NATIONAL INSTITUTE OF TECHNOLOGY DURGAPUR

CURRICULUM

OF

MASTER OF TECHNOLOGY IN ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

OFFERED BY

THE DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

2023 ONWARD ADMISSION BATCH

V0:

Curriculum and Syllabus Recommended by members of DAC	24.08.2024
Curriculum and Syllabus Recommended by PGAC	27.05.2025
Curriculum and Syllabus Approved by the Senate	Pending

M.Tech in Artificial Intelligence and Data Science

Course Curriculum

First Semester

Sl. No.	Sub. Code	Subject	L-T-P	Credits	Hours
1	CS1011	Mathematical foundation of Data Science – I	3-0-0	3	3
2	CS1012	Algorithms for Data science	3-0-0	3	3
3	CS1013	Artificial Intelligence	3-0-0	3	3
4	CS1014	Data Warehousing and Data Mining	3-0-0	3	3
5	CS1015	Quantitative Data Analysis	3-0-0	3	3
6	CS90XX	Elective-I	3-0-0	3	3
7	CS1061	Data Science Laboratory - I	0-0-6	3	6
TOTAL				**21**	**24**

Second Semester

Sl. No.	Sub. Code	Subject	L-T-P	Credits	Hours
1	CS2011	Mathematical foundation of Data Science – II	3-0-0	3	3
2	CS2012	Machine Learning	3-0-0	3	3
3	CS2013	Big Data Systems	3-0-0	3	3
4	CS90XX	Elective-II	3-0-0	3	3
5	CS90XX	Elective-III	3-0-0	3	3
6	CS2061	Data Science Laboratory - II	0-0-6	3	6
7	CS2062	Mini Project with Seminar	0-0-6	3	6
TOTAL				**21**	**27**

Third Semester

Sl. No.	Sub. Code	Subject	L-T-P	Credits	Hours
1	XX907X	Audit Lectures/ Workshops	0-0-0	0	2
2	CS3061	Dissertation – I	0-0-24	12	24
3	CS3062	Seminar – Non-Project/Evaluation of Summer Training	0-0-4	2	4
TOTAL				**14**	**30**

Fourth Semester

Sl. No.	Sub. Code	Subject	L-T-P	Credits	Hours
1	CS4061	Dissertation – II/Industrial Project	0-0-24	12	24
2	CS4062	Project Seminar	0-0-4	2	4
TOTAL				**14**	**28**
Total Program Credit				**70**	**109**

LIST OF ELECTIVE SUBJECTS (I, II & III)

Sub. Code	Subject	L-T-P	Credits
CS 9044	Natural Language Processing	3-0-0	3
CS 9098	Computational Intelligence	3-0-0	3
CS 9099	Data Visualisation	3-0-0	3
CS 9100	Advanced Graph Theory	3-0-0	3
CS 9101	Streaming Data Analytics	3-0-0	3
CS 9047	Information Retrieval	3-0-0	3
CS 9102	Societal Computing and Analytics	3-0-0	3
CS 9059	Block chain Technology and its Applications	3-0-0	3
CS 9072	Randomized Algorithms	3-0-0	3
CS 9103	Smart Healthcare	3-0-0	3
CS 9104	Spatial Data Analysis and GIS	3-0-0	3
CS 9048	Human Activity Recognition	3-0-0	3
CS 9037	Soft Computing Techniques	3-0-0	3
CS 9041	Introduction to Cognitive Computing	3-0-0	3
CS 9018	Advanced DBMS	3-0-0	3
CS 9045	Deep Learning	3-0-0	3
CS 9105	Bioinformatics	3-0-0	3
CS 9106	Computer Vision	3-0-0	3
CS 9035	Time Series Analysis	3-0-0	3
CS 9107	IoT and Data Analytics	3-0-0	3
CS 9108	Recommender System	3-0-0	3
CS 9109	Reinforcement Learning	3-0-0	3
CS 9042	Speech Processing	3-0-0	3
CS 9110	Ethics in Data Science	3-0-0	3
CS 9111	Scalable Systems for Data Science	3-0-0	3
CS 9112	Generative AI	3-0-0	3
CS 9113	Explainable AI	3-0-0	3
CS 9031	Big Data Analytics	3-0-0	3
CS 9114	Large Vision Models	3-0-0	3

Syllabus

Department of Computer Science and Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS1011	**Mathematical Foundation of Data Science I**	PCR	4		0	4	4
Pre-requisites		Course Assessment methods (Continuous (CT) and end assessment (EA))					
Probability and Statistics, Linear Algebra, Set Theory, Graphs		CT+EA **[CA: 15%, MT: 25%, ET: 60%]**					

Course Outcomes	• CO1: Understand the importance of mathematics for Data science. • CO2: Account for different mathematical principles of well-known AI models. • CO3: Familiarity with Linear Algebra and Optimization for Data Science. • CO4: To understand how mathematics used in AI and Data Science. • CO5: Applications of mathematics from the perspective of AI and data Science.
Topics to be Covered (40L)	• Basics of Data Science: Introduction to Data Science; Importance and application of linear algebra, statistics and optimization from on data science perspective;(2 L) • Probability Review : Sample Spaces, Conditional Probability and Independence, Density Functions , Expected Value Variance Joint, Marginal, and Conditional Distributions, Baye's Rule, Bayesian Inference, Expectations and moments; Covariance and correlation; Statistics and sampling distributions; Hypothesis testing of means, proportions, variances and correlations; Confidence (statistical) intervals; Correlation functions; White-noise process.(12L) • Convergence and Sampling : Sampling and Estimation, Probably Approximately Correct (PAC), Concentration of Measure, Union Bound and Examples, Importance of Sampling ,Sampling Without Replacement with Priority Sampling • Linear Algebra Review: Vectors and Matrices, Addition and Multiplication, Norms , Linear Independence, Rank , Inverse , Orthogonality, Eigen-value and eigenvectors, Notion of hyper-planes; half-planes.(6L) • Distances and Nearest Neighbors: Metrics , L_p Distances and their Relatives, L_p Distances , Mahalanobis Distance, Cosine and Angular Distance , KL Divergence ,Distances for Sets and Strings, Jaccard Distance, Edit Distance , Modeling Text with Distances, Bag-of-Words Vectors, k-Grams, Similarities, Normed Similarities, Set Similarities (6L) • Linear Regression: Simple Linear Regression, Linear Regression with Multiple Explanatory Variables, Polynomial Regression, Cross Validation, Regularized Regression, Tikhonov Regularization for Ridge Regression, Lasso, Dual Constrained Formulation, Orthogonal Matching Pursuit(6L) • Gradient Descent: Functions, Gradients, Gradient Descent, Learning Rate, Fitting a Model to Data, Least Mean Squares Updates for Regression, Decomposable Functions(3L) • Principal Component Analysis : Projections, Data Matrices, Singular Value Decomposition, Best Rank-k Approximation, Eigenvalues and Eigenvectors, The Power Method, Principal Component Analysis, Multidimensional Scaling(3L) • Graphs: Markov Chains , Ergodic Markov Chains, Metropolis Algorithm , PageRank, Spectral Clustering on Graphs, Laplacians and their Eigen-Structure, Communities in Graphs, Preferential Attachment, Betweenness, Modularity(4L)

Text Books, and/or reference material	**Text Books:** • Dan A. Simovici , Chabane Djeraba, Mathematical Tools for Data Mining, Springer • Gareth James , Daniela Witten , Trevor Hastie , Robert Tibshirani An Introduction to Statistical Learning, Springer • Jeff M. Phillips, Mathematical Foundations for Data Analysis, Springer **Reference Books:** • S. K. De and S. Sen; Mathematical Statistics, U. N. Dhur and Sons Private Ltd. • Sorin Mitran, Linear algebra for data science, Department of Mathematics, University of North Carolina at Chapel Hill (Online) • K. Hoffman and R. Kunze, Linear Algebra, pearson • A. Antoniou and Wu-Sheng Lu, Practical Optimization, Springer

Department of Computer Science and Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS1012	**Algorithms for Data Science**	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous (CT) and end assessment (EA))					
Basics of Algorithms and Probability		CT+EA [CA: 15%, MT: 25%, ET: 60%]					
Course Outcomes	• CO1: To be able to understand the algorithmic perspective of data science problem. • CO2: To be able to apply the gathered algorithmic knowledge to solve real life data science problem • CO3: Can learn tools and techniques for designing and analyzing algorithms in data science. • CO4: To be able recognize the state-of -the-art about the algorithmic perspective of data science						
Topics Covered	• Overview and Motivational Examples (1) • Indicator Random Variable, Linearity of expectation; Markov inequality; Chebyshev's inequality; Chernoff bound; Union bound. (3) • Bloom filters, Consistent hashing and Count-min sketch.(4) • Similarity metrics, Similarity Search and KD-Trees. (3) • Dimentionality reduction, Johnson-Lindenstrauss Transform, Locality sensitive hashing. (4) • Algorithms to find top k principal components (SVD and power iteration). (4) • Spectral Clustering/Partitioning. (3) • Reservoir sampling in data science. (2) • Markov Chain Monte Carlo (MCMC) and relation to data science. (3) • Online learning and the multiplicative weights algorithm. (3) • Advertising on the web (The matching problem and Adwords problems) (2) • Compressive sensing (2) • Fourier transform and convolution: an algorithmic perspective. (3) • **Conjoint Analysis: an algorithmic perspective (2)**						

	• Other Modern Applications (such as differential privacy in data science etc.). (3)
	Text Books: 1. Jure Leskovec, Anand Rajaraman, Jeffrey David Ullman: Mining of Massive Dataset, Cambridge University Press/ Dreamtech Press (India) 2. M. Mitzenmacher and E. Upfal, Probability and Computing: Randomized Algorithms and Probabilistic Analysis, Cambridge University Press. 3. Thomas H. Cormen, Charles Leiserson, Ronald Rivest, and Clifford Stein. Introduction to Algorithms. 3rd ed. MIT Press, 2009. ISBN: 9780262033848. **Reference Book/Lecture Notes:** 1. T. Roughgarden, CS 168: The Modern Algorithmic Toolbox (Stanford University), 2017 with Gregory Valiant. 2. Dimitri P. Bertsekas and John N. Tsitsiklis, Introduction to Probability, 2^{nd} Edition, Athena Scientific, July 2008. 3. T. Roughgarden, CS261: A Second Course in Algorithms (Stanford University), 2016 and Randomized Algorithms: COMS 4995 (2019)

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS1013	Artificial Intelligence	PCR	3	1	0	4	4
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					
Basic Concepts of Probability and Statistics, Knowledge of Algorithm analysis		CE+EA					
Course Outcomes	• CO1: Identify problems where artificial intelligence (AI) techniques are applicable • CO2: Understand to apply search strategies to solve the problems. • CO3: Demonstrate and enrich knowledge to select and apply AI tools to synthesize information and develop models within constraints of application area. • CO4: Formulate valid solutions for problems involving uncertain inputs or outcomes by using decision making techniques. • CO5: Examine the issues involved in knowledge bases, reasoning systems and planning.						
Topics Covered	**Introduction to Artificial Intelligence (AI):** What is Intelligence, Reasoning and Planning, Learning and Adaptation, and interaction with the real world, A brief history of AI, Application areas of AI, State of the art (2) **Intelligent Agents:** Agents and Environments, Concept of Rationality, The Nature of Environments, The Structure of Agents (3) **Problem solving by search:** Problem types, Illustrative search problems; Search Space, Search tree; BFS, DFS, UCS, Completeness, optimality; Lookup tables. Greedy search, Local search; Hill climbing; Heuristics; A* search; Admissibility and consistency of heuristics, Game trees; Minimax search; Alpha-beta pruning; Genetic algorithms; constraint satisfaction (8) **Knowledge Representation and Reasoning:** Formal methods (propositional, predicate logic, first order logic), resolution and unification; Informal methods (frames, scripts), answer extraction; knowledge based systems; logic programming,						

	Semantic Nets (8) **AI planning systems:** Definition and examples of planning systems; planning as search; operator-based planning; propositional planning; planning algorithms. (7) **Reasoning under Uncertainty and Learning:** Probabilistic reasoning (Bayes Theorem, Bayesian Inference); Fuzzy Systems and Reasoning; Case based reasoning, analytical reasoning and model based reasoning; Decision making (Simple and Complex); Introduction to neural networks and reinforcement learning. (12) **Philosophical Foundations:** Weak AI and Strong AI; Ethics and risks of developing AI (2)
Text Books, and/or reference material	**Text Books:** 1. 1.Artificial intelligence : A Modern Approach- Stuart Russell, Peter Norvig, Prentice Hall, Fourth edition, 2020 2. N. J. Nilsson, "Principles of Artificial Intelligence", Narosa Publishing House, 2002. **Reference Books:** 1. Elaine Rich, Kevin Knight and Shivashankar B Nair, “Artificial Intelligence”, Tata McGraw Hill, 3rd Edition 2017. 2. R.B. Mishra, “Artificial Intelligence”, PHI Learning Pvt. Ltd., 1st edition, 2010.

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS1014	**Data Warehousing and Data Mining**	PEL	3	0	0	3	3
Pre-Requisite: Database Management System		Course Assessment methods (Continuous (CT) and end assessment (EA))					
		CT+EA					

Course Outcomes	• CO1: To introduce basic principles, concepts and applications of data warehousing • CO2: Understand the design of data warehouse with dimensional modeling and apply OLAP operations • CO3: To introduce students to the basic concepts and techniques of Data Mining • CO4: To introduce a wide range of clustering, estimation, prediction, and classification algorithms • CO5: Apply data mining techniques in inter-disciplinary areas
Topics Covered	**Introduction to Data Warehousing**: Moving toward the Information Age, Evolution of Information Technology, Different types of data (Database Data, Data Warehouses, Transactional Data, Other Kinds of Data), Database Systems and Data Warehouses, Data warehousing applications (2) **Knowing the data and its preprocesing:** Data Objects and Attribute Types, Statistical Descriptions of Data: Measuring the Central Tendency, the Dispersion of Data, Data Similarity and Dissimilarity, Data Quality, Major Tasks in Data Preprocessing, Data Cleaning, Data Integration, Data Reduction, Data Transformation and Data Discretization (3) **Data Warehouse:** What Is a Data Warehouse? Differences between Operational Database Systems and Data Warehouses, Data Warehousing: A Multi-tiered Architecture, Data Warehouse Models: Enterprise Warehouse, Data Mart, and Virtual Warehouse, Extraction, Transformation, and Loading, Metadata Repository, A Business Analysis Framework for Data Warehouse Design (3)

	Data Warehouse Modeling and OLAP Operations: Data Cube and OLAP, Data Cube: A Multidimensional Data Model, Stars, Snowflakes, and Fact Constellations: Schemas for Multidimensional Data Models, Dimensions: The Role of Concept Hierarchies, Typical operations in OLAP, A Starnet Query Model for Querying Multidimensional Databases (4) **Introduction to Data Mining**: Data Mining as the Evolution of Information Technology, What Kinds of Data Can Be Mined? What Kinds of Patterns Can Be Mined? Technologies Used in data mining, Different Applications in data mining, Major Issues in Data Mining, Data Mining and Society (2) **Mining Frequent Patterns, Associations, and Correlations:** Basic Concepts - Frequent Itemsets, Closed Itemsets, and Association Rule, Apriori Algorithm: Finding Frequent Itemsets by Confined Candidate Generation, Generating Association Rules from Frequent Itemsets, Improving the Efficiency of Apriori, A Pattern-Growth Approach for Mining Frequent Itemsets, Mining Frequent Itemsets using Vertical Data Format (5) **Classification:** Basic Concepts (What Is Classification?, General Approach to Classification)**,** Decision Tree Induction, Bayes Classification Methods, Rule-Based Classification, Metrics for Evaluating Classifier Performance, Techniques to Improve Classification Accuracy**,** Classification by Backpropagation, Support Vector Machines, Lazy Learners (k-Nearest-Neighbor Classifier) (10) **Cluster Analysis:** Basic Concepts and Methods, Partitioning Methods (k-Means, k-Medoids), Hierarchical Methods (Agglomerative vs. Divisive Hierarchical Clustering), Density-Based Methods (DBSCAN), Grid-Based Methods (CLIQUE), Evaluation of Clustering, Clustering Graph and Network Data (Applications and Challenges, Similarity Measures, Graph Clustering Methods) (8) **Outlier Detection:** Outliers and Outlier Analysis, Types of Outliers, Challenges of Outlier Detection, Outlier Detection Methods (Statistical Methods, Proximity-Based Methods, Clustering-Based Approaches, Classification-Based Approaches) (5)
Text Books, and/or reference material	**Text Books:** 1. Building The Data Warehouse, W. H. Inmon, Wiley Computer Publication, 3rd Edition. 2. Data Mining Concepts and Techniques : Jiawei Han, Micheline Kamber and Jian Pei, Morgan Kaufmann Publishers, Elsevier, USA.
	Reference Books: 1. Data Modeling Techniques for Data Warehousing, Chuck Ballard, Dirk Herreman, Don Schau, Rhonda Bell, Eunsaeng Kim, Ann Valencic, IBM Red Book, February 1998 2. Mehmed Kantardzic, "Data Mining Concepts, Methods and Algorithms", John Wiley and Sons, USA, 2003.

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS1015	**Quantitative Data Analysis**	PCR	3		0	3	3
Pre-requisites		Course Assessment methods (Continuous (CT) and end assessment (EA))					
Basics of probability and statistics		CT+EA **[CA: 15%, MT: 25%, ET: 60%]**					
Course Outcomes	• CO 1: Understanding the fundamental concepts of Quantitative Data Analysis, research process and design • CO 2: Understanding different quantitative data analysis methods • CO 3: Understanding data with descriptive statistics • CO 4: Implementation and applications of quantitative analysis methods • CO 5: Manage, visualize, summarize and present data through quantitative analysis methods						
Topics to be Covered	1. Introduction to Quantitative Data Analysis: Define QDA, quantitative data analysis and						

(42L)	research process, casualty and research design, survey design, concept and measurements, summarizing data, measuring dispersion, shape of a distribution. (4L) 2. Distribution, Sampling and Statistical Significance: Discrete Distributions - Uniform distribution, Hyper Geometric distribution, Binomial distribution, Poisson distribution and their relationship, Continuous Distributions - Uniform distribution, Normal distribution, Exponential distribution; Sampling and sampling Distributions, statistical significance (8L) 3. Bivariate Analysis: Criteria for selecting bivariate tests, parametric vs non-parametric tests, categorical variables and non-parametric tests, non-categorical variables and non-parametric tests, non-categorical variables and parametric tests, analysis of variance, cross tabulation, correlation, bivariate relationships. (10L) 4. Regression: Exploring relationships between variables, Linear regression, multiple linear regression, polynomial, regression. (6L) 5. Multivariate Analysis: Multivariate design, multivariate analysis, exploring relationships, analysis through contingency tables, multivariate analysis and correlation, regression and multivariate analysis, path analysis. (5L) 6. Exploratory Factor Analysis: Aggregating variables, correlation matrix, principal component and factor analysis, rotation of factors. (4L) 7. Evaluative Quantitative Analysis: Hypothesis development and testing, T-test – the theory of stouts and stats, one way ANOVA. (5L)
Text Books, and/or reference material	**Text Books:** 1. Quantitative Analysis, 6th Edition by Day and Underwood, Pearson India. 2. Quantitative Data Analysis by Donald J. Treiman, John Wiley & Sons Inc. 3. Principles of Statistics by M.G. Bulmer, Dover Publications. 4. Quantitative Analysis for System Applications: Data Science and Analytics Tools and Techniques by Daniel A. McGrath, Technics Publications. 5. Principles Of Quantitative Analysis: An Introductory Course by Walter C. Blasdale, Kessinger Publishing.

Department of Computer Science and Engineering							
Course Code	Title of the Course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS1061	**Data Science Laboratory - I**	PCR	0	0	0	6	3
Pre-requisites		Course Assessment methods (Continuous (CT) and end assessment (EA))					
NA		CT+EA [CT: 60%, EA(Laboratory assignment + Viva Voce): 40%]					

Course Outcomes	• CO1: To be able to understand the algorithmic perspective of data science problems. • CO2: To be able to apply the gathered algorithmic knowledge to solve real-life data science problem • CO3: Can learn tools and techniques for designing and analyzing algorithms in data science.
Topics Covered	• Basic Data Science Tools and Techniques (Basic programming in Python, Google Sheets basic formulae and operations, Data Visualization, NumPy, Pandas) • Data Preprocessing (Handling missing data; Handling imbalanced classes: introduction to SMOTE algorithm; Feature selection; Noise removal; Data preprocessing of sensor data; Frequency domain tools; Fourier transform) • Fundamental Concepts on ML (exploration of online data repositories for machine learning – UCI, OpenML, Kaggle etc.; sklearn or related libraries: training, testing, evaluation; performance metrics; similarity computation; cross-validation, overfitting and underfitting; dimensionality reduction) • Machine Learning techniques - I (linear and logistic regression; Introduction to classification; KNN; Naïve Bayes; Decision Trees; Random Forests) • Machine Learning techniques – II (Hidden Markov Model; Support Vector Machine; Clustering techniques) • Case study on real-life problems on classification or regression. • Group Project • Say we need to allocate tasks (large number) on servers. Apply balls and bins techniques to allocate the tasks. Write a computer program to simulate the process. • Suppose, in a browser you are requesting a URL, like facebook.com or Google.com etc. You are requesting it again and again and in this case each time you go to the original server to fetch the page is not a good idea. In this case you can use web caching. Now one fine morning you thought to store (cache) every page request in your local NITDGP network. In this case number of servers will grow as more and more new requests pop-up. Simulate this idea with consistent hashing. • Say, as a sales manager of amazon or flipkart, you want to find the most frequently searched product of yesterday. Will the linear search be ok? In this context implement the Count min-sketch algorithm. • Given a data set, you want to fetch pairs or sets of similar items from the dataset. Also think of the setting where there is a reference dataset that you have processed already but given a new datapoint, you want to very quickly return a similar datapoint from the dataset. These two settings have many applications such as plagiarism detection in code/essays, mirror web sites detection, finding similar genes, collaborative filtering etc. Implement the idea this setting with kd-Trees and Locality sensitive hashing. • Implement Word embedding problem with SVD. • PAGERANK: Using Markov Chain Monte Carlo (MCMC) to evaluate the relevance of a given webpage. • Study of PROLOG programming language and its function. Write simple facts for the statements using PROLOG. • Write a program in PROLOG to implement the following: Simple arithmatic, Factorial of a given numbe, Depth First Search (DFS), Breadth First Search for Tic-Tac-Toe problem, 8-puzzle problem using Best First Search, A * algorithm. Hill climbing algorithm, Water Jug problem, N-Queen problem, Monkey Banana problem, Simple chatbot application.

Text Books, and/or reference material	**Text Books:** 1. Jure Leskovec, Anand Rajaraman, Jeffrey David Ullman: Mining of Massive Dataset, Cambridge University Press/ Dreamtech Press (India) 2. Ivan Bratko, PROLOG PROGRAMMING FOR ARTIFICIAL INTELLIGENCE, ADDISON-WESLEY PUBLISHING COMPANY. **Reference Book/Lecture Notes:** 1. T. Roughgarden, CS 168: The Modern Algorithmic Toolbox (Stanford University), 2017 with Gregory Valiant.

Department of Computer Science and Engineering								
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS2011	Mathematical Foundation of Data Science II	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					
Mathematical Foundation of Data Science I, AI, ML DL, Probability and Statistics, Python Programming		CE+EA(CA: 15%, MT: 25%, ET:60%)					
Course Outcomes	• CO1: Understand the importance of mathematics for Data science. • CO2: Account for different mathematical principles of well-known AI models. • CO3: Familiarity with Linear Algebra and Optimization for Data Science. • CO4: To understand how mathematics used in AI and Data Science. • CO5: Applications of mathematics from the perspective of AI and data Science.						
Topics Covered	Introduction: Importance of mathematical principles (Statistics, Linear Algebra, Vector Calculus, Optimization) underlying AI and Data Science. (2L) Statistics: Population, sample, and sampling distributions; Estimation for parametric models – Bayes Decisions and Estimators, Invariance, Minimaxity and Admissibility, The Method of Maximum Likelihood; Non-parametric models - Distribution Estimators, Statistical Functional and Linear Functions of Order Statistics. (6L) Linear Algebra: Linear Equations; Vector spaces- Subspaces, Bases and Dimension, Coordinates, Computation Concerning subspaces; Linear Transformations; Matrix Factorization - Determinant and Trace, Eigenvalues and Eigenvectors, Cholesky Decomposition, Eigen decomposition and Diagonalization, nonnegative, weighted and nonlinear matrix factorization, Matrix Approximation; Singular value Decomposition; Least squares. (12L) Vector Calculus: Differentiation of Univariate Functions, Partial Differentiation and Gradients, Gradients of Vector-Valued Functions, Gradients of Matrices, Useful Identities for Computing Gradients, Higher-Order Derivatives, Linearization and Multivariate Taylor Series, Differential equations. (5L) Optimization: Mathematical Optimization; Convex optimization – Convex set, convex functions, Convex optimization problems, Linear optimization problems, Vector optimization; Duality- The Lagrange dual function and problem, Geometric interpretation, Saddle-point interpretation, Optimality conditions, Perturbation and sensitivity analysis; Unconstraint Optimization - Descent methods, Gradient descent method, Steepest descent method, Newton's method , Self-concordance; Interior-point methods; Constraint Optimization- Primal Gradient method, Primal Coordinate Descent, Lagrangian Relaxation and Duality. (13L) Applications: Linear algebra for Similarity and Graphs Optimization for Graphs, Case studies for AI and data science problems. (4L)							

Text Books, and/or reference material	**Text Books:** 1. N.G. Das, Statistical Methods, McGraw Hill 2. Charu C. Aggarwal, Linear algebra and Optimization for Machine Learning, Springer 3. S. Boyd and L. Vandenberghe, Convex Optimization, Cambridge University Press 4. G. Strangm Linear Algebra and Its applications, Academic Press Inc 5. M. P. Deisenroth, A. Aldo Faisal and C. S. Ong, Mathematics for Machine Learning, Cambridge **Reference Books:** 1. S. K. De and S. Sen; Mathematical Statistics, U. N. Dhur and Sons Private Ltd. 2. Sorin Mitran, Linear algebra for data science, Department of Mathematics, University of North Carolina at Chapel Hill (Online) 3. K. Hoffman and R. Kunze, Linear Algebra, pearson 4. A. Antoniou and Wu-Sheng Lu, Practical Optimization, Springer

Department of Computer Science and Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS2012	Machine Learning	PCR	3	0	0	3	3

Pre-requisites	Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))
Basic probability and statistics, Algebra and calculus, Design and Analysis of Algorithms, Python Programming	CE+EA
Course Outcomes	• CO1: principal models used in machine learning and Apply them in machine learning to appropriate problems • CO2: Compare the assumptions made in each model and the strengths and weakness of each model • CO3: Different learning methods for Regression and Classification. • CO4: Deep Learning methods like CNN, RNN and Reinforcement Learning.
Topics Covered	Foundations for ML: Overview of ML Techniques, Training, Testing, Validation, Cross-Validation (4) Supervised Learning: Linear Regression, Multiple Linear Regression, Logistic Regression, GLM and SoftMax Regression, Bayes classifier, KNN, SVM, Decision Tree (10) Unsupervised Learning (clustering and dimensionality reduction): K-Means, DBSCAN, Gaussian Mixture Model, Hierarchical, PCA (8) Foundations of Neural Networks: Introduction to Neural Network, Perceptron, Feed forward network, Backpropagation, MLP, Overfitting, Bias, Variance, Regularization (4) Ensemble Learning: Bagging, boosting and Random forest (2) **Reinforcement learning:** MDPs. Bellman equations, Value iteration and policy iteration, Linear quadratic regulation (LQR), LQG, Q-learning. Value function approximation. (4) Recurrent Neural Networks: Building recurrent NN, Long Short-Term Memory,

	Time Series Forecasting (4) Basics of NLP, Applications and challenges. (2) Deep Learning: CNN, RNN, LSTM (4)
Text Books, and/or reference material	1. Tom M. Mitchell, "Machine Learning", McGraw Hill Education, International Edition, 2010 2. Christopher M Bishop, "Neural Networks for Pattern Recognition", New York, NY: Oxford University Press, 1995 3. Christopher M Bishop: "Pattern Recognition and Machine Learning", Springer, 2nd edition, 2006 4. Ethem Alpaydin, "Introduction to Machine Learning", Third Edition, , MIT Press, 2014 5. Marc Peter Deisenroth, A. Aldo Faisal, Cheng Soon Ong, "Mathematics for Machine Learning, Cambridge University Press, 2020 6. M. Gopal, "Applied Machine Learning", McGraw Hill Education 7. Class Notes and Video Lectures – Prof. Andrew Ng, Stanford University 8. Aurélien Géron Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, O'Reilly Media, Inc. 2nd Edition 9. Sebastian Raschka and Vahid Mirjalili, "Python Machine Learning: Machine Learning and Deep Learning with Python, scikit learn, and TensorFlow 2", Third Edition, Packt Publishing, 2020. 10. Arvind Narayanan, Twenty one definitions of fairness and their policies, ACM FAT, 2018, https://www.youtube.com/watch?v=jIXIuYdnyyk 11. Moritz Hardt, Eric Price, and Nathan Srebro, Equality of opportunity in supervised learning, 2016

Department of Computer Science and Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS2013	Big Data System	PEL	3	0	0	3	3
Pre-Requisite: Database Management System		Course Assessment methods (Continuous (CT) and end assessment (EA))					
		CT+EA					
Course Outcomes	• CO2: Understand the necessity of Big Data Infrastructure Plan in Information System Design • CO1: Recognize different types of data elements and their functional details – structural, characterization, modelling and operational • CO3: understand the big data ecosystem, resource management, optimization, storage system. • CO4: Apply techniques to handle streaming data						

Topics Covered	**Introduction:** Big data attributes and Definitions, Data Variety, Structured, Semi-structured and Unstructured, Defining Big Data from 3Vs to 3^2Vs - Data Domain, Business Intelligent (BI) Domain, Statistics Domain, Introduction of big data platforms: Hadoop, HDFS, MapReduce, Spark, Google File System (GFS) and HDFS. (3) **Database Techniques for Big Data:** Big data management - Data ingestion, Data storage, Data quality, Data operations, Data scalability and security; Big data management services - Data cleansing, Data integration; Storage models - Block-based storage, File-based storage, Object-based storage; Data Models - Navigational Data Models, Relational Data Models, XML, Canonical Data Model, NoSQL Movement, NoSQL Solutions for Big Data Management. (6) **NoSQL Data Models:** Key-Value Stores, Column-Based Stores, Graph-Based Stores, Document-Based Stores. (5) **Operation On NoSQL Databases:** CRUD operations - Creating, Updating, Accessing and Deleting Data; Query Non-DBMS Vs DBMS Approaches, Declarative Query Language (DQL), Hive Query Language (HQL), Cassandra Query Language (CQL), Spark SQL, Query for Document Store data, MapReduce functionality; Transaction Management, Isolation Levels and Isolation Strategies, BASE Theorem, CAP Theorem. (8) **Modelling Streaming Data:** Data stream and data model versus data format, Use cases of stream processing, Data streaming systems - Data harvesting, Data processing, Data analytics; Importance and implications of streaming data, streaming data solutions, exploring streaming sensor data, Analyzing the streaming data. (4) **Resource Management in Big Data Processing Systems:** Types of Resource Management - CPU, Storage, Network, Big Data Processing Systems and Platforms, Big data and Cloud Resources - Single-Resource Management, Multi-resource Management. (8) **System Optimization for Big Data Processing:** Basic Framework of the Hadoop Ecosystem, Parallel Computation Framework: MapReduce; Job Scheduling of Hadoop, Performance Optimization of HDFS, Performance Optimization of HBase, Performance Enhancement of Hadoop System. (4) **Security and Privacy in Big Data:** Secure Queries Over Encrypted Big Data - Threat Model and Attack Model, Secure Query Scheme in Clouds, Security Definition of Index-Based Secure Query Techniques, Implementations of Index-Based Secure Query Techniques; Privacy on Correlated Big Data (4)
Text Books, and/or reference material	Text Books: 1. Big Data Principles and Paradigms, Rajkumar Buyya; Rodrigo N Calheiros; Amir Vahid Dastjerdi, Elsevier/Morgan Kaufmann, Cambridge, MA. 2. Hands-On Big Data Modelling, James Lee, Tao Wei, Suresh Kumar Mukhiya, Packt Publishing. ISBN: 9781788620901.

Department of Computer Science and Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS2051	**Data Science Lab – II**	SESSIONAL	3	0	0	3	6
Pre-Requisite: Database Management System , Data Science Lab – I1		Course Assessment methods (Continuous (CT) and end assessment (EA))					
		CT+EA					

Course Outcomes	• CO2: Understand the components of Cloud Infrastructure and Distributed File System (DFS) • CO1: Introduction of NoSQl Databases and their usage • CO3: Apply data science techniques in DFS using interface language(s). • CO4: Introduction to Data Analytics over cloud system
Experiments Covered	(a) Installation and management basics of DFS and cloud using AWS/Posit/Cloudera. (b) Managing components of Cloud Infrastructures. (c) Introduction to data management using XML/XQuery and JSON (Java Script Object Notation) (d) Data Handling using NoSql DBs like MongoDB/Cassandra/Hbase (e) Query management in NoSql DBs (f) Managing NoSql dataset using Interface Language using Spark/R/Python (g) Application on Simple data analytics techniques over cloud infrastructure
Text Books, and/or reference material	• Posit Cloud Documentation - https://docs.posit.co/cloud/ • Amazon EC2 Documentation - https://docs.aws.amazon.com/ • Hands-On NoSQL: A Practical Guide to Design and Implementation with Technical Case Studies, Arsames Qajar, Dan Sullivan; Addison-Wesley Information Technology Series. • Python on AWS - https://aws.amazon.com/developer/language/python/

Department of Computer Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9044	Natural Language Processing	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					
Basics of probability and statistics Fundamentals of calculus and linear algebra Programming skills in Python		CE+EA					
Course Outcomes	• CO1: Knowing the fundamental concepts underlying natural language processing (NLP) and its applications • CO2: Understanding morphology, tokenization and stemming, language modeling, POS Tagging • CO3: Understand approaches to syntax and semantics in NLP. • CO2: understand morphology, context free and context-sensitive grammar, parsing issues. • CO4: Understand approaches to discourse, generation, dialogue and summarization within NLP. • CO5: Understand ambiguity resolution • CO6: Understand ML application in NLG. • CO7: Understanding some NLP applications						
Topics Covered	Introduction to NLP and Basic Text Processing (3) Spelling Correction, Morphology using FST (3) Language Modelling, smoothing for language modelling (3) POS tagging , Models for Sequential tagging – MaxEnt, CRF (4) Syntax – Constituency Parsing, Dependency Parsing (5) Semantics – Lexical, WordNet and WordNet based Similarity measures, Distributional						

	measures of Semantics , Lexical Semantics, Word Sense Disambiguation (7) Topic Models (3) Entity Linking, Information Extraction: Introduction to Named Entity Recognition and Relation Extraction (4) Text Summarization, Text Classification (3) Natural Language generation – using ML in NLG (3) Applications: Sentiment Analysis and Opinion Mining, Text Summarisation and classification, question answering, etc. (4)
Textbooks/Reference books	1. Jurafsky, David, and James H. Martin. Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics and Speech Recognition. Prentice-Hall, 2000. ISBN: 0130950696. 2. Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, Introduction to Information Retrieval, Cambridge University Press. 2008 3. Manning, Christopher D., and Hinrich Schütze. Foundations of Statistical Natural Language Processing. Cambridge, MA: MIT Press, 1999. ISBN: 0262133601. **4.** Machine Learning and Data mining: Methods and Applications, Michalski, Bratko, Kubat, Wiley.

Department of Computer Science and Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9098	Computational Intelligence	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					
Introduction to Computing, Data Structures, and Analysis of Algorithms		CE+EA					
Course Outcomes	• CO1: To familiarize with the real life problems which cannot be solved by exact algorithms and formulate them by mapping different soft computing techniques • CO2: To familiarize with the ideas of fuzzy sets, fuzzy logic and fuzzy inference • CO3: To familiarize with different architectures and learning algorithms of neural networks • CO4: To familiarize with different evolutionary computing techniques and their applications in optimization problems • CO5: To introduce different tools to use computational intelligence techniques to design algorithms and systems that can predict, recognize, and make decisions						
Topics Covered	**Introduction to Computational Intelligence** (6L) Introduction and different definitions of Computational Intelligence, Basic tools/members of Computational Intelligence, Requirement of Computational Intelligence, Characteristics of Computational Intelligence, Applications of Computational Intelligence **Fuzzy logic** (10L) Introduction to fuzzy logic; Fuzzy sets and membership functions; Operations on fuzzy sets; Fuzzy relations, Composition of fuzzy relations, Fuzzy rules, propositions, implications and inferences; Fuzzification; Defuzzification; Fuzzy Clustering and control **Artificial Neural Network (ANN)** (10L) Introduction to ANN: Biological neurons and its working, Artificial neuron and its model, Activation functions, Neural network architecture and learning algorithms/rules, Training and testing.						

	Perceptron model, single layer and multilayer perceptron (MLP), Error back propagation, Radial basis function network (RBFN), Self-organizing map network (SOMN), Recurrent neural network, Applications of ANN. **Evolutionary Computing** (12L) Introduction to evolutionary computing: Concept of genetics, fitness, evolution and evolutionary computing Genetic Algorithm: Basic concepts and working principle of simple GA (SGA); Genetic Operators: Selection, Crossover and Mutation, Chromosome Encoding & Decoding, fitness Function, Solving Travelling Salesman Problem using SGA using GAs. Introduction to Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Local Search and Memetic algorithm. Multi-objective Optimization: Multi-objective optimization problems (MOOPs) and their challenges; Multi-objective evolutionary algorithm (MOEA): Non-Pareto based approach (SPEA2) and Pareto-based approach (NSGA II); Some applications **Hybridized System** (4L) Genetic Algorithms–Fuzzy Logic, Genetic Algorithms–Neural Networks, Neural Networks–Fuzzy Logic **Applications of computational intelligence** techniques to solve some real life problems
Text Books, and/or reference material	**Text Books** 1. S. Rajsekharanand and Vijayalakshmi Pai, "Neural Networks, Fuzzy Logic and Genetic Algorithm: Synthesis and Applications", Prentice Hall of India. 2. Konar, "Computational Intelligence", Springer. 3. G. Klir and B. Yuan, "Fuzzy sets and Fuzzy logic", Prentice Hall of India. 4. K. H. Lee., "First Course on Fuzzy Theory and Applications", Springer-Verlag. 5. G. J. Klir and T. A. Folger: Fuzzy Sets, Uncertainty, and Information, PH. 6. D. E. Goldberg, "Genetic Algorithms in Search, Optimization and Machine learning", Second Edition, Addison Wesley, 2007. 7. Melanie Mitchell, "An Introduction to Genetic Algorithms", MIT Press, 2000. 8. D. K. Pratihar, "Soft Computing", Narosa, 2008. 9. Nikola K. Kasabov, "Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, 1998. **Reference Books** 1. Satish Kumar, "Neural Networks - A Classroom Approach", Tata McGraw-Hill, 2004. 2. Simon Haykin, "Neural Networks and Learning Machines", 3rd Edition, Prentice Hall of India, 2011. 3. Kumar Satish, "Neural Networks", Tata Mc. Graw Hill. Yegnanarayana, "Artificial Neural Networks" 4. Y. H. Pao: Adaptive Pattern Recognition and Neural Networks, Addison-Wesley. 5. J. Yen and R. Langari, "Fuzzy Logic, Intelligence, Control and Information", Pearson Education. 6. Timothy J. Rose, "Fuzzy Logic with Engineering Applications", Third Edition, John Wiley, 2010. 7. Ahmed M. Ibrahim, "Fuzzy Logic for Embedded Systems Applications", Elsevier Press, 2004. 8. J.-S. R. Jang, C.-T. Sun, and E. Mizutani, "Neuro-Fuzzy and soft Computing", PHI Learning, 2009. 9. R. A. Aliev, R. R. Aliev , Soft Computing and its Applications, World Scientific Publishing Co. Pte. Ltd., 2001.

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<tr><td colspan="9">Department of Computer Science and Engineering</td></tr>
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<tr><td>Lecture (L)</td><td>Tutorial (T)</td><td>Practical (P)</td><td>Total Hours</td></tr>
<tr><td>CS 9099</td><td>Data Visualization</td><td>PEL</td><td>3</td><td>0</td><td>0</td><td>3</td><td>3</td></tr>
<tr><td colspan="2">Pre-requisites</td><td colspan="6">Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))</td></tr>
<tr><td colspan="2">Linear algebra, Calculus, Vector and Vector Calculus, Probability and statistics</td><td colspan="6">CE+EA</td></tr>
<tr><td>Course Outcomes</td><td colspan="7">• CO1: To understand data visualization and its importance.
• CO2: To understand scalar, vector, tensor, image, volume and information visualization
• CO3: To achieve the knowledge of domain modelling techniques.
• CO4: To know visualisation softwares.</td></tr>
<tr><td>Topics Covered</td><td colspan="7">Introduction to Data Visualisation: Introduction to data visualization, what is visualizations and why visualization is important. Brief of visualization process, examples and applications of visualizations for problem solving. (4) Graphics to Visualization: Graphics rendering basics, rendering the height plot, texture mapping, transparency and blending, viewing (3)
Data Representation: Continuous data, sampled data, discrete data, cell types, grid types, attributes, computing derivatives of sampled data, implementation, advanced data representation. (3)
Visualization Pipeline: Conceptual Perspective, Implementation Perspective, Algorithm Classification. (3)
Scalar and Vector Visualization: Color Mapping, Contouring, Height Plots, Divergence and Vorticity, Vector Glyphs, Vector Color Coding, Texture-Based Vector Visualization, Representation of Vector Fields (5)
Tensor Visualization: Principal Component Analysis, Visualizing Components, Visualizing Scalar and Vector PCA Information, Tensor Glyphs, Fiber Rendering, Hyperstreamlines. (4)
Domain-Modeling Techniques: Cutting, Selection, Grid Construction from Scattered Points, Grid-Processing Techniques. (4)
Image Visualization: Image Data Representation, Image Processing and Visualization, Basic Imaging Algorithms, Shape Representation and Analysis. (4)
Volume Visualization: Volume Visualization Basics, Image Order Techniques, Object Order Techniques, Volume Rendering vs. Geometric Rendering. (3)
Information Visualization: What Is Infovis? Infovis vs. Scivis: A Technical Comparison, Table Visualization, Visualization of Relations, Multivariate Data Visualization, Text Visualization. (4)
Visualization Software: Taxonomies of Visualization Systems, Scientific Visualization Software, Imaging Software, Grid Processing Software, Information Visualization Software. (5)</td></tr>
<tr><td>Text Books, and/or reference material</td><td colspan="7">Text Book:
1. Alexandru Telea, Data Visualization Principles and Practice, CRC Press, 2015
Reference Books:
2. M. Ward, G, Grinstein, and D. Keim, Interactive Data Visualization-Foundations, Techniques, and Applications, CRC Press, 2010.
3. Claus O. Wilke, Fundamentals of Data Visualization, O'Reilly, 2019</td></tr>
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<tr><td>Lecture (L)</td><td>Tutorial (T)</td><td>Practical (P)</td><td>Total Hours</td><td></td></tr>
<tr><td>CS 9100</td><td>Advanced Graph Algorithms</td><td>PEL</td><td>3</td><td>0</td><td>0</td><td>3</td><td>3</td></tr>
<tr><td colspan="2">Pre-requisites</td><td colspan="6">Course Assessment methods (Continuous (CT) and end assessment (EA))</td></tr>
<tr><td colspan="2">Discrete Mathematics, Basics of Algorithms and Probability</td><td colspan="6">CT+EA [CA: 15%, MT: 25%, ET: 60%]</td></tr>
<tr><td colspan="2">Course Outcomes</td><td colspan="6">● CO1: Designing algorithm for network flow and matching.
● CO2: Designing graph algorithms using linear programming technique.
● CO3: Designing fixed parameter graph algorithms.
● CO4: To be able to understand the need for Graph theoretic problem in different application.</td></tr>
<tr><td colspan="2">Topics Covered</td><td colspan="6">● Introduction to graph theory: Basic Definitions and Notations,Intersection Graphs, Circular-arc Graphs, Interval Graphs, Line graphs of bipartite graphs, Perfect Graph, Chordal graph, Independent Set, Chromatic Number, Travelling salesperson problem, Set cover, Dominating Set, Subset Sum (6)
● Network Flows and Bipartite Matchings: Ford Fulkerson method and max-flow min-cut theorem. Dinitz Algorithm, and Preflow push algorithm for max-flow. Reduction from flows to bipartite matchings. Application of max-flow min-cut theorem for structural and algorithmic results. (8)
● Non-Bipartite Matchings: Edmonds Maximum Matching Algorithm, Gallai Edmonds Decomposition theorem and applications, Tutte-Berge Formula. (6)
● Linear Programming based graph algorithms: Introduction to Linear Programs, formulating combinatorial problems as Linear Programs, Notion of Dual, Primal Dual technique for exact and approximate algorithms -- weighted matchings, shortest paths. Steiner Tree Problem and a simple 2-approximation. (10)
● Shortest paths problem: Min-cost flow and shortest paths, successive shortest paths algorithms, Kargers algorithm for all-pairs-shortest paths. (5)
● Fixed parameter algorithms: A kernel for Vertex cover, a better search tree for vertex cover, Minimum fill-in problem, Homogeneous colouring of perfect graphs (7)</td></tr>
</table>

Text Books, and/or reference material	**Text Books:** 1. Introduction to Graph Theory by Douglas B. West (Pearson Education (Singapore)) 2. A Guide to Graph Algorithms by Mingyu Xiao and Ton Kloks (Springer)

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9101	**Streaming Data Analytics**	PEL	3	0	0	3	3

Pre-requisites	Course Assessment methods (Continuous (CT) and end assessment (EA))
Basics of Algorithms and Probability	CT+EA [CA: 15%, MT: 25%, ET: 60%]
Course Outcomes	• CO1: To be able to understand the need for space-efficient algorithm design. • CO2: Designing faster algorithms for massive data sets. • CO3: Can analyze the algorithms for data streams. • CO4: Can apply the tools and techniques learned to solve real life problems.
Topics Covered	• Overview and motivational examples. (1) • Finding frequent items deterministically. (2) • Estimating the number of distinct elements. (2) • A better estimate for distinct elements (2) • Approximate counting (3) • (linear) sketching (3) • Estimating frequency moments. (2) • The tug-of-War sketch. (2) • Estimating norms using stable distribution (2) • Sparse recovery (2) • Weight based sampling (2) • Finding the median (sublinear) (2) • Geometric streams and coresets (3) • Metric streams and clustering (3) • Graph streams: basic algorithms (2) • Finding maximum matching (2) • Graph sketching (2) • Counting triangles (2) • Communication complexity and lower bounds (3)

Text Books, and/or reference material	**Text Books:** 1. Amit Chakraborti, Data stream algorithms (draft version). 2. S. Muthukrishnan, Data Streams: Algorithms and Applications, (Now publishers Inc) (This survey may supplement the book: https://www.cs.princeton.edu/courses/archive/spr04/cos598B/bib/Muthu-Survey.pdf) **Reference Book/Lecture Notes:** 1. Amit Chakraborti, CS 35/135: Data Stream Algorithms, Spring 2020 (Dartmouth) 2. T. Roughgarden, CS168: Modern Algorithmic Toolbox (with Greg Valiant) (Spring 2017) 3. Cameron Musco, COMPSCI 614: Randomized Algorithms with Applications to Data Science (Spring 2024). 4. Prof. Justin Thaler (Georgetown University) COSC 548 - Streaming Algorithms (Fall 2018).

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9047	Information Retrieval	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					
Linear algebra, Probability and statistics, Machine Learning		CE+EA					
Course Outcomes	• CO1: To understand the underlined problems related to Information Retrieval. • CO2: To be familiar with various algorithms and systems • CO3: Analyze the performance of information retrieval using advanced techniques such as classification, clustering, and filtering • CO4: To understand the evaluation strategies						
Topics Covered	**Introduction to Information Retrieval**: Basic concept of information retrieval, Practical issues, The Retrieval process. (2) **Modelling:** A Taxonomy of Information Retrieval Models, *Classic Information Retrieval*: Basic Concepts, Boolean Model, Vector Model, Probabilistic Model, Comparison of Classic Models. *Set Theoretic Models*: Fuzzy Set Model, Extended Boolean Model. *Algebraic Models*: Generalized Vector Space Model, Latent Semantic Indexing Model, Neural Network Model. *Probabilistic Models:* Bayesian Networks, Inference Network Model, Belief Network Model. *Structured Text Retrieval Models*: Model Based on Non-Overlapping List, Model Based on Proximal Nodes. *Models for Browsing*: Flat Browsing, Structure Guided Browsing, the hypertext model (12) **Retrieval Performance Evaluation:** Introduction, Recall and Precision, Alternative Measures, F-measure, kappa measure. *Reference Collections*: TREC Collection, CACM and lSI Collections, Cystic Fibrosis Collection. (3) **Indexing and Index Compression:** Basic concept, Dictionary, Inverted Index, Forward Index, Partitioning, Caching, Dictionary compression, Posting file compressing. (5) **Text Classification and Filtering:**						

	Introduction to text classification. Naive Bayes models. Spam filtering. Vector space classification using hyperplanes; centroids; k Nearest Neighbours. Support vector machine classifiers. Kernel functions. Boosting. (7) **Text Clustering:** Clustering versus classification. Partitioning methods. k-means clustering. Mixture of gaussians model. Hierarchical agglomerative clustering. Clustering terms using documents. **Advanced Topics**: (4) *Multimedia Information Retrieval:* Similarity Queries, Feature-based Indexing and Searching, Spatial Access Methods, Searching in Multidimensional Spaces. *Web Searching*: Introduction, Challenges, Characterizing the Web, Indexing, Spidering/Crawling, Search Engines, Browsing, Metasearchers, Searching using Hyperlinks, XML retrieval, Semantic web. (9)
Text Books, and/or reference material	**Text Books:** 1. C. D. Manning, P. Raghavan and H. Schutze, Introduction to information retrieval, Cambridge, University Press, 2008. 2. R. Baeza-Yates, B. Ribeiro-Neto, Modern information retrieval, ACM Press / Addison Wesley, 1999 **Reference Books**: 1. G. Kowalski , Information Retrieval Architecture and Algorithms, Springer, 2011. 2. S. Buttcher, Charles L. A. Clarke, Gordon V. Cormack, Information Retrieval Implementing and Evaluating Search Engines, The MIT Press, 2010.

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9102	Societal Computing and Analytics	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous (CT) and end assessment (EA))					
Graph Theory, Data Structure and Algorithms, Linear Algebra		CT+EA **[CA: 15%, MT: 25%, ET: 60%]**					
Course Outcomes	• CO1: Formalize different types of entities and relationships as nodes and edge and represent this information as relational data • CO2: Plan and execute network analytical computations • CO3: Use advanced network analysis software to generate visualizations and perform empirical investigation of network data. • CO4: Interpret and synthesize the meaning of the results with respect to a question, goal or task. • CO5: Collect network data in different ways and from different sources while adhering to legal standards and ethics standards.						
Topics to be Covered (36L)	• Introduction to Social Networks: Networks/Graphs, Basic network measures, Random Graphs, Degree Distribution, connected components, Paths in Graph, Structures in networks. (4L)						
	• Walks: Basics of Random walk, modified random walk, modified random walks, Page Rank and Eigen Centrality. (4L)						
	• Node Centrality: Different Centrality, Centrality and Application. (4L)						
	• Community Detection: Community Detection, Modularity, Overlapping Communities. (5L)						
	• Epidemics Spreading: Epidemics vs Cascade Spreading, SI, SIR, SIS and SIRS Model. Use case: SARS prediction. (8L)						

	• Temporal Network Analysis: Empirical Networks, Temporal Graph, Temporal Measures, Temporal Centrality, Coefficient of Temporal Clustering (5L)
	• Spatial Network Analysis: Fundamentals, GIS, Geotagging, Spatial centrality, Spatial clustering and regression. (6L)
	• Deep Learning on Graph: Machine Learning on Graphs, Graph Neural Networks, Deep Neural Networks, ConvNets, Convolution on Graphs, Message Passing paradigm. (6L)
Text Books, and/or reference material	1. Charu C. Aggarwal, Social Network Data Analytics, Springer 2011. 2. S. Wasserman, K. Faust: Social Network Analysis: Methods and Application, Cambridge University Press, 1994. 3. Scott, J. (2007). Social Network Analysis: A handbook (2nd Ed). Newbury Park, CA: Sage 4. Knoke (2008). Social Network Analysis, (2nd Ed). Sage.

Department of Computer Science and Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9059	Blockchain Technology and its Applications	PEL	3	0	0	3	3
Pre-requisite		Course Assessment methods (Continuous (CT) and end assessment (EA))					
NIL		CT+EA					

Course Outcomes	• CO1: Understanding the basic blockchain technology. • CO2: Understanding the distributed consensus and atomic broadcast, Byzantine fault-tolerant consensus methods. • CO3: Understanding the smart contract. • CO4: Understanding the limitations and reality.
Topics Covered	**Introduction**: Concept of distributed ledger, Byzantine Generals problem, Consensus algorithms and their scalability problems, Introduction to Bitcoin based cryptocurrency, Block datastructure, Block chaining mechanism. (4) **Minting operation:** Concept of PoW, other model – Proof of Stack, Proof or Memory, Proof of Burn etc. Green computing vs Proof systems. (3) **Consensus Model**: Fault tolerance model. P2P network model, Byzantine fault tolerance model, Longest chain model. (2) **Cryptographic Tools:** Hash function, Collision resistant hash function, Elliptic Curve Digital signature (ECDSA). Markle tree representation, zero-knowledge proof. (4) **Bitcoin & Cryptocurrency:** Bitcoin network, Challenges and solutions, SIGHASH, Bitcoin scripting language and their use. (6) **Blockchain 2.0:** Blockchain network, Ethereum and Smart Contracts, The Turing Completeness of Smart Contract Languages, Application of smart contract, Bitcoin scripting vs. Ethereum Smart Contracts. (6) **Solidity:** Introduction to Solidity programming language, Security issues, Basic coding metric, ERC-20, ERC-721, ERC-777, ERC-1155, Design of distributed applications (DApps). (5) **Blockchain 3.0:** Plug-and-play platform, Permission less vs. permission oriented platform, Blockchain testnet and mainnet, Deployment of smartcontarct. (4)

	Anonymity: Pseudo anonymous, pseudonym, transaction analysis, Sybil attack, Issues related to inheritance, Defining of cryptoasser, Regulation and legal supports. (5) **Application:** Application in IoT, HealthCare, Equity and Financial asset, Some case studies. (3)
Text Books, and/or reference material	Text Books: 1. Mastering in Blockchain: Lorne Lantz, Daniel Cawrey 2. Mastering Ethereum: Building Smart Contracts and DApps: Andreas M. Antonopoulos, **Gavin Wood** 3. Mastering Bitcoin: Programming the Open Blockchain: Andreas M. Antonopoulos

Department of Computer Science and Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9072	**Randomized Algorithms**	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous (CT) and end assessment (EA))					
Basics of Algorithms and Probability		CT+EA [CA: 15%, MT: 25%, ET: 60%]					
Course Outcomes	• CO1: To be able to understand the principles of randomized algorithms. • CO2: To be able to apply the gathered algorithmic knowledge to solve real life data science problem with randomized algorithms. • CO3: Can learn tools and techniques for analyzing randomized algorithms. • CO4: To be able to recognize the state-of -the-art about randomized algorithms.						

Topics Covered	• Introduction (1) • Essential tools for analyzing randomized algorithms (concentration bounds, exponential tail bounds with balls and bins). (4) • Randomized algorithms for frequent items and item set finding (4) • Randomized hash functions and fingerprints. Applications to efficient communication protocols and Rabin-Karp pattern matching. (4) • Randomized Numerical Linear Algebra with applications to data science. (3) • Randomized Subspace Embedding. (3) • Gambler's ruin. Markov chain analysis and stationary distributions. A simple sublinear-time algorithm for computing a perfect matching in a regular bipartite graph (3) • Metropolis Hastings algorithm, sampling to counting reductions. (2) • Application of Chernoff bounds. Randomized rounding and low-congestion routing. (3) • Probabilistic method and the Lovasz Local Lemma. (3) • Schoning's randomized algorithm for 3-SAT.(3) • Regret-minimization in online learning. Geometric random variables and the FTPL (Follow-the-Perturbed-Leader) algorithm(3) • Property testing algorithms. (2) • Other Modern Applications solved via randomized algorithms.(4)
Text Books, and/or reference material	**Text Books:** 1. M. Mitzenmacher and E. Upfal, Probability and Computing: Randomized Algorithms and Probabilistic Analysis, Cambridge University Press. 2. Thomas H. Cormen, Charles Leiserson, Ronald Rivest, and Clifford Stein. Introduction to Algorithms. 3rd ed. MIT Press, 2009. ISBN: 9780262033848. 3. Notes on Randomized Algorithms: James Aspnes (available online). **Reference Book/Lecture Notes:** 1. T. Roughgarden, COMS 4995: Randomized Algorithms (Columbia University), 2019. 2. Cameron Musco, COMPSCI 614: Randomized Algorithms with Applications to Data Science (Spring 2024). 4. Dimitri P. Bertsekas and John N. Tsitsiklis, Introduction to Probability, 2nd Edition, Athena Scientific, July 2008. 5. T. Roughgarden, CS261: A Second Course in Algorithms (Stanford University), 2016. 6. T. Roughgarden, CS 168: The Modern Algorithmic Toolbox (Stanford University), 2017 with Gregory Valiant. Yadu Vasudev, Department of Computer Science & Engineering, IIT Madras, CS6170 - Randomized Algorithms.

Department of Computer Science and Engineering							
Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	

CS 9103	Smart Healthcare	PEL	3	0	0	3	3

Pre-requisites	Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))
Machine Learning, Deep Learning, Probability and statistics	CT+EA [CA: 15%, MT: 25%, ET: 60%]

Course Outcomes	• CO 1: To understand the principles and technologies underlying Smart Healthcare. • CO 2: To explore the applications of artificial intelligence, IoT, big data analytics, and wearable devices in healthcare. • CO 3: To analyze case studies of successful Smart Healthcare implementations and their impact on patient care and healthcare systems. • CO 4: To critically evaluate the opportunities and challenges of adopting Smart Healthcare solutions. • CO 5: To discuss the ethical, legal, and social implications of Smart Healthcare technologies. • CO 6: To develop practical skills in designing and implementing Smart Healthcare solutions.
Topics Covered	**Introduction to Smart Healthcare**: Overview of Smart Healthcare, Evolution of healthcare technologies, Challenges in traditional healthcare delivery. (4) **Artificial Intelligence in Healthcare:** Fundamentals of artificial intelligence, Applications of machine learning and deep learning techniques in diagnosis, treatment, and personalized medicine, Ethical considerations in AI-enabled healthcare. (8) **Internet of Things (IoT) in Healthcare:** Introduction to IoT and its components, IoT applications in remote patient monitoring, medical device management, and healthcare infrastructure, Security and privacy challenges in IoT-based healthcare systems. (4) **Big Data Analytics in Healthcare:** Introduction to big data and analytics, Utilizing big data for predictive analytics, population health management, and clinical decision support, Data governance and regulatory compliance in healthcare analytics. (4) **Wearable Devices and Remote Monitoring:** Wearable health technologies: sensors, smart watches, and fitness trackers, Remote patient monitoring and telemedicine applications, Design considerations for user-friendly wearable devices. (4) **Case Studies in Smart Healthcare:** Analysis of real-world implementations of Smart Healthcare solutions, Success factors and lessons learned from case studies, Opportunities for innovation in Smart Healthcare. (4) **Challenges and Opportunities in Smart Healthcare:** Addressing interoperability and data integration challenges, Overcoming barriers to adoption: cost, infrastructure, and workforce training, Future trends and opportunities for growth in Smart Healthcare. (6) **Ethical, Legal, and Social Implications of Smart Healthcare:** Privacy concerns and data security in Smart Healthcare, Regulatory frameworks and compliance requirements, Equity, access, and social justice considerations. (4) **Designing Smart Healthcare Solutions:** Principles of user-centered design, Prototyping and testing Smart Healthcare solutions, Group projects: designing a Smart Healthcare solution. (4)

Text Books, and/or reference material	Text Books: **1.** "Smart Healthcare Analytics: State of the Art" by Prasant Kumar Pattnaik et al. (Springer, 2021). **2.** "The Digital Revolution in Healthcare: Transforming Medicine with Artificial Intelligence, Big Data, and Blockchain" by Eric Topol (Basic Books, 2019). Reference Books: 1. "Artificial Intelligence in Healthcare" by Reza Shaker (Apress, 2020). 2. "Handbook of Smart Healthcare" by Rajiv D. Prabhakar (Academic Press, 2023).

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9104	Spatial Data Analysis and GIS	PEL	3	0	0	3	3
Pre-Requisite: Database Management Systems		Course Assessment methods (Continuous (CT) and end assessment (EA))					
		CT+EA					

Course Outcomes	• CO1: Process spatial and attribute data and prepare thematic maps • CO2: Classify the maps, coordinate systems and projections • CO3: Identify and rectify mapping inaccuracies • CO4: Analyse the basic components of GIS • CO5: Conceptualize a GIS project
Topics Covered	**Introduction:** Review of non-spatial statistics, overview of different types of spatial data (2) **Geostatistics:** Variograms and covariance functions, fitting variogram functions, kriging, spatial regression (6) **Spatial Analysis:** Proximity Analysis, Overlay Analysis, Buffer Analysis, Network Analysis – Route alignment, Canal alignment; Digital Elevation Models. Map composition, Preparation of qualitative and quantitative maps, levels of maps, map elements and map (12) **Areal data:** Neighborhoods, testing for spatial association, Global and local tests of association, CAR and SAR models, inference, phenomena mapping (4) **Point process data:** Types of spatial pattern, spatial clustering (4) **GIS:** Definition, advantages of digital maps, projections and coordinate systems, Conceptual framework - Database, Visualization, Modelling and Analysis (8) **GIS Project Planning and Implementation:** Understanding the Requirements, Phases of Planning, Specifications, and Procedure for analysis projects and design projects. (6)
Text Books, and/or reference material	**Text Books:** 1. O. Schabenberger and C.A. Gotway, "Statistical Methods for Spatial Data Analysis", CRC, 2005 2. Geographic Information systems and Science, Paul Longley., John Wiley & Sons, 4th Edition,2015.

	Reference Books: 1. S. Fotheringham, A. Stewart, C. Brunsdon and C. Martin, "Quantitative Geography: Perspectives on Spatial Data Analysis", SAGE publication, 2000. 2. ntroduction to Geographic Information Systems, 9th Edition, Kang Tsung Chang., Tata Mc Graw Hill Publishing Company Ltd, New Delhi, 2018.

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9048	Human Activity Recognition	PEL	3	0	0	3	3

Pre-requisites	Course Assessment methods (Continuous (CT) and end assessment (EA))
Basic Mathematics – Knowledge and ability to use calculus, probability, and statistics are essential.	CT+EA

Course Outcomes	• CO1: The objectives of this course is to provide foundations needed for the design, implementation, and evaluation of human activity recognition systems. • CO2: Will have knowledge to design and implement multiclassifier human activity recognition systems. • CO3: Will have knowledge to design and develop human activity recognition systems at large scales.
Topics Covered	• Overview: Introduction, activity set, attributes and sensors, obtrusiveness, data collection protocol, recognition performance, energy consumption, processing.[4] • Methods: Feature extraction, learning, evaluation methodologies, evaluation metrics. [3] • Design Challenges of Human Activity Recognition Systems [3] • Pattern Classification Techniques: Introduction, Bayesian decision theory, maximum likelihood and Bayesian parameter estimation, non-parametric techniques, linear discriminant functions, multilayer neural networks, nonmetric methods. [8] • State-of-the systems: Online systems, supervised offline systems, semi-supervised approaches. [6] • Incorporating physiological signals: Description, data collection, feature extraction, evaluation, and confusion matrix. [6] • Enabling real time systems: Existing systems, novel systems, evaluation. [5] • Multiple classifier systems: Types of systems, classifier level approaches, combination level approaches, probabilistic strategies, evaluation. [5] • Other methods: Motion templates, temporal methods, discriminative methods [2]
Text Books, and/or reference material	**Text Books:** 1. Miguel A. Labrador, Oscar D. Lara Yejas, Human Activity Recognition: Using Wearable Sensors and Smartphones, CRC Press, 2013. 2. Richard O. Duda, Peter E. Hart, David G. Stork, Pattern Classification, 2nd Edition, Wiley, 2000. **Reference Books:** • Yun Fu, Human Activity Recognition and Prediction, Springer, 2015.

<table>
<tr><td colspan="9">Department of Computer Science & Engineering</td></tr>
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<tr><td>Lecture (L)</td><td>Tutorial (T)</td><td>Practical (P)</td><td>Total Hours</td><td></td></tr>
<tr><td>CS 9042</td><td>Speech Processing</td><td>PEL</td><td>3</td><td>0</td><td>0</td><td>3</td><td>3</td></tr>
<tr><td colspan="3" rowspan="2">Pre-requisites
Discrete Mathematics, Probability and Statistics, Linear Algebra, Programming</td><td colspan="5">Course Assessment methods (Continuous (CT) and end assessment (EA))</td></tr>
<tr><td colspan="5">CT+EA</td></tr>
<tr><td>Course Outcomes</td><td colspan="7">• CO1: Understand the basics of speech modelling, recognition, and synthesis.
• CO2: More rapidly develop software, especially using skills in scripting and in the customization and combination of existing tools.
• CO3: Comfortably use basic machine learning concepts and techniques for speech processing
• CO4: Apply knowledge of Language and of English to improve everyday written and spoken, communication, including computer-mediated communication, personally and for groups, organizations, and society.</td></tr>
<tr><td>Topics Covered</td><td colspan="7">Basic Concepts: Speech Fundamentals: Articulatory Phonetics – Production and Classification of Speech Sounds; Acoustic Phonetics – acoustics of speech production; Review of Digital Signal Processing concepts; Short-Time Fourier Transform, Filter-Bank and LPC Methods. (10)

Speech Analysis: Features, Feature Extraction and Pattern Comparison Techniques: Speech distortion measures – mathematical and perceptual – Log Spectral Distance, Cepstral Distances, Weighted Cepstral Distances and Filtering, Likelihood Distortions, Spectral Distortion using a Warped Frequency Scale, LPC, PLP and MFCC Coefficients, Time Alignment and Normalization – Dynamic Time Warping, Multiple Time – Alignment Paths. (10)
Speech Modeling: Hidden Markov Models: Markov Processes, HMMs – Evaluation, Optimal State Sequence – Viterbi Search, Baum-Welch Parameter Re-estimation, Implementation issues. (7)

Speech Recognition: Large Vocabulary Continuous Speech Recognition: Architecture of a large vocabulary continuous speech recognition system – acoustics and language models – ngrams, context dependent sub-word units; Applications and present status. (7)

Speech Synthesis: Text-to-Speech Synthesis: Concatenative and waveform synthesis methods, subword units for TTS, intelligibility and naturalness – role of prosody, Applications and present status. (8)</td></tr>
<tr><td>Text Books, and/or reference material</td><td colspan="7">Text Books:

1. Lawrence Rabinerand Biing-Hwang Juang, “Fundamentals of Speech Recognition”, Pearson Education, 2003.
2. Daniel Jurafsky and James H Martin, “Speech and Language Processing – An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition”, Pearson Education.

Reference Book:
1. 1.Steven W. Smith, “The Scientist and Engineer’s Guide to Digital Signal Processing”, California Technical Publishing.</td></tr>
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<tr><td>Lecture (L)</td><td>Tutorial (T)</td><td>Practical (P)</td><td>Total Hours</td></tr>
<tr><td>CS 9037</td><td>Soft Computing and its application</td><td>PEL</td><td>3</td><td>0</td><td>0</td><td>3</td><td>3</td></tr>
<tr><td colspan="2">Pre-requisites</td><td colspan="6">Course Assessment methods (Continuous (CT) and end assessment (EA))</td></tr>
<tr><td colspan="2">Discrete Mathematics, Probability and Statistics, Optimization</td><td colspan="6">CT+EA</td></tr>
<tr><td>Course Outcomes</td><td colspan="7">CO: Conceptualize and parameterize various problems to be solved through basic soft computing techniques.
CO: Apply fuzzy logic and reasoning to handle uncertainty to solve various engineering problems.
CO: Analyze various neural network architectures and learning rules
CO: Apply genetic algorithms to combinatorial optimization problems.
CO: Identify, select and implement a suitable soft computing technique to solve the real life problem
CO: Use various tools to solve soft computing problems.</td></tr>
<tr><td>Topics Covered</td><td colspan="7">Introduction to Soft Computing: Characteristics of soft computing, soft computing vs. hard computing, soft computing constituents, hybrid computing, some applications of soft computing techniques. 3L
Fuzzy Logic: Crisp Sets vs. fuzzy sets, membership functions, Characteristics of fuzzy sets, Operations on fuzzy sets, Fuzzy Variable, Fuzzy Extension principles, Fuzzy and Crisp relations, Operations on Fuzzy Relations, Composition and Decomposition of Fuzzy Relations. Fuzzy Measures and Fuzzy Arithmetic, Fuzzification and Defuzzification, Fuzzy System, Fuzzy Inference /Approximate reasoning, fuzzy decision making.Applications: Pattern Recognition, Image Processing and Controller. 12L
Neural Networks: Introduction to Neural Networks, Biological Neural Networks, McCulloch Pitt model, Neuron and its model, Activation functions, Learning rules, Supervised Learning: Single Layer and Multi-layer perceptron, Delta learning rule, Back Propagation algorithm, Unsupervised Learning: Hebbian Learning, Competitive learning, Self-organizing Maps. 12L
Evolutionary Computing and Genetic Algorithm:Optimization and Some Traditional Methods.Evolutionary Computing, Basic concepts and working principle of simple GA (SGA), Genetic Operators: Selection, Crossover and Mutation, Algorithm and flow chart of SGA, Encoding & Decoding, Population Initialization, Objective/fitness Function, Applications: TSP. Multi-objective Genetic Algorithm (MOGA): Multi-objective optimization problems (MOOPs), Conflicting objectives, Non-Pareto and Pareto-based approaches to solve multi-objective optimization problems, Objective space and variable space, Domination, Pareto front, Pareto Set, NSGA-II: Non-domination Sorting, Crowding distance operator. 12L
Hybrid Systems: Integration of neural networks, fuzzy logic and genetic algorithms. 3L
Suggested Simulation/Experiments using Matlab/Python Lib: Study of neural network toolbox and fuzzy logic toolbox, Simple implementation of Artificial Neural Network, genetic Algorithm and Fuzzy Logic.</td></tr>
<tr><td>Text Books, and/or reference material</td><td colspan="7">Text Books:
1. S. Rajsekharan and VijayalakshmiPai, “Neural Networks, Fuzzy Logic and Genetic Algorithm: Synthesis and Applications”, Prentice Hall of India.
2. S.N. Sivanandam& S.N. Deepa, Principles of Soft Computing, Wiley</td></tr>
</table>

Publications, 2nd Edition, 2011.
3. Timothy J. Ross, "Fuzzy Logic with Engineering Applications".
4. K. Deb, Multi-objective Optimization using Evolutionary Algorithms, Wiley India.

Reference Books:
1. George J Klir, Bo Yuan, Fuzzy sets & Fuzzy Logic, Theory & Applications, PHI Publication, 1st Edition, 2009.
2. Neuro-Fuzzy Systems, Chin Teng Lin, C. S. George Lee, PHI.
3. Fuzzy Logic: A Pratical approach, F. Martin, Mc neill, and Ellen Thro, AP Professional, 2000.
4. An Introduction to Genetic Algorithms, Melanie Mitchell, MIT Press, 2000.
5. Neuro-Fuzzy and soft Computing, J.-S. R. Jang, C.-T. Sun, and E. Mizutani, PHI Learning, 2009.
6. Neural Networks and Learning Machines, (3rd Edn.), Simon Haykin, PHI.
7. Fuzzy Logic with Engineering Applications (3rd Edn.), Timothy J. Ross, Willey, 2010
8. Foundations of Neural Networks, Fuzzy Systems, and Knowldge Engineering, Nikola K. Kasabov, MIT Press, 1998.,

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<tr><td>Lecture (L)</td><td>Tutorial (T)</td><td>Practical (P)</td><td>Total Hours</td></tr>
<tr><td>CS 9041</td><td>Introduction to Cognitive Computing</td><td>PEL</td><td>3(42)</td><td>0</td><td>0</td><td>3(42)</td><td>3</td></tr>
<tr><td colspan="2">Pre-requisites</td><td colspan="6">Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))</td></tr>
<tr><td colspan="2">Basic Concepts of AI and Information Processing.</td><td colspan="6">CE+EA</td></tr>
<tr><td>Course Outcomes</td><td colspan="7">• CO1: The philosophical approach of working principle brain and mind;
• CO2: Cognitive approach towards Vision and Attention.
• CO3: Cognitive approach towards Memory, Language Processing.
• CO4: Cognitive Architecture and Basics of Neuroscience.</td></tr>
<tr><td>Topics Covered</td><td colspan="7">• The Cognitive Revolution, Part 1 (2)
• The Cognitive Revolution, Part 2 (Philosophical issues, neuropsychological perspective) (2)
• Working Principle of the Brain (2)
• Memory- Memory models: Episodic memory, Sensory memory, Short term memory, Long term memory, Explicit & Episodic Memory, Implicit Memory, Memory Accuracy, Nonverbal Memory, Semantic Memory knowledge) & Concepts (8)
• Attention and Perception, Part 1 (role of brain) (Review of different approaches) (5)
• Attention and Perception, Part 2 (Automaticity; Attention odds & ends(5)
• Cognitive approach to vision and pattern recognition: Template matching theory, Feature detection theory, Computational theory of vision, Feature integration theory (4)
• Cognition architecture of reasoning: ACT* model, Spread of activation</td></tr>
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	theory, General problem solver model, SOAR model (3) • Problem Solving (2) • Cognitive Load and its measurement (2) • Language and cognition: language formation and the brain, Word recognition, Surface level structures, Word and sentence production, Cognitive linguistic issues (3) • Introduction to Neuroscience - Looking into the Brain (4)
Text Books, and/or reference material	Text Books: 1. Cognitive Science-An Introduction to the Study of Mind, Jay Friedenberg, Gordon Silverman, SAGE 2. Cognition, Brain and Consciousness- Introduction to Cognitive Neuroscience, Bernard J. Baars, Nicole M Gage, Elsevier 3. The MIT Encyclopedia of the Cognitive Sciences edited by Robert A. Wilson and Frank C. Keil

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9018	Advanced Database Management Systems	PEL	3	0	0	3	3

<u>Pre-Requisite</u>: Database Management Systems	Course Assessment methods (Continuous (CT) and end assessment (EA))
	CT+EA
Course Outcomes	• CO1: To understand the basic concepts and terminology related to DBMS and Relational Database Design • CO2: To the design and implement Distributed Databases. • CO3:To understand advanced DBMS techniques to construct tables and write effective queries, forms, and reports • CO4: To understand the design and implementation of Data Warehousing.
Topics Covered	**Introduction:** Comparison between different databases: Significance of Databases, Database System Applications, Advantages and Disadvantages of different Database Management systems, Comparison between DBMS, RDBMS, Distributed and Centralized DB, Introduction of various types of index structures: Primary, Secondary, Multilevel, Dynamic multilevel (B-tree and B+- tree). (3) **Normalization:** Functional Dependency, Anomalies in a Database, The normalization process: Conversion to first normal form, Conversion to second normal form, Conversion to third normal form, The boyce-code normal form (BCNF), Fourth Normal form and fifth normal form, normalization and database design, Denormalization, Loss-less join decomposition, Dependency preservation. (4) **Transaction processing:** Introduction of transaction processing, advantages and disadvantages of transaction process system, online transaction processing system, serializability and recoverability, view serializability, Transaction management in multi-database system, long duration transaction, high-performance transaction system. (3) **Concurrency Control:** Serializability, Serializability by Locks, Locking Systems with Several, Lock Modes, Architecture for a Locking Scheduler Managing Hierarchies of Database Elements, Concurrency Control by Timestamps, Concurrency Control by

	Validation, Database recovery management. (4) **Query Optimization & Query Execution:** Algorithm for Executing Query Operations, External sorting, select operation, join operation, PROJECT and set operation, Aggregate operations, Outer join, Heuristics in Query Optimization, Converting Query Tree to Query Evaluation Plan, Efficient and extensible algorithms for multi-query optimization, Introduction to Physical-Query-Plan Operators, One-Pass Algorithms for Database, Operations, Nested-Loop Joins, Two-Pass Algorithms Based on Sorting, Two-Pass, Algorithms Based on Hashing, Index-Based Algorithms, Buffer Management, Parallel Algorithms for Relational Operations, Using Heuristics in Query Optimization. (6) **Distributed Database (DDB):** Introduction of DDB, DDBMS architectures, Homogeneous and Heterogeneous databases, Distributed data storage, Advantages of Data Distribution, Disadvantages of Data Distribution Distributed transactions, Commit protocols, Availability, Concurrency control & recovery in distributed databases, Directory systems, Data Replication, Data Fragmentation. Distributed database transparency features, distribution transparency. (5) **Object Oriented DBMS(OODBMS):** Overview of object: oriented paradigm, OODBMS architectural approaches, Object identity, procedures and encapsulation, Object oriented data model: relationship, identifiers, Basic OODBMS terminology, Inheritance , Basic interface and class structure, Type hierarchies and inheritance, Type extents and persistent programming languages, OODBMS storage issues. (5) **XML Query processing:** XML query languages: XML-QL, Lorel, Quilt, XQL, XQuery, and Approaches for XML query processing, Query processing on relational structure and storage schema, XML database management system. (3) **Data Warehousing:** Overview of DW, Multidimensional Data Model, Dimension Modelling, OLAP Operations, Warehouse Schema (Star Schema, Snowflake Schema), Data Warehousing Architecture (3) **Big Data:** Motivation, Big data storage systems, MapReduce paradigm, streaming data, Graph database (3) **Advanced database applications:** Multimedia database, Geographical Information System (GIS) (3)
Text Books, and/or reference material	**Text Books:** 1. C. J Date, Pearson Education, “An Introduction to Data Base Systems”. 2. Abraham Silberschatz, Henry F. Korth and S. Sudarshan, McGraw-Hill,“Database System Concepts”. 3. Stefano Ceri and Giuseppe Pelagatti, McGraw-Hill International Editions.“Distributed Databases Principles & Systems”. 4. Ramez Elmasri and Shamkant B. Navathe, Addison-Wesley, “Fundamentals of Database Systems”

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9045	Deep Learning	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					

Linear algebra, Calculus, Probability and statistics, Machine Learning	CE+EA
Course Outcomes	• CO1: To understand the mathematical, statistical and computational challenges of building stable representations for high-dimensional data, such as images, text and data. • CO2: To obtain a concept of deep learning and its advantages. • CO3: To understand deep network models, optimization for training of deep models. • CO4: To achieve the knowledge on some popular deep learning models. • CO5: To explore the research domain of deep learning.
Topics Covered	**Machine Learning Basics**: Extracting meaning from data, expert system, learning algorithms, overfitting and underfitting, regularization, hyperparameters and validation sets, estimator, bias and variance, ML estimation, Bayesian statistics, supervised learning, unsupervised learning, Stochastic Gradient Descent, building a machine learning algorithm, challenges motivating Deep Learning. (8) **Fundamentals of feedforward networks:** Single-layer and multilayer feedforward networks, Neural Network Graphs, activation functions, deep feedforward networks, hidden units, Learning XOR, gradient-based learning, Back-propagation algorithm and other differentiation algorithms. (4) **Regularization for deep learning** Parameter Norm Penalties, Norm Penalties as Constrained Optimization, Regularization and Under-Constrained Problems, Dataset Augmentation, Early Stopping, Sparse Representations, Dropout. (5) **Optimization for Training Deep Models**: How Learning Differs from Pure Optimization, Challenges in Neural Network Optimization, Basic Algorithms, Parameter Initialization Strategies, Algorithms with Adaptive Learning Rates, Approximate Second-Order Methods, Batch Normalization. (5) **Convolutional Networks:** The Convolution Operation, Pooling, Variants of the Basic Convolution Function, Structured Outputs, Structured outputs and datatypes. (4) **Sequence Modelling, Recurrent Neural Networks (RNN):** Unfolding Computational Graphs, RNNs, Bidirectional RNNs, LSTM. (5) **Autoencoders:** Undercomplete Autoencoders, Regularized Autoencoders, Stochastic Encoders and Decoders, Denoising Autoencoders, Contractive Autoencoders. (5) **Some Popular Deep Networks and Applications:** Generative Adversarial Networks, VGG net, ResNet, Inception Net, Transformer, Applications of deep learning. (6)
Text Books, and/or reference material	Text Books: 1. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, The MIT Press, 2017. 2. Charu C. Aggarwal, Neural Networks and Deep Learning, Springer, 2018. Reference Books: 3. Deep Learning, From Basics to Practice, Vol 1 and Vol 2, A. Glassner, Published by The Imaginary Institute, Seattle, WA, 2018 4. F. Chollet, Deep Learning with Python, Manning Publications Co., 2018. 5. N. Buduma, Fundamentals of deep learning: Designing Next-Generation Machine Intelligence Algorithms, O'REILLY, 2017

Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9105	Bioinformatics	PEL	3	0	0	3	3

Pre-requisites Introduction to Computing and data structures, Linear Algebra, Fundamentals of Probability and Statistics	Course Assessment methods (Continuous (CT) and End assessment (EA))
Course Out-comes	• CO1: To develop a basic knowledge about bioinformatics and its in-depth applications for solving several biological problems • CO2: To provide an enhanced understanding of computational techniques and resources available in the field of bioinformatics. • CO3: To develop algorithmic/statistical research approach in the field of computational biology and bioinformatics • CO4: To build up the knowledge for the formulation of computational problems to address intriguing biological questions. • CO5: To apply knowledge of bioinformatics in a practical project.
Topics Covered	1) Molecular Biology Introduction: Fundamental Concepts in Biology, including DNA, RNA, and Proteins, Genetic Inheritance Principles, Basics of Molecular Biology, Processes like DNA Replication, Transcription, and Translation, Central Dogma in Molecular Biology (6) 2) Introduction to Bioinformatics: Defining Bioinformatics and Its Significance in Contemporary Science, Exploring Tools and Biological Databases, Techniques for Accessing and Querying Databases. (5) 3) Sequence Analysis: Exploring DNA Sequencing, Different Sequence Formats like FASTA and GenBank, Aligning Sequences, Protein Sequencing and Structural Analysis, Visualization and prediction of Protein Structures.(8) 4) Computational Methods: Asymptotic notation, recursive techniques, divide-and-conquer strategies, algorithms for graphs, dynamic programming, and greedy algorithms. (5) 5) Math, Probability and Statistics: Differential Equations, Linear/Non-linear equations in solving optimization problem, Biostatistics (mean, median, mode, correlation, regression, etc), Graphical analysis (box plot, histogram, pie chart, etc), t-distribution, Chi-squared distribution, F-distribution, Joint Probability Distributions, Maximum Likelihood, Hypothesis Testing. (7) 6) Machine Learning for Biology: Data Preprocessing, Dimensionality Reduction, Scaling, Feature Selection, Regression, Clustering, Neural Network, Data visualization techniques. (8) 7) Practical Bioinformatics Applications (3)
Text Books, and/or reference material	**References:** 1. An Introduction to Bioinformatics Algorithms, Neil C. Jones, Pavel Pevzner, MIT Press. 2. Bioinformatics: the Machine Learning Approach, Pierre Baldi, Soren Brunak MIT Press. 3. Genetic Algorithms in Search, Optimization and Machine Learning, David E. Goldberg.

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Course Code	Title of the course	Program Core	Total Number of contact hours	Credit

		(PCR) / Electives (PEL)	Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9106	Computer Vision	PEL	3	0	0	3	3

Pre-requisites	Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))
Linear algebra, Calculus, Vector and Vector Calculus, Probability and statistics	CE+EA

Course Outcomes	• CO1: To understand and master basic knowledge, theories and methods in computer vision. • CO2: To identify, formulate and solve problems in computer vision. • CO3: To analyse, evaluate and examine existing practical computer vision systems. • CO4: To Design and develop practical and innovative computer vision applications.
Topics Covered	**Introduction to Computer Vision**: Brief introduction to Computer Vision, Applications of Computer Vision. (2) **Image formation and representation:** Image Digitization, Pixel Relationships, Geometrical Transformations, Camera Model and Imaging Geometry. (7) **Image Interpolation and Resampling:** Nearest Neighbour, Bilinear, Bicubic, B-Spline Interpolations. (2) **Image Processing:** Point operations, Image Enhancement, Linear filtering, Fourier Transforms, Pyramids, and wavelets. (7) **Image Alignment and Stitching**: Alignment using the Least Squares, Iterative Algorithms, and Global Stitching. (3) **Recognition:** Image Classification, Object Detection, Video Understanding, Vision and Language. (4) **Feature Description and Detection:** Points and patches, Edges and contours, Contour tracking, Lines and vanishing points, Segmentation. (5) **Motion Estimation:** Computing Motion Vectors, Computing the path of moving points, Detecting Significant Change in Video. (3) **3D Imaging:** Perceiving 3D from 2D images, Stereo Imaging, Camera model for 3D Imaging, 3D Object Reconstruction. (5) **Deep Learning and Computer Vision**: Deep Neural Networks (DNN), Convolutional Neural Networks, Other Complex Models, DNN in Computer Vision. (4)
Text Books, and/or reference material	Text Book: 1. Richard Szelisk, Computer Vision Algorithms and Applications, 2^{nd} Ed., Springer, 2022 2. Rafael C. Gonzalez, and Richard E. Woods, Digital Image Processing, 4^{th} Ed. Pearson Education Limited, 2018. Reference Books: 1. D. H. Ballard, and C. M. Brown, Computer Vision, Prentice Hall Inc., 1982. 2. Bernd Jahne, and Horst Houbecker, Computer Vision and Applications, Academic Press, 2000.

<table>
<tr><td colspan="9">Department of Computer Science and Engineering</td></tr>
<tr><td rowspan="2">Course Code</td><td rowspan="2">Title of the course</td><td rowspan="2">Program Core (PCR) / Electives (PEL)</td><td colspan="4">Total Number of contact hours</td><td rowspan="2">Credit</td></tr>
<tr><td>Lecture (L)</td><td>Tutorial (T)</td><td>Practical (P)</td><td>Total Hours</td></tr>
<tr><td>CS 9035</td><td>Time Series Analysis</td><td>PEL</td><td>3</td><td>0</td><td>0</td><td>3</td><td>3</td></tr>
<tr><td colspan="3">Pre-requisites</td><td colspan="5">Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))</td></tr>
<tr><td colspan="3">AI, ML DBMS</td><td colspan="5">CE+EA(CA: 15%, MT: 25%, ET:60%)</td></tr>
<tr><td>Course Outcomes</td><td colspan="7">• CO1: To make the students understand basic time series components and method to compute them.
• CO2: Estimate time series data through software
• CO3: Develop forecasts using SARIMA and Exponential Smoothing
• CO4: Introduce the concepts of spatiotemporal data analysis</td></tr>
<tr><td>Topics Covered</td><td colspan="7">Introduction to Time Series Analysis: Introduction to time series data, Collection of temporal data, Introduction to basis statistics, Analyzing time series via plot (4)

Regression Analysis: OLS estimation, Test for significance of Regression, Prediction of new observation, Model Accuracy, Residual Plot, Regression model for Time series data (6)

Exponential Smoothing: Simple Exponential Smoothing, Double Exponential Smoothing, Higher order Exponential Smoothing, Forecasting (4)

ARMA Process: Stationarity, White Noise, Backshift Operator, Invertibility, Duality, MA(q) Process, AR(q) Process, Yule Walker Estimation, Partial Autocorrelation Function (PACF), Autoregressive Moving Average Process (8)

ARIMA and Seasonal ARIMA: AIC, Non Stationarity, Integrated ARIMA, Seasonal ARIMA, Parsimony principal (8)

Time Series Analysis using Machine Learning: Limitation of ARIMA, kNN, Random Forest (4)

Time Series Analysis using Deep Learning: RNN, LSTM (5)

Introduction to Geostatistics: Concepts of Spatial data, Concept of Spatial and temporal Data, Collection of Spatiotemporal data, Importance of Geostatistics (3)</td></tr>
<tr><td>Text Books, and/or reference material</td><td colspan="7">Text Books:
1. Time Series Analysis and its Application with R Example by Robert H. Shumway, David S. Stoffer
2. Introduction to Time Series Analysis and Forecasting by Douglas C. Montgomery, Cheryl L. Jennings,Murat Kulahci</td></tr>
</table>

<table>
<tr><td colspan="8">Department of Computer Science and Engineering</td></tr>
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<tr><td>Lecture (L)</td><td>Tutorial (T)</td><td>Practical (P)</td><td>Total Hours</td></tr>
<tr><td>CS 9107</td><td>Basics of IoT & Its Applications/ IoT and</td><td>PEL</td><td>3</td><td>0</td><td>0</td><td>3</td><td>3</td></tr>
</table>

	Data Analytics						

Pre-requisites	Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))
Data Structure, Language like Python & C, Basics of Machine Learning	CT+EA [CA: 15%, MT: 25%, ET: 60%]
Course Outcomes	• CO 1: To understand and master basic knowledge, theories and methods in Internet of Things • CO2: To identify, formulate and solve problems in Internet of Things. • CO3: To analyse, evaluate and examine existing case studies of successful IoT based systems • CO 4: To develop practical skills in designing and implementing IoT based solutions like Environment Monitoring, Assistive living, Activity Monitoring, Transportation System
Topics Covered	**Introduction to IoT and Sensing:** Introduction to IoT, Sensing, Edge computing, Data processing, Learning, Basic principles of Physics. Design of a Sensor (like Touch Sensor) using resistance, Capacitor & Inductor, Different type of sensors, working principle of some sensors like (a) ultrasonic sensor (b) humidity and Temperature (c)IMU (Accelerometer, Gyroscope, Compass) (d)Sound Sensor & Camera (e) Pollutant Sensors (f) Flex Sensor (g) sEMG Sensor (h) Touch sensor. [8 Hours] **Physical Layer Protocols:** Inter-Integrated Circuit, or I2C Protocol, I2S (I2C Sound) Protocol, Universal Asynchronous Receiver/Transmitter (UART), Serial peripheral interface (SPI), CAN Protocol. [3 Hours] **Play with Sensors & Basic Programming in Microcontroller/TinyML Boards :** Open source hardware, Introduction to microcontrollers and microcomputers, Getting to know the domain-specific terminology, Architecture and specification of multiple microcontroller development boards. Play with Sensors using micro-python /C, Local data processing using Raspberry Pi Pico W, ESP32 S3, Raspberry Pi Zero 2 W, Milk V, Play with different Network Modules (Bluetooth, WiFi). [6 Hours] **Building a device Driver:** Introduction to sensor datasheets, building a driver using the information of datasheets of Basic sensors such as temperature sensor and dust particle sensor. [3 Hours] **Communication in IoT (10 Hours):** Concept of TCP/IP protocol Stack, 802.11 Protocol (WiFi Network), Bluetooth Network (802.15), Bluetooth Communication Protocol, Bluetooth Low Energy, LoRa Network, Delay Tolerant Network, MQTT Protocol, HTTP Protocol, COAP Protocol, Various tools and techniques for developing a companion IoT application, Socket Programming, and Wireshark Tool. [6 Hours] **Basic ML Algorithms & Exploration of TinyML Frameworks (6 Hours):** Basic Data Science Algorithms (Regression, Decision Tree, Random Forest), Basic Deep Neural Networks: Neural Network, Convolution Neural Network, Model development using Tensorflow, Quantization Aware Training, Introduction to Tensorflow Lite Micro, Deploying models onto microcontrollers using Tensorflow Lite Micro. [8 Hours] **Case Study:** (a) (activity Identification) Human Activity using Ultrasonic Sensors/Thermal Sensors, (b)(Environment Monitoring) Pollution Monitoring and Forecasting in Indoor and Outdoor, (c)(Road Transportation System) Important PoIs using GPS trails, Road Speed Identification, Street Light Monitoring (d) (Challenged

	Networks) offline Crisis Mapper Design, (e) (Disaster Management) offline Crisis Mapper for Post Disaster Management (f) (Telemedicine) IoT enabled rural telemedicine Framework, (g) (Noise Classification) System Design for Edged People using Indoor Sounds/Noise, (h) Implementation of Hand Gestures in TinyML board. (8 Hours)
Text Books, and/or reference material	Text Books: **1.** "Internet of Things: A Hands-On Approach Book " by Arshdeep Bahga & Vijay Madisetti (Universities Press) 2. Precision: Principles, Practices and Solutions for the Internet of Things", by Timothy Chou

Department of Computer Science and Engineering							
Course Code	Title of the Course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9109	**Reinforcement Learning**	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous (CT) and end assessment (EA))					
Basics of Algorithms and Probability		CT+EA [CA: 15%, MT: 25%, ET: 60%]					
Course Outcomes	• CO1: To be able to understand the principles of Reinforcement Learning. • CO2: To be able to apply the gathered knowledge to solve real life problems. • CO3: Can learn analyzing the behaviour of Reinforcement Learning. • CO4: To be able to recognize the state-of -the-art about Reinforcement Learning.						

Topics Covered	• Introduction: Examples and Motivations (1)
	• Multi-armed bandits (Data Efficient RL) (3)
	• Markov decision processes (3)
	• Dynamic Programming - Value and Policy Iteration Methods (3)
	• Model-Free Learning Approaches:
	  ○ Monte-Carlo Methods (2)
	  ○ Temporal Difference Learning (2)
	  ○ Q-learning, SARSA (3)
	  ○ Double Q-learning (2)
	• Eligibility Traces (2)
	• Value Function Approximation Methods -
	  ○ TD Learning with Linear Function Approximation (2)
	  ○ Deep Q-Network Algorithm (3)
	  ○ Policy Gradient Methods (2)
	  ○ Actor-Critic Algorithms. (3)
	• POMDPs. (2)
	• Multi-Agent RL: Cooperative vs. Competitive Settings, Mixed Setting, Games, MARL Algorithms. (3)
	• Recent development in Reinforcement learning (3)
	• Some case studies and implementations. (3)						

Text Books, and/or reference material	**Text Books:** 1. R. Sutton and A. Barto, Reinforcement Learning, MIT Press, 2'nd Ed., 2018 2. D.Bertsekas, Reinforcement Learning and Optimal Control, Athena Scientific, 2019 3. Csaba Szepesvari, Algorithms for Reinforcement Learning, Morgan and Claypool Publishers; 1st edition. 4. Maxim Lapan, Deep Reinforcement Learning Hands-On - Second Edition, Packt Publishing. 5. Sudharsan Ravichandiran, Hands-On Reinforcement Learning with Python, Packt Publishing. 6. Kaiqing Zhang, Zhuoran Yang, Tamer Başar; Multi-Agent Reinforcement Learning: A Selective Overview of Theories and Algorithms; ArXiv ePrint, 2021. **Reference Book/Lecture Notes:** 1. Balaraman Ravindran, Randomized Algorithms, IITM. 2. Shalabh Bhatnagar, Reinforcement Learning E1 277, IISc. Bangalore, August 2022. 3. Aritra Hazra, Reinforcement Learning, CS60077, IIT KGP, 2022. 4. Dr. Emma Brunskill, Reinforcement Learning, CS234, Stanford, USA, Spring 2024. 5. Dr. David Silver, Reinforcement Learning (Deepmind and UCL, UK).

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9108	**Recommender System**	PEL	3	0	0	3	3

Pre-requisites	Course Assessment methods (Continuous (CT) and end assessment (EA))
Basic concepts of vector, matrix and algebra	CT+EA [CA: 15%, MT: 25%, ET: 60%]

Course Outcomes	After successful completion of this course, students will be able to	Bloom's Level
	CO1: Familiarize with recommender systems and their applications	BL1, BL2
	CO2: Apply algorithms and methods to develop recommender system that are widely used in the internet industry.	BL3
	CO3: Analyze different methods, models, and associated parameter for designing a recommender system	BL4
	CO4: Design and evaluate an effective recommender system	BL5, BL6

Topics Covered	• **Introduction:** Association, Bayesian Ranking, Page Rank, Evaluating a Ranking, • Implicit and explicit ratings, Matrix operations, covariance matrices, Understanding ratings, Applications of recommendation systems, Recommender Systems: Past, Present and Future, Issues with recommender system. (5L) • **Collaborative recommendation:** User based nearest neighbor recommendation, • item based nearest neighbor recommendation, Ratings, Matrix factorization, Association Rule Mining, Probabilistic recommendation (6L) • **Content-based recommendation:** Content representation and similarity, Similarity based retrieval (3L) • **Knowledge-based recommendation:** Knowledge Representation and reasoning, • Interaction with constrained based recommenders, Interacting case-based recommenders (6L) • **Hybrid recommendation approaches:** Opportunities for hybridization, feature combination/ augmentation hybrids, parallelized hibridization design (6L) • **Evaluating recommender systems:** Introduction, General properties of evaluation research,Online Evaluation Techniques, Offline Evaluation Techniques, Evaluation designs: Accuracy, Coverage, confidence, novelty, diversity, scalability, serendipity, Evaluation on historical datasets, Offline evaluations. (6L) • **Advanced Topics in Recommender Systems:** Learning to Rank, PersonalizedRanking, Explainability in Machine Learning, Item-Based CF as Optimization Problem, Deep Learning Based Recommender System, Bias, fairness, bubbles, and ethics of recommender systems, Systems challenges such as scalability, data quality, and performanceCase studies of real-world implementations, Large- language models as part of recommender systems, Privacy and security. (10L)
Text Books, and/or reference material	**Text Books:** 1. Jannach D., Zanker M. and FelFering A., Recommender Systems: An Introduction, Cambridge University Press (2011), 1st ed. 2. Charu C. Aggarwal, Recommender Systems: The Textbook, Springer (2016), 1st ed. **Reference Book/Lecture Notes:** 1. Ricci F., Rokach L., Shapira D., Kantor B.P., Recommender Systems Handbook, Springer(2011), 1st ed. **2.** Manouselis N., Drachsler H., Verbert K., Duval E., Recommender Systems For Learning, Springer (2013), 1st ed

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9110	Ethics in Data Science	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous Assessment (CA), Mid-Term (MT), End Term (ET))					
Basic knowledge of programming and AI/ML		CA+ MT + ET **[**CA: 15%, MT: 25%, ET: 60%**]**					
Course Outcomes	• CO1: To understand professional and ethical responsibilities, including those defined in the ACM/IEEE Professional Code of Ethics.						

	• CO2: To ensure fairness, accountability, and transparency while working on machine learning, artificial intelligence and related fields. • CO3: To appreciate the threats to privacy posed by modern data aggregation and data processing techniques. • CO4: To design technologies incorporating ethical considerations from the specification provided.
Topics Covered	**Introduction:** What is Ethics? Ethics and Computer Science, Social consensus on unethical practices by computer professionals, Conventional issues, Emerging issues in the age of data driven (AI/ML based) decision making, History and Evolution of ethics with advances in computer science and engineering. (6L) **Ethics in Data collection and aggregation:** Basic mechanism of data driven (AI/ML based) decision making, Data aggregation and decision making, Data Ownership, Collection and collation of digital imprints of users, Data stealing and data broking, Informed consent, Data repurposing, Privacy, Anonymity, Data validity, Establishing data protection framework with legal backing, Concept of differential privacy, GPDR. (12L) **Algorithmic Fairness:** Discriminatory impact of imperfect decisions, Case study: Facial recognition software, Criminal justice using big data, recidivism models for sentencing guidelines, predictive policing, Trust in AI/ML based decision making, Algorithmic fairness, Notions of fairness, Parity based and preference based notions, Fairness and accuracy, Identifying and mitigating inherent bias in data and/or machine learning algorithms, Proper choice of representative sample, Making training data fair, Designing fairness aware classifiers, Algorithmic audit, Challenges, Audit based on user survey, Sock puppet audit, Audit based on scrapping/crawling. (12L) **AI Ethics:** Moral issues in autonomous and intelligent systems, Narrow (or Weak) AI and General (or Strong) AI, Weaponization of AI,Moral issues in autonomous robots, Robot ethics, Moral issues in self-driving cars, Moral Machine Quiz. (5L) **Personalization:** Personalized recommendation, search and newsfeed, Intellectual isolation associated with personalization, Objective search results, Personalized advertisement,Cross-domain tracking. (3L) **Code of Ethics:** Ethical standards by international professional societies, IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems, ACM Code of Ethics and Professional Conduct. (4L)
Text Books, and/or reference material	**Text Books:** 1. D J Patil, Hilary Mason, Mike Loukides, "Ethics and Data Science", O'Reilly Media, Inc.; 1st edition (July, 2018). 2. P. Singer, "Practical Ethics", Cambridge University Press, 3rd edition (February 2011) **Reference Books:** 1. Cathy O'Neil, "Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy", Crown; 1st edition (September 6, 2016). 2. John C. Havens, "Heartificial Intelligence: Embracing Our Humanity to Maximize Machines", TarcherPerigee; (February 2, 2016). 3. Wendell Wallach, Colin Allen, "Moral Machines: Teaching Robots Right from Wrong", Oxford University Press; 1st edition (June 3, 2010). 4. 4. Garry Kasparov, "Deep Thinking: Where Machine Intelligence Ends and Human Creativity Begins", PublicAffairs; 1st edition (May 2, 2017).

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Course Code	Title of the course	Program Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9111	Scalable Systems for Data Science	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					

Data Structures (e.g. Arrays, Queues, Trees,Hashmaps,Graphs) and **Algorithms** (e.g.Sorting, Searching,Graph-traversal,String algorithms, etc.)	CE+EA
Course Outcomes	• CO1: To understand Types of Big Data, Design goals of Big Data platforms, and where in the systems landscape these platforms fall. • CO2: To obtain the concept of Distributed programming models for Big Data, including Map Reduce, Stream processing and Graph processing. • CO3: To understand Scaling Data Science algorithms and analytics using Big Data platforms. • CO4: To achieve the knowledge on Runtime Systems for Big Data platforms and their optimizations on commodity clusters and Clouds • CO5: To explore the research domain of scalable system for data science.
Topics Covered	**Introduction to Big Data & Distributed Systems:** Intro to Big Data, Storage, compute, visualization, etc. platforms, Files vs. Overview of Relational Databases vs. NoSQL Databases: Contrast Big Data systems: HBase/Big Table, Cassandra/Key-Value Store, Graph DB overview, Understand the role of distributed systems for data-parallel processing. Clusters, Cloud computing, Edge computing. Understand distinction between weak and strong scaling. Distributed File Systems/HDFS/GFS, Cloud storage. (12) **Processing Large Volumes of Big Data:** Big Data Processing with Map Reduce and Spark, Spark Basics, RDD, transformations, action, Shuffle, Spark internals & Spark tuning. (8) **NoSQL Databases:** Consistency models and CAP theorem/BASE, Amazon Dynamo/Cassandra distributed key-value store, Spark DataFrames, Spark SQL, Catalyst optimizer, Overview of HBase/Big Table, Graph Databases, Overview of Data Warehousing, Data Lakes, ETL, Cloud NoSQL. (8) **Processing Fast Data & Linked Data**: Need for Fast Data Processing. Internet of Things (IoT) application domain, Difference between low-latency ingest, analytics and querying, Publish-subscribe systems and Apache Kafka, Streaming dataflows: Spark Streaming, Twitter Heron, Apache Flink, Distributed graph processing, Vertex Centric Programming, Pregel, Giraph algorithms. (8) **Machine Learning at Scale**: ML over Big Data, TensorFlow, Parameter server and Federated learning, Spark ML for ML pipelines. (6)
Text Books, and/or reference material	Text Books: 1. Select chapters from Data-Intensive Text Processing with MapReduce, Jimmy Lin and Chris Dyer, 1st Edition, Morgan & Claypool Publishers, 2010 2. Select chapters from Mining of Massive Datasets, Jure Leskovec, Anand Rajaraman and Jeff Ullman, 2nd Edition (v2.1), 2014. Reference Materials: 1. Toward Scalable Systems for Big Data Analytics: A Technology Tutorial. (IEEE publication).

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9112	Generative AI	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					
Machine Learning, Deep Learning, Probability and Statistics, Python Programming		CE+EA CE+EA(CA: 15%, MT: 25%, ET:60%)					

Course Outcomes	• CO1: Understand the theoretical foundations of Generative AI • CO2: Explore different types of generative models and their applications • CO3: Develop practical skills in implementing generative models • CO4: Analyze ethical implications and societal impacts of Generative AI • CO5: Conduct independent research in the field of Generative AI
Topics Covered	**Introduction to Generative AI**: History and evolution of Generative AI, Key concepts and applications, Probability distributions, Generative vs Discriminative models. (5L) **Fundamentals of Deep Learning:** Introduction to deep learning and neural networks, Training neural networks: Backpropagation, Optimization algorithms, Regularization techniques: Dropout, L1/L2 Regularization, Convolutional Neural Networks (CNNs) for generative tasks. (6L) **Variational Autoencoders (VAEs):** Introduction to Autoencoders, Understanding encoder, decoder and latent space. (3L) **Generative Adversarial Networks (GANs):** Introduction to GANs, Generator-Discriminator Architecture, Training process of GAN model, Advanced GAN architectures: DCGAN, WGAN, CGAN, etc. (5L) **Autoregressive Models:** Introduction to RNNs and their variants, Training techniques for sequence generation models, Sequence Generation with RNNs. (4L) **Transformer Models:** Introduction to transformer, Transformer Architecture, Application in Text Generation, BERT, Large Language Models (LLM). (5L) **Evaluation of Generative Models:** Evaluation Metrics, Objective Evaluation, Subjective Evaluation. (2L) **Applications of Generative Models:** Computer vision, Natural Language Processing, Speech Synthesis. (7L) **Emerging Topics in Generative AI:** PixelCNN, Glow, RealNVP, Adversarial examples and defences; Domain adaptation and transfer learning in generative AI; Ethical considerations and challenges in generative AI. (5L)
Text Books, and/or reference material	Text Books: 1. Ian Goodfellow, Yoshua Bengio, Aaron Courville, "Deep Learning". 2. Ian Goodfellow et al., "Generative Adversarial Networks" Reference Materials: 1. Papers and articles from top conferences (NeurIPS, ICML, CVPR, etc.) 2. Online tutorials and code repositories (e.g., TensorFlow, PyTorch)

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9113	Explainable AI (XAI)	PEL	3	0	0	3	3
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					

AI, ML DL, Linear Algebra, Probability and Statistics, Python Programming	CE+EA(CA: 15%, MT: 25%, ET:60%)
Course Outcomes	• CO1: Understand the importance of XAI. • CO2: Account for different approaches/techniques of well-known XAI methods. • CO3: Familiarity with different metrics of evaluating XAI methods. • CO4: To understand ethical considerations and the impact of explainability. • CO5: Case studies and future directions of XAI.
Topics Covered	**Introduction to Explainable AI**: Overview of AI, MLand DL, Importance of Explainability in AI, Definition and Scope of Explainable AI, Historical Context and Evolution. (7L) **Pre-Model Interpretability and Explainability:** Basic concepts and differences between interpretability and explainability, Exploratory Data Analysis, Feature engineering, Evaluation of interpretability, Properties and Human-friendly Explanations. (6L) **Visualization and Interpretability of Traditional Models:** Model validation, evaluation, selection and visualization; Classification, regression and clustering models visualization; Interpretable models: regression (linear and logistic), linear and adaptive models, decision trees, rule-based models, and other interpretable models. (8L) **Post-Hoc Interpretability and Explainability:** Visual explanation: partial dependence plots(PDP), Individual Conditional Expectation (ICE), Accumulated Local Effects (ALE) Plot; Feature importance: feature interaction and importance, Shapley Additive explanations (SHAP), global surrogate and Local Interpretable Model-agnostic Explanations (LIME). (6L) **Explainability in Deep Learning:** Challenges of explainability in deep learning, Various intrinsic, perturbation and gradient based methods for neural networks. (4L) **Ethical Considerations of XAI:** Fairness, accountability, and transparency in XAI, Legal implications of AI decisions, Current regulations impacting AI explainability. (4L) **Applications of XAI:** Real-world applications of XAI in healthcare, education, finance, law, etc. Case studies analysis. (5L) **Challenges and Future Directions of XAI:** Emerging trends and research directions, Challenges and opportunities in XAI research. (2L)
Text Books, and/or reference material	**Text Books:** 3. Uday Kamath and John Liu: Explainable Artificial Intelligence: An Introduction to Interpretable Machine Learning, Springer. 4. Christoph Molnar: Interpretable Machine Learning, LeanPUB. 5. Serg Masís, Interpretable Machine Learning with Python, Packt. **Reference Books:** 1. Michael Munn and David Pitman: Explainable AI for Practitioners, O’Reilly Media. 2. A. Anitha Kamaraj and Debi Prasanna Acharjya: Explainable Artificial Intelligence in Healthcare Systems, NOVA Science Publishers. 3. Online Study Materials and Relevant Research Articles will be provided in due time.

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9031	Big Data	PEL	3	0	0	3	3

	Analytics						
Pre-requisites		Course Assessment methods (Continuous evaluation (CE) and end assessment (EA))					
AI, ML DBMS		CE+EA(CA: 15%, MT: 25%, ET:60%)					
Course Outcomes	• CO1: To understand the financial value of big data analytics. • CO2:To explore tools and practices for working with big data. • CO3:To familiarize with different machine learning techniques that handles massive datasets. • CO4: To understand how big data analytics can leverage into a key component.						
Topics Covered	**Introduction to Big Data Analytics:** Motivation and significance, Big data analytics and use cases, Structured, unstructured and semi-structured data, Descriptive, diagnostic, predictive and prescriptive analytics (4) **Frequent itemsets and Association rules:** Market-basket model, Association rule mining, Apriori algorithm, FP-Growth method (4) **Large-Scale Machine Learning:** Support vector machines, Stochastic gradient descent, K-means clustering algorithm, Decision trees (6) **Analysis of massive graphs:** Link analysis: PageRank, Centrality measures: Degree, Closeness, Betweenness, etc., Community structures, Community detection techniques, Quality metrics: Modularity, Normalized mutual information (6) **Recommendation System:** Introduction, Collaborative and content-based filtering, Similarity measures, Prediction approaches, Precision, recall and F-measure (6) **Technologies for Handling Big Data:** Introduction to Hadoop, Functioning of Hadoop, Hadoop ecosystem (HDFS, Map-Reduce, etc.), Word count program using Map-Reduce (8) **Big Data Analytics - Case Studies:** Big data analytics in e-commerce, Big data analytics in agriculture, Text and social media big data analytics (8)						
Text Books, and/or reference material	**Text Books:** 6. Mining of Massive Datasets, Cambridge University Press, 3rd Edition, 2020. 7. Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, EMC Education Services (Editor), Wiley, 2015 **Reference Books:** 4. Big Data Analytics: From Strategic Planning to Enterprise Integration with Tools, Techniques, NoSQL, and Graph, David Loshin, Morgan Kaufmann, 2013 5. Big Data Analytics: A Practical Guide for Managers, Kim H. Pries, Robert Dunnigan, CRC Press, 2015						

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Course Code	Title of the course	Program Core (PCR) / Electives (PEL)	Total Number of contact hours				Credit
			Lecture (L)	Tutorial (T)	Practical (P)	Total Hours	
CS 9114	**Large Vision Models**	PEL	3		0	3	3
Pre-requisites		Course Assessment methods (Continuous (CT) and end assessment (EA))					
Design and analysis of algorithms, programming,		CT+EA **[CA: 15%, MT: 25%, ET: 60%]**					

probability and statistics, linear algebra, foundations of machine learning	
Course Outcomes	• CO 1: Understanding the fundamental aspects of neural networks and deep learning for large vision models • CO 2: Understanding different sub-systems and phases of large vision systems • CO 3: Understanding key operations of image processing and computer vision • CO 4: Applications of large vision models for image processing and computer vision
Topics to be Covered (42L)	1. Introduction: Introduction to large vision models, different components of a large vision model, design issues of large vision models, introduction to neural networks, multilayer perceptron, types of signals in MLP, forward and backward propagation, classification of learning problems, optimization and penalty for machine and deep learning, batch normalization, dropout, activation functions, fundamentals of computer vision and image processing techniques and operations. [7L] 2. Deep Convolutional and Recurrent Neural Network Models: Foundation of deep learning models, convolution operation, image filtering and filter dynamics, generic architecture of convolutional neural networks (CNN), LeNeT-5 model, VGG-19 model, InceptionNet model, ResNet model, MobileNet, RNN, BPTT, LSTM, Bi-LSTM, and GRU. [7L] 3. Vision Transformer and Attention: Introduction to vision transformer, introduction to attention mechanism, global versus local attention, attention models, uniform scale ViTs, multi-scale ViT, hybrid ViTs with convolutions, self-supervised ViTs and BERT. [6L] 4. Graph Neural Networks: Introduction to directed and undirected graphs, Graph Convolutional Networks (GCNs), GraphSAGE, Graph Attention Networks (GATs), Chebyshev Spectral Graph Convolution and Graph Isomorphism Networks (GINs). [4L] 5. Autoencoders and Generative Models: Introduction to autoencoders, types of autoencoders, undercomplete autoencoder, sparse autoencoder, contractive autoencoder, denoising autoencoder, convolutional autoencoder, variational autoencoder, generative adversarial networks and diffusion models.[5L] 6. Large Vision Models for Image Processing: Image denoising, image classification, object detection, image segmentation, image generation, image captioning, super resolution processing, and style transfer. [8L] 7. Large Vision Models for Computer Vision: 3D image reconstruction, 2D to 3D image reconstruction, pose estimation, motion detection, data efficient image transformer and neural architecture search. [5L]
Text Books, and/or reference material	**Text Books:** 1. Deep Learning Adaptive Computation and Machine Learning Series by Goodfellow, Bengio and Courville, MIT Press. 2. Understanding Deep Learning by Simon J. D. Prince, MIT Press. 3. Transformers for Natural Language Processing and Computer Vision by Denis Rothman, Packt Publications. 4. Digital Image Processing by Gonzalez and Woods, Pearson. 5. Neural Networks and Deep Learning by Michael Nielsen. 6. Deep Learning: A Practitioner's Approach, by Adam Gibson and Josh Patterson, Shroff/O'Reilly. 7. Deep Learning: Methods and Applications By Li Deng and Dong Yu, Now Publishers.