M. Tech.

IN

SIGNAL PROCESSING

CURRICULUM AND SYLLABI

(Applicable from 2023 admission onwards)

Department of Electronics and Communication Engineering

NATIONAL INSTITUTE OF TECHNOLOGY CALICUT

Kozhikode - 673601, KERALA, INDIA

The Programme Educational Objectives (PEOs) of M. Tech. in Signal Processing

PEO1	Graduates apply their strong theoretical foundation and research skills to identify, analyze and solve engineering problems pertaining to design, development and deployment of signal processing systems.
PEO2	Graduates demonstrate a high degree of creativity, critical thinking and communication skills for productive and successful careers in industries, R&D organizations and other allied professions.
PEO3	Graduates exhibit their competency to engage in lifelong learning in signal processing and its allied application areas.
PEO4	Graduates possess professionalism, ethical attitude, communication skills, synergistic and leadership qualities and ability to relate engineering solutions to broader social context.

Programme Outcomes (POs) & Programme Specific Outcomes (PSOs) of M. Tech. in Signal Processing

PO1	An ability to independently carry out research /investigation and development work to solve practical problems.
PO2	An ability to write and present a substantial technical report/document.
PO3	Students should be able to demonstrate a degree of mastery over the area as per the specialization of the programme. The mastery should be at a level higher than the requirements in the appropriate bachelor programme.
PSO 1	Possess strong mathematical skills and in-depth knowledge in signal theory required to analyze and solve complex problems in the domain of signal processing using modern technology and tools that results in optimal solutions and novel products that are technically sound, economically feasible and socially acceptable.
PSO 2	Ability to engage in lifelong learning, so as to face the challenges of the rapidly changing environment, by mastering latest technologies and products and adapting skills through reflective and continuous learning

CURRICULUM

The minimum number of credits to be earned by a student for the award of the degree is 75. The total credits must not exceed 77

COURSE CATEGORIES AND CREDIT REQUIREMENTS:

The structure of M. Tech. programme shall have the following Course Categories:

Sl. No.	Course Category	Minimum Credits
1.	Programme Core (PC)	20
2.	Programme Electives (PE)	18
3.	Institute Elective (IE)	2
4.	Projects	35

The effort to be put in by the student is indicated in the tables below as follows:
L: Lecture (One unit is of 50-minute duration)
T: Tutorial (One unit is of 50-minute duration)
P: Practical (One unit is of one-hour duration)
O: Outside the class effort / self-study (One unit is of one-hour duration)

PROGRAMME STRUCTURE

Semester I

Sl. No.	Course Code	Course Title	L	T	P	O	Credits	Category
1.	EC6401E	Linear Algebra and Analysis	3	1	0	8	4	PC
2.	EC6402E	Advanced Digital Signal Processing	3	0	2	7	4	PC
3.	EC6403E	Probability Theory and Applications	3	0	2	7	4	PC
4.	EC6404E	Machine Learning and Pattern Recognition	3	0	2	7	4	PC
5.		Elective 1					3	PE
6.		Institute Elective					2	
		Total					**21**	**--**

Semester II

Sl. No.	Course Code	Course Title	L	T	P	O	Credits	Category
1.	EC6405E	Statistical Signal Processing	3	0	2	7	4	PC
2.		Elective 2					3	PE
3.		Elective 3					3	PE
4.		Elective 4					3	PE
5.		Elective 5					3	PE
6.		Elective 6					3	PE
7.	EC6496E	Project Phase I	0	0	0	6	2	
		Total					**21**	**--**

Semester III

Sl. No.	Course Code	Course Title	L	T	P	O	Credits	Category
1.	EC7497E	Project Phase II	0	0	0	9	3	PC
2.	EC7498E	Project Phase III	0	0	0	45	15	PC
		Total					**18**	**--**

Semester IV

Sl. No.	Course Code	Course Title	L	T	P	O	Credits	Category
1.	EC7499E	Project Phase IV	0	0	0	45	15	PC
		Total					**15**	**--**

List of Electives

Institute Elective Basket (Students need to credit Minimum 2 credits from this basket):

Sl. No.	Course Code	Course Title	L	T	P	O	Credits
1	IE 6001E	Entrepreneurship Development	2	0	0	4	2
2	ZZ6001E	Research Methodology	2	0	0	4	2
3	MS6174E	Technical Communication and Writing	2	1	0	3	2

Elective Basket 1 (Students need to credit minimum 6 credits from this basket):

Sl. No.	Course Code	Course Title	L	T	P	O	Credits
1	EC6421E	Array Signal Processing	3	0	0	6	3
2	EC6422E	Compressive Sensing: Theory and Algorithms	3	0	0	6	3
3	EC6423E	Digital Image Processing Techniques	3	0	0	6	3
4	EC6424E	Linear and Non-linear Optimization	3	0	0	6	3
5	EC6425E	Multirate Signal Processing	3	0	0	6	3
6	EC6426E	Quantum Signal Processing	3	0	0	6	3
7	EC6427E	Speech Signal Processing	3	0	0	6	3
8	EC6428E	Wavelets: Theory and Construction	3	0	0	6	3
9	EC6429E	Signal Compression	3	0	0	6	3

Elective Basket 2 (Students need to credit minimum 6 credits from this basket):

Sl. No.	Course Code	Course Title	L	T	P	O	Credits
1	EC6441E	Advanced Matrix Theory for Machine Learning	3	0	0	6	3
2	EC6442E	Artificial Intelligence	3	0	0	6	3
3	EC6443E	Autonomous Intelligent System	2	0	2	5	3
4	EC6444E	Bayesian Data Analytics	3	0	0	6	3
5	EC6445E	Computer Vision	3	0	0	6	3
6	EC6446E	Deep Learning	3	0	0	6	3
7	EC6447E	Deep Learning in Computer Vision	3	0	0	6	3
8	EC6448E	Foundations of Data Analytics	2	0	2	5	3
9	EC6449E	Optimization for Machine Learning	3	0	0	6	3
10	EC6450E	Probabilistic Machine Learning	3	0	0	6	3
11	EC6451E	Reinforcement Learning	3	0	0	6	3

Students can take a maximum of two elective courses, each having minimum 3 credits, can be credited from courses offered in any M. Tech. specialization by the Institute, with the consent of the Programme Coordinator and the Course Faculty.

Syllabus for M. Tech in Signal Processing

EC6401E: LINEAR ALGEBRA AND ANALYSIS

Pre-requisites: NIL

L	T	P	O	C
3	1	0	8	4

Total Sessions: 39L +13T

Course Outcomes:

CO1: Understand basic algebraic structures
CO2: Demonstrate the principles of vector spaces and linear mappings in practical contexts.
CO3: Understand and apply the principles of inner product spaces and normed linear spaces.
CO4: Demonstrate the relevance of topology in normed linear spaces
CO5: Develop ability to think clearly and express precisely, coupled with systematic logical reasoning.

Basic Algebraic Structures and vector spaces
Definitions and properties of Semi-groups, Groups, Rings, Fields, and Vector Spaces, Homomorphisms**.** Linear Spaces: Linear Independence, Bases, and Dimension–Subspaces, Direct Sums – Linear Transformations, Linear Functionals, Bilinear Functionals, and Projections.

Finite-Dimensional Vector Spaces
Coordinate representation of vectors, change of basis and change of coordinates – Linear operators, Null space and Range space – Rank-Nullity theorem, Operator inverses, Application to matrix theory, range space and null space of a matrix - Matrix of an operator, Operator algebra, change of basis and similar matrices.

Inner Product Spaces
Definition of inner product, norms, angle between vectors – Orthogonal sets, Fourier coefficients and Parseval's identity, Gram-Schmidt process, QR factorization – Approximation and orthogonal projection, Computations using orthogonal and non-orthogonal sets, Normal equations – Projection operator, Orthogonal complements, Decomposition of vector spaces, Gram matrix and orthogonal change of basis, Rank of Gram matrix

Diagonalizable linear operators
Eigenvalues and eigenvectors, Spectrum and eigenspace of an operator, Properties of the characteristic polynomial, Geometric and algebraic multiplicities – Linear operators with an eigenbasis, Diagonalizability and Similarity Transformation – Cayley-Hamilton Theorem, Nilpotent Transformations.

Quadratic Forms and Factorizations
Definition and Properties of quadratic forms – Hermitian forms, Orthogonal Diagonalization and the Principal axis theorem, Direct-sum decompositions, invariant direct sums – Singular value Decompositions.

Mathematical Analysis and Normed Linear Spaces
Sets, sets of real numbers, countable and uncountable sets, Metric and metric spaces, Neighborhoods, open and closed sets, Dense and nowhere dense sets, compact, perfect and connected sets – Measure and sets of measure zero – Sequences and Series, Continuity and convergence – Norms, Completeness, Continuous linear transformations, Inverses and Continuous inverses, Complete Normed Linear Spaces – Norm induced by the Inner product, Hilbert spaces.

References:

1. G. Strang, *Introduction to Linear Algebra*, 4th Edn., Wellesley-Cambridge Press, MA, 2009.
2. K. Hoffman, R. Kunze, *Linear Algebra*, 2nd Edn., PHI Learning, Delhi, 2014.
3. S. Axler, *Linear Algebra Done Right*, 3rd Edn., Springer International Publishing, 2015.
4. A. N. Michel, C. J. Herget, *Applied Algebra and Functional Analysis*, Dover Publications, 1993.
5. W. Rudin, *Principles of Mathematical Analysis*, 3rd Edn., Tata McGraw-Hill Education, 2013.

EC6402E: ADVANCED DIGITAL SIGNAL PROCESSING

Pre-requisites: NIL

L	T	P	O	C
3	0	2	7	4

Total Sessions: 39L+26P

Course Outcomes:

CO1: Analyze the effect of sampling and quantisation of signals and appraise its relevance with reference to applications.
CO2: Formulate various transform domain representations of 1D and 2D signals and demonstrate their applications with reference to practical signals.
CO3: Examine finite word length effects and design practical filters for real life applications.
CO4: Demonstrate the effect of sampling rate converters and design distortion free digital filter banks illustrating their applications to process real life signals.
CO5: Analyze and choose architectures to efficiently implement the DSP systems for various applications taking into consideration the practical aspects.
CO6: Develop DSP applications using professional tools

Lecture Sessions:

Analysis of Discrete Time Signals

Basic elements of a DSP System – Review of Sampling and Quantisation – Sampling theorem for low pass and band pass signals, uniform and non uniform quantization, Application of quantisation in lossy compression of signals – Lloyd Max quantizer; Fourier analysis of Continuous and Discrete time signals –Review of Fourier series and Fourier transform, Discrete Time Fourier Transform (DTFT), Discrete Fourier Transform (DFT), Interpretation of DFT Spectrum, Review of DFT properties – Convolution and correlation, Convolution of long sequences, Leakage effect, Windowing – Introduction to other transforms : Discrete Cosine Transform (DCT), Walsh Hadamard Transform (WHT), Karhunen Loeve Transform (KLT) – Applications.

Digital Filters and Implementation

Review of FIR and IIR filter design – Notch filter– Comb filter– All pass filters– Applications– Structures for digital filter realization: Signal flow graph and block diagram representations, FIR and IIR Filter structures, Lattice structures – Finite word length effects – Fixed-point and floating-point DSP arithmetic, Effects of quantization, Scaling, Limit cycles in fixed point realizations of IIR digital filters, Limit cycles due to overflow. Quantization effect in DFT and FFT computation.

Multirate Signals and Systems

Introduction to multirate signal processing with applications, Multirate System Fundamentals – Decimation and Interpolation, Transform domain analysis of Decimators and Interpolators, Decimation and Interpolation filters, Fractional sampling rate alteration, Practical sampling rate converter design, Polyphase decomposition and efficient structures – Introduction to digital filter banks – The DFT filter bank, Two Channel Quadrature Mirror Filter bank (QMF), Perfect Reconstruction.

Introduction to 2-D Signals and Systems

Elementary 2D signals – Linear shift Invariant systems – Separability – 2D convolution – Introduction to 2D transforms :2D DFT, 2D DCT, Applications

Practical Sessions:

Suggested List of Experiments:

1. Analysis and interpretation of DFT Spectrum using simple and practical signals.
2. Convolution of two sequences – Convolution applied to audio/voice signals
3. IIR filter design and applications– Suppression of power supply hums in audio signals, artificial reverberations, Generation and detection of DTMF tones.
4. FIR filter design and applications – Filtering effects on voice signals, Filtering of Sinusoidal Noise interferences.
5. Implement filter structures and study the effects of quantization and overflow errors
6. Study the effect of decimation and interpolation operations using standard signals
7. Design and implement a 2-channel uniform DFT filter bank using linear phase FIR filters
8. Study the effect of sampling rate and quantization on the sound quality of audio signals.
9. Application of 2D convolution and 2D transforms
10. Study the effect of different noise models: Gaussian, Impulse (salt and pepper) and Poisson noise on images. Also study the effect of Mean, Median and Mode filters on signal-to-noise ratio of the noisy images.
11. Course Project

References:

1. John G. Proakis, Dimitris G. Manolakis, *Digital Signal Processing: Principles, Algorithms and Applications,* 4^{th} Edn., Pearson India, 2007.
2. P.P. Vaidyanathan, *Multirate systems and filter banks,* 2^{nd} Edn., Pearson Education India, 1992.
3. Lim J. S., *Two-dimensional signal and image processing,* Prentice Hall, 1990.
4. K Deergha Rao, M N S Swamy, *Digital Signal Processing: Theory and Practice,* Springer, 2018.
5. Steven W. Smith, *The Scientist and Engineer's Guide to Digital Signal Processing,* California,1999.
6. Mitra S. K., *Digital Signal Processing: A Computer Based Approach*, McGraw-Hill Publishing Company, 2013.

EC6403E: PROBABILITY THEORY AND APPLICATIONS

Pre-requisites: NIL

L	T	P	O	C
3	0	2	7	4

Total Sessions: 39L+26P

Course Outcomes:

CO1: Define random variables and random vectors corresponding to random experiments and to derive their conditional and unconditional probability distribution functions.
CO2: Demonstrate the use of the fundamental laws of large numbers and central limit theorem to signal processing and machine learning applications.
CO3: Demonstrate the use of random processes to stochastic modelling of real-life problems in signal processing.
CO4: Analyze linear systems involving random processes.
CO5: Apply information measures to analyze random variables and sources.

Lecture Sessions:

Random Variables and Random Vectors

Probability axioms, conditional probability, discrete and continuous random variables, cumulative distribution function (CDF), probability mass function (PMF), probability density function (PDF), conditional PMF/PDF, expected value, variance, functions of a random variable, expected value of the derived random variable, multiple random variables, joint CDF/PMF/PDF, functions of multiple random variables, multiple functions of multiple random variables, independent/uncorrelated random variables, sums of random variables, moment generating function, random sums of random variables.

Random Process

Sample mean, laws of large numbers, central limit theorem, convergence of sequence of random variables – Introduction to random processes, specification of random processes, nth order joint PDFs, independent increments, stationary increments, Markov property, Discrete-time Markov chains.

Second-order Theory

Mean and correlation of random processes, stationary, wide sense stationary and ergodic processes. Random processes as inputs to linear time invariant systems, power spectral density, Gaussian processes as inputs to LTI systems, white Gaussian noise

Fundamentals of Information Theory

Entropy: Memory less sources, Markov sources, Entropy of a discrete Random variable, Joint, conditional and relative entropy, Mutual Information and conditional mutual information – Source coding for discrete memory less source – Shannon source coding theorem.

Practical Sessions:

Suggested List of Experiments:

1. Generation of continuous and discrete random variables.
2. Empirical computation of distribution of conditional random variables.
3. Generation of vector random variables.
4. Application of law of large numbers to Monte Carlo integration.
5. Simulation of Discrete time Markov chain.
6. Estimation of power spectral density using white noise.
7. AEP and Shannon source coding theorem

References:

1. Papoulis and S. U. Pillai, *Probability, Random Variables and Stochastic Processes,* 4th Edn., McGraw Hill, 2002.
2. Geoffrey Grimmett, *Probability and Random Processes,* 3rd Edn., Oxford University Press, 2001.
3. Henry Stark and John W. Woods, *Probability and Random Processes with Applications to Signal Processing,* Prentice Hall, 3rd Edn. 2001.
4. Sheldon M. Ross, *A First Course in Probability,* Prentice Hall, 2013.
5. Cover, Thomas M., and Thomas, Joy A., *Elements of Information Theory,* 2nd Edn., Wiley, 2012.

EC6404E: MACHINE LEARNING AND PATTERN RECOGNITION

Pre-requisites: NIL

L	T	P	O	C
3	0	2	7	4

Total Sessions: 39L+26P

Course Outcomes:

CO1: Apply knowledge of linear systems, probability theory, statistics and optimization theory for data representation and classification.
CO2: Analyze basic mathematical and statistical techniques in machine learning.
CO3: Design machine learning algorithms to classify real world data.
CO4: Evaluate systems to make sound decisions on real world problems.
CO5: Develop skill for continuous learning and conduct independent research in the area of machine learning and pattern recognition.

Lecture Sessions:

Introduction to features, feature vectors and classification, Bayes theorem, Bayes decision theory, minimum-error-rate classification, Discriminant functions, Decision surfaces, Normal density and discriminant functions.
Estimation of unknown probability density function: parameter estimation methods, Maximum-Likelihood Estimation-Gaussian case, Maximum a Posteriori estimation– Bayesian estimation: Gaussian case –Nonparametric density estimation – Parzen-window method, EM algorithm.

Perceptron, learning algorithm, X-OR problem, multi-layer perceptrons, error surfaces, convex and nonconvex problems, Backpropagation algorithm, stochastic gradient descent, LMS, loss and activation functions, Radial basis function networks.
Features, dimensionality reduction, K-L Transform, Fisher linear discriminants, Haar transform, Boosting: combining classifiers, boosted cascades, Viola-Jones algorithm.

Databases, training, validation and testing: k-fold validation, iterations, data balance, accuracy, precision, Receiver Operating Characteristics (ROC), performance measures.
Markov chain models, Viterbi algorithm, Hidden Markov Models, Training markov models using neural networks.

Unsupervised learning and clustering: Criterion functions for clustering – Algorithms for clustering: K-Means, Hierarchical, Self Organizing Maps, DBSCAN. Cluster validation.
Factor Analysis, Decision trees, Classification and Regression Trees (CART).

Practical Sessions:

Suggested List of Experiments:

1. Simulating central limit theorem, estimation of probability density function using parametric and non-parametric methods.
2. Classification using Bayes discriminant function.
3. Dimensionality reduction using FLD and PCA
4. Simulation of an X-OR problem and its classification using an MLP.
5. Implementation of the back-propagation algorithm. Classification of a 4 dimensional 3-class problem using FLD and MLP.
6. Implementation of an ROC and result analysis from ROC.
7. Implementation of Viterbi algorithm
8. End semester mini project.

References:

1. C.M. Bishop, *Pattern Recognition and Machine Learning,* Springer, 2006.
2. R.O. Duda, P.E. Hart and D.G. Stork, *Pattern Classification,* 3rd Edn., John Wiley, 2001.
3. S. Theodoridis and K. Koutroumbas, *Pattern Recognition,* 4th Edn., Academic Press, 2009.

EC6405E: STATISTICAL SIGNAL PROCESSING

Pre-requisites: Probability Theory and Applications (EC6403E)

L	T	P	O	C
3	0	2	7	4

Total Sessions: 39L+26P

Course Outcomes:

CO1: Design parameter estimation techniques for various probability models and analyze the performance using Cramer-Rao bounds.
CO2: Design linear optimum filter for signal and spectrum estimation problems.
CO3: Develop optimum tracking algorithms for non-stationary systems.
CO4: Model decision making problems using various statistical hypotheses testing frameworks and analyze its performance:

Lecture Sessions:

Estimation Theory - Parameter Estimation – Unbiasedness – Minimum Variance Estimation –Cramer-Rao bound – Minimum Mean-Squared Error (MMSE) Estimators – Maximum Aposteriori Probability (MAP) Estimators – Maximum Likelihood (ML) Estimators – Linear Estimators – Best Linear Unbiased Estimators – Least Squares Estimators.

Linear Signal Waveform Estimation – Wiener Filters – Prediction – Levinson-Durbin recursion – Lattice filter – Spectral Estimation – Periodogram–Minimum Variance Spectral Estimation Dynamic Adaptive Filtering – Recursive Least Squares filtering–Kalman Filters – Particle Filtering.

Fundamentals of Detection Theory: Hypothesis Testing – General Modeling of Binary Hypothesis Testing Problem – Bayes' Detection – MAP Detection – ML Detection – Minimum Probability of Error Criterion- MinMax Criterion – Neyman-Pearson Criterion – Receiver Operating Characteristic Curves.

Practical Sessions:

Suggested List of Experiments:
1. Maximum likelihood modelling for various applications.
2. Empirical computation of estimator variance and comparison with CRLB
3. Sinusoidal frequency estimation
4. Least square modelling
5. AR and MA modelling for various practical applications
6. AR parameter estimation using Levinson-Durbin algorithm
7. FIR Weiner filtering
8. Innovations Algorithm
9. Binary hypothesis testing under various decision frameworks

References:

1. Dimitris G. Manolakis, Vinay K. Ingle, Stephen M. Kogon, *Statistical and Adaptive Signal Processing: Spectral Estimation, Signal Modeling, Adaptive Filtering, and Array Processing,* McGraw-Hill, 2005.
2. Monson H. Hayes, *Statistical Digital Signal Processing and Modeling,* 1st Edn., Wiley India Pvt Ltd, 2008.
3. Steven M. Kay, *Fundamentals of Statistical Signal Processing, Volume I: Estimation Theory,* Prentice Hall, 1993.
4. Harry L. Van Trees, Kristine L. Bell, Zhi Tian, *Detection Estimation and Modulation Theory, Part I: Detection, Estimation, and Filtering Theory*, 2nd Edn., Wiley-Blackwell, 2013.

EC6496E: PROJECT PHASE I

Pre-requisites: NIL

L	T	P	O	C
0	0	0	6	2

Course Outcomes:

CO1: Survey the literature on new research areas and compile findings on a particular topic
CO2: Organize and illustrate technical documentation with scientific rigor and adequate literal standards on the chosen topic strictly abiding by professional ethics while reporting results and stating claims
CO3: Develop aptitude for research and independent learning.
CO4: Demonstrate communication skills in conveying the collected data through technical reports and oral presentations using modern presentation tools.

The objective of this phase of the project is to impart training to the students in collecting materials on a specific topic in the broad domain of Engineering/Science from books, journals and other sources, compressing and organizing them in a logical sequence, and presenting the matter effectively both orally and in written format. The topic should not be a replica of what is contained in the syllabi of various courses of the M. Tech programme. The topic chosen by the student shall be approved by the project guide(s) and the evaluation committee. Based on the collected information and acquired knowledge, the student is expected to identify unresolved problems in the domain of the selected topic.

EC7497E: PROJECT PHASE II

Pre-requisites: NIL

L	T	P	O	C
0	0	0	9	3

Course Outcomes:

CO1: Develop aptitude for research and independent learning

CO2: Demonstrate the ability to select unresolved problems in the domain of the selected project topic and explore suitable solutions

CO3: Gain the expertise to use new tools and techniques for the design and development of novel solutions for unsolved problems.

CO4**:** Demonstrate communication skills in conveying the technical documentation via oral presentations using modern presentation tools.

The work carried out in EC7497E Project Phase II is a continuation of EC6496E Project Phase I and to be continued in EC7498E and/or EC7499E. In these project phases, students get an opportunity to apply and extend knowledge acquired in the first and second semesters of their M. Tech. programme. The work will be carried out individually. The objective of the Project Phase II is to identify unresolved problems in the domain of the selected topic (if not done at the end of the second semester) and explore possible solutions. The proposed solution(s) shall be compared with the ones which are available in the literature or in practice using suitable methods along with a feasibility study. The work can be analytical, simulation, hardware design or a combination of these in the emerging areas of Signal Processing under the supervision of a faculty from the ECE Department.

At the end of Project Phase II, students are expected to have a clear idea of the work to be done, and have learnt the analytical / software / hardware tools. Some preliminary designs and results are highly desirable. The students are also expected to submit an interim technical report including the project work carried out in this phase and the work plan for the forthcoming semester(s).

EC7498E: PROJECT PHASE III

Pre-requisites: NIL

L	T	P	O	C
0	0	0	45	15

Course Outcomes:

CO1: Develop aptitude for research and independent learning
CO2: Apply the knowledge and awareness to carry out cost-effective and environment friendly designs.
CO3: Demonstrate the expertise to use new tools and techniques for the design and development.
CO4**:** Develop the ability to write good technical report, to make oral presentation of the work, and to publish the work in reputed conferences/journals.

The work carried out in EC7498E Project Phase III is a continuation of EC7497E Project Phase II and shall be continued in EC7499E or it can be an internship work carried out in an industry. In both cases, the work will be carried out individually. The objective of the Project Phase III is to design/develop the solution proposed in the Project Phase II using one or more of the following approaches: (i) Analytical models (ii) Computer simulations (iii) Hardware implementation. The project work of a student during the third semester will be evaluated by a committee consisting of faculty members nominated by the DCC.

If a student plans for an internship in the fourth semester or exploring a different project topic in the fourth semester after doing the Project Phase III in the institute, the student should complete the work planned in the beginning of the third semester, attaining all the objectives and shall prepare a project report of the complete work starting from Project phase I to Project Phase III. If a student plans to continue the same work in the Project phase IV, a detailed project report should be submitted at the end of the Project Phase IV. In case of an internship, the work will be decided jointly by the guides of the student both in the institute and the internship organization. A detailed internship report shall be prepared and submitted by the student.

EC7499E: PROJECT PHASE IV

Pre-requisites: NIL

L	T	P	O	C
0	0	0	45	15

Course Outcomes:

CO1: Develop aptitude for research and independent learning.
CO2: Acquire the knowledge and awareness to carry out cost-effective and environment friendly designs.
CO3: Demonstrate the expertise to use new tools and techniques for the design and development.
CO4: Develop the ability to write good technical report, to make oral presentation of the work, and to publish the work in reputed conferences/journals.

The work carried out in EC7499E Project Phase IV is a continuation of EC7497E Project Phase II, and EC7498E Project Phase III or it can be an internship work carried out in an industry. The students are expected to communicate their innovative ideas and results to reputed conferences and/or journals. The project work of a student during the fourth semester will be evaluated by a committee consisting of faculty members nominated by the DCC.

IE6001E ENTREPRENEURSHIP DEVELOPMENT

Pre-requisites: NIL

L	T	P	O	C
2	0	0	4	2

Total Lecture Sessions: 26

Course Outcomes:

CO1: Describe the various strategies and techniques used in business planning and scaling ventures.
CO2: Apply critical thinking and analytical skills to assess the feasibility and viability of business ideas.
CO3: Evaluate and select appropriate business models, financial strategies, marketing approaches, and operational plans for startup ventures.
CO4: Assess the performance and effectiveness of entrepreneurial strategies and actions through the use of relevant metrics and indicators.

Entrepreneurial Mindset and Opportunity Identification

Introduction to Entrepreneurship Development - Evolution of entrepreneurship, Entrepreneurial mindset, Economic development, Opportunity Recognition and Evaluation - Market gaps - Market potential, Feasibility analysis - Innovation and Creativity in Entrepreneurship - Innovation and entrepreneurship, Creativity techniques, Intellectual property management.

Business Planning and Execution

Business Model Development and Validation - Effective business models, Value proposition testing, Lean startup methodologies - Financial Management and Funding Strategies - Marketing and Sales Strategies - Market analysis, Marketing strategies, Sales techniques - Operations and Resource Management - Operational planning and management, Supply chain and logistics, Stream wise Case studies.

Growth and Scaling Strategies

Growth Strategies and Expansion - Sustainable growth strategies, Market expansion, Franchising and partnerships - Managing Entrepreneurial Risks and Challenges - Risk identification and mitigation, Crisis management, Ethical considerations - Leadership and Team Development - Stream wise Case studies

References:

1. Kaplan, J. M., Warren, A. C., & Murthy V. (Indian Adoption) (2022). Patterns of entrepreneurship management. John Wiley & Sons.
2. Kuratko, D. F. (2016). Entrepreneurship: Theory, process, and practice. Cengage learning.
3. Barringer, B. R. (2015). Entrepreneurship: Successfully launching new ventures. Pearson Education India
4. Rajiv Shah, Zhijie Gao, Harini Mittal, Innovation, Entrepreneurship, and the Economy in the US, China, and India, 2014, Academic Press
5. Dr. K. Sundar, Entrepreneurship Development, 2nd Ed 2022 Vijaya Nichkol Imprints, Chennai
6. E. Gordon,Dr. K. Natarajan,Entrepreneurship Development, 6th Ed, 2017, Himalya Publishers,Delhi
7. Debasish Biswas, Chanchal Dey,Entrepreneurship Development in India, 2021, Taylor & Francis

ZZ6001E RESEARCH METHODOLOGY

Pre-requisites: NIL

L	T	P	O	C
2	0	0	4	2

Total Lecture sessions: 26

Course Outcomes

CO1: Explain the basic concepts and types of research
CO2: Develop research design and techniques of data analysis
CO3: Develop critical thinking skills and enhanced writing skills
CO4: Apply qualitative and quantitative methods for data analysis and presentation
CO5: Implement healthy research practice, research ethics, and responsible scientific conduct

Exploring Research Inquisitiveness
Philosophy of Scientific Research, Role of Research Guide, Planning the Research Project, Research Process, Research Problem Identification and Formulation, Variables, Framework development, Research Design, Types of Research, Sampling, Measurement, Validity and Reliability, Survey, Designing Experiments, Research Proposal, Research Communication, Research Publication, Structuring a research paper, structuring thesis/ dissertation,

Research Plan and Path
Developing a Research Plan: Reviewing the literature- Referencing – Information sources – Information retrieval – Role of libraries in information retrieval – Tools for identifying literatures – Reading and understanding a research article – Critical thinking and logical reasoning; Framing the research hypotheses, Converting research Question into a Model; Data collection- Types of data-Dataset creation- Primary and Secondary data- Scales of measurement- Sources and collection of data- Processing and analysis of data-Understanding Data-statistical analysis, displaying of data-Data visualization-Data interpretation; Research design- Qualitative and Quantitative Research- Designing of experiments- Validation of experiments- Inferential statistics and result interpretation

Scientific Conduct and Ethical Practice
Plagiarism– Ethics of Research- Scientific Misconduct- Forms of Scientific Misconduct. Plagiarism, Unscientific practices in thesis work-Conduct in the workplace and interaction with peers – Intellectual property: IPR and patent registration, copyrights; Current trends – Usage and ethics of AI tools in scientific research.

References:

1. Leedy, P D, "*Practical Research: Planning and Design",* USA: Pearson, Twelfth ed., 2018.
2. Krishnaswamy, K. N., Sivakumar, A. I., and Mathirajan, M., "*Management Research Methodology"*, Pearson Education, 2006.
3. Tony Greenfield and Sue Greener., Research Methods for Postgraduates, USA: John Wiley & Sons Ltd., Third ed., 2016.
4. John W. Creswell and J. David Creswell, "*Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*", USA: Sage Publications, Sixth ed., 2022

MS6174E TECHNICAL COMMUNICATION AND WRITING

Pre-requisites: NIL

L	T	P	O	C
2	1	0	3	2

Total Lecture Sessions: 26

Course Outcomes:

CO1: Apply effective communication strategies for different professional and industry needs.
CO2: Collaborate on various writing projects for academic and technical purposes.
CO3: Combine attributes of critical thinking for improving technical documentation.
CO4: Adapt technical writing styles to different platforms.

Technical Communication
Process(es) and Types of Speaking and Writing for Professional Purposes - Technical Writing: Introduction, Definition, Scope and Characteristics - Audience Analysis - Conciseness and Coherences - Critical Thinking - Accuracy and Reliability - Ethical Consideration in Writing - Presentation Skills - Professional Grooming - Poster Presentations

Grammar, Punctuation and Stylistics
Constituent Structure of Sentences - Functional Roles of Elements in a Sentence - Thematic Structures and Interpretations - Clarity - Verb Tense and Mood - Active and Passive Structures - Reporting Verbs and Reported Tense - Formatting of Technical Documents - Incorporating Visuals Elements - Proofreading

Technical Documentation
Types of Technical Documents: Reports, Proposals, Cover Letters - Manuals and Instructions - Online Documentation - Product Documentation - Collaborative Writing: Tools and Software - Version Control Document Management - Self Editing, Peer Review and Feedback Processes

References:

1. Foley, M., & Hall, D. (2018). *Longman advanced learner's grammar, a self-study reference & practice book with answers*. Pearson Education Limited.
2. Gerson, S. J., & Gerson, S. M. (2009). *Technical writing: Process and product*. Pearson.
3. Kirkwood, H. M. A., & M., M. C. M. I. (2013). *Hallidays introduction to functional grammar* (4th ed.). Hodder Education.
4. Markel, M. (2012). *Technical Communication* (10th ed.). Palgrave Macmillan.
5. Tuhovsky, I. (2019). *Communication skills training: A practical guide to improving your social intelligence, presentation, Persuasion and public speaking skills.* Rupa Publications India.
6. Williams, R. (2014). *The Non-designer's Design Boo*k. Peachpit Press.

EC6421E: ARRAY SIGNAL PROCESSING

Pre-requisites: Linear Algebra

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Obtain basic understanding of spatial signals and its analysis.
CO2: Familiarize with the basic knowledge of the sensor arrays.
CO3: Perform the spatial frequency analysis of array signals.
CO4: Implement various methods of beamforming, direction of arrival estimation, and target tracking

Spatial Signals and Sensor Arrays
Spatial Signals: Signals in space and time - Spatial frequency - Direction vs. frequency - Wave fields – Far field and Near field signals.
Sensor Arrays: Spatial sampling - Uniform linear arrays - Planar arrays - Random arrays - Array steering vector - Virtual array of MIMO configuration - Broadband arrays.

Spatial Frequency and Beamforming
Aliasing in spatial frequency domain - Spatial frequency transform and Spatial spectrum - Spatial Domain Filtering - Beamforming: Data-independent, Statistically optimum, and Adaptive beamforming techniques - Spatially white signal.

Direction of Arrival Estimation and Target Tracking
Non parametric methods: Beam forming and Capon methods - Resolution of Beamforming method – Signal Subspace methods: Subspace fitting, ESPRIT and Toeplitz approximation – Noise Subspace methods: Pisarenko, MUSIC and Minimum Norm - Spatial Smoothing.
Target Tracking: Kalman Filter, and Interacting multiple model filter.

References:

1. Harry L. Van Trees, *Optimum Array Processing: Part IV of Detection, Estimation, and Modulation Theory*, Wiley, 2002.
2. Don H. Johnson and Dan E. Dudgeon, *Array Signal Processing: Concepts and Techniques,* Prentice-Hall, 1993.
3. Prabhakar S. Naidu., *Sensor array signal processing*, 2nd Edn., CRC Press, 2001.
4. Dimitris G. Manolakis, Vinay K. Ingle, and Stephen M. Kogon, *Statistical and Adaptive Signal Processing: Spectral Estimation, Signal Modeling, Adaptive Filtering, and Array Processing,* Artech House, 2005.
5. Vijay K. Madisetti, *The Digital Signal Processing Handbook: Wireless, Networking, Radar, Sensor Array Processing, and Nonlinear Signal Processing,* CRC Press, 2nd Edn., 2010.

EC6422E: COMPRESSIVE SENSING: THEORY AND ALGORITHMS

Pre-requisites: Linear Algebra and Analysis (EC6401E)

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Develop mathematical framework for the representation of signals.
CO2: Apply compressed sampling for energy-efficient designs.
CO3: Apply mathematical principles for cost-effective practical designs.
CO4: Develop ability to think clearly with sound logical reasoning to unfold new theory and design methods.

Fundamentals of Sampling Analog Signals

Classical sampling theorem for band-limited signals – Bandpass sampling theorem – Sample-rate reduction and multi-channel sampling – Sampling of random signals – Sampling of duration-limited signals and motivation for compressed sampling.

Signal Models - Mathematical Preliminaries

Sampling as a signal representation problem – Signal spaces: normed linear spaces - topology, Convergence, completeness and stable signal synthesis – Finite and infinite dimensional signal spaces – Hamel basis, Schauder basis and Riesz basis – Orthogonality and bi-orthogonality – Frames; Linear transformations and change of basis – Sampling as an isomorphism – Separable signal spaces, Quotient spaces and, Decomposition of signals – Under-determined system of equations - methods of solution, sparse solution.

Compressed Sensing

Sparse representation of signals - Sparsity and compressibility – Construction of measurement matrix - Sensing matrix – Null-space conditions and the spark – Johnson-Lindenstrauss (JL) lemma – The Restricted Isometry Property (RIP) – relation between JL lemma and the RIP – RIP and null-space property – Measurement bounds and condition for stable recovery – Coherence of measurement basis – mutual coherence between sensing and representation bases.

Sparse Signal Recovery

Recovery through l_1-norm minimization – Recovery under noiseless and noisy conditions – Algorithms for sparse recovery - Design requirements – Convex optimization based methods: linear programming–Greedy algorithms: Matching pursuit, Orthogonal matching pursuit, Stage-wise orthogonal matching pursuit, Regularized orthogonal matching pursuit (ROMP) – Compressive sampling matching pursuit (CoSaMP) – Iterative reweighted least squares (IRLS) algorithm – Performance analysis.

References:

1. Y. C. Eldar and G. Kutyniok, *Compressed Sensing: Theory and Applications*, Cambridge University Press, 2012.
2. R. G. Baraniuk, M. A. Davenport, M. F. Duarte, C. Hegde (Collection Editors), *An Introduction to Compressive Sensing*, CONNEXIONS (Publishing) Rice University, Houston, Texas, 2012.
3. M. Elad, *Sparse and Redundant Representations*, Springer, New York, 2010.
4. S. G. Mallat, *A Wavelet Tour of Signal Processing: The Sparse Way*, Elsevier, 2009.
5. S. Foucart, H. Rauhut, *A Mathematical Introduction to Compressive Sensing*, Birkhauser, 2013.

EC6423E: DIGITAL IMAGE PROCESSING TECHNIQUES

Pre-requisites: NIL

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Demonstrate the methods of image acquisition, representation and manipulation to design and develop algorithms for solving image processing problems related to various applications like medicine, industry, communications etc.
CO2: Analyze various image processing algorithms for preprocessing, restoration, compression and segmentation using various spatial and frequency domain methods.
CO3: Identify and solve complex real world problems in image processing using modern signal processing tools, active cooperative learning and be able to demonstrate them effectively.
CO4: Analyze linear systems involving random processes.
CO5: Acquire skills to conduct independent study and analysis of image processing problems and techniques that would engage in lifelong learning

Image representation: Gray scale and colour Images, image sampling and quantization, colour spaces. Connectivity and relations between pixels – Simple manipulations of pixels: arithmetic, logical and geometric operations – Various techniques for image enhancement and restoration - filters in spatial and frequency domains, histogram-based processing, homomorphic filtering, Image Registration – Examples and case studies

Morphological Image Processing: The structuring element, Basic operations on sets, Erosion, Dilation, Opening and Closing, Hit-or-Miss Transform, Basic Morphological Algorithms and applications.
Image segmentation: Edge detection, line detection, curve detection, Edge linking and boundary extraction, boundary representation, region representation and segmentation - Thresholding, Otsu's Method, Variable and multi variable thresholding, Similarity based Segmentation - Segmentation Using Morphological Watersheds, Use of Motion in Segmentation – Image representation and object recognition: Descriptors for boundaries and regions, global descriptors – Pattern recognition as applied to images

Fundamental concepts of image compression: Compression models, Information theoretic perspective, Fundamental coding theorem – Lossless Compression: Huffman Coding, Arithmetic coding, Bit plane coding, Run length coding – Lossy compression: Quantization – Scalar and Vector, Transform coding – Image compression standards, Introduction to Sub band coding – Basic concepts of video compression, Introduction to video compression standards

References:

1. R. C. Gonzalez, R. E. Woods, *Digital Image Processing,* Pearson Education. 3rd Edn.,2016
2. Jain A.K., *Fundamentals of Digital Image Processing,* 7th Edn., Prentice-Hall, 2002.
3. Jae S. Lim, *Two Dimensional Signal and Image Processing,* Prentice-Hall, Inc., 1990.
4. Pratt W.K., *Digital Image Processing,* John Wiley, 4th Edn., 2007.
5. K. R. Castleman, *Digital image processing,* Prentice Hall, 1996.

EC6424E: LINEAR & NONLINEAR OPTIMIZATION

Pre-requisites: NIL

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Mathematical background: sequences and subsequences, mapping and functions, continuous functions infimum and supremum of functions minima and maxima of functions, differentiable functions – Vectors and vector spaces, matrices, linear transformation, quadratic forms, gradient and Hessian-Linear equations, solution of a set of linear equations, basic solution and degeneracy, convex sets and convex cones, convex hulls, extreme point, convex and concave functions, differentiable convex functions

Linear Programming: introduction, optimization model, formulation and applications – Classical optimization techniques: single and multi variable problems, types of constraints, graphical method – Linear optimization algorithms: simplex method, basic solution and extreme point, degeneracy, primal simplex method, dual linear programs, primal, dual, and duality theory, dual simplex method, primal dual algorithm – Post optimization problems: sensitivity analysis and parametric programming.

Nonlinear Programming: minimization and maximization of convex functions, local & global optimum, convergence – Unconstrained optimization: one dimensional minimization, elimination methods: Fibonacci & Golden section search, gradient methods – Constrained optimization: Lagrangian method, Kuhn-Tucker optimality conditions, convex programming problems,Augmented Lagrangian method (ALM)
Applications of optimization theory in signal processing: signal processing via convex optimization, applications in weight design, linearizing pre-equalization, robust Kalman filtering, online array weight design, basis pursuit denoising (BPDN), compressive sensing and orthogonal matching pursuit (OMP).

References:

1. David G Luenberger, *Linear and Non Linear Programming*, Addison-Wesley, 2nd Edn., 2001.
2. S.S. Rao, *Engineering Optimization.; Theory and Practice*, John Wiley, 4th Edn., 2013.
3. S.M. Sinha, *Mathematical programming: Theory and Methods*, Elsevier, 2006.
4. Hillier and Lieberman, *Introduction to Operations Research*,” McGraw-Hill, 8th Edn., 2005.
5. Kalyanmoy Deb, *Optimization for Engineering: Design Algorithms and Examples*, 2nd Edn., Prentice Hall, 1998.
6. Igor Griva, ArielaSofer, Stephen G. Nash: *Linear and Nonlinear Optimization*, 2nd Edn., SIAM, 2009.

EC6425E: MULTIRATE SIGNAL PROCESSING

Pre-requisites: NIL

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Multi-rate System Fundamentals – Basic multi-rate operations: up sampling and down sampling – time domain and frequency domain analysis – Aliasing and imaging, Interpolator and decimator design, Identities of multi-rate operations, Fractional sampling Rate operation, poly-phase representation. Multi-rate Filter Banks: Maximally decimated filter banks - Design of uniform DFT prefect reconstruction (PR) QMF banks, uniform and non-uniform tree structured filter banks.

Near perfect reconstruction (NPR) filter banks: Design of uniform and non-uniform cosine modulated filter banks and modified DFT filter banks, Reducing amplitude distortion-meta heuristic optimization techniques
Use of Interpolated FIR (IFIR) filters, Frequency response masking (FRM) filters and Farrow structure filters in filter banks, Multiplier-less filter banks to reduce hardware complexity, implementation

Quantization effects - Types of quantization effects in filter banks – Hardware complexity of filters and filter banks, Implementation
Applications of filter banks in Signal Processing and Communication such as hearing aids, cognitive radio, Software design radio channelizers.

References:

1. P. P. Vaidyanathan, *Multirate Systems and Filter Banks*, Pearson Education, 2006.
2. N.J. Fliege, *Multirate Digital Signal Processing*, John Wiley, 1994, K. K. Parhi, VLSI Digital Signal Processing Systems: Design and Implementation, Wiley, 1999.
3. Sanjit K. Mitra, *Digital Signal Processing: A Computer based Approach,* Special Indian Edition, McGraw Hill, 2013.
4. Fredric J Harris, *Multirate Signal Processing for Communication Systems*, 1st Edn., Pearson Education, 2007.

EC6426E: QUANTUM SIGNAL PROCESSING

Pre-requisites: Linear Algebra, Hilbert spaces

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Understand and apply the fundamental principles of Quantum Mechanics.
CO2: Analyze and apply the Quantum Formalism.
CO3: Understand Quantum Gates and design Quantum Circuits
CO4: Apply Quantum formalism to implement Integral Transforms.
CO5: Design Quantum Error Correction codes.

Fundamentals of Quantum Mechanics
The wave function: Schrödinger equation, normalization, momentum – Time-independent Schrödinger equation, quantum mechanical harmonic oscillator, solution, stationary states – Mathematical formalism: Quantum dynamics and the Hamiltonian operator, Hilbert space, observables as Hermitian operators, eigen functions of a Hermitian operator, Generalized statistical interpretation**,** and generalized uncertainty principle, Dirac notation.

Quantum Mechanical Framework
Fundamental postulates: Copenhagen interpretation – Quantum states: 2D-Hilbert space, qubits, spins and photons – Single qubit and multi-qubit systems, Bloch sphere; Tensor products and Entangled states – Mixed states and Density operator: negativity, partial traces and purification, fidelity – Measurement Operator.

Quantum Gates and Quantum Circuits
Simple quantum Gates, Hadamard gate, Swap-gate and controlled swap-gate, No-cloning theorem – Applications: dense coding, quantum teleportation.

Quantum Integral Transforms
Discrete Integral transform, Quantum Fourier Transform: implementation and application, Walsh-Hadamard transformation, Selective phase rotation transform.

Quantum Error Correction Codes (QECC)
Quantum Channels and their representation as super-operators – Basic notions of Decoherence in Quantum Systems – 3-qubit bit-flip QECC: encoding, transmission, error syndrome detection and correction, decoding, effect of entanglement, effect of continuous rotation–phase-flip QECC, examples.

References

1. M. Nakahara, T. Ohmi, *Quantum Computing: From Linear Algebra to Physical Realizations*, CRC Press, 2008.
2. D. C. Marinescu, G. M. Marinescu, *Approaching Quantum Computing*, Pearson Education, 2009.
3. J. Stolze, D. Suter, *Quantum Computing: A Short Course from Theory to Experiment*, Wiley-VCH Verlag GmbH & Co. KGaA, 2004.
4. M. A. Nielsen, I. L. Chuang, *Quantum Computation and Quantum Information*, Cambridge University press, 2000.
5. D. J. Griffiths, *Introduction to Quantum Mechanics*, 2nd Edn., Pearson Education, 2009.

EC6427E: SPEECH SIGNAL PROCESSING

Pre-requisites: NIL

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Obtain basic knowledge of Speech fundamentals, speech production
CO2: Derive mathematical models of speech production and fundamental speech units.
CO3: Design of front end and pattern comparison in speech/speaker recognition.
CO4: Design of Automatic speech / speaker recognition system

Anatomy and physiology of the speech production system, The mathematical (source-system) model of speech production, Relation between physiological model and mathematical model, Physiological and mathematical basis of categorization of speech sounds, Phonetics and phonemics, Representing speech in time and frequency domain, Speech sound and features

Discrete time speech signals, relevant properties of the fast Fourier transform and Z-transform for speech processing. Convolution, filter banks, and analytical pole-zero modeling of the speech signal, linear prediction (LP) analysis, perceptual linear prediction (PLP), analysis of speech, Homomorphic speech signal, deconvolution, pitch extraction using homomorphic speech processing, real and complex cepstrum, application of cepstral analysis to speech signals.

The speech recognition front end and pattern comparison techniques - Mel frequency cepstral co-efficients (MFCC), MVDR-MFCC, RASTA-PLP cepstral co-efficients, Issues in feature vector extraction for speech recongition, Static and dynamic feature vectors for speech recognition, robustness issues, discrimination in the feature space, feature selection - Log spectral distance, cepstral distances, weighted cepstral distances, distances for linear and warped scales

Statistical models for speech recognition - Vector quantization models for speech and speaker recognition, Gaussian mixture modeling for speaker, language and speech recognition, Hidden Markov modeling for isolated word and continuous speech recognition, multi-channel speech processing, Speech Recognition in practice.

References:

1. Thomas F. Quatieri, *Discrete-Time Speech Signal Processing: Principles and Practice*, 2008.
2. L. Rabiner and B. Juang, *Fundamentals of Speech Recognition*, Prentice-Hall Signal Processing Series,1993.
3. B. Gold and N. Morgan, *Speech and Audio Signal Processing: Processing and perception of speech and music*, Wiley 2000, ISBN: 0-471-35154-7.
4. JR Deller, JG Proakis, JH Hansen, *Discrete Time Processing of Speech Signals,* 1993, ISBN:0023283017.
5. LR Rabiner and RW Schafer, *Digital Processing of Speech Signals*, 4th Edn., Pearson Education,1978.

EC6428E: WAVELETS: THEORY AND CONSTRUCTION

Pre-requisites: Signals, Systems and Signal Processing

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Understand Sampling Theory, Fourier Theory and representation of signals.
CO2: Design and Apply Continuous Wavelets and Continuous Wavelet Transforms and its inverse
CO3: Understand the principles of Multi-resolution Analysis and the discrete wavelet bases.
CO4: Design Discrete Wavelets and compute Discrete Wavelet Transforms.

Sampling Theory and Fourier Theory
Generalized Fourier theory, Fourier transform, Short-time (windowed) Fourier transform, Time-frequency analysis - uncertainty relation, Fundamental notions of the theory of sampling.

Continuous Wavelets
The basic functions, Specifications, Continuous Wavelet Transform (CWT), Construction of a wavelet from a scaling function, Resolution of Identity (ROI) Theorem for wavelet transforms, Inverse Continuous Wavelet Transform (ICWT), Admissibility conditions, Cross-wavelet transform, Vanishing moments and approximation power of a wavelet – Computation of CWT using Frequency- domain and Time-domain methods. Computation of ICWT.

The Multi-resolution Analysis (MRA) of $L^2(R)$ and Discrete Wavelets
The MRA axioms, Construction of an MRA from scaling functions - The dilation equation and the wavelet equation, Compactly supported orthonormal wavelet bases – Necessary and sufficient conditions for orthonormality, Riesz basis formed out of discrete wavelets.

Construction of orthonormal wavelets
Regularity and selection of wavelets - Smoothness and approximation order – Criteria for wavelet selection with examples; Sub-band filtering, Construction of compactly supported orthonormal wavelet bases.

Discrete Wavelet Transform
Discrete wavelet transform (DWT): Wavelet decomposition and reconstruction of functions in L^2 (R), Fast wavelet transform algorithms, Relation to filter banks; Wavelet packets – Representation of functions, Selection of basis.

Construction of Bi-orthogonal wavelets
Bi-orthogonality and bi-orthogonal bases; Construction of bi-orthogonal system of wavelets: The Lifting scheme for constructing discrete wavelets and computing discrete wavelet transform.

References

1. S. Mallat, *A Wavelet Tour of Signal Processing: The Sparse Way*, Elsevier Inc., 2009.
2. M. Vetterli, and J. Kovacevic, *Wavelets and Sub-band Coding*, Prentice Hall Inc., 1995.
3. G. Strang and T. Q. Nguyen, *Wavelets and Filter banks*, 2nd Edn., Wellesley-Cambridge Press, 1998.
4. R. M. Rao and A. S. Bopardikar, *Wavelet Transforms: Introduction to Theory and Applications*, Pearson Education, 2000.
5. J. C. Goswami and A. K. Chan, *Fundamentals of Wavelets: Theory, Algorithms and Applications*, 2nd Edn., John Wiley, 2011.

EC6429E: SIGNAL COMPRESSION

Pre-requisites: NIL

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Acquire mathematical preliminaries for the theory behind Lossy and Lossless Compression of data and understand basic compression algorithms for Lossless and Lossy data Compression.
CO2: Identify, formulate and solve signal compression problems using modern signal processing tools recognizing the needs and challenges of our age and assessing the global and social impacts of data compression problems and its solutions.
CO3: Design data compression systems by choosing appropriate model for the data and integrate algorithms which leads to optimal solution satisfying the rate constraints of the given application.
CO4: Develop skills to explore advanced topics in the recent research areas of data compression through active cooperative learning, that enable them to solve complex problems and engage in lifelong learning.

Review of Information Theory: Entropy, Memory less sources, Markov sources, Entropy of a discrete Random variable, Joint, conditional and relative entropy, Mutual Information and conditional mutual information, Differential Entropy, Joint, relative and conditional differential entropy, Mutual information.
Lossless source coding, Uniquely decodable codes, Instantaneous codes, Kraft's inequality, Optimal codes, Huffman code, Shannon's Source Coding Theorem – Extended Huffman Coding, Adaptive Huffman Coding, Arithmetic Coding, Adaptive Arithmetic coding, Run Length Coding, Dictionary Techniques - Lempel-Ziv coding, Applications - Predictive Coding Techniques.

Lossy Compression: Rate distortion theory, Rate distortion function R(D), Properties of R(D) – Calculation of R(D) for the binary source and the Gaussian source, Rate distortion theorem, Converse of the Rate distortion theorem – Quantization: Uniform & Non-uniform - optimal and adaptive quantization, vector quantization and structures for VQ, Optimality conditions for VQ, Predictive Coding - Differential Encoding Schemes.

Review of Transforms, Transform coding, Subband coding, Wavelet Based Compression, Analysis/Synthesis Schemes – Data Compression standards: Speech Compression Standards, Audio Compression standards, Image Compression standards, Video Compression Standards.

References:

1. Khalid Sayood, *Introduction to Data Compression,* Morgan Kaufmann Publishers., 2nd Edn., 2005
2. David Salomon, *Data Compression: The Complete Reference,* Springer Publications, 4th Edn., 2006.
3. Thomas M. Cover, Joy A. Thomas, *Elements of Information Theory,* 2nd Edn., John Wiley & Sons, Inc., 2006.
4. David J. C. MacKay, *Information Theory, Inference and Learning Algorithms,* Cambridge University Press, 2003.
5. Toby Berger, *Rate Distortion Theory: A Mathematical Basis for Data Compression,* 2nd Edn., Prentice Hall,1971.

EC6441E: ADVANCED MATRIX THEORY FOR MACHINE LEARNING

Pre-requisites: Basic Skill in Matrix Theory

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Define matrix operations commonly used in Machine Learning
CO2: Design mathematical frameworks to formulate machine learning solutions for real-world problems.
CO3: Develop skill to conduct independent research in the area of Machine Learning.
.

Review of Eigenvectors and Diagonalizable Matrices – Symmetric Positive Definite Matrices, Matrix Norms, – Cholesky Factorization: Symmetric LU Decomposition – Machine Learning and Optimization Applications: Fast Matrix Operations, Examples of Diagonalizable Matrices, Symmetric Matrices in Quadratic Optimization, Eigenvectors in Norm-Constrained Quadratic Programming – Numerical Algorithms for Finding Eigenvectors: QR Method via Schur Decomposition, Power Method for Finding Dominant Eigenvectors.

Singular Value Decomposition (SVD): Principal Components and Low Rank Matrix, Truncated SVD, Principal Component Analysis – Applications of SVD: Dimensionality Reduction, Noise Removal, Finding the Four Fundamental Subspaces in Linear Algebra, Moore-Penrose Pseudoinverse, Solving Linear Equations and Linear Regression, Feature Preprocessing and Whitening in Machine Learning, Outlier Detection, Feature Engineering.
Robust Principal Component Analysis (RPCA): Low Rank and Sparse Matrix Decomposition, Nuclear Norm, Applications of RPCA.
Nonnegative Matrix Factorization (NMF): Optimization Problem with Frobenius Norm, Example of NMF.

Linear Algebra of Similarity: Equivalence of Data and Similarity Matrices, Efficient Data Recovery from Similarity Matrices, Energy of Similarity Matrix and Unit Ball Normalization, Norm of the Mean and Variance, Centering a Similarity Matrix in Kernel PCA. Feature Engineering from Similarity Matrix: Kernel Clustering, Kernel Outlier Detection, Kernel Classification, Kernel k-Means, Kernel SVM. Similarity Matrices and Linear Separability.

References:

1. Charu C. Aggarwal, *Linear Algebra and Optimization for Machine Learning,* Springer, 2020.
2. Gilbert Strang, *Linear Algebra and Learning from Data,* Cambridge: Wellesley-Cambridge Press, 2019.
3. Deisenroth, Marc Peter, A. Aldo Faisal, and Cheng Soon Ong., *Mathematics for Machine Learning,* Cambridge University Press, 2020.

EC6442E: ARTIFICIAL INTELLIGENCE

Pre-requisites: NIL

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Understand the use of artificial intelligence to tackle complex real-world problems.
CO2: Develop machine learning models to learn from data.
CO3: Model real world sequential and multi-player decision making problems using the mathematical tools of search, Markov decision process, and adversarial game theory.
CO4: Develop Bayesian networks as a foundational tool for representing knowledge using statistics and graph theory
.

Machine Learning
Empirical risk minimization, Linear regression and classification, Gradient descent and Stochastic gradient descent. Feature engineering and non-linear features – Introduction to neural networks and Backpropagation – Deep learning by composition. Generalization. Cross-validation. K-means algorithm.

Search
Single action to sequence – Define search problems. Basic search algorithms: BFS, DFS. Uniform cost search (UCS), Correctness of UCS, Speeding up UCS with heuristics – Correctness, efficiency, and admissibility. A* search and relaxations of A* search.

Markov Decision Process and Reinforcement Learning
Definition of Markov Decision Process (MDP), Policy evaluation. Value Iteration. Reinforcement Learning – Model-based Monte Carlo, Model-free Monte Carlo, SARSA, Q-learning. Epsilon-greedy exploration. Function approximation for reinforcement learning.

Games
Definition of games, Halving games – Expectimax: optimal policy against fixed random opponent policy, Minimax: optimal policy against worst case opponent policy, Expectiminimax – Alpha beta pruning, TD learning.

Factor Graphs and Bayesian Networks
Variable based models – Factor graphs – Dynamic ordering, Arc consistency, Beam search, Local Search
Bayesian Networks, Gibbs sampling, Conditional Independence – Inference in general Bayesian networks via reduction to Markov networks – Efficient exact inference algorithm for HMMs – Approximate inference algorithm for HMMs with large domains – EM algorithm.

References:

1. Russell and Norvig. *Artificial intelligence—a modern approach*, Prentice Hall. Series in Artificial Intelligence, Englewood Cliffs, N, 3rd Edn,1996.
2. Koller, Daphne, and Nir Friedman, *Probabilistic graphical models: principles and techniques*, MIT press, 2009.
3. R. Sutton and A. Barto, *Reinforcement Learning: An Introduction*, 2nd Edn., MIT Press, 2018.
4. Hastie, Tibshirani, and Friedman. *The elements of statistical learning: data mining, inference, and prediction*. Vol. 2., 2nd Edn., New York: springer, 2009.

EC6443E: AUTONOMOUS INTELLIGENT SYSTEM

Pre-requisites: Fundamentals of Linear Algebra, Probability and Computer Programming in Python, Exposure to basic concepts in signal processing and machine learning.

L	T	P	O	C
2	0	2	5	3

Total Sessions: 26L +26P

Course Outcomes:

CO1: Understand essential subsystems for autonomous intelligent systems.
CO2: Model autonomous decision-making tasks using the estimation, planning and control architecture.
CO3: Apply reinforcement learning approaches for autonomous decision making for complex environments.

Lecture Sessions:

Introduction to Autonomous Systems
Introduction to autonomous systems – Levels of autonomy. Example of autonomous systems: Self driving cars, autonomous drones – Architecture of autonomous systems: Sensorimotor architecture, Stateful architectures, Logical and physical architectures – Modelling and control for autonomous systems: Representations and models, PID control

Vision for Autonomous Systems
Vision: Introduction to projective geometry, Camera modeling and calibration, Image processing techniques for object detection – Machine learning techniques for object detection: Introduction to neural networks, Convolutional neural networks, One and two-stage object detection

State Estimation, Localization, and Planning
State estimation and localization: Bayes filtering framework, Parameterized methods (Kalman filter), Sampling-based methods (particle and histogram filter).
Planning: Formalization of the planning problem, Graphs, Graph search algorithms

Reinforcement Learning
Reinforcement Learning: Markov decision processes, Value functions, Q-learning, Exploration and Exploitation techniques.

Practical Session:

Lab experiments using simulator and AI enabled hardware. Lab experiments will include simulation of an autonomous driving environment and would involve designing a PID controller for control, developing image processing and machine learning algorithms for navigation, state estimation, and path planning.

References:

1. Ulrich Nehmzow, *Mobile robotics: a practical introduction*, 2nd Edn, Springer Science & Business Media, 2012.
2. Introduction to Autonomous Mobile Robots, By Roland Siegwart, Illah Reza Nourbakhsh, Davide Scaramuzza ,2nd Edn,2011
3. Luc Jaulin, *Mobile robotics*. John Wiley & Sons, 2019.
4. R. Sutton and A. Barto, *Reinforcement Learning: An Introduction*, 2nd Edn., MIT Press, 2018.
5. Stuart Jonathan Russell, Peter Norvig, *Artificial intelligence a modern approach*, 4th Edn, Pearson Education, Inc,2016

EC6444E: BAYESIAN DATA ANALYTICS

Pre-requisites: Probability Theory and Applications (EC6403E)

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Develop, analytically describe, and implement complex single and multiparameter probability models in the Bayesian framework

CO2: Demonstrate an understanding of the role of the prior distribution in Bayesian inference, and in particular the usage of non-informative priors and conjugate priors

CO3: Perform Bayesian computation using Markov chain Monte Carlo methods.

CO4: Formulate a Bayesian solution to real-data problems, including forming a hypothesis, collecting and analyzing data, and reaching appropriate conclusions.

.

Fundamentals of Bayesian Inference

Basics of probability theory, machine learning and statistic – distribution and density, independently and identically distributed, Bayes rule, prior distribution, posterior distribution, probability as measure of uncertainty, transformation of variables, inverse cumulative distribution function.

Bayesian inference - Binomial model, Posterior as compromise between data and prior information, Informative prior distributions, Gaussian model, Other single parameter models – exponential and Poisson, Noninformative priors, Weakly informative priors. Marginalization, Normal distribution with a noninformative prior, Normal distribution with a conjugate prior.

Markov Chain Monte Carlo

Monte Carlo – Overview of sampling algorithms: direct simulation and rejection sampling, Importance sampling.

Markov chain Monte Carlo (MCMC): Basics of Markov chain, Markov chain simulation, Gibbs sampler, Metropolis and Metropolis-Hastings, Inference and assessing convergence, Effective number of simulation draws – Hamiltonian Monte Carlo, Hamiltonian dynamics for a simple model.

Hierarchical Models

Introduction to regression models-Conditional modeling – Bayesian analysis of classical regression – Explanatory variables – Regularization and dimension reduction. Unequal variances and correlations.

Hierarchical linear models - exchangeability of parameters, Interpreting a normal prior distribution as extra data, Varying intercepts and slopes, ANOVA as Bayesian hierarchical linear model.

Generalized linear models - Parts of generalized linear model: linear predictor, link function, Outcome distribution model. Standard generalized linear model likelihoods. Weakly informative priors for logistic regression.

References:

1. Gelman, Carlin, Stern and Rubin, *Bayesian Data Analysis*, 2nd Edn., 2004
2. Andrew Gelman, Jennifer Hill, Aki Vehtari, Regression *and Other Stories*, Cambridge University Press, 2020.
3. Peter D. Hoff, *A First Course in Bayesian Statistical Methods*, New York: Springer, 2009
4. Christensen R, Johnson W, Branscum A, Hanson T. E., *Bayesian Ideas and Data Analysis, An Introduction for Scientists and Statisticians*, 2nd Edn, CRC press,2011

EC6445E: COMPUTER VISION

Pre-requisites: Basic Skill in Matrix Theory

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Apply knowledge of linear systems, probability theory, statistics and optimization theory for computer vision applications.
CO2: Design computer vision algorithms on real world data.
CO3: Evaluate computer vision systems to make sound decisions on real world problems.
CO4: Develop skill to conduct independent research in the area of computer vision.

Digital Image Formation and low-level processing: Overview and State-of-the-art, Fundamentals of Image Formation, Transformation: Orthogonal, Euclidean, Affine, Projective, etc, Fourier Transform, Convolution and Filtering, Image Enhancement, Restoration, Histogram Processing – Depth estimation and Multi-camera views: Perspective, Binocular Stereopsis: Camera and Epipolar Geometry – Homography, Rectification, DLT, RANSAC, 3-D reconstruction framework; Auto-calibration. apparel.

Feature Extraction: Edges - Canny, LOG, DOG – Line detectors (Hough Transform), Corners - Harris and Hessian Affine, Orientation Histogram, SIFT, SURF, HOG, GLOH, Scale-Space Analysis- Image Pyramids and Gaussian derivative filters, Gabor Filters and DWT. Image Segmentation: Region Growing, Edge Based approaches to segmentation, Graph-Cut, MeanShift, MRFs, Texture Segmentation – Object detection.

Motion Analysis: Background Subtraction and Modeling, Optical Flow, KLT, Spatio-Temporal Analysis, Dynamic Stereo – Motion parameter estimation – Object Recognition: Hough transforms and other simple object recognition methods, Shape correspondence and shape matching, Shape priors for recognition.
Deep Neural Networks in Computer Vision.

References:

1. Richard Szeliski, *Computer Vision: Algorithms and Applications*, 2nd Edn., Springer-Verlag London Ltd., 2022.
2. Richard Hartley and Andrew Zisserman, *Multiple View Geometry in Computer Vision*, 2nd Edn., Cambridge University Press, 2004.
3. K. Fukunaga, *Introduction to Statistical Pattern Recognition*, 2nd Edn., Academic Press, Morgan Kaufmann, 2014.
4. R.C. Gonzalez and R.E. Woods, *Digital Image Processing*, 3rd Edn., Prentice Hall, 2007.

EC6446E: DEEP LEARNING

Pre-requisites: Basic Skill in Matrix Theory

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Apply knowledge of linear systems, probability theory, statistics and optimization theory for deep learning applications.
CO2: Design deep learning algorithms on real world data.
CO3: Evaluate deep learning models to make sound decisions on real world problems.
CO4: Develop skill to conduct independent research in the area of neural networks and deep learning.
.

Review of Linear Models: Linear Regression, Linear Classifiers, Training a Linear Model, Perceptron Learning Rule, Activation Functions, Loss Functions.
Optimization: Formulation of Objective Function, Convex Functions, Local Minima, Global Minima, Visualizing Gradient Descent, Stochastic Gradient Descent (SGD), Problems and Workarounds in SGD, , Remedies, Adjusting Derivatives for Descent: Momentum-Based Learning, AdaGrad, RMSProp, Adam.
Multilayer Perceptron (MLP): Feedforward Neural Networks, Bias Vector, Weight Matrix, Activation Vector, Types of Activation Functions, Feature Learning, Deep and Shallow Networks.
Back Propagation: Multivariate Chain Rule, Representation using Computational Graph, Backpropagation Algorithm, Backpropagation on Multilayer Network.

Convolutional Neural Networks (CNN): Foundations on 2D Convolution, Convolutional Layers - Sparse Connectivity and Weight Sharing, CNN Architecture, Applications of CNN: Classification, Object Recognition.
Generalization of Trained Model, Reasoning about Generalization, Bias and Variance, Remedies for Overfitting. Transfer learning.

Recurrent Neural Networks (RNN): Sequence to Sequence Prediction, Concept of RNN, Self-loops, Backpropagation through Time, Applications of RNN, Exploding/Vanishing Gradients: LSTM Networks.
Residual Networks: Residual Blocks, Deep Residual Networks (ResNets), Residual Learning, Examples.

Attention and Transformer Networks: Encoder-Decoder Model, Learning to Align and Translate, Attention Networks, Transformers: Encoder-Decoder Stacks, Scaled Dot-product Attention, Self Attention, Multi-Head Attention, Transformer Architecture, Vision Transformer, Applications.

Generative Modeling: Generative Adversarial Networks (GAN), CycleGAN, Reversible Models: Reversible Blocks, Deep Reversible Architectures.

References:

1. Bengio, Yoshua, Ian Goodfellow, Aaron Courville, *Deep learning*, Vol. 1. Cambridge, MA, USA: MI press, 2017.
2. Nielsen, Michael A., *Neural networks and Deep Learning*, Vol. 25. San Francisco, CA, USA: Determination press, 2015.
3. Aggarwal, Charu C., *Neural Networks and Deep Learning*, Springer 10.978 ,2020.
4. Lyla B. Das, Sudhish N. George, Anup Aprem *Artificial Intelligence and Machine Learning: Theory and Practice*, IK International Publishing House, 2022.

EC6447E: DEEP LEARNING IN COMPUTER VISION

Pre-requisites: Basic Skill in Matrix Theory

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Apply knowledge of linear systems, probability theory, statistics and optimization theory for deep learning applications.
CO2: Design computer vision algorithms on real world data
CO3: Evaluate computer vision systems to make sound decisions on real world problems.
CO4: Develop skill to conduct independent research in the area of computer vision
.

Computer Vision Overview, Historical context, Applications. Image Classification with Linear Classifiers, Data-driven Approach, k-Nearest Neighbour, Linear Classifiers, Algebraic/Visual/Geometric viewpoints, SVM, Softmax loss – Regularization and Optimization: Regularization, Stochastic Gradient Descent, Momentum, AdaGrad, ADAM, Learning Rate Schedules – Neural Networks: Multi-layer Perceptron, Backpropagation.

Image Classification with Convolutional Neural Networks (CNN): History, Higher-level Representations, Image Features, Convolution and Pooling, CNN Architectures: Batch Normalization, Transfer Learning, AlexNet, VGG, GoogLeNet, ResNet.
Training Neural Networks: Activation Functions, Data Processing, Weight Initialization, Hyperparameter tuning, Data augmentation. Visualizing and Understanding, Feature Visualization and Inversion, Adversarial Examples. DeepDream, Style Transfer, Object Detection and Image Segmentation, Single-stage Detectors, Two-stage Detectors, Semantic/Instance/Panoptic Segmentation, Recurrent Neural Networks: RNN, LSTM, GRU, Language Modeling, Image Captioning, Sequence-to-sequence Prediction, Encoder–Decoder Architecture – Attention and Transformers: Self-Attention, Transformers, Vision Transformers.

Generative Models - Supervised vs. Unsupervised Learning, Pixel RNN, Pixel CNN, Variational Autoencoders, Generative Adversarial Networks, Self-supervised Learning - Pretext tasks, Contrastive Learning, Multisensory Supervision, Low-Level Vision - Optical Flow, Depth Estimation, Stereo Vision.

References:

1. Bengio, Yoshua, Ian Goodfellow, Aaron Courville., Deep learning, Vol. 1. Cambridge, MA, USA: MI press, 2017.
2. Nielsen, Michael A., *Neural networks and Deep Learning*, Vol. 25. San Francisco, CA, USA: Determination press, 2015.
3. Aggarwal, Charu C., *Neural Networks and Deep Learning*, Springer 10.978, 2020.
4. Szeliski R., *Computer Vision: Algorithms and Applications,* Springer Nature, 2022 Jan 3.
5. Lyla B. Das, Sudhish N. George, Anup Aprem, *Artificial Intelligence and Machine Learning: Theory and Practice*, IK International Publishing House, 2022.

EC6448E: FOUNDATIONS OF DATA ANALYTICS

Pre-requisites: Fundamentals of Probability and Statistics, Computer Programming

L	T	P	O	C
2	0	2	5	3

Total Sessions: 26L+26P

Course Outcomes:

CO1: Demonstrate ability to identify and integrate data of various types from a variety of sources, and make informed judgements about their use in data science research.
CO2: Critically evaluate the methodologies applied in data gathering, data processing and data exploration to disseminate findings using data visualization tools.
CO3: Apply different data science tools to create appropriate visualization of high dimensionality data, aligned to the student's area of interest.

Lecture Sessions:

Database for Data Science
Introduction to Data Science: Data, knowledge and information. Structured, semi-structured, and un-structured data – Database theory for data science - ACID properties in database - Relational database, primary key, secondary key– Database normal form: First normal form, second normal form, and third normal form–SQL database for structured data: adding/deleting/modifying tables, adding/deleting/modifying rows, searching and other essential operations– Semi-structured data: XML for semi-structured data, XML syntax and parsing XML using python–Big data: Characteristics of big data, Big data models: key value model, column model, document model, graph model. High level architecture of NoSQL systems.

Data Pre-processing
Data pre-processing: Introduction to Pandas in Python, Data cleaning and preparation: Duplicates, Missing data, transformation using a function/mapping, discretisation of data, errors and outliers – Data wrangling: Hierarchical indexing, combining and merging data, reshaping and pivoting – Data munging, Data cleaning – Quality of data, meta-data, Canonicalization, legal and ethical aspects.

Data Visualization
Introduction to data visualization – Visualization plots: Bar graph and pie charts, box plots, scatter plots and bubble charts, KDE plots – Introduction to data visualization libraries in Python: matplotlib, pandas and seaborn – Data transformation: Indexing, slicing, splitting, iterating, filtering, sorting, combining and reshaping – Introduction to data transformation libraries in Python: numpy and pandas – Exploratory data analytics: Univariate analytics, bivariate analytics and multi-variate analytics – Measures of central tendency and dispersion – Data aggregation, pivot tables and correlation – Scraping online/website data, Interactive visualization plots. Visualization of high-dimensional data.

Practical Sessions:

Suggested List of Experiments:
1. Python Programming Basics
2. Normalizing a database to normal form
3. Creating, Querying and searching in SQL
4. Parsing XML in Python
5. Pandas: Data cleaning and wrangling
6. Matplotlib: Basic data visualization
7. Advanced data visualization using ggplot2 (plotnine)

References:

1. Meysman, A., Cielen, D. and Ali, M, *Introducing Data Science: Big data, machine learning, and more, using Python tools*, Manning Publishers, 2016.
2. C J Date, *Database Design and Relational Theory: Normal Forms and All That Jazz,* O′Reilly, 2012
3. Cathy Tanimura. *SQL for Data Analysis: Advanced Techniques for Transforming Data into Insights,* O′Reilly, 2021.

4. Deborah Nolan, Duncan Temple Lang, *XML and Web Technologies for Data Sciences with R,* Springer, 2014.
5. Andreas Meier, Michael Kaufmann. *SQL & NoSQL Databases: Models, Languages, Consistency Options and Architectures for Big Data Management,* Springer, 2019.
6. Andy Kirk, *Data Visualisation: A Handbook for Data Driven Design,* 2nd Edn., SAGE Publications Ltd, 2016.
7. Kyran Dale., *Data Visualization with Python and JavaScript: Scrape, Clean, Explore & Transform Your Data,* O′Reilly, 2016.
8. Abha Belorkar, Sharath Chandra Guntuku., *Interactive Data Visualization with Python: Present your data as an effective and compelling story,* 2nd Edn, Packt Publishing Limited, 2020.

EC6449E: OPTIMIZATION FOR MACHINE LEARNING

Pre-requisites: Basic Skill in Matrix Theory

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Equip with basic optimization techniques commonly used in Machine Learning
CO2: Design optimization frameworks to formulate machine learning solutions for real-world problems.
CO3: Develop skill to conduct independent research in the area of Machine Learning.

The Basics of Optimization, Univariate Optimization, Gradient Descent, Multivariate Optimization, Convex Objective Functions, Convex Optimization, Properties of Optimization in Machine Learning, Typical Objective Functions and Additive Separability, Stochastic Gradient Descent, Tuning Hyperparameters, Feature Preprocessing, Computing Derivatives with Respect to Vectors, Useful Matrix Calculus Identities, The Chain Rule of Calculus for Vectored Derivatives, Optimization Models for Binary Targets: Least-Squares Classification, Support Vector Machine (SVM), Logistic Regression.

Challenges in Gradient-based Optimization: Local Optima and Flat Regions, Differential Curvature, Cliffs and Valleys – Adjusting First-Order Derivatives for Descent: Momentum based Learning, AdaGrad, RMSProp, Adam. Newton Method: Newton Method for Linear Regression, SVMs, Logistic Regression. Challenges and Solutions: Singular and Indefinite Hessian, Saddle-Point Problem, Convergence Problems.

Constrained Optimization and Duality – Primal Gradient Descent Methods – Linear Equality Constraints, Linear Inequality Constraints, Sequential Quadratic Programming, Lagrangian Relaxation and Duality, Kuhn-Tucker Optimality Conditions, General Procedure for using Duality, Application in SVM.

Optimization in Computational Graphs: Basics of Computational Graphs, Neural Networks as Directed Computational Graphs, Optimization in Directed Acyclic Graphs, Computational Graphs with Vector Variables, Application: Backpropagation in Neural Networks.

References:

1. Charu C. Aggarwal, *Linear Algebra and Optimization for Machine Learning*, Springer, 2020.
2. Gilbert Strang, *Linear Algebra and Learning from Data*, Cambridge: Wellesley-Cambridge Press, 2019.
3. Deisenroth, Marc Peter, A. Aldo Faisal, and Cheng Soon Ong., *Mathematics for Machine Learning*, Cambridge University Press, 2020.

EC6450E: PROBABILISTIC MACHINE LEARNING

Pre-requisites: Probability Theory and Applications (EC6403), Machine Learning and Pattern Recognition (EC6404)

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Develop, analytically describe, and implement linear and generalized linear models in the Bayesian framework.
CO2: Demonstrate an understanding of the non-linear regression in Bayesian regression using Gaussian Processes.
CO3: Perform approximate Bayesian inference using Markov chain Monte Carlo and variational inference techniques**.**
CO4: Formulate Bayesian deep learning solution to complex machine learning problems involving uncertainty quantification.

Parameter Estimation and Linear Models
Probabilistic machine learning vs classical machine learning – uncertainty quantification, out of distribution performance.
Review of Likelihood, prior, posterior, marginal likelihood, predictive distribution. Review of parameter estimation via Maximum Likelihood (ML), MAP and fully Bayesian inference.
Conjugate priors – MAP and fully Bayesian inference using conjugate priors – Examples of conjugacy: Beta-Bernoulli, Dirichlet-Multinomial.
Probabilistic linear regression: Bayesian inference for mean and variance of Gaussian, Linear Gaussian model – Exponential family of distributions. ML and exponential family, ML and moment matching. Bayesian inference for exponential family of distributions.
Bayesian inference for logistic regression – Laplace Approximation of Posterior Distribution – Introduction to Generalized Linear Models (GLM).

Gaussian Process
Limitations of linear models – Learning non-linear function using Gaussian Process (GP) – Prediction using GP – GP regression: weight space view vs function space view – GP classification – Learning hyper-parameters in GP – Neural networks and GP – Active Learning and Bayesian Optimization – GP surrogate functions, Acquisition functions – Probability of improvement, expected improvement, Upper confidence bound. Regret bounds in Bayesian optimization.

Approximate Inference
Review of multiparameter and latent variable models – Conditional posterior and local conjugacy – Gibs sampling for multiparameter posterior – Parameter estimation in latent variable models – Expectation-Maximization (EM) algorithm.
Variational Inference (VI): Deriving the ELBO – Variational Inference and Expectation Maximization. Mean-Field VI – VI by Computing ELBO Gradients – VI for Non-conjugate Models - Black-Box VI, VI using Reparametrization Trick – Amortized VI, Structured VI, Automatic Differentiation VI.
Approximate inference using sampling - Rejection Sampling, Markov Chain Monte Carlo - Metropolis Hastings (MH), Gibbs sampling, Langevin Dynamics, Hamiltonian Monte Carlo (HMC).

Bayesian Deep Learning
Review of neural networks and deep learning – Bayesian neural networks (BNN). Inference for BNN. Deep ensembles – Classical models for unsupervised learning – Factor analysis and Probabilistic PCA, Gaussian Process Latent Variable Models – Deep Generative models – Variational autoencoder, Generative Adverserial Networks, Invertible neural networks and inverse problems.

References:

1. Kevin Murphy, *Probabilistic Machine Learning: An Introduction (PML-1)*, MIT Press, 2022
2. Kevin Murphy, *Probabilistic Machine Learning: Advanced Topics (PML-2)*, MIT Press, 2022.
3. Christopher Bishop, *Pattern Recognition and Machine Learning (PRML)*, Springer,2006.

EC6451E: REINFORCEMENT LEARNING

Pre-requisites: Familiarity with machine learning and training neural networks with modern libraries and Background in Linear Algebra, Probability and Statistics, Computer Programming (Python)

L	T	P	O	C
3	0	0	6	3

Total Lecture Sessions: 39

Course Outcomes:

CO1: Model real-world sequential decision-making problems using Markov decision process and knowledge of associated solution methodologies.
CO2: Analyze classical model-free reinforcement learning algorithms and state-of-art deep reinforcement learning algorithms.
CO3: Solve sequential decision-making problems with hidden dynamics using exact and reinforcement learning techniques.
CO4: Demonstrate the potential of reinforcement learning in real-world problems through a course project.

Review of probability and statistics: Random variable, Expectation, Conditional Probability, Conditional Expectation, Markov Property, and Markov Chains.
Markov Reward Process: Definition, Finite and Infinite horizon reward process, Value function and Bellman equation. Markov Decision Process (MDP): Definition, Finite and Infinite horizon MDP, Bellman dynamic programming equations for MDP. Numerical solution methods: Value iteration, Policy iteration (Generalized policy iteration), Linear programming.

Reinforcement learning: model free methods.
Monte Carlo and Temporal Difference Learning methods: Estimation of value function using Monte Carlo: first-visit and every-visit – Q-learning and Q-learning with exploration – Temporal difference methods: TD (0) and TD (λ) – Policy iteration using TD learning – Double Learning – Deep reinforcement methodologies: Deep Q-learning (DQN), Double DQN, and Duelling DQN.
Policy Gradient reinforcement learning methods: Policy gradient, Policy gradient theorem (finite and infinite horizon), REINFORCE, REINFORCE with baseline – Actor-Critic algorithm. Advantage Actor-Critic (A2C) and Asynchronous A2C (A3C) – Exploration in policy gradient.
Recent advances in policy gradient reinforcement learning: Trust region policy gradient algorithms and its variants such as Natural Policy Gradient, Trust Region Policy Optimization, Proximal Policy Optimization, Deterministic Policy Gradient and Deep Deterministic Policy Gradient, Soft-Q learning and Soft actor-critic.

Partially Observed Markov Decision Process
Partially Observed Markov Decision Process (POMDP): Definition, Belief and Belief state formulation of POMDP, Belief computation using Hidden Markov Model (HMM) – Bellman dynamic programming for Finite and Infinite horizon POMDP – Exact algorithms for POMDP, Reinforcement learning in POMDP: Policy gradient and Deep Recurrent Q-learning networks (DQRN).
Other topics in reinforcement learning: Multi-agent learning, Meta-learning, Ethics in reinforcement learning, Application of reinforcement learning to real-world problems.

References:

1. Lyla B. Das, Sudhish N. George, Anup Aprem, *Artificial Intelligence and Machine Learning: Theory and Practice*, IK International Publishing House, 2022.
2. R. Sutton and A. Barto, *Reinforcement Learning: An Introduction,* 2nd Edn., MIT Press, 2018.
3. C. Szepesvari. Morgan and Claypool Publishers, *Algorithms for Reinforcement Learning,* 2010.
4. M. Wiering and M. van Otterlo, *Reinforcement Learning: State-of-the-Art*, Springer, 2012.