Pokhara University
Faculty of Science and Technology

Course No.: CMP 364 (3 Credits)	Full marks: 100
Course title: Machine Learning (3-1-2)	Pass marks: 45
Nature of the course: Theory and Practical	Total Lectures: 45 hrs
Level: Bachelor	Program: BE (Computer)

1. Course Description

This course is designed to provide the fundamental principles and methodologies of machine learning. Students will learn to develop algorithms that can automatically learn from data, improve with experience, and make predictions or decisions. The course covers supervised, unsupervised machine learning alongside in-depth concepts of neural networks, and model evaluation and validation with a focus on both theoretical understanding and practical implementation.

2. General Objectives

- To provide the students with key concepts and principles of machine learning.
- To acquaint the students with the skills to develop and implement different machine learning algorithms.
- To develop the skills in students to use popular machine learning tools and frameworks and apply machine learning techniques to solve real-world problems.
- To acquaint the students with the knowledge of advanced topics in neural networks, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).
- To provide the students with the knowledge to evaluate and interpret the performance of machine learning models.

3. Methods of Instruction

Lecture, Discussion, Readings, Practical works and Project works.

4. Contents in Detail

Specific Objectives	**Contents**

• Describe the machine learning process in detail.	**1. Introduction to Machine Learning (5 hrs)** **1.1.** Definition and Evolution of Machine Learning **1.2.** Types of Machine Learning **1.2.1.** Supervised Learning **1.2.2.** Unsupervised Learning **1.2.3.** Reinforcement Learning **1.2.4.** Active Learning **1.3.** Machine Learning Workflow **1.3.1.** Problem Definition **1.3.2.** Data Collection and Preprocessing **1.3.3.** Model Selection **1.3.4.** Model Evaluation and Validation **1.3.5.** Model Deployment **1.4.** Challenges in Machine Learning **1.4.1.** Data Quality Issues **1.4.2.** Computational Complexity **1.4.3.** Interpretability and Explainability **1.4.4.** Ethical Considerations
● Design and implement supervised learning algorithms to solve real world problems.	**2. Supervised Learning (10 hrs)** **2.1.** Types of Supervised Learning **2.1.1.** Regression **2.1.2.** Classification **2.2.** Regression **2.2.1.** Linear Regression **2.2.1.1.** Simple and multiple regression **2.2.1.2.** Polynomial Regression **2.2.2.** Regularization Techniques **2.2.2.1.** Ridge regression **2.2.2.2.** Lasso regression **2.2.2.3.** Bias-variance tradeoff **2.2.3.** Support Vector Regression **2.3.** Classification **2.3.1.** Logistic Regression **2.3.1.1.** Binary classification **2.3.1.2.** Multi-class classification **2.3.2.** K-Nearest Neighbors (KNN) **2.3.3.** Support Vector Machine (SVM) **2.3.3.1.** Hyperplane and Support Vectors **2.3.3.2.** Kernels and its Types: Linear, Polynomial, Radial Basis Function (RBF) **2.3.3.3.** SVM for Linear and Non-linear Classification **2.3.4.** Decision Trees **2.3.4.1.** Construction and pruning of decision trees **2.3.4.2.** Ensemble methods: Bagging, Random Forests

• Design and implement unsupervised learning algorithms to solve real world problems.	**3. Unsupervised Learning (10 hrs)** **3.1.** Basic Concept of Unsupervised Learning **3.2.** Types of Unsupervised Learning **3.2.1.** Clustering **3.2.2.** Dimensionality Reduction **3.2.3.** Association Rule Learning **3.3.** Clustering **3.3.1.** K-Means Clustering **3.3.2.** Hierarchical Clustering **3.3.2.1.** Agglomerative Clustering **3.3.2.2.** Divisive Clustering **3.3.3.** Density-based Clustering **3.3.3.1.** DBSCAN **3.4.** Dimensionality Reduction **3.4.1.** Principal Component Analysis (PCA) **3.4.2.** Linear Discriminant Analysis (LDA)
• Design and implement Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).	4. **Artificial Neural Network (12 hrs)** 4.1. Introduction to Neural Network 4.1.1. Neural Network Architectures 4.1.1.1. Feedforward 4.1.1.2. Convolution 4.1.1.3. Recurrent 4.1.2. Perceptrons 4.1.2.1. Single layer perceptron 4.1.2.2. Multilayer Perceptron 4.1.2.3. Backpropagation 4.2. Training Neural Network 4.2.1. Forward and Backward Propagation 4.2.1.1. Forward Propagation 4.2.1.2. Backpropagation and Gradient Descent 4.2.2. Loss functions 4.2.2.1. Role of loss function 4.2.2.2. Mean Squared Error (MSE) 4.2.2.3. Cross-Entropy Loss 4.2.3. Regularization Techniques 4.2.3.1. Overfitting and underfitting 4.2.3.2. Regularization methods: L1, L2, Dropout, Batch Normalization 4.3. Advanced Neural Network Architecture 4.3.1. Convolution Neural Network (CNNs) 4.3.1.1. CNNs and their components 4.3.1.2. Convolution, Pooling and fully connected layers 4.3.1.3. Applications in image processing and computer vision 4.3.2. Recurrent Neural Networks (RNNs) 4.3.2.1. Basics of RNNs 4.3.2.2. Long Short-Term Memory (LSTM)

	4.3.2.3. Gradient Recurrent Units (GRU) 4.3.2.4. Applications in time-series prediction
● Apply the various techniques to evaluate and validate machine learning algorithms.	5.**Model Evaluation and Validation (8 hrs)** 5.1. Need of Model Evaluation in ML 5.2. Model Evaluation Metrics 5.2.1. Classification Metrics 5.2.1.1. Accuracy 5.2.1.2. Precision, Recall and F_β score 5.2.1.3. Confusion Matrix 5.2.1.4. ROC and PR-Curve 5.2.2. Regression Metrics 5.2.2.1. Mean Absolute Error (MAE) 5.2.2.2. Mean-Squared Error (MSE) 5.2.2.3. Root Mean-Squared Error (RMSE) 5.2.2.4. R-Squared 5.3. Model Validation Techniques 5.3.1. Train-Test Split 5.3.2. Cross-Validation 5.3.2.1. K-Fold Cross Validation 5.4. Hyperparameter Tuning 5.4.1. Grid Search 5.4.2. Random Search

5. Practical Works

Laboratory work of 30 hours per group of a maximum of 24 students must cover the following lab works:

SN	Implementation Description
1	Implement and evaluate a support vector machine.
2	Implement linear regression on a dataset (e.g., housing prices) and evaluate its performance. Apply ridge and lasso regression to prevent overfitting and compare results.
3	Implement k-means clustering and visualize the clusters on a dataset (e.g., customer segmentation) and apply PCA to reduce dimensionality and visualize data
4	Implement k-fold cross-validation on a classification or regression model
5	Build and train CNNs for image classification and RNNs for sequence prediction.

Students must submit a project work that uses all the knowledge obtained from this course to solve any problem they choose. The marks for the practical evaluation must be based on the project work submitted by students.

6. List of Tutorials

The various tutorial activities that suit your course should cover all the content of the course to give students a space to engage more actively with the course content in the presence of the instructor. Students should submit tutorials as assignments or class works to the instructor for evaluation. The following tutorial activities of 15 hours per group of maximum 24 students should be conducted to cover the content of this course:

A. Discussion-based Tutorials: (3 hrs)
   a. Evolution of Machine Learning (Class discussion).
   b. Group debate on the challenges in Machine Learning. (Oral Presentation).

B. Problem solving-based Tutorials: (6 hrs)
   a. Design CNNs for image classification.
   b. Design RNNs for sequence prediction.

C. Review and Question/Answer-based Tutorials: (6 hrs)
   a. A detailed case study on recent Tools and Frameworks for example TensorFlow, PyTorch and Python (Oral Presentation in class).
   b. Case study on model evaluation and validation.
   c. Students ask questions within the course content, assignments and review key course content in preparation for tests or exams.

7. Evaluation System and Students' Responsibilities

Evaluation System

The internal evaluation of a student may consist of assignments, attendance, internal assessment, lab reports, project works etc. The internal evaluation scheme for this course is as follows:

Internal Evaluation	Weight	Marks	External Evaluation	Marks
Theory		30	Semester-End examination	50
Attendance & Class Participation	10%			
Assignments	20%			
Presentations/Quizzes	10%			
Internal Assessment	60%			
Practical		20		
Attendance & Class Participation	10%			
Lab Report/Project Report	20%			
Practical Exam/Project Work	40%			
Viva	30%			
Total Internal		50		
Full Marks: 50 + 50 = 100				

Student Responsibilities

Each student must secure at least 45% marks separately in internal assessment and practical evaluation with 80% attendance in the class in order to appear in the Semester End Examination. Failing to get such a score will be given NOT QUALIFIED (NQ) to appear for the Semester-End Examinations. Students are advised to attend all the classes, formal exam, test, etc. and complete all the assignments within the specified time period. Students are required to complete all the requirements defined for the completion of the course.

8. Prescribed Books and References

Text Books

1. Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.
2. Murphy, K. P. (2012). *Machine learning: a probabilistic perspective.* MIT press.

References

1. Géron, A. (2022). *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow.* O'Reilly Media, Inc.
2. Ian, G. (2016). *Deep learning/Ian Goodfellow, Yoshua Bengio and Aaron Courville*.MIT press.