Gyanmanjari Innovative University

Course Syllabus
Faculty of Engineering & Technology
Semester-1(M. Tech.)

Subject: Machine Learning - METCE11504

Type of course: Minor Stream

Prerequisite Data Structures, Basics of Probability and Statistics

Rationale:

Machine learning is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention. This subject will help students to learn patterns and concepts from data without being explicitly programmed in various IOT nodes and also motivates them to design and analyze various machine learning algorithms and techniques with a modern outlook focusing on recent advances.

Teaching and Examination Scheme:

Teaching Scheme			Credits	Examination Marks					Total Marks
CI	T	P	C	Theory Marks		Practical Marks		CA	
				ESE	MSE	V	P	ALA	
4	0	2	5	60	30	10	20	30	150

Legends: CI-ClassRoom Instructions; T – Tutorial; P - Practical; C – Credit; ESE - End Semester Examination; MSE- Mid Semester Examination; V – Viva; CA - Continuous Assessment; ALA- Active Learning Activities.

Course Content:

Sr. No	Course content	Hrs	% Weightage
1	Supervised Learning Techniques: Introduction to Machine Learning and Learning Paradigms, Regression Methods:Linear Regression, Logistic Regression, Generalized Linear Models, Classification Methods: Distance-based Methods, k-Nearest Neighbours (k-NN), Decision Trees, Naïve Bayes Classifier, Support Vector Machines: Linear SVM, Non-linear SVM, Kernel Methods, Beyond Binary Classification: Multi-class Classification, Structured Outputs, Ranking Problems	13	20
2	Unsupervised Learning and Dimensionality Reduction: Introduction to Unsupervised Learning, Clustering Techniques: K-Means Clustering, Kernel K-Means, Dimensionality Reduction: Principal Component Analysis (PCA), Kernel PCA Matrix Factorization: Matrix Completion, Generative Models: Mixture Models, Latent Factor Models	10	20
3	Model Evaluation, Statistical Learning and Ensemble Methods: Evaluating Machine Learning Algorithms, Bias–Variance Tradeoff, Model Selection and Validation Techniques, Introduction to Statistical Learning Theory, Ensemble Learning Methods: Bagging, Boosting, Random Forests	12	20
4	Sparse Modelling, Time-Series and Deep Learning: Sparse Modelling and Estimation, Regularization Techniques, Modelling Sequential and Time-Series Data, Deep Learning: Introduction to Neural Networks, Deep Learning Architectures Feature Representation Learning	13	15
5	Advanced Machine Learning and Applications: Scalable Machine Learning, Online Learning, Distributed Learning, Advanced Learning Paradigms, Semi-supervised Learning, Active Learning, Reinforcement Learning, Probabilistic Learning, Bayesian Learning, Bayesian Inference, Graphical Models, Recent Trends and Applications: Machine Learning for IoT, Classification Models for IoT Applications	12	25

Continuous Assessment:

Sr. No	Active Learning Activities	Marks
1	**Supervised Learning Model Design and Evaluation** In this activity, students will select a real-world dataset (such as healthcare, finance, education, or social media) and implement **supervised learning algorithms** such as Linear Regression, Logistic Regression, Decision Tree, Naïve Bayes, K-NN, or Support Vector Machine. Students will perform data preprocessing, feature selection, model training, and evaluation using appropriate performance metrics (accuracy, precision, recall, F1-score, RMSE). The implementation will be done using **Python (Scikit-learn)**. A short report including dataset description, methodology, results, and observations will be submitted on the **GMIU Web Portal**.	10
2	**Unsupervised Learning and Dimensionality Reduction Case Study** In this activity, students will apply **unsupervised learning techniques** such as K-Means clustering, Kernel K-Means, PCA, or Kernel PCA on a given dataset. Students will analyze clustering behavior, visualize results, and interpret the reduced feature space. The activity aims to develop understanding of data structure without labeled outputs. Students will submit a **Jupyter Notebook** along with a brief explanation of algorithm selection, results, and conclusions on the **GMIU Web Portal**.	10
3.	**Advanced Machine Learning / Application-Based Mini Project** In this activity, students will work on a **mini project or case study** based on advanced machine learning concepts such as Ensemble Methods (Bagging, Boosting, Random Forests), Deep Learning basics, Time-Series Modeling, Bayesian Learning, or Machine Learning applications for IoT. Students may work individually or in small groups. The submission will include problem formulation, model implementation, performance analysis, and future scope. A concise project report or presentation will be submitted on the **GMIU Web Portal**.	10
	Total	30

Suggested Specification table with Marks (Theory):60

Distribution of Theory Marks (Revised Bloom's Taxonomy)						
Level	Remembrance (R)	Understanding (U)	Application (A)	Analyze (N)	Evaluate (E)	Create (C)
Weightage	10%	20%	30%	20%	10%	10%

Note: This specification table shall be treated as a general guideline for students and teachers. The actual distribution of marks in the question paper may vary slightly from above table.

Course Outcome:

After learning the course the students should be able to:	
CO1	Explain the fundamental concepts, learning paradigms, and problem formulation of **Machine Learning**, including supervised and unsupervised learning techniques.
CO2	Design, implement, and evaluate **supervised learning models** such as regression, classification, and support vector machines using appropriate performance metrics.
CO3	Apply **unsupervised learning techniques** including clustering, dimensionality reduction, and generative models to analyze and discover patterns in unlabeled data.
CO4	Analyze and implement **model evaluation strategies, ensemble methods, sparse modelling, time-series analysis, and deep learning techniques** for feature representation learning.
CO5	Apply **advanced machine learning approaches** such as scalable learning, semi-supervised learning, reinforcement learning, Bayesian learning, and machine learning applications for **IoT and real-world problems.**

List of Practical:

Sr. No	Descriptions	Unit No	Hrs
1	Install and familiarize with Machine Learning tools such as Python (Anaconda, Jupyter Notebook) and/or WEKA. Demonstrate basic interface, datasets, and workflow.	1	02
2	Create and load a dataset (CSV/ARFF) and explore dataset structure including attributes, instances, and data types using WEKA / Python (Pandas).	1	02
3	Perform data preprocessing techniques such as data cleaning, normalization, transformation, handling missing values, and feature scaling on a given dataset.	2	02
4	Implement Linear Regression and Logistic Regression models and evaluate performance using appropriate metrics.	1	04
5	Implement Classification Algorithms such as K-Nearest Neighbours, Naïve Bayes, and Decision Tree and compare their performance.	1	04
6	Implement Support Vector Machine (SVM) with linear and non-linear kernels and analyze the classification results.	1	04
7	Implement Unsupervised Learning Algorithms such as K-Means Clustering and visualize clustering results.	2	02
8	Apply Dimensionality Reduction techniques such as Principal Component Analysis (PCA) and analyze reduced feature space.	2	02
9	Implement Ensemble Learning Methods such as Bagging, Boosting, or Random Forests and evaluate model performance.	3	02

GYANMANJARI INNOVATIVE UNIVERSITY
BHAVNAGAR

10	Implement a basic Neural Network / Deep Learning model for classification or regression using Python libraries (TensorFlow / Keras / PyTorch – basic level).	4	02
11	Mini Case Study / Application-Based Experiment: Apply Machine Learning techniques to a real-world problem such as IoT data analysis, time-series forecasting, or predictive analytics, and present observations.	5	04
		Total	30

Instructional Method:

The course delivery method will depend upon the requirement of content and need of students. The teacher in addition to conventional teaching method by black board, may also use any of tools such as demonstration, role play, Quiz, brainstorming, MOOCs etc.

From the content 10% topics are suggested for flipped mode instruction.

Students will use supplementary resources such as online videos, NPTEL/SWAYAM videos, e-courses, Virtual Laboratory

The internal evaluation will be done on the basis of Active Learning Assignment

Practical/Viva examination will be conducted at the end of semester for evaluation of performance of students in laboratory.

Reference Books:

1. Machine Learning: A Probabilistic Perspective, Kevin Murphy, MIT Press, 2012.
2. The Elements of Statistical Learning, Trevor Hastie, Robert Tibshirani, Jerome Friedman, Springer 2009 (freely available online)
3. Machine Learning in Action, Peter Harrington, Manning, dreamtech press
4. Machine Learning for Big Data, Jason Bell, Wiley
5. Machine Learning in Python, Michael Bowles, Wiley
6. Machine Learning with TensorFlow for dummies, Matthew Scarpino, Wiley
7. Python Machine Learning By Example, Yuxi Liu, Packt.
8. Advance Machine Learning with Python, John Hearty, Packt
9. Deep Learning, Ian Goodfellow, Yoshua Bengio, Aaron Courville, MIT Press
10. Pattern Recognition and Machine Learning, Christopher Bishop, Springer, 2007.