Code: BCA- 4005T (For theory) BCA-4005P (For practical)	DSEC-IV	Group-A: Elective – II Introduction to Machine Learning	1L+T:4P	3 Credits (15 hours theory and 60 hours practical)

Max Marks; Theory: 100 (Int: 25; Ext: 75); Practical: 100

Course Outcomes: Upon competition of the course, students will be able to

CO1: Define and explain machine learning concepts, types, and basic metrics.

CO2: Implement and apply supervised learning techniques (e.g., KNN, Linear Regression, and Logistic Regression) and un supervised learning methods (e.g., K-Means, Hierarchical Clustering, Association Rules).

CO3: Develop and evaluates implemachine learning models(e.g., Perceptron, single-layer neural networks) and analyze and apply appropriate machine learning algorithms depending on the problems with some real-world data.

Course Outcomes after Lab Programs:

CO1: Implement and evaluate supervised learning techniques, including K-Nearest Neighbors, linear regression, and logistic regression, and measure model performance using accuracy, precision, recall, and F1 score.

CO2: Apply and visualize clustering algorithms such as K-Means, hierarchical clustering, and DBSCA Non data sets. This practical application helps you understand their real- world use.

CO3: Perform dimensionality reduction using Principal Component Analysis (PCA) and interpret the results.

CO4: Develop and assess classification models using random forests, support vector machines, and neural networks.

CO5: Demonstrate ensemble learning concepts through bagging with random forests and boosting with the AdaBoost algorithm.

Unit	Topics	Proposed Lectures
I	**Introduction to Machine Learning:** Introduction: Definition, History and Application of Machine Learning, Types of Machine Learning: Supervised, Unsupervised, Semi-Supervised, and Reinforcement Learning. Labeled and Unlabeled Dataset. Supervised Learning Tasks: Regression vs. Classification, Learning Framework: Training, Validation and Testing of ML models. Performance Evaluation Parameters: Confusion matrix, Accuracy, Precision, Recall, F1 Score, and AUC.	7
II	**Supervised Learning and Unsupervised Learning:** Regression: Linear and Non-linear Regression, Logistic Regression. Classification: Naïve Bayes, K-Nearest Neighbors, Decision Trees. Linear model: Introduction to Artificial Neural Networks, Perceptron Learning Algorithm, Single Layer Perceptron, Introduction to Support Vector Machine for linearly separable data. Clustering: K-Means, Hierarchical Clustering, DBSCAN, Clustering Validation Measures. ML Applications: Ethical Considerations in Machine Learning, Case Study and Real-world Applications.	8
Lab Prog rams	**1.** Implement linear regression on a data set and visualize the regression line. **2.** Implement logistic regression on a binary classification data set and plot the decision boundary. **3.** Implement and evaluate the performance of Decision tree ID3/Cart classifier for any given dataset. **4.** Implement and evaluate the performance of the Naïve Bayes Classifier on a given dataset. **5.** Build and evaluate a random forest classifier using a numerical dataset. **6.** Implement a support vector machine for linearly separable classes and visualize the margins and decision boundary. **7.** Implement K-Means clustering on a point dataset and visualize and evaluate the clusters. **8.** Implement hierarchical clustering on a dataset and plot the	

	dendrogram. 9. Implement DBSCAN clustering on a dataset and visualize and evaluate the clusters. 10. Perform Principal Components Analysis (PCA) and apply any one or more classifiers to show the performance variation with or without feature reduction. 11. Build a single layer perceptron model to classify AND, OR, and XOR problems (may use TensorFlow/ Keras) and visualize their decision boundaries. Also evaluate its performance. 12. Demonstrate the concept of boosting using the AdaBoost algorithm.	

Text Books:

1. Mitchell, Tom M. *Machine Learning*. 1st ed., McGraw-Hill, 1997.
2. Kalita, J. K., D. K. Bhattacharyya, and S. Roy. *Fundamentals of Data Science: Theory and Practice*. Elsevier, 2023.
3. Chopra, Rajiv. *Machine Learning and Machine Intelligence*. Khanna Publishing House, 2024.
4. Jose, Jeeva. *Introduction to Machine Learning*. Khanna Publishing House, 2023.

Reference Books:

1. Flach, Peter A. *Machine Learning: The Art and Science of Algorithms that Make Sense of Data*. Cambridge University Press, 2012.
2. Duda, Richard O., Peter E. Hart, and David G. Stork. *Pattern Classification*. 2nd ed., John Wiley & Sons, 2007.
3. Haykin, Simon. *Neural Networks and Learning Machines*. 3rd ed., PHI Learning, 2009.
4. Chollet, François. *Deep Learning with Python*. Manning Publications, 2018.
5. Bishop, Christopher M. *Pattern Recognition and Machine Learning*. Springer, 2006.
6. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. *Deep Learning*. MIT Press, 2016.
7. Géron, Aurélien. *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. 1st ed., O'Reilly Media, 2017.