THE ASSAM
ROYAL GLOBAL UNIVERSITY
GUWAHATI

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

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Section 1:

Overview

1.1. Introduction

India is one of the fastest-growing economies globally, with knowledge creation and research playing a pivotal role in sustaining this momentum. As the nation aspires to establish itself as a leading knowledge society and one of the largest economies, there is an urgent need to expand research capabilities and outputs across disciplines.

At Royal Global University, we align ourselves with this national vision by fostering a robust ecosystem of research and innovation, nurturing a vast talent pool that is critical for achieving these ambitious goals.

The National Education Policy (NEP) 2020 emphasizes the transformation of higher education to support India’s transition to a knowledge-driven economy. Key initiatives such as multidisciplinary education with multiple entry and exit options, undergraduate research opportunities, and a learning outcomes-based curriculum are at the forefront of this transformation.

The postgraduate (PG) programmes at Royal Global University are designed to advance students’ expertise in their chosen fields and equip them for higher research pursuits. These programmes provide the advanced knowledge and specialized skills necessary for students to evolve from learners to innovators, contributing meaningfully to the nation's knowledge economy.

In line with NEP 2020, Royal Global University offers restructured degree programmes to provide flexible and holistic education. The policy envisions undergraduate programmes with various certification options, including:

- A UG certificate after completing 1 year of study,
- A UG diploma after 2 years,
- A Bachelor’s degree after a 3-year programme, or
- A preferred 4-year multidisciplinary Bachelor's degree, offering students the opportunity to explore holistic and multidisciplinary education alongside their chosen major and minors.

Similarly, postgraduate programmes at Royal Global University are designed with flexibility to cater to diverse academic and professional aspirations, fostering a new generation of knowledge creators who will shape India's future as a global leader.

Royal Global University remains committed to empowering students and creating an educational environment that embodies the principles of NEP 2020, driving innovation and excellence in higher education.

1.2. Recommendations of NEP 2020 Pertinent to Postgraduate Education

- A 2-year PG programme may be offered, with the second year exclusively dedicated to research for students who have completed a 3-year Bachelor's programme.
- For students who have completed a 4-year Bachelor's programme with Honours or Honours with Research, a 1-year PG programme could be introduced.
- An integrated 5-year Bachelor's/Master's programme may also be offered.
- Universities are encouraged to provide PG programmes in core areas such as Machine Learning, multidisciplinary fields like AI + X, and professional domains such as healthcare, agriculture, and law.
- A National Higher Education Qualifications Framework (NHEQF) will define higher education qualifications in terms of learning outcomes. The PG programme levels will correspond to Levels 6, 6.5, and 7 under the NHEQF.
- The PG framework must align with the National Credit Framework (NCrF) to facilitate the creditization of learning, including the assignment, accumulation, storage, transfer, and redemption of credits, subject to appropriate assessment.
- For professional PG programmes such as M.E., M.Tech., etc., a 2-year (4-semester) PG programme at level 7 of the NHEQF requires a 4-year Bachelor's degree (e.g., B.E., B.Tech.) with a minimum of 160 credits.

1.3. About M. Tech Course

The Master of Technology (M. Tech) in Computer Science and Engineering (CSE) program at The Assam Royal Global University is designed to provide advanced knowledge and skills in various domains of computer science, aligning with the guidelines of the National Credit Framework (NCrF).

1.3.1. Program Objectives

- *Advanced Knowledge Acquisition:* Equip students with in-depth understanding of core and emerging areas in computer science, such as Artificial Intelligence, Data Analytics, Internet of Things, and Networking.
- *Research and Innovation:* Foster a research-oriented mindset, encouraging students to

undertake innovative projects that address real-world challenges.

- Skill Development: Enhance practical skills through hands-on experience, ensuring graduates are proficient in modern tools and technologies relevant to the industry.
- *Interdisciplinary Approach:* Promote an interdisciplinary learning environment, enabling students to integrate knowledge from various fields to develop comprehensive solutions.

1.3.2. Alignment with National Credit Framework (NCrF)

In accordance with the NCrF, the program ensures a holistic and flexible education system by:

- *Credit Assignment and Accumulation:* Implementing a standardized credit system where 30 notional learning hours equate to one credit, facilitating the accumulation and transfer of credits across different educational levels and institutions.
- *Multiple Entry and Exit Options:* Providing students with the flexibility to enter and exit the program at various stages, with appropriate certification, diploma, or degree awarded based on the credits earned, thereby accommodating diverse learning needs and career paths.
- *Integration of Academic and Vocational Education:* Bridging the gap between theoretical knowledge and practical application by incorporating skill-based modules and experiential learning opportunities into the curriculum.

1.3.3. Program Structure

The M. Tech (CSE) program spans two years, divided into four semesters, with a total of 80 credits. Each semester comprises core courses, electives, and project work, designed to provide both breadth and depth in the subject matter. Specializations offered include:

- Artificial Intelligence: Focusing on machine learning, neural networks, and intelligent systems.
- Data Analytics: Emphasizing data mining, big data technologies, and statistical analysis.
- Image Processing: Covering sensor networks, IoT architectures, and applications.

1.3.4. Learning Outcomes

Graduates of the program will:

- Demonstrate advanced knowledge in specialized areas of computer science and engineering.
- Exhibit proficiency in research methodologies, contributing to technological advancements.
- Apply interdisciplinary approaches to solve complex engineering problems.

- Possess the skills and knowledge required for successful careers in academia, industry, or entrepreneurship.

By integrating the principles of the National Credit Framework, The Assam Royal Global University's M. Tech (CSE) program ensures a comprehensive, flexible, and industry-relevant education, preparing students to excel in the dynamic field of computer science and engineering.

1.4. Vision

To offer globally integrated opportunities in the domain of computer science and engineering, fostering the development of students as global citizens with the skills and perspectives needed to thrive in an interconnected world.

1.5. Mission

- To achieve academic excellence in computer science education through dynamic curriculum, research-driven initiatives, and industry-aligned programs.
- To instil ethical values and a spirit of community service
- To give back responsible leaders equipped to drive positive change and innovation in the global technological landscape.

1.6. Credits in Indian Context

1.6.1. Choice Based Credit System (CBCS)

Under the CBCS system, the requirement for awarding a degree or diploma or certificate is prescribed in terms of the number of credits to be earned by the students. This framework is being implemented in several universities across States in India. The main highlights of CBCS are as below:

- The CBCS provides flexibility in designing curriculum and assigning credits based on the course content and learning hours.
- The CBCS provides for a system wherein students can take courses of their choice, learn at their own pace, undergo additional courses and acquire more than the required credits, and adopt an interdisciplinary approach to learning.
- CBCS also provides opportunity for vertical mobility to students from a bachelor's degree programme to masters and research degree programmes.

1.6.2. Academic Credit

An academic credit is a unit by which a course is weighted. It is fixed by the number of hours of instructions offered per week. As per the National Credit Framework:

1 Credit = 30 NOTIONAL CREDIT HOURS (NCH)

Yearly Learning Hours = 1200 Notional Hours (@40 Credits x 30 NCH)

30 Notional Credit Hours		
Lecture/Tutorial	**Practicum**	**Experiential Learning**
1 Credit = 15 -22 Lecture Hours	10-15 Practicum Hours	0-8 Experiential Learning Hours

1 Hr. Lecture (L) per week 1 credit	1 credit
1 Hr. Tutorial (T) per week	1 credit
1 Hr. Practical (P) per week	0.5 credits
2 Hours Practical (Lab) per week	1 credit

1.6.3. Course of Study

Couse of study indicate pursuance of study in a particular discipline/programme. Discipline/Programmes shall offer Professional Core Courses, Professional Elective Courses relevant to chosen specialization, Project Dissertation and Summer Training/ Internship.

1.6.3.1. Disciplinary Major/ Professional Core Courses

Professional core courses in M. Tech. programs are those that directly relate to the specific field of engineering in which a student is majoring. These courses delve deep into the foundational principles, theories, and practical applications of the chosen engineering discipline. These courses focus on the specific areas of specialization. Many professional core courses include laboratory work and design projects to provide students with hands-on experience and practical skills. In laboratory sessions, students may conduct experiments to reinforce theoretical concepts and develop their technical skills. Design projects challenge students to apply their knowledge to solve real-world engineering problems and to work collaboratively in teams.

1.6.3.2. *Disciplinary Minor/ Professional Elective Courses*

These subjects are offered to offer students the opportunity to tailor their education to align with their interests, career goals, and emerging industry trends within their chosen engineering discipline. These courses allow students to delve deeper into specific areas of specialization or to explore interdisciplinary topics that complement their core engineering curriculum. By offering a range of professional elective courses, students are empowered to customize their education according to their individual interests and career aspirations. These elective courses complement the core engineering curriculum and enable students to develop specialized expertise, practical skills, and professional competencies that enhance their competitiveness in the job market and prepare them for future leadership roles in their field.

1.6.3.3. *Summer Internship*

Students need to undergo minimum 1 month of mandatory internship during their course of study which is a total of 2 credits and will be evaluated towards the end of 3rd semester. The students can undergo 1 month internship during their semester break. The intention is induction into actual work situations. All students must undergo internships / Apprenticeships in a firm, industry, or organization or Training in labs with faculty and researchers in their own or other HEIs/research institutions during the summer/winter term. Students should take up opportunities for internships with local industry, business organizations, health and allied areas, local governments (such as panchayats, municipalities), Parliament or elected representatives, media organizations, artists, crafts persons, and a wide variety of organizations so that students may actively engage with the practical side of their learning and, as a by-product, further improve their employability. Students who wish to exit after the first two semesters will undergo a 4-credit work-based learning/internship during the summer term to get a UG Certificate.

- *Community engagement and service:* The curricular component of 'community engagement and service' seeks to expose students to the socio-economic issues in society so that the theoretical learnings can be supplemented by actual life experiences to generate solutions to real-life problems. This can be part of summer term activity or part of a major or minor course depending upon the major discipline.
- *Field-based learning/minor project:* The field-based learning/minor project will attempt to provide opportunities for students to understand the different socio-economic contexts. It will aim at giving students exposure to development-related issues in rural and urban settings. It will provide opportunities for students to observe situations in rural and urban contexts, and to observe and study actual field situations regarding issues related to

socioeconomic development. Students will be given opportunities to gain a first-hand understanding of the policies, regulations, organizational structures, processes, and programmes that guide the development process. They would have the opportunity to gain an understanding of the complex socio-economic problems in the community, and innovative practices required to generate solutions to the identified problems. This may be a summer term project or part of a major or minor course depending on the subject of study.

1.6.3.4. Experiential Learning

One of the most unique, practical & beneficial features of the National Credit Framework is assignment of credits/credit points/ weightage to the experiential learning including relevant experience and professional levels acquired/ proficiency/ professional levels of a learner/student. Experiential learning is of two types:

a. Experiential learning as part of the curricular structure of academic or vocational program. E.g., projects/OJT/internship/industrial attachments etc. This could be either within the Program- internship/ summer project undertaken relevant to the program being studied or as a part time employment (not relevant to the program being studied- up to certain NSQF level only). In case where experiential learning is a part of the curricular structure the credits would be calculated and assigned as per basic principles of NCrF i.e., 40 credits for 1200 hours of notional learning.

b. Experiential learning as active employment (both wage and self) post completion of an academic or vocational program. This means that the experience attained by a person after undergoing a particular educational program shall be considered for assignment of credits. This could be either Full or Part time employment after undertaking an academic/ Vocation program.

In case where experiential learning is as a part of employment the learner would earn credits as weightage. The maximum credit points earned in this case shall be double of the credit points earned with respect to the qualification/ course completed. The credit earned and assigned by virtue of relevant experience would enable learners to progress in their career through the work hours put in during a job/employment.

Section 2

Award of Degree

The structure and duration of Postgraduate programmes of study offered by the University as per NEP 2020 include:

2.1. Postgraduate programmes of 4-year duration with Single Major, with multiple entry and exit options, with appropriate certifications:

2.1.1. PG Diploma: Students who opt to exit after completion of the first year and have secured 40 credits will be awarded a PG Diploma certificate if, in addition, they complete one vocational course of 4 credits during the summer vacation of the first year.

2.1.2. M. Tech.: A Master of Technology (M. Tech.) degree in the major discipline will be awarded to those who complete a two-year degree programme with 80 credits and have satisfied the credit requirements along with a mention of the specialised domain like M. Tech-CSE in Artificial Intelligence, etc.

Section 3

Credit, Credit Points & Credit hours for different types of courses

3.1. Introduction:

'Credit' is recognition that a learner has completed a prior course of learning, corresponding to a qualification at a given level. For each such prior qualification, the student would have put in a certain volume of institutional or workplace learning, and the more complex a qualification, the greater the volume of learning that would have gone into it. Credits quantify learning outcomes that are subject achieving the prescribed learning outcomes to valid, reliable methods of assessment.

The ***credit points*** will give the learners, employers, and institutions a mechanism for describing and comparing the learning outcomes achieved. The credit points can be calculated as credits attained multiplied with the credit level.

The workload relating to a course is measured in terms of credit hours. A credit is a unit by which the coursework is measured. It determines the number of hours of instruction required per week over the duration of a semester (minimum 15 weeks).

Each course may have only a lecture component or a lecture and tutorial component or a lecture and practicum component or a lecture, tutorial, and practicum component, or only practicum component.

A course can have a combination of ***lecture credits, tutorial credits, practicum credits and experiential learning credits.*** The following types of courses/activities constitute the programmes of study. Each of them will require a specific number of hours of teaching/guidance and laboratory/studio/workshop activities, field-based learning/projects, internships, and community engagement and service.

- **Lecture courses:** Courses involving lectures relating to a field or discipline by an expert or qualified personnel in a field of learning, work/vocation, or professional practice.
- **Tutorial courses:** Courses involving problem-solving and discussions relating to a field or discipline under the guidance of qualified personnel in a field of learning, work/vocation, or professional practice. Should also refer to the Remedial Classes, flip classrooms and focus on both Slow and Fast Learners of the class according to their merit.

- **Practicum or Laboratory work:** A course requiring students to participate in a project or practical or lab activity that applies previously learned/studied principles/theory related to the chosen field of learning, work/vocation, or professional practice under the supervision of an expert or qualified individual in the field of learning, work/vocation or professional practice.
- **Internship:** A course requiring students to participate in a professional activity or work experience, or cooperative education activity with an entity external to the education institution, normally under the supervision of an expert of the given external entity. A key aspect of the internship is induction into actual work situations. Internships involve working with local industry, government or private organizations, business organizations, artists, crafts persons, and similar entities to provide opportunities for students to actively engage in on-site experiential learning.
- **Field practice/projects:** Courses requiring students to participate in field-based learning/projects generally under the supervision of an expert of the given external entity.

Table:2: Course wise Distribution of Credits

Sl. No	***Category***	***Abbreviation***	***Credit Breakup***
1	Professional core courses	PCC	35
2	Professional Elective courses relevant to chosen specialization/branch	PEC	19
3	Project work, seminar and internship in industry or elsewhere	PROJ	26
		Total	**80**

Section 4

Level of Courses

4.1 NHEQF levels:

The NHEQF levels represent a series of sequential stages expressed in terms of a range of learning outcomes against which typical qualifications are positioned/located. Postgraduate programmes fall between Level 6.5 and Level 7, as outlined in the NHEQF. The framework ensures that PG students acquire both depth in their subject knowledge and the ability to apply their learning to complex, real-world challenges.

Table: 4.1: NHEQF Levels

NHEQF level	Examples of higher education qualifications located within each level	Credit Requirements
Level 4.5	Undergraduate Certificate. Programme duration: First year (first two semesters) of the undergraduate programme, followed by an exit 4-credit skills-enhancement course(s).	40
Level 5	Undergraduate Diploma. Programme duration: First two years (first four semesters) of the undergraduate programme, followed by an exit 4-credit skills-enhancement course(s) lasting two months.	80
Level 5.5	Bachelor's Degree. Programme duration: First three years (Six semesters) of the four-year undergraduate programme.	120
Level 6	Bachelor's Degree (Honours/ Honours with Research). Programme duration: Four years (eight semesters).	160
Level 6	Post-Graduate Diploma. Programme duration: One year (two semesters) for those who exit after successful completion of the first year (two semesters) of the 2-year master's programme	160
Level 6.5	Master's degree. Programme duration: Two years (four semesters) after obtaining a 3- year Bachelor's degree (e.g. B.A., B.Sc., B.Com. etc.).	80
Level 6.5	Master's degree. Programme duration: One year (two semesters) after obtaining a 4 -year Bachelor's degree (Honours/ Honours with Research) (e.g. B.A., B.Sc., B.Com. etc.).	40
Level 7	Master's degree. (e.g., M.E./M.Tech. etc.) Programme duration: Two years (four semesters) after obtaining a 4-year Bachelor's degree. (e.g., B.E./B.Tech. etc.)	80
Level 8	Doctoral Degree	Credits for course work, Thesis, and published work

Section 5

Graduate Attributes & Learning Outcomes

5.1 Introduction

As per the NHEQF, each student on completion of a programme of study must possess and demonstrate the expected ***Graduate Attributes*** acquired through one or more modes of learning, including direct in-person or face-to-face instruction, online learning, and hybrid/blended modes. The graduate attributes indicate the quality and features or characteristics of the graduate of a programme of study, including learning outcomes relating to the disciplinary area(s) relating to the chosen field(s) of learning and generic learning outcomes that are expected to be acquired by a graduate on completion of the programme(s) of study.

5.2 Graduate Attributes

Qualifications that signify completion of the postgraduate degree are awarded to students who:

- **GA1:** have demonstrated knowledge and understanding that is founded upon and extends and/or enhances that typically associated with the first cycle, and that provides a basis or opportunity for originality in developing and/or applying ideas, often within research context.
- **GA2:** can apply their knowledge and understanding, and problem-solving abilities in new or unfamiliar environments within broader (or multidisciplinary) contexts related to their field of study.
- **GA3:** have the ability to integrate knowledge and handle complexity, and formulate judgments with incomplete or limited information, but that include reflecting on social and ethical responsibilities linked to the application of their knowledge and judgments.
- **GA4:** can communicate their conclusions, and the knowledge and rationale underpinning these, to specialist and non-specialist audiences clearly and unambiguously.
- **GA5:** have the learning skills to allow them to continue to study in a manner that may be largely self-directed or autonomous.

The PG degree (e.g. M.E./M.Tech. etc.) is awarded to students who have demonstrated the achievement of the outcomes located at level 7 on the NHEQF. Table 5.2 are the descriptors for qualifications at levels 7 on the NHEQF.

Table 5.1

Element of the descriptor	**NHEQF level descriptors** *The graduates should be able to demonstrate the acquisition of:*
Knowledge and understanding	• advanced knowledge about a specialized field of enquiry with a critical understanding of the emerging developments and issues relating to one or more fields of learning, • advanced knowledge and understanding of the research principles, methods, and techniques applicable to the chosen field(s) of learning or professional practice, • procedural knowledge required for performing and accomplishing complex and specialized and professional tasks relating to teaching, and research and development.
General, technical and professional skills required to perform and accomplish tasks	• advanced cognitive and technical skills required for performing and accomplishing complex tasks related to the chosen fields of learning. • advanced cognitive and technical skills required for evaluating research findings and designing and conducting relevant research that contributes to the generation of new knowledge. • specialized cognitive and technical skills relating to a body of knowledge and practice to analyse and synthesize complex information and problems.
Application of knowledge and skills	• apply the acquired advanced theoretical and/or technical knowledge about a specialized field of enquiry or professional practice and a range of cognitive and practical skills to identify and analyse problems and issues, including real-life problems, associated with the chosen fields of learning. • apply advanced knowledge relating to research methods to carry • out research and investigations to formulate evidence-based solutions to complex and unpredictable problems.
	Effective Communication and Presentation • Analyse texts and research papers critically and present complex information clearly and concisely to diverse audiences. • Communicate technical information, research findings, and their applications in a structured and concise manner, considering emerging developments and issues.

Generic learning outcomes	**Critical Thinking and Analytical Skills** • Evaluate the reliability and relevance of evidence, identify flaws in arguments, and synthesize data from multiple sources. • Draw valid conclusions supported by evidence while addressing opposing viewpoints. **Research Design and Execution** • Define problems, formulate research questions and hypotheses, and use quantitative and qualitative data to test and establish hypotheses. • Develop appropriate tools for data collection and apply statistical and analytical techniques for data interpretation. • Plan, execute, and report research findings while adhering to ethical standards. **Self-Directed Learning and Professional Growth** • Meet personal learning needs in chosen fields of study or practice through self-paced and self-directed learning. • Upgrade knowledge and research-related skills to pursue advanced education and contribute to professional practice. • **Problem-Solving and Decision-Making** • Generate solutions to real-world problems through informed judgments and decision-making based on analysis and empirical evidence. • Take responsibility and accountability for individual and group actions in addressing challenges within the chosen field or profession. Application and Synthesis • Synthesize and articulate issues, design research proposals, and explore the relevance and implications of findings in professional and academic contexts. • Predict cause-and-effect relationships and make strategic decisions to address challenges in a multidisciplinary environment.

Constitutional, humanistic, ethical, and moral values	• embrace and practice constitutional, humanistic, ethical, and moral values in one's life, • adopt objective and unbiased actions in all aspects of work related to the chosen fields/subfields of study and professional practice, • participate in actions to address environmental protection and sustainable development issues, • support relevant ethical and moral issues by formulating and presenting coherent arguments, • follow ethical principles and practices in all aspects of research and development, including inducements for enrolling participants, avoiding unethical practices such as fabrication, falsification or misrepresentation of data or committing plagiarism.
Employability & job-ready skills, entrepreneurship skills and capabilities/qualities and mindset	• adapting to the future of work and responding to the demands of the fast pace of technological developments and innovations that drive shift in employers' demands for skills, particularly with respect to the transition towards more technology-assisted work involving the creation of new forms of work and rapidly changing work and production processes. • exercising full personal responsibility for the output of own work 1. as well as for group/team outputs and for managing work that are complex and unpredictable requiring new strategic approaches.

5.3 Programme Learning Outcomes (PLO)

The term 'programme' refers to the entire scheme of study followed by learners leading to a qualification. Individual programmes of study will have defined learning outcomes that must be attained for the award of a specific certificate/diploma/degree. Programme Learning Outcomes describe what students are expected to know or be able to do by the time of graduation. PLOs are statements about the knowledge, skills and attitudes (attributes) the graduate of a formal engineering program should have. PLOs deal with the general aspect of graduation for a particular program, and the competencies and expertise a graduate will possess after completion of the program. Apply the knowledge of mathematics and computing fundamentals to various real-life applications for any given requirement. Design and develop applications to analyse and solve all computer science related problems. This is accomplished through the following learning goals and objectives:

- **PO1- Knowledge of mathematics and computing fundamentals:** Apply the knowledge of mathematics and computing fundamentals to various real-life applications for any given requirement.
- **PO2- Design and develop applications:** Design and develop applications to analyse and solve all computer science related problems.
- **PO3- Effective Communication:** Students will use various forms of business communication, supported by effective use of appropriate technology, logical reasoning, and articulation of ideas. Graduates are expected to develop effective oral and written communication especially in business applications, with the use of appropriate technology (business presentations, digital communication, social network platforms and so on).
- **PO4- Leadership and Teamwork:** Students will acquire skills to demonstrate leadership roles at various levels of the organization and leading teams. Graduates are expected to collaborate and lead teams across organizational boundaries and demonstrate leadership qualities, maximize the usage of diverse skills of team members in the related context.
- **PO5- Global Exposure and Cross-Cultural Understanding:** Graduate will be able to demonstrate a global outlook with the ability to identify aspects of the global business and Cross -Cultural Understanding.
- **PO6- Integrate and apply efficient tools.** Integrate and apply efficiently the contemporary IT tools to all computer applications.
- **PO7- Designing innovative methodologies:** Create and design innovative methodologies to solve complex problems for the betterment of society.
- **PO8- Applying inherent skills:** Apply the inherent skills with absolute focus to function as a successful entrepreneur.
- **PO9- Social Responsiveness and Ethics:** Students will demonstrate responsiveness to contextual social issues/ problems and exploring solutions, understanding ethics, and resolving ethical dilemmas. Demonstrate awareness of ethical issues and can distinguish ethical and unethical behaviour.

5.4 Programme Educational Objectives (PEOs)

The Programme Educational Objectives (PEOs) are defined and developed for each program with the consultation and involvement of various stakeholders such as management, students, industry, regulating authorities, alumni, faculty and parents. Their interests, social relevance and contributions are taken in to account in defining and developing the PEOs. The Program Educational Objectives (PEOs) of the Computer Science and Engineering are listed below:

- **PEO1**: Independently design and develop computer software systems and products based on sound theoretical principles and appropriate software development skills.
- **PEO2**: Demonstrate knowledge of technological advances through active participation in life-long learning.
- **PEO3**: Accept to take up responsibilities upon employment in the areas of teaching, research, and software development
- **PEO4**: Exhibit technical communication, collaboration and mentoring skills and assume roles both as team members and as team leaders in an organization.

5.5 Programme Specific Outcomes (PSOs)

- **PSO1:** Analyze and understand the need of research and development, Intellectual property rights, patents and plagiarism checking tools.
- **PSO2:** Ability to understand the need of human values and professional ethics while publishing research papers, writing and developing research projects, research grants, books and dissertations.
- **PSO3:** Pursue a career in software development, entrepreneurship, database administration, network and cyber security, artificial intelligence, machine learning, higher studies, teaching or quality testing using available CASE tools.

5.6 The Qualification Specifications

The levels of PG programmes as per the NHEQF are summarized in Table 5.2

Table 5.2:

Level	Credits	Qualification	Credit Requirement Per year	Credit Points	Total Notional Learning hours
6	160	1 – yr P.G. Diploma	40	240	1200
6.5	160	1-Year PG after a 4-year UG	40	260	1200
6.5	120	2-Year PG after a 3-year UG	40	260	1200
7	160	2-Year PG after a 4-year UG such as B.E., B. Tech. etc	40	280	1200

5.7 Credit Distribution for 2-year PG

Table: 5.3

<table>
<tr><th colspan="2" rowspan="2">Curricular Components</th><th colspan="4">PG Programme (one year) for 4-yr UG (Hons. /Hons. with Research)
Minimum Credits</th></tr>
<tr><th>Course Level</th><th>Coursework</th><th>Research thesis/project /Patent</th><th>Total Credits</th></tr>
<tr><td colspan="2">PG Diploma</td><td>400</td><td>40</td><td>--</td><td>40</td></tr>
<tr><td colspan="2">1st Year
(1st & 2nd Semester)</td><td>400
500</td><td>24
16</td><td>--</td><td>40</td></tr>
<tr><td colspan="6">Students who exit at the end of 1st year shall be awarded a Postgraduate Diploma</td></tr>
<tr><td rowspan="3">2nd Year (3rd & 4th Semester)</td><td>Coursework & Research</td><td>500</td><td>20</td><td>20</td><td>40</td></tr>
<tr><td>Coursework (or)</td><td>500</td><td>40</td><td>--</td><td>40</td></tr>
<tr><td>Research</td><td></td><td></td><td>40</td><td>40</td></tr>
</table>

- ***<u>Exit Point:</u> For those who join 2-year PG programmes, there shall only be one exit point. Students who exit at the end of 1st year shall be awarded a Postgraduate Diploma.***

5.7 Course Levels

- **400-499:** Advanced courses which would include lecture courses with practicum, seminar-based course, term papers, research methodology, advanced laboratory experiments/software training, research projects, hands-on-training, internship/apprenticeship projects at the undergraduate level or First year Postgraduate theoretical and practical courses

- **500-599:** For students who have graduated with a 4-year bachelor's degree. It provides an opportunity for original study or investigation in the major or field of specialization, on an individual and more autonomous basis at the postgraduate level.

Course Structure and Syllabus of the Framework

6.1 Course Structure of M. Tech.

1st semester							
S.N	**Subject Code**	**Names of subjects**	**L**	**T**	**P**	**C**	**TCP**
Programme Specific Core Courses (PSC)							
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
Programme Specific Elective Courses (PSE)							
7	CSE024D10X	PEC-I	4	0	0	4	4
8	CSE024D11X	PEC-I Lab	0	0	2	1	2
		TOTAL	**16**	**0**	**8**	**20**	**24**
2nd semester							
S.N	**Subject Code**	**Names of subjects**	**L**	**T**	**P**	**C**	**TCP**
Programme Specific Core Courses (PSC)							
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
Programme Specific Elective Courses (PSE)							
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
		TOTAL	**16**	**0**	**8**	**20**	**24**
Exit Option after 1st Year: PG Diploma in Computer Application/ Information Technology/ Cohort Course Additional Credits to be acquired: 4 (Internship/Apprenticeship)							
3rd semester							
S.N	**Subject Code**	**Names of subjects**	**L**	**T**	**P**	**C**	**TCP**
Programme Specific Core Courses (PSC)							
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
Programme Specific Elective Courses (PSE)							
5	CSE024D30X	PEC-IV	4	0	0	4	4
6	CSE024D31X	PEC-IV Lab	0	0	2	1	2
Summer Training/ Internship							

7	CSE024C324	Summer Training/ Internship	0	0	0	2	0
Project							
8	CSE024C325	Dissertation-I	0	0	16	8	16
		TOTAL	**7**	**0**	**22**	**24**	**33**
4th semester							
S.N	**Subject Code**	**Names of subjects**	**L**	**T**	**P**	**C**	**TCP**
Project							
1	CSE024C421	Dissertation-II	0	0	32	16	32
		TOTAL	**0**	**0**	**32**	**16**	**32**

SEMESTER	TOTAL CREDITS
I	**20**
II	**20**
III	**24**
IV	**16**
TOTAL	**80**

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

DSE Tracks	Subject Name
Track 1: Artificial Intelligence	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)
Track 2: Data Analytics	Minor 1: Data Mining (CSE024D102)
	Minor 2: Statistical Computing (CSE024D203)
	Minor 3: Big Data Analytics (CSE024D204)
	Minor 4: Cloud Computing for Big Data (CSE024D302)
Track 3: Image Processing/ Computer Vision	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)

6.2 Detailed Syllabus of 1st Semester

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

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

Detailed Syllabus:

Modules	Topics	Course Contents	Hours
I.	**Fundamentals of Internet Protocols and Addressing**	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.	**Routing Protocols and Network Layer Design**	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.	**Advanced Network Architectures and Internet Technologies**	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**

IV	**Security in Internet Protocols and Network Design Considerations**	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	**12**
		TOTAL	**48**

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

Reference Books:

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

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

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	**Understand** number theory in cryptographic algorithms.	**BT 2**
CO 2	**Apply** set theory, logic, and proof techniques in computing problems	**BT 3**
CO 3	**Analyze** and **evaluate** probabilistic models in computing, machine learning, and cryptography.	**BT 4 & 5**
CO 4	**Solve** problems related to formal languages, automata, and computational complexity.	**BT 6**

Detailed Syllabus:

Modules	Topics	Course Contents	Hours
I.	**Logic, Set Theory**	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.	**Combinatorics, Graph Theory & Number Theory**	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.	**Probability, Statistics and Randomized Algorithms**	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	**Formal Languages, Automata, and Computational Complexity**	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**
		TOTAL	**48**

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, 7th Edition, 2017, McGraw-Hill
2. *Introduction to Algorithms,* Cormen, Leiserson, Rivest, & Stein (CLRS), 3rd Edition, 2009, MIT Press
3. *Introduction to Automata Theory, Languages, and Computation,* John E. Hopcroft, Rajeev Motwani, Jeffrey D. Ullman, 3rd Edition, 2008, Pearson

Reference Books:

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

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

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

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

Detailed Syllabus:

Modules	Topic	Course Content	Hours
I.	**Introduction**	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	**12**
II.	**Process Synchronization, Scheduling and Resource Management**	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	**12**
III.	**Distributed File System & Memory Management**	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	**12**

IV.	**Fault Tolerance, Security and Advanced Topics**	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**
		TOTAL	**48**

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, 2nd Edition, 2016, Pearson
2. *Advanced Concepts in Operating Systems,* Mukesh Singhal & Niranjan G. Shivaratri, 2017, McGraw-Hill
3. *Distributed Operating Systems: Concepts and Design*, Pradeep K. Sinha, 1st 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,* 5th Edition, 2017, Pearson Education

Paper IV/Subject Name: Internet Protocols and Network Design Lab		**Subject Code: CSE024C111**
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 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	**Demonstrate** knowledge of Internet Protocols and their layered architecture.	**BT 2**
CO 2	**Implement** IP addressing schemes and subnetting for efficient network design.	**BT 3**
CO 3	**Analyze and evaluate** various routing protocols (RIP, OSPF, BGP, etc.).	**BT 4 & 5**
CO 4	**Design** scalable, high-performance networks for cloud and IoT applications.	**BT 6**

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.

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

Reference Books:

1. Larry L. Peterson and Bruce S. Davie, *Computer Networks: A System Approach,* 5th Edition, 2012, Morgan Kaufmann, Elsevier, 2012.
2. Behrouz A. Forouzan, *Data Communications and Networking,* 5th 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	**Understand** number theory in cryptographic algorithms.	**BT 2**
CO 2	**Apply** set theory, logic, and proof techniques in computing problems	**BT 3**
CO 3	**Analyze** and **evaluate** probabilistic models in computing, machine learning, and cryptography.	**BT 4 & 5**
CO 4	**Solve** problems related to formal languages, automata, and computational complexity.	**BT 6**

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, 7th Edition, 2017, McGraw-Hill
2. *Introduction to Algorithms,* Cormen, Leiserson, Rivest, & Stein (CLRS), 3rd Edition, 2009, MIT Press
3. *Introduction to Automata Theory, Languages, and Computation,* John E. Hopcroft, Rajeev Motwani, Jeffrey D. Ullman, 3rd Edition, 2008, Pearson

Reference Books:

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

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

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

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

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.

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. *Distributed Systems: Principles and Paradigms,* Andrew S. Tanenbaum & Maarten Van Steen, 2nd Edition, 2016, Pearson
2. *Advanced Concepts in Operating Systems,* Mukesh Singhal & Niranjan G. Shivaratri, 2017, McGraw-Hill
3. *Distributed Operating Systems: Concepts and Design*, Pradeep K. Sinha, 1st 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,* 5th Edition, 2017, Pearson Education

Paper VII/Subject Name: Foundations of AI (PEC-I)		**Subject Code: CSE024D101**
Paper Type: PEC-I		**Specialization: Artificial Intelligence**
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 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	**Explain** fundamental concepts, applications, and ethical implications of AI.	**BT 2**
CO 2	**Apply** uninformed and informed search algorithms to solve AI problems	**BT 3**
CO 3	**Analyze** and implement knowledge representation techniques, including logic-based and probabilistic reasoning	**BT 4**
CO 4	**Assess** and **design** AI-based solutions using reasoning, decision-making, and planning techniques	**BT 5 & 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods

I.	**Introduction**	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)	**12**
II.	**Knowledge Representation & Reasoning**	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	**12**
III.	**Planning in AI**	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	**12**
IV	**AI Applications**	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	**12**
TOTAL			**48**

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. *Artificial Intelligence: A Modern Approach,* Stuart Russell & Peter Norvig, 4th Edition, 2020, PHI
2. *Artificial Intelligence,* Elaine Rich, Kevin Knight, Shivashankar B. Nair, 3rd 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	**Explain** fundamental concepts, applications, and ethical implications of AI.	**BT 2**
CO 2	**Apply** uninformed and informed search algorithms to solve AI problems	**BT 3**
CO 3	**Analyze** and implement knowledge representation techniques, including logic-based and probabilistic reasoning	**BT 4**
CO 4	**Assess** and **design** AI-based solutions using reasoning, decision-making, and planning techniques	**BT 5 & 6**

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, 4th Edition, 2020, PHI
2. *Artificial Intelligence,* Elaine Rich, Kevin Knight, Shivashankar B. Nair, 3rd Edition, 2017, Tata McGraw Hill

Reference Books:

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

Paper VII/Subject Name: Data Mining		**Subject Code: CSE024D102**
Paper Type: PEC-I		**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 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	**Explain** the fundamentals of data mining, preprocessing techniques, and data warehousing.	**BT 2**
CO 2	**Apply** classification, clustering, and association rule mining techniques to real-world datasets.	**BT 3**
CO 3	**Analyze** data mining models and **evaluate** their effectiveness using appropriate performance metrics.	**BT 4 & 5**
CO 4	**Develop** and optimize machine learning models for predictive data mining applications	**BT 6**

Detailed Syllabus:

Module	**Topics**	**Course Content**	**Periods**
I.	**Introduction**	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.	**Classification and Association Rule Mining**	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.	**Clustering and Anomaly Detection**	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	**Advanced Topics**	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**
TOTAL			**48**

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, 3rd Edition, 2011, Morgan Kaufmann
2. *Introduction to Data Mining,* Pang-Ning Tan, Michael Steinbach, Vipin Kumar, 1srt Edition, 2016, Pearson

Reference Books:

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

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

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	**Explain** the fundamentals of data mining, preprocessing techniques, and data warehousing.	**BT 2**
CO 2	**Apply** classification, clustering, and association rule mining techniques to real-world datasets.	**BT 3**
CO 3	**Analyze** data mining models and **evaluate** their effectiveness using appropriate performance metrics.	**BT 4 & 5**
CO 4	**Develop** and optimize machine learning models for predictive data mining applications	**BT 6**

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, 3rd Edition, 2011, Morgan Kaufmann
2. *Introduction to Data Mining,* Pang-Ning Tan, Michael Steinbach, Vipin Kumar, 1srt Edition, 2016, Pearson

Reference Books:

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

Paper VII/Subject Name: Digital Image Processing		**Subject Code: CSE024D103**
Paper Type: PEC-I		**Specialization: Image Processing**
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 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	**Explain** the fundamentals of data mining, preprocessing techniques, and data warehousing.	**BT 2**
CO 2	**Apply** classification, clustering, and association rule mining techniques to real-world datasets.	**BT 3**
CO 3	**Analyze** data mining models and **evaluate** their effectiveness using appropriate performance metrics.	**BT 4 & 5**
CO 4	**Develop** and optimize machine learning models for predictive data mining applications	**BT 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	**Introduction**	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	**12**
II.	**Image Enhancement and Restoration**	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	**12**
III.	**Segmentation, Feature Extraction and Object**	Thresholding-Based Segmentation, Global vs. Adaptive Thresholding, Otsu's Method, Watershed Algorithm, Region-Based Segmentation, Region Growing and Region Splitting & Merging, K-	**12**

	Recognition	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	
IV	**Image Compression, Wavelets and Advanced Applications**	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	**12**
TOTAL			**48**

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

Reference Books:

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

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

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	**Explain** the fundamentals of data mining, preprocessing techniques, and data warehousing.	**BT 2**
CO 2	**Apply** classification, clustering, and association rule mining techniques to real-world datasets.	**BT 3**
CO 3	**Analyze** data mining models and **evaluate** their effectiveness using appropriate performance metrics.	**BT 4 & 5**
CO 4	**Develop** and optimize machine learning models for predictive data mining applications	**BT 6**

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, 4th Edition, 2018, Pearson
2. *Fundamentals of Digital Image Processing,* Anil K. Jain, 1st Edition, 2015, Pearson

Reference Books:

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

6.3 Detailed Syllabus of 2nd Semester

Paper I/Subject Name: Modern Database Systems		**Subject Code: CSE024C201**
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 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	**Understand** data security, consistency, and ACID properties in modern database architectures.	**BT 2**
CO 2	**Apply** cloud, in-memory, and multi-model databases in real-world scenarios.	**BT 3**
CO 3	**Analyze** query optimization and indexing techniques for modern databases	**BT 4**
CO 4	**Assess** and **Design** scalable and distributed database systems.	**BT 5 & 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	**Advanced Relational Databases & Query Optimization**	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.	**NoSQL, NewSQL & Distributed Databases**	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.	**Cloud Databases, Big Data & In-Memory Databases**	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**

IV.	**Advanced Topics – Graph, Time-Series, and Blockchain Databases**	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	**12**
TOTAL			**48**

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

Reference Books:

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

Paper II/Subject Name: Advanced Algorithm Designing		**Subject Code: CSE024C202**
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 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	**Demonstrate** adequate comprehension of the theory of intractability and prove when certain kinds of problems are intractable	**BT 2**
CO 2	**Apply** various problem-solving techniques and **analyze** them	**BT 3 & 4**
CO 3	**Determine** the most suitable algorithm for any given task and then apply it to the problem.	**BT 5**

CO 4	**Design** efficient algorithms for given problems	BT 6

Detailed Syllabus:

Modules	Topics	Course Contents	Hours
I	**Sorting & Graphs**	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.	12
II	**Matroids & Flow Networks**	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.	12
III	**Graph Algorithms**	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.	12
IV	**Linear Programming**	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.	12
		TOTAL	**48**

Credit Distribution		
Lecture/ Tutorial	**Practicum**	**Experiential Learning**
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, 3rd 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,* 2nd Edition, 2009, Galgotia Publications

Paper III/Subject Name: Modern Database Systems Lab		**Subject Code: CSE024C211**
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 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	**Understand** data security, consistency, and ACID properties in modern database architectures.	**BT 2**
CO 2	**Apply** cloud, in-memory, and multi-model databases in real-world scenarios.	**BT 3**
CO 3	**Analyze** query optimization and indexing techniques for modern databases	**BT 4**
CO 4	**Assess** and **Design** scalable and distributed database systems.	**BT 5 & 6**

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, 2nd Edition, 2008, Pearson
2. *Database Management Systems,* Raghu Ramakrishnan & Johannes Gehrke, 3rd McGraw-Hill
3. *Professional NoSQL,* Shashank Tiwari, 1st Edition, 2011, Wrox

Reference Books:

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

Paper IV/Subject Name: Advanced Algorithm Designing Lab		Subject Code: CSE024C212
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 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	**Demonstrate** adequate comprehension of the theory of intractability and prove when certain kinds of problems are intractable	**BT 2**
CO 2	**Apply** various problem-solving techniques and **analyze** them	**BT 3 & 4**
CO 3	**Determine** the most suitable algorithm for any given task and then apply it to the problem.	**BT 5**
CO 4	**Design** efficient algorithms for given problems	**BT 6**

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, 3rd 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,* 2nd Edition, 2009, Galgotia Publications

Paper V/Subject Name: Machine Learning and Deep Learning		**Subject Code: CSE024D201**
Paper Type: PEC-II	**Specialization: Artificial Intelligence/ Image Processing**	
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 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	**Understand** the key concepts of ML, DL, and their applications.	**BT 2**
CO 2	**Apply** ML algorithms like regression, classification, and clustering.	**BT 3**

CO 3	**Analyze** and **assess** different neural network architectures and training techniques.	**BT 4 & 5**
CO 4	**Design** and implement deep learning models for real-world applications	**BT 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	**ML Fundamentals**	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^2 Score, Logistic Regression, k-Nearest Neighbors (k-NN), Decision Trees & Random Forest, Evaluation Metrics: Confusion Matrix, Precision, Recall, F1-Score	**12**
II.	**Advanced AL Techniques**	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	**12**
III.	**Deep Learning Fundamentals**	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	**12**
IV	**Advanced DL Concepts**	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	**12**
		TOTAL	**48**

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. *Pattern Recognition and Machine Learning,* Christopher M. Bishop, 1st 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,* 2nd Edition, 1998, Bradford Books
3. Michael Nielsen, *Neural Networks and Deep Learning*, 2010

Paper VI/Subject Name: Machine Learning and Deep Learning Lab		**Subject Code: CSE024D211**
Paper Type: PEC-II		**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 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	**Understand** the key concepts of ML, DL, and their applications.	**BT 2**
CO 2	**Apply** ML algorithms like regression, classification, and clustering.	**BT 3**
CO 3	**Analyze** and **assess** different neural network architectures and training techniques.	**BT 4 & 5**
CO 4	**Design** and implement deep learning models for real-world applications	**BT 6**

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, 1st 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,* 2nd Edition, 1998, Bradford Books
3. Michael Nielsen, *Neural Networks and Deep Learning*, 2010

Paper VII/Subject Name: Natural Language Processing		**Subject Code: CSE024D202**
Paper Type: PEC-III		**Specialisation: Artificial Intelligence**
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 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	**Understand** fundamental NLP concepts, text processing techniques, and linguistic properties.	**BT 2**
CO 2	**Apply** traditional ML algorithms for text classification, sentiment analysis, and topic modeling.	**BT 3**
CO 3	**Analyze** and **assess** deep learning models for NLP tasks, including transformers and attention mechanisms.	**BT 4 & 5**
CO 4	**Design** and implement NLP applications such as chatbots, summarization, and text generation.	**BT 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods

I.	**Introduction**	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.	**Classical NLP Techniques and Language Modelling**	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.	**Deep Learning for NLP**	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	**Advanced NLP Applications**	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**
		TOTAL	**48**

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

Reference Books:

1. Nitin Indurkhya & Fred J. Damerau, *Handbook of Natural Language Processing*, 2nd Edition, 2010, Taylor & Francis

Paper VIII/Subject Name: Natural Language Processing Lab		**Subject Code: CSE024D212**
Paper Type: PEC-III		**Specialisation: 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 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	**Understand** fundamental NLP concepts, text processing techniques, and linguistic properties.	**BT 2**
CO 2	**Apply** traditional ML algorithms for text classification, sentiment analysis, and topic modeling.	**BT 3**
CO 3	**Analyze** and **assess** deep learning models for NLP tasks, including transformers and attention mechanisms.	**BT 4 & 5**
CO 4	**Design** and implement NLP applications such as chatbots, summarization, and text generation.	**BT 6**

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, 2nd Edition, 2008, Pearson
2. *Natural Language Processing with Python,* Steven Bird, Ewan Klein, Edward Loper, 1st Edition, 2009, O'Reily
3. *Deep Learning for Natural Language Processing,* Palash Goyal, Sumit Pandey, Karan Jain, 1sr Edition, 2018, Apress

Reference Books:

1. Nitin Indurkhya & Fred J. Damerau, *Handbook of Natural Language Processing*, 2nd Edition, 2010, Taylor & Francis

Paper V/Subject Name: Statistical Computing		**Subject Code: CSE024D203**
Paper Type: PEC-II		**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 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	**Understand** fundamental concepts of statistical computing and probability distributions.	**BT 2**
CO 2	**Apply** statistical inference, hypothesis testing, and regression techniques.	**BT 3**
CO 3	**Analyze** and **assess** multivariate data and use Bayesian inference methods	**BT 4 & 5**
CO 4	**Develop** statistical models using high-performance computing techniques.	**BT 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods

I.	**Fundamental Concepts**	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.	**Statistical Inference and Regression Analysis**	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.	**Multivariate Analysis and Bayesian Computing**	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	**High Performance Statistical Computing and Applications**	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**
		TOTAL	**48**

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

Reference Books:

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

Paper VI/Subject Name: Statistical Computing Lab		**Subject Code: CSE024D213**
Paper Type: PEC-II		**Specialization: Data Analytics**
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 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	**Understand** fundamental concepts of statistical computing and probability distributions.	**BT 2**
CO 2	**Apply** statistical inference, hypothesis testing, and regression techniques.	**BT 3**
CO 3	**Analyze** and **assess** multivariate data and use Bayesian inference methods	**BT 4 & 5**
CO 4	**Develop** statistical models using high-performance computing techniques.	**BT 6**

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, 2nd Edition, 2009, Springer
2. *Statistical Computing with R,* Maria L. Rizzo, 2nd Edition, 2019, Chapman and Hall
3. *Bayesian Data Analysis,* Andrew Gelman, John B. Carlin, 3rd Edition, 2019, Chapman and Hall

Reference Books:

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

Paper VII/Subject Name: Big Data Analytics		**Subject Code: CSE024D204**
Paper Type: PEC-II		**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 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	**Understand** fundamental concepts of statistical computing and probability distributions.	**BT 2**
CO 2	**Apply** statistical inference, hypothesis testing, and regression techniques.	**BT 3**
CO 3	**Analyze** and **assess** multivariate data and use Bayesian inference methods.	**BT 4 & 5**
CO 4	**Design** statistical models using high-performance computing techniques	**BT 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods

I.	**Introduction to Big Data and Storage Systems**	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.	**Hadoop & Spark**	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.	**Machine Learning & Streaming Analytics**	Machine Learning with Big Data, Challenges of Machine Learning on Big Data, Scalable ML Algorithms (Decision Trees, Clustering, Regression), Apache Spark MLlib, 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	**Cloud Based Big Data Analytics**	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**
TOTAL			**48**

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

Reference Books:

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

Paper VIII/Subject Name: Big Data Analytics Lab		**Subject Code: CSE024D214**
Paper Type: PEC-II		**Specialization: Data Analytics**
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 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	**Understand** fundamental concepts of statistical computing and probability distributions.	**BT 2**
CO 2	**Apply** statistical inference, hypothesis testing, and regression techniques.	**BT 3**
CO 3	**Analyze** and **assess** multivariate data and use Bayesian inference methods.	**BT 4 & 5**
CO 4	**Design** statistical models using high-performance computing techniques	**BT 6**

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

Reference Books:

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

Paper VII/Subject Name: Remote Sensing and GIS		**Subject Code: CSE024D206**
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 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	**Understand** the fundamentals of remote sensing and GIS.	**BT 2**
CO 2	**Process** and **interpret** satellite images for spatial analysis.	**BT 3**
CO 3	**Analyze** and **assess** GIS solutions for urban planning and disaster management.	**BT 4 & 5**
CO 4	**Design** AI/ML techniques for remote sensing image classification.	**BT 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods

I.	**Remote Sensing Fundamentals**	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.	**Image Processing and Interpretation**	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.	**Geographic Information System (GIS)**	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	**Applications**	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**
TOTAL			**48**

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

Reference Books:

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

Paper VIII/Subject Name: Remote Sensing and GIS Lab		**Subject Code: CSE024D216**
Paper Type: PEC-III		**Specialization: Data Analytics**
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 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	**Understand** the fundamentals of remote sensing and GIS.	**BT 2**
CO 2	**Process** and **interpret** satellite images for spatial analysis.	**BT 3**
CO 3	**Analyze** and **assess** GIS solutions for urban planning and disaster management.	**BT 4 & 5**
CO 4	**Design** AI/ML techniques for remote sensing image classification.	**BT 6**

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.

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

Reference Books:

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

6.4 Detailed Syllabus of 3rd Semester

Paper I/Subject Name: Soft Computing		Subject Code: CSE024C301
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 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	**Understand** the fundamentals of soft computing and its components.	**BT 2**
CO 2	**Apply** fuzzy logic principles to design decision-making systems.	**BT 3**
CO 3	**Analyze** optimization problems using genetic and evolutionary algorithms.	**BT 4**
CO 4	**Assess** and **design** hybrid models integrating multiple soft computing techniques.	**BT 5 & 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	**Introduction**	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.	**Artificial Neural Networks**	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.	**Genetic Algorithms and Evolutionary Computing**	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.	**Hybrid Soft Computing & Applications**	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**

TOTAL	48

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. S. N. Deepa, *Principles of Soft Computing,* S. N. Sivanandam, 2nd 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 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

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

Detailed Syllabus:

Modules	Topics	Course Contents	Hours

I	**Introduction**	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	**Public Key Cryptography & Key Management**	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	**Hash Functions and Authentication Protocols**	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	**Internet Security Protocols**	**SSL/TLS Protocol:** Architecture, Handshake, Certificates, Vulnerabilities, **HTTPS:** Integration with Web Servers, Secure Sessions, **IPSec:** AH, ESP, Security Associations, IKE, **SSH Protocol:** Secure Shell Architecture and Usage, **Email Security:** PGP and S/MIME, **DNS Security:** DNSSEC Basics, Web Attacks and Countermeasures: XSS, CSRF, Clickjacking	**12**
TOTAL			**48**

Credit Distribution		
Lecture/ Tutorial	**Practicum**	**Experiential Learning**
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*, 2nd Edition, 2016, Pearson
2. Bruce Schneier, *Applied Cryptography*, 20th 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	**Understand** the fundamentals of soft computing and its components.	**BT 2**
CO 2	**Apply** fuzzy logic principles to design decision-making systems.	**BT 3**
CO 3	**Analyze** optimization problems using genetic and evolutionary algorithms.	**BT 4**
CO 4	**Assess** and **design** hybrid models integrating multiple soft computing techniques.	**BT 5 & 6**

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, 2nd 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	**Demonstrate** the goals and principles of cryptographic security.	**BT 2**
CO 2	**Apply** symmetric and asymmetric encryption techniques to secure data.	**BT 3**
CO 3	**Analyze** widely used Internet security protocols like TLS, IPsec, and SSH.	**BT 4**
CO 4	**Evaluate** authentication, key exchange, and digital signature mechanisms.	**BT 5**
CO 5	**Design** and implement secure communication scenarios using cryptographic tools.	**BT 6**

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*, 2nd Edition, 2016, Pearson
2. Bruce Schneier, *Applied Cryptography*, 20th Anniversary Edition, 2017, Wiley

Paper V/Subject Name: Generative AI and LLMs		**Subject Code: CSE024D301**
Paper Type: PEC-IV		**Specialization: Artificial Intelligence**
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 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	**Understand** the theoretical foundations of generative models and LLMs.	**BT 2**
CO 2	**Implement** transformer-based generative models for text and other modalities.	**BT 3**
CO 3	**Analyze** architectures like GPT, BERT, and Diffusion Models in various domains.	**BT 4**
CO 4	**Evaluate** the performance and ethical implications of LLM-based applications.	**BT 5**
CO 5	**Design** and fine-tune generative AI solutions using open-source models.	**BT 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods

I.	**Introduction**	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.	**Transformers and Self Attention Mechanism**	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.	**LLMs**	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	**Multimodal Generative Models and Ethical Considerations**	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**
		TOTAL	**48**

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, 1st Edition, 2018, Apress

Reference Books:

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

Paper VI/Subject Name: Generative AI and LLMs Lab		**Subject Code: CSE024D311**
Paper Type: PEC-IV	**Specialization: Artificial Intelligence/ Image Processing**	
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 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	**Understand** the theoretical foundations of generative models and LLMs.	**BT 2**
CO 2	**Implement** transformer-based generative models for text and other modalities.	**BT 3**
CO 3	**Analyze** architectures like GPT, BERT, and Diffusion Models in various domains.	**BT 4**
CO 4	**Evaluate** the performance and ethical implications of LLM-based applications.	**BT 5**
CO 5	**Design** and fine-tune generative AI solutions using open-source models.	**BT 6**

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

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. *Machine Learning with PyTorch and Scikit-Learn,* Sebastian Raschka, 2022, Packt
2. *Deep Learning for Natural Language Processing,* Palash Goyal, Sumit Pandey, Karan Jain, 1st 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	**Understand** the architecture and service models of cloud computing.	**BT 2**
CO 2	**Apply** big data frameworks like Hadoop and Spark in cloud environments.	**BT 3**
CO 3	**Analyze** cloud infrastructure required for scalable big data analytics.	**BT 4**
CO 4	**Evaluate** various cloud-based data storage, processing, and visualization tools.	**BT 5**
CO 5	**Design** a cloud-native big data pipeline for real-time analytics.	**BT 6**

Detailed Syllabus:

Module	Topics	Course Content	Periods
I.	**Introduction**	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.	**Big Data Ecosystem**	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.	**Apache Spark**	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	**Applications**	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)	
TOTAL			**48**

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

Reference Books:

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

Paper VI/Subject Name: Cloud Computing for Big Data Lab		**Subject Code: CSE024D312**
Paper Type: PEC-III		**Specialization: Data Analytics**
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 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	**Understand** the architecture and service models of cloud computing.	**BT 2**
CO 2	**Apply** big data frameworks like Hadoop and Spark in cloud environments.	**BT 3**
CO 3	**Analyze** cloud infrastructure required for scalable big data analytics.	**BT 4**
CO 4	**Evaluate** various cloud-based data storage, processing, and visualization tools.	**BT 5**

CO 5	**Design** a cloud-native big data pipeline for real-time analytics.	**BT 6**

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)

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

Reference Books:

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