Course Title:	Machine Learning
Course Code:	
Credit:	3
Class Load:	3 hours

Course Objectives:
To provide knowledge on machine learning algorithms and build skills on applying machine learning algorithms in a diverse set of problems.

Detailed Syllabus

1. Introduction **(3 hours)**
Machine learning, types of machine learning; classification, regression, supervised learning, un-supervised learning, reinforcement learning

2. Supervised learning **(12 hours)**
Regression: Linear Regression (simple/multiple), Closed Solution vs Gradient Descent.
Classification: Logistic Regression, K-Nearest Neighbor, Kernel Methods (e.g. SVM), Bayes Classifier
Model Performance: Generalization, overfitting and underfitting, Validation, Cross-Validation, Regularization, Bias-Variance Tradeoff
Classification Performance: Accuracy, Sensitivity & Specificity, AUROC, Confusion Matrix

3. Deep Networks **(12 hours)**
Feedforward Networks, Gradient-based learning, Cost function, Output Units (Linear, sigmoid, softmax), Hidden Units (Relu, LeakyRelu), Architecture Design, Automatic Differentiation & Backpropagation
Regularization for Deep Learning: L1, L2 regularization, Dataset Augmentation, Early Stopping, Dropout
Optimization: SGD,Momentum, Adaptive learning rate. Plateau, Saddle point & flat regions. Cliffs & Exploding gradients, Parameter Initialization, Batch Normalization

4. Convolutional Neural Networks **(6 hours)**
Convolution Operation, *Properties of Convolution*: Sparse Connectivity, Parameter Sharing & Equivariance. Pooling, *Variants of Convolution:* Strided Convolution, Transpose Convolution, Dilated Convolution. Neuroscientific Basis for Convolutional Networks

5. Managing machine learning projects **(3 hours)**
Baseline Model, Hyperparameter tuning, Performance Metrics, Debugging Strategies

6. Unsupervised learning(Clustering) **(3 hours)**
Introduction to clustering, k-means, expectation maximization, mixture models

7. Project Work **(6 hours)**

Text books:

A First Course in Machine Learning, Simon Rogers and Mark Girolami, Chapman & Hall, Second Edition 2016.

- This book is especially useful for the early part of the course namely, *Linear Regression.* The book derives in detail the closed form solution for *Linear Regression, Vector Matrix Notation.*

Murphy, Kevin P. *Probabilistic machine learning: an introduction*. MIT press, 2022. (openaccess https://probml.github.io/pml-book/book1.html)

- This book (*draft Book 1*) has links to the corresponding jupyter notebooks in the text itself.

Deep Learning, Ian Goodfellow and Yoshua Bengio and Aaron Courville, The MIT Press, 2016. (openaccess www.deeplearningbook.org)

Practicals References:

Weidman, Seth. *Deep learning from scratch: building with python from first principles*. O'Reilly Media, 2019.