पुण्यश्लोक अहिल्यादेवी होळकर
सोलापूर विद्यापीठ
।। विद्यया संपन्नता ।।
NAAC Accredited 2022
'B++' Grade (CGPA 2.96)

PUNYASHLOK AHILYADEVI HOLKAR SOLAPUR UNIVERSITY, SOLAPUR.

Name of the Faculty : Science and Technology

Syllabus: Computer Science

NEP 2020

Name of the Course:

M. Sc. (AI & ML) Part- I (Semester I & II)

With Effect from : Academic Year 2026-27

Eligibility:- 1. B.Sc. (Computer Science/Entire Computer Science /Statistics /Mathematics/Electronics/Physics)

2. BCA

Structure of the Syllabus- M.Sc. (AI & ML) Part – I

Part-I Semester-I						
Paper Code	**Title of the Paper**	**Hrs./week**	**Distribution of Marks for Examination**			**Credits**
			Internal	**University**	**Total**	
Discipline Specific Course Theory (DSC)						
DSC1-1	Mathematical and Statistical Foundations for Machine Learning	04	40	60	100	4
DSC1-2	Fundamentals of Artificial Intelligence	04	40	60	100	4
Discipline Specific Elective Theory (DSE) (Any One)						
DSE1-1	1. Python Programming 2. R Programming Essentials for AI & ML	04	40	60	100	4
Minor						
Minor	Research Methodology in Computer Science	04	40	60	100	4
Practical						
DSC-P-1-1	Practical based on DSC1-1	04	20	30	50	2
DSC-P-1-2	Practical based on DSC1-2	04	20	30	50	2
DSE-P-1-1	Practical based on DSE1-1	04	20	30	50	2
Total		**28**	**220**	**330**	**550**	**22**

Part-I Semester-II						
Paper Code	**Title of the Paper**	**Hrs./week**	**Distribution of Marks for Examination**			**Credits**
			Internal	University	Total	
Discipline Specific Course Theory (DSC)						
DSC1-3	Database Systems Using NoSQL	04	40	60	100	4
DSC1-4	Machine Learning Algorithms	04	40	60	100	4
Discipline Specific Elective Theory (DSE) (Any One)						
DSE1-2	1. Cloud Computing 2. Git & GitHub	04	40	60	100	4
Practical / Project						
DSC-P-1-3	Practical based on DSC1-3	04	20	30	50	2
DSC-P-1-4	Practical based on DSC1-4	04	20	30	50	2
DSE-P1-2	Practical based on DSE1-2	04	20	30	50	2
Project-1	Project	04	40	60	100	4
Total		**28**	**220**	**330**	**550**	**22**

Preamble:

1) Provide a strong foundation in Artificial Intelligence, Machine Learning, and Data Science.
2) Equip students with practical skills to develop and deploy intelligent systems.
3) Enable the application of AI/ML techniques to real-world problems across diverse domains.
4) Foster research, innovation, and analytical thinking in emerging AI technologies.
5) Promote ethical and responsible use of AI for societal and technological advancement.

Objective of the Course:

1. To provide students with a strong foundation in the core concepts of Artificial Intelligence, Machine Learning, Data Science, and related computational techniques.
2. To train students to analyse complex problems and develop intelligent solutions using advanced algorithms, statistical methods, and data-driven approaches.
3. To equip students with hands-on experience in modern AI and ML tools, programming languages, frameworks, and platforms used in real-world applications.
4. To encourage research-oriented thinking and innovation in emerging areas such as deep learning, natural language processing, computer vision, and intelligent systems.
5. To enable students to design and implement AI-based solutions across various sectors such as healthcare, finance, agriculture, education, and smart technologies.
6. To create awareness about ethical considerations, data privacy, fairness, and responsible use of Artificial Intelligence technologies.
7. To prepare graduates for professional careers as AI engineers, machine learning specialists, data scientists, researchers, and technology consultants.
8. To motivate students to continuously update their knowledge and skills in rapidly evolving AI technologies and interdisciplinary fields.

Course Outcomes (COs): –

CO1: Understand the fundamental concepts, theories, and principles of Artificial Intelligence, Machine Learning, and Data Science.

CO2: Apply statistical, mathematical, and computational techniques to analyze and interpret complex datasets.

CO3: Design and develop machine learning models using appropriate algorithms for solving real-world problems.

CO4: Implement advanced AI techniques such as deep learning, natural language processing, and computer vision using modern tools and frameworks.

CO5: Evaluate and optimize the performance of AI and ML models using suitable metrics, validation techniques, and optimization methods.

CO6: Develop intelligent applications by integrating AI technologies into practical domains such as healthcare, finance, business analytics, and automation.

CO7: Demonstrate research, innovation, and problem-solving skills in emerging areas of Artificial Intelligence and Machine Learning.

CO8: Understand ethical, legal, and social implications of AI and ensure responsible and secure use of intelligent systems.

Eligibility Criteria: M.Sc. Artificial Intelligence & Machine Learning

The eligibility criteria for admission to the M.Sc. Artificial Intelligence and Machine Learning (AI & ML) program are as follows:

1. **Educational Qualification**

   The candidate must have completed a Bachelor's degree from a recognized university in any of the following disciplines:

I. Computer Science

II. Information Technology

III. Artificial Intelligence / Data Science

IV. Mathematics / Statistics

V. Electronics / Engineering

VI. Any other related discipline with a strong background in mathematics and computing.

2. Obtained at least 50% marks (45 % marks in case of candidates belonging to reserved category) in the qualifying Examination.

Type: DSC Semester-I

Course Title: Mathematical and Statistical Foundations for Machine Learning

Unit 1: (30 Hours)

1.1 Linear Algebra and Its Applications in ML

Scalars, Vectors, Matrices, Tensors, Matrix operations: addition, multiplication, transpose, inverse, rank, Linear Independence, Span, Basis, Dimension, Norms (L1, L2), Dot Product, Orthogonality, Eigenvalues, Eigenvectors, Diagonalization, Singular Value Decomposition (SVD), Principal Component Analysis (PCA) – intro and geometric intuition, Linear Discriminant Analysis (LDA)

1.2 Probability Theory and Random Variables

Axioms of probability, conditional probability, Bayes' theorem, Random variables (discrete & continuous), Expectation, Variance, Covariance, Correlation, Joint, Marginal and Conditional Distributions, Important Distributions: Bernoulli, Binomial, Poisson, Normal, Exponential, Central Limit Theorem (CLT), Law of Large Numbers (LLN), Application in Naive Bayes, Gaussian assumptions in ML, Bayesian Inference (MAP, MLE) and Probability Density Estimation (KDE).

Unit 2: (30 Hours)

1.1 Statistics, Inference & Hypothesis Testing

Descriptive statistics: mean, median, mode, range, variance, standard deviation, Sampling techniques and distributions**,** Resampling techniques (Bootstrapping, Jackknife), Estimation theory: point and interval estimation, Hypothesis Testing: Z-test, T-test, Chi-square test, ANOVA, Confidence Intervals and Significance levels, Correlation and Regression Analysis (Simple & Multiple), Overfitting, Underfitting, Bias-Variance Trade-off

2.2 Calculus and Optimization for Machine Learning

Functions, Limits, Continuity, Derivatives and Differentiation Rules, Gradient, Partial Derivatives, Jacobian, Hessian, Multivariable Optimization, Convex Functions, Minima and Maxima, Gradient Descent, Stochastic Gradient Descent (SGD), Introduction to Lagrange Multipliers (Constrained Optimization), Application in Neural Networks: Backpropagation concept

Reference Books:

1. **Mathematics for Machine Learning** – Marc Peter Deisenroth, A. Aldo Faisal, Cheng Soon Ong (Cambridge)
2. **Hands-On ML with Scikit-Learn, Keras, and TensorFlow** – Aurélien Géron (for applied perspective)
3. **"Introduction to Linear Algebra"** by Gilbert Strang
4. **"Probability and Statistics for Engineers and Scientists"** by Walpole et al.
5. **"All of Statistics"** by Larry Wasserman
6. **"Statistics for Engineers and Scientists"** by William Navidi
7. **"Calculus"** by James Stewart
8. **"Introduction to Optimization"** by Chong & Zak

Type: DSC Semester-I

Course Title: Fundamentals of Artificial Intelligence

Unit 1: (30 Hours)

1.1 Foundations and Intelligent Agents

Introduction to AI: History, Definitions, and Applications, AI Problem Solving and Approaches, Intelligent Agents: Concept, Types, Agent Architectures, Environment Types: Deterministic vs. Stochastic, fully vs. Partially Observable, Episodic vs. Sequential, Problem-Solving Methods: State Space Search, Problem Formulation, Uninformed Search Strategies: BFS, DFS, Uniform Cost Search, Informed Search Strategies: Best-First Search, A*, AO*, Heuristics

1.2 Knowledge Representation and Reasoning

Knowledge Representation: Facts, Objects, Events, Propositional Logic: Syntax, Semantics, Inference, Predicate Logic: Syntax, Semantics, Quantifiers, Inference Techniques: Forward Chaining, Backward Chaining, Resolution, Rule-Based Systems and Production Systems, Introduction to Semantic Networks and Frames, **Knowledge Graphs** and **Ontologies**

Unit 2: (30 Hours)

2.1 Machine Learning and Probabilistic Reasoning

Overview of Machine Learning in AI, Supervised, Unsupervised, and Reinforcement Learning, Decision Trees, Neural Networks, Probabilistic Reasoning: Bayes Theorem, Bayesian Networks, Handling Uncertainty: Fuzzy Logic, Markov Decision Processes (MDP), Introduction to Natural Language Processing (NLP).

2.2 Advanced Topics and AI Applications

Planning and Scheduling: Classical Planning, STRIPS, Partial-Order Planning, Multi-Agent Systems and Game Playing: Minimax Algorithm, Alpha-Beta Pruning, Robotics and Perception: Sensors, Actuators, Robot Architecture, AI Ethics, Social Impact, and Future Trends, AI in Real-World Applications: Healthcare, Finance, Autonomous Vehicles, etc., Introduction to Deep Learning and Neural Networks.

Reference Books:

1. Artificial Intelligence: A Modern Approach- Stuart Russell & Peter Norvig (Pearson)
2. Artificial Intelligence: Foundations of Computational Agents
   - David Poole & Alan Mackworth (Cambridge University Press)
3. Introduction to Artificial Intelligence-Wolfgang Ertel (Springer)
4. Machine Learning-Tom M. Mitchell (McGraw-Hill)
5. Probabilistic Robotics-Sebastian Thrun, Wolfram Burgard, and Dieter Fox (MIT Press)

Type: DSE **Semester-I**

Course Title: Python Programming

Unit 1: (30 Hours)

1.1 Python Programming Essentials for AI & ML

Introduction to Python: History, Features, Applications in AI/ML, Data Types & Variables, Operators and Expressions, Control Flow: Conditional Statements (if, else, elif), Loops (for, while, break, continue), Functions: User-defined, lambda, built-in functions, Python Libraries: math, random, date time, OS, Data Structures in Python: Strings, Lists, Tuples, Sets, Dictionaries

1.2 OOP with Python

Features, Concept of Class & Objects, Constructor, Types of Variables, Namespaces, Types of Methods, Inner Classes, Constructors in Inheritance, Overriding Super Class Constructors and Methods, Types of Inheritance, Abstract Classes and Interfaces, The Super() Method, Operator Overloading, Method Overloading, Method Overriding, MRO, Decorators**,** Generators**,** and Context Managers

Threading, Exception Handling and File: Threading- about Thread, Starting a Thread, Daemon Threads, join() a Thread, Working With Many Threads, Thread, Race Conditions, Synchronization, Deadlock, Exception :- Errors in a Program, Exceptions, Exception handling, Types of Exceptions, User defined Exceptions, Python File Operation:- Types of File, Opening and Closing a File, Reading and writing to files, Manipulating directories and files.

Unit 2: (30 Hours)

2.1 NumPy and Data Handling for ML

Introduction to NumPy: Arrays, Array indexing and slicing, Broadcasting, vectorized operations, array functions and aggregations, Introduction to Pandas: Series and Data Frames, Reading/writing CSV/Excel files, handling missing data, filtering, sorting, Data Preprocessing Techniques: Handling missing values, Feature scaling: normalization, standardization, Encoding categorical data

2.2 Data Visualization and ML Libraries: Data Visualization with: Matplotlib: Line, bar, scatter, histogram, pie charts, Seaborn: Heatmaps, pair plots, distribution plots, Introduction to Scikit-learn: Machine Learning pipeline: load data, preprocess, model, evaluate, Datasets module (e.g., iris, digits), Introduction to: train_test_split, cross_val_score, Performance metrics: accuracy, precision, recall, confusion matrix, Model Evaluation: Overfitting/Underfitting, Cross-validation, Hyperparameter tuning (overview)

Reference Books:

1. **“Python Machine Learning”** by Sebastian Raschka & Vahid Mirjalili (Packt)
2. **“Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow”** by Aurélien Géron (O'Reilly)
3. **“Python for Data Analysis”** by Wes McKinney (O'Reilly)
4. **“Introduction to Machine Learning with Python”** by Andreas C. Müller & Sarah Guido (O'Reilly)
5. **“Artificial Intelligence with Python”** by Prateek Joshi (Packt)

Type: DSE Semester-I

Course Title: R Programming Essentials for AI & ML

Unit 1: (30 Hours)

1.1 R Programming Essentials for AI & ML

Introduction to R: History and Features of R, Applications in AI/ML and Data Science, RStudio IDE overview, **R Basics:** Data Types: numeric, integer, character, logical, factor, Variables and Assignment, Operators: arithmetic, relational, logical, assignment, **Control Structures:** Conditional Statements: if, else, ifelse(), Loops: for, while, repeat, break, next, **Functions:** User-defined functions, Anonymous functions (function()), Built-in functions and R packages (base, stats, utils), **Data Structures in R:** Vectors, Lists, Matrices, Arrays, Factors and Data Frames

1.2 Object-Oriented Programming and Advanced Concepts in R

OOP in R: S3, S4, and R6 class systems, Defining and using classes and methods, Constructors and method dispatch, Inheritance and method overriding, **Exception Handling:** try(), tryCatch(), stop(), warning(), **File Handling:** Reading/writing text, CSV, Excel using read.csv(), write.csv(), readxl, writexl, Directory manipulation using file.exists(), dir.create(), unlink(), etc., **Parallel and Threaded Programming (basic overview):** Introduction to parallel processing in R using parallel, foreach, and doParallel, Concepts of multicore and cluster processing

Unit 2: (30 Hours)

2.1 Data Handling and Preprocessing with Tidyverse

Tidyverse Packages Overview: dplyr, tidyr, readr, tibble, lubridate **Data Manipulation:** Importing data from CSV, Excel, and text files, Filtering, selecting, arranging, and mutating data, Grouping and summarizing using dplyr, **Data Preprocessing for ML:**Handling missing data: na.omit(), is.na(), imputation, Feature scaling: normalization and standardization with scale(), Encoding categorical variables: factorization, one-hot encoding with model.matrix(), **Intro to Data Tables and Efficient Data Handling:** data.table package

2.2 Data Visualization and ML with R

Data Visualization: Base R plotting functions, ggplot2 for advanced visualization: line, bar, histogram, scatter, box, density plots, Heatmaps, correlation plots with corrplot and ggcorrplot, **Intro to ML with R**

(using caret, mlr, or tidymodels): Machine Learning pipeline: load data, preprocess, model, evaluate, Dataset examples: iris, mtcars, Boston, Titanic, Splitting data: createDataPartition(), train_test_split() (via caret), Model training and evaluation: accuracy, precision, recall, confusion matrix, Overfitting/Underfitting, Cross-validation, Hyperparameter tuning (grid search)

Reference Books:

1. **"R for Data Science"** by Hadley Wickham & Garrett Grolemund
2. **"Hands-On Programming with R"** by Garrett Grolemund
3. **"Advanced R"** by Hadley Wickham
4. **"Machine Learning with R"** by Brett Lantz
5. **"The Art of R Programming"** by Norman Matloff
6. **“Practical Data Science with R”** – Nina Zumel & John Mount (Manning)
7. **Official Documentation:**

I. https://cran.r-project.org
II. https://r4ds.hadley.nz

Type: Minor Semester-I

Course Title: Research Methodology in Computer Science

Unit 1: (30 Hours)

1.1 Foundations of Research in AI & ML

Meaning, Objectives, and Importance of Research in Computer Science & AI, Types of Research: Fundamental, Applied, Experimental, Descriptive, Research Approaches: Qualitative, Quantitative, Mixed Methods, Difference between Traditional CS Research and AI/ML Research, Scientific Method in ML Research, Formulating Research Questions & Hypotheses in AI, Research Process in ML: Problem Definition, Hypothesis, Modeling, Validation, Reproducibility and Replicability in AI Experiments, Research Ethics: Plagiarism, Bias, Fairness, Safety, Confidentiality

1.2 Literature Review, Tools & Research Design

Purpose and Process of Literature Review, Tools for Literature Review: Google Scholar, ArXiv, Semantic Scholar, IEEE, ACM, Citation Tools: Mendeley, Zotero, EndNote, BibTeX, Critical Evaluation of AI/ML Research Papers (e.g., from NeurIPS, ICML, ICLR), Dataset Identification and Benchmark Analysis, Types of Research Design: Exploratory, Descriptive, Experimental, Variables and Measurement Scales (Nominal, Ordinal, Interval, Ratio), Sampling Methods: Probability and Non-Probability, Research Proposal Writing and Experiment Planning

Unit 2: (30 Hours)

2.1 Experimental Design, Data Analysis & Evaluation

Types of Data: Structured, Unstructured; Primary vs. Secondary, Data Collection Techniques: Surveys, Interviews, Experiments, Tools: Google Forms, Excel, Python, R, Data Preparation: Cleaning, Coding, Categorizing, Data Splitting: Train/Test, K-Fold, LOOCV, Hyperparameter Tuning: Grid Search, Random Search, Bayesian Optimization, Evaluation Metrics: Classification: Accuracy, Precision, Recall, F1, ROC-AUC, Regression: MAE, MSE, RMSE, R^2, Clustering: Silhouette Score, ARI, NMI, Statistical Testing: t-test, ANOVA, McNemar's test, Tools: scikit-learn, SPSS, TensorBoard, MLflow, Interpretation of Results and Common Pitfalls

2.2 Research Communication, Publishing & Ethics

Structure of Research Papers, Dissertations, Theses in AI/ML, Writing: Abstract, Introduction, Method, Results, Discussion, Conclusion, Referencing Styles: IEEE, APA, MLA, Writing Tips for AI/ML Papers: Clarity, Contribution, Reproducibility, LaTeX & Overleaf for Research Writing, Research Repositories: GitHub, PapersWithCode, Publishing Process: Peer Review (Double-Blind, Single-Blind), Journal vs.

Conference, Top Publication Venues: NeurIPS, ICLR, ICML, CVPR, ACL, IEEE T-PAMI, Ethical Issues in Publishing: Plagiarism, Authorship Disputes, Data Integrity, Introduction to Patents and IPR in AI Research

Reference Books:

1. **C.R. Kothari & Gaurav Garg** – *Research Methodology: Methods and Techniques*, New Age
2. **Ranjit Kumar** – *Research Methodology: A Step-by-Step Guide for Beginners*, SAGE
3. **Ian Goodfellow, Yoshua Bengio, and Aaron Courville** – *Deep Learning*, MIT Press
4. **Aurélien Geron** – *Hands-On ML with Scikit-Learn, Keras & TensorFlow*, O'Reilly
5. **Uma Sekaran & Roger Bougie** – *Research Methods for Business*, Wiley

Type: DSC Semester-II

Course Title: Database Systems Using NoSQL

Unit 1: (30 Hours)

1.1 Introduction to NoSQL Databases

Need for NoSQL: Limitations of RDBMS in Big Data and Web Applications, Characteristics and Advantages of NoSQL, ACID vs BASE Properties, CAP Theorem (Consistency, Availability, Partition Tolerance), NoSQL vs SQL: Key Differences, Classification of NoSQL Databases: Key-Value Stores, Document Stores, Column-Family Stores, Graph Databases, Use Cases of NoSQL in Industry, Time-Series Databases (e.g., Influx DB, Timescale DB), Graph Neural Networks (GNNs)

1.2 Document and Key-Value Databases

Document-Oriented Databases (e.g., MongoDB): BSON format, CRUD Operations, Indexing and Aggregation, Schema Design Best Practices, Data Modeling in MongoDB, Key-Value Databases (e.g., Redis, Riak): Key-value structure, Use of TTL (Time to Live), In-memory operations, Persistence in Redis

Unit 2: (30 Hours)

2.1 Column-Family and Graph Databases

Column-Family Databases (e.g., Cassandra, HBase): Architecture and Data Model, Partitioning and Replication, CQL (Cassandra Query Language), Write and Read Paths in Cassandra, **Graph Databases (e.g., Neo4j):** Nodes, Edges, and Properties, Cypher Query Language, Graph Traversal and Pattern Matching

2.2 NoSQL in Practice and Advanced Topics

NoSQL Integration with Applications- Using NoSQL with Python/Node.js, REST APIs for MongoDB/CouchDB, Performance Tuning and Scaling: Indexing, Sharding, Replication, Query Optimization in MongoDB and Cassandra, Backup and Recovery, Security and Authentication in NoSQL, Comparative Study of NoSQL Systems- MongoDB vs Cassandra vs Redis vs Neo4j

Reference Books:

1. **"NoSQL Distilled: A Brief Guide to the Emerging World of Polyglot Persistence"** by Pramod J. Sadalage & Martin Fowler
2. **"MongoDB: The Definitive Guide"** by Shannon Bradshaw, Kristina Chodorow (O'Reilly)
3. **"Cassandra: The Definitive Guide"** by Jeff Carpenter & Eben Hewitt (O'Reilly)
4. **"Graph Databases"** by Ian Robinson, Jim Webber, and Emil Eifrem (O'Reilly)
5. **"Seven Databases in Seven Weeks"** by Luc Perkins, Eric Redmond, and Jim Wilson (Pragmatic Bookshelf)

Type: DSC Semester-II

Course Title: Machine Learning Algorithms

Unit 1: (30 Hours)

1.1: Introduction to Machine Learning and Supervised Learning

Introduction to Machine Learning: Machine Learning Workflow: Data Collection, Preprocessing, Training, Testing, Evaluation; Linear, Regression: Model, Cost Function, Gradient Descent;

Logistic Regression: Classification, Sigmoid Function, Decision Boundary;

Performance Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, Confusion Matrix;

Overfitting and Underfitting, Bias-Variance Tradeoff; Feature Selection and Feature Engineering Basics

1.2: Advanced Supervised Learning Algorithms

Decision Trees: Construction, Pruning, Information Gain, Gini Index; Random Forests and Ensemble Methods: Bagging, Boosting (XGBoost, LightGBM); Support Vector Machines (SVM): Kernel Trick, Hyperplanes, Margin; K-Nearest Neighbors (KNN): Distance Metrics, Applications; Naive Bayes Classifiers: Bayes Theorem, Conditional Independence; Regularization Techniques: L1 (LASSO), L2 (Ridge), ElasticNet

Unit 2: (30 Hours)

2.1 Unsupervised Learning and Dimensionality Reduction

Clustering Techniques: K-Means, Hierarchical Clustering, DBSCAN; Cluster Evaluation: Silhouette Score, Davies-Bouldin Index; Dimensionality Reduction: PCA (Principal Component Analysis) - Theory and Use Cases, t-SNE and UMAP for High-Dimensional Visualization; Association Rule Mining: Apriori Algorithm and Support-Confidence Framework

2.2 Neural Networks, Reinforcement Learning, and Emerging Topics

Model Selection and Evaluation: Cross-Validation (k-fold, Stratified), Performance Trade-offs;

Hyperparameter Tuning: Grid Search, Random Search;

Neural Networks: Perceptron, Multi-Layer Perceptron (MLP), Activation Functions; Backpropagation Algorithm

Introduction to Reinforcement Learning: Basics: Agent, Environment, Rewards, States, Actions, Markov Decision Processes (MDPs), Exploration vs. Exploitation, Q-Learning and Temporal Difference Learning (introductory concepts), Applications of RL in Game Playing and Robotics, Ethical and Responsible AI: Bias, Fairness, Transparency

Reference Books:

1. **Pattern Recognition and Machine Learning** – Christopher M. Bishop (Springer)
2. **Machine Learning: A Probabilistic Perspective** – Kevin P. Murphy (MIT Press)
3. **Hands-On Machine Learning with Scikit-Learn, Kera's, and TensorFlow** – Aurélien Géron (O'Reilly)
4. **Introduction to Machine Learning with Python** – Andreas C. Müller & Sarah Guido (O'Reilly)
5. **Machine Learning** – Tom M. Mitchell (McGraw-Hill)
6. **Reinforcement Learning: An Introduction** – Richard S. Sutton and Andrew G. Barto (MIT Press)

Type: DSE Semester-II

Course Title: Cloud Computing

Unit 1: (30 Hours)

1.1Fundamentals of Cloud Computing

Introduction to Cloud Computing: Definitions, Characteristics, Benefits, Cloud Computing Service Models: IaaS, PaaS, SaaS, Cloud Deployment Models: Public, Private, Hybrid, Community, Virtualization Concepts: Hypervisors, Types of Virtualizations, Cloud Architecture and Components, Basics of Cloud Storage and Data Management, Cloud Security Challenges and Issues

1.2 Cloud Service Models and Platforms

Infrastructure as a Service (IaaS): Compute, Storage, Network, Platform as a Service (PaaS): Development and Deployment Platforms, Software as a Service (SaaS): Examples and Use Cases, Introduction to Major Cloud Providers: AWS, Azure, Google Cloud, Managing Cloud Resources: Instances, Storage, Load Balancers, Cloud APIs and SDKs, Introduction to Cloud SDKs and Boto3

Unit 2: (30 Hours)

2.1 Cloud Security, Management, and Virtualization

Cloud Security Fundamentals: Confidentiality, Integrity, Availability, Identity and Access Management (IAM), Encryption and Key Management in Cloud, Compliance and Governance in Cloud Computing, Resource Management and Monitoring in Cloud, Containerization and Orchestration: Docker, Kubernetes Basics, Serverless Computing Concepts,

2.2 Advanced Cloud Computing Concepts and Applications

Cloud Storage Services: Object, Block, and File Storage, Cloud Networking: Virtual Private Clouds (VPC), Subnets, Gateways, Cloud Migration Strategies and Challenges, Cloud-based Big Data and Analytics, Edge Computing and Fog Computing Overview, Case Studies: Cloud in AI/ML, Healthcare, Finance, IoT, Future Trends in Cloud Computing, MLOps in the Cloud**:** CI/CD for ML using tools like SageMaker, Vertex AI, or Azure ML.

Reference Books:

1. **Cloud Computing:** Concepts, Technology & Architecture-Thomas Erl, Ricardo Puttini, Zaigham Mahmood (Pearson)
2. **Cloud Computing:** Principles and Paradigms-Rajkumar Buyya, James Broberg, Andrzej M. Goscinski (Wiley)
3. **Architecting the Cloud:** Design Decisions for Cloud Computing Service Models (SaaS, PaaS, and IaaS)- Michael J. Kavis (Wiley)
4. **Cloud Security and Privacy:** An Enterprise Perspective on Risks and Compliance- Tim Mather, Subra Kumaraswamy, Shahed Latif (O'Reilly)
5. **Mastering Cloud Computing**- Rajkumar Buyya, Christian Vecchiola, S. Thamarai Selvi (McGraw-Hill)

Type: DSE Semester-II

Course Title: Git & GitHub

Unit 1: (30 Hours)

1.1Introduction to Version Control and Git Basics

Introduction to Version Control Systems (VCS): Concepts and Importance, Types of VCS: Local, Centralized, Distributed, Introduction to Git: History and Features, Installing Git and Setting up Environment, Git Configuration: username, email, aliases, Basic Git Workflow: Repository Initialization, Cloning, Git States: Working Directory, Staging Area, Repository, Basic Git Commands: add, commit, status, log, Understanding Commits and Commit History

1.2 Branching, Merging, and Collaboration using Git

Branching in Git: Creating, Switching, Deleting Branches, Merging Branches: Fast-Forward and Three-Way Merge, Handling Merge Conflicts, Git Tags: Lightweight and Annotated Tags, Remote Repositories: Concept and Setup, Working with Remotes: git remote, fetch, pull, push, Forking Repositories and Pull Requests Overview, Introduction to Git Workflows: Centralized, Feature Branch, Gitflow

Unit 2: (30 Hours)

2.1 Advanced Git and GitHub Features

Git Stashing and Cleaning, Rebasing: Interactive Rebase and Rebase vs Merge, Git Cherry-Pick and Revert Commands, Working with Submodules, Git Hooks: Client-side and Server-side Hooks, Introduction to GitHub: Features and Interface, Creating Repositories on GitHub, Managing Issues, Labels, and Projects on GitHub

2.2 Collaboration and Automation in GitHub

Pull Requests and Code Review Process, Branch Protection Rules and Managing Collaborators, GitHub Actions for Continuous Integration (CI) and Continuous Deployment (CD), GitHub Pages for Project Hosting, Using GitHub CLI and GitHub Desktop, Best Practices for Commit Messages and Repository Management, Integrating GitHub with IDEs and Other Tools, Case Studies: Open Source Contribution and Team Collaboration, **Semantic Versioning**, **Changelogs**, and **Release Tags**

Reference Books:

1. Pro Git (2nd Edition)- Scott Chacon and Ben Straub (Apress)
   (Available free at https://git-scm.com/book/en/v2)
2. Git Pocket Guide-Richard E. Silverman (O'Reilly)
3. GitHub Essentials-Achilleas Anagnostopoulos (Packt)
4. Learning Git and GitHub-Dawn Griffiths and David Griffiths (O'Reilly)
5. Version Control with Git-Jon Loeliger and Matthew McCullough (O'Reilly)