DFS, BFS, and brute-force algorithms.
3. To analyze the performance of Merge Sort, Quick Sort, and Binary Search algorithms.
4. To understand dynamic programming methodology for optimization problems.
5. To analyze the efficiency and limitations of backtracking and branch-and-bound approaches.

**UNIT I INTRODUCTION AND FUNDAMENTALS OF THE ANALYSIS OF ALGORITHM EFFICIENCY — 9 hours**

**INTRODUCTION:** Algorithm, Fundamentals of Algorithmic Problem Solving, Important Problem Types.

**FUNDAMENTALS OF THE ALGORITHMS EFFICIENCY:** The Analysis Framework, Asymptotic Notations and Basic efficiency classes, Mathematical Analysis of Non-recursive and Recursive Algorithms.

**UNIT II BRUTE FORCE AND DECREASE AND CONQUER — 9 hours**

**BRUTE FORCE:** Sequential search and Brute-Force String Matching algorithms with complexity analysis, Closest-Pair and Convex-Hull Problems by Brute Force, Exhaustive search, Depth First Search, Breadth First Search

**DECREASE AND CONQUER:** General method, Insertion Sort, Topological Sorting with complexity analysis

**UNIT III DIVIDE AND CONQUER AND TRANSFORM AND CONQUER — 9 hours**

**DIVIDE AND CONQUER:** General Method, Merge sort, Quick sort, Binary Search algorithms with Complexity analysis.

**TRANSFORM AND CONQUER:** General method, Balanced Search Trees, Heaps and Heap sort algorithms with complexity analysis

**UNIT IV DYNAMIC PROGRAMMING AND GREEDY TECHNIQUE — 9 hours**

**DYNAMIC PROGRAMMING:** General method, The Knapsack problem and memory function, Optimal Binary Search Trees, Warshall's and Floyd's Algorithms

**GREEDY TECHNIQUE:** General Method, Prim's Algorithm, Kruskal's Algorithm, Dijkstra's Algorithm, Huffman Trees and codes

**UNIT V BACKTRACKING AND BRANCH AND BOUND** **9 hours**

**BACKTRACKING:** General method, n-Queens problem, Subset-sum problem, Knapsack Problem
**BRANCH AND BOUND:** General method, Knapsack Problem, Traveling Salesman Problem

**Course Outcomes:**

At the end of this course students will demonstrate the ability to
**CO1.** Analyze algorithm efficiency using analysis framework and asymptotic notations.
**CO2.** Design and analyse brute force techniques for searching, sorting, and string matching problems.
**CO3.** Design and analyse using divide-and-conquer techniques and and transform-and-conquer techniques.
**CO4.** Apply Dynamic programming and Greedy method to solve problems.
**CO5.** Apply Backtracking and Branch & bound strategy to solve problems.

**Text Books:**

1. "Introduction to the Design & Analysis of Algorithms", Anany Levitin, 3rd Edition, Pearson Education, 2017.
2. "Fundamentals of Computer Algorithms", Ellis Horowitz, Sartaj Sahani, Sanguthevar Rajasekaran, 2nd Edition, Computer Science Press, 2007

**Reference Books:**

1. "Introduction to Algorithms", Thomas H., Cormen, Charles E. Leiserson, Ronal L. Rivest, Clifford Stein, 4th Edition, PHI, 2022
2. "Design and Analysis of Algorithms", S. Sridhar, 1st Edition, Oxford University Press, 2014.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**M. Tech I Year II Semester**

## 25MBCAMTC02 PROGRAMMING FOR ARTIFICIAL INTELLIGENCE

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Python Programming**

**Course Description:**

This course introduces Python programming for AI applications, covering programming fundamentals, object-oriented programming, development environments, data handling and visualization, scientific computing, and AI libraries. It also provides practical knowledge of Git, GitHub, collaborative development, and AI application deployment, enabling students to develop and deploy basic end-to-end AI applications.

**Course Objectives:**

1. Understand Python programming concepts and AI development environments.
2. Apply data handling and visualization techniques using Python libraries.
3. Analyze scientific computing and AI frameworks for problem solving.
4. Apply version control and collaborative development tools in AI projects.
5. Develop and deploy basic end-to-end AI applications.

**UNIT I PYTHON ESSENTIALS FOR AI AND ML 9 hours**

Functional Programming (lambdas, map, filter, and reduce), Advanced Regular Expressions, Iterators, Generators, Closures, Decorators, List Comprehensions, Concurrency & Parallelism, File Handling using CSV, JSON and Pickle, Exception Handling

**UNIT II OBJECT ORIENTED PROGRAMMING AND DEVELOPMENT ENVIRONMENT 9 hours**

Classes and Objects, Inheritance, Polymorphism for AI Applications, Virtual Environments, Docker Basics, Jupyter Notebook, Google Colab Environment Setup, Debugging Techniques, Python Logging, API Basics and RESTful Services.

**UNIT III DATA HANDLING AND VISUALIZATION 9 hours**

Data Handling using Pandas (Reading, Writing, Manipulation), Data Cleaning, Handling Missing Data, Feature Scaling, Encoding Techniques, Data Visualization using Matplotlib and Seaborn.

**UNIT IV SCIENTIFIC COMPUTING AND AI LIBRARIES 9 hours**

NumPy Arrays, Broadcasting, Vectorization, Matrix Operations, Scientific Computing with SciPy, Optimization, Linear Algebra, Statistical Modules, Introduction to TensorFlow and PyTorch, Tensors vs Arrays, Automatic Differentiation (Autograd).

**UNIT V ESSENTIAL TOOLS, VERSION CONTROL AND DEPLOYMENT 9 hours**

Introduction to Git and GitHub, Collaborative Development, Introduction to OpenCV, Cloud Deployment Basics, Running Notebooks on Google Colab, AI Project Structure and Modularization, End-to-End Mini Projects, AI Model Deployment, GitHub Repository Creation and Versioning.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1.** Explain Python programming fundamentals and object-oriented concepts for AI applications.

**CO2.** Apply data preprocessing, handling, and visualization techniques using Python tools.

**CO3.** Analyze scientific computing and AI libraries for numerical problem solving.

**CO4.** Demonstrate the use of Git, GitHub, and collaborative development practices.

**CO5.** Develop AI models and end-to-end AI applications.

**Text Books:**

1. "Python for Data Analysis", Wes McKinney, 3rd Edition, O'Reilly Media, 2022.
2. "Effective Python", Brett Slatkin, 3rd Edition, Pearson Education (US), 2024
3. "Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems", Aurelien Geron, 2nd Edition, Sebastopol: O'Reilly Media, 2019.

**Reference Books:**

1. "Python Data Science Handbook", Jake VanderPlas, 1st Edition, O'Reilly Media, 2016.
2. "Python Machine Learning: Machine Learning and Deep Learning with Python, Scikit-learn, and TensorFlow 2", Raschka, Sebastian Raschka, Vahid Mirjalili, 3rd Edition, Birmingham: Packt Publishing, 2019.
3. "Learning Python", Mark Lutz, 6th Edition, O'Reilly Media, 2025.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**M. Tech I Year I Semester**

**25MBCOMTC01 RESEARCH METHODOLOGY AND IPR**

| L | T | P | C |
|---|---|---|---|
| 2 | 0 | 0 | 2 |

**Pre-requisite** Nil

**Course Description:**

This course aims to provide students with a comprehensive understanding of research methodology and the principles and practices of intellectual property rights (IPR). The course will equip students with the skills needed to design, conduct, and evaluate research effectively while also understanding the legal and ethical considerations surrounding intellectual property.

**Course Objectives:**

To impart knowledge on

1. Formulation of research problems, design of experiment, collection of data, interpretation and presentation of result
2. Intellectual property rights, patenting and licensing

**UNIT I RESEARCH PROBLEM FORMULATION 9 hours**

Objectives of research, types of research, research process, approaches to research; conducting literature review- information sources, information retrieval, tools for identifying literature, Indexing and abstracting services, Citation indexes, summarizing the review, critical review, identifying research gap, conceptualizing and hypothesizing the research gap

**UNIT II RESEARCH DESIGN AND DATA COLLECTION 9 hours**

Statistical design of experiments- types and principles; data types & classification; data collection - methods and tools

**UNIT III DATA ANALYSIS, INTERPRETATION AND REPORTING 9 hours**

Sampling, sampling error, measures of central tendency and variation,; test of hypothesis- concepts; data presentation- types of tables and illustrations; guidelines for writing the abstract, introduction, methodology, results and discussion, conclusion sections of a manuscript; guidelines for writing thesis, research proposal; References – Styles and methods, Citation and listing system of documents; plagiarism, ethical considerations in research

**UNIT IV INTELLECTUAL PROPERTY RIGHTS 9 hours**

Concept of IPR, types of IPR – Patent, Designs, Trademarks and Trade secrets, Geographical indications, Copy rights, applicability of these IPR, IPR & biodiversity; IPR development process, role of WIPO and WTO in IPR establishments, common rules of IPR practices, types and features of IPR agreement, functions of UNESCO in IPR maintenance.

**UNIT V PATENTS 9 hours**

Patents – objectives and benefits of patent, concept, features of patent, inventive steps, specifications, types of patent application; patenting process - patent filling, examination of patent, grant of patent, revocation; equitable assignments; Licenses, licensing of patents; patent agents, registration of patent agents.

**Course Outcomes:**

Upon completion of the course, the student can

**CO1:** Describe different types of research; identify, review and define the research problem

**CO2:** Select suitable design of experiment s; describe types of data and the tools for collection of data

**CO3:** Explain the process of data analysis; interpret and present the result in suitable form

**CO4:** Explain about Intellectual property rights, types and procedures

**CO5:** Execute patent filing and licensing

**Text Book(s)**

1. Cooper Donald R, Schindler Pamela S and Sharma JK, "Business Research Methods", Tata McGraw Hill Education, 11e (2012).
2. Soumitro Banerjee, "Research methodology for natural sciences", IISc Press, Kolkata, 2022.
3. Catherine J. Holland, "Intellectual property: Patents, Trademarks, Copyrights, Trade Secrets", Entrepreneur Press, 2007.

**Reference Books**

1. David Hunt, Long Nguyen, Matthew Rodgers, "Patent searching: tools & techniques", Wiley, 2007.
2. The Institute of Company Secretaries of India, Statutory body under an Act of parliament, "Professional Programme Intellectual Property Rights, Law and practice", September 2013.

**Mode of Evaluation:** Assignments, Mid Term Tests, End Semester Examination.

**M. Tech I Year I Semester**

**25MBCAMLC01 ADVANCED DATA STRUCTURES AND ALGORITHMS LABORATORY**

| L | T | P | C |
|---|---|---|---|
| 0 | 0 | 4 | 2 |

**Pre-requisite: Data Structures**

**Course Description:**

This course introduces fundamental concepts of algorithm design, analysis, and problem-solving. It focuses on searching, sorting, graph, and optimization algorithms, along with advanced techniques such as dynamic programming, greedy methods, backtracking, and branch-and-bound. Students develop skills to analyze algorithm efficiency and design effective solutions for real-world computational and engineering problems.

**Course Objectives:**

1. To introduce the fundamental concepts of algorithm design and problem-solving techniques for computational applications.
2. To provide practical exposure to implementing sorting, searching, graph, and optimization algorithms using programming tools.
3. To develop the ability to analyze algorithm efficiency using appropriate time and space complexity measures.
4. To familiarize students with advanced algorithmic strategies such as dynamic programming, greedy methods, and branch-and-bound techniques.
5. To enhance logical thinking and programming skills for solving real-world engineering and data-processing problems.

**List of Programs:**

1. A university wants to check whether a specific keyword or phrase appears in a student's assignment document. Develop a program using the Brute-Force String Matching algorithm to search for the given phrase in the text document and display the starting index of occurrence.
2. a. A university campus has multiple buildings connected by walkways. A student wants to find the minimum number of walkways needed to reach the library from the hostel. Develop a program using Breadth First Search to find the shortest path between two buildings in the campus map represented as a graph.

   b. An operating system stores folders and subfolders in a hierarchical structure. A program must list all files inside deeply nested folders. Develop a program using Depth First Search to traverse the complete directory structure and display all files.
3. a. A multinational company maintains employee salary records across departments. The HR team needs salaries sorted for payroll analysis and tax processing. Develop a program using Merge Sort to sort employee salaries. Execute the program for different dataset sizes and evaluate the algorithm's time complexity experimentally.

   b. A university examination cell must process and sort marks of students from multiple departments before publishing results. Develop a program using Quick Sort to sort employee salaries. Execute the program for different dataset sizes and evaluate the algorithm's time complexity experimentally.
4. An IoT monitoring application stores sensor readings in sorted order. Engineers need to determine whether a particular reading exists in the dataset. Implement Binary Search to locate

the target sensor value and evaluate the algorithm's performance for large datasets.

5. To implement an AVL Tree for storing and managing student records efficiently with balanced insertion and deletion operations.
6. A logistics company must load valuable packages into a delivery truck with limited carrying capacity. Each package has a specific weight and profit value. Develop a program using the 0/1 Knapsack Dynamic Programming algorithm to determine the set of packages that maximizes total profit without exceeding the truck capacity.
7. A dictionary application stores words alphabetically. Certain commonly used words are searched more frequently by users. Develop a program to build an Optimal Binary Search Tree to reduce the average search cost for word lookup operations.
8. An airline company maintains flight connections between cities with varying travel costs. The company wants to identify the cheapest route between two cities. Design a program using Dijkstra's Algorithm to find the minimum-cost flight path in a weighted graph representing airline routes.
9. A smart home system records the power usage of different appliances. The homeowner wants to know whether a subset of appliances consumes exactly the available backup battery power. Create a program using the Subset Sum technique to determine whether the target energy consumption can be achieved.
10. A sales representative must visit multiple cities to promote products and return to the starting city while minimizing total travel cost. Develop a program using the Branch and Bound approach for the Traveling Salesman Problem (TSP) to determine the minimum-cost tour covering all cities exactly once.

**Course Outcomes:**

At the end of this course, students will be able to

**CO1:** Apply fundamental algorithmic techniques to design and implement efficient solutions for real-world computational problems.

**CO2:** Analyze the performance of sorting, searching, graph traversal, and optimization algorithms using time and space complexity measures.

**CO3:** Develop problem-solving skills by constructing algorithmic solutions using brute force, divide-and-conquer, greedy, dynamic programming, and branch-and-bound strategies.

**CO4:** Evaluate and compare different algorithms experimentally for scalability, correctness, and computational efficiency across varying datasets.

**CO5:** Create optimized programs for practical applications involving data processing, graph analysis, resource allocation, and decision-making problems.

**Reference Books:**

**1.** "Introduction to the Design & Analysis of Algorithms", Anany Levitin, 3rd Edition, Pearson Education, 2017.

**2.** "Fundamentals of Computer Algorithms", Ellis Horowitz, Sartaj Sahani, Sanguthevar Rajasekaran, 2nd Edition, Computer Science Press, 2007

**3.** "Fundamentals of Data Structures in C++", Horowitz Ellis, Sahni Sartaj, Mehta, Dinesh,2nd Edition, Universities Press, 2006.

**Mode of Evaluation:** Continuous Internal Evaluation and End Semester Examination.

**M. Tech I Year I Semester**

**25MBCAMLC02 PROGRAMMING FOR ARTIFICIAL INTELLIGENCE LABORATORY**

| L | T | P | C |
|---|---|---|---|
| 0 | 0 | 4 | 2 |

**Pre-requisite:** Python Programming

**Course Description:**

This laboratory course provides hands-on experience in Python programming for AI applications, covering object-oriented programming, data preprocessing and visualization, numerical computing, machine learning, and tensor operations. Students also gain practical skills in Git/GitHub, Google Colab, and developing, testing, and deploying basic AI applications.

**Course Objectives:**

1. To understand Python programming, object-oriented concepts, and AI development environments.
2. To apply data handling, preprocessing, and visualization techniques using Python libraries.
3. To implement numerical computing and machine learning methods using modern AI frameworks.
4. To create collaborative development and version control practices using Git and GitHub.
5. To develop, test, and deploy basic AI applications using cloud-based platforms and tools.

**List of Programs:**

1. Write a Python program using loops, functions, file handling, and exception handling to automate employee salary processing for a company and securely store the salary details in a file.
2. Implement a Python-based library management system using classes, inheritance, and polymorphism to manage book issuing and returning operations in a college library.
3. Implement matrix addition, multiplication, transpose, and inversion operations using NumPy for a data analyst working on image processing applications.
4. Develop a Python program that use Pandas to clean, process, and analyze a retail sales dataset containing missing and duplicate values for generating business insights.
5. Write a Python program to create visualizations using Matplotlib and Seaborn to identify trends and patterns in healthcare datasets for patient data analysis.
6. Write a Python program to apply preprocessing techniques such as feature scaling and categorical encoding to prepare inconsistent data for machine learning model training.
7. Write a Python program to build and evaluate a Linear Regression model using Scikit-Learn to help a real estate company predict house prices based on given features.
8. Write a Python program to develop a Logistic Regression classifier to predict customer loan repayment status for a bank and evaluate the model performance.
9. Write a Python program to perform tensor creation, reshaping, slicing, and arithmetic operations using PyTorch or TensorFlow for testing deep learning computations.
10. Write a Python program to use Git and GitHub to create repositories, manage branches, and maintain version control for a collaborative AI software development project.

11. Create and execute an AI notebook in Google Colab with dataset upload, processing, and visualization capabilities for students performing online AI experiments.
12. Develop a python program to train, save, and test a simple AI prediction model using the Google Colab cloud environment for a startup company testing AI solutions online.

**Course Outcomes:**

At the end of this course, students will be able to

**CO1:** Apply Python programming concepts, object-oriented principles.

**CO2:** Apply data preprocessing, handling, and visualization techniques using Python libraries.

**CO3:** Implement machine learning, numerical computing, and tensor operations for AI applications.

**CO4:** Create collaborative development and version control practices using Git and GitHub.

**CO5:** Build, test, and deploy basic AI applications using cloud-based platforms such as Google Colab.

**Text Books:**

**1.** "Python for Data Analysis", Wes McKinney, 3rd Edition, O'Reilly Media, 2022.

**2.** "Effective Python", Brett Slatkin, 3rd Edition, Pearson Education (US), 2024

**3.** "Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems", Aurelien Geron, 2nd Edition, Sebastopol: O'Reilly Media, 2019.

**Reference Books:**

**1.** "Python Data Science Handbook", Jake VanderPlas, 1st Edition, O'Reilly Media, 2016.

**2.** "Python Machine Learning: Machine Learning and Deep Learning with Python, Scikit-learn, and TensorFlow 2", Raschka, Sebastian Raschka, Vahid Mirjalili, 3rd Edition, Birmingham: Packt Publishing, 2019.

**Mode of Evaluation:** Continuous Internal Evaluation and End Semester Examination.

**M. Tech I Year I Semester**
**Skill Enhancement Course - I**

## 25MBCAMSC01 DATA SCIENCE USING PYTHON

| L | T | P | C |
|---|---|---|---|
| 1 | 0 | 2 | 2 |

**Pre-requisite: Python Programming**

**Course Description:**
This course introduces the fundamental concepts and techniques of data science using Python. It covers data collection, preprocessing, exploratory data analysis, data visualization, statistical analysis, and feature engineering using Python-based tools and libraries. Students learn to apply NumPy, Pandas, Matplotlib, Seaborn, and Scikit-learn for analysing real-world datasets and developing data-driven solutions. The course also emphasizes practical data analysis workflows, interpretation of results, and effective communication of insights.

**Course Objectives:**

1. To introduce the Python ecosystem and core libraries used in data science.
2. To develop skills in data acquisition, preprocessing, and cleaning using Python.
3. To apply exploratory data analysis and visualization techniques for insight generation.
4. Understand statistical analysis and hypothesis testing for data-driven decisions.
5. To design and implement end-to-end data science pipelines including machine learning workflows.

**UNIT I INTRODUCTION TO DATA SCIENCE AND PYTHON ECOSYSTEM 6 hours**
Overview of Data Science - Python for Data Science - Setting up Data Science Environment - NumPy Arrays - Pandas DataFrames - Introduction to Python Visualization Libraries.

1. Configuring a Python-Based Data Science Workspace for AI Research Applications
2. Analyzing Student Performance Data Using NumPy Array Operations
3. Building and Managing Smart Retail Sales Records Using Pandas DataFrames

**UNIT II DATA ACQUISITION, PREPROCESSING AND CLEANING 6 hours**
Data Collection from Multiple Sources - Handling Missing Data - Outlier Detection and Treatment - Data Normalization and Standardization - Encoding Categorical Variables - Feature Engineering and Feature Selection.

1. Designing a Real-World Data Cleaning Pipeline for Healthcare Analytics Using Python
2. Extracting and Integrating Web and API Data for E-Commerce Business Intelligence Using Python

**UNIT III EXPLORATORY DATA ANALYSIS AND VISUALIZATION 6 hours**
Descriptive Statistics - Matplotlib - Seaborn - Plotly and Plotly Express - Correlation Analysis - Time Series Visualization - Geospatial Visualization.

1. Performing Comprehensive Exploratory Data Analysis on Public Healthcare Datasets Using Python
2. Developing Interactive Business Intelligence Dashboards Using Plotly and Dash Frameworks

**UNIT IV STATISTICAL ANALYSIS AND HYPOTHESIS TESTING 6 hours**
Probability Distributions - Central Limit Theorem and Sampling Techniques - Hypothesis Testing - Statistical Tests - Linear Regression - Logistic Regression - Model Evaluation - Time Series Analysis.

1. Performing Statistical Hypothesis Testing on Real-World Healthcare Data Using Python
2. Building and Evaluating Regression Models for House Price Prediction Using Python

**UNIT V MACHINE LEARNING WITH PYTHON AND CASE STUDIES 6 hours**

Introduction to Scikit-learn - Supervised Learning - Unsupervised Learning - Model Evaluation and Selection - Model Interpretability - Real-World Case Studies - End-to-End Data Science Project.

1. Developing an End-to-End Machine Learning Pipeline for Customer Churn Prediction Using Python

   Case Study Implementation on Kaggle Dataset for Predictive Analytics and Model Evaluation

**Course Outcomes:**

At the end of this course, students will be able to

**CO1:** Apply Python libraries for data manipulation and analysis tasks.

**CO2:** Analyze and clean real-world datasets using appropriate techniques.

**CO3:** Apply exploratory data analysis from structured and unstructured data.

**CO4:** Evaluate statistical tests and build regression models for data-driven decision making.

**CO5:** Design and implement end-to-end data science pipelines integrating machine learning models.

**Text Books:**

**1.** "Python for Data Analysis: Data Wrangling with Pandas, NumPy, and Jupyter", Wes McKinney, 3rd Edition, O'Reilly Media, 2022.

**2.** "Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow", Aurélien Géron, 3rd Edition, O'Reilly Media, 2022.

**Reference Books:**

**1.** "Data Science from Scratch: First Principles with Python", Joel Grus, 2nd Edition, O'Reilly Media, 2019.

**2.** "Python Data Science Handbook: Essential Tools for Working with Data", Jake VanderPlas, O'Reilly Media, 2016.

**3** "Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python", Peter Bruce, Andrew Bruce & Peter Gedeck, 2nd Edition, O'Reilly Media, 2020.

**4** "Introduction to Machine Learning with Python: A Guide for Data Scientists", Andreas Müller & Sarah Guido, O'Reilly Media, 2016.

**Mode of Evaluation:** Continuous Internal Evaluation , Assignments, Mid Term Tests and End Semester Examination.

**Mandatory Course**

## 26BFCIVVC01 DISASTER MANAGEMENT

| L | T | P | C |
|---|---|---|---|
| 2 | 0 | 0 | 2 |

**Pre-requisite:** Nil

**Course Description:**

This course provides a comprehensive understanding of natural and human-induced disasters, their causes, characteristics, and consequences. It examines the social, economic, environmental, and life-safety impacts of disasters with emphasis on disaster-prone regions in India. The course introduces disaster preparedness and management through monitoring, risk evaluation, remote sensing, meteorological information, and community participation. It develops knowledge of disaster risk assessment, disaster risk reduction, early warning, and national and global cooperation. The course also focuses on structural and non-structural mitigation strategies and emerging approaches for reducing disaster vulnerability and impacts.

**Course Objectives:**

Upon the completion of subject student will be able to-

1. Develop fundamental knowledge of different natural and man-made disasters, their characteristics, causes, and associated hazards.
2. Examine the economic, environmental, ecological, and human consequences of disasters and identify disaster-prone regions in India.
3. Develop an understanding of disaster preparedness and management using monitoring systems, remote sensing, meteorological information, and community-based approaches.
4. Introduce the concepts, elements, and techniques of disaster risk assessment, risk reduction, early warning, and national and global cooperation.
5. Develop knowledge of structural and non-structural disaster mitigation strategies, emerging mitigation practices, and disaster mitigation programmes in India.

**UNIT I DISASTER CLASSIFICATION** **6 hours**

Disaster: definition, factors and significance; difference between hazard and Disaster; natural disaster: earthquakes, volcanisms, cyclones, tsunamis, floods, droughts and famines, landslides and avalanches; man-made disasters: nuclear reactor meltdown, industrial accidents, oil slicks and spills, outbreaks of disease and epidemics, war and conflicts

**UNIT II REPERCUSSIONS OF DISASTERS** **6 hours**

Economic damage, loss of human and animal life, destruction of ecosystem. Disaster Prone Areas in India: Study of seismic zones; areas prone to floods and droughts, landslides and Avalanches; areas prone to cyclonic and coastal hazards with special reference to tsunami.

**UNIT III DISASTER PREPAREDNESS AND MANAGEMENT** **6 hours**

Preparedness: monitoring of phenomena triggering a disaster or hazard; Evaluation of risk: application of remote sensing, data from meteorological and Other agencies, media reports: governmental and community preparedness.

**UNIT IV RISK ASSESSMENT** **6 hours**

Disaster risk: concept and elements, disaster risk reduction, global and national disaster risk situation. Techniques of risk assessment, global co-operation in risk assessment and warning.

**UNIT V DISASTER MITIGATION** **6 hours**

Meaning, concept and strategies of disaster mitigation, emerging trends in Mitigation. Structural mitigation and non-structural mitigation, programs of Disaster mitigation in India.

**Course outcomes:**

After the completion of the subject following outcomes can be achieved-

**CO1:** Classify natural and man-made disasters and explain their causes, characteristics, and associated hazards.

**CO2:** Assess the major economic, environmental, ecological, and human impacts of disasters and identify disaster-prone regions in India.

**CO3:** Explain disaster preparedness and management practices using hazard monitoring, remote sensing, meteorological data, and community preparedness mechanisms.

**CO4:** Apply appropriate techniques for disaster risk assessment and explain disaster risk reduction, early warning systems, and national and global cooperation mechanisms.

**CO5:** Evaluate and recommend suitable structural and non-structural mitigation measures for reducing disaster risk and impacts.

**Reference Books:**

1. Ghosh G.K., 2006, Disaster Management, APH Publishing Corporation
2. R. Nishith, Singh AK, "Disaster Management in India: Perspectives, issues and strategies "'New Royal book Company.
3. Sahni, PardeepEt.Al. (Eds.)," Disaster Mitigation Experiences and Reflections", Prentice Hall Of India, New Delhi.
4. Goel S. L., Disaster Administration And Management Text and Case Studies" ,Deep&Deep Publication Pvt. Ltd., New Delhi

**Mode of Evaluation:** Assignments, Mid Term Tests

# I Year II Semester

**M. Tech I Year II Semester**

## 25MBCAMTC03 MACHINE LEARNING FOR INTELLIGENT SYSTEMS

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Machine Learning**

**Course Description:**

This course introduces fundamental and advanced machine learning concepts for developing intelligent systems. It covers supervised, unsupervised, and reinforcement learning techniques, model evaluation, optimization, and data-driven decision-making. Emphasis is placed on designing adaptive, predictive, and intelligent solutions for engineering, automation, and diverse real-world applications using modern computational tools and methods.

**Course Objectives:**

1. Understand the fundamentals of machine learning systems, concept learning, and decision tree learning techniques.
2. Learn neural network models, backpropagation learning, and genetic algorithm-based optimization techniques.
3. Understand Bayesian learning methods and computational learning models used in machine learning.
4. Study instance-based learning methods and rule-based learning approaches for knowledge representation.
5. Understand analytical learning approaches and reinforcement learning techniques for adaptive systems.

**UNIT I INTRODUCTION, CONCEPT LEARNING AND DECISION TREES 9 hours**

Learning Problems – Designing Learning systems, Perspectives and Issues – Concept Learning – Version Spaces and Candidate Elimination Algorithm – Inductive bias – Decision Tree learning – Representation – Algorithm – Heuristic Space Search

**UNIT II NEURAL NETWORKS AND GENETIC ALGORITHMS 9 hours**

Neural Network Representation – Problems – Perceptrons – Multilayer Networks and Back Propagation Algorithms – Advanced Topics – Genetic Algorithms – Hypothesis Space Search – Genetic Programming – Models of Evolution and Learning.

**UNIT III BAYESIAN AND COMPUTATIONAL LEARNING 9 hours**

Bayes Theorem – Concept Learning – Maximum Likelihood – Minimum Description Length Principle – Bayes Optimal Classifier – Gibbs Algorithm – Naïve Bayes Classifier– Bayesian Belief Network – EM Algorithm – Probably Learning – Sample Complexity for Finite and Infinite Hypothesis Spaces – Mistake Bound Model.

**UNIT IV INSTANT BASED LEARNING AND LEARNING SET OF RULES 9 hours**

K- Nearest Neighbor Learning – Locally Weighted Regression – Radial Basis Functions –Case-Based Reasoning – Sequential Covering Algorithms – Learning Rule Sets – Learning First Order Rules – Learning Sets of First Order Rules – Induction as Inverted Deduction – Inverting Resolution

**UNIT V ANALYTICAL LEARNING AND REINFORCED LEARNING 10 Hours**

Perfect Domain Theories – Explanation Based Learning – Inductive-Analytical Approaches - FOCL Algorithm – Reinforcement Learning – Task – Q-Learning – Temporal Difference Learning

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1.** Explain concept learning methods and analyze decision tree learning algorithms for solving learning problems.

**CO2.** Apply neural network and genetic algorithm techniques for solving machine learning problems.

**CO3.** Analyze Bayesian classifiers and computational learning models for probabilistic learning tasks.

**CO4.** Apply instance-based and rule-based learning algorithms for pattern recognition and decision-making problems.

**CO5.** Analyze reinforcement learning methods and analytical learning algorithms for intelligent learning systems.

**Text Books:**

**1.** "Machine Learning", Tom M. Mitchell, Mc Graw- Hill Publication, 2017

**Reference Books:**

**1.** "Machine Learning: An Algorithmic Perspective", Stephen Marsland, 2nd Edition, Taylor & Francis, 2014.

**2.** "Machine Learning Theory and Practice", M N Murthy, V S Anantha narayana, Universities Press (India), 2024.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**M. Tech I Year II Semester**

## 25MBCAMTC04 DATA MANAGEMENT FOR MACHINE LEARNING

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites:** Database Management Systems

**Course Description:**

This course focuses on the principles and techniques for managing, preprocessing, and organizing data for machine learning applications. It covers data collection, cleaning, integration, transformation, storage, and feature engineering methods to ensure data quality and reliability. The course also covers scalable data management techniques, database systems, and data governance concepts essential for building effective machine learning solutions.

**Course Objectives:**

1. Understand the fundamentals of data engineering and modern data systems.
2. Analyze modern data architectures and platforms used for analytics and machine learning applications.
3. Apply data ingestion and management techniques in machine learning workflows.
4. Develop feature engineering and training data management strategies for ML systems.
5. Evaluate fairness, privacy, and ethical considerations in responsible AI and ML deployment.

**UNIT I FOUNDATIONS OF DATA ENGINEERING 9 hours**

Introduction to Data Engineering, Data Engineering Lifecycle, Evolution of the Data Engineer, Data Engineering and Data Science, Data Maturity and the Data Engineer, Data Engineers inside an Organization.

**UNIT II MODERN DATA PLATFORM 9 hours**

Data Architectures, Principles of good Data Architecture, Examples and types of Data Architectures, Modern Data Stack, Data Pipelines and patterns, Data Storage, Data Science Infrastructure, Serving Data for Analytics and ML.

**UNIT III DATA MANAGEMENT IN ML WORKFLOW 9 hours**

ML workflow lifecycle, ML Pipeline stages, Training / Serving pipeline, Data management challenges in ML workflow, Data Ingestion, Diverse data sources, Data generation in source systems, Batch Ingestion, Message and Stream Ingestion, Ingestion strategies.

**UNIT IV FEATURE AND TRAINING DATA 9 hours**

Feature Selection and Engineering, Lifecycle of a Feature, Feature Systems, Labels, Human-Generated Labels, Annotation Workforces, Measuring Human Annotation Quality, An Annotation Platform, Active Learning and AI-Assisted Labeling, Documentation and Training for Labelers, Metadata, Metadata Systems Overview, Dataset Metadata, Feature Metadata, Label Metadata, Pipeline Metadata.

**UNIT V FAIRNESS, PRIVACY, AND ETHICAL ML SYSTEMS 9 hours**

Fairness, Definitions of Fairness, Reaching Fairness, Fairness as a Process Rather than an Endpoint, Privacy, Methods to Preserve Privacy, Responsible AI, Effectiveness, Social and Cultural Appropriateness Responsible AI Along the ML Pipeline, Use Case Brainstorming, Data Collection and Cleaning, Model Creation and Training, Model Validation and Quality Assessment, Model Deployment.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to
**CO1.** Describe the lifecycle, roles, and importance of data engineering in organizations.
**CO2.** Analyze and compare modern data architectures, pipelines, and storage systems.
**CO3.** Apply suitable data ingestion and management methods in ML pipelines.
**CO4.** Develop effective feature engineering and metadata management solutions for ML workflows.
**CO5.** Evaluate fairness, privacy, and ethical practices in the design and deployment of AI systems.

**Text Books:**

1. "Fundamentals of Data Engineering: Plan and Build Robust Data Systems", Joe Reis and Matt Housley, O'Reilly Media, 2022.
2. "Reliable Machine Learning", Cathy Chen, O'Reilly Media, 2022.

**Reference Books:**

1. "Designing Data-Intensive Applications", Martin Kleppmann, O'Reilly Media, 2017.
2. "Building Machine Learning Pipelines: Automating Model Life Cycles with TensorFlow", Hannes Hapke and Catherine Nelson, O'Reilly Media, First Edition, 2020.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**M. Tech I Year II Semester**

**25MBCAMLC03 MACHINE LEARNING FOR INTELLIGENT SYSTEMS LABORATORY**

| L | T | P | C |
|---|---|---|---|
| 0 | 0 | 4 | 2 |

**Pre-requisite: Machine Learning**

**Course Description:**

This laboratory provides hands-on experience in implementing machine learning algorithms for intelligent systems. Students design, train, evaluate, and optimize supervised, unsupervised, and reinforcement learning models using real-world datasets. The course emphasizes practical skills in data preprocessing, model selection, performance analysis, experimentation, and development of intelligent engineering applications using modern computational tools.

**Course Objectives:**

1. Develop practical skills in implementing machine learning algorithms using programming tools and datasets.
2. Apply supervised and unsupervised learning techniques to solve real-world classification, prediction, and clustering problems.
3. Analyze the behavior and performance of machine learning models through experimental evaluation.
4. Build and test machine learning applications using standard programming libraries and data preprocessing techniques.
5. Evaluate and compare different machine learning algorithms for suitable problem domains.

**List of Programs:**

1. A bank wants to automate loan approval decisions based on customer attributes such as income, credit score, and employment status. Build a Decision Tree using the ID3 algorithm with an appropriate dataset and classify whether a new applicant is eligible for a loan.
2. A hospital intends to predict the likelihood of a disease based on patient health parameters. Implement an Artificial Neural Network using the Backpropagation algorithm and test the model using suitable medical datasets.
3. An email service provider wants to classify incoming emails as spam or non-spam using historical email data stored in a .CSV file. Implement the Naïve Bayesian classifier and evaluate its accuracy using test datasets.
4. A healthcare organization wants to assist doctors in diagnosing heart disease using patient medical records. Construct a Bayesian Network model using the standard Heart Disease dataset and demonstrate disease prediction using Java/Python ML libraries.
5. A retail company aims to group customers based on purchasing behavior stored in a .CSV file. Apply both EM and K-Means clustering algorithms, compare their clustering quality, and analyze which method provides better customer segmentation.
6. A botanical research center wants to classify flower species based on petal and sepal measurements from the Iris dataset. Implement the k-Nearest Neighbor algorithm and display both correct and incorrect predictions.
7. A real estate company wants to predict house prices based on factors such as area, location, and number of rooms. Implement the non-parametric Locally Weighted Regression algorithm using

an appropriate dataset and visualize the fitted regression curves through graphs.

8. A telecom company wants to identify customers who are likely to discontinue their services. Students must analyze the customer churn dataset, perform preprocessing, feature engineering, model selection, training, testing, and evaluation. Students should apply suitable machine learning algorithms and identify the model that gives the best accuracy. [Dataset link: https://www.kaggle.com/datasets/blastchar/telco-customer-churn]
9. A real estate company wants to predict house prices based on features such as location, area, number of bedrooms, age of the property, and nearby facilities. Students must preprocess the dataset, perform feature engineering, apply suitable regression algorithms and compare model performance using evaluation metrics. Students should identify the regression model that provides the best prediction accuracy.
   [Dataset link: https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/data]
10. A retail company wants to group customers based on their purchasing behavior for targeted marketing and personalized recommendations. Students must preprocess the dataset, perform feature selection, apply suitable clustering algorithms and compare the clustering performance using appropriate evaluation metrics such as Silhouette Score, Davies–Bouldin Index, and Within-Cluster Sum of Squares (WCSS). Students should identify the most suitable clustering model for effective customer segmentation.
   [Dataset link: https://www.kaggle.com/datasets/vjchoudhary7/customer-segmentation-tutorial-in-python]

**Course Outcomes:**
At the end of this course, students will be able to

**CO1:** Implement basic machine learning algorithms using datasets.

**CO2:** Apply classification and prediction techniques to real-world problems.

**CO3:** Analyze the performance of machine learning models.

**CO4:** Implement clustering and regression algorithms using ML tools.

**CO5:** Compare different machine learning techniques for data analysis.

**Text Books:**

**1.** “Machine Learning”, Tom M. Mitchell, MGH, 2017

**2.** “Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow”, Aurélien Géron, 2nd Edition, O’Reilly, 2019.

**Reference Books:**

**1.** “Machine Learning: An Algorithmic Perspective”, Stephen Marsland, 2nd Edition, Taylor & Francis, 2014.

**2.** “Pattern Recognition and Machine Learning”, Bishop C. M., 1st Edition, Springer, 2006.

**Mode of Evaluation** Continuous Internal Evaluation and End Semester Examination.

**B. Tech I Year II Semester**

**25MBCAMLC04 DATA MANAGEMENT FOR MACHINE LEARNING LABORATORY**

| L | T | P | C |
|---|---|---|---|
| 0 | 0 | 4 | 2 |

**Pre-requisite: Database Management Systems**

**Course Description:**

This laboratory course provides hands-on experience in data collection, preprocessing, cleaning, transformation, and storage for machine learning applications. It includes modern tools and platforms to manage datasets, perform feature engineering, and ensure data quality. Practical exercises focus on preparing scalable and reliable data pipelines for machine learning workflows.

**Course Objectives:**

1. To understand the fundamentals of data engineering and modern data systems.
2. To analyze modern data architectures and platforms used for analytics and machine learning applications.
3. To apply data ingestion and management techniques in machine learning workflows.
4. To develop feature engineering and training data management strategies for ML systems.
5. To evaluate fairness, privacy, and ethical considerations in responsible AI and ML deployment.

**List of Experiments**

1. A multinational e-commerce company processes millions of user interactions daily and requires low-latency analytics for recommendations. Design a distributed data pipeline using batch and streaming architectures. Evaluate scalability, throughput, and fault tolerance under varying workloads.
2. A smart city infrastructure continuously collects traffic data from IoT devices and cameras for congestion prediction. Implement a real-time analytics pipeline using stream processing frameworks and compare performance with batch processing systems.
3. A healthcare organization stores structured and unstructured patient data across multiple hospitals. Develop a cloud-based data lake architecture and analyze storage optimization, security, and query performance.
4. A banking system receives high-volume transaction data that must be processed for fraud detection in near real time. Build a distributed ETL workflow and evaluate latency, scalability, and reliability using large datasets.
5. An industrial IoT company monitors thousands of sensors generating continuous streams of telemetry data. Implement stream ingestion with fault tolerance and evaluate data consistency and recovery mechanisms.
6. A university wants to automate student performance prediction using continuously updated academic data. Develop an end-to-end ML workflow including preprocessing, model training, validation, deployment, and monitoring.
7. A video streaming platform requires reusable and real-time features for multiple recommendation models. Design and implement a feature management system and evaluate feature reuse, consistency, and serving latency.
8. A medical AI company requires accurate annotation of radiology images for disease diagnosis. Develop an annotation workflow integrating active learning and evaluate annotation quality using agreement metrics.

9. A loan approval AI system exhibits demographic bias in decision-making. Measure fairness metrics, compare mitigation strategies, and analyze the trade-off between fairness and accuracy.
10. A manufacturing company deploys AI models for predictive maintenance across multiple industrial plants. Develop and deploy a production ML pipeline with monitoring, drift detection, retraining, and performance evaluation.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1.** Describe the lifecycle, roles, and importance of data engineering in organizations.

**CO2.** Analyze and compare modern data architectures, pipelines, and storage systems.

**CO3.** Apply suitable data ingestion and management methods in ML pipelines.

**CO4.** Develop effective feature engineering and metadata management solutions for ML workflows.

**CO5.** Evaluate fairness, privacy, and ethical practices in the design and deployment of AI systems.

**Text Books:**

1. "Fundamentals of Data Engineering: Plan and Build Robust Data Systems", Joe Reis and Matt Housley, O'Reilly Media, 2022.
2. "Reliable Machine Learning", Cathy Chen, O'Reilly Media, 2022.

**Reference Books:**

1. "Designing Data-Intensive Applications", Martin Kleppmann, O'Reilly Media, 2017.
2. "Building Machine Learning Pipelines: Automating Model Life Cycles with TensorFlow", Hannes Hapke and Catherine Nelson, O'Reilly Media, First Edition, 2020.

**Mode of Evaluation:** Continuous Internal Evaluation and End Semester Examination.

**M. Tech I Year II Semester**
**Skill Enhancement Course – II**

## 25MBCAMSC02 GENERATIVE AI TECHNIQUES

| L | T | P | C |
|---|---|---|---|
| 1 | 0 | 2 | 2 |

**Pre-requisite: Python Programming & Machine Learnning**

**Course Description:**

This course introduces the fundamental concepts, architectures, and techniques of Generative Artificial Intelligence. It covers generative models, representation learning, autoencoders, generative adversarial networks, transformers, large language models, prompt engineering, retrieval-augmented generation, and multimodal generative AI. Students learn to understand, develop, evaluate, and apply generative AI techniques for text, image, audio, and other real-world applications, with emphasis on responsible, ethical, and reliable AI systems.

**Course Objectives:**

1. To understand the theoretical foundations and taxonomy of generative AI models.
2. To explore Generative Adversarial Networks (GANs) and their variants for image synthesis.
3. To learn Variational Autoencoders and Diffusion Models for generative applications.
4. To apply Transformer-based Large Language Models for text and multimodal generation.
5. To analyze ethical considerations, responsible use, and emerging trends in Generative AI.

**UNIT I INTRODUCTION TO GENERATIVE AI AND AUTOENCODERS 6 hours**

Overview of Generative AI - Discriminative vs Generative Models - Probability Distributions - Autoencoders - Types of Autoencoders - Latent Space and Representation Learning - Evaluation Metrics for Generative Models.

1. Implementing an Autoencoder for Handwritten Digit Reconstruction Using the MNIST Dataset
2. Visualizing and Exploring Latent Space Representations in Deep Generative Models

**UNIT II GENERATIVE ADVERSARIAL NETWORKS (GANs) 6 hours**

GAN Framework - GAN Loss Functions - Training Challenges in GANs - Conditional GAN (cGAN) - Deep Convolutional GAN (DCGAN) - CycleGAN - Progressive GAN and StyleGAN2 - Applications of GANs.

1. Implementing Deep Convolutional Generative Adversarial Networks (DCGAN) for Synthetic Image Generation
2. Developing Conditional GAN Models for Class-Specific Image Synthesis Using Deep Learning

**UNIT III VARIATIONAL AUTOENCODERS AND DIFFUSION MODELS 6 hours**

Variational Autoencoder (VAE) - Conditional VAE (CVAE) - β-VAE and Disentangled Representations - Score-Based and Energy-Based Generative Models - Denoising Diffusion Probabilistic Models (DDPM) - Stable Diffusion - DALL-E 2 and Imagen - ControlNet.

1. Implementing Variational Autoencoders (VAE) for Deep Learning-Based Image Generation,
2. Experimenting with Stable Diffusion Pipelines for Text-to-Image Synthesis Using Hugging Face Diffusers

**UNIT IV LARGE LANGUAGE MODELS AND TRANSFORMER-BASED GENERATION 6 hours**

Transformer Architecture - GPT Family Models - Text Generation Strategies - Instruction Tuning and RLHF - Parameter Efficient Fine-Tuning - Multimodal Generative Models - Retrieval Augmented Generation (RAG) - Code Generation Models.

1. Implementing Text Generation Using GPT-2 and HuggingFace Transformer Models
2. Fine-Tuning Pre-trained Large Language Models Using LoRA on Custom Domain-Specific Datasets

**UNIT V APPLICATIONS, PROMPT ENGINEERING, AND ETHICS IN GENERATIVE AI 6 hours**

Generative AI for Art, Music, Video, and 3D Content Generation - Building RAG Applications - Advanced Prompt Engineering - AI Agents and Tool Use - Deepfakes - Bias and Fairness in Generative Models - Intellectual Property and Copyright in Generative AI - Regulatory Landscape and Responsible AI Guidelines.

1. Developing a Retrieval-Augmented Generation (RAG) Based Question Answering System Using LangChain
2. Evaluating Bias in Generative AI Models and Implementing Prompt-Based Mitigation Techniques

**Course Outcomes:**

At the end of this course, students will be able to

**CO1:** Apply fundamental concepts of generative models to implement basic generative systems.

**CO2:** Implement GAN variants for image synthesis and translation.

**CO3:** Analyze and apply VAEs and Diffusion Models for image and multimodal applications.

**CO4:** Apply Transformer-based LLM for text generation, fine-tuning, and RAG-based applications.

**CO5:** Analyze ethical implications, bias, and responsible use of Generative AI in real-world.

**Text Books:**

**1.** "Generative Deep Learning: Teaching Machines to Paint, Write, Compose, and Play", David Foster, 2nd Edition, O'Reilly Media, 2023.

**2.** "Deep Learning", Ian Goodfellow, Yoshua Bengio and Aaron Courville, MIT Press, 2016.

**Reference Books:**

**1.** "Generative AI in Practice: 100+ Amazing Ways Generative Artificial Intelligence is Changing Business and Society", Bernard Marr, 1st Edition, Wiley, 2023.

**2.** "Transformers for Natural Language Processing and Computer Vision: Explore Generative AI and Large Language Models with Hugging Face", Denis Rothman, 3rd Edition, Packt Publishing, 2024.

**3** "Building LLM Powered Applications", Valentina Alto, Packt Publishing, 2024.

**4** "Hands-On Generative AI with Transformers and Diffusion Models", Omar Sanseviero, Pedro Cuenca, Apolinário Passos, Jonathan Whitaker, O'Reilly Media, 2024.

**Mode of Evaluation:** Continuous Internal Evaluation , Assignments, Mid Term Tests and End Semester Examination.

# Discipline Electives

**Discipline Elective – I**

## 25MBCAMDC01 MATHEMATICAL FOUNDATIONS FOR MACHINE LEARNING

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Nil**

**Course Description:**

This course focuses on the mathematical foundations of Artificial Intelligence and Machine Learning through linear algebra, probability, optimization, and statistical modeling. It provides the theoretical framework for analysing intelligent learning systems and modern AI models.

**Course Objectives:**

1. Develop a rigorous understanding of the mathematical foundations underlying intelligent learning systems.
2. Apply concepts from linear algebra, matrix theory, tensor analysis, and affine geometry to represent and analyse high-dimensional data.
3. Formulate mathematical models for learning systems using function spaces, hypothesis spaces, and statistical representations.
4. Analyse probabilistic models, latent variable models, and stochastic processes used in generative AI
5. Employ optimization techniques and mathematical principles underlying deep learning and modern machine learning architectures.

**UNIT I MATHEMATICAL TOOLS FOR INTELLIGENT LEARNING SYSTEMS 9 hours**

Data Sets, Vectors, and Matrices, Norms of Vectors, Functions and Matrices, Factoring Matrices and Tensors, Changes in $A^{-1}$ from Changes in A, Derivative of Eigen and Singular Values, Completing Rank One Matrices, Distance Matrices.

**UNIT II MATHEMATICAL REPRESENTATION OF LEARNING SYSTEMS 9 hours**

Classification of Remote Sensors, Selection of Sensor Parameters, Resolution Concept, Spectral Resolution, Radiometric Resolution, Temporal Resolution, Quality of Images, Imaging Modes, Photographic Camera, Opto-Mechanical Scanners, Pushbroom and Whiskbroom Cameras, Panchromatic Sensors, Multispectral Sensors, Thermal Sensors, Hyperspectral Scanners, Microwave Sensors

**UNIT III OPTIMIZATION FOR LEARNING 9 hours**

Convex sets and convex functions, Gradients of Vector-Valued Functions, Gradients of Matrices, Minimum Problems: Convexity and Newton's Method, Lagrange Multipliers: Derivatives of the Cost, Gradient Descent Toward the Minimum, Stochastic Gradient Descent and ADAM.

**UNIT IV STATISTICAL TOOLS FOR GENERATIVE AI 9 hours**

Probability measures and probability spaces, Measure-theoretic foundations, Random vectors, Covariance matrix and joint probabilities, Mixture distributions, Latent variable models, High-dimensional probability.

**UNIT V LEARNING FROM DATA 9 hours**

Mathematical Construction of Deep Neural Networks, Convolutional Neural Nets, Backpropagation and the Chain Rule, Computational Graphs, Hyperparameters, The World of Machine Learning, Mathematical Challenges in Deep Learning.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1:** Apply vectors, matrices, tensors, and matrix decompositions to mathematical modeling of intelligent learning systems.

**CO2:** Construct mathematical representations of learning systems using function spaces, affine mappings, hypothesis spaces, and high-dimensional vector spaces.

**CO3:** Formulate and solve optimization problems arising in intelligent systems using convex analysis, matrix calculus, gradient methods, and duality theory.

**CO4:** Analyse probabilistic models, stochastic processes, latent variable models, and statistical methods for generative AI.

**CO5**: Explain the mathematical foundations of deep neural networks, computational graphs, backpropagation, and emerging challenges in intelligent learning systems.

**Text Books:**

**1.** "Mathematics for Machine Learning", Marc Peter Deisenroth, A. Aldo Faisal, and Cheng Soon Ong, Cambridge University Press, 2020.

**2.** "Linear Algebra and Learning from Data", Gilbert Strang, , Wellesley-Cambridge Press, 2019.

**Reference Books:**

**1.** "Linear Algebra and Optimization for Machine Learning", Charu C. Aggarwal, Springer Nature Switzerland AG, 2020.

**2.** "Linear Algebra for Data Science, Machine Learning, and Signal Processing", Jeffrey A. Fessler, Raj Rao Nadakuditi, Cambridge University Press, 2024.

**3.** "Convex Optimization", Stephen Boyd and Lieven Vandenberghe, Cambridge University Press, 2004.

**4.** "Machine Learning: A Probabilistic Perspective ", Kevin P. Murphy, MIT Press, 2012.

**5.** "Deep Learning", Ian Goodfellow, Yoshua Bengio, and Aaron Courville, MIT Press, 2016.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – I**

## 25MBCAMDC02 DevOps

| L | T | P | C |
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**Prerequisites: NIL**

**Course Description:**

This course introduces the principles, practices, and lifecycle of DevOps. It covers version control, continuous integration, Docker, configuration management, Kubernetes, Helm, deployment strategies, monitoring, logging, and security. Students gain practical skills to develop, integrate, deploy, manage, and monitor applications efficiently using modern DevOps tools and automation techniques.

**Course Objectives:**

1. To explain the principles, culture, and benefits of DevOps along with its lifecycle stages.
2. To apply version control techniques and continuous integration concepts using Git and Jenkins.
3. To describe containerization technologies such as Docker and fundamentals of configuration management.
4. To implement deployment strategies and application orchestration using Kubernetes and Helm.
5. To analyse monitoring, logging, and security integration approaches in DevOps pipelines.

**UNIT I INTRODUCTION TO DEVOPS 9 hours**

Software development models: Waterfall, Agile, DevOps. DevOps principles, culture, and benefits. DevOps lifecycle stages: Plan, Develop, Build, Test, Release, Deploy, Operate, Monitor. The Three Ways: Flow, Feedback, and Continual Learning. Overview of DevOps tools: Git, Jenkins, Docker, Kubernetes, Ansible, Prometheus. Value Stream Mapping. DevOps metrics: Deployment frequency, Lead time, MTTR, Change failure rate. Case studies of DevOps adoption.

**UNIT II VERSION CONTROL AND CONTINUOUS INTEGRATION 9 hours**

Version Control Systems: Centralized vs. Distributed. Git basics: repository, commit, branch, merge, pull and push. Git workflows: Feature Branch, Gitflow, Trunk-Based Development. Continuous Integration concepts. Jenkins: architecture, pipeline, Jenkinsfile. Build tools: Maven and Gradle. Code quality analysis using SonarQube. Automated testing integration: unit, integration, and smoke tests.

**UNIT III CONTAINERIZATION AND CONFIGURATION MANAGEMENT 9 hours**

Virtualization vs. Containerization. Docker architecture: daemon, client, images, containers, registry. Dockerfile syntax and best practices. Docker Compose for multi-container applications. Docker networking and volumes. Configuration Management: idempotency and desired state. Ansible: inventory, playbooks, modules, roles. Overview of Puppet and Chef. Infrastructure as Code (IaC) principles.

**UNIT IV CONTINUOUS DELIVERY, DEPLOYMENT, AND ORCHESTRATION 9 hours**

Continuous Delivery vs. Continuous Deployment. Deployment strategies: Rolling updates, Blue-Green, Canary releases. Kubernetes architecture: Pods, Services, Deployments, ConfigMaps, Secrets. kubectl commands and YAML manifests. Application deployment workflows. Helm: package management for Kubernetes. GitOps principles and ArgoCD overview. Service mesh concepts.

**UNIT V MONITORING, LOGGING, AND DEVSECOPS 9 hours**

Role of monitoring and observability in DevOps. Prometheus: architecture, metrics collection, PromQL basics. Grafana: dashboards and alerting. Logging fundamentals: ELK stack — Elasticsearch, Logstash, Kibana. Distributed tracing: Jaeger and Zipkin overview. Introduction to DevSecOps. SAST and DAST. Vulnerability scanning with Trivy. Cloud-based DevOps: AWS CodePipeline, Azure DevOps, Google Cloud Build.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1:** Explain the DevOps lifecycle, culture, and its role in agile software delivery.
**CO2:** Apply version control and continuous integration practices using Git and Jenkins.
**CO3:** Build and manage containerized applications using Docker and Docker Compose.
**CO4:** Deploy and orchestrate applications using Kubernetes and Helm.
**CO5:** Implement monitoring, logging, and security integration in DevOps pipelines.

**Text Books:**

1. "Continuous Delivery: Reliable Software Releases through Build, Test, and Deployment Automation", Jez Humble, David Farley, Addison-Wesley, 2010.
2. "Infrastructure as Code: Dynamic Systems for the Cloud Age", Kief Morris, O'Reilly, 2nd Edition, 2021.

**Reference Books:**

1. "Continuous Delivery: Reliable Software Releases through Build, Test, and Deployment Automation", Jez Humble, David Farley, Addison-Wesley, 2010.
2. "Infrastructure as Code: Dynamic Systems for the Cloud Age", Kief Morris, O'Reilly, 2nd Edition, 2021.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – I**

## 25MBCAMDC03 EXPLAINABLE AI

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**Prerequisites: Python Programming & Machine Learning**

**Course Description:**

This course introduces the principles, methods, and techniques of Explainable Artificial Intelligence for developing transparent and interpretable machine learning systems. It covers model interpretability, feature importance, local and global explanations, surrogate models, LIME, SHAP, counterfactual explanations, visualization-based methods, and explainability for deep learning models. Students learn to analyse and communicate model decisions, evaluate explanation quality, and develop trustworthy AI solutions with emphasis on transparency, fairness, accountability, and responsible AI.

**Course Objectives:**

1. To understand the motivation, taxonomy, and evaluation criteria for Explainable AI (XAI).
2. To learn and implement model-agnostic local and global explanation methods.
3. To explore gradient-based and concept-based explainability techniques for deep learning models.
4. To analyze fairness, accountability, and transparency requirements in AI systems.
5. To apply XAI techniques in domain-specific applications including healthcare, finance, and NLP.

**UNIT I INTRODUCTION TO EXPLAINABILITY AND INTERPRETABILITY IN AI — 9 hours**

Motivation for XAI - Interpretability vs Explainability - Taxonomy of Explanations - Inherently Interpretable Models - Properties of Good Explanations - Challenges in XAI - Regulatory Context - Overview of XAI Frameworks.

**UNIT II MODEL-AGNOSTIC EXPLANATION METHODS — 9 hours**

Partial Dependence Plots (PDP) - Individual Conditional Expectation (ICE) Plots - Accumulated Local Effects (ALE) - Permutation Feature Importance - LIME - SHAP - TreeSHAP - SHAP Summary Plots - Counterfactual Explanations - Anchors.

**UNIT III EXPLAINABILITY FOR DEEP LEARNING MODELS — 9 hours**

Gradient-Based Methods - Backpropagation-Based Attribution - Class Activation Mapping (CAM) - Gradient-weighted CAM (Grad-CAM) and Grad-CAM++ - Integrated Gradients - DeepSHAP - Attention as Explanation - Concept-Based Explanations - Explainability for Natural Language Processing - Explainability for CNNs and RNNs.

**UNIT IV FAIRNESS, ACCOUNTABILITY AND TRANSPARENCY IN AI — 9 hours**

Bias in AI - Fairness Definitions - Fairness-Accuracy Trade-offs - Bias Mitigation Techniques - Algorithmic Accountability - Model Documentation - Human-in-the-Loop Systems - Robustness and Adversarial Examples - Privacy-Preserving Explainability.

**UNIT V DOMAIN-SPECIFIC XAI APPLICATIONS AND EMERGING TRENDS — 9 hours**

XAI in Healthcare - XAI in Finance - XAI in Autonomous Systems - XAI for Natural Language Processing - XAI in Cybersecurity - Evaluating XAI Methods - Emerging Trends in XAI - Tools and Libraries for Explainable AI.

**Course Outcomes:**
At the end of this course students will demonstrate the ability to
**CO1:** Understand and apply fundamental concepts of Explainable AI systems.
**CO2:** Implement model-agnostic explanation methods and importance techniques.
**CO3:** Apply gradient-based, backpropagation-based, and concept-based explainability methods for deep learning models.
**CO4:** Analyze bias, fairness, and accountability in AI systems and apply appropriate mitigation strategies.
**CO5:** Design and evaluate XAI solutions tailored to domain-specific applications.

**Text Books:**

1. "Interpretable Machine Learning: A Guide for Making Black Box Models Explainable", Christoph Molnar, 2nd Edition, Lulu.com, 2022.
2. "Explainable AI: Interpreting, Explaining and Visualizing Deep Learning", Wojciech Samek, Grégoire Montavon, Andrea Vedaldi, Lars Kai Hansen, Klaus-Robert Müller (Eds.), Springer, 2019.

**Reference Books:**

1. "Responsible Machine Learning: Actionable Strategies for Mitigating Risks and Driving Adoption", Patrick Hall and Navdeep Gill, O'Reilly Media, 2022.
2. "Trustworthy Machine Learning", Kush R. Varshney, Independently Published, 2022.
3. "Human-Compatible: Artificial Intelligence and the Problem of Control", Stuart Russell, Viking Press, 2019.
4. "Fairness and Machine Learning: Limitations and Opportunities", Solon Barocas, Moritz Hardt and Arvind Narayanan, MIT Press, 2023.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – I**

## 25MBCAMDC04 DEEP NEURAL NETWORKS

| L | T | P | C |
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**Prerequisites: Python Programming & Machine Learning**

**Course Description:**

This course introduces the mathematical foundations and fundamental concepts of deep learning. It covers feedforward neural networks, optimization and regularization techniques, convolutional and recurrent neural networks, autoencoders, and generative models. Students develop an understanding of deep learning architectures and techniques used to build effective models for solving real-world applications.

**Course Objectives:**

1. To understand the mathematical foundations for deep learning.
2. To learn the concepts of feedforward neural networks.
3. To understand regularization and optimization techniques.
4. To learn convolutional and recurrent network architectures.
5. To understand generative models and autoencoders.

**UNIT I INTRODUCTION AND MACHINE LEARNING BASICS 9 hours**

Introduction to Deep Learning. Historical Trends in Deep Learning. Learning Algorithms. Capacity, Overfitting and Underfitting. Hyperparameters and Validation Sets. Estimators, Bias and Variance. Maximum Likelihood Estimation. Supervised and Unsupervised Learning.

**UNIT II DEEP FEEDFORWARD NETWORKS 9 hours**

Learning XOR Problem. Gradient-Based Learning. Hidden Units: ReLU, Sigmoid, Tanh. Output Units. Architecture Design. Back-Propagation Algorithm. Computational Graphs.

**UNIT III REGULARIZATION AND OPTIMIZATION 9 hours**

Parameter Norm Penalties: L1 and L2 Regularization. Dropout. Early Stopping. Data Augmentation. Gradient Descent Variants. Learning Rate Scheduling. Challenges in Optimization: Local Minima, Saddle Points.

**UNIT IV CONVOLUTIONAL AND RECURRENT NETWORKS 9 hours**

Convolution Operation. Pooling. Convolution and Pooling as Infinitely Strong Prior. Basic CNN Structure. Unfolding Computational Graphs. Recurrent Neural Networks. Bidirectional RNNs. Long Short-Term Memory (LSTM).

**UNIT V AUTOENCODERS AND GENERATIVE MODELS 9 hours**

Undercomplete Autoencoders. Regularized Autoencoders. Denoising Autoencoders. Representational Learning. Introduction to Generative Models. Generative Adversarial Networks: Generator and Discriminator Concepts.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1:** Explain the fundamentals of machine learning and deep learning.

**CO2:** Describe feedforward networks and back-propagation algorithm.

**CO3:** Apply regularization and optimization concepts to neural networks.

**CO4:** Explain the architecture of CNNs and RNNs.

**CO5:** Describe autoencoders and generative models.

**Text Books:**


1. "Deep Learning", Ian Goodfellow, Yoshua Bengio, and Aaron Courville, MIT Press, 2016.
2. "Neural Networks and Deep Learning: A Textbook", Charu C. Aggarwal, Springer, 2018


**Reference Books:**


1. "Neural Networks and Learning Machines", Simon Haykin, 3rd Edition, Pearson, 2009.
2. "Neural Networks and Deep Learning", Michael Nielsen, Determination Press, 2015.


**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – II**

## 25MBCAMDC05 STOCHASTIC MODELS AND APPLICATIONS

| L | T | P | C |
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| 3 | 0 | 0 | 3 |

**Prerequisites: Nil**

**Course Description:**

This course introduces the mathematical foundations of stochastic modelling and its applications in Artificial Intelligence, Machine Learning, Computer Science, and Engineering. It covers stochastic processes, Markov chains, Poisson processes, queueing models, and statistical regression techniques for modelling uncertainty and analyzing real-world data.

**Course Objectives:**

1. Understand stochastic processes and Markov chains for modelling random systems.
2. Analyse exponential distributions and Poisson processes in stochastic modelling.
3. Apply queueing theory to analyse service and communication systems.
4. Develop simple linear regression models and perform ANOVA for statistical analysis.
5. Build multiple linear regression models for prediction and data analysis.

### UNIT I STOCHASTIC PROCESSES AND MARKOV CHAINS 9 hours

Introduction to Stochastic Processes and Markov Chains, Transition probability matrix, Chapman–Kolmogorov equations, Classification of states, Limiting Probabilities, Mean Time Spent in Transient States.

### UNIT II POISSON PROCESS 9 hours

Definition of Exponential distribution, Properties of the Exponential Distribution, hazard rate function, Definition of the Poisson Process, Inter-arrival and Waiting Time Distributions, Properties of Poisson Processes.

### UNIT III QUEUING THEORY 9 hours

Introduction, Preliminaries- Cost Equations - Steady-State Probabilities, Exponential Models - A Single-Server Exponential Queueing System - Single-Server Exponential Queueing System Having Finite Capacity -Birth and Death Queueing Models -A Shoe Shine Shop -A Queueing System with Bulk Service, Network of Queues.

### UNIT IV SIMPLE LINEAR REGRESSION AND ANOVA 9 hours

Simple Linear Regression – Model and parameter estimation, Confidence Interval Estimation and Hypothesis testing, Residual analysis. ANOVA: One-Way classification (with equal and unequal replicates), Two-Way classification.

### UNIT V MULTIPLE LINEAR REGRESSION 9 hours

Least-Squares procedure for Multiple Linear Regression Model fitting, Properties of Least-Squares estimators, testing hypothesis for model parameters, Criteria for variable selection.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1:** Apply the Knowledge of stochastic processes and Markov chains in AI and Machine Learning.

**CO2:** Analyse the exponential distribution and Poisson processes.

**CO3:** Evaluate queueing models and their performance measures.

**CO4:** Develop regression models for predictive data analysis.

**CO5**: Apply statistical modelling techniques to solve AI and machine learning problems.

**Text Books:**

1. "Introduction to Probability Models", S.M. Ross, 10th edition, Academic Press, 2009
2. "Introduction to Probability and Statistics", J.S. Milton and J.C. Arnold, 4th edition, Tata McGraw-Hill Publications, 2003.

**Reference Books:**

1. "Probability and Information ", A M Yagolam, I.M. Yagolam, Hindustan Pub. Corp, 1983.
2. "Probability Essentials ", J. Jacob, P. Protter, 2nd edition Springer Verlag, 2013.
3. "An Introduction to Applied Probability", Blake, John Wiley, 2011.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – II**

## 25MBCAMDC06 AGENTIC AI

| L | T | P | C |
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**Prerequisites: Python Programming & Machine Learning**

**Course Description:**

This course introduces the mathematical foundations of stochastic modelling and its applications in Artificial Intelligence, Machine Learning, Computer Science, and Engineering. It covers stochastic processes, Markov chains, Poisson processes, queueing models, and statistical regression techniques for modelling uncertainty and analyzing real-world data.

**Course Objectives:**

1. To introduce the fundamentals of generative AI and the core concepts, architectures, and applications of agentic AI systems.
2. To provide knowledge of representation and reasoning techniques used in intelligent and adaptive agents.
3. To understand tool usage, planning, coordination, and collaboration in multi-agent systems.
4. To familiarize with memory architectures, context management, prompting strategies, and knowledge-grounded agentic systems.
5. To create awareness about safety, explainability, governance, ethical issues, and real-world applications of agentic AI systems.

**UNIT I FOUNDATIONS OF AGENTIC AI — 9 hours**

Types of generative AI models – VAEs, GANs, Autoregressive Models, Transformer Architecture. Foundations of Agentic AI: LLM-powered AI agents, characteristics of intelligent agents, self-governance, agency and autonomy. Architectures of agentic systems – Deliberative, Reactive and Hybrid Architectures. Industry use cases of agentic systems. Challenges and limitations of generative AI

**UNIT II KNOWLEDGE REPRESENTATION AND REASONING — 9 hours**

Knowledge representation: Semantic Networks, Frames, Logic-based Representations.
Reasoning mechanisms: Deductive, Inductive and Abductive Reasoning. Learning mechanisms for adaptive agents, Meta-reasoning, Self-explanation and Self-modeling.

**UNIT III TOOL USE AND MULTI-AGENT COLLABORATION — 9 hours**

Tool and Function Calling, Defining and Integrating Tools, Types of Tools. Planning for tool use and reasoning with tools. Practical implementations using CrewAI, AutoGen and LangGraph.
Multi-Agent Systems (MAS) – Characteristics, Interaction Mechanisms, Communication, Coordination and Negotiation. Coordinator–Worker–Delegator (CWD) model, role assignments and collaborative workflows. Sequential and Parallel Processing in agentic workflows. Building a goal-driven LLM agent with tool calling.

**UNIT IV MEMORY, CONTEXT MANAGEMENT AND KNOWLEDGE-GROUNDED AGENTIC SYSTEMS — 9 hours**

Prompt engineering for agents – Focused system prompts, task specifications, objectives and contextual awareness. State spaces and environment modeling. Agent memory architecture and context management – Short-term memory, Long-term memory and Episodic memory. Integration of memory with decision-making. Monitoring and adaptation in agentic systems. Knowledge-grounded agentic systems and interaction patterns. System prompts, instruction formatting and agent behavior design.

**UNIT V SAFETY, EXPLAINABILITY, DEPLOYMENT AND APPLICATIONS OF AGENTIC AI 9 hours**

Safety, Governance and Explainability in Agentic AI – Transparency, Explainability, User Control and Consent, Ethical Development and Responsibility. Managing risks in generative AI – Adversarial attacks, Bias and Discrimination, Hallucinations, Privacy Violations and Intellectual Property Risks. Ethical guidelines and frameworks, accountability and human-centric design. Common applications of agentic AI – Conversational agents, Decision-support agents, Robotics and Autonomous Systems, Financial and E-commerce applications.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1.** Understand the foundations, architectures, capabilities, and limitations of generative and agentic AI systems.

**CO2.** Apply knowledge representation, reasoning, and learning mechanisms in intelligent agent design.

**CO3.** Develop multi-agent and tool-integrated AI systems using contemporary agentic AI frameworks and workflows.

**CO4.** Design memory-enabled and knowledge-grounded agentic systems with effective context management and adaptive behavior.

**CO5.** Analyze the safety, ethical, explainability, governance, and application aspects of agentic AI systems in real-world domains.

**Text Books:**

1. "Building Agentic AI Systems", Anjanava Biswas, Wrick Talukdar, Packt Publishing, 2025.
2. "Artificial Intelligence: A Modern Approach", Russell, Norvig, $4^{th}$ Edition, Pearson Education, 2022.

**Reference Books:**

1. "Agentic Artificial Intelligence: Harnessing AI Agents to Reinvent Business, Work, and Life", Bornet, Jochen Wirtz, Thomas H Davenport, Irreplaceable Publishing, 2025
2. "Agentic AI Unleashed A Guide to Designing, Building, and Deploying Autonomous AI Systems", Jayaram Nanduri, Anand Oka, BPB Publications, 2026.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – II**

## 25MBCAMDC07 STATISTICAL NATURAL LANGUAGE PROCESSING

| L | T | P | C |
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**Prerequisites: Python Programming & Machine Learning**

**Course Description:**

This course introduces statistical and computational approaches to Natural Language Processing, covering text preprocessing, probability models, language modeling, syntactic and semantic analysis, parsing, and information extraction. It explores neural networks, word embeddings, RNNs, LSTMs, transformers, BERT, GPT, and large language models. Students study NLP applications including sentiment analysis, machine translation, information retrieval, question answering, conversational AI, and generative AI, with emphasis on multilingual NLP, RAG, ethical AI, explainability, and emerging research trends.

**Course Objectives:**

1. To introduce the fundamental concepts of Natural Language Processing (NLP), computational linguistics, and statistical approaches used in language processing systems.
2. To develop proficiency in probabilistic language modeling, text preprocessing, syntactic analysis, semantic processing, and statistical machine learning techniques for NLP applications.
3. To provide knowledge of neural networks, deep learning architectures, transformer models, and large language models used in modern NLP systems.
4. To enable students to understand NLP applications such as machine translation, information retrieval, sentiment analysis, question answering, and conversational AI systems.
5. To familiarize students with advanced research trends in Statistical NLP including multilingual NLP, ethical AI, explainable NLP systems, and generative AI applications.

**UNIT I INTRODUCTION TO NATURAL LANGUAGE PROCESSING AND STATISTICAL FOUNDATIONS 9 hours**

Introduction to Natural Language Processing, Applications of NLP, Challenges in Natural Language Understanding, Levels of Language Analysis: Phonology, Morphology, Syntax, Semantics, Pragmatics and Discourse, Corpus Linguistics and Text Corpora, Text Preprocessing Techniques: Tokenization, Stop-word Removal, Stemming and Lemmatization, Regular Expressions and Finite State Automata, Statistical Foundations for NLP, Probability Theory, Bayes Theorem, Conditional Probability, N-gram Language Models, Smoothing Techniques: Laplace Smoothing, Good-Turing Estimation, Kneser-Ney Smoothing, Hidden Markov Models (HMM), Statistical Approaches in NLP.

**UNIT II SYNTACTIC ANALYSIS AND STATISTICAL PARSING 9 hours**

Part-of-Speech Tagging, Rule-based and Statistical POS Tagging, Markov Models for POS Tagging, Context Free Grammars (CFG), Dependency Grammar, Parsing Techniques: Top-down Parsing, Bottom-up Parsing, CYK Parsing Algorithm, Probabilistic Context Free Grammars (PCFG), Statistical Parsing Methods, Treebanks and Annotation Techniques, Named Entity Recognition (NER), Chunking and Shallow Parsing, Word Sense Disambiguation, Semantic Similarity and Lexical Semantics, Information Extraction Techniques.

**UNIT III NEURAL NETWORKS AND DEEP LEARNING FOR NLP 9 hours**

Introduction to Neural Networks for NLP, Distributed Word Representations, Word Embeddings: Word2Vec, GloVe and FastText, Neural Language Models, Feed Forward Neural Networks, Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Sequence Modeling in NLP, Attention Mechanism, Encoder-Decoder Architectures, Sequence-to-Sequence Learning, Transformer Architecture, BERT, GPT and Pre-trained Language Models, Transfer Learning in NLP, Fine-tuning Techniques, Text Classification using Deep Learning, Sentiment Analysis, Neural Machine Translation, Text Summarization and Conversational AI Systems.

**UNIT IV ADVANCED NLP APPLICATIONS AND GENERATIVE AI 9 hours**

Question Answering Systems, Information Retrieval and Search Engines, Dialogue Systems and Chatbots, Speech and Language Integration, Cross-lingual and Multilingual NLP, Low-resource Language Processing, Knowledge Graphs and Semantic Web Technologies, Explainable AI in NLP, Ethical Issues in NLP and Responsible AI, Bias and Fairness in Language Models, Privacy and Security in NLP Applications, Generative AI and Large Language Models (LLMs), Prompt Engineering Techniques, Retrieval Augmented Generation (RAG), Few-shot and Zero-shot Learning, Multimodal NLP, NLP in Healthcare, Finance and Social Media Analytics, Current Research Trends in Statistical NLP.

**UNIT V ADVANCED STATISTICAL NLP AND LARGE LANGUAGE MODELS 9 hours**

Statistical Machine Translation, Probabilistic Graphical Models for NLP, Conditional Random Fields (CRF), Topic Modeling using Latent Dirichlet Allocation (LDA), Sequence Labeling Techniques, Transformer-based Statistical Models, Large Language Models (LLMs), GPT Architecture and Variants, Prompt Engineering and In-context Learning, Fine-tuning of Pre-trained Language Models, Retrieval Augmented Generation (RAG), Conversational AI and Dialogue Systems, Multilingual and Cross-lingual NLP, Explainable and Ethical NLP, Bias and Fairness in Language Models, Applications of Statistical NLP in Healthcare, Finance and Social Media Analytics, Recent Research Trends in Statistical NLP.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1:** Explain the fundamental concepts of Natural Language Processing, computational linguistics, corpus processing, and statistical foundations used in NLP systems.
**CO2:** Apply probabilistic models, language modeling techniques, syntactic parsing, semantic analysis, and statistical methods for solving NLP tasks.
**CO3:** Design and implement neural network and deep learning based NLP models using word embeddings, RNNs, LSTMs, transformers, and pre-trained language models.
**CO4:** Develop NLP applications such as sentiment analysis, machine translation, information retrieval, question answering, text summarization, and conversational AI systems.
**CO5:** Analyze advanced topics in Statistical NLP including large language models, generative AI, multilingual NLP, ethical AI, explainable NLP systems, and recent research trends in NLP applications.

**Text Books:**

1. "Foundations of Statistical Natural Language Processing", Christopher D. Manning and Hinrich Schütze, MIT Press, 1999.
2. "Natural Language Processing with Transformers", Lewis Tunstall, Leandro von Werra and Thomas Wolf, O'Reilly Media, 2022.

**Reference Books:**


**1.** Natural Language Processing with Python", Steven Bird, Ewan Klein and Edward Loper, O'Reilly Media, 2009.

**2.** "Neural Network Methods for Natural Language Processing", Yoav Goldberg, Morgan & Claypool Publishers, 2017.


**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – II**

## 25MBCAMDC08 MACHINE LEARNING FOR IMAGE PROCESSING

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**Prerequisites: Python Programming & Machine Learning**

**Course Description:**

This course introduces the fundamentals of machine learning and digital image processing, covering image preprocessing, enhancement, feature extraction, segmentation, and classification techniques. It also explores deep learning, CNNs, image restoration, and advanced AI-based image processing applications for real-world problems.

**Course Objectives:**

1. Understand the fundamentals of machine learning and digital image processing techniques.
2. Apply image enhancement, preprocessing, and feature extraction methods for image analysis.
3. Develop image segmentation and classification models using machine learning algorithms.
4. Implement deep learning techniques for image recognition and processing applications.
5. Analyze advanced image processing techniques for real-world applications.

**UNIT I INTRODUCTION TO MACHINE LEARNING AND IMAGE PROCESSING — 9 hours**

Introduction to Machine Learning, Types of Machine Learning – Supervised, Unsupervised and Reinforcement Learning, Applications of Machine Learning in Image Processing, Digital Image Fundamentals, Image Representation, Image Sampling and Quantization, Image Datasets, Image Preprocessing Techniques, Feature Extraction Basics.

**UNIT II IMAGE ENHANCEMENT AND FEATURE ENGINEERING — 9 hours**

Image Enhancement in Spatial Domain, Gray Level Transformations, Histogram Processing, Spatial Filtering Techniques, Smoothing and Sharpening Filters, Feature Extraction Methods, Edge Features, Texture Features, Color Features, Dimensionality Reduction Techniques – PCA and LDA.

**UNIT III IMAGE SEGMENTATION AND CLASSIFICATION — 9 hours**

Thresholding Techniques, Edge-based and Region-based Segmentation, Image Classification Fundamentals, k-Nearest Neighbors (k-NN), Support Vector Machine (SVM), Decision Trees, Naïve Bayes, Clustering Techniques – K-Means and Hierarchical Clustering, Performance Evaluation Metrics.

**UNIT IV DEEP LEARNING FOR IMAGE PROCESSING — 9 hours**

Introduction to Deep Learning, Artificial Neural Networks, Convolutional Neural Networks (CNN), Image Classification using CNN, Transfer Learning, Object Detection Basics, Image Compression Techniques, Autoencoders, Image Compression Standards.

**UNIT V ADVANCED IMAGE PROCESSING AND APPLICATIONS — 9 hours**

Morphological Image Processing – Dilation, Erosion, Opening and Closing, Color Image Processing, Color Models, Image Restoration and Reconstruction, Image Recognition Applications, Medical Image Analysis, Face Recognition, Image Generation Basics, Recent Trends in AI-based Image Processing.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1.** Understand the concepts of machine learning and digital image processing fundamentals.
**CO2.** Apply image enhancement, filtering, and feature extraction techniques for image analysis.
**CO3.** Develop image segmentation and classification models using machine learning algorithms.
**CO4.** Implement deep learning models such as CNNs for image recognition tasks.
**CO5.** Analyze and design intelligent image processing applications using advanced AI techniques.

**Text Books:**

1. "Digital Image Processing: Illustration using Python", William McKinney, 1st Edition, Springer Nature, 2025.
2. "Image Processing and Machine Learning", Chapman & Hall, 1st Edition, CRC, 2024.
3. "Digital Image Processing", Rafael C. Gonzalez, Richard E. Woods, 4th Edition, Pearson Education, 2022

**Reference Books:**

1. "Practical Machine Learning for Computer Vision", Valliappa Lakshmanan, Martin Görner, Ryan Gillard, O'Reilly Media, 2021.
2. "Computer Vision: Algorithms and Applications", Richard Szeliski, 2nd Edition, Springer, 2022.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – III**

## 25MBCAMDC09 STATISTICAL DATA ANALYTICS FOR ARTIFICIAL INTELLIGENCE

| L | T | P | C |
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| 3 | 0 | 0 | 3 |

**Prerequisites: Python Programming, Probability & Statistics**

**Course Description:**

This course introduces statistical methods for data analysis, including sampling, experimental design, non-parametric tests, and multivariate analysis. It covers linear programming, optimization techniques, and time series analysis. Students develop practical skills to analyze data, solve optimization problems, build forecasting models, and support effective decision-making using statistical and computational tools.

**Course Objectives:**

1. Understand sampling methods, experimental design, and statistical analysis using software tools.
2. Apply non-parametric statistical tests to analyze different types of data.
3. Understand and analyze multivariate data using statistical techniques.
4. Solve optimization problems using linear programming and related methods.
5. Analyze and model time series data for forecasting and decision-making.

**UNIT I SAMPLING AND DESIGN OF EXPERIMENTS — 9 hours**

Sampling(review) F-test, Analysis of variance- one way and two-way classifications. Randomized block design, Resampling Techniques and Bootstrapping. Introduction to contemporary statistical packages-SPSS(JASP), R

**UNIT II NON-PARAMETRIC METHODS — 9 hours**

Introduction -The Sign Test, The Mann–Whitney U Test, The Kruskal–Wallis H Test, The H Test Corrected for Ties, The Runs Test for Randomness, Further Applications of the Runs Test, Spearman's Rank Correlation

**UNIT III MULTIVARIATE ANALYSIS — 9 hours**

Multivariate distributions: multivariate normal distribution and its properties, distributions of linear and quadratic forms, tests for partial and multiple correlation coefficients and regression coefficients and their associated confidence regions. Data analytic illustrations

**UNIT IV OPTIMIZATION TECHNIQUES — 9 hours**

Model Classification, Mathematical modelling of linear programming, graphical method, simplex method, degeneracy, Big M method, Transportation and Assignment problems

**UNIT V TIME SERIES ANALYSIS — 9 hours**

Introduction, Review of basic statistics, Stationarity, Ergodicity, Autocorrelation, Partial Autocorrelation, Linear Models, Autoregressive Models, Moving Average Models. Introduction to Conditional Heteroscedastic Models, ARCH Model, GARCH

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1.** Apply sampling techniques, ANOVA, experimental designs, and statistical software for data analysis.

**CO2.** Analyse datasets using appropriate non-parametric statistical methods.

**CO3.** Apply multivariate statistical techniques to analyse relationships among multiple variables.

**CO4.** Formulate and solve optimization problems using linear programming and related methods.
**CO5.** Analyse and interpret time series data using forecasting models such as AR, MA, ARCH, and GARCH.

**Text Books:**

**1.** "Introduction to mathematical Statistics", Hogg and Craig, 6th Edition, Pearson Education, 2018.

**2.** "An Introduction to Multivariate Statistical Analysis", T. W. Anderson, Wiley, 2009.

**Reference Books:**

**1.** "Fundamentals of Mathematical Statistics", Gupta, S. C. & Kapoor, V. K.,$11^{th}$ Edition., S.Chand and Company Pvt. Ltd., 2014.

**2.** "Probability and Statistics ", Schaum Outlines, $3^{rd}$ Edition, Mc Graw Hill, 2010.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – III**

## 25MBCAMDC10 ADVANCES IN SYSTEM AND NETWORK SECURITY

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Computer Networks, Cyber Security Fundamentals**

**Course Description:**

This course introduces fundamental concepts of system and network security, including software vulnerabilities, secure coding, operating system security, intrusion detection, firewalls, and secure communication. It covers database, data center, cloud, and IoT security, along with risk assessment, security controls, security management, and physical security practices for protecting information systems.

**Course Objectives:**

1. To understand software vulnerabilities, secure coding, and operating system security.
2. To understand intrusion detection, firewalls, and intrusion prevention techniques.
3. To understand network security protocols and secure communication mechanisms.
4. To understand security issues in databases, data centers, cloud, and IoT systems.
5. To understand security management, risk assessment, security controls, and physical security.

**UNIT I SOFTWARE AND SYSTEM SECURITY — 9 hours**

Software Security: Software Security Issues, Handling Program Input, Writing Safe Program Code, Interacting with the Operating System and Other Programs, Handling Program Output.
Operating System Security: System Security Planning, Operating Systems Hardening, Application Security, Security Maintenance, Linux/Unix Security, Windows Security.

**UNIT II INTRUSION DETECTION, FIREWALLS AND INTRUSION PREVENTION SYSTEMS — 9 hours**

Intrusion Detection: Analysis Approaches, Host-Based Intrusion Detection, Network-Based Intrusion Detection, Distributed or Hybrid Intrusion Detection, Intrusion Detection Exchange Format, Honeypots
Firewalls and Intrusion Prevention Systems: Firewall Characteristics and Access Policy, Types of Firewalls, Firewall Basing, Firewall Location and Configurations, Intrusion Prevention Systems

**UNIT III NETWORK AND COMMUNICATION SECURITY — 9 hours**

Secure E-mail and S/MIME, Domain keys Identified Mail, Secure Sockets Layer (SSL) and Transport Layer Security (TLS), IPv4 and IPv6 Security, Kerberos, X.509, Wireless Security, Mobile Device Security, IEEE 802.11 Wireless LAN Overview, IEEE 802.11i Wireless LAN Security.

**UNIT IV ADVANCED DATA, CLOUD AND IoT SECURITY — 9 hours**

Database and Data Center Security: SQL Injection Attacks, Database Access Control, Inference, Database Encryption, Data Center Security.
Cloud and IoT Security: Cloud Security Concepts, Cloud Security Approaches, The Internet of Things, IoT Security.

**UNIT V MANAGEMENT ISSUES** **9 hours**

IT Security Management and Risk Assessment: IT Security Management, Organizational Context and Security Policy, Security Risk Assessment, Detailed Security Risk Analysis.
IT Security Controls, Plans, and Procedures: IT Security Management Implementation, Security Controls or Safeguards, IT Security Plan, Implementation of Controls, Monitoring Risks.
Physical and Infrastructure Security: Physical Security Threats, Physical Security Prevention and Mitigation Measures, Recovery from Physical Security Breaches.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1.** Explain software and operating system security concepts and vulnerabilities.

**CO2.** Apply intrusion detection, firewall, and intrusion prevention techniques to secure networks.

**CO3.** Analyze network security protocols and mechanisms for secure communication.

**CO4.** Analyze security threats and protection mechanisms in databases, cloud, data centers, and IoT systems.

**CO5.** Evaluate security risks and select appropriate security controls, policies, and protection measures.

**Text Books:**

**1.** "Computer Security Principles and Practice", William Stallings, Lawrie Brown, 4th Edition, Pearson Education Limited, 2018.
**2.** "Cryptography and Network Security", Behrouz A. Forouzan, McGraw-Hill Education, 2007.

**Reference Books:**

**1.** "Network Security Essentials: Applications and Standards", William Stallings, Pearson Education Limited, 2014
**2.** "Security in Computing", Charles P. Pfleeger, Shari Lawrence Pfleeger and Jonathan Margulies, 5th Edition, Pearson Education, 2018.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – III**

## 25MBCAMDC11 REMOTE SENSING AND GIS

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Nil**

**Course Description:**

This course introduces the principles, physics, and applications of remote sensing and Geographic Information Systems (GIS). It covers remote sensing sensors, satellite data reception, data products, storage formats, spatial data models, and data input methods. Students learn GIS data output, web-based GIS, and practical applications for spatial data analysis and decision-making.

**Course Objectives:**

1. Understand the basic principles and physics of remote sensing.
2. Learn the concepts and characteristics of different remote sensing sensors.
3. Understand satellite data reception, data products, and storage formats.
4. Learn the fundamentals of GIS, spatial data models, and data input methods.
5. Understand GIS data output, web-based GIS, and its practical applications.

**UNIT I PHYSICS OF REMOTE SENSING 9 hours**

Remote Sensing, Definition, Components, Electro Magnetic Spectrum, Basic Wave Theory, Particle Theory, Stefan Boltzmann Law, Wien's Displacement Law, Radiometric Quantities, Effects of Atmosphere, Scattering, Different Types, Absorption, Atmospheric Window, Energy Interaction with Surface Features, Spectral Reflectance of Vegetation, Soil and Water, Atmospheric Influence on Spectral Response Patterns, Multi Concept in Remote Sensing.

**UNIT II SENSORS 9 hours**

Classification of Remote Sensors, Selection of Sensor Parameters, Resolution Concept, Spectral Resolution, Radiometric Resolution, Temporal Resolution, Quality of Images, Imaging Modes, Photographic Camera, Opto-Mechanical Scanners, Pushbroom and Whiskbroom Cameras, Panchromatic Sensors, Multispectral Sensors, Thermal Sensors, Hyperspectral Scanners, Microwave Sensors

**UNIT III DATA RECEPTION AND DATA PRODUCTS 9 hours**

Ground Segment Organization, Data Product Generation, Sources of Errors in Received Data, Referencing Scheme, Data Product Output Medium, Digital Products, Super Structure, FAST, GeoTIFF, Hierarchical and HDF Formats, Indian and International Satellite Data Products, Ordering of Data.

**UNIT IV GIS DATA MODELS AND DATA INPUT 9 hours**

Definition of GIS, Evolution of GIS, Components of GIS, Digital Cartography Concepts, 3D GIS, Point, Line, Polygon/Area, Elevation and Surface, Tessellations, Attributes and Levels of Measurement, Data Sources, Ground and Remote Sensing Survey, Collateral Data Collection, Input, Map Scanning and Digitization, Registration and Georeferencing, Concepts of RDBMS, Raster Data Model, Grid, Data Encoding, Data Compression, Vector Data Model,

**UNIT V DATA OUTPUT AND WEB BASED GIS 9 hours**

Map Compilation, Cartographic Functionalities for Map Design, Symbolization, Conventional Signs and Symbols, Spatial Data Quality, Lineage, Positional Accuracy, Attribute Accuracy, Completeness, Logical Consistency, Metadata, Web-Based GIS Merits, Architecture, Map Server, Spatial Data Infrastructure, Spatial Data Standards, OGC Standards, Free and Open Source GIS, Proprietary GIS Software.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1.** Explain the fundamental principles, electromagnetic radiation, and atmospheric interactions involved in remote sensing.

**CO2.** Describe the characteristics and applications of different remote sensing sensors and imaging systems.

**CO3.** Explain satellite data reception, data products, storage formats, and their applications in remote sensing.

**CO4.** Apply GIS concepts, spatial data models, and data input techniques for creating geospatial databases.

**CO5.** Analyze GIS data, generate map outputs, and utilize web-based GIS tools for geospatial applications.

**Text Books:**

1. "Remote Sensing and Image interpretation ", Lillesand T.M., and Kiefer, R.W, 6th Edition, John Wiley & Sons, 2015.
2. "Introduction to Geographic Information Systems ", Kang-tsung Chang, 9th Edition, McGraw-Hill Education, 2018.

**Reference Books:**

1. "Fundamentals of Remote Sensing ", George Joseph, 3rd Edition, Universities Press (India) Pvt Ltd, Hyderabad, 2018
2. "An Introduction to Geographical Information Systems", Ian Heywood, Sarah Cornelius, Steve Carver, 4th Edition, Pearson Education, 2011.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – III**

## 25MBCAMDC12 HUMAN AI INTERACTION

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Human Computer Interaction**

**Course Description:**

Human AI Interaction introduces the principles and foundations of designing intelligent systems that effectively interact with humans. The course covers Human centered AI design, cognitive aspects, explainable and trustworthy AI, conversational and multimodal interaction, user experience, usability, accessibility, ethics, and responsible AI. It also explores applications of Human AI Interaction in healthcare, education, robotics, generative AI, and emerging intelligent systems.

**Course Objectives:**

1. Understand the fundamental concepts and principles of Human–AI Interaction systems and intelligent interfaces.
2. Study human-centered AI design methodologies and cognitive aspects involved in AI-based interaction systems.
3. Analyze explainable, trustworthy, ethical, and responsible AI frameworks for real-world applications.
4. Explore conversational AI, multimodal interaction systems, and adaptive intelligent user interfaces.
5. Evaluate user experience, usability, accessibility, and human factors in AI-enabled applications.

**UNIT I FOUNDATIONS OF HUMAN–AI INTERACTION 9 hours**

Introduction to Human–AI Interaction, evolution from Human–Computer Interaction to Human–AI systems, intelligent interactive systems, fundamentals of Artificial Intelligence, intelligent agents and machine learning concepts, human cognition and perception, human behavior in interactive systems, user-centered AI design, adaptive interfaces, intelligent user interfaces, recommendation systems and smart assistants.

**UNIT II EXPLAINABLE, ETHICAL AND TRUSTWORTHY AI 9 hours**

Explainable AI concepts, transparency and interpretability in AI systems, visualization techniques for explainability, trust and reliability in AI systems, human trust calibration, bias and fairness in AI applications, ethical issues in AI systems, responsible AI frameworks, accountability and governance, privacy and security in AI systems, privacy-preserving AI techniques and ethical data management.

**UNIT III CONVERSATIONAL AND MULTIMODAL AI SYSTEMS 9 hours**

Conversational AI fundamentals, dialogue systems and chatbot architectures, Natural Language Processing for interaction, intent recognition and sentiment analysis, speech recognition systems, voice-based interaction systems, multimodal interaction techniques, gesture and emotion recognition, context-aware intelligent systems, adaptive AI assistants and smart interaction environments.

**UNIT IV USER EXPERIENCE AND HUMAN FACTORS IN AI 9 hours**

User experience design principles for AI systems, intelligent interface design, human factors engineering, ergonomics in interaction systems, cognitive workload analysis, usability evaluation techniques, heuristic evaluation, accessibility testing, human-AI collaboration models, decision support systems, collaborative intelligence, accessibility and inclusive AI design principles.

**UNIT V APPLICATIONS AND FUTURE TRENDS IN HUMAN–AI INTERACTION 9 hours**

AI applications in healthcare interaction, intelligent medical systems, AI in education and smart learning environments, intelligent tutoring systems, human-AI interaction in robotics, collaborative robots and autonomous systems, generative AI technologies, Large Language Models, emotional AI, social robotics, ethical future of AI systems and emerging research trends in Human–AI Interaction.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1**: Explain the concepts, principles, and foundations of Human–AI Interaction systems and intelligent interfaces.
**CO2**: Analyze explainability, trustworthiness, fairness, privacy, and ethical issues in AI-enabled systems.
**CO3**: Design conversational and multimodal AI interaction models using intelligent technologies.
**CO4**: Evaluate usability, accessibility, and user experience aspects in AI-driven applications.
**CO5**: Develop human-centred AI solutions for real-world applications using responsible AI principles.

**Text Books:**

**1.** "Human-Computer Interaction", Alan Dix, Janet Finlay, Gregory D. Abowd and Russell Beale, 3rd Edition, Pearson Education, 2004.
**2.** "Artificial Intelligence: A Modern Approach", Stuart Russell and Peter Norvig, 4th Edition, Pearson Education, 2021.

**Reference Books:**

**1.** "Designing the User Interface: Strategies for Effective Human-Computer Interaction", Ben Shneiderman, Catherine Plaisant, Maxine Cohen and Steven Jacobs, 6th Edition, Pearson, 2016.
**2.** "The Ethical Algorithm: The Science of Socially Aware Algorithm Design", Michael Kearns and Aaron Roth, 1st Edition, Oxford University Press, 2019.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – IV**

## 25MBCAMDC13 MLOps

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Machine Learning & DevOps**

**Course Description:**

This course introduces the principles and practices of operationalizing machine learning systems throughout their lifecycle. It covers data engineering workflows, experiment and model management, model versioning, CI/CD for machine learning, deployment, monitoring, model and data drift, continuous retraining, governance, security, and emerging MLOps practices. The course enables students to understand how machine learning models are transitioned from development to reliable and maintainable production systems.

**Course Objectives:**

1. Understand the principles and lifecycle of operational machine learning systems
2. Analyze workflows for managing data, models, and deployment pipelines
3. Study CI/CD practices for ML applications
4. Evaluate monitoring and maintenance strategies for production ML systems
5. Examine governance, security, and emerging MLOps paradigms

**UNIT I FOUNDATIONS OF MLOPS 9 hours**

Introduction to Machine Learning Operations, Evolution of DevOps, DataOps, and MLOps, Machine Learning lifecycle in production, Challenges in operationalizing ML systems, Reproducibility in ML workflows, Experiment tracking concepts, Version control for ML artifacts

**UNIT II DATA ENGINEERING AND WORKFLOW AUTOMATION 9 hours**

Data ingestion workflows, ETL/ELT concepts for ML systems, Data validation and quality assurance, Feature engineering pipelines, Feature store concepts, Dataset versioning, Workflow orchestration fundamentals

**UNIT III MODEL LIFECYCLE AND CI/CD FOR MACHINE LEARNING 9 hours**

Model development lifecycle, Hyperparameter tuning concepts, Model versioning, Model registry, Continuous Integration for ML, Automated testing of ML systems, Continuous Delivery and Continuous Deployment for ML

**UNIT IV DEPLOYMENT AND MONITORING OF MACHINE LEARNING SYSTEMS 9 hours**

Model deployment architectures, Batch inference and online inference, API-based model serving, Containerization concepts, Monitoring deployed models, Performance monitoring metrics, Logging and alerting mechanisms

**UNIT V GOVERNANCE, SECURITY, AND ADVANCED MLOPS 9 hours**

Model drift and data drift, Continuous retraining strategies, Explainability in deployed ML systems, Bias and fairness in operational AI, ML security fundamentals (MLSecOps), Governance and compliance, Introduction to LLMOps

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1:** Explain core concepts and lifecycle stages of MLOps systems.

**CO2:** Analyze data engineering and automation workflows in operational ML systems.

**CO3:** Evaluate model lifecycle management and CI/CD practices for ML deployment.

**CO4:** Assess deployment and monitoring strategies for scalable ML applications.

**CO5:** Examine governance, security, and advanced operational challenges in AI systems.

**Text Books:**

1. "Practical MLOps: Operationalizing Machine Learning Models", 1st Edition, O'Reilly Media, 2021.
2. "Introducing MLOps: How to Scale Machine Learning in the Enterprise", 1st Edition, O'Reilly Media, 2020.

**Reference Books:**

1. "Building Machine Learning Powered Applications: Going from Idea to Product", 1st Edition, O'Reilly Media, 2020.
2. "Machine Learning Design Patterns: Solutions to Common Challenges in Data Preparation, Model Building, and MLOps", 1st Edition, O'Reilly Media, 2020.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – IV**

## 25MBCAMDC14 RECOMMENDER SYSTEMS

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Machine Learning**

**Course Description:**

This course introduces the fundamental concepts and techniques used to design and develop intelligent recommender systems. Students will learn about content-based filtering, collaborative filtering, hybrid recommendation approaches, similarity measures, and evaluation techniques. The course also covers real-world applications of recommender systems in e-commerce, entertainment, social media, and online learning platforms.

**Course Objectives:**

1. To understand the fundamentals of recommender systems and information retrieval techniques.
2. To learn mathematical concepts and rating analysis used in recommendation systems.
3. To study content-based filtering and feature extraction methods.
4. To explore collaborative filtering and matrix factorization techniques.
5. To analyze hybrid recommender system models and their applications.

**UNIT I INTRODUCTION TO RECOMMENDER SYSTEMS 9 hours**

Overview of Information Retrieval, Retrieval Models, Search and Filtering Techniques, Relevance Feedback, User Profiles, Recommender System Functions, Applications of Recommender Systems, Issues and Challenges in Recommender Systems.

**UNIT II MATHEMATICAL FOUNDATIONS AND RATING ANALYSIS 9 hours**

Matrix Operations, Covariance Matrices, Understanding Ratings, Similarity Measures, Data Pre-processing Techniques, Feature Extraction Methods.

**UNIT III CONTENT-BASED FILTERING 9 hours**

High Level Architecture of Content-Based Systems, Advantages and Drawbacks of Content-Based Filtering, Item Profiles, Discovering Features of Documents, Obtaining Item Features from Tags, Methods for Learning User Profiles, Similarity-Based Retrieval, Classification Algorithms.

**UNIT IV COLLABORATIVE FILTERING TECHNIQUES 9 hours**

User-Based Collaborative Recommendation, Item-Based Collaborative Recommendation, Model-Based Approaches, Matrix Factorization Techniques, Attacks on Collaborative Recommender Systems.

**UNIT V HYBRID RECOMMENDER SYSTEMS 9 hours**

Opportunities for Hybridization, Monolithic Hybridization Design: Feature Combination, Feature Augmentation, Parallelized Hybridization Design: Weighted, Switching, Mixed Approaches, Pipelined Hybridization Design: Cascade and Meta-Level Approaches, Limitations of Hybridization Strategies.

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1:** Explain the basic concepts and applications of recommender systems.
**CO2:** Apply matrix operations and similarity measures for recommendation analysis.
**CO3:** Implement content-based filtering techniques for personalized recommendations.
**CO4:** Analyze collaborative filtering and model-based recommendation methods.
**CO5:** Evaluate hybrid recommender systems and their performance strategies.

**Text Books:**

1. "Recommender Systems: An Introduction", Jannach D., Zanker M., Fel Fering A, 1st Edition, Cambridge University Press, 2011.
2. "Recommender Systems: The Textbook", Charu C. Aggarwal, 1st Edition, Springer, 2016.

**Reference Books:**

1. "Recommender Systems Handbook", Ricci F., Rokach L., Shapira D., Kantor B.P., Springer, 2011.
2. "Recommender Systems for Learning", Manouselis N., Drachsler H., Verbert K., Duval E., Springer, 2013.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – IV**

## 25MBCAMDC15 VIDEO ANALYSIS

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Machine Learning, Computer Vision & Deep Learning**

**Course Description:**

This course introduces the fundamental concepts and techniques for analysing and understanding video data using computer vision and artificial intelligence. It covers video representation, preprocessing, motion estimation, object detection and tracking, action recognition, temporal analysis, video classification, and deep learning-based video understanding. Students learn to apply convolutional and recurrent neural networks, 3D convolutional networks, and transformer-based approaches for developing intelligent video analysis applications in areas such as surveillance, healthcare, transportation, sports, and human activity recognition.

**Course Objectives:**

1. To understand the fundamentals of video representation, formats, and processing techniques.
2. To learn feature extraction, motion estimation, and optical flow computation in video data.
3. To apply deep learning architectures for object detection and tracking in video streams.
4. To develop and evaluate models for action recognition and temporal sequence analysis.
5. To explore advanced video analysis applications including video generation, anomaly detection, and autonomous driving.

**UNIT I INTRODUCTION TO VIDEO PROCESSING AND REPRESENTATION 9 hours**

Video Fundamentals - Video Formats and Codecs - Color Spaces and Conversions - Video Compression - Temporal vs Spatial Analysis in Video - Video Pre-processing - Keyframe Extraction - OpenCV for Video Processing - Video Datasets.

**UNIT II FEATURE EXTRACTION AND OPTICAL FLOW 9 hours**

Video Feature Extraction - Background Subtraction - Temporal Difference and Frame Differencing - Optical Flow - Sparse Optical Flow - Dense Optical Flow - Deep Optical Flow - Motion Estimation - Trajectory Analysis - Video Saliency Detection.

**UNIT III OBJECT DETECTION AND TRACKING IN VIDEOS 9 hours**

Object Detection Frameworks Applied to Video - Challenges in Video Object Detection - Single Object Tracking (SOT) - Multi-Object Tracking (MOT) - Online vs Offline Tracking Paradigms - Re-Identification (ReID) - Multi-Camera Tracking and Cross-Camera Association - MOT Evaluation Metrics - Video Instance Segmentation - Real-Time Tracking on Edge Devices.

**UNIT IV ACTION RECOGNITION AND TEMPORAL MODELING 9 hours**

Action Recognition Overview - Traditional Approaches - Two-Stream Networks - 3D Convolutional Neural Networks - Long Short-Term Memory (LSTM) and GRU - Temporal Segment Networks (TSN) - Non-local Neural Networks - Video Transformers - Skeleton-Based Action Recognition - Temporal Action Localization.

**UNIT V ADVANCED VIDEO ANALYSIS APPLICATIONS 9 hours**

Video Captioning and Dense Video Description - Video Question Answering (VideoQA) - Anomaly Detection in Surveillance Videos - Deepfake Detection in Videos - Video Semantic Segmentation - Video Panoptic Segmentation - Video Generation and Prediction - Crowd Analysis - Autonomous Driving Video Analysis - Sports Video Analytics.

**Course Outcomes:**

At the end of this course, students will be able to
CO1: Apply video processing techniques from video data.
CO2: Implement optical flow algorithms and motion estimation techniques of video sequences.
CO3: Design and evaluate object detection and multi-object tracking systems for real-time video streams.
CO4: Analyze and apply 3D CNN, Video Transformer, and graph-based architectures for modeling.
CO5: Develop and evaluate advanced video analysis applications.

**Text Books:**

1. "Computer Vision: Algorithms and Applications", Richard Szeliski, 2nd Edition, Springer, 2022.
2. "Deep Learning for Vision Systems", Mohamed Elgendy, 1st Edition, Manning Publications, 2020.

**Reference Books:**

1. "Programming Computer Vision with Python: Tools and Algorithms for Analyzing Images", Jan Erik Solem, O'Reilly Media, 2012.
2. "Learning OpenCV 4 Computer Vision with Python 3: Get to grips with tools, techniques, and algorithms for computer vision and machine learning", Joseph Howse and Joe Minichino, 3rd Edition, Packt Publishing, 2020.
3. "Action Recognition in Still Images and Videos", Arif Mahmood, Springer, 2022.
4. "Computer Vision: Models, Learning, and Inference", Simon J.D. Prince, Cambridge University Press, 2012.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.

**Discipline Elective – IV**

## 25MBCAMDC16 MULTIMODAL INFORMATION RETRIEVAL

| L | T | P | C |
|---|---|---|---|
| 3 | 0 | 0 | 3 |

**Prerequisites: Machine Learning & Deep Learning**

**Course Description:**

This course introduces methods for retrieving, representing, and analyzing information across multiple modalities, including text, images, audio, and video. It covers feature extraction, multimodal fusion, similarity measurement, indexing, ranking, and cross-modal retrieval. Emphasis is placed on designing intelligent retrieval systems for large-scale, heterogeneous, and real-world information sources and digital repositories.

**Course Objectives:**

1. Understand principles of multimodal data representation and retrieval
2. Analyze techniques for integrating visual, textual, and audio information
3. Study cross-modal retrieval and multimodal embedding methods
4. Evaluate deep learning architectures for multimodal search systems
5. Examine modern applications of multimodal retrieval in AI systems

**UNIT I FOUNDATIONS OF MULTIMODAL INFORMATION RETRIEVAL 9 hours**

Introduction to Information Retrieval, Fundamentals of multimedia information retrieval, Types of multimodal data: text, image, audio, video. Challenges in multimodal retrieval, Retrieval models and ranking fundamentals, Similarity measures for multimodal data, Feature representation fundamentals, Applications of multimodal retrieval.

**UNIT II MULTIMODAL REPRESENTATION LEARNING 9 hours**

Feature extraction for text modalities, Feature extraction for visual modalities, Audio feature representation, Joint embedding spaces, Representation learning for multimodal data, Feature fusion techniques, Early fusion and late fusion methods, Similarity learning for retrieval.

**UNIT III CROSS-MODAL RETRIEVAL USING DEEP LEARNING 9 hours**

Cross-modal retrieval concepts, Text-to-image retrieval, Image-to-text retrieval, Deep neural architectures for multimodal retrieval, Siamese networks, Contrastive learning fundamentals, Metric learning for retrieval, Transformer-based retrieval concepts.

**UNIT IV VISION-LANGUAGE MODELS FOR RETRIEVAL 9 hours**

Vision-language learning fundamentals, Joint multimodal embeddings, CLIP architecture concepts, Transformer-based multimodal representation, Retrieval using pretrained multimodal models, Zero-shot multimodal retrieval, Retrieval evaluation metrics, Benchmark datasets for multimodal retrieval.

**UNIT V ADVANCED APPLICATIONS AND EMERGING TRENDS 9 hours**

Retrieval-Augmented Generation (RAG) for multimodal systems, Multimodal search engines, Conversational multimodal retrieval, Video retrieval systems, Medical multimodal retrieval applications Explainability in multimodal retrieval, Ethical considerations and bias, Future directions in multimodal AI retrieval

**Course Outcomes:**

At the end of this course students will demonstrate the ability to

**CO1:** Explain core principles of multimodal information retrieval systems.
**CO2:** Analyze multimodal representation learning and feature integration methods.
**CO3:** Evaluate cross-modal retrieval techniques using deep learning models.
**CO4:** Assess transformer-based and vision-language retrieval systems.
**CO5:** Examine advanced applications and emerging challenges in multimodal retrieval.

**Text Books:**

1. " Modern Information Retrieval: The Concepts and Technology Behind Search ", Ricardo Baeza-Yates, Berthier Ribeiro-Neto, 2nd Edition, Addison-Wesley, 2011.
2. " ImageCLEF: Experimental Evaluation in Visual Information Retrieval", Henning Müller, Paul Clough, Thomas Deselaers, Barbara Caputo, Springer, 2010.

**Reference Books:**

1. "Multimedia Information Retrieval ", Stefan Rueger, 1st Edition, Morgan & Claypool Publishers, 2009.
2. " Deep Learning: Methods and Applications ", Li Deng, Dong Yu, Foundations and Trends in Signal Processing, 2014.

**Mode of Evaluation:** Assignments, Mid Term Tests and End Semester Examination.