Master of Technology

in

Computer Science & Engineering

[Artificial Intelligence]

Course Structure & Syllabus

Department of Computer Science & Engineering

National Institute of Technology Hamirpur

Hamirpur (HP) - 177005, India

1st Semester							
Sr. No.	Subject Code	Subject Name	Teaching Schedule			Hours/Week	Credit
			L	T	P		
1	CS-631	Artificial Intelligence and Intelligent Systems	4	0	0	4	4
2	CS-632	Mathematics for Machine Learning	4	0	0	4	4
3	CS-633	Applied Optimization	4	0	0	4	4
4	CS-7MN	Programme Elective-I	4	0	0	4	4
5	CS-7MN	Programme Elective-II	4	0	0	4	4
6	CS-634	AI based Programming Lab	1	0	2	3	2
Total			**21**	**0**	**2**	**23**	**22**

2nd Semester							
Sr. No.	Subject Code	Subject Name	Teaching Schedule			Hours/Week	Credit
			L	T	P		
1	CS-641	Deep Learning	4	0	0	4	4
2	CS-642	Natural Language Processing	4	0	0	4	4
3	CS-643	Reinforcement Learning	4	0	0	4	4
4	CS-7MN	Programme Elective-III	4	0	0	4	4
5	CS-70X	Institute Elective	4	0	0	4	4
6	CS-644	Deep Learning and Data Analytics Lab	1	0	2	3	2
Total			**21**	**0**	**2**	**23**	**22**

3rd Semester							
Sr. No.	Subject Code	Subject Name	Teaching Schedule			Hours/Week	Credit
			L	T	P		
1	CS-798	M.Tech. Dissertation	-	-	-	-	18
Total			**-**	**-**	**-**	**-**	**18**

4th Semester							
Sr. No.	Subject Code	Subject Name	Teaching Schedule			Hours/Week	Credit
			L	T	P		
1	CS-799	M.Tech. Dissertation	-	-	-	-	18
Total			**-**	**-**	**-**	**-**	**18**

Semester	1st	2nd	3rd	4th	Total
Credits	22	22	18	18	80

Annexure
List of Programme Electives

CS-741 Big Data Analytics
CS-742 Speech Information Processing
CS-743 Probabilistic Graphical Models
CS-744 Probabilistic models for Deep Learning
CS-745 Large Language Models
CS-746 Computer Vision and Image Processing
CS-747 Deep Learning for Computer Vision
CS-748 Information Retrieval
CS-749 Text Mining and Analytics
CS-750 Exploratory Data Analytics and Explainable AI
CS-751 Machine Translation
CS-752 Neural Network and Fuzzy Logic
CS-753 IPR in Artificial Intelligence
CS-754 Generative AI

In addition to these electives, any other core/elective of M.Tech. Computer Science & Engineering may also be floated as elective for M.Tech. Artificial Intelligence.

List of Institute Electives

CS-701: Artificial Intelligence
CS-702: Machine Learning for Engineers
CS-703: Data Structures & Algorithms
CS-704: Computer Networks
CS-705: Programming for Problem Solving

Course Name: **Artificial Intelligence and Intelligent Systems**

Course Code: **CS-631**

Course Type: **Programme Core**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about Artificial Intelligence.
- To give understanding of the main abstractions and reasoning for intelligent systems.
- To enable the students to understand the basic principles of Artificial Intelligence in various applications.

Course Content

Introduction: Overview of AI problems, AI problems as NP, NP-Complete and NP Hard problems. Strong and weak, neat and scruffy, symbolic and sub-symbolic, knowledge-based and data-driven AI. Search Strategies: Problem solving by search, Heuristics and informed search, Minmax Search, Alpha-beta pruning. Constraint satisfaction (backtracking and local search methods). A* and AO* algorithms, BFS, DFS algorithms. Knowledge representation and reasoning: propositional and predicate logic, Resolution and theorem proving, Temporal and spatial reasoning. Probabilistic reasoning, Bayes theorem. Totally-ordered and partially-ordered Planning. Goal stack planning, Nonlinear planning.

Learning: Learning from example, Learning by advice, Explanation based learning, Learning in problem solving, Classification, Inductive learning, Naive Bayesian Classifier, decision trees. Agents: Definition of agents, Agent architectures (e.g., reactive, layered, cognitive), Multi-agent systems- Collaborating agents, Competitive agents, Swarm systems and biologically inspired models. Intelligent Systems: Representing and Using Domain Knowledge, Expert System Shells, Explanation, Knowledge Acquisition. Key Application Areas: Expert system, decision support systems, Speech and vision, Natural language processing, Information Retrieval, Semantic Web.

Course Outcomes

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

CO1: Solve basic AI based problems.

CO2: Define the concept of Artificial Intelligence.

CO3: Apply AI techniques to real-world problems to develop intelligent systems.

CO4: Select appropriately from a range of techniques when implementing intelligent systems.

Text Books:

1. Artificial Intelligence by Elaine Rich, Kevin Knight and Shivashankar B Nair, Tata McGraw Hill.
2. Introduction to Artificial Intelligence and Expert Systems by Dan W. Patterson, Pearson Education.
3. Artificial Intelligence: A Modern Approach by S. Russell and P. Norvig, Prentice Hall.

Reference Books:

1. Human Compatible: Artificial Intelligence and the Problem of Control by Stuart Russel, Viking.
2. A First Course in Artificial Intelligence by Deepak Khemani, Tata McGraw Hill.
3. Life 3.0 Being Human in the Age of Artificial Intelligence by Max Tegmark, Penguin UK.

Course Name: **Mathematics for Machine Learning**
Course Code: **CS-632**
Course Type: **Programme Core**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about the various machine learning approaches.
- To introduce the fundamental mathematical concepts relevant to understand the machine learning theory.
- To introduce the working of various state of the art ML algorithms.
- To learn to choose the appropriate ML algorithm to solve the given problem.

Course Content

Probability Theory: conditional probability, Bayes' theorem, independence, discrete and continuous distributions, joint distributions, and covariance. Linear Algebra: Vector spaces and subspaces, basis and dimensions, linear transformation, Norms and spaces, eigenvalues and eigenvectors, Special Matrices and their properties.
Convex Optimization: Unconstrained and Constrained optimization, Newton's method, Steepest descent method, Penalty function method Statistical Decision Theory - Regression, Classification, Bias Variance, Linear Regression, Multivariate Regression, Subset Selection, Shrinkage Methods, Principal Component Regression, Partial Least squares, Linear Classification, Logistic Regression, Linear Discriminant Analysis, Perceptron, Support Vector Machines. Decision Trees, Regression Trees, Stopping Criterion & Pruning loss functions, Categorical Attributes, Multiway Splits, Missing Values, Decision Trees - Instability Evaluation Measures Bootstrapping & Cross Validation, Class Evaluation Measures, ROC curve, MDL, Ensemble Methods - Bagging, Committee Machines and Stacking, Boosting Gradient Boosting, Random Forests, Multi-class Classification, Naive Bayes, Bayesian Networks Undirected Graphical Models, HMM, Variable Elimination, Belief Propagation Partitional Clustering, Hierarchical Clustering, Birch Algorithm, Density-based Clustering, Gaussian Mixture Models, Expectation Maximization.

Course Outcomes

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

CO1: Understand the concepts from matrix algebra, calculus and optimization.
CO2: Understand and apply the concepts related to probability, probability distributions and Matrix theory.
CO3: Solve a given problem by selecting appropriate technique.
CO4: Devise solutions to new problems by applying the concepts of optimization to machine learning.

Text Books:

1. Mathematics for Machine Learning by Marc Peter, Aldo Faisal, Cheng Soon, Cambridge University Press.
2. Discrete mathematics and its applications by Kenneth Rosen.
3. Linear Algebra and Optimization for Machine Learning by Charu C Aggarwal, Springer

Reference Books:

1. Introduction to Linear Algebra by Gilbert Strang, Wellesley.
2. The elements of statistical learning by Trevor Hastie, Robert Tibshirani, Jerome Friedman, Springer.
3. Pattern Recognition and Machine Learning, by Christopher Bishop.

Course Name: **Applied Optimization**
Course Code: **CS-633**
Course Type: **Programme Core**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about the various approaches of optimization theory.
- To introduce the fundamental & relevant concepts like first order methods, LPPs, Langrangian duality, second order methods, etc.
- To enable the students to solve real world problem by using concepts of optimization theory.
- To impart the knowledge related to the role of optimization in Machine learning and AI.

Course Content

Introduction, Convex Sets, Convex Functions, Optimization Basics, First-Order Methods Gradient Descent, More Gradient Descent and Sub gradients, The Sub gradient Method and Oracle Lower Bounds, Projected Gradient Descent and the Proximal Method, More Proximal Method Stochastic Gradient Descent, Mirror Descent, Duality, LPs and Lagrangian Duality, More Lagrangian Duality and KKT, Fenchel Conjugates and Fenchel Duals Newton method, conjugate direction method, quasi newton method, projected gradient methods, penalty methods (Nearly)-Convex Optimization Sums of Squares, Second-order optimization: Newton's method and Preconditioned Gradient Descent Adaptive optimization algorithms Limitations of convex optimization, Introduction to Non-convex optimization

Course Outcomes

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

CO1: Understand the basic concepts from optimization theory like first order methods, etc.

CO2: Understand and apply the concepts related to gradient descent, LPPs, duality, second order optimization.

CO3: Solve a given problem by selecting appropriate optimization technique.

Text Book:

1. Convex optimization theory by Dimitri P, MIT.
2. Convex Optimization by Stephen Boud, Lieven Vandenberghe, Cambridge University Press.
3. Numerical optimization by Nocedal, Jorge, and Stephen Wright, Springer Science.
4. Introductory lectures on convex optimization: a basic course , by Yurii, Nesterov,. Kluwer Academic Publishers.

Reference Books:

1. Engineering Optimization: Theory and Practice by S. S. Rao, John Wiley & Sons
2. Nonlinear optimization with engineering applications by Michael C. Bartholomew-Biggs, Springer.

Course Name: **AI based Programming Lab**
Course Code: **CS-634**
Course Type: **Programme Core 'Lab'**

Contact Hours/Week: **1 L & 2P** Course Credits: **02**

Course Objectives

- To provide skills for designing and analyzing AI based algorithms.
- To enable students to work on various AI tools.
- Study uninformed and heuristic search techniques.
- Learn techniques for reasoning under uncertainty.
- Learn the techniques to solve NP-hard problems using meta-heuristic techniques.
- Learn the basics of deep learning using neural networks.

List of Experiments

1. Installation and working on various AI tools viz. Python, R tool, GATE, NLTK, MATLAB, etc.
2. Data preprocessing and annotation and creation of datasets.
3. Implementation of searching techniques in AI.
4. Implementation of Knowledge representation schemes.
5. Natural language processing tool development.
6. Application of Machine learning algorithms.
7. Application of Classification and clustering problem.
8. Working on parallel algorithms.
9. Scientific distributions used in python for Data Science - Numpy, scify, pandas, scikitlearn, statmodels, nltk.
10. Implementation of Uninformed search algorithms (BFS, DFS).
11. Implementation of Informed search algorithms (A*, memory-bounded A*).
12. Implement naïve Bayes models.
13. Implement Bayesian Networks.
14. Implementation of AO* Algorithm.
15. Implementation of Alpha-Beta Pruning algorithm.
16. Implementation of Genetic Algorithm.
17. Implementation of PSO Algorithm.
18. Build simple NN models.
19. Build deep learning NN models.

Note: *The concerned Course Coordinator will prepare the actual list of experiments/problems at the start of semester based on above generic list.*

Course Outcomes

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

CO1: Elicit, analyze and specify software requirements.
CO2: Simulate given problem scenario and analyze its performance.
CO3: Develop programming solutions for given problem scenario.

Course Name: **Deep Learning**
Course Code: **CS-641**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To introduce the principles of deep learning and its applications.
- To enable the students in practical skills to design, implement, and train practical deep learning systems.
- To provide a structured approach covering Fundamentals of Machine Learning, Neural Networks, Modern Deep Learning, and Applications and other advanced topics.

Course Content

Introduction to Deep Learning: Overview of neural networks and deep learning, Historical perspective and key milestones in deep learning, Deep learning applications in computer vision, natural language processing, and reinforcement learning; Deep Neural Networks: Early Models, Perceptron Learning, Multilayer Perceptrons (MLPs) and feedforward neural networks, Backpropagation, Initialization, Training & Validation, Parameter Estimation - MLE, MAP, Bayesian Estimation, Activation functions, loss functions, and optimization techniques, Regularization methods and hyperparameter tuning; Convolutional Neural Networks (CNNs): Architecture of CNNs and convolutional layers, Pooling layers, batch normalization, and dropout, Applications of CNNs in image recognition and computer vision tasks; Recurrent Neural Networks (RNNs): Introduction to RNNs and Long Short-Term Memory (LSTM) networks, Sequence modeling, text generation, and time series prediction, Attention mechanisms and Transformer models; Generative Adversarial Networks (GANs): Fundamentals of GANs and adversarial training, Conditional GANs, StyleGAN, and CycleGAN, Applications of GANs in image generation, style transfer, and data augmentation; Advanced Topics in Deep Learning: Transfer learning and domain adaptation, Autoencoders, Variational Autoencoders (VAEs), and unsupervised learning, Reinforcement learning with deep neural networks, Transformers, LLMs.

Course Outcomes

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

CO1: Demonstrate the ability to apply concepts from linear algebra, probability, optimization, and machine learning to solve complex problems in the context of deep learning.

CO2: Evaluate the advantages and disadvantages of deep learning neural network architectures and compare them with other approaches in the context of case studies.

CO3: Design, implement, and train deep learning models using convolutional, recurrent, and other neural network architectures to address real-world problems effectively.

CO4: Analyze, design, and implement solutions to real-world computer vision problems, NLP and other problems using deep learning techniques.

Text Books:

1. Deep Learning by Ian Goodfellow, Yoshua Bengio, and Aaron Courville, MIT Press.
2. Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow by Aurélien Géron, O'Reilly Media.
3. Neural Networks and Deep Learning by Michael Nielsen, Determination Press.

Reference Books:

1. Deep Learning for Computer Vision by Rajalingappaa Shanmugamani, Packt Publishing.
2. Generative Deep Learning by David Foster, O'Reilly Media.

Course Name: **Natural Language Processing**

Course Code: **CS-642**

Course Type: **Programme Core**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To learn about the concepts and principles of natural language processing.
- To explore both theoretical and practical issues of natural language processing.
- To develop skills of finding solutions and building software using natural language processing techniques.

Course Content

Introduction: Knowledge of Natural Language Processing, Components of NLP, NLP Stages, challenges of NLP, Ambiguity, Applications of NLP, Language, Thought, and Understanding, Text representation in computers, encoding schemes Word Level Analysis: Regular expression, finite automata, Morphological analysis –survey of English Morphology, Inflectional & Derivational morphology, Stemming, Lemmatization, finite state transducers (FST), Morphological parsing with FST, Lexicon free FST Porter stemmer. N-GRAM Language Models: Counting words in Corpora, word prediction, N-Gram probabilities, Smoothing, Evaluating N-Gram Perplexity, N-gram for spelling correction. Syntax and Semantic analysis: Word Classes and Part-of-Speech Tagging, Tag sets for English - Penn Treebank POS tags, Rule-based Part-of-speech Tagging, Stochastic POS tagging, HMM, Transformation based tagging (TBL), Multiple tags and multiple words, Handling of unknown words, NLP grammar: Context-Free Grammars, parsing with Context Free Grammars, Meaning representation, semantic analysis, lexical semantics, WordNet, Word Sense Disambiguation- Selection Restriction-Based Disambiguation, Limitations of Selection Restrictions, Robust Word Sense Disambiguation, machine learning approaches, and dictionary based approaches

Pragmatics & Corpora: Discourse, Reference Resolution, Reference Phenomena, Syntactic and Semantic Constraints on Coreference, Preferences in Pronoun Interpretation, Text Coherence and Inference Based Resolution Algorithm, Balanced corpus, Concordance and corpora, characteristics of Gold Standard Corpora, Training and Test sets, corpus types, TreeBank, PropBank, WordNet, VerbNet etc., NLTK, Inter-Annotator Agreement Tests, kappa statistics. Corpus annotation tools. NLP Applications: Information Extraction, multi word expressions, Names Entity Recognition, Information Retrieval, Sentiment analysis, Machine Translation and Performance Metrics, Question Answering and Summarization, Summarization Evaluation.

Course Outcomes

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

CO1: Understand concept of natural language processing.

CO2: Understand various research issues in natural language processing.

CO3: Apply various tools and techniques in natural language processing.

Text Books:

1. Speech and Language Processing by Daniel Jurafsky and James H. Martin, Prentice Hall.
2. Language as a Cognitive Process by T. Winograd, Addison-Wesley.

Reference Books:

1. Natural Language Understanding by James Allen, the Benajmins/Cummings.
2. Natural language processing: a Paninian perspective by A. Bharati, R. Sangal, and V. Chaitanya, PHI.

Course Name: **Reinforcement Learning**
Course Code: **CS-643**
Course Type: **Programme Core**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To introduce the fundamental concepts relevant to reinforcement learning and formulate tasks.
- To impart knowledge about the various approaches to design solutions using various reinforcement learning approaches.
- To impart knowledge about advanced concepts such as meta learning & multi-agent learning and applications.

Course Content

Task Formulation: Action space, state space, and environment definition; Defining RL environments; Markov Chains: Basics of finite Markov chains; classical Markov Chains including Coupon Collection, Gambler's Ruin, Polya's urn, Birth and Death chains; Tabular Based Solutions: Dynamic programming; Monte Carlo methods; Temporal difference learning; Function Approximation Solutions: Deep Q-networks; Linear value function approximation; Non-linear value function approximation; Policy Gradient Methods: REINFORCE; Proximal policy optimization; Deep deterministic policy gradient; Model-Based Reinforcement Learning: Model-based RL; Model-free RL; Imitation Learning: Behavioral cloning; Inverse RL; Generative adversarial imitation learning; Meta-Learning: Meta-learning in RL; Applications of meta-learning in RL; Multi-Agent Learning: Multi-agent RL; Partially observable environments

Course Outcomes

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

CO1: Understand Markov chains and setup the reinforcement learning problem.

CO2: Understand and apply various reinforcement learning problem solving techniques.

CO3: Solve given problem by selecting the appropriate technique and justify the selection.

CO4: Formulate a solution to new problems using the concepts and techniques from reinforcement learning.

Text Books:

1. Reinforcement Learning: An Introduction by Richard S. Sutton, Andrew G. Barto · 2018 19 October 2018 MIT Press

2. Reinforcement Learning and Stochastic Optimization by Warren B. Powell, Wiley.

3. Markov Chains and Mixing Times by D. A. Levin, Y. Peres, and E. Wilmer, American Mathematical Society.

Reference Books:

1. Deep Reinforcement Learning in Action by Brandon Brown, Alexander Zai, Manning.

2. Deep Reinforcement Learning Hands-on by Maxim Lapan, Packt Publishing.

Course Name: **Deep Learning and Data Analytics Lab**
Course Code: **CS-644**
Course Type: **Programme Core 'Lab'**

Contact Hours/Week: **1 L & 2P** Course Credits: **02**

Course Objectives

- To provide exposure of working on Deep learning and Data Analytics platforms.
- To design and implement solutions for real life problems.

List of Experiments

1. Installation and working on various tools viz. Hadoop, Python, Spark, NoSQL, ANACONDA, Tensorflow, Keras, AWS, etc.
2. Understanding key technology foundations required for Big Data.
3. Implement multilayer neural network with nonlinear activation functions, such as, sigmoidal and bipolar sigmoidal functions to analyze the response of the multilayer neural network.
4. Implement a perceptron model to realize logic functions/gate, namely, AND, OR, and XOR.
5. Design a neural network to implement logical OR and NOT function using bipolar-output patterns.
6. Design convolutional neural network for image classification in presence of limited data.
7. Apply autoencoder to produce a compressed representation of a high-dimensional input.
8. Implement L2 regularization to avoid overfitting in any deep learning model
9. To implement sentiment analysis using Long Short Term Memory Understanding.
10. Development of real-time data based application using times series prediction.
11. Apply transformers for parallel processing to substantially speed up the training process.
12. Apply Generative Adversarial Networks (GANs) to generate realistic images.
13. Development of application using pytorch library based on reinforced learning with deep neural network.

Note: *The concerned Course Coordinator will prepare the actual list of experiments/problems at the start of semester based on above generic list.*

Course Outcomes

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

CO1: Simulate/implement given problem scenario and analyze its performance.

CO2: Design solutions for real life problems.

Course Name: **Big Data Analytics**

Course Code: **CS-741**

Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To understand the Big Data Platform and its Use cases.
- Apply analytics on Structured and Unstructured Data.
- Acquire the knowledge and working on Big Data platforms.

Course Content

Introduction to Big Data: Types of Digital Data, Concept, importance and characteristics of data, Challenges with big data, Big Data stack, Big Data 1.0, 2.0 and 3.0, Traditional BI versus Big Data Environment, NoSQL Databases, NoSQL Vs. RDBMS, New SQL Analyzing Data with Hadoop, IBM Big Data Strategy. Introduction of Hadoop HDFS, Design, Concepts, Command Line Interface, Hadoop I/O: Compression, Serialization, Avro and File-Based Data structures. Map Reduce, Anatomy of a Map Reduce Job Run, Failures, Job Scheduling, Shuffle and Sort, Task Execution. Introduction to YARN, Architecture, Daemons, Word Count Example using Java, Introduction to Hadoop 3.0, Difference among Hadoop1.0, Hadoop2.0, Hadoop3.0 Introduction to Mongo DB: RDBMS vs. MongoDB, JSON, Unique Key, Dynamic Queries, Sharding, Replication, MongoDB QL: Create, Drop Database. Cassandra DB: Features of Cassandra, CQL Data Types, CQLSH: Counter, TTL, List, Set, Map, Tracing. Introduction to Apache Pig: Execution Modes of Pig, Comparison of Pig with Databases, Grunt, Pig Latin, Data Processing operators, Piggy Bank. Hive: Hive Shell, Hive Services, Hive Metastore, Comparison with Traditional Databases, HiveQL, Tables, Querying Data and User Defined Functions. HBase: Concepts, Characteristics, HBase Versus RDBMS.

Course Outcomes

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

CO1: Understand the concept and challenges of big data.

CO2: Describe and analyze various Big Data Analytics with Hadoop.

CO3: Collect, manage, store, and query in Mongo DB and Cassandra.

CO4: Query and analyze over big data with Pig and Hive.

Textbooks:

1. Big Data and Analytics by Seema Acharya and Subhashini Chellappan, Wiley
2. Taming the Big Data Tidal Wave: Finding Opportunities in Huge Data Streams with Advanced Analytics by Bill Franks, John Wiley & Sons.
3. Hadoop: The Definitive Guide by Tom White, O'reily Media.

Reference Books:

1. Big Data and Business Analytics by Jay Liebowitz, Auerbach Publications, CRC Press.
2. Hadoop in Action by Chuck Lam Manning Publications.

Course Name: **Speech Information Processing**
Course Code: **CS-742**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To understand the concept of speech processing.
- To build speech-based systems.
- To analyze the performance of speech processing systems.

Course Content

Introduction: Speech and Language, Phonetics-Speech Sounds and phonetic transcription, Articulatory Phonetics, Phonological Categories and Pronunciation variation, The Speech Chain, Applications of Speech Processing, Hearing and Auditory Perception: The Human Ear, Perception of Loudness, Critical Bands, Pitch Perception, Auditory Masking, Complete Model of Auditory Processing Speech Analysis: Short-Time Analysis of Speech: Autocorrelation Function (STACF), Short-Time Fourier Transform (STFT), Sampling the STFT in Time and Frequency, The Speech Spectrogram, Relation of STFT to STACF, Homomorphic Speech Analysis: Cepstrum and Complex Cepstrum, The Short-Time Cepstrum, Computation of the Cepstrum, Short-Time Homomorphic Filtering of Speech, Application to Pitch Detection, Applications to Pattern Recognition, The Role of the Cepstrum Linear Predictive Analysis: Linear Prediction and the Speech Model, Computing the Prediction Coefficients, The Levinson–Durbin Recursion, LPC Spectrum, Equivalent Representations, The Role of Linear Prediction, Digital Speech Coding: Sampling and Quantization of Speech (PCM), Digital Speech Coding, Closed-Loop Coders, Open-Loop Coders, Frequency-Domain Coders, Evaluation of Coders
Text-to-Speech Synthesis Methods: Text Normalization, Phonetic Analysis, Prosodic Analysis, Diphone waveform Synthesis, Unit Selection Synthesis, Evaluation, TTS Applications, TTS Future Needs, Automatic Speech Recognition (ASR): Speech Recognition Architecture, building a Speech Recognition System, The Decision Processes in ASR, Representative Recognition Performance, Challenges in ASR Technology, Practical Techniques for Improving ASR and Performance. ASR for Large Vocabularies.

Course Outcomes

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

CO1: Explain the mechanism of human speech production and perception.
CO2: Explain each component of speech recognition systems.
CO3: Understand the importance of probabilistic modeling in speech recognition.
CO4: Build a speech recognition system.

Text Books:

1. Digital Speech Processing: Synthesis, and Recognition by Sadaoki Furui, CRC Press.
2. Speech Synthesis and Recognition by Wendy Holmes, CRC Press.

Reference Book:

1. Audio Signal Processing and Coding by Andreas Spanias, Ted Painter and Venkatraman Atti, Willey.
2. Introduction to Digital Speech Processing by Lawrence R. Rabiner and Ronald W. Schafer, Foundations and Trends® in Signal Processing.

Course Name: **Probabilistic Graphical Models**
Course Code: **CS-743**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To introduce the fundamental concepts relevant to probability theory and Markov chains.
- To impart knowledge about the various approaches to probabilistic graphical models such as Bayesian models and Graph Neural Networks.
- To impart knowledge about relevant advanced concepts such as temporal networks, inference & parameter estimation in PGMs.

Course Content

Introduction to Probability Theory: Basic concepts of probability, Conditional probability and Bayes' theorem, Random variables and probability distributions; Markov Chains: Definition and properties of Markov chains, Transition probabilities and stationary distributions, Applications of Markov chains in modeling sequential data; Bayesian Models: Bayesian inference and parameter estimation, Bayesian Networks (BNs) and Directed Graphical Models (DGMs), Conditional Probability Distributions (CPDs) and Causal Inference; Graph Neural Networks: Introduction to Graph Neural Networks (GNNs), Probabilistic Graphical Models with Neural Networks, Learning and decision-making in evolving structured environments; Advanced Topics: Temporal Bayesian Networks, Probabilistic Graphical Models for structured data, Inference and parameter estimation in PGMs.

Course Outcomes

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

CO1: Understand basic concepts of probability and Markov chains.
CO2: Understand and apply various Probabilistic Graphical Models.
CO3: Solve given problem by selecting the appropriate PGM technique and justify the selection.
CO4: Formulate a solution to new problems using the concepts and techniques from Probabilistic Graphical Models.

Text Books:

1. Probabilistic Graphical Models: Principles and Techniques by Daphne Koller and Nir Friedman, MIT Press.
2. Pattern Recognition and Machine Learning by Christopher M. Bishop, Springer.
3. Bayesian Reasoning and Machine Learning by David Barber, Cambridge University Press.

Reference Books:

1. Graphical Models for Machine Learning and Digital Communication by Brendan J. Frey, MIT Press.
2. Deep Learning by Ian Goodfellow, Yoshua Bengio, and Aaron Courville, MIT Press.

Course Name: **Probabilistic models for Deep Learning**
Course Code: **CS-744**
Course Type: **Programme Elective**
Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about the basic probability theory and Bayesian networks.
- To introduce the fundamental concepts about the various deep networks such as deep belief networks.
- To introduce the students about the relevant advanced topics such as VAE, GAN, etc.

Course Content

Introduction to probability theory, Marginal, conditional and Joint Distributions, Representations of joint distributions, graphs to represent joint distributions. Bayesian networks, Types of reasoning in Bayesian networks, Independences in Bayesian networks, I-Maps, Markov networks, Factors and Independences in markov networks.

Latent variables, Restricted Boltzmann machines, Deep belief networks, RBMs as stochastic neural networks, Sampling. Markov chains, Markov chains for RBMs, Training RBMs using Gibbs sampling and contrastive divergence.

Variational Autoencoders: Neural network perspective, Variational Autoencoders: The Graphical model perspective, Neural Autoregressive density estimator, Masked Autoencoder density estimator (MADE). Generative Adversarial networks (GANs). GAN architecture, Mathematics behind GAN, Applications

Course Outcomes

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

CO1: Understand the concepts related to probability, probability distributions and Markov chains.
CO2: Understand and apply the different probabilistic models such as Bayesian networks, DBNs, etc.
CO3: Solve a given problem by selecting appropriate technique and justify the selection.
CO4: Formulate a solution to new problems using the concepts and techniques from probabilistic models.

Text Books:

1. Probabilistic Deep Learning by Elvis Murina, Oliver Duerr, Beate Sick.
2. Probabilistic Machine Learning by Kevin P. Murphy, MIT Press, Cambridge.

Reference Books:

1. Probabilistic Graphical Models by Daphene koller, Nir Friedman, MIT Press, Cambridge

Course Name: **Large Language Models**
Course Code: **CS-745**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To give students an overview of language models in the context of natural language processing.
- To impart knowledge about the various approaches to design solutions using LLMs.
- To impart knowledge about advanced concepts such as transformers etc.

Course Content

Introduction: The Structure, Statistics, and Representation of Language, Basics of machine learning and deep learning concepts for large language models, Transformers: Introduction to transformers - Self-attention - cross- attention-Masked attention-Positional encoding, A deep dive into number of parameters, computational complexity and FLOPs-Introduction to language modelling, Causal Language Modeling: Generative Pretrained Transformers (GPT) - Training and inference, Masked Language Modeling : Bidirectional Encoder Representations of Transformers (BERT) - Fine-tuning - A deep dive into tokenization: BPE, SentencePiece, wordpiece, Data: Datasets, Pipelines, effectiveness of clean data, Architecture: Types of attention, positional encoding (PE) techniques, scaling techniques, Training: Revisiting optimizers, Loss functions, Learning schedules, Gradient Clipping, typical failures during training, Fine Tuning: Prompt Tuning,Multi-task Fine-tuning,Parametric Efficient Fine-Tuning, Instruction fine-tuning datasets, Benchmarks: MMLU, BigBench, HELM,OpenLLM, Evaluation Frameworks, Training Large Models, Recent advances, LLMs and Society.

Course Outcomes

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

CO1: Be able to explain the architecture of modern LLMs

CO2: Understand and apply various LLM techniques.

CO3: Understanding the concepts of Transformers and its applications.

Text Books:

1. Speech and Language Processing by Jurafsky and Martin. 3rd Ed. https://web.stanford.edu/~jurafsky/slp3/.
2. Natural Language Processing by Eisenstein MIT Press.

Reference Books:

1. Neural Network Methods for Natural Language Processing by Goldberg, Morgan & Claypool Publishers.

Course Name: **Computer Vision and Image Processing**

Course Code: **CS-746**

Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To study the basic image processing concepts and fundamentals.
- To understand image enhancement and transformation techniques.
- To understand the basic concepts of Computer Vision.
- To enable students to apply the various concepts of Computer Vision in other application areas.

Course Content

Introduction: Computer vision and its applications, Digital image formation and low-level processing: Fundamentals of Image Formation, Image Transformation: Orthogonal, Euclidean, Affine, etc. Digital Image Fundamentals: Image Enhancement in Spatial Domain; Gray Level Transformation, Histogram Processing, Spatial Filters. Image Transforms: Fourier Transform and their properties, Fast Fourier Transform, Other Transforms, Colour Image Processing, Image Segmentation Image Descriptors and Feature Extraction: Texture Descriptors, Colour Features, Edges/Boundaries. Interest or Corner Point Detectors, Histogram of Oriented Gradients, Scale Invariant Feature Transform, Speeded up Robust Features Pattern Analysis: Basics of Probability and Statistics, Clustering: K-Means, K-Medoids, Mixture of Gaussians, Classification: Discriminant Function, Supervised, Un-supervised, Semi-supervised; Classifiers: Bayes, Artificial Neural Network models; Dimensionality Reduction: Principal Component Analysis.

Image Classification: Feature-based methods, Deep networks, Object Detection, Semantic Segmentation.

Course Outcomes

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

CO1: Understand the fundamental concepts of digital image processing system.

CO2: Implement various techniques and algorithms used in computer vision.

CO3: Analyze and evaluate critically the building and integration of computer vision algorithms.

CO4: Demonstrate awareness of the current key research issues in computer vision.

Text Books:

1. Digital Image Processing by R. Gonzalez and r. E. Wood, Prentice Hall of India
2. Computer Vision Algorithms and Applications, Richard Szeliski, Springer.
3. Computer Vision: A Modern Approach Hardcover, David Forsyth and Jean Ponce, Pearson.
4. Introductory Computer Vision and Image Processing by Andrian low, McGraw Hill CO.

References Books:

1. Digital Image Processing by W.K. Pratt, McGraw Hill.
2. Computer Vision: Models, Learning, and Inference by Simon J. D. Prince, Cambridge University Press.

Course Name: **Deep Learning for Computer Vision**
Course Code: **CS-747**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To study the deep learning models used in various computer vision problems.
- To understand the working of deep learning models.
- To understand and visualize CNN architectures.
- To enable students to apply the various concepts of deep learning for computer vision tasks.

Course Content

Introduction and Overview: Introduction to Image Formation, Capture and Representation; Linear Filtering, Correlation, Convolution, Edge, Blobs, Corner Detection; Scale Space and Scale Selection; SIFT, SURF; HoG, LBP,etc
Deep Learning Review: Multi-layer Perceptron's, Backpropagation, Introduction to CNNs; Evolution of CNN Architectures: AlexNet, VGG, Inception Nets, ResNets, DenseNets Visualization and Understanding CNNs: Visualization of Kernels; Backprop-to-image/Deconvolution Methods; Deep Dream, Hallucination, Neural Style Transfer; CAM, Grad-CAM, Grad-CAM++; Recent Methods (IG, Segment-IG, SmoothGrad) CNNs for Recognition, Verification, Detection, Segmentation: CNNs for Recognition and Verification (Siamese Networks, Triplet Loss, Contrastive Loss, Ranking Loss); CNNs for Detection: Background of Object Detection, R-CNN, Fast R-CNN, Faster R-CNN, YOLO, SSD, CNNs for Segmentation: FCN, SegNet, U-Net, Mask-RCNN Deep Generative Models: Review of (Popular) Deep Generative Models: GANs, VAEs; Other Generative Models: Pixel RNNs etc. Applications of Generative Models in Vision: Image Editing, Inpainting, Super resolution, 3D Object Generation, Security; Variants: CycleGANs

Course Outcomes

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

CO1: Understand the fundamental concepts of deep learning.
CO2: Implement various deep learning techniques and algorithms used in computer vision.
CO3: Analyze and evaluate deep learning models in terms of their understanding.
CO4: Demonstrate awareness of the current key research issues using deep learning for computer vision .

Text Books:

1. Deep Learning, Ian Goodfellow, Yoshua Bengio, Aaron Courville
2. Neural Networks and Deep Learning, Michael Nielsen
3. Computer Vision Algorithms and Applications, Richard Szeliski, Springer.
4. Computer Vision: A Modern Approach Hardcover, David Forsyth and Jean Ponce, Pearson.

References Books:

1. Digital Image Processing by W.K. Pratt, McGraw Hill.
2. Computer Vision: Models, Learning, and Inference by Simon J. D. Prince, Cambridge University Press.

Course Name: **Information Retrieval**
Course Code: **CS-748**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To learn concepts of Information Retrieval from documents and web portals.
- To evaluate the efficiency of existing Information Retrieval approaches.
- To implement Information Retrieval approaches in real applications.

Course Content

Introduction to Information Retrieval: Concepts, Boolean Retrievals- An Example Information Retrieval Problem, A First Take at Building an Inverted Index, Processing Boolean Queries. Term Vocabulary and Postings Lists: Document Delineation and Character Sequence Decoding, Determining the Vocabulary of Terms. Dictionaries and Tolerant Retrieval: Search Structures for Dictionaries, Wildcard Queries, Spelling Correction, Phonetic Correction.
Index Construction: Hardware Basics Blocked Sort-Based Indexing. Scoring, Term Weighting and the Vector Space Model: Parametric and Zone Indexes, Term Frequency and Weighting, The Vector Space Model for Scoring. Evaluation in Information Retrieval: Information Retrieval System Evaluation, Standard Test Collections, Evaluation of Unranked Retrieval Sets, Evaluation of Ranked Retrieval Results. XML Retrieval: Basic XML Concepts, Challenges in XML Retrieval, A Vector Space Model for XML Retrieval, Evaluation of XML Retrieval, Text-Centric vs. Data-Centric XML Retrieval. Web Search Basics: Web Characteristics, Advertising as the Economic Model, The Search User Experience, Index Size and Estimation, Near- Duplicates and Shingling. Web Crawling and Indexes: Overview, Crawling, Distributing Indexes, Connectivity Servers. Link Analysis: The Web as a Graph, Page Rank, Hubs and Authorities.

Course Outcomes

Upon successful completion of the course, the students will be able to
CO1: Understand different Information Retrieval models.
CO2: Evaluate various Information Retrieval models.
CO3: Evaluate and optimize search engines and develop optimized web search.

Textbooks:

1. Introduction to Information Retrieval by C. Manning, P. Raghavan, and H. Schutze, Cambridge University Press.
2. Modern Information Retrieval: The Concepts and Technology behind Search by Ricardo Baeza Yates and Berthier Ribeiro Neto, ACM Press.

Reference Books:

1. Search Engines: Information Retrieval in Practice by Bruce Croft, Donald Metzler and Trevor Strohman, Pearson.
2. An Introduction to Search Engines and Web Navigation by Mark Levene, Wiley.

Course Name: **Text Mining and Analytics**
Course Code: **CS-749**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about fundamentals of text mining and analytics.
- To introduce the fundamental steps for preprocessing text data.
- To enable the students to apply text mining techniques in different applications.

Course Content

Introduction to Text Mining and Analytics: Overview of unstructured text data, Importance and applications of text mining, Challenges in text mining, Preprocessing Text Data - Tokenization, Stopword removal, Stemming and lemmatization, Text normalization Sentiment Analysis & Topic Modeling: Understanding sentiment analysis, Approaches to sentiment analysis (lexicon-based, machine learning-based), Sentiment analysis applications, Introduction to topic modeling, Latent Dirichlet Allocation (LDA), Non-negative Matrix Factorization (NMF), Applications of topic modelling. Text Classification: Introduction to text classification, Naive Bayes Classifier, Support Vector Machines (SVM), Evaluation metrics for text classification, Text Mining Tools and Libraries: Introduction to Python libraries (NLTK, spaCy, scikit-learn), Hands-on exercises using text mining tools. Advanced Topics, Applications and Case Studies: Named Entity Recognition (NER), Text summarization, Deep learning approaches to text mining, Real-world applications of text mining and analytics, Case studies from various domains (e.g., social media analysis, customer feedback analysis, healthcare)

Course Outcomes

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

CO1: Understand the fundamentals of text mining and analytics.
CO2: Apply text mining techniques to real-world datasets.
CO3: Interpret and communicate the results of text mining analyses effectively.
CO4: Gain proficiency in performing text mining tasks such as sentiment analysis, topic modeling, and text classification.

Textbooks:

1. Text Mining: Applications and Theory by Michael W. Berry and Jacob Kogan, Willey.
2. Text Data Management and Analysis: A Practical Introduction to Information Retrieval and Text Mining by Cheng Xiang Zhai and Sean Massung, ACM.
3. Text Analytics with Python: A Practical Real-World Approach to Gaining Actionable Insights from your Data by Dipanjan Sarkar, Apress.

Reference Books:

1. Practical Text Mining and Statistical Analysis for Non-structured Text Data Applications by Gary Miner, John Elder IV, Thomas Hill, Robert Nisbet, and Dursun Delen, Academic Press, an imprint of Elsevier.
2. Text Mining: Predictive Methods for Analyzing Unstructured Information by Sholom M. Weiss, Nitin Indurkhya, and Tong Zhang, Springer.

Course Name: **Exploratory Data Analytics and Explainable AI**
Course Code: **CS-750**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about fundamental concept of exploratory data analysis and explainable AI.
- To introduce the techniques for exploring and visualizing datasets.
- To enable the students to apply EDA and XAI techniques to real-world applications.

Course Content

Introduction to Exploratory Data Analysis (EDA): Definition and objectives of EDA, Importance of data exploration in the data analysis process, Overview of EDA techniques and tools, Data Preprocessing and Cleaning: Handling missing values, Data normalization and scaling, Outlier detection and treatment, Descriptive Statistics and Data Visualization: Summary statistics (mean, median, standard deviation, etc.), Histograms, box plots, and scatter plots, Heatmaps, pair plots, and correlation matrices, Exploratory Data Analysis Techniques: Univariate analysis, Bivariate analysis, Multivariate analysis Introduction to Machine Learning and Explainable AI (XAI): Overview of supervised and unsupervised learning, Basics of classification and regression, Importance of explainability in AI systems, Ethical and societal implications of black-box AI models, Overview of XAI techniques. Interpretable Models and Feature Importance: Linear models (e.g., linear regression, logistic regression), Decision trees and ensemble methods, Feature importance techniques (e.g., permutation importance, SHAP values), Model-Agnostic Interpretability Techniques: Partial dependence plots (PDPs), Individual conditional expectation (ICE) plots, Local interpretable model-agnostic explanations (LIME), Evaluation and Validation of AI Models: Model performance metrics (accuracy, precision, recall, etc.), Cross-validation and model validation techniques, Case Studies and Applications: Real-world applications of EDA and XAI, Case studies on interpreting and explaining AI model predictions.

Course Outcomes

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

CO1: Understand the principles and importance of exploratory data analysis and concept of explainable artificial intelligence.

CO2: Learn techniques for exploring and visualizing datasets.

CO3: Learn techniques for interpreting and explaining AI model predictions.

CO4: Apply EDA and XAI techniques to real-world datasets and AI models.

Textbooks:

1. Python for Data Analysis: Data Wrangling with Pandas, NumPy, and IPython by Wes McKinney, O'REILLY
2. Interpretable Machine Learning: A Guide for Making Black Box Models Explainable by Christoph Molnar, Leanpub

Reference Books:

1. Explainable AI: Interpreting, Explaining and Visualizing Deep Learning by Wojciech Samek, Grégoire Montavon, Andrea Vedaldi, Lars Kai Hansen and Klaus-Robert Müller, Springer
2. Practical Statistics for Data Scientists: 50 Essential Concepts by Peter Bruce, Andrew Bruce and Peter Gedeck, O'REILLY

Course Name: **Machine Translation**

Course Code: **CS-751**

Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To teach students Machine Translation approaches.
- To evaluate the performance of Machine Translation Systems.
- To develop translation models for Indian Languages.

Course Content

Introduction: Machine Translation (MT) and its approaches, Challenges of Machine Translation, History of MT, N-gram language models, smoothing techniques for language modelling. Language Modeling Probability, conditional language models, Very large language models. Statistical Machine Translation: Word alignment and the expectation maximization algorithm, IBM Models, HMM, Word-based Statistical Machine Translation, From Noisy channel model to Log-linear Model, Phrase based Machine Translation, Phrase extraction. Estimating phrase translation probabilities and the problem of overfitting. Phrase reordering models. Stack Decoding Algorithm, Pruning System combination. Syntax-based translation, Hierarchical and syntax-based MT, Introduction to Moses, Human Evaluation, BLEU Score, METEOR, TER, ROUGE-N Score.

Neural Machine Translation: encoder-decoder model, Reccurent Neural Network Language Model, Neural Translation Model, embedding layer representation, Training of NMT models, Variable Length source representation, RNNs, CNNs, and SANs for NMT Architecture, Multi-head attention, Tranformers, Sequence to Sequence model with attention; Attention and Augmented Recurrent Neural Networks, Bidirectional inference and non-autoregressive NMT, Open-vocabulary translation, Very Large Target Vocabulary for Neural Machine Translation, Unsupervised NMT, Semi-Supervised NMT, Multilingual NMT, transfer learning, Zero-shot NMT, Open-source NMT toolkit. MT for low-resource languages: issues for low resource languages, vocabulary, learning from monolingual data, learning from multilingual data, multilinual machine translation, Pivoting, data augumentation, target-side monolingual data, Back-translation (BT), source-side monolingual data, both source and target side monolingual data approaches, Case studies for Indic languages.

Course Outcomes

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

CO1: Understand machine translation system.

CO2: Explain, apply, and assess manual and automatic evaluation methods for machine translation.

CO3: Build their own translation model using existing tools for machine translation.

Textbooks:

1. Statistical Machine Translation by Philipp Koehn, Cambridge University Press.
2. Neural Machine Translation by Philipp Koehn, Cambridge University Press.

Reference Books:

1. Deep Learning by Ian Goodfellow, Yoshua Bengio and Aaron Courville, MIT Press.
2. Linguistic Fundamentals for Natural Language Processing by Emily Bender, Morgan & Claypool.

Course Name: **Neural Network and Fuzzy Logic**
Course Code: **CS-752**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about the basic principles, techniques, and applications of neural network and fuzzy logic
- Provide the mathematical background for carrying out the optimization associated with neural network learning.
- Develop the skills to gain basic understanding of the areas of Artificial Neural Networks and Fuzzy Logic.

Course Content

Neural Networks: Introduction, biological neuro-system, neurons and its mathematical models, ANN architecture, learning rules, supervised and unsupervised learning model, reinforcement learning, ANN training Algorithms-perceptions, Training rules, Delta, Back propagation algorithm, Multilayer perceptron model, Hopfield networks, Associative memories. Fuzzy Logic: Classical and Fuzzy Sets, Membership Function, Fuzzy rule generation, Operations on Fuzzy Sets: Compliment, Intersections, Unions, Combinations of operations, aggregation operations. Fuzzy Arithmetic: Fuzzy numbers, Linguistic variables, Arithmetic operations on intervals and numbers, Lattice of fuzzy numbers, Fuzzy equations. Fuzzy Logic: Classical Logic, Multivalued Logics, Fuzzy Propositions, Fuzzy Qualifiers, Linguistic Hedges. Uncertainty based Information: Significance of uncertainty, Uncertainty and information, Principles of uncertainty, Reasoning under uncertainty: heuristics, empirical associations, objective and subjective probabilities, Non-specificity of Fuzzy and Crisp Sets, Fuzziness of Fuzzy Sets.

Course Outcomes

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

CO1: Comprehend the fuzzy logic and the concept of fuzziness.

CO2: Understand the concepts of fuzzy sets, knowledge representation using fuzzy rules, approximate reasoning, fuzzy inference systems, and fuzzy logic.

CO3: Understand the fundamental theory and concepts of neural networks, Identify different neural network architectures, algorithms, applications and their limitations.

CO4: Understand appropriate learning rules for each of the architectures and learns several neural network paradigms and its applications.

Text Books:

1. Learning and Soft Computing by V. Kecman, Pearson.
2. Genetic Algorithms in Search Optimization and Machine Learning by D. E. Goldberg, Addison Wesley.

Reference Books:

1. Neural Network and fuzzy systems by B. Kosko, Prentice Hall of India.
2. Intelligent Hybrid Systems by S. Goonatilake and S. Khebbal, Wiley.

Course Name: **IPR in Artificial Intelligence**
Course Code: **CS-753**
Course Type: **Programme Elective**
Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To explain the art of interpretation and documentation of research work.
- To explain various forms of intellectual property rights.
- To discuss leading international regulations regarding Intellectual Property Rights.

Course Content

Defining the Research Problem in AI, Reviewing the literature in AI, Research Design, Data Collection, Validation, Interpretation and Report Writing, LaTeX tool, presentation preparation, History and theory of AI Regulation, AI and Copyright: Authorship, Ownership and Infringement, Automated Copyright Enforcement. AI, Data and Big Data: Ownership and Protection, Patenting AI. AI-generated Inventions: Inventiveness and Ownership, AI and Patent Enforcement, Trade Secrets, and Product Innovation, Autonomous Driving, AI and Blockchain. The Concept, Intellectual Property System in India, World Intellectual Property Organization, WIPO and WTO, National Treatment, Right of Priority, Common Rules, Patents, Marks, Industrial Designs, Trade Names, Indications of Source, Unfair Competition, Patent Cooperation Treaty, Copyright and Related Rights, Trademarks, Geographical indications, Industrial Designs, Patents, Patentable Subject Matter, Rights Conferred, Exceptions, Term of protection, Conditions on Patent Applicants, Process Patents, Other Use without Authorization of the Right Holder, Layout-Designs of Integrated Circuits, Protection of Undisclosed Information, Enforcement of Intellectual Property Rights, UNSECO.

Course Outcomes

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

CO1: Document the research outcome of the work carried out in the area of Artificial Intelligence.

CO2: Generate Copyright or patent in the area of Artificial Intelligence.

Books and References

1. Professional Programme Intellectual Property Rights, Law and Practice, the Institute of Company Secretaries of India, Statutory Body under an Act of Parliament.
2. World Intellectual Property Organisation (WIPO). https://www.wipo.int/about-ip/en/artificial_intelligence/

Course Name: **Generative AI**
Course Code: **CS-754**
Course Type: **Programme Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- A conceptual understanding of the basic concepts of Generative AI
- How to build Generative AI systems to generate output targeting their domain of interest

Course Content

Introduction to Generative AI: Definition and scope, Applications of Generative AI, Importance of Generative AI in various domains, Ethical considerations and challenges, Introduction to language models and their role in AI, Traditional approaches to language modelling, Deep learning based approaches, Overview of popular LLM architectures: RNNs, LSTMs, and Transformers, Introduction to GPT and its significance, Pre-training and fine-tuning processes in GPT, Architecture and working of GPT models, Overview of GPT variants and their use cases, Introduction to LangChain and its objectives, Overview of the LangChain framework and its components, Understanding the concept and significance of prompt engineering, Strategies for designing effective prompts, Best practices for prompt engineering in generative AI. Understanding the ethical implications of generative models, Addressing bias and fairness in generative AI systems, Ensuring responsible use and deployment of generative models, Use cases in natural language processing, content generation, and creative applications, Case studies highlighting successful implementations Potential future applications and emerging trends.

Course Outcomes

Upon successful completion of the course, the students will be able to
CO1: Understand the concepts of Generative AI.
CO2: Understand and apply LLMs .
CO3: Understanding GPT models.

Text Books:

1. Generative Deep Learning by David Foster, 2nd Edition, O'Reilly.
2. Neural Network Methods for Natural Language Processing by Goldberg, Morgan & Claypool Publishers.

Course Name: **Artificial Intelligence**
Course Code: **CS-701**
Course Type: **Institute Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about Artificial Intelligence.
- To give understanding of the main abstractions and reasoning for intelligent systems.
- To enable the students to understand the basic principles of Artificial Intelligence in various applications

Course Content

Introduction: Overview of AI problems, AI problems as NP, NP-Complete and NP Hard problems. Strong and weak, neat and scruffy, symbolic and sub-symbolic, knowledge-based and data-driven AI. Problem spaces (states, goals and operators), problem solving by search, Heuristics and informed search, Minmax Search, Alpha-beta pruning. Constraint satisfaction (backtracking and local search methods). Knowledge Representation and Reasoning: propositional and predicate logic, Resolution and theorem proving, Temporal and spatial reasoning. Probabilistic reasoning, Bayes theorem. Totally-ordered and partially-ordered Planning. Goal stack planning, Nonlinear planning, Hierarchical planning. Learning: Learning from example, Learning by advice, Explanation based learning, Learning in problem solving, Classification, Inductive learning, Naive Bayesian Classifier, decision trees. Definition of agents, Agent architectures (e.g., reactive, layered, cognitive), Multi-agent systems- Collaborating agents, Competitive agents, Swarm systems and biologically inspired models. Representing and Using Domain Knowledge, Expert System Shells, Explanation, Knowledge Acquisition.

Course Outcomes

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

CO1: Solve basic AI based problems.
CO2: Define the concept of Artificial Intelligence.
CO3: Apply AI techniques to real-world problems to develop intelligent systems.
CO4: Select appropriately from a range of techniques when implementing intelligent systems.

Text Books:

1. Artificial Intelligence by Elaine Rich, Kevin Knight and Shivashankar B Nair, Tata McGraw Hill.
2. Introduction to Artificial Intelligence and Expert Systems by Dan W. Patterson, Pearson Education.
3. Artificial Intelligence: A Modern Approach by S. Russell and P. Norvig, Prentice Hall.

References Books:

1. A First Course in Artificial Intelligence by Deepak Khemani, McGraw Hill Education.
2. Artificial Intelligence By Example: Acquire advanced AI, machine learning, and deep learning design skills, 2nd Edition.

Course Name: **Machine Learning for Engineers**
Course Code: **CS-702**
Course Type: **Institute Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- Introduce concepts in linear algebra and to use it as a platform for machine learning.
- Introduce concepts of gradient descent, the concepts of constrained and nonlinear optimization
- Introduce the concepts of dimensionality reduction, principal components analysis, machine learning basic and optimization.

Course Content

The Statistical Theory of Machine Learning: Classification, Regression, Aggregation, Regularization, Linear Algebra, Probability and Statistics, Vectors Spaces: - linear independence, basis and rank, Norms, Lengths and distances, Angles and orthogonality, Vector Calculus: - Partial differentiation and gradients, Gradients of vector-valued functions, Gradients of matrices, Backpropagation and automatic differentiation. optimization using gradient descent.
Nonlinear Optimization - Minutiae of Gradient Descent – learning rate decay, initialization, Properties of optimization in learning – typical objective functions, stochastic gradient descent, how optimization in machine learning is different, tuning hyperparameters, importance of feature pre-processing, Challenges in Gradient-based optimization, local optima and flat regions, differential curvature, examples of difficult topologies like cliffs and valleys, momentum-based learning, AdaGrad, RMSProp, Adam. Dimensionality reduction and PCA – problem setting, maximum variance perspective, projection perspective, eigenvector and low-rank approximations, PCA in high dimensions, key steps of PCA in practice, latent variable perspective, Mathematical preliminaries of SVM, primal/dual perspective for SVM, nonlinear SVM - kernels. Vectors Spaces - linear independence, basis and rank, affine spaces, Norms, inner products, Lengths and distances, Angles and orthogonality, Orthonormal basis. Machine Learning and Evaluation Method: Introduction to Machine Learning, Problems, data, and tools, Visualization tools, Decision Tree Learning, Artificial Neural Networks, Bayesian Learning, Deep Learning, Instance-Based Learning, Regression Techniques, Linear regression, SSE. data models, data transformations, handling of missing data, time-dependent data, and textual data. Data reduction: feature selection, principal components, smoothing data, case subsampling Evaluation Precision, Recall, F-measure, Measure, Normalized recall, Latent Semantic Indexing, Low rank, approximation, Problems with Lexical Semantics.

Course Outcomes

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

CO1: Learn concepts of linear algebra that form the foundation of data science problems.
CO2: Learn different optimization methods and apply for machine learning.
CO3: Learn the concepts of dimensionality reduction, and principal components analysis.
CO4: Understand the basics of machine learning algorithms and their evaluation method.

Text Books:

1. Introduction to Machine Learning by Ethem Alpaydin, PHI Learning.
2. Machine Learning: An Algorithmic Perspective by Stephen Marsland, Chapman and Hall/CRC.
3. Machine Learning by Tom Mitchell, McGraw Hill Education.

Reference Books:

1. Pattern Recognition and Machine Learning by Christopher M. Bishop, Springer.
2. Probabilistic Graphical Models by D. Koller, and N. Friedman, MIT Press.

Course Name: **Data Structures & Algorithms**
Course Code: **CS-703**
Course Type: **Institute Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about basic data structures
- To impart knowledge about the various approaches to design an algorithm.
- To introduce the fundamental concepts relevant to understand the concepts of time and space complexity, worst case, average case and best-case complexities.
- To enable the students to understand the basics of algorithms.

Course Content

Introductions to Data Structures and Algorithms: Algorithm complexity, concept of algorithmic efficiency, run time analysis of algorithms, Asymptotic Notations, Arrays, Linked List, Stack, Queues, Minimum and maximum priority queue, Trees and Graphs (Memory Representation of each and a few basic operations)
Algorithm Design Approaches: Divide and Conquer approach, examples of some sorting techniques like Merge and Quick Sort; Greedy Algorithms; Graph Algorithms: Representation of graphs, BFS, DFS, single source shortest path, all pair shortest path; Dynamic programming: Overview, difference between dynamic programming and divide and conquer, Traveling salesman Problem, longest Common sequence, 0/1 knapsack., Backtracking: 8-Queen Problem, Sum of subsets, graph coloring, Hamiltonian cycles. Computational Complexity: Complexity measures, Polynomial vs non-polynomial time complexity; NP-hard and NP-complete classes and examples.

Course Outcomes

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

CO1: Understand asymptotic notations to analyze the performance of algorithms.

CO2: Understand and apply various problem-solving techniques such as divide and conquer, greedy algorithm, dynamic programming, etc.

CO3: Solve given problem by selecting the appropriate algorithm design technique and justify the selection.

CO4: Know the concepts of P, NP, NP-hard and NP-complete problems.

Text Books:

1. Fundamentals of Computer Algorithms by E. Horowitz and S. Sahni, Galgotia.
2. Introduction to Algorithms by T.H. Cormen, C.E.Leiserson, R.L. Rivest, MIT Press, Cambridge.
3. Data Structure Using C by Aaron M. Tenenbaum, Y. Langsam, M. Augensten, Pearson

Reference Books:

1. The Design and Analysis of Computer Algorithms by A.V. Aho, J.E. Hopcroft and J.D. Ullman, Addison Wesley.
2. Algorithm Design by J. Kleinberg and É. Tardos, Addison-Wesley.

Course Name: **Computer Networks**
Course Code: **CS-704**
Course Type: **Institute Elective**
Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To impart knowledge about the network models and architectures.
- To introduce the fundamental concepts relevant to performance of various routing protocols and design of new routing protocol.
- To enable the students to understand computers, software, networking technologies and information assurance to an organization's management, operations, and requirements.

Course Content

Introductory Concepts: Goals and Applications of Networks, LAN, WAN, MAN, Network software: Protocol hierarchies, design issues of layers, Interfaces and services. Reference Model: The OSI reference model, TCP/IP reference model, Example networks: Novell Netware, The ARPANET, The Internet, X-25 Networks, network standards. Introduction and basics of Physical Layer, Data Link Layer, Medium access sublayer, network layer, session layer, presentation and application layer.
Introduction to Wireless Networks, basic concepts and issues of wireless networks like hidden layer problem etc. wireless technologies like GSM, CDMA, and evolution from 1G to 6G. Type of wireless networks like Ad-hoc networks, MANETS, sensor networks etc.

Course Outcomes

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

CO1 Understand network models and architectures
CO2 Identify the pros and cons of choosing a suitable MAC layer protocol
CO3 Analyze the performance of various routing protocols and design of new routing protocol
CO4: Solve basic network design problems using knowledge of common local and wide area network architectures
CO5: Understanding wireless networks and basic concepts

Text Books:

1. Computer Networks by A.S. Tanenbaum, Prentice Hall of India.
2. Computer Networking: A Top-Down Approach Featuring the Internet by J. Kurose and K.W. Ross, Addison-Wesley.
3. Data and Computer Communication by W. Stallings, Prentice Hall of India.

Reference Books:

1. Network Programmability and Automation, Jason Edelman, 1st edition, O'Reilly.
2. Computer Networks A Top Down Approach, A Forouzan and F Mosharraf, Mc Graw Hill

Course Name: **Programming for Problem Solving**
Course Code: **CS-705**
Course Type: **Institute Elective**

Contact Hours/Week: **4L** Course Credits: **04**

Course Objectives

- To introduce students to the basic applications, concepts, of different tools used in research.
- To develop skills for using recent software or simulators to solve practical problems in a variety of disciplines.
- To gain experience doing independent study and research.

Course Content

Introduction to Research and Problem solving: Overview of Research in Programming, Importance of research in developing solutions, Fundamentals of Problem-Solving, Importance of defining problems clearly and understanding requirements, Divide and conquer, abstraction, and algorithmic thinking, Research Methods in Programming; Research methodologies applicable to programming-experimental, empirical, and theoretical research.
Foundations of Programming in Python and MATLAB: Introduction to Python and Matlab: Overview of Python and MATLAB as a high-level, interpreted programming language, Applications of Python and MATLAB in research, data science, and scientific computing, Basic Syntax and Data Types: Introduction to Python and MATLAB's basic syntax, Control Structures, Functions and Modular Programming, Importance of modular programming for code organization and reusability, Data Manipulation and Visualization; Object Oriented Programming (OOPs), Introduction to libraries and modules for data manipulation and visualization in Python and MATLAB (e.g., NumPy, Pandas, Matplotlib), Error Handling and Debugging. ML libraries and tools: Probabilistic problems, General ML libraries and tools for solving probabilistic problems, preprocessing techniques (Digital Image Processing, such as, gaussian filters, canny edge detection, quantization, thresholding, etc. Natural Language Preprocessing, such as, Stemming, Lemmatization, etc., sound preprocessing, etc.), Logic implementation (TensorFlow, PyTorch, Scikit learn, etc.) (contains algorithms to implement rnn, cnn, lstm, etc. and customise them to bring your own novelty), Visualisation tools **-** (Matplotlib, seaborn, etc).

Course Outcomes

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

CO1: Categorize and carefully differentiate between situations for applying different tools and techniques.

CO2: Design and implement of different problems.

CO3: Evaluate the performance of different algorithms.

CO4: Propose implementation solutions for different applications.

Text Books:

1. Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow by Aurélien Géron.
2. Programming and problem solving with python by Ashok Namdev Kamthane and Amit Ashok Kamthane.
3. Engineering Problem Solving with MATLAB: Second Edition by Delores M. Etter.

Reference Books:

1. Computer Networking Problems and Solutions by Russ White
2. Designing Data-Intensive Applications by Martin Kleppmann

END OF SYLLABUS