Learning Outcomes Based Curriculum Framework (LOCF)

for

Computer Science & Information Technology

Postgraduate Programme

2021

Department of Computer Science & Information Technology

Cotton University

Panbazar, Guwahati

Assam

PART I

1.1 Introduction

"Computers are incredibly fast, accurate, and stupid. Human beings are incredibly slow, inaccurate, and brilliant. Together they are powerful beyond imagination."- Albert Einstein

The study of computing, automation, and information is known as computer science. Theoretical disciplines (such as algorithms, theory of computing, and information theory) and practical disciplines (such as programming) are all part of computer science (including the design and implementation of hardware and software). Computer science is distinct from computer programming in that it is a field of academic research.

Computer science is based on algorithms and data structures. The theory of computing is concerned with abstract models of computation and the general types of problems that they may solve. The areas of cryptography and computer security are concerned with the development of methods for secure communication and the prevention of security flaws. Image generation is addressed by computer graphics and computational geometry. Database theory is concerned with the administration of data repositories, whereas programming language theory is concerned with methods to the representation of computer operations. Human–computer interaction studies the interactions between humans and computers, whereas software engineering studies the design and concepts of software development. Operating systems, networks, and embedded systems are all research areas that look at the concepts and design of complex systems. The building of computer components and computer-operated equipment is referred to as computer architecture. Artificial intelligence and machine learning aspire to synthesize goal-oriented processes present in people and animals, such as problem-solving, decision-making, environmental adaptability, planning, and learning. Computer vision tries to comprehend and process image and video data, whereas natural-language processing strives to understand and process textual and linguistic data in artificial intelligence.

This postgraduate programme in computer science and information technology is designed to introduce the basic concepts of the subject and to enable the students to understand and analyze the current-edge technologies, issues and challenges through the various applications of computer science. The programme covers fundamental concepts of the subject - the foundation subjects, core subjects, and department specific elective subjects. The programme is designed in such a manner that it enables the students to apply core and programming knowledge to solve a wide range of real-life problems and issues and acquire research skills to produce research findings using in-depth subject knowledge, statistical tools, programming skills and current-edge technologies.

1.2 Learning Outcomes-based Approach to Curriculum Planning and Development

The basic objective of the learning outcome based approach to curriculum planning and development is to focus on demonstrated achievement of outcomes (expressed in terms of knowledge, understanding, skills, attitudes and values) and academic standards expected of graduates of a programme of study. Learning outcomes specify what graduates completing a particular programme of study are expected to know, understand and be able to do at the end of their programme of study.

The expected learning outcomes are used to set the benchmark to formulate the course outcomes, programme specific outcomes, programme outcomes and graduate attributes. These outcomes are essential for curriculum planning and development, and in the design, delivery and review of academic programmes. They provide general direction and guidance to the teaching-learning process and assessment of student learning levels under a specific programme.

The overall objectives of the learning outcomes-based curriculum framework are to:

- Help formulate graduate attributes, qualification descriptors, programme learning outcomes and course learning outcomes that are expected to be demonstrated by the holder of a qualification;
- Enable prospective students, parents, employers and others to understand the nature and level of learning outcomes (knowledge, skills, attitudes and values) or attributes a graduate of a programme should be capable of demonstrating on successful completion of the programme of study;
- Maintain national standards and international comparability of learning outcomes and academic standards to ensure global competitiveness, and to facilitate student/graduate mobility;
- Provide higher education institutions an important point of reference for designing teaching-learning strategies, assessing student learning levels, and periodic review of programmes and academic standards.

1.3 Key outcomes underpinning curriculum planning and development

The learning outcomes-based curriculum framework is a framework based on the expected learning outcomes and academic standards that are expected to be attained by graduates of a programme of study. The key outcomes that underpin curriculum planning and development include Graduate Attributes, Programme Outcomes, Programme Specific Outcomes, and Course Outcomes.

1.3.1 Graduate Attributes

The disciplinary expertise or technical knowledge that has formed the core of the university courses. They are qualities that also prepare graduates as agents for social good in future. Some of the characteristic attributes that a graduate should demonstrate are as follows:

1. **Disciplinary knowledge**: Capable of demonstrating comprehensive knowledge and understanding of one or more disciplines.
2. **Research-related skills**: A sense of inquiry and capability for asking relevant/appropriate questions, problematising, synthesizing and articulating.
3. **Analytical reasoning**: Ability to evaluate the reliability and relevance of evidence; identify logical flaws and holes in the arguments of others.
4. **Critical thinking**: Capability to apply analytic thought to a body of knowledge.
5. **Problem solving**: Capacity to extrapolate from what one has learned and apply their competencies to solve different kinds of non-familiar problems.
6. **Communication Skills**: Ability to express thoughts and ideas effectively in writing and orally.
7. **Information/digital literacy**: Capability to use ICT in a variety of learning situations, demonstrate ability to access, evaluate, and use a variety of relevant information sources; and use appropriate software for analysis of data.
8. **Self-directed learning**: Ability to work independently, identify appropriate resources required for a project, and manage a project through to completion.
9. **Cooperation/Team-work**: Ability to work effectively and respectfully with diverse teams.
10. **Scientific reasoning**: Ability to analyze, interpret and draw conclusions from quantitative/qualitative data; and critically evaluate ideas, evidence and experiences from an open-minded and reasoned perspective.
11. **Reflective thinking**: Critical sensibility to lived experiences, with self-awareness and reflexivity of both self and society.
12. **Multicultural competence**: Possess knowledge of the values and beliefs of multiple cultures and a global perspective.
13. **Moral and ethical awareness/reasoning**: Ability to embrace moral/ethical values in conducting one’s life, formulate a position/argument about an ethical issue from multiple perspectives, and use ethical practices in all work.
14. **Leadership readiness/qualities**: Capability for mapping out the tasks of a team or an organization, and setting direction, formulating an inspiring vision, building a team who can help achieve the vision, motivating and inspiring team members to engage with that vision, and using management skills to guide people to the right destination, in a smooth and efficient way.
15. **Lifelong learning**: Ability to acquire knowledge and skills, including ‘learning how to learn’, that are necessary for participating in learning activities throughout life, through self-paced and self-directed learning aimed at personal development, meeting economic,

social and cultural objectives, and adapting to changing trades and demands of work place through knowledge/skill development/reskilling.

1.3.2 Programme Outcomes (POs) for Postgraduate programme

POs are statements that describe what the students graduating from any of the educational programmes should be able to do. They are the indicators of what knowledge, skills and attitudes a graduate should have at the time of graduation.

1. **In-depth knowledge**: Acquire a systematic, extensive and coherent knowledge and understanding of their academic discipline as a whole and its applications, and links to related disciplinary areas/subjects of study; demonstrate a critical understanding of the latest developments in the subject, and an ability to use established techniques of analysis and enquiry within the subject domain.
2. **Understanding Theories**: Apply, assess and debate the major schools of thought and theories, principles and concepts, and emerging issues in the academic discipline.
3. **Analytical and critical thinking**: Demonstrate independent learning, analytical and critical thinking of a wide range of ideas and complex problems and issues.
4. **Critical assessment**: Use knowledge, understanding and skills for the critical assessment of a wide range of ideas and complex problems and issues relating to the chosen field of study.
5. **Research and Innovation**: Demonstrate comprehensive knowledge about current research and innovation, and acquire techniques and skills required for identifying problems and issues to produce a well-researched written work that engages with various sources employing a range of disciplinary techniques and scientific methods applicable.
6. **Interdisciplinary Perspective:** Commitment to intellectual openness and developing understanding beyond subject domains; answering questions, solving problems and addressing contemporary social issues by synthesizing knowledge from multiple disciplines.
7. **Communication Competence:** Demonstrate effective oral and written communication skills to covey disciplinary knowledge and to communicate the results of studies undertaken in an academic field accurately in a range of different contexts using the main concepts, constructs and techniques of the subject(s) of study
8. **Career development**: Demonstrate subject-related knowledge and skills that are relevant to academic, professional, soft skills and employability required for higher education and placements.
9. **Teamwork**: Work in teams with enhanced interpersonal skills and leadership qualities.
10. **Commitment to the society and to the Nation:** Recognise the importance of social, environmental, human and other critical issues faced by humanity at the local, national and

international level; appreciate the pluralistic national culture and the importance of national integration.

1.3.3 Programme Specific Outcomes (PSOs) in in Computer Science & Information Technology

Programme specific outcomes include subject-specific skills and generic skills, including transferable global skills and competencies, the achievement of which the students of a specific programme of study should be able to demonstrate for the award of the degree. The programme specific outcomes would also focus on knowledge and skills that prepare students for further study, employment, and citizenship. They help ensure comparability of learning levels and academic standards across universities and provide a broad picture of the level of competence of graduates of a given programme of study. The attainment of PSOs for a programme is computed by accumulating PSO attainment in all the courses comprising the programme.

PSO1: Ability to gather basic concepts of applied mathematics and programming as well as grasp the theoretical knowledge of computers to solve real life computational problems using efficient techniques.

PSO2: Ability to acquire knowledge about the proficient use of programming languages and ICT tools to solve domain specific problems.

PSO3: Ability to improvise existing tools and techniques to solve computational intensive real world problems.

PSO4: Ability to analyze a problem critically and designing system, component, or process for its solution using relevant techniques, resources, and tools of Information Technology.

PSO5: Ability to acquire domain specific expertise through discipline specific elective and project works.

PSO6: Ability to understand different computing techniques, apply these to one’s own work and develop methodology/solutions for the problems which are multidisciplinary in nature.

PSO7: Ability to have competency to take up higher studies, research and development activities and ability to recognize the need for and to engage in life-long learning.

1.3.4 Course Level Learning Outcome Matrix

Course Level Learning Outcomes Matrix – Core Course

Programme Specific Outcomes	0101	0102	0103	0104	0201	0202	0203	0204	0401	0402
PSO1	X	X	X	X	X	X	X	X		
PSO2		X		X			X		X	
PSO3	X		X	X	X	X	X	X	X	X
PSO4	X	X	X	X	X	X	X	X	X	X
PSO5	X		X	X						
PSO6	X	X	X	X	X	X	X	X	X	X
PSO7	X			X	X	X	X		X	X

Course Level Learning Outcomes Matrix – Elective papers

Programme Specific Outcomes	E01	E02	E03	E04	E05	E06
PSO1	X	X	X	X	X	X
PSO2				X		
PSO3	X	X	X	X	X	X
PSO4						X
PSO5	X		X		X	X
PSO6	X	X	X	X	X	
PSO7	X	X	X	X	X	

1.4 Teaching-learning process

The department of Computer Science & Information Technology, Cotton University has student-centric teaching-learning pedagogies to enhance the learning experiences of the students. All classroom lectures are interactive using ICT-enable techniques, allowing the students to have meaningful discussions, question and answer sessions. Apart from the physical classes, lectures are also held in online mode where students can have doubt clearing and discussions with the teachers. Most of the teachers use ICT facilities with power-point presentations, e-learning platforms and other innovative e-content platforms for student-centric learning methods. Apart from these, special lectures by invited experts, workshops, and seminars are held to augment knowledge, encourage innovative ideas and expose the students to global academic and research advancement.

The short-term projects, research projects, and assignments, which are the integral components of all the courses, enable the students to solve practical problems. Students are also being engaged in the in-house and external research projects for acquiring experiential learning. The laboratories of the department offer hands-on learning experiences to the students.

1.5 Assessment methods

A variety of assessment methods that are appropriate to the discipline are used to assess progress towards the course/programme learning outcomes. Priority is accorded to formative assessment. Progress towards achievement of learning outcomes is assessed using the following: closed-book examinations; problem based assignments; practical assignment; laboratory reports; individual project reports (case-study reports); team project reports; oral presentations, including seminar presentation; viva voce interviews; computerized testing and any other pedagogic approaches as per the context.

PART II

Structure of Post-Graduate programme in Computer Science & Information Technology

I. Outline of the courses under Choice Based Credit System:

The Postgraduate programmes consist of four semesters with minimum credits required for the complete programme being 80.

Each course in a programme will be from one of the following categories:

1. Core Course (Core): A course that should compulsorily be studied by a candidate as a core requirement is termed a Core Course. Each core course is of 5 credits.

2. Elective Course: A course that can be chosen from a pool of courses and which may extend the discipline/subject of study or provides exposure to some other discipline/subject or which enhances the student's proficiency or skill is termed an Elective course. Each elective course is of 5 credits.

3. Practical/Tutorials: A practical and tutorial component (or both) is to be provided with every core and elective paper.

4. Dissertation/Project Work (DPW): A course designed for students to acquire special/ advanced knowledge that they study on their own with advisory support by a teacher/faculty member is a dissertation/project work. A DPW course is of 20 credits.

- The credits for a course will be of the structure L+T+P, where L, T and P stand for lecture, tutorial and practical respectively.
- Each 5 credit course with tutorial and practical is of the pattern 3+1+1=5.
- Each Elective course will be open to students from his/her own discipline.

· For the purpose of computation of workload, the mechanism adopted will be:

- 1 credit = 1 theory period of 1 hour duration per week.
- 1 credit = 1 tutorial period of 1 hour duration per week.
- 1 credit = 1 practical period of 2 hours duration per week.

II. Distribution of Courses and Credits

Postgraduate Programme (Computer Science & Information Technology)

A student in the M.Sc. in AI & ML programme will take the following minimum number of courses in different categories of courses:

Table 1: Credit distribution for courses: M.Sc.

Category	**Number of courses**	**Credits for each course**	**Total Credits**
Core	8	5	40
Elective	4	5	20
DPW	1	20	20
			80

The distribution of credits and courses in each of the four semesters for the M.Sc. in AI & ML programme will be according to the following scheme:

Sem	**Core**	**Elective**	**DPW**	**Credit**
I	C1(5) C2(5) C3(5) C4(5)			20
II	C5(5) C6(5) C7(5) C8(5)			20
III		E1(5) E2(5) E3(5) E4(5)		20
IV			DPW(20)	20

Credit	20	20	20	80

COTTON UNIVERSITY

DEPARTMENT OF COMPUTER SCIENCE & INFORMATION TECHNOLOGY

Postgraduate Syllabus

COURSE STRUCTURE OF COMPUTER SCIENCE & INFORMATION TECHNOLOGY (POSTGRADUATE PROGRAMME)

Paper Code	Subject Title	L+T+P
Semester I		
AIML0101	Foundations of ML	3+1+1
AIML0102	Programming with Python	3+1+1
AIML0103	Data Management	3+1+1
AIML0104	Artificial Intelligence	3+1+1
Semester II		
AIML0201	Predictive Analytics	3+1+1
AIML0202	Machine Learning	3+1+1
AIML0203	Statistical Decision Making	3+1+1
AIML0204	Business Use Cases	0+0+5
Semester III		
AIMLEXX	Elective	3+1+1

AIMLEXX	Elective	3+1+1
AIMLEXX	Elective	3+1+1
AIMLEXX	Elective	3+1+1
Semester IV		
AIML0401	Project	0+0+18
AIML0402	Seminar	0+0+2

Elective Papers

AIMLE01	Deep Learning	3+1+1
AIMLE02	Natural Language Processing	3+1+1
AIMLE03	Advanced Optimization Algorithms	3+1+1
AIMLE04	Algorithmic Data Mining	3+1+1
AIMLE05	Speech Recognition and Synthesis	3+1+1
AIMLE06	Computer Vision	3+1+1

Paper Code: AIML0101
Paper Title: Foundations on ML (5 Credits, L+T+P = 3+1+1)

The course is intended to give an insight into different learning mechanisms for machine learning problems. This course includes different problem solving algorithms, Heuristic methods, Knowledge representation and different Numerical Methods.

After completion of the course the students will be able to:

1. Explain various terminologies used in probability theory and statistics, Expert systems, Linear models, neural networks, linear discriminant functions.
2. Apply various problem solving approaches, heuristic algorithms to solve real-life problems.
3. Explain the mathematics behind knowledge-representation as well as machine learning.

Unit	Content	No. of Lectures
1	**Introduction to Data Science & ML** Introduction to ML, Its application areas, Evolution, types; Production system: Its main components, problem solving; Expert system design using ML; Use Cases in Business and Scope; Scientific Method; Modeling Concepts; CRISP-DM Method	8
2	**Problem solving** Is the good solution absolute or relative, production systems, production system characteristics, problem solving: defining the problem as a state space search, Water Jug Problem ,Basic problem solving methods : Reason forward from the initial states , Reason backward from the goal states, Problem trees versus Problem Graphs, Knowledge representation: Matching and Indexing.	10
3	**Heuristic methods** Heuristic search, Heuristic functions, Or graph, AND OR graph, Weak methods: Generate and Test, Hill Climbing, Breadth first search, Best first search, OR graph, Problem reduction, Constraints satisfaction, Means End Analysis.	10
4	**Game playing and Knowledge representation** The Minimax Procedure , Adding Alpha Beta Cutoffs, Knowledge Representation using predicate logic, Representing simple facts in logic, Augmenting the representation with computable functions and predicates, Resolution, Conversion to clause form, The basis of resolution, Resolution in propositional logic , The Unification algorithm, Resolution in predicate logic , Resolution algorithm for predicate logic, Introduction to Non-monotonic Reasoning, Statistical and probabilistic reasoning.	8

5	**Numerical Methods** Solving system of linear equations: Gauss-Jordan (concept of pivoting), Solving non-linear equations: Newton-Raphson, Steepest Descent, Optimizing cost functions: Gradient descent, Least Square regression, Iterative methods in Linear Algebra: Power iteration, Eigenvalues, SVD.	12
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement AND, OR, NOT graph problems using neural networks. 2. Implement Water Jug algorithm. 3. Implement Hill Climbing algorithm. 4. Implement Breadth first search and Best first search algorithm. 5. Use Newton-Raphson method to solve nonlinear equations.	1 Credit

Reading List:

- Artificial Intelligence Elaine Rich McGraw Hill book Co. 1982.
- Artificial Intelligence PH Winston, Addison Wesley, 1983.
- Artificial Intelligence Concepts, Techniques and Applications. Yoshikai Shirai & Junichi Tsujii, John Willey sons
- Christopher Bishop, "Pattern recognition and Machine Learning" Springer 2006.
- Tom Mitchell, "Machine Learning", McGraw Hill, 1997.

Paper Code: AIML0102
Paper Title: Programming with Python (5 Credits, L+T+P = 3+1+1)

The objective of this course is to provide basic knowledge of Python. Python programming is intended for software engineers, system analysts, program managers and user support personnel who wish to learn the Python programming language. This course covers data types, control structures, functions, parameter passing, library functions, arrays, inheritance and object oriented design.

After completion of the course the students will be able to:

1. Learn and understand Python programming basics and paradigm.
2. Acquire Object Oriented Skills in Python.
3. Learn and know the concepts of file handling, exception handling.
4. Design and implement a program to solve a real world problem.

Unit	Content	No. of

		Lectures
1	**Introduction to Python** The basic elements of python, Branching Programs, Control Structures, Strings and Input, Iteration, Functions, Higher Order Functions Scoping and Abstraction, Function and scoping, Specifications, Recursion, Global variables, Modules, Files, Systems Functions and Parameters.	8
2	**Working with Python Data Structures** Structure Types, Mutability, Tuples, Lists and Dictionaries, Lists and Mutability, Files, Files I/O and all related File operations, Exceptions and Assertions, Types of testing- Black-box and Glass-box, Debugging, Handling Exceptions, Assertions, Simple Algorithms and Data Structure, Search Algorithms, Sorting Algorithms: Selection, merge sort and higher order sorting, Hash Tables.	10
3	**Object Oriented Python** Classes and Object-oriented Programming, Abstract Data Types and Classes, Inheritance, Encapsulations and Information Hiding	10
4	**Regular Expressions** REs and Python, Plotting using PyLab	10
5	**Files** Files and Exceptions, File I/O, All file related operations	10
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Using for loop, print a table of Celsius/Fahrenheit equivalences. Let c be the Celsius temperatures ranging from 0 to 100, for each value of c, print the corresponding Fahrenheit temperature. 2. Using a while loop, produce a table of sins, cosines and tangents. Make a variable x in range from 0 to 10 in steps of 0.2. For each value of x, print the value of sin(x), cos(x) and tan(x). 3. Write a program that reads an integer value and prints —leap year‖ or —not a leap year. 4. Write a program that takes a positive integer n and then produces n lines of output shown as follows. For example enter a size: 5 * ** *** ****	1 Credit

	***** 5. Write a function that takes an integer _n_ as input and calculates the value of 1 + 1/1! + 1/2! + 1/3! + … + 1/n 6. Write a function that takes an integer input and calculates the factorial of that number. 7. Write a function that takes a string input and checks if it's a palindrome or not. 8. Write a list function to convert a string into a list, as in list (abc) gives [a, b, c]. 9. Write a program to generate Fibonacci series. 10. Write a program to check whether the input number is even or odd. 11. Write a program to compare three numbers and print the largest one. 12. Write a program to print factors of a given number. 13. Write a method to calculate GCD of two numbers. 14. Write a program to create Stack Class and implement all its methods. (Use Lists). 15. Write a program to create Queue Class and implement all its methods. (Use Lists) 16. Write a program to implement linear and binary search on lists. 17. Write a program to sort a list using insertion sort and bubble sort and selection sort.	

Reading List:

- John V Guttag, “Introduction to Computing and Programming Using Python”, Prentice Hall of India.
- Michael T. Goodrich, Roberto Tamassia, Michael H Goldwasser, “Data Structures and Algorithms in Python”, Wiley

Paper Code: AIML0103
Paper Title: Data Management (5 Credits, L+T+P = 3+1+1)

This course is intended to give an introduction to the basics of data management. Detailed discussion on all the aspects of data management like, data acquisition, data preprocessing, data preparation, data quality, data handling, etc., will be performed. Advanced data management for large volumes of data using Big Data Frameworks like Hadoop, Spark and NoSQL will be introduced. Commands, packages and libraries of R programming language, that can be used for data management, will also be introduced.

After completion of the course the students will be able to:

1. Understand basics of data management.
2. Use Big Data frameworks like Hadoop, Spark and NoSQL.
3. Use Commands, packages and libraries of R programming language.

Unit	Content	No. of Lectures
1	**Data Acquisition** Gather information from different sources; Internal systems and External systems; Web APIs, Open Data Sources, Data APIs, Web Scraping; Relational Database access (queries) to process/access data	5
2	**Data Pre-processing and Preparation** Data Munging, Wrangling; Plyr packages; Cast/Melt	6
3	**Data Quality and Transformation** Data imputation; Data Transformation (minmax, log transform, z-score transform etc.,); Binning, Classing and Standardization; Outlier/Noise & Anomalies	6
4	**Handling Text Data** Bag-of-words; Regular Expressions; Sentence Splitting and Tokenization; Punctuations and Stop words, Incorrect spellings; Properties of words and Word cloud; Lemmatization and TermDocument TxD computation; Sentiment Analysis (Case Study)	7
5	**Principles of Big Data** Introduction to Big Data; Challenges of processing Big Data (Volume, Velocity and Variety perspective); Use Cases	6
6	**Big Data Frameworks – Hadoop, Spark and NoSQL** Processing, Storage and Programming Framework; Hadoop ecosystem Components and their functions; Essential Algorithms (Word count, Page Rank, IT-IDF); Spark: RDDs, Streaming and Spark ML; NoSQL concepts (CAP, ACID, NoSQL types)	8
7	**R Essentials** Commands and Syntax; Packages and Libraries; Introduction to Data Types; Data Structures in R - Vectors, Matrices, Arrays, Lists, Factors, Data Frames; Importing and Exporting Data; Control structures and Functions; Data exploration (histograms, bar chart, box plot, line graph, scatter plot); Qualitative and Quantitative Data; Measure of Central Tendency (Mean, Median and Mode); Measure of Positions (Quartiles, Deciles, Percentiles and Quantiles),; Measure of Dispersion (Range, Median, Absolute deviation about median, Variance and Standard deviation), Anscombe's quartet; Other Measures: Quartile and Percentile, Interquartile Range	10

	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement date pre-processing techniques for speech, image and numerical data. 2. Implement data transformation techniques for numerical and categorical based data. 3. Implement various data exploration (histograms, bar chart, box plot, line graph, scatter plot) techniques using R.	1 Credit

Reading List:

- Database Systems: The Complete Handbook, by Hector Garcia Molina, Jennifer Widom, and Jeffrey Ullman.
- Data Mining Techniques. Arun K. Pujari, Universities Press (2016)
- Mastering Data Mining. Michael A. Berry and Gordon S. Linoff. John Wiley & Sons (2000)
- Data Mining: Concepts and Techniques. Jiawei Han and Michelline Kamber. Elsevier (2011)

Paper Code: AIML0104
Paper Title: Artificial Intelligence (5 Credits, L+T+P = 3+1+1)

The course basically provides an introductory idea of what artificial intelligence (AI) is and how an intelligent system works when it is equipped with artificial intelligence. This course discusses the various aspects of AI such as searching, reasoning, learning and understanding and how these notions help an autonomous agent to get ideas about its surrounding environment to act intelligently.

After completion of the course the students will be able to:

1. Foundations of Artificial Intelligence, its application and future trends.
2. Learn about autonomous systems, searching space problems and different algorithms to find solutions for searching space problems
3. Understanding the notions of uncertainty and decision making in real world problems
4. Understanding natural language, its behavior and analyzing different steps involved in natural language understanding.
5. Develop an ability to create and apply different techniques of AI in various applications in areas.

Unit	Content	No. of

		Lectures
1	**Foundations for AI** Introduction to Artificial Intelligence, Numerical computation, information storage, repetitive operations, other definitions of artificial intelligence, numeric versus symbolic, algorithm versus non algorithms, area if artificial intelligence, expert system, natural language processing, speech recognition, automatic programming, organization of artificial intelligence system, the underlying assumptions, artificial intelligence techniques.; Modeling a Problem as Search Problem; Uninformed/Blind Search; Heuristic Search; Characteristics of Heuristic Functions	15
2	**Advanced Concepts** Domain relaxations, Local search, Genetic algorithms, Metaheuristic Search (PSO, Ant Colony optimization etc), Adversarial search, Constraint Satisfaction, Knowledge and Reasoning: Propositional logic and Satisfiability; Predicate logic; Knowledge Representation; Planning, Partial order planning, Uncertainty in AI; Bayesian Network, Bayesian network learning and Inference, Decision Theory, Introduction to ANN, Markov Decision Process, Reinforcement learning.	15
3	**Natural Language Understanding** Natural language Understanding, Introduction to Understanding, What makes understanding hard, Understanding single sentences, Keyword matching, Syntactic analysis, semantic analysis, semantic grammars, Case grammars Learning: Introduction to learning, Random learning and Neural nets, Learning by parameter adjustment, Learning in General Problem Solver (GPS), Concept Learning.	18
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement various informed and uninformed search algorithms such as BFS, DFS, Best First Search, A* search etc. 2. Implement local search algorithms such as PSO, Ant-colony optimization. 3. Implement a few adversarial search techniques such as Alpha-beta pruning.	1 Credit

Reading List:

- S. Russell and P. Norvig, Artificial Intelligence: A modern Approach, Prentice Hall, 2003.
- Artificial Intelligence Elaine Rich McGraw Hill book Co. 1982.
- Artificial Intelligence PH Winston, Addison Wesley,1983
- Artificial Intelligence Concepts, Techniques and Applications. Yoshikai Shirai & Junichi Tsujii, John Willey sons

Paper Code: AIML0201
Paper Title: Predictive Analytics (5 Credits, L+T+P = 3+1+1)

The course is intended to make an insight into different predictive analytics applicable in data science. This course introduces Linear Regression, Non-Linear Regression and their application in forecasting models.

After completion of the course the students will be able to:

1. Recall regression methods for building predictive models.
2. Explain Linear Regression, Multiple Linear Regression, Non-Linear Regression.
3. Apply regression based methods and algorithms for various predictions.
4. Analyze various Forecasting models in different real world applications.
5. Evaluate the performance of various models used for different predictive problems.

Unit	Content	No. of Lectures
1	**Linear Regression** Regression basics: Relationship between attributes using Covariance and Correlation; Relationship between multiple variables: Regression (Linear, Multivariate) in prediction. Residual Analysis; Identifying significant features, feature reduction using AIC, multicollinearity; Non-normality and Heteroscedasticity; Hypothesis testing of Regression Model; Confidence intervals of Slope; R-square and goodness of fit; Influential Observations – Leverage	11
2	**Multiple Linear Regression** Polynomial Regression; Regularization methods; Lasso, Ridge and Elastic nets; Categorical Variables in Regression	10
3	**Non-Linear Regression** Logit function and interpretation; Types of error measures (ROCR); Logistic Regression in classification	12

4	**Forecasting models** Trend analysis; Cyclical and Seasonal analysis; Smoothing; Moving averages; Box-Jenkins, Holt-winters, Auto-correlation; ARIMA; Examples: Applications of Time Series in financial markets	15
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement linear regression technique for stock price prediction. 2. Use regularization methods to overcome overfitting problems. 3. Use logistic regression to perform binary classification problems. 4. Implement forecasting models for time-series analysis based problems.	1 Credit

Reading List:

- Hands-On Predictive Analytics with Python by Alvaro Fuentes, Packt Publishing; 1st edition (28 December 2018)
- Learning Predictive Analytics with Python by Ashish Kumar, Packt Publishing Limited (6 January 2016)
- Mastering Predictive Analytics with Python by Joseph Babcock, Packt Publishing Limited (6 January 2016)

Paper Code: AIML0202
Paper Title: Machine Learning (5 Credits, L+T+P = 3+1+1)

This course teaches students how to create machine learning challenges for a variety of applications. To have a better understanding of machine learning methods that are focused on classifications and grouping. To become familiar with a variety of publicly available machine learning software libraries and data sets. To create a machine learning-based system that can solve a variety of real-world challenges. To determine how a machine-learning algorithm's selection affects a system's accuracy.

After completion of the course the students will be able to:

1. Formulate machine learning problems corresponding to different applications: data, model selection, model complexity
2. Demonstrate understanding of a range of machine learning algorithms along with their strengths and weaknesses
3. Implement machine learning solutions to classification, regression, and clustering problems

4. Design and implement various machine learning algorithms in a range of real-world applications
5. Evaluate and analyze the performance of a machine-learning algorithm or a system based on a machine learning algorithm.

Unit	Content	No. of Lectures
1	**Foundations for ML** ML Techniques overview; Validation Techniques (Cross-Validations); Feature Reduction/Dimensionality reduction; Principal components analysis (Eigen values, Eigen vectors, Orthogonality)	7
2	**Clustering** Distance measures; Different clustering methods (Distance, Density, Hierarchical); Iterative distance-based clustering;Dealing with continuous, categorical values in K-Means; Constructing a hierarchical cluster; K-Medoids, k-Mode and density-based clustering; Measures of quality of clustering	10
3	**Classification** Naïve Bayes Classifier: Model Assumptions, Probability estimation, Required data processing, M-estimates, Feature selection: Mutual information, Classifier; K-Nearest Neighbours: Computational geometry; Voronoi Diagrams; Delaunay Triangulations, K-Nearest Neighbour algorithm; Wilson editing and triangulations, Aspects to consider while designing K-Nearest Neighbour; Support Vector Machines: Linear learning machines and Kernel space, Making Kernels and working in feature space, SVM for classification and regression problems; Decision Trees: ID4, C4.5, CART; Ensembles methods: Bagging & boosting and its impact on bias and variance, C5.0 boosting, Random forest, Gradient Boosting Machines and XGBoost Graphical Models: Hidden Markov Models, Bayesian Networks, Markov Random Fields, Conditional Random Fields.	12
4	**Association Rule mining** The applications of Association Rule Mining: Market Basket, Recommendation Engines, etc.; A mathematical model for association analysis; Large item sets; Association Rules; Apriori: Constructs large item sets with mini sup by iterations; Interestingness of discovered association rules;Application examples; Association analysis vs. classification; FP-trees	10
5	**Neural Network** NN basics (Perceptron and MLP, FFN, Backpropagation)	9

	Tutorial - Tutorials will be based on theory.	16
	Practical - For later exercises, students can create/use their own datasets or utilize datasets from online repositories like UCI Machine Learning Repository (http://archive.ics.uci.edu/ml/) 1. Implement Linear Regression problem. For example, based on a dataset consisting of the existing set of prices and area/size of the houses, predict the estimated price of a given house. 2. Based on multiple features/variables perform Linear Regression. For example, based on a number of additional features like number of bedrooms, servant room, number of balconies, number of houses of years a house has been built – predict the price of a house. 3. Implement a classification/ logistic regression problem. For example, based on different features of a student's data, classify whether a student is suitable for a particular activity. Based on the available dataset, a student can also implement another classification problem like checking whether an email is spam or not. 4. Use some function for regularization of the dataset based on problem 3. 5. Use some function for neural networks, like Stochastic Gradient Descent or backpropagation - algorithm to predict the value of a variable based on the dataset of problem 3.	1 Credit

Reading List:

- Christopher Bishop, “Pattern recognition and Machine Learning” Springer 2006.
- Tom Mitchell, “Machine Learning”, McGraw Hill, 1997.
- R.O. Duda, P E Hart and D G Stork, Pattern Classification
- Jiawei Han, Michelline Kimber, Data Mining: Tools and Techniques.
- Hastie Tibshirani and Friedman, Elements of Statistical Learning, Springer.

Paper Code: AIML0203
Paper Title: Statistical Decision Making (5 Credits, L+T+P = 3+1+1)

This module helps the students to have a good understanding of the methods, methodologies and techniques from the basics of statistics and probability, obtain supporting evidence through data, isolate or identify factors to construct models that can uncover relationships and variation in processes.

After completion of the course the students will be able to:

1. Have a clear understanding of the subject which is foundational to Data Scientists.
2. Understand the real-world problems.
3. Visualize and communicate clearly and effectively about the patterns found in data which is a key skill for a successful data professional.
4. Develop an intuition how to understand the data, attributes, distributions Procedure for statistical testing.

Unit	Content	No. of Lectures
1	**Data Visualization** Science of Visualization; Visualization Periodic Table; Aesthetics and Story telling; Concepts of measurement - scales of measurement; Design of data collection formats with illustration; Principles of data visualization - different methods of presenting data in business analytics.; Concepts of Size, Shape, Color; Various Visualization types; Bubble charts; Geo-maps (Chlorpeths); Gauge charts; Tree map; Heat map; Motion charts; Force Directed Charts etc.	15
2	**Sampling and Estimation** Sample versus population; Sample techniques (simple, stratified, clustered, random); Sampling Distributions; Parameter Estimation; Unbalanced data treatment	15
3	**Inferential Statistics** Develop an intuition how to understand the data, attributes, distributions; Procedure for statistical testing, etc.; Test of Hypothesis (Concept of Hypothesis testing, Null Hypothesis and Alternative Hypothesis); Cross Tabulations (Contingency table and their use, Chi-Square test, Fisher's exact test); One Sample t test (Concept, Assumptions, Hypothesis, Verification of assumptions, Performing the test and interpretation of results); Independent Samples t test; Paired Samples t test; One-way ANOVA (Post hoc tests: Fisher's LSD, Tukey's HSD); z-test and F-test	18
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement different data visualization techniques for a real-life problem. 2. Implement various sampling techniques and distributions to tackle imbalance data problems.	1 Credit

	3. Implement hypothesis testing using various algorithms.	

Reading List:

- Statistical Analysis for Decision Making by Morris Hamburg, Wadsworth Publishing Co Inc; 6th Revised edition (1 November 1993)
- Business Cases in Statistical Decision Making: Computer Based Applications by Lawrence H. Peters, Prentice-Hall; Har/Dskt edition (13 October 1993)
- Christopher Bishop, "Pattern recognition and Machine Learning" Springer 2006.
- R.O. Duda, P E Hart and D G Stork, Pattern Classification
- Hastie Tibshirani and Friedman, Elements of Statistical Learning, Springer.

Paper Code: AIML0204
Paper Title: Business Use Cases (5 Credits, L+T+P = 0+0+5)

This course is aimed at providing an opportunity to explore and practically apply the knowledge obtained through different courses learnt in this program to solve realistic problems in various domains of AI such as disease identification, image processing, and portfolio risk prediction.

After completion of the course the students will be able to:

1. Understand the potential of AI
2. Be familiar with realistic problems
3. Get hands on experience to work with real datasets
4. Develop an ability to analyze problem domain and employ various techniques to obtain efficient solution
5. Develop the skill to measure the performance of different AI techniques

Unit	Content	No. of Lectures
1	**Case Study 1: AI in Computer Aided Disease Detection** ● Feature Extraction and Selection ● Classification/Clustering using ML and DL	5 Credits
2	**Case Study 2: Image Classification** ● Identifying images in digital photographs ● Automated image organization	

3	**Case Study 3: Portfolio Risk prediction** ● Portfolio volatility level downside risk	

Reading List:

- Christopher Bishop, "Pattern recognition and Machine Learning" Springer 2006.
- Tom Mitchell, "Machine Learning", McGraw Hill, 1997.
- R.O. Duda, P E Hart and D G Stork, Pattern Classification
- Jiawei Han, Michelline Kimber, Data Mining: Tools and Techniques.
- Hastie Tibshirani and Friedman, Elements of Statistical Learning, Springer.

Paper Code: AIMLE01
Paper Title: Deep Learning (5 Credits, L+T+P = 3+1+1)

This course allows students to investigate the various applications of neural networks. To comprehend how Convolutional Neural Networks, Recurrent Neural Networks, and Auto-encoders function. To learn about the fundamentals of deep learning and the function of regularization in it.

After completion of the course the students will be able to:

1. Able to differentiate between machine learning and deep learning
2. Identify problems suitable for application of deep learning.
3. Illustrate the working of Feed Forward Neural Networks and their modifications.
4. Apply Convolutional & Recurrent Neural Networks to solve problems.
5. Analyze the efficiency of deep learning systems.
6. Use of Regularization techniques in deep learning.

Unit	Content	No. of Lectures
1	**Neural Network Basics** Learning via gradient descent; recursive chain rule (backpropagation); if time: bias-variance trade-off; Regularization; output units: linear, softmax; hidden units: tanh, RELU; Regularization, Drop-out; Convolutional neural networks; Recurrent neural networks; Autoencoders; Deep generative models	10
2	**Convolutional Neural Networks** Image classification; Text classification; Image classification and hyper-parameter tuning; Emerging NN architectures	11
3	**Recurrent Neural Networks**	12

	Building recurrent NN; Long-Short Term Memory; Time-Series Forecasting	
4	**Deep learning** Auto-encoders and unsupervised learning; Stacked auto-encoders and semi-supervised learning; Regularization – Dropout and Batch Normalization	15
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement a feed-forward neural network for solving (a) regression and (b) 2-class classification problem. Also experiment with hyper-parameter tuning. 2. Train and test a feed-forward neural network for multi-class classification using softmax layer as output. 3. Create a 2D CNN for image classification. Experiment with different depth of network, striding and pooling values. 4. Implement (a) RNN for image/time-series data classification, and (b) Implement LSTM networks 5. Implement an auto-encoder, de-noising auto-encoders and sparse auto-encoders. 6. Design stochastic encoders and decoders.	1 Credit

Reading List:

- I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016
- Artificial Neural Networks, B. Yegnanarayana, PHI (2009)
- Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools and Techniques to Build Intelligent Systems, Aurelien Geron, O'Reilly (2017)

Paper Code: AIMLE02
Paper Title: Natural Language Processing (5 Credits, L+T+P = 3+1+1)

The course is intended to give an insight into different techniques used for Natural Language Processing. This course introduces Text Classification, Language Modeling, Context Free Grammar, and advanced concepts like machine translation .

After completion of the course the students will be able to:

1. Describe the concepts of morphology, syntax, semantics, discourse & pragmatics of natural language.
2. Demonstrate understanding of the relationship between NLP and statistics & machine learning.

3. Discover various linguistic and statistical features relevant to the basic NLP task, namely, spelling correction, morphological analysis, parts-of-speech tagging, parsing and semantic analysis.
4. Develop systems for various NLP problems with moderate complexity.
5. Evaluate NLP systems, identify shortcomings and suggest solutions for these shortcomings.

Unit	Content	No. of Lectures
1	**Introduction** Introduction to NLP; Text Classification; Neural Networks for Text Classification	15
2	**Language characteristics** Language Modeling; Vector Semantics; Word Embedding; Sequence Labeling: POS & HMM; Sequence Labeling: Viterbi & Forward Algorithm	16
3	**Parsing and applications** Context Free Grammar; Constituency Parsing; Dependency Parsing Syntax; Dependency Parsing; Computational Ethics; Information Extraction; Conversational Agents; Machine Translation; Generation; Computational Social Science	17
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement a text classification model using machine learning. 2. Implement word embedding and parts-of-speech tagging in NLP. 3. Build a machine translation mechanism using machine/deep learning.	1 Credit

Reading List:

- Jurafsky Dan and Martin James H. “Speech and Language Processing” ,3rd Edition, 2018.
- Jurafsky D. and Martin J. H., “Speech and language processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition”, 2nd Edition, Upper Saddle River, NJ: Prentice-Hall, 2008.

- Goldberg Yoav “A Primer on Neural Network Models for Natural Language Processing”.

Paper Code: AIMLE03
Paper Title: Advanced Optimization Algorithms (5 Credits, L+T+P = 3+1+1)

This course is aimed at providing an overview of different optimization techniques. It helps to have a better understanding of optimization techniques widely used for design and development of solution methods for modern day problems. The course discusses the basic mathematical foundation of optimization, its application in problem domains which are discrete, continuous and unconstrained in nature.

After completion of the course the students will be able to:

1. Understand the need of different types of optimization techniques
2. How to formulate optimization problems
3. Analyze the efficacy of existing optimization techniques for modern days problems in different field of computer and mathematical science
4. Develop an ability to apply different techniques to solve the formulated optimization problems for various applications in an efficient way

Unit	Content	No. of Lectures
1	**Mathematical background and introduction to optimization** Linear classification and the Perceptron algorithm; Review of linear algebra and multivariate calculus; Convex functions and sets, basics of convex optimization; Need for constrained methods in solving constrained problems. Examples of discrete and continuous optimization problems; Gradient descent algorithm; Introduction to optimization. Examples of discrete and continuous optimization problems: classification and learning problems (least squares, LASSO, SVM), maximum flows and minimum cuts, maximum cut, minimum independent set	10
2	**Continuous Optimization** Optimality conditions for general and convex problems; Oracle models, iterative methods, and gradient descent; Gradient descent for smooth and strongly convex functions; Prediction using expert advice: majority algorithms, multiplicative weights update algorithm; Applications of multiplicative weights update framework; Online optimization and learning,	11

	follow the leader algorithm for online convex optimization; Online convex optimization continued: follow the regularized leader, online gradient descent. Introduction to linear programming; Modeling using LPs, LP duality; Applications of duality I: 2-player games, Nash equilibria, minimax theorem; Applications of duality II: mini-max theorem, boosting theorem, maxflow-mincut theorem	
3	**Discrete Optimization** Graph optimization: maximum flow and minimum cut, maximum cut; Sub-modular function minimization; Sub-modular function maximization; Approximation algorithms for combinatorial optimization problems; Applications in algorithms and theoretical computer science, machine learning, statistics, data mining	12
4	**Unconstrained and Constrained Optimization** Unconstrained optimization: Optimality conditions, Line Search Methods, Quasi Newton Methods, Trust Region Methods. Conjugate Gradient Methods. Least Squares Problems. Constrained Optimization: Optimality Conditions and Duality. Convex Programming Problem. Linear Programming Problem. Quadratic Programming. Dual Methods, Penalty and Barrier Methods, Interior Point Methods.	15
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement techniques for learning and classification problems such as least squares, LASSO, SVM etc. 2. Implement optimization techniques like gradient descent, max flow min cut 3. Implement linear and quadratic programming using tools like CPLEX.	1 Credit

Reading List:

- Stephen Boyd and Lieven Vandenberghe, “ Convex Optimization”, Cambridge press.
- Jorge Nocedal and Stephen J. Wright, “ Numerical Optimization”, Springer.
- R. Tyrrell Rockafellar, “Convex Analysis”, Princeton Landmarks in Mathematics and Physics

Paper Code: AIMLE04
Paper Title: Algorithmic Data Mining (5 Credits, L+T+P = 3+1+1)

This course will introduce students to the concepts and techniques of data mining, develop skills of using recent data mining software for solving practical problems, study the methodology of engineering legacy databases for data warehousing and data mining to derive business rules for decision support systems, develop and apply critical thinking, problem-solving, and decision-making skills.

After completion of the course the students will be able to:

1. Understand data mining principles and techniques and acquaint the students with the data mining techniques for building competitive advantage through proactive analysis, predictive modeling, and identifying new trends and behaviors.
2. Learn how to gather and analyze large sets of data to gain useful business understanding.
3. Produce a quantitative analysis report/memo with the necessary information to make decisions.
4. Describe and demonstrate basic data mining algorithms, methods, and tools.
5. Identify business applications of data mining
6. Overview of the developing areas - web mining, text mining.

Unit	Content	No. of Lectures
1	**Introduction** What is data mining; Distance functions, finding similar objects; Finding similar entities: locality-sensitive hashing (min-wise permutations); Dimensionality reduction	10
2	**Clustering** Clustering; Hierarchical Clustering, Clustering aggregation; Covering and Influence maximization; Clustering: graph cuts and spectral graph partitioning; Network models	11
3	**Classification** Classification methods (Decision Trees, Naive Bayes, Boosting); Link Analysis Ranking, Voting Systems; Time-series segmentation; Recommender systems, Matrix completion	12

4	**Advanced Techniques** Web mining – Introduction; Web content mining; Web structure mining; Web usage mining; Text mining – Unstructured text; Episode rule discovery from text; Text clustering; Temporal data mining – Temporal association rules; Sequence mining; Episode discovery; Time series analysis; Spatial data mining – Spatial mining tasks; Spatial clustering; Spatial trends.	15
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement various distance measures for clustering. 2. Implement different dimensionality reduction techniques. 3. Implement various classification methods (Decision Trees, Naive Bayes, Boosting).	1 Credit

Reading List:

- Data Mining Techniques. Arun K. Pujari, Universities Press (2016)
- Mastering Data Mining. Michael A. Berry and Gordon S. Linoff. John Wiley & Sons (2000)
- Data Mining: Concepts and Techniques. Jiawei Han and Michelline Kamber. Elsevier (2011)

Paper Code: AIMLE05
Paper Title: Speech Recognition and Synthesis (5 Credits, L+T+P = 3+1+1)

This course allows students to describe the principles of speech production, as well as its perception and intrinsic characteristics, in this course. Develop the capacity to analyze speech signal parameter estimates and feature representations. Develop the capacity to analyze voice recognition pattern comparison and design difficulties. To establish the notion of statistical and pattern recognition models, as well as their application. To create and use various classifiers and features for a variety of real-world applications..

After completion of the course the students will be able to:

1. Demonstrate the understanding of the speech production, its perception and features.
2. Analyze various components of parameter estimation and feature representations of speech signals.
3. Illustrate various models for speech synthesis and automatic recognition.
4. Analyze the speech recognition and implementation issues.

5. Develop an ability to create and apply the speech recognition techniques in various applications in different areas.

Unit	Content	No. of Lectures
1	**Basic Concepts** Introduction to automatic speech recognition and speech synthesis; Speech Fundamentals: Articulatory Phonetics – Production and Classification of Speech Sounds; Acoustic Phonetics – acoustics of speech production; Review of Digital Signal Processing concepts; Short-Time Fourier Transform, Filter-Bank and LPC Methods. Speech processing tasks, such as speaker and language identification and the use of forced alignment for automatic phonetic labeling.	9
2	**Speech Analysis** Features, Feature Extraction and Pattern Comparison Techniques: Speech distortion measures –mathematical and perceptual – Log Spectral Distance, Cepstral Distances, Weighted Cepstral Distances and Filtering, Likelihood Distortions, Spectral Distortion using a Warped Frequency Scale, LPC, PLP and MFCC Coefficients, Time Alignment and Normalization – Dynamic Time Warping, Multiple Time – Alignment Paths.	9
3	**Speech Modeling** Representation of the acoustic signal like MFCC coefficients and the use of Gaussian Mixture Models (GMMs) and context-dependent triphones for acoustic modeling. Key algorithms in the noisy channel paradigm; focusing on the standard 3-state Hidden Markov Model (HMM); Markov Processes, HMMs – Evaluation, Optimal State Sequence – Viterbi Search, Baum-Welch Parameter Re-estimation, Implementation issues.	10
4	**Speech Recognition** Large Vocabulary Continuous Speech Recognition: Architecture of a large vocabulary continuous speech recognition system – acoustics and language models – n-grams, context dependent sub-word units; Applications and present status.	10
5	**Speech Synthesis** Text-to-Speech Synthesis: Concatenative and waveform synthesis methods, sub-word units for TTS, intelligibility and naturalness – role of prosody, Applications and present status. Concatenative synthesis, covering text normalization, grapheme-to-phoneme conversion, prosodic modeling, and waveform synthesis.	10

	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement a language identification model extracting LPC, PLP, and MFCC features either for the publicly available speech dataset or creating a recorded dataset. 2. Implement a language identification model using HMM model. 3. Implement a language identification model using deep learning architectures. 4. Implement a speaker verification model using machine learning as well as deep learning techniques.	1 Credit

Reading List:

- Lawrence Rabiner and Biing-Hwang Juang, "Fundamentals of Speech Recognition", Pearson
- Daniel Jurafsky and James H Martin, "Speech and Language Processing – An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition", Pearson Education.

Paper Code: AIMLE06
Paper Title: Computer Vision (5 Credits, L+T+P = 3+1+1)

The objective of this course is to introduce students to the fundamentals of image formation, introduce students to the major ideas, methods, and techniques of computer vision and pattern recognition. It also aims to develop an appreciation for various issues in the design of computer vision and object recognition systems and to provide the student with programming experience from implementing computer vision and object recognition applications.

After completion of the course the students will be able to:

1. Identify basic concepts, terminology, theories, models and methods in the field of computer vision.
2. Describe basic methods of computer vision related to multi-scale representation, edge detection and detection of other primitives, stereo, motion and object recognition.
3. Design of a computer vision system for a specific problem.

Unit	Content	No. of Lectures
1	**Image Formation and Filtering**	9

	Camera Projection and Image Filtering; Light and Color and Sensors; Light and Color and Sensors	
2	**Feature Detection and Matching** Interest points and corners; Local image features; Model fitting, Hough Transform; RANSAC and transformations	9
3	**Multiple Views and Motion** Stereo intro; Camera Calibration, Epipolar Geometry, and Structure from Motion; Stereo Correspondence and Optical Flow	10
4	**Recognition** Machine learning crash course; Recognition and bag of words; Object Detection with a sliding window; Big Data; Crowdsourcing and Human Computation	10
5	**Deep Learning** Neural networks Basics and Convolutional Networks; Object Detectors Emerge in Deep Scene CNNs and Deeper Deep Architectures; "Unsupervised" Learning and Colorization; Structured Output from Deep Networks; Semantic and Panoptic Segmentation; 3D CNNs and Lidar; Transformer architectures	10
	Tutorial - Tutorials will be based on theory.	16
	Practical - 1. Implement Image Manipulation. Read, write, view images and conversion between different formats. 2. Implement Spatial Transformations. Convolution and correlation. 3. Implement Frequency Transformations. Fourier transform. 4. Implement Histogram Modification. Explore histogram as an enhancement technique. 5. Implement Filtering. Noise identification and filtering techniques to remove it. 6. Implement Morphological Transformations. Dilatation and erosion as fundamental morphological operations. 7. Implement Segmentation using Edge Detection. Detection of boundaries between two regions using different gradient approximations. 8. Implement Segmentation using Thresholding. Divide the image in regions depending on the gray level.	1 Credit

Reading List:

- R.C. Gonzalez and R.E. Woods, Digital Image Processing, Addison Wesley, 2008.

- R.O. Duda and P.E. Hart, Pattern Classification and Scene Analysis, John Wiley, 2003.
- A.K. Jain, Fundamentals of Digital Image Processing, Pearson Education, 2009.

Paper Code: AIML0401
Paper Title: Major Project (18 Credits, L+T+P = 0+0+18)

In the Major Project, students are expected to have a thorough understanding of the theoretical principles learned in earlier three semesters through prolonged practical experience in a real life project. The major project is oriented towards developing requisite skills, knowledge of latest technologies and an entrepreneurial attitude in a student which are needed to make an effective start as a computer/IT professional. A dissertation report depicting the work, in specified format, has to be submitted in the department. The progress of the project will be continuously monitored and evaluated. The final evaluation of the project will be done at the end of the semester through presentation and viva.

Paper Code: AIML0402
Paper Title: Seminar (2 Credits, L+T+P = 3+1+1)

While doing a Major Project, students are expected to present a seminar briefing their project proposal. The Evaluation of the seminar will be done at the mid of the semester through presentation and viva.