PONDICHERRY UNIVERSITY

(A CENTRAL UNIVERSITY)

SCHOOL OF ENGINEERING AND TECHNOLOGY

DEPARTMENT OF COMPUTER SCIENCE

M.Tech. Data Science & Artificial Intelligence

REGULATIONS, CURRICULUM & SYLLABUS

In compliance to the UGC - Curriculum and Credit Framework for PG Programmes, June 2024

(Under the National Education Policy 2020)

Effective from the Academic Year 2025 - 2026

July 2025

Board of Studies - Centre for Data science and Artificial Intelligence

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2	Dr. P. Sujatha	Professor	Members
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1. PREAMBLE & PROGRAMME OUTCOMES

1.1. Preamble

In the digital transformation eco-system, Data Science and Artificial Intelligence (AI) have emerged as the most significant drivers of innovation across industries and research domains. The exponential growth of data and the advancement of intelligent systems have opened up vast opportunities for solving complex problems in healthcare, finance, agriculture, cybersecurity, smart cities and beyond. To address this critical demand, the M.Tech programme in Data Science and Artificial Intelligence is designed to produce skilled professionals and researchers capable of building intelligent data-driven solutions.

This postgraduate programme aims to equip students with a strong foundation in mathematical modeling, statistical inference, machine learning, deep learning and big data technologies. It emphasizes both theoretical rigor and practical application, encouraging a multidisciplinary approach to problem-solving. With an industry-relevant curriculum, state-of-the-art laboratories and exposure to real-world projects, the program prepares the students to lead innovations in AI-powered systems while upholding ethical standards and social responsibility.

1.2 Vision and Mission

Vision: To become a Center of Excellence in Data Science and Artificial Intelligence by empowering students through quality education, innovation and research.

Mission:

- To impart in-depth knowledge of Data Science and AI with strong theoretical and practical foundations.
- To promote research, innovation, ethical practices and continuous learning.
- To encourage industry collaboration for solving real-world problems.

1.3 Programme Educational Objectives (PEOs)

PEO1: Graduates will excel in Data science and AI careers or advanced studies by applying theoretical and practical knowledge.

PEO2: Graduates will design intelligent systems that contribute to societal and industrial development.

PEO3: Graduates will demonstrate leadership, communication skills and ethical responsibility in their professional careers.

PEO4: Graduates will engage in continuous learning to stay abreast of technological advancements.

1.4 Programme Outcomes (POs)

PO1: Scholarship of Knowledge: Acquire in-depth knowledge of recent trends and technologies, and apply it for solving complex engineering and societal problems.

PO2: Modern Tool Usage: Use modern computational tools, frameworks and simulation environments in finding solutions for contemporary problems.

PO3: Problem Solving: Formulate novel problem solving techniques and technologies for real world problems.

PO4: Design/Development of Solutions: Design systems, algorithms and models that fulfil functional, performance, quality, safety and ethical constraints.

PO5: Research and Innovation: Apply research methodology including literature survey, conduct experiments, analysis and interpretation to provide innovative solutions.

PO6: Collaborative and Multidisciplinary Work: Extending computational solutions for multidisciplinary problem solving such as healthcare, finance, robotics, education, socio-economic challenges etc.

PO7: Communication: Communicate effectively with engineering community and society at large through documentation and presentations.

PO8: Life-long Learning: Understand the need for life-long learning so as to adapt to rapidly evolving technologies to meet the challenges of the future.

1.5 Programme Specific Outcomes (PSOs)

PSO1: Analyse large amounts of data to uncover hidden patterns and help organizations and society harness their data to identify new opportunities.

PSO2: Apply data analytics, machine learning and AI techniques to solve real-world problems in domains such as healthcare, finance, transportation etc.

PSO3: Develop scalable, secure and interpretable AI applications using advanced tools and frameworks.

PSO4: Conduct research and innovation in emerging areas of AI such as deep learning, reinforcement learning, natural language processing etc.

2. DEFINITIONS

Terms used in the NEP Regulations shall have the meaning assigned to them as given below unless the context otherwise requires:

A. Credit: "Credit" is a unit by which the coursework is measured. It determines the number of hours of instruction required per week during a semester (Minimum 15 weeks). One credit is equivalent to 15 hours of teaching (lecture and /or tutorial) or 30 hours of practical and/or field work or community engagement and service per semester.

B. Academic Year: "Academic Year" means the year starting in the month of June and ending in the succeeding month of May.

C. Semester: “Semester” means 15-16 weeks of teaching-learning session of which two weeks shall be set apart for examination and evaluation; A semester comprises of 90 working days and an academic year is divided into two semesters.

D. Summer Term: “Summer term” is for 8 weeks during summer vacation. Internship / projects in higher educational institutions / research organisations evaluated by a internally constituted committee can be carried out during the summer term, especially by students who wish to exit after two semesters.

E. Grade: “Grade” means a letter grade assigned to a student in a Course for her / his performance at academic sessions as denoted in symbols of: O(Outstanding), A+(Excellent), A(Very good), B+ (Good), B(Above average), C(Average), P(Pass), F(Fail) and Ab(Absent) with a numeric value of O=10, A+=9, A=8, B+=7, B=6, C=5, P=4, F=0 and Ab=0.

F. SGPA: “Semester Grade Point Average (SGPA)” is computed from the grades as a measure of the students’ performance in a given semester.

G. CGPA: “Cumulative GPA (CGPA)” is the weighted average of all courses the student has taken in a given programme.

H. Programme: “Programme” means a set of courses that allows a student to structure and study to attain the status of being admitted to a Degree / Diploma of the University.

I. Programme Committee: “Programme Committee” means an Academic Committee constituted by the University for the purpose of conducting an Academic Programme.

J. Credit Requirement: “Credit Requirement” for a Degree / Diploma / Certificate Programme means the minimum number of credits that a student shall accumulate to achieve the status of being qualified to receive the said Degree / Diploma / Certificate as the case may be.

K. Exit Option: “Exit option” means the option exercised by the students, to leave the Programme at the end of any given Academic year.

L. Lateral Entry: "Lateral entry" means a student being admitted into an ongoing Programme of the University other than in the first year of the programme.

3. DURATION, ELIGIBILITY & AWARD OF M.Tech. DEGREE IN DATA SCIENCE & ARTIFICIAL INTELLIGENCE

3.1. Duration of the Programme

The duration of the M.Tech (Data Science & Artificial Intelligence) PG programme is 2 years or 4 semesters.

3.2. Eligibility

Candidates seeking admission to the M.Tech in Data Science and Artificial Intelligence programme must have completed a 4-year undergraduate degree (e.g., B.E., B.Tech., or equivalent) with a minimum of 160 credits, in accordance with the requirements for a 2-year (4-semester) postgraduate program at Level 7 of the National Higher Education Qualifications Framework (NHEQF).

Additionally, candidates who have completed any of the following are also eligible, subject to specific conditions:

- A **4-year UG program + 1 year PG program** in STEM disciplines
- A **3-year UG program + 2 year PG program** in STEM disciplines
- A **5-year integrated PG program** in STEM disciplines

All candidates should also qualify through a National-level or University-level entrance examination in the subjects deemed relevant for the M.Tech. (DS & AI) programme, as specified in the admission brochure issued by the University.

4. PROGRAMME OVERVIEW

Under the National Higher Education Qualifications Framework (NHEQF), higher education qualifications are classified along a continuum of levels from level 4.5 to level 8. 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. Learning outcomes, are statements of what the learner is expected to know, understand, and/or be able to do on the successful completion of an approved programme of study / learning at a specified level. Students on completion of the chosen programme(s) of study under the NHEQF must possess and demonstrate the graduate attributes defined in terms of the expected learning outcomes.

In accordance with the NHEQF (https://www.ugc.gov.in/pdfnews/2990035_Final-NHEQF.pdf), the levels for the PG programme are given in the Table.1. Accordingly, students of this M.Tech programme will study courses of Level 7 for a total of 80 credits, spread across 4 semesters in 2 years.

Table 1: Levels of PG Programme

S.No.	Qualification	Level	Credits
1	P.G. Diploma	6	40
2	1-Year PG after a 4-year UG	6.5	40
3	2-Year PG after a 3-year UG	6.5	40+40
4	2-Year PG after a 4-year UG such as B.E., B.Tech. etc.	7	40+40

4.1 Exit Option and Nomenclature

Candidates can exercise the exit option at the end of the first year. Candidates who exercise such option shall be awarded a PG Diploma in Data Science and Artificial Intelligence if the candidate acquires at least 40 credits from the courses registered in the 1st and 2nd semesters as per the curriculum. Students who wish to exit after two semesters should also complete internship / project during the summer term in a higher educational institution / research organisation / industry which will be evaluated by an internally constituted committee.

4.2. Description of Types of Courses

The following are the types of courses in this programme:

1. Hardcore
2. Softcore
3. Audit Course
4. MOOC
5. Summer Term Internship / Project

4.2.1 Hardcore

The compulsory core or essential subjects or components that are considered fundamental and mandatory for a particular field of study. It represents the foundational knowledge and skills that are deemed necessary for students to master, forming the basis for further learning and specialization. In the curriculum, hardcore courses are assigned 3 credits for theory courses, 4 credits for theory and practice combined courses and 2 credits for practical courses. Research project work is assigned 30 credits.

4.2.2 Softcore

Optional courses that students can choose from a specific pool of subjects within a program or specialization, in contrast to hardcore (compulsory) courses. They are typically electives that allow students to tailor their learning to their interests or chosen specialization. Softcore subjects are assigned 3 credits in the curriculum.

4.2.3. Audit Course

Audit courses offered do not carry any credits. The courses may be completed in online (MOOC platform)/offline mode. The faculty advisor will verify the equivalence of the selected online/

offline courses and approve them. Students may be given a pass on presenting the pass certificate or based on the assessment done by the faculty in charge/internally constituted committee.

Audit course 1 & 2

1. English for Research Paper Writing
2. Disaster Management
3. Sanskrit for Technical Knowledge
4. Value Education
5. Constitution of India
6. Pedagogy Studies
7. Stress Management by Yoga
8. Personality Development through Life Enlightenment Skills.

4.2.4 MOOC Course

Students may only register for proctored exam-based MOOC courses offered by the SWAYAM platform for credit transfer, as guided by UGC. Hard Core Course cannot be substituted by a MOOC course. Students cannot choose MOOC courses equivalent to the hard core courses in their respective curriculum. Students are encouraged to finish the 2 electives offered in the III semester through MOOC platform. Students may enrol for at least 2 courses in MOOC platform anytime after joining the M.Tech. Course. Students should register the course only when approved by the Faculty advisor. The faculty advisor will verify the equivalence of the selected MOOC courses and approve them. Upon successful completion of the MOOC courses, the faculty advisor will facilitate the students' registration in SAMARTH for the subsequent semester under the approved course codes. Registration of online courses in SAMARTH will only be permitted in the subsequent semester. 12-week specialisation-based MOOC courses will be treated as Soft-core

(Elective) courses. Students can earn a maximum of 3 credits for a 12-week course. No student may register for online MOOC courses during the final semester of their programme. Students must register for and complete the exam at the end of each MOOC course. After receiving their results, students must submit their e-certificate to their faculty advisor. The faculty advisor will normalize the marks based on the e-certificate produced by the students and generate grades for the MOOC courses.

4.2.5 Summer Term Internship / Project

Summer Internship / project do not carry any credits. Students who wish to exit after two semesters should complete internship / project during the summer term in a higher educational institution / research organisation / industry which will be evaluated by an internally constituted committee.

4.3. Credit-hours for Different Types of Courses

A three-credit lecture course in a semester means three one-hour lectures per week with each one-hour lecture counted as one credit. One credit for tutorial work means one hour of engagement per week. A one-credit course in lab work in a semester means two-hours engagement per week. In a semester of 15 weeks duration, a one-credit lab work in a course is equivalent to 30 hours of engagement. The Faculty to Student Ratio in all the practical / laboratory classes shall be maintained at 1:15.

4.3.1. Pedagogical Styles

In order to achieve the expected learning outcomes, the following Pedagogical approaches listed in Table 2 are practised.

Table 2: Pedagogical Approaches

PEDAGOGY	APPROACH
Lecture	Regular classroom lectures by qualified / experienced expert teachers ● These Lectures may also include classroom discussion, demonstrations, case analysis and flipped classroom approach. ● Use of Models, Audio-Visual contents, Documentaries, PPTs, may supplement.
Tutorial	Problem solving exercise classes, guided discussion, supplementary readings etc.
Lab work	Algorithm design, Program development and executions, Application of tools, simulations and Mini projects.
Seminar	Students study contemporary topics and engage in Group Discussions and Debate, Oral presentation, Poster presentation, Role play participation, Quiz competitions, Business plan preparation & presentation, etc.
Internship / Project	Students *Learn by Doing* in the workplace external to the parent institution. Internships involve working in Software Companies, Research and Higher Educational Institution Laboratories, Corporate Offices, etc. All Internships should be properly guided and inducted for focused learning.
Research Project	Literature review and analysis in their area of specialization, devise and implement innovative techniques and technologies. Outcome of the project work need to be presented as a thesis or research report with necessary experimental results.
Field Visit	Real time learning through an industrial visit and gain insights into industry practise.

5. ADMISSION ELIGIBILITY, LATERAL ENTRY

5.1 Admission Eligibility

Candidates seeking admission to the M.Tech in Data Science and Artificial Intelligence must have completed a 4-year undergraduate degree (e.g., B.E., B.Tech., or equivalent) with a minimum of 160 credits, in accordance with the requirements for a 2-year (4-semester) postgraduate program at Level 7 of the National Higher Education Qualifications Framework (NHEQF).

Additionally, candidates who have completed any of the following are also eligible, subject to specific conditions:

- A **4-year UG program + 1 year PG program** in STEM disciplines
- A **3-year UG program + 2 year PG program** in STEM disciplines
- A **5-year integrated PG program** in STEM disciplines

All candidates should also qualify through a National-level or University-level entrance examination in the subjects deemed relevant for the M.Tech. (DS & AI) programme, as specified in the admission brochure issued by the University.

5.2 Admission by Lateral Entry

Candidates seeking lateral entry in the second year, should have completed the relevant PG Diploma with the any of the above mentioned eligibility requirements mentioned in section 5.1 and should have accumulated the necessary minimum credits in the Academic Bank of Credits (ABC). Such students who get admitted in the second year, other than first year will be guided by the following clauses:

- that the University shall notify the admission process and number of vacancies open for lateral entry.

- that the Lateral entrants shall be admitted only after such transparent screening process and such procedure that the University may prescribe from time to time.

University may prescribe different methods of screening for different programmes depending on the circumstances prevailing in each case.

- Lateral entry shall be permissible only in the beginning of the second year, provided that the students seeking lateral entry shall have obtained the minimum necessary qualification.

6. ACADEMIC BANK OF CREDITS (ABC)

The scheme of academic bank of credits will facilitate the transfer and consolidation of credits by using an 'Academic Bank Account' opened by students across the country by taking up courses in any of the eligible Higher Education Institutions. The validity of the credits earned and kept in the academic credit account will be to a maximum period of seven years or as specified by the ABC time to time.

7. MINIMUM CREDITS FOR ENROLMENT, ONLINE COURSES, STUDENT STRENGTH AND MENTORSHIP

a) To be considered a full-time student, a student must be enrolled at least for 12 credits in each and every semester. No student, unless specifically permitted by the programme committee, be permitted to enrol in more than 30 credits in any semester (excluding the credits for writing arrear exams).

b) While the hardcore courses are mandatory, students shall be permitted to drop other courses within the time limits prescribed in the Academic Calendar.

c) 40% of the credits of elective courses may be earned through online mode (Swayam or such other similar platforms approved by the department and the University as per the existing UGC regulations). Such decisions may be taken by the department / centre after considering the course requirements and learning outcomes planned and duly approved by the Programme Committee. This does not apply to the hardcore courses which need to be completed in offline / physical mode.

Course code for online courses and the number of credits to be assigned to each such course will be approved by the programme committee and these will be uploaded in the SAMARTH portal.

d) No softcore course shall be offered unless a minimum of 10 students register.

e) Every student upon admission to the University shall be associated with a member of the faculty (faculty advisor) of the programme to which she / he is admitted to, who shall advise and help the student as a mentor in choosing courses that is most appropriate for the goals of the student.

8. EXIT OPTION PROCEDURES

a) Students enrolled in this programme shall have an option to exit at the end of 1st year, subject to fulfilment of required conditions.

b) A student desiring an exit shall give a notice of such intention in writing in the prescribed format at least 8 weeks before the scheduled end of the 1st Academic year.

c) On receipt of the notice, department shall recommend for a PG Diploma, based on the fulfilment of requirements (refer section 4.1) for such award. In case of arrear papers, the PG Diploma shall be provided after passing the arrear papers.

9. LEARNING ASSESSMENT AND GRADES

All credit courses are evaluated for 100 marks. The courses are in three categories and the assessment methods are defined for each category.

9.1. Category of Courses

Category A	Theory Courses with Lecture hours and Tutorial hours.
Category B	Practical Courses with only Laboratory hours, Internships, Research Project.
Category C	Theory & Practice combined Courses.

9.2. Learning Assessment

Course Types	Internal Assessment		End Semester Assessment
Category A **IA: 40 Marks** **EA: 60 Marks**	**40 Marks**		**60 Marks** **(Evaluation Details given in Table 3)**
	Evaluation Component	**Marks**	
	I. Internal Exams for 15 Marks (Two)	30	
	II. Assignments/Seminars/Others	10	
	Total	**40**	
Category B **IA: 40 Marks** **EA: 60 Marks**	**40 Marks**		**60 Marks** **(Evaluation Details given in Table 3)**
	For Practical / Internship Courses		
	Evaluation Component	**Marks**	
	I. Weekly Observation Book / Report	15	
	II. Practical Record / Internship Report	10	
	III. Model Practical Exam	15	
	Total	**40**	
	40 Marks		
	For Research Project Work Course		
	Evaluation Component	**Marks**	
	I. Monthly Review (3 Reviews – 10 Marks each) Average of 3 reviews	20	
	II. Project Report	10	
	III. Project Work	10	
	Total	**40**	
Category C **IA: 40 Marks** **EA: 60 Marks**	**40 Marks**		**60 Marks** **(Evaluation Details given in Table 3)**
	Evaluation Component	**Marks**	
	I. Internal Exams for 10 Marks (Two)	20	
	II. Observation Records	05	
	III. Model Practical Exam	15	
	Total	**40**	

9.3. End Semester Assessment

The Department schedules the End-Semester exams for all theory and practical subjects based on university calendar. For Theory courses with Practical components, End semester exams shall be conducted separately for Theory and Practicals. A detailed Exam Time Table shall be circulated at least 15 days before the start of exams. Question Papers shall be set based on BoS approved syllabus. All students who have a minimum of 70% attendance are eligible to attend the end-semester exams.

9.4. Breakup of End Semester Marks

The question paper shall be set as per the Bloom's Taxonomy. Table 3 below gives the details of evaluation methods for Category A, B and C courses. Various levels along with it's description and sample questions are as follows:

Knowledge: Recall or remember previously learned information.

Example: List the basic data types in Python

Comprehension: Demonstrate understanding of facts and ideas by organizing, comparing, translating, interpreting, giving descriptions, and stating the main ideas.

Example: Explain how a stack data structure works.

Application: Apply knowledge and concepts to solve problems in new situations. Use learned information in a different context.

Example: Write a Python program to solve the deadlock problem.

Analysis: Break down information into parts and examine the relationships between the parts. Identify motives or causes.

Example: Analyse the efficiency of two sorting algorithms and compare their advantages and disadvantages.

Synthesis: Create a new whole by combining elements in novel ways. Use creativity to produce something original.

Example: Design a web application that can generate a time table of a school.

Table3: End Semester exam assessment details for all three categories of courses

Course Components	Max. Marks	End-Sem Exam Duration
Category A. Theory subjects: Sec A: 10 Questions of 2 Marks each (20 Marks) *(Knowledge: 3, Comprehension: 2, Application: 3, Analysis:2)* Sec B: 5 out of 7 Questions of 4 Marks each (20 Marks) *(Knowledge: 1, Comprehension: 2, Application: 1, Analysis:3)* Sec C: 2 Either/OR choice questions of 10 Marks each (20 Marks) *(Application: 1, Analysis:1)* **Questions from all units of Syllabus equally distributed.**	60 Marks	3 Hours
Category B. Practical: Based on Practical examinations conducted. **Internship / Research Project Work:** Presentation of the work / Report / Viva-voce examinations	60 Marks	3 Hours
Category C. Theory Subjects with Practical Components: * **i. Theory Component:** Sec A: 10 Questions of 2 Marks each (20 Marks) *(Knowledge: 3, Comprehension: 2, Application: 3, Analysis:2)* Sec B: 5 out of 7 Questions of 4 Marks each (20 Marks) *(Comprehension: 2, Application: 3, Analysis:2)* Sec C: 2 Either or type questions of 10 Marks each (20 Marks) *(Analysis / Synthesis)* **Questions from all units of Syllabus equally distributed.** **The examination shall be conducted for 60 Marks and reduced to 40 Marks.**	40 Marks	3 Hours
ii. Practical Component: Based on Practical examinations / Presentation / Viva-voce with external examiner appointed by the University Controller of Examinations, and schedules exclusively prepared for such practical examinations by the University Examination Section. **The examination shall be conducted for 40 Marks and reduced to 20 Marks.** **Total Marks: 60 (Theory: 40 Marks + Practical: 20 Marks)**	20 Marks	2 Hours

**It is mandatory for the student to appear in both Theory Component and Practical Component of the End Semester Examination. Absence in either component shall be treated as absence in the*

entire End Semester Examination, and the student shall be required to re-register and repeat the course in its entirety during the next available term.

9.5. Consolidation of Marks and Passing Minimum

The Course Teacher of Course shall consolidate the Internal Assessment marks and marks secured by students in End-Semester examinations. The total marks will be converted into letter grades.

A student shall be declared to have passed the course only if she/he gets, a minimum of 40% marks in end semester exam and a minimum of 40% marks in aggregate (Internal Assessment + End Semester Assessment put together). However, Pondicherry University considers 40% marks as pass and students who secured less than 50 will be awarded 'P' (Pass Grade).

9.6. Supplementary Examination

- A student who gets 'F' grade in a course shall be permitted to register for the supplementary examination in the following semester or in the subsequent semesters.
- A student who gets 'F' grade in a course shall be given an option either to retain the previously awarded internal assessment mark or to improve it, and the higher mark out of these two options will be considered for the supplementary examination.
- A student who gets 'Ab' grade in a course is mandated to repeat the course and undergo all the stages of assessment in subsequent semesters.

9.7. Attendance Requirement

Student who has less than 70% attendance in any course shall not be permitted to participate in end semester examination and she / he shall be given 'Ab' Grade - failure due to lack of attendance. She / he shall be required to re-register and repeat that course as and when it is offered.

10. LETTER GRADES, GRADE POINTS, GRADE CARD

Performance of students in each paper will be expressed as marks as well as Letter Grades.

Letter Grade	Grade Point
O (Outstanding)	10
A+ (Excellent)	9
A (Very good)	8
B+ (Good)	7
B (Above average)	6
C (Average)	5
P (Pass)	4
F (Fail)	0
Ab (due to lack of attendance)	0

In case of fractions the marks shall be rounded off to nearest integer.

The class interval K will be calculated by the formula given below:

$K = (X-50)/6$, where X is the highest mark secured.

According to K value, one of the following grading schemes will be followed.

(i) If $K \geq 5$, then the grades shall be awarded as given in the following table.

Range of Marks in %	Letter Grade Points	Grade Points
X to (X-K) + 1	O	10
(X-K) to (X-2K) + 1	A+	9
(X-2K) to (X-3K) + 1	A	8
(X-3K) to (X-4K) + 1	B+	7
(X-4K) to (X-5K) + 1	B	6
(X-5K) to 50	C	5
40 – 49	P	4
Below 40	**F**	**0**
Absent (Lack of Attendance)	**Ab**	**0**

(ii) If K< 5, then the grades shall be awarded as given in the following table.

Range of Marks in %	Letter Grade Points	Grade Points
80-100	O	10
71-79	A+	9
66-70	A	8
61-65	B+	7
56-60	B	6
50-55	C	5
40-49	P	4
Below 40	F	0
Absent (lack of attendance)	Ab	0

The Semester Grade Point Average (SGPA) is computed from the grades as a measure of the student's performance in a given semester. The SGPA is based on the grades of the current term, while the Cumulative GPA (CGPA) is based on the grades in all courses taken after joining the programme of study.

10.1. Computation of SGPA and CGPA

The following procedure shall be followed to compute the Semester Grade Point Average (SGPA) and Cumulative Grade Point Average (CGPA):

The SGPA is the ratio of the sum of the product of the number of credits with the grade points scored by a student in all the courses taken by a student and the sum of the number of credits of all the courses undergone by a student, i.e. SGPA (Si) = $\Sigma(Ci \times Gi) / \Sigma Ci$

Where Ci is the number of credits of the i^{th} course and Gi is the grade point scored by the student in the i^{th} course.

10.1.1. Example for Computation of SGPA where candidate has not failed in any course.

Semester	Course	Credit	Letter Grade	Grade Point	Credit Point (Credit x Grade)
I	Course 1	3	A	8	3 X 8 = 24
I	Course 2	4	B+	7	4 X 7 = 28
I	Course 3	3	B	6	3 X 6 = 18
I	Course 4	3	O	10	3 X 10 = 30
I	Course 5	3	C	5	3 X 5 = 15
I	Course 6	4	B	6	4 X 6 = 24
		20			139
	SGPA				139/20=6.95

10.1.2. Example for Computation of SGPA where candidate has failed in one course.

Semester	Course	Credit	Letter Grade	Grade Point	Credit Point (Credit x Grade)
I	Course 1	3	A	8	3 X 8 = 24
I	Course 2	4	B+	7	4 X 7 = 28
I	Course 3	3	B	6	3 X 6 = 18
I	Course 4	3	O	10	3 X 10 = 30
I	Course 5	3	C	5	3 X 5 = 15
I	Course 6	4	F	0	4 X 0 = 00
		20			115
	SGPA				115/20=5.75

10.1.3. Example for Computation of SGPA where candidate has failed in two courses.

Semester	Course	Credit	Letter Grade	Grade point	Credit Point (Credit x Grade)
I	Course 1	3	A	8	3 X 8 = 24
I	Course 2	4	B+	7	4 X 7 = 28
I	Course 3	3	F	0	3 X 0 = 00

I	Course 4	3	B	6	3 X 6 = 18
I	Course 5	3	C	5	3 X 5 = 15
I	Course 6	4	F	0	4 X 0 = 00
		20			85
	SGPA				85/20=4.25

The CGPA shall also be calculated in the same manner taking into account all the courses undergone by a student over all the semesters of a programme, i.e.

CGPA = Σ(Ci x Si) / Σ Ci, where Si is the SGPA of the ith semester and Ci is the total number of credits in that semester.

Example for Computation of CGPA

Semester 1	**Semester 2**	**Semester 3**	**Semester 4**
Credit 20 SGPA 6.9	Credit 20 SGPA 7.8	Credit 20 SGPA 5.6	Credit 20 SGPA 6.0
CGPA= (20 x 6.9 + 20 x 7.8 + 20 x 5.6 + 20 x 6.0)/80 = 6.6			

However, if any student fails more than once in the same subject, then while calculating CGPA, the credit and grade point related to the subject in which the student fails in multiple attempts will be restricted to one time only. The SGPA and CGPA shall be rounded off to 2 decimal points and reported in the transcripts.

In case of audit courses offered, the students may be given (P) or (F) grade without any credits. This may be indicated in the mark sheet. Audit courses will not be considered towards the calculation of CGPA.

10.2. Grade Card

The University shall issue a Grade card for the students, containing the marks and grades obtained by the student in the previous Semester Grade Point Average (SGPA) and Cumulative Grade Point Average (CGPA).

The grade card shall list:

a. The title, semester and course code of the courses taken by the student.

b. The credits associated with the course.

c. The marks and grade secured by the student.

d. The total credits earned by the student in that semester

e. The SGPA of the student.

f. The total credits earned by the students till that semester.

g. The CPGA of the student.

11. DISTINCTION, RANK AND DIVISIONS

Distinction: On successful completion of the programme, students with a CGPA of 9.00 and above who passed all the courses in first attempt shall be awarded the degree in First Class with Distinction.

University Rank: University Rank in a programme will be awarded to the student who secures the highest CGPA in a batch and passed all the courses in first attempt.

Divisions: The following table summarises the range of CGPA and their respective divisions.

Range of CGPA	Divisions
9.0 – 10	First Class with Distinction#
6.0 - 8.99	First Class
5.0 - 5.99	Second Class
4.0 - 4.99	Pass

Distinction will be awarded ONLY to those candidates who have cleared ALL subjects in the first attempt.

12. BRIDGE COURSE

A two-week bridge course will be conducted at the beginning of the first semester to introduce students to various facets of digital technologies. This foundational course is designed to facilitate effective learning in the domain of data analytics, particularly for students entering the program from diverse academic backgrounds.

13. COURSE CODE

- **Course code** **:** 7 Characters: 4 Alphabets and 3 Digits.
- **Alphabets** **:** 1st and 2nd Alphabets: Department Code (CS – Computer Science)
  3rd and 4th Alphabets: Programme Category
  (DS - Data Science and Artificial Intelligence)
- **Digits** **:** 1st Digit: Level - 7
  2nd and 3rd Digits: semester wise serial number of the course
  (01-50 odd semester, 51-99 even semester)

Ex: Odd Semester course- CSDS701; Even Semester course - CSDS751

M.Tech. (Data Science and Artificial Intelligence)

CURRICULUM

FIRST SEMESTER

S.No	Course Code	Course Title	H/S	L	T	P	Credits
1.	CSDS701	Advanced Data Structures and Algorithms	H	3	0	0	3
2.	CSDS702	Mathematical Foundations for Data Science	H	2	1	0	3
3.	CSDS703	Artificial Intelligence and Data Mining	H	3	0	0	3
4.	CSDS704	Advanced Databases	H	3	0	2	4
5.		Elective -1	S	3	0	0	3
6.	CSDS705	Laboratory - I (Advanced Data Structures and Algorithms Lab)	H	0	0	2	2
7.	CSDS706	Laboratory - II (AI and Data Mining Lab)	H	0	0	2	2
8		Audit Course-01	H	0	0	0	0
						TOTAL CREDITS	**20**

SECOND SEMESTER

S.No	Course Code	Course Title	H/S	L	T	P	Credits
1.	CSDS751	Machine Learning and Deep Learning	H	3	0	0	3
2.	CSDS752	Big Data Analytics	H	3	0	0	3
3.	CSDS753	Security for Data Science	H	3	0	2	4
4.		Elective-2	S	3	0	0	3
5.		Elective-3	S	3	0	0	3
6.	CSDS754	Laboratory- III (ML and DL Lab)	H	0	0	2	2
7.	CSDS755	Laboratory- IV (Big Data Analytics Lab)	H	0	0	2	2
8		Audit Course-02	H	0	0	0	0
						TOTAL CREDITS	**20**

THIRD SEMESTER

S.No.	Course Code	Course Title	H/S	L	T	P	Credits
1.		Elective-4	S	3	0	0	3
2.		Open Elective-1*	S	3	0	0	3
3.	CSDS707	Research Methodology	H	3	1	0	4
4.	CSDS708	Project Work (Phase-1)	H	-	-	-	10
						TOTAL CREDITS	**20**

FOURTH SEMESTER

S.No.	Course Code	Course Title	H/S	L	T	P	Credits
1.	CSDS756	Project Work (Phase-2)	H	-	-	-	10
2.	CSDS757	Project Report and Viva voce	H	-	-	-	10
						TOTAL CREDITS	**20**

LIST OF ELECTIVES

Sl.No.	Code	Course Title
		Semester-I
1.	CSDS731	Business Analytics
2.	CSDS732	Web Analytics
3.	CSDS733	Social Networking Analytics
4.	CSDS734	Data Visualisation and Interpretation
5.	CSDS735	Recommender Systems
6.	CSDS736	Responsible AI
		Semester-II
7.	CSDS771	Parallel and GPU Computing
8.	CSDS772	Cloud Computing
9.	CSDS773	Multimodal Analytics
10.	CSDS774	IoT and Predictive Analytics
11.	CSDS775	Optimisation Techniques for Analytics

12.	CSDS776	Financial and Risk Analytics
13.	CSDS777	Computational Intelligence
14.	CSDS778	Blockchain and Cryptocurrency
Semester-III		
15.	CSDS737	Big Data Security
16.	CSDS738	Explainable AI
17.	CSDS739	Natural Language Processing
18.	CSDS740	Reinforcement Learning
19.	CSDS741	Federated Learning
20.	CSDS742	Computer Vision
21.	CSDS743	Time Series Data Analysis
22.	CSDS744	Large Language Models
23.	CSDS745	Quantum Artificial Intelligence
24.	CSDS746	Robotics
25.	CSDS747	Agentic AI
26.	CSDS748	Digital Twins
27.	CSDS749	MLOps
28.	CSDS750	Generative AI

*** Open Elective**

Student can credit one course

1. In any other Department (Non Computer Science) in the University (or)
2. In MOOC platform after approved by the faculty advisor (or)
3. Offered as level 7 elective in Computer Science department

M.Tech. (Data Science and Artificial Intelligence)

SYLLABUS

SEMESTER I

<table>
<tr><td>Year</td><td>I</td><td rowspan="2">Course Code: CSDS701
Course Title : ADVANCED DATA STRUCTURES AND ALGORITHMS</td><td>Credits</td><td>3</td></tr>
<tr><td>Sem.</td><td>I</td><td>Hours</td><td>45</td></tr>
<tr><td colspan="3"></td><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="4">Basic knowledge of data structures and algorithm design</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="2">End Semester Marks: 60</td><td colspan="2">Duration of ESA : 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="4">1. Apply advanced data structures to solve complex computational problems.
2. Design efficient algorithms using divide-and-conquer, dynamic programming, and greedy strategies.
3. Analyze the performance of algorithms using asymptotic notations.
4. Implement graph algorithms for problems like shortest paths, maximum flow, and bipartite matching.
5. Evaluate computational complexity of problems.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="4">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO 1</th><th>PSO 2</th><th>PSO 3</th><th>PSO 4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>3</td><td>2</td><td>-</td><td>1</td><td>-</td><td>2</td><td>2</td><td>2</td><td>3</td><td>1</td></tr>
<tr><td>CO2</td><td>3</td><td>2</td><td>3</td><td>3</td><td>-</td><td>1</td><td>-</td><td>2</td><td>2</td><td>2</td><td>2</td><td>1</td></tr>
<tr><td>CO3</td><td>3</td><td>1</td><td>3</td><td>2</td><td>-</td><td>-</td><td>-</td><td>1</td><td>2</td><td>1</td><td>2</td><td>-</td></tr>
<tr><td>CO4</td><td>3</td><td>2</td><td>3</td><td>3</td><td>1</td><td>2</td><td>-</td><td>2</td><td>2</td><td>2</td><td>3</td><td>2</td></tr>
<tr><td>CO5</td><td>3</td><td>1</td><td>3</td><td>2</td><td>2</td><td>-</td><td>-</td><td>1</td><td>2</td><td>1</td><td>2</td><td>2</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation
</td></tr>
<tr><th>Unit No.</th><th colspan="3">Course Content</th><th>Hours</th></tr>
<tr><td>Unit I</td><td colspan="3">Introduction
Advanced data structures: B-Trees, Fibonacci heaps, data structures for disjoint sets, hash tables. Role of Algorithms in Computing - Analysing Algorithms – Designing Algorithms. Growth Functions: Asymptotic Function - Standard Notations and common Functions.</td><td>9</td></tr>
</table>

Unit II	**Divide and Conquer** Maximum-subarray problem - Strassen's algorithm for matrix multiplication - Substitution method for solving recurrence - Recursion-tree method for solving recurrences - Master method for solving recurrences.	9
Unit III	**Advanced Design and Analysis Techniques** Dynamic Programming: Rod Cutting - Matrix-Chain Multiplication - Elements of Dynamic Programming - Longest Common Subsequence - Optimal Binary Search Trees. Greedy Algorithms: Elements of Greedy Strategy - Huffman Codes - Matroids and Greedy Methods- Amortized Analysis: Aggregate Analysis - The Accounting Method.	9
Unit IV	**Advanced graph algorithms** Johnsons Algorithm for Sparse Graphs - Maximum Flow: Flow Networks - The Ford-Fulkerson Method - Maximum Bipartite Matching.	9
Unit V	**String matching and approximation algorithms** String Matching Algorithms: Naïve approach - Rabin-Karp Algorithm - String Matching with Finite Automata -The Knuth-Morris-Pratt Algorithm. NP Hard- NP Complete.	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest, and Clifford Stein, Introduction to Algorithms, MIT Press, Fourth Edition, 2022. 2. Ellis Horowitz, Sartaj Sahni, and Sanguthevar Rajasekaran, Computer Algorithms/C++, Universities Press, Second Edition, 2008. **REFERENCE BOOKS:** 1. Sanjoy Dasgupta, Christos H. Papadimitriou, and Umesh V. Vazirani, Algorithms, McGraw Hill Education, First Edition, 2024. 2. G. Brassard and P. Bratley, Algorithmics: Theory and Practice, Prentice -Hall, 1988.	
Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.		

<table>
<tr><td>Year</td><td>I</td><td rowspan="3">Course Code: CSDS702
Course Title : MATHEMATICAL FOUNDATIONS FOR DATA SCIENCE</td><td>Credits</td><td>3</td></tr>
<tr><td>Sem.</td><td>I</td><td>Hours</td><td>45</td></tr>
<tr><td></td><td></td><td>Category</td><td>A</td></tr>
<tr><td>course Prerequisites, if any</td><td colspan="4">Basic understanding of linear algebra, calculus, and probability</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="2">End Semester Marks: 60</td><td colspan="2">Duration of ESA : 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="4">1. Understand and apply linear algebra concepts.
2. Analyze and implement matrix decompositions and dimensionality reduction techniques.
3. Solve optimization problems.
4. Apply probability concepts in data analysis.
5. Perform statistical analysis using sampling, hypothesis testing, and confidence intervals.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="4">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>-</td><td>3</td><td>2</td><td>-</td><td>1</td><td>-</td><td>2</td><td>2</td><td>2</td><td>3</td><td>1</td></tr>
<tr><td>CO2</td><td>3</td><td>2</td><td>3</td><td>3</td><td>-</td><td>1</td><td>-</td><td>2</td><td>2</td><td>2</td><td>2</td><td>1</td></tr>
<tr><td>CO3</td><td>3</td><td>1</td><td>3</td><td>2</td><td>-</td><td>-</td><td>-</td><td>1</td><td>2</td><td>1</td><td>2</td><td>-</td></tr>
<tr><td>CO4</td><td>3</td><td>2</td><td>3</td><td>3</td><td>1</td><td>2</td><td>-</td><td>2</td><td>2</td><td>2</td><td>3</td><td>2</td></tr>
<tr><td>CO5</td><td>3</td><td>1</td><td>3</td><td>2</td><td>2</td><td>-</td><td>-</td><td>1</td><td>2</td><td>1</td><td>2</td><td>2</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation</td></tr>
<tr><th>Unit No.</th><th colspan="2">Course Content</th><th colspan="2">Hours</th></tr>
<tr><td>Unit I</td><td colspan="2">Basics of Linear Algebra
Representation of vectors - Linear dependence and independence - vector space and subspaces (definition, examples, and concepts of basis) - linear transformations - range and null space - matrices associated with linear transformations - special matrices - eigenvalues and eigenvectors with applications to data problems - Least square solutions.</td><td colspan="2">9</td></tr>
</table>

Unit II	**Matrices in Machine Learning Algorithms** Projection transformation - orthogonal decomposition - singular value decomposition - principal component analysis and linear discriminant analysis. Gradient Calculus: Basic concepts of calculus: partial derivatives - gradient - directional derivatives - Jacobian-Hessian matrix.	9
Unit III	**Optimization** Convex sets - convex function-properties - Unconstrained and Constrained Optimization - Numerical Optimization Techniques for Constrained/Unconstrained Optimization - Methods using Derivatives (Newton's Method - Steepest Descent Method) - Penalty Function Methods for Constrained Optimization.	9
Unit IV	**Probability** Basic concepts of probability - conditional probability - total probability - independent events - Bayes' theorem - random variable - Moments - moment generating functions - distributions - Joint distribution - conditional distribution - covariance - correlation.	9
Unit V	**Statistics** Random sample - sampling techniques - statistics - sampling distributions - Hypothesis testing of means and proportions - variances and correlations - confidence intervals.	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Marc Peter Deisenroth, A. Aldo Faisal, and Cheng Soon Ong, Mathematics for Machine Learning, Cambridge University Press, First Edition, 2020. 2. Sheldon Axler, Linear Algebra Done Right, Springer International Publishing, Fourth Edition, 2024. 3. Jorge Nocedal and Stephen J. Wright, Numerical Optimization, Springer, Second Edition, 2006. 4. Richard A. Johnson, Irwin Miller, and John E. Freund, Miller & Freund's Probability and Statistics for Engineers, Pearson, Ninth Edition, 2023. **REFERENCE BOOKS:** 1. Erwin Kreyszig, Advanced Engineering Mathematics, John Wiley & Sons, Tenth Edition, 2020. 2. Chander Mohan and Kusum Deep, Optimization Techniques, New Age International Publishers, First Edition, 2009.	
Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.		

Year	I	Course Code: CSDS703 Course Title : ARTIFICIAL INTELLIGENCE AND DATA MINING	Credits	3
Sem.	I		Hours	45
			Category	A

Course Prerequisites, if any	Basic knowledge of databases, data structures, algorithms and statistics.	
Internal Assessment Marks: 40	End Semester Marks: 60	Duration of ESA : 03 hrs.

Course Outcomes

1. Understand the scope of AI and the role of data mining in intelligent systems.
2. Apply data preprocessing techniques for cleaning, integration, reduction, and transformation.
3. Implement association rule mining, classification algorithms, and advanced classifiers.
4. Perform clustering using partitioning, hierarchical, density-based, and grid-based methods.
5. Analyze and mine complex data types.

CO, PO & PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	2	2	2	-	1	1	2	2	2	2	1
CO2	2	3	2	2	2	-	-	3	3	3	2	1
CO3	3	3	3	3	2	-	-	2	3	3	3	2
CO4	3	3	3	3	2	-	-	2	3	3	3	2
CO5	3	2	3	2	3	1	-	3	3	3	3	3

1-low, 2-medium, 3-high, '-"- no correlation

Unit No.	Course Content	Hours
Unit I	**Introduction to AI** Scope of AI: Games - Theorem Proving - Natural language Processing - Vision & speech processing - Robotics - Expert System - Intelligent agents - Uninformed search strategies - Informed search strategy : A* algorithm - Data mining and AI.	9
Unit II	**Data Mining and Data Preprocessing** Data Mining: Motivation - Application - Attribute types - Data Mining Functionalities - Data Mining Task Primitives - Major Issues in Data Mining - Similarity & Dissimilarity measures - Data Preprocessing: Data Cleaning - Data	9

	Integration - Data Reduction - Data Transformation & Discretization - Data Warehouse and OLAP.	
Unit III	**Association Rule Mining and Classification** Basic Concepts - Frequent Itemset Mining Methods and Association Algorithms - Decision Tree Induction - Nearest neighbor - Bayesian Classification – Rule Based Classification. Advanced Methods: Classification by Back propagation - Support Vector Machines.	9
Unit IV	**Clustering** Clustering techniques - Partitioning methods - k-means - Hierarchical Methods – distance based agglomerative and divisible clustering - Density-Based Methods - Grid Based Methods – Outlier Analysis.	9
Unit V	**Mining complex data objects** Spatial databases – Temporal databases – Multimedia databases – Time series and sequence data – Text mining – Web mining – Case study - Mining social networks.	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Stuart J. Russell and Peter Norvig, Artificial Intelligence: A Modern Approach, Pearson, Fourth Edition, 2020 2. Jiawei Han, Jian Pei, and Hanghang Tong, Data Mining: Concepts and Techniques, Morgan Kaufmann, Fourth Edition, 2022. **REFERENCE BOOKS:** 1. Jure Leskovec, Anand Rajaraman, and Jeffrey David Ullman, Mining of Massive Datasets, Cambridge University Press, Third Edition, 2020. 2. Margaret H. Dunham, Data Mining: Introductory and Advanced Topics, Pearson Education, First Edition, 2002.	
Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.		

<table>
<tr><td>Year</td><td>I</td><td colspan="3" rowspan="2">Course Code: CSDS704
Course Title: ADVANCED DATABASES</td><td>Credits</td><td>4</td></tr>
<tr><td>Sem.</td><td>I</td><td>Hours</td><td>75</td></tr>
<tr><td colspan="4"></td><td>Category</td><td>C</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="6">Database Management Systems (Basic Concepts)</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="3">End Semester Marks: 60</td><td colspan="3">Duration of ESA : 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="6">1. Explain advanced indexing and storage structures in databases.
2. Analyze and optimize complex query processing techniques.
3. Apply concurrency control and recovery protocols to ensure data integrity.
4. Evaluate transaction management and isolation levels.
5. Design distributed database solutions with appropriate consistency models.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="6">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO 1</th><th>PSO 2</th><th>PSO 3</th><th>PSO 4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>2</td><td>2</td><td>1</td><td>1</td><td>-</td><td>2</td><td>3</td><td>2</td><td>2</td><td>-</td></tr>
<tr><td>CO2</td><td>3</td><td>2</td><td>3</td><td>3</td><td>2</td><td>1</td><td>-</td><td>2</td><td>3</td><td>3</td><td>3</td><td>-</td></tr>
<tr><td>CO3</td><td>3</td><td>2</td><td>3</td><td>3</td><td>2</td><td>1</td><td>1</td><td>2</td><td>3</td><td>3</td><td>2</td><td>1</td></tr>
<tr><td>CO4</td><td>3</td><td>2</td><td>2</td><td>3</td><td>2</td><td>1</td><td>1</td><td>2</td><td>3</td><td>2</td><td>2</td><td>1</td></tr>
<tr><td>CO5</td><td>3</td><td>2</td><td>3</td><td>3</td><td>2</td><td>1</td><td>2</td><td>2</td><td>3</td><td>3</td><td>3</td><td>1</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation</td></tr>
<tr><th>Unit No.</th><th colspan="4">Course Content</th><th>Hours</th></tr>
<tr><td>Unit I</td><td colspan="4">Storage and Indexing
Overview of database system architecture - Storage hierarchy, buffer management - B+-Tree indexes, insertion, deletion, and balancing - Other indexing techniques: hashing, bitmap indexes - Indexing for text and spatial data</td><td>9</td></tr>
<tr><td>Unit II</td><td colspan="4">Query Processing and Optimization
Query evaluation: relational algebra operators - External sorting and join algorithms (nested loops, hash join, sort-merge join) - Query optimization: cost estimation, statistics - Heuristics and plan enumeration</td><td>9</td></tr>
<tr><td>Unit III</td><td colspan="4">Transactions and Concurrency Control
ACID properties revisited - Serializability theory: conflict and view serializability - Lock-based protocols and timestamp ordering -Multiversion concurrency control (MVCC)</td><td>9</td></tr>
</table>

Unit IV	**Recovery Systems** Log-based recovery: undo, redo - Checkpoints and recovery algorithms - ARIES protocol (overview) - Media recovery and advanced recovery techniques	9
Unit V	**Distributed Databases and Advanced Topics** Distributed data storage and fragmentation - Replication and consistency models (eventual, strong) - Distributed transactions and two-phase commit - Emerging trends: NoSQL databases - Graph Models - Properties - Neo4J – IBMGraph.	9
Practical Component		
Exercises	1. Implement B+-Tree insertion and deletion on sample data. 2. Develop and benchmark different join algorithms on datasets. 3. Simulate lock-based concurrency control and detect deadlocks. 4. Implement a basic logging and recovery mechanism. 5. Model distributed database replication and consistency in a small setup. 6. Use PostgreSQL or similar DBMS to experiment with MVCC and isolation levels, vector DB. 7. Evaluate query plans using EXPLAIN tools and optimize queries.	30
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Raghu Ramakrishnan & Johannes Gehrke, *Database Management Systems*, 3rd Ed., McGraw Hill, 2014. 2. Guy Harrison, Next-Generation Databases, 2016 . Apress, 2016. ISBN: 978148421329. **REFERENCE BOOKS:** 1. Alex Petrov, *Database Internals: A Deep Dive into How Distributed Data Systems Work*, O'Reilly, 2019. 2. Hector Garcia-Molina, Jeffrey Ullman, Jennifer Widom, Database Systems: The Complete Book, Second Edition, Pearson, 2008 .	
Syllabus Design: Dr. Pothula Sujatha, Professor, PUDoCS.		

<table>
<tr><td>Year</td><td>I</td><td colspan="3" rowspan="3">Course Code: CSDS731
Course Title: BUSINESS ANALYTICS</td><td>Credits</td><td>3</td></tr>
<tr><td>Sem.</td><td>II</td><td>Hours</td><td>45</td></tr>
<tr><td colspan="4"></td><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="6">Students should have completed prior coursework or demonstrated proficiency in the following areas: fundamentals of computer science, basic mathematics and statistics.</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="3">End Semester Marks: 60</td><td colspan="3">Duration of ESA : 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="6">1. Understand and apply business analytics methodologies to derive actionable insights.
2. Develop proficiency in data cleansing, transformation, and exploratory data analysis using Python and R.
3. Build predictive models to solve real-world business problems.
4. Collaborate effectively using version control systems like GitHub.
5. Measure and communicate the success of analytics projects.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="6">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>3</td><td>2</td><td>2</td><td>1</td><td>1</td><td>2</td><td>3</td><td>3</td><td>2</td><td>1</td></tr>
<tr><td>CO2</td><td>2</td><td>3</td><td>2</td><td>2</td><td>2</td><td>-</td><td>-</td><td>2</td><td>3</td><td>3</td><td>2</td><td>1</td></tr>
<tr><td>CO3</td><td>3</td><td>2</td><td>3</td><td>3</td><td>2</td><td>-</td><td>-</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO4</td><td>1</td><td>2</td><td>2</td><td>2</td><td>-</td><td>3</td><td>2</td><td>2</td><td>2</td><td>2</td><td>2</td><td>-</td></tr>
<tr><td>CO5</td><td>2</td><td>1</td><td>2</td><td>2</td><td>2</td><td>1</td><td>3</td><td>2</td><td>2</td><td>2</td><td>2</td><td>1</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation
</td></tr>
<tr><th>Unit No.</th><th colspan="4">Course Content</th><th>Hours</th></tr>
<tr><td>Unit I</td><td colspan="4">Introduction
Overview and its significance in modern enterprises- Role of a Business Analyst - Bridging technical and business domains-analytics tools and technologies - data types and sources</td><td>9</td></tr>
<tr><td>Unit II</td><td colspan="4">Data Preparation and Transformation
Data cleansing techniques: Handling missing values-outliers-and inconsistencies - Data transformation: Normalization, encoding, and feature engineering - Utilizing Python and R for data preparation.</td><td>9</td></tr>
</table>

Unit III	**Exploratory Data Analysis (EDA)** Techniques for summarizing and visualizing data-Identifying patterns, trends, and anomalies-Using visualization libraries: Matplotlib, Seaborn, ggplot2	9
Unit IV	**Predictive Modeling** Introduction and machine learning concepts-Building models: Regression, classification, clustering-Model evaluation and validation techniques-Implementing models using scikit-learn and caret.	9
Unit V	**Collaboration and Measuring Success** Version control and collaboration using GitHub-Best practices for documenting and sharing analytics projects-Defining and tracking Key Performance Indicators (KPIs)-Communicating results to stakeholders effectively	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Deanne Larson, *Modern Business Analytics*, O'Reilly Media, December 2024. **REFERENCE BOOKS:** 1. H.K. Dangi & Gurveen Kaur, Business Analytics, Taxmann, 2024. 2. Ali Emrouznejad, Business Analytics and Decision Making in Practice, Springer, 2024.	
Syllabus Design: Dr. Sukhvinder Singh, Assistant Professor, PUDoCS		

Year	I	Course Code: CSDS732 Course Title: WEB ANALYTICS	Credits	3
Sem.	I		Hours	45
			Category	A

Course Prerequisites, if any	Students should have basic knowledge of digital marketing, statistics, and data visualization tools.	
Internal Assessment Marks: 40	End Semester Marks: 60	Duration of ESA : 03 hrs.

Course Outcomes

1. Understand web analytics fundamentals and their applications.
2. Master tools like Google Analytics 4, Tag Manager, and Looker Studio.
3. Develop skills in data-driven decision-making for websites and apps.
4. Apply ethical, privacy-compliant analytics.
5. Perform case-based analysis for different industries.

CO, PO & PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	2	3	2	1	1	1	2	3	3	2	-
CO2	2	3	2	2	1	-	-	2	3	3	2	1
CO3	3	2	3	3	2	1	-	3	3	3	3	2
CO4	2	1	2	2	2	-	2	2	2	2	2	2
CO5	2	2	3	3	3	2	1	3	3	3	3	2

1-low, 2-medium, 3-high, '-"- no correlation

Unit No.	Course Content	Hours
Unit I	**Foundations of Web Analytics** Introduction-Digital Marketing Ecosystem: Channels & Traffic Sources-Understanding Data Types: Clickstream, Behavioural, Transactional-Foundational Metrics: Traffic, Engagement, Conversion, Retention-KPI Development Frameworks	9
Unit II	**Tools & Techniques for Data Collection** Clickstream Analysis: Data Collection & Reporting - Google Analytics 4 Essentials: Properties, Events, Goals - Google Tag Manager: Variables, Triggers, Tags - Behaviour Analysis: User Journeys, Flow Visualization, Heatmaps - App and Mobile Analytics Basics	9

Unit III	**Testing, Attribution & Optimization** Experimentation Techniques: A/B Testing, Multivariate Testing - Attribution Models: Last Click, Linear, Time Decay, Data-Driven Models - Multi-Channel Funnels - Conversion Rate Optimization	9
Unit IV	**Privacy, Governance & Reporting** Data Privacy Regulations: GDPR, CCPA, Data Governance - Ethical Data Collection & Usage - Dashboards and Reporting: Data Storytelling Techniques - Google Looker Studio - Dashboard Creation & Visualization	9
Unit V	**Applications, Case Studies & Careers** Case Studies: eCommerce, SaaS, Media Analytics - Cross-Platform Analytics - Web + Mobile Integration - Career Paths in Web Analytics: Roles & Certifications - Future Trends: AI in Analytics, Predictive Web Analytics	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Avinash Kaushik, Web Analytics 2.0: The Art of Online Accountability & Science of Customer Centricity, 1st ed, Wiley, 2009. 2. Clifton B., Advanced Web Metrics with Google Analytics, 2nd ed, Wiley Publishing, Inc. 2010. **REFERENCE BOOKS:** 1. A. Karim Feroz, Gohar F. Khan, Marshall Sponder, Digital Analytics for Marketing, 2nd Edition, Routledge, January 2024.	
Syllabus Design: Dr. Sukhvinder Singh, Assistant Professor, PUDoCS		

<table>
<tr><td>Year</td><td>I</td><td colspan="2" rowspan="2">Course Code: CSDS733
Course Title: SOCIAL NETWORKING ANALYTICS</td><td>Credits</td><td>3</td></tr>
<tr><td>Sem.</td><td>I</td><td>Hours</td><td>45</td></tr>
<tr><td colspan="4"></td><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="5">● Basic understanding of graphs, linear algebra, probability, and algorithms.
● Basic programming knowledge, preferably in Python, for implementing network analysis techniques.</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="2">End Semester Marks: 60</td><td colspan="3">Duration of ESA: 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="5">1. Understand social media mining concepts and apply graph basics to represent networks.
2. Analyze network measures like centrality, similarity, and transitivity.
3. Evaluate network models to explain real-world network structures.
4. Apply methods to detect communities and understand information diffusion.
5. Analyze influence, homophily, and apply recommendation techniques.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="5">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>2</td><td>2</td><td>-</td><td>1</td><td>-</td><td>2</td><td>3</td><td>2</td><td>2</td><td>1</td></tr>
<tr><td>CO2</td><td>3</td><td>2</td><td>3</td><td>2</td><td>-</td><td>-</td><td>-</td><td>3</td><td>3</td><td>3</td><td>2</td><td>1</td></tr>
<tr><td>CO3</td><td>3</td><td>1</td><td>3</td><td>3</td><td>1</td><td>-</td><td>1</td><td>2</td><td>2</td><td>2</td><td>3</td><td>2</td></tr>
<tr><td>CO4</td><td>3</td><td>2</td><td>3</td><td>3</td><td>2</td><td>-</td><td>-</td><td>2</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO5</td><td>3</td><td>2</td><td>3</td><td>3</td><td>2</td><td>1</td><td>-</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation</td></tr>
<tr><th>Unit No.</th><th colspan="3">Course Content</th><th>Hours</th></tr>
<tr><td colspan="5">Theory Component</td></tr>
<tr><td>Unit I</td><td colspan="3">Introduction
Social Media Mining - New Challenges for Mining - Graph Essentials: Graph basics - Graph Representation - Types of Graphs - Connectivity in Graphs - Special Graphs - Graph Algorithms.</td><td>9</td></tr>
</table>

Unit II	**Network Measures** Centrality - Degree Centrality - Eigenvector Centrality - Katz Centrality – PageRank - Betweenness Centrality - Closeness Centrality - Group Centrality - Transitivity and Reciprocity - Balance and Status – Similarity - Structural Equivalence - Regular Equivalence.	9
Unit III	**Network Models** Properties of Real-World Networks - Degree Distribution - Clustering Coefficient - Average Path Length - Random Graphs - Evolution - Properties - Small-World Model - Preferential Attachment Model.	9
Unit IV	**Communities and Interactions** Community Analysis: Community Detection - Community Evolution - Community Evaluation. Information Diffusion in Social Media : Herd Behaviour - Information Cascades - Diffusion of Innovations - Epidemics.	9
Unit V	**Applications** Influence and Homophily **-** Measuring Assortativity - Measuring and Modelling Influence - Measuring and Modelling Homophily - Distinguishing Influence and Homophily - Shuffle Test - Edge-Reversal Test - Randomization Test - Recommendation in Social Media. Case study: Classification and Analysis of Facebook Metrics Dataset Using Supervised Classifiers	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Zafarani, Reza, Mohammad Ali Abbasi, and Huan Liu, Social Media Mining: An Introduction, First Edition, Cambridge University Press, 2014. **REFERENCE BOOKS:** 1. Nilanjan Dey Samarjeet Borah Rosalina Babo Amira Ashour, Social Network Analytics – Computational Research Methods and Techniques, First Edition, Academic Press, 2018. 2. Cioffi-Revilla, Claudio, Introduction to Computational Social Science, First Edition, Springer, 2014.	
Syllabus Design: Dr. M. Sathya, Assistant Professor, PUDoCS		

<table>
<tr><td>Year</td><td>I</td><td colspan="2">Course Code: CSDS734</td><td>Credits</td><td>3</td></tr>
<tr><td rowspan="2">Sem.</td><td rowspan="2">I</td><td colspan="2" rowspan="2">Course Title: DATA VISUALIZATION AND INTERPRETATION</td><td>Hours</td><td>45</td></tr>
<tr><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="5">Knowledge on basics of Data Analytics and Python coding.</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="2">End Semester Marks: 60</td><td colspan="3">Duration of ESA : 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="5">1. Analyze the different data types, visualization types to bring out the insight.
2. Relate the visualization towards the problem based on the dataset to analyze and bring out valuable insight on large dataset.
3. Design visualization dashboard to support the decision making on large scale data
4. Demonstrate the analysis of large dataset using various visualization techniques and tools</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="5">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>3</td><td>2</td><td>1</td><td>1</td><td>1</td><td>2</td><td>3</td><td>2</td><td>2</td><td>-</td></tr>
<tr><td>CO2</td><td>3</td><td>2</td><td>3</td><td>3</td><td>1</td><td>2</td><td>1</td><td>2</td><td>3</td><td>3</td><td>2</td><td>1</td></tr>
<tr><td>CO3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>3</td><td>2</td><td>3</td><td>3</td><td>3</td><td>3</td><td>1</td></tr>
<tr><td>CO4</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>2</td><td>2</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation
</td></tr>
<tr><th>Unit No.</th><th colspan="3">Course Content</th><th>Hours</th></tr>
<tr><td>Unit I</td><td colspan="3">Introduction to Data Visualization
Overview of data visualization – data abstraction – Task abstraction – Dimensions and measures – Analysis: Four Levels for validation. Statistical Charts (Bar Chart – stacked bar chart – Line chart – Histogram – Pie Chart – Frequency Polygon – Box Plot – Scatter Plot – Regression Curves.)</td><td>9</td></tr>
<tr><td>Unit II</td><td colspan="3">Visualization Techniques
Introduction to various data visualization tools – scalar and point techniques – vector visualization techniques – multidimensional Techniques – Visualizing cluster analysis - Means and Hierarchical Cluster Techniques.</td><td>9</td></tr>
</table>

Unit III	**Spatio-Temporal Data visualization** Time series data visualization – text data visualization – spatial data visualization – Visual Analytics: Networks and Trees – Heat Map – Tree Map – Map Color and other Channels Manipulate View – Visual Attributes.	9
Unit IV	**Multivariate Data Visualization** Multivariate data visualization – Geometric Projection techniques – Icon-Based techniques – Pixel-Oriented techniques – hierarchical techniques – scatter plot Matrix – Hyper Box – Trellis display – parallel; coordinates.	9
Unit V	**Data Visualization Tools** Tableau Functions and logics: Marks and Channels – Arrange Tables – arrange spatial data – Facets into multiple views. Data Dashboard – Taxonomies – User interaction – Organizational Functions – Dashboard Design – worksheets – workbook optimization – Protection and common mistakes. Dashboard Creation using Visualization tools – Use case: Financial Marketing – Insurance – Healthcare.	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Tamara Munzer, Visualization Analysis and Design, 1st edition, CRC Press, United Sates, 2015. 2. Michael Fry, Jeffrey Ohlmann, Jeffrey Camm, James Cochran, Data Visualization: Exploring and Explaining with Data, South-Western College Publishing, 2021. **REFERENCE BOOKS:** 1. Dr. Chun-hauh Chen, W. K. Hardle, A. Unwin, Handbook of Data Visualization, 1st edition, Springer publication, Germany, 2008. 2. Ben Fry, Visualizing Data, 1st edition, O'Reilly Media, United States, 2008. 3. Avril Coghlan, A little book of R for multivariate analysis, 1st edition, Welcome Trust Sanger Institute, United Kingdom, 2013.	
Syllabus Design: Dr. Pothula Sujatha, Professor, PuDoCS.		

<table>
<tr><td>Year</td><td>I</td><td colspan="2" rowspan="3">Course Code: CSDS735
Course Title: RECOMMENDER SYSTEMS</td><td>Credits</td><td>3</td></tr>
<tr><td>Sem.</td><td>I</td><td>Hours</td><td>45</td></tr>
<tr><td></td><td></td><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="5">Basic knowledge of data structures, statistics, linear algebra, machine learning, and Python programming .</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="2">End Semester Marks: 60</td><td colspan="3">Duration of ESA (Theory): 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="5">1. Understand the importance and challenges of recommender systems.
2. Apply content-based filtering techniques.
3. Implement collaborative filtering methods.
4. Develop hybrid recommendation models.
5. Design and evaluate a domain-specific recommender system.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="5">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>2</td><td>2</td><td>2</td><td>1</td><td>2</td><td>2</td><td>3</td><td>2</td><td>2</td><td>1</td></tr>
<tr><td>CO2</td><td>3</td><td>3</td><td>3</td><td>2</td><td>3</td><td>1</td><td>1</td><td>2</td><td>3</td><td>3</td><td>2</td><td>2</td></tr>
<tr><td>CO3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>1</td><td>1</td><td>2</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO4</td><td>3</td><td>3</td><td>3</td><td>2</td><td>3</td><td>1</td><td>1</td><td>2</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO5</td><td>3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>2</td><td>2</td><td>3</td><td>3</td><td>3</td><td>3</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation
</td></tr>
<tr><th>Unit No.</th><th colspan="3">Course Content</th><th>Hours</th></tr>
<tr><td>Unit I</td><td colspan="3">Introduction
Introduction, Recommender Systems Function, Data and Knowledge Sources, Recommendation Techniques, Application and Evaluation, Recommender Systems and Human Computer Interaction, Recommender Systems as a Multi-Disciplinary Field, Recommender Systems Challenges.</td><td>9</td></tr>
<tr><td>Unit II</td><td colspan="3">Content-based Filtering
High level architecture of content-based systems, Advantages and drawbacks of content based filtering, Item profiles, Discovering features of documents, pre-processing and feature extraction, Obtaining item features from tags, Methods for learning user profiles, Similarity based retrieval, Classification algorithms.</td><td>9</td></tr>
</table>

Unit III	**Collaborative Filtering** User-based recommendation, Item-based recommendation, Model based approaches, Matrix factorization, Attacks on Collaborative recommender systems.	9
Unit IV	**Hybrid approaches** Opportunities for hybridization, Monolithic hybridization design: Feature combination, Feature augmentation, Parallelized hybridization design: Weighted, Switching, Mixed, Pipelined hybridization design: Cascade Meta-level, Limitations of hybridization strategies.	9
Unit V	**Evaluating Recommender System** Recommendation System Properties: Accuracy, Coverage, confidence, Trust, novelty, serendipity, diversity, Experimental Settings: Offline Experiments and Online Evaluation. Case Studies: Recommender systems in personalized web search and knowledge-based recommender system.	9
Recommended Learning Resources		
Print Resources	**Text Books:** 1. Ricci F., Rokach L., Shapira D., Kantor B.P., Recommender Systems Handbook, Springer, First edition, 2011. 2. Jannach D., Zanker M. and FelFering A., Recommender Systems: An Introduction, Cambridge University Press First edition, 2011. 3. Charu C. Aggarwal, Recommender Systems: The Textbook, Springer, First edition, 2016. **Reference Books:** 1. Manouselis N., Drachsler H., Verbert K., Duval E., Recommender Systems For Learning, Springer, First Edition, 2013.	
Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.		

Year	I	Course Code: CSDS736 Course Title: RESPONSIBLE AI	Credits	3
Sem.	I		Hours	45
			Category	A

Course Prerequisites, if any	-

Internal Assessment Marks: 40	End Semester Marks: 60	Duration of ESA (Theory): 03 hrs.

Course Outcomes

1. Understand concepts of fairness, accountability, bias, and privacy in AI.
2. Assess fairness and ethics in AI models.
3. Apply methods to reduce bias and ensure fairness in data and models.
4. Implement privacy-preserving techniques in AI.
5. Develop responsible AI solutions with awareness of accuracy trade-offs.

CO, PO & PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	2	2	2	3	2	3	3	3	-	-	2	2
CO2	2	3	-	2	-	3	2	2	-	2	2	2
CO3	2	3	2	2	-	3	3	3	-	2	3	3
CO4	3	2	-	1	2	3	2	2	3	3	3	3
CO5	3	2	3	2	2	2	3	3	3	3	3	3

1-low, 2-medium, 3-high, '-"- no correlation

Unit No.	Course Content	Hours
Unit I	**Introduction** Introduction to responsible AI:Need for ethics in AI, AI for Society and Humanity. Fairness and Bias: Sources of Biases, Exploratory data analysis, limitation of a dataset, Preprocessing, inprocessing and postprocessing to remove bias, Group fairness and Individual fairness, Counterfactual fairness.	9
Unit II	**Interpretability and explainability** Interpretability through simplification and visualization, Intrinsic interpretable methods, Post Hoc interpretability, Explainability through causality, Model agnostic interpretation.	9

Unit III	**Ethics and Accountability** Auditing AI models, fairness assessment, Principles for ethical practices .Accountability: Black-box problem, Algorithmic accountability, responsibility in decision-making by AI, case studies of AI failures	9
Unit IV	**Privacy preservation** Attack models, Privacy-preserving Learning, Differential privacy, Federated learning - concepts, significance and applications..	9
Unit V	**Case study** Recommendation systems, Medical diagnosis, Hiring/ Education, Computer Vision, Natural Language Processing, smart cities.	9
Recommended Learning Resources		
Print Resources	**Text Books:** 1. Virginia Dignum, "Responsible Artificial Intelligence: How to Develop and Use AI in a ResponsibleWay", Springer Nature, 2019. 2. Christoph Molnar "Interpretable Machine Learning", Lulu, 1st Edition, 2019.	
Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.		

Year	I	**Course Code: CSDS705** **Course Title : ADVANCED DATA STRUCTURES AND ALGORITHMS LAB**	**Credits**	2
Sem.	I		**Hours**	30
			Category	B
Internal Assessment Marks: 40	End Semester Marks: 60		Duration of ESA : 03 hrs.	

Skills to be acquired:

Analytical thinking and the ability to design efficient algorithmic solutions for complex problems.

Lab Software Requirements:

C/C++/JAVA/Python

Course Outcome:

1. Understand and implement advanced algorithmic strategies including dynamic programming, greedy, and graph algorithms.
2. Solve complex problems involving optimization, string matching, and flow networks using efficient techniques.
3. Develop the ability to analyse and compare algorithmic performance in terms of time and space complexity.

CO, PO & PSO Mapping :

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	2	3	3	1	-	-	2	2	2	2	1
CO2	3	2	3	3	2	1	-	2	3	3	2	2
CO3	3	2	3	2	2	-	-	2	2	2	3	2

1-low, 2-medium, 3-high, '-"- no correlation

List of Exercises:

1. Implement Maximum Subarray problem.
2. Implement Strassen's matrix multiplication.
3. Implement the Rod Cutting algorithm.
4. Implement Matrix-Chain Multiplication.
5. Implement the Longest Common Subsequence algorithm.
6. Implement Optimal Binary Search Trees.
7. Implement Huffman Codes using Greedy Algorithm.
8. Implement the Ford-Fulkerson Method.
9. Implement Maximum Bipartite Matching.
10. Implement the Rabin-Karp Algorithm.
11. Implement String Matching with Finite Automata.
12. Implement the Knuth-Morris-Pratt Algorithm.

Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.

Year	I	**Course Code: CSDS706** **Course Title : AI AND DATA MINING LAB**	**Credits**	2
Sem.	I		**Hours**	30
			Category	B
Internal Assessment Marks: 40	End Semester Marks: 60		Duration of ESA : 03 hrs.	

Skills to be acquired:
Proficiency in Weka and Python libraries in performing various data analysis tasks.

Lab Software Requirements:
Weka and Python with Jupyter or IDE, and libraries: Pandas, NumPy, Matplotlib, Seaborn, Scikit-learn, and SciPy.

Course Outcome:

1. Gain hands-on experience in data analysis, preprocessing, and model implementation using Weka and Python.
2. Apply classification, clustering, and association algorithms on real-world datasets.
3. Develop the ability to evaluate and interpret model performance and data patterns effectively.

CO, PO & PSO Mapping :

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	3	2	2	1	-	-	2	3	3	2	1
CO2	3	3	3	3	2	1	-	2	3	3	2	2
CO3	3	3	3	3	2	-	1	3	3	3	3	2

1-low, 2-medium, 3-high, '-"- no correlation

List of Exercises:

1. Implement exploratory data analysis on a downloaded dataset using Weka
2. Implement exploratory data analysis on a downloaded dataset using Python
3. Implement data preprocessing on the dataset using Weka
4. Implement data preprocessing on the dataset using Python
5. Implement Apriori algorithm using Python/Weka
6. Implement the following classification algorithms in Python
   - Naive Bayes
   - Decision Tree
   - KNN
   - SVM
   - Neural network
7. Implement the following clustering algorithms in Python
   - K Means
   - DBSCAN
   - Agglomerative

Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.

SEMESTER II

<table>
<tr><td>Year</td><td>I</td><td colspan="3" rowspan="3">Course Code: CSDS751
Course Title : MACHINE LEARNING AND DEEP LEARNING</td><td>Credits</td><td>3</td></tr>
<tr><td rowspan="2">Sem.</td><td rowspan="2">II</td><td>Hours</td><td>45</td></tr>
<tr><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="6">Basic knowledge of AI, linear algebra, probability and statistics</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="3">End Semester Marks: 60</td><td colspan="3">Duration of ESA : 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="6">1. Understand foundational machine learning concepts.
2. Ability to implement decision tree algorithm and clustering techniques.
3. Design and train neural networks for classification tasks.
4. Explore deep learning models like CNN and LSTM.
5. Understand and Implement various generative models.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="6">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>3</td><td>2</td><td>-</td><td>-</td><td>-</td><td>2</td><td>3</td><td>3</td><td>2</td><td>-</td></tr>
<tr><td>CO2</td><td>3</td><td>3</td><td>3</td><td>3</td><td>1</td><td>1</td><td>1</td><td>3</td><td>3</td><td>3</td><td>2</td><td>1</td></tr>
<tr><td>CO3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>-</td><td>-</td><td>2</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO4</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>2</td><td>2</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO5</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>1</td><td>-</td><td>2</td><td>3</td><td>3</td><td>3</td><td>3</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation</td></tr>
<tr><th>Unit No.</th><th colspan="5">Course Content</th><th>Hours</th></tr>
<tr><td>Unit I</td><td colspan="5">Introduction

Basic Concepts, Introduction to Machine Learning, Applications of ML, Design Perspective and Issues in ML, Supervised, Unsupervised, Semi-supervised learning with applications and issues.</td><td>9</td></tr>
<tr><td>Unit II</td><td colspan="5">Machine Learning

Linear regression - Logistic regression - SVM - Ensemble learning : Bagging - Boosting - Stacking. Performance measures - Notion of Generalization and concern of Overfitting - Bias - Notion of Training, Validation and Testing - Connect to generalisation and overfitting.</td><td>9</td></tr>
</table>

Unit III	**Deep Networks** Introduction to Neural Networks, Feed-forward Networks, Deep Feed- forward Networks - Learning XOR, Gradient Based learning, Hidden Units, Back- propagation and other Differential Algorithms, Regularization for Deep Optimization for training Deep Models.	9
Unit IV	**Convolutional Networks and Sequence modelling** Convolution operation, Motivation, Pooling, Efficient convolution algorithms, Sequence Modeling: Recurrent and Recursive Nets, LSTM Networks, Applications - Computer Vision, Speech Recognition, Natural Language Processing..	9
Unit V	**Deep Learning Frameworks** Introduction to Keras and Tensorflow, Deep Learning for computer vision - convnets, Deep Learning for Text and Sequences, Generative deep learning - Text Generation with LSTM, Deep Dream, Neural Style Transfer, Generating images with variational autoencoders, Generative Adversarial Networks (GAN)	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Kevin Murphy, Machine Learning: A Probabilistic Perspective, MIT Press, 2nd edition, 2020. 2. Stephen Marsland, Machine Learning: An Algorithmic Perspective, Chapman & Hall/CRC, Second Edition, 2015. 3. Ethem Alpaydin, Introduction to Machine Learning, Fourth Edition, MIT Press, 2020. 4. Francois Chollet, Deep Learning with Python, Manning Publications, 2017. **REFERENCE BOOKS:** 1. Tom M.Mitchell, Machine Learning, First Edition, McGraw-Hill, 1997. 2. lan Goodfellow, Yoshua Bengio, Aaron Courville, Deep Learning, The MIT Press, 2016.	
Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.		

Year	I	Course Code: CSDS752 Course Title: BIG DATA ANALYTICS	Credits	3
Sem.	II		Hours	45
			Category	A

Course Prerequisites, if any	Basic programming knowledge (python) and basics of statistics.	
Internal Assessment Marks: 40	End Semester Marks: 60	Duration of ESA : 03 hrs.

Course Outcomes

1. Process data in Big Data platform and explore the big data analytics techniques for business applications
2. Analyze Map Reduce technologies in big data analytics
3. Develop Big Data solutions using Hadoop Eco System
4. Design efficient algorithms for stream data mining on big data platform

CO, PO & PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	2	3	2	2	1	1	2	3	3	2	1
CO2	3	3	3	3	2	-	-	2	3	3	2	2
CO3	3	3	3	3	2	1	1	2	3	3	3	2
CO4	3	3	3	3	2	2	-	3	3	3	3	3

1-low, 2-medium, 3-high, '-"- no correlation

Unit No.	Course Content	Hours
Unit I	**Introduction** Need of big data - classification of data - characteristics - handling Techniques. Scalability and parallel Processing - Designing Data Architecture – Preprocessing- Data Storage and Analysis - big data Analytics Applications and case studies.	9
Unit II	**Hadoop** Introduction - Hadoop and its Ecosystem - Hadoop Distributer File System - Mapreduce Framework and Programming - Yarn - Tools - Spark and Big Data Analytics	9
Unit III	**Data Stream Mining** Data Stream Concepts and Data Stream Management - Data Stream Concepts - Data Stream Model - Architecture - management Systems - Examples - Stream Queries -stream Computing Aspects - Frequent Item sets - Counting Frequent Items in a stream – Spark Streaming	9

Unit IV	**AI and ML solutions for Big Data** Requirements and Applications for Smart Healthcare, Digital Learning, Customer Experience Management, Business Intelligence , Electric Power Systems.	9
Unit V	**Tools for real time analytics** Apache Kafka- Architecture- Kafka stream processing Examples-Apache Storm - Real-time stream processing use cases	9
Recommended Learning Resources		
	TEXT BOOKS: 1. Raj Kamal and Preeti Saxena, Big Data Analytics: Introduction to Hadoop, Spark, and Machine Learning, MC Graw Hill, 2019. **REFERENCE BOOKS:** 1. Shilpi Saxena, Saurabh Gupta, Practical Real-time Data Processing and Analytics, Packt Publishing, 2017. 2. Gwen Shapira, Todd Palino, Rajini Sivaram, Krit Petty, Kafka – The Definitive Guide: Real-time data and stream processing at scale, Second Edition, O'Reilly Media, 2021. 3. Ankit Jain, Mastering Apache Storm: Processing big data streams in real time, Packt Publishing, 2017.	
Syllabus Design: Dr. Pothula Sujatha, Professor, PuDoCS.		

<table>
<tr><td>Year</td><td>I</td><td colspan="3" rowspan="2">Course Code: CSDS753
Course Title: SECURITY FOR DATA SCIENCE</td><td>Credits</td><td>4</td></tr>
<tr><td>Sem.</td><td>II</td><td>Hours</td><td>75</td></tr>
<tr><td colspan="5"></td><td>Category</td><td>C</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="6">Basic knowledge of data science and machine learning.
Familiarity with cybersecurity concepts and Python programming.</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="3">End Semester Marks: 60</td><td colspan="3">Duration of ESA: 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="6">1. Understand basic concepts of data security, privacy, and cyber threats in data science.
2. Use data science methods to detect malware and insider threats.
3. Analyze how attacks affect machine learning and how to defend against them.
4. Evaluate decision tree methods that protect data privacy.
5. Create secure data science solutions for smart systems like connected transportation.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="6">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>2</td><td>2</td><td>2</td><td>2</td><td>2</td><td>2</td><td>3</td><td>2</td><td>2</td><td>1</td></tr>
<tr><td>CO2</td><td>3</td><td>3</td><td>3</td><td>2</td><td>3</td><td>2</td><td>1</td><td>2</td><td>3</td><td>3</td><td>3</td><td>1</td></tr>
<tr><td>CO3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>2</td><td>2</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO4</td><td>3</td><td>2</td><td>2</td><td>2</td><td>2</td><td>1</td><td>2</td><td>2</td><td>3</td><td>2</td><td>2</td><td>2</td></tr>
<tr><td>CO5</td><td>3</td><td>3</td><td>3</td><td>2</td><td>3</td><td>2</td><td>3</td><td>2</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation
</td></tr>
<tr><th>Unit No.</th><th colspan="4">Course Content</th><th>Hours</th></tr>
<tr><th colspan="6">Theory Component</th></tr>
<tr><td>Unit I</td><td colspan="4">Introduction
Data Security and Privacy - Security Policies - Policy Enforcement and Related Issues - Data Privacy - Data Mining Techniques - Cyber Security Threats - Data Mining for Cyber Security - Security and Privacy-Enhanced Data Mining - Semantic Web and Security - Big Data Security and Privacy - Issues and Research Challenges - Big Data Management and Analytics - Cyber Security for Big Data Analytics.</td><td>9</td></tr>
</table>

Unit II	**Data Science for Cyber Security** Data Science for Malicious Executables - Stream Analytics for Malware Detection: Stream Mining - Novel Class Detection - Evaluation - Security Applications and Malware Detection - Cloud-Based Data Science for Malware Detection - Stream Analytics for Insider Threat Detection: Big Data Techniques for Scalability - Ensemble Learning - Ensemble for Unsupervised Learning and Supervised Learning - Insider Threat Detection for Sequence Data - Classifying Sequence Data - USSL - Anomaly Detection.	9
Unit III	**Security and Privacy Enhanced Data Science** Adversarial Learning: Adversarial Attack Models - Free-range Attack - Restrained Attack - Adversarial SVM Learning - AD-SVM against Free-range Attack Model - AD-SVM against Restrained Attack Model - Experiments on Artificial Dataset and Real Datasets. Adversarial Learning Using Relevance Vector Machine Ensembles: Relevance Vector Machine - Kernel Parameter Fitting - Experiments on Artificial Dataset and Real Datasets.	9
Unit IV	**Privacy Preserving Decision Trees** Privacy Metrics - Decision Tree Construction - Splitting Criterion - Discretizing Continuous Attributes - Stopping Criteria - Naive Bayes Classifier - Over Perturbed Numeric Data - PPDTC4.5 - Splitting Criterion - Splitting Training Data Set - Classifying the Perturbed Instance - Local vs. Global Data Mining - Reconstruction-Based Approaches Results - PPDTC4.5 Classifier Accuracy - Algorithm Complexity.	9
Unit V	**Emerging Applications for Secure Data Science** Internet of Transportation Systems - Integration of Cyber Security and AI - Security and Privacy for the Internet of Transportation Systems - AI and Security for Cloud-based Internet of Transportation Systems - Directions for Secure Data Science.	9
Practical Component		
Exercises	1. Implement basic access control policy enforcement in a sample system. 2. Apply stream mining techniques for real-time malware detection. 3. Use ensemble learning models to detect insider threats from user activity data. 4. Simulate adversarial attacks on SVM and analyze model vulnerability.	30

	5. Implement an Adversarial SVM (AD-SVM) to defend against attack models. 6. Evaluate privacy metrics such as information loss and disclosure risk. 7. Design a secure data pipeline for the Internet of Transportation Systems. 8. Develop an AI-based anomaly detection model for cloud-based ITS security. 9. Perform big data analytics on cybersecurity logs using Apache Spark. 10. Evaluate the privacy and security robustness of a data mining model.	
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Bhavani Thuraisngham, Murat Kantarcioglu, and Latifur Khan, Secure Data Science: Integrating Cyber Security and Data Science, First Edition, CRC Press, Taylor & Francis Group, 2022. **REFERENCE BOOKS:** 1. Joshua Saxe with Hillary Sanders, Malware Data Science: Attack Detection and Attribution, First Edition, No Starch Press, Inc., 2018. 2. Cioffi-Revilla, Claudio, Data Driven Security: Analysis, Visualization and Dashboards, First Edition, John Wiley & Sons, Inc., 2014. 3. Clarence Chio and David Freeman, Machine Learning and Security: Protecting Systems with Data and Algorithms, First Edition, O'reilly Media, Inc., 2018.	
Syllabus Design: Dr. M. Sathya, Assistant Professor, PUDoCS		

<table>
<tr><td>Year</td><td>I</td><td rowspan="3">Course Code: CSDS771
Course Title: PARALLEL AND GPU COMPUTING</td><td>Credits</td><td>3</td></tr>
<tr><td>Sem.</td><td>II</td><td>Hours</td><td>45</td></tr>
<tr><td></td><td></td><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="4">Basic knowledge of computer architecture, programming and data structures.</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="2">End Semester Marks: 60</td><td colspan="2">Duration of ESA (Theory): 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="4">1. Understand parallel computing, architectures, and performance metrics.
2. Apply parallel programming models for concurrent execution.
3. Develop GPU-based programs using the CUDA programming model.
4. Implement parallel algorithms and analyze their efficiency.
5. Explore real-world applications of GPU computing.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="4">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>3</td><td>2</td><td>1</td><td>-</td><td>-</td><td>2</td><td>3</td><td>2</td><td>2</td><td>1</td></tr>
<tr><td>CO2</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>-</td><td>-</td><td>2</td><td>3</td><td>2</td><td>2</td><td>2</td></tr>
<tr><td>CO3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>-</td><td>1</td><td>3</td><td>3</td><td>2</td><td>3</td><td>2</td></tr>
<tr><td>CO4</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>-</td><td>-</td><td>2</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO5</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>2</td><td>1</td><td>3</td><td>3</td><td>3</td><td>3</td><td>3</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation
</td></tr>
<tr><th>Unit No.</th><th colspan="3">Course Content</th><th>Hours</th></tr>
<tr><td>Unit I</td><td colspan="3">Introduction to Parallel Computing
Overview of Parallel Computing – Need and Scope – Flynn’s Taxonomy – Types of Parallelism – Shared Memory and Distributed Memory Architectures – Amdahl’s Law – Performance Metrics – Applications in Data Analytics</td><td>9</td></tr>
<tr><td>Unit II</td><td colspan="3">Parallel Programming Models and Tools
Message Passing Interface (MPI) – Concepts of Communication and Synchronization – Point-to-Point and Collective Communication – OpenMP Programming Model – Fork-Join Model – Parallel Directives and Synchronization Constructs – Parallel Debugging and Profiling Tools</td><td>9</td></tr>
</table>

Unit III	**GPU Architecture and Programming Basics** Introduction to GPUs – Differences Between CPU and GPU Architectures – CUDA Programming Model – Threads, Blocks, and Grids – Memory Hierarchy in CUDA – Writing and Launching CUDA Kernels – CUDA Memory Management – Synchronization and Thread Divergence	9
Unit IV	**Parallel Algorithms and Data Structures** Parallel Algorithms for Matrix Operations – Reduction – Scan – Sorting – Searching – MapReduce Model – Load Balancing and Scalability Issues – Data Parallelism in Data Analytics Workflows	9
Unit V	**Applications and Advanced Topics in GPU Computing** High-Performance Computing (HPC) for Data Analytics – Use Cases: Deep Learning, Image Processing, Real-Time Analytics – GPU Libraries (cuBLAS, cuDNN, Thrust) – Introduction to TensorFlow and PyTorch with GPU Acceleration – Future Trends in Parallel and GPU Computing	9
Recommended Learning Resources		
Print Resources	**Text Books:** 1. Michael J. Quinn, Parallel Programming in C with MPI and OpenMP, McGraw Hill Education India, 2017. 2. Jason Sanders and Edward Kandrot, CUDA by Example: An Introduction to General-Purpose GPU Programming, Addison-Wesley, 2010. 3. Brian Tuomanen, Hands-On GPU Programming with Python and CUDA: Explore high-performance parallel computing with CUDA, Packt Publishing, 2018.	
Syllabus design: Dr. T. Vengattaraman, Associate Professor, PUDoCS		

Year	I	Course Code: CSDS772 Course Title: CLOUD COMPUTING	Credits	3
Sem.	II		Hours	45
			Category	A

Course Prerequisites, if any	Basic understanding of networking, operating systems, databases, and programming.	
Internal Assessment Marks: 40	End Semester Marks: 60	Duration of ESA (Theory): 03 hrs.

Course Outcomes

1. Understand core concepts, models, and technologies in cloud computing.
2. Analyse cloud infrastructure for scalable data analytics solutions.
3. Use cloud platforms and services for big data and real-time analytics.
4. Implement secure and efficient data processing using cloud-based tools.
5. Apply cloud AI/ML services for advanced analytics applications.

CO, PO & PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	2	2	2	1	-	-	2	2	2	2	1
CO2	3	3	3	3	2	1	-	2	3	3	3	2
CO3	3	3	3	3	2	1	1	2	3	3	3	2
CO4	3	3	3	3	2	2	1	2	3	3	3	3
CO5	3	3	3	3	2	2	1	3	3	3	3	3

1-low, 2-medium, 3-high, '-"- no correlation

Unit No.	Course Content	Hours
Unit I	**Fundamentals of Cloud Computing** Definition and characteristics – Service models: IaaS, PaaS, SaaS – Deployment models: public, private, hybrid – Virtualization technologies – Benefits and challenges in data analytics.	9
Unit II	**Cloud Infrastructure and Services** Compute and storage services – Elasticity and scalability – Cloud networking basics – Load balancing – Introduction to containerization (Docker, Kubernetes) for analytics workloads.	9
Unit III	**Cloud Platforms for Data Analytics** AWS, Azure, Google Cloud overview – Cloud-native analytics tools (Amazon Redshift, BigQuery, Azure Synapse) – Data lakes vs data warehouses – Serverless computing for ETL.	9

Unit IV	**Data Management and Processing on Cloud** Big data processing frameworks: Hadoop, Spark – Cloud storage options: S3, Blob storage – Stream data processing with cloud services – Data security and compliance in cloud analytics.	9
Unit V	**Advanced Topics and Applications** Cloud-based ML and AI services – AutoML tools – Edge and fog computing – Cost optimization strategies – Case studies: real-time analytics, predictive analytics in the cloud.	9
Recommended Learning Resources		
Print Resources	**Text Books:** 1. Rajkumar Buyya, Christian Vecchiola, and Thamarai Selvi, Mastering Cloud Computing: Foundations and Applications Programming, McGraw Hill Education, 2022. 2. Gautam Shroff, Enterprise Cloud Computing: Technology, Architecture, Applications, Cambridge University Press, Reprint Edition, 2021.	
Syllabus design: Dr. T. Vengattaraman, Associate Professor, PUDoCS		

<table>
<tr><td>Year</td><td>I</td><td colspan="3" rowspan="2">Course Code: CSDS773
Course Title: MULTIMODAL ANALYTICS</td><td>Credits</td><td>3</td></tr>
<tr><td>Sem.</td><td>II</td><td>Hours</td><td>45</td></tr>
<tr><td colspan="4"></td><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="6">Student should have Basic Programming, Mathematics, Machine Learning, Data Analysis, and understanding of Data Types</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="3">End Semester Marks: 60</td><td colspan="3">Duration of ESA : 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="6">1. Understand the principles of multimodal data integration
2. Learn representation and fusion techniques
3. Apply multimodal analytics in real-world scenarios
4. Develop skills for ethical data handling and decision-making</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="6">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>2</td><td>2</td><td>1</td><td>1</td><td>-</td><td>2</td><td>2</td><td>2</td><td>2</td><td>1</td></tr>
<tr><td>CO2</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>-</td><td>-</td><td>2</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>1</td><td>1</td><td>2</td><td>3</td><td>3</td><td>3</td><td>3</td></tr>
<tr><td>CO4</td><td>2</td><td>2</td><td>2</td><td>2</td><td>3</td><td>2</td><td>2</td><td>3</td><td>2</td><td>2</td><td>2</td><td>3</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation</td></tr>
<tr><th>Unit No.</th><th colspan="4">Course Content</th><th>Hours</th></tr>
<tr><td>Unit I</td><td colspan="4">Introduction to Multimodal Analytics
Definitions & Scope - Importance and Challenges - Types of Modalities - Overview of Use-Cases: Healthcare, Autonomous Vehicles, Retail, Security - Tools & Libraries: Python, TensorFlow, PyTorch, HuggingFace Multimodal toolkit</td><td>9</td></tr>
<tr><td>Unit II</td><td colspan="4">Representation Learning for Multimodal Data
Data Preprocessing Techniques - Feature Extraction: Text, Image, Audio - Representation Models: Autoencoders, Word2Vec, CNN, Transformers - Data Alignment Techniques Temporal & Spatial</td><td>9</td></tr>
<tr><td>Unit III</td><td colspan="4">Fusion Techniques for Multimodal Data
Early Fusion, Late Fusion, and Hybrid Fusion - Tensor Fusion Networks - Attention Mechanisms - Architectures: Multimodal Transformers, Multimodal Variational Autoencoders</td><td>9</td></tr>
</table>

Unit IV	**Applications of Multimodal Analytics** Sentiment Analysis across modalities - Multimodal Healthcare Analytics - Recommendation Systems using multimodal data - Human Activity Recognition using video and sensor fusion - Robotics and Autonomous Systems	9
Unit V	**Case Studies, Ethics, and Future Directions** Multimodal Analytics for Smart Cities - Privacy, Security, and Ethical Challenges - Interpretability and Explainability in Multimodal Models - Career Paths and Industry Trends - Future of Multimodal AI	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Susan Shu Chang, Rikin Gandhi, Suhas Pai, Nahid Alam, Anthony Susevski, Andrei Betlen, Shekhar Iyer, Jingying Gao, Antje Barth, Omar Aldughayem, Chris Fregly, AI Superstream: Multimodal Generative AI, O'Reilly Media, 2024. **REFERENCE BOOKS:** 1. Santosh Kumar & Sanjay Kumar Singh, Multimodal Machine Learning: Techniques and Applications, Elsevier, 2021.	
Syllabus Design: Dr. Sukhvinder Singh, Assistant Professor, PUDoCS		

Year	I	Course Code: CSDS774 Course Title: IOT AND PREDICTIVE ANALYTICS	Credits	3
Sem.	II		Hours	45
			Category	A

Course Prerequisites, if any	Basic knowledge of programming, statistics, machine learning, databases, and computer networks.	
Internal Assessment Marks: 40	End Semester Marks: 60	Duration of ESA (Theory): 03 hrs.

Course Outcomes

1. Describe IoT architecture, components, and communication protocols.
2. Collect, store, and preprocess IoT data for analytics.
3. Apply predictive models for analysis and forecasting.
4. Perform predictive analytics on IoT data for real-world use cases.
5. Evaluate IoT platforms and explore future trends.

CO, PO & PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	2	2	2	-	2	1	2	2	2	1	-
CO2	3	3	3	2	2	2	-	2	3	2	2	1
CO3	3	3	3	3	3	1	-	2	3	3	3	2
CO4	3	3	3	3	3	2	-	2	3	3	3	3
CO5	2	2	2	2	3	2	2	3	2	2	2	3

1-low, 2-medium, 3-high, '-"- no correlation

Unit No.	Course Content	Hours
Unit I	**Introduction to IoT** Definition and Evolution of IoT – IoT Ecosystem – IoT Architecture – Physical and Logical Design – IoT Enabling Technologies – Sensors and Actuators – Communication Protocols (Zigbee – Bluetooth – MQTT – HTTP – CoAP) – IoT Applications in Data Analytics	9
Unit II	**IoT Data Acquisition and Management** Data Collection from IoT Devices – Streaming Data and Time-Series – Edge vs. Cloud Computing – Data Storage Solutions (InfluxDB – MongoDB – AWS IoT Core) – Real-Time Data Processing – Sensor Data Characteristics – Preprocessing IoT Data for Analytics	9

Unit III	**Introduction to Predictive Analytics:** Definition and Importance – Types of Predictive Models – Supervised Learning Techniques – Linear and Logistic Regression – Decision Trees – Random Forests – Time Series Forecasting – Model Evaluation: MAE – RMSE – R^2 – Cross-Validation	9
Unit IV	**Predictive Analytics on IoT Data** Data Integration from IoT Sources – Feature Engineering for Sensor Data – Predictive Maintenance – Anomaly Detection – Forecasting with IoT Data (ARIMA – LSTM – Prophet) – Visualization and Dashboarding – Case Studies in Smart Cities, Healthcare, and Industry 4.0	9
Unit V	**IoT Platforms and Future Trends:** Overview of IoT Platforms (ThingSpeak – AWS IoT – Google Cloud IoT – Azure IoT Hub) – Security and Privacy in IoT Data – Ethics in Predictive Analytics – Federated Learning for IoT – Edge AI – Role of AI/ML in Future IoT Systems – Research Directions	9
Recommended Learning Resources		
Print Resources	**Text Books:** 1. Arshdeep Bahga & Vijay Madisetti, Internet of Things: A Hands-On Approach, Orient Blackswan, 1st Edition, 2015 2. Eric Siegel, Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die, John Wiley & Sons Inc, 2016.	
Syllabus design: Dr. T. Vengattaraman, Associate Professor, PUDoCS		

<table>
<tr><td>Year</td><td>I</td><td rowspan="3">Course Code: CSDS775
Course Title: OPTIMIZATION TECHNIQUES FOR ANALYTICS</td><td>Credits</td><td>3</td></tr>
<tr><td>Sem.</td><td>II</td><td>Hours</td><td>45</td></tr>
<tr><td colspan="2"></td><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="4">● Basic knowledge of linear algebra, calculus, and probability.
● Familiarity with Python programming and data analysis techniques.</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="2">End Semester Marks: 60</td><td colspan="2">Duration of ESA: 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="4">1. Describe basic optimization concepts and methods like least squares, SVM, and convex functions.
2. Use descent methods to solve convex and smooth optimization problems.
3. Analyze momentum and stochastic gradient methods in machine learning.
4. Apply first-order methods to constrained and non-smooth optimization.
5. Develop dual optimization algorithms and apply them to real-world problems.</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="4">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>2</td><td>3</td><td>2</td><td>-</td><td>-</td><td>-</td><td>2</td><td>2</td><td>3</td><td>2</td><td>-</td></tr>
<tr><td>CO2</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>-</td><td>-</td><td>2</td><td>2</td><td>3</td><td>2</td><td>-</td></tr>
<tr><td>CO3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>-</td><td>-</td><td>2</td><td>2</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO4</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>-</td><td>-</td><td>2</td><td>2</td><td>3</td><td>3</td><td>2</td></tr>
<tr><td>CO5</td><td>3</td><td>3</td><td>3</td><td>3</td><td>3</td><td>1</td><td>1</td><td>2</td><td>2</td><td>3</td><td>3</td><td>3</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation</td></tr>
<tr><th>Unit No.</th><th colspan="2">Course Content</th><th colspan="2">Hours</th></tr>
<tr><td colspan="5">Theory Component</td></tr>
<tr><td>Unit I</td><td colspan="2">Introduction
Data Analysis and Optimization - Least Squares - Matrix Factorization Problems - SVM - LR - Deep Learning - Foundations of Smooth Optimization - A Taxonomy of Solutions to Optimization Problems - Taylor’s Theorem - Characterizing Minima of Smooth Functions - Convex Sets and Functions - Strongly Convex Functions.</td><td colspan="2">9</td></tr>
<tr><td>Unit II</td><td colspan="2">Descent Methods
Descent Directions - Steepest-Descent Method - General Case - Convex Case - Strongly Convex Case - Comparison between Rates - Descent Methods: Convergence - Line-Search Methods - Convergence to Approximate Second-Order Necessary Points - Mirror Descent - The KL and PL Properties.</td><td colspan="2">9</td></tr>
</table>

Unit III	**Gradient Methods Using Momentum** Differential Equations - Nesterov's Method: Convex Quadratics - Convergence for Strongly Convex Functions and Weakly Convex Functions - Conjugate Gradient Methods - Lower Bounds on Convergence Rates - Stochastic Gradient : Noisy Gradients - Incremental Gradient Method - Classification and Perceptron - Empirical Risk Minimization - Randomness and Step-length - Convergence Analysis - Epochs - Mini-batching. **Coordinate Descent** Coordinate Descent in Machine Learning - Coordinate Descent for Smooth Convex Functions - Block-Coordinate Descent.	9
Unit IV	**First-Order Methods for Constrained Optimization** Optimality Conditions - Euclidean Projection - Projected Gradient Algorithm - Conditional Gradient (Frank–Wolfe) Method **Non-smooth Functions and Sub-gradients** Sub-gradients and Subdifferentials - Subdifferential and Directional Derivatives - Calculus of Subdifferentials - Convex Sets and Convex Constrained Optimization - Optimality Conditions for Composite Non-smooth Functions - Non-smooth Optimization Methods.	9
Unit V	**Duality and Algorithms** Quadratic Penalty Function - Lagrangians and Duality - First-Order Optimality Conditions - Strong Duality - Dual Algorithms - Applications of Dual Algorithms: Consensus Optimization - Utility Maximization - Linear and Quadratic Programming. **Differentiation and Adjoints** Chain Rule for a Nested Composition of Vector Functions - Method of Adjoints - Adjoints in Deep Learning - Automatic Differentiation - Derivations via Lagrangian and Implicit Function Theorem.	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Stephen J. Wright, Benjamin Recht, Optimization for Data Analysis, Cambridge University Press, First Published 2022. **REFERENCE BOOKS:** 1. Richard W. Cottle and Mukund N. Thapa, Linear and Nonlinear Optimization, First Edition, Springer New York, 2017. 2. Gerard Cornuejols and Reha Tutuncu, Optimization Methods in Finance, Fourth Edition, Cambridge University Press, 2013.	
Syllabus Design: Dr. M. Sathya, Assistant Professor, PUDoCS		

<table>
<tr><td>Year</td><td>I</td><td colspan="3" rowspan="3">Course Code: CSDS776
Course Title: FINANCIAL AND RISK ANALYTICS</td><td>Credits</td><td>3</td></tr>
<tr><td>Sem.</td><td>II</td><td>Hours</td><td>45</td></tr>
<tr><td></td><td></td><td>Category</td><td>A</td></tr>
<tr><td>Course Prerequisites, if any</td><td colspan="6">Student should have Basic Programming, Mathematics, Machine Learning, Data Analysis, and understanding of Data Types</td></tr>
<tr><td>Internal Assessment Marks: 40</td><td colspan="3">End Semester Marks: 60</td><td colspan="3">Duration of ESA : 03 hrs.</td></tr>
<tr><td>Course Outcomes</td><td colspan="6">1. Understand and classify major types of financial risks.
2. Apply quantitative risk measurement techniques.
3. Analyze the structure and functions of financial institutions
4. Evaluate the impact of modern challenges
5. Design integrated risk management strategies</td></tr>
<tr><td>CO, PO & PSO Mapping</td><td colspan="6">
<table>
<tr><th>CO</th><th>PO1</th><th>PO2</th><th>PO3</th><th>PO4</th><th>PO5</th><th>PO6</th><th>PO7</th><th>PO8</th><th>PSO1</th><th>PSO2</th><th>PSO3</th><th>PSO4</th></tr>
<tr><td>CO1</td><td>3</td><td>-</td><td>2</td><td>-</td><td>-</td><td>2</td><td>1</td><td>2</td><td>3</td><td>2</td><td>-</td><td>-</td></tr>
<tr><td>CO2</td><td>3</td><td>2</td><td>3</td><td>2</td><td>3</td><td>1</td><td>1</td><td>2</td><td>3</td><td>3</td><td>2</td><td>-</td></tr>
<tr><td>CO3</td><td>3</td><td>-</td><td>2</td><td>2</td><td>2</td><td>2</td><td>2</td><td>2</td><td>2</td><td>2</td><td>-</td><td>-</td></tr>
<tr><td>CO4</td><td>2</td><td>2</td><td>2</td><td>2</td><td>3</td><td>2</td><td>2</td><td>2</td><td>2</td><td>3</td><td>2</td><td>2</td></tr>
<tr><td>CO5</td><td>3</td><td>2</td><td>3</td><td>3</td><td>3</td><td>3</td><td>2</td><td>2</td><td>3</td><td>3</td><td>3</td><td>2</td></tr>
</table>
1-low, 2-medium, 3-high, ‘-“- no correlation</td></tr>
<tr><th>Unit No.</th><th colspan="4">Course Content</th><th>Hours</th></tr>
<tr><td>Unit I</td><td colspan="4">Foundations of Financial Risk and Institutions
Introduction - Importance and Objectives - Types of Financial Risks - Risk vs. Uncertainty - Financial Institutions Overview - Regulatory Environment - Risk Management by Central Authorities</td><td>9</td></tr>
<tr><td>Unit II</td><td colspan="4">Market Risk and Measurement Techniques
Fundamentals - Value at Risk - Stress Testing and Scenario Analysis - Measuring Volatility - Historical Simulation, Delta-Normal Method - Model Risk Management - Governance Frameworks for Models</td><td>9</td></tr>
</table>

Unit III	**Credit Risk and Liquidity Risk** Credit Risk Management - Credit Scoring and Rating Systems - Credit Derivatives and Credit Default Swaps - Counterparty Risk - Liquidity Risk - Types: Funding vs. Market Liquidity Risk - Measuring and Managing Liquidity Risk - Collateral Management	9
Unit IV	**Operational, Cyber, and Climate Risks** Definition, Framework, and Mitigation - Cyber Risk - Risks from Digital Transformation - Cyber Risk Regulations - Climate Risk - ESG Risk Management - Integrating Climate Risk in Financial Models	9
Unit V	**Risk Management Best Practices & Regulatory Compliance** Enterprise Risk Management - Integrating Risks Across the Enterprise - Financial Regulation Overview - Stress Tests and Reporting Requirements - Future Trends in Risk Management - AI & Machine Learning in Risk Analytics - RegTech innovations	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. John C. Hull, Risk Management and Financial Institutions, 6th Edition, Wiley, 2023. **REFERENCE BOOKS:** 1. Angelo Corelli, Understanding Financial Risk Management, 3rd Edition, Emerald Publishing, 2024.	
Syllabus Design: Dr. Sukhvinder Singh, Assistant Professor, PUDoCS		

Year	I	Course Code: CSDS777 Course Title: COMPUTATIONAL INTELLIIGENCE	Credits	3
Sem.	II		Hours	45
			Category	A

Course Prerequisites, if any	-	
Internal Assessment Marks: 40	End Semester Marks: 60	Duration of ESA : 03 hrs.

Course Outcomes

1. Understand the fundamentals and techniques of Computational Intelligence.
2. Implement basic neural networks for problem-solving.
3. Apply Evolutionary Computation and genetic algorithms to optimization tasks.
4. Use swarm intelligence to enhance problem-solving skills.
5. Develop fuzzy logic systems to handle uncertainty in engineering problems.

CO, PO & PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	2	2	2	2	-	1	2	3	2	-	-
CO2	3	3	3	2	3	1	1	2	3	3	2	2
CO3	3	3	3	2	3	1	1	2	3	3	3	2
CO4	3	3	3	2	3	1	1	2	3	3	3	2
CO5	3	3	3	2	2	1	1	2	3	3	3	3

1-low, 2-medium, 3-high, '-"- no correlation

Unit No.	Course Content	Hours
Unit I	**Introduction** Background and history of evolutionary computation - Behavioral Motivations for Fuzzy Logic, Myths and Applications areas of Computational Intelligence. Adaption - Self organization and Evolution - Historical Views of Computational Intelligence - Adaption and Self organization for Computational Intelligence - Ability to Generalize - Computational Intelligence and Soft Computing Vs Artificial Intelligence and Hard Computing.	9
Unit II	**Neural Network Concepts And Paradigms** Neural Network History - What Neural Networks are and Why they are useful - Neural Networks Components and Terminology - Neural Networks Topology - Neural Network Adaption - Comparing Neural Networks and Other information Processing Methods - Preprocessing and Post Processing.	9

Unit III	**Evolutionary Computation Theory And Concepts** History of Evolutionary Computation, Evolution Computation Overview, Genetic algorithms, Evolutionary programming, Evolution strategies, genetic programming, and particle swarm optimization.	9
Unit IV	**Swarm Intelligence** Particle Swarm Optimization: Particle Swarm Optimization Algorithm - PSO System Parameters - Modifications to PSO - Cooperative PSO - Particle Swarm Optimization versus Evolutionary Computing and Cultural Evolution – Applications. Ant Colony Optimization.	9
Unit V	**Fuzzy Systems** Fuzzy systems: Fuzzy Sets - Membership Functions - Fuzzy Operators - Fuzzy Set Characteristics - Linguistics Variables and Hedges - Fuzziness and Probability - Fuzzy Inferencing systems: Fuzzification: Inferencing – Defuzzification - Fuzzy Controllers: Components of Fuzzy Controllers - Fuzzy Controller Types.	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Eberhart, E. and Y. Shi., Computational Intelligence: Concepts and Implementations, Morgan Kauffmann, San Diego, 2007. 2. Engelbrecht, A.P. Computational Intelligence: An Introduction, Second Edition, John Wiley and Sons, 2007. **REFERENCE BOOKS:** 1. S.Rajasekaran and G.A. Vijayalakshmi Pai, Neural Networks, Fuzzy logic and Genetic Algorithms-Synthesis and Applications, PHI Learning, 2003. 2. Marsland S, Machine Learning: An Algorithmic Perspective, CRC Press, 2009. 3. J.S.R.Jang, C.T.Sun and E.Mizutani, Neuro-Fuzzy and Soft Computing, PHI, Pearson Education, 2004.	
Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.		

Year	I	Course Code: CSDS778 Course Title: BLOCKCHAIN AND CRYPTOCURRENCY	Credits	3
Sem.	II		Hours	45
			Category	A

Course Prerequisites, if any	-	
Internal Assessment Marks: 40	End Semester Marks: 60	Duration of ESA : 03 hrs.

Course Outcomes

1. Explain the core technology components of Blockchain and decentralized applications.
2. Describe distributed ledger technologies and consensus mechanisms.
3. Develop smart contracts on Ethereum and understand its architecture.
4. Analyze the working of Bitcoin and identify its limitations.
5. Utilize various blockchain development frameworks effectively.

CO, PO & PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	2	2	2	2	1	-	2	-	-	2	2
CO2	3	3	3	2	3	-	1	2	3	1	2	2
CO3	3	3	3	2	3	1	1	2	1	1	3	2
CO4	3	3	3	2	3	1	1	2	3	2	3	2
CO5	3	2	3	2	2	1	1	2	-	2	3	2

1-low, 2-medium, 3-high, '-"- no correlation

Unit No.	Course Content	Hours
Unit I	**Introduction to Blockchain** The history of blockchain and Bitcoin - Electronic cash - Peer-to-peer- structure-genesis block - Distributed ledger-Cryptographically-secure Append-only - Updatable via consensus - Generic elements of a blockchain - How blockchain works -How blockchain accumulates blocks-Benefits and limitations - Tiers of blockchain technology -Features -Types of blockchain.	9
Unit II	**Distributed Ledgers** Distributed Ledger Technology - Public blockchains-Private blockchains- Semiprivate blockchainsSidechains - Permissioned ledger- Shared ledger - Fully private and proprietary blockchains -Tokenized blockchains - Tokenless blockchains – Consensus-Consensus mechanism - Types of consensus mechanisms- Consensus in blockchain.	9

Unit III	**Decentralization** Methods of decentralization – Disintermediation -Contest-driven decentralization - Routes to decentralization - The decentralization framework example - Blockchain and full ecosystem decentralization -Storage – Communication -Computing power and decentralization - Smart contractsDecentralized Organizations - Decentralized Autonomous Corporations - Decentralized Application - DApp examples -OpenBazaar - Platforms for decentralization -Ethereum -MaidSafe – Lisk.	9
Unit IV	**Bitcoin – Cryptocurrency** Bitcoin definition - Digital keys and addresses - Private keys in Bitcoin -Public keys in Bitcoin -Addresses in Bitcoin – Transactions- The transaction life cycle - Transaction fee- Transaction pools -The transaction data structure -Metadata-Inputs -Outputs -Verification - The script language -Types of transactions -Coinbase transactions – Contracts - Tasks of the miners - Mining rewards - Proof of Work (PoW).	9
Unit V	**Development Tools and Framework** Ethereum network – Mainnet- Testnet - Private net - Ether cryptocurrency / tokens (ETC and ETH) - Ethereum Virtual Machine (EVM) -Solidity language-types-function types - reference types -control structures - Introducing Web3 - Contract deployment - POST requests- Truffle -Interaction with the contract – Oracles -Deployment on decentralized storage using IPFS – Hyperledger-reference architecture - Hyperledger Fabric - Membership services -Blockchain services -consensus services.	9
Recommended Learning Resources		
Print Resources	**TEXT BOOKS:** 1. Imran Bashir, Mastering Blockchain: Distributed Ledger Technology, Decentralization and Smart Contracts Explained, Third Edition, Packt Publishing, 2020. **REFERENCE BOOKS:** 1. Arvind Narayanan, Joseph Bonneau, Edward Felten, Andrew Miller, and Steven Goldfeder Bitcoin and Cryptocurrency Technologies: A Comprehensive Introduction. Princeton University Press ,2016. 2. Antonopoulos, Mastering Bitcoin, Second Edition , O'Reilly Publishers, 2017. 3. D. Drescher, 'Blockchain Basics' First Edition , Apress, 2017. 4. Antonopoulos and G. Wood, Mastering Ethereum, First Edition, O'Reilly Publishers, 2018.	
Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.		

Year	I	**Course Code: CSDS754**	**Credits**	2
Sem.	II	**Course Title : ML AND DL LAB**	**Hours**	30
			Category	B
Internal Assessment Marks: 40	End Semester Marks: 60		Duration of ESA : 03 hrs.	

Skills to be acquired:
Proficiency in Python libraries such as scikit-learn, numpy, pandas, and tensorflow/keras for machine learning tasks.

Lab Software Requirements:
Python, Jupyter Notebook or any IDE, with libraries: NumPy, Pandas, Matplotlib, Seaborn, Scikit-learn, SciPy, TensorFlow/Keras

Course Outcome:

1. Understand and implement core machine learning algorithms using Python from scratch and with libraries.
2. Explore various types of models including regression, classification, probabilistic models, and neural networks.
3. Develop the ability to evaluate, compare, and optimize machine learning models for different problem types.

CO, PO & PSO Mapping:

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	3	2	2	1	-	1	2	2	3	2	-
CO2	3	2	3	3	1	1	1	2	2	3	3	1
CO3	3	3	3	3	2	1	2	2	3	3	3	2

1-low, 2-medium, 3-high, '-"- no correlation

List of Exercises:

1. Implement Linear Regression.
2. Implement Logistic Regression.
3. Implement Naïve Bayes.
4. Implement Bayesian Belief Networks.
5. Implement the Expectation Maximization algorithm.
6. Implement Neural NetworkS:
   a) Feedforward Neural Network (FNN)
   b) Backpropagation Algorithm
7. Implement Support Vector Machine (SVM).
8. Implement Ensemble Learning:
   a) Random Forest
   b)XGBoost

Syllabus Design: Dr. V.Uma , Associate Professor, PUDoCS.

Year	I	Course Code: CSDS755	Credits	2
Sem.	II	Course Title : BIG DATA ANALYTICS LAB	Hours	30
			Category	B
Internal Assessment Marks: 40	End Semester Marks: 60		Duration of ESA : 03 hrs.	

Skills to be acquired:
Statistical Analysis, programming (Python, R, SQL), Data Visualization.

Lab Software Requirements:
Open Source Hadoop and Spark

Course Outcome:

1. Implement various applications using Map Reduce programming
2. Implement and evaluate the data manipulation procedures using pig.
3. Implement and evaluate the data manipulation procedures using hive.
4. Implement and evaluate the data manipulation procedures using spark.

CO, PO & PSO Mapping:

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PSO1	PSO2	PSO3	PSO4
CO1	3	3	2	2	1	1	1	2	3	3	2	-
CO2	3	2	3	3	1	1	1	2	3	3	2	-
CO3	3	2	3	3	1	1	1	2	3	3	2	-
CO4	3	3	3	3	1	1	1	2	3	3	3	1

1-low, 2-medium, 3-high, '-"- no correlation

List of Exercises:

1. Installing and configuring the Hadoop frame work. HDFS Commands,
2. Map Reduce Program to show the need of combiner
3. Map Reduce I/O Formats – Text, Key – Value
4. Map Reduce I/O Formats – NLine – Multiline
5. Installing and Configuring Apache PIG and HIVE
6. Sequence File Input / Output Formats
7. Distributed Cache & Map side Join, Reduce Side Join
8. Building and Running Spark Application
9. Word count in Hadoop and Spark
10. Manipulation RDD
11. Spark Implementation of Matrix algorithms in Spark Spark Sql programming, Building Spark Streaming application

Syllabus Design: P. Pothula Sujatha, Professor, PuDoCS.