**JAYPEE INSTITUTE OF INFORMATION TECHNOLOGY  
DEPARTMENT OF COMPUTER APPLICATIONS**

**M.Sc. AI/ML**

**Course Outline**

**Semester: I**

**Course Title: Artificial Intelligence -**25M21CA111

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester**: I

**Credits**: 3

**Course Objective:**

This course provides a comprehensive introduction to the foundational principles, methodologies, and applications of Artificial Intelligence (AI). It explores both classical and modern AI techniques, equipping students with the theoretical background and practical skills necessary to develop intelligent systems.

Key topics include problem-solving using search algorithms, knowledge representation and reasoning, planning, probabilistic models, machine learning basics, and natural language processing. The course emphasizes both symbolic and statistical approaches to AI, fostering a deep understanding of how intelligent behavior can be modeled, designed, and implemented.

**Course Outline:**

Introduction to AI, History and evolution of AI, Applications of AI, Intelligent agents and environments, AI ethics and societal impact, Search and problem solving, Problem formulation, Uninformed search (BFS, DFS), Informed search (Greedy, A\*), Heuristic functions, Adversarial search, Minimax, Alpha-beta pruning, Knowledge representation and reasoning, Propositional logic, First-order logic, Inference mechanisms, Rule-based systems, Ontologies, Semantic networks, Planning and decision making, Classical planning, State-space planning, Planning graphs, Markov Decision Processes (MDPs), Utility theory, Reinforcement learning (basics), Probabilistic reasoning, Bayesian networks, Conditional independence, Inference algorithms, Hidden Markov Models (HMMs), Probabilistic reasoning over time, Machine learning in AI, Supervised learning (e.g., decision trees, SVM), Unsupervised learning (e.g., clustering), Basics of neural networks, ML integration in AI systems, Natural language processing, Text processing, Bag-of-words, Syntax and parsing, Semantics, Introduction to language models, Chatbots and conversational agents, Ethical and societal impacts of AI, AI bias and fairness, Explainable AI (XAI), Transparency and accountability, AI governance, AI for social good.

**Course Title: Artificial Intelligence Lab -25M21CA511**

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: I**

**Credits**: 1

**Course Objective:**

This lab course offers hands-on experience in implementing fundamental Artificial Intelligence techniques using a programming language chosen by the instructor (e.g., Python, LISP, etc.). Students will develop skills in search algorithms, reasoning systems, planning, and symbolic problem solving through practical experiments and mini-projects.

**Course Outline:**

​Introduction to AI programming language (e.g., syntax, data types, basic operations), Problem Solving with Search: Implement uninformed and informed search algorithms (e.g., BFS, DFS, A\*), Game Playing and Minimax: Develop a simple two-player game using minimax and alpha-beta pruning, Knowledge Representation: Represent knowledge using propositional and predicate logic; implement forward and backward chaining, Rule-Based Systems: Design simple expert systems using rule-based reasoning, Planning and Decision Making: Create basic planning systems (e.g., STRIPS-like representations, simulate MDPs), Probabilistic Reasoning (Conceptual): Simulate basic probabilistic inference scenarios, Natural Language Processing (Basic): Perform basic text manipulation, pattern matching, syntactic parsing, AI Ethics in Code: Simulate AI ethics scenarios (fairness, transparency, bias), Mini Project: Build a small intelligent system (e.g., chatbot, game AI, or planner) integrating multiple lab concepts.

**Course Title: Python Programming-**25M21CA112

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester**: I

**Credits**:4

**Course Objective:**

No prior programming knowledge is required, though basic understanding of mathematics is recommended.

**Course Outline**:

Overview of Python programming, Basic syntax and structures, Introduction to programming concepts (variables, data types, operators, control structures), Functions (defining, using, parameters, return values), Modular programming, Error handling (try, except blocks, custom exceptions), Introduction to OOP concepts (classes, objects, methods, attributes), Classes and Objects (defining and using classes, object instantiation, constructors, destructors, instance vs. class variables), Inheritance and Polymorphism (inheriting from base classes, method overriding, polymorphic behavior), Encapsulation and Abstraction (access modifiers, getter and setter methods, private attributes, abstract classes), Advanced Python features (decorators, generators, lambda functions, higher-order functions), File I/O (reading from and writing to files), Working with external libraries, Practical applications of OOP in problem-solving, Final project integrating programming and OOP concepts.

**Course Title: Python Programming Lab-25M21CA512**

**Program:** M.Sc. Artificial Intelligence & Machine Learning

**Semester: I**

**Credits:2**

**Course Objective:**

This course aims to provide students with a strong foundation in Python programming, emphasizing both programming and object-oriented concepts. It prepares students to design and implement Python programs using OOP principles, error handling, and file operations while solving real-world problems..

**Prerequisites:**

None, though prior experience with basic mathematics is recommended.

**Course Outline**:

Python syntax, basic data structures, object-oriented design principles, creating classes and objects, designing and implementing basic classes, instantiating objects, using constructors and destructors, inheritance and polymorphism, implementing inheritance, method overriding, polymorphic behavior in class hierarchy, encapsulation and abstraction, designing a class with encapsulated data, implementing getters and setters, creating abstract classes and interfaces, using advanced Python features, implementing decorators, generators, context managers, higher-order functions, error and exception handling, implementing try-except blocks, custom exceptions, logging, file handling and serialization, performing file I/O operations, serializing data using pickle, JSON, or CSV format, real-world project, designing a real-world application using OOP principles (e.g., simple AI/ML system or data-driven application).

**Course Title: Mathematics for AI/ML-I**

**Program:** M.Sc. Artificial Intelligence & Machine Learning

**Semester: I**

**Credits: 3**

**Course Objective:**

This course introduces the foundational mathematical concepts essential for understanding and applying Artificial Intelligence (AI) and Machine Learning (ML) techniques. It covers discrete mathematics, linear algebra, probability theory, and calculus, providing students with the necessary tools to grasp advanced topics in AI and ML. Emphasis is placed on developing a strong mathematical intuition and problem-solving skills relevant to the field..

### Prerequisites:

* Basic understanding of high school-level mathematics, including algebra and functions.
* Familiarity with fundamental concepts in probability and statistics.
* An introductory course in programming (preferably in Python) is beneficial but not mandatory

**Course Outline:**

Introduction to AI and ML, types of learning, Sets, relations, and functions, propositional logic, Vectors, Tensors, QR and Singular Value Decomposition, Orthogonalization, Principal Component Analysis (PCA), dimensionality reduction, Gaussian distribution, Multinomial distribution, Bayes' theorem and Bayesian networks, Entropy, mutual information, KL-divergence and cross-entropy, Constrained and unconstrained optimization, convex optimization, Stochastic Gradient Descent (SGD), Quasi Newton Method, Maximum Likelihood Estimation (MLE), UMVUE, Polynomial Regression, Regularization for Overfitting : Ridge (L2) and Lasso (L1) regression

**Course Title: Data Structures & Algorithms -25M21CA113**

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: I**

**Credits**: 4

**Course Objective:**

This course covers data structures and algorithms that form the foundation for efficient problem-solving. Topics include graph algorithms, dynamic programming, advanced tree structures, and algorithm design techniques.

**Course Outline:**

C programming basics, Static and dynamic memory allocation, Abstract data types, control structures, arrays, functions, advanced C programming, pointers, structures, unions, strings and data structures, string operations, searching algorithms, sorting algorithms (bubble, quick, merge), stacks and queues, stack operations, postfix conversion, queue types (circular, priority, double-ended), linked lists, singly linked list operations, doubly linked lists, circular linked lists, tree types (binary tree, binary search tree, AVL tree), tree traversal methods, heaps (min-heap, max-heap, skew heap), graph fundamentals, graph traversal (DFS, BFS), shortest path algorithms (Dijkstra's), minimum spanning tree algorithms (Prim’s, Kruskal’s).

**Course Title: Data Structures & Algorithms Lab -25M21CA511**

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: I**

**Credits**: 1

**Course Objective:**

This course covers data structures and algorithms that form the foundation for efficient problem-solving. Topics include graph algorithms, dynamic programming, advanced tree structures, and algorithm design techniques.

**Course Outline**:

Control Statements, Static and dynamic memory allocation, Abstract data types, Arrays, Functions, Pointers, User-defined Data Types, Strings, Searching Algorithms, Sorting Algorithms, Linear Data Structures, Stack, Polish and Reverse Polish Expressions, Recursion, Queue, Circular Queue, Priority Queue, Double-Ended Queue, Linked Lists, Singly Linked List, Doubly Linked List, Circular Linked List, Tree, Binary Search Tree, AVL Tree, B-Tree, Graph, Adjacency Matrix, Graph Traversal, Depth-First Search, Breadth-First Search, Shortest Path, Minimum Spanning Tree.

**Electives to be offered in I sem (PEC I)- -25M22CA111**

**Course Title: Data Mining & Warehousing**

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: I**

**Credits**: 3

**Course Outline:**

Data mining functionalities, classification of data mining systems, major issues in data mining, data warehouse and OLAP technology, multidimensional data model, data warehouse architecture, data warehouse implementation, data cube technology, data preprocessing, data cleaning, data integration and transformation, data reduction, concept hierarchy generation, data mining primitives, data mining query languages, data mining system architectures, data generalization, summarization-based characterization, analytical characterization, mining class comparisons, mining descriptive statistical measures, association rule mining, mining single-dimensional Boolean association rules, mining multilevel association rules, mining multidimensional association rules, correlation analysis, constraint-based association mining, classification methods, prediction techniques, accuracy and error measures, evaluating classifier accuracy, clustering methods, density-based clustering, grid-based clustering, outlier analysi**s.**

**Course Title: Cloud Computing Ecosystem**

**Credits**: 3

**Course Outline:**

Cloud computing overview, characteristics, challenges, benefits, limitations, evolution of cloud computing, cloud computing architecture, cloud reference model (NIST architecture), open group cloud ecosystem reference model, service models (IaaS, PaaS, SaaS), characteristics of service models, benefits of service models, enabling technologies, deployment models (public, private, multi-cloud), shared resources, resource pool, usage and administration portal, resource management, elastic environment, resilient environment, security, workload distribution, dynamic provisioning, cloud ecosystems, actors and roles in the cloud ecosystem, cloud adoption vision, identifying use cases, developing adoption plan, implications of cloud service layers, utilizing cloud for strategic advantage, business needs for DevOps, DevOps culture, processes and technology in DevOps, DevOps myths, path to DevOps adoption, planning and measurement, collaborative and continuous development and testing, release and deployment, monitoring and optimization, continuous customer feedback, DevOps capabilities, cloud data centers, OpenStack architecture, OpenStack compute, OpenStack network, OpenStack object storage, automation, OpenStack installations, historical perspective of data centers, data center components, design considerations, power calculations, evolution of data centers.

**Semester: II**

**Course Title:** Machine Learning

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: II**

**Credits**: 3

**Course objective:**

This course introduces the mathematical foundations essential for machine learning, covering probability, linear algebra, and statistics. It explores core ML concepts such as supervised, unsupervised, and reinforcement learning, with algorithms like linear/logistic regression, decision trees, and neural networks. The course includes hands-on experience with Python libraries such as NumPy, Pandas, Scikit-learn, PyTorch, and Keras. Advanced topics like dimensionality reduction, CNNs, deep learning architectures, and ensemble methods are covered. Real-world case studies and public datasets are used for practical model building and evaluation.

**Course Outline:**

Introduction to Machine Learning: Definition, history, applications, Supervised learning, Unsupervised learning, Reinforcement learning, Data collection, Data preprocessing, Model training, Model evaluation, Model deployment, Features, Labels, Instances, Ethical considerations in machine learning, Data cleaning, Handling missing data, Handling outliers, Feature selection, Feature engineering, Exploratory Data Analysis (EDA), Linear regression – single and multiple variables, Gradient descent, Bias-variance trade-off, Overfitting, Underfitting, Regularization, Generalization, Logistic regression, Decision Trees, Naive Bayes, Support Vector Machines – linear and non-linear kernel functions, Accuracy, Precision, Recall, F1-score, ROC, AUC, Clustering – Partitioned, Hierarchical, Density-based, K-Means clustering, K-Mode clustering, Expectation maximization, Dimensionality reduction – t-SNE, Anomaly detection, Random forests, Bagging, Boosting – AdaBoost, XGBoost, Metrics, Error correction, Hyperparameter optimization, Bias, Fairness, Transparency, Accountability, Agents, Environments, Rewards, Markov Decision Processes (MDPs), Q-learning, Deep Q Networks (DQNs), Policy gradients, Actor-critic methods.

**Course Title:** Natural Language Processing (NLP)

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: II**

**Credits**: 3

**Course Objective:**

This course offers an in-depth exploration of Natural Language Processing (NLP), emphasizing AI and machine learning methods. It begins with language modeling, probability theory, and information theory fundamentals, moving into morphological analysis and part-of-speech tagging using HMMs, CRFs, and deep learning models. Students will study syntactic parsing, semantic role labeling, and word-sense disambiguation with both supervised and unsupervised approaches. The course also covers discourse analysis, coreference resolution, and contextual embeddings (e.g., Word2Vec, BERT). Practical applications include machine translation, named entity recognition, relation extraction, sentiment analysis, and question answering, enabling students to develop intelligent, language-aware AI systems.

**Course Outline:**

Origins and challenges of Natural Language Processing, NLP tasks in syntax, semantics, pragmatics, Knowledge in language processing, NLP applications, Role of machine learning in NLP, Probability basics, Information theory, Language and grammar, Grammar-based language models – Lexical Functional Grammar, Government and Binding, Statistical language models – N-gram models, Smoothing techniques, Evaluating language models, Regular expressions, Morphology, Word and sentence tokenization, Stemming, Lemmatization, Spelling error detection and correction, Word classes, Part-of-Speech tagging – Rule-based, Hidden Markov Models, Maximum Entropy Models, Conditional Random Fields, Treebanks, Grammar formalisms, Context-Free Grammar, Constituency and dependency parsing, Top-down and bottom-up parsing, Ambiguity resolution – Earley and CYK algorithms, Probabilistic CFGs, Lexical semantics, Word senses and relations, WordNet, Word-sense disambiguation – supervised, unsupervised, dictionary-based approaches, Word similarity, Compositional semantics, Semantic Role Labeling, Semantic parsing, Reference and anaphora resolution, Co-reference resolution, Discourse analysis, Named Entity Recognition, Relation extraction, Sequence labeling for Information Extraction, Machine translation – word alignment, phrase-based translation, Statistical translation, Question answering, Large Vocabulary Continuous Speech Recognition, Subword units and models, Statistical language modeling for speech, Perplexity, Semantic post processing in speech, Computational phonology, Phoneme and phonological rules, HMM-based speech synthesis, F0 modeling, Text-to-speech conversion.

**Course Title:** Ethical Implications of AI(SEC-I)

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: II**

**Credits**: 2

**Course Objective**: This course introduces students to the ethical, social, and legal challenges posed by artificial intelligence systems. It focuses on identifying ethical risks, applying ethical frameworks, and promoting responsible AI development practices to ensure fairness, transparency, privacy, and accountability.

**Course Outline:** Introduction to AI ethics and ethical theories, historical context of AI and real-world ethical cases, recognizing and mitigating bias in AI systems, fairness definitions and fairness assessment techniques, transparency and explainability in AI models, privacy and security considerations in AI, GDPR and ethical data handling, accountability and responsibility in AI development, ethical design of autonomous systems, global perspectives on AI ethics and regulations, cultural and cross-border ethical challenges in AI.

**Course Title:** Mathematics for AI & ML- II

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: II Credits**: 3

**Course objective:**

This course aims to equip students with advanced mathematical tools essential for AI and Machine Learning. It focuses on optimization techniques, numerical methods, and statistical analysis to enhance the understanding and implementation of complex AI/ML models.

### Prerequisites

* Completion of Mathematics for AI & Machine Learning – I, covering foundational topics in linear algebra, probability, and calculus.
* Basic programming proficiency, preferably in Python, to implement mathematical concepts and algorithms

**Course Outline:**

LU decomposition, QR decomposition, Cholesky decomposition, matrix norms, condition number of a matrix, Hessian matrix and second-order methods, Tensor algebra, automatic differentiation, Gradients, gradient descent, stochastic gradient descent, learning-rate scheduling techniques, convex optimization principles, root-finding algorithms: Newton–Raphson method, Secant method, derivation of normal equations for linear regression, logistic regression: cost function and gradient derivation, gradient derivation for L1 and L2 regularization, Ridge regression, Lasso, Training Error, Testing Error, Model assessment and hypothesis testing, Type I and Type II Errors, hypothesis testing using z-test, t-test, chi-square test, Bias–variance trade-off analysis, cross-validation methods: k-fold, leave-one-out, Numerical integration: trapezoidal rule, Simpson’s rule, Interpolation: Lagrange polynomials, spline interpolation.

**Course Title:** Personality Development & Decision-making Skills (HSC)

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: II**

**Credits**: 2

**Course Objective:**

This course aims to enhance students’ personal and professional effectiveness through self-awareness, communication, and critical thinking. It focuses on personality development, emotional intelligence, leadership, time management, and teamwork—key soft skills essential for AI/ML professionals. Students will also learn structured approaches to problem-solving and decision-making using logical, creative, and data-driven methods. Through activities, case studies, and reflective learning, the course builds confidence, ethics, resilience, and the ability to make effective decisions in dynamic, real-world environments.

**Course Outline:**

Understanding professional soft skills in research and industry, advanced personality profiling, growth vs. fixed mindset, self-awareness and meta-cognition, stressors in professional environment, cognitive reframing, mindfulness and resilience, Eisenhower matrix, deep work strategies, balancing deadlines and emotional intelligence in leadership, contemporary leadership theories, building high-performing teams, managing diversity, intercultural communication frameworks, conflict resolution in multicultural teams, rational vs. intuitive decision-making, risk analysis, negotiation styles in professional settings, principled negotiation, ethics in decision-making, handling ethical dilemmas in research, learn, unlearn, relearn framework, capacity-building strategies, fostering creativity and innovation, networking for professional development, building a personal brand and professional identity.

**Course Title:** Machine Learning lab

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: II**

**Credits**: 1

**Course Objective:**

This lab-based course provides hands-on experience in applying machine learning algorithms to natural language processing tasks. Students will learn core techniques like tokenization, lemmatization, POS tagging, parsing, text classification, and topic modeling. It emphasizes the application of both supervised and unsupervised learning models—including HMMs, SVMs, CRFs, RNNs, LSTMs, and EM algorithms—on real-world datasets. Advanced topics include document summarization, sentiment analysis, named entity recognition, machine translation, and generative AI using large language models. The course strengthens theoretical understanding while focusing on practical implementation, model evaluation, and solving real-time problems using ML and NLP techniques. Apply all learning algorithms over appropriate real-time dataset. Evaluate the algorithms based on corresponding metrics identified

**Course Outline:**

Data preprocessing and visualization, Data analysis using statistical measures like mean, median, variance, and standard deviation, Matrix operations and mathematical concepts for ML implementation, Linear regression and multiple linear regression, Logistic regression, Lasso and Ridge regression, Naïve Bayes classifier, Decision tree classifiers including ID3 and CART, Support vector machines with linear and non-linear kernel functions, K-nearest neighbors (K-NN) algorithm, K-means and K-mode clustering, Random forest classifier, Ensemble techniques including AdaBoost and XGBoost, Principal component analysis (PCA) for dimensionality reduction, Singular value decomposition (SVD), Self-organizing maps, Design and training of neural networks including single-layer and multi-layer perceptrons, Basics of convolutional neural networks (CNNs) including convolution and activation layers, Transfer learning, Training techniques including batch normalization, dropout, and early stopping, Confusion matrix and model evaluation metrics, Implementation using libraries such as Matplotlib, SciPy, Scikit-learn, and Pandas, Reinforcement learning using Q-learning.

**Course Title:** Natural Language Processing (NLP) Lab

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: II**

**Credits**: 1

**Course Objective:**

The **Natural Language Processing (NLP) Lab** focuses on fundamental concepts and applications in NLP and automatic speech recognition. Students will learn to use tools like NLTK, SpaCy, and Speech Recognition for tasks such as POS tagging, syntax parsing, and text classification. The course includes implementing N-gram models, word embeddings, and deep learning techniques like CNNs and RNNs for sentiment analysis, named entity recognition, and text summarization. Students will also work on projects such as building a chatbot, machine translation systems, and developing speech recognition systems for voice commands and continuous speech. By the end, students will integrate these techniques to create real-world NLP and speech processing applications.

**Course Outline**:

Installing and setting up essential Python packages for natural language and speech processing such as NLTK, SpaCy, and Speech Recognition, Performing part-of-speech tagging and syntactic parsing using built-in NLP tools, Representing and classifying text using Bag-of-Words and topic modeling approaches, Building N-gram language models for predicting the next word in a sequence, Implementing word embedding-based models for text classification, Developing convolutional neural network (CNN) models for sentiment analysis, Applying recurrent neural networks (RNN) for named entity recognition, Implementing deep learning-based approaches for text summarization, Designing chatbots using sequence models and neural networks, Developing machine translation systems using encoder-decoder models, Building speech recognition systems for simple voice command recognition, Recognizing continuous speech using audio signal processing, and Applying CNNs with mel spectrograms for speech-to-text systems

**Semester: III**

**Course Title:** Neural Network & Deep learning

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: III**

**Credits**: 3

**Course Objective:**

The **Deep Learning** course for M.Sc. AI & ML provides an in-depth exploration of neural network architectures and their applications. It covers foundational topics such as machine learning versus deep learning, representation learning, and various activation functions like ReLU, Leaky ReLU, and ELU. The course delves into Convolutional Neural Networks (CNNs), including architectures like LeNet, ResNet, VGGNet, and AlexNet, and explores transfer learning techniques. Students will gain practical experience in training neural networks using optimization methods like Adam and RMSprop, and will work with frameworks such as PyTorch and TensorFlow. The curriculum also includes recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and autoencoders, emphasizing their applications in sequence modeling and generative tasks. By the end of the course, students will have a comprehensive understanding of deep learning models and their implementation in real-world scenarios.

**Course Outline:**

Introduction to Deep Learning and Architectures, Machine Learning vs Deep Learning, Representation Learning, Width vs Depth of Neural Networks, Activation Functions (ReLU, Leaky ReLU, ELU), Unsupervised Training of Neural Networks, Regularization Techniques, Dropout, Drop Connect, Optimization Methods (Adagrad, Adadelta, RMSprop, Adam, NAG), Convolutional Neural Networks and Transfer Learning, CNN Architecture and Motivation, CNN Layers and Filters, Parameter Sharing, Regularization in CNNs, LeNet, AlexNet, VGGNet, ResNet, DenseNet, PixelNet, Transfer Learning Techniques, Training Neural Networks, Deep Learning Hardware (CPU, GPU, TPU), PyTorch and TensorFlow, Dynamic vs Static Computation Graphs, Data Preprocessing, Data Augmentation, Batch Normalization, Transfer Learning Strategies, Update Rules, Hyperparameter Tuning, Learning Rate Scheduling, CNN Variants (ResNet, GoogleNet, Xception), Recurrent Neural Networks, RNNs and Bidirectional RNNs, Encoder-Decoder Architectures, Sequence-to-Sequence Models, Backpropagation Through Time, Long Short-Term Memory (LSTM) Networks, Autoencoders and Deep Generative Models, Undercomplete Autoencoders, Regularized Autoencoders, Sparse Autoencoders, Denoising Autoencoders, Representational Power, Encoder Depth and Size, Stochastic Encoders and Decoders, Contractive Encoders, Deep Belief Networks, Boltzmann Machines, Deep Boltzmann Machine, Generative Adversarial Networks (GANs).

**Course Title:** Neural Network & Deep learning Lab

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: III**

**Credits**: 1

**Course Objective:**

The **Deep Learning Lab** for M.Sc. AI & ML provides hands-on experience in implementing and deploying advanced neural network architectures using frameworks like PyTorch and TensorFlow. Students will gain practical skills in building and training models for tasks such as image classification, object recognition, segmentation, sentiment analysis, and text generation. The lab emphasizes the application of convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, autoencoders, and generative adversarial networks (GANs) to real-world datasets. Through projects and experiments, students will explore techniques like style transfer, data augmentation, and reinforcement learning, preparing them to tackle complex problems in computer vision and natural language processing. By the end of the course, students will have developed a portfolio of deep learning applications and be equipped to contribute to cutting-edge AI research and development.

**Course Outline:**

Google Collaborator setup, GitHub repository cloning, Kaggle dataset import and file operations, Implementation of Perceptron, MNIST digit classification using shallow neural networks, Multi-layer Perceptron (MLP), Mini-batch gradient descent, Hyperparameter tuning, Regularization techniques, CNN for MNIST classification using TensorFlow and Keras, Face recognition using CNN, Transfer learning for object detection, Image denoising using Autoencoders, Stacked Autoencoders for color image denoising, Text processing using RNN, Language modeling using RNN, LSTM for sentiment analysis, Transfer learning models for image classification, Image generation using GANs, Deep learning model deployment techniques, Sample object recognition project, Sample image segmentation project.

**Course Title:** Generative AI

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: III**

**Credits**: 3

**Course Objective:**

This course introduces students to the principles, models, and applications of Generative AI, focusing on methods like GANs, VAEs, and diffusion models. Students will learn to build, train, and evaluate generative models and understand their real-world uses and ethical considerations..

**Prerequisite:**

Basic knowledge of Machine Learning, Deep Learning fundamentals, and Python programming.

**Course Outline:**

Introduction to Generative AI, history and evolution of generative models, types of generative models (explicit density models, implicit models), introduction to probabilistic models, Gaussian Mixture Models (GMMs), introduction to generative adversarial networks (GANs), architecture and training dynamics of GANs, challenges in training GANs, variants of GANs (DCGAN, CycleGAN, StyleGAN), applications of GANs in image synthesis, text generation and data augmentation, introduction to variational autoencoders (VAEs), encoder-decoder frameworks, latent variable models, applications of VAEs, energy-based models, normalizing flows, diffusion models and denoising score matching, evaluation metrics for generative models (Inception Score, FID), ethical considerations in generative AI, biases and fairness in generated content, adversarial attacks and defenses in generative models, case studies of generative AI applications in art, healthcare, and entertainment.

**Course Title:** Generative AI Lab

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: III**

**Credits**: 1

**Course Objective:**

This lab course aims to provide hands-on experience with designing, training, and evaluating generative models such as GANs, VAEs, and diffusion models. Students will apply theoretical knowledge to build practical generative AI systems and explore their creative applications

**Prerequisite:**

Fundamental understanding of Machine Learning, Deep Learning techniques, and Python programming skills.

**Course Outline:**

Introduction to generative modeling concepts, hands-on implementation of Variational Autoencoders (VAEs), building basic Generative Adversarial Networks (GANs), conditional GANs and their applications, CycleGANs for image-to-image translation, introduction to diffusion models, fine-tuning pre-trained generative models, text-to-image generation using diffusion or transformer-based models, prompt engineering for generative models, evaluating generative models using metrics like Inception Score and FID, bias and fairness issues in generative models, ethical considerations and responsible use of generative AI, mini-project integrating multiple generative techniques.

**Course Title:** Information Retrieval & Semantic Web

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: III**

**Credits**: 3

**Course objective:**

This course explores the foundations of information retrieval (IR) with a strong emphasis on AI and machine learning techniques. Students will learn traditional IR models and how they evolve into intelligent systems using probabilistic models, vector space representations, and neural embeddings (Word2Vec, GloVe). It covers Boolean and ranked retrieval, index construction, and error-tolerant search. The course integrates ML for relevance scoring, document classification, and language modeling. It concludes with web-scale IR, link analysis, and intelligent web search through PageRank and graph-based algorithms, aligning IR systems with modern AI-driven search engines.

**Course Outline:**

Theory of Information Retrieval, Boolean Retrieval, Ranked Retrieval, Vector Space Model, Term Frequency and Weighting, TF-IDF Variants, Probabilistic Models, Language Models, Word Co-occurrence, Word Embeddings (Word2Vec, GloVe), Evaluation Metrics for IR Systems, Index Construction – Static and Dynamic Inverted Indices, Index Compression, Query Processing and Query Languages, Relevance Feedback, Query Expansion, Spelling and Phonetic Correction, Wildcard Queries, Text Classification – Naïve Bayes, Support Vector Machines, Clustering – Flat and Hierarchical, Latent Semantic Indexing, Fusion and Meta Learning, Search Engine Architecture, Web Search and its Characteristics, Static and Dynamic Ranking, Web Crawling – Parallel, Distributed, Focused, Page Ranking Algorithms, Information Retrieval Tools – Web Directory, Search Engines, Meta Search Engines, XML Retrieval, Multimedia IR, Parallel and Distributed IR, Taxonomy and Ontology, Ontology Creation and Lifecycle, Semantic Web, Resource Description Framework (RDF), Privacy, Fairness, Fake News and Disinformation, Deep Learning for Information Retrieval.

**Course Title:** Information Retrieval & Semantic Web Lab

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: III**

**Credits**: 1

**Course Objective:**

This lab course provides hands-on experience in the implementation of information retrieval (IR) systems and the creation of semantic web applications. Students will work with various IR models, indexing techniques, and search engines. They will also explore text classification, clustering, and link analysis algorithms, such as PageRank, while applying machine learning techniques to text data. Additionally, students will gain proficiency in semantic web technologies, including RDF, OWL, and SPARQL for creating and querying ontologies. The course focuses on building practical solutions using open-source IR tools, web crawlers, and developing semantic search systems.

**Course Outline:**

Introduction to information retrieval systems, Data retrieval techniques, Information retrieval on the web, Architecture of information retrieval tools, Boolean queries processing, Extended Boolean model vs. ranked retrieval, Blocked-sort-based indexing, Single-pass-in-memory indexing, Distributed and dynamic indexing, Wild card queries, Spelling correction techniques, Phonetic correction methods, Term frequency and weighting techniques, Implementation of vector space model, Variant TF-IDF scoring, Probabilistic Information Retrieval (IR), Language modeling, Distributed word representations, Word co-occurrence, Word embeddings (GLOVE, Word2Vec), Evaluation of information retrieval systems, Web as a graph, Page ranking algorithms, Implementing web directories, Meta search engines, Search engine architecture, Searching algorithms like Fish and Shark, Web crawling techniques, Web crawler architecture, Parallel, distributed, and focused web crawling, Domain-specific ontology creation, Ontology life cycle, Introduction to the Semantic Web, Resource Description Framework (RDF) implementation.

**Course Title:** Entrepreneurship and Start-up ecosystem( SEC)

**Program**: M.Sc. Artificial Intelligence & Machine Learning

**Semester: III**

**Credits**: 2

**Course Objective:**

The **Entrepreneurship and Start-up Ecosystem** course, tailored for M.Sc. AI & ML students under the Skill Enhanced category, aims to cultivate an entrepreneurial mindset and equip students with the necessary skills to navigate the start-up landscape. The curriculum encompasses key areas such as opportunity recognition, business model development, lean start-up methodologies, and go-to-market strategies. Students will delve into customer discovery processes, financial planning, legal aspects of start-ups, and team building. Emphasis is placed on integrating AI and ML innovations into viable business solutions, fostering the ability to translate technical expertise into entrepreneurial ventures. Through interactive sessions, case studies, and project-based learning, students will gain practical insights into launching and scaling technology-driven start-ups within the dynamic AI & ML ecosystem.

**Course Outline:**

Introduction to entrepreneurship, Entrepreneurial mindset and opportunity recognition, Traits of successful entrepreneurs, Types of entrepreneurs – serial, social, and intrapreneurs, Case studies of Indian entrepreneurs, Start-up ecosystem and key stakeholders, Funding sources – angel investors, venture capital, incubators, Government initiatives and start-up schemes, Idea generation techniques, Feasibility analysis and market validation, Business model innovation, Business Model Canvas and value propositions, Financial planning and budgeting, Funding strategies and break-even analysis, Scaling strategies for start-ups, Marketing and branding for start-up growth, Team building and leadership in start-ups, Entrepreneurial challenges and risk management, Ethical practices and sustainability in entrepreneurship, Long-term impact and scalability of ventures.