Syllabus:

INTRODUCTION:
Introduction to computer vision and its applications, Image formation, Liner Filtering, Image transformations and Colour models. [**07 Hours]**

FEATURE DETECTION AND MATCHING:
Edge Detection methods (Laplacian detectors and Canny edge detector)**,** Points and patches, Harris corner detector, Histogram of Gradients, Difference of Gaussian detector, SIFT, Colour and Texture, Feature based alignment, least squares and RANSAC [**09 Hours]**

CAMERA CALIBRATION:

Camera models, Camera calibration, Stereo vision, Stereo correspondence, Epipolar geometry

[08 Hours]

TRACKING:

Optical flow, Lucas Kanade method, KLT tracking method, Mean shift method, Dense motion estimation. **[06 Hours]**

OBJECT RECOGNITION:
Support Vector Machines, Face detection and recognition, Bag of words, Deep learning.
[06 Hours]

Outcomes:
After studying this course, students will be able to:

- Understand the concepts of image formation, colour models and linear filtering.
- Understand the mathematics behind feature detection and description methods.
- Demonstrate a thorough understanding of fundamental concepts in camera calibration.
- Understand and analyze various object tracking algorithms.
- Comprehend object and scene recognition and categorization from images.

References:

1. Szeliski R., *Computer Vision: Algorithms and Applications*, Springer 2011.
2. David A. F. and Ponce J., *Computer Vision: A Modern Approach, PHI learning* 2009.
3. Solem J. E., *Programming Computer Vision with Python*, O'Reilly, 2012.

IT_4032: MACHINE LEARNING [3 0 0 3]

Objectives:

This course will enable students to

- Gain basic knowledge about the key algorithms and theory that forms the foundation of machine learning and computational intelligence
- Get a practical knowledge of machine learning algorithms and methods

Abstract:

Introduction to Machine Learning, Mathematical Preliminaries, Supervised Learning-LMS, logistic regression, GDA, Naive Bayes, SVM, model selection, Learning theory-bias/variance tradeoff, union and Chernoff bounds, VC dimensions, Unsupervised learning-clustering, k-means, Gaussian mixture, factor analysis, PCA, ICA, Reinforcement learning-MDPs, Bellman equations, value and policy iteration, LQR, LQG, Q-learning, policy search, POMDPs

Syllabus:

Introduction:
Machine learning basics, Examples of Machine learning application, Steps in developing machine learning application [**3 Hour**]

CLASSIFICATION AND REGRESSION:

Bayesian Decision Theory: Continuous features, Minimum Error Rate Classification, Classifiers, Discriminate Functions, Error Probabilities and Integral, Bayesian Belief Network, Maximum likelihood ratio, parametric classification, regression, Multivariate methods, Naïve Bayesian Model. Non-Parametric Techniques: Density Estimation, Parzen Windows, k_n- Nearest-Neighbor Estimation, Nearest – Neighbor Rule, K- nearest neighbor classification. **[14 Hours]**

SUPERVISED LEARNING:

Linear discrimination, Gradient descent, Logistic discrimination, Single layer Perceptron, Training a perceptron, Multilayer perceptron, Back-Propagation Algorithm, Genetic algorithms, Decision trees, Support vector machines. **[12 Hours]**

UNSUPERVISED LEARNING:

Clustering, K-Means clustering, EM-algorithm, Hierarchical clustering, Competitive learning, and Radial basis functions. **[5 Hours]**

COMBINING MULTIPLE LEARNERS:

Voting, Error correcting output codes, Bagging, Boosting. [**2 Hours**]

Outcomes:

- Understand the principles, advantages, limitations and possible applications of machine learning.
- Identify and apply the appropriate machine learning technique for classification, using pattern recognition system.
- Analyze simple algorithms for supervised learning, reinforcement learning, and unsupervised learning.
- Understand unsupervised learning for data clustering.
- Validation of a combined machine learning system.

References:

1. Murphy K.P., *Machine Learning: A Probabilistic Perspective*, MIT Press, 2012.
2. Mohri M., Rostamizadeh A., and Talwalkar A., *Foundations of Machine Learning*, MIT Press, 2012.
3. Koller D., and Friedman N, *Probabilistic Graphical Models: Principles and Techniques*, MIT Press, 2009.
4. Bishop C.M., *Pattern Recognition and Machine Learning* (2e), Springer, 2013.

CSE_4054: SOFT COMPUTING PARADIGMS [3 0 0 3]

Course objectives:

This course will enable students to

- To Conceptualize the working of human brain using ANN.
- To become familiar with neural networks that can learn from available examples and generalize to form appropriate rules for inference systems.
- To introduce the ideas of fuzzy sets, fuzzy logic and use of heuristics based on human experience.
- To provide the mathematical background for carrying out the optimization and familiarizing genetic algorithm for seeking global optimum in self-learning situation.

Abstract:

Soft Computing, Artificial Intelligence, Soft-Computing Techniques, Expert Systems Types of Problems, Modeling the Problem, Machine Learning, Handling Impreciseness, Clustering , Hazards of Soft Computing, Road Map for the Future Artificial Neural Networks, The Biological Neuron, The Artificial Neuron, Multilayer Perceptron, Modeling the Problem, Types of Data Involved, Training, Issues in ANN, Example of Time Series Forecasting Types of Artificial Neural Networks, Radial Basis Function Network, Learning Vector Quantization, Self-Organizing Maps, Recurrent Neural Network, Hopfield Neural Network, Adaptive Resonance Theory, Character Recognition by Commonly Used ANNs Fuzzy Systems, Fuzzy Logic, Membership Functions, Fuzzy Logical Operators, More Operations, Fuzzy Inference Systems, Type-2 Fuzzy systems, Other Sets, Sugeno Fuzzy Systems, Example: Fuzzy Controller Evolutionary Algorithms: Evolutionary Algorithms, Biological Inspiration Evolutionary Algorithms Genetic Algorithms, Fitness Scaling, Selection, Mutation, Crossover, Other Genetic Operators, Algorithm Working, Diversity, Grammatical