KERALA TECHNOLOGICAL UNIVERSITY

Master of Technology

Curriculum, Syllabus and Course Plan

Cluster	**:**	*01*
Branch	**:**	*Interdisciplinary**
Stream	**:**	*Artificial Intelligence*
Year	**:**	*2020*
No. of Credits	**:**	*67*

*Note: The branches are restricted to the following disciplines.

- Computer Science and Engineering
- Electronics and Communication Engineering
- Mechanical Engineering

SEMESTER 1

Examination Slot	Course Number	Name	L-T-P	Internal Marks	End Semester Examination		Credits
					Marks	Duration (hours)	
A	01EC6301	Applied Linear Algebra	3-0-0	40	60	3	3
B	01EC6303	Random Processes and Applications	3-1-0	40	60	3	4
C	01CS6601	Foundations of Artificial Intelligence	3-1-0	40	60	3	4
D	01CS6603	Introduction to Machine Learning	3-0-0	40	60	3	3
E	01ME6901	Data Analytics	3-0-0	40	60	3	3
S	01ME6999	Research Methodology	0-2-0	100			2
T	01EC6991	Seminar I	0-0-2	100			2
U	01CS6693	Artificial Intelligence Lab	0-0-2	100			1
		TOTAL	**15-4-4**	**500**	**300**	**-**	**22**

TOTAL CONTACT HOURS: 23

TOTAL CREDITS : 22

SEMESTER 2

Examination Slot	Course Number	Name	L-T-P	Internal Marks	End Semester Examination		Credits
					Marks	Duration (hours)	
A	01EC6902	Deep Learning and Applications	3-1-0	40	60	3	4
B	01EC6906	Numerical Optimization	3-0-0	40	60	3	3
C	01CS6654	Data Mining	3-0-0	40	60	3	3
D		Elective-II	3-0-0	40	60	3	3
E		Elective-III	3-0-0	40	60	3	3
V	01CS6692	Mini Project	0-0-4	100			2
U	01EC6994	Deep Learning Lab	0-0-2	100			1
		TOTAL	**15-1-6**	**400**	**300**	**-**	**19**

TOTAL CONTACT HOURS : 22

TOTAL CREDITS : 19

Elective II	
01EC6114	Digital Image Processing and computer vision
01CS6672	Internet of Things
01CS6674	Natural Language Processing
01CS6676	AI in Cyber Security
01ME6414	Data Analytics using R& Python

Elective III	
01EC6218	Soft Computing
01CS6682	Reinforcement Learning
01CS6684	Hardware Architecture for Machine Learning
01ME6128	Robotics
01EC6904	Signal Detection and Estimation

SEMESTER 3

Examination Slot	Course Number	Name	L-T-P	Internal Marks	End Semester Examination		Credits
					Marks	Duration (hours)	
A		Elective IV	3-0-0	40	60	3	3
B		Elective V	3-0-0	40	60	3	3
T	01ME7991	Seminar II	0-0-2	100			2
W	**01CS7693**	Project (Phase 1)	0-0-12	50			6
		TOTAL	**6-0-14**	**230**	**120**	**-**	**14**

TOTAL CONTACT HOURS : 20

TOTAL CREDITS : 14

Elective IV	
01EC7933	Convex Optimization
01CS7651	Statistical Machine Learning
01CS7653	Deep Learning for Natural language processing
01ME7415	Heuristic Solution Methods
01CS7655	Data Structures and Algorithms

Elective V	
01EC7315	Computer Vision
01CS7177	Advanced Software Project Management
01EC7935	Machine Learning for Signal Processing
01CS7671	Graph Data Bases for AI

SEMESTER 4

Examination Slot	Course Number	Name	L-T-P	Internal Marks	End Semester Examination		Credit
					Marks	Duration (hours)	
W	**01CS7694**	Project (Phase 2)	0-0-23	70	30		12
		TOTAL	**0-0-23**	**70**	**30**	**-**	**12**

TOTAL CONTACT HOURS : 23

TOTAL CREDITS : 12

TOTAL NUMBER OF CREDITS: 67

SEMESTER – I

Syllabus and Course Plan

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC6301	Applied Linear Algebra	**3-0-0**	**3**	**2015**

Course Objectives

1. To develop the skills in abstract algebra
2. To develop the skills to identify linear transformation and transforms and its role in linear systems
3. To develop the skills to formulate linear transformation problems in matrix form

Syllabus

Vector spaces, Linear independence, Linear Transformation, Coordinate transformation, System of linear equations, projection, pseudo inverse, Generalized Eigen vectors, Singular Value Decomposition

Expected Outcome

By the end of the course, the students will be able to :

1. Understand the formulation of problems in abstract algebra framework
2. Understand and represent linear transformations
3. Understand the role of matrices in linear transformation representations

References

1. Introduction to Linear Algebra 2e, Serge Lang, Springer
2. Introduction to Linear Algebra, Gilbert Strang, MIT Press
3. G.F.Simmons, Topology and Modern Analysis , McGraw Hill
4. Frazier, Michael W. An Introduction to Wavelets Through Linear Algebra, Springer Publications.
5. Hoffman Kenneth and Kunze Ray, Linear Algebra, Prentice Hall of India.
6. Linear Algebra, Reichard Bronson, Academic Press

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Algebraic Structures: Group, Ring, Field Vector Spaces, Subspaces, Linear Combinations, Subspace spanned by set of vectors, Linear dependence and Linear independence, Spanning set and basis, Finite dimensional vector spaces	**7**	**15**
II	Solutions to Linear System of Equations : Simple systems, Homogeneous and Non-homogeneous systems, Gaussian elimination, Null Space and Range, Rank and nullity, Consistency conditions in terms of rank, General Solution of a linear system, Elementary Row and Column operations, Row Reduced Form, existence and uniqueness of solutions, projection, least square solution -pseudo inverse.	**7**	**15**
FIRST INTERNAL EXAM			
III	Linear Transformations -four fundamental subspaces of linear transformation -inverse transformation - rank nullity theorem - Matrix representation of linear transformation, Change of Basis operation,	**7**	**15**
IV	Inner product, Inner product Spaces, Cauchy – Schwarz inequality, Norm, Orthogonality, Gram – Schmidt orthonormalization, Orthonormal basis, Expansion in terms of orthonormal basis, Orthogonal complement, Decomposition of a vector with respect to a subspace and its orthogonal complement – Pythagoras Theorem	**7**	**15**
SECOND INTERNAL EXAM			
V	Eigenvalue – Eigenvector pairs, characteristic equation, Algebraic multiplicity, Eigenvectors, Eigenspaces and geometric multiplicity, Diagonalization criterion, The diagonalizing matrix, Projections, Decomposition of the matrix in terms of projections, Real Symmetric and Hermitian matrices , Properties of Eigen values, Eigen vectors, Unitary/Orthogonal diaganalizability of Comples Hermitian/Real Symmetric Matrices, Spectral Theorem, Positive and Negative Definite and Semi Definite matrices.	**7**	**20**
VI	General Matrices : Rank, Nullity, Range and Null Space of AAT and ATA, Singular Values, Singular Value Decomposition, Pseudoinverse and Optimal solution of a linear system of equations, The Geometry of Pseudoinverse	**7**	**20**
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC6303	Random Processes and Applications	**3-1-0**	**4**	**2015**

Course Objectives

1. To provide necessary basic concepts in statistical signal analysis
2. To study about random processes and its properties
3. Apply the basic concepts to various elementary and some advanced applications

Syllabus

Probability theory, Random variable, Probability Density function, Conditional and Joint Distributions and densities, Functions of Random Variables, Expectation, Conditional Expectations, Random Vector, Random Processes, Chapman- Kolmogorov Equations, WSS Processes and LTI Systems, Inequalities, Central limit theorem, Random Sequences, Advanced Topics.

Expected Outcome

By the end of the course, the students will

1. Have a fundamental knowledge of the basic probability concepts
2. Have a good knowledge of standard distributions which can describe real life phenomena
3. Acquire skills in handling situations involving several random variable and functions of random variables
4. Understand and characterize phenomena which evolve with respect to time in probabilistic manner

References

1. Henry Stark and John W. Woods "Probability and Random Processes with Applications to Signal Processing", Pearson Education, Third edition.

2. Athanasios Papoulis and S. Unnikrishna Pillai. Probability, Random Variables and Stochastic Processes, TMH

3. Gray, R. M. and Davisson L. D., An Introduction to Statistical Signal Processing. Cambridge University Press, 2004(Available at: http://www.ee.stanford.edu/~gray/sp.pdf)

4. Oliver C. Ibe. , Fundamentals of Applied Probability and Random Process, Elseiver, 2005.

5. Christopher M. Bishop, Pattern Recognition and Machine Learning, Springer, 2006

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Introduction: Sets, Fields and Events, Definition of probability, Joint, Conditional and Total Probability, Bayes' Theorem and applications. Random Variable:- Definition, Probability Distribution Function, Probability Density function, Common density functions, Continuous, Discrete and Mixed random Variables.	8	12
II	Conditional and Joint Distributions and densities, independence of random variables. Functions of Random Variables: One function of one random variable, One function of two random variables, Two functions of two random variables.	10	18
FIRST INTERNAL EXAM			
III	Expectation: Fundamental Theorem of expectation, Moments, Joint moments, Moment Generating functions, Characteristic functions, Conditional Expectations, Correlation and Covariance, Jointly Gaussian Random Variables. Random Vector: - Definition, Joint statistics, Covariance matrix and its properties.	10	15
IV	Random Processes: -Basic Definitions, Poisson Process, Wiener Process, Markov Process, Birth- Death Markov Chains, Chapman-Kolmogorov Equations, Stationarity, Wide sense Markov Process Stationarity, WSS Processes and LTI Systems, Power spectral density, White Noise.	10	15
SECOND INTERNAL EXAM			
V	Chebyshev and Schwarz Inequalities, Chernoff Bound, Central Limit Theorem. Random Sequences: Basic Concepts, WSS sequences and linear systems, Markov Random sequences, Markov Chains, Convergence of Random Sequences: Definitions, Laws of large numbers.	10	24
VI	Advanced Topics: Ergodicity, Karhunen- Leove Expansion, Representation of Band limited and periodic Processes: WSS periodic Processes, Fourier Series for WSS Processes	8	16
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS6601	Foundations of Artificial Intelligence	3-1-0	4	2020

Course Objectives

1. Identify problems where artificial intelligence techniques are applicable
2. Apply selected basic AI techniques; judge applicability of more advanced techniques.
3. Participate in the design of systems that act intelligently and learn from experience

Syllabus

Intelligent agents, problem-solving through search, knowledge representation and reasoning, planning, representing and reasoning with uncertain knowledge, decision making, machine learning and knowledge acquisition.

Expected Outcome

By the end of the course, the students will be able to

1. Identify problems that are amenable to solution by AI methods.
2. Identify appropriate AI methods to solve a given problem.
3. Formalize a given problem in the language/framework of different AI methods.
4. Implement basic AI algorithms.
5. Design and carry out an empirical evaluation of different algorithms on a problem formalization, and state the conclusions that the evaluation supports.

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Introduction to AI - foundations, scope, problems, and approaches of AI. Intelligent agents: reactive, deliberative, goal-driven, utility-driven, and learning agents	7	15
II	Problem-solving through Search: forward and backward, state-space, blind, heuristic, problem-reduction, A, A*, AO*, minimax, constraint propagation, neural, stochastic, and evolutionary search algorithms, sample applications.	7	15
	FIRST INTERNAL EXAM		
III	Knowledge Representation and Reasoning: ontologies, foundations of knowledge representation and reasoning, representing and reasoning about objects, relations, events, actions, time, and space; predicate logic, situation calculus, description logics, reasoning with defaults, reasoning about knowledge, sample applications.	7	15
IV	Planning: planning as search, partial order planning, construction and use of planning graphs Representing and Reasoning with Uncertain Knowledge: probability, connection to logic, independence, Bayes rule, bayesian networks, probabilistic inference, sample applications.	7	20
	SECOND INTERNAL EXAM		
V	Decision-Making: basics of utility theory, decision theory, sequential decision problems, elementary game theory, sample applications.	7	20
VI	Machine Learning and Knowledge Acquisition: learning from memorization, examples, explanation, and exploration. learning nearest neighbour, naive Bayes, and decision tree classifiers, Q-learning for learning action policies, applications.	7	15
	END SEMESTER EXAM		

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS6603	Introduction to Machine Learning	3-0-0	3	2020

Course Objectives

1. To learn practical side of machine learning for applications
2. To learn the process of applying machine learning to a variety of problems
3. To learn unsupervised learning
4. To learn supervised learning

Syllabus

Basic classification/regression techniques such as Naive Bayes', decision trees, SVMs, boosting/bagging and linear/logistic regression, maximum likelihood estimates, regularization, perceptron rule/multi-layer perceptrons, back-propagation, dimensionality reduction techniques like PCA, unsupervised learning: k-means clustering, Gaussian mixture models

Expected Outcome

By the end of the course, the students will be able to

1. Gain familiarity with key areas of machine learning including classification, regression, clustering, dimensionality Reduction
2. Apply machine learning techniques to solve practical problems.
3. Explain the relative strengths and weaknesses of different machine learning methods.
4. Be able to select an appropriate algorithm for a particular task.
5. Be able to appropriately use validation and test data to tune and evaluate machine learning algorithms.

References

1. Kevin Murphy, Machine Learning: A Probabilistic Perspective (MLAPP), MIT Press, 2012
2. Christopher Bishop, Pattern Recognition and Machine Learning (PRML), Springer, 2007.
3. David G. Stork, Peter E. Hart, and Richard O. Duda. Pattern Classification (PC), Wiley-Blackwell, 2000
4. Trevor Hastie, Robert Tibshirani, Jerome Friedman, The Elements of Statistical Learning (ESL), Springer, 2009 (freely available online)

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester**
I	Overview of machine learning: supervised, semi-supervised, unsupervised learning, reinforcement learning Basics of parameter estimation: maximum likelihood and maximum a posteriori - Bayesian formulation	**6**	**15**
II	Classification algorithms: linear and non-linear algorithms, perceptrons, logistic regression, linear discriminant analysis, quadratic discriminant analysis, naive Bayes, decision trees Neural networks : concept of perceptron and Artificial neuron, Feed Forward Neural Network, back propagation algorithm, weight initialization.	**8**	15
FIRST INTERNAL EXAM			
III	Support vector machines and large-margin classifiers - Kernel methods Regression algorithms: least squares linear regression, gradient descent, closed form, normal equations, regularization techniques (LASSO, RIDGE), polynomial regression, locally weighted regression algorithm	**7**	**15**
IV	Unsupervised learning: clustering, k-means, K Nearest Neighbours, hierarchical clustering, Gaussian mixture models: Expectation Maximization (EM) algorithm for Gaussian mixture model	**7**	**20**
SECOND INTERNAL EXAM			
V	Representation learning and matrix factorization - sparse coding - dimensionality reduction: PCA, SVD, tSNE Basics of graphical models - Bayesian networks, hidden Markov model - inference and estimation, Ensemble methods: bagging, boosting, random forests	**7**	**20**
VI	Practical aspects in machine learning: data preprocessing, overfitting, accuracy estimation, parameter and model selection, bias variance tradeoff	**7**	**15**
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01ME6901	Data Analytics	3-0-0	3	2020

Course Objectives

1. To understand basic statistical techniques and their applications in the context of business and industry problems.
2. To perform and interpret elementary statistical procedures (such as confidence intervals and hypothesis tests).
3. To utilize single and multi variable measures to make decisions.
4. To extract information from data and use it to predict trends and behavior patterns.

Syllabus

Data collection, classification and tabulation – Measures of Central Tendency – Measures of Dispersion – Sampling and Sampling Distributions – Estimation and Confidence Intervals – Hypothesis Testing – Non Parametric Tests – Analysis of Variance – Correlation Analysis – Regression Analysis – Introduction to Multivariate Analysis – Introduction to R and Big data.

Expected Outcome

1. Students will be able to apply statistical techniques for analyzing and interpreting data to real-world datasets relevant to varied fields of business and industry.
2. Students will be able to critically evaluate reports presenting statistical data and translate and communicate the results of statistical analyses.

References

1. P. E. Green, D. S. Tull, G. Albaum, "Research for Marketing decisions", Prentice- hall of India Pvt. Ltd
2. Thomas C. Kinnear, James R. Taylor, "Marketing Research: An Applied approach", McGraw-Hill
3. A. B. Bowker and G. J. Liberman, "Engineering Statistics", Asia, 1972.
4. F. E. Brown, "Marketing Research: A structure for decision making",Addison-Wesley publishing Co., California.
5. J.K. Sharma, "Business Statistics", Pearson Education.
6. R. Panneerselvam, "Research Methodology", Prentice Hall India.
7. Amir D Aczel and Jayavel Sounderpandian, "Complete Business Statistics", Tata McGraw-Hill
8. Richard I Levin and David S Rubin, "Statistics for Management", Pearson Education
9. Hair et al., "Multivariate Data Analysis", Pearson Education
10. Richard Cotton, "Learning R", O'Reilly, 2013
11. Brain S. Everitt, "A Handbook of Statistical Analysis Using R", Second Edition, LLC, 2014.
12. Glenn J Myatt, "Making Sense of Data", John Wiley & Sons, 2007
13. Bart Baesens "Analytics in a Big Data World: The Essential Guide to Data Science and its Applications (WILEY Big Data Series)", John Wiley & Sons,2014

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	**Data Collection, Classification and Tabulation:** Need for data, Types of Data, Scale of measurement, Sources of data, Classification and Tabulation of data, Data Visualization	**4**	**10**
II	**Measures of Central Tendency:** Significance, Classification - Mean, Median, Mode; **Measures of Position:** Quartiles, Deciles and Percentiles.	**4**	**20**
	Measures of Dispersion: Significance, Classification – Range, Inter-quartile range, Mean Absolute Deviation, Variance and Standard deviation, Coefficient of variation, Skewness and Kurtosis.	**4**	
FIRST INTERNAL EXAM			
III	**Sampling and Sampling Distributions:** Population parameters and Sample statistics, Sampling methods, Sampling distribution of sample mean, Sampling distribution of sample proportions.	**4**	**15**
	Estimation and Confidence Intervals: Confidence Interval estimation – Interval estimation of population means (σ known and σ unknown).	**2**	
IV	**Hypothesis Testing:** Procedure, Hypothesis testing for population parameters with large samples and small samples. Hypothesis testing based on F- Distribution.	**4**	**20**
	Non Parametric tests: Chi-square test, Mann-Whitney U-test, Median test, Kruskal-Waliis test.	**4**	
SECOND INTERNAL EXAM			
V	**Design of Experiments:** Analysis of Variance – One way and Two way Anova, Factorial design: 2^n Factorial experiment, Yate's algorithm.	**4**	**15**
	Correlation Analysis: Karl Pearson's correlation, Spearman's rank correlation	**2**	
VI	**Regression Analysis:** Simple and Multiple Linear Regression models, Determination of regression coefficients, Coefficient of determination, Significance test of Regression model, Polynomial regression	**6**	**20**
	Introduction to Multivariate Analysis: Overview of Discriminant Analysis, Factor Analysis, Cluster Analysis, Multidimensional scaling and Conjoint Analysis; **Introduction to Big data:** Challenges of processing; **Introduction to 'R'.**	**4**	
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01ME6999	Research Methodology	**0-2-0**	**2**	**2015**

Course Objectives

1. To prepare the student to do the M. Tech project works with a research bias.
2. To formulate a viable research question.
3. To develop skill in the critical analysis of research articles and reports.
4. To analyze the benefits and drawbacks of different methodologies.
5. To understand how to write a technical paper based on research findings.

Syllabus

Introduction to Research Methodology-Types of research- Ethical issues- Copy right-royalty-Intellectual property rights and patent law-Copyleft- Openacess-
Analysis of sample research papers to understand various aspects of research methodology:
Defining and formulating the research problem-Literature review-Development of working hypothesis-Research design and methods- Data Collection and analysis- Technical writing-Project work on a simple research problem

Approach

Course focuses on students' application of the course content to their unique research interests. The various topics will be addressed through hands on sessions.

Expected Outcome

Upon successful completion of this course, students will be able to

1. Understand research concepts in terms of identifying the research problem
2. Propose possible solutions based on research
3. Write a technical paper based on the findings.
4. Get a good exposure to a domain of interest.
5. Get a good domain and experience to pursue future research activities.

References

1. C. R. Kothari, Research Methodology, New Age International, 2004
2. Panneerselvam, Research Methodology, Prentice Hall of India, New Delhi, 2012.
3. J. W. Bames, Statistical Analysis for Engineers and Scientists, Tata McGraw-Hill, New York.
4. Donald Cooper, Business Research Methods, Tata McGraw-Hill, New Delhi.
5. Leedy P. D., Practical Research: Planning and Design, McMillan Publishing Co.
6. Day R. A., How to Write and Publish a Scientific Paper, Cambridge University Press, 1989.
7. Manna, Chakraborti, Values and Ethics in Business Profession, Prentice Hall of India, New Delhi, 2012.
8. Sople, Managing Intellectual Property: The Strategic Imperative, Prentice Hall ofIndia, New Delhi, 2012.
9. Vinod Chandra S. S., Anand H. S. "Research Methodology", ISBN: 978-93-528-6351-8, Pages:328, Pearson Education, Chennai, 2017

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Introduction to Research Methodology: Motivation towards research - Types of research: Find examples from literature. Professional ethics in research - Ethical issues-ethical committees. Copy right - royalty - Intellectual property rights and patent law - Copy left- Open access -Reproduction of published material - Plagiarism - Citation and acknowledgement. Impact factor. Identifying major conferences and important journals in the concerned area. Collection of at least 4 papers in the area.	5	No end semester written examination
II	Defining and formulating the research problem -Literature Survey- Analyze the chosen papers and understand how the authors have undertaken literature review, identified the research gaps, arrived at their objectives, formulated their problem and developed a hypothesis.	4	
FIRST INTERNAL EXAM			
III	Research design and methods: Analyze the chosen papers to understand formulation of research methods and analytical and experimental methods used. Study of how different it is from previous works.	4	
IV	Data Collection and analysis. Analyze the chosen papers and study the methods of data collection used. - Data Processing and Analysis strategies used– Study the tools used for analyzing the data.	5	
SECOND INTERNAL EXAM			
V	Technical writing - Structure and components, contents of a typical technical paper, difference between abstract and conclusion, layout, illustrations and tables, bibliography, referencing and footnotes-use of tools like Latex.	5	
VI	Identification of a simple research problem – Literature survey- Research design- Methodology –paper writing based on a hypothetical result.	5	
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC6991	Seminar I	**0-0-2**	**2**	**2020**

Course Objectives

To make students

1. Identify the current topics in the specific stream.
2. Collect the recent publications related to the identified topics.
3. Do a detailed study of a selected topic based on current journals, published papers and books.
4. Present a seminar on the selected topic on which a detailed study has been done.
5. Improve the writing and presentation skills.

Approach

Students shall make a presentation for 20-25 minutes based on the detailed study of the topic and submit a report based on the study.

Expected Outcome

Upon successful completion of the seminar, the student should be able to

1. Get good exposure in the current topics in the specific stream.
2. Improve the writing and presentation skills.
3. Explore domains of interest so as to pursue the course project.

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS6693	Artificial Intelligence Lab	0-0-2	1	2020

Course objectives

This course will enable students to

1. Implement basic algorithm in AI
2. Make use of Data sets in implementing the machine learning algorithms
3. Implement the machine learning concepts and algorithms in any suitable language of choice

Expected outcomes

The students should be able to:

1. Apply AI algorithms to solve real world problems
2. Understand the implementation procedures for the machine learning algorithms.
3. Design Java/Python programs for various Learning algorithms.
4. Apply appropriate data sets to the Machine Learning algorithms.
5. Identify and apply Machine Learning algorithms to solve real world problems.

Syllabus

Experiments are based on but not limited to the topics covered in *Artificial Intelligence* and *Machine Learning*.

Sl. No.	List of Experiments
1	Implement A* algorithm for the following problems: i) 8 puzzle ii) Missionaries and Cannibals.
2	Implement and testhill climbing based search algorithms to solve Travelling Salesman Problem.
3	Solve and implement map coloring problem by backtracking and constraint propagation
4	Solve and implement the game of tic-tac-toe using mini-max.
5	Solve and implement towers of Hanoi problem by planning.
6	Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and use it to classify a new sample.

7	Build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.
8	Write a program to implement the naive Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets. Calculate the accuracy, precision, and recall for your data set
9	Write a program to construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using any standard Heart Disease Data Set.
10	Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering.
11	Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions.
12	Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw the corresponding graphs.

SEMESTER – II

Syllabus and Course Plan

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC6902	Deep Learning and Applications	**3-1-0**	**4**	**2020**

Pre-requisite: Fundamentals of Probability and Random process, Machine learning and artificial intelligence.

Course Objectives

The purpose of this course is:

1. To familiarize students the fundamentals of deep learning for computer vision and understand how to build neural networks.
2. To familiarize students different computer vision tasks and how deep learning is employed in each task.
3. Understand major technology trends driving deep learning.
4. Get proficient in deep neural networks and its applications

Syllabus

Image classification, Convolutional Neural Networks, Training Neural Networks , CNN architectures for classification ,Recurrent Neural Networks, Semantic segmentation ,Object detection, Visualizing CNN features, Generative Networks

Expected Outcome

By the end of the course, the students will be able :

1. To understand the fundamentals of deep learning.
2. To design and implement deep neural network systems to produce amazing solutions to computer vision challenges.
3. To identify the deep learning algorithms which are more appropriate for various types of learning tasks in various domains

References

1. Ian Goodfellow, Yoshua Bengio, Aaron Courville, Deep Learning, MIT Press, 2016
2. Bishop, C. ,M., Pattern Recognition and Machine Learning, Springer, 2006
3. Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani, Introduction to Statistical Learning, Springer, 2013.
4. Michael Nielsen, Neural Networks and Deep Learning

COURSE PLAN

Module	Contents	Hours Allotted	% of Marks in End-Semester Examination
I	Computer Vision: A historical perspective. Different machine learning tasks. Image Classification : Data-driven Approach, K-nearest neighbour. Linear classification: Loss function, Multiclass SVM, Softmax classifier. Image features optimization, Numeric and Analytic gradients.	7	15
II	Convolutional Neural Networks: Back propagation, Gradient-Based Learning. Model of a biological neuron, activation functions:- different types, comparison, Convolutional Neural Networks: Convolution / Pooling Layers, spatial arrangement, layer patterns, layer sizing patterns	6	15
FIRST INTERNAL EXAM			
III	Training Neural Networks: Initialization, batch normalization, Hyper parameter optimization ,Optimization algorithms:-SGD, Nesterov Momentum, Adagrad, RMS Prop, Adam. Regularization methods: drop outs, ensembles, data augmentation, ,Update rules, transfer learning	6	15
IV	CNN architectures: LeNet, AlexNet, VGG, ResNet, Inception case studies, computational considerations, Recurrent Neural Networks: RNN, Bidirectional RNNs, LSTM, GRU. Applications of RNN: word prediction ,Chatbots, Image captioning	7	15
SECOND INTERNAL EXAM			
V	Semantic Segmentation, Object Detection : RCNN,Fast RCNN,Faster RCNN, YOLO, Mask RCNN. Understanding and Visualizing Convolutional Neural Networks. Gradient ascent, Deep dream, Texture Synthesis, Neural Style Transfer	8	20
VI	Generative Networks: Pixel RNN/CNN,Variational Autoencoders(VAE),GANs. Typical applications of GANs and VAE. Deep learning hardware and software: CPUs,GPUs and TPUs Tensorflow and Pytorch frameworks.	9	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC6906	Numerical Optimization	3-0-0	3	2020

Course Objectives

1. To familiarize the students with the need of numerical optimization in engineering.
2. To introduce the students with the different types of optimization algorithms.
3. To enable the students to select the suitable optimization technique for the particular problem.

Syllabus

One dimensional- necessary and sufficient conditions, Search methods, Gradient methods, Multivariable- Search methods, Gradient based methods, Linear programming, Theory of Simplex method, Two phase method, Non Linear Programming, search method, Meta-heuristic optimization Techniques, Differential Evolution, Harmony Search Algorithm, Artificial Bee Colony Algorithm

Expected Outcome

By the end of the course, the students will be able to

1. Understand the role of optimization in engineering design.
2. Understand the working principle of optimization algorithms.
3. Understand the formulation of the problem and usage of optimization algorithms

References

1. Optimization for Engineering Design, Algorithms and Examples. –PHI, ISBN -978-81-203 0943-2, Kalyanmoy Deb, IIT Kanpur.
2. Optimization by Vector Space Methods, David G. Leunberger,
3. Stephen Boyd and LeivenVandenberghe, Convex Optimization, Cambridge Press.
4. Numerical Optimization, Jorge Nocadel, Stephen J Wright, Springer

COURSE PLAN

Module	Contents	Hours Allotted	% of Marks in End-Semester Examination
I	One Dimensional Optimization Algorithms– necessary and sufficient conditions (proofs), Search methods- Fibonacci search, golden section search, Gradient methods- Newton- Raphson method, cubic search.	7	15
II	Multivariable Optimization Algorithms- necessary and sufficient conditions (proofs), Gradient based methods- steepest descent, Newton's method, conjugate gradient method.	7	15
FIRST INTERNAL EXAM			
III	Linear Programming - Systems of linear equations & inequalities, Two dimensional linear programs, Convex polyhedra and linear programs, Standard forms of linear programs.	7	15
IV	Theory of Simplex method, Simplex Algorithm, Matrix form, Two phase method-Duality, Dual Simplex method.	7	15
SECOND INTERNAL EXAM			
V	Non-Linear Programming- Kuhn-Tucker conditions- Necessary and Sufficiency theorem – transformation method – penalty function method search method –random search method, linearized search - Frank-Wolf method.	7	20
VI	Meta-heuristic optimization Techniques-Particle Swarms, Ant Colony Algorithm, Evolutionary Algorithms-Genetic Algorithm.	7	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS6654	Data Mining	**3-0-0**	**3**	**2020**

Course Objectives

1. To understand and practice the fundamental and advanced concepts Data Warehousing and Data Mining

Syllabus

Data warehousing – OLAP, schema, Data architecture, Data Mining. Mining Tasks, Issues, Metrics, KDD Vs Data mining, DMQL, Classification Clustering, Association, Web mining, Spatial mining, temporal mining.

Expected Outcome

By the end of the course, the students will be able to

1. Ability to explain Data warehousing, OLAP and basic data mining activities
2. Ability to apply data mining algorithms for classification and clustering
3. Ability to explain and apply association rule mining techniques
4. Ability to explain Web mining and Spatial mining

References

1. Margaret H Dunham, "Data Mining – Introductory and Advanced Topics", Pearson India,2005.
2. Ian H. Witten, Eibe Frank,Mark A. Hall," Data Mining: Practical Machine Learning Tools and Techniques", 3/e, Morgan Kaufmann, 2011.
3. J. Han, M. Kamber, "Data Mining: Concepts and Techniques", 2/e, Morgan Kaufman, 2006.

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Data warehousing – Multidimensional data model, OLAP operation, Warehouse schema, Data Warehousing architecture, warehouse server, Metadata, OLAP engine, Data warehouse Backend Process , Data Warehousing to Data Mining.	07	15
II	Basic Data Mining Tasks, Data Mining Issues, Data Mining Metrics, Data Mining from a Database Perspective, Knowledge Discovery in Database Vs Data mining. Data Preprocessing**:** Preprocessing, Cleaning, Integration, Transformation, Reduction, Discretization, Concept Hierarchy Generation, Introduction to DMQL.	09	20
FIRST INTERNAL EXAM			
III	Similarity measures, Bayes Theorem, Classification - regression, Bayesian classification, Decision tree based algorithm-ID3, Neural network based algorithm- supervised learning, back propagation, gradient-descent algorithm, Rule based algorithm-IR, PRISM,	09	20
IV	Clustering algorithms – Hierarchical algorithm – Dendrograms-Single link algorithm, Partitional algorithm- Minimum spanning tree, squared error, K-means, PAM algorithm.	05	15
SECOND INTERNAL EXAM			
V	Association Rules : Apriori algorithm, Sampling algorithm, Partitioning algorithm, Parallel and distributed algorithms, Web mining-web content mining, web structure mining, web usage mining,	07	20
VI	Spatial mining- spatial queries, spatial data structures, Generalization and specialization, spatial classification, spatial clustering, Introduction to temporal mining.	05	10
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC6114	Digital Image Processing and Computer Vision	**3-0-0**	**3**	**2015**

Course Objectives

1. Understand the various steps in digital image processing.
2. Get a thorough understanding of digital image representation and processing techniques.
3. Ability to process the image in spatial and transform domain for better enhancement.

Syllabus

Image processing fundamentals, Two-dimensional transform techniques, Image representation and sampling, Image enhancement techniques, Image restoration techniques, Image and video compression standards, Image description and recognition, Mathematical morphology, Computer tomography, Image texture analysis

Expected Outcome

1. Understand various techniques for image representation
2. Understand various low level image processing techniques including reconstruction from Projections
3. Understand the fundamentals of high level image processing

References

1. Gonzalez and Woods, Digital image processing, Prentice Hall, 2002.
2. A. K. Jain, Fundamentals of digital image processing, Prentice Hall of India, 1989.
3. M. Haralick, and L.G. Shapiro, Computer and Robot Vision, Vol-1, Addison Wesley, Reading, MA, 1992

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Image processing fundamentals. Two dimensional orthogonal transforms - DFT, FFT, WHT, Haar transform, KLT, DCT, Hough Transform.	8	15
II	Image representation - Gray scale and colour images. Image sampling and quantization. Image enhancement - filters in spatial and frequency domains, histogram-based processing, homomorphic filtering.	6	15
FIRST INTERNAL EXAM			
III	Edge detection - non parametric and model based approaches, LOG filters, localization problem. Image Restoration - PSF, circulant and block - circulant matrices, deconvolution, restoration using inverse filtering, Wiener filtering and maximum entropy-based methods.	7	15
IV	Image and Video Compression Standards: Lossy and lossless compression schemes: Transform Based, Sub-band Decomposition, Entropy Encoding, JPEG, JPEG2000, MPEG. Image description and recognition - boundary detection, chain coding, segmentation and thresholding methods.	7	15
SECOND INTERNAL EXAM			
V	Mathematical morphology - binary morphology, dilation, erosion, opening and closing, duality relations, gray scale morphology, applications such as hit-and-miss transform, thinning and shape decomposition.	7	20
VI	Computer tomography - parallel beam projection, Radon transform, and its inverse, Back-projection operator, Fourier-slice theorem, CBP and FBP methods, ART, Fan beam projection. Image texture analysis - co-occurrence matrix, measures of textures, statistical models for textures.	7	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS6674	Natural Language Processing	**3-0-0**	**3**	**2020**

Course Objectives

1. To introduce the fundamental concepts and theory of Natural Language Processing and its practical applications
   Linguistic (knowledge-based) and statistical approaches to language processing in the three major subfields of NLP: syntax (language structures), semantics (language meaning), and pragmatics/discourse (the interpretation of language in context).

Syllabus

Linguistic (knowledge-based) and statistical approaches to language processing in the three major subfields of NLP: syntax (language structures), semantics (language meaning), and pragmatics/discourse (the interpretation of language in context).

Expected Outcome

1. Understand approaches to syntax and semantics in NLP.
2. Understand approaches to discourse, generation, dialogue and summarization within NLP.
3. Understand current methods for statistical approaches to machine translation.
4. Understand machine learning techniques used in NLP, including hidden Markov models and probabilistic context-free grammars, clustering and unsupervised methods, log-linear and discriminative models, and the EM algorithm as applied within NLP

References

1. Daniel Jurafsky, James H. Martin: "Speech and Language Processing", 2/E, Prentice Hall, 2008.
2. James Allen, "Natural Language Understanding", 2/E, Addison-Wesley, 1994
3. Christopher D. Manning, Hinrich Schutze: "Foundations of Statistical Natural Language Processing", MIT Press, 1999
4. Steven Bird, Natural Language Processing with Python, 1st Edition, O'Reilly, 2009.
5. Jacob Perkins, Python Text Processing with NLTK 2.0 Cookbook, Packt Publishing, 2010.

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Introduction : Origins and challenges of NLP – Language Modelling: Grammar-based LM, Statistical LM – Regular Expressions, Finite-State Automata – English Morphology, Transducers for lexicon and rules, Tokenization, Detecting and Correcting Spelling Errors, Minimum Edit Distance	7	15
II	Word Level Analysis : Unsmoothed N-grams, Evaluating N-grams, Smoothing, Interpolation and Backoff – Word Classes, Part-of-Speech Tagging, Rule-based, Stochastic and Transformation-based tagging, Issues in PoS tagging – Hidden Markov and Maximum Entropy models.	7	15
FIRST INTERNAL EXAM			
III	Syntax Analysis : Context-Free Grammars, Grammar rules for English, Treebanks, Normal Forms for grammar – Dependency Grammar – Syntactic Parsing, Ambiguity, Dynamic Programming parsing – Shallow parsing – Probabilistic CFG, Probabilistic CYK, Probabilistic Lexicalized CFGs – Feature structures, Unification of feature structures.	7	15
IV	Semantics and Pragmatics : Requirements for representation, First-Order Logic, Description Logics – Syntax-Driven Semantic analysis, Semantic attachments – Word Senses, Relations between Senses, Thematic Roles, selectional restrictions – Word Sense Disambiguation, WSD using Supervised, Dictionary & Thesaurus, Bootstrapping methods – Word Similarity using Thesaurus and Distributional methods.	7	15
SECOND INTERNAL EXAM			

V	Discourse Analysis and Lexical Resources - Discourse segmentation, Coherence – Reference Phenomena, Anaphora Resolution using Hobbs and Centering Algorithm – Coreference Resolution – Resources: Porter Stemmer, Lemmatizer, Penn Treebank, Brill's Tagger, WordNet, PropBank, FrameNet, Brown Corpus, British National Corpus (BNC).	7	20
VI	Applications- Machine Translation, Information Retrieval and Extraction, Text Categorization and Summarization	7	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01ME6414	Data Analytics Using R and Python	**3-0-0**	**3**	**2015**

Course Objectives

1. Learn about what it's like to be a Data Scientist.
2. Learn R and Python for Data Analytics.

Syllabus

Introduction to R; R and Rstudio; Basics of R; Advanced Data Structures; Reading Data into R; Statistical Graphics; R programming; Data Munging; String Manipulation; Basic Statistics; Linear Models; Predictive Modeling; Time Series Analysis; Clustering; Association Rules; Text Mining; Sentiment Analysis; Social Network Analysis; Reports and Slideshows; R Package Building.

Introduction to Python; Python Programming; NumPy; Pandas; Data Loading, Storage , File formats, Data Wrangling; Plotting and Visualization; Data Aggregation and Group Operations; Time Series Analysis; Financial and Economic Data Applications

Expected Outcome

After Completion of course, the students will be able to use R and Python to:

1. Manipulate and extract information from data
2. Make informative plots
3. Construct and apply statistical learning methods for predictive modelling,
4. Properly select, tune, and assess models
5. Reproduce and present results from data analysis

References

1. Jarad Lander, "R for Everyone: Advanced Analytics and Graphics" , Addison Wesley.
2. Mark Gardener, "R The Statistical Programming" , Wiley.
3. James, Witten, Hastie and Tibshirani,"An Introduction to Statistical Learning: with Applications in R", free electronic version of this book available at http://www-bcf.usc.edu/~gareth/ISL/.
4. Johannes Ledolter, "Data mining and business analytics with R", John Wiley & Sons.
5. Torgo, Luís, "Data mining with R : learning with case studies", CRC Press
6. Dirk Eddelbuettel, "Seamless R and C++ Integration with Rcpp", Springer
7. http://www.rdatamining.com/
8. Wes McKinney, "Python for Data Analysis", O'Reilly.
9. Peter Wang and Aron Ahmadia, "Fundamentals of Data Analytics in Python", Addison Wesley Live Lessons

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Introduction to R; Installation of R and R Studio; Installing and loading	1	10
	Basic building blocks in R; Advanced Data Structures in R; Reading data into R; Statistical Graphs in R	3	
	R Programming	3	
II	Data Munching-Group manipulation, Reshaping; String Manipulation	3	20
	Basic Statistics; Linear Models	4	
FIRST INTERNAL EXAM			
III	Predictive Modeling: Generalized Linear Models; Model Diagnostics; Regularization and Shrinkage	3	20
	Nonlinear Models; Time Series and Autocorrelation; Multivariate data exploration and discrimination.	3	
IV	Clustering; Association Rules; Text Mining; Sentiment Analysis; Social Network Analysis; Reports and Slideshows	4	10
	R Package Building, Introduction to Rcpp, Data structures, Using Rcpp in package, Modules, Operators, Functions, Applications	4	
SECOND INTERNAL EXAM			
V	Introduction to Python: Python Libraries, Installation and Setup; Python Programming: Data Types and Variables, Python input and output, If statements, while loops, for loops, Iterators, Lists, Functions , Modules, Object Oriented Programming, Inheritance, Exception Handling, Using Data Structures.	7	20
VI	Basic Analytics with Python; Numerical Analysis with NumPy, Advanced Analytics with SciPy and sci-kit learn Tabular Data Analysis with Pandas; Python Visualization Tools, Financial and Economic Data Applications	7	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC6218	Soft Computing	**3-0-0**	**3**	**2015**

Course Objectives

1. To familiarize various components of soft computing.
2. To give an overview of fuzzy Logic
3. To give a description on artificial neural networks with its advantages and application.

Syllabus

Basics of Fuzzy Sets, Fuzzy relations, Concepts of Artificial Neural Networks, Integration of Fuzzy and Neural Systems, Types of Neural Fuzzy Controllers, Survival of the Fittest, Predicate calculus, Semantic networks, Applications

Expected Outcome

After Completion of course, the students will be able to

1. Identify and describe soft computing techniques and their roles in building intelligent machines
2. Recognize the feasibility of applying a soft computing methodology for a particular problem
3. Apply fuzzy logic and reasoning to handle uncertainty and solve engineering problems

References

1. Chin –Teng Lin and C.S. George Lee, (1996) "Neural Fuzzy Systems" – A neuro fuzzy synergism to intelligent systems, Prentice Hall International.
2. JyhShing Roger Jang, Chuen-Tsai Sun, EijiMizutani, (1997), Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine, Prentice Hall.
3. Yanqing Zhang and Abraham Kandel (1998), Compensatory Genetic Fuzzy Neural Network and Their Applications, World Scientific.
4. T. J. Ross (1995)-Fuzzy Logic with Engineering Applications, McGraw-Hill, Inc.
5. NihJ.Nelsson, "Artificial Intelligence - A New Synthesis", Harcourt Asia Ltd., 1998.
6. D.E. Goldberg, "Genetic Algorithms: Search, Optimization and Machine Learning", Addison Wesley,N.Y, 1989

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Basics of Fuzzy Sets: Fuzzy Relations. Methodology of Fuzzy Control Systems – Basic structure and operation of fuzzy logic control systems.	8	15
II	Concepts of Artificial Neural Networks: Basic Models and Learning rules of ANN's. Single layer perceptron networks – Feedback networks – Supervised and unsupervised learning approaches – Neural Networks in Control Systems.	8	15
FIRST INTERNAL EXAM			
III	Integration of Fuzzy and Neural Systems: Neural Realization of Basic fuzzy logic operations – Neural Network based fuzzy logic inference – Neural Network based Fuzzy Modelling.	7	15
IV	Types of Neural Fuzzy Controllers. Data clustering algorithms - Rule based structure identification-Neuro-Fuzzy controls.	6	15
SECOND INTERNAL EXAM			
V	Survival of the Fittest - Fitness Computations - Cross over - Mutation -Reproduction - Rank method–Rank space method AI search algorithm	6	20
VI	Predicate calculus - Rules of interference – Semantic networks - Frames - Objects - Hybrid models-Applications.	7	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS6682	Reinforcement Learning	3-0-0	3	2020

Course Objectives

1. The aim of the course will be to familiarize the students with the basic concepts as well as with the state-of-the-art research literature in deep reinforcement learning.

Syllabus

Overview of reinforcement learning: the agent environment framework, successes of reinforcement learning - Bandit problems and online learning - Markov decision processes - Returns, and value functions - Solution methods: dynamic programming, Monte Carlo learning, Temporal difference learning learning - Eligibility traces - Value function approximation (function approximation) - Models and planning.

Expected Outcome

Students will be able

1. To structure a reinforcement learning problem
2. To understand and apply basic RL algorithms for simple sequential decision making problems in uncertain conditions
3. To evaluate the performance of the solution
4. To interpret state-of-the-art RL research and communicate their results

References

1. R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. 1998.
2. Csaba Szepesvari. Algorithms for Reinforcement learning. Morgan & Claypool Publishers.
3. Marco Wiering and Martijn van Otterlo, Eds. Reinforcement Learning: State-of-the-Art. Sprinkler.
4. Stuart J. Russell and Peter Norvig. Artificial Intelligence: A Modern Approach. Pearson.
5. Ian Goodfellow, Yoshua Bengio,and Aaron Courville. Deep Learning. MIT Press.

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	The Reinforcement Learning problem: evaluative feedback, nonassociative learning, Rewards and returns, Markov Decision Processes, Value functions, optimality and approximation	7	15
II	Bandit Problems: Explore-exploit dilemma, Binary Bandits, Learning automata, exploration schemes Dynamic programming: value iteration, policy iteration, asynchronous DP, generalized policy iteration	7	15
	FIRST INTERNAL EXAM		
III	Monte-Carlo methods: policy evaluation, roll outs, on policy and off policy learning, importance sampling Temporal Difference learning: TD prediction, Optimality of TD(0), SARSA, Q-learning, R-learning, Games and after states	7	15
IV	Eligibility traces: n-step TD prediction, TD (lambda), forward and backward views, Q(lambda), SARSA(lambda), replacing traces and accumulating traces.	7	20
	SECOND INTERNAL EXAM		
V	Function Approximation: Value prediction, gradient descent methods, linear function approximation, Control algorithms, Fitted Iterative Methods Policy Gradient methods: non-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methods	7	20
VI	Hierarchical RL: MAXQ framework, Options framework, HAM framework, Option discovery algorithms Case studies: Elevator dispatching, Samuel's checker player, TDgammon, Acrobot, Helicopter piloting, Computational Neuroscience	7	15
	END SEMESTER EXAM		

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01ME6128	Robotics	**3-0-0**	**3**	**2015**

Course Objectives

1. To introduce the basic concepts, parts of robots and types of robots.
2. To make the student familiar with the various drive systems for robot, sensors and their applications in robots and programming of robots.
3. To discuss about the various applications of robots, justification and implementation of robot

Syllabus

Introduction and classification of robots
Robot kinematics and dynamics
Robot drives and power transmission systems
Robot end effectors
Path planning & programming
Robot Language- Software- Industrial application

Expected Outcome

At the end of the course :

1. The Student must be able to design automatic manufacturing cells with robotic control using
2. The student could understand the principle behind robotic drive system, end effectors, sensor, machine vision robot kinematics and programming.

References

1. Deb S. R. and Deb S., "Robotics Technology and Flexible Automation", Tata McGraw Hill Education Pvt. Ltd, 2010.
2. John J.Craig , "Introduction to Robotics", Pearson, 2009.
3. Mikell P. Groover et. al., "Industrial Robots - Technology, Programming and Applications", McGraw Hill, New York, 2008.
4. Richard D Klafter, Thomas A Chmielewski, Michael Negin, "Robotics Engineering – An Integrated Approach", Eastern Economy Edition, Prentice Hall of India Pvt. Ltd., 2006.
5. Fu K S, Gonzalez R C, Lee C.S.G, "Robotics : Control, Sensing, Vision and Intelligence", McGraw Hill, 1987

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Specifications of Robots- Classifications of robots – Work envelope	04	15
	Flexible automation versus Robotic technology – Applications of Robots	03	
II	ROBOT KINEMATICS AND DYNAMICS :Positions, Orientations and frames, Mappings: Changing descriptions from frame to frame, Operators: Translations, Rotations and Transformations.	04	15
	Transformation Arithmetic - D-H Representation - Forward and inverse Kinematics Of Six Degree of Freedom Robot Arm – Robot Arm dynamics	02	
FIRST INTERNAL EXAM			
III	ROBOT DRIVES AND POWER TRANSMISSION SYSTEMS: Robot drive mechanisms, hydraulic – electric – servomotor- stepper motor	03	15
	Pneumatic drives, Mechanical transmission method - Gear transmission, Belt drives, cables, Roller chains, Link - Rod systems	02	
	Rotary-to-Rotary motion conversion, Rotary-to-Linear motion conversion, Rack and Pinion drives, Lead screws, Ball Bearing screws	02	
IV	ROBOT END EFFECTORS : Classification of End effectors – Tools as end effectors.	03	15
	Drive system for grippers-Mechanical adhesive-vacuum-magnetic-grippers. Hooks& scoops. Gripper force analysis and gripper design. Active and passive grippers.	03	
SECOND INTERNAL EXAM			
V	Drive system for grippers-Mechanical adhesive-vacuum-magnetic-grippers. Hooks &scoops.	04	20
	Gripper force analysis and gripper design. Active and passive grippers.	04	
VI	Robot languages -.computer control and Robot software	04	20
	Industrial Application of robots	04	
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC6904	Signal Detection and Estimation	3-0-0	3	2020

Pre-requisite: Basic concepts of Probability and Random Process and Linear algebra

Course Objectives

1. Familiarize the basic concepts of detection theory, decision theory and elementary hypothesis testing
2. Acquire knowledge about parameter estimation, and linear signal waveform estimation
3. Get a broad overview of applications of detection and estimation

Syllabus

Detection theory, Hypothesis testing, Detection with unknown signal parameters, Non-parametric detection, Parameter estimation, Cramer-Rao lower bound, Bayesian approach for estimation and applications of estimation and detection

Expected Outcome

1. Apply various Signal detection techniques in the presence of noise
2. Apply different classical and Bayesian estimation techniques for a given problem.
3. Utilize the concepts of estimation and detection in various signal processing applications

References

1. S.M. Kay, Fundamentals of Statistical Signal Processing: Detection Theory, Prentice Hall, 1998
2. S.M. Kay, Fundamentals of Statistical Signal Processing: Estimation Theory, Prentice Hall, 1993.
3. H.L. Van Trees, Detection, Estimation and Modulation Theory, Part I, Wiley, 1968.
4. H.V. Poor, An Introduction to Signal Detection and Estimation, 2nd edition, Springer, 1994.
5. L.L. Scharf, Statistical Signal Processing, Detection and Estimation Theory, Addison-Wesley:1990

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Detection Theory and Hypothesis Testing: Elementary hypothesis testing, Neyman-Pearson Theorem, Minimum probability of error, Bayes risk.	8	15
II	Matched filter, Composite hypothesis testing: Generalized likelihood ratio test. Detection of Signals with unknown Amplitude.	7	15
FIRST INTERNAL EXAM			
III	Parameter Estimation: Minimum Variance Unbiased Estimator, Cramer Rao lower bound, Fisher information matrix, Linear Models, Best Linear Unbiased Estimator.	7	15
IV	Maximum Likelihood Estimation, Invariance principle, Least Square Estimation, Minimum mean square estimation, Maximum A Posteriori Estimators	7	15
SECOND INTERNAL EXAM			
V	Linear Signal Waveform Estimation: Basic concepts of Wiener Filter and Kalman Filter.	7	20
VI	Applications of detection and estimation: Applications in pattern recognition, speech processing, and image processing.	6	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS6692	Mini Project	**0-0-4**	**2**	**2020**

Course Objectives

To make students

Design and develop a system or application in the area of their specialization.

Approach

The student shall present two seminars and submit a report. The first seminar shall highlight the topic, objectives, methodology, design and expected results. The second seminar is the presentation of the work / hardware implementation.

Expected Outcome

Upon successful completion of the mini project, the student should be able to

1. Identify and solve various problems associated with designing and implementing a intelligent system or application.
2. Test the designed system or application.

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC6994	Deep Learning Lab	**0-0-2**	**1**	**2020**

Course Objectives

1. Implement the various deep learning algorithms in Python.
2. Learn to work with different deep learning frameworks like Keras, Tensor flow, PyTorch, Caffe etc.

List of Exercises / Experiments

1. **Basic image processing operations :** Histogram equalization, thresholding, edge detection, data augmentation, morphological operations
2. **Implement SVM/Softmax classifier for CIFAR-10 dataset:** (i) using KNN, (ii) using 3 layer neural network
3. **Study the effect of batch normalization and dropout in neural network classifier**
4. **Familiarization of image labelling tools for object detection, segmentation**
5. **Image segmentation using Mask RCNN, UNet, SegNet**
6. **Object detection with single-stage and two-stage detectors (Yolo, SSD, FRCNN, etc.)**
7. **Image Captioning with Vanilla RNNs**
8. **Image Captioning with LSTMs**
9. **Network Visualization: Saliency maps, Class Visualization**
10. **Generative Adversarial Networks**
11. **Chatbot using bi-directional LSTMs**
12. **Familiarization of cloud based computing like Google colab**

Expected Outcome

1. Expert knowledge in solving real world problems using state-of-art deep learning techniques

References

1. Francois Chollet, "Deep learning with Python" – Manning Publications.

SEMESTER – III

Syllabus and Course Plan

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC7933	Convex Optimization	**3-0-0**	**3**	**2018**

Course Objectives :

The purpose of this course is:-

1. To introduce concepts of convex optimization.
2. To understand more about advanced numerical optimization techniques in engineering.
3. To understand and analyze various applications of optimization in inverse problems, signal processing, image reconstruction, communications, statistics, and machine learning.

Syllabus

Basic convex analysis and optimization. Line Search methods, Trust region methods, Gradient based methods, Non-linear least square problems, Linear Programming, Quadratic Programming, Penality, Barrier and Augmented Lagrangian methods.

Expected Outcome

By the end of the course, the students will be able to :

1. Understand the ideas of convex optimization in engineering.
2. Understand the process flow of important optimization algorithms.
3. Analyze and formulate an engineering problem in an optimization perspective, and use suitable optimization algorithms to solve them.

References

1. Stephen Boyd, Lieven Vandenberghe, "Convex Optimization", Cambridge University Press.
2. Edwin K P Chong, Stanislaw H Zak, "An Introduction to Optimization", Wiley-Second edition.
3. David G Luenberger and Yinyu Ye, "Linear and nonlinear programming", Springer
4. Jorge Nocedal, Stephen J Wright, "Numerical optimization", Springer

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Introduction to the theory of convex sets – affine and convex sets, operations preserving convexities etc. Convex functions – basic properties, operations preserving convexities, conjugate functions etc.	8	15
II	Line search methods – step length, convergence step length selection. Trust region methods – Cauchy's point and related algorithms.	7	15
FIRST INTERNAL EXAM			
III	Conjugate gradient methods – Linear CG, conjugate directions, Non-linear CG, Fletcher-Reeves, Polak-Ribiere methods. Quasi-Newton methods – BFGS, SR1, Broyden Class of methods.	6	15
IV	Non-linear least square problems – modeling, algorithms, Gauss-Newton, Levenberg-Marquardt methods, large residue problems.	7	15
SECOND INTERNAL EXAM			
V	Linear Programming – Optimality and duality, feasible set, Simplex method, Interior point methods	7	20
VI	Quadratic Programming – Equality constrained QP, Solving KKT system, Inequality constrained problems, Active set method for convex QP.	7	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS7651	Statistical Machine Learning	3-0-0	3	2020

Course Objectives

1. To impart fundamental principles of machine learning from a statistical standpoint.

Syllabus

Linear and logistic regression, classification, clustering, resampling methods, model selection and regularization, and non-linear regression.

Expected Outcome

By the end of the course, the students will be able to :

1. Formulate appropriate models for empirical data
2. Estimate the parameters of a statistical model
3. Interpret the fit of a model to data
4. Justify the choice of a model/technique to analyze empirical data
5. Implement statistical learning algorithms
6. Explain the mathematical/statistical mechanisms of most common machine learning algorithms

References

1. T. Hastie, R. Tibshirani, J Friedman, Elements of Statistical Learning, Springer, 2009.
2. K. Murphy, Machine Learning: a Probabilistic Perspective, MIT Press, 2012.
3. C. Bishop, Pattern Recognition and Machine Learning, Springer, 2007.

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Introduction - Introduction to Statistical Learning, Variance and bias trade-off, Model evaluation. Linear Regression - Linear regression review, Model assessment, Some practical issues.	8	15
II	Introduction: supervised and unsupervised learning, loss functions, train and test errors, bias-variance tradeoff, model complexity and overfitting, linear regression, k-nearest neighbors. Statistical Inference: Maximum Likelihood Estimators, Bayes Estimator, Method of Moments	7	15
FIRST INTERNAL EXAM			
III	Regression: linear regression, model selection, ridge and Lasso. Basis function models : Basis expansions, smoothing splines, additive models, backfitting, sparse additive models	7	15
IV	Classification: Gaussian discriminant analysis, linear discriminant analysis, logistic regression. Resampling methods: cross-validation, bootstrap.	7	20
SECOND INTERNAL EXAM			
V	Support vector machines and kernels : perceptron algorithm, Max margin classification, separating hyper-planes, the kernel trick, nonlinear decision boundaries, Tree-based methods: classification and regression trees, bagging, random forests.	7	20
VI	Boosting: AdaBoost, gradient boosting machines. Unsupervised learning: principal component analysis, k-means, Gaussian mixtures and the EM algorithm.	7	15
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01ME7415	Heuristic Solution Methods	3-0-0	3	2015

Course Objectives

The main objectives of this course are:-

1. To introduce the students to various meta heuristic solution algorithms.
2. To demonstrate the applications of these algorithms for solving large real life problems

Syllabus

Introduction to Non-traditional optimization; Computational Complexity; Classification of heuristic solution techniques; Meta heuristics; Introduction to evolutionary computation; Genetic Algorithms: Concepts, Algorithm, Binary GA, Continuous GA, Hybrid GA, Parallel GA. Scatter Search-Components, Algorithm, Applications. Multi objective evolutionary optimization; Greedy Randomized Adaptive Search Procedure, Ant Colony Algorithms: Overview, Basic algorithm, Variants; Particle Swarm Optimization; Lagrangean Relaxation; Local Search Algorithms; Tabu Search; Simulated Annealing, Components, Variants of Simulated Annealing; Artificial Neural Networks- Biological and Artificial Neural Networks, Basic Concepts, Generic Algorithm, Constraint Programming- Problem Formulation in Constraint Programming, Basic Search and Constraint Propagation, Constraint Programming vs Mathematical Programming; Applications of the above mentioned heuristic methods to solve different types of optimization problems.

Expected Outcome

After Completion of course,

1. The students will have the knowledge of various meta heuristic solution algorithms and their applications.
2. The students will have the skill to model real life problems and will be able to apply proper heuristic techniques to solve them.

References

1. GüntherZäpfel , Roland Braune, Michael Bögl, "Metaheuristic Search Concepts-A Tutorial with Applications to Production and Logistics", Springer.
2. Michalewicz Z, "Genetic Algorithms + Data Structures = Evolution Programms", Springer-Verlag,Berlin.
3. J.Dreo,A.Petrowski, EricTaillard , "Metaheuristics for Hard Optimization:Methods and case studies", Springer.
4. Colin R. Reeves, "Modern Heuristic Techniques for Combinatorial Problems", John Wiley and Sons.

COURSE PLAN			
Module	**Contents**	**Hours allotted**	**% of Marks in End-Semester Examination**
I	Introduction to Non-traditional optimization, Computational, Complexity; Heuristics – classification: Construction Heuristics, Local Search, Multi-Start Procedures; Assessing the Quality of Heuristics. Metaheuristics- Definition, Classification.Introduction to evolutionary computation	6	10
II	Genetic Algorithm - Genetic Algorithms: Basic concepts, Encoding, Selection, Crossover, Mutation-Binary GA, Continuous GA, Hybrid GA, Parallel GA application of GA in solving Constrained and Combinatorial Optimization problems, Reliability problem, Sequencing problem, Scheduling problem, Transportation problem etc. Scatter Search-Components, Algorithm, Applications Multi objective evolutionary optimization: Pareto optimality, Multi- objective evolutionary algorithms.	8	20
FIRST INTERNAL EXAM			
III	Greedy Randomized Adaptive Search Procedure Ant Colony Algorithms: Overview, Basic algorithm, Variants, Formalization and properties of ant colony optimization, Applications in Scheduling, VRP etc Particle Swarm Optimization – Basic Concepts: Social Concepts, Swarm Intelligence Principles, Computational Characteristics; PSO in Real Number Space: Velocity Updating, Topology of the Particle Swarm, Parameter Selection; Discrete PSO; PSO Variants; PSO Applications in TSP, Knapsack Problems, Quadratic Assignment Problem etc.	**8**	20

IV	Lagrangean Relaxation: Basic Methodology, Lagrangean heuristic and problem reduction , Lagrangean multipliers, Dual Ascent algorithm, Tree search. Applications of Lagrangean Relaxation in solving facility location problems, Logistics, Inventory Problems etc.	9	10
SECOND INTERNAL EXAM			
V	Local Search Algorithms, Tabu Search –Tabu Search Principles, Neighborhood, Candidate list, Short term and Long term memory, Threshold Accepting, Application of TS in Planning and Scheduling, Telecommunications, Portfolio management , Facility layout, Transportation, Routing and Network Design. Simulated Annealing -Main Components of Simulated Annealing, Homogenous vs. Inhomogenous Simulated Annealing, Annealing Schedules, Applications in sequencing and scheduling, Travelling salesman problem etc. Variants of Simulated Annealing.	8	20
VI	Artificial Neural Networks- Biological and Artificial Neural Networks, Basic Concepts, Generic Algorithm, Application Areas, Application of ANN to solve TSP, Knapsack Problems etc. Constraint Programming- Problem Formulation in Constraint Programming, Basic Search and Constraint Propagation, Constraint Programming vs Mathematical Programming, Application of Constraint Programming in Bin Packing, Scheduling, Sequencing, Facility Location problems etc.	6	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS7655	Data Structures and Algorithms	3-0-0	3	2020

Course objectives

1. To understand about advanced data structures.
2. To understand how to analyze and establish correctness of algorithms
3. To understand the theory behind various classes of algorithms.

Syllabus

Amortized Analysis – aggregate, accounting and potential methods. Advanced data structures: binomial heap, fibonacci heap, disjoint sets – applications. Number Theoretic algorithms- maxflow mincut theorem. String matching. Probabilistic algorithms -Numerical algorithms Las Vegas algorithms. Geometric Algorithms.

Expected Outcome

Upon successful completion of this course, the student will:

1. have deep conceptual understanding of advanced data structures and their applications
2. know the theory behind various classes of algorithms.
3. be able to design, prove the correctness and analyze new algorithms

References

1. T. H. Cormen, C. E. Leiserson, R. L. Rivest and C. Stein, “Introduction toalgorithms”, Prentice-hall of India Private Limited, New Delhi, 2010.

2. Gilles Brassard and Paul Bratley, “Fundamentals of algorithms”, Prentice-hall of India Private Limited, New Delhi,2001.
3. Rajeev Motwani, Prabhakar Raghavan, “Randomized Algorithms”, Cambridge University Press, 2000.

4. Ellis Horowitz, SartajSahni and Dinesh Mehta, “Fundamentals Of Data Structures In C++”, Galgotia Publications,2006.

5. Dexter C. Kozen, “The Design and Analysis of Algorithms”, Springer.
6. Jon Kleinberg and Eva Tardos, “Algorithm Design”, Pearson Education,2006.
7. M. H. Alsuwaiyal, “Algorithms Design Techniques and Analysis”, WorldScientific Publishing Co. Beijing, 1999.

8. S. K. Basu, “Design Methods and Analysis of Algorithms”, Prentice Hall India,2005.

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Amortized Analysis – aggregate, accounting and potential methods	3	15
	Advanced data structures: binomial heap, Fibonacci heap, disjoint sets - applications.	6	
II	Number-Theoretic algorithms: GCD algorithm, Extended Euclid's algorithm	3	15
	Primality testing, Miller-Rabin test	3	
	Integer factorization - Pollard Rho heuristic.	2	
FIRST INTERNAL EXAM			
III	Network flow algorithms: flow properties, augmenting path	2	15
	Ford-Fulkerson method, Edmonds-Karp heuristics	3	
	Maxflow-mincut theorem	3	
IV	String matching: Rabin-Karp, Knuth-Morris-Pratt algorithms.	6	15
SECOND INTERNAL EXAM			
V	Monte-Carlo algorithms - verifying matrix multiplication, min-cut in a network.	3	20
	Las Vegas algorithms, selection sort, quick sort,	3	
VI	Geometric Algorithms: Plane sweep technique, role of sweep- line status and event-point schedule, line segment intersection problem.	4	20
	Convex Hull: Graham's scan algorithm, Jarvis March algorithm.	3	
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01EC7315	Computer Vision	**3-0-0**	**3**	**2020**

Course Objectives

1. Introduce the standard computer vision problems and identify the solution methodologies.

Syllabus

Image Formation, Depth estimation and multiview cameras, Shape from X, feature extraction, Segmentation, Pattern analysis, Motion Analysis, Object Detection and Recognition.

Expected Outcome

By the end of the course, the students will be able to :

1. Understand and implement the algorithms for 3D reconstruction from various cues.
2. Understand and implement the various segmentation, pattern analysis, objection detection/recognition methods.

References

1. Computer Vision: Algorithms and Applications, Richard Szeliski, Springer 2010
2. Computer vision: A modern approach, by Forsyth and Ponce. Prentice Hall, 2002.
3. Computer & Machine Vision: Theory Algorithms Practicalities, E. R. Davies, ELSEIVER, Academic Press, 2012
4. Multiple View Geometry in Computer Vision, Richard Hartley and Andrew Zisserman, Second Edition, Cambridge University Press, March 2004

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Fundamentals of Image Formation, Transformation: Orthogonal, Euclidean, Affine, Projective, etc. Perspective Projection, Homogeneous Coordinates, Vanishing points, Orthographic projection, Parallel Projection. Photometric image formation, The digital camera.	7	15
II	Depth estimation and Multiview cameras: Binocular Stereopsis: Camera and Epipolar Geometry; Homography, Rectification, RANSAC, 3-D reconstruction framework; Auto-calibration. Shape from X: Light at Surfaces; Phong Model; Reflectance Map; Albedo estimation; Photometric Stereo; Use of Surface Smoothness Constraint; Shape from Texture, color, motion and edges.	8	15
FIRST INTERNAL EXAM			
III	Feature Extraction: Edges - Canny, LOG, DOG; Line detectors (Hough Transform), Corners - Harris and Hessian Affine, Orientation Histogram, SIFT, SURF, HOG, Scale-Space Analysis- Image Pyramids and Gaussian derivative filters, Gabor Filters and DWT.	7	15
IV	Image Segmentation and Pattern Analysis : Image Region Growing, Edge Based approaches to segmentation, Graph-Cut, Mean-Shift, MRFs, Clustering: K-Means, Mixture of Gaussians, Dimensionality Reduction: PCA, LDA, ICA; Non-parametric methods.	7	15
SECOND INTERNAL EXAM			
V	Motion Analysis: Background Subtraction and Modeling, Optical Flow, KLT, Spatio-Temporal Analysis, Dynamic Stereo; Motion parameter estimation.	6	20
VI	Object Detection and Recognition: Face detection, Pedestrian detection, Face recognition, Eigen faces, Active appearance and 3D shape models, Instance recognition, Category recognition, Context and scene understanding.	7	20
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS7177	Advanced Software Project Management	**3-0-0**	**3**	**2015**

Course Objectives

1. To impart comprehensive knowledge of software project management
2. To familiarize with the planning and implementing of complex software projects.

Syllabus

Planning a software project; Project evaluation; Selection of Process model; Software effort estimation; Activity planning; Risk analysis and risk management; Resource allocation; Project tracking and control; Contract management; People management; Software quality assurance; Configuration management.

Expected Outcome

By the end of the course, the students will have :

1. Ability to explain and exemplify to the different stages of planning a software project and managing it.
2. Capability to plan a large software project, and to effectively monitor and control it.

References

1. Bob Hughes and Mike Cotterell, "Software Project Management", 5/e, 2011,McGraw Hill
2. PankajJalote, "Software Project Management in Practice", 2002, Pearson Education Asia.
3. Roger S. Pressman, "Software Engineering: A practitioner's Approach", 7/e, 2010,
    a. McGraw Hill
4. Robert T. Futrell, Donald F. Shafer, and Linda I. Shafer, "Quality Software Project Management", 2002, Pearson Education Asia.
5. Ramesh Gopalaswamy, "Managing Global Software Projects", 2003, Tata McGraw Hill.

COURSE PLAN			
Module	**Contents**	**Hours Allotted**	**% of Marks in End-Semester Examination**
I	Introduction to Software Project Management: Stakeholders; Software product, process, resources, quality, and cost; Objectives, issues, and Problems relating to software projects.	03	15
	Project Planning: Defining scope and objectives; Work Breakdown structure; Time, cost, and resource estimation. Case studies.	03	
II	Project Evaluation: Strategic assessment; Technical assessment; Cost benefit analysis; Risk evaluation. Choice of process model: Rapid application development; Waterfall model; V-process model; Spiral model; Prototyping; Incremental delivery, Agile methods. Case studies.	05	15
FIRST INTERNAL EXAM			
III	Software Effort Estimation: Effort estimation techniques; Algorithmic methods; Function point analysis; COCOMO model. Case studies.	04	15
	Activity Planning: Network planning model; Critical path; Slack and float.	03	
IV	Risk Analysis and Management: Risk Identification; Risk assessment; Risk mitigation, monitoring, and management.	04	15
	Resource Allocation: project resources; Allocating and scheduling resources; cost of resources; Cost variance; time-cost tradeoff. Case studies.	04	
SECOND INTERNAL EXAM			
V	Project Tracking and Control: Measurement of physical and financial progress; Status reports; Change control.	04	20
	Contract Management: Outsourcing; Types of contracts; Stages and Terms of contract; Contract monitoring; Managing People and Organizing Teams: Recruitment; Motivation; Group behaviour; Leadership Mini and leadership styles; forms of organizational structures.	06	

VI	Software Quality Assurance: Planning for quality; Product versus process quality; Defect analysis and prevention; Statistical process control; Pareto analysis; Causal analysis; Quality standards and Models; Quality audit.	04	20
	Configuration Management: CM Process; Change control; Configuration audit; Status reporting.	02	
END SEMESTER EXAM			

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01ME7991	Seminar II	**0-0-2**	**2**	**2020**

Course Objectives

To make students

1. Identify the current topics in the specific stream.
2. Collect the recent publications related to the identified topics.
3. Do a detailed study of a selected topic based on current journals, published papers and books.
4. Present a seminar on the selected topic on which a detailed study has been done.
5. Improve the writing and presentation skills.

Approach

Students shall make a presentation for 20-25 minutes based on the detailed study of the topic and submit a report based on the study.

Expected Outcome

Upon successful completion of the seminar, the student should be able to

1. Get good exposure in the current topics in the specific stream.
2. Improve the writing and presentation skills.
3. Explore domains of interest so as to pursue the course project.

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS7693	Project (Phase 1)	**0-0-12**	**6**	**2020**

Course Objectives

To make students

1. Do an original and independent study on the area of specialization.
2. Explore in depth a subject of his/her own choice.
3. Start the preliminary background studies towards the project by conducting literature survey in the relevant field.
4. Broadly identify the area of the project work, familiarize with the tools required for the design and analysis of the project.
5. Plan the experimental platform, if any, required for project work.

Approach

The student has to present two seminars and submit an interim Project report. The first seminar would highlight the topic, objectives, methodology and expected results. The first seminar shall be conducted in the first half of this semester. The second seminar is the presentation of the interim project report of the work completed and scope of the work which has to be accomplished in the fourth semester.

Expected Outcome

Upon successful completion of the project phase 1, the student should be able to

1. Identify the topic, objectives and methodology to carry out the project.
2. Finalize the project plan for their course project.

SEMESTER – IV

Syllabus and Course Plan

Course No.	Course Name	L-T-P	Credits	Year of Introduction
01CS7694	Project (Phase II)	**0-0-23**	**12**	**2020**

Course Objectives

1. To continue and complete the project work identified in project phase 1.

Approach

There shall be two seminars (a midterm evaluation on the progress of the work and pre submission seminar to assess the quality and quantum of the work). At least one technical paper has to be prepared for possible publication in journals / conferences based on their project work.

Expected Outcome

Upon successful completion of the project phase II, the student should be able to

1. Get a good exposure to a domain of interest.
2. Get a good domain and experience to pursue future research activities.