Vidyalankar Institute of Technology

Accredited A+ by NAAC

Vidyalankar Institute of Technology

An Autonomous Institute affiliated to University of Mumbai

Honours/Minor Degree Programme

for

Bachelor of Technology

in

Computer Engineering

(R-2022 Curriculum)

(As per AICTE guidelines, with effect from the Academic Year 2024-25)

Preamble

To meet the challenge of ensuring excellence in engineering education, the issue of quality needs to be addressed, debated, and taken forward in a systematic manner. Therefore, autonomy for Vidyalankar Institute of Technology is not merely a transition from pre-cooked syllabi to self-designed curriculum. The autonomous curriculum of the Institute offers required academic flexibility with emphasis on industry requirements and market trends, employability and problem-solving approach which leads to improving competency level of learners with diverse strengths. In line with this, the curriculum framework designed is **Choice-Based Credit and Grading System (CBCGS)**. The number of credits for each category of courses learnt by learners, internships and projects is finalized considering the scope of study and the ability that a learner should gain through the programme. The overall credits and approach of curriculum proposed is in line with AICTE model curriculum.

The curriculum comprises courses from various categories like basic sciences, humanities and social sciences, engineering sciences, general education and branch specific courses including professional electives and open electives. The curriculum has core courses of branch of engineering positioned and sequenced to achieve sequential and integral learning of the entire breadth of the specific branch. These courses are completed by the third year of the engineering programme that enables learners to prepare for higher education during their final year. Professional elective courses, that begin from third year of programme, offer flexibility and diversity to learners to choose specialization from a basket of recent developments in their field of technology. The selection of unique professional elective courses based on industrial requirements and organizing them into tracks is a salient feature of this curricula ensuring employability. Open Elective courses cover multi-disciplinary, special skill development, project management and similar knowledge that make learners capable of working in an industrial environment. For holistic development of learners, apart from technical courses, Humanities and Social Science courses develop the required soft-skills and attitude amongst learners. Our curriculum also introduces Social Service Internship and Internship with institutes abroad along with courses like Design Thinking, Wellness-Body, Mind & Spirit, Indian Traditional Knowledge System under General Education category. These general education courses aim to create balance in brain hemispheres and hence improve learners' clarity in thoughts and responses.

Additionally, curriculum provides add-on Honours/ Minor degree that involves field/ domain study. Learners can avail themselves of this degree by completing requirement of additional 18 credits.

Thus, the academic plan of VIT envisages a shift from summative to formative and competency-based learning system which will enhance learner's ability towards higher education, employability and entrepreneurship.

Chairman, Board of Studies
Department of Computer Engineering
Vidyalankar Institute of Technology

VIT
Vidyalankar Institute of Technology
VIDYALANKAR INSTITUTE OF TECHNOLOGY WADALA MUMBAI-37

Chairman, Academic Council
Vidyalankar Institute of Technology

[A] Guidelines for Award of Honours/ Minor Degree Programme

Honours and Minor Degree programme is introduced in order to facilitate learners to enhance the depth of knowledge, diversity, breadth and skills in emerging fields. An Honours or Minor Degree typically refers to a higher level of academic achievement either for research orientation or for improving employability. Learners can select any Honours or Minor Degree programme as per his/her choice.

In our curriculum, learners can choose to avail Honours/ Minor Degree programme by completing requirements of 18 credits, which will be over and above the minimum credits required for B.Tech. degree i.e. credit requirement for the award of degree programme and Honours/ Minor degree programme are required to be explicitly carried out. Learners shall opt for Honours or Minor specialisations during the break of Semester 5 and Semester 6. **Learners may complete the B.Tech. Degree programme without opting for Honours/ Minor Degree programme** i.e. opting for Honours/ Minor Degree programme is not mandatory as a part of B.Tech. degree programme

For Honours/ Minor Degree, the learner shall select an Honours/ Minor programme offered by his/her home department.

Eligibility Criteria

- Basic eligibility for opting for Honours/Minor shall be minimum CGPA of 6.75 at the end of 4th semester and earned 80 credits from Sem 1 to Sem 4 (41 credits for DSY students).
- If student has already completed any course(s) that is listed in the chosen Honours/ Minor degree programme, as additional learning course(s), then the transfer credits for such course(s) can be carried out towards Honours/ Minor degree programme.
- For a student to get Honours/ Minor degree, it is mandatory that the student completes the relevant courses before graduating.

Syllabus Scheme Template

Course		Head of Learning	Preferred Semester	Credits	Assessment Guidelines (Marks)			Total marks (Passing@40% of total marks)
Code	Name				ISA	MSE	ESE	
HM01	Industry Interaction	Theory	Break of Sem5 and Sem6	1	25	-	-	025
HMXX	Honours / Minor Degree Course 1	Theory	6	2	15	20	40	075
HMXX	Honours / Minor Degree Course 1 Lab	Practical	6	1	25	-	25	050
HM02	Survey Report/ Paper	Theory	Break of Sem6 and Sem7	2	25	-	25	050
HMXX	Honours / Minor Degree Course 2	Theory	7	2	15	20	40	075
HMXX	Honours / Minor Degree Course 2 Lab	Practical	7	1	25	-	25	050
HM03	Seminar	Theory	Break of Sem7 and Sem8	2	25	-	25	050
HMXX	Honours / Minor Degree Course 3	Theory	8	2	15	20	40	075
HMXX	Honours / Minor Degree Course 3 Lab	Practical	8	1	25	-	25	050
HM04	Capstone Project	Practical	8	4	75	-	50	125
			Total	**18**				

[B] Honours/ Minor Degree Programmes for B.Tech. Computer Engineering students

The Institute offers the listed Honours Degree Programme for learners of B.Tech. Computer Engineering.

Honours/ Minor Degree Programmes Offered

<table>
<tr><th>Sr.No.</th><th>Honours/Minor Degree Programme</th><th>Department offering Honours</th><th>Honours applicable for</th><th>Minors applicable for</th></tr>
<tr><td>1</td><td>Next-Gen Artificial Intelligence and Machine Learning</td><td>Computer Engineering</td><td>B.Tech. Computer Engineering students who have opted for Artificial Intelligence and Machine Learning specialization track.</td><td>None</td></tr>
<tr><td>2</td><td>Next-Gen Data Science</td><td>Computer Engineering</td><td>B.Tech. Computer Engineering students who have opted for Data Science specialization track.</td><td>None</td></tr>
<tr><td>3</td><td>Artificial Intelligence and Machine Learning</td><td>Computer Engineering</td><td>B.Tech. Computer Engineering students excluding those who have opted for Artificial Intelligence and Machine Learning specialization track.</td><td rowspan="3">UG students of any other department who haven’t completed the courses mentioned in this degree programme (or equivalent courses) as a part of their B.Tech. degree. Bridge courses as needed would be required to be completed by the student. Admission to this degree, as Minor, is subject to permission from Head of Computer Engineering Department.</td></tr>
<tr><td>4</td><td>Data Science</td><td>Computer Engineering</td><td>B.Tech. Computer Engineering students excluding those who have opted for Data Science specialization track.</td></tr>
<tr><td>5</td><td>Cyber Security</td><td>Computer Engineering</td><td>B.Tech. Computer Engineering students excluding those who have opted for Cyber Security specialization track.</td></tr>
</table>

Sr.No.	Honours/Minor Degree Programme	Department offering Honours	Honours applicable for	Minors applicable for
6	Next-Gen Cyber Security	Information Technology	B.Tech. Computer Engineering students who have opted for Cyber Security specialization track.	As stated in Honours/ Minor Degree document of Information Technology.
7	UI/ UX	Information Technology	All B.Tech. Computer Engineering students	As stated in Honours/ Minor Degree document of Information Technology.
8	Blockchain	Information Technology	All B.Tech. Computer Engineering students	As stated in Honours/ Minor Degree document of Information Technology.
9	Next-Gen Internet of Things	Electronics and Telecommunication Engineering	B.Tech. Computer Engineering students who have opted for Internet of Things specialization track.	As stated in Honours/ Minor Degree document of Electronics and Telecommunication.

List of courses under each Honours/ Minor Programme:

1. **Next-Gen Artificial Intelligence and Machine Learning**

Semester	Course Code	Course Name
VI	HMCE01T	Ethics in AI
VI	HMCE01P	Ethics in AI Lab
VII	HMCE02T	Scalable ML and BDA
VII	HMCE02P	Scalable ML and BDA Lab
VIII	HMCE03T	Generative AI models
VIII	HMCE03P	Generative AI models Lab

2. **Next-Gen Data Science**

Semester	Course Code	Course Name
VI	HMCE04T	Responsible AI and Data Ethics
VI	HMCE04P	Responsible AI and Data Ethics Lab
VII	HMCE05T	Cloud native & BDA
VII	HMCE05P	Cloud native & BDA Lab
VIII	HMCE06T	Realtime Data Analytics
VIII	HMCE06P	Realtime Data Analytics Lab

3. Artificial Intelligence and Machine Learning

Semester	Course Code	Course Name
VI	HMCE07T	Soft Computing
VI	HMCE07P	Soft Computing Lab
VII	HMCE08T	Natural language processing
VII	HMCE08P	Natural language processing Lab
VIII	HMCE09T	Deep Learning
VIII	HMCE09P	Deep Learning Lab

4. Data Science

Semester	Course Code	Course Name
VI	HMCE10T	Advanced Databases
VI	HMCE10P	Advanced Databases Lab
VII	HMCE11T	Big Data Analytics
VII	HMCE11P	Big Data Analytics Lab
VIII	HMCE12T	Text, Web & Social Media Analytics
VIII	HMCE12P	Text, Web & Social Media Analytics Lab

5. Cyber Security

Semester	Course Code	Course Name
VI	HMCE13T	Cryptography and Network Security
VI	HMCE13P	Cryptography Lab and Network Security Lab
VII	HMCE14T	Web Application Security
VII	HMCE14P	Web Application Security Lab
VIII	HMCE15T	Digital Forensics
VIII	HMCE15P	Digital Forensics Lab

6. Next-Gen Cyber Security

Semester	Course Code*	Course Name
VI	HMIT13T	IT Security Strategic Planning, Policy and Leadership
VI	HMIT13P	IT Security Strategic Planning, Policy and Leadership Lab
VII	HMIT14T	Advance Threat Intelligence and Penetration Testing
VII	HMIT14P	Advance Threat Intelligence and Penetration Testing Lab
VIII	HMIT15T	Advanced Computer Forensics Analysis
VIII	HMIT15P	Advanced Computer Forensics Analysis Lab

*Detailed syllabus of these courses can be obtained from the Honours/ Minor Degree document of Information Technology department applicable for R-2022

7. UI/ UX

Semester	Course Code*	Course Name
VI	HMIT01T	Foundation of UI/UX
VI	HMIT01P	Foundation of UI/UX Lab
VII	HMIT02T	UX Design, Evaluation and ARVR
VII	HMIT02P	UX Design, Evaluation and ARVR Lab
VIII	HMIT03T	Use cases in UI/UX
VIII	HMIT03P	Use cases in UI/UX Lab

* Detailed syllabus of these courses can be obtained from the Honours/ Minor Degree document of Information Technology department applicable for R-2022.

8. Blockchain

Semester	Course Code*	Course Name
VI	HMIT04T	Blockchain Technology
VI	HMIT04P	Blockchain Technology Lab
VII	HMIT05T	Smart Contract and Crypto Currencies
VII	HMIT05P	Smart Contract and Crypto Currencies Lab
VIII	HMIT06T	Decentralize & Blockchain Technologies
VIII	HMIT06P	Decentralize & Blockchain Technologies Lab

*Detailed syllabus of these courses can be obtained from the Honours/ Minor Degree document of Information Technology department applicable for R-2022.

9. Next-Gen Internet of Things

Semester	Course Code*	Course Name
VI	HMET01T	Embedded Linux System
VI	HMET01P	Embedded Linux System Lab
VII	HMET02T	IoT and Data Analytic
VII	HMET02P	IoT and Data Analytic Lab
VIII	HMET03T	IoT Applications and Web Development
VIII	HMET03P	IoT Applications and Web Development Lab

* Detailed syllabus of these courses can be obtained from the Honours/ Minor Degree document of Electronics and Telecommunication department applicable for R-2022.

Learners of Computer Engineering Department who wish to opt for Minor Degree Programme offered by other department can obtain details of the same from Section-B and Section C of the Honour/ Minor Degree Programme document of respective department.

[C] Honours/ Minor Degree Programmes Course Syllabus

Course Name: Ethics in AI

Course Code: HMCE01T

Category: Honors in Next-Gen Artificial Intelligence and Machine Learning

Preamble:

The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized numerous industries and daily life, introducing unprecedented opportunities and challenges. As these technologies integrate deeply into societal structures, it becomes imperative to consider their ethical, social, and environmental implications. This course aims to provide learners with a foundational understanding of ethical principles and frameworks as applied to AI/ML systems.

Pre-requisites:

Artificial Intelligence, Machine Learning

Course Objectives:

- Understand ethical considerations in AI and ML development and deployment.
- Explore frameworks for ethical decision-making in AI systems.
- Assess potential biases, privacy issues, and impacts of AI on society.
- Learn legal and policy implications related to AI and ML.
- Develop skills to implement ethical practices in AI projects.
- Foster critical thinking to address ethical challenges in real-world scenarios.

Course Outcomes:

Learner will be able to:

1. Demonstrate understanding of ethical principles in AI/ML.
2. Identify and mitigate bias and fairness issues in datasets and algorithms.
3. Apply ethical frameworks to evaluate AI systems.
4. Design AI systems with accountability, transparency, and fairness.
5. Understand societal impacts
6. Engage in ethical decision-making during AI system development.

Course Scheme:

Contact Hours		**Credits Assigned**	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	075

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	Introduction to Ethics in AI/ML	Overview of Ethics: Moral principles, ethics vs. legality. Why Ethics in AI/ML? Risks and challenges. Key Ethical Issues in AI: Bias, fairness, accountability, transparency. Case Studies: Real-world AI ethical dilemmas.	5
2	Bias and Fairness in AI/ML	Definition and Types of Bias in AI: Dataset bias, algorithmic bias. Techniques to Detect and Mitigate Bias in ML Models. Fairness Frameworks: Disparate impact, equalized odds. Ethical Data Collection and Preprocessing.	5
3	Privacy and Security Concerns	Privacy Challenges in AI: Data collection, storage, and sharing. Ethical Guidelines for User Data Protection. Security Risks in AI Systems: Deepfakes, adversarial attacks. GDPR and Other Privacy Regulations.	5
4	Accountability and Transparency	Need for Explainable AI (XAI). Strategies for Creating Transparent AI Systems. Accountability in AI Decision-Making. Ethical Implications of Autonomous Systems.	5
5	Societal Impacts of AI/ML	Impacts on Employment and Workforce. AI and Social Inequality. Misinformation and AI-Generated Content. AI in Healthcare, Education, and Governance.	5
6	Legal and Ethical Frameworks in AI	Overview of AI Ethics Guidelines (IEEE, UNESCO, etc.). AI Laws and Policies: International and regional perspectives. Intellectual Property and AI-Generated Content. Future Directions in AI Ethics.	5
Total			**30**

Textbooks:

1. AI Ethics: A Textbook by Paula Boddington - A comprehensive introduction to ethical challenges in AI systems.
2. Atlas of AI by Kate Crawford - Discusses the societal and environmental impact of AI

Reference Books:

1. The Ethical Algorithm by Aaron Roth & Michael Kearns - Explores designing socially aware algorithms
2. Human Compatible by Stuart Russell - Focuses on aligning AI with human values
3. Moral Machines: Teaching Robots Right From Wrong by Wendell Wallach and Colin Allen - Examines embedding ethics into AI systems.

Online Resources for Learning:

1. **Responsible AI Toolkit Reading List** - A curated set of academic papers and books focusing on responsible AI development and ethics Responsible AI Toolkit

.2. **Oxford Academic Journals** - Offers edited volumes on AI ethics and related fields, often authored by leading experts

Course Name: Ethics in AI Lab

Course Code: HMCE01P

Category: Honors in Next-Gen Artificial Intelligence and Machine Learning

Preamble:

The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized numerous industries and daily life, introducing unprecedented opportunities and challenges. As these technologies integrate deeply into societal structures, it becomes imperative to consider their ethical, social, and environmental implications. This lab manual is designed to equip learners with practical skills to address ethical concerns in AI and ML systems while fostering a deeper understanding of fairness, accountability, transparency, and privacy. Through guided experiments and critical discussions, students will explore the balance between technological innovation and ethical responsibility, preparing them to design and deploy AI systems that respect human values and promote societal good.

Pre-requisites:

Artificial Intelligence Lab, Machine Learning Lab

Course Objectives:

- Understand ethical considerations in AI and ML development and deployment.
- Explore frameworks for ethical decision-making in AI systems.
- Assess potential biases, privacy issues, and impacts of AI on society.
- Learn legal and policy implications related to AI and ML.
- Develop skills to implement ethical practices in AI projects.
- Foster critical thinking to address ethical challenges in real-world scenarios.

Course Outcomes:

Learner will be able to:

1. Demonstrate understanding of ethical principles in AI/ML.
2. Identify and mitigate bias and fairness issues in datasets and algorithms.
3. Apply ethical frameworks to evaluate AI systems.
4. Design AI systems with accountability, transparency, and fairness.
5. Understand societal impacts
6. Engage in ethical decision-making during AI system development.

Course Scheme:

Contact Hours		**Credits Assigned**	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	50

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practicals:

1. Bias Detection and Mitigation in ML Models
2. Privacy Preservation Using Differential Privacy
3. Explainable AI (XAI): Interpreting Black-Box Models
4. Adversarial Attack and Defense Strategies
5. Fairness in AI-Powered Recommendation Systems
6. Simulating Ethical Dilemmas in Autonomous Systems
7. Energy Efficiency Analysis of ML Models
8. Ethical Concerns in NLP Models for Sentiment Analysis
9. Misinformation Detection Using AI
10. Guidelines for Ethical Data Collection and Labeling

Course Name: Scalable ML and BDA

Course Code: HMCE02T

Category: Honors in Next-Gen Artificial Intelligence and Machine Learning

Preamble:

This course, Scalable Machine Learning & Big Data Analytics, is designed to bridge the gap between traditional machine learning and the demands of modern, large-scale data environments. Building on foundational ML knowledge, the course explores distributed computing frameworks (Spark, Hadoop), scalable model training techniques (parallel algorithms, federated learning), and end-to-end deployment strategies (MLOps, cloud platforms). Students will gain hands-on experience with real-world tools (PySpark, TensorFlow, Kubernetes) while critically analyzing challenges like data volume, model efficiency, and ethical implications.

Pre-requisites: Machine Learning.

Course Objectives:

- Equip students with scalable ML techniques to handle large datasets using distributed frameworks (Spark, TensorFlow) and Big Data tools (Hadoop, Kafka).
- Develop proficiency in deploying ML models in production environments using MLOps practices (Docker, Kubernetes, TF Serving).
- Foster critical analysis of real-world ML systems, including performance optimization, ethical considerations, and trade-offs in distributed architectures.
- Enable end-to-end project execution by designing and implementing a scalable ML pipeline (data ingestion → training → deployment) on cloud platforms (AWS/GCP).

Course Outcomes:

Learner will be able to:

CO1: Recall fundamental challenges in scaling ML models and list key Big Data technologies (Hadoop, Spark, Flink).
CO2: Explain distributed ML paradigms (data/model parallelism) and ETL workflows for large-scale data.
CO3: Implement scalable ML pipelines using PySpark and train models with distributed frameworks (MLlib/TensorFlow).
CO4: Compare streaming vs. batch ML architectures and evaluate feature engineering techniques (TF-IDF, PCA).
CO5: Assess model deployment strategies (TF Serving, Kubernetes) and critique ethical implications in large-scale ML systems.
CO6: Design and deploy an end-to-end scalable ML pipeline (data-to-production) using cloud platforms (AWS/GCP).

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	25	--	25	50

The assessment guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to propose her/his assessment methodology based on the nature of the course. However, the proposed assessment methodology shall be approved by a panel constituted at Institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No	Module name	Content	No of Hours
1	Introduction to Scalable ML & Big Data	Challenges in Scaling ML Models (Data Volume, Velocity, Variety). Overview of Big Data Technologies (Hadoop, Spark, Flink). Distributed vs. Traditional ML: Trade-offs. Data Ingestion & Preprocessing at Scale (ETL Pipelines). Hands-on: Setting up Spark/PySpark for ML	5
2	Distributed Machine Learning	Parallel & Distributed ML Algorithms (SGD, Federated Learning). Model & Data Parallelism (TensorFlow/PyTorch Distributed). Parameter Servers & All-Reduce Communication. Case Study: Scaling Deep Learning (Horovod, Ray). Hands-on: Distributed Training with PySpark MLlib	5
3	Big Data Analytics for ML	Feature Engineering at Scale (TF-IDF, Embeddings, PCA). Handling High-Dimensional & Sparse Data. Streaming ML (Kafka + Spark Streaming). Graph-Based ML (GraphFrames, Neo4j). Hands-on: Real-time Sentiment Analysis with Spark	4
4	Scalable Model Deployment & MLOps	Model Serving at Scale (TF Serving, ONNX, FastAPI). Containerization & Orchestration (Docker, Kubernetes). AutoML & Hyperparameter Tuning (Optuna, Ray Tune). Monitoring & Explainability in Production (MLflow, SHAP). Hands-on: Deploying ML Model on Cloud (AWS/GCP)	5
5	Advanced Topics in Scalable ML	Federated Learning & Privacy-Preserving ML. Reinforcement Learning at Scale (Ray RLlib). Edge ML & TinyML (TensorFlow Lite, ONNX Runtime). Case Study: Recommender Systems (Apache Mahout). Hands-on: Federated Learning Simulation.	5
6	Real-World Case Studies & Project	Industry Use Cases (Netflix, Uber, Google) Performance Optimization (GPU Acceleration, Quantization)	5

Module No	Module name	Content	No of Hours
		Ethics & Bias in Large-Scale ML Final Project Discussion (End-to-End Pipeline) 6.5 Project Presentations & Evaluation	
Total			**30**

Text Books:

1. **Jure Leskovec, Anand Rajaraman & Jeffrey Ullman**, *Mining of Massive Datasets*, Cambridge University Press.
2. **Holden Karau et al.**, *Learning Spark: Lightning-Fast Data Analytics*, O'Reilly.
3. **Ian Goodfellow, Yoshua Bengio & Aaron Courville**, *Deep Learning*, MIT Press.
4. **Karl Matthias & Sean P. Kane**, *Docker: Up and Running*, O'Reilly.
5. **Tyler Akidau et al.**, *Streaming Systems: The What, Where, When, and How of Large-Scale Data Processing*, O'Reilly.

Reference Books:

1. **Aurélien Géron**, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, O'Reilly.
2. **Chip Huyen**, *Designing Machine Learning Systems*, O'Reilly.
3. **Sandy Ryza et al.**, *Advanced Analytics with Spark*, O'Reilly.

Course Name: Scalable ML and BDA Lab

Course Code: HMCE02P

Category: Honors in Next-Gen Artificial Intelligence and Machine Learning

Preamble:

This course, Scalable Machine Learning & Big Data Analytics, is designed to bridge the gap between traditional machine learning and the demands of modern, large-scale data environments. Building on foundational ML knowledge, the course explores distributed computing frameworks (Spark, Hadoop), scalable model training techniques (parallel algorithms, federated learning), and end-to-end deployment strategies (MLOps, cloud platforms). Students will gain hands-on experience with real-world tools (PySpark, TensorFlow, Kubernetes) while critically analyzing challenges like data volume, model efficiency, and ethical implications.

Pre-requisites: Machine Learning.

Course Objectives:

- Equip students with scalable ML techniques to handle large datasets using distributed frameworks (Spark, TensorFlow) and Big Data tools (Hadoop, Kafka).
- Develop proficiency in deploying ML models in production environments using MLOps practices (Docker, Kubernetes, TF Serving).
- Foster critical analysis of real-world ML systems, including performance optimization, ethical considerations, and trade-offs in distributed architectures.
- Enable end-to-end project execution by designing and implementing a scalable ML pipeline (data ingestion → training → deployment) on cloud platforms (AWS/GCP).

Course Outcomes:

Learner will be able to:

CO1: Recall fundamental challenges in scaling ML models and list key Big Data technologies (Hadoop, Spark, Flink).
CO2: Explain distributed ML paradigms (data/model parallelism) and ETL workflows for large-scale data.
CO3: Implement scalable ML pipelines using PySpark and train models with distributed frameworks (MLlib/TensorFlow).
CO4: Compare streaming vs. batch ML architectures and evaluate feature engineering techniques (TF-IDF, PCA).
CO5: Assess model deployment strategies (TF Serving, Kubernetes) and critique ethical implications in large-scale ML systems.
CO6: Design and deploy an end-to-end scalable ML pipeline (data-to-production) using cloud platforms (AWS/GCP).

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	50

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Experiments:

Sr No.	Suggested Topic(s)
1.	**PySpark Data Preprocessing at Scale** **Problem Statement:** Given a 10GB dataset of customer reviews (CSV), clean and preprocess it using PySpark to handle missing values, tokenize text, and remove stopwords. **Desired Outcome:** Demonstrate scalable ETL pipelines using PySpark RDDs/DataFrames. Compare runtime vs. pandas for the same task.
2.	**Distributed Model Training with MLlib** **Problem Statement:** Train a logistic regression model on a 5GB dataset using PySpark MLlib, comparing batch SGD vs. distributed SGD. **Desired Outcome:** Implement distributed training and analyze speedup vs. single-node scikit-learn. Visualize convergence rates for both approaches.
3.	**Real-Time Sentiment Analysis with Spark Streaming** **Problem Statement:** Build a streaming sentiment analyzer using Spark Structured Streaming + Kafka, processing live tweets. **Desired Outcome:** Ingest real-time data from Kafka and apply ML model (pre-trained). Measure latency/throughput for varying batch intervals.
4.	**Graph-Based ML with GraphFrames** **Problem Statement:** Analyze a social network graph (e.g., Twitter data) using GraphFrames to detect communities (Louvain algorithm). **Desired Outcome:** Implement graph algorithms and visualize communities. Compare runtime vs. NetworkX (single-node).

5.	**Hyperparameter Tuning with Ray Tune** **Problem Statement:** Optimize hyperparameters for a TensorFlow CNN on CIFAR-10 using Ray Tune (distributed search). **Desired Outcome:** Compare Bayesian optimization vs. random search. Profile resource usage (CPU/GPU) across workers.
6.	**Model Serving with TF Serving + Kubernetes** **Problem Statement:** Deploy a ResNet model as a REST API using TF Serving, containerize with Docker, and scale via Kubernetes. **Desired Outcome:** Benchmark QPS (queries per second) for 1 vs. 3 replicas. Monitor GPU utilization under load.
7.	**Federated Learning Simulation** **Problem Statement:** Simulate federated learning for MNIST classification using TensorFlow Federated with 3 clients. **Desired Outcome:** Analyze accuracy vs. centralized training. Visualize weight divergence across clients.
8	**Ethical Bias Detection with SHAP** **Problem Statement:** Audit a loan approval model for racial/gender bias using SHAP and fairness metrics (demographic parity). **Desired Outcome:** Generate bias reports and propose mitigation strategies. Compare SHAP explanations for biased vs. debiased models.
9	**AutoML Pipeline with MLflow** **Problem Statement:** Build an AutoML pipeline for a tabular dataset using Optuna + MLflow, tracking 100+ experiments. **Desired Outcome:** Automate feature engineering/model selection. Analyze MLflow's visualization dashboard.
10	**End-to-End Cloud ML Pipeline (AWS/GCP)** **Problem Statement:** Design a pipeline to ingest, train, and deploy a fraud detection model on AWS SageMaker/GCP Vertex AI. **Desired Outcome:** Trigger retraining via cloud functions (e.g., AWS Lambda). Monitor drift using SageMaker Model Monitor.

Course Name: Generative AI Models

Course Code: HMCE03T

Category: Honours/ Minor Programme in Next-Gen Artificial Intelligence and Machine Learning

Preamble:
This course, Generative AI has emerged as a transformative field, enabling machines to create realistic text, images, audio, and video. This course provides a deep dive into the architectures, training methodologies, and ethical considerations of modern generative models. Students will explore state-of-the-art frameworks (e.g., GANs, VAEs, Diffusion Models, LLMs) and their applications in creative and industrial domains while critically assessing challenges like hallucination, bias, and misuse.

Pre-requisites: Machine Learning, Deep Learning.

Course Objectives:
- Understand the theoretical foundations of generative models (likelihood-based vs. implicit models).
- Implement and fine-tune advanced architectures (GANs, VAEs, Diffusion Models, Transformers).
- Evaluate challenges in generative AI: mode collapse, hallucination, and ethical risks.
- Apply generative models to real-world problems (text, image, audio synthesis).
- Analyze societal impacts, including misinformation and intellectual property concerns.

Course Outcomes:
Learner will be able to:
CO1: Compare generative model families (GANs, VAEs, Diffusion Models, Autoregressive Models).
CO2: Implement and optimize generative architectures using PyTorch/TensorFlow.
CO3: Assess quality metrics (FID, Inception Score, BLEU, ROUGE) for generated outputs.
CO4: Adapt pretrained models (e.g., GPT, Stable Diffusion) for domain-specific tasks.
CO5: Critique ethical and security risks (deepfakes, bias, copyright infringement).
CO6: Design a novel generative AI application with deployment considerations.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	20	15	40	75

The assessment guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to propose her/his assessment methodology based on the nature of the course. However, the proposed assessment methodology shall be approved by a panel constituted at Institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No	Module name	Content	No of Hours
1	Introduction to Generative AI	Generative vs. Discriminative Models: Key Differences. Applications: Text, Image, Audio, Video Generation. Challenges: Mode Collapse, Hallucination, Ethical Risks. Hands-on: Generating Text with GPT-2.	5
2	Autoregressive & Latent Variable Models	Autoregressive Models (PixelRNN, WaveNet). Variational Autoencoders (VAEs): Architecture & Training. Normalizing Flows (RealNVP, Glow). Hands-on: Image Generation with VAE.	5
3	Generative Adversarial Networks (GANs)	GAN Architecture: Generator vs. Discriminator. Training Challenges: Nash Equilibrium, Mode Collapse. Advanced GANs (DCGAN, StyleGAN, CycleGAN). Hands-on: Face Generation with StyleGAN	5
4	Diffusion Models & Score-Based Methods	Denoising Diffusion Probabilistic Models (DDPM). Score-Based Generative Models (SDEs). Stable Diffusion & Latent Diffusion Models. Hands-on: Text-to-Image Generation with Stable Diffusion	5
5	Large Language Models (LLMs) & Multimodal AI	Transformer-based Generative Models (GPT, BERT, T5). Prompt Engineering & Fine-tuning (LoRA, RLHF). Multimodal Models (DALL·E, CLIP, Flamingo). Hands-on: Fine-tuning LLMs for Domain-Specific Tasks.	5
6	Ethics, Deployment, and Future Trends	Ethical Risks: Deepfakes, Bias, Copyright. Deployment: Quantization, Edge AI, Censorship. Industry Applications (Healthcare, Art, Gaming).	5
Total			**30**

Text Books:

1. Generative Deep Learning – David Foster (O'Reilly).
2. Deep Learning – Ian Goodfellow, Yoshua Bengio, Aaron Courville (MIT Press).

Reference Books:

1. Hands-On Generative AI with Transformers – Kennedy & Tunstall (O'Reilly).
2. Probabilistic Machine Learning: Advanced Topics – Kevin Murphy (MIT Press).

Course Name: Generative AI Models Lab

Course Code: HMCE03P

Category: Honours/ Minor Programme in Next-Gen Artificial Intelligence and Machine Learning

Preamble:
This course, Generative AI has emerged as a transformative field, enabling machines to create realistic text, images, audio, and video. This course provides a deep dive into the architectures, training methodologies, and ethical considerations of modern generative models. Students will explore state-of-the-art frameworks (e.g., GANs, VAEs, Diffusion Models, LLMs) and their applications in creative and industrial domains while critically assessing challenges like hallucination, bias, and misuse.

Pre-requisites: Machine Learning, Deep Learning.

Course Objectives:

- Understand the theoretical foundations of generative models (likelihood-based vs. implicit models).
- Implement and fine-tune advanced architectures (GANs, VAEs, Diffusion Models, Transformers).
- Evaluate challenges in generative AI: mode collapse, hallucination, and ethical risks.
- Apply generative models to real-world problems (text, image, audio synthesis).
- Analyze societal impacts, including misinformation and intellectual property concerns.

Course Outcomes:
Learner will be able to:
CO1: Compare generative model families (GANs, VAEs, Diffusion Models, Autoregressive Models).
CO2: Implement and optimize generative architectures using PyTorch/TensorFlow.
CO3: Assess quality metrics (FID, Inception Score, BLEU, ROUGE) for generated outputs.
CO4: Adapt pretrained models (e.g., GPT, Stable Diffusion) for domain-specific tasks.
CO5: Critique ethical and security risks (deepfakes, bias, copyright infringement).
CO6: Design a novel generative AI application with deployment considerations.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	--	25	50

The assessment guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to propose her/his assessment methodology based on the nature of the course. However, the proposed assessment methodology shall be approved by a panel constituted at Institute level and published to the learners before the commencement of the semester.

Suggested List of Practical's:

Sr No.	Suggested Topic(s)
1.	**Domain-Specific Text Generation** **Problem Statement:** Technical content in niche domains (e.g., legal, medical) is scarce and time-consuming to produce. Can an LLM generate coherent, domain-specific articles? **Desired Outcome:** - Fine-tune GPT-3/LLaMA on a domain-specific dataset. - Evaluate output quality using ROUGE/BLEU scores and expert review. **Tools/Framework:** Hugging Face Transformers, OpenAI API
2.	**Deepfake Detection** **Problem Statement:** Malicious actors use GANs to create deepfake videos. How can we build a discriminator to identify synthetic media?. **Desired Outcome:** - Train a CNN-GAN hybrid to distinguish real vs. synthetic faces (CelebA dataset). - Achieve >90% accuracy on unseen data. **Tools/Framework:** TensorFlow, Keras, OpenCV
3.	**Medical Data Augmentation** **Problem Statement:** Medical imaging datasets for rare diseases are small. Can VAEs synthesize realistic training samples? **Desired Outcome:** Generate synthetic MRI scans using a VAE. Measure realism with Fréchet Inception Distance (FID < 30). **Tools/Framework:** PyTorch, MONAI Library
4.	**Artistic Style Transfer** **Problem Statement:** Converting real-world photos to artistic styles (e.g., Van Gogh) requires manual effort. Can CycleGAN automate this? **Desired Outcome:** - Implement CycleGAN to transform photos to paintings. - Evaluate style fidelity using SSIM (>0.7). **Tools/Framework:** TensorFlow, CycleGAN-PyTorch
5.	**AI-Composed Music** **Problem Statement:**

	Music composition is resource-intensive. Can transformers generate royalty-free background music? **Desired Outcome:** - Train a transformer (e.g., Jukebox) on piano MIDI files. - Survey listeners for "human-like" quality (≥70% approval). **Tools/Framework:** OpenAI Jukebox, Magenta
6.	**Ethical Adversarial Testing** **Problem Statement:** LLMs can generate harmful content. How can we "jailbreak" them to expose vulnerabilities? **Desired Outcome:** - Craft adversarial prompts to bypass safety filters. - Propose RLHF-based mitigations. **Tools/Framework:** LLaMA-2, OpenAI Moderation API
7.	**Sustainable Fashion Design** **Problem Statement:** Fast fashion harms the environment. Can AI generate eco-friendly clothing designs? **Desired Outcome:** - Use Stable Diffusion + CLIP to create designs from prompts like "vegan leather jacket." - Validate design-market fit via surveys. **Tools/Framework:** Stable Diffusion, CLIP
8	**Low-Resource Translation** **Problem Statement:** LLMs perform poorly on low-resource languages (e.g., Swahili). Can we adapt them? **Desired Outcome:** - Fine-tune BLOOM on a Swahili-English corpus. - Achieve BLEU score >25 vs. Google Translate. **Tools/Framework:** Hugging Face BLOOM
9	**Anomaly Detection in Logs** **Problem Statement:** Cyberattacks often hide in system logs. Can GANs learn normal patterns to flag anomalies? **Desired Outcome:** - Train a GAN on normal network traffic. - Detect anomalies with >85% precision. **Tools/Framework:** PyTorch, Scikit-learn
10	**Deploying Generative APIs** **Problem Statement:** Generative models are computationally expensive. How can we deploy them efficiently? **Desired Outcome:** - Containerize Stable Diffusion with FastAPI. - Achieve <500ms latency per request on a T4 GPU.

	Tools/Framework: Docker, FastAPI, ONNX Runtime

Text Books:

1. Generative Deep Learning – David Foster (O'Reilly).
2. Deep Learning – Ian Goodfellow, Yoshua Bengio, Aaron Courville (MIT Press).

Reference Books:

1. Hands-On Generative AI with Transformers – Kennedy & Tunstall (O'Reilly).
2. Probabilistic Machine Learning: Advanced Topics – Kevin Murphy (MIT Press).

Online Resources:

- Hugging Face Transformers Library (huggingface.co)
- OpenAI Research Papers (openai.com/research)
- PyTorch Tutorials on GANs/VAEs (pytorch.org/tutorials)

Course Name: Responsible AI and Data Ethics

Course Code: HMCE04T

Category: Honors in Next-Gen Data Science

Preamble:

This course explores the intersection of technology and ethics, focusing on building AI systems that are fair, transparent, and accountable. It equips learners with the tools to address challenges like bias, privacy, and societal impacts while adhering to global ethical standards. Through case studies, hands-on labs, and governance frameworks, students will learn to balance innovation with responsibility. This course prepares professionals to lead in designing AI systems that align with ethical and legal expectations.

Pre-requisites:

Artificial Intelligence, Data warehousing and Mining

Course Objectives:

- Understand Ethical and Societal Implications: To provide foundational knowledge of ethical principles, challenges, and societal impacts of AI and data analytics.
- Foster Fairness, Privacy, and Accountability: To equip students with techniques for bias mitigation, privacy preservation, and building transparent, accountable AI systems.
- Implement Governance and Ethical Standards: To enable students to integrate global ethical guidelines and governance frameworks into AI and data workflows.

Course Outcomes:

Learner will be able to:

1. Explain Core Ethical Concepts: Demonstrate a clear understanding of key ethical issues such as transparency, fairness, and accountability in AI and data analytics.
2. Analyze and Mitigate Bias: Apply fairness frameworks and mitigation techniques to reduce bias in datasets and machine learning models.
3. Ensure Data Privacy: Implement strategies like anonymization, encryption, and federated learning to preserve user privacy while adhering to regulations such as GDPR and CCPA.
4. Design Transparent Systems: Develop AI systems that incorporate explainability and accountability, ensuring ethical decision-making and compliance with standards.
5. Evaluate Societal Impacts: Critically analyze the societal risks of AI in various domains and propose solutions to balance innovation with ethical responsibility.
6. Apply Ethical Governance Frameworks: Design and implement ethical governance policies for AI systems, including practical compliance checklists and reporting guidelines.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	075

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	Introduction to Responsible AI and Data Ethics	Defining Ethics in AI: Moral Principles, Ethics vs. Legality. Risks and Challenges in AI Ethics: Privacy, Bias, Accountability. Key Ethical Concepts: Transparency, Fairness, and Responsibility. Case Studies: Real-world ethical dilemmas in AI and data usage.	5
2	Bias, Fairness, and Ethical Data Practices	Types of Bias in AI: Dataset, Algorithmic, and Systemic Bias. Frameworks for Fairness: Disparate Impact, Equalized Odds. Ethical Data Collection, Preprocessing, and Governance. Tools and Techniques for Mitigating Bias in AI Models.	5
3	Privacy and Security in AI Systems	Privacy Challenges: Data Collection, Storage, and Sharing. Data Protection Strategies: Anonymization, Encryption, Consent Management. Security Risks in AI: Adversarial Attacks, Deepfakes, and Model Vulnerabilities. Overview of Privacy Laws: GDPR, CCPA, HIPAA.	5
4	Transparency and Accountability in AI	Need for Explainable AI (XAI). Designing Transparent and Trustworthy AI Systems. Accountability in AI Decision-Making: Ethical and Legal Considerations. Strategies for Auditing and Validating AI Systems.	5

Module No.	Module Name	Content	No of Hours
5	Societal and Ethical Impacts of AI	Impacts of AI on Employment, Inequality, and Society. Addressing Misinformation and AI-Generated Content. AI in Critical Sectors: Healthcare, Education, and Governance. Balancing Innovation with Ethical Responsibility.	5
6	Ethical Applications and Governance Frameworks	Global Ethical Guidelines: IEEE, UNESCO, and AI Ethics Standards. Best Practices for Integrating Ethical AI in Organizations. Ethical Reporting: Principles for Clear and Honest Communication. Creating Practical Compliance Checklists for AI Systems.	5
Total			**30**

Textbooks:

1. AI Ethics: A Textbook by Paula Boddington - A comprehensive introduction to ethical challenges in AI systems.
2. "Responsible Data Science" by Peter C. Bruce, Grant Fleming, and Peter Gedeck
3. Atlas of AI by Kate Crawford - Discusses the societal and environmental impact of AI
4. "Ethics of Artificial Intelligence and Robotics" by Bernd Carsten Stahl

Reference Books:

1. "AI Ethics" by Mark Coeckelbergh
2. "The Big Data Agenda: Data Ethics and Critical Data Studies" by Annika Richterich
3. The Ethical Algorithm by Aaron Roth & Michael Kearns
4. Human Compatible by Stuart Russell - Focuses on aligning AI with human values
5. Moral Machines: Teaching Robots Right From Wrong by Wendell Wallach and Colin Allen - Examines embedding ethics into AI systems.

Online Resources for Learning:

1. "Data Ethics, AI, and Responsible Innovation" (edX)
2. "Privacy in Data Analytics" (Udemy)

Course Name: Responsible AI and Data Ethics Lab

Course Code: HMCE04P

Category: Honors in Next-Gen Data Science

Preamble:

This course explores the intersection of technology and ethics, focusing on building AI systems that are fair, transparent, and accountable. It equips learners with the tools to address challenges like bias, privacy, and societal impacts while adhering to global ethical standards. Through case studies, hands-on labs, and governance frameworks, students will learn to balance innovation with responsibility. This course prepares professionals to lead in designing AI systems that align with ethical and legal expectations.

Pre-requisites:

Artificial Intelligence Lab, Data warehousing and Mining Lab

Course Objectives:

- Understand Ethical and Societal Implications: To provide foundational knowledge of ethical principles, challenges, and societal impacts of AI and data analytics.
- Foster Fairness, Privacy, and Accountability: To equip students with techniques for bias mitigation, privacy preservation, and building transparent, accountable AI systems.
- Implement Governance and Ethical Standards: To enable students to integrate global ethical guidelines and governance frameworks into AI and data workflows.

Course Outcomes:

Learner will be able to:

1. Explain Core Ethical Concepts: Demonstrate a clear understanding of key ethical issues such as transparency, fairness, and accountability in AI and data analytics.
2. Analyze and Mitigate Bias: Apply fairness frameworks and mitigation techniques to reduce bias in datasets and machine learning models.
3. Ensure Data Privacy: Implement strategies like anonymization, encryption, and federated learning to preserve user privacy while adhering to regulations such as GDPR and CCPA.
4. Design Transparent Systems: Develop AI systems that incorporate explainability and accountability, ensuring ethical decision-making and compliance with standards.
5. Evaluate Societal Impacts: Critically analyze the societal risks of AI in various domains and propose solutions to balance innovation with ethical responsibility.
6. Apply Ethical Governance Frameworks: Design and implement ethical governance policies for AI systems, including practical compliance checklists and reporting guidelines.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	50

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practicals:

1. Case Study Analysis: Ethical Breaches in AI and Data Use
2. Bias Detection and Correction in Data Pipelines
3. Designing a Data Governance Framework
4. Data Privacy Preservation Using Federated Learning
5. Auditing AI Systems for Accountability
6. Simulating Privacy Violations and Mitigations
7. Fairness Evaluation in Multi-Domain AI Applications
8. Ethical Data Visualization and Reporting
9. Evaluating AI Systems for Societal Impacts
10. Creating a Responsible AI Deployment Checklist

Course Name: Cloud native & BDA

Course Code: HMCE05T

Category: Honors in Next-Gen Data Science

Preamble:

This course is designed to equip students with the foundational and advanced skills required to leverage cloud-native technologies for scalable and efficient Big Data Analytics solutions. Through a blend of theoretical concepts and hands-on labs, students will explore cloud infrastructure, storage, processing frameworks (like Hadoop and Spark), and AI/ML services, all within modern cloud platforms such as AWS and Azure. Emphasis will be placed on practical implementation, security best practices, and integrating end-to-end analytics workflows to solve real-world business problems, ensuring proficiency in designing, deploying, and managing cloud-native Big Data applications.

Pre-requisites: Responsible AI and Data Ethics, Responsible AI and Data Ethics Lab

Course Objectives:

- To introduce students to cloud-native principles, Big Data characteristics (5Vs), and cloud service models (IaaS/PaaS/SaaS), enabling them to recall and explain their roles in modern analytics.
- To equip students with hands-on skills to deploy cloud infrastructure (AWS/Azure), configure Big Data services (Hadoop/Spark), and integrate storage/database solutions for scalable analytics.
- To develop the ability to assess the effectiveness of cloud-native AI/ML services, security frameworks (IAM), and processing tools for real-world use cases.
- To enable students to design, build, and deploy end-to-end cloud-native Big Data solutions, incorporating infrastructure, processing, AI/ML, and security best practices.

Course Outcomes:

Learner will be able to:

1. Students will recall cloud-native concepts, Big Data characteristics, and cloud service models.
2. Students will explain how cloud-native architectures support Big Data processing.
3. Students will deploy cloud infrastructure and configure Big Data services.
4. Students will evaluate storage solutions and processing frameworks for specific use cases.
5. Students will assess security implementations and AI/ML service effectiveness.
6. Students will design and implement end-to-end cloud-native Big Data solutions.

Course Scheme:

Contact Hours		**Credits Assigned**	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	075

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	Introduction to Cloud-Native Big Data Analytics	Overview of Cloud Computing concepts, Cloud-Native architectures, and principles Big Data characteristics (Volume, Velocity, Variety, Veracity, Value) Importance of integrating Big Data Analytics with Cloud-native platforms Deployment models and service models (IaaS, PaaS, SaaS)	4
2	Cloud-Native Infrastructure and Virtualization	Virtualization concepts and hosted virtualization (VirtualBox, KVM) Cloud-Native Infrastructure using AWS EC2 and Azure Compute Deploying, managing, and scaling virtual machines in the cloud Hands-on Lab: Setting up Linux/Windows VM on AWS EC2/Azure Compute	5
3	Cloud Storage and Database Services	Storage as a Service (AWS S3, Azure Storage) Database as a Service (AWS RDS, Azure SQL, MongoDB Atlas, Firebase) SQL vs NoSQL databases: CAP theorem, key-value, document, columnar, graph databases Hands-on Lab: CRUD operations in cloud-managed databases (MongoDB Atlas/AWS RDS)	5
4	Cloud-Native Big Data Processing	Hadoop ecosystem: HDFS architecture, MapReduce programming model Apache Spark architecture: RDDs, DataFrames, DAG Stream processing fundamentals: Bloom Filter, Flajolet-Martin algorithm, DGIM algorithm Hands-on Lab: Hadoop and Spark deployment in cloud environments (AWS EMR, Azure HDInsight)	6
5	Cloud-Native AI, ML, and Cognitive Services	Introduction to cloud-based AI/ML services (AWS SageMaker, Azure ML) AI-driven analytics: Predictive analytics, real-time insights Cognitive services: Computer	5

		Vision, NLP, ML APIs Hands-on Lab: Deploying and using ML models on cloud platforms	
6	Security, Identity Management, and Capstone	Cloud Security principles and IAM (AWS IAM, Azure AD) Best practices in security, compliance, and access management for Big Data Mini Capstone Project: Develop and deploy an end-to-end cloud-native Big Data Analytics solution covering infrastructure, data storage, processing (Spark/Hadoop), AI/ML integration, security, and visualization on AWS or Azure.	5
Total			**30**

Textbooks:

1. Cloud Native Data Center Networking" by Dinesh G. Dutt (O'Reilly, 2020, ISBN 978-1492045607).
2. Big Data: Principles and Best Practices of Scalable Realtime Data Systems" by Nathan Marz & James Warren (Manning, 2015, ISBN 978-1617290343).
3. Cloud Native Data Center Networking" by Dinesh G. Dutt (O'Reilly, 2020, ISBN 978-1492045607).
4. Learning Spark: Lightning-Fast Data Analytics (2nd Ed.)" by Jules S. Damji et al. (O'Reilly, 2020, ISBN 978-1492050045)

Reference Books:

1. Designing Data-Intensive Applications" by Martin Kleppmann (O'Reilly, 2017, ISBN 978-1449373320).
2. Cloud Computing for Science and Engineering" by Ian Foster & Dennis B. Gannon (MIT Press, 2017, ISBN 978-0262037242).

Online Resources for Learning:

1. Google Cloud Big Data & Machine Learning Documentation: https://cloud.google.com/big-data
2. Databricks Documentation (Spark + MLflow): https://docs.databricks.com

Course Name: Cloud native & BDA Lab

Course Code: HMCE05P

Category: Honors in Next-Gen Data Science

Preamble:

Pre-requisites: Responsible AI and Data Ethics, Responsible AI and Data Ethics Lab

Course Objectives:

- To introduce students to cloud-native principles, Big Data characteristics (5Vs), and cloud service models (IaaS/PaaS/SaaS), enabling them to recall and explain their roles in modern analytics.
- To equip students with hands-on skills to deploy cloud infrastructure (AWS/Azure), configure Big Data services (Hadoop/Spark), and integrate storage/database solutions for scalable analytics.
- To develop the ability to assess the effectiveness of cloud-native AI/ML services, security frameworks (IAM), and processing tools for real-world use cases.
- To enable students to design, build, and deploy end-to-end cloud-native Big Data solutions, incorporating infrastructure, processing, AI/ML, and security best practices.

Course Outcomes:

Learner will be able to:

1. Students will recall cloud-native concepts, Big Data characteristics, and cloud service models.
2. Students will explain how cloud-native architectures support Big Data processing.
3. Students will deploy cloud infrastructure and configure Big Data services.
4. Students will evaluate storage solutions and processing frameworks for specific use cases.
5. Students will assess security implementations and AI/ML service effectiveness.
6. Students will design and implement end-to-end cloud-native Big Data solutions.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	50

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practical's:

1. Cloud VM Setup Real-world Problem: Provisioning and management of virtual resources for web application deployment. Input Required: AWS/Azure account, Linux image. Suggested Outcome: Fully functional Linux VM deployed and accessible via SSH
2. Windows Server Cloud Deployment Real-world Problem: Enterprise application deployment requiring Windows infrastructure. Input Required: Azure account, Windows Server image. Suggested Outcome: Accessible and scalable Windows VM deployed on Azure
3. Cloud Storage for Large Dataset Real-world Problem: Storage solution for healthcare or financial sector’s extensive data. Input Required: Large synthetic dataset, AWS account. Suggested Outcome: Efficient storage and retrieval using AWS S
4. Mo Cloud-based Database Management Real-world Problem: Customer database management for e-commerce applications. Input Required: MongoDB Atlas account, sample e-commerce dataset. Suggested Outcome: CRUD operations performed efficiently via MongoDB Atlas.
5. Hadoop Cluster Deployment Real-world Problem: Analyzing massive web log data. Input Required: AWS EMR setup, weblog dataset.
   Suggested Outcome: Operational Hadoop cluster for data analytics.
6. MapReduce Data Processing Real-world Problem: Analyzing textual data for insights. Input Required: Textual dataset. Suggested Outcome: Accurate word frequency count via MapReduce jobs.
7. Apache Spark Data Analysis Real-world Problem: Transaction analysis for fraud detection. Input Required: Transactional data. Suggested Outcome: Analytical insights from Spark DataFrame transformations.
8. Stream Analytics Algorithms Real-world Problem: Real-time social media data processing. Input Required: Simulated social media data stream. Suggested Outcome: Effective implementation and evaluation of Bloom Filter and DGIM algorithms.
9. Predictive Modeling with SageMaker Real-world Problem: Sales forecasting for retail businesses. Input Required: Historical sales dataset. Suggested Outcome: Predictive model deployment and evaluation using AWS SageMaker.
10. Sentiment Analysis using Azure Cognitive Services Real-world Problem: Analyzing customer reviews. Input Required: Dataset of customer reviews. Suggested Outcome: Automated sentiment analysis with accurate classification
11. Cloud IAM Implementation Real-world Problem: Secure access to cloud resources. Input Required: AWS IAM account. Suggested Outcome: Properly configured IAM policies and secure access management.
12. Capstone Cloud-Native Analytics Project Real-world Problem: Comprehensive analytics solution for business intelligence. Input Required: Integrated dataset, cloud services. Suggested Outcome: End-to-end solution with infrastructure, analytics, AI, and security components.

Course Name: Real-Time Data Analytics

Course Code: HMCE06T

Category: Honours/ Minor Programme in Next-Gen Data Science

Preamble:

This course equips students with advanced techniques to process, analyze, and derive actionable insights from high-velocity data streams. Covering real-time architectures (e.g., Kafka, Flink), edge analytics, and scalable ML deployments, the course bridges the gap between batch processing and instantaneous decision-making. Students will gain hands-on experience with industry tools (Apache Spark Streaming, AWS Kinesis) while addressing challenges like latency, fault tolerance, and ethical streaming data practices.

Pre-requisites: HMCE04T, HMCE05T

Course Objectives:

- Understand real-time data pipelines and their differences from batch processing.
- Implement stream processing frameworks (Kafka, Flink) for high-velocity data.
- Deploy ML models in real-time environments (e.g., fraud detection, IoT analytics).
- Optimize latency, throughput, and fault tolerance in streaming architectures.
- Address ethical considerations in real-time data collection and usage..

Course Outcomes:

Learner will be able to:
CO1: Compare batch vs. stream processing paradigms and their trade-offs
CO2: Design real-time data pipelines using Kafka/Flink for scalable ingestion.
CO3: Implement windowing, stateful operations, and event-time processing.
CO4: Deploy ML models (e.g., anomaly detection) on streaming data.
CO5: Evaluate performance metrics (latency, throughput) in real-time systems.
CO6: Critique ethical risks (privacy, bias) in continuous data analytics.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	20	15	40	75

The assessment guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to propose her/his assessment methodology based on the nature of the course. However, the proposed assessment methodology shall be approved by a panel constituted at Institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No	Module name	Content	No of Hours
1	Introduction to Real-Time Analytics	Batch vs. Stream Processing: Use cases and trade-offs. Real-time vs. Near-real-time systems. Hands-on: Setting up a Kafka producer/consumer	4
2	Stream Processing Frameworks	Apache Kafka: Architecture, topics, partitions. Apache Flink: Event-time processing, state management. Hands-on: Flink job for real-time word count.	6
3	Windowing & Stateful Operations	Tumbling vs. sliding windows. Stateful transformations (e.g., session tracking). Hands-on: Fraud detection using time-windowed aggregates.	5
4	ML on Streaming Data	Challenges in real-time ML (concept drift, latency). Deploying models with PySpark Streaming/TensorFlow Serving. Hands-on: Anomaly detection in IoT sensor data.	5
5	Edge & Distributed Stream Processing	Edge analytics (Flink Stateful Functions). Federated learning for decentralized streams. Hands-on: Processing edge device data with MQTT + Flink.	5
6	Ethics & Scalability in Real-Time Systems	Privacy in streaming (GDPR compliance). Scaling Kafka/Flink clusters (Kubernetes integration). Capstone: End-to-end pipeline for real-time sentiment analysis.	5
		Total	**30**

Text Books:

1. Streaming Systems – Tyler Akidau, Slava Chernyak, Reuven Lax (O'Reilly).
2. Kafka: The Definitive Guide – Neha Narkhede, Gwen Shapira (O'Reilly).

Reference Books:

1. Designing Data-Intensive Applications – Martin Kleppmann (O'Reilly).
2. Flink in Action – Fabian Hueske, Vasiliki Kalavri (Manning).

Online Resources:

- Apache Flink Documentation: https://flink.apache.org
- Confluent Kafka Tutorials: https://developer.confluent.io

Course Name: Real-Time Data Analytics Lab

Course Code: HMCE06P

Category: Honours/ Minor Programme in Next-Gen Data Science

Preamble:

This course equips students with advanced techniques to process, analyze, and derive actionable insights from high-velocity data streams. Covering real-time architectures (e.g., Kafka, Flink), edge analytics, and scalable ML deployments, the course bridges the gap between batch processing and instantaneous decision-making. Students will gain hands-on experience with industry tools (Apache Spark Streaming, AWS Kinesis) while addressing challenges like latency, fault tolerance, and ethical streaming data practices.

Pre-requisites: HMCE04T, HMCE05T

Course Objectives:

- Understand real-time data pipelines and their differences from batch processing.
- Implement stream processing frameworks (Kafka, Flink) for high-velocity data.
- Deploy ML models in real-time environments (e.g., fraud detection, IoT analytics).
- Optimize latency, throughput, and fault tolerance in streaming architectures.
- Address ethical considerations in real-time data collection and usage..

Course Outcomes:

Learner will be able to:
CO1: Compare batch vs. stream processing paradigms and their trade-offs
CO2: Design real-time data pipelines using Kafka/Flink for scalable ingestion.
CO3: Implement windowing, stateful operations, and event-time processing.
CO4: Deploy ML models (e.g., anomaly detection) on streaming data.
CO5: Evaluate performance metrics (latency, throughput) in real-time systems.
CO6: Critique ethical risks (privacy, bias) in continuous data analytics.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	--	25	50

The assessment guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to propose her/his assessment methodology based on the nature of the course. However, the proposed assessment methodology shall be approved by a panel constituted at Institute level and published to the learners before the commencement of the semester.

Suggested List of Practical's:

Sr No.	Suggested Topic(s)
1.	**Real-Time Log Monitoring** **Problem Statement:** T systems generate massive logs. How can we detect anomalies in real-time? **Desired Outcome:** - Implement Kafka pipeline to ingest server logs - Build Flink job to flag anomalies (e.g., error spikes) - Achieve <1s latency **Tools/Framework:** Kafka, Flink, ELK Stack
2.	**Fraud Detection for Payment** **Problem Statement:** Payment gateways need instant fraud detection. **Desired Outcome:** - Process transaction streams using windowed aggregates - Deploy pre-trained ML model (TF Serving) - Detect 90%+ fraud cases with <500ms latency **Tools/Framework:** Flink, TensorFlow Serving.
3.	**IoT Predictive Maintenance** **Problem Statement:** Factory sensors stream equipment data. Predict failures before they happen. **Desired Outcome:** - Calculate rolling metrics (vibration, temp) - Trigger alerts on threshold breaches - Integrate with MQTT/WebSocket dashboards **Tools/Framework:** MQTT, Flink, Grafana
4.	**Live Social Media Sentiment** **Problem Statement:** Brands need real-time perception tracking. **Desired Outcome:** - Ingest Twitter/Reddit streams via API - Run sentiment analysis (NLP model) - Update dashboard every 10s **Tools/Framework:** Kafka, Spark Streaming, Hugging Face
5.	**Smart Traffic Management** **Problem Statement:** Cities want to optimize traffic flow using real-time data. **Desired Outcome:** - Process camera/vehicle telemetry streams - Calculate congestion scores per junction - Simulate traffic light adjustments **Tools/Framework:** Flink, Kafka, SUMO (simulator)
6.	**Algorithmic Trading** **Problem Statement:** Trading firms need microsecond advantage. **Desired Outcome:** - Process market feed (WebSocket)

	- Implement moving average crossover strategy - Backtest latency impact on profits **Tools/Framework:** Flink, Binance API, Pandas
7.	**Personalized Ad Targeting** **Problem Statement:** Ad platforms must serve relevant ads in <100ms. **Desired Outcome:** - Track user clickstreams with session windows - Update recommendation model in real-time - A/B test recommendation quality **Tools/Framework:** Kafka, Flink, Redis
8	**Telemedicine Alerts** **Problem Statement:** Remote patients need instant health monitoring. **Desired Outcome:** - Process wearable device streams (heart rate) - Detect anomalies with stateful functions - Trigger SMS alerts via Twilio API **Tools/Framework:** Flink, MQTT, Twilio
9	**Supply Chain Tracking** **Problem Statement:** Global shipments require real-time visibility. **Desired Outcome:** - Ingest RFID/GPS event streams - Predict delays using route analytics - Visualize on map with ETA updates **Tools/Framework:** Kafka, Flink, Folium
10	**Energy Grid Optimization** **Problem Statement:** Utilities must balance load in real-time. **Desired Outcome:** - Aggregate smart meter readings - Forecast demand with 5-min windows - Simulate load shedding decisions **Tools/Framework:** Flink, PyTorch, Grafana

Text Books:

1. Streaming Systems – Tyler Akidau, Slava Chernyak, Reuven Lax (O'Reilly).
2. Kafka: The Definitive Guide – Neha Narkhede, Gwen Shapira (O'Reilly).

Reference Books:

1. Designing Data-Intensive Applications – Martin Kleppmann (O'Reilly).
2. Flink in Action – Fabian Hueske, Vasiliki Kalavri (Manning).

Course Name: Soft Computing

Course Code: HMCE07T

Category: Honours/ Minor in Artificial Intelligence and Machine Learning

Preamble:

Soft computing is an emerging approach to computing based on some biological inspired methodologies such as genetics, evolution, ant's behaviors, particles swarming, human nervous systems, etc. Now, soft computing is the only solution when we don't have any mathematical modeling of problem solving (i.e., algorithm), need a solution to a complex problem in real time, easy to adapt with changed scenario and can be implemented with parallel computing. It has enormous applications in many application areas such as medical diagnosis, computer vision, handwritten character reconditions, pattern recognition, machine intelligence, weather forecasting, network optimization, VLSI design, etc.

Pre-requisites:

- Engineering Mathematics (All Semesters)

Course Objectives:

After completing this course, you will be able to learn:

- Fuzzy logic and its applications.
- Artificial neural networks and its applications.
- Solving single-objective optimization problems using GAs.
- Solving multi-objective optimization problems using Evolutionary algorithms (MOEAs).
- Applications of Soft computing to solve problems in varieties of application domains.

Course Outcomes:

Learner will be able to learn:
CO1: Explain the fundamentals of soft computing, its constituents, and its adaptability.
CO2: Apply fuzzy set theory and design membership functions for imprecise data.
CO3: Develop fuzzy inference systems using Mamdani and Sugeno models for decision-making.
CO4: Solve optimization problems using genetic algorithms and their operators.
CO5: Implement neural network algorithms for supervised and unsupervised learning tasks.
CO6: Design hybrid systems like ANFIS by integrating neural networks and fuzzy logic.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	75

The assessment guidelines for the courses of different credits are mentioned above. Notwithstanding the above, each course faculty shall have the choice to propose her/his assessment methodology based on the nature of the course. However, the proposed assessment methodology shall be approved by a panel constituted at Institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No. of Hours
1	Introduction to Soft Computing	Soft computing Constituents, Characteristics of Neuro Computing and Soft Computing, Difference between Hard Computing and Soft Computing, Concepts of Learning and Adaptation.	4
2	Fuzzy Set Theory	Fuzzy Sets, Fuzzy relations, Fuzzification and Defuzzification. Features of the membership Functions, Fuzzy Max-Min and Max-Product Composition	4
3	Fuzzy Rules, Reasoning and Inference System	Fuzzy Rules: Fuzzy If-Then Rules, Fuzzy Reasoning Fuzzy Inference System (FIS): Mamdani FIS, Sugeno FIS, Comparison between, Mamdani and Sugeno FIS	4
4	Genetic Algorithm	An Introduction to genetic Algorithms Genetic Algorithms Mathematical Foundations, Schemata Revisited Implementation of a Genetic Algorithm: Data Structures, Reproduction, Crossover, and Mutation, Algorithm for Handwriting Recognition Using GA Generation of Graph, Fitness Function of GA, Generation of Graph Results of Handwriting Recognition, Effect of Genetic Algorithms, Distance Optimization, Style Optimization Solving single-objective optimization problems using GA, Multi-objective Optimization Problem Solving	6
5	Neural Networks	Basics of Neural Networks: Introduction to Neural Networks, Biological Neural Networks, McCulloch Pitt model Supervised Learning algorithms: Perceptron (Single Layer, Multi-layer), Linear separability, Delta learning rule, Back Propagation algorithm	8

Module No.	Module Name	Content	No. of Hours
		Un-Supervised Learning algorithms: Hebbian Learning, Winner take all, Self Organizing Maps, Learning Vector Quantization.	
6	Hybrid system	Introduction to Hybrid Systems, Adaptive Neuro Fuzzy Inference System (ANFIS).	4
Total			**30**

Text Books:

1. Principles of Soft Computing, S.N. Sivanandam, S.N. Deepa, Willey, 2nd
2. An Introduction to Genetic Algorithms, Melanie Mitchell, MIT Press
3. Neural Networks, Fuzzy Logis and Genetic Algorithms : Synthesis, and Applications, S. Rajasekaran, and G. A. Vijayalakshmi Pai, Prentice Hall of India
4. Fuzzy Logic with Engineering Applications (3rd Edn.), Timothy J. Ross, Willey

Reference Books:

1. Practical Genetic Algorithms, Randy L. Haupt and sue Ellen Haupt, John Willey & Sons, 2002.
2. Genetic Algorithms In Search, Optimization And Machine Learning, David E. Goldberg, Pearson Education
3. Fuzzy Logic: A Pratical approach, F. Martin, Mc neill, and Ellen Thro, AP Professional
4. Hagan, Demuth, Beale,"Neural Network Design" CENGAGE Learning, India Edition.Margaret.H.Dunham, ―Data Mining Introductory and Advanced Topics‖, Pearson Education
5. Satish Kumar, “Neural Networks –A classroom approach”, Second Edition,TMH Publication

Course Name: Soft Computing Lab

Course Code: HMCE07P

Category: Honours/ Minor in Artificial Intelligence and Machine Learning

Preamble:
Soft computing provides a reliable solution when we don't have any mathematical modeling of problem solving (i.e., algorithm), need a solution to a complex problem in real time, easy to adapt with changed scenario and can be implemented with parallel computing. It has enormous applications in many application areas such as medical diagnosis, computer vision, handwritten character reconditions, pattern recognition, machine intelligence, weather forecasting, network optimization, VLSI design, etc

Pre-requisites:

- Engineering Mathematics (All Semesters)

Course Objectives:

After completing this course, you will be able to learn:

- Fuzzy logic and its applications.
- Artificial neural networks and its applications.
- Solving single-objective optimization problems using GAs.
- Solving multi-objective optimization problems using Evolutionary algorithms (MOEAs).
- Applications of Soft computing to solve problems in varieties of application domains.

Course Outcomes:

Learners will be able to learn:
CO1: Explain the fundamentals of soft computing, its constituents, and its adaptability.
CO2: Apply fuzzy set theory and design membership functions for imprecise data.
CO3: Develop fuzzy inference systems using Mamdani and Sugeno models for decision-making.
CO4: Solve optimization problems using genetic algorithms and their operators.
CO5: Implement neural network algorithms for supervised and unsupervised learning tasks.
CO6: Design hybrid systems like ANFIS by integrating neural networks and fuzzy logic.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	25	--	25	50

The assessment guidelines for the courses of different credits are mentioned above. Notwithstanding the above, each course faculty shall have the choice to propose her/his assessment methodology based on the nature of the course. However, the proposed assessment methodology shall be approved by a panel constituted at Institute level and published to the learners before the commencement of the semester.

Suggested List of Practical's:

Sr No.	Suggested Topic(s)
1.	Study of Fuzzy set and Theory
2.	Implementing basic fuzzy Operations
3.	Implementation of fuzzy set close to N
4.	Study of the Fuzzy toolbox.
5.	Implementing Train Controller problem
6.	Implementing Washing machine problem
7.	Implementing Water purification problem
10.	Implementing Tipper problem
11.	Study of different learning rules.
12.	Implementing the Perceptron learning rule.
13.	Implementing the Curve Fitting using Genetics algorithm.

Text Books:

1. Principles of Soft Computing, S.N. Sivanandam, S.N. Deepa, Willey, 2nd
2. An Introduction to Genetic Algorithms, Melanie Mitchell, MIT Press
3. Neural Networks, Fuzzy Logis and Genetic Algorithms : Synthesis, and Applications, S. Rajasekaran, and G. A. Vijayalakshmi Pai, Prentice Hall of India
4. Fuzzy Logic with Engineering Applications (3rd Edn.), Timothy J. Ross, Willey

Reference Books:

1. Practical Genetic Algorithms, Randy L. Haupt and sue Ellen Haupt, John Willey & Sons, 2002.
2. Genetic Algorithms In Search, Optimization And Machine Learning, David E. Goldberg, Pearson Education
3. Fuzzy Logic: A Practical approach, F. Martin, , Mc neill, and Ellen Thro, AP Professional

Course Name: Natural language processing

Course Code: HMCE08T

Category: Honors/ Minor in Artificial Intelligence and Machine Learning

Preamble:

Natural Language Processing (NLP) is a foundational field at the intersection of Artificial Intelligence and Linguistics, concerned with the design and development of algorithms that enable computers to understand, interpret, and generate human language. With the increasing demand for intelligent systems that can process text and speech, NLP has become an essential area in computer science and data science. This course introduces the theoretical and practical aspects of NLP, covering linguistic fundamentals, core text analysis techniques, parsing, semantics, discourse processing, and real-world applications. Emphasis is also placed on the challenges of processing Indian languages and the development of interpretable NLP systems.

Pre-requisites: Soft Computing, Soft Computing Lab

Course Objectives:

- Understand the fundamental concepts of Natural Language Processing, including language structure, morphology, grammar, ambiguities, and foundational language modeling techniques.
- Apply various parsing algorithms, semantic analysis, and word representation models to process and analyze natural language data in both English and regional Indian languages.
- Analyze neural network-based language models and embedding techniques such as Word2Vec, GloVe, LSTM, and attention mechanisms for NLP tasks.
- Evaluate and implement NLP applications like machine translation, text summarization, sentiment analysis, and question answering using modern tools and deep learning approaches.

Course Outcomes:

Learner will be able to:

1. Recall fundamental concepts of NLP such as stages of language processing, grammar, and basic text preprocessing techniques like tokenization and stemming.
2. Explain morphological, syntactic, and semantic components of language using appropriate models and tools.
3. Apply parsing algorithms and semantic techniques (like WSD and discourse resolution) to analyze linguistic structures.
4. Analyse the structure and relationships in lexical resources (e.g., WordNet, BabelNet) and evaluate semantic similarity and ambiguity.
5. Evaluate the performance of various neural language models and word embedding techniques on language tasks.
6. Design and implement real-world NLP applications like machine translation or sentiment analysis using advanced deep learning models.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	075

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	Foundations of NLP and Language Modelling	Language, Knowledge and Grammar in language processing; Stages in NLP; Ambiguities and its types in English and Indian Regional Languages; Challenges of NLP; Applications of NLP. Basic Terms: Tokenization, Stemming, Lemmatization; Survey of English Morphology, Inflectional Morphology, Derivational Morphology; Morphological Models: Dictionary lookup, finite state morphology; Lexicon free FST Porter Stemmer algorithm; Grams and its variation: Bigram, Trigram; Simple (Unsmoothed) N-grams; N-gram Sensitivity to the Training Corpus; Unknown Words: Open versus closed vocabulary tasks; Evaluating N-grams: Perplexity; Smoothing: Laplace Smoothing, Good-Turing Discounting. ***Self-Learning Topics***: *Variety types of tools for regional languages pre-processing and other functionalities, Noisy channel models, various edit distance, Advance Issues in Language Modelling.*	6
2	Parsing Techniques and Syntax Modelling	Parsers: Top down and bottom up; Modelling constituency; Bottom-Up Parser: CYK, PCFG (Probabilistic Context Free Grammar), Shift Reduce Parser; TopDown Parser: Early Parser, Predictive Parser. ***Self-Learning Topics***: *Evaluating parsers, Parsers based language modelling, Regional languages POS tree banks*	5

3	Semantics, and Discourse	Introduction, meaning representation; Lexical Semantics; Corpus study; Knowledge Graphs & Ontologies; Study of Various language dictionaries like WorldNet, Babelnet; Relations among lexemes & their senses –Homonymy, Polysemy, Synonymy, Hyponymy; Semantic Ambiguity; Word Sense Disambiguation (WSD); Semantic Similarity and Relatedness. Discourse: Reference Resolution, Reference Phenomena, Syntactic & Semantic constraint on coherence; Anaphora Resolution using Hobbs Algorithm ***Self-Learning Topics***: *Dictionaries for regional languages, Topic Models, Discourse segmentation, Conference resolution*	5
4	Word Representations and Embedding Models	Word2Vec, CBOW and Skip-Gram Models, One word learning architecture, Forward pass for Word2Vec, Matrix Operations, Word Representation: Word2Vec & fastText, Word Representation: GloVe, Tokenization Strategies	6
5	Neural Language Models and Sequence Learning	Neural Language Models - CNN, RNN, RNN - Based Language Model, LSTM, GRU, Sequence-to-Sequence Models, Greedy Decoding, Beam search, Other Decoding Strategies: Nucleus Sampling, Temperature Sampling, Top-k Sampling, Attention in Sequence-to-Sequence Models	5
6	Applications of NLP in Real-World Scenarios	Case studies on (preferable in regional language): Machine translation; Text Summarization; Sentiment analysis; Information retrieval; Question Answering system ***Self-Learning Topics***: *Applications based on Deep Neural Network with NLP such as LSTM network, Recurrent Neural network etc.*	3
		Total	**30**

Textbooks:

1. Daniel Jurafsky and James H Martin, “Speech and Language Processing”, 3e, Pearson Education, 2018
2. Christopher D.Manning and Hinrich Schutze, — Foundations of Statistical Natural Language Processing —, MIT Press, 1999.
3. Steven Bird, Ewan Klein and Edward Loper, —Natural Language Processing with Python, First Edition, OReilly Media, 2009.
4. Daniel and James H. Martin “Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics and Speech Recognition”, Second Edition, Prentice Hall of India, 2008

Reference Books:

1. Tanveer Siddiqui, U.S. Tiwary, —Natural Language Processing and Information Retrieval, Oxford University Press, 2008.
2. Alexander Clark (Editor), Chris Fox (Editor), Shalom Lappin (Editor) — The Handbook of Computational Linguistics and Natural Language Processing
3. James Allen "Natural Language Understanding", Pearson Publication 8th Edition. 2012

Online Resources for Learning:

1. NLTK Project (Natural Language Toolkit): https://www.nltk.org
2. spaCy Documentation: https://spacy.io

Course Name: Natural language processing Lab

Course Code: HMCE08P

Category: Honors/ Minor in Artificial Intelligence and Machine Learning

Preamble:

Natural Language Processing (NLP) is a foundational field at the intersection of Artificial Intelligence and Linguistics, concerned with the design and development of algorithms that enable computers to understand, interpret, and generate human language. With the increasing demand for intelligent systems that can process text and speech, NLP has become an essential area in computer science and data science. This course introduces the theoretical and practical aspects of NLP, covering linguistic fundamentals, core text analysis techniques, parsing, semantics, discourse processing, and real-world applications. Emphasis is also placed on the challenges of processing Indian languages and the development of interpretable NLP systems.

Pre-requisites: Soft Computing, Soft Computing Lab

Course Objectives:

- Understand the fundamental concepts of Natural Language Processing, including language structure, morphology, grammar, ambiguities, and foundational language modeling techniques.
- Apply various parsing algorithms, semantic analysis, and word representation models to process and analyze natural language data in both English and regional Indian languages.
- Analyze neural network-based language models and embedding techniques such as Word2Vec, GloVe, LSTM, and attention mechanisms for NLP tasks.
- Evaluate and implement NLP applications like machine translation, text summarization, sentiment analysis, and question answering using modern tools and deep learning approaches.

Course Outcomes:

Learner will be able to:

1. Recall fundamental concepts of NLP such as stages of language processing, grammar, and basic text preprocessing techniques like tokenization and stemming.
2. Explain morphological, syntactic, and semantic components of language using appropriate models and tools.
3. Apply parsing algorithms and semantic techniques (like WSD and discourse resolution) to analyze linguistic structures.
4. Analyse the structure and relationships in lexical resources (e.g., WordNet, BabelNet) and evaluate semantic similarity and ambiguity.
5. Evaluate the performance of various neural language models and word embedding techniques on language tasks.
6. Design and implement real-world NLP applications like machine translation or sentiment analysis using advanced deep learning models.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	50

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practical's:

1. Build a Tokenizer and Stemmer for English and a selected Indian regional language (e.g., Hindi or Tamil).
2. Implement a language model to predict the next word using Trigram with Laplace smoothing.
3. Linguistic Analysis using POS Tagging and Named Entity Recognition
4. Feature Extraction: TF-IDF, N-grams, and Word Embedding
5. Build a Word Sense Disambiguation (WSD) tool using dictionary-based and machine learning approaches.
6. Develop an Anaphora Resolver using Hobbs' Algorithm for English narratives
7. Train Word2Vec (CBOW and Skip-Gram) models on a regional language corpus.
8. Build and train an RNN-based language model to generate simple sentences from a dataset
9. Create a Seq2Seq translation model with attention for English to regional language (e.g., English to Hindi).
10. Design a sentiment analysis system for product reviews in a regional language using LSTM.

Course Name: Deep Learning

Course Code: HMCE09T

Category: Honors/ Minor in Artificial Intelligence and Machine Learning

Preamble:

Deep Learning has emerged as a transformative technology powering advancements in artificial intelligence, from computer vision and natural language processing to healthcare and autonomous systems. This course provides a comprehensive introduction to the foundational concepts, architectures, and applications of deep neural networks. Students will gain hands-on experience with modern frameworks (e.g., TensorFlow/PyTorch) and learn to design, train, and evaluate models for real-world problems.

Pre-requisites:

- Proficiency in Python programming.
- Familiarity with linear algebra, calculus, and probability.
- Basic knowledge of machine learning (supervised/unsupervised learning).

Course Objectives:

After completing this course, you will be able to learn:

- Understand the mathematical and computational principles behind deep learning.
- Implement and experiment with key architectures (CNNs, RNNs, Transformers, etc.).
- Develop skills in data preprocessing, model optimization, and hyperparameter tuning.
- Apply deep learning techniques to tasks like image classification, sequence modeling, and generative AI.
- Critically analyze the ethical and societal implications of deployed systems.

Course Outcomes:

Learner will be able to learn:

CO1: Explain fundamental concepts of neural networks (perceptrons, MLPs, activation functions) and analyze their representation power
CO2: Implement feedforward networks using gradient-based optimization and derive backpropagation mathematically.
CO3: Design autoencoders and apply regularization techniques to mitigate overfitting in deep networks.
CO4: Optimize deep architecture using advanced techniques (batch norm, attention, word embeddings).
CO5: Develop CNN/RNN models for vision and sequence tasks and diagnose vanishing gradient problems.
CO6: Build generative models (VAEs, GANs, transformers) and critique their ethical implications.

Course Scheme:

Contact Hours		**Credits Assigned**	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	75

The assessment guidelines for the courses of different credits are mentioned above. Notwithstanding the above, each course faculty shall have the choice to propose her/his assessment methodology based on the nature of the course. However, the proposed assessment methodology shall be approved by a panel constituted at Institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No. of Hours
1	Introduction to Deep Learning	History of Deep Learning, Deep Learning Success Stories, McCulloch Pitts Neuron, Thresholding Logic, Perceptrons, Perceptron Learning Algorithm, Multilayer Perceptrons (MLPs), Representation Power of MLPs, Sigmoid Neurons	2
2	Neural Network Training Fundamentals	Gradient Descent, Feedforward Neural Networks, Representation Power of Feedforward Neural Networks, FeedForward Neural Networks, Backpropagation	4
3	Autoencoders & Regularization	Autoencoders and relation to PCA, Regularization in autoencoders, Sparse autoencoders, Contractive autoencoders, Regularization: Bias Variance Tradeoff, L2 regularization, Early stopping, Dataset augmentation, Parameter sharing and tying, Injecting noise at input, Ensemble methods, Dropout	6
4	Advanced Architectures & Representations	Greedy Layerwise Pre-training, Better activation functions, Better weight initialization methods, Batch Normalization, Learning Vectorial Representations Of Words, Encoder Decoder Models, Attention Mechanism, Attention over image	6
5	Advancement of CNNs and RNNs	Convolutional Neural Networks, LeNet, AlexNet, ZF-Net, VGGNet, GoogLeNet, ResNet, Visualizing Convolutional Neural Networks, Guided Backpropagation, Deep Dream, Deep Art, Fooling Convolutional Neural Networks, Recurrent Neural Networks, Backpropagation through time (BPTT), Vanishing and Exploding Gradients, Truncated BPTT, GRU, LSTMs	6
6	Generative Deep Learning	Variational Autoencoders (VAEs): Latent space, reparameterization trick, Applications in image generation, Transformer-based Gen Models: GPT architecture (decoder-only), Self-attention for text generation, Autoregressive Models: PixelRNN, WaveNet, Token-based generation (e.g., char-RNNs)	6
Total			**30**

Textbooks:

1. Deep Learning, Goodfellow, Ian, author, Cambridge, Massachusetts: The MIT Press
2. Neural Networks and Deep Learning: A Textbook, Charu C. Aggarwal, Springer
3. Pattern Recognition and Machine Learning, Christopher Bishop, Springer

Reference books:

1. Artificial Intelligence: A Modern Approach, Russell & Norvig, 4th Edition, Pearson
2. Machine Learning: A Probabilistic Perspective, Kevin Murphy, MIT Press
3. Speech and Language Processing, Jurafsky & Martin, Pearson

Course Name: Deep Learning Lab

Course Code: HMCE09P

Category: Honors/ Minor in Artificial Intelligence and Machine Learning

Preamble:

This hands-on lab complements the theoretical foundations of deep learning by providing practical experience in designing, training, and evaluating neural networks. Through coding exercises, projects, and experiments, students will gain proficiency in modern frameworks (e.g., TensorFlow/PyTorch) and learn to solve real-world problems using state-of-the-art architectures.

Pre-requisites:

- Basic Python programming.
- Familiarity with linear algebra and calculus (gradients).
- Core deep learning concepts

Course Objectives:

After completing this course, you will be able to learn:

- Implement Core Neural Network Components.
- Develop End-to-End Deep Learning Pipelines
- Optimize Models with Advanced Techniques
- Generate and Evaluate Synthetic Data.

Course Outcomes:

Learner will be able to learn:

CO1: Implement Neural Networks from Scratch
CO2: Build and Deploy CNN/RNN Models.
CO3: Debug and Improve Model Performance.
CO4: Generate Data with Generative Models.
CO5: Evaluate Ethical and Technical Trade-offs.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	2

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	25	-	25	50

The assessment guidelines for the courses of different credits are mentioned above. Notwithstanding the above, each course faculty shall have the choice to propose her/his assessment methodology based on the nature of the course. However, the proposed assessment methodology shall be approved by a panel constituted at Institute level and published to the learners before the commencement of the semester.

Suggested List of Practical's:

Sr. No.	Suggested Topic(s)
1	Train a single-layer perceptron to perform binary classification (e.g., AND/OR gates) using Python and NumPy.
2	Develop an MLP using PyTorch/TensorFlow to classify handwritten digits (MNIST dataset).
3	Plot the loss landscape for a simple model and compare convergence rates of SGD, Momentum, and Adam optimizers.
4	Experiment with dropout, L2 regularization, and early stopping to improve model generalization on a noisy dataset.
5	Design a CNN (e.g., LeNet or custom architecture) to classify images from the CIFAR-10 dataset.
6	Fine-tune a pre-trained CNN (e.g., ResNet, VGG) on a custom dataset using PyTorch/TensorFlow.
7	Train an LSTM/GRU model to predict stock prices or perform sentiment analysis on text data.
8	Build and train a denoising autoencoder to reconstruct corrupted images (e.g., noisy MNIST digits).
9	Train a DCGAN to generate synthetic images (e.g., faces or handwritten digits) and evaluate output quality.
10	Implement a transformer-based model (e.g., simplified GPT or seq2seq with attention) for language translation tasks.

Textbooks:

1. Deep Learning with Python – François Chollet
2. Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow – Aurélien Géron
3. PyTorch Pocket Reference" – Joe Papa

Reference books:

1. Deep Learning for Computer Vision with Python – Adrian Rosebrock
2. Natural Language Processing with PyTorch – Delip Rao & Brian McMahan
3. Generative Deep Learning – David Foster

Course Name: Advanced Databases

Course Code: HMCE10T

Category: Honours/ Minor in Data Science

Preamble:

Mastering advanced database systems requires a well-structured and comprehensive approach. Our roadmap encompasses key areas such as query processing, advanced data management, distributed databases, NoSQL and enhanced data models. These modules integrates theoretical concepts with practical applications, offering hands-on experience. This carefully designed curriculum equips learners with a thorough understanding of modern database systems, preparing them to tackle the complexities of today's data-driven environments.

Pre-requisites:

Database Management System

Course Objectives:

- To provide insights into distributed database designing
- To impart knowledge related to query processing and query optimization phases of a database management system.
- To introduce the concepts of access control models (DAC, MAC, and RBAC) and their implementation in database management systems.
- To specify the various approaches used for using XML and JSON technologies.
- To apply the concepts behind the various types of NoSQL databases and utilize it for Mongodb
- To learn about the trends in advance databases

Course Outcomes:

Learner will be able to:
CO1: Design distributed database using the various techniques for query processing
CO2: Measure query cost and perform distributed transaction management
CO3: Analyze and implement access control mechanisms such as Discretionary Access Control (DAC), Mandatory Access Control (MAC), and Role-Based Access Control (RBAC) to ensure data security in database systems
CO4: Organize the data using XML and JSON database for better interoperability
CO5: Compare different types of NoSQL databases
CO6: Describe various trends in advance databases through temporal, graph based and spatial based databases

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment Guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	75

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall decide her/his assessment methodology based on the course's nature. Faculty may propose the revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	Distributed Databases	Introduction, Distributed DBMS Architecture, Data Fragmentation, Replication and Allocation Techniques for Distributed Database Design.	4
2	Query Processing and Optimization	Introduction, Query processing in DBMS, Steps of Query Processing, Measures of Query Cost Selection Operation, Sorting, Join Operation, Evaluation of Expressions. Query Optimization Overview, Goals of Query Optimization, Approaches of Query Optimization, Transformations of Relational Expression, Estimating Statistics of Expression Results Choice of Evaluation Plans.	6
3	Advanced Database Access protocols	Discretionary Access Control Based on Granting and Revoking Privileges. Mandatory Access Control and Role Based Access Control, Remote Database access protocol.	4
4	Data interoperability – XML and JSON	XML Databases: Document Type Definition, XML Schema, Querying and Transformation: XPath and XQuery. Basic JSON syntax, (Java Script Object Notation),JSON data types, Stringifying and parsing the JSON for sending & receiving, JSON Object retrieval using key-value pair and JQuery, XML Vs JSON	6
5	NoSQL Distribution Model	NoSQL database concepts: NoSQL data modeling, Benefits of NoSQL, comparison between SQL and NoSQL database system. Types of NoSQL databases: Key-value data store, Document database and Column Family Data store, Comparison of NoSQL databases w.r.t CAP theorem and ACID properties.	5

Module No.	Module Name	Content	No of Hours
6	Trends in advance databases	Temporal database: Concepts, time representation, time dimension, incorporating time in relational databases. Graph Database: Introduction, Features, Transactions, consistency, Availability, Querying, Case Study Neo4J. Spatial database: Introduction, data types, models, operators and queries	5
Total			**30**

Textbooks:

1. Korth, Siberchatz, Sudarshan, "Database System Concepts", 6thEdition, McGraw Hill.
2. Elmasri and Navathe, "Fundamentals of Database Systems", 5thEdition, Pearson Education
3. Pramod Sadalge, Martin Fowler, NoSQL Distilled: A Brief Guide to the Emerging World of Polyglot Persistence, Addison Wesely/ Pearson
4. Jeff Friesen , Java XML and JSON,Second Edition, 2019, après Inc.

Reference Books:

1. Peter Rob and Carlos Coronel,Database Systems Design, Implementation and Management, Thomson Learning, 5th Edition.
2. Dr. P.S. Deshpande, SQL and PL/SQL for Oracle 10g, Black Book, Dreamtech Press.
3. Adam Fowler, NoSQL for dummies, John Wiley & Sons, Inc.

Course Name: Advanced Databases Lab

Course Code: HMCE10P

Category: Honours/ Minor in Data Science

Preamble:

The Advanced Database Lab focuses on practical applications of advanced database concepts. Students will work on EER modeling, SQL-based database design, distributed database fragmentation, query cost estimation, and security features in PostgreSQL. The lab also covers XML databases, MongoDB setup, queries, triggers, and database connectivity with front-end applications. This hands-on approach equips students with the skills to manage and implement advanced database systems effectively.

Pre-requisites:

Database Management System Lab

Course Objectives:

- To understand advanced database concepts through practical applications.
- To design and implement Enhanced Entity-Relationship (EER) models.
- To explore distributed database techniques like fragmentation.
- To analyze and estimate query costs for efficient database operations.
- To gain hands-on experience with NoSQL databases like MongoDB.
- To explore database security, triggers, and connectivity with front-end systems

Lab Outcomes:

Learners will be able to:
LO1: Students will create and implement EER models for real-world scenarios.
LO2: They will perform distributed database fragmentation and query optimization.
LO3: Students will demonstrate secure database access using PostgreSQL.
LO4: They will implement and query XML and MongoDB databases.
LO5: Learners will create active database triggers and understand their functionalities.
LO6: They will connect databases to front-end applications and perform operations seamlessly.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	050

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose the revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practical:

Sr No.	Title of Practical
1	Design EER Model for a real-life scenario and implement it using SQL
2	Implementation of fragmentation in distributed database environment.
3	Implement the Program to estimate cost of the query for various join operation
4	Explore the security and access control features of PostgreSQL (or equivalent system)
5	Implement XML Database
6	Install and Configure client and server for MongoDB
7	Design and implement any 5 queries using MongoDB
8	Implementation of triggers for understanding features of active database
9	Implement Database connectivity with any front end and perform database operations

Textbooks:

1. Ramez Elmasri, Shamkant B. Navathe, “Fundamentals of Database Systems”, 4th Edition, Pearson/Addision wesley, 2007 [2].
2. Abraham Silberschatz, Henry F. Korth, S. Sudharshan, “Database System Concepts”, 6th edition, Tata McGraw Hill, 2011

Reference Books:

1. T. Ozsu and P. Valduriez, Distributed Database Systems. Prentice Hall, Oct. 2011. [ISBN: 013616736X]
2. "NoSQL Distilled: A Brief Guide to the Emerging World of Polyglot Persistence" by Martin Fowler and Pramod J. Sadalage

Course Name: Big Data Analytics

Course Code: HMCE11T

Category: Honors in Data-Science

Preamble:

In today's digital era, organizations generate and process enormous volumes of structured and unstructured data. Big Data Analytics has emerged as a critical area in computing to extract actionable insights and support data-driven decisions. This course equips students with foundational knowledge and hands-on skills to handle Big Data using modern platforms and tools like Hadoop, MapReduce, NoSQL, and Apache Spark. It bridges theoretical understanding with industry-relevant applications across domains like e-commerce, healthcare, transportation, and finance.

Pre-requisites: Advance Databases

Course Objectives:

- Introduce the fundamental concepts, characteristics, and architecture of Big Data systems including HDFS, NoSQL, and Spark components
- Explain the working principles and models of distributed storage and processing frameworks like HDFS, MapReduce, and stream mining systems.
- Provide practical exposure to implementing distributed algorithms, similarity metrics, and stream data processing techniques.
- Equip students to design and develop scalable Big Data solutions by integrating storage, computation, and analytics for real-world applications.

Course Outcomes:

Learners will be able to:

1. Recall fundamental concepts: Big Data characteristics (5Vs), HDFS components, NoSQL database types, stream mining algorithms, and Spark architecture.
2. Explain the working of HDFS, MapReduce model, NoSQL types, and Big Data stream algorithms with examples.
3. Implement MapReduce algorithms (Word Count, Join), streaming algorithms (like Bloom filters, DGIM, and Flajolet-Martin), similarity metrics, and Spark transformations.
4. Analyze trade-offs between traditional vs. Big Data systems, CAP theorem applications, stream algorithm efficiency, and clustering performance (CURE)
5. Design integrated Big Data solutions using HDFS/NoSQL storage, MapReduce/Spark processing, real-time stream mining, and similarity/clustering analytics for real-world applications

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	075

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	Introduction to Big Data and Hadoop	Introduction to Big Data & Its characteristics (5 Vs); Type of Big Data; Traditional vs Big Data systems; Hadoop architecture; Core Hadoop Components; Hadoop Limitations. (CO1, CO2).	6
2	HDFS & MapReduce	HDFS: Namenode, Datanode, block storage, replication; Reading & Writing Mechanism in HDFS; MapReduce programming model: mapper, reducer, combiner; Algorithms: Word Count, Matrix multiplication, Union, Join.	5
3	NoSQL	Need for NoSQL database; Types of NoSQL: Document, Key-Value, Columnar, Graph; CAP Theorem.	4
4	Mining Data Streams	Stream processing model & Examples of Stream Sources; Stream Queries & Issues in Stream Processing; Filtering Streams: Bloom Filter with Analysis; Counting distinct elements: Flajolet-Martin algorithm; Counting frequent items in a stream, decaying windows; Counting ones in a sliding window: DGIM algorithm.	6
5	Similarity Measures & Clustering	Similarity Measures: Euclidean, Jaccard, Cosine, Edit distance, and Hamming distance; Frequent Itemset Mining: Apriori Algorithm, Algorithm of Park Chen-Yu; Clustering algorithms in big data; CURE algorithm **Self-Learning:** Practice similarity metrics and clustering using Scikit-learn or PySpark. Explore recommendation systems based on similarity scores	5
46	Introduction to Apache Spark	Spark architecture: RDDs, DataFrames, DAG; Transformations & Actions; Spark SQL **Self-Learning:** Build Spark jobs in Databricks / Google Colab	4

		Watch Spark tutorials from DataBricks, LinkedIn Learning	
Total			**30**

Textbooks:

1. Marz, N., & Warren, J. (2015). *Big Data: Principles and best practices of scalable real-time data systems*. Manning Publications.
2. White, T. (2015). *Hadoop: The definitive guide* (4th ed.). O'Reilly Media.

Reference Books:

1. Leskovec, J., Rajaraman, A., & Ullman, J. D. (2020). Mining of massive datasets (3rd ed.). Cambridge University Press.
2. Sadalage, P. J., & Fowler, M. (2012). NoSQL distilled: A brief guide to the emerging world of polyglot persistence. Addison-Wesley.
3. Damji, J. S., Wenig, B., Das, T., & Lee, D. (2020). Learning Spark: Lightning-fast big data analysis (2nd ed.). O'Reilly Media.

Online Resources for Learning:

1. Databricks. (n.d.). *Databricks Academy*. Retrieved June 6, 2025, from https://academy.databricks.com
2. University of California, San Diego. (n.d.). *Big Data Specialization* [Online course]. Coursera. Retrieved June 6, 2025, from https://www.coursera.org/specializations/big-data

Course Name: Big Data Analytics Lab

Course Code: HMCE11P

Category: Honors in Data Science

Preamble:

In today's digital era, organizations generate and process enormous volumes of structured and unstructured data. Big Data Analytics has emerged as a critical area in computing to extract actionable insights and support data-driven decisions. This course equips students with foundational knowledge and hands-on skills to handle Big Data using modern platforms and tools like Hadoop, MapReduce, NoSQL, and Apache Spark. It bridges theoretical understanding with industry-relevant applications across domains like e-commerce, healthcare, transportation, and finance

Pre-requisites: Advance Databases

Course Objectives:

- Introduce the fundamental concepts, characteristics, and architecture of Big Data systems including HDFS, NoSQL, and Spark components
- Explain the working principles and models of distributed storage and processing frameworks like HDFS, MapReduce, and stream mining systems.
- Provide practical exposure to implementing distributed algorithms, similarity metrics, and stream data processing techniques.
- Equip students to design and develop scalable Big Data solutions by integrating storage, computation, and analytics for real-world applications.

Course Outcomes:

Learner will be able to:

1. Recall fundamental concepts: Big Data characteristics (5Vs), HDFS components, NoSQL database types, stream mining algorithms, and Spark architecture.
2. Explain the working of HDFS, MapReduce model, NoSQL types, and Big Data stream algorithms with examples.
3. Implement MapReduce algorithms (Word Count, Join), streaming algorithms (like Bloom filters, DGIM, and Flajolet-Martin), similarity metrics, and Spark transformations.
4. Analyze trade-offs between traditional vs. Big Data systems, CAP theorem applications, stream algorithm efficiency, and clustering performance (CURE)
5. Design integrated Big Data solutions using HDFS/NoSQL storage, MapReduce/Spark processing, real-time stream mining, and similarity/clustering analytics for real-world applications .

Course Scheme:

Contact Hours		**Credits Assigned**	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	50

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practical's:

1. Install and configure Hadoop in pseudo-distributed mode.
2. Perform file operations (upload, read, delete) in HDFS using CLI.
3. Implement Word Count using MapReduce.
4. Implement Reduce Side Join using MapReduce.
5. Perform CRUD operations on MongoDB and visualize documents.
6. Implement Bloom Filter for stream filtering
7. Implement Flajolet-Martin and DGIM algorithms for stream frequency and distinct counting
8. Apply similarity metrics (Jaccard, Cosine, Edit Distance) on sample datasets.
9. Implement Apriori algorithm for frequent itemset mining.
10. Set up Apache Spark and execute RDD transformations and actions.
11. Perform clustering using CURE or KMeans algorithm and visualize clusters.
12. Capstone Project: Design an End-to-End Big Data Solution – Ingest, process, analyse, and visualize a large dataset using Hadoop/Spark, and NoSQL

Course Name: Text, Web and Social Media Analytics

Course Code: HMCE12T

Category: Honors in Data Science

Preamble:

In today's data-driven world, understanding insights from unstructured and dynamic sources such as text, web, and social media has become vital for organizations. This course introduces the foundational concepts and advanced techniques in Text, Web & Social Media Analytics. Students will explore the structure of social networks, analyze user actions, hyperlinks, and geospatial trends, and apply modern tools for visualizing and interpreting online behavior. The course bridges traditional analytics with the evolving landscape of digital interaction. By the end, students will be equipped to design actionable strategies using analytics tools across multiple online platforms.

Pre-requisites:

Web Design Lab (CE12P), Data Warehousing and Data Mining (CE22T)

Course Objectives:

- To provide foundational knowledge of social media platforms, their core characteristics, and the evolving landscape that drives the need for Social Media Analytics (SMA) in business contexts.
- To equip students with analytical skills for interpreting social network structures and applying network analysis tools to understand influence, engagement, and connectivity in digital environments.
- To develop competency in extracting actionable insights from social media text, user behavior (actions), and hyperlink structures using modern text and action analytics techniques.
- To introduce students to location-based and search engine analytics by exploring data sources, privacy concerns, user query behaviour, and relevant analytics tools and dashboards.
- To enable learners to design data-driven strategies through web analytics, recommendation systems, KPI measurement, and privacy-conscious approaches for managing social media and web presence effectively

Course Outcomes:

Learner will be able to:
CO1: Understand the concepts, characteristics, and evolving trends of social media and its analytics.
CO2: Apply appropriate techniques to analyze social media data, including text, actions, and networks.
CO3: Use tools and platforms to perform social media, web, and search engine analytics effectively.
CO4: Analyze user behavior, content diffusion, and engagement metrics across social and web platforms.
CO5: Evaluate the impact of social media analytics on strategic decision-making and digital marketing.
CO6: Design ethical, privacy-aware, and data-driven strategies for social media and web-based environments.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	15	20	40	075

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose the revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	Social Media Analytics: An Overview	o Core Characteristics of social media, social media landscape and trends, Need for Social Media Analytics for small & large organizations. o Social Media vs. Traditional Business Analytics, Seven Layers of Social Media Analytics, Types of Social Media Analytics, Social Media Analytics Cycle, Challenges to Social Media Analytics, Social Media Analytics Tools.	6
2	Social Network Structure, Measures & Visualization	Introduction to social network structures including nodes, edges, and ties. Network measures such as degree distribution, density, connectivity, centralization, tie strength, and trust. Basics of network visualization including graph layouts, visualization of features, and scale-related challenges. Key graph terminologies such as hubs, authorities, bridges, ego networks, modularity, clustering coefficient, and homophily. Introduction to network analysis tools such as Gephi, NodeXL, and SocNetV.	6
3	Social Media Text, Action & Hyperlink Analytics	Social Media Text Analytics - Types, purpose of text analytics in extracting user sentiment, intent, and trends and tools. Steps in social media text analytics including data collection, cleaning, tokenization, sentiment detection, and topic modeling. Action analytics —definition, scope, and significance of analyzing user actions and tools. Hyperlink analytics—types of hyperlinks used in social platforms, categories of hyperlink analysis (inbound, outbound, anchor text, etc.), and tools.	8

4	Social Media Location and Search Engine Analytics	Location Analytics- sources of location data in social media, including GPS tags, check-ins, and user metadata, categories of location analytics, privacy concerns related to location-based. Search engine analytics, exploring types of search engines like crawler-based and metasearch engines, methods for analyzing user queries and search behaviors, and popular tools such as Google Analytics, Search Console, and SEMrush.	6
5	Social Information Filtering	Social Sharing and filtering, Type of Recommendation Traditional vs social recommendation systems, understanding social media and Business Alignment, social media KPI, formulating a Social Media Strategy, Managing Social Media Risks. Privacy policies	6
6	Web Analytics	Fundamentals of web analytics, user behavior metrics such as page views, bounce rate, and session duration. Search engine performance analysis using rank positions, click-through rates, and keyword tracking. challenges like spam content and techniques to ensure data accuracy and quality	5
Total			**30**

Textbooks:

1. Matthew Ganis and Avinash Kohirkar, "Social Media Analytics: Techniques and Insights for Extracting Business Value Out of Social Media", First Edition, IBM Press..
2. Marshall Sponder, "Social Media Analytics: Effective Tools for Building, Interpreting, and Using Metrics", First Edition, McGraw-Hill Education.

Reference Books:

1. Charu C. Aggarwal, "Social Network Data Analytics", First Edition, Springer.
2. Glen L. Urban, "Digital Marketing Strategy: Analytics, Technology, and Customer Engagement", First Edition, Pearson Education.
3. S. Srinivasan, "Web and Social Media Analytics: A Practical Guide to Data Collection and Analysis", First Edition, Wiley.

Course Name: Text, Web and Social Media Analytics Lab

Course Code: HMCE12P

Category: Honors in Data Science

Preamble:

In today's data-driven world, understanding insights from unstructured and dynamic sources such as text, web, and social media has become vital for organizations. This course introduces the foundational concepts and advanced techniques in Text, Web & Social Media Analytics. Students will explore the structure of social networks, analyse user actions, hyperlinks, and geospatial trends, and apply modern tools for visualizing and interpreting online behaviour. The course bridges traditional analytics with the evolving landscape of digital interaction. By the end, students will be equipped to design actionable strategies using analytics tools across multiple online platforms.

Pre-requisites:

Web Design Lab (CE12P), Data Warehousing and Data Mining Lab (CE22P)

Course Objectives:

- To provide foundational knowledge of social media platforms, their core characteristics, and the evolving landscape that drives the need for Social Media Analytics (SMA) in business contexts.
- To equip students with analytical skills for interpreting social network structures and applying network analysis tools to understand influence, engagement, and connectivity in digital environments.
- To develop competency in extracting actionable insights from social media text, user behavior (actions), and hyperlink structures using modern text and action analytics techniques.
- To introduce students to location-based and search engine analytics by exploring data sources, privacy concerns, user query behaviour, and relevant analytics tools and dashboards.
- To enable learners to design data-driven strategies through web analytics, recommendation systems, KPI measurement, and privacy-conscious approaches for managing social media and web presence effectively

Course Outcomes:

Learner will be able to:
CO1: Understand the concepts, characteristics, and evolving trends of social media and its analytics.
CO2: Apply appropriate techniques to analyze social media data, including text, actions, and networks.
CO3: Use tools and platforms to perform social media, web, and search engine analytics effectively.
CO4: Analyze user behavior, content diffusion, and engagement metrics across social and web platforms.
CO5: Evaluate the impact of social media analytics on strategic decision-making and digital marketing.
CO6: Design ethical, privacy-aware, and data-driven strategies for social media and web-based environments.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	050

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose the revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practical's:

Sr No.	Title of Practical
1.	Sentiment Analysis of YouTube Comments
2.	Visualize a Twitter Follower Network Using Gephi
3.	Trend and Sentiment Analysis for a Twitter Hashtag.
4.	Analyze Social Media Metrics of a Brand Page.
5.	Explore tools like Hootsuite, Brandwatch, and Sprinklr and compare them based on features and usability.
6.	Follower Engagement Network for Instagram Influencer
7.	Location Heatmap using Social Media Metadata.
8.	Web Analytics Dashboard Interpretation.
9.	Design a content recommendation system based on user preferences and sentiment data collected from YouTube video interactions or tweets liked/shared.
10.	Perform tokenization, stop word removal, stemming, and vectorization on sample tweets or posts.
11.	Conduct a case-based discussion or prepare a brief report on data privacy, consent, and platform policies when scraping user data.

Textbooks:

1. Matthew Ganis and Avinash Kohirkar, "Social Media Analytics: Techniques and Insights for Extracting Business Value Out of Social Media", First Edition, IBM Press.
2. Marshall Sponder, "Social Media Analytics: Effective Tools for Building, Interpreting, and Using Metrics", First Edition, McGraw-Hill Education.

Reference Books:

1. Charu C. Aggarwal, "Social Network Data Analytics", First Edition, Springer.
2. Glen L. Urban, "Digital Marketing Strategy: Analytics, Technology, and Customer Engagement", First Edition, Pearson Education.

Course Name: Cryptography & Network Security

Course Code: HMCE13T

Category: Honours/ Minor in Cyber Security

Preamble:

Most today's computing devices support network connectivity, from your laptops and desktops to web servers, to Internet-of-Things devices. This connectivity is essential for enhancing the capabilities of computer technology. However, it has also fostered an environment rampant with network security and privacy concerns. This course aims to provide a thorough grounding in network security suitable for those interested in working in or conducting research in the area, as well as students more generally interested in either security or networking. We will examine core network protocols and their security, as well as broader issues relating to Internet security for which networking plays a role. Through this course, you should learn the fundamentals of how computer networks should operate, and what can and does go wrong.

Pre-requisites:

Operating system

Course Objectives:

- Basic concepts computer networks and security
- Various cryptography algorithms including secret key management and different authentication techniques.
- Different types of malicious software's and its effect on security
- Various secure communication standards including IPSEC, SSL/TLS and email.
- Network management security and network access control techniques in computer security.
- Different attacks on network and infer the use of firewalls and security protocol.

Course Outcomes:

Learner will be able to:
CO1: Explain the fundamentals concepts of computer security and network security.
CO2: Identify the basic cryptographic techniques using classical and block encryption methods.
CO3: Study and describe the system security malicious software.
CO4: Describe the Network layer security, Transport layer security and application layer security.
CO5: Explain the need of network management security and illustrate the need for NAC.
CO6: Identify the function of an IDS and firewall for system security.

Course Scheme:

Contact Hours		**Credits Assigned**	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	075

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose the revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	**Introduction to Network Security & cryptography**	Computer security and Network Security(Definition), CIA, Services, Mechanisms and attacks, The OSI security architecture, Network security model. Classical Encryption techniques (mono-alphabetic and poly-alphabetic substitution techniques: Vigenere cipher, playfair cipher, transposition techniques: keyed and keyless transposition ciphers). Introduction to steganography	4
2	**Cryptography: Key management, distribution and user authentication**	Cryptography: Key management, distribution and user authentication Block cipher modes of operation, Data Encryption Standard, Advanced Encryption Standard (AES). RC5 algorithm. Public key cryptography: RSA algorithm. Hashing Techniques: SHA256, SHA-512, HMAC and CMAC, Digital Signature Schemes – RSA, DSS. Remote user Authentication Protocols, Kerberos, Digital Certificate: X.509, PKI	8
3	**Malicious Software**	Malicious Software: SPAM, Trojan horse, Viruses, Worms, System Corruption, Attack Agents, Information Theft, Trapdoor, Keyloggers, Phishing, Backdoors, Rootkits, Denial of Service Attacks, Zombie	4
4	**IP Security**	IP Security, Transport level security and Email Security: IP level Security: Introduction to IPSec, IPSec Architecture, Protection Mechanism (AH and ESP), Transport level security: VPN. Need Web Security considerations, Secure Sockets Layer (SSL)Architecture, Transport Layer Security (TLS), HTTPS, Secure Shell (SSH) Protocol Stack. Email Security: Secure Email S/MIME Screen reader support enabled.	8
5	**Network Management Security and**	Network Management Security and Network Access Control: Network Management Security:SNMPv3, NAC: Principle elements of NAC, Principle NAC enforcement	4

Module No.	Module Name	Content	No of Hours
	Network Access Control	methods, How to implement NAC Solutions, Use cases for network access control	
6	**System Security**	System Security: IDS, Firewall Design Principles, Characteristics of Firewalls, Types of Firewalls	2
Total			**30**

Textbooks:

1. Cryptography and Network Security: Principles and Practice by William Stallings, 6th edition Pearson publication
2. Cryptography and Network security by Behrouz A. Forouzan, Tata Mc Graw Hill
3. Information Security Principles and Practice, Mark Stamp, Wiley publication

Reference Books:

1. Security in Computing by Charles P. Pfleeger, Pearson publication
2. Computer Security Art and Science by Matt Bishop, Addison- Wesley publication

Course Name: Cryptography & Network Security Lab

Course Code: HMCE13P

Category: Honours/ Minor in Cyber Security

Preamble:

The purpose of this security lab is to provide hands-on experience and practical knowledge in understanding various aspects of cybersecurity and information security practices. Through this lab, students will explore different security mechanisms, tools, techniques, and methodologies to safeguard digital assets, mitigate risks, and respond effectively to security incidents. Security lab provides a valuable opportunity for participants to gain practical skills, insights, and hands-on experience in the field of cybersecurity. By actively engaging in lab activities and embracing security best practices, students will be better equipped to address the evolving challenges and complexities of today's cybersecurity landscape.

Pre-requisites:

Operating system

Course Objectives:

- To apply the knowledge of symmetric cryptography to implement classical ciphers
- To analyze and implement public key encryption algorithms, hashing and digital signature algorithms
- To explore the different network reconnaissance tools to gather information about networks
- To explore the tools like sniffers, port scanners and other related tools for analyzing
- To Scan the network for vulnerabilities and simulate attacks
- To set up intrusion detection systems using open source technologies and to explore email security

Course Outcomes:

Learner will be able to:
LO1: Illustrate symmetric cryptography by implementing classical ciphers.
LO2: Demonstrate Key management, distribution and user authentication.
LO3: Explore the different network reconnaissance tools to gather information about networks.
LO4: Use tools like sniffers, port scanners and other related tools for analyzing packets in a network.
LO5: Use open-source tools to scan the network for vulnerabilities and simulate attacks
LO6: Demonstrate the network security system using open-source tools.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	050

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose the revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practicals:

Sr No.	Title of Practicals
1	Classical Encryption techniques (mono-alphabetic and poly-alphabetic substitution techniques: Vigenere cipher, playfair cipher)
2	1)Block cipher modes of operation using a) Data Encryption Standard b)Advanced Encryption Standard (AES). 2)Public key cryptography: RSA algorithm. 3)Hashing Techniques: HMAC using SHA 4)Digital Signature Schemes – RSA, DSS
3	Study the use of network reconnaissance tools like WHOIS, dig, traceroute, nslookup to gather information about networks and domain registrars.
4	1) Download and install nmap. 2) Use it with different options to scan open ports, perform OS fingerprinting, ping scan, tcp port scan, udp port scan, etc.
5	a) Keylogger attack using a keylogger tool. b) Simulate DOS attack using Hping or other tools c) Use the NESSUS/ISO Kali Linux tool to scan the network for vulnerabilities
6	1) Set up IPSec under Linux. 2) Set up Snort and study the logs. 3) Explore the GPG tool to implement email security
7	Design a network and demonstrate. 1) Path the network follows before implementing VPN 2) Path the network follows after implementing VPN
8	Demonstrate Phishing attack over LAN and WAN network using Kali Linux
9	Demonstrate SQL Injection attack using Kali Linux
10	Demonstrate Fake Email attack using Kali Linux

Textbooks:

1. Build your own Security Lab, Michael Gregg, Wiley India.
2. CCNA Security, Study Guide, TIm Boyles, Sybex.
3. Hands-On Information Security Lab Manual, 4th edition, Andrew Green, Michael Whitman, Herbert Mattord.
4. The Network Security Test Lab: A Step-by-Step Guide Kindle Edition, Michael Gregg.

Reference Books:

1. Network Security Bible, Eric Cole, Wiley India.
2. Network Defense and Countermeasures, William (Chuck) Easttom.
3. Principles of Information Security + Hands-on Information Security Lab Manual, 4th Ed. , Michael Whitman , Herbert Mattord.

Course Name: Web Application Security

Course Code: HMCE14T

Category: Honors/ Minor in Cyber Security

Preamble:

This course focuses on identifying, analysing, and mitigating vulnerabilities specific to web applications. It empowers students with practical skills using industry-standard tools and frameworks and promotes secure web development practices aligned with OWASP and modern threat landscapes.

Pre-requisites:

Course Objectives:

- To reveal the underlying web application.
- To identify and aid in fixing any security vulnerabilities during the web development process.
- To understand the security principles in developing a reliable web application.

Course Outcomes:

Learner will be able to:

1. Identify the vulnerabilities in the web applications
2. Identify the various types of threats and mitigation measures of web applications.
3. Apply the security principles in developing a reliable web application.
4. Use industry standard tools for web application security.
5. Create detailed reports on findings, mitigations, and secure design.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	075

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	Overview of Web Applications	Introduction history of web applications interface and structure benefits and drawbacks of web applications Web application Vs Cloud application, Web architecture, HTTP/HTTPS, sessions, cookies, authentication, same-origin policy, common attack vectors.	4
2	Web Application Security Fundamentals	Security Fundamentals: Input Validation - Attack Surface Reduction Rules of Thumb- Classi- fying and Prioritizing Threads, Origin Policy - Exceptions to the Same-Origin Policy - Cross-Site Scripting and Cross-Site Request Forgery - Reflected XSS - HTML Injection.	7
3	Web Application Vulnerabilities	Understanding vulnerabilities in traditional client server applications and web applications, client state manipulation, cookie-based attacks, SQL injection, cross domain attack (XSS/XSRF/XSSI) http header injection. SSL vulnerabilities and testing - Proper encryption use in web application - Session vulnerabilities and testing - Cross-site request forgery, OWASP Top 10: SQLi, XSS, CSRF, IDOR, File Inclusion, SSRF, XXE. Understanding root causes and testing techniques	6
4	Tools for Security Testing	Burp Suite, ZAP Proxy, Nikto, WFuzz, HTTP interceptors, crawling, fuzzing, authentication testing	6
5	Secure Website Design	Secure website design: Architecture and Design Issues for Web Applications, Deployment Considerations Input Validation, Authentication, Authorization, Configuration Management, Sensitive Data, Session Management, Cryptography, Parameter Manipulation, Exception Management, Auditing and Logging, Design Guidelines, Forms and validity, technical implementation	4
6	Case Studies and Emerging Trends	Recent high-profile web application breaches, evolving attack trends (e.g., API abuse, supply chain), real-world secure architecture examples	3
Total			**30**

Textbooks:

1. Stuttard, D., & Pinto, M. (2011). The Web Application Hacker's Handbook: Finding and Exploiting Security Flaws (2nd ed.). Indianapolis: Wiley Publishing. ISBN: 978-1118026472
2. Gowadia, V., & Parekh, A. (2022). Web Application Security: Exploitation and Countermeasures for Java, Python, and Node.js. Berkeley, CA: Apress. ISBN: 978-1484285066

Reference Books:

1. Shema, M. (2014). Hacking Web Apps: Detecting and Preventing Web Application Security Problems. Waltham, MA: Syngress. ISBN: 978-0124166004
2. Erickson, J. (2008). Hacking: The Art of Exploitation (2nd ed.). San Francisco, CA: No Starch Press. ISBN: 978-1593271442
3. Andress, J. (2014). The Basics of Information Security: Understanding the Fundamentals of InfoSec (2nd ed.). Waltham, MA: Syngress. ISBN: 978-0128007440

Online Resources for Learning:

1. OWASP Foundation. Web Security Testing Guide (WSTG). Retrieved from https://owasp.org/www-project-web-security-testing-guide/
2. PortSwigger. Web Security Academy (Interactive Learning Platform). Retrieved from https://portswigger.net/web-security

Course Name: Web Application Security Lab

Course Code: HMCE14P

Category: Honors/ Minor in Cyber Security

Preamble:

This course focuses on identifying, analysing, and mitigating vulnerabilities specific to web applications. It empowers students with practical skills using industry-standard tools and frameworks and promotes secure web development practices aligned with OWASP and modern threat landscapes.

Pre-requisites:

Course Objectives:

- To reveal the underlying web application.
- To identify and aid in fixing any security vulnerabilities during the web development process.
- To understand the security principles in developing a reliable web application.

Course Outcomes:

Learner will be able to:

1. Identify the vulnerabilities in the web applications
2. Identify the various types of threats and mitigation measures of web applications.
3. Apply the security principles in developing a reliable web application.
4. Use industry standard tools for web application security.
5. Create detailed reports on findings, mitigations, and secure design.

Course Scheme:

Contact Hours		Credits Assigned	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Practical	25	-	25	50

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practical's:

1. Web application reconnaissance and spidering using ZAP/Burp Suite
2. Exploit SQL Injection on a vulnerable application (DVWA or Juice Shop)
3. Detect and exploit Cross-Site Scripting (XSS)
4. Perform vulnerability scans using Nikto or ZAP
5. Analyse secure HTTP headers and apply security configurations (CSP, HSTS, etc.)
6. Build and Deploy a Secure Login Module (Design login with input sanitization, secure cookies, and rate-limiting.)
7. Prepare a Security Assessment Report

Course Name: Digital Forensics

Course Code: HMCE15T

Category: Honors/ Minor in Cyber Security

Preamble:

This course introduces students to the principles, techniques, and methodologies of digital forensics. It covers the investigation and analysis of digital evidence, including file systems, network traffic, and digital devices. Emphasis is placed on legal and ethical considerations, as well as practical hands-on experience with forensic tools and techniques.

Pre-requisites:

Computer and Network Security

Course Objectives:

- To explore the fundamentals of digital forensics, digital evidence and incident response
- To learn the tools and techniques required for computer forensics.
- To understand the network attacks and tools and techniques required to perform network forensics.
- To learn how to investigate attacks on mobile platforms.
- To generate forensics, report after investigation.

Course Outcomes:

Learners will be able to:
CO1: Recognize the need of digital forensics and define the concept of digital evidence and incident response
CO2: Apply knowledge of computer forensics using different tools and techniques.
CO3: Detect the network attacks and analyse the evidence.
CO4: Apply the knowledge of computer forensics using different tools and techniques.
CO5: List the method to generate legal evidence and supporting investigation reports
CO6: Understand the legal framework in Digital forensics

Course Scheme:

Contact Hours		Credit Assigned	
Theory	Practical	Theory	Practical
2	-	2	-

Assessment guidelines:

Head of Learning	ISA	MSE	ESE	Total
Theory	15	20	40	75

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose the revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Detailed Syllabus:

Module No.	Module Name	Content	No of Hours
1	Introduction to Digital Forensics	Introduction to Digital Forensics, Need and Objectives of Digital Forensics, Types of Digital Forensics, Process of Digital Forensics, Benefits of Digital Forensics, Chain of Custody, Anti Forensics. Digital Evidence and its Types, Rules of Digital Evidence. Incident Response, Methodology of Incident Response, Roles of CSIRT in handling incident.	4
2	Computer Forensics	Introduction to Computer Forensics, Evidence collection (Disk, Memory, Registry, Logs etc), Evidence Acquisition, Analysis and Examination (Window, Linux, Email, Web, Malware) , Challenges in Computer Forensics, Tools used in Computer Forensics.	6
3	Network Forensics	Introduction, Evidence Collection and Acquisition (Wired and Wireless), Analysis of network evidence (IDS, Router,), Challenges in network forensics, Tools used in network forensics	6
4	Mobile Forensics	Introduction, Evidence Collection and Acquisition, Analysis of Evidence, Challenges in mobile forensics, Tools used in mobile forensics	4
5	Report Generation	Goals of Report, Layout of an Investigative Report, Guidelines for Writing a Report, sample for writing a forensic report.	4
6	Introduction to Legal Frameworks	Overview of legal principles in digital forensics Sources of law relevant to digital evidence (statutory, case law, regulations), Jurisdictional considerations in digital investigations, Admissibility of digital evidence in court Rules of evidence (e.g., hearsay, authentication, best evidence rule) Chain of custody requirements and documentation, GDPR (General Data Protection Regulation) and its implications for digital forensics, HIPAA (Health Insurance Portability and Accountability Act) considerations, Other relevant privacy laws and their impact on digital investigations, Challenges with encryption and decryption Anti-forensic techniques and legal implications	6
Total			**30**

Textbooks:

1. John Sammons, "The Basics of Digital Forensics: The Premier for Getting Started in Digital Forensics", 2nd Edition, Syngress, 2015.
2. Nilakshi Jain, Dhananjay Kalbande, "Digital Forensic: The fascinating world of Digital Evidences" Wiley India Pvt Ltd 2017.
3. Jason Luttgens, Matthew Pepe, Kevin Mandia, "Incident Response and computer forensics",3rd Edition Tata McGraw Hill, 2014.

Reference Books:

1. Sangita Chaudhuri, Madhumita Chatterjee, "Digital Forensics", Staredu, 2019.
2. Bill Nelson,Amelia Phillips,Christopher Steuart, "Guide to Computer Forensics and Investigations" Cengage Learning, 2014.
3. Debra Littlejohn Shinder Michael Cross "Scene of the Cybercrime: Computer Forensics Handbook", 2nd Edition Syngress Publishing, Inc.2008.

Course Name: Digital Forensics Lab

Course Code: HMCE15P

Category: Honors/ Minor in Cyber Security

Preamble:

This lab course facilitates rigorous and impartial digital investigations through the application of scientific methods and best practices in forensic analysis. Aim is to provide reliable evidence to support legal proceedings, internal investigations, and proactive security measures.

Pre-requisites:

Computer Networks Lab
Operating system Lab
Computer & Network Security Lab

Course Objectives:

- Conduct thorough examinations of digital devices, networks, and storage media to uncover relevant evidence while maintaining chain of custody and integrity.
- Utilize state-of-the-art forensic tools and methodologies to extract, analyze, and interpret digital evidence effectively and efficiently.
- Foster collaboration with law enforcement agencies, legal teams, and internal stakeholders to ensure the accuracy and relevance of forensic findings.
- Uphold ethical principles and legal guidelines in all investigative processes, respecting privacy rights and confidentiality.

Course Outcomes:

CO1: Understanding of Digital Forensics Principles
CO2: Proficiency in Forensic Tools and Techniques
CO3: Ability to Conduct Forensic Examinations
CO4: Evidence Handling and Chain of Custody
CO5: Report Writing and Presentation Skills
CO6: Ethical and Legal Considerations

Course Scheme:

Contact Hours		**Credits Assigned**	
Theory	Practical	Theory	Practical
-	2	-	1

Assessment guidelines:

Head of Learning	**ISA**	**MSE**	**ESE**	**Total**
Practical	25	-	25	050

The assessment/evaluation guidelines for the courses of different credits are mentioned in the above table. Notwithstanding the above, each course faculty shall have the choice to decide her/his assessment methodology based on the nature of the course. Faculty may propose a revised assessment methodology for his/her course. However, the revised assessment methodology shall be approved by a panel constituted at institute level and published to the learners before the commencement of the semester.

Suggested List of Practicals:

Sr No.	Title of Practicals
1	Use tools like Nmap to scan a network for active hosts and services. Enumerate services to gather information about versions and configurations.
2	Identify common vulnerabilities (e.g., using CVE database) in a target system. Use vulnerability scanners like OpenVAS or Nessus to detect vulnerabilities.
3	Exploit common vulnerabilities such as buffer overflows, SQL injection, or XSS attacks. Use frameworks like Metasploit to automate exploitation.
4	Use tools like John the Ripper or Hashcat to crack passwords from hashed files. Experiment with different password cracking techniques (dictionary attacks, brute force, etc.).
5	Perform SQL injection attacks on vulnerable web applications. Cross-Site Scripting (XSS) attacks to inject malicious scripts into web pages. Directory traversal and file inclusion attacks.
6	Crack Wi-Fi passwords using tools like Aircrack-ng or Wifite. Perform rogue access point attacks and man-in-the-middle (MITM) attacks on Wi-Fi networks.
7	Use tools like Autopsy or Sleuth Kit to analyze disk images for evidence of security breaches. Investigate system logs and network traffic to reconstruct security incidents.
8	Configure firewalls and intrusion detection/prevention systems (IDS/IPS).
9	Conduct physical penetration tests to gain unauthorized access to facilities or systems.
10	Mini project

Textbooks:

1. "Computer Forensics: Investigating Network Intrusions and Cybercrime" by EC-Council
2. "Digital Forensics with Open Source Tools" by Cory Altheide and Harlan Carvey
3. "The Art of Memory Forensics: Detecting Malware and Threats in Windows, Linux, and Mac Memory" by Michael Hale Ligh, Andrew Case, Jamie Levy, and AAron Walters
4. "Practical Forensic Imaging: Securing Digital Evidence with Linux Tools" by Bruce Nikkel

Reference Books:

1. "Handbook of Digital Forensics and Investigation" edited by Eoghan Casey
2. "Windows Forensic Analysis Toolkit: Advanced Analysis Techniques for Windows 10" by Harlan Carvey
3. "Network Forensics: Tracking Hackers through Cyberspace" by Sherri Davidoff and Jonathan Ham
4. "Mobile Forensic Investigations: A Guide to Evidence Collection, Analysis, and Presentation" by Lee Reiber