



**Royal School of Engineering and Technology (RSET)**

**Department of Computer Science and Engineering (CSE)**

**Course Structure & Syllabus**

**(Based on National Education Policy 2020)**

**For**

**Master of Technology**

**In**

**Computer Science & Technology**

**W.E.F**

**AY: 2025-2026**

## Course Structure and Syllabus of the Framework

### 1 Course Structure of M. Tech.

1st semester							
S.N	Subject Code	Names of subjects	L	T	P	C	TCP
<b>Programme Specific Core Courses (PSC)</b>							
1	CSE024C101	Internet Protocols and Network Design	4	0	0	4	4
2	CSE024C102	Mathematical Foundations of Computer Science	4	0	0	4	4
3	CSE024C103	Distributed Operating Systems	4	0	0	4	4
4	CSE024C111	Internet Protocols and Network Design Lab	0	0	2	1	2
5	CSE024C112	Mathematical Foundations of Computer Science Lab	0	0	2	1	2
6	CSE024C113	Distributed Operating Systems Lab	0	0	2	1	2
<b>Programme Specific Elective Courses (PSE)</b>							
7	CSE024D10X	PEC-I	4	0	0	4	4
8	CSE024D11X	PEC-I Lab	0	0	2	1	2
<b>TOTAL</b>			<b>16</b>	<b>0</b>	<b>8</b>	<b>20</b>	<b>24</b>
2nd semester							
S.N	Subject Code	Names of subjects	L	T	P	C	TCP
<b>Programme Specific Core Courses (PSC)</b>							
1	CSE024C201	Modern Database Systems	4	0	0	4	4
2	CSE024C202	Advanced Algorithm Designing	4	0	0	4	4
3	CSE024C211	Modern Database Systems Lab	0	0	2	1	2
4	CSE024C212	Advanced Algorithm Designing Lab	0	0	2	1	2
<b>Programme Specific Elective Courses (PSE)</b>							
5	CSE024D20X	PEC-II	4	0	0	4	4
6	CSE024D21X	PEC-II Lab	0	0	2	1	2
7	CSE024D20X	PEC-III	4	0	0	4	4
8	CSE024D21X	PEC-III Lab	0	0	2	1	2
<b>TOTAL</b>			<b>16</b>	<b>0</b>	<b>8</b>	<b>20</b>	<b>24</b>
<b>Exit Option after 1st Year: PG Diploma in Computer Application/ Information Technology/ Cohort Course</b> <b>Additional Credits to be acquired: 4 (Internship/Apprenticeship)</b>							
3rd semester							
S.N	Subject Code	Names of subjects	L	T	P	C	TCP
<b>Programme Specific Core Courses (PSC)</b>							
1	CSE024C301	Soft Computing	4	0	0	4	4
2	CSE024C302	Internet Security and Cryptographic Protocols	4	0	0	4	4
3	CSE024C301	Soft Computing Lab	0	0	2	1	2
4	CSE024C302	Internet Security and Cryptographic Protocols Lab	0	0	2	1	2
<b>Programme Specific Elective Courses (PSE)</b>							
5	CSE024D30X	PEC-IV	4	0	0	4	4
6	CSE024D31X	PEC-IV Lab	0	0	2	1	2
<b>Summer Training/ Internship</b>							
7	CSE024C324	Summer Training/ Internship	0	0	0	2	0
<b>Project</b>							

8	CSE024C325	Dissertation-I	0	0	16	8	16
		<b>TOTAL</b>	<b>7</b>	<b>0</b>	<b>22</b>	<b>24</b>	<b>33</b>
<b>4th semester</b>							
<b>S.N</b>	<b>Subject Code</b>	<b>Names of subjects</b>	<b>L</b>	<b>T</b>	<b>P</b>	<b>C</b>	<b>TCP</b>
<b>Project</b>							
1	CSE024C421	Dissertation-II	0	0	32	16	32
		<b>TOTAL</b>	<b>0</b>	<b>0</b>	<b>32</b>	<b>16</b>	<b>32</b>

SEMESTER	TOTAL CREDITS
I	20
II	20
III	24
IV	16
<b>TOTAL</b>	<b>80</b>

**Note:** \*\*\* All Engineering Graduates have to undergo 2-year PG Course  
\*\*\* Exit after 1st year will be awarded PG Diploma

DSE Tracks	Subject Name
<b>Track 1: Artificial Intelligence</b>	Minor 1: Foundations of AI (CSE024D101)
	Minor 2: Machine Learning & Deep Learning (CSE024D201)
	Minor 3: Natural Language Processing (CSE024D202)
	Minor 4: Computer Vision/ Generative AI and LLMs (CSE024D301)
<b>Track 2: Data Analytics</b>	Minor 1: Data Mining (CSE024D102)
	Minor 2: Statistical Computing (CSE024D203)
	Minor 3: Big Data Analytics (CSE024D204)
	Minor 4: Cloud Computing for Big Data (CSE024D302)
<b>Track 3: Image Processing/ Computer Vision</b>	Minor 1: Digital Image Processing (CSE024D101)
	Minor 2: Machine Learning & Deep Learning (CSE024D201)
	Minor 3: Remote Sensing and GIS (CSE024D206)
	Minor 4: Computer Vision/ Generative AI and LLMs (CSE024D301)

## 2. Detailed Syllabus of 1<sup>st</sup> Semester

<b>Paper I/Subject Name: Internet Protocols and Network Design</b>	<b>Subject Code: CSE024C101</b>
<b>L-T-P-C – 4-0-0-5</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

### Objective:

The objectives of the course are to make the students understand fundamentals of Internet Protocols (IP) and their role in network communication, different routing and addressing techniques in both IPv4 and IPv6, the design and architecture of scalable networks.

**Prerequisites:** Computer Networks (Basic), Data Communication, Network Security Fundamentals

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Demonstrate</b> knowledge of Internet Protocols and their layered architecture.	<b>BT 2</b>
CO 2	<b>Implement</b> IP addressing schemes and subnetting for efficient network design.	<b>BT 3</b>
CO 3	<b>Analyze and evaluate</b> various routing protocols (RIP, OSPF, BGP, etc.).	<b>BT 4 &amp; 5</b>
CO 4	<b>Design</b> scalable, high-performance networks for cloud and IoT applications.	<b>BT 6</b>

### Detailed Syllabus:

Modules	Topics	Course Contents	Hours
I.	<b>Fundamentals of Internet Protocols and Addressing</b>	Overview of Computer Networks, TCP/IP Protocol Stack and OSI Model Comparison, IPv4 and IPv6 Addressing, Address Classes, Subnetting, and Supernetting, CIDR (Classless Inter-Domain Routing), IPv6 Transition Mechanisms, Network Address Translation (NAT) and Port Address Translation (PAT), IP Address Allocation Techniques (Static vs. Dynamic), ICMP and ICMPv6 (Error handling and troubleshooting), DNS, DHCP, and Address Resolution Protocol (ARP/RARP)	12
II.	<b>Routing Protocols and Network Layer Design</b>	Routing Basics and Types (Static vs. Dynamic Routing), Interior Gateway Protocols (IGPs): Routing Information Protocol (RIP), Open Shortest Path First (OSPF), Enhanced Interior Gateway Routing Protocol (EIGRP), Exterior Gateway Protocols (EGPs): Border Gateway Protocol (BGP), Autonomous Systems (AS) and BGP Routing Policies, Quality of Service (QoS) in IP Networks, Load Balancing and Traffic Engineering, Multicast Routing and Protocols	12
III.	<b>Advanced Network Architectures and Internet Technologies</b>	Software-Defined Networking (SDN) and Network Function Virtualization (NFV), Cloud Networking & Virtual Private Networks (VPNs), Data Center Networking & Content Delivery Networks (CDNs), Wireless and Mobile Internet Protocols (Mobile IP, LTE, 5G), IoT and Low-Power WAN Protocols, Inter-domain Routing & MPLS (Multiprotocol Label Switching), Future Internet Architectures & 6G Networks	12

<b>IV</b>	<b>Security in Internet Protocols and Network Design Considerations</b>	Network Security Threats (DDoS, Man-in-the-Middle, Spoofing), Secure IP Protocols: IPsec, TLS, SSL, Firewall Architectures and IDS/IPS Systems, Zero Trust Networking (ZTN) and Secure Access Service Edge (SASE), Cryptographic Techniques for Secure Communication, Blockchain for Secure Internet Transactions, Case Studies on Secure Network Architectures	<b>12</b>
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Books:**

1. *Computer Networks*, Tannenbaum, 5<sup>th</sup> Edition, 2013, Pearson Education.
2. *Data and Computer Communication*, William Stallings, 9<sup>th</sup> Edition, 2011, Pearson Education, Inc.

**Reference Books:**

1. Larry L. Peterson and Bruce S. Davie, *Computer Networks: A System Approach*, 5<sup>th</sup> Edition, 2012, Morgan Kaufmann, Elsevier, 2012.
2. Behrouz A. Forouzan, *Data Communications and Networking*, 5<sup>th</sup> Edition, 2017, McGraw Hill

<b>Paper II/Subject Name: Mathematical Foundations of Computer Science</b>	<b>Subject Code: CSE024C102</b>
<b>L-T-P-C - 4-0-0-5</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

**Objective:**

The objectives of the course are to enable students develop a strong mathematical foundation for computing and problem-solving for concepts like logic, set theory, relations, functions, graph theory, combinatorics, number theory, probability and statistical techniques.

**Prerequisites:** Discrete Mathematics, Linear Algebra, Probability and Statistics, Basic Understanding of Algorithms.

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Understand</b> number theory in cryptographic algorithms.	<b>BT 2</b>
<b>CO 2</b>	<b>Apply</b> set theory, logic, and proof techniques in computing problems	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> and <b>evaluate</b> probabilistic models in computing, machine learning, and cryptography.	<b>BT 4 &amp; 5</b>
<b>CO 4</b>	<b>Solve</b> problems related to formal languages, automata, and computational complexity.	<b>BT 6</b>

**Detailed Syllabus:**

Modules	Topics	Course Contents	Hours
I.	<b>Logic, Set Theory</b>	Propositional Logic and Predicate Logic, Logical Connectives, Truth Tables, Normal Forms, Logical Inference, Resolution, Proof Techniques, Set Theory and Relations, Sets, Operations, Power Sets, Types of Relations: Reflexive, Symmetric, Transitive, Equivalence Relations, Functions: Injective, Surjective, Bijective, Mathematical Induction and Recursion, Inductive Proofs, Recursive Definitions and Structural Induction	12
II.	<b>Combinatorics, Graph Theory &amp; Number Theory</b>	Counting Principles, Permutations and Combinations, Pigeonhole Principle, Inclusion-Exclusion Principle, Graph Theory and Applications, Graph Representation: Adjacency Matrix, Adjacency List, Eulerian and Hamiltonian Graphs, Shortest Path Algorithms (Dijkstra, Floyd-Warshall), Planar Graphs and Graph Coloring, Number Theory and Applications, Divisibility, Prime Numbers, Congruences, Fermat's Theorem, Euler's Theorem, Modular Arithmetic and Cryptography	12
III.	<b>Probability, Statistics and Randomized Algorithms</b>	Probability Theory, Axioms of Probability, Conditional Probability and Bayes' Theorem, Random Variables and Expectation, Statistical Methods, Mean, Variance, Standard Deviation, Probability Distributions (Binomial, Poisson, Normal), Hypothesis Testing and Confidence Intervals, Randomized Algorithms and Markov Chains, Monte Carlo and Las Vegas Algorithms, Markov Chains and Applications	12
IV	<b>Formal Languages, Automata, and Computational Complexity</b>	Formal Languages and Automata, Regular Expressions and Finite Automata, Pushdown Automata and Context-Free Grammars, Turing Machines and Computability, Turing Machine Models, Decidability and Undecidability, Computational Complexity, P, NP, NP-Complete, and NP-Hard Problems, Approximation Algorithms and Hardness of Approximation	12
<b>TOTAL</b>			<b>48</b>

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
4*12 NCH = 48 NCH	--	72 NCH (Problem Solving, Internship, Seminar, Case Study, Discussion)

**Text Books:**

1. Discrete Mathematics and Its Applications, Kenneth H. Rosen, 7<sup>th</sup> Edition, 2017, McGraw-Hill
2. *Introduction to Algorithms*, Cormen, Leiserson, Rivest, & Stein (CLRS), 3<sup>rd</sup> Edition, 2009, MIT Press
3. *Introduction to Automata Theory, Languages, and Computation*, John E. Hopcroft, Rajeev Motwani, Jeffrey D. Ullman, 3<sup>rd</sup> Edition, 2008, Pearson

**Reference Books:**

1. Sheldon Ross, *Introduction to Probability Models*, 11<sup>th</sup> Edition, 2014, Academic Press
2. Richard Johnsonbaugh, *Discrete Mathematics*, 7<sup>th</sup> Edition, 2014, Pearson
3. Michael Sipser, *Introduction to the Theory of Computation*, 3<sup>rd</sup> Edition, 2014, Cengage
4. Narsingh Deo, *Graph Theory with Applications to Engineering and Computer Science*, New Edition, 1979, PHI

<b>Paper III/Subject Name: Distributed Operating System</b>	<b>Subject Code: CSE024C103</b>
<b>L-T-P-C – 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

**Objective:**

The objectives of the course are to make students understand fundamental concepts and design principles of distributed operating systems, process synchronization, communication, and concurrency in distributed systems, distributed file systems, fault tolerance, security, and recovery mechanisms in distributed environments.

**Prerequisites:** Operating Systems, Computer Networks, Basic Knowledge of Algorithms

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Understand</b> the architecture, models, and communication mechanisms of distributed operating systems.	<b>BT 2</b>
<b>CO 2</b>	<b>Implement</b> inter-process communication and synchronization in distributed systems.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> distributed file systems and memory management techniques.	<b>BT 4</b>
<b>CO 4</b>	<b>Evaluate</b> fault tolerance and security mechanisms in distributed environments.	<b>BT 5</b>

**Detailed Syllabus:**

<b>Modules</b>	<b>Topic</b>	<b>Course Content</b>	<b>Hours</b>
<b>I.</b>	<b>Introduction</b>	Fundamentals of Distributed Systems, Definition, Characteristics, Advantages, Challenges, Centralized vs. Distributed vs. Network OS, Architectural Models, Client-Server, Peer-to-Peer, Hybrid Models, Layered and Microkernel Architectures, Distributed Communication Mechanisms, Remote Procedure Call (RPC), Remote Method Invocation (RMI), Message Passing and Sockets	<b>12</b>
<b>II.</b>	<b>Process Synchronization, Scheduling and Resource Management</b>	Concurrency and Synchronization, Mutual Exclusion, Deadlock, and Starvation, Distributed Mutual Exclusion Algorithms (Ricart-Agrawala, Maekawa's Algorithm), Process Management & Scheduling, Distributed Process Coordination, Load Balancing and Load Sharing, Scheduling Algorithms in Distributed Systems, Resource Management in Distributed OS, Distributed Deadlock Detection and Prevention, Distributed Process Migration and Load Balancing	<b>12</b>
<b>III.</b>	<b>Distributed File System &amp; Memory Management</b>	Distributed File Systems (DFS), Design and Architecture of DFS, Naming, Consistency, and Replication in DFS, Case Studies: NFS (Network File System), Google File System (GFS), Hadoop Distributed File System (HDFS), Distributed Shared Memory (DSM), Memory Coherence and Consistency Models, Synchronization in DSM, Case Studies: IVY, Munin, and Linda	<b>12</b>

Modules	Topic	Course Content	Hours
IV.	<b>Fault Tolerance, Security and Advanced Topics</b>	Fault Tolerance in Distributed Systems, Checkpointing and Recovery Techniques, Byzantine Fault Tolerance, Replication Techniques (Active, Passive, Quorum-Based), Security in Distributed Operating Systems, Authentication and Authorization in Distributed Systems, Secure Communication Protocols (SSL/TLS, Kerberos), Blockchain for Secure Distributed Computing, Advanced Topics and Case Studies, Distributed Computing in IoT, Cloud OS and Kubernetes, Edge Computing and Serverless Architectures	12
<b>TOTAL</b>			<b>48</b>

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
4 * 22 NCH = 88 NCH	2 * 15 NCH = 30 NCH	8 * 4 NCH = 32 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

#### Text Books:

1. *Distributed Systems: Principles and Paradigms*, Andrew S. Tanenbaum & Maarten Van Steen, 2<sup>nd</sup> Edition, 2016, Pearson
2. *Advanced Concepts in Operating Systems*, Mukesh Singhal & Niranjana G. Shivaratri, 2017, McGraw-Hill
3. *Distributed Operating Systems: Concepts and Design*, Pradeep K. Sinha, 1<sup>st</sup> Edition, 1998, Prentice Hall

#### Reference Books:

1. Rajkumar Buyya, *High Performance Cluster Computing: Architectures and Systems*, 1999, Prentice Hall
2. George Coulouris, Jean Dollimore, Tim Kindberg, *Distributed Systems: Concepts and Design*, 5<sup>th</sup> Edition, 2017, Pearson Education

<b>Paper IV/Subject Name: Internet Protocols and Network Design Lab</b>	<b>Subject Code: CSE024C111</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>
	<b>Scheme of Evaluation: P</b>

#### Objective:

The objectives of the course are to make the students understand fundamentals of Internet Protocols (IP) and their role in network communication, different routing and addressing techniques in both IPv4 and IPv6, the design and architecture of scalable networks.

**Prerequisites:** Computer Networks (Basic), Data Communication, Network Security Fundamentals

#### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level

<b>CO 1</b>	<b>Demonstrate</b> knowledge of Internet Protocols and their layered architecture.	<b>BT 2</b>
<b>CO 2</b>	<b>Implement</b> IP addressing schemes and subnetting for efficient network design.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze and evaluate</b> various routing protocols (RIP, OSPF, BGP, etc.).	<b>BT 4 &amp; 5</b>
<b>CO 4</b>	<b>Design</b> scalable, high-performance networks for cloud and IoT applications.	<b>BT 6</b>

**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Implementation of client server programs for different network applications.
- Study and analysis of IP Addressing, Subnetting, Wireshark for Packet Analysis.
- Implementation of OSPF and BGP in Network Simulators.
- Implementation of SDN Simulation using Mininet, VPN Setup.
- Implementation of Firewall Configuration, Network Intrusion Detection using Snort.

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
-	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Books:**

1. *Computer Networks*, Tannenbaum, 5<sup>th</sup> Edition, 2013, Pearson Education.
2. *Data and Computer Communication*, William Stallings, 9<sup>th</sup> Edition, 2011, Pearson Education, Inc.

**Reference Books:**

1. Larry L. Peterson and Bruce S. Davie, *Computer Networks: A System Approach*, 5<sup>th</sup> Edition, 2012, Morgan Kaufmann, Elsevier, 2012.
2. Behrouz A. Forouzan, *Data Communications and Networking*, 5<sup>th</sup> Edition, 2017, McGraw Hill

**Paper V/Subject Name: Mathematical Foundations of Computer Science Lab Subject Code: CSE024C112**

**L-T-P-C – 0-0-2-1**

**Credit Units: 01**

**Scheme of Evaluation: P**

**Objective:**

The objectives of the course are to enable students develop a strong mathematical foundation for computing and problem-solving for concepts like logic, set theory, relations, functions, graph theory, combinatorics, number theory, probability and statistical techniques.

**Prerequisites:** Discrete Mathematics, Linear Algebra, Probability and Statistics, Basic Understanding of Algorithms.

## Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> number theory in cryptographic algorithms.	<b>BT 2</b>
CO 2	<b>Apply</b> set theory, logic, and proof techniques in computing problems	<b>BT 3</b>
CO 3	<b>Analyze</b> and <b>evaluate</b> probabilistic models in computing, machine learning, and cryptography.	<b>BT 4 &amp; 5</b>
CO 4	<b>Solve</b> problems related to formal languages, automata, and computational complexity.	<b>BT 6</b>

## Detailed Syllabus:

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Implement propositional logic in Prolog.
- Write Python programs for set operations and relation properties.
- Implement graph traversal algorithms (BFS, DFS).
- Implement modular exponentiation for cryptography.
- Simulate randomized algorithms in Python.
- Implement Bayes' Theorem for spam filtering.
- Implement finite automata for pattern matching.
- Simulate Turing Machines using Python.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1*12 NCH = 12 NCH	18 NCH (Problem Solving, Internship, Seminar, Case Study, Discussion)

## Text Books:

1. Discrete Mathematics and Its Applications, Kenneth H. Rosen, 7<sup>th</sup> Edition, 2017, McGraw-Hill
2. *Introduction to Algorithms*, Cormen, Leiserson, Rivest, & Stein (CLRS), 3<sup>rd</sup> Edition, 2009, MIT Press
3. *Introduction to Automata Theory, Languages, and Computation*, John E. Hopcroft, Rajeev Motwani, Jeffrey D. Ullman, 3<sup>rd</sup> Edition, 2008, Pearson

## Reference Books:

1. Sheldon Ross, *Introduction to Probability Models*, 11<sup>th</sup> Edition, 2014, Academic Press
2. Richard Johnsonbaugh, *Discrete Mathematics*, 7<sup>th</sup> Edition, 2014, Pearson
3. Michael Sipser, *Introduction to the Theory of Computation*, 3<sup>rd</sup> Edition, 2014, Cengage
4. Narsingh Deo, *Graph Theory with Applications to Engineering and Computer Science*, New Edition, 1979, PHI

<b>Paper VI/Subject Name: Distributed Operating System Lab</b>	<b>Subject Code: CSE024C113</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>
	<b>Scheme of Evaluation: P</b>

**Objective:**

The objectives of the course are to make students understand fundamental concepts and design principles of distributed operating systems, process synchronization, communication, and concurrency in distributed systems, distributed file systems, fault tolerance, security, and recovery mechanisms in distributed environments.

**Prerequisites:** Operating Systems, Computer Networks, Basic Knowledge of Algorithms

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Understand</b> the architecture, models, and communication mechanisms of distributed operating systems.	<b>BT 2</b>
<b>CO 2</b>	<b>Implement</b> inter-process communication and synchronization in distributed systems.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> distributed file systems and memory management techniques.	<b>BT 4</b>
<b>CO 4</b>	<b>Evaluate</b> fault tolerance and security mechanisms in distributed environments.	<b>BT 5</b>

**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Implement client-server communication using RPC/RMI in Python or Java.
- Simulate message-passing systems using MPI (Message Passing Interface).
- Implement Lamport’s Logical Clocks for event ordering.
- Simulate distributed scheduling algorithms.
- Implement a basic distributed file system using Python.
- Set up and analyze HDFS in Hadoop.
- Implement fault-tolerant leader election algorithms.
- Set up Docker and Kubernetes clusters for distributed applications.

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Books:**

1. *Distributed Systems: Principles and Paradigms*, Andrew S. Tanenbaum & Maarten Van Steen, 2<sup>nd</sup> Edition, 2016, Pearson
2. *Advanced Concepts in Operating Systems*, Mukesh Singhal & Niranjana G. Shivaratri, 2017, McGraw-Hill
3. *Distributed Operating Systems: Concepts and Design*, Pradeep K. Sinha, 1<sup>st</sup> Edition, 1998, Prentice Hall

**Reference Books:**

1. Rajkumar Buyya, *High Performance Cluster Computing: Architectures and Systems*, 1999, Prentice Hall
2. George Coulouris, Jean Dollimore, Tim Kindberg, *Distributed Systems: Concepts and Design*, 5<sup>th</sup> Edition, 2017, Pearson Education

<b>Paper VII/Subject Name: Foundations of AI (PEC-I)</b>		<b>Subject Code: CSE024D101</b>
<b>Paper Type: PEC-I</b>		<b>Specialization: Artificial Intelligence</b>
<b>L-T-P-C – 4-0-0-4</b>	<b>Credit Units: 04</b>	<b>Scheme of Evaluation: T</b>

**Objective:**

The objectives of the course are to make the students understand fundamental AI concepts, core AI techniques, explore machine learning and neural networks as key AI components, etc.

**Prerequisites:** Fundamentals of Propositional Logic, mathematics.

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Explain</b> fundamental concepts, applications, and ethical implications of AI.	<b>BT 2</b>
<b>CO 2</b>	<b>Apply</b> uninformed and informed search algorithms to solve AI problems	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> and implement knowledge representation techniques, including logic-based and probabilistic reasoning	<b>BT 4</b>
<b>CO 4</b>	<b>Assess</b> and <b>design</b> AI-based solutions using reasoning, decision-making, and planning techniques	<b>BT 5 &amp; 6</b>

**Detailed Syllabus:**

<b>Module</b>	<b>Topics</b>	<b>Course Content</b>	<b>Periods</b>
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<b>I.</b>	<b>Introduction</b>	Definition, History, and Evolution of AI, Applications of AI (Healthcare, Finance, Robotics, NLP, etc.), AI vs. Machine Learning vs. Deep Learning, Strong AI vs. Weak AI, AI as Search: Problem Formulation, State-Space Representation, Rational Agents, Types of Agents, Breadth-First Search (BFS), Depth-First Search (DFS), Depth-Limited Search & Iterative Deepening DFS, Uniform Cost Search, Heuristic Function & Admissibility, Greedy Best-First Search, A* Algorithm (Manhattan, Euclidean Heuristics), Hill Climbing & Local Search Algorithms, Definition and Examples (Sudoku, N-Queens), Backtracking Algorithm, Constraint Propagation: Forward Checking, Arc Consistency (AC-3)	<b>12</b>
<b>II.</b>	<b>Knowledge Representation &amp; Reasoning</b>	Types of Knowledge: Declarative vs. Procedural, Common Sense Knowledge, Knowledge-Based Systems, Propositional Logic: Syntax, Semantics, Logical Connectives, Truth Tables, First-Order Logic (FOL): Predicates, Functions, Quantifiers, Unification & Resolution in FOL, Forward Chaining vs. Backward Chaining, Expert Systems & Case Study: MYCIN (Medical Diagnosis System), Bayesian Networks: Structure, Conditional Probability Tables (CPT), Exact & Approximate Inference in Bayesian Networks, Hidden Markov Models (HMM), Fuzzy Sets, Membership Functions Fuzzy Inference Systems (Mamdani & Sugeno), Defuzzification Techniques	<b>12</b>
<b>III.</b>	<b>Planning in AI</b>	Definition of Planning in AI, STRIPS Representation and PDDL (Planning Domain Definition Language), State-Space Search in Planning, Forward & Backward Planning, Partial Order Planning (POP), Graph Plan Algorithm, Decision Trees & Utility Theory, Game Theory in AI, Adversarial Search: Minimax Algorithm & Alpha-Beta Pruning, MDP Formulation, Bellman Equations, Policy Evaluation & Policy Iteration, Q-Learning Algorithm	<b>12</b>
<b>IV</b>	<b>AI Applications</b>	NLP: Text Processing & Tokenization, Named Entity Recognition (NER), Sentiment Analysis Computer Vision: Image Classification & Object Detection, Feature Extraction Techniques Reinforcement Learning: Deep Q-Learning & Neural Networks in RL, Case Study: AI for Self-Driving Cars AI Bias & Fairness, Explainable AI (XAI), AI for Social Good	<b>12</b>
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

#### **Text Books**

1. *Artificial Intelligence: A Modern Approach*, Stuart Russell & Peter Norvig, 4<sup>th</sup> Edition, 2020, PHI
2. *Artificial Intelligence*, Elaine Rich, Kevin Knight, Shivashankar B. Nair, 3<sup>rd</sup> Edition, 2017, Tata McGraw Hill

#### **Reference Books:**

1. Nils J. Nilsson, *Principles of Artificial Intelligence*, 1993, Morgan Kaufmann Publishers

Paper-VIII/Subject Name: Foundations of AI Lab

Subject Code: CSE024D111

Paper Type: PEC-I

Specialization: Artificial Intelligence

L-T-P-C – 0-0-2-1

Credit Units: 01

Scheme of Evaluation: P

**Objective:**

The objectives of the course are to make the students understand fundamental AI concepts, core AI techniques, explore machine learning and neural networks as key AI components, etc.

**Prerequisites:** Fundamentals of Propositional Logic, mathematics.

**Course Outcomes**

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Explain</b> fundamental concepts, applications, and ethical implications of AI.	<b>BT 2</b>
CO 2	<b>Apply</b> uninformed and informed search algorithms to solve AI problems	<b>BT 3</b>
CO 3	<b>Analyze</b> and implement knowledge representation techniques, including logic-based and probabilistic reasoning	<b>BT 4</b>
CO 4	<b>Assess</b> and <b>design</b> AI-based solutions using reasoning, decision-making, and planning techniques	<b>BT 5 &amp; 6</b>

**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Implement BFS & DFS in Python
- Solve a pathfinding problem using A\* Search
- Constraint satisfaction solver for Sudoku
- Implement logical inference using Propositional Logic.
- Build a Rule-Based Expert System for disease diagnosis.
- Implement a Bayesian Network for predicting weather conditions.
- Develop a Fuzzy Logic Controller for temperature regulation.
- Implement STRIPS-based AI Planning for a block-stacking problem.
- Develop a Tic-Tac-Toe AI using Minimax Algorithm.
- Implement Q-Learning for a simple game (Grid World).
- Sentiment Analysis on Twitter Data using NLP.
- Implement a Handwritten Digit Classifier using OpenCV.
- Train an AI model using Q-Learning for a custom environment.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

### Text Books

1. *Artificial Intelligence: A Modern Approach*, Stuart Russell & Peter Norvig, 4<sup>th</sup> Edition, 2020, PHI
2. *Artificial Intelligence*, Elaine Rich, Kevin Knight, Shivashankar B. Nair, 3<sup>rd</sup> Edition, 2017, Tata McGraw Hill

### Reference Books:

1. Nils J. Nilsson, *Principles of Artificial Intelligence*, 1993, Morgan Kaufmann Publishers

<b>Paper VII/Subject Name: Data Mining</b>	<b>Subject Code: CSE024D102</b>
<b>Paper Type: PEC-I</b>	<b>Specialization: Data Analytics</b>
<b>L-T-P-C – 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

### Objective:

The objectives of the course are to make the students understand the fundamentals of data mining, explore data mining techniques & algorithms, analyze advanced topics in data mining and apply data mining for real-world applications

**Prerequisites:** Probability & Statistics, Database Management Systems (DBMS)

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Explain</b> the fundamentals of data mining, preprocessing techniques, and data warehousing.	<b>BT 2</b>
CO 2	<b>Apply</b> classification, clustering, and association rule mining techniques to real-world datasets.	<b>BT 3</b>
CO 3	<b>Analyze</b> data mining models and <b>evaluate</b> their effectiveness using appropriate performance metrics.	<b>BT 4 &amp; 5</b>
CO 4	<b>Develop</b> and optimize machine learning models for predictive data mining applications	<b>BT 6</b>

### Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	<b>Introduction</b>	Introduction to Data Mining, Definition and significance of Data Mining, Applications in Business, Healthcare, and Cybersecurity, Data Mining vs. Machine Learning vs. Statistics, Types of Data & Data Exploration, Structured, Semi-structured, and Unstructured Data, Data Quality: Missing Values, Noisy Data, Inconsistencies, Exploratory Data Analysis (EDA), Data Preprocessing & Feature Engineering, Data Cleaning: Handling Missing & Noisy Data, Data Transformation: Normalization, Standardization, Binning, Feature Selection & Feature Extraction, Data Warehousing & OLAP, Data Warehouses vs. Databases, Online Analytical Processing (OLAP) and its operations, ETL (Extract, Transform, Load) Process	12
II.	<b>Classification and Association Rule Mining</b>	Classification & Prediction, Decision Tree Classifiers (ID3, C4.5, CART), Naïve Bayes Classifier, k-Nearest Neighbors (k-NN), Model Evaluation & Performance Metrics, Confusion Matrix, Precision,	12

		Recall, F1-Score, ROC-AUC Curve, Cross-Validation, Association Rule Mining, Market Basket Analysis, Apriori Algorithm, FP-Growth Algorithm, Advanced Classification Techniques. Random Forest Classifier, Support Vector Machines (SVM), Ensemble Learning	
III.	<b>Clustering and Anomaly Detection</b>	Clustering Techniques, k-Means Clustering, Hierarchical Clustering (Agglomerative & Divisive), DBSCAN, Cluster Evaluation Methods, Silhouette Score, Davies-Bouldin Index, Outlier Detection & Anomaly Detection, Statistical Outlier Detection (Z-Score, IQR), Isolation Forests, Local Outlier Factor (LOF), Text Mining & Web Mining, Sentiment Analysis, Web Crawling and Web Data Mining PageRank Algorithm	12
IV	<b>Advanced Topics</b>	Big Data & Scalable Data Mining, Challenges in Big Data Mining, Hadoop & MapReduce for Data Mining, Apache Spark for Large-Scale Data Processing, Sequential Pattern Mining & Time Series Analysis, Sequence Mining Algorithms, Time Series Forecasting (ARIMA, LSTMs), Privacy & Ethical Considerations in Data Mining, Data Privacy Challenges, GDPR & Data Protection Laws, Fairness & Bias in Data Mining, Real-World Case Studies & Applications, Data Mining in Healthcare (Predictive Analytics), Fraud Detection in Finance, Recommendation Systems	12
<b>TOTAL</b>			<b>48</b>

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Books**

1. *Data Mining: Concepts and Techniques*, Jiawei Han, Micheline Kamber, Jian Pei, 3<sup>rd</sup> Edition, 2011, Morgan Kaufmann
2. *Introduction to Data Mining*, Pang-Ning Tan, Michael Steinbach, Vipin Kumar, 1<sup>st</sup> Edition, 2016, Pearson

**Reference Books:**

1. Christopher Bishop, *Pattern Recognition and Machine Learning*, 1<sup>st</sup> Edition, 2006, Springer
2. Jure Leskovec, Anand Rajaraman, Jeff Ullman, *Mining of Massive Datasets*, 2<sup>nd</sup> Edition, 2016, Dreamtech Press

<b>Paper VIII/Subject Name: Data Mining Lab</b>	<b>Subject Code: CSE024D112</b>
<b>Paper Type: PEC-I</b>	<b>Specialization: Data Analytics</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 02</b>
	<b>Scheme of Evaluation: P</b>

**Objective:**

The objectives of the course are to make the students understand the fundamentals of data mining, explore data mining techniques & algorithms, analyze advanced topics in data mining and apply data mining for real-world applications

**Prerequisites:** Probability & Statistics, Database Management Systems (DBMS)

## Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Explain</b> the fundamentals of data mining, preprocessing techniques, and data warehousing.	<b>BT 2</b>
CO 2	<b>Apply</b> classification, clustering, and association rule mining techniques to real-world datasets.	<b>BT 3</b>
CO 3	<b>Analyze</b> data mining models and <b>evaluate</b> their effectiveness using appropriate performance metrics.	<b>BT 4 &amp; 5</b>
CO 4	<b>Develop</b> and optimize machine learning models for predictive data mining applications	<b>BT 6</b>

## Detailed Syllabus:

**Total Lab Hours for the semester = 30 (2 hours per week)**

### Minimum 10 Laboratory experiments based on the following-

- Perform exploratory data analysis (EDA) on a dataset using Pandas and Matplotlib.
- Implement missing data handling techniques and data normalization.
- Use SQL queries for data warehouse operations
- Implement Decision Tree and Naïve Bayes for classification tasks.
- Apply Apriori Algorithm for market basket analysis.
- Evaluate model performance using precision, recall, and ROC curves
- Implement k-Means and Hierarchical Clustering on a real-world dataset.
- Perform anomaly detection using Isolation Forest.
- Conduct sentiment analysis using text mining techniques
- Use Apache Spark for handling big data tasks.
- Perform time series forecasting on stock market data.
- Implement a recommendation system using collaborative filtering.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

## Text Books

1. *Data Mining: Concepts and Techniques*, Jiawei Han, Micheline Kamber, Jian Pei, 3<sup>rd</sup> Edition, 2011, Morgan Kaufmann
2. *Introduction to Data Mining*, Pang-Ning Tan, Michael Steinbach, Vipin Kumar, 1<sup>st</sup> Edition, 2016, Pearson

## Reference Books:

1. Christopher Bishop, *Pattern Recognition and Machine Learning*, 1<sup>st</sup> Edition, 2006, Springer
2. Jure Leskovec, Anand Rajaraman, Jeff Ullman, *Mining of Massive Datasets*, 2<sup>nd</sup> Edition, 2016, Dreamtech Press

<b>Paper VII/Subject Name: Digital Image Processing</b>	<b>Subject Code: CSE024D103</b>
<b>Paper Type: PEC-I</b>	<b>Specialization: Image Processing</b>
<b>L-T-P-C - 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

**Objective:**

The objectives of the course are to make the students understand the fundamentals of digital image processing, learn image enhancement and restoration techniques, analyze image segmentation, feature extraction, and object recognition techniques, implement advanced techniques in image processing, etc.

**Prerequisites:** Linear Algebra, Probability and Statistics, Signal Processing, Python Programming

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Explain</b> the fundamentals of data mining, preprocessing techniques, and data warehousing.	<b>BT 2</b>
<b>CO 2</b>	<b>Apply</b> classification, clustering, and association rule mining techniques to real-world datasets.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> data mining models and <b>evaluate</b> their effectiveness using appropriate performance metrics.	<b>BT 4 &amp; 5</b>
<b>CO 4</b>	<b>Develop</b> and optimize machine learning models for predictive data mining applications	<b>BT 6</b>

**Detailed Syllabus:**

<b>Module</b>	<b>Topics</b>	<b>Course Content</b>	<b>Periods</b>
<b>I.</b>	<b>Introduction</b>	Fundamentals of Digital Image Processing, Definition and Applications, Components, Image Representation: Pixels, Resolution, and Bit Depth, Image Perception & Color Models, Human Visual System and Image Perception, Color Spaces: RGB, CMY, HSV, YCbCr, Converting Between Color Models, Image Sampling & Quantization, Sampling and Aliasing, Quantization and Bit-Depth Reduction, Histogram Analysis and Contrast Stretching, Image File Formats & Transformations: BMP, JPEG, PNG, TIFF, Geometric Transformations (Translation, Scaling, Rotation), Affine and Perspective Transformations	<b>12</b>
<b>II.</b>	<b>Image Enhancement and Restoration</b>	Spatial Domain Processing, Point Processing: Log Transform, Power-Law Transform, Histogram Equalization and Contrast Stretching, Smoothing Filters: Mean, Median, Gaussian, Frequency Domain Processing, Fourier Transform and Frequency Representation of Images, Low-pass and High-pass Filtering, Image Sharpening using Laplacian and Unsharp Masking, Noise Models & Image Restoration, Types of Noise: Gaussian, Salt & Pepper, Speckle Image Denoising Techniques: Spatial and Frequency Domain Filters Wiener Filter and Inverse Filtering, Edge Detection & Morphological Processing, Gradient-Based Edge Detection: Sobel, Prewitt, Canny, Morphological Operations: Dilation, Erosion, Opening, Closing, Skeletonization and Boundary Detection	<b>12</b>
<b>III.</b>	<b>Segmentation, Feature Extraction</b>	Thresholding-Based Segmentation, Global vs. Adaptive Thresholding, Otsu's Method, Watershed Algorithm, Region-Based Segmentation, Region Growing and Region Splitting & Merging, K-	<b>12</b>

	<b>and Object Recognition</b>	Means and Mean-Shift Clustering, Active Contours (Snakes), Feature Extraction Techniques, Shape Features: Area, Perimeter, Circularity, Texture Features: Gray Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG), Object Recognition & Classification, Template Matching, Feature Matching using SIFT and SURF, Introduction to Convolutional Neural Networks (CNNs) for Image Recognition	
<b>IV</b>	<b>Image Compression, Wavelets and Advanced Applications</b>	Image Compression Techniques, Lossless Compression: Huffman Coding, Run-Length Encoding, Lossy Compression: JPEG, MPEG, WebP, Discrete Cosine Transform (DCT) and Quantization, Wavelet Transform & Multiresolution Analysis, Introduction to Wavelets, Discrete Wavelet Transform (DWT), Applications of Wavelets in Image Compression and Denoising, Deep Learning for Image Processing, Introduction to CNNs (LeNet, AlexNet, ResNet), Transfer Learning for Image Classification, Object Detection (YOLO, SSD, Faster R-CNN), Real-Time Image Processing & Applications, Image Processing for Medical Imaging (MRI, X-Ray, CT), Remote Sensing & Satellite Image Processing, Augmented Reality (AR) & Virtual Reality (VR) in Image Processing	<b>12</b>
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

#### **Text Books**

1. *Digital Image Processing*, Rafael C. Gonzalez, Richard E. Woods, 4<sup>th</sup> Edition, 2018, Pearson
2. *Fundamentals of Digital Image Processing*, Anil K. Jain, 1<sup>st</sup> Edition, 2015, Pearson

#### **Reference Books:**

1. Richard Szeliski, *Computer Vision: Algorithms and Applications*, 11<sup>th</sup> Edition, 2011, Springer

<b>Paper VIII/Subject Name: Digital Image Processing Lab</b>	<b>Subject Code: CSE024D113</b>
<b>Paper Type: PEC-I</b>	<b>Specialization: Image Processing</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: P</b>

#### **Objective:**

The objectives of the course are to make the students understand the fundamentals of digital image processing, learn image enhancement and restoration techniques, analyze image segmentation, feature extraction, and object recognition techniques, implement advanced techniques in image processing, etc.

**Prerequisites:** Linear Algebra, Probability and Statistics, Signal Processing, Python Programming

## Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Explain</b> the fundamentals of data mining, preprocessing techniques, and data warehousing.	<b>BT 2</b>
CO 2	<b>Apply</b> classification, clustering, and association rule mining techniques to real-world datasets.	<b>BT 3</b>
CO 3	<b>Analyze</b> data mining models and <b>evaluate</b> their effectiveness using appropriate performance metrics.	<b>BT 4 &amp; 5</b>
CO 4	<b>Develop</b> and optimize machine learning models for predictive data mining applications	<b>BT 6</b>

### Detailed Syllabus:

**Total Lab Hours for the semester = 30 (2 hours per week)**

### Minimum 10 Laboratory experiments based on the following-

- Read, display, and manipulate images using Python (OpenCV, PIL).
- Convert images between different color models.
- Perform geometric transformations on images.
- Apply histogram equalization and contrast enhancement.
- Implement noise reduction techniques (Mean, Median, Gaussian filtering).
- Perform edge detection using Canny and Sobel operators.
- Implement region-based segmentation using K-means clustering.
- Extract shape and texture features from images.
- Perform feature matching using SIFT and ORB descriptors.
- Implement JPEG compression using DCT.
- Apply wavelet-based denoising techniques.
- Build a simple CNN model for image classification.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

### Text Books

1. *Digital Image Processing*, Rafael C. Gonzalez, Richard E. Woods, 4<sup>th</sup> Edition, 2018, Pearson
2. *Fundamentals of Digital Image Processing*, Anil K. Jain, 1<sup>st</sup> Edition, 2015, Pearson

### Reference Books:

1. Richard Szeliski, *Computer Vision: Algorithms and Applications*, 11<sup>th</sup> Edition, 2011, Springer

### 6.3 Detailed Syllabus of 2<sup>nd</sup> Semester

<b>Paper I/Subject Name: Modern Database Systems</b>	<b>Subject Code: CSE024C201</b>
<b>L-T-P-C – 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

#### Objective:

The objectives of the course are to make the students understand advanced database architectures, explore NoSQL, NewSQL, and Distributed Databases, understand Big Data storage, indexing, and query optimization.

**Prerequisites:** Fundamentals of Database Management Systems (DBMS), SQL and NoSQL Databases, Basic Understanding of Data Structures and Algorithms

#### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> data security, consistency, and ACID properties in modern database architectures.	<b>BT 2</b>
CO 2	<b>Apply</b> cloud, in-memory, and multi-model databases in real-world scenarios.	<b>BT 3</b>
CO 3	<b>Analyze</b> query optimization and indexing techniques for modern databases	<b>BT 4</b>
CO 4	<b>Assess</b> and <b>Design</b> scalable and distributed database systems.	<b>BT 5 &amp; 6</b>

#### Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	<b>Advanced Relational Databases &amp; Query Optimization</b>	Review of Relational Database Systems (RDBMS), Extended ER Model, SQL vs. NoSQL, Relational Algebra & Calculus, Query Processing & Optimization, Query Parsing, Optimization Heuristics, Cost-Based Optimization, Query Execution Plans, Indexing & Hashing (B-Trees, B+ Trees, Bitmap Indexing), Transaction Management & Concurrency Control, ACID Properties & Two-Phase Locking, Multi-Version Concurrency Control (MVCC), Deadlock Detection & Prevention	12
II.	<b>NoSQL, NewSQL &amp; Distributed Databases</b>	Introduction to NoSQL, Types: Key-Value Stores, Document Stores, Column-Family Stores, Graph Databases, CAP Theorem, BASE Properties vs. ACID, Case Studies: MongoDB, Apache Cassandra, Redis, NewSQL and Distributed Databases, Spanner, CockroachDB, VoltDB, Distributed Transactions, Replication, Sharding, Eventual Consistency & Conflict Resolution, Paxos & Raft Consensus Algorithms, CRDTs (Conflict-Free Replicated Data Types).	12
III.	<b>Cloud Databases, Big Data &amp; In-Memory Databases</b>	Cloud Databases & Storage Systems, AWS RDS, Google Cloud Spanner, Azure Cosmos DB, Data Lake vs. Data Warehouse (Snowflake, Google BigQuery), Big Data & Scalable Database Architectures, Apache Hadoop, Apache Spark SQL, Real-Time Databases: Kafka Streams, Flink SQL, In-Memory Databases & Performance Optimization, Redis, Memcached, Columnar Storage & Vectorized Execution	12

<b>IV.</b>	<b>Advanced Topics – Graph, Time-Series, and Blockchain Databases</b>	Graph Databases & Applications, Neo4j, Amazon Neptune, Graph Query Languages: Cypher, Gremlin, Applications in Social Networks & Fraud Detection, Time-Series Databases, InfluxDB, TimescaleDB, Use Cases: IoT, Financial Markets, Real-Time Monitoring, Blockchain & Secure Databases, Distributed Ledger Technology (DLT), Smart Contracts & Ethereum Databases, Security & Privacy in Modern Databases	<b>12</b>
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

#### **Text Books**

1. *Database Systems: The Complete Book*, Hector Garcia-Molina, Jeffrey Ullman, Jennifer Widom, 2<sup>nd</sup> Edition, 2008, Pearson
2. *Database Management Systems*, Raghu Ramakrishnan & Johannes Gehrke, 3<sup>rd</sup> McGraw-Hill
3. *Professional NoSQL*, Shashank Tiwari, 1<sup>st</sup> Edition, 2011, Wrox

#### **Reference Books:**

1. Martin Kleppmann, *Designing Data-Intensive Applications*, 1<sup>st</sup> Edition, 2017, O'Reilly
2. George Coulouris, Jean Dollimore, Tim Kindberg, *Distributed Systems: Concepts and Design*, 5<sup>th</sup> Edition, 2017, Pearson Education
3. Ian Robinson, Jim Webber, Emil Eifrem, *Graph Databases*, 2013, O'Reilly

<b>Paper II/Subject Name: Advanced Algorithm Designing</b>	<b>Subject Code: CSE024C202</b>
<b>L-T-P-C – 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

#### **Objective:**

The objectives of the course are to teach the students the fundamental design, analysis, and implementation of basic data structures, basic concepts in the specification and analysis of programs.

**Prerequisites:** Concepts of Mathematics I

#### **Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Demonstrate</b> adequate comprehension of the theory of intractability and prove when certain kinds of problems are intractable	<b>BT 2</b>
<b>CO 2</b>	<b>Apply</b> various problem-solving techniques and <b>analyze</b> them	<b>BT 3 &amp; 4</b>
<b>CO 3</b>	<b>Determine</b> the most suitable algorithm for any given task and then apply it to the problem.	<b>BT 5</b>

<b>CO 4</b>	<b>Design</b> efficient algorithms for given problems	<b>BT 6</b>
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**Detailed Syllabus:**

<b>Modules</b>	<b>Topics</b>	<b>Course Contents</b>	<b>Hours</b>
<b>I</b>	<b>Sorting &amp; Graphs</b>	Sorting: Review of various sorting algorithms, topological sorting Graph: Definitions and Elementary Algorithms: Shortest path by BFS, shortest path in edge-weighted case (Dijkstra's), depth-first search and computation of strongly connected components, emphasis on correctness proof of the algorithm and time/space analysis, example of amortized analysis.	<b>12</b>
<b>II</b>	<b>Matroids &amp; Flow Networks</b>	Matroids: Introduction to greedy paradigm, algorithm to compute a maximum weight maximal independent set. Application to MST. Graph Matching: Algorithm to compute maximum matching. Characterization of maximum matching by augmenting paths, Edmond's Blossom algorithm to compute augmenting path.  Flow-Networks: Maxflow-mincut theorem, Ford-Fulkerson Method to compute maximum flow, Edmond-Karp maximum-flow algorithm. Matrix Computations: Strassen's algorithm and introduction to divide and conquer paradigm, inverse of a triangular matrix, relation between the time complexities of basic matrix operations, LUP- decomposition.	<b>12</b>
<b>III</b>	<b>Graph Algorithms</b>	Shortest Path in Graphs: Floyd-Warshall algorithm and introduction to dynamic programming paradigm. More examples of dynamic programming. Modulo Representation of integers/polynomials: Chinese Remainder Theorem, Conversion between base representation and modulo-representation. Extension to polynomials. Application: Interpolation problem. Discrete Fourier Transform (DFT): In complex field, DFT in modulo ring. Fast Fourier Transform algorithm. Schonhage-Strassen Integer Multiplication algorithm.	<b>12</b>
<b>IV</b>	<b>Linear Programming</b>	Linear Programming: Geometry of the feasibility region and Simplex algorithm NP-completeness: Examples, proof of NP-hardness and NP-completeness. Recent Trends in problem solving paradigms using recent searching and sorting techniques by applying recently proposed data structures.	<b>12</b>
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Book:**

1. *Introduction to Algorithms*, T. H. Cormen, C. E. Leiserson, R. L. Rivest, 3<sup>rd</sup> Edition, 2009, The MIT Press, Cambridge, Massachusetts.

**Reference Books:**

1. Aho, Hopcroft & Ullman, *The Design and Analysis of Algorithms*, 1974, Addison- Wesley
2. Horowitz & Sahani, *Fundamentals of Algorithms*, 2<sup>nd</sup> Edition, 2009, Galgotia Publications

<b>Paper III/Subject Name: Modern Database Systems Lab</b>	<b>Subject Code: CSE024C211</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>
	<b>Scheme of Evaluation: P</b>

**Objective:**

The objectives of the course are to make the students understand advanced database architectures, explore NoSQL, NewSQL, and Distributed Databases, understand Big Data storage, indexing, and query optimization.

**Prerequisites:** Fundamentals of Database Management Systems (DBMS), SQL and NoSQL Databases, Basic Understanding of Data Structures and Algorithms

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Understand</b> data security, consistency, and ACID properties in modern database architectures.	<b>BT 2</b>
<b>CO 2</b>	<b>Apply</b> cloud, in-memory, and multi-model databases in real-world scenarios.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> query optimization and indexing techniques for modern databases	<b>BT 4</b>
<b>CO 4</b>	<b>Assess</b> and <b>Design</b> scalable and distributed database systems.	<b>BT 5 &amp; 6</b>

**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Implement query optimization using EXPLAIN PLAN in MySQL/PostgreSQL.
- Experiment with indexing and hashing techniques in SQL databases. Advanced SQL
- Implement sharding & replication in MongoDB.
- Experiment with Apache Cassandra for large-scale data storage.
- Set up Google BigQuery for large-scale analytics.
- Implement Apache Spark SQL queries for big data processing.
- Implement graph queries using Neo4j & Cypher.
- Set up a basic blockchain ledger using Hyperledger Fabric.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

### Text Books

1. *Database Systems: The Complete Book*, Hector Garcia-Molina, Jeffrey Ullman, Jennifer Widom, 2<sup>nd</sup> Edition, 2008, Pearson
2. *Database Management Systems*, Raghu Ramakrishnan & Johannes Gehrke, 3<sup>rd</sup> McGraw-Hill
3. *Professional NoSQL*, Shashank Tiwari, 1<sup>st</sup> Edition, 2011, Wrox

### Reference Books:

1. Martin Kleppmann, *Designing Data-Intensive Applications*, 1<sup>st</sup> Edition, 2017, O'Reilly
2. George Coulouris, Jean Dollimore, Tim Kindberg, *Distributed Systems: Concepts and Design*, 5<sup>th</sup> Edition, 2017, Pearson Education
3. Ian Robinson, Jim Webber, Emil Eifrem, *Graph Databases*, 2013, O'Reilly

<b>Paper IV/Subject Name: Advanced Algorithm Designing Lab</b>	<b>Subject Code: CSE024C212</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>
	<b>Scheme of Evaluation: P</b>

### Objective:

The objectives of the course are to teach the students the fundamental design, analysis, and implementation of basic data structures, basic concepts in the specification and analysis of programs.

**Prerequisites:** Concepts of Mathematics I

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Demonstrate</b> adequate comprehension of the theory of intractability and prove when certain kinds of problems are intractable	<b>BT 2</b>
CO 2	<b>Apply</b> various problem-solving techniques and <b>analyze</b> them	<b>BT 3 &amp; 4</b>
CO 3	<b>Determine</b> the most suitable algorithm for any given task and then apply it to the problem.	<b>BT 5</b>
CO 4	<b>Design</b> efficient algorithms for given problems	<b>BT 6</b>

### Detailed Syllabus:

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Implement assignment problem using Brute Force method

- Perform multiplication of long integers using divide and conquer method.
- Implement solution for knapsack problem using Greedy method.
- Implement Gaussian elimination method.
- Implement LU decomposition
- Implement Warshall algorithm
- Implement Rabin Karp algorithm.
- Implement KMP algorithm.
- Implement Harspool algorithm
- Implement max-flow problem.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Book:**

1. *Introduction to Algorithms*, T. H. Cormen, C. E. Leiserson, R. L. Rivest, 3<sup>rd</sup> Edition, 2009, The MIT Press, Cambridge, Massachusetts.

**Reference Books:**

1. Aho, Hopcroft & Ullman, *The Design and Analysis of Algorithms*, 1974, Addison- Wesley
2. Horowitz & Sahani, *Fundamentals of Algorithms*, 2<sup>nd</sup> Edition, 2009, Galgotia Publications

<b>Paper V/Subject Name: Machine Learning and Deep Learning</b>	<b>Subject Code: CSE024D201</b>
<b>Paper Type: PEC-II</b>	<b>Specialization: Artificial Intelligence/ Image Processing</b>
<b>L-T-P-C – 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

**Objective:**

The objectives of the course are to make the students understand the fundamentals of machine learning, apply supervised and unsupervised learning techniques, develop advanced machine learning models, explore deep learning architectures and algorithms and design and train ai models using modern deep learning techniques

**Prerequisites:** Linear Algebra, Probability & Statistics, Python Programming

**Course Outcomes**

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> the key concepts of ML, DL, and their applications.	<b>BT 2</b>
CO 2	<b>Apply</b> ML algorithms like regression, classification, and clustering.	<b>BT 3</b>

<b>CO 3</b>	<b>Analyze</b> and <b>assess</b> different neural network architectures and training techniques.	<b>BT 4 &amp; 5</b>
<b>CO 4</b>	<b>Design</b> and implement deep learning models for real-world applications	<b>BT 6</b>

**Detailed Syllabus:**

<b>Module</b>	<b>Topics</b>	<b>Course Content</b>	<b>Periods</b>
<b>I.</b>	<b>ML Fundamentals</b>	Definition and Types of ML: Supervised, Unsupervised, Reinforcement Learning, Applications of ML in Healthcare, Finance, NLP, and Computer Vision, Overview of ML Pipelines, Linear Algebra: Vectors, Matrices, Eigenvalues, and Eigenvectors, Probability Theory: Bayes' Theorem, Conditional Probability, Optimization: Gradient Descent, Stochastic Gradient Descent (SGD), Linear Regression: Least Squares Method, Gradient Descent, Polynomial Regression, Ridge & Lasso Regression, Evaluation Metrics: MSE, RMSE, R <sup>2</sup> Score, Logistic Regression, k-Nearest Neighbors (k-NN), Decision Trees & Random Forest, Evaluation Metrics: Confusion Matrix, Precision, Recall, F1-Score	<b>12</b>
<b>II.</b>	<b>Advanced AL Techniques</b>	Support Vector Machines (SVM): Hard Margin & Soft Margin SVM Kernel Trick: RBF, Polynomial Kernels, Unsupervised Learning, Clustering: k-Means, Hierarchical Clustering, DBSCAN, Dimensionality Reduction: Principal Component Analysis (PCA), t-SNE, Ensemble Learning & Boosting Techniques, Bagging & Random Forest Boosting: AdaBoost, Gradient Boosting, XGBoost Neural Networks Basics, Perceptron & Multi-Layer Perceptron (MLP), Activation Functions: Sigmoid, ReLU, Tanh, Backpropagation Algorithm	<b>12</b>
<b>III.</b>	<b>Deep Learning Fundamentals</b>	Introduction to Deep Learning, Difference Between ML and DL, Applications of Deep Learning (NLP, Image Recognition, Generative Models), Neural Networks & Optimization, Deep Neural Networks (DNN): Weight Initialization, Vanishing & Exploding Gradient Problems, Optimizers: SGD, Adam, RMSprop, Convolutional Neural Networks (CNNs), Convolution & Pooling Layers: Popular CNN Architectures: LeNet, AlexNet, VGG, ResNet, Recurrent Neural Networks (RNNs) & Sequence Models, RNNs & Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Applications in NLP & Time-Series Forecasting	<b>12</b>
<b>IV</b>	<b>Advanced DL Concepts</b>	Generative Models: Autoencoders & Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), Transformers & Attention Mechanisms, Self-Attention and Multi-Head Attention, Transformer Architecture (BERT, GPT, T5), Reinforcement Learning Basics, Markov Decision Process (MDP), Q-Learning & Deep Q Networks (DQN), Ethics & Deployment of AI Models. Bias in AI Models, Fairness & Explainability, Model Deployment: Flask, FastAPI, TensorFlow Serving	<b>12</b>
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

### Text Books

1. *Pattern Recognition and Machine Learning*, Christopher M. Bishop, 1<sup>st</sup> Edition, 2006, Springer
2. *Deep Learning*, Ian Goodfellow, Yoshua Bengio, Aaron Courville, 2016, MIT Press

### Reference Books:

1. Kevin P. Murphy, *Machine Learning: A Probabilistic Perspective*, 2012, MIT Press
2. Richard S. Sutton, Andrew G. Barto, *Reinforcement Learning: An Introduction*, 2<sup>nd</sup> Edition, 1998, Bradford Books
3. Michael Nielsen, *Neural Networks and Deep Learning*, 2010

<b>Paper VI/Subject Name: Machine Learning and Deep Learning Lab</b>	<b>Subject Code: CSE024D211</b>
<b>Paper Type: PEC-II</b>	<b>Specialization: Artificial Intelligence</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>
	<b>Scheme of Evaluation: P</b>

### Objective:

The objectives of the course are to make the students understand the fundamentals of machine learning, apply supervised and unsupervised learning techniques, develop advanced machine learning models, explore deep learning architectures and algorithms and design and train ai models using modern deep learning techniques

**Prerequisites:** Linear Algebra, Probability & Statistics, Python Programming

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> the key concepts of ML, DL, and their applications.	<b>BT 2</b>
CO 2	<b>Apply</b> ML algorithms like regression, classification, and clustering.	<b>BT 3</b>
CO 3	<b>Analyze</b> and <b>assess</b> different neural network architectures and training techniques.	<b>BT 4 &amp; 5</b>
CO 4	<b>Design</b> and implement deep learning models for real-world applications	<b>BT 6</b>

### Detailed Syllabus:

**Total Lab Hours for the semester = 30 (2 hours per week)**

### Minimum 10 Laboratory experiments based on the following-

- Implement Linear and Polynomial Regression on a dataset.
- Implement Logistic Regression for a classification task.
- Apply k-NN and Decision Trees for classification and compare their performance.
- Implement SVM with different kernels.
- Perform k-Means clustering and PCA on real-world datasets.
- Apply Random Forest and Boosting techniques for a classification problem.
- Implement a simple Deep Neural Network using TensorFlow/PyTorch.
- Train a CNN for image classification (MNIST/CIFAR-10).
- Build an RNN/LSTM model for sentiment analysis or stock price prediction.

- Implement a GAN for image generation.
- Fine-tune a pre-trained Transformer model for text classification.
- Deploy a deep learning model as an API using Flask or FastAPI.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

### Text Books

1. *Pattern Recognition and Machine Learning*, Christopher M. Bishop, 1<sup>st</sup> Edition, 2006, Springer
2. *Deep Learning*, Ian Goodfellow, Yoshua Bengio, Aaron Courville, 2016, MIT Press

### Reference Books:

1. Kevin P. Murphy, *Machine Learning: A Probabilistic Perspective*, 2012, MIT Press
2. Richard S. Sutton, Andrew G. Barto, *Reinforcement Learning: An Introduction*, 2<sup>nd</sup> Edition, 1998, Bradford Books
3. Michael Nielsen, *Neural Networks and Deep Learning*, 2010

<b>Paper VII/Subject Name: Natural Language Processing</b>	<b>Subject Code: CSE024D202</b>
<b>Paper Type: PEC-III</b>	<b>Specialisation: Artificial Intelligence</b>
<b>L-T-P-C - 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

### Objective:

The objectives of the course are to make the students understand the application of AI in the field of Natural Language Processing, learn the fundamentals of NLP and design NLP based applications.

**Prerequisites:** Probability & Statistics, Linear Algebra, Machine Learning, Python

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> fundamental NLP concepts, text processing techniques, and linguistic properties.	<b>BT 2</b>
CO 2	<b>Apply</b> traditional ML algorithms for text classification, sentiment analysis, and topic modeling.	<b>BT 3</b>
CO 3	<b>Analyze</b> and <b>assess</b> deep learning models for NLP tasks, including transformers and attention mechanisms.	<b>BT 4 &amp; 5</b>
CO 4	<b>Design</b> and implement NLP applications such as chatbots, summarization, and text generation.	<b>BT 6</b>

### Detailed Syllabus:

Module	Topics	Course Content	Periods
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I.	<b>Introduction</b>	Overview of NLP: Definition and importance of NLP, Applications: Chatbots, Machine Translation, Sentiment Analysis, Speech Recognition, Challenges in NLP: Ambiguity, Data Sparsity, Context Understanding, Text Processing & Linguistic Basics, Text Normalization: Tokenization, Stemming, Lemmatization, Stopword Removal and Part-of-Speech (POS) Tagging, Named Entity Recognition (NER), Regular Expressions & Text Representation, Regex for text preprocessing, Bag-of-Words (BoW), TF-IDF, Word Frequency Analysis, Word Embeddings & Semantic Representation, Word2Vec: Skip-gram & CBOW models, GloVe (Global Vectors for Word Representation), FastText	12
II.	<b>Classical NLP Techniques and Language Modelling</b>	N-gram Language Models: Unigram, Bigram, Trigram Models, Probability Estimation: Smoothing Techniques (Laplace, Kneser-Ney), Perplexity and Evaluation of Language Models, Text Classification & Sentiment Analysis, Naïve Bayes Classifier for Text Classification, Logistic Regression & SVM for NLP Tasks, Sentiment Analysis Using ML Techniques, Topic Modeling & Information Retrieval, Latent Semantic Analysis (LSA), Latent Dirichlet Allocation (LDA), TF-IDF for Document Retrieval, Machine Translation & Sequence Labeling, Statistical Machine Translation (SMT), Hidden Markov Models (HMM) for POS Tagging, Conditional Random Fields (CRF) for Sequence Labeling	12
III.	<b>Deep Learning for NLP</b>	Neural Networks for NLP: Basics of Neural Networks for NLP, Word Embeddings with Neural Networks (Word2Vec, GloVe), Feedforward and Recurrent Neural Networks (RNNs), Sequence Models & Attention Mechanism, Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) & Gated Recurrent Unit (GRU), Attention Mechanism & Self-Attention, Transformers & Pretrained Language Models, Transformer Architecture (Vaswani et al.), BERT (Bidirectional Encoder Representations from Transformers), GPT (Generative Pretrained Transformer), T5, XLNet, Text Generation & Summarization, Seq2Seq Models for Text Generation, Abstractive & Extractive Text Summarization, Fine-Tuning Transformers for Summarization	12
IV	<b>Advanced NLP Applications</b>	Conversational AI & Chatbots: Rule-Based Chatbots vs. AI-Based Chatbots, Intent Recognition and Response Generation, DialogFlow, Rasa, GPT-based Chatbots, Speech Processing & Text-to-Speech (TTS). Speech Recognition Models (CMU Sphinx, DeepSpeech, Whisper), Text-to-Speech Synthesis (Tacotron, WaveNet), Bias & Ethics in NLP, Challenges of Bias in NLP Models, Fairness in NLP & Model Interpretability, Ethical Considerations in AI-Powered Language Models, NLP Model Deployment, Deploying NLP models using Flask/FastAPI, Optimizing NLP Models for Production, Cloud-based NLP Services (AWS, Google AI, Hugging Face API)	12
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

### Text Books

1. *Speech and Language Processing*, Daniel Jurafsky & James H. Martin, 2<sup>nd</sup> Edition, 2008, Pearson
2. *Natural Language Processing with Python*, Steven Bird, Ewan Klein, Edward Loper, 1<sup>st</sup> Edition, 2009, O'Reilly
3. *Deep Learning for Natural Language Processing*, Palash Goyal, Sumit Pandey, Karan Jain, 1<sup>st</sup> Edition, 2018, Apress

### Reference Books:

1. Nitin Indurkha & Fred J. Damerau, *Handbook of Natural Language Processing*, 2<sup>nd</sup> Edition, 2010, Taylor & Francis

<b>Paper VIII/Subject Name: Natural Language Processing Lab</b>	<b>Subject Code: CSE024D212</b>
<b>Paper Type: PEC-III</b>	<b>Specialisation: Artificial Intelligence</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>
	<b>Scheme of Evaluation: P</b>

### Objective:

The objectives of the course are to make the students understand the application of AI in the field of Natural Language Processing, learn the fundamentals of NLP and design NLP based applications.

**Prerequisites:** Probability & Statistics, Linear Algebra, Machine Learning, Python

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> fundamental NLP concepts, text processing techniques, and linguistic properties.	<b>BT 2</b>
CO 2	<b>Apply</b> traditional ML algorithms for text classification, sentiment analysis, and topic modeling.	<b>BT 3</b>
CO 3	<b>Analyze</b> and <b>assess</b> deep learning models for NLP tasks, including transformers and attention mechanisms.	<b>BT 4 &amp; 5</b>
CO 4	<b>Design</b> and implement NLP applications such as chatbots, summarization, and text generation.	<b>BT 6</b>

### Detailed Syllabus:

**Total Lab Hours for the semester = 30 (2 hours per week)**

### Minimum 10 Laboratory experiments based on the following-

- Implement tokenization, stemming, and lemmatization using NLTK/spaCy.
- Perform POS tagging and Named Entity Recognition (NER).
- Build word embeddings using Word2Vec and visualize embeddings.
- Train an N-gram model and evaluate it using perplexity.
- Implement Naïve Bayes and SVM for sentiment analysis.
- Perform topic modeling using LDA on a real-world dataset.
- Implement RNN, LSTM, and GRU models for text generation.
- Fine-tune BERT for text classification.
- Train a Seq2Seq model for machine translation.
- Build and deploy a chatbot using Rasa or OpenAI GPT API.

- Train a speech-to-text model using DeepSpeech.
- Deploy an NLP model as an API using Flask.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

### Text Books

1. *Speech and Language Processing*, Daniel Jurafsky & James H. Martin, 2<sup>nd</sup> Edition, 2008, Pearson
2. *Natural Language Processing with Python*, Steven Bird, Ewan Klein, Edward Loper, 1<sup>st</sup> Edition, 2009, O'Reily
3. *Deep Learning for Natural Language Processing*, Palash Goyal, Sumit Pandey, Karan Jain, 1<sup>st</sup> Edition, 2018, Apress

### Reference Books:

1. Nitin Indurkha & Fred J. Damerau, *Handbook of Natural Language Processing*, 2<sup>nd</sup> Edition, 2010, Taylor & Francis

<b>Paper V/Subject Name: Statistical Computing</b>	<b>Subject Code: CSE024D203</b>
<b>Paper Type: PEC-II</b>	<b>Specialization: Data Analytics</b>
<b>L-T-P-C - 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

### Objective:

The objectives of the course are to make the students understand the fundamentals of statistical computing, implement statistical methods computationally, analyze real-world datasets using statistical computing techniques, develop computational tools for data-driven decision making

**Prerequisites:** Probability and Statistics, Linear Algebra

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> fundamental concepts of statistical computing and probability distributions.	BT 2
CO 2	<b>Apply</b> statistical inference, hypothesis testing, and regression techniques.	BT 3
CO 3	<b>Analyze</b> and <b>assess</b> multivariate data and use Bayesian inference methods	BT 4 & 5
CO 4	<b>Develop</b> statistical models using high-performance computing techniques.	BT 6

### Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	<b>Fundamental Concepts</b>	Introduction to Statistical Computing, Importance of statistical computing in data analysis, Statistical computing vs. theoretical statistics, Role of Python/R in statistical computing, Random Variables & Probability Distributions, Discrete & Continuous Probability Distributions, Bernoulli, Binomial, Poisson, Normal, Exponential Distributions, Probability Density Function (PDF) and Cumulative Distribution Function (CDF), Statistical Sampling & Simulation, Random Sampling Techniques, Law of Large Numbers & Central Limit Theorem, Monte Carlo Simulation, Statistical Data Analysis & Visualization, Exploratory Data Analysis (EDA), Data Visualization with Matplotlib, Seaborn (Python) / ggplot2 (R), Histogram, Boxplot, KDE plots	12
II.	<b>Statistical Inference and Regression Analysis</b>	Estimation & Hypothesis Testing, Maximum Likelihood Estimation (MLE), Confidence Intervals, Parametric vs. Non-Parametric Hypothesis Testing, Resampling Techniques, Bootstrap Method, Jackknife Estimation, Permutation Testing, Regression Analysis, Simple & Multiple Linear Regression, Assumptions of Regression Models, Generalized Linear Models (GLMs), Non-Linear & Robust Regression, Polynomial Regression, Ridge & Lasso Regression, Robust Regression Techniques	12
III.	<b>Multivariate Analysis and Bayesian Computing</b>	Multivariate Statistical Methods, Principal Component Analysis (PCA), Factor Analysis, Canonical Correlation Analysis, Bayesian Statistics, Bayesian Inference Basics, Conjugate Priors, Bayesian Regression, Markov Chain Monte Carlo (MCMC) Methods, Metropolis-Hastings Algorithm, Gibbs Sampling, Bayesian Networks, Time Series Analysis & Forecasting, Autoregressive (AR) and Moving Average (MA) Models, ARIMA and SARIMA Models, Hidden Markov Models (HMM)	12
IV	<b>High Performance Statistical Computing and Applications</b>	Numerical Optimization in Statistics, Gradient Descent & Stochastic Gradient Descent (SGD), Newton-Raphson Method, Convex Optimization in Statistical Models, Parallel Computing & Big Data Statistics, Introduction to Parallel Computing in R (foreach, parallel), Distributed Computing with Apache Spark for Statistical Computing, Cloud-Based Statistical Computing (Google Cloud, AWS), Statistical Learning & Machine Learning Integration, Overview of Supervised & Unsupervised Learning, Statistical Foundations of Machine Learning, Ensemble Methods: Bagging, Boosting, Random Forest, Case Studies & Real-World Applications, Statistical Computing in Finance, Bioinformatics & Healthcare Statistics, Econometrics & Social Science Applications	12
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

#### Text Books

1. *The Elements of Statistical Learning*, Trevor Hastie, Robert Tibshirani, Jerome Friedman, 2<sup>nd</sup> Edition, 2009, Springer
2. *Statistical Computing with R*, Maria L. Rizzo, 2<sup>nd</sup> Edition, 2019, Chapman and Hall
3. *Bayesian Data Analysis*, Andrew Gelman, John B. Carlin, 3<sup>rd</sup> Edition, 2019, Chapman and Hall

**Reference Books:**

1. Gareth James, Daniela Witten, *Introduction to Statistical Learning with Applications in R*, 7<sup>th</sup> Edition, 2017, Springer
2. James E. Gentle, *Computational Statistics*, 9<sup>th</sup> Edition, 2009, Springer-Verlag New York Inc

<b>Paper VI/Subject Name: Statistical Computing Lab</b>	<b>Subject Code: CSE024D213</b>
<b>Paper Type: PEC-II</b>	<b>Specialization: Data Analytics</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>
	<b>Scheme of Evaluation: P</b>

**Objective:**

The objectives of the course are to make the students understand the fundamentals of statistical computing, implement statistical methods computationally, analyze real-world datasets using statistical computing techniques, develop computational tools for data-driven decision making

**Prerequisites:** Probability and Statistics, Linear Algebra

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Understand</b> fundamental concepts of statistical computing and probability distributions.	<b>BT 2</b>
<b>CO 2</b>	<b>Apply</b> statistical inference, hypothesis testing, and regression techniques.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> and <b>assess</b> multivariate data and use Bayesian inference methods	<b>BT 4 &amp; 5</b>
<b>CO 4</b>	<b>Develop</b> statistical models using high-performance computing techniques.	<b>BT 6</b>

**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Implement probability distributions and visualize them.
- Perform random sampling and compare theoretical vs. empirical distributions.
- Implement Monte Carlo simulations for probability estimation.
- Implement hypothesis testing using real-world datasets.
- Perform Bootstrap and Jackknife estimation in R/Python.
- Develop a regression model and validate assumptions
- Perform PCA for dimensionality reduction.
- Implement Bayesian inference using PyMC3/Stan.
- Apply ARIMA models for time series forecasting.
- Implement optimization algorithms for statistical models.
- Use Apache Spark for large-scale statistical analysis.
- Perform statistical computing on a cloud platform.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

#### Text Books

1. *The Elements of Statistical Learning*, Trevor Hastie, Robert Tibshirani, Jerome Friedman, 2<sup>nd</sup> Edition, 2009, Springer
2. *Statistical Computing with R*, Maria L. Rizzo, 2<sup>nd</sup> Edition, 2019, Chapman and Hall
3. *Bayesian Data Analysis*, Andrew Gelman, John B. Carlin, 3<sup>rd</sup> Edition, 2019, Chapman and Hall

#### Reference Books:

1. Gareth James, Daniela Witten, *Introduction to Statistical Learning with Applications in R*, 7<sup>th</sup> Edition, 2017, Springer
2. James E. Gentle, *Computational Statistics*, 9<sup>th</sup> Edition, 2009, Springer-Verlag New York Inc

<b>Paper VII/Subject Name: Big Data Analytics</b>	<b>Subject Code: CSE024D204</b>
<b>Paper Type: PEC-II</b>	<b>Specialization: Data Analytics</b>
<b>L-T-P-C – 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

#### Objective:

The objectives of the course are to make the students understand the fundamentals of big data and its challenges, learn big data processing techniques and tools, apply machine learning techniques on big data, develop big data solutions for real-world applications, etc.

**Prerequisites:** Probability & Statistics, Database Management Systems (DBMS), Python/Java Programming, Basic Data Structures and Algorithms

#### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> fundamental concepts of statistical computing and probability distributions.	BT 2
CO 2	<b>Apply</b> statistical inference, hypothesis testing, and regression techniques.	BT 3
CO 3	<b>Analyze</b> and <b>assess</b> multivariate data and use Bayesian inference methods.	BT 4 & 5
CO 4	<b>Design</b> statistical models using high-performance computing techniques	BT 6

#### Detailed Syllabus:

Module	Topics	Course Content	Periods
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I.	<b>Introduction to Big Data and Storage Systems</b>	Introduction to Big Data: Definition and Characteristics (3Vs: Volume, Velocity, Variety), Challenges in Big Data Analytics, Applications in Healthcare, Finance, and IoT, Big Data Storage & Management, Traditional Databases vs. Big Data Storage, NoSQL Databases (MongoDB, Cassandra, HBase), Distributed File Systems (HDFS, Amazon S3, Google Bigtable), Data Acquisition & Preprocessing, Data Ingestion: Batch vs. Stream Processing, Data Cleaning and Transformation, Schema Design for Big Data, Introduction to Distributed Computing, Basics of Parallel and Distributed Processing, CAP Theorem and BASE Properties, Google's Big Data Technologies: Bigtable, MapReduce, Spanner	12
II.	<b>Hadoop &amp; Spark</b>	Hadoop Ecosystem, Hadoop Architecture and Components (HDFS, YARN, MapReduce), Hadoop Cluster Setup, Hadoop vs. Spark, MapReduce Programming Model, Understanding the MapReduce Workflow, Writing MapReduce Programs (Java/Python), Combiner and Partitioner in MapReduce, Apache Spark & Resilient Distributed Datasets (RDDs), Spark Core Concepts and Architecture Transformations and Actions in RDDs, Spark DataFrames and Datasets, Advanced Spark Concepts, Spark SQL and DataFrames, Spark MLib for Machine Learning, Performance Tuning in Spark	12
III.	<b>Machine Learning &amp; Streaming Analytics</b>	Machine Learning with Big Data, Challenges of Machine Learning on Big Data, Scalable ML Algorithms (Decision Trees, Clustering, Regression), Apache Spark MLib, Big Data Streaming Analytics, Introduction to Stream Processing, Apache Kafka and Apache Flink Real-time Data Processing with Spark Streaming, Graph Processing with Big Data, Introduction to Graph Analytics, Apache Giraph and GraphX in Spark, PageRank Algorithm, Text & Social Media Analytics, Sentiment Analysis on Large-scale Text Data, Natural Language Processing (NLP) using Spark, Twitter and Social Media Data Analysis	12
IV	<b>Cloud Based Big Data Analytics</b>	Big Data on Cloud Platforms, Google Cloud BigQuery, AWS Big Data Services (Redshift, EMR), Microsoft Azure Data Lake, Big Data Security & Privacy, Data Governance & Compliance (GDPR, CCPA), Secure Data Storage & Access Control, Ethical Considerations in Big Data Analytics, Big Data Use Cases & Applications, Fraud Detection in Banking & Finance, Healthcare Analytics for Disease Prediction Smart Cities and IoT Data Analysis, Future Trends in Big Data Analytics, AI and Big Data Integration, Quantum Computing for Big Data, Edge Computing and IoT Analytics	12
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Books**

1. *Hadoop: The Definitive Guide*, Tom White, 3<sup>rd</sup> Edition, 2012, O'Reilly
2. *Spark: The Definitive Guide*, Bill Chambers, Matei Zaharia, 1<sup>st</sup> Edition, 2017, O'Reilly
3. *Mining of Massive Datasets*, Jure Leskovec, Anand Rajaraman, 2<sup>nd</sup> Edition, 2016, Dreamtech Press

**Reference Books:**

1. Nathan Marz, *Big Data: Principles and Best Practices of Scalable Real-Time Data Systems*, 1<sup>st</sup> Edition, 2015, Manning Publications
2. Mohammad Guller, *Big Data Analytics with Spark*, 1<sup>st</sup> Edition, 2015, Apress

<b>Paper VIII/Subject Name: Big Data Analytics Lab</b>		<b>Subject Code: CSE024D214</b>
<b>Paper Type: PEC-II</b>		<b>Specialization: Data Analytics</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>	<b>Scheme of Evaluation: P</b>

**Objective:**

The objectives of the course are to make the students understand the fundamentals of big data and its challenges, learn big data processing techniques and tools, apply machine learning techniques on big data, develop big data solutions for real-world applications, etc.

**Prerequisites:** Probability & Statistics, Database Management Systems (DBMS), Python/Java Programming, Basic Data Structures and Algorithms

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Understand</b> fundamental concepts of statistical computing and probability distributions.	<b>BT 2</b>
<b>CO 2</b>	<b>Apply</b> statistical inference, hypothesis testing, and regression techniques.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> and <b>assess</b> multivariate data and use Bayesian inference methods.	<b>BT 4 &amp; 5</b>
<b>CO 4</b>	<b>Design</b> statistical models using high-performance computing techniques	<b>BT 6</b>

**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Setup and configure Hadoop Distributed File System (HDFS).
- Perform CRUD operations on NoSQL databases (MongoDB, Cassandra).
- Implement batch and stream data ingestion techniques.
- Write a MapReduce program for word count and log processing.
- Implement data transformations using Spark RDDs and DataFrames.
- Perform SQL operations on Spark DataFrames
- Implement a recommendation system using Spark MLlib.
- Process real-time streaming data using Apache Kafka.
- Perform sentiment analysis on Twitter data.
- Deploy and analyze Big Data workloads on AWS/Azure.
- Perform fraud detection using Big Data techniques.
- Build a predictive model for healthcare analytics.

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
4 * 22 NCH = 88 NCH	2 * 15 NCH = 30 NCH	8 * 4 NCH = 32 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

### Text Books

1. *Hadoop: The Definitive Guide*, Tom White, 3<sup>rd</sup> Edition, 2012, O'Reily
2. *Spark: The Definitive Guide*, Bill Chambers, Matei Zaharia, 1<sup>st</sup> Edition, 2017, O'Reily
3. *Mining of Massive Datasets*, Jure Leskovec, Anand Rajaraman, 2<sup>nd</sup> Edition, 2016, Dreamtech Press

### Reference Books:

1. Nathan Marz, *Big Data: Principles and Best Practices of Scalable Real-Time Data Systems*, 1<sup>st</sup> Edition, 2015, Manning Publications
2. Mohammad Guller, *Big Data Analytics with Spark*, 1<sup>st</sup> Edition, 2015, Apress

<b>Paper VII/Subject Name: Remote Sensing and GIS</b>	<b>Subject Code: CSE024D206</b>
<b>Paper Type: PEC-III</b>	<b>Specialization: Data Analytics</b>
<b>L-T-P-C - 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

### Objective:

The objectives of the course are to make the students understand the fundamental concepts of remote sensing and its applications, learn about GIS (Geographic Information Systems) and spatial data processing, explore satellite image acquisition, preprocessing, and classification techniques, etc.

**Prerequisites:** Basics of Digital Image Processing, Linear Algebra & Probability, Python Programming

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> the fundamentals of remote sensing and GIS.	<b>BT 2</b>
CO 2	<b>Process</b> and <b>interpret</b> satellite images for spatial analysis.	<b>BT 3</b>
CO 3	<b>Analyze</b> and <b>assess</b> GIS solutions for urban planning and disaster management.	<b>BT 4 &amp; 5</b>
CO 4	<b>Design</b> AI/ML techniques for remote sensing image classification.	<b>BT 6</b>

### Detailed Syllabus:

Module	Topics	Course Content	Periods
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I.	<b>Remote Sensing Fundamentals</b>	Fundamentals of Remote Sensing, Definition & Historical Development, Electromagnetic Spectrum & Remote Sensing Principles, Energy Interactions with Atmosphere & Earth's Surface, Remote Sensing Platforms & Sensors, Satellite & Aerial Remote Sensing Systems, Optical, Infrared, Microwave, and Hyperspectral Sensors, Types of Satellites: Landsat, Sentinel, MODIS, LIDAR, Resolution in Remote Sensing, Spatial, Spectral, Temporal & Radiometric Resolutions, Sensor Characteristics and Their Applications, Remote Sensing Data Acquisition, Passive vs. Active Remote Sensing, Satellite Data Sources and Accessibility	12
II.	<b>Image Processing and Interpretation</b>	Preprocessing of Satellite Images, Radiometric & Geometric Corrections, Image Enhancement Techniques, Image Rectification & Registration, Image Classification Techniques, Supervised & Unsupervised Classification, Machine Learning Approaches in Image Classification, Object-Based Image Analysis (OBIA), Vegetation Indices & Environmental Applications, NDVI (Normalized Difference Vegetation Index), Land Use/Land Cover (LULC) Mapping, Change Detection Techniques, Thermal & Radar Remote Sensing, Thermal Infrared Remote Sensing, Microwave & SAR (Synthetic Aperture Radar) Imaging	12
III.	<b>Geographic Information System (GIS)</b>	Fundamentals of GIS, GIS Concepts, Components & Data Models, Spatial Data Representation (Vector & Raster Data), GIS Software (ArcGIS, QGIS, Google Earth Engine), Spatial Data Acquisition & Integration, GPS (Global Positioning System) & Field Data Collection, Remote Sensing Data Integration with GIS, Spatial Analysis & Modeling, Buffering, Overlay, and Proximity Analysis, Network Analysis & Terrain Modeling, 3D GIS and DEM (Digital Elevation Model), Web GIS & Cloud-Based GIS Services, Google Earth Engine & OpenStreetMap, Cloud GIS Technologies (ArcGIS Online, Google Earth Engine)	12
IV	<b>Applications</b>	Environmental & Agricultural Applications, Deforestation & Land Degradation Monitoring, Crop Yield Estimation & Precision Agriculture, Urban & Disaster Management, Urban Growth Analysis & Smart Cities, Flood, Earthquake, and Forest Fire Mapping, Climate Change & Hydrological Applications, Glacier & Coastal Change Detection, Watershed Management & Hydrological Modeling, Artificial Intelligence & Deep Learning in Remote Sensing, AI-Based Image Segmentation, Deep Learning for Land Cover Classification, Real-Time Remote Sensing Applications	12
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 22 NCH = 88 NCH	2 * 15 NCH = 30 NCH	8 * 4 NCH = 32 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Books**

1. *Remote Sensing and Image Interpretation*, Thomas M. Lillesand, Ralph W. Kiefer, Jonathan Chipman, 6<sup>th</sup> Edition, 2011, Wiley
2. *Introduction to Geographic Information Systems*, Kang-Tsung Chang, 4<sup>th</sup> Edition, 2017, McGraw Hill Education
3. *Fundamentals of Remote Sensing*, George Joseph, 3<sup>rd</sup> Edition, 2018, The Orient Blackswan

**Reference Books:**

1. John A. Richards, *Remote Sensing Digital Image Analysis*, 4<sup>th</sup> Edition, 2005, Springer
2. Peter A. Burrough, Rachael McDonnell, *Principles of Geographic Information Systems*, 3<sup>rd</sup> Edition, 2016, Oxford University Press

<b>Paper VIII/Subject Name: Remote Sensing and GIS Lab</b>		<b>Subject Code: CSE024D216</b>
<b>Paper Type: PEC-III</b>		<b>Specialization: Data Analytics</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>	<b>Scheme of Evaluation: P</b>

**Objective:**

The objectives of the course are to make the students understand the fundamental concepts of remote sensing and its applications, learn about GIS (Geographic Information Systems) and spatial data processing, explore satellite image acquisition, preprocessing, and classification techniques, etc.

**Prerequisites:** Basics of Digital Image Processing, Linear Algebra & Probability, Python Programming

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Understand</b> the fundamentals of remote sensing and GIS.	<b>BT 2</b>
<b>CO 2</b>	<b>Process</b> and <b>interpret</b> satellite images for spatial analysis.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> and <b>assess</b> GIS solutions for urban planning and disaster management.	<b>BT 4 &amp; 5</b>
<b>CO 4</b>	<b>Design</b> AI/ML techniques for remote sensing image classification.	<b>BT 6</b>

**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Download and analyze Landsat/Sentinel satellite images.
- Explore spectral bands and their applications.
- Visualize remote sensing data using GIS software (QGIS/ArcGIS).
- Perform radiometric and geometric corrections on satellite imagery.
- Implement NDVI for vegetation analysis.
- Classify land use using supervised and unsupervised learning methods.
- Create and analyze spatial data using QGIS/ArcGIS.
- Perform spatial interpolation and terrain modeling.
- Develop a simple Web GIS application.
- Perform flood risk analysis using GIS.
- Use machine learning models for land cover classification.
- Develop a GIS-based disaster monitoring system.

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Books**

1. *Remote Sensing and Image Interpretation*, Thomas M. Lillesand, Ralph W. Kiefer, Jonathan Chipman, 6<sup>th</sup> Edition, 2011, Wiley
2. *Introduction to Geographic Information Systems*, Kang-Tsung Chang, 4<sup>th</sup> Edition, 2017, McGraw Hill Education
3. *Fundamentals of Remote Sensing*, George Joseph, 3<sup>rd</sup> Edition, 2018, The Orient Blackswan

**Reference Books:**

1. John A. Richards, *Remote Sensing Digital Image Analysis*, 4<sup>th</sup> Edition, 2005, Springer
2. Peter A. Burrough, Rachael McDonnell, *Principles of Geographic Information Systems*, 3<sup>rd</sup> Edition, 2016, Oxford University Press

## 6.4 Detailed Syllabus of 3<sup>rd</sup> Semester

<b>Paper I/Subject Name: Soft Computing</b>	<b>Subject Code: CSE024C301</b>
<b>L-T-P-C – 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

### Objective:

The objectives of the course are to make the students understand fundamental concepts of soft computing techniques such as fuzzy logic, neural networks, and evolutionary algorithms, develop skills for designing intelligent systems using soft computing paradigms, enable solving real-world problems where conventional techniques fail, etc.

**Prerequisites:** Basic programming knowledge, Foundations of algorithms and data structures, Basic knowledge of linear algebra and probability, Introduction to Artificial Intelligence

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> the fundamentals of soft computing and its components.	<b>BT 2</b>
CO 2	<b>Apply</b> fuzzy logic principles to design decision-making systems.	<b>BT 3</b>
CO 3	<b>Analyze</b> optimization problems using genetic and evolutionary algorithms.	<b>BT 4</b>
CO 4	<b>Assess</b> and <b>design</b> hybrid models integrating multiple soft computing techniques.	<b>BT 5 &amp; 6</b>

### Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	<b>Introduction</b>	Soft Computing vs Hard Computing, Components of Soft Computing: Fuzzy Logic, ANN, Genetic Algorithms, Hybrid Systems, Fuzzy Sets: Membership Functions, Operations, Fuzzy Relations, Fuzzy Inference Systems (FIS): Mamdani and Sugeno Models, Defuzzification Techniques, Applications of Fuzzy Logic: Control Systems, Decision Making	12
II.	<b>Artificial Neural Networks</b>	Biological Neurons and Artificial Neurons, McCulloch-Pitts Model, Perceptron Model, Backpropagation Algorithm (Gradient Descent), Multilayer Perceptron (MLP) and Training, Radial Basis Function (RBF) Networks, Self-Organizing Maps (SOM), Applications: Pattern Recognition, Classification, Forecasting	12
III.	<b>Genetic Algorithms and Evolutionary Computing</b>	Introduction to Genetic Algorithms (GA), Genetic Operators: Selection, Crossover, Mutation, Fitness Function, Encoding Techniques, Convergence Issues and Parameter Tuning, Applications: Feature Selection, Scheduling, Design Optimization, Brief Overview of other Evolutionary Techniques: PSO, DE, ACO	12
IV.	<b>Hybrid Soft Computing &amp; Applications</b>	Hybrid Systems: Neuro-Fuzzy, GA-NN, GA-Fuzzy, ANFIS, Adaptive Neuro-Fuzzy Inference System (ANFIS) Architecture and Training Case Studies: Credit Scoring, Intrusion Detection, Disease Diagnosis, IoT and Edge AI using Soft Computing, Current Trends and Research Directions in Soft Computing	12

<b>TOTAL</b>	<b>48</b>
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<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

#### **Text Books**

1. S. N. Deepa, *Principles of Soft Computing*, S. N. Sivanandam, 2<sup>nd</sup> Edition, 2011, Wiley India
2. *Fuzzy Logic with Engineering Applications*, Timothy J. Ross, 3<sup>rd</sup> Edition, 2010, Wiley.

#### **Reference Books:**

1. David E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, 1989, Pearson
2. J.-S. R. Jang, C.-T. Sun, E. Mizutani, *Neuro-Fuzzy and Soft Computing*, 1997, Prentice Hall.

**Paper II/Subject Name: Internet Security and Cryptographic Protocols Subject Code: CSE024C302**

**L-T-P-C – 4-0-0-4**

**Credit Units: 04**

**Scheme of Evaluation: T**

#### **Objective:**

The objectives of the course are to teach the students the principles of secure communication over the Internet, explore symmetric and asymmetric cryptographic algorithms, learn security protocols used in Internet and web applications, etc.

**Prerequisites:** Computer Networks, Operating Systems, Basics of Cryptography or Network Security, Programming knowledge.

#### **Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Demonstrate</b> the goals and principles of cryptographic security.	<b>BT 2</b>
<b>CO 2</b>	<b>Apply</b> symmetric and asymmetric encryption techniques to secure data.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> widely used Internet security protocols like TLS, IPsec, and SSH.	<b>BT 4</b>
<b>CO 4</b>	<b>Evaluate</b> authentication, key exchange, and digital signature mechanisms.	<b>BT 5</b>
<b>CO 5</b>	<b>Design</b> and implement secure communication scenarios using cryptographic tools.	<b>BT 6</b>

#### **Detailed Syllabus:**

<b>Modules</b>	<b>Topics</b>	<b>Course Contents</b>	<b>Hours</b>
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I	<b>Introduction</b>	Security Goals: Confidentiality, Integrity, Authentication, Non-repudiation, Attacks: Passive vs Active, MITM, Replay, Spoofing, DoS, Cryptographic Models: Private-key, Public-key, Hash Functions, Classical Cryptosystems: Caesar Cipher, Vigenère Cipher, Modern Block Ciphers: Feistel Structure, DES, AES, Modes of Operation: ECB, CBC, CFB, OFB, CTR	12
II	<b>Public Key Cryptography &amp; Key Management</b>	Number Theory: Modular Arithmetic, GCD, Euler's Theorem, Fermat's Theorem, RSA Algorithm: Key Generation, Encryption, Decryption, Diffie-Hellman Key Exchange, ElGamal Cryptosystem, Digital Signatures: RSA-based, DSA, ECDSA, Certificate Authorities (CAs), Public Key Infrastructure (PKI), Key Distribution and Management	12
III	<b>Hash Functions and Authentication Protocols</b>	Cryptographic Hash Functions: MD5, SHA-1, SHA-2, SHA-3, Message Authentication Codes (MACs), HMAC, Password-Based Authentication, Challenge-Response Authentication, One-Time Passwords (OTP) and Two-Factor Authentication (2FA), Kerberos Protocol, Biometrics and Token-Based Authentication	12
IV	<b>Internet Security Protocols</b>	<b>SSL/TLS Protocol:</b> Architecture, Handshake, Certificates, Vulnerabilities, <b>HTTPS:</b> Integration with Web Servers, Secure Sessions, <b>IPSec:</b> AH, ESP, Security Associations, IKE, <b>SSH Protocol:</b> Secure Shell Architecture and Usage, <b>Email Security:</b> PGP and S/MIME, <b>DNS Security:</b> DNSSEC Basics, Web Attacks and Countermeasures: XSS, CSRF, Clickjacking	12
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Book:**

1. *Cryptography and Network Security: Principles and Practice*, William Stallings, 7th Edition, 2017, Pearson
2. *Cryptography and Network Security*, Behrouz A. Forouzan, 2007, McGraw-Hill

**Reference Books:**

1. Charlie Kaufman, Radia Perlman, Mike Speciner, *Network Security: Private Communication in a Public World*, 2<sup>nd</sup> Edition, 2016, Pearson
2. Bruce Schneier, *Applied Cryptography*, 20<sup>th</sup> Anniversary Edition, 2017, Wiley

**Paper III/Subject Name: Soft Computing Lab**

**Subject Code: CSE024C311**

**L-T-P-C – 0-0-2-1**

**Credit Units: 01**

**Scheme of Evaluation: P**

**Objective:**

The objectives of the course are to make the students understand fundamental concepts of soft computing techniques such as fuzzy logic, neural networks, and evolutionary algorithms, develop skills for designing intelligent systems using soft computing paradigms, enable solving real-world problems where conventional techniques fail, etc.

**Prerequisites:** Basic programming knowledge, Foundations of algorithms and data structures, Basic knowledge of linear algebra and probability, Introduction to Artificial Intelligence

**Course Outcomes**

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> the fundamentals of soft computing and its components.	<b>BT 2</b>
CO 2	<b>Apply</b> fuzzy logic principles to design decision-making systems.	<b>BT 3</b>
CO 3	<b>Analyze</b> optimization problems using genetic and evolutionary algorithms.	<b>BT 4</b>
CO 4	<b>Assess</b> and <b>design</b> hybrid models integrating multiple soft computing techniques.	<b>BT 5 &amp; 6</b>

**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Implementation of Fuzzy Logic Controller
- Design of Membership Functions and Rule Base
- Simulation of Perceptron and MLP in Python/MATLAB
- Backpropagation Network for handwritten digit recognition (MNIST subset)
- Design and Analysis of Genetic Algorithm for function optimization
- GA-based Feature Selection for a classification dataset
- Implementation of ANFIS using MATLAB or Python
- Development of Hybrid Soft Computing System (e.g., GA-ANN)
- Case Study: Medical diagnosis system using neuro-fuzzy model
- Mini Project: Soft computing-based intelligent system for real-world data (agriculture/healthcare/finance)

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

### Text Books

1. S. N. Deepa, *Principles of Soft Computing*, S. N. Sivanandam, 2<sup>nd</sup> Edition, 2011, Wiley India
2. *Fuzzy Logic with Engineering Applications*, Timothy J. Ross, 3rd Edition, 2010, Wiley.

### Reference Books:

1. David E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, 1989, Pearson
2. J.-S. R. Jang, C.-T. Sun, E. Mizutani, *Neuro-Fuzzy and Soft Computing*, 1997, Prentice Hall.

**Paper IV/Subject Name: Internet Security and Cryptographic Protocols Lab Subject Code: CSE024C312**

**L-T-P-C – 0-0-2-1**

**Credit Units: 01**

**Scheme of Evaluation: P**

### Objective:

The objectives of the course are to teach the students the principles of secure communication over the Internet, explore symmetric and asymmetric cryptographic algorithms, learn security protocols used in Internet and web applications, etc.

**Prerequisites:** Computer Networks, Operating Systems, Basics of Cryptography or Network Security, Programming knowledge.

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Demonstrate</b> the goals and principles of cryptographic security.	<b>BT 2</b>
CO 2	<b>Apply</b> symmetric and asymmetric encryption techniques to secure data.	<b>BT 3</b>
CO 3	<b>Analyze</b> widely used Internet security protocols like TLS, IPsec, and SSH.	<b>BT 4</b>
CO 4	<b>Evaluate</b> authentication, key exchange, and digital signature mechanisms.	<b>BT 5</b>
CO 5	<b>Design</b> and implement secure communication scenarios using cryptographic tools.	<b>BT 6</b>

### Detailed Syllabus:

**Total Lab Hours for the semester = 30 (2 hours per week)**

### Minimum 10 Laboratory experiments based on the following-

- Implement basic symmetric and asymmetric encryption
- SSL/TLS handshake analysis using Wireshark
- Digital signature creation and verification
- Password hashing and brute-force simulation
- Secure email using PGP
- Simulating MITM and implementing countermeasures
- Setting up and configuring IPsec and SSH
- Build a secure file-sharing or chat application using OpenSSL sockets

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Book:**

1. *Cryptography and Network Security: Principles and Practice*, William Stallings, 7th Edition, 2017, Pearson
2. *Cryptography and Network Security*, Behrouz A. Forouzan, 2007, McGraw-Hill

**Reference Books:**

1. Charlie Kaufman, Radia Perlman, Mike Speciner, *Network Security: Private Communication in a Public World*, 2<sup>nd</sup> Edition, 2016, Pearson
2. Bruce Schneier, *Applied Cryptography*, 20<sup>th</sup> Anniversary Edition, 2017, Wiley

<b>Paper V/Subject Name: Generative AI and LLMs</b>	<b>Subject Code: CSE024D301</b>
<b>Paper Type: PEC-IV</b>	<b>Specialization: Artificial Intelligence</b>
<b>L-T-P-C – 4-0-0-4</b>	<b>Credit Units: 04</b>
	<b>Scheme of Evaluation: T</b>

**Objective:**

The objectives of the course are to make the students understand the fundamental concepts of generative models in AI, provide in-depth knowledge of transformer architecture and large language models (LLMs), enable students to apply generative models for various real-world tasks like text generation, summarization, translation, image generation, and code synthesis.

**Prerequisites:** Basics of Machine Learning and Deep Learning, Familiarity with Python, PyTorch/TensorFlow, Linear Algebra, Probability, and NLP fundamentals

**Course Outcomes**

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> the theoretical foundations of generative models and LLMs.	<b>BT 2</b>
CO 2	<b>Implement</b> transformer-based generative models for text and other modalities.	<b>BT 3</b>
CO 3	<b>Analyze</b> architectures like GPT, BERT, and Diffusion Models in various domains.	<b>BT 4</b>
CO 4	<b>Evaluate</b> the performance and ethical implications of LLM-based applications.	<b>BT 5</b>
CO 5	<b>Design</b> and fine-tune generative AI solutions using open-source models.	<b>BT 6</b>

**Detailed Syllabus:**

Module	Topics	Course Content	Periods
I.	<b>Introduction</b>	Generative vs. Discriminative Models, Overview of Generative AI in NLP, Vision, and Code, Probabilistic Foundations: Language Modeling, Markov Chains, n-gram Models, RNNs, LSTMs and their limitations, Introduction to Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs): Architecture, Applications	12
II.	<b>Transformers and Self Attention Mechanism</b>	Attention Mechanisms and Scaled Dot-Product Attention, Positional Encoding and Multi-Head Attention, Encoder-Decoder Architecture, The Transformer Model (Vaswani et al., 2017), Training Transformers from Scratch vs. Fine-tuning, Transfer Learning and Pretraining Paradigms (BERT-style vs GPT-style)	12
III.	<b>LLMs</b>	GPT Family (GPT-2, GPT-3, GPT-4, ChatGPT): Architecture, Tokenization, RLHF, BERT, T5, BART: Pretraining + Finetuning for downstream tasks, Prompt Engineering and In-context Learning, Finetuning vs Instruction Tuning, LLM Tool Use (Function Calling, Plugins, Memory-Augmented LLMs), Evaluation: Perplexity, BLEU, ROUGE, Human Evaluation	12
IV	<b>Multimodal Generative Models and Ethical Considerations</b>	Vision-Language Models: CLIP, Flamingo, BLIP, Diffusion Models for Image Generation (e.g., DALL-E, Stable Diffusion), Code Generation Models: Codex, StarCoder, CodeT5, Prompt Tuning, LoRA, PEFT Techniques for Finetuning LLMs, Societal Impact of Generative AI: Bias, Hallucination, Misuse, Safety, Explainability, and Responsible AI Design, Open Source Models: LLaMA, Mistral, Falcon, Gemma	12
<b>TOTAL</b>			<b>48</b>

Credit Distribution		
Lecture/ Tutorial	Practicum	Experiential Learning
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

#### Text Books

1. *Machine Learning with PyTorch and Scikit-Learn*, Sebastian Raschka, 2022, Packt
2. *Deep Learning for Natural Language Processing*, Palash Goyal, Sumit Pandey, Karan Jain, 1<sup>st</sup> Edition, 2018, Apress

#### Reference Books:

1. Andrej Karpathy's lectures, *CS231n, CS25 (Transformer Circuits)*

<b>Paper VI/Subject Name: Generative AI and LLMs Lab</b>	<b>Subject Code: CSE024D311</b>
<b>Paper Type: PEC-IV</b>	<b>Specialization: Artificial Intelligence/ Image Processing</b>
<b>L-T-P-C - 0-0-2-1</b>	<b>Credit Units: 01</b>
	<b>Scheme of Evaluation: P</b>

#### Objective:

The objectives of the course are to make the students understand the fundamental concepts of generative models in AI, provide in-depth knowledge of transformer architecture and large language models (LLMs),

enable students to apply generative models for various real-world tasks like text generation, summarization, translation, image generation, and code synthesis.

**Prerequisites:** Basics of Machine Learning and Deep Learning, Familiarity with Python, PyTorch/TensorFlow, Linear Algebra, Probability, and NLP fundamentals

**Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Understand</b> the theoretical foundations of generative models and LLMs.	<b>BT 2</b>
<b>CO 2</b>	<b>Implement</b> transformer-based generative models for text and other modalities.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> architectures like GPT, BERT, and Diffusion Models in various domains.	<b>BT 4</b>
<b>CO 4</b>	<b>Evaluate</b> the performance and ethical implications of LLM-based applications.	<b>BT 5</b>
<b>CO 5</b>	<b>Design</b> and fine-tune generative AI solutions using open-source models.	<b>BT 6</b>

**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Text generation using GPT-2
- Prompt engineering for summarization and translation
- Fine-tune a transformer for sentiment classification
- Build an AI assistant using LangChain and LLM APIs
- Generate images using Stable Diffusion
- Implement content moderation using zero-shot classification
- Compare LLM responses and detect hallucinations
- Deploy a generative chatbot or Q&A system

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

**Text Books**

1. *Machine Learning with PyTorch and Scikit-Learn*, Sebastian Raschka, 2022, Packt
2. *Deep Learning for Natural Language Processing*, Palash Goyal, Sumit Pandey, Karan Jain, 1<sup>st</sup> Edition, 2018, Apress

**Reference Books:**

1. Andrej Karpathy’s lectures, *CS231n, CS25 (Transformer Circuits)*

PEC-V/Subject Name: Cloud Computing for Big Data

Subject Code: CSE024D302

Paper Type: PEC-III

Specialization: Data Analytics

L-T-P-C – 4-0-0-4

Credit Units: 04

Scheme of Evaluation: T

### Objective:

The objectives of the course are to make the students understand cloud computing architecture and its service models, explore cloud platforms and their support for big data processing, learn big data frameworks like Hadoop and Spark in cloud environments.

**Prerequisites:** Basic programming knowledge, Foundations of Operating Systems and Computer Networks, Introductory knowledge of Big Data

### Course Outcomes

On successful completion of the course the students will be able to:		
SI No	Course Outcome	Blooms Taxonomy Level
CO 1	<b>Understand</b> the architecture and service models of cloud computing.	<b>BT 2</b>
CO 2	<b>Apply</b> big data frameworks like Hadoop and Spark in cloud environments.	<b>BT 3</b>
CO 3	<b>Analyze</b> cloud infrastructure required for scalable big data analytics.	<b>BT 4</b>
CO 4	<b>Evaluate</b> various cloud-based data storage, processing, and visualization tools.	<b>BT 5</b>
CO 5	<b>Design</b> a cloud-native big data pipeline for real-time analytics.	<b>BT 6</b>

### Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	<b>Introduction</b>	Definition and Characteristics of Cloud Computing, Cloud Service Models: IaaS, PaaS, SaaS, Cloud Deployment Models: Public, Private, Hybrid, Multi-cloud, Virtualization: VMs, Hypervisors, Containers (Docker, Kubernetes), Cloud Providers Overview: AWS, Azure, Google Cloud, IBM, Elasticity, Auto-scaling, Load Balancing, Billing Models	12
II.	<b>Big Data Ecosystem</b>	Big Data: Definitions, V's, Challenges, and Opportunities, Hadoop Ecosystem: HDFS, MapReduce, YARN, Hadoop Installation on Cloud (AWS EMR, GCP Dataproc), HDFS vs Cloud Storage (S3, GCS, Azure Blob), Data Ingestion Tools: Sqoop, Flume, Kafka (Overview), Use Cases: Batch processing for log files, analytics	12
III.	<b>Apache Spark</b>	Apache Spark Architecture: RDDs, DAG, Lazy Evaluation, Spark Core: Transformations, Actions, Spark SQL, Spark Streaming and Structured Streaming, Spark with Cloud Storage (S3, GCS), Integrating Kafka with Spark for Streaming Data, Cluster Management with YARN, Mesos, Kubernetes	12
IV	<b>Applications</b>	Serverless Computing (AWS Lambda, GCP Cloud Functions) for Big Data, Cloud Data Warehousing: BigQuery, Redshift, Snowflake, Data Lake Architecture on Cloud, ETL Pipelines with Airflow and	12

		Dataflow, Visualization using Tableau, AWS QuickSight, Google Data Studio, Case Studies: Real-time fraud detection, IoT data analytics, recommendation systems, Security and Governance: IAM, Data Encryption, Compliance (GDPR, HIPAA)	
<b>TOTAL</b>			<b>48</b>

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
4 * 12 NCH = 48 NCH	--	72 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

#### **Text Books**

1. *Mastering Cloud Computing*, Rajkumar Buyya, Christian Vecchiola, S. Thamarai Selvi, 2013, McGraw Hill
2. *Hadoop: The Definitive Guide*, Tom White, 4<sup>th</sup> Edition, O'Reilly Media

#### **Reference Books:**

1. Jules S. Damji et al., *Learning Spark: Lightning-Fast Big Data Analysis*, 2<sup>nd</sup> Edition, O'Reilly

<b>Paper VI/Subject Name: Cloud Computing for Big Data Lab</b>	<b>Subject Code: CSE024D312</b>
<b>Paper Type: PEC-III</b>	<b>Specialization: Data Analytics</b>
<b>L-T-P-C – 0-0-2-1</b>	<b>Credit Units: 01</b>
	<b>Scheme of Evaluation: P</b>

#### **Objective:**

The objectives of the course are to make the students understand cloud computing architecture and its service models, explore cloud platforms and their support for big data processing, learn big data frameworks like Hadoop and Spark in cloud environments.

**Prerequisites:** Basic programming knowledge, Foundations of Operating Systems and Computer Networks, Introductory knowledge of Big Data

#### **Course Outcomes**

<b>On successful completion of the course the students will be able to:</b>		
<b>SI No</b>	<b>Course Outcome</b>	<b>Blooms Taxonomy Level</b>
<b>CO 1</b>	<b>Understand</b> the architecture and service models of cloud computing.	<b>BT 2</b>
<b>CO 2</b>	<b>Apply</b> big data frameworks like Hadoop and Spark in cloud environments.	<b>BT 3</b>
<b>CO 3</b>	<b>Analyze</b> cloud infrastructure required for scalable big data analytics.	<b>BT 4</b>
<b>CO 4</b>	<b>Evaluate</b> various cloud-based data storage, processing, and visualization tools.	<b>BT 5</b>

<b>CO 5</b>	<b>Design</b> a cloud-native big data pipeline for real-time analytics.	<b>BT 6</b>
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**Detailed Syllabus:**

**Total Lab Hours for the semester = 30 (2 hours per week)**

**Minimum 10 Laboratory experiments based on the following-**

- Setup a cloud-based Hadoop cluster and run MapReduce
- Store and query data using Spark SQL on cloud storage
- Perform real-time analytics with Spark Streaming and Kafka
- Deploy a Lambda function to process incoming S3 data
- Run an ETL pipeline using Apache Airflow
- Analyze IoT sensor data using BigQuery
- Visualize a processed dataset using Tableau / GCP Studio
- Mini Project: Build a cloud-native analytics solution for a domain (healthcare/finance/retail)

<b>Credit Distribution</b>		
<b>Lecture/ Tutorial</b>	<b>Practicum</b>	<b>Experiential Learning</b>
--	1 * 12 NCH = 12 NCH	18 NCH (Problem Solving, Seminar, Case Study, Discussion, Internship, Projects)

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**Reference Books:**

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