Shirpur Education Society's

R. C. Patel Institute of Technology, Shirpur

(An Autonomous Institute)

Course Structure and Syllabus

Final Year B. Tech

Computer Science and Engineering (Data Science)

With effect from Year 2026-27
(RCP23 NEP Scheme)

Shahada Road, Near Nimzari Naka, Shirpur, Maharashtra 425405
Ph: 02563 259 802, Web: www.rcpit.ac.in

R. C. PATEL
INSTITUTE OF TECHNOLOGY
An Autonomous Institute

R. C. Patel Institute of Technology, Shirpur

Institute Vision

To become a leading Institute in Technical education fostering innovation, research, ethical values, and sustainable development for the betterment of society.

Institute Mission

To impart high quality Technical Education through:

M1: Innovative and Interactive learning process and high quality, globally recognized instructional programs.

M2: Fostering a collaborative scientific temper among students with ethical responsibility towards the society.

M3: Preparing students from diverse backgrounds to have aptitude for employment, entrepreneurship and research with a spirit of professionalism.

M4: To contribute to nation's sustainable development.

Department of Computer Science & Engineering (Data Science)

Department Vision

To provide cutting-edge Computer Engineering education in Data Science while instilling socio-moral values.

Department Mission

M1: To deliver state-of-the-art, ICT-enabled teaching and learning to achieve excellence in Data Science education.

M2: To develop professionally competent Data Science Engineers, meeting evolving industrial and societal needs.

M3: To prepare employable professionals with ethical values and a commitment to professional and social responsibility.

Program Educational Objectives (PEOs) of the Department

PEO1: Graduates will achieve proficiency in Data Science and pursue lifelong learning to advance as professionals, entrepreneurs, and leaders.

PEO2: Graduates will operate effectively in diverse, dynamic professional and cultural environments, respecting societal perspectives.

PEO3: Graduates will demonstrate ethical values and social responsibility in their professional and personal lives.

Program Specific Outcomes (PSOs) of the Department

PSO1: Apply programming concepts, algorithms, and data structures to develop data-driven software and web solutions.

PSO2: Develop intelligent solutions using machine learning, data analysis, and cloud technologies for practical problem-solving.

Final Year B. Tech Computer Science and Engineering (Data Science) Semester-VII/VIII (w.e.f. 2026-27)

Sr	Course Category	Course Code	Course Title	Teaching Scheme			Evaluation Scheme					Total	Credit	
							Continuous Assessment (CA)							
							TA	Term Test 1 (TT1)	Term Test 2 (TT2)	Average of (TT1 & TT2)	ESE			
				L	T	P	[A]			[B]	[C]	[A+B+C]		
1	PC	RCP23DCPC701	Language and Reasoning Models	3			25	15	15	15	60	100	3	4
	PC	RCP23DLPC701	Language and Reasoning Models Laboratory			2	25					25	1	
2	PC	RCP23DCPC702	High Performance Computing	3			25	15	15	15	60	100	3	4
	PC	RCP23DLPC702	High Performance Computing Laboratory			2	25				25	50	1	
3@	PE	RCP23DCPE711	Geospatial Data Science	3			25	15	15	15	60	100	3	4
		RCP23DLPE711	Geospatial Data Science Laboratory			2	25					25	1	
		RCP23DCPE712	Computational Motion Planning	3			25	15	15	15	60	100	3	
		RCP23DLPE712	Computational Motion Planning Laboratory			2	25					25	1	
		RCP23DCPE713	Quantum Computing	3			25	15	15	15	60	100	3	
		RCP23DLPE713	Quantum Computing Laboratory			2	25					25	1	
		RCP23DCPE714	Adversarial Machine Learning	3			25	15	15	15	60	100	3	
		RCP23DLPE714	Adversarial Machine Learning Laboratory			2	25					25	1	
4	MD	RCP23DCMD701	Data Ethics	3			25	15	15	15	60	100	3	4
	MD	RCP23DTMD701	Data Ethics Tutorial		1		25					25	1	
5	EL	RCP23ITELX08	Research Ecosystem		2		50					50	2	2
6	EL	RCP23IPEL701	Project Stage-II			8	50				50	100	4	4
7	HS	RCP23ICHSX09	Disaster Management and Preparedness	2									Audit Course	
8	SC	RCP23DCSC701	Generative AI	1			40					40	1	1
			Total	15	3	14	340			60	315	715	23	

@ Any 1 Programme Elective Course

Prepared by:
Dr. M. S. Patil

Prof. Dr. U. M. Patil
BOS Chairman

Prof. Dr. P. J. Deore
Dean Academics/Dy. Director

Checked by:
Dr. P. S. Sanjekar

Prof. S. P. Shukla
C.O.E.

Prof. Dr. J. B. Patil
Director

R.C.Patel Institute of Technology
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Semester-VII/VIII(w.e.f. 2026-27)														
Sr	Course Category	Course Code	Course Title	Teaching Scheme			Evaluation Scheme					Total	Credit	
							Continuous Assessment (CA)							
							TA	Term Test 1 (TT1)	Term Test 2 (TT2)	Average of (TT1 &TT2)	ESE			
				L	T	P	[A]			[B]	[C]	[A+B+C]		
1	PE	RCP23DCPE811	Bioinformatics*	3			25	15	15	15	60	100	3	3
		RCP23DCPE812	Green Data Science*	3			25	15	15	15	60	100	3	
		RCP23DCPE813	Causal Inference and Decision Intelligence*	3			25	15	15	15	60	100	3	
		RCP23DCPE814	Immersive Systems: AR/VR and Human-Computer Interaction*	3			25	15	15	15	60	100	3	
			NPTEL/Swayam Course#	3			25	15	15	15	60	100	3	
2	EL	RCP23IPELX10	Internship (OJT) cum Project			36	200				200	400	18	
3	SC	RCP23DCSC801	Agentic AI	1			40					40	1	
			Total	4		36	265			15	260	540	22	

1. @ Any 1 Programme Elective Course.
2. * Programme Elective Courses offered for the students doing Internship(OJT).
3. # Programme Elective Courses offered for the students doing Internship(OJT).
   These courses are to be studied in self-study mode using NPTEL/SWAYAM platform.
   Students doing Internship (OJT) shall submit certificates of NPTEL examination OR they have to appear examinations conducted by institute like TT1, TT2 and ESE.
   Students undergoing Internship (OJT) have the option to appear for both the NPTEL examination and End Semester Examination (ESE) conducted by institute for respective course. In such cases, the better of the two scores (NPTEL or ESE) shall be considered for final grading.
   List of NPTEL courses will be declared by concerned BOS at the beginning of semester.

Prepared by:
Dr. M. S. Patil

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BOS Chairman

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Dean Academics/Dy. Director

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Semester - VII

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII
Language and Reasoning Models (RCP23DCPC701)		
Language and Reasoning Models Laboratory (RCP23DLPC701)		

Prerequisite: Machine Learning and Natural Language Processing.

Course Objective(s):

To introduce the fundamentals of natural language models, pre-training, fine-tuning, and evaluation techniques. The course aims to provide hands-on experience in developing and deploying large language models (LLMs) while addressing ethical concerns and safety measures.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Apply the principles of Transformers, BERT, and GPT to develop Solution for natural language processing tasks.	L3	Apply
CO2	Apply pre-training and fine-tuning techniques to optimize language models for real-world applications.	L3	Apply
CO3	Analyze various evaluation metrics to assess the performance and reliability of language models.	L4	Analyze

Language and Reasoning Models (RCP23DCPC701) Course Contents

Unit-I **06 Hrs.**

Natural Language Generation:

Limitations of RNNs & LSTMs in Language Modeling, Encoder-Decoder Models

Attention Mechanism: Motivation & Evolution, Seq2Seq with Attention.

Transformers:

Self-Attention Mechanism: Query-Key-Value Representation ,Scaled Dot-Product Attention , Multi-Head Attention, Positional Encoding, Transformer-based Encoder- Decoder Architectures.

Unit-II **10 Hrs.**

Large Language Models Architectures:

Encoder Models: BERT architecture and working, BERT variants: RoBERTa, ALBERT, DistilBERT, Applications: Text Classification, Named Entity Recognition (NER) Decoder Models (Autoregressive LLMs, GPT Family (GPT-3, GPT-4, GPT-4 Turbo).

Open-source models: LLaMA.

Limitations of LLMs:

Hallucination, Cost, Latency, Environmental Impact, Data Privacy Concerns.

Pre-training Strategies:

Self-Supervised Learning in LLMs, Next Token Prediction (Auto-regressive) vs. Masked Language Models (Auto-encoding), Pre-training Methods: Causal LM, Prefix LM, Sequence-to-Sequence Pre-training.

Unit-III **07 Hrs.**

Small Language Models (SLMs) & Efficient AI::

Need for Small Language Models in Real-world Systems, Resource-constrained AI Applications, Edge AI and On-device Inference.

Model Compression Techniques:

Knowledge Distillation, Quantization, Pruning, Low-rank Adaptation (LoRA), Adapter Layers. Performance vs Efficiency Trade-offs, Memory and Latency Optimization.

Unit-IV **07 Hrs.**

LLM/SLM Applications & Intelligent Systems:

Prompt Engineering Techniques: Zero-shot, One-shot, Few-shot Prompting, Chain-of-Thought Prompting, ReAct Prompting. Fine-tuning and Instruction Tuning, Transfer Learning, Parameter-efficient Fine-tuning (PEFT).

Retrieval-Augmented Generation (RAG), Vector Databases and Embeddings,LangChain Framework.

Applications: Chatbots, AI Assistants, Document QA Systems, Legal and Medical NLP Systems, Autonomous AI Agents.

Unit-V 06 Hrs.

Reinforcement Learning with Human Feedback (RLHF) & Safety:

RLHF Process in Modern LLMs: Reward Modelling for LLM Alignment, Reinforcement Learning Techniques: Proximal Policy Optimization (PPO), Comparative Ranking & Preference Learning, Group Relative Policy Optimization (GRPO).

RLAF: Reinforcement Learning through Agent Feedback (RLAF) ,How RLAF works, Difference between RLAF and RLHF.

Unit-VI 06 Hrs.

Deployment, Evaluation & Responsible AI:

Deployment Pipelines for LLMs and SLMs using APIs, Cloud, Local and Edge Devices. Latency and Cost Optimization Strategies, GPU and Hardware Considerations.

Evaluation Metrics: BLEU, ROUGE, METEOR, BERTScore, MMLU, HELM, TruthfulQA, Human Evaluation Methods.

Responsible AI: Bias, Fairness, Hallucination Mitigation, Adversarial Attacks, Safety Alignment.

Language and Reasoning Models Laboratory (RCP23DLPC701)

List of Laboratory Experiments

Suggested Experiments

1. Implement Sequence-to-Sequence (Seq2Seq) and Attention-based Models for Language Translation.

2. Implement Self-Attention and Multi-Head Attention using Transformer Architecture.

3. Build Transformer-based NLP Applications for Text Classification or Summarization.

4. Perform Tokenization using BPE and WordPiece Techniques.

5. Use Pretrained LLMs (GPT/BERT Family) for Text Generation and Question Answering.

6. Fine-tune Pretrained Language Models using LoRA / PEFT Techniques.

7. Implement Prompt Engineering Techniques: Zero-shot, Few-shot, and Chain-of-Thought Prompting.

8. Develop Retrieval-Augmented Generation (RAG) System using LangChain and Vector Database.

9. Deploy Lightweight Language Models Locally and Compare Performance Metrics with Large Language Models.

10. Apply Quantization and Pruning Techniques for Efficient Small Language Model (SLM) Deployment.

11. Build and Deploy a Chatbot / Document Question Answering System using LLM or SLM.

12. Mini Project

Above-suggested list or any other experiment or mini project based on syllabus will be included, which would help the learner to apply the concept learnt.The Term Work will be calculated based on Laboratory Performance.

Text Books:

1. Tanmoy Chakraborty “Introduction to Large Language Models” Wiley India 1^{st} Edition,2025.

2. Jurafsky and Martin, “Speech and Language Processing”, Prentice Hall, 4^{th} Edition, 2020.

3. Uday Kamath, “Deep Learning for NLP and Speech Recognition”, 1^{st} Edition, 2019.

Reference Books:

1. Jelinek, F., “Statistical Methods for Speech Recognition”, The MIT Press, 2022.

2. Yuli Vasiliev “Natural Language Processing with Python and spaCy - A Practical Introduction”, No Starch Press, 2022.

3. Sowmya Vajjala, Bodhisattwa Majumder, Anuj Gupta, Harshit Surana, “Practical Natural Language Processing: A Comprehensive Guide to Building Real-World NLP Systems”, O’Reilly, 1^{st} Edition, 2020.

Web Links:

1. NPTEL link: Introduction to Large Language Models (LLMs) - Announcements

2. NPTEL Course: https://cse.iitm.ac.in/ miteshk/llm-course.html

3. NPTEL Course: https://onlinecourses.swayam2.ac.in/imb24_mg116/preview

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII
High Performance Computing (RCP23DCPC702)		
High Performance Computing Laboratory (RCP23DLPC702)		

Prerequisite: Computer System Fundamentals.

Course Objective(s):

This course in High-Performance Computing (HPC) for Data Science with an emphasis on GPU parallel computing introduces students to the fundamental concepts and practical skills necessary for harnessing the power of Graphics Processing Units (GPUs) in data-intensive computations. Throughout the course, students will explore GPU architecture, CUDA programming, memory optimization techniques, parallel programming patterns, and performance optimization strategies. They will also delve into advanced topics like GPU-accelerated libraries and the integration of GPUs with popular data science frameworks. By the end of this course, students will be equipped to leverage GPU parallel computing to significantly enhance the efficiency and performance of data science applications.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Apply the principles of parallel computing, parallel programming models, performance metrics, and the architectural features of multicore CPUs and GPUs.	L3	Apply
CO2	Apply shared-memory programming techniques and the CUDA programming model to develop parallel solutions for data- and task-parallel applications.	L3	Apply
CO3	Analyze GPU performance metrics, including memory coalescing, thread scheduling, and control divergence impacts.	L4	Analyze
CO4	Analyze GPU performance by evaluating memory access patterns, thread execution efficiency, and optimization techniques to improve the scalability and performance of parallel applications.	L4	Analyze

High Performance Computing (RCP23DCPC702) Course Contents

Unit-I 07 Hrs.

Introduction to Parallel Computing and Programming Models:

Introduction to Parallel Computing:

Sequential vs Parallel Computing, Need and Applications of Parallel Computing, Limitations of Single-Core CPUs, Multicore CPU Architecture, Flynn's Taxonomy, Shared Memory and Distributed Memory Architectures.

Parallel Computing Architectures and Models:

Shared Memory and Distributed Memory Architectures, Data Parallel Model, Task Parallel Model

Unit-II 07 Hrs.

Parallel Programming Issues and Performance Analysis:

Programmability Issues:

Challenges in Parallel Programming, Communication and Synchronization Overheads, Race Conditions and Critical Sections.

Data Dependency Analysis:

Flow Dependency, Anti Dependency, Output Dependency, Loop Dependency Basics.

Performance Metrics:

Speedup, Efficiency, Scalability and Amdahl's Law.

Unit-III 07 Hrs.

Shared Memory and GPU Parallel Programming using CUDA

Shared Memory Programming: Shared Memory Concepts, Mutual Exclusion, Locks and Mutex, Barriers and Synchronization.

Thread-based Implementation:

Introduction to Threads, Thread Creation and Execution, POSIX Threads/OpenMP Concepts.

CUDA Parallelism Model: Architecture of a Modern GPU, CUDA Programming Model, CUDA C Program Structure, Kernel Functions and Threading, Vector Addition Kernel, Device Global Memory and Data Transfer, CUDA Thread Organization, Thread Scheduling and Latency Tolerance.

Unit-IV 08 Hrs.

GPU Memory Architecture and Performance Analysis

Memory Access Performance: Global Memory Bandwidth, Memory Coalescing in CUDA, Channels and Banks in Dram Systems, Techniques for Reducing Memory Transfers Between CPU and

GPU.

Memory and Data Locality: CUDA Memories, Tiled Parallel Algorithms, Tiled Matrix Multiplication, Tiled Matrix Multiplication Kernel, Boundary Checks, Memory as A Limiting Factor to Parallelism.

Thread Execution Efficiency: Warps and SIMD Hardware, Dynamic Partitioning of Resources, Performance Impact of Control Divergence.

Unit-V 06 Hrs.

Parallel Computation Patterns

Convolution Patterns: 1d Parallel Convolution - A Basic Algorithm, Constant Memory and Caching, Tiled 1d Convolution with Halo Cells, A Simpler Tiled 1d Convolution - General Caching.

Histogram Patterns: Atomic Operations in CUDA, Atomic Operation Performance- Block versus Interleaved Partitioning, Latency versus Throughput of Atomic Operations, Atomic Operation in Cache Memory, Privatization Technique for Improved Throughput.

Unit-VI 07 Hrs.

GPU Performance Tuning and Optimization:

Efficient Host-Device Data Transfer: Pinned Host Memory, Task Parallelism in CUDA, Overlapping Data Transfer with Computation, CUDA Unified Memory.

Techniques for optimizing GPU performance: Warp Divergence, Loop Unrolling, Vectorization, Memory Bandwidth Optimization Techniques, Advanced GPU Programming Concepts (Shared Memory Atomics, Warp Shuffling).

High Performance Computing Laboratory (RCP23DLPC702)

List of Laboratory Experiments

Suggested Experiments

1. Demonstrate dependency analysis on parallel loops/programs to identify data dependencies affecting parallel execution.
2. Implement multithreading using POSIX Threads/OpenMP to understand thread creation and synchronization.
3. Demonstrate mutual exclusion in shared memory programming using mutex/locks.
4. Set up the CUDA environment and implement vector addition using CUDA to understand parallelism, thread management, and memory allocation.
5. Develop a CUDA program for matrix multiplication to understand parallelism and optimization techniques in GPU computing.

6. Apply CUDA for image processing tasks, like blurring and edge detection, to learn how to process images efficiently using GPU parallelism.

7. Implement parallel reduction operations (e.g., sum, min, max) to grasp the concept of efficient parallel reduction.

8. Implement 1D convolution using CUDA to understand parallel convolution and shared memory optimization.

9. Implement histogram computation using CUDA atomic operations and analyze synchronization overheads.

10. Demonstrate the impact of warp divergence and memory coalescing on GPU performance using CUDA kernels.

Above-suggested list or any other experiment or mini project based on syllabus will be included, which would help the learner to apply the concept learnt.The Term Work will be calculated based on Laboratory Performance.

Oral examination will be based on the entire syllabus including, the practicals performed during laboratory sessions.

Text Books:

1. Georg Hager, Gerhard Wellein, “Introduction to High Performance computing for Scientist and Engineers”, CRC press, 2019.

2. Duane Storti and Mete Yurtoglu, ”CUDA for Engineers”, Addison-Wesley, 1^{st} Edition, 2016.

3. M. Sasikumar, Dinesh Shikhare, P. Ravi Prakash, “Introduction to Parallel Processing”, Prentice-Hall of India, 2005.

Reference Books:

1. David B. Kirk and Wen-mei W. Hwu, ”Programming Massively Parallel Processors: A Hands-on Approach”, Morgan Kaufmann, 2^{nd} Edition, 2012.

2. Charles Severance and Kevin Dowd, ”High Performance Computing”, O’Reilly Media, 2^{nd} Edition, 1998.

3. Jason Sanders and Edward Kandrot, ”CUDA by Example: An Introduction to General-Purpose GPU Programming”, Addison-Wesley, 2010.

4. NVIDIA Corporation, ”GPU Gems”, Addison-Wesley

5. Gerhard Hager and Markus Hadwiger, ”Programming the GPU with CUDA”, Springer

6. Brian Tuomanen and Daniel Kim, ”Deep Learning with CUDA”, O’Reilly Media

Web Links:

1. HPC: https://archive.nptel.ac.in/courses/106/105/106105033/.

2. HPC Springer Journal: https://link.springer.com/book/10.1007/978-3-030-13325-2.

3. Programming Model:

   https://homepage.physics.uiowa.edu/ ghowes/teach/phys5905/lect/NumLec11_IntroHPC.pdf.

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII
Geospatial Data Science (RCP23DCPE711)		
Geospatial Data Science Laboratory (RCP23DLPE711)		

Prerequisite: Fundamentals of Data Analysis and Machine Learning.

Course Objective(s):

This course introduces geospatial data sources, satellite imagery, GPS, and open datasets. Students will learn to work effectively with spatial data through pre-processing, cleaning, and geocoding techniques for seamless integration.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Apply tools and techniques used to analyze and visualize geospatial data.	L3	Apply
CO2	Apply data science methods to solve real-world problems with geospatial data.	L3	Apply
CO3	Analyze geospatial large data models and ethical issues.	L4	Analyze

Geospatial Data Science (RCP23DCPE711)
Course Contents

Unit-I 06 Hrs.

Introduction to Geospatial Data:

Introduction to Geographic Information Systems (GIS), Data Collection and Sources, Remote sensing and satellite imagery, GPS data and tracking, Coordinate systems and projections, Overview of geospatial data: Coordinates, attributes, temporal information; static and dynamic data

Spatial Data Types: vector and raster data, network data and Spatial

Data Formats: shape files, geodatabases

Spatial data structures: Geometric objects (Points, lines and polygon), qualitative binary relation between geometrics and GSD applications.

Unit-II 08 Hrs.

Geospatial Data Modeling:

Feature based approach: point, curve, surface, geometry collection; Algebra and calculi of qualitative spatial relations, topological relations, RCC-8, cardinal directions, Field based approach. Spatial regression, clustering, and optimization, Geo statistics and spatial modeling, Predictive modeling with geospatial data.

Case study: Predicting property values, Spatial Analysis, Buffer analysis, spatial joins, spatial econometrics and geographically weighted regression (GWR).

Unit-III 09 Hrs.

Linked Geospatial Data:

Visualizing Linked Geospatial Data, Querying Geospatial Data Expressed in RDF, Transforming Geospatial Data into RDF, Introduction to SPARQL: Query structure and its Components, Geospatial queries using SPARQL, Interlinking Geospatial Data Sources, Incomplete Geospatial Information, Geospatial RDF stores, Geospatial Knowledge Graphs, Question Answering Engines for Geospatial Knowledge Graphs, choropleth mapping.

Unit-IV 06 Hrs.

Geospatial Visualization:

Introduction to data visualization libraries (e.g., Matplotlib, Folium, Plotly), Creating basic maps and charts, customizing geospatial visualizations, creating maps and charts, Python toolkits for Geospatial Visualization. Spatial Data, GIS, Geospatial Data, Geospatial Analysis, Data Visualization

Unit-V 08 Hrs.

Data Ingestion & Big Data:

web scraping and APIs, distributed computing frameworks (e.g., Google Earth Engine, Hadoop GIS, GeoSpark, and Dask for geospatial data), and Google BigQuery GIS for scalable processing;

Streaming Geospatial Data: IoT devices, GPS tracking, weather stations, and OpenStreetMap live updates.

Spatial Analysis: Role in decision-making and pattern discovery,Spatial queries and operations;

Spatial Query optimization using Spatial Data Indexing: Quadtrees, R-trees, and Hilbert Curves to optimize geospatial queries.

Spatial Relationships & Topology: topological consistency (e.g., via OGC Simple Features Specification).

Spatial Statistics: spatial autocorrelation (Moran's I,Geary's C), and spatial interpolation techniques (Kriging,IDW).

Unit-VI 05 Hrs.

GIS Softwares:

Introduction to web mapping tools (e.g., Leaflet), Exploring GIS software (e.g., QGIS, ArcGIS), Introduction to geospatial libraries (e.g., Geopandas, Fiona, Shapely), Building interactive web maps, Geospatial big data and distributed computing, Machine learning for geospatial data, Geo Spatial Data Ethics, Ethical considerations in geospatial data analysis.

Geospatial Data Science Laboratory (RCP23DLPE711)

List of Laboratory Experiments

Suggested Experiments

1. Apply cyberGIS techniques to analyze and visualize big geospatial data in Python using advanced cyberinfrastructure and high-performance computing.

2. Apply Python tools for developing high-performance geospatial computing solutions. Optimize and speed up geospatial computation using Python libraries like Numba, Cython and Dask, Ray, or PySpark for large-scale geospatial processing.

3. Implement open source mapping and large-scale geospatial visualization libraries such as Leaflet, D3, Plotly Kepler.gl, Deck.gl and Cesium.js for 3D geospatial applications and mash up these libraries to create interactive and dynamic visualization tools and GIS applications.

4. Apply tools to investigate and identify patterns, clusters, classes, and anomalies based on various types of geospatial data and apply these techniques to a variety of geospatial applications.

5. Apply advanced techniques of spatial analysis, including spatial autocorrelation, trend surface analysis, grouping and regionalization procedures, and point pattern analysis to solve

geospatial problems. spatial clustering methods (e.g., DBSCAN, K- Means with spatial constraints,HDBSCAN) and spatial econometrics modeling (spatial lag and spatial error models).

6. Solve given geospatial problem using ESRI ArcGIS solutions stack.
7. Identify right tool to interlink dataset to transform unlinked geospatial data into linked data using geospatial semantic technologies (geospatial ontologies, stRDF, stSPARQL, GeoSPARQL, OBDA mappings techniques. thing (e.g., a dataset containing information about roads in Crete can be interlinked with a dataset containing land cover information about Crete).
8. Analyze and visualize the data with the help of appropriate linked data tools using asequence of GeoSPARQL queries.
9. Geospatial science in forestry and watershed management. Geospatial science in urban planning and resource management.
10. Use geospatial libraries for Geospatial Data Analysis with Python (e.g., Geopandas, Fiona Shapely for Analyzing and visualizing geospatial data in Python.
11. Demonstrate the use of Apache, Jena and Stardog for managing large-scale geospatial knowledge graphs.

Above-suggested list or any other experiment or mini project based on syllabus will be included, which would help the learner to apply the concept learnt.The Term Work will be calculated based on Laboratory Performance.

Text Books:

1. Geospatial Data Science: A Hands-on Approach for Building Geospatial Applications Using Linked Data Technologies June 2023.
2. David S. Jordan "Applied Geospatial Data Science with Python", Feb 2023.

Reference Books:

1. Chris Garrard, "Geoprocessing with Python", Manning Publisher, 2016.
2. Michael J. de Smith, Michael F. Goodchild, and Paul A. Longley, "Geospatial Analysis: A Comprehensive Guide", Winchelsea Press, 2018.
3. The Ultimate Guide to Geospatial Data Science, Geospatial Data Science Explained: A Full Guide - Aya Data
4. Janahan Gnanachandran, "Geospatial data analysis on AWS", ACM Publisher,2023.
5. Paul A. Zandbergen, "Geospatial Data Science: Techniques and Applications",2020.

6. Kang-Tsung Chang, "Introduction to Geographic Information Systems" , McGraw-Hill Education,2019.

Web Links:

1. The Ultimate Guide to Geospatial Data Science, Geospatial Data Science Explained: A Full Guide - Aya Data https://www.ayadata.ai/the-ultimate-guide-to-geospatial-data-science/

2. https://www.safegraph.com/guides/geospatial-data

3. https://geographicdata.science/book/intro.htmlgeographic-data-science-with-python

4. https://www.spatialanalysisonline.com/HTML/index.html geospatial_analysis_and_model_.htm

5. https://docs.qgis.org/3.44/en/docs/gentle_gis_introduction/

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII/VIII
Computational Motion Planning (RCP23DCPE712)		
Computational Motion Planning Laboratory (RCP23DLPE712)		

Prerequisite: Linear Algebra, Data Structures, Artificial Intelligence.

Course Objective(s):

To equip students with the ability to model, analyze, and implement computational algorithms for efficient and collision-free motion planning in robotic and autonomous systems.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Analyze motion planning techniques in robotics.	L3	Apply
CO2	Apply efficient path planning algorithms for real-world scenarios.	L3	Apply
CO3	Apply sampling-based and optimization-based planning methods.	L4	Apply
CO4	Evaluate planning strategies under uncertainty and constraints.	L5	Evaluate

Computational Motion Planning (RCP23DCPE712) Course Contents

Unit-I **07 Hrs.**

Introduction to Motion Planning:

Robotics overview, Motion planning problem, Configuration Space (C-space), Degrees of Freedom (DoF), Workspace vs C-space, Obstacles and free space, Problem formulation (start, goal, constraints), Complexity of motion planning.

Unit-II **07 Hrs.**

Geometric Motion Planning:

Exact Cell Decomposition, Approximate Cell Decomposition, Vertical decomposition, Roadmap methods: Visibility graphs, Voronoi diagrams, Minkowski sum, Obstacle expansion, Shortest path in polygonal environments.

Unit-III **07 Hrs.**

Advanced Search and Replanning Techniques:

Limitations of classical search in motion planning, Heuristic design for robotics, State lattices and motion primitives, Incremental search algorithms: D*, D* Lite, Anytime algorithms: ARA, Anytime RRT, Real-time replanning in dynamic environments.

Unit-IV **08 Hrs.**

Sampling-Based Motion Planning:

Limitations of exact planning in high dimensions, Overview of sampling-based planning (PRM, RRT), Advanced methods: RRT*, Informed RRT*, BIT*, Optimization-based planning (CHOMP, STOMP), Learning-based motion planning, Sampling strategies, Nearest neighbor search, Probabilistic completeness, Comparison of PRM and RRT.

Unit-V **07 Hrs.**

Kinodynamic and Constrained Planning:

Forward and Inverse Kinematics, Non-holonomic constraints, Differential constraints, Trajectory planning, Time-parameterized planning, Path smoothing, Introduction to optimal control.

Unit-VI **06 Hrs.**

Planning Under Uncertainty and Applications:

Motion planning under uncertainty, Basics of SLAM, Belief space planning (intro), Markov Decision

Process (overview), Multi-robot motion planning, Task and Motion Planning (TAMP), Applications: autonomous vehicles, drones, robotic manipulation.

Computational Motion Planning Laboratory (RCP23DLPE712)

List of Laboratory Experiments

Suggested Experiments

1. Dynamic Replanning – D Lite*
   - Implement D* Lite algorithm
   - Analyze performance in dynamic environments.
2. Heuristic Analysis in Dynamic Planning
   - Study role of heuristics in D* Lite
   - Compare performance under different heuristic choices.
3. Geometric Planning – Visibility Graph Construction
   - Construct visibility graph for polygonal obstacles
   - Represent nodes and edges.
4. Geometric Planning – Shortest Path Computation
   - Compute shortest path using visibility graph
   - Analyze optimality and efficiency
5. Sampling-Based Planning – PRM (Roadmap Generation)
   - Implement PRM
   - Generate roadmap using random sampling
6. Sampling-Based Planning – PRM (Query Phase)
   - Perform path query using PRM
   - Analyze connectivity
7. Sampling-Based Planning – RRT
   - Implement Rapidly-exploring Random Tree
   - Study exploration behavior
8. Comparative Study – PRM vs RRT

- Compare: Path quality, Computation time, Success rate

9. Kinodynamic Planning

   - Generate trajectories under motion constraints
   - Apply path smoothing techniques.

10. Mini Project: Autonomous Robot Navigation

    - Implement complete motion planning pipeline
    - Use ROS/Python for simulation

Above-suggested list or any other experiment or mini project based on syllabus will be included, which would help the learner to apply the concept learnt.The Term Work will be calculated based on Laboratory Performance.

Text Books:

1. Planning Algorithms, Cambridge University Press, 2006.
2. Principles of Robot Motion, MIT Press, 2005.

Reference Books:

1. Kevin M. Lynch and Frank C. Park, Modern Robotics: Mechanics, Planning, and Control, Cambridge University Press, 2017.
2. Steven M. LaValle, Virtual Reality, Cambridge University Press, 2017.
3. Roland Siegwart, Illah Reza Nourbakhsh, Davide Scaramuzza, Introduction to Autonomous Mobile Robots, MIT Press, 2^{nd} Edition, 2011.
4. Sebastian Thrun, Wolfram Burgard, Dieter Fox, Probabilistic Robotics, MIT Press, 2005.

Web Links:

1. NPTEL Course in Computational Geometry https://nptel.ac.in/courses/106102011
2. Foundations of Robotics, Cornell University https://www.cs.cornell.edu/courses/cs5750/2025fa/

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII
Quantum Computing (RCP23DCPE713)		
Quantum Computing Laboratory (RCP23DLPE713)		

Prerequisite: Computer System Fundamentals, Machine Learning.

Course Objective(s):

This course introduces the basics of Quantum Computing, Quantum state transformation, and classical computation versions. Students will also learn advanced Quantum Computation Algorithms and the basics of Quantum Machine Learning.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Analyze the fundamental principles of quantum computing, including qubits, superposition, and entanglement, to interpret their impact on computational models.	L4	Analyze
CO2	Evaluate quantum algorithms such as Shor's and Grover's algorithms in terms of efficiency and applicability compared to classical approaches.	L5	Evaluate
CO3	Apply Quantum Machine Learning (QML) and Quantum Deep Learning (QDL) techniques to solve data-driven problems and compare their performance with classical approaches.	L3	Apply

Quantum Computing (RCP23DCPE713)
Course Contents

Unit-I 07 Hrs.

Basics of Linear Algebra:

Complex Numbers, Complex Conjugation and Norm, Vector Space, Basic set, Dirac Notation, Ket and Bra, Inner Product,Linearly Dependent and Independent Vectors, Dual Vector Space, Outer Product, Spin.

Unit-II 07 Hrs.

Quantum Computing vs. Classical Computing:

History of quantum computation and quantum information, Quantum State, Bloch sphere, Dense coding, Physical quantum phenomena: Spin, Quantum superposition, Interference and Entanglement.

Logic Gates and Circuits: Boolean Algebra, Functional Completeness, Gates, Circuits, Universal Gates, Gates and Computation

Quantum Gates and Circuits: Qubits, Single-qubit gates (Pauli-X, Y, Z, Hadamard), Multi-qubit gates (CNOT, Toffoli, SWAP), Quantum Gate, Analyzing Pauli gates, Analyzing Cascade of gates, Analyzing Two-qubit gates, Tensor Product, Quantum Gates Acting on one Qubit, No Cloning Theorem, Quantum Computation, Multiple qubit gates, Qubit copying circuit, Example: Bell states, quantum teleportation.

Unit-III 06 Hrs.

Quantum Computing algorithms:

Classical computations on a quantum computer, Quantum parallelism, Quantum key distribution, Superdense coding, quantum teleportation, applications of teleportation, probabilistic versus quantum algorithms, phase kick-back, Deutsch-Jozsa Algorithm, Grover's Search Algorithm, Shor's Factoring Algorithm, Quantum Fourier Transform (QFT).

Unit-IV 06 Hrs.

Quantum Cryptography algorithm:

Cryptography using principles of quantum computing, No-cloning theorem, Quantum key distribution Algorithm, Quantum secret sharing Algorithm, Quantum one time pad, Quantum public key encryption, Quantum fully homomorphic encryption

Unit-V 08 Hrs.

Quantum Machine Learning Basic (QML):

Variational Quantum Circuits, Parameterized quantum circuits, Parameterized quantum circuit properties,entangling capability, Parameterized quantum circuits for machine learning Data encoding Methods, Basis encoding, Amplitude encoding, Angle encoding, Arbitrary encoding, Supervised learning, Quantum variational classification, Quantum kernel estimation, Variational training, Quantum Support Vector Machine (QSVM).

Unit-VI 08 Hrs.

Quantum Deep Learning (QDL):

Basics of Quantum Neural Networks, Finite difference gradients, Analytic gradients, Natural gradients, Simultaneous Perturbation Stochastic Approximation, Training in practice, exponentially vanishing gradients (barren plateaus), Quantum Convolutional Neural Network, Quantum Generative Adversarial Networks

Quantum Computing Laboratory (RCP23DLPE713)

List of Laboratory Experiments

Suggested Experiments

1. Implementing Quantum Programs with the Qiskit SDK.
2. Implementing logic of Quantum Gates and Universal Gates with Qiskit.
3. Implementing a Quantum Random Number Generator with Qiskit.
4. Implementation of Quantum Key Distribution Using the BB84 Protocol with Qiskit.
5. Experimentation with Quantum Teleportation Protocols.
6. Implementation and Analysis of Shor's Algorithm Using Qiskit SDK.
7. Implementation of Quantum key distribution Algorithm..
8. Implementation of Grover's Search Algorithm with Qiskit.
9. Implementation and Exploration of Quantum Machine Learning Techniques: Parameterized Circuits, Data Encoding Methods, and Training Strategies in Qiskit.
10. Implementation of Supervised Strategies in Quantum Machine Learning: Exploring Quantum variational classification.
11. Implementation of Quantum key distribution Algorithm.

Above-suggested list or any other experiment or mini project based on syllabus will be included, which would help the learner to apply the concept learnt.The Term Work will be calculated based on Laboratory Performance.

Text Books:

1. Parag K. Lala, "Quantum Computing", McGraw Hill, 1^{st} Edition, 2020.

2. Chris Bernhardt, "Quantum Computing for Everyone", MIT Press, 1^{st} Edition, 2020.

Reference Books:

1. Jack D. Hidary, "Quantum Computing: An Applied Approach", Springer, 2^{nd} Edition, 2021.

2. Johan Vos, "Quantum Computing in Action", Manning Publications, 1^{st} Edition, 2022.

Web Links:

1. https://qiskit.org/leam

2. https://eleam.nptel.ac.in/shop/iit-workshops/completed/quantum-computing/

3. https://omscs.gatech.edu/sites/default/files/documents/2023/Syllabi-CS

4. https://www.cse.iitd.ac.in/ suban/quantum/

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII
Adversarial Machine Learning (RCP23DCPE714)		
Adversarial Machine Learning Laboratory (RCP23DLPE714)		

Prerequisite: Machine Learning.

Course Objective(s):

This course introduces the fundamentals of adversarial machine learning (AML), including vulnerabilities in supervised, unsupervised, and reinforcement learning models, and the nature of causative and evasion attacks. Students will analyze and implement defense mechanisms and secure learning frameworks to enhance the robustness of machine learning models against adversarial threats. The course also explores practical applications and advanced techniques in AML, such as model programming, adversarial data augmentation, and applications in cybersecurity, computer vision, and natural language processing.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Apply fundamental ML/DL techniques in adversarial settings, including supervised,unsupervised, and reinforcement learning, to identify vulnerabilities and threat models.	L3	Apply
CO2	Categorize adversarial attacks such as causative (data poisoning) and evasion attacks, and their impact on machine learning models in security-critical domains.	L4	Analyze
CO3	Apply robust defense strategies against adversarial attacks, including adversarial training,detection techniques, and secure learning frameworks.	L3	Apply
CO4	Design secure and resilient machine learning solutions for applications in cybersecurity, medical imaging, and NLP under adversarial conditions.	L6	Create

Adversarial Machine Learning (RCP23DCPE714) Course Contents

Unit-I **07 Hrs.**

Foundations of Adversarial Machine Learning

Machine Learning Preliminaries: Supervised Learning, Supervised Learning in Adversarial Settings, Unsupervised Learning, Unsupervised Learning in Adversarial Settings, Reinforcement Learning in Adversarial Settings, Categories of Attacks on Machine Learning.

Threat Models: White-box, Black-box, Gray-box Introduction to Adversarial Machine Learning: Adversarial Machine Learning Taxonomy and History, Statistical Machine Learning,

A Framework for Secure Learning: Analyzing the Phases of Learning, Framework, Security Analysis, Exploratory Attacks vs Causative Attacks.

Unit-II **07 Hrs.**

Causative Attacks and Data Integrity:

Causative (Data Poisoning) Attacks in ML, Availability vs Integrity Attacks, Availability Attack Case Study: SpamBayes, The SpamBayes Spam Filter, Threat Model for Spam Bayes, The Reject on Negative Impact (RONI) Defense,

Causative Attacks on Machine Learning: Integrity Attack.Label Manipulation and Dataset Bias Attacks, Robust Training Techniques.

Unit-III **09 Hrs.**

Evasion Attacks and Robustness: Evasion Attacks Overview,

White-box Attacks: Fast gradient sign method (FGSM) attack. Projected gradient descent (PGD) attack.

black-box Attacks: Query based attacks, Transferability Attacks, Attacks on Real Models.

Defenses Against Evasion Attacks: Adversarial Training, Detection Techniques, Gradient Masking (limitations), Robust Optimization, Model Evaluation under Adversarial Conditions, Accuracy vs Robustness Tradeoff.

Unit-IV **07 Hrs.**

Adversarial Machine Learning in Cyber Security: Taxonomy of AML Attacks in Cyber Systems.

Malware Detection and Classification: Machine Learning in cybersecurity, Malware detection and classification, Adversarial attacks on ML-based malware classifiers.

Network Intrusion Detection Systems: ML-based anomaly detection, Adversarial attacks on

NIDS, Datasets for network intrusion detection, Anomaly detection with Machine Learning.

Security in Medical Imaging Systems (PACS/DICOM vulnerabilities) Data Integrity and Privacy Risks in Healthcare ML, Adversarial Threats in Cloud-based ML Systems.

Unit-V 06 Hrs.

Adversarial Machine Learning in NLP:

NLP Fundamentals in Adversarial Settings.

Text-based Adversarial Attacks: Synonym substitution attacks, Text perturbation attacks, Prompt-based adversarial attacks. Attacks on NLP Models: Sentiment Analysis, Spam Detection, Chatbots /LLM vulnerabilities.

Defenses in NLP: Robust embeddings, Adversarial training for NLP, Input sanitization, Security risks in LLMs and Generative AI, Bias and fairness issues in NLP models.

Unit-VI 06 Hrs.

Practical Applications and Challenges:

Adversarial Machine Learning in Computer Vision, Adversarial Machine Learning in Autonomous Systems.

Applications beyond attack and defense: Model Programming, Contrastive explanations, model watermarking and fingerprinting, Data augmentation for unsupervised Learning.

Challenges and Open Problems: Adversarial Game Theory Basics,Limitations of current defenses, Explainable AI under adversarial settings Ethical and Regulatory Issues in healthcare and AI Security.

Adversarial Machine Learning Laboratory (RCP23DLPE714)

List of Laboratory Experiments

Suggested Experiments

1. Implement non-targeted white-box evasion attacks using FGSM and PGD on a deep learning image classification model and compare their impact on model accuracy.

2. Implement a targeted white-box evasion attack using PGD to force input images into a predefined target class and measure the targeted attack success rate.

3. Apply a PGD attack on a ResNet50 model and evaluate the transferability of generated adversarial examples on logistic regression and SVM classifiers.

4. Implement a non-targeted PGD attack on a logistic regression model on images and analyze the change in prediction probabilities.

5. Implement adversarial training and input preprocessing defenses against FGSM and PGD attacks on a CNN model and evaluate robustness improvement.

6. Analyze and compare the effectiveness of FGSM, PGD, and targeted attacks across image and cybersecurity datasets using accuracy and robustness metrics.

7. Apply adversarial evasion attacks on a machine learning-based Network Intrusion Detection System using NSL-KDD dataset and evaluate changes in intrusion detection rate.

8. Implement adversarial perturbations on malware feature vectors and evaluate the misclassification rate of a machine learning-based malware detection model.

9. Implement a spam filtering model and apply adversarial text modifications to evaluate degradation in classification performance.

10. Mini Project: Integrate adversarial attack methods (FGSM, PGD) and defense strategies into a unified pipeline and evaluate robustness on real-world datasets.

Above-suggested list or any other experiment or mini project based on syllabus will be included, which would help the learner to apply the concept learnt.The Term Work will be calculated based on Laboratory Performance.

Text Books:

1. Anthony D. Joseph, Blaine Nelson, "Adversarial Machine Learning", Cambridge University Press 2019, ISBN: 978-1-107-04346-6.

2. Soma Halder, "Hands-On Machine Learning for Cybersecurity: Safeguard your system by making your machines intelligent using the Python ecosystem", Packt Publishing ltd.

3. Zhang, Z. Lipton, and A. Smola, "Dive into Deep Learning", 2020.

Reference Books:

1. Yevgeniy Vorobeychik and Murat Kantarcioglu, "Adversarial Machine Learning", Morgan & Claypool,2018.

2. Pin-Yu Chen and Cho-Jui Hsieh, "Adversarial Robusteness for MAchine Learning", Academic Press animprint of Elsevier, 1^{st} Edition, 2022.

3. Shuhe Wang, Kuan-Chieh Wang, "Adversarial Machine Learning", Springer, 2014.

Web Links:

1. Goodfellow (2014) Explaining and Harnessing Adversarial Examples).
https://arxiv.org/abs/1412.6572

2. Carlini (2017) Towards Evaluating the Robustness of Neural Networks.
https://arxiv.org/abs/1608.04644

3. Brendel (2017) Decision-Based Adversarial Attacks: Reliable Attacks Against Black-Box Machine Learning Models.
https://arxiv.org/abs/1712.04248

4. Bhagoji (2017) Exploring the Space of Black-box Attacks on Deep Neural Networks.
https://arxiv.org/abs/1712.09491

5. Xu (2019) Adversarial Attacks and Defenses in Images, Graphs and Text: A Review
https://arxiv.org/pdf/1909.08072

6. Tramer (2018) Ensemble Adversarial Training: Attacks and Defenses.
https://arxiv.org/abs/1705.07204

7. Rosenberg (2021) Adversarial Machine Learning Attacks and Defense Methods in the Cyber Security Domain.
https://arxiv.org/abs/2007.02407

8. Severi (2021) Explanation-Guided Backdoor Poisoning Attacks Against Malware Classifiers.
https://arxiv.org/abs/2003.01031

9. Kuleshov (2018) Adversarial Examples for Natural Language Classification Problems (pdf).
https://openreview.net/pdf?id=r1QZ3zbAZ

10. Erba (2019) Constrained Concealment Attacks against Reconstruction-based Anomaly Detectors in Industrial Control Systems (pdf).
https://arxiv.org/abs/1907.07487

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII
Data Ethics (RCP23DCMD701)		
Data Ethics Tutorial (RCP23DTMD701)		

Prerequisite: Fundaments of Data Analysis, Intelligent Systems and Machine Learning.

Course Objective(s):

To equip learners with the knowledge and skills to apply ethical principles in AI and data science, focusing on privacy, fairness, transparency, and responsible governance for developing trustworthy and socially responsible systems.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Apply ethical principles, privacy-preserving practices, and relevant regulatory frameworks to design responsible AI and data-driven systems.	L3	Apply
CO2	Analyze, identify, and mitigate bias in machine learning systems while enhancing transparency and trust through Explainable AI techniques.	L4	Analyze
CO3	Analyze AI systems from governance, societal, sustainability, and policy perspectives to ensure accountable and responsible deployment.	L4	Analyze

Data Ethics (RCP23DCMD701)
Course Contents

Unit-I — 08 Hrs.

Foundations of Data Ethics and Responsible AI:

What is data ethics and why it matters in data science, Historical and philosophical background (autonomy, beneficence, justice, non-maleficence), Ethical theories (consequentialism, deontology, virtue ethics), Responsible AI and the data lifecycle, AI-driven decision systems, Human-in-the-loop AI, Value-sensitive design.

Case study: Cambridge Analytica and Facebook

Unit-II — 10 Hrs.

Data Privacy and Security:

Data privacy concepts and challenges in centralized systems, Informed consent, anonymization, and user data rights, Global privacy laws: GDPR, HIPAA, CCPA, DPDP, Data breach response.

Introduction to Federated Learning (FL):

Decentralized training and its privacy advantages, Ethical issues in FL: data leakage, model inversion, ownership, Differential Privacy, Secure Multi-party Computation.

Case study: Google's Federated Learning for mobile devices

Unit-III — 08 Hrs.

Fairness, Bias, and Accountability in Machine Learning:

Types and sources of bias (sampling, labeling, algorithmic), Fairness metrics in AI (demographic parity, equal opportunity), Detecting and mitigating bias in datasets and models, Algorithmic accountability and auditability.

Case study: Bias in the COMPAS recidivism prediction system

Unit-IV — 09 Hrs.

Transparency, Explainable AI (XAI), and Ethical Model Interpretability: Importance of transparency and trust in AI systems, Explainable AI (XAI): concepts, tools, and methods (LIME, SHAP, Grad-CAM), Ethical challenges in black-box AI models, Balancing accuracy vs. explainability, Regulatory importance of explainability (EU AI Act, IEEE Standards).

Case study: Explainability in medical AI diagnosis

Unit-V — 07 Hrs.

Governance, Emerging Issues, and Future Directions:

Ethical data governance and stewardship, AI ethics frameworks (OECD, EU, UNESCO, IEEE), So-

cietal and environmental impact of AI (energy use, carbon footprint), Digital divide, inclusion, and global data justice, Emerging ethical issues: generative AI, misinformation, deepfakes, Green AI.
Student capstone: Develop an ethical policy for a data science project

Data Ethics Tutorial (RCP23DTMD701)

List of Tutorials

Suggested Tutorials

1. Introduction to Data Ethics through Case Analysis
2. Ethical Frameworks and Decision-Making Models
3. Privacy and Data Protection in Practice
4. Federated Learning and Ethical Implications
5. Identifying Bias in Datasets
6. Fairness and Accountability in AI Systems
7. Introduction to Explainable AI (XAI)
8. XAI in High-Stakes Domains
9. Trade-offs in Explainability and Ethics
10. Ethical Governance and Policy Frameworks
11. Emerging Ethical Challenges (Deepfakes, Generative AI)
12. Capstone Project Presentation and Ethical Review

Any 10 tutorials from the given list through Group Activities/Debate/Discussions/Research Paper Reviews/ Presentations/Hands-on Exercise.

Text Books:

1. Christoph Stückelberger, Pavan Duggal, Data Ethics: Building Trust: How Digital Technologies Can Serve Humanity, Globethics Publications, 1st Ediiton, 2023.
2. Explainable AI: Foundations and Practical Techniques - Paresh Patil, Sushant Gaikwad, Akash Hatkangane (Walnut Publication, 2024)
3. Federated Learning: Decentralized Machine Learning for Privacy and Security by Lavanya Arora, Kindle Edition.

Reference Books:

1. Ian Foster, Rayid Ghani, Ron S. Jarmin, Frauke Kreuter, Julia Lane, Big Data and Social Science: Data Science Methods and Tools for Research and Practice, Chapman and Hall/CRC, 2^{nd} Edition, 2020.

2. Evren Eryurek, Uri Gilad, Valliappa Lakshmanan, Data Governance: The Definitive Guide - People,Processes, and Tools to Operationalize Data Trustworthiness, Shroff/O'Reilly, 1^{st} Edition, 2021.

3. Bonawitz et al., Federated Learning: Collaborative Machine Learning without Centralized Training Data, Google AI Blog.

Web Links:

1. Ethics in Data Science: https://www.analyticsvidhya.com/blog/2022/02/ethics-in-data-science-andproper-privacy-and-usage-of-data/

2. Business Insights Harvard: https://online.hbs.edu/blog/post/data-ethics

3. Data Science Professionals: https://emeritus.org/blog/data-science-and-analytics-data-sciencecourse-curriculum/

4. Federated Learning in Practice: Google AI Blog : https://research.google/blog/federated-learning-withformal- differential-privacy-guarantees/

5. Explainable AI Principles: IBM Research Blog : https://research.ibm.com/blog/ai-explainability-360

6. Green AI Papers: https://arxiv.org/abs/1907.10597

Frameworks and Guidelines

1. EU AI Act (2024 draft) - Requirements for transparency and accountability.

2. OECD AI Principles (2019) - Human-centered values and fairness.

3. IEEE (2022). Ethically Aligned Design, Version 2

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII
Research Ecosystem (RCP23ITELX08)		

Prerequisite:

1. Basic understanding of Engineering concepts and problem-solving techniques.
2. Fundamental knowledge of project-based learning, data analysis, and domain-specific tools.
3. Basic exposure to project development, technical report writing, and emerging technologies.

Course Objective(s):

1. To understand and identify complex engineering, societal, and industrial problems suitable for research through structured analysis of literature, patents, and real-world needs.
2. To learn and apply advanced research methodologies—including experimental, simulationbased, and data-driven approaches—for designing and validating engineering solutions.
3. To gain proficiency in selecting and using appropriate tools, software, and platforms (AI/ML, simulation, CAD, IoT, etc.) for experiment design, data acquisition, and performance evaluation.
4. To transform research insights into innovative prototypes, products, or startup concepts by engaging with innovation ecosystems, TRLs, and funding mechanisms.
5. To analyze socio-technical systems, ethics, and sustainability implications of engineering solutions, ensuring responsible and impactful outcomes.
6. To integrate systems thinking, multidisciplinary perspectives, policy awareness, future technology trends, and technical documentation skills to develop comprehensive research proposals and outputs (papers, patents, reports).

Course Outcomes:

On completion of the course, the learner will be able to:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Analyze complex engineering and societal problems through literature and patent analysis to identify research gaps.	L4	Analyze
CO2	Apply advanced research methods and tools to acquire data and assess solution performance	L3	Apply
CO3	Apply innovation frameworks and Technology Readiness Levels (TRL) for prototype and startup development.	L3	Apply
CO4	Analyze ethical, socio-technical, and sustainability issues related to engineering solutions.	L4	Analyze
CO5	Analyze multidisciplinary knowledge for engineering research proposal preparation.	L4	Analyze

Research Ecosystem (RCP23ITELX08) Course Contents

Unit-I — 05 Hrs.

Research Gap Identification & Problem Formulation

- Identifying high-impact problems from:
  - Industry and Society
  - Emerging technologies (AI, IoT, Blockchain, EV, etc.)
- Research gap identification techniques:
  - Systematic Literature Review (SLR)
  - Patent analysis
- Defining objectives, scope, constraints, and feasibility of the identified problem
- Writing problem statement for:
  - Research paper
  - Product/Startup idea

Activities:

- Convert Industry/ Societal problem into research problem.
- Analyze research articles and extract research gaps.

Unit-II — 06 Hrs.

Experimental Design, Tools & Validation Techniques

- Advanced research methodologies:
  - Experimental, simulation, data-driven, design thinking
- Tool selection:
  - Computational tools and software, simulation and analysis platforms, system prototyping and testing platforms
- Data acquisition:
  - Data collection interfaces, Principles of data cleaning and organization (primary / secondary data)
- Validation techniques:

  - Accuracy and performance metrics
  - Benchmarking with existing solutions
- Result interpretation & visualization

Activities:

- Selection of Research Design for final year project.
- Apply evaluation metrics (e.g., ML model accuracy, system efficiency).

Unit-III 05 Hrs.

Research to Innovation, Product & Startup Ecosystem

- Research → Prototype → Product → Startup lifecycle
- Intellectual Property Rights (IPR), patents, copyrights
- Technology readiness levels (TRL)
- Case studies:
  - AI startups, EV ecosystem, Smart Cities
- Industry-academia collaboration models
- Funding opportunities (grants, incubation, government schemes - Anusandhan National Research Foundation (ANRF))

Activities:

- Convert project into startup idea or product pitch.
- Analyze failure of a technology/product.

Unit-IV 06 Hrs.

Socio-Technical Systems, Ethics & Sustainability

- Socio-technical systems: Interaction of people, technology and environment
- Intellectual Property Rights (IPR), patents, copyrights
- Ethical issues:
  - Plagiarism, AI bias, data privacy
- Sustainability in Engineering:
  - Green practices, resource optimization and lifecycle considerations
- Impact assessment:

- Social, economic, environmental

- Policies and governance (data protection laws, standards and compliance requirements)

Activities:

- Case study: Facial recognition ethics / smart surveillance.
- Impact analysis of student's own project.

Unit-V 06 Hrs.

Integrated Research, Policy and Future Engineering Challenges

- Systems thinking and holistic analysis
- Multidisciplinary problem solving:
  - Healthcare tech, climate tech, smart mobility
- Writing research proposals:
  - Problem → Methodology → Expected outcomes
- Future trends:
  - AI ethics, Quantum computing, Industry 5.0 / 6.0
- Scaling solutions from lab to society

Activities:

- Capstone Task:
  - Identify real-world problem.
  - Apply research methodology.
  - Propose: Technical solution, Societal impact,Possible commercialization

Term Work Guidelines

The Term Work (TW) shall consist of continuous assessment based on tutorials activities and a final group presentation.

a) Part A (25 Marks):

Each student shall complete a minimum of five tutorials based on the syllabus topics during the semester. The tutorials may include activities such as research gap identification, literature survey, case study analysis, tool-based experimentation, impact analysis, technical report writing, and innovation-oriented problem solving.

b) Part B (25 Marks):

Students shall work in groups and select a project/research topic based on emerging engineering, industrial, or societal challenges.

The group presentation shall include:

- Identification of a real-world problem
- Application of appropriate research methodology
- Proposed technical solution
- Analysis of societal impact
- Possible commercialization/startup opportunities

Reference Books:

1. Kothari, C. R., Research Methodology: Methods and Techniques, New Age International Publishers, New Delhi, 2023.
2. Booth, W. C., Colomb, G. G., Williams, J. M., Bizup, J., & FitzGerald, W. T., The Craft of Research, University of Chicago Press, Chicago, 2024.
3. Montgomery, D. C., Design and Analysis of Experiments, Wiley, New York, 2020.
4. Singh, Pooja, Katiyar, Aman, Rawat, Shalini, Dhuri, Archana, Research Methodology and IPR,RK Publications, India, 2025.
5. Blok, Vincent (Ed.), Putting Responsible Research and Innovation into Practice: A Multi-Stakeholder Approach, Springer Cham, Switzerland, 2022.

Web Links:

1. Research Methodology: Quantitative Methods and Computer Application
   (https://onlinecourses.swayam2.ac.in/e-learning/preview/ini26_ma02)
2. Research Methodology and IPR
   (https://onlinecourses.swayam2.ac.in/e-learning/preview/ntr26_ed28)
3. Research and Publication Ethics
   (https://onlinecourses.swayam2.ac.in/e-learning/preview/nou26_ge46)
4. Research Ethics and Plagiarism
   (https://onlinecourses.swayam2.ac.in/e-learning/preview/nou26_ge26)
5. Quantitative and Mixed Methods Research for Management
   (https://onlinecourses.swayam2.ac.in/e-learning/preview/imb26_mg21)
6. Doing Qualitative Research
   (https://onlinecourses.swayam2.ac.in/e-learning/preview/nou26_ge61)

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII
Project Stage - II (RCP23IPEL701)		

Course Objectives:

- To implement the solution as per the problem statement.
- To develop the team building, writing, logical reasoning and management skills.
- To provide the connections between the designs and concepts across different disciplinary boundaries.
- To encourage students to become independent personnel, critical thinkers and lifelong learners

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Analyze the problem statement and produce solution of the problem considering cultural, social, environmental and economic factors using appropriate tool and method.	L4	Analyze
CO2	Interpret project based learning that allows students to transfer existing ideas into new applications.	L2	Understand
CO3	Apply the ability to work in teams and manage to conduct the project development activity.	L3	Apply
CO4	Use different perspectives from relevant disciplines which help them to get internships, jobs, and admission for higher studies.	L3	Apply
CO5	Explain the project development in the form of technical writing, and interpret what constitutes plagiarism and the use of proper referencing styles.	L2	Understand

Syllabus:

Project-I work done in VI semester shall be continued as Project-II in semester VII.

Students should complete remaining implementation of ideas given in synopsis/Abstract of semester VI.

Students / group must plan their execution of project, so that project work should be completed before end of semester.

Project-II involves fabrication, design, experimentation, data analysis within realistic constraints such as economic, environmental, social, ethical, health and safety, manufacturability, and sustainability. The stage also includes testing, possible results and report writing.

Each project group is required to maintain log book for documenting various activities of Project-II and submit group project report at the end of Semester-VII in the form of Hard bound.

Domain knowledge (any beyond) needed from the various areas in the field of Computer Science & Engineering (Data Science) for the effective implementation of the project.

The above areas can be updated based on the technological innovations and development needed for specific project.

Guidelines:

The main purpose of this activity is to improve the students' technical skills, communication skills by integrating writing, presentation and teamwork opportunities.

Each group will be reviewed twice in a semester and marks will be allotted based on the various points mentioned in the evaluation scheme.

In the first review of this semester, each group is expected to complete 70% of project.

In the second review of this semester, each group is expected to complete 100% of project.

The students may use this opportunity to learn different computational techniques towards development of a product.

Interaction with alumni mentor will also be appreciated for the improvement of project.

Student is expected to:

- Maintain Log Book of weekly work done(Log Book Format will be as per Table 1).
- Report weekly to the project guide along with log book.

Table 1: Log Book Format

Sr	Week (Start Date:End Date)	Work Done	Sign of Guide	Sign of Coordinator
1				
2				

Assessment Criteria:

- At the end of the semester, after confirmation by the project guide, each project group will submit project completion report in prescribed format for assessment to the departmental committee (including project guide).
- Assessment of the project (at the end of the semester) will be done by the departmental committee (including project guide).
- The candidate must bring the Project Stage-I report and the final report completed in all respect while appearing for End Semester Examination.
- Oral examination should be conducted by Internal and External examiners. Students have to give presentation and demonstration based on their project.

Prescribed project report guidelines:

Every group should prepare hard bound report (preferrable LaTeX) of about minimum 40 pages on the work carried out by a batch of students in respect of the project work done during semester-VII. Project Report should include appropriate content for:

- Title
- Abstract
- Introduction
- Problem identification and project objectives
- Literature Survey
- Related Theory
- Project design and Implementation details
- Case study/Analysis/Design Methodology
- Project Outcomes
- Result and Conclusion
- Future scope
- References

Assessment criteria for the departmental committee for Continuous Assessment:

Guide will monitor weekly progress and marks allocation will be as per Table 2.

Assessment criteria for the departmental committee for End Semester Exam:

Departmental committee will evaluate project as per Table 3.

Table 2: Continuous Assessment Table

Sr	Exam Seat No	Name of Student	Student Attendance	Log Book Logbook Maintenance	Literature Review	Depth of Understanding	Report	Total
			10	10	10	10	10	50

Assessment criteria for the departmental committee (including project guide) for End Semester Exam:

Each group will be reviewed twice in a semester by faculty guide and faculty coordinator based on the following criteria:

- Project progress
- Documentation/Technical paper writing
- Key findings
- Validation of results
- Product Development

Each review consists of 50 marks. Average of the marks scored in both the two reviews will be considered for final grading. The final certification and acceptance of TW ensures the satisfactory performance on the above aspects.

Table 3: Evaluation Table

Sr	Exam Seat No	Name of Student	Project Selection	Design/ Methodology	Implementation/ Modelling/ Simulation	Result Verification	Presentation	Total
			10	10	10	10	10	50

Program: Computer Science & Engineering (Data Science)	**Final Year B.Tech**	**Semester: VIII**
Disaster Management and Preparedness (RCP23ICHSX09)		

Course Objective(s):

1. To provide basic understanding of hazards, disasters and various types and categories of disaster occurring around the world.
2. To identify extent and damaging capacity of a disaster.
3. To study and understand the means of losses and methods to overcome /minimize it.
4. To understand roles and responsibilities of individual and various organizations during and after disaster.
5. To appreciate the significance of GIS, GPS in the field of disaster management.
6. To understand the emergency government response structures before, during and after disaster.

Course Outcomes:

CO	**Course Outcomes**	**Blooms Level**	**Blooms Description**
CO1	Apply disaster management principles & guidelines.	L3	Apply
CO2	Analyse risk assessments.	L4	Analyze
CO3	Demonstrate community awareness & participation.	L3	Apply
CO4	Use Science & Technology tools (GIS, GPS).	L3	Apply
CO5	Prepare disaster management plans.	L3	Apply

Disaster Management and Preparedness (RCP23ICHSX09) Course Contents

Unit-I 06 Hrs.

Understanding Disasters & Hazards:

• Definition and types of disasters: Natural, Man-made and hybrid disasters, Study of Natural disasters: Flood, drought, cloud burst, Earthquake, Landslides, Avalanches, Volcanic eruptions, Mudflow, Cyclone, Storm, Storm Surge, climate change, global warming, sea level rise, ozone depletion etc.

• Study of Human/Technology Induced Disasters: Chemical, Industrial and Nuclear disasters, internally displaced persons, road and train accidents Fire Hazards, terrorism, militancy, • Hazard & Vulnerability profiles of India (seismic zones, flood-prone areas).

• India's vulnerability to disasters, and the impact of disasters on National development.

Unit-II 06 Hrs.

Disaster Risk Reduction (DRR) & Mitigation:

• Disaster Management Cycle: Prevention, Mitigation, Preparedness, Response, Recovery. Need for disaster prevention and mitigation, mitigation guiding principles, challenging areas, structural and non-structural measures for disaster risk reduction.

• Risk Assessment & Vulnerability Analysis.

Science & Technology: Use of information management, Geo informatics like RS, GIS, GPS and remote sensing mitigation measure.

Unit-III 04 Hrs.

Disaster Preparedness & Response:

• Preparedness Planning, Early Warning Systems (EWS), & Communication.

• Emergency Response: Search & Rescue, Logistics, Medical Aid.

• Psychological Response & Management (Trauma, Stress).

• Role of IT, Media, Govt., NGOs, & Community

Unit-IV 04 Hrs.

Recovery, Rehabilitation & Reconstruction:

• Post-disaster damage assessment.

• Rehabilitation, Reconstruction, & Livelihood Restoration.

• Sanitation, Hygiene, & Waste Management.

Unit-V 04 Hrs.

Policy, Governance & Capacity Building:

• National Disaster Management Authority (NDMA) & Legislation.

• Institutional Mechanisms & Community Mobilization. Non-Structural Mitigation: Community based disaster preparedness, risk transfer and risk financing, capacity development and training, awareness and education, contingency plans

Unit-VI 04 Hrs.

Case studies on disaster (National /International):

• Case study discussion of National Disasters: Tsunami (2004), Bhopal gas tragedy, Kerala and Uttarakhand flood disaster, 26th July 2005 Mumbai flood

• Case study discussion of International Disasters: Hiroshima – Nagasaki (Japan), Cyclone Phailin(2013), Fukushima, Daiichi nuclear disaster (2011), Chernobyl meltdown

Reference Books:

1. Harsh K. Gupta, "Disaster Management", Universities Press Publications, 2003.
2. O. S. Dagur, "Disaster Management: An Appraisal of Institutional Mechanisms in India",published by Centre for land warfare studies, New Delhi, 2011.
3. Damon Copolla, Butterworth Heinemann, "Introduction to International Disaster Management", Elsevier Publications, 2015.
4. Jack Pinkowski, CRC Press, "Disaster Management Handbook", Taylor and Francis group, 2008.
5. Rajdeep Dasgupta, "Disaster management & rehabilitation", Mittal Publications, New Delhi,2007.
6. R B Singh, "Natural Hazards and Disaster Management, Vulnerability and Mitigation", Rawat Publications, 2006.
7. C. P. Lo Albert, K.W. Yonng, "Concepts and Techniques of GIS", Prentice Hall (India) Publications, 2006.
8. Claudia G. Flores Gonzales, "Risk management of natural disasters", KIT Scientific Publishing, 2010.
9. W. Nick Carter, "Disaster Management – a disaster manger's handbook", Asian Development Bank, 2008.
10. R. K. Srivastava, "Disaster Management in India", Ministry of Home Affairs, GoI, New Delhi, 2011.

11. Wil Mara, "The Chernobyl Disaster: Legacy and Impact on the Future of Nuclear Energy", Marshall Cavendish Corporation, New York, 2011.

12. Ronald Eisler, "The Fukushima 2011 Disaster", Taylor & Francis, Florida, 2013. (Learners are expected to refer reports published at national and international level and updated information available on authentic web sites.)

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII
Generative AI (RCP23DCSC701)		

Course Objective(s):

1. To analyze the architectures and applications of Generative Artificial Intelligence.
2. To examine Neural Style Transfer, Auto encoders, Vibrational Auto encoders (VAEs), and Generative Adversarial Networks (GANs).
3. To apply Generative AI techniques for Large Language Model fine-tuning and Data Science applications.
4. To analyze ethical, privacy, and governance aspects of responsible Generative AI.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Analyze the architectures and applications of Generative AI models for solving real-world problems.	L4	Analyze
CO2	Apply Neural Style Transfer, Autoencoder, Variational Autoencoders (VAEs), and Generative Adversarial Networks (GANs) for image and data generation tasks.	L3	Apply
CO3	Demonstrate the use of Large Language Models (LLMs) for fine-tuning, local deployment, and Data Science applications.	L3	Apply
CO4	Analyze ethical, privacy, bias, and governance challenges in Generative AI and recommend responsible AI practices.	L4	Analyze

Generative AI (RCP23DCSC701)
Course Contents

Unit-I 05 Hrs.

Introduction to Generative AI and Neural Style Transfer:

Introduction to Generative AI, history and evolution of generative models, applications of Generative AI in Data Science, image generation and anomaly detection, fundamentals of Neural Style Transfer, style and content representations, image preprocessing, feature extraction using deep neural networks, content loss, style loss, total loss optimization, Gram Matrix, image generation process, Total Variation Loss, Fast Neural Style Transfer, and practical applications.

Unit-II 06 Hrs.

Auto encoders and Variational Auto encoders:

Fundamentals of Autoencoders, encoder-decoder architecture, latent space representation, basic Autoencoders, Deep Autoencoders, Convolutional Autoencoder, denoising Autoencoders, dimensionality reduction, Variational Autoencoders (VAE), probabilistic latent representation, sampling and reparameterization, VAE loss function, model training, image synthesis, and applications of VAEs.

Unit-III 06 Hrs.

Generative Adversarial Networks and Large Language Models:

Fundamentals of Generative Adversarial Networks (GANs), generator and discriminator architecture, adversarial training, Deep Convolutional GANs (DCGANs), face generation, evaluation of generated outputs, introduction to Large Language Models (LLMs), challenges in fine-tuning open-source LLMs, model quantization, Low-Rank Adaptation (LoRA), parameter-efficient fine-tuning, local deployment of LLMs, and practical implementation of generative AI models.

Unit-IV 04 Hrs.

Generative AI for Data Science and Responsible AI:

Applications of Generative AI in marketing analytics and feature engineering, text analytics, predictive model development, synthetic data generation, data privacy, bias and fairness in Generative AI, responsible AI principles, ethical development and deployment, privacy-preserving synthetic data, governance, emerging trends, and industrial applications of Generative AI.

Web Links:

https://www.coursera.org/learn/generative-deep-learning-with-tensorflow

https://www.coursera.org/learn/generative-ai-for-data-science

Evaluation Scheme:

Continuous Assessment (CA):

- Course Completion Certificate: 15 marks.
- Faculty Curated Test: 15 Marks.
- Assignments/Case Study: 10 marks.

Semester - VIII

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII/VIII
Bioinformatics (RCP23DCPE811)		

Prerequisite: Linear Algebra, Probability and Statistics, Machine Learning Fundamentals

Course Objective(s):

To develop analytical skills in learners for applying data science techniques to biological datasets, including sequence analysis, statistical methods, and data-driven approaches in genomics and proteomics.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Apply statistical and data pre-processing techniques to analyze biological datasets including genomic, transcriptomic, and proteomic data.	L3	Apply
CO2	Analyze biological sequences and genomic data using sequence alignment methods, feature engineering, and exploratory data analysis techniques.	L4	Analyze
CO3	Analyze protein data and bioinformatics applications to interpret biological patterns and solve real-world problems in healthcare and precision medicine.	L4	Analyze

Bioinformatics (RCP23DCPE811)
Course Contents

Unit-I — 06 Hrs.

Introduction to Bioinformatics:

Role of bioinformatics in data science, Types of biological datasets: Genomics, Transcriptomics, Proteomics, Data Fromats: FASTA, FASTQ, GenBank, EMBL, UniProt, PDB. Data retrieval, storage, and challenges, Characteristics of biological datasets. Applications in healthcare and precision medicine.

Unit-II — 06 Hrs.

Statistical Analysis of Biological Data:

Probability distributions in biological data, Hypothesis testing (t-test, chi-square), Correlation analysis, Regression, Variance analysis, Biological vs technical variation.

Unit-III — 08 Hrs.

Sequence Analysis:

Biological sequences as data, Sequence Analysis Algorithms: Pairwise Sequence Alignment (Needleman-Wunsch Algorithm (global), Smith-Waterman Algorithm(local)), Multiple Sequence Alignment (MSA), Heuristic Search Methods (BLAST, FASTA). Scoring schemes (PAM, BLOSUM).

Unit-IV — 08 Hrs.

Genomics Data Analysis:

Genome and genomics, Biological sequences as data structures, preprocessing of genomic data (quality filtering, handling ambiguous bases, sequence transformation), feature engineering for sequences (one-hot encoding, integer encoding, k-mer representation, GC-content), exploratory data analysis of genomic datasets (nucleotide distribution, k-mer frequency analysis, gene expression matrix analysis, correlation analysis), visualization techniques (sequence composition plots, gene expression heatmaps, boxplots).

Unit-V — 08 Hrs.

Protein Data Analysis:

Protein data as structured and sequence-based representations, amino acid sequences as data, levels of protein structure (primary, secondary, tertiary, quaternary), structure– function relationship as pattern interpretation, protein data sources (Protein Data Bank)(PDB)), preprocessing and transformation of protein structural data, feature extraction (amino acid composition, physicochemical properties, structural descriptors), analysis of protein–protein interactions as network/graph data, visualization of protein structures and interaction networks.

Unit-VI 06 Hrs.

Application of Bioinformatics in Data Science:

Disease gene identification, biomarker discovery, precision medicine, drug discovery, protein–protein interaction network analysis, cancer genomics analysis, gene expression profiling.

Text Books:

1. David A. Hendrix, Applied Bioinformatics, 2020. 1^{st} Edition, 2020.
2. Lesk, A. M., Introduction to Bioinformatics, University Press, 5^{th} Edition, 2019.

Reference Books:

1. Shotts, W. E., The Linux Command Line: A Complete Introduction, No Starch Press, 2^{nd}Edition, 2019.
2. Pevsner, J., Bioinformatics and Functional Genomics, Wiley-Blackwell, 3^{rd} Edition, 2015.
3. M. Michael Gromiha, Protein Bioinformatics: From Sequence to Function, Academic Press,2010.
4. Harisha, S., Fundamentals of Bioinformatics, I K International Publishing House, 2010.

Weblinks:

1. Oregon State University: https://open.oregonstate.education/appliedbioinformatics/
2. NPTEL Course: https://onlinecourses.nptel.ac.in/noc26_bt34/preview

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII/VIII
Green Data Science (RCP23DCPE812)		

Prerequisite: Fundamentals of Data Analysis, and Applied Data Science.

Course Objective(s):

To develop understanding of Green Data Science principles for designing energyefficient data acquisition, processing, and machine learning systems; To enable analysis of sustainability-driven data science applications considering computational efficiency, infrastructure optimization, and ethical frameworks such as ESG and Responsible AI.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Analyze the role of Green Data Science in promoting sustainability and addressing environmental challenges.	L4	Analyze
CO2	Describe data collection and energy-efficient processing methods.	L2	Understand
CO3	Analyze data science applications in areas like climate, energy, and smart systems.	L4	Analyze
CO4	Assess environmental impact, ethics, and policy aspects in data-driven systems.	L5	Evaluate

Green Data Science (RCP23DCPE812)
Course Contents

Unit-I 06 Hrs.

Introduction to Green Data Science:

Fundamentals of Green Data Science, sustainability in data-driven systems, environmental impact of large-scale computing, carbon footprint of AI/ML pipelines, energy consumption in training and inference, Green AI vs conventional AI, efficiency–accuracy trade-offs, and role of data science in achieving SDGs.

Unit-II 06 Hrs.

Sustainable Data Acquisition and Management:

Data acquisition methods including adaptive sampling, duty cycling, wake-up radio, sensor selection/scheduling, event-triggered sensing, in-sensor processing, sensor fusion, and data compression, along with data quality assessment, missing data handling, bias detection, and ethical data management.

Unit-III 07 Hrs.

Energy-Efficient and Sustainable Data Processing:

Energy-efficient processing techniques including structured pruning, mixed-precision quantization, knowledge distillation, structured and dynamic sparsity, hardware-aware NAS, TinyML, early-exit networks, and low-rank adaptation, with emphasis on performance-per-watt and reduced training/inference cost.

Unit-IV 08 Hrs.

Data Science for Sustainability Applications:

Application methods including graph-based spatio-temporal modeling, digital twin modeling, climate informatics, reinforcement learning for smart-grid optimization, semantic segmentation for remote sensing, and physics-informed machine learning, for sustainability problems in climate, energy, agriculture, and environmental monitoring.

Unit-V 07 Hrs.

Green Computing & Infrastructure:

Infrastructure techniques including carbon-aware scheduling, dynamic voltage and frequency scaling (DVFS), energy-proportional computing, VM/container scheduling, edge-cloud collaborative computing, thermal-aware data center optimization, and renewable-aware workload management.

Unit-VI 08 Hrs.

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Sustainability Assessment and Reporting

Introduction to Sustainability Assessment, Sustainability Metrics for Data Science Systems, Energy Consumption Assessment of Machine Learning Models, Carbon Footprint Measurement and Analysis using CodeCarbon and CarbonTracker, Resource Utilization Analysis, Lifecycle Assessment (LCA) of Data Science Solutions, ESGBased Evaluation of Data-Driven Systems, Sustainability Reporting and Dashboard using Microsoft Sustainability Manager, Case Studies on Sustainable Data Science Applications.

Text Books:

1. Raghavendra Selvan, Sustainable AI: Tools for Moving Toward Green AI, O'Reilly Media, 2024.
2. Wu-Chun Feng (Ed.), Green Computing: Large Scale Energy Efficiency, CRC Press,2014.
3. Bhuvan Unhelkar, Green IT Strategies and Applications – Using Environmental Intelligence,CRC Press, 2014.

Reference Books:

1. Green Artificial Intelligence: Sustainable Techniques and Applications, Springer, 2025.
2. Data Science Applied to Sustainability Analysis, Jennifer Dunn and Prasanna Balaprakash (Eds.), Elsevier, 2021.
3. TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers, Pete Warden and Daniel Situnayake, O'Reilly Media, 2019.
4. Building Green Software: A Sustainable Approach to Software Development and Operations, Anne Currie, Sarah Hsu, and Sara Bergman, O'Reilly Media, 2024.
5. Life Cycle Assessment: Theory and Practice, Michael Z. Hauschild, Ralph K. Rosenbaum, and Stig Irving Olsen (Eds.), Springer, 2018.

Weblinks:

1. NPTEL: https://onlinecourses.nptel.ac.in/noc26_hs100/preview
2. MIT Sustainability AI: https://www.mit.edu
3. Cornell AI for Sustainability: https://sustainability.ai.cornell.edu/
4. UN SDG Platform: https://sdgs.un.org/goals
5. UN Data Portal: https://data.un.org

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII/VIII
Causal Inference & Decision Intelligence (RCP23DCPE813)		

Prerequisite: Statistics for data science and Machine learning

Course Objective(s):

To equip students with the principles and tools of causal inference for making reliable, datadriven decisions beyond prediction.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Apply and differentiate correlation and causation using causal reasoning frameworks and real-world scenarios.	L3	Apply
CO2	Analyze causal graphs (DAGs) to identify confounders, mediators, and colliders in practical problems.	L4	Analyze
CO3	Analyze and estimate causal effects using techniques such as ATE, propensity score methods, and RCTs.	L4	Analyze
CO4	Evaluate the decision-making strategies by integrating causal inference methods, experimentation, and policy learning.	L5	Evaluate

Causal Inference & Decision Intelligence (RCP23DCPE813)
Course Contents

Unit-I — 06 Hrs.

Introduction to Causality & Decision Failures:

Correlation vs causation; limits of predictive ML, Real-world failures (healthcare, policy, recommendation systems), Introduction to causal thinking, Introduction to Judea Pearl's causal reasoning framework, Pearl's Ladder of Causation (association, intervention, counterfactuals), Case-led: misleading dashboards, Simpson's paradox.

Unit-II — 08 Hrs.

Causal Graphs, DAGs & Structural Models:

Directed Acyclic Graphs, assumptions in causal diagrams, Structural Causal Models, confounders/mediators/collid d-separation and conditional independence. Visual problem solving through DAG drawing for education, pricing, and traffic scenarios.

Unit-III — 08 Hrs.

Identification & Estimation of Causal Effects:

Potential outcomes framework (Rubin model), Counterfactual reasoning & fundamental problem, SUTVA, ignorability, overlap, ATE (Average Treatment Effect: effect of treatment on the overall population. ATT (Average Treatment Effect on the Treated), ATC (Average Treatment Effect on the Control), ATE = E[Y(1) Y(0)]: Average difference between treated and untreated outcomes, Backdoor & front door criteria (DAG intuition), Do-operator (conceptual understanding), Propensity score: Estimation Matching (nearest neighbor, caliper), Covariate balance checking, Inverse Probability Weighting (IPW),Sensitivity to hidden confounders.

Unit-IV — 06 Hrs.

Experimental Design, RCTs & A/B Testing:

Randomized Controlled Trials (RCTs), A/B testing design (industry practices) Randomization strategies, Bias control & confounders, Metric selection (north-star vs proxy), Power analysis (intuition), Pitfalls: Peeking, novelty effect, interference (network effects) and online experimentation practices used in companies like Google and Netflix.

Unit-V — 07 Hrs.

Advanced Causal Methods & Causal ML:

Instrumental variables, Regression discontinuity, Difference-in-differences, Heterogeneous treatment effects, Uplift modeling, Causal ML additions: Metalearners: T-learner, S-learner, X-learner, Intro to Double Machine Learning (DML),Basic idea of causal forests.

Case studies: Retail (coupon targeting), Banking (risk intervention), Mobility (pricing& demand)

Unit-VI 06 Hrs.

Decision Intelligence & Real Applications:

Decision-making under uncertainty, Translating causal insights into policies, Policy learning basics, Connection to Reinforcement Learning: Offline vs. online decisionmaking, Counterfactual policy evaluation (conceptual), Building decision pipelines: Problem → DAG → Estimation → Decision, Ethics in causal decision-making, Capstone-style case studies: Product analytics, Healthcare decisions, Economic policy.

Text Books:

1. Miguel Hernán & James Robins, "Causal Inference: What If", Oxford University Press, 2025.
2. Causal Inference: The Mixtape – Scott Cunningham, Yale University Press, 2021.

Reference Books:

1. Causal Inference for Data Science – Aleix Ruiz de Villa, Publisher: Miguel Hernán James Robins, Oxford University Press, 2025.
2. Judea Pearl, "Causality: Models, Reasoning, and Inference". Cambridge Press, 2009.

Weblinks:

1. Johns Hopkins Engineering for Professionals: Introduction to Causal Inference - 625.691 — Hopkins EP Online : https://ep.jhu.edu/courses/625691-introduction-to-causal-inference/
2. Causal Inference — Coursera: https://www.coursera.org/learn/causal-inference
3. Causal AI: An Introduction : https://www.udemy.com/course/causal-ai-an-introduction/

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VII/VIII
Immersive Systems: AR/VR and Human-Computer Interaction (RCP23DCPE814)		

Prerequisite: Computer System Fundamentals and Design Thinking.

Course Objective(s):

To understand the principles of Human-Computer Interaction (HCI), design and develop AR/VRbased interactive systems, apply 3D visualization and interaction techniques for data-driven applications, and evaluate user experience (UX) and usability in immersive environments.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Analyze principles of Human-Computer Interaction to design user-centered and accessible interactive systems.	L4	Analyze
CO2	Examine interaction design principles and usability testing methods to improve user experience in software systems	L4	Analyze
CO3	Analyze user requirements using research methods, task analysis, and prototyping techniques to develop effective user interfaces.	L4	Analyze
CO4	Evaluate AR/VR technologies and develop immersive solutions for practical applications.	L5	Evaluate

Immersive Systems: AR/VR and Human-Computer Interaction (RCP23DCPE814) Course Contents

Unit-I **06 Hrs.**

Foundations of HCI:

Introduction to Human-Computer Interaction, History and evolution of user interfaces, Interaction paradigms (CLI, GUI, touch, voice, immersive), Human factors: cognition, perception, memory; Usability principles (learnability, efficiency, satisfaction).

Unit-II **08 Hrs.**

User-Centered Design (UCD):

Principles of user-centered design, User research methods (interviews, surveys, personas), Task analysis and user journey mapping, Prototyping (low-fidelity highfidelity), Accessibility and inclusive design standards, UX Design Considerations for Immersive Environments, Applications of Immersive Technologies in Human– Computer Interaction.

Unit-III **07 Hrs.**

Interaction Design & Evaluation:

Interaction design principles (affordances, feedback, constraints), Heuristic evaluation (e.g., Jakob Nielsen's heuristics), Usability testing methods (A/B testing, think-aloud protocol), UX metrics and evaluation techniques, Cognitive models (e.g., GOMS, Fitts' Law).

Unit-IV **06 Hrs.**

Introduction to AR & VR:

Basics of Augmented Reality and Virtual Reality, Differences between AR, VR, and MR (Mixed Reality), Hardware overview (headsets, sensors, controllers), Key platforms (e.g., Unity, Unreal Engine), Applications in gaming, healthcare, education, industry.

Unit-V **07 Hrs.**

Designing for AR/VR Experiences:

3D interaction techniques (gaze, gesture, controllers), Spatial UI/UX design principles, Presence, immersion, and user experience in VR, Challenges: motion sickness, latency, ergonomics, Storyboarding and prototyping immersive environments.

Unit-VI **08 Hrs.**

Development & Future Trends in AR/VR:

Basics of AR/VR development workflows, SDKs and tools (ARCore, ARKit, WebXR) Testing and evaluation of immersive systems, Ethics and privacy in immersive tech Future trends: metaverse, haptics, AI integration.

Text Books:

1. Ben Shneiderman et al. ”Designing the User Interface: Strategies for Effective Human-Computer Interaction”, Pearson, 2022.
2. Dieter Schmalstieg, Tobias Höllerer, ”Augmented Reality Principles and Practice”, Addison-Wesley, 2016.
3. Alan Dix, Janet Finlay, Gregory D. Abowd, Russell Beale,”Human-Computer Interaction”,Pearson, Latest Edition, 2004.

Reference Books:

1. Helen Sharp, Yvonne Rogers, Jenny Preece,”Interaction Design Beyond Human-Computer Interaction”,Wiley, 2019.
2. Rex Hartson, Pardha Pyla,”The UX Book: Agile UX Design for a Quality User Experience”,Elsevier, 2019.
3. Designing Immersive 3D Experiences – Focused on AR/VR UX design (modern addition).
4. Augmented Human: How Technology Is Shaping the New Reality – O’Reilly, 2017.
5. Steven M. LaValle,”Virtual Reality”,Cambridge University Press, 2017.

Weblinks:

1. NPTEL: https://nptel.ac.in/courses (HCI & UI/UX Courses)
2. MIT OpenCourseWare (HCI): https://ocw.mit.edu
3. Stanford University: https://hci.stanford.edu
4. Unity Technologies Learn Platform: https://learn.unity.com
5. Google AR & VR Development (ARCore): https://developers.google.com/ar
6. Apple ARKit Resources: https://developer.apple.com/augmented-reality/

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech.	Semester: VIII
Internship (OJT) cum Project (RCP23IPELX10)		

Prerequisites:

1. Fundamental knowledge of engineering concepts and programming
2. Basic understanding of professional ethics and communication skills
3. Exposure to laboratory courses and mini-projects
4. Teamwork and problem-solving skills

Course Objective(s):

1. To provide practical exposure to industrial and professional environments.
2. To bridge the gap between academic learning and industry practices.
3. To develop technical, communication, teamwork, and managerial skills.
4. To enable application of engineering knowledge for solving real-world problems.
5. To familiarize students with modern tools, technologies, and professional ethics.
6. To prepare students for industry-oriented careers through project implementation and professional experience.

Course Outcomes:

On completion of the course, the learner will be able to:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Apply engineering knowledge and technical skills in industrial environments.	L3	Apply
CO2	Analyze and solve practical engineering problems using appropriate tools and techniques.	L4	Analyze
CO3	Demonstrate professional ethics, teamwork, communication, and organizational skills.	L3	Apply
CO4	Utilize modern engineering tools and technologies for assigned tasks and projects.	L3	Apply
CO5	Prepare technical reports, presentations, and project documentation effectively.	L6	Create
CO6	Adapt to professional work culture and demonstrate readiness for professional careers.	L3	Apply

Internship (OJT) cum Project (RCP23IPELX10) Course Contents

Overview of the OJT Process

The On-Job Training (OJT) program begins with an introduction to workplace ethics, safety practices, organizational culture, and professional conduct to prepare students for industrial environments. Students are then exposed to industrial processes, workflow practices, tools, and modern technologies relevant to their domain of study.

During the technical training phase, students work on assigned industrial tasks and projects under the guidance of faculty mentors and industry supervisors. The program emphasizes the application of engineering concepts, teamwork, communication skills, and problem-solving abilities in real-world professional settings.

The later stages of the OJT focus on project implementation, report writing, technical documentation, and presentation preparation. Students are required to maintain logbooks and progress records throughout the training period. At the end of the semester, students present their project work through demonstrations and viva-voce examinations, followed by comprehensive evaluation and feedback.

Internship (OJT) Schedule, Duration and Credits

The Internship / On-Job Training (OJT) cum Project is an integral part of the Final Year B.Tech. program and carries a total of **18 academic credits** toward completion of the degree requirements. Each credit corresponds to **40 hours** of work, resulting in approximately **550–600 hours** of industrial training and project work over one semester.

The full-time OJT program is conducted during the designated semester as per the academic schedule. The duration of the OJT is one complete semester in the final year. Faculty mentors are assigned for mentoring, monitoring, and evaluating students throughout the OJT period.

Approximately 50% of the students undergo OJT during Semester VII while the remaining students continue academic activities in the institute. In Semester VIII, the arrangement is interchanged to ensure equal academic and industrial exposure for all students.

To avoid academic scheduling conflicts and ensure fair evaluation, oral, practical, and End Semester Examinations for both Semester VII and Semester VIII will be conducted at the end of Semester VIII. Students are issued a combined marksheet covering both semesters.

Types of External OJT Opportunities

Sr. No.	Type of OJT	Examples / Description
1	Industry OJT	Industrial internships with or without stipend.
2	Government / PSU OJT	BARC, SAMEER, Railways, ISRO, etc.
3	Research OJT	IITs, NITs, IISc, IIMs, and other research institutes.
4	Institute-Based OJT	OJT at institutes approved by t&p and departments.
5	Other Approved OJT	Any approved industrial/research work relevant to the domain.

OJT / Internship Sources

To facilitate OJT and internship opportunities, AICTE has signed Memorandums of Understanding (MoUs) with various industries, government organizations, and training institutions. These collaborations provide students with industrial exposure, skill development opportunities, research internships, and professional training through multiple recognized platforms and organizations.

Students may also approach organizations such as the Board of Apprenticeship Training (BOAT) and Board of Practical Training (BOPT) for additional training opportunities.

Major OJT / Internship Sources

Sr. No.	Organization / Platform	Nature of Opportunity
1	Internshala	Internship and industry training opportunities
2	NETiit (Taiwan)	International internship opportunities
3	HireMee	Skill-based internships and employability support
4	IGNCA	Research and cultural project opportunities
5	CCEI, Republic of Korea	International innovation and creative economy internships
6	IIWM, Bangalore	Waste management and sustainability projects
7	Engineering Council of India (ECI)	Engineering and professional development activities
8	Fourth Ambit	Industry training and technical internships
9	LinkedIn	Professional networking and internship opportunities
10	Telecom Sector Skill Council (TSSC)	Telecom and communication technology training
11	SCHOLARSMERIT	Internship and skill enhancement programs
12	Studenting Era	Student internship and academic support activities
13	MSME	Industry exposure and entrepreneurship opportunities
14	BOAT	Apprenticeship and industrial training programs
15	BOPT	Practical and apprenticeship-based training opportunities

Evaluation Metrics

Sr. No.	Evaluation Component	Marks
1	Internal Review 1	100
2	Final Internal Review	100
3	End Semester Evaluation (OJT Viva / Presentation)	200
Total		**400**

Evaluation Parameters

The student shall be evaluated based on the following parameters:

- Understanding of assigned work.
- Progress and task completion.
- Technical skill development.
- Learning ability and initiative.
- Professional behaviour and discipline.
- Communication and presentation skills.
- Problem solving and contribution.
- Quality of work and innovation.
- Logbook maintenance and report documentation.
- Application of engineering knowledge.

Necessary Documents

Students are required to submit and maintain the following documents during the OJT period:

1. No Objection Certificate (NOC)
2. Undertaking for opting OJT
3. OJT Joining Form
4. Parent/Guardian Undertaking Form
5. Contact Details and OJT Objectives Form
6. Student Logbook / Daily Activity Record
7. Internal Review Evaluation Sheets

8. External Supervisor Evaluation Form
9. Internal Supervisor Feedback Form
10. Student Feedback Form
11. SDG Mapping Form
12. Final OJT Report and Presentation
13. OJT Completion Certificate

Scheme of Examination

Component	Marks
Continuous Internal Assessment	200
End Semester OJT Evaluation (Report and Presentation)	200
Total	**400**

Credits

- Total Credits: 18
- 1 Credit = 40 Hours of Work
- Minimum Duration: 550–600 Hours of OJT and Project Work over one semester.

Program: Computer Science & Engineering (Data Science)	Final Year B.Tech	Semester: VIII
Agentic AI (RCP23DCSC801)		

Course Objective(s):

1. To analyze the architecture, design principles, and applications of Agentic AI systems.
2. To apply open-source Agentic AI frameworks for developing autonomous and collaborative AI agents.
3. To implement advanced prompt engineering techniques and AI tooling for intelligent task automation.
4. To analyze the design, development, deployment, and optimization of Agentic AI applications using structured workflows and tool integration.

Course Outcomes:

CO	Course Outcomes	Blooms Level	Blooms Description
CO1	Analyze the architecture, workflows, and design patterns of Agentic AI systems	L4	Analyze
CO2	Develop autonomous and multi-agent applications using LangGraph, CrewAI, BeeAI, and AG2 frameworks.	L6	Create
CO3	Apply advanced prompt engineering, function calling, and structured outputs to build intelligent AI solutions.	L3	Apply
CO4	Implement Agentic AI applications by integrating external tools, testing workflows, and optimizing AI agent performance.	L3	Apply

Agentic AI (RCP23DCSC801))
Course Contents

Unit-I 05 Hrs.

Introduction to Agentic AI and Agent Design Patterns:

Fundamentals of Agentic AI, autonomous AI agents, open-source agentic frameworks, architecture of intelligent agents, AI agent lifecycle, design principles for agentic systems, orchestrator design pattern, evaluator-optimizer design pattern, multi-agent workflows, planning, reasoning, and real-world applications of Agentic AI.

Unit-II 06 Hrs.

Agentic AI Frameworks and Multi-Agent Development:

Design and implementation of AI agents using LangGraph, CrewAI, BeeAI, and AG2 (AutoGen), agent orchestration, structured outputs, YAML-based workflow design, CrewBase framework and classes, custom tools and functions, agent communication, tool integration, task coordination, and deployment of collaborative multi-agent systems.

Unit-III 05 Hrs.

Advanced Prompt Engineering and AI Tooling:

Advanced prompt engineering techniques, prompt refinement, prompt generation, decomposition strategies, self-consistency, self-critique, function calling, structured prompting, AI-assisted workflow automation, designing robust prompts for reasoning and task execution, and practical applications in agentic systems.

Unit-IV 04 Hrs.

Agentic AI Application Development and Deployment:

Applications of Generative AI in marketing analytics and feature engineering, text analytics, predictive model development, synthetic data generation, data privacy, bias and fairness in Generative AI, responsible AI principles, ethical development and deployment, privacy-preserving synthetic data, governance, emerging trends, and industrial applications of Generative AI.

Web Links:

https://www.coursera.org/learn/agentic-ai-with-langgraph-crewai-autogen-and-beeai

https://www.coursera.org/learn/packt-advanced-prompting-ai-tooling-yormm

Evaluation Scheme:

Continuous Assessment (CA):

- Course Completion Certificate: 15 marks.
- Faculty Curated Test: 15 Marks.
- Assignments/Case Study: 10 marks.