Shri Vile Parle Kelavani Mandal's

Dwarkadas J. Sanghvi College of Engineering

(Autonomous College Affiliated to the University of Mumbai)

Scheme and Detailed syllabus (DJS23)

Final Year B.Tech

in

Computer Science and Engineering (Data Science)

(Semester VII)

Shri Vile Parle Kelavani Mandal's
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)

Scheme of Semester VII for Department of Computer Science and Engineering (Data Science)
Academic Year 2026-2027

Sr	Course Code	Course	Teaching Scheme				Semester End Examination (SEE) - A						Continuous Assessment (CA) - B						Aggregate (A+B)	Credits Earned	
			Theory (Hrs.)	Practical (Hrs.)	Tutorial (Hrs.)	Credits	Duration (Hrs)	Theory	Oral	Pract	Oral & Pract	SEE Total (A)	Term Test 1 (TT1)	Term Test 2 (TT2)	Term Test 3 (TT3)	Term Test Total (TT1 + TT2+TT3)	Term Work	Total CA (B)			
1	DJS23DCPC701	Language and Reasoning Models	3	--	--	3	2	60	--	--	--	60	15	15	10	40	--	40	100	3	4
	DJS23DLPC701	Language and Reasoning Models Laboratory	--	2	--	1	--	--	--	--	--	--	--	--	--	--	25	25	25	1	
2	DJS23DCPC702	High Performance Computing	3	--	--	3	2	60	--	--	--	60	15	15	10	40	--	40	100	3	4
	DJS23DLPC702	High Performance Computing Laboratory	--	2	--	1	2	--	25	--	--	25	--	--	--	--	25	50	50	1	
3@	DJS23DCPE711	Geospatial Data Science	3	--	--	3	2	60	--	--	--	60	15	15	10	40	--	40	100	3	4
	DJS23DLPE711	Geospatial Data Science Laboratory	--	2	--	1	--	--	--	--	--	--	--	--	--	--	25	25	25	1	
	DJS23DCPE712	Computational Motion Planning	3	--	--	3	2	60	--	--	--	60	15	15	10	40	--	40	100	3	4
	DJS23DLPE712	Computational Motion Planning Laboratory	--	2	--	1	--	--	--	--	--	--	--	--	--	--	25	25	25	1	
	DJS23DCPE713	Quantum Computing	3	--	--	3	2	60	--	--	--	60	15	15	10	40	--	40	100	3	4
	DJS23DLPE713	Quantum Computing Laboratory	--	2	--	1	--	--	--	--	--	--	--	--	--	--	25	25	25	1	
	DJS23DCPE714	Adversarial Machine Learning	3	--	--	3	2	60	--	--	--	60	15	15	10	40	--	40	100	3	4
	DJS23DLPE714	Adversarial Machine Learning Laboratory	--	2	--	1	--	--	--	--	--	--	--	--	--	--	25	25	25	1	
4	DJS23DCMD701	Data Ethics	3	--	--	3	2	60	--	--	--	60	15	15	10	40	--	40	100	3	4
	DJS23DTMD701	Data Ethics Tutorial	--	--	1	1	--	--	--	--	--	--	--	--	--	--	25	25	25	1	
5	DJS23ITELX12	Research Ecosystem	--	--	2	2	--	--	--	--	--	--	--	--	--	--	50	50	50	2	2
6	DJS23IPELX13	Major Project	--	8	--	4	2	--	--	--	50	50	--	--	--	--	50	50	100	4	4
7	DJS23DCSC701	Generative AI	1	--	--	1	--	--	--	--	--	--	15	15	10	40	--	40	40	1	1
8	DJS23ICHSX11	Disaster Management and Preparedness	2	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
		Total	**15**	**14**	**3**	**23**	**12**	**240**	**25**	**--**	**50**	**315**	**75**	**75**	**50**	**200**	**200**	**425**	**715**	**23**	**23**

Any one Programme Elective Course (PEC) from 3@

Continuous Assessment (A):

Course	Assessment Tools	Marks	Time (hrs.)
Theory	a. Term Test 1 (based on 40 % syllabus)	15	45
	b. Term Test 2 (on next 40 % syllabus)	15	45
	c. Assignment / course project / group discussion / presentation / quiz/ any other.	10	--
	Total marks (a + b + c)	40	--
Audit course	Performance in the assignments / quiz / power point presentation / poster presentation / group project / any other tool.	--	As applicable
Laboratory	Performance in the laboratory and documentation.	25	
Tutorial	Performance in each tutorial & / assignment.	25	
Laboratory &Tutorial	Performance in the laboratory and tutorial.	50	

The final certification and acceptance of term work will be subject to satisfactory performance upon fulfilling minimum passing criteria in the term work / completion of audit course.

Semester End Assessment (B):

Course	Assessment Tools	Marks	Time (hrs.)
Theory / * Computer based	Written paper based on the entire syllabus. * Computer based assessment in the college premises.	60	2
Oral	Questions based on the entire syllabus.	25	As applicable
Practical	Performance of the practical assigned during the examination and the output / results obtained.	25	2
Oral & Practical	Project based courses - Performance of the practical assigned during the examination and the output / results obtained. Based on the practical performed during the examination and on the entire syllabus.	As per the scheme	2

Prepared by Checked by Head of the Department Principal

PROGRAM CORE COURSE

Program: B.Tech in Computer Science and Engineering (Data Science) **Semester: VII**

Course: Language and Reasoning Models (DJS23DCPC701)
Language and Reasoning Models Laboratory (DJS23DLPC701)

Pre-requisite: Machine Learning and Natural Language Processing.

Objectives: To introduce the fundamentals of neural 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.

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

1. Apply the principles of Transformers, BERT, and GPT to develop Solution for natural language processing tasks.
2. Apply pre-training and fine-tuning techniques to optimize language models for real-world applications.
3. Analyze various evaluation metrics to assess the performance and reliability of language models.

Language and Reasoning Models (DJS23DCPC701)		
Unit	**Description**	**Duration**
1	**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.	**06**
2	**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.	**10**
3	**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.	**07**
4	**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).	**07**

	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.	
5	**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.	**06**
6	**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.	**06**
	Total	**42**

Language and Reasoning Models Laboratory (**DJS23DLPC701**)	
Exp.	**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.
13	Implement Sequence-to-Sequence (Seq2Seq) and Attention-based Models for Language Translation.

*The Term Work will be calculated based on Laboratory Performance.

Books Recommended:

Text Books:

1. Tanmoy Chakraborty "Introduction to Large Language Models" Wiley India 1st Edition,2025.
2. Jurafsky and Martin, "Speech and Language Processing", Prentice Hall, 3rd Edition, 2020.
3. Uday Kamath, "Deep Learning for NLP and Speech Recognition", 1st 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, 1st 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

Prepared by	Checked by	Head of the Department	Principal

Program: B.Tech. in Computer Science and Engineering (Data Science) **Semester: VII**

Course: High Performance Computing (DJS23DCPC702)

High Performance Computing Laboratory (DJS23DLPC702)

Pre-requisite: Computer System Fundamentals

Objectives: 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.

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

1. Apply the principles of parallel computing, parallel programming models, performance metrics, and the architectural features of multicore CPUs and GPUs.
2. Apply shared-memory programming techniques and the CUDA programming model to develop parallel solutions for data- and task-parallel applications.
3. Analyze GPU performance metrics, including memory coalescing, thread scheduling, and control divergence impacts.
4. Analyze GPU performance by evaluating memory access patterns, thread execution efficiency, and optimization techniques to improve the scalability and performance of parallel applications.

High Performance Computing (DJS23DCPC702)		
Unit	**Description**	**Duration**
1	**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, Multi-core 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	**07**
2	**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	**07**
3	**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	**07**

	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.	
4	**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.	**08**
5	**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.	**06**
6	**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).	**07**
	Total	**42**

High Performance Computing Laboratory (DJS23DLPC702)	
Exp.	**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.

*The Term Work will be calculated based on Laboratory Performance (15m) and Assignments (10m).

Books Recommended:

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, 1st 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, 2nd Edition, 2012.
2. Charles Severance and Kevin Dowd, "High Performance Computing", O'Reilly Media, 2nd 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.

Prepared by   Checked by   Head of the Department   Principal

Shri Vile Parle Kelavani Mandal's
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)

PROGRAM ELECTIVE COURSE

Program: B.Tech in Computer Science and Engineering (Data Science) Semester: VII

Course: Geospatial Data Science (DJS23DCPE711)

Geospatial Data Science Laboratory (DJS23DLPE711)

Pre-requisite: Fundaments of Data Analysis and Machine Learning

Objectives: 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.

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

1. Apply tools and techniques used to analyze and visualize geospatial data.
2. Applying data science methods to solve real-world problems with geospatial data.
3. Analyze geospatial large data models and ethical issues.

Geospatial Data Science (DJS23DCPE711)		
Unit	**Description**	**Duration**
1	**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.	**06**
2	**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).	**08**
3	**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.	**09**
4	**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	**06**

5	**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).	**08**
6	**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.	**05**
	Total	**42**

Geospatial Data Science Laboratory (DJS23DLPE711)	
Exp.	**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 a sequence 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.

*The Term Work will be calculated based on Laboratory Performance.

Books Recommended:

Text Books

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

Reference Books

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

Prepared by Checked by Head of the Department Principal

Program: B.Tech in Computer Science and Engineering (Data Science) **Semester: VII**

Course: Computational Motion Planning (DJS23DCPE712)

Computational Motion Planning Laboratory (DJS23DLPE712)

Pre-requisite: Linear Algebra, Data Structures and Artificial Intelligence.

Course Objectives: 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.

Outcomes: On completion of the course, learner will be able to:
1. Analyze motion planning techniques in robotics
2. Apply efficient path planning algorithms for real-world scenarios.
3. Apply sampling-based and optimization-based planning methods
4. Evaluate planning strategies under uncertainty and constraints

Computational Motion Planning (DJS23DCPE712)		
Unit	**Description**	**Duration**
1	**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	**07**
2	**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.	**07**
3	**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.	**07**
4	**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.	**08**
5	**Kinodynamic and Constrained Planning:** Forward and Inverse Kinematics, Non-holonomic constraints, Differential constraints, Trajectory planning, Time-parameterized planning, Path smoothing, Introduction to optimal control.	**07**

6	**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.	**06**
	Total	**42**

Computational Motion Planning Laboratory (DJS23DLPE712)	
Exp.	**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

*The Term Work will be calculated based on Laboratory Performance (15m).

Books Recommended:

Textbooks

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, 2nd Edition, 2011.
4. Sebastian Thrun, Wolfram Burgard, Dieter Fox, Probabilistic Robotics, MIT Press, 2005.

Weblinks:

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/

Prepared by	Checked by	Head of the Department	Principal

Program: B.Tech in Computer Science and Engineering (Data Science) **Semester: VII**

Course: Quantum Computing (DJS23DCPE713)

Quantum Computing Laboratory (DJS23DLPE713)

Pre-requisite: Computer System Fundamentals and Machine Learning.

Objectives: 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.

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

1. Analyze the fundamental principles of quantum computing, including qubits, superposition, and entanglement, to interpret their impact on computational models.
2. Evaluate quantum algorithms such as Shor's and Grover's algorithms in terms of efficiency and applicability compared to classical approaches.
3. Apply Quantum Machine Learning (QML) and Quantum Deep Learning (QDL) techniques to solve data-driven problems and compare their performance with classical approaches.

Quantum Computing (DJS23DCPE713)		
Unit	**Description**	**Duration**
1	**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.	**07**
2	**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.	**07**
3	**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).	**06**

4	**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	**06**
5	**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).	**08**
6	**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	**08**
	Total	**42**

Quantum Computing Laboratory (DJS23DLPE713)	
Exp.	**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. SVM.
11	Implementation of Quantum key distribution Algorithm.

*The Term Work will be calculated based on Laboratory Performance.

Books Recommended:

Textbooks:

1. Parag K. Lala, 'Quantum Computing', McGraw Hill**,** 1st Edition, 2020.
2. Chris Bernhardt, 'Quantum Computing for Everyone', MIT Press, 1st Edition, 2020.

Reference Books:

1. Jack D. Hidary, 'Quantum Computing: An Applied Approach', Springer, 2nd Edition, 2021.
2. Johan Vos, 'Quantum Computing in Action', Manning Publications, 1st 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%208803%20O13%202023-3.pdf
4. https://www.cse.iitd.ac.in/~suban/quantum/

Prepared by	Checked by	Head of the Department	Principal

Program: B.Tech in Computer Science and Engineering (Data Science) **Semester: VII**

Course: Adversarial Machine Learning (DJS23DCPE714)

Adversarial Machine Learning Lab (DJS23DLPE714)

Pre-requisite: Machine Learning

Objectives: 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.

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

1. Apply fundamental ML/DL techniques in adversarial settings, including supervised, unsupervised, and reinforcement learning, to identify vulnerabilities and threat models.
2. Categorize adversarial attacks such as causative (data poisoning) and evasion attacks, and their impact on machine learning models in security-critical domains.
3. Apply robust defense strategies against adversarial attacks, including adversarial training, detection techniques, and secure learning frameworks.
4. Design secure and resilient machine learning solutions for applications in cybersecurity, medical imaging, and NLP under adversarial conditions.

Adversarial Machine Learning (DJS23DCPE714)		
Unit	**Description**	**Duration**
1	**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.	**07**
2	**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.	**07**

3	**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 Trade-off.	**09**
4	**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.	**07**
5	**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.	**06**
6	**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.	**06**
	Total	**42**

Adversarial Machine Learning Laboratory (DJS23DLPE714)	
Exp.	**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.

*The Term Work will be calculated based on Laboratory Performance.

Books Recommended:

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 an imprint of Elsevier, 1st Edition, 2022.
3. Shuhe Wang, Kuan-Chieh Wang, "Adversarial Machine Learning", Springer, 2014.

Web Links:

1. Goodfellow (2014) *Explaining and Harnessing Adversarial Examples)*
2. Carlini (2017) Towards Evaluating the Robustness of Neural Networks
3. Brendel (2017) Decision-Based Adversarial Attacks: Reliable Attacks Against Black-Box Machine Learning Models
4. Bhagoji (2017) Exploring the Space of Black-box Attacks on Deep Neural Networks
5. Xu (2019) *Adversarial Attacks and Defenses in Images, Graphs and Text: A Review*
6. Tramer (2018) *Ensemble Adversarial Training: Attacks and Defenses*
7. Rosenberg (2021) *Adversarial Machine Learning Attacks and Defense Methods in the Cyber Security Domain*
8. Severi (2021) *Explanation-Guided Backdoor Poisoning Attacks Against Malware Classifiers*
9. Kuleshov (2018) *Adversarial Examples for Natural Language Classification Problems (pdf)*
10. Erba (2019) *Constrained Concealment Attacks against Reconstruction-based Anomaly Detectors in Industrial Control Systems (pdf)*

Prepared by Checked by Head of the Department Principal

MULTIDISCIPLINARY MINOR

Program: B.Tech. in Computer Science and Engineering (Data Science) Semester: VII

Course: Data Ethics (DJS23DCMD701)

Data Ethics Tutorial (DJS23DTMD701)

Pre-requisite: Fundaments of Data Analysis, Intelligent Systems and Machine Learning

Objectives:
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.

Outcomes: On completion of the course, learner will be able to:
1. Apply ethical principles, privacy-preserving practices, and relevant regulatory frameworks to design responsible AI and data-driven systems.
2. Analyze, identify, and mitigate bias in machine learning systems while enhancing transparency and trust through Explainable AI techniques.
3. Analyze AI systems from governance, societal, sustainability, and policy perspectives to ensure accountable and responsible deployment.

Data Ethics (DJS23DCMD701)		
Unit	**Description**	**Duration**
1	**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**	**8**
2	**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**	**10**
3	**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.	**8**

	Case study: Bias in the COMPAS recidivism prediction system	
4	**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**	**9**
5	**Governance, Emerging Issues, and Future Directions:** Ethical data governance and stewardship, AI ethics frameworks (OECD, EU, UNESCO, IEEE), Societal 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**	**7**
	Total	**42**

Data Ethics Tutorial (DJS23DTMD701):

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

Tut.	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

The Term Work will be calculated based on Tutorial Performance.

Books Recommended:

Textbooks:

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, 2nd 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, 1st 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- and-proper-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-science-course-curriculum/
4. Federated Learning in Practice: Google AI Blog : https://research.google/blog/federated-learning-with-formal-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

Prepared by	Checked by	Head of the Department	Principal

RESEARCH METHODOLOGY

Program: All programs (Final Year B. Tech.) **Semester: VII**

Course: Research Ecosystem (DJS23ITELX12)

Pre-requisites:

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.

Objectives:

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, simulation-based, 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).

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

1. Analyze complex engineering and societal problems to evaluate literature and patents and formulate clear research gaps.
2. Design and apply advanced research methods and tools to acquire data and evaluate solution performance.
3. Transform research insights into prototypes or startup concepts using innovation frameworks and Technology Readiness Levels.
4. Evaluate ethical, socio-technical, and sustainability issues and create responsible engineering solutions.
5. Synthesize multidisciplinary knowledge to create research proposals and scalable, future-ready solutions.

<table>
<tr><td colspan="3">Research Ecosystem (DJS23ITELX12)</td></tr>
<tr><th>Unit</th><th>Description</th><th>Duration</th></tr>
<tr><td>1</td><td>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</td><td>5</td></tr>
</table>

	• 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.	

2	**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).
		6

3	**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.	**5**

4	**Socio-Technical Systems, Ethics & Sustainability**
	• Socio-technical systems: Interaction of people, technology and environment
	• 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.
		6

5	**Integrated Research, Proposals 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:
	    o Technical solution
	    o Societal impact
	    o Possible commercialization
		6

	Total	**28**

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:
   i. Identification of a real-world problem
   ii. Application of appropriate research methodology
   iii. Proposed technical solution
   iv. Analysis of societal impact
   v. Possible commercialization/startup opportunities

Books Recommended:

Reference Books:

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

Web References:

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

PROJECT

Program: B. Tech. (Common to all Programmes) **Semester: VII**

Course: Major Project (DJS23IPELX13)

Objectives

The primary purpose of the Major Project is to enable students to apply the knowledge and skills acquired across the programme to conceive, design, implement, and evaluate a comprehensive solution to a real-world problem. The project strengthens technical competence, communication, and teamwork by integrating design, development, technical writing, presentation, and collaborative work. It emphasises professional engineering practice and addresses a range of non-technical considerations such as economic factors, safety, reliability, ethics, sustainability, and environmental and societal impact.

Course Outcomes (CO)

On successful completion of the Major Project, the student will be able to:

CO1: Apply technical knowledge gained from previous courses to identify real-life, industry, or societal problems and design appropriate solutions.

CO2: Demonstrate the technical skills required to design, develop, build, and test engineering systems, products, software, or hardware using modern engineering and IT tools.

CO3: Apply project-management skills — scheduling work, procuring resources/components, budgeting, documenting technical and non-technical details, and working within defined deadlines as an effective team.

CO4: Develop and demonstrate the ability to test, validate, debug, and troubleshoot engineering systems (including software, hardware, and process components) and analyse the results.

CO5: Create technical reports and research papers in the prescribed format and effectively communicate and present the work to evaluators.

Scope and Nature of the Project Work

Final-year students have already undertaken project assignments in their pre-final year through Innovative Product Design / Mini Project work. In the final year, a group of a maximum of four students completes a comprehensive project based on the courses studied. The project work may be internally assigned or externally assigned by research institutes, industry, or similar organisations. Each group is assigned one faculty member as supervisor. The final-year project may be an extension of the Mini Project carried out in the pre-final year.

The main intention of the project work is to enable students to apply the knowledge and skills learnt across the programme to solve or implement a well-defined practical problem. The work may go beyond the scope of the curriculum or build upon courses studied, but the thrust should be on:

- Learning additional skills relevant to the chosen domain;

- Developing the ability to define, design, analyse, and implement a problem and carry it through to completion with proper planning;
- Learning behavioural science and professional ethics by working effectively in a group;
- Selecting a project area aligned with the student's intended higher education, employment, or self-employment goals;
- Choosing a topic that differs from, or meaningfully advances, the Mini Project topic;
- Using the opportunity to learn modern computational techniques, tools, and model development through an appropriate choice of project.

Continuous Assessment and Term Work

The department maintains a proper record of the progress of each project throughout the semester. At the end of the semester, the work is assessed for the award of Term Work (TW) marks by an approved internal faculty member appointed by the Head of the Institute, on the basis of:

- Scope and objectives of the project work;
- Extent and quality of the literature survey;
- Progress of the work (continuous assessment across reviews);
- Design, implementation, and analysis of the project work;
- Results, conclusions, and future scope;
- Report prepared in the prescribed University / institutional format.

Oral / Practical Examination: An approved external examiner together with an internal examiner appointed by the Head of the Institute assesses the project during the oral examination. The oral examination consists of a presentation by the group along with a demonstration of the work done. Each student is assessed individually for their contribution, understanding, and the knowledge gained.

Project Guide / Topic Allocation Policy

The project guide and topic-allocation policy is explained to students during the Orientation held in Semester VI. Each faculty member is allocated a minimum of one and a maximum of four project groups. As per the timeline in the academic calendar, the list of project topics and areas offered by each faculty member — three topics per faculty member — is displayed on the notice board. Allocation is carried out over successive rounds, and in each round students submit their preferences against the available topics and guides.

If a topic is preferred by only one group, that group is allocated to the corresponding guide and topic. If a topic is preferred by more than one group, the concerned faculty member reviews the applications and selects one group; the remaining groups carry forward to the next round. After each round, the list of groups and guides allotted so far is displayed, along with the topics and guides that remain available. Unallotted groups then submit fresh preferences from the available list. This process continues over successive rounds until every group has been allotted a guide, ensuring a uniform distribution of project groups among the faculty members.

Assessment Scheme

The Major Project carries a total of 100 marks — **Term Work (50)** assessed internally through continuous evaluation, and **Oral / Practical Examination (50)** assessed jointly by internal and external examiners. Each criterion is scored against three performance levels — Excellent, Satisfactory, and Below Expectation — as detailed below.

Rubric for Term Work (50 Marks)

Assessment Criteria (mapped CO)	Max	Excellent	Satisfactory	Below Exp.
Problem Definition, Objectives & Literature Survey (CO1)	**10**	8–10	5–7	0–4
Design, Methodology & Implementation Progress – Continuous Assessment (CO2)	**10**	8–10	5–7	0–4
Project Management & Teamwork (CO3)	**10**	8–10	5–7	0–4
Report / Thesis Writing – Written Communication (CO5)	**10**	8–10	5–7	0–4
Research Paper Writing / IPR – Patent or Copyright (CO5)	**10**	8–10	5–7	0–4
TOTAL	**50**			

Rubric for Oral / Practical / Presentation / Demonstration (50 Marks)

Assessment Criteria (mapped CO)	Max	Excellent	Satisfactory	Below Exp.
Concept & Problem Definition (CO1)	**5**	4–5	3	0–2
Design, Methodology & Implementation (CO2)	**15**	12–15	7–11	0–6
Project Management Skills (CO3)	**5**	4–5	3	0–2
Demonstration, Testing & Result Analysis (CO4)	**15**	12–15	7–11	0–6
Presentation & Oral Communication (CO5)	**10**	8–10	5–7	0–4
TOTAL	**50**			

Descriptive Assessment Rubric (Performance-Level Descriptors)

The following descriptors define each performance level and are applied consistently across all programmes. Examiners map a student's performance to the most appropriate level for each criterion before awarding the corresponding marks from the tables above.

Criteria	Excellent	Satisfactory	Below Expectation
Concept & Problem Definition	All major and minor objectives are identified and correctly prioritised. The problem statement is precise, relevant and well-scoped. All relevant information is gathered from valid sources and the proposed solution is well justified.	Major objectives identified but one or two minor ones missing or priorities not fully set. Problem statement mostly clear. Sufficient information from largely valid sources; solution mostly justified.	Several major objectives not identified. Problem statement vague or too broad. Insufficient information and/or invalid sources; proposed solution not justified.
Literature Survey	Comprehensive, current and well-organised survey of journals, standards, patents and existing products/systems. Research gap / novelty clearly identified and the chosen approach is well justified.	Adequate survey covering most key sources. Gap / novelty identified but only partially justified.	Sparse or outdated survey. Little or no identification of the gap; chosen approach not justified.
Design, Methodology & Implementation	Design is based on stated criteria, sound analysis and realistic constraints. Methodology is appropriate and well justified. Implementation is complete and robust and makes effective use of modern engineering / software tools.	Design is reasonable and methodology mostly appropriate. Implementation is largely complete; deeper analysis of alternatives or constraints could improve the outcome.	Only one solution considered or alternatives ignored. Weak methodology and incomplete implementation. Many constraints and criteria ignored.
Project Management & Teamwork	Responsibilities delegated fairly and every member contributes valuably. All members attend meetings and meet deliverable deadlines. Schedule, resources and budget are well managed.	Minor inequities in delegation; some members contribute more than others but all meet their responsibilities. Meetings mostly attended and deadlines mostly met.	Major inequities in delegation, with free-riders or dominating members. Meetings and deadlines frequently missed; poor planning of schedule and resources.

Criteria	Excellent	Satisfactory	Below Expectation
Demonstration, Testing & Result Analysis	Develops and follows logical testing / validation / experimental procedures. Selects appropriate tools, equipment, platforms or datasets and operates them confidently. Aware of errors / limitations, accounts for them, and interprets and relates the results to the objectives and underlying theory.	Procedures mostly followed with occasional oversight. Needs some guidance in selecting tools / equipment and is tentative in operating them. Aware of errors but accounts for them only minimally.	Does not follow a proper procedure. Cannot select appropriate tools / equipment or operates them incorrectly, needing frequent supervision. Makes no attempt to relate results to objectives.
Report / Thesis Writing (Written Communication)	Report is well organised and clearly written; the logic is easy to follow. Wording is precise; figures, tables and analyses enhance understanding. Grammatically correct, free of spelling errors, properly cited and free of plagiarism.	Report is mostly organised and clear; a few sections are harder to follow. Wording is good with minor exceptions; figures are consistent. Few grammatical / spelling errors that do not hinder the reader; some sources not fully cited.	Report lacks organisation and the logic is hard to follow. Figures absent or inconsistent. Grammatical and spelling errors hinder reading. Evidence of plagiarism or inadequate citation.
Research Paper Writing / IPR (Patent or Copyright)	A research / technical paper is drafted to publication standard in the required format, or a patent / copyright application is prepared and filed. Novelty and contribution are clearly articulated, claims and results are well supported, and the work is original with proper citations and no plagiarism.	A paper draft or IPR document is prepared and largely follows the required format. Novelty and contribution are stated but only partially developed, with minor gaps in supporting evidence or formatting.	No paper / IPR document, or a weak draft that does not follow the required format. Novelty or contribution is unclear or unsupported, with evidence of plagiarism or inadequate citation.
Presentation & Oral Communication	Slides are error-free and logically present the work and findings; they are readable and the graphics support the main ideas. Speakers	Slides are error-free and logical and mostly readable. Speakers are mostly fluent with minimal reliance on notes and answer most	Slides contain errors and lack logical flow; key aspects are absent and graphics confuse the audience. Speakers are inaudible or

Criteria	Excellent	Satisfactory	Below Expectation
	are audible and fluent, do not rely on notes and answer questions accurately. Confident body language and eye contact convey strong engagement.	questions well. Slight discomfort or occasional distracting gestures.	hesitant and rely heavily on notes, with difficulty answering questions. Body language conveys discomfort.

Prepared by Checked by Head of the Department Principal

ABILITY ENHANCEMENT COURSE

Program: B. Tech in Computer Science and Engineering (Data Science) **Semester: VII**

Course: Disaster Management and Preparedness (DJS23ICHSX11)

Objectives:
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.

Outcomes: On completion of the course, learner will be able to:
1. Apply disaster management principles & guidelines.
2. Conduct risk assessments.
3. Develop community awareness & participation.
4. Utilize Science & Technology tools (GIS, GPS).
5. Prepare disaster management plans.

Disaster Management and Preparedness (DJS23ICHSX11)		
Unit	**Description**	**Duration**
1	**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.	**06**
2	**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.	**06**
3	**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.	**04**

4	**Recovery, Rehabilitation & Reconstruction** Post-disaster damage assessment. Rehabilitation, Reconstruction, & Livelihood Restoration. Sanitation, Hygiene, & Waste Management.	04
5	**Policy, Governance & Capacity Building** National Disaster Management Authority (NDMA) & Legislation. Institutional Mechanisms & Community Mobilization. Non-Structural Mitigation: Community based disaster preparedness, capacity development and training, awareness and education, contingency plans. **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	08
	Total	**28**

Books Recommended:

Reference Books and Reports:

1. Disaster Management, by Harsh K. Gupta, Universities Press Publications (2003).
2. Disaster Management: An Appraisal of Institutional Mechanisms in India, by O. S. Dagur, published by Centre for land warfare studies, New Delhi, 2011.
3. Introduction to International Disaster Management, by Damon Copolla, Butterworth Heinemann Elsevier Publications (2015).
4. Disaster Management Handbook, by Jack Pinkowski, CRC Press, Taylor and Francis group (2008).
5. Disaster management & rehabilitation, by Rajdeep Dasgupta, Mittal Publications, New Delhi (2007).
6. Natural Hazards and Disaster Management, Vulnerability and Mitigation, by R B Singh, Rawat Publications (2006).
7. Concepts and Techniques of GIS, by C. P. Lo Albert, K.W. Yonng, Prentice Hall (India) Publications (2006).
8. Risk management of natural disasters, by Claudia G. Flores Gonzales, KIT Scientific Publishing (2010).
9. Disaster Management – a disaster manger's handbook, by W. Nick Carter, Asian Development Bank (2008).
10. Disaster Management in India, by R. K. Srivastava, Ministry of Home Affairs, GoI, New Delhi (2011)
11. The Chernobyl Disaster: Legacy and Impact on the Future of Nuclear Energy, by Wil Mara, Marshall Cavendish Corporation, New York, 2011.
12. The Fukushima 2011 Disaster, by Ronald Eisler, Taylor & Francis, Florida, 2013.

(Learners are expected to refer reports published at national and international level and updated information available on authentic web sites.)

Prepared by　　Checked by　　Head of the Department　　Principal