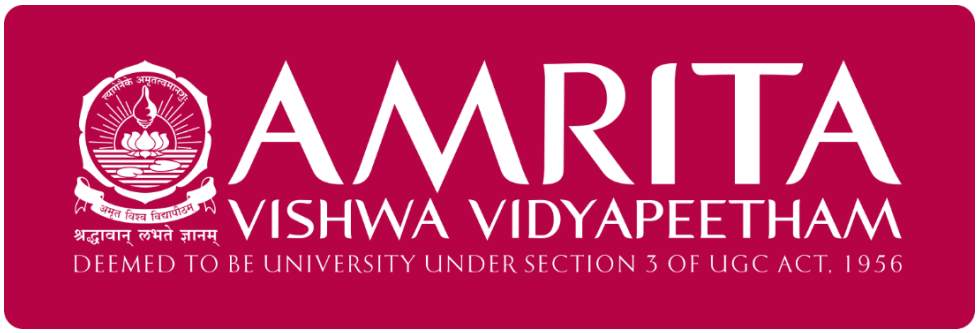


School of Computing

M.TECH ARTIFICIAL INTELLIGENCE

CURRICULUM 2026

M.TECH – Artificial Intelligence

Department of Computer Science and Engineering

M.Tech in Artificial Intelligence programme has been designed for students who aim to embark their career on Data intensive computing. The programme is a graduate degree that develops the skillsets and knowledge required in various paradigms of Artificial Intelligence such as Machine Learning, Big data analytics, and Deep Learning. The degree is suitable for students with a bachelor's degree in a computing related field as well as students who want to demonstrate computer science expertise in addition to a degree in another field. The curriculum has been designed to prepare students for highly prolific careers in industry. Some of the job profiles include: Application analyst, Data Scientist, Data analyst, Database administrator, Information systems manager, IT consultant, Multimedia analyst.

Artificial Intelligence has revolutionized the modern world. Technologies that we now use for granted - Internet, mobile phones, medical technology, has various paradigms of Artificial Intelligence inherently. This M.Tech programme offers an integrated course of study covering the theory, implementation and design of Artificial Intelligence systems with core focus on Machine learning and Deep learning systems. The programme has specialized courses in the streams of Computer Vision, IoT and High Performance Computing with significant focus on research. As a part of the programme during the period of study, students have the opportunity to intern at leading companies and R&D labs for a period of six months to one year. There are opportunities for the students to take up a semester or one-year study at International Universities like Virje University, Netherlands, UC Davis, UNM for an exchange programme or to pursue a dual degree programme.

Graduates of this programme are well represented in Oracle, IBM, HP, Cerner, Nokia, GE, Bosch, Intuit and other major MNCs as well as in research in premier academic institutions in India and abroad. The graduates are competent to take up R&D positions in Industry, academia and research labs.

Program Educational Objectives (PEOs)

1. Build strong foundations in Artificial Intelligence so that they can contribute significantly in the area of research and innovation.
2. Develop highly competent professionals in the field of AI to adapt with the latest trends and techniques.
3. Bring out professionals and entrepreneurs to design and develop solutions for real world inter- disciplinary problems having positive societal impacts.

Graduate Attributes prescribed by NBA for M-Tech Program

GA1: Scholarship of knowledge

GA2: Critical thinking

GA3: Problem solving

GA4: Research skill

GA5: Usage of modern tools

GA6: Collaborative and multidisciplinary work

GA7: Project management and finance

GA8: Communication

GA9: Lifelong learning

GA10: Ethical practices and social responsibility

GA11: Independent and reflective learning.

Program Outcomes (POs)

1. Enable graduates to understand, design and build novel concepts and algorithms to leverage the power of AI in various application domains. (GA1, GA2, GA3).
2. Develop the skillsets to support the requirements of current trends in industry. (GA3, GA5, GA7, GA9).
3. An ability to independently carry out research /investigation and development work to solve practical problems while adhering to professional ethics. (GA4, GA9, GA11).
4. Students should be able to demonstrate a degree of mastery over the area as per the specialization of the program. The mastery should be at a level higher than the requirements in the appropriate bachelor program. (GA4, GA6, GA7, GA10).
5. Build the ability to write and present a substantial technical report/document. (GA8, GA9).

Program Outcomes PO3 PO4 and PO5 have been adopted from NBA (Ref. https://www.nbaind.org/files/PG_Eng_Annexure/PG_Engineering_Manual.pdf). PO4 has been elaborated to suit our M.Tech AI program.

M.TECH - ARTIFICIAL INTELLIGENCE
CURRICULUM 2026

Semester I				
Course Code	**Type**	**Courses**	**L T P**	**Credit**
26AI601	FC	Foundations of Artificial Intelligence	3-0-2	4
26MA604	FC	Mathematical Foundations of Computing	3-1-0	4
26AI602	FC	Machine Learning	3-0-2	4
	SC	Soft Core - I	3-0-2	4
26RM606	FC	Research Methodology	2-0-0	2
25AVP501	HU	Mastery Over Mind (MAOM)	1-0-2	2
	HU	Amrita Values Program*		P/F
26CDS601	HU	Career Development Skills I	0 0 3	P/F
		Total Credits		**20**

*Non-credit course

Semester II				
Course Code	**Type**	**Courses**	**L T P**	**Credit**
	SC	Soft Core - II	3-0-2	4
	SC	Soft Core - III	3-0-2	4
	SC	Elective - I	2-0-2	3
	E	Elective - II	2-0-2	3
	E	Elective - III	2-0-2	3
26AI681	FC	Case Study	0-0-4	2
26CDS611	HU	Career Development Skills II	0 0 3	1
26CUL500	HU	Integrated Amrita Meditation Technique	0-0-2	1
		Total Credits		**21**

Semester III				
Course Code	**Type**	**Courses**	**L T P**	**Credit**
	E	Elective - IV	2 0 2	3
	E	Elective - V	3 0 0	3
26AI798		Dissertation Phase I		10
		Total Credits		**16**

Semester IV				
Course Code	**Type**	**Courses**	**L T P**	**Credit**
26AI799		Dissertation Phase II		16
		Total Credits		**16**

Sl. No	Type	Courses	Credit
1	FC	Foundation Core	16
2	SC	Soft Core	12
3	E	Elective	15
4	HU	Amrita Values Program / Career Competency / MAOM/IAM	4
5		Dissertation	26
		Total Credits	**73**

Foundation Core			
Course Code	**Courses**	**L T P**	**Credit**
26AI601	Foundations of Artificial Intelligence	3-0-2	4
26MA604	Mathematical Foundations of Computing	3-1-0	4
26AI602	Machine Learning	3-0-2	4
26RM606	Research Methodology	2 0 0	2
26AI681	Case Study	0 0 4	2

Soft Core			
Course Code	**Courses**	**L T P**	**Credit**
26AI631	Foundations of Data Science	3-0-2	4
26AI632	Advanced Algorithm Design	3-0-2	4
26AI633	Probabilistic Graphical Models	3-0-2	4
26AI634	Computational Intelligence	3-0-2	4
26AI635	Deep Learning	3-0-2	4
26AI636	Reinforcement Learning	3-0-2	4
26AI637	Mining of Massive Datasets	3-0-2	4

26AI638	Generative AI	3-0-2	4

Electives List			
Course Code	**Courses**	**L T P**	**Credit**
26AI731	Machine Learning for Big Data	2 0 2	3
26AI732	Applications of Machine Learning	2 0 2	3
26AI733	Evolutionary Machine Learning	2 0 2	3
26AI734	Applied Predictive Analytics	2 0 2	3
26AI735	Federated Learning	2 0 2	3
26AI736	Explainable AI	2 0 2	3
26AI737	Artificial Intelligence for Robotics	2 0 2	3
26AI738	Data Visualization	2 0 2	3
26AI739	Stochastic Modeling	2 0 2	3
26AI740	Networks and Spectral Graph Theory	2 0 2	3
26AI741	Parallel and Distributed Data Management	2 0 2	3
26AI742	Computer Vision	2 0 2	3
26AI743	Natural Language Processing	2 0 2	3
26AI744	GPU Architecture and Programming	2 0 2	3
26AI745	Artificial Intelligence for IoT	2 0 2	3
26AI746	Quantum Artificial Intelligence	2 0 2	3
26AI747	Artificial Intelligence for Bioinformatics	2 0 2	3
26AI748	Cloud and Big Data Analytics	2 0 2	3
26AI749	AI Product Engineering and Innovation	2-0-2	3
26AI750	MLOps and AI Systems Engineering	2-0-2	3

* Students can take Electives from other M.Tech branches in place of any one elective. Students can select online courses in place of Elective IV and Elective V as per the university norms with the consent and approval from the department.

26AI601 Foundations of Artificial Intelligence 3-0-2-4

Preamble:

Artificial Intelligence is concerned with building intelligent agents that can search for solutions, represent knowledge, reason under uncertainty, plan actions, learn from experience, and act responsibly. This course introduces these foundational capabilities and the principles that underpin modern AI systems, providing students with a rigorous conceptual framework for advanced study and research.

Course Objectives:

- Provide a comprehensive foundation in the principles, paradigms, and methodologies of Artificial Intelligence.
- Develop the ability to model intelligent agents using search, knowledge representation, reasoning, planning, and learning techniques.
- Develop the ability to model intelligent agents using search, knowledge representation, reasoning, planning, and learning techniques.
- Expose students to modern AI paradigms, including foundation models and responsible AI principles, while preparing them for advanced AI courses and research.

Course Outcomes:

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

COs	Description
CO1	Analyze AI problems by formulating intelligent agents and selecting appropriate search and knowledge representation techniques.
CO2	Apply logical, probabilistic, and planning techniques to model and solve intelligent decision-making problems.
CO3	Evaluate machine learning approaches for enabling intelligent systems to learn, adapt, and make decisions from data.
CO4	Critically evaluate modern AI systems with respect to their capabilities, limitations, and ethical, fair, accountable, transparent, and trustworthy deployment.

Prerequisites:

Syllabus:

Intelligent agents and search: Intelligent agents, rationality, PEAS framework and agent architectures. Problem formulation, state-space representation, and computational complexity of search. Uninformed, informed, and local search paradigms including Breadth-First Search, Depth-First Search, Uniform Cost Search, Iterative Deepening Search, Greedy Best-First Search, A* Search, Hill Climbing, Simulated Annealing, and Beam Search. Heuristic design, admissibility, and consistency. Evolutionary optimization using Genetic Algorithms. Adversarial search using Minimax and Alpha-Beta Pruning.

Knowledge representation and reasoning: Knowledge-based agents, symbolic knowledge

representation, propositional and first-order logic, inference mechanisms, constraint satisfaction problems, ontologies, and knowledge graphs.

Reasoning under uncertainty: Probability and probabilistic reasoning, Bayes' theorem, conditional independence, exact and approximate inference, decision making under uncertainty, and foundations of probabilistic graphical models.

Planning and sequential decision making: Goal formulation, classical planning, STRIPS representation, state-space and plan-space planning, deterministic and uncertain planning, and Markov Decision Processes as a foundation for sequential decision making.

Learning and responsible artificial intelligence: Machine learning paradigms, supervised and unsupervised learning, decision tree learning, probabilistic learning, neural networks and representation learning, foundation models, generative AI, and principles of ethical, fair, accountable, transparent and trustworthy AI.

Textbook

1. Russell, S. J., & Norvig, P. Artificial Intelligence: A Modern Approach, 4th Edition, Pearson.

Reference Books

2. Brachman, R. J., & Levesque, H. J. Knowledge Representation and Reasoning, Morgan Kaufmann, 2004.
3. LaValle, S. M. Planning Algorithms, Cambridge University Press, 2006
4. Murphy, K. P. Probabilistic Machine Learning: An Introduction, MIT Press, 2022.
5. David L. Poole and Alan K. Mackworth, Artificial Intelligence, Foundations of Computational Agents, Cambridge University Press, 2023.

Contemporary Readings

6. Selected recent survey papers, technical reports, and standards on Foundation Models, Knowledge Graphs, Generative AI, and Responsible AI.
7. Artificial Intelligence Index Report 2026, Stanford University, HAI- Human centered Artificial Intelligence, 2026

CO-PO Mapping:

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Analyze AI problems by formulating intelligent agents and selecting appropriate search and knowledge representation techniques.	3	2	1	3	-
CO2	Apply logical, probabilistic, and planning techniques to model and solve intelligent decision-making problems.	3	2	2	3	-
CO3	Evaluate machine learning approaches for enabling intelligent systems to learn, adapt, and make decisions from data.	3	3	2	3	-
CO4	Critically evaluate modern AI systems with respect to their capabilities, limitations, and ethical, fair, accountable, transparent, and trustworthy deployment.	2	2	3	3	1

Evaluation Pattern:70:30

- Midterm Exam - 20% (Assess conceptual understanding and analytical problem-solving.)
- Quizzes - 20% (Reinforce continuous learning and foundational concepts.)
- Lab Assignments & Case Study – 30% (Interactive experiments, algorithm analysis, visualizations, comparative studies, GPT-assisted implementation, and concise investigation reports.)
- End Semester Exam (2 hours) - 30% (Evaluate integrated understanding through theory, problem analysis, and algorithmic reasoning.)

26MA604 Mathematical Foundations of Computing 3-1-0-4

Course Objectives

- To equip students with advanced mathematical tools and techniques: This course aims to provide students with a comprehensive understanding of vector spaces, matrix decompositions, optimization methods, and statistical analysis, enabling them to solve engineering problems with precision and efficiency.
- To develop analytical and problem-solving skills in engineering contexts: This course focuses on enhancing students' ability to apply theoretical concepts in practical scenarios, including optimization, probabilistic analysis, and statistical inference, preparing them for research and professional practice in engineering and related fields.

Course Outcomes

COs	Description
CO1	Analyze and apply vector space concepts and matrix decompositions to solve engineering problems.
CO2	Demonstrate proficiency in using mathematical theorems and transformations to find solutions to engineering problems.
CO3	Solve optimization problems relevant to engineering contexts.
CO4	Analyze and interpret statistical data and apply probabilistic and Bayesian methods for rigorous analysis and parameter estimation.

Prerequisites

- Basic programming knowledge

Syllabus

Vector Space: Basis and Dimensions - Change of Basis, Orthogonality – Fundamental Vector Spaces Associated with a Matrix, Matrix Decompositions: LU, QR, Eigen Decomposition and SVD, Cayley Hamilton Theorem, Fourier Transform and Fourier Basis

Function Optimization – Constrained and Unconstrained Optimization - Linear Programming - Linear Regression – Ordinary Least Squares – Gradient Descent – Conjugate Gradient Descent – Lagrange Multipliers – KKT Multipliers – ADMM – SVM

Random Variables – Moments - Covariance and Correlation - Probability Distributions – Moment generating functions – Transforming a random variable and Jacobean- Central limit theorem. Bayes Theorem - Naïve Bayes Classification - Parameter Estimation: MLE – Statistical testing: Mean of two random variables and statistical testing for proportions. Information Theory, Matrix Calculus for Deep Learning, Automatic Differentiation and Convex Optimization for ML.

Text Book / References

1. Gilbert Strang, Linear Algebra and Learning from Data, Wellesley-Cambridge Press, 2019.

2. William Flannery, Mathematical Modeling and Computational Calculus, Vol-1, Berkeley Science Books, 2013.

3. Stephen Boyd and Lieven Vandenberghe, Convex Optimization, Cambridge University Press, 2018.

4. Douglas C. Montgomery and George C. Runger, Applied Statistics and Probability for Engineers, John Wiley & Sons Inc., 2005.

5. Axler Sheldon, Linear Algebra Done Right, Springer Nature, 2024.

6. Howard Anton and Chris Rorrers, Elementary Linear Algebra, Tenth Edition, John Wiley & Sons, Inc., 2010.

7. David Forsyth, Probability and Statistics for Computer Science, Springer International Publishing, 2018.

8. Ernest Davis, Linear Algebra and Probability for Computer Science Applications, CRC Press, 2012.

9. Deisenroth, M. P., Faisal, A. A., & Ong, C. S., *Mathematics for Machine Learning*, Cambridge University Press, 2020.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Analyze and apply vector space concepts and matrix decompositions to solve engineering problems.	3	-	3	2	-
CO2	Demonstrate proficiency in using mathematical theorems and transformations to find solutions to engineering problems.	3	3	3	2	-
CO3	Solve optimization problems relevant to engineering contexts.	3	3	3	2	2
CO4	Analyze and interpret statistical data and apply probabilistic and Bayesian methods for rigorous analysis and parameter estimation.	2	-	3	1	3

Evaluation Pattern - 60:40

- Midterm Exam - 30%
- Continuous Assessment – 30%
- End Semester Exam (3 hours) - 40%

26AI602 Machine Learning 3-0-2-4

Preamble

This course deals with various algorithms to enable computers to learn data without being explicitly programmed. An insight into various types of machine learning algorithms, strategies for model generation and evaluation are given in this course. The fundamental machine learning algorithms required in industries are covered together with their concrete implementations.

Course Objectives

- To introduce the fundamental concepts and techniques of Machine Learning
- To become familiar with various classification and regression methods
- Apply neural networks, Bayes classifier and k nearest neighbor algorithms in machine learning.
- To develop skills using recent machine learning techniques and solving real world case study

Course Outcomes

COs	Description
CO1	Understand and apply the basic of ML, learning paradigms and concepts of regression
CO2	Design and develop classifier models and evaluate their performance
CO3	Acquire skills to build probabilistic model and deep network models for classification
CO4	Develop and build clustering models for real world applications
CO5	Understand and apply the concepts of dimensionality reduction and Reinforcement Learning

Prerequisites

- Basics of Linear Algebra, Probability Theory and Optimization: Vectors, Inner product, Outer product, Inverse of a matrix, Eigen analysis, Probability distributions – Discrete distributions and Continuous distributions; Independence of events, Conditional probability distribution and Joint probability distribution, Bayes theorem, Unconstrained optimization, Constrained optimization.

Syllabus

Introduction to machine learning - different forms of learning- Linear regression - Ridge and Lasso regression, Logistic regression, Discriminant Functions and models, Bayesian regression, regression with basic functions.

Classification - Perceptron –Multilayer Perceptron - Feed forward network - Backpropagation – Support vector machine - Decision trees - evaluation of classifiers – bias and variance. Gaussian mixture models -- Expectation-Maximization - Naive Bayes classifier - Ensemble

Methods - Bagging – Boosting -Time series Prediction and Markov Process - application of classification algorithm

Clustering - K-means – Hierarchical and Density Based Clustering – DBSCAN- Assessing Quality of Clustering - Dimensionality reduction - Principal Component Analysis. Understanding of Machine Learning Project Life Cycle - each stages of the cycle, Examples of ML projects. Model interpretability basics, Cross-validation strategies, Hyperparameter optimization, ML pipelines and MLOps introduction, Imbalanced learning.

Text Book / References

1. Alpaydin, Ethem. Introduction to machine learning (4th edition). MIT press, 2020
2. Bishop, Christopher M. Pattern recognition and machine learning. springer, 2006.
3. Murphy, Kevin P. Machine learning: a probabilistic perspective. MIT press, 2012.
4. Tom Mitchell, "Machine Learning", McGraw-Hill, 1997
5. Duda, Richard O., and Peter E. Hart. Pattern classification (2nd edition). John Wiley & Sons, 2006.
6. Han, Jiawei, Micheline Kamber, and Jian Pei. "Data mining concepts and techniques (4th edition)" The Morgan Kaufmann Series in Data Management Systems 5.4 (2011): 83-124.
7. Roi Yehoshua, Machine Learning Foundations, 1st edition, Addison-Wesley Professional, 2026
8. Christian Kästner, Machine Learning in Production - From Models to Products. MIT Press, 2025
9. Chip Huyen. Designing Machine Learning Systems: An Iterative Process for Production-Ready Applications, O'Reilly Media, Inc, 2022.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and apply the basic of ML, learning paradigms and concepts of regression	3	1	-	2	-
CO2	Design and develop classifier models and evaluate their performance	3	3	2	-	1
CO3	Acquire skills to build probabilistic model and deep network models for classification	3	1	2	2	-
CO4	Develop and build clustering models for real world applications	3	3	-	-	1
CO5	Understand and apply the concepts of dimensionality reduction and Reinforcement Learning	3	1	-	2	-

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam (2 hours) - 30%

26RM606 Research Methodology 2-0-0-2

Preamble:

Artificial Intelligence (AI) research is increasingly driven by empirical experimentation, benchmark evaluation, reproducibility, and responsible scientific practices. While conventional research methodology courses provide a foundation in scientific inquiry, they do not adequately address the unique methodological challenges of AI research such as dataset selection, experimental design, evaluation metrics, statistical validation, reproducibility, explainability, and responsible use of AI tools. This course equips students with the knowledge and skills required to conduct rigorous AI research by emphasizing problem formulation, critical literature analysis, reproducible experimentation, scientific communication, and ethical research practices. The course serves as a strong foundation for M.Tech. dissertation work, industrial R&D, and doctoral research.

Course Objectives:

- Understand the principles, methodologies, and ethical practices underlying scientific research in Artificial Intelligence.
- Develop the ability to critically analyze AI literature and identify research problems and opportunities.
- Design reproducible and statistically rigorous AI experiments using appropriate datasets, benchmarks, and evaluation methodologies.
- Communicate AI research effectively through scientific writing, presentations, and responsible use of AI-assisted research tools.

Course Outcomes:

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

COs	Description
CO1	Explain the principles of AI research, formulate research problems, and identify novel research contributions using appropriate scientific methodologies.
CO2	Analyze AI literature to identify research gaps, evaluate existing approaches, and synthesize research directions through systematic literature review.
CO3	Design reproducible AI experiments by selecting appropriate datasets, benchmarks, evaluation metrics, baselines, and statistical validation techniques.
CO4	Evaluate AI systems using explainability, robustness, fairness, and reproducibility principles, and develop scientific reports and presentations adhering to ethical research practices.

Prerequisites: Basic Probability and Statistics

Syllabus:

Foundations of AI Research: AI research paradigm; differences from traditional engineering research; categories of AI contributions (algorithms, models, systems, datasets, benchmarks, theory); AI research lifecycle; problem formulation, research questions, novelty identification, hypothesis development; research ethics and responsible AI research; major AI conferences and journals; evaluation of scientific

contributions.

Literature Review and Research Gap Identification: Systematic literature review, survey papers, citation analysis, taxonomy construction, bibliographic management, and AI-assisted literature exploration; efficient reading of AI papers; understanding experimental methodology; identifying assumptions, limitations, research gaps, and novel contributions.

Experimental Design and Reproducible AI Research: Design of rigorous AI experiments; dataset selection, benchmark design, train-validation-test protocols, cross-validation, hyperparameter optimization, baseline selection, random seed management; reproducibility, replication studies, experiment tracking, version control, compute budgeting, documentation of experimental pipelines, and fair experimental comparison.

Evaluation and Statistical Analysis of AI Systems: Evaluation metrics for AI systems; robustness testing, uncertainty estimation, confidence intervals, statistical significance testing, effect size, error and sensitivity analysis, ablation studies; computational efficiency, scalability, and multi-objective evaluation.

Explainability, Responsible AI, and Research Communication: Interpretability and explainability, fairness, bias, privacy, transparency, reproducibility checklists, and responsible AI deployment; scientific writing, figures and tables, reproducible methodology sections, conference presentations, peer review and reviewer response; responsible use of generative AI tools in writing, coding, experimentation, and literature review with academic integrity.

Textbook and References

1. Booth, W. C., Colomb, G. G., Williams, J. M., Bizup, J., & Fitzgerald, W. T., The Craft of Research, 5th Edition, University of Chicago Press, 2024.
2. Chen, C., Talagala, N., & Srinivasan, K., Reliable Machine Learning: Applying SRE Principles to ML in Production, O'Reilly Media, 2022.
3. Huyen, C., Designing Machine Learning Systems, O'Reilly Media, 2022.

Contemporary Readings

4. Pineau, J., et al., Improving Reproducibility in Machine Learning Research, Journal of Machine Learning Research, 2021.
5. Gundersen, O. E., & Kjensmo, S., State of the Art: Reproducibility in Artificial Intelligence, AAAI Conference on Artificial Intelligence, 2018.
6. Lipton, Z. C., & Steinhardt, J., Troubling Trends in Machine Learning Scholarship, 2018.
7. Gebru, T., et al., Datasheets for Datasets, Communications of the ACM, 2021.
8. Mitchell, M., et al., Model Cards for Model Reporting, FAT*, 2019.
9. Demšar, J., Statistical Comparisons of Classifiers over Multiple Data Sets, Journal of Machine Learning Research, 2006.
10. Kapoor, S., et al., REFORMS: Reporting Standards for Machine Learning Based Science, 2023.

11. NeurIPS Machine Learning Reproducibility Checklist (Latest Version).

CO-PO Mapping:

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Explain the principles of AI research, formulate research problems, and identify novel research contributions using appropriate scientific methodologies.	3	2	1	2	1
CO2	Analyze AI literature to identify research gaps, evaluate existing approaches, and synthesize research directions through systematic literature review.	2	3	2	2	1
CO3	Design reproducible AI experiments by selecting appropriate datasets, benchmarks, evaluation metrics, baselines, and statistical validation techniques.	2	2	3	3	2
CO4	Evaluate AI systems using explainability, robustness, fairness, and reproducibility principles, and develop scientific reports and presentations adhering to ethical research practices.	2	2	3	3	3

Evaluation Pattern: 70:30

- Mid-Term Examination – 20
- Continuous Assessment - 50
    - Critical Review of AI Research Papers – 10
    - Literature Survey and Research Gap Analysis – 10
    - Experimental Design and Reproducibility Assignment – 15
    - Research Study (Conference-style Paper + Presentation + Viva) - 15
- End Semester (2 hours) - 30

26AI681 Case Study 0-0-4-2

Course Outcomes

COs	Description
CO1	To develop skills in doing project, technical presentation and report preparation.
CO2	To enable project identification and execution of preliminary works on final semester

Prerequisites

- None

Syllabus

This course is intended to give orientation towards research and innovation by developing skills in paper reading, programming and presentation skills. Each student can select an area for project in consultation with the faculty. This can be the initial phase of their dissertation as well. It should involve literature review, devising innovative solutions, implementation, testing and performance analysis in different application specific contexts. Students will be required to make an in-class presentation, project demonstration and a project report. The course will be evaluated by a panel of (at least) two faculty members.

Text Book / References

1. Relevant literature for the computing problem.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	To develop skills in doing project, technical presentation and report preparation.	1	1	1	2	3
CO2	To enable project identification and execution of preliminary works on the second year project	2	3	3	2	2

Evaluation Pattern - 80:20

- Internal - 80%
- External - 20%

26AI631 Foundations of Data Science 3-0-2-4

Preamble

Data Science is about drawing useful conclusions from large and diverse data sets through exploration, prediction, and inference. In this course, the students will learn the foundations of data science that focuses on pre-processing, exploration and visualization of data alongside the statistical and mathematical aspects of select techniques for prediction and classification using popular machine learning algorithms. The course also focuses on the associated inferencing techniques based on statistical models and tests for quantifying the degree of certainty of predictions.

Course Objectives

- To understand the important steps in drawing useful conclusions from data.
- To ask appropriate questions about data after data exploration using visualization and descriptive statistics
- To apply machine learning and optimization techniques to make predictions.
- To correctly interpret the answers generated by inferential and computational tools.

Course Outcomes

COs	Description
CO1	Understand the statistical foundations of data science
CO2	Learn techniques to pre-process raw data so as to enable further analysis
CO3	Conduct exploratory data analysis and create insightful visualizations to identify patterns
CO4	Apply machine learning algorithms for prediction/classification and to derive insights
CO5	Evaluate the degree of certainty of predictions using statistical test and models in Python

Prerequisites

- Basic Probability

Syllabus

Introduction to Data Science, Causality and Experiments, Data Pre-processing - Data cleaning - Data reduction - Data transformation, Visualization and Graphing: Visualizing Categorical Distributions - Visualizing Numerical Distributions - Overlaid Graphs and plots - Summary statistics of exploratory data analysis, Randomness, Probability, Introduction to Statistics, Sampling, Sample Means and Sample Sizes.

Probability distributions and density functions (univariate and multivariate), Error Probabilities; Expectations and moments; Covariance and correlation; Sampling and Empirical distributions; Permutation Testing, Statistical Inference; Hypothesis testing of means,

proportions, variances and correlations - Assessing Models - Decisions and Uncertainty, Comparing Samples - A/B Testing, P-Values, Causality.

Estimation - Resampling and Bootstrap - Confidence Intervals, Properties of Mean - Central Limit Theorem - Variability of mean -Choosing Sample Size, Prediction - Regression - Method of Least Squares - Visual and Numerical Diagnostics - Inference for true slope - Prediction intervals, Classification - Nearest neighbors - accuracy of a classifier, Updating Predictions - Making Decisions - Bayes Theorem, Graphical Models

Text Book / References

1. Ani Adhikari and John DeNero, "Computational and Inferential Thinking: The Foundations of Data Science" (2nd edition), e-book.
2. Joel Grus, "Data Science from Scratch: First Principles with Python", 2/e, O'Reilly Media, 2019.
3. Peter Bruce, Andrew Bruce and Peter Gedeck, "Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python" (3rd edition), O'Reilly Media, 2020.
4. Allen B. Downey, "Think Stats: Probability and Statistics for Programmers", (3rd edition), by O'Reilly Media, 2014.
5. Cathy O'Neil and Rachel Schutt, "Doing Data Science", O'Reilly Media, 2013.
6. Peter Bruce, Andrew Bruce and Peter Gedeck, Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python, Second Edition, O'Reilly Media, Inc

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the statistical foundations of data science	1	2	3	1	1
CO2	Learn techniques to pre-process raw data so as to enable further analysis	1	2	3	1	1
CO3	Conduct exploratory data analysis and create insightful visualizations to identify patterns	1	2	3	3	1
CO4	Apply machine learning algorithms for prediction and classification to derive insights	3	2	1	2	1
CO5	Evaluate the degree of certainty of predictions using statistical test and models	1	2	2	1	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam (2 hours) - 30%

26AI632 Advanced Algorithm Design 3-0-2-4

Preamble

This course builds upon the basic courses on data structures and algorithm design. It aims to enable students to design and adapt algorithms to solve complex problems especially relevant for AI domain. The focus will be on design and concrete implementations of various algorithmic techniques and their use in different application scenarios with proper analysis

Course Objectives

- To provide an understanding of algorithm design and analysis used in real life domain
- To solve complex problems by applying appropriate algorithmic design strategies
- To critically analyze the complexity of various algorithms
- To select appropriate design strategy to solve real world problems in AI domain

Course Outcomes

COs	Description
CO1	Explain the motivation behind the different algorithmic strategies and/or suitable data structures and their applications.
CO2	Articulate different algorithmic design techniques, compare and contrast them, and their application to real-world problems
CO3	Apply asymptotic and amortized analysis to determine the time and space complexities of an algorithm
CO4	Solve real world problems, especially in ML & AI domain, by identifying and applying appropriate design techniques
CO5	Concrete implementations of data structures and algorithms using Programming Language such as Java or Python

Prerequisites

- Basic Data Structures
- Basic Mathematics
- Basic Programming Language

Syllabus

Algorithm Analysis - Methodologies for Analyzing Algorithms, Asymptotic growth rates, Amortized Analysis. Array based structures, lists and. Number Theory: Preliminaries, FLT, Euclid's algorithm (extended), Totient function, Sieve for primes, Modular exponentiation.

Applications of Divide-and-Conquer, Greedy and Dynamic programming, Randomized techniques - Knapsack, Median finding, Scheduling algorithms, Party planning, bitonic TSP. String matching algorithms: Z Algorithm, KMP algorithm, Rabin-Karp, Universal hashing, consistent hashing, load balancing, power of two choices. Applications of graph algorithms: Topological sort, Strongly connected Components, Bi-connected Components, Bridges, Articulation points, All Pairs Shortest Paths, Single Source Shortest Paths.

Flow Networks: Ford-Fulkerson algorithm, Edmonds Karp algorithm, Applications of maximum flows - Maximum bipartite matching, minimum cost matching. Data Structures: Balanced binary trees, Suffix trees, Segment trees, Hash tables. Computational Geometry: Convex Hull, Closest pair of points. NP-Completeness: Important NP-Complete Problems, Polynomial time reductions, Approximation and Probabilistic algorithms, Approximate nearest neighbour search, Algorithms for foundation models, and Graph algorithms for AI.

Text Book / References

1. Cormen T H, Leiserson CE, Rivest R L and Stein C, "Introduction to Algorithms", Prentice Hall of India Private Limited. Fourth Edition 2009.
2. Michael T Goodrich and Roberto Tamassia, "Algorithm Design and Applications", Wiley, 2014.
3. Goodrich M T, Tamassia R and Michael H. Goldwasser, “Data Structures and Algorithms in Python++”, Wiley publication, 2013.
4. Rajeev Motwani and Prabhakar Raghavan, "Randomized Algorithms", Cambridge University Press, 1995.
5. Vijay V. Vazirani, "Approximation Algorithm", Springer Science and Business Media, 2003.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Explain the motivation behind the different algorithmic strategies and/or suitable data structures and their applications.	3	3	1	-	1
CO2	Articulate different algorithmic design techniques, compare and contrast them, and their application to real-world problems	3	3	1	-	1
CO3	Apply asymptotic and amortized analysis to determine the time and space complexities of an algorithm	3	3	1	-	1
CO4	Solve real world problems, especially in ML & AI domain, by identifying and applying appropriate design techniques	3	3	3	-	1
CO5	Concrete implementations of data structures and algorithms using Programming Language such as Java or Python	3	3	3	1	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam (2 hours) - 30%

26AI633 Probabilistic Graphical Models 3-0-2-4

Preamble

Probabilistic graphical models use a graph-based representation for encoding complex distributions over a high-dimensional space. This course deals with representation, inference, and learning of probabilistic graphical models. Students will gain an in-depth understanding of several types of graphical models; basic ideas underlying exact inference in probabilistic graphical models and learning probabilistic models from data.

Course Objectives

- To enable students to model problems using graphical models
- To design inference algorithms
- To learn the structure of the graphical model from the data set

Course Outcomes

COs	Description
CO1	Understand the process of encoding probability distributions using graphs
CO2	Analyze the independence properties of the graph structure
CO3	Understand and analyze Markov networks for the graphical modeling of probability distributions
CO4	Familiarize methods that approximate joint distributions
CO5	Study and evaluate methods to learn the parameters of networks with known and unknown structures

Prerequisites

- Probability and Statistics
- Programming Languages
- Algorithm Design

Syllabus

Introduction: Probability distributions, random variables, joint distributions, random process, graphs, undirected and Directed Graphical Models. Representation: Bayesian Networks – Independence in graphs – d-separation, I-equivalence, minimal I-maps. Undirected Graphical models: Gibbs distribution and Markov Networks, Markov models and Hidden Markov Models. From Bayesian to Markov and Markov to Bayesian networks, Triangulation and Chordal Graphs. Directed Gaussian graphical models. Exponential Family Models. Factor Graph Representation. Conditional Random Fields. Other special Cases: Chains, Trees.

Inference: Variable Elimination (Sum Product and Max-Product). Junction Tree Algorithm. Forward Backward Algorithm (for HMMs). Loopy Belief Propagation. Markov Chain Monte Carlo Metropolis Hastings. Importance Sampling. Gibbs Sampling. Variational Inference.

Learning Graphical models: Discriminative vs. Generative Learning., Density estimation, learning as optimization, maximum likelihood estimation for Bayesian networks, structure learning in Bayesian networks, Parameter Estimation in Markov Networks. Structure Learning. Learning undirected models- EM: Handling Missing Data. Applications in Vision, Web/IR, NLP and Biology. Advanced Topics: Statistical Relational Learning, Markov Logic Networks
.

Text Book / References

1. Daphne Koller and Nir Friedman, "Probabilistic Graphical Models: Principles and Techniques", First Edition, MIT Press, 2009.
2. Michael Jordan, "Learning in Graphical Models". MIT Press, 1998. Collection of Papers.
3. Judea Pearl, Morgan Kaufmann, " Probabilistic Reasoning in Intelligent Systems", 1988.
4. Kevin P. Murphy, "Machine Learning, a probabilistic perspective", The MIT Press Cambridge, Massachusetts, 2012.
5. Darwiche Adnan, "Modeling and reasoning with Bayesian networks", Cambridge university press, 2009.
6. Jacqueline Maasch, Willie Neiswanger, Stefano Ermon and Volodymyr Kuleshov, Probabilistic Graphical Models: A Concise Tutorial, 2025

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the process of encoding probability distributions using graphs	3	2	3	1	2
CO2	Analyze the independence properties of the graph structure	3	3	3	1	2
CO3	Understand and analyze Markov networks for the graphical modeling of probability distributions	3	2	3	2	2
CO4	Familiarize methods that approximate joint distributions	3	2	2	-	-
CO5	Study and evaluate methods to learn the parameters of networks with known and unknown structures using real life data sets	3	3	4	2	4

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation - 50%
- End Semester Exam (2 hours) - 30%

26AI634 Computational Intelligence 3-0-2-4

Preamble

This course covers the principles and applications of computational intelligence techniques, including artificial neural networks, evolutionary algorithms, and fuzzy systems. Students will gain theoretical knowledge and practical skills to design, implement, and analyze intelligent systems

Course Objectives

- Gain comprehensive knowledge of neural network architectures and training techniques, including backpropagation, gradient descent, and hyperparameter tuning.
- Develop proficiency in designing and implementing genetic algorithms and fuzzy logic systems, with a focus on real-world applications and hybrid computational intelligence systems.

Course Outcomes

COs	Description
CO1	Understand the foundational concepts of computational intelligence.
CO2	Apply computational intelligence techniques to solve real-world problems.
CO3	Develop the ability to critically analyze and compare different computational intelligence methods.
CO4	Gain hands-on experience with software tools and libraries for computational intelligence.

Prerequisites

- Basic programming knowledge (Python or MATLAB)
- Introductory courses in linear algebra, calculus, and probability

Syllabus

Introduction to Neural Networks: Biological inspiration, Perceptron and its limitations, Multilayer Perceptron, Training Neural Networks: Backpropagation algorithm, Gradient descent optimization, Overfitting and regularization, Hyper parameter tuning, Kohonen's Self-Organizing Networks - Hopfield Networks, Boltzmann Machine, Introduction to Advanced Architectures: CNN, RNN and Auto encoders

Introduction to Evolutionary Algorithms: Biological inspiration, Genetic algorithms (GA), Evolution strategies (ES), Genetic programming (GP), Genetic Algorithms: Representation and initialization, Selection, crossover, and mutation, Fitness evaluation, Convergence and diversity maintenance, Advanced Evolutionary Techniques: Differential evolution (DE), Particle swarm optimization (PSO)

Introduction to Fuzzy Logic: Fuzzy sets and membership functions, Fuzzy rules and reasoning,

Fuzzy inference systems, Defuzzification methods, Designing Fuzzy Systems: Fuzzy controllers, Fuzzy clustering, Fuzzy decision making, Applications in control systems and data analysis

Hybrid Computational Intelligence Systems: Neuro-fuzzy systems, Genetic-fuzzy systems, Applications and case studies.

Text Book / References

1. R.C. Eberhart, “Computational Intelligence: Concept to Implementations”, Morgan Kaufmann Publishers, 2007.
2. Timothy J. Ross, "Fuzzy Logic with Engineering Applications," 4th Edition, Wiley, 2016.
3. Laurence Fausett, “Fundamentals of Neural Networks”, Prentice Hall,1994.
4. Nazmul Siddique, Hojjat Adeli, “Computational Intelligence: Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing”, Willey 2013.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the foundational concepts of computational intelligence.	3	-	-	-	-
CO2	Apply computational intelligence techniques to solve real-world problems.	-	3	-	-	-
CO3	Develop the ability to critically analyze and compare different computational intelligence methods.	3	-	2	2	-
CO4	Gain hands-on experience with software tools and libraries for computational intelligence.	-	3	3	-	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments & Case Study – 50%
- End Semester Exam (2 hours) - 30%

26AI635 Deep Learning 3-0-2-4

Preamble

With the advent of high-end computing facilities and with the availability of huge amount of data, deep learning became the de facto standard machine learning strategy to learn complicated patterns and is offering the state of the art results in diverse fields including but not limited to automatic language translation, speech processing, medical diagnoses and in almost all fields of computer vision. This course provides core understanding in different deep learning architectures, design principles, learning strategies and encourages the usage of many deep learning tools in designing and deploying solutions.

Course Objectives

- To introduce to students, different deep neural network architectures, training strategies/ algorithms, possible challenges, tools and techniques available in designing and deploying solutions to different practical/Engineering problems.

Course Outcomes

COs	Description
CO1	Understand and apply the basics of neural networks and address practical aspects of deep learning
CO2	Design and implement CNNs and apply them to real-world tasks such as object detection, face recognition
CO3	Develop and utilize RNNs, GRUs, LSTMs, and attention models for NLP applications including word embedding and speech processing
CO4	Understand and implement advanced deep learning models and apply them to solve complex problems

Prerequisites

- Computational Linear Algebra

Syllabus

Neural Networks basics – Linear Separable Problems and Perceptron – Multi layer neural networks and Back Propagation, Practical aspects of Deep Learning: Train/ Dev / Test sets, Bias/variance, Vanishing/exploding gradients, Gradient checking, Hyper Parameter Tuning

Convolutional Neural Networks – Basics and Evolution of Popular CNN architectures – Transfer Learning–Applications: Object Detection and Localization, Face Recognition, Neural Style Trans- fer Recurrent Neural Networks – GRU – LSTM – NLP – Word Embeddings – Transfer Learning – Attention Models – Applications: Sentinel Classification, Speech Recognition, Action Recognition

Auto Encoders – Applications: Semi-Supervised classification, Noise Reduction, Non-linear Dimensionality Reduction. Goal

Oriented Decision Making – Policy and Target Networks – Deep Quality Network for Reinforcement Learning

Introduction to GAN – Encoder/Decoder, Generator/Discriminator architectures. Challenges in NN training – Data Augmentation – Hyper parameter Settings – Transfer Learning– Developing and Deploying ML Models (e.g., Matlab/Tensor Flow/PyTorch)
Vision Transformer – Graph Neural Networks - Explainable AI, Responsible AI, and basic MLOps/deployment concepts.

Text Book / References

1. Ian Goodfellow, YoshuaBengio and Aeron Courville, "Deep Learning", MIT Press, First Edition, 2016.
2. Adam Gibson and Josh Patterson, " Deep Learning, A practitioner's approach", O'Reilly, First Edition, 2017.
3. Francois Chollet, "Deep Learning with Python", Manning Publications Co, Second Edition, 2018.
4. "Aurélien Géron, Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow", 3rd Edition, O'Reilly Media, 2022.
5. François Chollet, Deep Learning with Python, Third edition, Manning, 2025.
6. Aston Zhang, Zachary C. Lipton, Mu Li, and Alexander J. Smola, Dive into Deep Learning, 2024
7. Research Papers on Relevant Topics and Internet Resources.
8. S. J. D. Prince, *Understanding Deep Learning*. Cambridge, MA, USA: MIT Press, 2023.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and apply the basics of neural networks and address practical aspects of deep learning	3	1	-	2	-
CO2	Design and implement CNNs and apply them to real-world tasks such as object detection, face recognition	3	3	2	-	1
CO3	Develop and utilize RNNs, GRUs, LSTMs, and attention models for NLP applications including word embedding and speech processing	3	1	2	2	1
CO4	Understand and implement advanced deep learning models and apply them to solve complex problems	3	3	2	-	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments & Case Study – 50%
- End Semester Exam (2 hours) - 30%

26AI636 Reinforcement Learning 3-0-2-4

Preamble

Artificial intelligence techniques face challenges in learning from dynamic environment with minimal data. This course deals with various algorithms to learn such an environment. Elements of Reinforcement Learning, Model Based Learning, Temporal Difference Learning and Policy Search are the main focus topics of this course.

Course Objectives

- Good understanding of various types of algorithms for Reinforcement Learning
- Be able to design an RL system

Course Outcomes

COs	Description
CO1	Understand the fundamentals of reinforcement learning and recognize how it complements other ML techniques.
CO2	Acquire knowledge of different RL algorithms and apply them in practical applications
CO3	Learn to model tasks as reinforcement learning problems within the framework of Markov Decision Processes and develop solutions
CO4	Implement RL algorithms using a scientific programming language

Prerequisites

- Machine Learning basics
- Probability Theory basics
- Programming basics

Syllabus

Introduction to Machine Learning and its various types, Motivation and Introduction to Reinforcement Learning, Multi arm Bandits, Markov Decision Process, Value functions; Dynamic programming: Policy evaluation and improvement, Value iteration and Policy iteration algorithms

Value prediction problems: Temporal difference learning in finite state spaces Algorithms for large state spaces Control: Closed loop interactive learning, online and active learning in bandits, Q learning in finite MDPs, Q learning with function approximation,

On policy approximation of action values: Value Prediction with Function Approximation, Gradient- Descent Methods, Policy approximation: Actor critic methods, Monte Carlo Methods: Monte-carlo prediction, estimation of action values, off policy prediction via importance sampling, Deep RL, PPO, Actor-Critic, Multi-agent RL.

Text Book / References

1. Sutton and Barto, " Reinforcement Learning: An Introduction," 2nd edition, The MIT Press Cambridge, Massachusetts London, England, 2015
2. Csaba Szepesvari, "Algorithms for Reinforcement Learning", Morgan & Claypool, United States, 2010.
3. Xiao, Z. (2024). "Reinforcement Learning: Theory and Python Implementation," Springer, 2024, ISBN 9789811949326.
4. Li, S. E. "Reinforcement Learning for Sequential Decision and Optimal Control", Springer. 2024, ISBN 9789811689093.
5. Maxim Lapan, Deep Reinforcement Learning Hands-On: A practical and easy-to-follow guide to RL from Q-learning and DQNs to PPO and RLHF, Third Edition, Packt Publishing, 2024.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the fundamentals of reinforcement learning and recognize how it complements other ML techniques.	3	-	-	-	-
CO2	Acquire knowledge of different RL algorithms and apply them in practical applications	3	2	1	-	-
CO3	Learn to model tasks as reinforcement learning problems within the framework of Markov Decision Processes and develop solutions	3	3	3	3	-
CO4	Implement RL algorithms using a scientific programming language	3	3	3	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessments - Lab Assignments – 25%
- Continuous assessment - Project – 25%
- End Semester Exam (2 hours) - 30%

26AI637 Mining of Massive Datasets 3-0-2-4

Preamble

With the rise of user-web interaction and networking, as well as technological advances in processing power and storage capability, the demand for effective and sophisticated knowledge discovery techniques has grown exponentially. Businesses need to transform large quantities of information into intelligence that can be used to make smart business decisions. The importance of data to business decisions, strategy and behavior has proven unparalleled in recent years. Predictive analytics, data mining and machine learning are tools giving us new methods for analyzing massive data sets. Companies place true value on individuals who understand and manipulate large data sets to provide informative outcomes.

Course Objectives

- To acquire knowledge of existing systems and approaches to handle large scale data science problems.
- Apply different data mining techniques to handle large amounts of data.
- Analyze the performance of various data mining techniques when applied to diverse data sets.
- To gain insights into the design of different machine learning algorithms applied for data mining.

Course Outcomes

COs	Description
CO1	Understand the importance of data to be applied for predictive analytics that considers data mining and machine learning as tools to analyze massive data sets.
CO2	Introduce the design and operation of various big-data systems like Hadoop, Spark and Hive.
CO3	Apply suitable data mining algorithms to handle huge document databases and infinite streams of data to mine large social networks and web graphs.
CO4	Use case studies as a powerful analytical tool that will provide first-hand insight into how big data problems and their solutions allow companies like Google to succeed in the market.
CO5	Design large scale machine learning algorithms with practical hands-on experience for analyzing very large amounts of data.

Prerequisites

- Machine Learning.

Syllabus

Basics of Data Mining - Computational Approaches - Statistical Limits on Data Mining - Bonferroni’s Principle - Importance of Words in Documents - Hash Functions - Indexes - Secondary

Storage - The Base of Natural Logarithms - Power Laws -MapReduce – Distributed File Systems- Algorithms Using MapReduce, Extensions to MapReduce. Finding Similar Items - Applications of Near-Neighbor Search - Shingling of Documents - Similarity-Preserving Summaries of Sets - Locality-Sensitive Hashing for Documents - Distance Measures.

Mining Data Streams: The Stream Data Model - Sampling Data in a Stream - Filtering Streams – Blooms Filter. Link Analysis: PageRank - Efficient Computation of PageRank - Topic-Sensitive PageRank - Link Spam. Frequent Itemsets: The Market-Basket Model - Market Baskets and the A-Priori Algorithm - Handling Larger Datasets in Main Memory- The Algorithm of Park, Chen, and Yu - The Multistage Algorithm - The Multi-hash Algorithm.

Clustering: Introduction to Clustering Techniques -Points, Spaces, and Distances - Clustering Strategies - The Curse of Dimensionality. Hierarchical Clustering - K-means Algorithms – The Algorithm of Bradley, Fayyad, and Reina - CURE algorithm - Clustering in Non-Euclidean Spaces. Recommendation Systems: A Model for Recommendation Systems - Content-Based Recommendations - Collaborative Filtering – UV Decomposition. Dimensionality Reduction. Mining Social-Network Graphs: Social Networks as Graphs - Clustering of Social-Network Graphs - Direct Discovery of Communities - Partitioning of Graphs - Finding Overlapping Communities – Simrank. Dimensionality Reduction: Eigenvalues and Eigenvectors of Symmetric Matrices- Principal-Component Analysis - Singular-Value Decomposition

Text Book / References

1. Jeffrey David Ullman, Jure Leskovec, Anand Rajaraman, “Mining of Massive Data Sets”, e-book (3rd edition), Cambridge University Press, 2020.
2. Jiawei Han, Micheline Kamber, Jian Pei, “Data Mining. Concepts and Techniques”, 4th Edition (The Morgan Kaufmann Series in Data Management Systems), Elsevier, 2012.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the importance of data to be applied for predictive analytics that considers data mining and machine learning as tools to analyze massive data sets.	3	1	-	-	-
CO2	Introduce the design and operation of various big-data systems like Hadoop, Spark and Hive.	2	2	-	-	3
CO3	Apply suitable data mining algorithms to handle huge document databases and infinite streams of data to mine large social networks and web graphs.	3	-	3	3	2
CO4	Use case studies as a powerful analytical tool that will provide first-hand insight into how big data problems and their solutions allow companies like Google to succeed in the market.	2	3	2	2	2
CO5	Design large scale machine learning algorithms with practical hands-on experience for analyzing very large amounts of data.	3	3	3	-	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessment - Lab Assignments – 25%
- Continuous assessment - Project – 25%
- End Semester Exam (2 hours) - 30%

26AI638 Generative AI 3-0-2-4

Preamble

This course offers an in-depth exploration of Generative AI, focusing on Generative Adversarial Networks (GANs) and Large Language Models (LLMs). Generative AI represents a cutting-edge field that aims to create models capable of generating realistic data, encompassing images, music, and text. Students will gain an understanding of generative models' principles and historical impact. The course covers GANs' architecture, and types like DCGANs and StyleGANs, and applications. It also addresses performance challenges and improvement techniques. For LLMs, the course examines models like GPT-4 and BERT, their training on extensive text data, and applications in NLP tasks such as text generation, translation, and summarization. Students will learn to implement and fine-tune LLMs for specific purposes.

Course Objectives

- To understand basic principles of Artificial Intelligence.
- To understand the basic areas of artificial intelligence including problem solving, knowledge representation, reasoning, decision making, planning, perception and action.
- To understand automatic learning methods in artificial intelligence

Course Outcomes

COs	Description
CO1	To understand and design architectures for various Generative Adversarial Network (GAN) variants.
CO2	To implement and train GANs for practical real-world applications.
CO3	To apply techniques for assessing and improving the performance of GANs.
CO4	Apply the principles and optimization techniques of Large Language Models (LLMs) like GPT-4 and BERT for various downstream tasks
CO5	To implement and fine-tune LLMs for various natural language processing (NLP) tasks.

Prerequisites

- Basic knowledge of Deep Learning
- Familiarity with Python programming

Syllabus

Recap of Deep neural networks, Variational Autoencoders (VAEs), and attention mechanisms. Generative Adversarial Networks (GANs) GAN components, DCGANs using convolutional layers, control your GAN and build conditional GAN. Use GANs for data augmentation and privacy preservation, GANs applications, Pix2Pix and CycleGAN for image translation. Comparison of generative models, FID method to assess GAN fidelity and diversity, Bias in GAN, StyleGAN techniques.

Principles of Transformers, Word embeddings, Introduction to Large Language Models – Decoder-only LLMs: A deep dive into GPT, Encoder Only LLMs-BERT, Prompting – different prompting strategies – Instruction tuning – fine tuning – parameter efficient fine-tuning – quantized fine tuning. Small Language models. Training LLMs using reinforcement Learning. Retrieval-Augmented Generation (RAG), Agentic AI, Tool Calling, Vector Databases, Multimodal Foundation Models, Fine-tuning using LoRA/QLoRA, LMOps.

Evaluating LLMs: Benchmarks, evaluation frameworks and popular leaderboards. Applications/Case study of Large Language Models - Text Generation, Translation, and Summarization - Question Answering, Sentiment Analysis, Chatbots, Application of LLMs in healthcare and Code generation, latest advancements in LLMs.

Text Book / References

1. BB. Marr, Generative AI in Practice: 100+ Amazing Ways Generative Artificial Intelligence Is Changing Business and Society. Hoboken, NJ, USA: Wiley, Mar. 2024. ISBN: 978-1394245567.
2. Jay Alammar, Maarten Grootendorst, “Hands-On Large Language Models”, December 2024 Publisher(s): O'Reilly Media.
3. Ian Goodfellow, YoshuaBengio and Aeron Courville, “Deep Learning”, MIT Press, 2016.
4. Jason Browlee, “Deep Learning for Natural Language Processing: Develop Deep Learning Models for your Natural Language Problems (Ebook)”, Machine Learning Mastery, 2017.
5. udharsan Ravichandiran, “Getting Started with Google BERT: Build and train state-of-the-art natural language processing models using BERT”, Packt Publishing Limited January 2021.
6. Comprehensive Overview of LLMs - A survey paper: https://arxiv.org/pdf/2307.06435. Other research papers on LLM
7. Daniel Jurafsky, James H Martin, “Speech & language processing”, preparation [cited 2020 June 1] Available from: https://web.stanford.edu/~jurafsky/slp3/.
8. S. Raschka, *Build a Large Language Model (From Scratch)*. Shelter Island, NY, USA: Manning Publications, 2024.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	To understand and design architectures for various Generative Adversarial Network (GAN) variants.	3	1	-	-	-
CO2	To implement and train GANs for practical real-world applications.	2	3	2	-	-
CO3	To apply techniques for assessing and improving the performance of GANs.	3	2	2	-	-
CO4	Apply the principles and optimization techniques of Large Language Models (LLMs) like GPT-4 and BERT for various downstream tasks	3	1	-	2	-
CO5	To implement and fine-tune LLMs for various natural language processing (NLP) tasks.	3	1	-	2	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Assessment - Theory - 10%
- Continuous Assessment - Lab – 40%
- End Semester Exam (2 hours) - 30%

26AI731 Machine Learning for Bigdata 2-0-2-3

Preamble

This course deals with two aspects of big data analytics. The first one is the infrastructure for big data analytics. Introduction to tools and algorithms that can be used to generate models from big data and to scale those models up to big data problems. Spark framework is the chosen platform. The second is the understanding and implementation of scalable and streaming algorithms to analyze voluminous data that is growing exponentially

Course Objectives

- To understand various scalable machine learning algorithms to solve big data problems.
- To understand the SPARK architecture
- To implement Machine Learning algorithms using PySpark

Course Outcomes

COs	Description
CO1	Understand and explain how machine learning algorithm is made scalable to solve big data problems.
CO2	Implement scalable Machine Learning algorithms using PySpark.

CO3	Apply and compare different strategies for big data analytics using various machine learning algorithms
CO4	Understand Streaming algorithms and Coreset concept to analyze high dimensional data

Prerequisites

- Machine Learning.

Syllabus

Introduction to Spark : Spark Architecture, Spark Jobs and APIs. Resilient Distributed Datasets- Creating RDDs, Transformation, Actions. Dataframes- Python to RDD communications, Creating Dataframes, Dataframe queries. MLlib -Loading and Transforming the data. Implementation of Machine Learning algorithms such as Classification and Clustering using the MLlib

Approaches to Modelling- Importance of Words in Documents - Hash Functions- Indexes - Secondary Storage -The Base of Natural Logarithms - Power Laws - Map Reduce. Finding similar items: Shingling – LSH - Distance Measures. Mining Data Streams: Stream data model - Sampling data - Filtering streams. Link Analysis: Page Rank, Link Spam.

Frequent Item Sets: Market Basket Analysis, A-Priori Algorithm - PCY Algorithm, Big data Clustering: Clustering in Non-Euclidean Spaces, BFR, CURE. Structured Streaming: Spark Streaming, Application dataflow. Coresets: Coresets for K-means, K -median clustering

Text Book / References

1. Leskovec, J., Rajaraman, A., & Ullman, J. D. (2020). Mining of Massive Datasets (3rd ed.). Cambridge University Press.
2. Kevin P. Murphey, “Probabilistic Machine Learning”, The MIT Press Cambridge, Massachusetts, 2022.
3. Tomasz Drabas, Denny Lee , ”Learning Pyspark”, Packt, February 2017.
4. Jeff M. Phillips, ”Coresets and Sketches”, arXiv:1601.00617,2016.
5. Adi Polak, Scaling Machine Learning with Spark: Distributed ML With MLlib, TensorFlow, and PyTorch, O’Reilly Media, Inc, 2023.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and explain how machine learning algorithm is made scalable to solve big data problems.	3	-	-	-	-
CO2	Implement scalable Machine Learning algorithms using PySpark.	3	3	3	3	3
CO3	Apply and compare different strategies for big data analytics using various machine learning algorithms	3	2	1	1	-
CO4	Understand Streaming algorithms and Coreset concept to analyze high dimensional data	3	2	1	1	-

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%

End Semester Exam (2 hours) - 30%

26AI732 Applications of Machine Learning 2-0-2-3

Preamble

Voluminous and high-dimensional data persist in almost all domains. This course deals with applications of machine learning in various domains to solve complex optimization problems such as recommendation systems, web advertising, and customer segmentation. The entire life cycle of data analytics is dealt with in this course.

Course Objectives

- To understand the design and implementation strategies of various applications of machine learning
- To apply techniques of preprocessing, model generation, and evaluation on a given dataset from a particular domain.
- To compare different strategies of machine learning on a particular application

Course Outcomes

COs	Description
CO1	Understand how Machine learning is applied to solve problems in various applications like game playing, recommendation systems, high dimensional analysis, and targeted web advertising
CO2	Present and Implement ML algorithms to solve real world problems
CO3	Apply and compare different types of Machine learning approaches for a given application problem in the context of performance
CO4	Design a machine learning system by incorporating various components of ML and evaluate the performance

Prerequisites

- Machine Learning.

Syllabus

Review of machine learning concepts; design of ML system – data cleaning, feature engineering, model selection, model building & fine tuning, and model deployment. Bias, variance, learning curves, and error analysis. Recommendation Systems – Model for Recommendation Systems, Utility Matrix, Content-Based Recommendations, Discovering Features of Documents, Collaborative Filtering. Usage of UV and NMF decomposition in Recommendation systems

Advertising on the Web: Issues in Online Advertising, Online and offline algorithms, The matching Problem, The AdWords Problem, The Balance Algorithm, A Lower Bound on Competitive Ratio for Balance. Customer segmentation – Subspace Clustering, Types of Subspace clustering, Top down and bottom-up approach: PROCLUS and, CLIQUE and their

applications in Indexing in databases. Application of dimensionality reduction-SVD for Latent Semantic Indexing, CUR for approximate query processing from databases, PCA, for Image Processing – compression, identification and Visualization.

Sparse models, State space models, Markov Decision Process, Bellman equations, Value iteration and Policy iteration, Linear Quadratic Regulation (LQR), Non-linear dynamics to LQR, Linear Quadratic Gaussian (LQG), Independent component Analysis (ICA) for speech processing

Text Book / References

1. Anand Raja Raman, Jure Leskovec and J.D. Ullman, "Mining of Massive Datasets", Cambridge University Press, Third edition, 2020.
2. Kevin P. Murphey, "Probabilistic Machine Learning", MIT Press, Cambridge, Massachusetts, 2022.
3. Dipanjan Sarkar, Raghav Bali and Tushar Sharma, Practical Machine Learning with Python A Problem-Solver's Guide to Building Real-World Intelligent Systems, A press, 2017.
4. David Forsyth, Applied Machine Learning, Springer, 2019.
5. Selected Journal papers to be given as case study from each module.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand how Machine learning is applied to solve problems in various applications like game playing, recommendation systems, high dimensional analysis, and targeted web advertising	3	3	3	2	2
CO2	Present and Implement ML algorithms to solve real world problems	3	3	3	2	2
CO3	Apply and compare different types of Machine learning approaches for a given application problem in the context of performance	1	3	3	2	2
CO4	Design a machine learning system by incorporating various components of ML and evaluate the performance	3	3	3	2	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam (2 hours) - 30%

26AI733 Evolutionary Machine Learning 2-0-2-3

Preamble

This course explores the intersection of evolutionary computation and machine learning. It provides an in-depth understanding of how evolutionary techniques can enhance machine learning methods. The course covers a wide range of topics, from fundamental concepts to advanced applications, and equips students with the skills to apply these techniques to real-world problems. It's a blend of theoretical knowledge and practical implementation, designed to prepare students for future academic or professional roles in this exciting field.

Course Objectives

- To understand the fundamental concepts of evolutionary algorithms and their applications in various learning paradigms in machine learning.
- To develop proficiency in implementing evolutionary computation techniques for clustering, classification, regression, and ensemble learning.
- To learn to enhance machine learning models through evolutionary approaches for data preparation, model parametrization, design, and validation.
- To critically evaluate and compare the effectiveness of evolutionary computation methods with traditional machine learning techniques.

Course Outcomes

COs	Description
CO1	Understand the principles and techniques of evolutionary computation in machine learning
CO2	Develop the ability to formulate and solve problems using evolutionary computation techniques.
CO3	Demonstrate the ability to apply evolutionary algorithms to solve problems in clustering, classification, regression, and ensemble learning
CO4	Design, validate, and optimize machine learning models using evolutionary computation.

Prerequisites

- Mathematical Foundations of Computing
- Machine Learning

Syllabus

Evolutionary Machine Learning Basics: Fundamentals of Evolutionary Machine Learning - Introduction to Evolutionary Computation, Biological Inspiration behind Evolutionary Algorithms. Evolutionary Supervised Machine Learning - Introduction to Supervised Learning, Evolutionary Algorithms for Regression and Classification, Feature Selection using Evolutionary Algorithms. Evolutionary Machine Learning for Unsupervised Learning - Introduction to Unsupervised Learning, Evolutionary Clustering Algorithms, Evolutionary

Dimensionality Reduction Techniques. Evolutionary Computation and the Reinforcement Learning Problem - Introduction to Reinforcement Learning, Evolutionary Algorithms for Policy Optimization, Balancing Exploration and Exploitation using Evolutionary Techniques.

Evolutionary Computation as Machine Learning: Evolutionary Regression and Modelling - Evolutionary Algorithms for Regression Problems, Model Selection and Optimization using Evolutionary Techniques. Evolutionary Clustering and Community Detection - Community Detection in Networks using Evolutionary Techniques. Evolutionary Classification - Evolutionary Algorithms for Binary and Multi-class Classification, Hyperparameter Tuning and Model Selection using Evolutionary Techniques. Evolutionary Ensemble Learning - Evolutionary Algorithms for Ensemble Model Construction, Diversity and Performance Optimization using Evolutionary Techniques.

Evolutionary Computation for Machine Learning: Genetic Programming as an Innovation Engine for Automated Machine Learning: The Tree-Based Pipeline Optimization Tool (TPOT), Evolutionary Model Validation—An Adversarial Robustness Perspective, Evolutionary Approaches to Explainable Machine Learning, Evolutionary Algorithms for Fair Machine Learning.

Text Book / References

1. Banzhaf, W., Machado, P., Zhang, M. (Eds.) (2023). Handbook of Evolutionary Machine Learning. Springer.
2. Song, T., Zheng, P., Wong, M. L. D., Wang, X. (2019). Bio-Inspired Computing Models and Algorithms. World Scientific.
3. Floreano, D., Mattiussi, C. (2008). Bio-Inspired Artificial Intelligence. MIT Press.
4. Mitchell, T. M., & Balasubramanian, V. N. (2026). Machine Learning (2nd ed.). McGraw Hill.
5. Eiben, A. E., Smith, J. E. (2015). Introduction to Evolutionary Computing. Springer.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the principles and techniques of evolutionary computation in machine learning	3	2	3	1	-
CO2	Develop the ability to formulate and solve problems using evolutionary computation techniques.	3	3	3	2	1
CO3	Demonstrate the ability to apply evolutionary algorithms to solve problems in clustering, classification, regression, and ensemble learning	3	3	3	2	1
CO4	Design, validate, and optimize machine learning models using evolutionary computation.	3	3	3	3	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 50%
- End Semester Exam (2 hours) - 30%

26AI734 Applied Predictive Analytics 2-0-2-3

Preamble

Predictive analytics is used to predict future outcomes based on historical data using statistical and machine learning techniques. This course provides a comprehensive review of various analytics methods. Students will gain an in-depth understanding of supervised and unsupervised learning for predictive analytics. The course will also cover the principles of forecasting analytics.

Course Objectives

- To familiarize students with the methods for exploration and visualization of data
- To develop machine learning models for predictive tasks
- To choose suitable performance measures for predictive models
- To apply predictive modelling techniques in real world data

Course Outcomes

COs	Description
CO1	Understand and describe analytical methods used in predictive analytics
CO2	Evaluate the measures to access predictive performance of data mining tasks
CO3	Understand and design prediction, classification methods
CO4	Learn and identify appropriate methods for forecasting different types of time series data
CO5	Apply suitable predictive methods in real-life problems

Prerequisites

- Linear Algebra and Probability

Syllabus

Introduction and Overview of the Predictive Analytics – Building a Predictive Model - Predictive Power and Overfitting - Data Partitioning – Exploratory Data Analysis - Data Visualization - Dimension Reduction - Principal Components Analysis - Performance Evaluation - Evaluating Predictive Performance - Judging Classifier Performance – Lift and Decile Charts – Oversampling.

Prediction and Classification Methods - Multiple Linear Regression - Explanatory vs. Predictive Modeling - Estimating the Regression Equation and Prediction - The k-NN Classifier (Categorical Outcome) - The Naive Bayes Classifier - Classification and Regression Trees - Logistic Regression - Neural Nets - Discriminant Analysis - Combining Methods: Ensembles - Uplift Modeling - Association Rules and Collaborative Filtering - Clustering.

Forecasting Time Series – Components of a Time Series – Data Partitioning and Performance Evaluation for Time Series – Naive Forecasts - Smoothing Methods - Introduction - Moving Average - Simple Exponential Smoothing – Advanced Exponential Smoothing–Regression-Based Forecasting - Autocorrelation and ARIMA Models - Data Analytics - Social Network Analytics - - Text Mining - predictive analytics in business application - Other Case Studies.

Text Book / References

1. Max Kuhn and Kjell Johnson, "Applied Predictive Modeling", Springer, 2018.
2. Galit Shmueli, Peter Gedeck, Peter C. Bruce, Nitin R. Patel, "Data Mining for Business Analytics: Concepts, Techniques, and Applications in Python", Global edition, Wiley, 2023.
3. Daniel T. Larose and Chantal D. Larose, "Data Mining and Predictive Analytics" (Wiley Series on Methods and Applications in Data Mining), Second edition, Wiley, 2019.
4. Ratner Bruce, "Statistical and Machine-Learning Data Mining:: Techniques for Better Predictive Modeling and Analysis of Big Data", CRC Press, 2017.
5. Abbott Dean, "Applied predictive analytics: Principles and techniques for the professional data analyst", John Wiley & Sons, 2014.
6. Foster Provost and Tom Fawcett, Data Science for Business, Special Edition for Data Science for Business Analytics, O'Reilly Media, Inc, 2013.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and describe analytical methods used in predictive analytics	3	1	-	-	-
CO2	Evaluate the measures to access predictive performance of data mining tasks	3	3	2	-	-
CO3	Understand and design prediction, classification methods	3	3	3	1	-
CO4	Learn and identify appropriate methods for forecasting different types of time series data	3	2	2	1	-
CO5	Apply suitable predictive methods in real-life problems	3	3	3	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam (2 hours) - 30%

26AI735 Federated Learning 2-0-2-3

Preamble

Federated learning can improve the performance of models by leveraging the diversity of the data across different devices. In this course, students will learn basics of Federated Learning and will be able to apply the real-time updates of the model in various practical scenarios.

Course Objectives

- Get exposure to need for distributed model updates
- To understand the importance of privacy and security in machine learning techniques

Course Outcomes

COs	Description
CO1	Describe the key concepts and architecture of Federated Learning.
CO2	Apply different methods to develop federated learning systems.
CO3	Apply optimization techniques in Federated Learning
CO4	Construct and scale a simple federated system
CO5	Evaluate privacy and security concerns in Federated Learning and implement privacy-preserving techniques.

Prerequisites

- Machine Learning

Syllabus

Introduction to Federated Learning - Overview of Federated Learning: Definition, History, and Applications - Concepts and Terminology - Federated Learning Architecture -Machine Learning Perspective -Security & Privacy in Federated Learning - Federated Learning vs Centralized Learning: Comparison and Contrast

Horizontal Federated Learning (HFL) -Definition and Architecture of Horizontal Federated Learning - Federated Averaging (FedAvg) Algorithm - Improvements on the FedAvg Algorithm. Vertical Federated Learning (VFL) - Definition and Architecture of Vertical Federated Learning - VFL Algorithms: Secure Federated Linear Regression, Secure Federated Tree Boosting. Federated Learning with Non-IID Data - Heterogeneity in Federated Learning -Stratification and Local Updated Rules - Advanced Optimization Techniques in Federated Learning - Adaptive Learning Rate -Momentum and Weight Decay.

Federated Transfer Learning (FTL) - Framework of Federated Transfer Learning - Homomorphic Encryption in FTL - FTL Training Process -FTL Prediction Process - Security Analysis of FTL - Secret Sharing based FTL. Security in Federated Learning - Protecting Against Data Leakage in FL -Private Parameter Aggregation for FL - Data Leakage in FL Advanced Security Issues -Dealing with Byzantine Threats to Neural Networks in FL. Practical Applications and Case Studies -Real-world Applications of Federated Learning.

Text Book / References

1. H. Ludwig and N. Baracaldo, Eds., Federated Learning: A Comprehensive Overview of Methods and Applications. Cham, Switzerland: Springer Nature Switzerland, 2022.
2. Q. Yang, Y. Liu, Y. Cheng, Y. Kang, T. Chen, and H. Yu, Federated Learning. Cham, Switzerland: Springer, Synthesis Lectures on Artificial Intelligence and Machine Learning, 2022
3. Y. Jin, H. Zhu, J. Xu, and Y. Chen, Federated Learning: Fundamentals and Advances. Singapore: Springer, 2023.
4. Yaochu Jin, Yang Chen, Hangyu Zhu, Jinjin Xu, Federated Learning Fundamentals and Advances, Springer, 2023.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Describe the key concepts and architecture of Federated Learning.	3	-	3	2	-
CO2	Apply different methods to develop federated learning systems.	3	2	1	-	2
CO3	Apply optimization techniques in Federated Learning	2	-	2	3	3
CO4	Construct and scale a simple federated system	2	3	2	3	-
CO5	Evaluate privacy and security concerns in Federated Learning and implementing privacy-preserving techniques.	2	2	3	2	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam (2 hours) - 30%

26AI736 Explainable AI 2-0-2-3

Preamble

This course provides an introduction to Explainable AI (XAI) through practical applications and real-world examples. Students will gain a basic proficiency in interpreting and explaining the decisions of ML and AI systems, in a transparent and understandable manner to humans. The course will cover various XAI techniques and algorithms, including rule-based models, feature importance analysis, model-agnostic approaches, and post-hoc explanations.

Course Objectives

- To understand how to explain machine learning models with various techniques.
- To explain various factors affecting the efficiency of machine learning models.
- To apply the explainability while applying ML models in practical applications.

Course Outcomes

COs	Description
CO1	Understand the concept and importance of explainability in AI models
CO2	Apply visual explanations techniques such as PDP, ICE, Surrogate Models, and Feature Importance
CO3	Explain structured data, images, and unstructured data using Deep Explainers and LLMs
CO4	Evaluate the application of explainability techniques in model development processes

Prerequisites

- Machine Learning, Python Programming

Syllabus

Explainability –What and Why, When not to use explainability; Types of explainability and Taxonomy, Explainability in the model development process.

Visual Explanations – Transparent models and RuleFit, Partial Dependency Plots, Partial Dependency plot (PDP), Individual conditional expectations (ICE), Applications of these plots, Global Explanations – Surrogate Models, Feature Importance; Local Explanations – LIME, Shapley values.

Explaining Structured Data, Explaining Images and Unstructured Data and Text Deep Explainers, Time Series Explainers, LLM, Foundation Models.

Text Book / References

1. Denis Rothman “Hands-On Explainable AI (XAI with Python”, Packt Publishing, 2020.
2. Explainable AI for Practitioners by Michael Munn, David Pitman, O'Reilly

Media 2022, ISBN: 9781098119133.

3. Explainable AI: Interpreting, Explaining and Visualizing Deep Learning, Lecture Notes in Artificial Intelligence, Springer Nature, 2019.
4. Christoph Molnar, Interpretable Machine Learning: A Guide for Making Black Box Models Explainable
5. Christoph Molnar, Interpretable Machine Learning: A Guide for Making Black Box Models Explainable, 2025.
6. Mayuri Mehta,Vasile Palade and Indranath Chatterjee, Explainable AI: Foundations, Methodologies and Applications, Intelligent Systems Reference Library, Springer 2023.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the concept and importance of explainability in AI models	2	2	1	2	-
CO2	Apply visual explanations techniques such as PDP, ICE, Surrogate Models, and Feature Importance	2	2	3	2	-
CO3	Explain structured data, images, and unstructured data using Deep Explainers and LLMs	3	2	2	3	1
CO4	Evaluate the application of explainability techniques in model development processes	1	1	3	2	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessment - Quizzes - 20%
- Continuous assessment - Lab Assignments & Case Study – 30%
- End Semester Exam (2 hours) - 30%

26AI737 Artificial Intelligence for Robotics 2-0-2-3

Preamble

In recent years, several off-the-shelf robots have become available, and some of them have made their way into our homes, offices, and factories. The ability to program robots has therefore become an important skill; e.g., for robotics research as well as in several companies (such as iRobot, ReThink Robotics, Willow Garage, medical robotics, and others). We study the problem of how a robot can learn to perceive its world well enough to act in it, to make reliable plans, and to learn from its own experience. The focus will be on algorithms and machine learning techniques for autonomous operation of robots.

Course Objectives

- To understand the principles of reinforcement learning, which is one of the key learning techniques for robots.
- To understand uncertainty handling in robotics through probabilistic approaches.
- To learn how measurements work for robots.

Course Outcomes

COs	Description
CO1	Learn the foundations of reinforcement learning for robotics
CO2	Understand basic probabilistic principles behind Robotics intelligence
CO3	Learn different measurement techniques for robotics
CO4	Understand POMDP and its significance for robotics
CO5	Implement principles of robotics intelligence for solving real world problems

Prerequisites

- Data Structures and Algorithms
- Foundation of Data Science
- Linear Algebra and Optimization
- Principles of AI and ML

Syllabus

Overview: Robotics introduction, historical perspective on AI and Robotics, Uncertainty in Robotics Reinforcement Learning: Basic overview, examples, elements, Tabular Solution Methods - Multi- armed bandits, Finite Markov decision process, Dynamic programming (Policy Evaluation, Policy Iteration, Value Iteration), Monte Carlo Methods, Temporal-Difference Learning (Q-learning, SARSA).

Approximate Solution Methods - On-policy Prediction with Approximation, Value function approximation, Non-linear function approximation, Reinforcement Learning in robotics,

Recursive state estimation: Robot Environment Interaction, Bayes filters, Gaussian filters – The Kalman filter, The Extended Kalman Filter, The information filter, The particle filter Robot motion: Velocity Motion Model, Odometry Motion Model, Motion and maps.

Measurement: Beam Models of Range Finders, Likelihood Fields for Range Finders, Correlation- Based Sensor Models, Feature-Based Sensor Models, Overview of POMDP.

Text Book / References

1. Sebastian Thrun, Wolfram Burgard, Dieter Fox, Probabilistic Robotics, MIT Press 2005
2. Richard S. Sutton, Andrew G. Barto, Reinforcement Learning: An Introduction", Second edition, MIT Press, 2018
3. Jens Kober, Jan Peters, Learning Motor Skills: From Algorithms to Robot Experiments, Springer, 2014
4. Francis X. Govers, Artificial Intelligence for Robotics, Packt, 2018.
5. M. Mohri, S. Roumeliotis, and M. Valstar, Eds., The Robot Learning Handbook. Cambridge, UK: Cambridge University Press, 2025.
6. Donald R. Franceschetti, Principles of Robotics & Artificial Intelligence, SALEM PRESS A Division of EBSCO Information Services Ipswich, Massachusetts, 2018.
7. Ashutosh Kumar Dubey, Abhishek Kumar, S. Rakesh Kumar and N. Gayathri, Prasenjit Das, AI and IoT-Based Intelligent Automation in Robotics, Scrivener Publishing LLC, Wiley, 2021.
8. P. Corke, Robotics, Vision and Control: Fundamental Algorithms in Python, 3rd Edition, Springer, 2023.
9.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Learn the foundations of reinforcement learning for robotics	3	1	3	-	1
CO2	Understand basic probabilistic principles behind Robotics intelligence	3	1	3	-	1
CO3	Learn different measurement techniques for robotics	3	-	3	-	1
CO4	Understand POMDP and its significance for robotics	3	-	3	-	1
CO5	Implement principles of robotics intelligence for solving real world problems	3	-	3	1	-

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessment - Lab Assignments – 25%
- Continuous assessment - Project – 25%
- End Semester Exam (2 hours) - 30%

26AI738 Data Visualization 2-0-2-3

Preamble

Data visualization is an essential aspect of the data science portfolio and finds applications across diverse disciplines which use visualization techniques to explore and present data. This course lays a road map to data-driven storytelling by focusing on the principles, methods, and techniques of scientific visualization that help to create powerful and engaging visuals, tailored to the needs of diverse stakeholders.

Course Objectives

- To understand the important role of visualization in the analysis of data.
- To apply data visualization, best practices to choose the appropriate visualization tailored to the needs of the audience.
- To learn some of the latest tools and software to produce effective visuals that capture the stories within the data

Course Outcomes

COs	Description
CO1	Understand and explain the key techniques used in data visualization
CO2	Apply effective visualizations to explore and analyze input data
CO3	Present the insights and findings in engaging formats that produce compelling stories
CO4	Evaluate data visualization systems for their effectiveness
CO5	Design and build data visualization systems following the best practices using popular software tools for visualization such as Tableau/QlikView

Prerequisites

- Basic Data Science.

Syllabus

Value of Visualization – What is Visualization and Why do it: External representation – Interactivity – Difficulty in Validation. Data Abstraction: Dataset types – Attribute types – Semantics. Task Abstraction – Analyze, Produce, Search, Query. Four levels of validation – Validation approaches – Validation examples. Marks and Channels

Rules of thumb – Arrange tables: Categorical regions – Spatial axis

orientation – Spatial layout density. Arrange spatial data: Geometry – Scalar fields – Vector fields – Tensor fields. Arrange networks and trees: Connections, Matrix views – Containment. Map color: Color theory, Color maps and other channels.

Manipulate view: Change view over time – Select elements – Changing viewpoint – Reducing attributes. Facet into multiple views: Juxtapose and Coordinate views – Partition into views - Static and Dynamic layers – Reduce items and attributes: Filter – Aggregate. Focus and context: Elide – Superimpose - Distort, Case Studies using Tableau/Qlikview – Tabular Data - Graphs - Networks - Trees - Spatial Data - Text/Logs - Time Series Complex Combinations.

Text Book / References

1. Tamara Munzner, "Visualization Analysis and Design", A K Peters Visualization Series, CRC Press, 2014.
2. Claus O. Wilke, "Fundamentals of Data Visualization: A primer for making informative and compelling figures", O'Reilly, 2019.
3. Kieran Healy, "Data Visualization: A Practical Introduction", Princeton University Press, 2019.
4. Andy Kirk, "Data Visualization, A Handbook for Data Driven Design", 2nd edition, Sage Publications, 2019.
5. Daniel Murray, "Tableau Your Data!: Fast and Easy Visual Analysis with Tableau Software", Wiley, 2016.
6. Cole nussbaumer knaflic, "Storytelling with data - A data visualization guide for business professionals", Wiley, 2015.
7. Knaflic, C. N. "Storytelling with Data: Let's Practice!", Wiley, 2016.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the key techniques and theory used in visualization of data	3	-	-	-	-
CO2	Apply effective visualizations to explore and analyze input data	3	-	-	1	-
CO3	Present the insights and findings in engaging formats that produce compelling stories	3	-	-	-	1
CO4	Evaluate data visualization systems for their effectiveness	3	2	-	-	-
CO5	Design and build data visualization systems following the best practices using popular software tools for visualization such as Tableau/QlikView	3	3	3	3	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Lab Assignments – 25%
- Project – 25%
- End Semester Exam (2 hours) - 30%

26AI739 Stochastic Modeling 2-0-2-3

Preamble

This course provides an in-depth exploration of stochastic processes with a focus on their applications in artificial intelligence.

Course Objectives

- Gain a foundational understanding of finite Markov chains in discrete time.
- Develop a comprehensive understanding of martingales in discrete time, covering fundamental theoretical concepts and their practical implications.
- Explore the essential principles of stochastic processes in continuous time, focusing on key examples such as the Poisson process and Brownian motion.
- Acquire insights into elementary stochastic calculus applied to Brownian motion, enhancing comprehension of its theoretical underpinnings.

Course Outcomes

COs	Description
CO1	Demonstrate a deep understanding of the theoretical foundations of finite Markov chains in discrete time.
CO2	Apply martingale theory to analyze algorithms and decision-making processes in AI.
CO3	Understand the essential principles of stochastic processes in continuous time, with a focus on the Poisson process.
CO4	Apply elementary stochastic calculus techniques to Brownian motion and related processes.

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quisites

- None.

Syllabus

Introduction to Stochastic Processes: Overview of stochastic processes - Introduction to conditional expectations. Conditional Expectations: Definition and properties of conditional expectations - Conditional expectations in the context of stochastic processes - Bayesian inference and decision theory.

Discrete Time Martingales: Definition and properties of martingales - Stopping times and optional stopping theorem - Discrete Time Markov Chains: Definition and properties of Markov chains - Classification of states, ergodicity - Stationary distributions and convergence - Markov decision processes (MDPs) and modelling sequential decision problems.

Poisson Process: Interarrival times and memory lessness - Poisson processes in queuing theory and AI applications - Brownian Motion: - Stochastic integration and differential equations - Geometric Brownian motion and its applications in finance and AI. Elements of Ito Stochastic Calculus: Ito integral and Ito's lemma - Stochastic differential equations and models in continuous time.

Text Book / References

1. Lawler, G. F, “Introduction to Stochastic Processes", Second edition, Cambridge University Press, 2018.
2. Del Moral, P, “Stochastic Processes: From Applications to Theory”, Springer, 2014.
3. Shreve, S. E, “Stochastic Calculus for Finance II: Continuous-Time Models”, First edition, Springer, 2004.
4. Brzezniak, Z., & Zastawniak, T., "Basic Stochastic Processes”, First edition, Springer, 2000.
5. Taylor, H. M., & Karlin, S. “An Introduction to Stochastic Modeling", Fourth edition, Academic Press, 2014.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Demonstrate a deep understanding of the theoretical foundations of finite Markov chains in discrete time.	2	2	2	1	2
CO2	Apply martingale theory to analyze algorithms and decision-making processes in AI.	2	1	2	2	2
CO3	Understand the essential principles of stochastic processes in continuous time, with a focus on the Poisson process.	2	2	2	2	1
CO4	Apply elementary stochastic calculus techniques to Brownian motion and related processes.	2	2	2	2	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Quiz – 20%
- Lab Continuous Assessment – 30%
- End Semester Exam (2 hours) / Project - 30%

26AI740 Networks and Spectral Graph Theory 2-0-2-3

Preamble

Network science is an interdisciplinary field that combines mathematics, social science, computer science, and many other areas. This course is essentially bringing an understanding of the behavior of networked systems such as the Internet, social networks, and biological networks.

Course Objectives

- Exploring graph models in networked systems; understanding the structure and the behavior.
- Empirical study and hands-on experience on social networks and other systems

Course Outcomes

COs	Description
CO1	Understanding the key concepts in network graphs
CO2	Apply a range of measures and models for characterizing network structure
CO3	Define methodologies for analyzing networks of different fields
CO4	Apply graph algorithms to different networks
CO5	Demonstrate knowledge of network graphs with the help of software tools such NetworkX and Gephi

Prerequisites

- Primary knowledge of linear algebra and familiarity with graphs.
- Working knowledge in Python for data science.

Syllabus

Graphs and Networks - Review of basic graph theory, Mathematics of networks - Networks and their representation, Graph spectra, Graph Laplacian, Structure of complex networks, Clustering, Community structures, social networks - the web graph, the internet graph, citation graphs. Measures and metrics - Degree centrality, Eigenvector centrality, Katz centrality, PageRank, Hubs and authorities, Closeness centrality, Betweenness centrality, Transitivity, Reciprocity, Similarity, assortative mixing.

Networks models - Random graphs, Generalized random graphs, The small-world model, Exponential random graphs, The large-scale structure of networks - small world effect, Degree distributions, Power laws and scale-free networks; Structure of the Internet, Structure of the World Wide Web. Fundamental network algorithms - Graph partitioning, Maximum flows and minimum cuts, Spectral graph partitioning, Community detection, Girvan and Newman Algorithm, Simple modularity maximization, Spectral modularity maximization, Fast methods based on the modularity.

Models of network Formation - Preferential attachment, Model of Barabasi and Albert, Vertex copying models, Network optimization models; Epidemics on networks- Models of the spread of disease, SI model, SIR model, SIS model, SIRS model; Network Search-Web search, Searching distributed databases. Graph databases like Neo4j, Graph Convolutional Neural Networks, Graph algorithms and implementation using NetworkX and Gephi.

Textbook / References

1. M.E.J. Newman, “Networks: An Introduction”, Oxford University

Press, 2018.

2. Dougles West, “Introduction to Graph Theory”, Third Edition, PHI Learning Private Limited, 2021.
3. Guido Caldarelli, “Scale-Free Networks - Complex Webs in Nature and Technology (2nd ed.)”, Oxford University Press, 2020.
4. Alain Barrat, Marc Barthelemy and Alessandro Vespignani, “Dynamical processes on Complex networks”, Cambridge University Press, 2008.
5. Reuven Cohen and Shlomo Havlin, “Complex Networks: Structure, Robustness and Function”, Cambridge University Press, 2010.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understanding the key concepts in network graphs	-	3	-	1	-
CO2	Apply a range of measures and models for characterizing network structure	3	2	-	-	-
CO3	Define methodologies for analyzing networks of different fields	3	-	2	-	-
CO4	Apply graph algorithms to different networks	-	-	2	3	-
CO5	Demonstrate knowledge of network graphs with the help of software tools such NetworkX and Gephi	-	-	-	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessment - Lab Assignments – 20%
- Continuous assessment - Project – 30%
- End Semester Exam (2 hours) - 30%

26AI741 Parallel and Distributed Data Management 2-0-2-3

Preamble

The improvements in Database Management System (DBMS) technology have resulted in significant developments in distributed computing and parallel processing technologies. This has led to the development of distributed database management systems and parallel database

management systems that are now the dominant data management tools for highly data-intensive applications. In addition to an introduction to parallel and distributed database architectures and their implementation features, this course covers advanced query processing and optimization approaches for parallel and distributed systems. The students also gain knowledge in setting up a distributed database application using the latest technologies.

Course Objectives

- To provide an understanding of the distributed and parallel database architectures so as to make a choice while implementing a distributed application;
- To learn how a distributed database can be implemented for an application;
- To get trained in distributed query processing and optimization for various distributed or parallel database applications

Course Outcomes

COs	Description
CO1	Understand the need for different distributed and parallel database architectures and study its characteristics.
CO2	Design algorithms for distributed and parallel data processing.
CO3	Understand the concepts of fragmentation and allocation algorithms.
CO4	Implement optimized parallel and distributed queries for such a system.
CO5	Design and build an application using one of the latest distributed or parallel database technology.

Prerequisites

- DBMS
- Algorithms and Data Structures
- Advanced Java, Apache Spark

Syllabus

Introduction: Parallel and Distributed architectures, models, complexity measures, Communication aspects, A Taxonomy of Distributed Systems - Models of computation: shared memory and message passing systems, synchronous and asynchronous systems, Global state and snapshot algorithms.

Distributed and Parallel databases: Centralized versus Distributed Systems, Parallel versus Distributed Systems, Distributed Database Architectures-Shared disk, shared nothing, Distributed Database Design

– Fragmentation and Allocation, Optimization.

Query Processing and Optimization – Parallel/ Distributed Sorting, Parallel/Distributed Join, Parallel/Distributed Aggregates, Network Partitions, Replication, Publish/Subscribe Systems-Case study on Apache Kafka Distributed Publish/Subscribe messaging Hadoop and Map Reduce – Data storage and analysis, Design and concepts of HDFS, YARN, Map Reduce workflows and Features, Setting up a Hadoop cluster.

Text Book / References

1. M. Tamer Özsu and Patrick Valduriez, "Principles of Distributed Database Systems", 4th Edition, 2020, Springer
2. Dimitri P. Bertsekas and John N. Tsitsiklis, "Parallel and distributed computation : Numerical methods", 3rd Edition, 2020
3. Andrew S. Tannenbaum and Maarten van Steen, "Distributed Systems: Principles and Paradigms", Third Edition, Prentice Hall, October 2017.
4. Ajay D. Kshemkalyani and Mukesh Singhal, "Distributed Computing: Principles, Algorithms and Systems", Cambridge University Press, 2011.
5. Vijay K. Garg, "Elements of Distributed Computing", Wiley-IEEE Press, May 2002
6. David DeWitt and Jim Gray, "Parallel database systems: The future of high performance database systems", CACM, 1992
7. Tom White, "Hadoop-The Definitive Guide", 4th ed., O'Reilly, 2015

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the need for different distributed and parallel database architectures and study its characteristics.	3	-	-	-	-
CO2	Design algorithms for distributed and parallel data processing.	3	2	2	2	-
CO3	Understand the concepts of fragmentation and allocation algorithms.	3	2	-	-	-
CO4	Implement optimized parallel and distributed queries for such a system.	3	2	-	-	-
CO5	Design and build an application using one of the latest distributed or parallel database technology.	3	3	3	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 30%
- Continuous Evaluation – 40%
- End Semester Exam (2 hours) - 30%

26AI742 Computer Vision 2-0-2-3

Preamble

Computer Vision is one of the fastest growing and most exciting AI (Artificial Intelligence) disciplines in today's academia and industry. This course is designed to open the doors for students who are interested in learning about the fundamental principles and important applications of computer vision. The course starts with the basic understanding of image formation and various image pre-processing techniques. It also deals with visual object detection and recognition algorithms. Object tracking and Motion segmentation from videos are also introduced as part of the course. The course also gives exposure to image reconstruction, camera calibration, stereo vision camera projection models etc. which enable students to understand the concepts required for implementing modern AI applications which can perceive understand and reconstruct complex visual world like robots navigating space and performing duties, smart cars which can drive safe etc.

Course Objectives

- To introduce students to the state-of-the-art algorithms in the area of image analysis and object recognition
- Give an exposure to video analysis techniques for object tracking and motion estimation
- To build good understanding on the computer vision concepts and techniques to be applied for robotic vision applications
- Enable students to apply the vision algorithms and develop applications in the domain of image analysis, robotic navigation

Course Outcomes

COs	Description
CO1	Understand and apply preprocessing algorithms for image enhancement and segmentation.
CO2	Implement different techniques of image analysis through image feature extraction and object recognition.
CO3	Apply fundamental algorithms for video analysis such as object tracking, motion segmentation etc.
CO4	Analyze the major technical approaches involved in image registration, camera calibration, pose estimation, stereo vision etc.
CO5	Apply the algorithms and develop applications in the domain of image analysis and robotic vision

Prerequisites : None.

Syllabus

Introduction to Image Processing-Basic mathematical concepts: Image enhancement: Grey level transforms, Spatial filtering. Extraction of special features: edge and corner detection. Morphological processing, Image transforms, Discrete Fourier Transform, Frequency domain enhancement.

Image Segmentation Algorithms: contextual, non-contextual segmentation, texture segmentation. Motion based Segmentation, Optical Flow & Tracking Algorithms, Feature Detectors and Descriptors, Feature Matching-Object Recognition.

Deep neural networks for computer vision applications object detection in images and video with YOLO, ResNet, DeepSORT: Deep Learning to Track Custom Objects in a Video, classification with Convolutional Neural Networks, RNN, Vision Transformers.

Image registration, 2D and 3D feature-based alignment, Pose estimation, Geometric intrinsic calibration, -Camera Models and Calibration: Camera Projection Models – orthographic, affine, perspective, projective models. Projective Geometry, transformation of 2-d and 3-d, Internal Parameters, Lens Distortion Models, Geometry of Multiple views- Stereopsis, Camera and Epipolar Geometry, Introduction to SLAM (Simultaneous Localization and Mapping).

Text Book / References

1. Deep Learning (Adaptive Computation and Machine Learning series) Ian Goodfellow, Yoshua Bengio, Aaron Courville, Francis Bach, January 2017, MIT Press
2. Richard Szelinski, Computer Vision: Algorithms and Applications, 2010
3. E. Trucco and A. Verri, Prentice Hall, 1998.Introductory techniques for 3D Computer Vision.
4. Marco Treiber, “An Introduction to Object Recognition Selected Algorithms for a Wide Variety of Applications”, Springer, 2010.
5. Forsyth and Ponce, “Computer Vision – A Modern Approach”, Second Edition, Prentice Hall, 2011.
6. R. C. Gonzalez, R. E. Woods, ‘Digital Image Processing’, 4th edition Addison-Wesley, 2016.
7. Mohamed Elgendy, Deep Learning for Vision Systems, O’Reilly Media, Inc, 2020
8. Zonunfeli Ralte , Mastering New Age Computer Vision: Advanced techniques in computer vision object detection, segmentation, and deep learning, BPB Publications, 2025
9. M. Arshad Siddiqui , Mastering Computer Vision with PyTorch 2.0: Discover, Design, and Build Cutting-Edge High Performance Computer Vision Solutions with PyTorch 2.0 and Deep Learning

Techniques, Orange education

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and explain the different models of image formation	3	3	1	-	-
CO2	Understand and implement different techniques of image analysis through image feature extraction and object recognition.	3	2	-	-	1
CO3	Apply fundamental algorithms for video analysis such as object tracking, motion segmentation etc.	3	3	2	-	-
CO4	Analyze the major technical approaches involved in image registration, camera calibration, pose estimation, stereo vision etc. to be applied to develop vision algorithms for robotic applications.	-	-	3	1	2
CO5	Apply the algorithms and develop applications in the domain of image analysis and robotic vision	-	-	-	3	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessment - Lab Assignments – 25%
- Continuous assessment - Project – 25%
- End Semester Exam (2 hours) - 30%

26AI743 Natural Language Processing 2-0-2-3

Preamble

This course introduces the fundamental concepts and techniques of Natural Language Processing (NLP). Students will gain an in-depth understanding of the computational properties of natural languages and the commonly used algorithms for processing linguistic information. The course examines NLP models and algorithms using both the traditional symbolic and the more recent statistical approaches.

Course Objectives

- The objective of this course is to provide students with a comprehensive understanding of both the theoretical foundations and practical applications of NLP. Students will gain expertise in various NLP techniques, tools, and models, enabling them to address complex language-related challenges in diverse domains. The course aims to equip students with the skills needed to develop advanced NLP systems and conduct innovative research in the field

Course Outcomes

COs	Description
CO1	Understand and Apply Fundamental NLP concepts for text preprocessing
CO2	Develop and Implement Advanced Word Embeddings and Language Models
CO3	Apply Deep Learning Techniques to NLP Tasks
CO4	Utilize NLP Toolkits and Develop Practical NLP Applications

Prerequisites

- Basics of Machine Learning
- Python Programming Language
- Basics of Probability

Syllabus

Foundations of NLP: Introduction to NLP: Syntax, Semantics, Morphology, Word Representation: One-hot Encoding, Bag-of-Words (BoW), Term Frequency – Inverse Document Frequency (TF-IDF), Language Models: n-grams, Neural Network-based Word Embedding Algorithms, Advanced Text Embeddings: Word2Vec, GloVe, FastText, Contextual Embeddings (BERT, ELMo, GPT, XLNet, RoBERTa, Sequences and Sequential Data

Deep Learning for NLP: Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Gated Recurrent Units (GRUs), Sequence to Sequence Modelling, Encoder-Decoder Architectures, Attention Mechanism- self and Multi head attention, Transformer Networks, fine tuning Large Language Models, Retrieval-Augmented Generation (RAG), Text generation, conversational AI, Topic Modelling: LSA, LDA, Dynamic Topic Models

Practical Tools and Applications: NLP Toolkits (Eg. NLTK, SpaCy, Stanford NLP, OpenNLP) and case studies, Applications: Part-of-Speech Tagging, Named Entity Recognition (NER), Dependency Parsing, Sentiment Analysis, Machine Translation, Text Summarization, Evaluation Metrics, Chatbot, question and answering, Indic NLP Multilingual and Cross-lingual Models.

Text Book / References

1. Daniel Jurafsky, James H Martin, Speech & language processing, preparation [cited 2020 June 1] Available: from: https://web. stanford.edu/~ jurafsky/slp3 (2018).
2. Christopher Manning and Hinrich Schütze, Foundations of Statistical Natural Language Processing, MIT press, 1999.

3. Steven Bird, Ewan Klein and Edward Loper, Natural Language Processing with Python, O'Reilly Media, Inc., 2009.

4. Jason Browlee, Deep Learning for Natural Language Processing: Develop Deep Learning Models for your Natural Language Problems (Ebook), Machine Learning Mastery, 2017.

5. Leandro von Werra, Lewis Tunstall, and Thomas Wolf, Natural Language Processing with Transformers, O'Reilly Media, Inc, 2022
6. Shashank Mohan Jain, Introduction to Transformers for NLP With the Hugging Face Library and Models to Solve Problems, Springer, 2022

7. Research papers and articles from recent NLP conferences (ACL, EMNLP, NAACL).

8.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and Apply Fundamental NLP Concepts	3	1	-	2	-
CO2	Develop and Implement Advanced Word Embeddings and Language Models	3	1	-	2	-
CO3	Apply Machine Learning and Deep Learning Techniques to NLP Tasks	3	1	2	-	-
CO4	Utilize NLP Toolkits and Develop Practical NLP Applications	-	3	1	-	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessment - Lab Assignments – 25%
- Continuous assessment - Project – 25%
- End Semester Exam (2 hours) - 30%

26AI744 GPU Architecture and Programming 2-0-2-3

Preamble

GPU-accelerated processors are being actively used nowadays for general purpose and scientific computing. These massively parallel, off-the shelf devices are used to run compute-intensive and time-consuming part of applications. This course introduces the students to the Single Instruction Multiple Thread (SIMT) architecture of modern GPUs and architecture-aware programming frameworks like Compute Unified Device Architecture (CUDA) and OpenCL. While CUDA programming model is a proprietary framework for the students to learn to interface with

GPUs, OpenCL allows them to be familiarized with an open, heterogeneous parallel computing model. Modern day applications of GPUs are also introduced to the students through case studies.

Course Objectives

- To introduce the fundamentals of GPU computing architectures and programming models.
- To familiarize the student with GPU aware programming frameworks like proprietary NVIDIA CUDA(C) and open heterogeneous programming standards like OpenCL.
- To create GPGPU accelerated real world applications.

Course Outcomes

COs	Description
CO1	Understand and analyze parallel programming architectures, including SIMT architecture of modern GPUs, and their implications for AI and industry applications.
CO2	Master GPU-aware programming using NVIDIA CUDA and OpenCL frameworks to develop efficient GPU-accelerated applications.
CO3	Design and implement heterogeneous computing solutions across CPU/GPU architectures using OpenCL, emphasizing performance optimization and scalability.
CO4	Apply GPU computing techniques to real-world applications such as convolution, video processing, histogram analysis, and mixed particle simulations, and evaluate their performance metrics and scalability.

Prerequisites

- Computer Architecture
- Programming Fundamentals
- Data Structures

Syllabus

Introduction to Parallel Programming – Types of Parallelism – SIMD and SIMT – GPU architecture- Threads, Blocks and Grids- GPU Memory Organization- CUDA Programming Model- CUDA Mem- ory Model- Multidimensional thread management with CUDA- Basic CUDA Programming Examples -CUDA Streams – Synchronization and Warp Scheduling, Optimization.
Introduction to OpenCL - OpenCL Device Architectures - Basic OpenCL Programming Model – OpenCL Memory Model - Concurrency and Execution Model - Dissecting a CPU/GPU - OpenCL for Heterogeneous Computing - OpenCL Implementation – examples.

Case study: Convolution, Video Processing, Histogram and Mixed Particle Simulation - OpenCL Extensions - OpenCL Profiling and Debugging – WebCL, Applications of GPU Architecture like Gaming,

Computer Vision, etc.

Text Book / References

1. David B. Kirk, Wenmei W. Hwu, Morgan Kaufmann, Programming Massively Parallel Processors: A Hands-on Approach, 2016.
2. Elliot Arledge, CUDA for Deep Learning, Manning, 2026
3. Benedict R. Gaster, Lee Howes, David, R. Kaeli, Perhaad Mistry and Dana Schaa, "Heterogeneous Computing with OpenCL", Elsevier, 2013.
4. Jason Sanders, Edward Kandrot, "CUDA by Example: An Introduction to General-Purpose GPU Programming", Addison-Wesley Professional, 2010
5. Shane Cook, "CUDA Programming: A Developer's Guide to Parallel Computing with GPUs", Newnes, 2012
6. Aaftab Munshi, Benedict Gaster, Timothy G. Mattson, James Fung and Dan Ginsburg, "OpenCL Programming Guide", Addison-Wesley Professional, 2011.
7. Ryoji Tsuchiyama, Takashi Nakamura, Takuro Iizuka and Akihiro Asahara, "The OpenCL Programming Book", Fixstars Corporation, 2010.
8. Matthew Scarpio, "OpenCL in Action: How to Accelerate Graphics and Computations", Manning Publications, 2011.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and analyze parallel programming architectures, including SIMT architecture of modern GPUs, and their implications for AI and industry applications.	1	2	2	1	-
CO2	Master GPU-aware programming using NVIDIA CUDA and OpenCL frameworks to develop efficient GPU-accelerated applications.	1	3	2	-	-
CO3	Design and implement heterogeneous computing solutions across CPU/GPU architectures using OpenCL, emphasizing performance optimization and scalability.	1	3	3	1	1
CO4	Apply GPU computing techniques to real-world applications such as convolution, video processing, histogram analysis, and mixed particle simulations, and evaluate their performance metrics and scalability.	1	2	2	2	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessment - Lab Assignments – 25%
- Continuous assessment - Project – 25%
- End Semester Exam (2 hours) - 30%

26AI745 Artificial Intelligence for IoT 2-0-2-3

Preamble

This course introduces the architectural overview and design principles of IoT, how to develop a machine learning application using Raspberry Pi and building Machine learning models for edge devices using Raspberry Pi. Deep learning models using TensorFlowLite is also discussed in this course.

Course Objectives

- Understand the general concepts in IoT and get familiar with the various hardware and software components of it
- Understand how to build real-life IoT based projects for different application domains
- Hands-on training to implement IoT with Raspberry Pi

Course Outcomes

COs	Description
CO1	Understand the architecture, the design principles and elements of IoT.
CO2	Gain the necessary skills needed to build Machine learning models for edge devices
CO3	Be able to design, deploy and evaluate scalable real-life IoT systems for different application domains
CO4	Understand and build scalable ML pipeline using Flask, Python, uWSGI, TensorFlow

Prerequisites

- Basic knowledge on Python Programming
- Basic knowledge on Machine Learning

Syllabus

Introduction to IoT, Architectural Overview and Design Principles, Elements of IoT (Arduino, Rasp- berry Pi, NodeMCU, Sensors & Actuators), IoT Applications, Sensing, Actuation, Networking Basics, Embedded OS, IoT and Cloud, Security aspects in IoT.

IoT Application Development, Introduction to Raspberry Pi, Integrating Sensors and Actuators with Raspberry Pi, Pushing and Managing Data in IoT Clouds, Programming APIs (Python/Node.js/Arduino) for communication protocols (MQTT, ZigBee, Bluetooth, UDP, TCP), Implementation of IoT with Raspberry Pi (lab - sensor, MQTT, visualization)

Introduction to ML and Deep learning models for IoT (challenges,

opportunities, solutions), Sensor data classification using ML in Raspberry Pi (lab), Introduction to TensorFlowLite, Image classification on Raspberry Pi (lab), building scalable ML pipeline using Flask, Python, uWSGI, TensorFlow.

Text Book / References

1. Pradeep Kumar Singh, Sławomir T. Wierzchoń, Wiesław Pawłowski, Arpan Kumar Kar, Yugal Kumar, IoT, Big Data and AI for Improving Quality of Everyday Life: Present and Future Challenges IOT, Data Science and Artificial Intelligence Technologies, Springer, 2023
2. Vijay Madisetti, Arshdeep Bahga, ¨Internet of Things, "A Hands on Approach", University Press
3. Raj Kamal, "Internet of Things: Architecture and Design", McGraw Hill
4. Stuart Russell and Peter Norvig, "Artificial Intelligence: A Modern Approach", 3rd Edition, Prentice Hall
5. Sudip Misra, Anandarup Mukherjee, Arijit Roy, "Introduction to IoT", Cambridge University Press, 2020
6. Elaine Rich and Kevin Knight, "Artificial Intelligence", Tata McGraw Hill
7. Amita Kapoor, Hands-On Artificial Intelligence for IoT, 2019, Packt Publishing

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the architecture, the design principles and elements of IoT.	1	2	3	1	1
CO2	Gain the necessary skills needed to build Machine learning models for edge devices	3	2	2	-	1
CO3	Be able to design, deploy and evaluate scalable real-life IoT systems for different application domains	3	3	3	1	3
CO4	Understand and build scalable ML pipeline using Flask, Python, uWSGI, TensorFlow	1	3	3	1	3

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessment - Lab Assignments – 25%
- Continuous assessment - Project – 25%
- End Semester Exam (2 hours) - 30%

26AI746 Quantum Artificial Intelligence 2-0-2-3

Preamble

This course deals with how to use quantum algorithms in artificial intelligence. The course also covers Quantum physics-based information and probability theory, and their relationships to artificial intelligence by associative memory and Bayesian networks. Students will get an introduction to the principles of quantum computation and its mathematical framework.

Course Objectives

- To understand how the physical nature, as described by quantum physics, can lead to algorithms that imitate human behavior
- To explore possibilities for the realization of artificial intelligence by means of quantum computation
- To learn computational algorithms as described by quantum computation

Course Outcomes

COs	Description
CO1	Understand the computation with Qubits
CO2	Apply Quantum algorithms - Fourier Transform and Grover's amplification
CO3	Apply Quantum problem solving using tree search
CO4	Understand and explore the models of Quantum Computer and Quantum Simulation tools
CO5	Explore open-source Quantum computer libraries for applications

Prerequisites

- Machine Learning
- Programming Languages
- Probability

Syllabus

Introduction - artificial intelligence - computation - Cantor's diagonal argument - complexity theory - Decision problems - P and NP - Church–Turing Thesis - Von Neumann architecture - Problem Solving - Rules - Logic-based operators - Frames - Categorial representation - Binary vector representation - Production System - Deduction systems - Reaction systems - Conflict resolution - Human problem-solving - Information and measurement - Reversible Computation - Reversible circuits - Toffoli gate

Introduction to quantum physics - Unitary Evolution - Quantum Mechanics - Hilbert space - Quantum Time Evolution - Von Neumann Entropy - Measurement -

Heisenberg's uncertainty principle - Randomness - Computation with Qubits - Computation with m Qubit - Matrix Representation of Serial and Parallel Operations - Quantum Boolean Circuits - Periodicity - Quantum Fourier Transform - Unitary Transforms - Search and Quantum Oracle - Grover's Amplification - Circuit Representation - Speeding up the Traveling Salesman Problem - The Generate-and-Test Method - Quantum Problem-Solving - Heuristic Search - Quantum Tree Search - Tarrataca's Quantum Production System.

A General Model of a Quantum Computer - Cognitive architecture - Representation - Quantum Cognition - Decision making - Unpacking Effects - Quantum Walk on a graph - Quantum annealing - Optimization problems - Quantum Neural Computation - Applications on Quantum annealing Computer - Development libraries - Quantum Computer simulation tool kits.

Text Book / References

1. Davide Pastorello, Concise Guide to Quantum Machine Learning, Springer, 2023.
2. Andreas Wichert, Principles of Quantum Artificial Intelligence, First edition, World Scientific Publishing, 2014
3. Peter Wittek, Quantum Machine Learning, First edition, Academic Press, 2014.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand the computation with Qubits	2	2	2	-	3
CO2	Apply Quantum algorithms - Fourier Transform and Grover's amplification	2	2	2	-	3
CO3	Apply Quantum problem solving using tree search	3	3	3	2	3
CO4	Understand and explore the models of Quantum Computer and Quantum Simulation tools	3	3	3	3	3
CO5	Explore open- source Quantum computer libraries for applications	3	3	2	2	3

Evaluation Pattern - 70:30

- Midterm Exam - 30%
- Continuous Evaluation – 40%
- End Semester Exam (2 hours) - 30%

26AI747 Artificial Intelligence for Bioinformatics 2-0-2-3

Preamble

This course exposes the students to apply AI technology in the domain of Bioinformatics.

Course Objectives

- To incorporate the concepts of bioinformatics using statistics.
- To enhance the application of programming for bioinformatics.
- To explore the challenges in bioinformatics and apply AI for solutions.

Course Outcomes

COs	Description
CO1	Understand and appreciate the role of bioinformatics in solving biological problems.
CO2	Demonstrate working proficiency with statistical techniques in Bioinformatics
CO3	Apply the concepts of deep learning problems in bioinformatics

Prerequisites

- Basic knowledge of Deep Learning
- Python programming

Syllabus

Introduction to the Basics of Molecular Biology - DNA,RNA, Genes and Proteins,Central Dogma of Molecular biology, Cell regulation, What is Bioinformatics, Challenges in Bioinformatics - Genome, Transcriptome, Proteome. –Python programming for bioinformatics.

AI in Bioinformatics Applications - Decision Trees, Neural Networks, Application guidelines, Genetic Algorithms, Probabilistic Graphical Models in Bioinformatics, Hybrid Models and Neural Network Parameterization of Graphical Models, Cellular Automata.

Internet Resources and Public Structure Databases in Molecular Biology, Sequences.

Text Book / References

1. Chiara Zucco, Marianna Milano, Giuseppe Agapito, Mario Cannataro, Pietro Hiram Guzzi, “Artificial Intelligence in Bioinformatics: From Omics Analysis to Deep Learning and Network Mining”, Elsevier, 2022.
2. Karthik Raman, “An Introduction to Computational Systems Biology (Systems Level Modeling of Cellular Networks)”, CRC Press, 2021.
3. Phillip Compeau and Pavel Pevzner, “Bioinformatics algorithm, An active learning Approach”, Vol.1. and Vol. 2 ,2015.
4. JinXiong, “Essential Bioinformatics”, Cambridge University Press, 2006.
5. Edward Keedwell and Ajit Narayanan, “Intelligent Bioinformatics”, John Wiley & Sons Ltd, 2005

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Understand and appreciate the role of bioinformatics in solving biological problems.	1	2	3	-	-
CO2	Demonstrate working proficiency with statistical techniques in Bioinformatics	-	2	2	3	-
CO3	Apply the concepts of deep learning problems in bioinformatics	3	3	2	2	2

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous Evaluation – 50%
- End Semester Exam (2 hours) - 30%

26AI748 Cloud and Big Data Analytics 2-0-2-3

Preamble

There is an unprecedented amount of data that is generated in today's world by both humans and machines. Being able to store, manage, analyze, and building intelligent applications has a critical impact on business, scientific discovery, social and environmental challenges. This course helps students to use cloud platform with its tools and distributed computing techniques to quickly build prototypes and applications for scalable data and workloads.

Course Objectives

- To introduce principles of cloud computing and build applications on cloud platforms.
- To understand distributed computing paradigms and its implementations on cloud platform.
- To apply principles of Big Query for handling big data.

Course Outcomes

COs	Description
CO1	To introduce principles of cloud computing.
CO2	Develop and deploying applications on cloud platform.
CO3	Understand Distributed Machine learning with hadoop and spark.
CO4	Create data analytics applications on distributed cloud computing platforms for using Spark and its Tools.

CO5	Develop methods to handle Containers and Kubernetes in Google Cloud.

Prerequisites

- Basics of Machine Learning.

Syllabus

Cloud computing fundamentals - Principles of Cloud Computing Systems, Elastic Cloud Systems for Scalable Computing, Cloud Architectures Compared with Distributed Systems, Service Models, Ecosystems and Scalability Analysis, Building Compute Service - Storage Service – Databases Service - Serverless Models on Cloud.

Frameworks for Big data: Hadoop – Hadoop Framework – Hadoop Daemon - Map Reduce Programming- Hadoop Ecosystem - Spark - Framework – RDD – Advanced RDD - Structured data - SQL, Dataframes, and Datasets – Streaming in Spark - Spark Distributed Processing - Building Spark ML on Cloud platform.

Cloud dataflow – dataflow templates, data transformation with cloud dataflow, working with

apache beam, cloud publisher subscriber - architecture, message flow, implementation. Cloud data processing. Introduction to Containers and Kubernetes in Google Cloud, Introduction to AI platform pipelines

Text Book / References

1. Kai Hwang, “Cloud Computing for Machine Learning and Cognitive Applications”, MIT Press, 2017.
2. Murari Ramuka, “Data Analytics with Google Cloud Platform “, BPB PUBN, 2019.
3. Anand Deshpande, Manish Kumar, Vikram Chaudhari, “Hands-On Artificial Intelligence on Google Cloud Platform”, Packt Publishing, 2020.
4. Jeffrey Jackovich, Ruze Richards, “Machine Learning with AWS”, Packt Publishing, 2018.
5. Jules S. Damji, Brooke Wenig, Tathagata Das, Denny Lee, “Learning Spark Lightning fast data analysis”, O’Reilly Media, Inc, 2020.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	To introduce principles of cloud computing.	2	1	-	-	-
CO2	Develop and deploying applications on cloud platform.	2	3	-	-	-
CO3	Understand Distributed Machine learning with hadoop and spark.	2	3	3	-	-
CO4	Create data analytics applications on distributed cloud computing platforms for using Spark and its Tools.	2	3	3	2	1
CO5	Develop methods to handle Containers and Kubernetes in Google Cloud.	2	3	3	2	1

Evaluation Pattern - 70:30

- Midterm Exam - 20%
- Continuous assessment - Lab Assignments – 25%
- Continuous assessment - Project – 25%
- End Semester Exam (2 hours) - 30%

26AI749 AI Product Engineering and Innovation 2-0-2-3

Preamble:
Artificial Intelligence is transforming the way products are conceived, developed, and delivered across industries. Modern AI engineers are expected not only to build intelligent models but also to design AI-powered products that solve real-world problems, deliver measurable value, and scale reliably. This course introduces a product-centric approach to AI engineering by integrating foundation models, AI application development, user-centered design, evaluation, deployment, and innovation methodologies. Through extensive hands-on development and a semester-long product incubation project, students will learn to transform AI ideas into deployable products with entrepreneurial potential.

Course Objectives:

- Apply AI engineering principles to design and develop intelligent products that address real-world problems.
- Integrate foundation models, retrieval systems, AI agents, and modern AI services into deployable applications.
- Evaluate AI products from technical, usability, business, ethical, and scalability perspectives.
- Develop entrepreneurial skills for transforming AI prototypes into sustainable products and technology ventures.

Course Outcomes:

COs	Description
CO1	Analyze real-world problems and formulate AI product requirements

	using user-centered and design-thinking approaches.
CO2	Design and develop AI-powered applications by integrating foundation models, retrieval systems, AI agents, and modern AI engineering techniques.
CO3	Evaluate and optimize AI products for usability, reliability, performance, safety, scalability, and responsible deployment.
CO4	Evaluate and optimize AI products for usability, reliability, performance, safety, scalability, and responsible deployment.

Prerequisites: Machine Learning, Deep Learning, Python Programming, Software, Engineering, Database Systems, Basic Web Application Development, Foundation Models (desirable)

Syllabus:

AI Product Engineering Fundamentals: AI Product Engineering Lifecycle, Product Thinking, Design Thinking for AI, Opportunity Identification, Problem Discovery, Customer Needs Analysis, AI Product Ideation, Product Requirement Specification, AI Product Architecture, User Experience for AI Applications, Human-Centered AI Design, AI Product Roadmaps, Rapid Prototyping, Lean Startup Principles.

AI Application Development: Foundation Models, Prompt Engineering, Structured Outputs, Retrieval-Augmented Generation (RAG), Embeddings, Vector Databases, Knowledge Integration, AI Agents, Function Calling, Tool Use, Multi-Agent Systems, Workflow Automation, AI Application Frameworks, Context Management, Memory, AI APIs, Rapid AI Prototyping.

Product Engineering, Evaluation and Deployment: AI Product Architecture, Frontend and Backend Integration, API Design, AI Microservices, Testing AI Applications, AI Evaluation Metrics, Human Evaluation, LLM-as-a-Judge, Hallucination Detection, AI Safety, Guardrails, Performance Optimization, Cost Optimization, Observability, Continuous Improvement, Deployment Strategies, User Feedback Analytics.

AI Innovation, Entrepreneurship and Product Incubation: Responsible AI, AI Governance, Intellectual Property for AI Products, AI Business Models, Product Validation, Product-Market Fit, Technology Commercialization, AI Startup Ecosystem, Product Pitching, Minimum Viable Product (MVP), Scaling AI Products, Product Analytics, AI Product Case Studies, Emerging Trends in AI Engineering

Textbook:

1. Chip Huyen, AI Engineering: Building Applications with Foundation Models, 1st Edition, O'Reilly Media, 2025.

References:

2. Emmanuel Ameisen, Building Machine Learning Powered Applications, O'Reilly Media, 2020.

3. Martin Kleppmann, Designing Data-Intensive Applications, O'Reilly Media, 2017.
4. Marty Cagan, Inspired: How to Create Tech Products Customers Love, 3rd Edition, Wiley, 2024.
5. Ash Maurya, Running Lean, 3rd Edition, O'Reilly Media, 2022.
6. Steve Blank and Bob Dorf, The Startup Owner's Manual, K&S Ranch, 2020.

CO-PO Mapping:

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Analyze real-world problems and formulate AI product requirements using user-centered and design-thinking approaches.	3	3	2	2	2
CO2	Design and develop AI-powered applications by integrating foundation models, retrieval systems, AI agents, and modern AI engineering techniques.	2	3	3	2	3
CO3	Evaluate and optimize AI products for usability, reliability, performance, safety, scalability, and responsible deployment.	2	3	3	3	3
CO4	Evaluate and optimize AI products for usability, reliability, performance, safety, scalability, and responsible deployment.	3	3	3	3	3

Evaluation Pattern: 70:30

- Product Concept Note and Mid-Semester Design Review (Problem identification, user study, solution architecture, prototype plan) - 20
- Hands-on Laboratory (AI application development, RAG, agents, APIs, evaluation, deployment) - 20
- AI Product Sprint Reviews (Prototype demonstrations, code quality, usability testing, peer and instructor feedback) - 20
- Final AI Product (working MVP, deployment, documentation, GitHub repository, business canvas, product pitch and viva) - 10
- End Semester Product Demonstration, Technical Viva and Innovation Pitch (in lieu of a written examination) - 30

26AI750 MLOps and AI Systems Engineering 2-0-2-3

Preamble:

Artificial Intelligence models increasingly transition from research prototypes to large-scale production systems deployed across cloud, edge, and enterprise environments. While traditional machine learning courses emphasize model development, successful AI applications require robust engineering practices for data management, experiment tracking, scalable deployment, monitoring, continuous integration, and lifecycle management. This course introduces students to the principles, tools, and methodologies

of Machine Learning Operations (MLOps) and AI Systems Engineering, enabling them to design, deploy, operate, and maintain reliable AI systems. Through extensive hands-on laboratories and a semester-long engineering project, students will gain practical experience in building production-ready AI pipelines using modern industry tools and frameworks.

Course Objectives:

- Understand the complete lifecycle of production-grade AI systems and the role of MLOps in modern AI engineering.
- Design scalable, reproducible, and maintainable machine learning pipelines using industry-standard tools and best practices.
- Develop skills in deploying, monitoring, optimizing, and maintaining AI applications in cloud and distributed environments.
- Apply engineering principles to build reliable, secure, and continuously improving AI systems suitable for real-world applications.

Course Outcomes:

COs	Description
CO1	Explain the architecture, components, and lifecycle of production AI systems, including data engineering, model development, deployment, and monitoring.
CO2	Develop reproducible machine learning pipelines incorporating data versioning, experiment tracking, model management, and continuous integration practices.
CO3	Deploy, monitor, and optimize AI models using modern MLOps frameworks, cloud platforms, and scalable serving infrastructures.
CO4	Design and evaluate end-to-end AI systems that satisfy requirements for scalability, reliability, security, maintainability, and responsible AI deployment.

Prerequisites: Machine Learning, Deep Learning, Python Programming, Data Structures, Database Management Systems, Basic Linux commands, Software Engineering fundamentals

Syllabus:

Introduction to MLOps and AI Systems Engineering: AI Systems Engineering: Concepts and Lifecycle, MLOps Principles and Workflows, AI Development Life Cycle, From Research Prototype to Production AI, Software Engineering for AI Systems, AI System Architecture, Data-centric AI, AI Infrastructure, Reproducibility, Production Readiness, AI Engineering Best Practices.

Data Engineering, Model Development and Experiment Management: Data Collection and Data Pipelines, Data Validation and Quality Assessment, Data Versioning, Feature Engineering and Feature Stores, Experiment Tracking, Hyperparameter Optimization, Model Versioning, Model Registry, Reproducible Machine Learning Pipelines, Distributed Training, GPU Computing, Transfer Learning, Fine-tuning Foundation Models, Parameter-Efficient Fine-Tuning (PEFT), LoRA, Quantization and Model Optimization.

Model Deployment, LLMOps and AI Application Serving: Model Packaging and Containerization, REST APIs and gRPC, Docker, Kubernetes, CI/CD for Machine Learning, Continuous Training, Batch and Online Inference, Model Serving Frameworks, High-Performance LLM Serving, Introduction to LLMOps, Prompt Engineering and Prompt Versioning, Embeddings, Vector Databases, Retrieval-Augmented Generation (RAG), Knowledge Integration, Function Calling, Tool Use, Agentic AI Pipelines, Prompt Evaluation, LLM Cost and Latency Optimization.

Monitoring, Observability and Scalable AI Systems: AI System Monitoring, Logging and Observability, Model Monitoring, Data Drift and Concept Drift, Hallucination Detection, Prompt Injection and AI Security, Guardrails for Foundation Models, Explainability, A/B Testing, Canary Deployment, Shadow Deployment, Distributed AI Systems, Pipeline Orchestration, Workflow Automation, Distributed Inference, GPU Scheduling, AI Infrastructure Optimization, Cloud-native AI Systems, Enterprise AI Architecture.

Responsible AI and Production AI Systems: Responsible AI, AI Governance, Privacy and Security, AI Reliability and Robustness, Continuous Evaluation, Continuous Deployment, Feedback Loops, Human-in-the-Loop Systems, Cost Optimization, AI Operations in Enterprise Environments, AI System Maintenance, Lifecycle Management, Enterprise Case Studies, Emerging Trends in MLOps and AI Systems Engineering.

Textbook:

1. Chip Huyen, Designing Machine Learning Systems: An Iterative Process for Production-Ready Applications, O'Reilly Media, 2022.

References:

2. Chip Huyen, AI Engineering: Building Applications with Foundation Models, 1st Edition, O'Reilly Media, 2025.
3. Andriy Burkov, Machine Learning Engineering, True Positive Inc., 2020.
4. Cathy Chen, Nisha Talagala, Emily Gorcenski, Reliable Machine Learning, O'Reilly Media, 2022.
5. Martin Kleppmann, Designing Data-Intensive Applications, O'Reilly Media, 2017.
6. Emmanuel Ameisen, Building Machine Learning Powered Applications, O'Reilly Media, 2020.
7. Trevor Grant, Tarry Singh, Kubeflow for Machine Learning, O'Reilly Media, 2020.

CO-PO Mapping:

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Explain the architecture, components, and lifecycle of production AI systems, including data engineering, model development, deployment, and monitoring.	3	2	1	1	2
CO2	Develop reproducible machine learning pipelines incorporating data versioning, experiment tracking, model management, and continuous integration practices.	2	3	3	2	3
CO3	Deploy, monitor, and optimize AI models using modern MLOps frameworks, cloud platforms, and scalable serving infrastructures.	2	3	3	3	3
CO4	Design and evaluate end-to-end AI systems that satisfy	3	3	3	3	3

	requirements for scalability, reliability, security, maintainability, and responsible AI deployment.					

Evaluation Pattern: 70:30

- Mid-Term Examination – 20
- Continuous Assessment - 50
  - Hands on Laboratory Assignments – 20
  - Mini Project / Case Study – 20
  - Quiz - 10
- End Semester (2 hours) - 30

26AI798 Dissertation Phase I 10

Course Objectives

The student is expected to carry out supervised research in this course. An intensive literature in the chosen area, should result in sound knowledge in the area and result in the identification of a suitable research problem, and its formulation and analysis. Study of relevant supplementary literature, mastering useful programming languages and tools for the problem, are also expected at this stage of the project. The student is expected to present three reports at different evaluation points during the semester, with clearly defined achievements and plans for further steps.

References

1. Relevant literature for the computing problem.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Demonstrate sound fundamentals in a chosen area of computing.	3	2	2	2	2
CO2	Identify and formulate a problem of research interest in the chosen area of computing	2	3	3	3	2
CO3	Analyze the computing problem and propose solutions.	3	3	3	2	2
CO4	Effectively communicate the work at all stages of the project.	2	3	3	2	2

Evaluation Pattern - 80:20

- Internal - 80%
- External - 20%

26AI799 Dissertation Phase II 16

Course Objectives

The student is expected to demonstrate the core competency aimed by this course, i.e., the development of enhancements to the knowledge base in the area of interest in computing. The secondary competencies include the management of time bound projects involving research, analysis of problem complexities, design and development of effective solutions and communication of the project's progress, adhering to ethical practices at every stage. This stage of the project evaluates the state of maturity of these competencies. The student is expected to present two reports at intermediate stages, as well as prepare and defend a thesis on his research work.

Course Outcomes

COs	Description
CO1	Reflectively analyze proposed solutions to the identified computing problem.
CO2	Design and develop solutions to the problem and analyze results.
CO3	Prepare a thesis report and defend the thesis on the work done.
CO4	Augment the knowledge base in the chosen area of computing, adhering to ethical practices at every stage.

Prerequisites

- Dissertation Phase I

References

1. Relevant literature for the computing problem.

CO-PO Mapping

COs	Description	PO1	PO2	PO3	PO4	PO5
CO1	Reflectively analyze proposed solutions to the identified computing problem	3	3	3	3	-
CO2	Design and develop solutions to the problem and analyze results.	3	3	3	3	2
CO3	Prepare a thesis report and defend the thesis on the work done.	3	3	3	2	2
CO4	Augment the knowledge base in the chosen area of computing, adhering to ethical practices at every stage.	3	3	3	2	3

Evaluation Pattern - 80:20

- Internal - 80%
- External - 20%

** Evaluations patterns mentioned in the syllabus are recommendations from BOS. Final decision on the same can be done at the class committee.

25AVP501 Mastery Over Mind (MAOM) 1-0-2 2

Course Outcomes

CO01: Relate to the causes of stress in one's life.

CO02: Experiment with a range of relaxation techniques

CO03: Model a meditative approach to work, study, and life.

CO04: Develop appropriate practice of MA-OM technique that is effective in one's life

CO05: Inculcate a higher level of awareness and focus.

CO06: Evaluate the impact of a meditation technique

1. Course Overview

Master Over the Mind (MAOM) is an Amrita initiative to implement schemes and organise university-wide programs to enhance health and wellbeing of all faculty, staff, and students (UN SDG -3). This program as part of our efforts for sustainable stress reduction gives an introduction to immediate and long-term benefits and equips every attendee to manage stressful emotions and anxiety facilitating inner peace and harmony.

With a meditation technique offered by Amrita Chancellor and world-renowned humanitarian and spiritual leader, Sri Mata Amritanandamayi Devi (Amma), this course has been planned to be offered to all students of all campuses of AMRITA, starting off with all first years, wherein one hour per week is completely dedicated for guided practical meditation session and one hour on the theory aspects of MAOM. The theory section comprises lecture hours within a structured syllabus and will include invited guest lecture series from eminent personalities from diverse fields of excellence. This course will enhance the understanding of experiential learning based on university's mission: "Education for Life along with Education for Living", and is aimed to allow learners to realize and rediscover the infinite potential of one's true Being and the fulfilment of life's goals.

2. Course Syllabus

Unit 1 (4 hours)

Causes of Stress: The problem of not being relaxed. Need for meditation -basics of stress management at home and workplace. Traditions and Culture. Principles of meditation– promote a sense of control and autonomy in the Universal Human Value System. Different stages of Meditation. Various Meditation Models. Various practices of Meditation techniques in different schools of philosophy and Indian Knowledge System.

Unit 2 (4 hours)

Improving work and study performance. Meditation in daily life. Cultivating compassion and good mental health with an attitude of openness and acceptance. Research and Science of Meditation: Significance of practising meditation and perspectives from diverse fields like science, medicine, technology. philosophy, culture, arts, management, sports, economics, healthcare, environment etc. The role of meditation for stress and anxiety reduction in one's life with insights based on recent cutting-edge technology. The effect of practicing meditation for the wholesome wellbeing of an individual.

Unit 3 (4 hours)

Communications: principles of conscious communication. Relationships and empathy: meditative

approach in managing and maintaining better relationships in life during the interactions in the world, role of MAOM in developing compassion, empathy and responsibility, instilling interest, and orientation to humanitarian projects as a key to harness intelligence and compassion in youth. Methodologies to evaluate effective awareness and relaxation gained from meditation. Evaluating the global transformation through meditation by instilling human values which leads to service learning and compassion driven research.

TEXT BOOKS:

1.Mata Amritanandamayi Devi, "Cultivating Strength and vitality," published by Mata Amritanandamayi Math, Dec 2019

2.Swami Amritaswarupananda Puri ,"The Color of Rainbow " published by MAM, Amritapuri.

REFERENCES:

1.Craig Groeschel, "Winning the War in Your Mind: Change Your Thinking, Change Your Life" Zondervan Publishers, February 2019

2.R Nagarathna et al, "New Perspectives in Stress Management "Swami Vivekananda Yoga Prakashana publications, Jan 1986

3. Swami Amritaswarupananda Puri "Awaken Children Vol 1, 5 and 7 - Dialogues with Amma on Meditation", August 2019

4. Swami Amritaswarupananda Puri "From Amma's Heart - Amma's answer to questions raised during world tours" March 2018

5. Secret of Inner Peace- Swami Ramakrishnananda Puri, Amrita Books, Jan 2018.

6. Mata Amritanandamayi Devi "Compassion :The only way to Peace:Paris Speech", MA Center, April 2016.

7. Mata Amritanandamayi Devi "Understanding and collaboration between Religions", MA Center, April 2016.

8. Mata Amritanandamayi Devi "Awakening of Universal Motherhood: Geneva Speech" M A center, April 2016.

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26CUL500 INTEGRATED AMRITA MEDITATION TECHNIQUE L-T-P-C 0-0-2-1
A. Nature of Course: Lab/Practical
B. Course Description: The course introduces students to the Integrated Amrita Meditation Technique (IAM 20), a structured practice that combines yogic stretches, regulated breathing (pranayama), and guided meditation. The course integrates both theoretical understanding and experiential practice to enhance emotional balance, stress resilience, concentration, and overall holistic development. Aligned with United Nations Sustainable Development Goal 3 (SDG 3): Good Health and Well-Being, the course promotes preventive mental health care, emotional well-being, and sustainable lifestyle practices among students. By fostering inner stability, self-awareness, and self-regulation, the programme supports academic excellence and contributes to the development of healthy individuals and communities.

The course is expected to improve student well-being, enhance academic focus and cognitive clarity, reduce stress-related indicators, and promote compassionate and emotionally supportive culture.

C. Course Objectives:

- To promote overall health and well-being of students.
- To train students in the structured practice of IAM 20.
- To develop emotional regulation and stress management skills.
- To encourage reflective awareness and compassionate living.

D. Course Outcomes:

After successful completion of the course, students will be able to:

CO	Course Outcomes	owledge Level oom's Taxonomy)
01	plain principles and components of IAM 20	derstand (L2)
02	monstrate and correct meditation practice independently	ply (L3)
03	alyze personal stress patterns using meditation insights	alyse (L4)
04	aluate personal growth through daily practice	aluate (L5)

E. CO-PO Mapping: [affinity: 3 – high; 2- moderate; 1- slightly]

CO's	Program Outcomes (PO's)											ogram Specific Outcomes (PSF's)		
	01	02	03	04	05	06	07	08	09	010	011	O1	O2	O3
01	-	-	-	-	-	1	-	2	-	-	1	-	-	-
02	-	-	-	-	-	2	2	1	1	-	1	-	-	-
03	-	-	-	-	-	1	1	2	-	-	1	-	-	-
04	-	-	-	-	-	1	1	1	1	-	1	-	-	-

F. Syllabus

Unit 1: Foundations of Meditation (CO1)

- Meaning and purpose of meditation
- Demonstration and supervised training
- Overview of structure of IAM
- Guidance for safe and effective practice
- Importance of mental health

Unit 2: Theoretical Foundations (CO2)

- Structure and components of IAM: yogic stretches, regulated breathing, and guided meditation
- Breath–mind connection
- Integration of IAM practice into daily routine and academic life
- Application of IAM for stress management, concentration, and holistic student development

Unit 3: IAM Practical Training (CO3)

- Preparatory stretches
- Pranayama components
- Guided meditation sequence
- Corrections and common challenges

Unit 4: Integration and Transformation (CO4)

- Building daily discipline
- Research evidence in higher education
- Compassion and mindful communication

G. Evaluation Pattern:

sessment	**ternal (60)**	**ternal (40)**
tendance	Marks	
ass Participation	Marks	
tivity	Marks	
ctical Demonstration		Marks
va		Marks

CIR Course – PG – Paper I

Sem: 1	**26CDS101 Career Development Skills I**	**L-T-P-C: 0 0 3 P/F**

Pre-requisite:

An open mind and the urge for self-development, basic English language skills and knowledge of high school level arithmetic.

Course Objectives:

- To strengthen professional skills for academic and research environments.
- To enhance presentation skills for seminars, reviews, and academic discussions.
- To guide students in effective goal setting and time management for postgraduate studies.
- Support them in developing their problem solving and reasoning skills
- Inspire students to enhance their diction, grammar, verbal reasoning and communication skills

Course Outcomes:

CO1: Soft Skills - To develop a positive mindset, communicate professionally, manage time effectively, set personal goals and achieve them.

CO2: Soft Skills - To make formal and informal presentations with self-confidence.

CO3: Aptitude - To analyze, understand and employ the most suitable methods to solve questions on arithmetic and algebra.

CO4: Aptitude - To analyze, understand and apply suitable techniques to solve questions in

data analysis.

C05: Verbal - To infer the meaning of words and use them in the right context. To have a clearer understanding of the nuances of English grammar and become capable of applying them effectively.

C06: Verbal - To identify the relationship between words using reasoning skills. To understand and analyze arguments and use verbal reasoning skills to arrive at conclusions and communicate ideas/perspectives convincingly.

CO-PO Mapping - MTech

PO / CO	PO1	PO2	PO3
CO1	2	1	-
CO2	2	1	-
CO3	2	1	-
CO4	2	1	-
CO5	1	2	-
CO6	2	2	-

CO-PO Mapping - PG **ASAS**

PO / CO	PO1	PO2
CO1	2	1
CO2	2	1
CO3	2	1
CO4	2	1
CO5	1	2
CO6	2	2

Syllabus

Soft Skills

Introduction: Campus to corporate transition based on the expectations of the corporate

Communication and listening skills: Professional & Academic Communication Skills, Interpersonal Communication in Teams, Cross-cultural & Global Communication, Netiquette in Corporate Settings, Communicating in Hybrid & Remote Teams

Assertiveness skills: Necessity of being Assertive, Passive Aggression & Aggressiveness, Assertive & Non-assertive differences, Dealing with demands, criticism & Compliments, Assertive Techniques

Presentation skills: Adult learning principles, Preparation, planning, practice delivery, Principles of Effective Technical Presentations, Verbal & Non-verbal Communication in Presentations, Effective Slide Design, Using AI & Digital Tools for Presentations

Presentations by the students

Perception: Locus of control, Bridging Self & Social perception, Attribution theories, Importance of Perspective Taking, Impression management

Goal setting & Time management: Aligning Personal, Academic & Career Goals, SMART Goals, SWOT Analysis, Time Management Strategies, Prioritization Techniques & Planning Tools, Avoiding Procrastination & Distractions

Verbal

Vocabulary: Familiarize students with the etymology of words, help them realize the relevance of word analysis and enable them to answer vocabulary based MCQ questions through practice in etymology, synonyms, antonyms, commonly confused words, and contextual usage.

Grammar: Train students to understand the nuances of English Grammar and thereby enable them to spot grammatical errors in sentences.
Reasoning: Stress the importance of understanding the relationship between words through analogy questions. Emphasize the importance of avoiding the gap (assumption) in arguments/ statements/ communication.
Oral Communication Skills: Improve the professional spoken communication by introducing corporate register, workplace expressions, and structured group activities such as debates and panel discussions.

Aptitude

Numbers - Power Cycles, Divisibility, and HCF & LCM, **Percentages -** Profit, Loss & Discount, and Simple & Compound Interest, **Ratio, Proportion & Variation -** Alligations, Mixtures, and Partnership Problems, **Averages, Time and Work -** Pipes & Cistern, and Work Equivalence, **Time, Speed and Distance -** Boats & Streams, Races and Circular tracks, **Statistics -** Mean, Median, Mode, Standard Deviation and Quartile Deviation, **Data Interpretation -** Tables, Bar Diagrams, Line Graphs, Pie Charts, Caselets and Mixed Varieties, **Equations –** Linear and Quadratic Equations, **Logarithms, Inequalities, Puzzles -** Optimization Puzzles, Fermi Problems, Game-Based Puzzles, Sudoku, Anagrams, Futoshiki and Rebus Puzzles, **Speed Mathematics**, **Shortcuts.**

References

Soft Skills

1. Student's Guide For Career Planning, CIR, 2018
2. Andrew J DuRbin , "Applied Psychology: Individual and organizational effectiveness", Pearson- Merril Prentice Hall, 2004
3. Michael G Aamodt, "An Applied Approach, 6th edition", Wadsworth Cengage Learning, 2010
4. Robert Bolton, Dorothy Grover Bolton, "People Style at Work..and Beyond: Making Bad Relationships Good and Good", Ridge Associates Inc., 2009
5. John Hayes "Interpersonal skills at work", Routledge, 2003
6. Nord, W. R., Brief, A. P., Atieh, J. M., & Doherty, E. M., "Meanings of occupational work: A collection of essays (pp. 21- 64)", Lexington, MA: Lexington Books, 1990
7. Mark J Martinko, "Attribution theory: an organizational perspective", St. Lucie, 1995
8. Miles Hewstone,"Attribution Theory: Social and Functional Extensions", Blackwell, 1983
9. Stephen Covey, "The habits of highly effective people", Free press Revised edition, 2004
10. Kenneth H Blanchard ,"The 25 Best Time Management Tools & Techniques: How to Get More Done Without Driving Yourself Crazy" , Peak Performance Press, 1st edition 2005
11. Kenneth H. Blanchard and Spencer Johnson, "The One Minute Manager", William Morrow, 1984

Verbal

1. Verbal Skills Workbook (PG), CIR
2. Erica Meltzer, “The Ultimate Guide to SAT Grammar”
3. Green, Sharon, and Ira K. Wolf, “Barron's New GRE”, Barron's Educational Series, 2011
4. Jeff Kolby, Scott Thornburg & Kathleen Pierce, “Nova’s GRE Prep Course”
5. Kaplan, “Kaplan New GRE Premier”, 2011-2012
6. Kaplan’s GRE Comprehensive Programme
7. Lewis Norman, “Word Power Made Easy”, Goyal Publishers, Reprint edition, 1 June 2011
8. Manhattan Prep, “GRE Verbal Strategies Effective Strategies Practice from 99th Percentile Instructors”
9. Pearson- “A Complete Manual for CAT”, 2013
10. R.S. Aggarwal, “A Modern Approach to Verbal Reasoning”
11. S. Upendran, “Know Your English”, Universities Press (India) Limited, 2015
12. Sharon Weiner Green, Ira K. Wolf, “Barron's New GRE, 19th edition (Barron's GRE)”, 2019
13. Wren & Martin, “English Grammar & Composition”
14. www.bbc.co.uk/learningenglish
15. www.cambridgeenglish.org
16. www.englishforeveryone.org
17. www.merriam-webster.com

Aptitude

1. Arun Sharma, “How to Prepare for Quantitative Aptitude for the CAT Common Admission Test”, Tata Mc Graw Hills, 5th Edition , 2012
2. Arun Sharma, “How to Prepare for Logical Reasoning for the CAT Common Admission Test”, Tata Mc Graw Hills, 2nd Edition, 2014
3. Arun Sharma, “How to Prepare for Data Interpretation for the CAT Common Admission Test”, Tata Mc Graw Hills, 3nd Edition, 2015
4. R.S. Aggarwal, “Quantitative Aptitude For Competitive Examinations”, S. Chand Publishing, 2015
5. R.S. Aggarwal, “A Modern Approach To Verbal & Non-Verbal Reasoning”, S. Chand Publishing, Revised -2015
6. Sarvesh Verma, “Quantitative Aptitude-Quantum CAT” , Arihant Publications, 2016
7. www.mbatious.com
8. www.campusgate.co.in
9. www.careerbless.com

Evaluation Pattern

Assessment	Internal	External
Continuous Assessment (CA)* – Soft Skills	30	-
Continuous Assessment (CA)* – Aptitude	10	25
Continuous Assessment (CA)* – Verbal	10	25
Total	50	50

Pass / Fail

*CA - Can be **presentations, speaking activities and tests.**

CIR Course – PG – Paper II

Sem: 2	26CDS111 Career Development Skills II	L-T-P-C: 0 0 3 1

Pre-requisite:

Willingness to learn, team spirit, foundational proficiency in English language and communication and knowledge of high school level arithmetic.

Course Objectives:

- To equip students with conflict management strategies for effective teamwork and collaboration.
- To prepare students for recruitment processes through interview etiquette, group discussions and professional conduct.
- Help students to sharpen their problem solving and reasoning skills
- Empower students to communicate effectively by using the correct diction, grammar, comprehension and verbal reasoning skills

Course Outcomes:

CO1: Soft Skills - To demonstrate good interpersonal skills, solve problems and effectively participate in group discussions.
CO2: Soft Skills - To write technical resumes and perform effectively in interviews.
CO3: Aptitude - To identify, investigate and arrive at appropriate strategies to solve questions in geometry, probability, permutations & combinations, and statistics by managing time effectively.
CO4: Aptitude - To investigate, understand and use appropriate techniques to solve questions in logical reasoning and data analysis by managing time effectively.
C05: Verbal - To be able to use diction that is more refined and appropriate and to be competent in knowledge of grammar to correct and improve sentences
C06: Verbal - To be able to examine, interpret and investigate passages and to be able to generate ideas, structure them logically and express them in spoken or written style that is comprehensible to the audience/recipient.

CO-PO Mapping - MTech

PO / CO	PO1	PO2	PO3
CO1	2	1	-
CO2	2	1	-
CO3	2	1	-
CO4	2	1	-
CO5	1	2	-
CO6	2	2	-

CO-PO Mapping - PG **ASAS**

PO / CO	PO1	PO2
CO1	2	1
CO2	2	1

CO3	2	1
CO4	2	1
CO5	1	2
CO6	2	2

Syllabus

Soft Skills

Corporate Culture and Managing Diversity: Understanding Corporate Culture & Organizational Values, Corporate Culture in Indian & Global Organizations

Unconscious Bias, Adapting to Corporate Culture as a New Professional, Diversity Policies & Best Practices

Critical Thinking & problem solving: Problem Identification & Problem Framing, Problem solving process, Handling Ambiguity & Open-Ended Problems, Brainstorming techniques for Critical Thinking, Agile Thinking & Continuous Improvement

Conflict Management: Intrapersonal, Interpersonal & Task-Based Conflict, Conflict Management Styles, Steps in Conflict Resolution, Conflict in Hybrid & Remote Work Environments, Learning from Conflict

Team building and working effectively in teams: Communication & Collaboration in Teams, Stages of Team Development, Diversity, Inclusion & Cultural Sensitivity in Teams, Trust, Accountability & Psychological Safety, Leadership Dynamics

Group discussion: Critical Thinking & Perspective Building, Clarity, Fluency & Professional Language, Body Language & Eye Contact, Handling Interruptions & Disagreements, Self-Reflection & Improvement

Interview skills: Types of Interviews (Technical, HR, Managerial, Research), Understanding Job Descriptions & Role Expectations, Competency-Based & Behavioural Interviews, STAR Technique for Behavioral Questions, AI-Based Interview Screening & Preparation, Interview Netiquette & Modern Interview Contexts

Mock Interview: One on one Mock interview process for all the students

Verbal

Vocabulary: Enhance vocabulary skills through focused practice in idioms, phrasal verbs, and sentence completion, with emphasis on contextual usage and MCQ-based strategies.

Grammar: Develop grammatical accuracy by training students to identify and correct sentence-level errors through sentence correction and cloze test practice.

Reasoning: Strengthen critical reasoning and logical thinking skills through systematic practice in critical reasoning questions and logical ordering of sentences.

Reading Comprehension: Equip students with effective strategies to analyze and respond to reading comprehension passages through guided discussion and practice.

Public Speaking Skills: Enhance oral communication through storytelling for professional success and personal branding, and assess speaking competence through individual speeches and open forum discussions on current affairs.

Writing Skills / Professional Communication: Develop formal writing competence with emphasis on professional email etiquette and the drafting of job application and workplace emails.

Aptitude

Sequence, Series, Geometry - 2D, 3D, Coordinate Geometry, and Heights & Distance, **Permutations & Combinations –** Circular & Linear Arrangements and Derangements, **Probability -** Addition & Multiplication Theorems and Conditional Probability, **Logical Reasoning -** Arrangements, Sequencing, Scheduling, Venn Diagram, Network Diagrams, Binary Logic, and Logical Connectives, Clocks, Calendars, Cubes, Non-Verbal reasoning, Blood Relations, Direction Test, Syllogisms, Series, Odd One Out, Coding & Decoding,

Cryptarithmetic and Input-Output Reasoning, **Data Sufficiency, Campus Recruitment Papers, Puzzles** - Lateral Thinking Problems, Riddles, Logical Puzzles, Deduction Puzzles, Calculation Puzzles, and Other Interview Puzzles, **Time Management Strategies**.

References

Soft Skills

1. Student's Guide for Career Planning, CIR
2. Thomas L. Quick, "Successful team building", AMACOM Div American Mgmt Assn, 1992
3. Brian Cole Miller, "Quick Team-Building Activities for Busy Managers: 50 Exercises That Get Results in Just 15 Minutes", AMACOM; 1 edition, 2003.
4. Patrick Lencioni, "The Five Dysfunctions of a Team: A Leadership Fable", Jossey-Bass, 1st Edition, 2002
5. How to Win Friends & Influence People, Dale Carnegie, 1998 Edition.
6. I'm OK--You're OK, Thomas A. Harris, 2012 Edition.
7. Personality Development and Soft Skills, Barun K.Mitra, Oxford, 2nd Edition
8. Effective Group Discussion, Theory and Practice, Gloria J. Galanes McGraw Hill, 15th Edition

Verbal

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Evaluation Pattern

Assessment	Internal	External
Continuous Assessment (CA)* – Soft Skills	30	-
Continuous Assessment (CA)* – Aptitude	10	25
Continuous Assessment (CA)* – Verbal	10	25
Total	50	50

*CA - Can be **presentations, speaking activities and tests.**

26CUL500 INTEGRATED AMRITA MEDITATION TECHNIQUE 0-0-2-1

Course Overview

The course introduces students to the Integrated Amrita Meditation Technique (IAM 20), a structured practice that combines yogic stretches, regulated breathing (pranayama), and guided meditation. The course integrates both theoretical understanding and experiential practice to enhance emotional balance, stress resilience, concentration, and overall holistic development.

Aligned with United Nations Sustainable Development Goal 3 (SDG 3): Good Health and Well-Being, the course promotes preventive mental health care, emotional well-being, and sustainable lifestyle practices among students. By fostering inner stability, self-awareness, and self-regulation, the programme supports academic excellence and contributes to the development of healthy individuals and communities.

The course is expected to improve student well-being, enhance academic focus and cognitive clarity, reduce stress-related indicators, and promote compassionate and emotionally supportive culture.

Course Outcomes

CO1	Explain principles and components of IAM 20.
CO2	Demonstrate and correct meditation practice independently.
CO3	Analyze personal stress patterns using meditation insights.
CO4	Evaluate personal growth through daily practice.

CO-PO Mapping

PO/PSO	PO1	PO2	PO3	PO4	PO5	PO6
CO						
CO1			1			

CO2			1			
CO3			1	1		
CO4			1			

1- Weak affinity, 2-Moderate affinity, 3-Strong affinity

Syllabus

Unit 1: Foundations of Meditation (CO1)

- Meaning and purpose of meditation
- Demonstration and supervised training
- Overview of structure of IAM
- Guidance for safe and effective practice
- Importance of mental health

Unit 2: Theoretical Foundations (CO2)

- Structure and components of IAM: yogic stretches, regulated breathing, and guided meditation
- Breath–mind connection
- Integration of IAM practice into daily routine and academic life
- Application of IAM for stress management, concentration, and holistic student development

Unit 3: IAM Practical Training (CO3)

- Preparatory stretches
- Pranayama components
- Guided meditation sequence
- Corrections and common challenges

Unit 4: Integration and Transformation (CO4)

- Building daily discipline
- Research evidence in higher education
- Compassion and mindful communication

Evaluation Pattern

Assessment	**Internal (60)**	**External (40)**
Attendance	20 Marks	
Class Participation	20 Marks	
Activity	20 Marks	
Practical Demonstration		30 Marks
Viva		10 Marks

Lecture Plan

Lectures	**Topics**
Week 1	Introduction to IAM, signing agreement form, conduct Pre Test
Week 2	Practice of Yogic Stretches
Week 3	Practice of Yogic Stretches

Week 4	Practice of Deep Breathing, Visualization, and Meditation
Week 5	Practice of Full Cycle of IAM 20
Week 6	Mid-Intervention data collection
Week 7	Practice of Full Cycle of IAM 20
Week 8 and Week 9	Evaluation Activities: (Faculty can Decide) Poster Presentation, Viva, Role Play, Paper Presentation, or Video Presentation
Week 10	Conduct Post Test and Feedback
Week 11	Practice of Full Cycle of IAM 20
Week 12	Practice of Full Cycle of IAM 20