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(Accredited by NAAC)

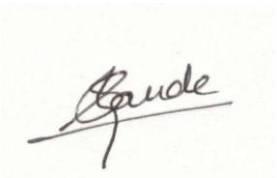
GU/Acad –PG/BoS -NEP/2023/184/2 Date:04.07.2023

CIRCULAR

The University has notified Ordinance OA-35 governing the **Master of Science in Artificial Intelligence** Programme offered at the Goa Business School, Goa University Campus for implementation from the Academic year 2023-2024 onwards.

The approved Semester I and II Syllabus of the **Master of Science in Artificial Intelligence** Programme is attached.

The Dean/ Vice-Deans of the Goa Business School are requested to take note of the above and bring the contents of the Circular to the notice of all concerned**.**



(Sanket Gaude)
Offg. Assistant Registrar – Academic-PG

To,

1. The Dean, Goa Business School, Goa University.
2. The Vice-Deans, Goa Business School, Goa University.

Copy to:

1. The Chairperson, Board of Studies in Computer Science and Technology (PG).
2. The Programme Director, M.Sc Artificial Intelligence, Goa University.
3. The Controller of Examinations, Goa University.
4. The Assistant Registrar, PG Examinations, Goa University.
5. Directorate of Internal Quality Assurance, Goa University for uploading the Syllabus on the University website.

Goa University

M.Sc in Artificial Intelligence to be effective from Academic Year 2023-24

M.Sc in Artificial Intelligence Programme Specific Outcomes:

The course is aimed at imparting the following core things -

1. Core programming skills and techniques, including designing and coding applications, and the important principles of code design and development.
2. Data science tools and techniques, including the principles of data science, data analysis, visualisation and interpretation, and the use of "big data".
3. Artificial intelligence tools and techniques, including problem-solving, knowledge representation, machine learning, computer vision, human-computer interactions and (mis) information diffusion.
4. Ethical computing and data science, exploring the ethical, legal, social and professional frameworks in which data scientists must operate, in business and society.
5. The application of AI and data science in research and industry

Pathway

Fundamentals (Mathematics and Problem Solving, Programming)➔ Core Courses (AI, Machine Learning, Deep Learning, etc.,)➔ Specialization (Natural Language Processing, Computer Vision)➔Research and Dissertation (Core Research – Language Models, or Application Oriented Research or Product Based Research (MLOps, DevOps, Design Thinking , Pragmatic AI)

As per the above pathway vision, the structure for programme has been designed as follows –

M.Sc. in Artificial Intelligence to be effective from Academic Year 2023-24		
SEMESTER I – Total 20 credits		
Discipline Specific Core(DSC) Courses		
Course Code	**Course Title**	**Credits**
CSI-500	Fundamentals of Artificial Intelligence	**2**
CSI-501	Fundamentals of Artificial Intelligence Lab	**2**
CSI-502	Algorithms and Data structures	**2**
CSI-503	Algorithms and Data structures Lab	**2**
CSI-504	Mathematical Foundations for Artificial Intelligence	**2**
CSI-505	Mathematical Foundations for Artificial Intelligence Lab	**2**
CSI-506	Data Science Fundamentals	**2**
CSI-507	Data Science Fundamentals Lab	**2**
	Total Credits for DSC	**16**
Discipline Specific Elective(DSE) Courses – any one to be opted		
Course Code	**Course Title**	**Credits**
CSI-521	Natural Language Processing	**4**
CSI-522	Computer Vision	**4**
CSI-523	Robotics	**4**
CSI-524	IoT Architecture and Protocols	**4**
	Total Credits for DSE	**4**
SEMESTER II – Total 20 credits		
Discipline Specific Core(DSC) Courses		
Course Code	**Course Title**	**Credits**
CSI-508	Deep Learning	**2**
CSI-509	Deep Learning Lab	**2**
CSI-510	Big Data Frameworks	**2**
CSI-511	Big Data Frameworks Lab	**2**
CSI-512	Reinforcement Learning	**2**
CSI-513	Reinforcement Learning Lab	**2**
CSI-514	Software Engineering for AI Enabled systems	**2**
CSI-515	Software Engineering for AI Enabled systems Lab	**2**
	Total Credits for DSC	**16**
Discipline Specific Elective(DSE) Courses – any one to be opted		
Course Code	**Course Title**	**Credits**
CSI-525	Machine Translation	**4**
CSI-526	Mathematics for Computer Vision and Robotics	**4**
CSI-527	Soft computing	**4**
CSI-528	Regression Analytics and Predictive Models	**4**
CSI-529	Essentials of Data Analytics	**4**
	Total Credits for DSE	**4**

SEMESTER III – Total 20 credits		
Research Specific Elective(RSE) Courses – any two to be opted…		
Course Code	**Course Title**	**Credits**
CSI-600	Speech Processing	**4**
CSI-601	Advanced Machine Translation	**4**
CSI-602	Simulation and Modelling	**4**
CSI-603	MLOps	**4**
CSI-604	Generative Deep Learning Models	**4**
CSI-605	Data Engineering	**4**
CSI-606	Sensors , Actuators and Signal Conditioning	**4**
CSI-607	Signal Processing	**4**
CSI-608	Image Processing	**4**
	Total Credits for RSE	**8**
Generic Elective(GE) Courses - total 12 credits to be opted		
Course Code	**Course Title**	**Credits**
CSI-621	Corporate Skills	**4**
CSI-622	Research Methodology	**4**
	To be opted from Courses from other Disciplines	**4**
	Total Credits for GE Courses	**12**
SEMESTER IV – Total 20 credits		
One Research Specific Elective(RSE) Course to be opted from the RSE list given below in consultation with the Mentor. It can be completed in Semester 3.		
RSE List		
Course Code	**Course Title**	**Credits**
CSI-609	Financial Machine Learning	**4**
CSI-610	AI for Atmospheric Science	**4**
CSI-611	Pragmatic AI	**4**
CSI-612	AI for Medical Specialization	**4**
CSI-613	Design thinking for AI	**4**
CSI-614	Recommender Systems	**4**
CSI-615	Text Mining and Sentiment Analysis	**4**
CSI-616	Digital Twin	
	Total Credits for RSE Courses	**4**
Dissertation Type		**Credits**
CSD-651	Research Project in Academic or Research Institutes	16
Total Credits for Dissertation		**16**

Semester I
Name of the Programme: M.Sc. in Artificial Intelligence
Course code: CSI-500
Title of course: Fundamentals of Artificial Intelligence
Number of credits: 2(2L+0T+0P)
Effective from AY: 2023-24

Prerequisites for the course	Programming back programming and probability and statistics and linear algebra	
Objectives	To develop a basic understanding of problem solving, knowledge representation, reasoning and learning methods of AI.	
Content	Introduction -Intelligent Agents, Problem-solving Solving Problems by Searching -Search in Complex Environments - Adversarial Search and Games- Constraint Satisfaction Problems	5 hours
	Knowledge, reasoning, and planning Knowledge Representation-First-Order Predicate Logic - Unification Forward and Backward Chaining - Resolution - Ontological Engineering	3 hours
	Categories and Objects - Events-Mental Events and Mental Objects - Reasoning Systems for Categories - Reasoning with Default Information	
	Uncertain knowledge and reasoning Quantifying Uncertainty - Probabilistic Reasoning - Probabilistic Reasoning over Time Probabilistic Programming -Making Simple Decisions - Making Complex Decisions –MultiAgent Decision Making	3 hours
	Machine Learning from Examples - Learning Probabilistic Models - Deep Learning - Reinforcement Learning - Communicating, Perceiving, and Acting	6 hours
	Natural Language Processing - Deep Learning for Natural Language Processing - Computer Vision - Robotics.	2 hours
	Artificial Intelligence applications Language Models - Information Retrieval - Information Extraction	
	Natural Language Processing - Machine Translation - Speech Recognition	
	Robotics-Hardware and Software for Robots - Planning and Perception	
	Explainable AI - Definitions and concepts such as black-box models, transparency, interpretable machine learning and explanations. - Decision-making and decision support, Human-Computer Interaction (HCI) and AI. - Explainable AI. - Methods for Explainable AI. - Applications and examples. - Trust and acceptance-Evaluation methods and metrics. - Ethical, legal and social issues of explainable AI.	7 hours
	Contemporary issues in AI- Philosophy, Ethics, and Safety of AI - The Future of AI	4 hours
Pedagogy	Tutorials / Hands-on-assignments / Self-study	
References/ Reading	1. A Classical Approach to Artificial Intelligence, M.C. Trivedi, Khanna Book Publishing, 2019. 2. Artificial Intelligence: A modern approach by Stuart Russel, Pearson Education, 2010. 3. Artificial Intelligence by Rich and Knight, The McGraw Hill, 2017. 4. Artificial Intelligence: A new synthesis by Nils and Nilson, Elsevier, 1997. 5. Artificial Intelligence by Luger, Pearson Education, 2002. 6. Artificial Intelligence by Padhy, Oxford Press, 2005.	

	7.https://www.edx.org/course/artificial-intelligence-ai 8.https://www.udemy.com/course/artificial-intelligence-az/
Course Outcomes	1. Understand the basic concepts and techniques of Artificial Intelligence. 2. Apply AI algorithms for solving practical problems. 3. Describe human intelligence and AI. 4. Explain Expert System and implementation, neural network and fuzzy logic

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-501
Title of the Course: Fundamentals of Artificial Intelligence Lab
Number of Credits: 2 (0L+0T+2P)
Effective from AY: 2023-24

Prerequisites for the course:	Artificial Intelligence theory, probability and statistics , linear algebra and Python programming	
Objectives:	To develop a basic understanding of problem solving, knowledge representation, reasoning and learning methods of AI and implement AI algorithms	
Content:	Assignment-1 -Real-world path planning for pedestrians. In the first part, students implement A* over a map that includes roads/paths as well as elevations. In the second part, students collect actual data through walking around the real world, and the cost model is then learned via regression techniques.	10 hours
	Assignment-2 -Solve maze via search -this assignment involves formulating maze-solving as a search problem, image processing (via OpenCV) as a step in maze-solving, as well as guided performance/quality analysis of representational parameters.	10 hours
	Assignment 3-Within the context of an artificial intelligence course, students are taught to identify ethical issues within technical projects and to engage in moral problem solving with regard to such issues.	10 hours
	Assignment 4-Neural network for face recognition using tensor flow -build feedforward neural networks for face recognition using TensorFlow. Students then visualize the weights of the neural networks they train. The visualization allows students to understand feedforward one-hidden layer neural networks in terms of template matching, and allows students to explore overfitting.	10 hours
	Assignment -5 -Organic path finding -Students develop a “human-like” pathfinding technique by specializing a generic search algorithm with custom action cost and heuristic cost functions. Students apply classical search algorithms and reflect on example organic paths to achieve “human-like” pathfinding.	10 hours
	Assignment - 6 -Implement a genetic algorithm in Python to evolve strategies for Robby the Robot to collect empty soda cans that lie scattered around his rectangular grid world. And also Compare the performances of a brute-force search and a search employing the Minimum Remaining Values (MRV) heuristic in solving Sudoku puzzles.	10 hours
Pedagogy:	lectures/practical/ tutorials/assignments/self-study	

References /Readings:	1. A Classical Approach to Artificial Intelligence, M.C. Trivedi, Khanna Book Publishing, 2019. 2. Artificial Intelligence: A modern approach by Stuart Russel, Pearson Education, 2010. 3. Artificial Intelligence by Rich and Knight, The McGraw Hill, 2017. 4. Artificial Intelligence: A new synthesis by Nils and Nilson, Elsevier, 1997. 5. Artificial Intelligence by Luger, Pearson Education, 2002. 6. Artificial Intelligence by Padhy, Oxford Press, 2005. 7.https://www.edx.org/course/artificial-intelligence-ai 8.https://www.udemy.com/course/artificial-intelligence-az/
Course Outcomes:	1.The students need to understand existing implementation of algorithms 2.learn to extend an existing implementation of the back-propagation algorithm and use it to recognize static hand gestures in images. 3.Students learn about feedforward neural networks and the backpropagation algorithm by implementing a perceptron network for AND and XOR Boolean functions and, given an implementation of a feedforward network, learn digit recognition using the MNIST data set. 4. students extend a Tic Tac Toe program to Ultimate Tic Tac Toe and implement a different search strategy than the example code.

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-502
Title of the Course: Algorithms and Data Structure
Number of Credits: 2 (2L+0T+0P)
Effective from AY: 2023-24

Prerequisites for the course:	Programming in Python	
Objectives:	The aim of the course is to introduce the fundamental concept of data structures and to emphasize the importance of data structures in developing and implementing efficient algorithms. It provides an exposure to various data structures and algorithm analysis including lists, stacks, queues, trees, and various sorting and searching algorithms.	
Content:	Introduction: Three level Approach - Application/User level, Abstract/Logical level, Physical/Implementation level; Concept of Abstract Data Types (ADTs), Data Structure definition, Data type vs. data structure, Applications of data structures,	3 hours
	Algorithms analysis and its complexity, Best case, worst case , and Average case performance, time-space tradeoff, Asymptotic Analysis, Big-O notation.	3 hours
	Linear Data Structures: Array and its application: Polynomials, Sparse matrices, String-pattern Matching. Linked Lists, Doubly linked list, Circular linked list, Stack and Queues.	5 hours
	Nonlinear Data Structures: Trees: Binary tree representation, Binary Search Trees, AVL Trees, M-way Search Trees, B-trees. B tree algorithms, Heap Structures.	5 hours
	Graphs: Graph representations; Graph Traversals	2 hours
	Complexity of Searching & Sorting algorithms: Bubble sort, Quick sort, Selection sort, Insertion sort, Merge sort and Heap sort. An Empirical Comparison of Sorting Algorithms, Lower bounds for Sorting. Linear search, binary search.	8 hours
	Dynamic programming and Greedy algorithms: Assembly line scheduling, Matrix-chain multiplication; Prim‟s Algorithm, Kruskal‟s Algorithm	4 hours
Pedagogy:	Practical/ tutorials/assignments/self-study	
References /Readings:	1. Horowitz, Ellis, Sartaj Sahni, and Susan Anderson-Freed. Fundamentals of data structures in C. WH Freeman & Co., 1992. 2. Benjamin Baka, Basant Agarwal, “Hands on Data Structure and Algorithms with Python”, Second Edition, O‟Reilly, 2018 3. Cormen Thomas, L. Charles, R. Ronald, S. Clifford, “Introduction to Algorithms”, Second Edition,EEE, PHI. 4. Allen, Weiss Mark. Data structures and algorithm analysis in C. Pearson Education India, 2011. 5. Algorithms, by Dasgupta, Papadimitriou, and Vazirani, McGraw-Hill.	
Course Outcomes:	1. Understanding of various data structures. 2. Proficiency in algorithmic problem-solving. 3. Practical implementation and application of data structures. 4. Enhanced critical thinking and problem analysis skills.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-503
Title of the Course: Algorithms and Data Structure Lab
Number of Credits: 2 (0L+0T+2P)
Effective from AY: 2023-24

Prerequisites for the course:	Programming in Python	
Objectives:	The aim of the course is to introduce the fundamental concept of data structures and to emphasize the importance of data structures in developing and implementing efficient algorithms. It provides an exposure to various data structures and algorithm analysis including lists, stacks, queues, trees, and various sorting and searching algorithms.	
Content:	Object-Oriented Design Goals, Object-Oriented Design Principles. 1.The programming assignment should introduce and enforce the concepts of encapsulation, polymorphism and Inheritance. ADT Specifications and Implementation of following basic data structures	3 hours
	2. Singly Linked Linear Lists	3 hours
	3. Singly Linked Circular Lists	2 hours
	4. Doubly Linked Linear Lists	2 hours
	5. Doubly Linked circular Lists	2 hours
	6. Stack using linked list	2 hours
	7. Queue using linked list	2 hours
	ADT Specifications and Implementation of following non-linear data structures 8. Binary Trees	4 hours
	9. Binary Search Trees	3 hours
	10. AVL Trees	3 hours
	11. B-Trees and its variants	3 hours
	Application of stack 12. Program to convert the given infix expression to postfix expression using stack	3 hours
	13. Program to evaluate a postfix expression using stack.	2 hours
	14. Program to traverse a binary tree in the following way: Pre-order, In-order, Post-order	3 hours
	Applications of Binary Trees 15. Write a program to implement Huffman encoding using Binary tree.	2 hours
	16. Write a program to create a binary tree for the given infix expression.	2 hours
	Applications of AVL Trees 17. Write a program that reads a list of names and telephone number from a text file and inserts them into an AVL tree. Write a function to allow the user to search the tree. Searching and sorting	3 hours
	18. Program to implement Binary search technique using Iterative method and Recursive methods.	3 hours
	19. Programs to implement following sorting algorithm- Bubble sort, Selection sort, Insertion sort, Quicksort, Merge sort and Heap sort	3 hours
	Implementation of Dynamic programming 20. Assembly line scheduling	4 hours

	21. Matrix-chain multiplication	3 hours
	Implementation of Greedy algorithms 22. Prim‟s Algorithm	3 hours
	23. Kruskal‟s Algorithm	
Pedagogy:	Lectures/Practical/ tutorials/assignments/self-study	
References/Readings:	1. Horowitz, Ellis, Sartaj Sahni, and Susan Anderson-Freed. Fundamentals of data structures in C. WH Freeman & Co., 1992. 2. Benjamin Baka, Basant Agarwal, “Hands on Data Structure and Algorithms with Python”, Second Edition, O‟Reilly, 2018 3. Cormen Thomas, L. Charles, R. Ronald, S. Clifford, “Introduction to Algorithms”, Second Edition,EEE, PHI. 4. Allen, Weiss Mark. Data structures and algorithm analysis in C. Pearson Education India, 2011. 5. Algorithms, by Dasgupta, Papadimitriou, and Vazirani, McGraw-Hill.	
Course Outcomes:	1. Implement common data structures such as lists, stacks, queues, graphs, and binary trees for solving programming problems. 2. Identify and use appropriate data structures in the context of a solution to a given problem. 3. Learn to understand the implementation issues 4. Overall learn the foundation required for programming	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-504
Title of course: Mathematics foundation for Artificial Intelligence
Number of credits: 2 (2L-0T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Basic mathematics	
Objectives	To build a strong foundation in maths required for learning computer science/data science subjects. To understand fundamental concepts and tools in calculus, linear algebra etc with emphasis on their applications to computer science in particular data science/machine learning	
Content	**Introduction** Importance of mathematics and their applications for computer science/machine learning/data science/deep learning Functions, variables, equations, graphs revision	3 hours
	Probability and Statistics: Probability Rules & Axioms, Bayes' Theorem, Random Variables, Variance and Expectation, Conditional and Joint Distributions, Standard Distributions (Bernoulli, Binomial, Multinomial, Uniform and Gaussian), Moment Generating Functions, Maximum Likelihood Estimation (MLE), Prior and Posterior, Maximum a Posteriori Estimation (MAP) and Sampling Methods-confidence intervals, Hypothesis testing, p-values, A/B testing-ANOVA, t-test,Linear regression, regularization	7 hours
	Calculus Overview of Differential and Integral Calculus, Partial Derivatives Product and chain rule-Taylor's series, infinite series summation/integration concepts-Fundamental and mean value-theorems of integral calculus, evaluation of definite and improper integrals-Beta and Gamma functions, Functions of multiple variables, limit, continuity, partial derivatives-Basics of ordinary and partial differential equations - Applications of Calculus	4 hours
	Linear Algebra: Systems of Linear Equations-Matrices-Solving Systems of Linear Equations-Vector Spaces-Linear Independence-Basis and Rank-Linear Mappings Affine Spaces	3 hours
	Analytic Geometry Norms-(Inner Products-Lengths and Distances Angles and Orthogonality-Orthonormal Basis Orthogonal Complement-Inner Product of Functions-Orthogonal Projections-Rotations) - Eigen value decomposition and SVD	6 hours
	Optimization Differentiation of Univariate Functions-Partial Differentiation and Gradients-Gradients of Vector-Valued Functions-Gradients of Matrices Useful Identities for Computing Gradients-Backpropagation and	7 hours

	Automatic Differentiation-Higher-Order Derivatives-Linearization and Multivariate Taylor Series-Gradient Descent-Constrained Optimization -Lagrange Multipliers-Convex Optimization,	
Pedagogy	Problem solving approach and carrying out small project work using matlab tools	
References/ Readings	1. Statistics Written, Robert S. Witte and John S. Witte 2. Barron's AP Statistics, 8th Edition, Martin Sternstein, PhD. 3. Statistics for Business and Economics by- James T. McClave, P. George Benson and Terry T Sincich 4. Naked Statistics: Stripping the Dread from the Data, Charles Wheelan 5. Introduction to Linear Algebra, Gilbert Strang 6. Linear Algebra and Its Applications, David C. Lay 7. No bullshit guide to Linear algebra, Ivon Savov 8. Functions and Graphs by I M Gelfand 9. Cartoon guide to calculus, Larry Gonick 10. Optimization Methods in Business Analytics — edX, MIT	
Course Outcomes	1. Strong understanding of mathematical concepts relevant to AI. 2. Application of mathematics in AI problem-solving. 3. Proficiency in quantitative analysis and data interpretation. 4. Development of algorithmic thinking skills for AI algorithms.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course code: CSI-505
Title of course: Mathematics Foundation for AI using Matlab
Number of credits: 2 (0L-0T-2P)
Effective from AY: 2023-24

Prerequisites for the course	Mathematical foundation theory and programming background	
Objectives	The lab assignment are aimed at demonstration of the following regarding statistics	
Content	Revision of the following : NumPy is a third-party library for numerical computing, optimized for working with single- and multi-dimensional arrays. Its primary type is the array type called ndarray. This library contains many routines for statistical analysis. SciPy is a third-party library for scientific computing based on NumPy. It offers additional functionality compared to NumPy, including scipy.stats for statistical analysis. Pandas is a third-party library for numerical computing based on NumPy. It excels in handling labeled one-dimensional (1D) data with Series objects and two-dimensional (2D) data with DataFrame objects. Matplotlib is a third-party library for data visualization. It works well in combination with NumPy, SciPy, and Pandas.	6 hours
	Assignment 1 - Write program to implement the following concepts using python libraries -Numpy,Pandas, matplotlib, seaborn,scipy, scrapy and beautiful soup, and tensor flow ,keras and pytorch etc	
	Assignment -2 - Sampling ,Variables in Statistics, Frequency Distributions. Generate frequency distribution tables,Generate grouped frequency distribution tables and -Visualizing Frequency Distributions -Generate bar plots, pie charts, and histograms ,Employ bar plots, pie charts and histograms.	6 hours
	Assignment-3-Comparing Frequency Distributions -grouped bar plots- step-type histogram-kernel density estimate plots- strip plots and box plots	6 hours
	Assignment-4 -Multidimensional image operations,Solving differential equations and the Fourier transform using scipy	6 hours
	Assignment-5 -Optimization algorithms using scipy.	6 hours
	Assignment -6 -Linear algebra using scipy	6 hours
	Assignment- 7-Program in python to implement the concepts such as Vector space, subspace, span, coumn space, row space, null space, left-null space, rank, basis, orthogonal matrix, symmetric matrix	6 hours
	Assignment -8 – Implement Eigen value decomposition in python.	6 hours
	Assignment-9 – implement SVD using python.	6 hours
	Assignment -10 – implement some of optimization algorithm using the python library	6 hours
Pedagogy	lab assignments /Project	
References/ Readings	1. Statistics Written, Robert S. Witte and John S. Witte 2. Barron's AP Statistics, 8th Edition, Martin Sternstein, PhD. 3. Statistics for Business and Economics 4. Naked Statistics: Stripping the Dread from the Data, Charles Wheelan 5. Introduction to Linear Algebra, Gilbert Strangsss	

Course Outcomes	1. Practical application of mathematical concepts in AI. 2. Proficiency in data manipulation, analysis, and visualization. 3. Implementation and experimentation with AI algorithms. 4. Development of critical thinking and problem-solving skills in AI.

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-506
Title of the Course: Data Science Fundamentals
Number of Credits: 2(2L+ 0T+ 0P)
Effective from AY: 2023-24

Prerequisites for the course	Statistics and Probability theory and Python Programming	
Objectives	To get started with basics of Data Science and learn all aspects of Data Science in its entirety	
Content	Introduction: Typology of problems - Data science in a big data world: Benefits and uses of data science and big data-Facets of data-The data science process-The big data ecosystem and data science-The data science process: Overview of the data science process- Defining research goals and creating a project charter-Retrieving data-Cleansing, integrating, and transforming data-Exploratory data analysis-Build the models- Presenting findings and building applications on top of them.	4 hours
	Mathematics for Data science - Importance of linear algebra, statistics and optimization from a data science perspective; Structured thinking for solving data science problems. Linear Algebra: Matrices and their properties (determinants, traces, rank, nullity, etc.); Eigenvalues and eigenvectors; Matrix factorizations; Inner products; Distance measures; Projections; Notion of hyperplanes; half-planes. Probability, Statistics and Random Processes: Probability theory and axioms; Random variables; Probability distributions and density functions (univariate and multivariate); 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. Data clearing (EDA)	8 hours 3 hours
	Introduction to Data Science Methods: Linear regression as an exemplar function approximation problem; Linear classification problems-PCA	4 hours
	Handling large data on a single computer The problems you face when handling large data-General techniques for handling large volumes of data-General programming tips for dealing with large data sets - Case study 1: Predicting malicious URLs - First steps in big data-Distributing data storage and processing with frameworks	4 hours
	Introduction to NoSQL The rise of graph databases Introducing connected data and graph databases Introducing Neo4j: a graph database Data visualization to the end user Data visualization options Crossfilter, the JavaScript MapReduce library Creating an interactive dashboard with dc.js Dashboard development tools	3 hours 4 hours
Pedagogy	Lectures/ Tutorials/Hands-on assignments/Self-study	
References / Readings	1. Practical statistics for data science by peter bruce and andrew bruce 2. Naked statistics by charles wheelon	

	3. Business data science by matt taddy 4. Elements of statistical learning by Trevor Hastie, Robert and jerome 5. Python for data analysis 6. Data science and big data analytics -EMC2
Course Outcomes	1. Understanding of data science principles. 2. Proficiency in data manipulation and preprocessing. 3. Ability to visualize and communicate data insights. 4. Knowledge of statistical analysis and predictive modeling techniques.

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Name of the Programme: M.Sc. in Artificial Intelligence
Course code: CSI-507
Title of course: Data Science Fundamentals Lab
Number of credits: 2(0L+0T+2P)
Effective from AY: 2023-24

Prerequisites for the course	Basic programming skills, Statistics	
Objectives	To introduce Basic process of data science, Python and Jupyter notebooks. To understanding how to manipulate and analyze uncurated datasets To learn basic statistical analysis and machine learning methods and effectively visualize results	
Content	Jupyter and Numpy: Jupyter notebooks are one of the most commonly used tools in data science as they allow you to combine your research notes with the code for the analysis. After getting started in Jupyter, we'll learn how to use numpy for data analysis. numpy offers many useful functions for processing data as well as data structures which are time and space efficient.	10 hours
	Pandas: Pandas, built on top of numpy, adds data frames which offer critical data analysis functionality and features.	10 hours
	Visualization: When working with large data sets you often need to visualize your data to gain a better understanding of it. Also, when you reach conclusions about the data, you'll often wish to use visualizations to present your results.	10 hours
	Mini Project: With the tools of Jupyter notebooks, numpy, pandas, and Visualization, you're ready to do sophisticated analysis on your own. You'll pick a dataset we've worked with already and perform an analysis for this first project.	10 hours
	Machine Learning: To take your data analysis skills one step further, we'll introduce you to the basics of machine learning and how to use sci-kit learn - a powerful library for machine learning.	10 hours
	Working with Text and Databases: You'll find yourself often working with text data or data from databases. This week will give you the skills to access that data. For text data, we'll also give you a preview of how to analyze text data using ideas from the field of Natural Language Processing and how to apply those ideas using the Natural Language Processing Toolkit (NLTK) library.	5 hours
	Mini-Project	5 hours
Pedagogy	Tutorials/ Lab assignments/ Project work	
References/ Readings	1. Practical statistics for data science by Peter Bruce and Andrew Bruce 2. Naked statistics by Charles Wheelon 3. Business data science by Matt Taddy 4. Elements of statistical learning by Trevor Hastie, Robert and jerome 5. Python for data analysis 6. Data science and big data analytics -EMC2	
Course Outcomes	1. Application of data science techniques to real-world problems. 2. Proficiency in data acquisition and preprocessing. 3. Ability to perform exploratory data analysis. 4. Building and evaluating predictive models.	

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Semester II
Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-508
Title of the Course: Deep Learning
Number of Credits: 2(2L-0T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Programme prerequisites	
Objectives	To study the basics of Neural Networks and their various variants such as the Convolutional Neural Networks and Recurrent Neural Networks, to study the different ways in which they can be used to solve problems in various domains such as Computer Vision, Speech and NLP.	
Content	History of Deep Learning, McCulloch Pitts Neuron, Thresholding Logic, Perceptron Learning Algorithm and Convergence	1 hours
	Multilayer Perceptrons (MLPs), Representation Power of MLPs, Sigmoid Neurons, Gradient Descent	1 hours
	Feedforward Neural Networks, Representation Power of Feedforward Neural Networks, Backpropagation	2 hours
	Gradient Descent(GD), Momentum Based GD, Nesterov Accelerated GD, Stochastic GD, Adagrad, AdaDelta,RMSProp, Adam,AdaMax,NAdam, learning rate schedulers	2 hours
	Autoencoders and relation to PCA, Regularization in autoencoders, Denoising autoencoders, Sparse autoencoders, Contractive autoencoders	3 hours
	Bias Variance Tradeoff, L2 regularization, Early stopping, Dataset augmentation, Parameter sharing and tying, Injecting noise at input, Ensemble methods, Dropout	3 hours
	Greedy Layer Wise Pre-training, Better activation functions, Better weight initialization methods, Batch Normalization	3 hours
	Learning Vectorial Representations of Words, Convolutional Neural Networks, LeNet, AlexNet, ZF-Net, VGGNet, GoogLeNet, ResNet	3 hours
	Visualizing Convolutional Neural Networks, Guided Backpropagation, Deep Dream, Deep Art, Fooling Convolutional Neural Networks	3 hours
	Recurrent Neural Networks, Backpropagation Through Time (BPTT), Vanishing and Exploding Gradients, Truncated BPTT	3 hours
	Gated Recurrent Units (GRUs), Long Short Term Memory (LSTM) Cells, Solving the vanishing gradient problem with LSTM	3 hours
	Encoder Decoder Models, Attention Mechanism, Attention over images, Hierarchical Attention, Transformers.	3 hours
Pedagogy	Lectures/ Tutorials/Hands-on assignments/Self-study	
References/ Readings	1. Ian Goodfellow and Yoshua Bengio and Aaron Courville. Deep Learning. An MIT Press book. 2016. 2. Charu C. Aggarwal. Neural Networks and Deep Learning: A Textbook. Springer. 2019. 3. Dive into Deep Learning by Ashton Zang. 4. Introduction to Deep Learning by Sandro Skansi.	
Course Outcomes	1. Understanding of deep learning concepts and principles. 2. Implementation and training of deep learning models. 3. Practical application of deep learning in various domains. 4. Evaluation and interpretation of deep learning model performance.	

Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-509
Title of the Course: Deep Learning Lab
Number of Credits: 2(0L-0T-2P)
Effective from AY: 2023-24

Prerequisites for the course	Programming, Machine Learning Skills. Statistics,Calculus,Linear Algebra.Probability.	
Objectives	1. To make students comfortable with tools and techniques required in handling large amounts of datasets. 2. They will also uncover various deep learning methods in NLP, Neural Networks etc.	
Content	**Tensorflow with Python** Introducing Tensorflow - Tensorflow as an Interface - Tensorflow as an environment - Tensors - Computation Graph - Installing Tensorflow - Tensorflow training - Prepare Data - Tensor types - Loss and Optimization - Running tensorflow programs.	5 hours
	Building Neural Networks using Tensorflow Building Neural Networks using Tensorflow - Tensorflow data types - CPU vs GPU vs TPU - Tensorflow methods - Introduction to Neural Networks - Neural Network Architecture - Linear Regression example revisited - The Neuron - Neural Network Layers - The MNIST Dataset - Coding MNIST NN.	5 hours
	Deep Learning using Tensorflow Deepening the network - Images and Pixels - How humans recognise images - Convolutional Neural Networks - ConvNet Architecture - Overfitting and Regularization - Max Pooling and ReLU activations - Dropout - Strides and Zero Padding - Coding Deep ConvNets demo - Debugging Neural Networks - Visualising NN using Tensorflow - Tensorboard.	5 hours
	Transfer Learning using Keras and TFLearn Transfer Learning Introduction - Google Inception Model - Retraining Google Inception with our own data demo - Predicting new images - Transfer Learning Summary - Extending Tensorflow - Keras - TFLearn - Keras vs TFLearn Comparison.	5 hours
	Suggest ideas for lab work	
	Assignment -1 Cat vs. Dog Image Classifier	3 hours
	Assignment -2- Covid-19 Detection in Lungs	3 hours
	Assignment -3- Digit Recognition System	3 hours
	Assignment - 4- Facial Recognition Application	3 hours
	Assignment -5- Face Mask Detection	3 hours
	Assignment -6- Cyber-Attack Prediction	3 hours
	Assignment -7- Automated Attendance System	3 hours
	Assignment -8 Emotion Recognition	3 hours
	Assignment -9- Object Detection System	3 hours

	Assignment 10 - Recommender System	3 hours
Pedagogy	Lab assignment/mini project	
References/ Readings	1. Ian Goodfellow and Yoshua Bengio and Aaron Courville. Deep Learning. An MIT Press book. 2016. 2. Charu C. Aggarwal. Neural Networks and Deep Learning: A Textbook. Springer. 2019. 3. Grokking Artificial Intelligence Algorithms by Rishal Hurbans published by Manning Publications. 4. Deep Learning From Scratch: Building with Python from First Principles by Seth Weidman published by O`Reilley. 5. Deep learning in Python/ Pytorch by Manning Publications. 6. Deep Learning with Python by francois chollet. 7. Dive into Deep Learning by Ashton Zang. 8. Introduction to Deep Learning by Sandro Skansi.	
Course Outcomes	1. Practical application of deep learning techniques. 2. Implementation and training of deep learning models. 3. Data preprocessing and augmentation for deep learning. 4. Model evaluation and optimization.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-510
Title of the Course: Big Data Frameworks
Number of Credits: 2(2L-0T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Probability and statistics and programming background	
Objectives	1. To understand the need of Big Data, challenges and different analytical architectures 2. Installation and understanding of Hadoop Architecture and its ecosystems 3. Processing of Big Data with Advanced architectures like Spark. 4. Describe graphs and streaming data in Spark	
Content	**Introduction to big data** Data Storage and Analysis - Characteristics of Big Data – Big Data Analytics - Typical Analytical Architecture – Requirement for new analytical architecture – Challenges in Big Data Analytics – Need of big data frameworks **Hadoop framework** Hadoop – Requirement of Hadoop Framework - Design principle of Hadoop –Comparison with other system - Hadoop Components – Hadoop 1 vs Hadoop 2 – Hadoop Daemon's – HDFS Commands – Map Reduce Programming: I/O formats, Map side join, Reduce Side Join, Secondary sorting, Pipelining MapReduce jobs - **Hadoop Ecosystem** Introduction to Hadoop ecosystem technologies: Serialization: AVRO, Co-ordination: Zookeeper, Databases: HBase, Hive, Scripting language: Pig, Streaming: Flink, Storm **Spark framework** Introduction to GPU Computing, CUDA Programming Model, CUDA API, Simple Matrix, Multiplication in CUDA, CUDA Memory Model, Shared Memory Matrix Multiplication, Additional CUDA API Features. **Data analysis with spark shell** Writing Spark Application - Spark Programming in Scala, Python, R, Java - Application Execution **Spark SQL and Graph X** SQL Context – Importing and Saving data – Data frames – using SQL – GraphX overview – Creating Graph – Graph Algorithms. **Spark streaming** Overview – Errors and Recovery – Streaming Source – Streaming live data with spark **Recent trends in big data analytics**	3 hrs 6 hrs 3 hrs 4 hrs 4 hrs 5hrs 3 hrs 2 hr
Pedagogy	Assignment / Quiz / Project / Seminar	
References/ Readings	1. Mike Frampton, "Mastering Apache Spark", Packt Publishing, 2015. 2. TomWhite,"Hadoop:TheDefinitiveGuide",O'Reilly,4thEdition,2015. 3. NickPentreath,MachineLearningwithSpark,PacktPublishing, 2015. 4. Mohammed Guller, Big Data Analytics with Spark, Apress, 2015. 5. Donald Miner, Adam Shook, "Map Reduce Design Pattern", O'Reilly, 2012.	
Course Outcomes	1. students would have a good understanding of Big Data 2. understand the basics of the frameworks like Hadoop and spark and 3. have a knowledge of Spark SQL 4. have understanding of Spark streaming.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-511
Title of the Course: Big Data Frameworks Lab
Number of Credits: 2(0L -0T-2P)
Effective from AY: 2023-24

Prerequisites for the course	Should have knowledge of one Programming Language (Java preferably), Practice of SQL (queries and sub queries), exposure to Linux Environment.	
Objectives	Understand the Big Data Platform and its Use cases • Provide an overview of Apache Hadoop • Provide HDFS Concepts and Interfacing with HDFS • Understand Map Reduce Jobs • Provide hands on Hodoop Eco System • Apply analytics on Structured, Unstructured Data.	
Content	**List of Experiments:** 1. Implement the following Data structures in Java Linked Lists,Stacks,Queues,Set,Map 2. Perform setting up and Installing Hadoop in its three operating modes: Standalone, Pseudo Distributed, Fully distributed. 3. Implement the following file management tasks in Hadoop: Adding files and directories,Retrieving files (Deleting files Hint: A typical Hadoop workflow creates data files (such as log files) elsewhere and copies them into HDFS using one of the above command line utilities. 4. Run a basic Word Count Map Reduce program to understand Map Reduce Paradigm. 5. Write a Map Reduce program that mines weather data. Weather sensors collecting data everyhour at many locations across the globe gather a large volume of log data, which is a goodcandidate for analysis with MapReduce, since it is semi structured and record-oriented. 6. Implement Matrix Multiplication with Hadoop Map Reduce 7. Install and Run Pig then write Pig Latin scripts to sort, group, join, project, and filter your data. 8. Install and Run Hive then use Hive to create, alter, and drop databases, tables, views, functions, and indexes. 9. Solve some real life big data problems. - Traffic control using big data - Medical insurance fraud detection - Recommendation system - Anomaly detection in cloud servers - Tourist behavior analysis - Web server log analysis	5 hrs 5 hrs 5 hrs 5 hrs 5 hrs 5 hrs 5 hrs 5 hrs 20 hrs
Pedagogy	Lab assignments/mini project/ seminar	
References/ Readings	Text Books • Tom White " Hadoop: The Definitive Guide" Third Edit on, O'reily Media, 2012. • Seema Acharya, Subhasini Chellappan, "Big Data Analytics" Wiley 2015. References • Michael Berthold, David J. Hand, "Intelligent Data Analysis", Springer, 2007. • Jay Liebowitz, "Big Data and Business Analytics" Auerbach Publications, CRC press (2013) • Anand Rajaraman and Jef rey David Ulman, "Mining of Massive Datasets", Cambridge University Press, 2012. • Bill Franks, "Taming the Big Data Tidal Wave: Finding Opportunities in Huge	

	Data Streams with Advanced Analytics", John Wiley & sons, 2012. • Glen J. Myat, "Making Sense of Data", John Wiley & Sons, 2007
Course Outcomes	1. Identify Big Data and its Business Implications. 2.List the components of Hadoop and Hadoop Eco-System 3. Access and Process Data on Distributed File System and Manage Job Execution in Hadoop Environment 3. Develop Big Data Solutions using Hadoop Eco System 4. Analyze Infosphere BigInsights Big Data Recommendations.

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-512
Title of the Course: Reinforcement Learning
Number of Credits: 2(2L-0T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Linear algebra, multivariable calculus Basic machine learning knowledge	
Objectives	To enable the student to understand the reinforcement learning paradigm, to be able to identify when an RL formulation is appropriate, to understand the basic solution approaches in RL, to implement and evaluate various RL algorithms.	
Content	Review of ML fundamentals – Classification, Regression. Review of probability theory and optimization concepts. RL Framework; Supervised learning vs. RL; Explore-Exploit Dilemma; Examples. MAB: Definition, Uses, Algorithms, Contextual Bandits, Transition to full RL, Intro to full RL problem Intro to MDPs: Definitions , Returns, Value function, Q-function. Bellman Equation, DP, Value Iteration, Policy Iteration, Generalized Policy Iteration. Evaluation and Control: TD learning, SARSA, Q-learning, Monte Carlo, TD Lambda, Eligibility Traces. Maximization-Bias & Representations: Double Q learning, Tabular learning vs. Parameterized, Q-learning with NNs Function approximation: Semi-gradient methods, SGD, DQNs, Replay Buffer. Policy Gradients: Introduction, Motivation, REINFORCE, PG theorem, Introduction to AC methods Actor-Critic Methods, Baselines, Advantage AC, A3C Advanced Value-Based Methods: Double DQN, Prioritized Experience Replay, Dueling Architectures, Expected SARSA. Advanced PG/A-C methods: Deterministic PG and DDPG, Soft Actor-Critic (SAC) HRL: Introduction to hierarchies, types of optimality, SMDPs, Options, HRL algorithms POMDPS: Intro, Definitions, Belief states, Solution Methods; History-based methods, LSTMS, Q-MDPs, Direct Solutions, PSR. Model-Based RL: Introduction, Motivation, Connections to Planning, Types of MBRL, Benefits, RL with a Learnt Model, Dyna-style models, Latent variable models, Examples, Implicit MBRL. Case study on design of RL solution for real-world problems.	2 hrs 2 hrs 2 hrs 2 hrs 2 hrs 2 hrs 2 hrs 2 hrs 3 hrs 3 hrs 4 hrs 4 hrs
Pedagogy	Hands-on assignments / tutorials / peer-teaching / flip classroom/ presentations.	
References/ Readings	1. Reinforcement learning -Introduction by Richard sutton and Andrew barto, 2nd edition, MIT press. 2. Algorithms for reinforcement learning by Csaba Szepesvari, Ronald Brachman, et al,2010.	
Course Outcomes	1.Solid understanding of reinforcement learning concepts, theories, and algorithms. 2.Ability to implement and apply reinforcement learning algorithms to real-world problems. 3.Evaluation and analysis of reinforcement learning systems. 4.Critical thinking skills, staying updated with current research and trends.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-513
Title of the Course: Reinforcement Learning Lab
Number of Credits: 2(0L-0T-2P)
Effective from AY: 2023-24

Prerequisites for the course	Linear algebra, multivariable calculus , Basic machine learning knowledge and programming background.	
Objectives	To understand the theory by carrying out the lab assignment based on the key ideas of reinforcement learning.	
Content	1. RL task formulation (action space, state space, environment definition) 2. Tabular based solutions (dynamic programming, Monte Carlo, temporal-difference) 3. Function approximation solutions (Deep Q-networks) 4. Policy gradient from basic (REINFORCE) towards advanced topics (proximal policy optimization, deep deterministic policy gradient, etc.) 5. Model-based reinforcement learning 6. Imitation learning (behavioral cloning, inverse RL, generative adversarial imitation learning) 7. Meta-learning 8. Multi-agent learning, partial observable environments	7 hours 7 hours 7 hours 7 hours 7 hours 7 hours 8 hours 10 hours
Pedagogy	Lab assignments/ mini project	
References/ Readings	1. Richard S. Sutton and Andrew G. Barto, "Reinforcement learning: An introduction", Second Edition, MIT Press, 2019. 2. Li, Yuxi. "Deep reinforcement learning." arXiv preprint arXiv:1810.06339 (2018). 3. Wiering, Marco, and Martijn Van Otterlo. "Reinforcement learning." Adaptation, learning, and optimization 12 (2012): 3. 4. Russell, Stuart J., and Peter Norvig. "Artificial intelligence: a modern approach."Pearson Education Limited, 2016. 5. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. "Deep learning." MIT press, 2016. 6. David Silver's course on Reinforcement Learning (link).	
Course Outcomes	1. Practical implementation skills of reinforcement learning algorithms. 2. Ability to design and analyze experiments for evaluating reinforcement learning systems. 3. Contribution to the field through novel research or innovative applications. 4. Improved collaboration and communication skills within a research lab setting.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course code:CSI-514
Title of course: Software Engineering for AI Enabled systems
Number of credits: 2 (2L-0T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Programming & Data Structures, Python	
Objectives	Gain an in-depth understanding of Software Engineering including its importance. Learn Scrum, Kanban, Agile, Waterfall, Prototyping, Incremental, RAD and Spiral Software Process Models. Learn to perform systematic Software Requirement Engineering. Applying SE approach to developing AI solutions	
Content	Software Engineering: Software Processes, SDLC , agile approaches to SE	5 hours
	Requirements Engineering: elicitation techniques, specification. SCRUM and user stories.	5 hours
	Test Driven Development: Refactoring and Unit testing	5 hours
	Use of frameworks and APIS and handling of big data	5 marks
	Configuration management, continuous integration,and automated software engineering	5 hours
	Cloud based software development, DevOps	5 hours
Pedagogy	Classroom/handson instructions, assignments, miniprojects	
References/ Readings	1. Hands-On Software Engineering with Python: Move beyond basic programming and construct reliable and efficient software with complex code, Brian Allbee, Packt Publishing. 2. A concise Introduction to Software Engineering, Pankaj Jalote-2008n- Springer. 3. Agile Estimating and Scrum, Mike Cohn, Prentice Hall.	
Course Outcomes	1. Application of SE principles for AI and Data Sceince projects 2. How to work in self organizing teams 3. Use of tools and techniques for automating and managing software development 4. Understand cloud based software development	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course code:CSI-515
Title of course: Software Engineering for AI Enabled Systems Lab
Number of credits: 2 (0L-0T-2P)
Effective from AY: 2023-24

Prerequisites for the course	Programming & Data Structures, Python	
Objectives	Applying SE approach to developing AI solutions Use of modern software engineering tools and frameworks	
Content	1)Version Control Tools- Git and Github 2)TDD –Unit testing and refactoring with Python 3)Working with Python libraries and frameworks 4)Use of testing tools- selenium, Jmeter 5) Cloud based software development & DevOps	12 hours 12 hours 12 hours 12 hours 12 hours
Pedagogy	Lab sessions and projects	
References/ Readings	1. Hands-On Software Engineering with Python: Move beyond basic programming and construct reliable and efficient software with complex code, Brian Allbee, Packt Publishing. 2. A concise Introduction to Software Engineering, Pankaj Jalote-2008n- Springer. 3. Agile Estimating and Scrum, Mike Cohn, Prentice Hall.	
Course Outcomes	1. Application of SE principles for AI and Data Science projects 2. How to work in self organzing teams 3. Use of tools and techniques for automating and managing software development 4. Understand how to implement devop	

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Elective Courses
Semester I
Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-521
Title of Course: Natural Language Processing
Number of Credits: 4 (2L-2T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Fundamentals of Artificial Intelligence; Mathematical Foundations for Artificial Intelligence. Machine Learning and Programming background. Introduction to NLP (Theory), Mathematical foundations for AI.	
Objectives	This course will focus on understanding the essentials of Natural Language Processing (NLP), areas in NLP, algorithms, and NLP tasks. Students who complete this course will gain a foundational understanding in natural language processing methods and strategies. They will also learn how to evaluate the strengths and weaknesses of various NLP technologies and frameworks as they gain practical experience in the NLP toolkits available.	
Content: Theory	Part I: Foundations of Natural Language Processing Introduction ● Natural Language Processing - Problems and perspectives ● Introduction/Recall to/of probability calculus ○ N-grams and Language Models ○ Markov Models ● Introduction to Machine Learning and Deep Learning ● Recurrent Neural Network Language Models ● The evaluation of NLP applications Corpora ● Corpora and their construction: representativeness ● Concordances, collocations and measures of words association ● Methods for Text Retrieval ● Regular expressions	8 hours
	Part II: Natural Language Processing ● Computational Phonetics and Speech Processing ○ Speech samples: properties and acoustic measures ○ Analysis in the frequency domain, Spectrograms ○ Applications in the acoustic-phonetic field. ○ Speech recognition with HMM and Deep Neural Networks ● Tokenisation and Sentence splitting ● Computational Morphology ○ Morphological operations ○ Static lexica, Two-level morphology ● Computational Syntax ○ Part-of-speech tagging ○ Grammars for natural language ○ Natural language Parsing ○ Supplementary worksheet: formal grammars for NL ■ Formal languages and Natural languages. Natural language complexity ■ Phrase structure grammars, Dependency Grammars ■ Treebanks ■ Modern formalisms for parsing natural languages ● Computational Semantics ○ Lexical semantics: WordNet and FrameNet	16 hours

	○ Word Sense Disambiguation ○ Distributional Semantics & Word-Space models ○ Logical approaches to sentence semantics	
	Part III: Applications and Case studies: ● Solving Downstream Tasks: Document classification, Sentiment Analysis, Named Entity Recognition, Semantic Textual Similarity ● Prompting Pre-Trained Language Models ● Network Embedding	6 hours
	Sample list of Assignments and a Mini Project using all these functionalities to be discussed and implemented during Tutorial Slots Assignment -1 -Import nltk and download the 'stopwords' and 'punkt' packages. Assignment-2 -Import spacy and load the language model. Assignment -3 -How to tokenize a given text? Assignment-4 -How to get the sentences of a text document? Assignment- 5-How to tokenize a text using the `transformers` package? Assignment -6 - How to tokenize text with stopwords as delimiters? Assignment- 7- How to remove stop words in a text?	20 * 1 = 20 hours for Assignment Discussion + 10 hours for a Mini Project
	Assignment -8- How to add custom stop words in spaCy? Assignment- 9 -How to remove punctuations? Assignment-10 - How to perform stemming? Assignment -11 -How to lemmatize a given text? Assignment-12 -How to extract usernames from emails? Assignment -13-How to find the most common words in the text excluding stopwords Assignment -14- How to do spell correction in a given text? Assignment -15- How to tokenize tweets? Assignment -16- How to extract all the nouns in a text? Assignment -17- How to extract all the pronouns in a text? Assignment - 18 - How to find similarity between two words? Assignment -19- How to find similarity between two documents? Assignment -20 -How to find the cosine similarity of two documents?	
Pedagogy	Hands-on assignments/tutorials / peer-teaching / pair programming/presentations / mini-project. Lectures / Practical / tutorials / assignments / self-study / mini-project	
References/ Readings	1. Allen, James, Natural Language Understanding, Second Edition, Benjamin/Cumming, 1995. 2. Charniack, Eugene, Statistical Language Learning, MIT Press, 1993. 3. Jurafsky, Dan and Martin, James, Speech and Language Processing, Second Edition, Prentice Hall, 2008. 4. Manning, Christopher and Heinrich, Schutze, Foundations of Statistical 5. Natural Language Processing, MIT Press, 1999. 6. Tamburini, F.. Neural Models for the Automatic Processing of Italian, Bologna: Pàtron. 2022 7. T. McEnery and A. Wilson. Corpus Linguistics, EUP. 2001 **8.** https://corpora.ficlit.unibo.it/NLP/ 9. https://www.machinelearningplus.com/nlp/nlp-exercises/ 10. Deep Learning by Goodfellow, Bengio, and Courville free online	

	11. Machine Learning — A Probabilistic Perspective by Kevin Murphy online 12. Natural Language Processing by Jacob Eisenstein free online Speech and Language Processing by Dan Jurafsky and James H. Martin (3rd ed. draft)
Course Outcomes	1. Learners will learn about the concepts in natural language processing. 2. Learners will have a fair idea of different areas in NLP 3. Learners will appreciate the complexities involved in natural language processing. 4. Through lectures and practical assignments, students will learn the necessary tricks for making their models work on practical problems.

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-522
Title of Course: Computer Vision
Number of Credits: 4 (2L-2T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Python programming, linear algebra and calculus , array manipulation	
Objectives	The aim of the course is to introduce the fundamental concept of computer vision and to emphasize the importance of computer vision in developing and implementing different projects	
Theory:	Image Formation - Geometric Camera Models - Light and Shading - Color - Early Vision: Just One Image	6 hours
	Linear Filters - Local Image Features - Texture - Early Vision: Multiple Images - Stereopsis - Structure from Motion - Mid-Level Vision	6 hours
	Segmentation by Clustering - Grouping and Model Fitting- Tracking - High-Level Vision- Registration- Smooth Surfaces and Their Outlines - Range Data - Learning to Classify - Classifying Images	6 hours
	Detecting Objects in Images- Topics in Object Recognition Applications	6 hours
	Image-Based Modeling and Rendering - Looking at People- Image Search and Retrieval - Optimization Techniques	6 hours
Tutorial session/Practical assignments:	1. Open CV setup and demo on getting started up.	3 hours
	2. Image representation and image manipulation using open CV	3 hours
	3. Image storage and manipulation.	3 hours
	4. Photographs and perspective projections	3 hours
	5. Gaussian smoothings	3 hours
	6. Canny edge detection	3 hours
	7. Corner detection	3 hours
	8. Gabor filters	3 hours
	9. Hough transformation for lines	3 hours
	10. Hough transformation for circles	3 hours
Pedagogy:	lectures/Practical/ tutorials/assignments/self-study	
References/Readings:	1. Computer Vision: Algorithms And Applications by Richard Szeliski https://www5.cs.fau.de/lectures/ss-14/computer-vision-cv/mputer-vision-exercises/index.html Read more at: https://viso.ai/computer-vision/computer-vision-books/ 2. Computer Vision: Models, Learning, and Inference Read more at: https://viso.ai/computer-vision/computer-vision-books/ 3. Modern Computer Vision with PyTorch by Yeshwanth Reddy and V Kishore Ayyadevara	

	Read more at: https://viso.ai/computer-vision/computer-vision-books/ 4. Learning OpenCV 4 Computer Vision with Python 3 Read more at: https://viso.ai/computer-vision/computer-vision-books/
Course Outcomes:	1. Acquire and process raw image data and Relate image data to 3D scene structures. 2. Know the concepts behind and how to use several model-based object representations, and critically compare them. 3. Know many of the most popularly used current computer vision techniques by carrying out suitable lab experiments listed above 4. Undertake computer vision work in MATLAB or python OpenCV

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-523
Title of Course: Robotics
Number of Credits: 4 (2L-2T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Linear Algebra, Set Theory, Complex Analysis, Matrices	
Objectives	1. To summarize and analyze the fundamentals of robotics. 2. To introduce students the kinematics and dynamics of robots. 3. To elucidate students the types of motion control. 4. To familiarize students with the basic techniques of designing the robots.	
Theory:	**Module:1 Fundamentals** Introduction – Components, Degrees of Freedom, Joints, Coordinates, Mechanisms, Controller. **Module:2 Kinematics** Position and Orientation of Objects, Coordinate Transformation, Joint Variables and Position of End Effector, Inverse Kinematics Problem, Jacobian Matrix, Statics and Jacobian Matrices. **Module:3 Dynamics** Lagrangian and Newton-Euler Formulations, Derivation of Dynamics Equations Based on Lagrangian Formulation, Derivation of Dynamic Equations Based on Newton-Euler, Formulation, Use of Dynamics Equations and Computational Load, Identification of Manipulator Dynamics. **Module:4 Manipulability** Manipulability Ellipsoid and Manipulability Measure, Best Configurations of Robotic Mechanisms from Manipulability Viewpoint, Various Indices of Manipulability, Dynamic Manipulability. **Module:5 Position Control** Generating a Desired Trajectory, Linear Feedback Control, Two-Stage Control by Linearization and Servo Compensation, Design and Evaluation of Servo Compensation, Decoupling Control, Adaptive Control. **Module:6 Force Control** Impedance Control - Passive-Impedance Method, Active-Impedance Method-One- Degree-of- Freedom Case, Active-Impedance Method-General Case. **Module:7 Hybrid Control** Hybrid Control - Hybrid Control via Feedback Compensation, Dynamic Hybrid Control.	5 hours 5 hours 5 hours 5 hours 5 hours 3 hours 2 hours
Practicals to be discussed and implemented during the Tutorial Slots:	1. Assignment on introduction to Robot Configuration. 2. Demonstration of Robot with 2 dof, 3 dof, 4 dof etc. 3. Two assignments on programming the Robot for some simple real life applications. 4. Two assignments on programming the Robot for applications in Val II. 5. Two programming exercises for robots. 6. Two case studies of applications in industry. 7. Exercise on robotic simulation software.	3 hours 2 hours 5 hours 5 hours 5 hours 5 hours 5 hours

Pedagogy	Lectures/Practical/ Tutorials/Assignments	
References/ Readings	**Text Book(s)** 1. Tsuneo Yoshikawa, "Foundations of Robotics Analysis and Control", The MIT Press Cambridge, 1990. 2. Saeed B Niku, “Introduction to Robotics Analysis, Control, Applications”, 3rd Edition, Wiley, 2020. **Reference Books** 1. Robert J. Schilling, “Fundamentals of Robotics, Analysis and Control”, Prentice Hall India, 2003. 2. John J. Craig, “Introduction to Robotics, Mechanics and Control”, 3rd Edition, Pearson Prentice Hall, 2005.	
Course Outcomes	After the completion of the course, student will be able to: 1. Comprehend, classify and analyze the fundamentals of robotics. 2. Analyze the kinematics in robots. 3. Gain knowledge about the dynamics of robots. 4. Elucidate the motion control in robotics.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-524
Title of Course: IoT Architecture and Protocols
Number of Credits: 4 (2L-2T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Internet Technologies, Computer Organization and architecture, Operating Systems.	
Objectives	To understand the fundamentals of Internet of Things and the protocols and standards designed for IoT	
Theory	Introduction to IoT: Introduction, IoT ecosystem, Applications, Challenges. Fundamentals: IoT Devices - Sensors, Actuators, and gateways, Basics of the wireless sensor network. IoT Architecture & Design: oneM2M, IoTWF, Additional Reference Models, Core functional stack, Data Management and compute stack. Communicating smart objects: Communication criteria, communication models, IoT access technologies – 3GPP MTC, IEEE 802.11, IEEE 802.15, WirelessHART, ZWave, Bluetooth Low Energy, Zigbee Smart Energy, DASH7 IoT Network Layer: IP as IoT network layer, IPv6, 6LoWPAN, 6TiSCH, RPL, CORPL, CARP IoT Transport and Application protocols: Transport Layer: TCP, UDP, DCCP, SCTP, TLS, DTLS IoT application transport methods, HTTP, CoAP, XMPP, MQTT, AMQP, DDS Security in IoT: MAC802.15.4, 6LoWPAN, RPL, Application Layer security. IoT Application case study: Discuss any 3 applications of IoT	2 hours 4 hours 4 hours 8 hours 3 hours 3 hours 3 hours 3 hours
Any 15 Case Studies / Systems to be discussed during the Tutorial Slots:	1. Smart Agriculture System 2. Weather Reporting System 3. Home Automation System 4. Face Recognition Bot 5. Smart Garage Door 6. Smart Alarm Clock 7. Air Pollution Monitoring System 8. Smart Parking System 9. Smart Traffic Management System 10. Smart Cradle System 11. Smart Gas Leakage Detector Bot 12. Streetlight Monitoring System 13. Smart Anti-Theft System 14. Liquid Level Monitoring System 15. Night Patrol Robot 16. Health Monitoring System 17. Smart Irrigation System 18. Flood Detection System	15 * 2 = 30 hours

	19. Mining Worker Safety Helmet 20. Smart Energy Grid	
Pedagogy	lectures/ tutorials/Hands-on assignments/self-study	
References/ Readings	1. David Hanes, Gonzalo Salgueiro, Patrick Grossetete, Robert Barton, Jerome Henry, "IoT Fundamentals: Networking Technologies, Protocols, and Use Cases for the Internet of Things", CISCO Press, 2017 2. Hersent, Olivier, David Boswarthick, and Omar Elloumi, The internet of things: Key applications and protocols. John Wiley & Sons, 2011. 3. Buyya, Rajkumar, and Amir Vahid Dastjerdi, eds. Internet of Things: Principles and Paradigms. Elsevier, 2016.	
Course Outcomes	1. Understanding and knowledge of various IoT protocols. 2. Ability to select and implement appropriate IoT protocols based on application requirements. 3. Awareness of security and privacy considerations in IoT protocols. 4. Familiarity with interoperability, performance optimization, and emerging trends in IoT protocols.	

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Semester II
Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-525
Title of Course: Machine Translation
Number of Credits: 4 (2L-2T-0P)
Effective from AY: 2023-24

Prerequisites for the course	Knowledge of Mathematics for Computer Science and Machine Learning will prove beneficial, A previous course on Artificial Intelligence and Natural Language Processing will help; Exposure to Linguistics is useful, though not mandatory	
Objectives:	The objective of the course is to understand and get an insight into the different approaches used for Machine Translation (MT).	
Content:	Introduction: Data-driven MT, MT Approaches, Language divergence, three major paradigms of MT, MT Evaluation,	8 hours
	Bilingual Word Mappings: Combinatorial Argument, One-to-One Alignment, Heuristic and Iterative bases computation, Mathematics of Alignment, Expectation Maximization, IBM models of Alignment	4 hours
	Phrase-Based Machine Translation (PBMT): Need, Examples, Phrase Table, Mathematics of Phrase-Based SMT, Decoding.	10 hours
	Rule-Based Machine Translation (RBMT): Kinds, UNL, Interlingua and Word Knowledge, UNL conversion, Transfer-based MT.	5 hours
	Example-Based Machine Translation (EBMT): Essential steps of EBMT, Text similarity computation, Translation memory, Statistical Machine Translation	3 hours
	Assignments to be discussed during the Tutorial Slots -	30 hours
	Assignment 1: Data-driven MT, MT Approaches, Language divergence, three major paradigms of MT, MT Evaluation,	8 hours
	Assignment 2: Bilingual Word Mappings: Combinatorial Argument, One-to-One Alignment, Heuristic and Iterative bases computation, Mathematics of Alignment, Expectation Maximization, IBM models of Alignment	4 hours
	Assignment 3: Phrase-Based Machine Translation (PBMT): Need, Examples, Phrase Table, Mathematics of Phrase-Based SMT, Decoding.	10 hours
	Assignment 4: Rule-Based Machine Translation (RBMT): Kinds, UNL, Interlingua and Word Knowledge, UNL conversion, Transfer-based MT.	5 hours
	Assignment 5: Example-Based Machine Translation (EBMT): Essential steps of EBMT, Text similarity computation, Translation memory, Statistical Machine Translation	3 hours
Pedagogy:	lectures/ tutorials/assignments/self-learning/ flipped classroom	
References/ Readings	1. Machine Translation by Pushpak Bhattacharyya, Chapman and Hall/CRC, February 2015 2. Machine Translation on Coursera by Prof. Alexander Waibel and Jan Niehues https://www.coursera.org/learn/machinetranslation 3. An Open Source Neural Machine Translation System https://opennmt.net/ 4. Bhashini Project – https://bhashini.gov.in/bhashadaan/en/likho-india	
Course Outcomes	1.Understand the Machine Translation Approaches andUnderstand the differences between Phrase-Based, Rule-Based, and Example-Based Machine	

	Translation 2.explain, apply, and assess evaluation methods for machine translation;describe and critically discuss the architecture of machine translation systems; 3.build their own translation model using existing tools for machine translation and evaluate and analyse the translation results;compare different types of machine translation strategies, such as rule-based, statistical, and neural machine translation; 4.implement components of machine translation systems or components used in evaluation or pre-processing

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-526
Title of the Course: Mathematics for Computer Vision and Robotics
Number of Credits: 4(2L+2T+P)
Effective from AY: 2023-24

Prerequisites for the course	Linear Algebra, Probability and Statistics, Signal Processing	
Objectives	To understand basic concepts of linear algebra and to illustrate its power and utility through applications to computer vision. To apply the concepts of vector spaces, linear transformations, matrices and inner product spaces in engineering. To understand the concepts of curves and surfaces and solving linear programming problems that arise in engineering.	
Theory:	Vectors and Matrices Points, vectors, vector spaces(Rn only), lines and planes as subspaces -Matrices and four fundamental spaces- Gaussian elimination. Factorization of Matrices LU factorizations-Cholesky decomposition –eigenvalues and eigenvectors-–SVD - Applications of the SVD .- Solving Linear Systems and the Pseudoinverse - Principal Components Analysis (PCA) Linear transformations Linear transformations(R^n only) – Basic properties-invertible linear transformation - matrices of linear transformations. Geometry in Linear Transformation Projections, Rotations and reflection and applications Orthogonality Dot products and inner products(R^n only) – lengths and angles of vectors –orthogonal matrices- Gram Schmidt orthogonalizations - QR factorization- orthogonal projections– Least Square solutions Differential geometry Introduction to differential geometry - curves-curvature-torsion-osculating plane –surfaces Linear programming Linear programming – Formulation of LPP- Graphical method - Simplex method	3 hours 6 hours 6 hours 6 hours 3 hours 3 hours 3 hours
Assignments to be discussed during Tutorial Slots:	Assignment 1- Getting to Know the Python math Module, Constants of the math Module:Pi, Tau, Euler's Number, Infinity, Not a Number (NaN) and Arithmetic Functions,Find Factorials With Python factorial(), Find the Ceiling Value With ceil(), Find the Floor Value With floor(), Truncate Numbers With trunc(), Find the Closeness of Numbers With Python isclose() Assignment-2 - Power Functions, Calculate the Power of a Number With pow(),Find the Natural Exponent With exp(),Practical Example With exp(),Logarithmic Functions, Python Natural Log With log(),Understand log2() and log10(), Practical Example With Natural Log Assignment-3 -Other Important math Module Functions, Calculate the Greatest Common Divisor, Calculate the Sum of Iterables, Calculate the Square Root, Convert Angle Values, Calculate Trigonometric Values Assignment -4 -New Additions to the math Module in Python 3.8.cmath vs math, NumPy vs math,	7 * 3 = 21 hours + 9 hours for a Mini Project

	Assignment -5 -Calculating combinations and permutations using factorials, Calculating the height of a pole using trigonometric functions, Calculating radioactive decay using the exponential function, Calculating the curve of a suspension bridge using hyperbolic functions, Solving quadratic equations Assignment - 6 -Simulating periodic functions, such as sound and light waves, using trigonometric functions, Assignment -7 -Vector algebra in python, Physical Quantities, Vector and Scalars, Representation of vectors, Types of Vectors, Operations on Vectors, Section Formula, Concept of Euclidean Distance between two vectors,	
Pedagogy	Lectures/ Lab Assignments/ Seminar Presentations /Project Work	
References/ Readings	1. Linear Algebra, Jin Ho Kwak and Sungpyo Hong, Second edition Springer, 2004. 2. Mathematics for Machine Learning, Marc Peter Deisenroth, A. Aldo Faisal, Cheng Soon Ong,Cambridge University Press, 2020. 3. Operations Research principles and applications, G.Srinivasan, 3rd edition, PHI learning, 2017, 4. Differential Geometry of Curves and Surfaces: Revised and Updated Second Edition, Manfredo P. do Carmo, Dover publications 2016. 5. Linear Algebra and Optimization with Applications to Machine Learning - Volume I. 6. Linear Algebra for Computer Vision, Robotics, and Machine Learning, Jean H. Gallier, Jocelyn Quaintance, World Scientific Publishing Company, 2020. 7. Basics of Matrix Algebra for Statistics with R, Nick Fieller, CRC press, 2016. 8. Introduction to Linear Algebra, Gilbert Strang, 5th Edition, Cengage Learning (2015). 9. Modern Mathematics And Applications In Computer Graphics And Vision, Hongyu Guo, World scientific publishing company,2014. 10. Computer Vision: A Modern Approach, Forsyth and Ponce, 2nd Edition Pearson 2012.	
Course Outcomes	At the end of this course the students are expected to learn 1. The abstract concepts of matrices and system of linear equations using decomposition methods and applications in engineering 2. Understand the geometry behind linear transforms which is used in computer graphics,Understand the concepts of orthogonality through linear algebra 3. Understating properties curves and surfaces and Solving linear programming problems arise in engineering 4. Solving problems in Linear algebra, linear programming and differential geometry using matplotlib or Python.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-527
Title of the Course: Soft Computing
Number of Credits: 4 (2L+2T+0P)
Effective from AY: 2023-24

Prerequisites for the course	Machine Learning, Statistics	
Objectives	The objective of this course is to introduce methods for handling imprecise and uncertain data using Rough sets, Neuro Fuzzy Systems and foster their abilities in designing and implementing optimal solutions for real-world and engineering problems using derivative free optimization techniques.	
Content	**Introduction to Soft Computing** Soft Computing Overview – Uncertainty in data, Hard vs Soft Computing **Neural Networks** Introduction, RBF Networks, Self-Organizing Map, Boltzmann Machines, Convolutional Neural Networks. **Fuzzy Systems** Fuzzy Sets, Fuzzy Relations, and Membership functions, Properties of Membership functions, Fuzzification and Defuzzification. **Fuzzy logic** Fuzzy Rule based systems, Fuzzy Decision making, Fuzzy Classification, Fuzzy CMeans Clustering. **Rough Sets** Rough Sets – Definition, Upper and Lower Approximations, Boundary Region, Decision Tables and Decision Algorithms. Properties of Rough Sets. Rough K-means clustering, Rough **Optimization Techniques** Introduction, Genetic Algorithm, Memetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, Frog-Leaping. **Hybrid Systems** GA Based Back Propagation Networks, Fuzzy Back Propagation Networks, Evolutionary Ensembles	3 hours 2 hours 5 hours 5 hours 5 hours 5 hours 5 hours
Assignments and Mini Project Discussions during the Tutorial Slots:	**List of Assignments:** 1. To demonstrate the working of Hebbian learning rule 2. To demonstrate the working of perceptron learning rule 3. To demonstrate the working of Delta learning rule 4. To demonstrate the working of Widrow-Hoff learning rule 5. To demonstrate the working of Radial basis function network 6. To demonstrate the working of Learning vector quantization 7. To demonstrate the working of Self-Organizing maps 8. To demonstrate the working of Recurrent neural networks 9. To demonstrate the working of Fuzzy inference system 10. To demonstrate the working of Genetic algorithm 11. To demonstrate the working of Particle Swarm Optimization 12. To demonstrate the working of Ant Colony Optimizations and TSP	12 * 2 = 24 hours + 6 hours for a Mini Project

Pedagogy	Lectures / Assignments / Quiz / Mini Project / Seminar Presentations	
References/ Readings	**Main Readings** 1. S.N. Sivanandham and S.N.Deepa, “Principles of Soft Computing”, 2nd Edition, Wiley Publications. 2. Andries P. Engelbrecht, "Computational Intelligence: An Introduction", John Wiley & Sons, 2007. 3. Laurene V. Fausett “Fundamentals of Neural Networks: Architectures, Algorithms And Applications”, Pearson, 1993. 4. Simon Haykin "Neural Networks and Learning Machines" Prentice Hall, 2008. Timothy Ross, “Fuzzy Logic with Engineering Applications”, Third Edition,Wiley.	
Course Outcomes	1. Have a general understanding of soft computing methodologies, to deal with imprecise and uncertain data 2. Develop computational neural network models for some simple biological systems; 3. Develop fuzzy models for engineering systems, particularly for control systems; 4. Apply derivative free optimization methods to solve real world problems 5. Demonstrate some applications of computational intelligence.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-528
Title of the Course: Regression Analytics and Predictive Models
Number of Credits: 4 (2L+2T+0P)
Effective from AY: 2023-24

Prerequisites for the course	Probability Theory and Distributions	
Objectives	● Develop an understanding of regression analysis and model building. ● Provide the ability to develop relationship between variables ● Investigate possible diagnostics in regression techniques ● Formulate feasible solutions using a regression model for real-life problems.	
Theory:	**Simple Regression Analysis** Introduction to a linear and nonlinear model. Ordinary Least Square methods. Simple linear regression model, using simple regression to describe a linear relationship. Fitting a linear trend to time series data, Validating simple regression model using t, F and p test. Developing confidence interval. Precautions in interpreting regression results.	4 hours
	Multiple Regression Analysis Concept of Multiple regression model to describe a linear relationship, Assessing the fit of the regression line, inferences from multiple regression analysis, problem of overfitting of a model, comparing two regression model, prediction with multiple regression equation.	4hours
	Fitting Curves and Model Adequacy Checking Introduction, fitting curvilinear relationship, residual analysis, PRESS statistics, detection and treatment of outliers, lack of fit of the regression model, test of lack of fit, Problem of autocorrelation and heteroscedasticity. Estimation of pure errors from near neighbors.	4 hours
	Transformation techniques Introduction, variance stabilizing transformations, transformations to linearize the model, Box Cox methods, transformations on the repressors variables, Generalized and weighted least squares, Some practical applications.	4 hours
	Multicollinearity Introduction, sources of multicollinearity, effects of multicollinearity. Multicollinearity diagnostics: examination of correlation matrix, variance Inflation factors (VIF), Eigen system analysis of X1X. Methods of dealing with Multicollinearity: collecting additional data, model re-specification, and ridge regression.	4 hours
	Generalized Linear Models Generalized linear model: link functions and linear predictors, parameter estimation and inference in the GLM, prediction and estimation with the GLM, Residual Analysis, and concept of over dispersion.	4 hours
	Model building and Nonlinear Regression Variable selection, model building, model misspecification. Model validation techniques: Analysis of model coefficients, and predicted values, data splitting method. Nonlinear regression model, nonlinear least squares, transformation to linear model, parameter estimation in nonlinear system, statistical inference in nonlinear regression.	6 hours

Assignments and a Mini Project to be discussed during the Tutorial slots:	1. Linear Regression 2. Minimum Least Square Method 3. Calculating coefficients values 4. Ascombe's Quartet 5. Regression Equations- x on y & y on x 6. Predicting mom's height based on daughter's height 7. Regression-Solved problem-2 8. Probable Error- Calculating correlation coefficient of POPULATION 9. Predictive modelling project for credit card fraud detection 10. Predictive modelling project for customer value prediction 11. Predictive modelling project for stock market forecasting 12. Predictive modelling project for corporate bankruptcy prediction	12 * 2 = 24 hours + 6 hours for Mini Project discussions
Pedagogy	Lectures/ tutorials/assignments/self-study	
References/ Readings	1. Douglas C. Montgomery, Elizabeth A. Peck, G. Geoffrey Vining, Introduction to Linear Regression Analysis, Third Ed., Wiley India Pvt. Ltd., 2016. Norman R. 2. Draper, Harry Smith; Applied Regression Analysis, WILEY India Pvt. Ltd. New Delhi; Third Edition, 2015. 3. Johnson, R A., Wichern, D. W., Applied Multivariate Statistical Analysis, Sixth Ed., PHI learning Pvt., Ltd., 2013. 4. Iain Pardoe, Applied Regression Modeling, John Wiley and Sons, Inc, 2012.	
Course Outcomes	1.Develop in-depth understanding of the linear and nonlinear regression model. 2.Demonstrate the knowledge of regression modeling and model selection techniques. 3.Examine the relationships between dependent and independent variables. 4.Estimate the parameters and fit a model.	

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Name of the Programme: M.Sc. in Artificial Intelligence
Course Code: CSI-529
Title of the Course: Essentials of Data Analytics
Number of Credits: 4(2L+2T+0P)
Effective from AY: 2023-24

Prerequisites for the course	Probability and Statistics	
Objectives	1. To understand the concepts of analytics using various machine learning models. 2. To appreciate supervised and unsupervised learning for predictive analysis. 3. To understand data analytics as the next wave for businesses looking for competitive advantage. 4. Carry out rule-based analysis of the data in line with the analysis plan. 5. Validate the results of their analysis according to statistical guidelines. 6. Validate and review data accurately and identify anomalies. 7. To learn aspects of computational learning theory. 8. Apply statistical models to perform Regression Analysis, Clustering and Classification.	
Theory:	**Module:1** Regression Analysis Linear regression: simple linear regression - Regression Modelling - Correlation, ANOVA, Forecasting, Autocorrelation	5 hours
	Module:2 Classification Logistic Regression, Decision Trees, Naïve Bayes-conditional probability - Random Forest - SVM Classifier	5 hours
	Module:3 Clustering K-means, K-medoids, Hierarchical clustering	5 hours
	Module:4 Optimization Gradient descent - Variants of gradient descent - Momentum - Adagrad - RMSprop - Adam - AMSGrad	5 hours
	Module:5 case study -Managing Health and Safety Comply with organization's current health, safety and security policies and procedures - Report any identified breaches in health, safety, and security policies and procedures to the designated person - Identify and correct any hazards that they can deal with safely, competently and within the limits of their authority - Report any hazards that they are not competent to deal with to the relevant person in line with organizational procedures and warn other people who may be affected.	5 hours
	Module:6- requirement analysis - Data and Information Management Establish and agree with appropriate people the data/information they need to provide, the formats in which they need to provide it, and when they need to provide it - Obtain the data/information from reliable sources - Check that the data/information is accurate, complete and up-to-date	3 hours
	Module:7 Learning and Self Development Obtain advice and guidance from appropriate people to develop their knowledge, skills and competence - Identify accurately the knowledge and skills they need for their job role - Identify accurately their current level of knowledge, skills and competence and any learning and development needs - Agree with appropriate people a plan of learning and development activities to address their learning needs	2 hours

Practicals to be discussed during Tutorial Slots:	1. Web Scraping:- a. While you'll find no shortage of excellent (and free) public data sets on the internet, you might want to show prospective employers that you're able to find and scrape your own data as well. Plus, knowing how to scrape web data means you can find and use data sets that match your interests, regardless of whether or not they've already been compiled. b. If you know some Python, you can use tools like Beautiful Soup or Scrapy to crawl the web for interesting data. If you don't know how to code, don't worry. You'll also find several tools that automate the process (many offer a free trial), like Octoparse or ParseHub. c. If you're unsure where to start, here are some websites with interesting data options to inspire your project: d. Reddit, Wikipedia, Job portals 2. Data Cleaning a. A significant part of your role as a data analyst is cleaning data to make it ready to analyze. Data cleaning (also called data scrubbing) is the process of removing incorrect and duplicate data, managing any holes in the data, and making sure the formatting of data is consistent. b. As you look for a data set to practice cleaning, look for one that includes multiple files gathered from multiple sources without much curation. Some sites where you can find "dirty" data sets to work with include: c. CDC Wonder, Data.gov, World Bank, Data.world/r/datasets 3. Exploratory data analysis (EDA) a. Data analysis is all about answering questions with data. Exploratory data analysis, or EDA for short, helps you explore what questions to ask. This could be done separate from or in conjunction with data cleaning. Either way, you'll want to accomplish the following during these early investigations. b. Ask lots of questions about the data. c. Discover the underlying structure of the data. d. Look for trends, patterns, and anomalies in the data. e. Test hypotheses and validate assumptions about the data. f. Think about what problems you could potentially solve with the data. 4. Sentiment analysis a. Sentiment analysis, typically performed on textual data, is a technique in natural language processing (NLP) for determining whether data is neutral, positive, or negative. It may also be used to detect a particular emotion based on a list of words and their corresponding emotions (known as a lexicon). b. This type of analysis works well with public review sites and social media platforms, where people are likely to offer public opinions on various subjects. c. To get started exploring what people feel about a certain topic, you can start with sites like: Amazon (product reviews), Rotten Tomato (movie reviews), Facebook witter, News sites 5. Data visualization a. Humans are visual creatures. This makes data visualization a powerful tool for transforming data into a compelling story to	5 * 6 = 30 hours

	encourage action. Great visualizations are not only fun to create, they also have the power to make your portfolio look beautiful.	
Pedagogy	Lectures/Assignments/Seminar Presentations/Mini-Project	
References/ Readings	1.Cathy O'Neil and Rachel Schutt. "Doing Data Science, Straight talk from the Frontline",O'Reilly. 2014. 2.Dan Toomey, "R for Data Science", Packt Publishing, 2014. 3.Trevor Hastie, Robert Tibshirani and Jerome Friedman. "Elements of Statistical Learning",Springer , Second Edition. 2009. 4.Kevin P. Murphy. "Machine Learning: A Probabilistic Perspective", MIT Press; 1st Edition, 2012. **Reference Books** Glenn J. Myatt, "Making Sense of Data: A Practical Guide to Exploratory Data Analysis and Data Mining", John Wiley & Sons, Second Edition, 2014. G. K. Gupta, —Introduction to Data Mining with Case Studies", Easter Economy Edition, Prentice Hall of India, 2006. Michael Berthold, David J. Hand, "Intelligent Data Analysis", Springer, 2007. Colleen Mccue, "Data Mining and Predictive Analysis: Intelligence Gathering and Crime Analysis", Elsevier, 2007. R N Prasad, Seema Acharya, "Fundamentals of Business Analytics", Wiley; Second edition, 2016. https://www.sscnasscom.com/qualification-pack/SSC/Q2101/ Mode of Evaluation: ISA/Assignment / Quiz / Project / Seminar	
Course Outcomes	1. Identify and apply the appropriate supervised learning techniques to solve real world problems with labeled data. 2. Choose and implement typical unsupervised algorithms for different types of applications with unlabelled data. 3. Implement statistical analysis techniques for solving practical problems. 4. Understand different techniques to optimize the learning algorithms.	

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