Course Code	21CSC401J	Course Name	DEEP LEARNING TECHNIQUES		Course Category	C	PROFESSIONAL CORE	L 3	T 0	P 2	C 4
Pre-requisite Courses	Nil	Co- requisite Courses	Nil		Progressive Courses	Nil				
Course Offering Department		School of Computing	Data Book / Codes / Standards			Nil				

Course Learning Rationale (CLR):	The purpose of learning this course is to:
CLR-1:	Illustrate the basic concepts of deep learning
CLR-2:	Gain knowledge in Optimization algorithms and dimensionality reduction
CLR-3:	Develop a broad understanding of word2vec models and Convolution Neural Network models
CLR-4:	Acquire knowledge in Transfer learning and Sequential Models
CLR-5:	Implement the attention mechanism and advanced deep learning models

Course Outcomes (CO):	At the end of this course, learners will be able to:	1 Engineering Knowledge	2 Problem Analysis	3 Design/development of solutions	4 Conduct investigations of complex problems	5 Modern Tool Usage	6 The engineer and society	7 Environment & Sustainability	8 Ethics	9 Individual & Team Work	10 Communication	11 Project Mgt. & Finance	12 Life Long Learning	PSO-1	PSO-2	PSO-3
CO-1:	Understand the basic concepts of deep learning	-	3	-	-	-	-	-	-	2	-	-	-		-	2
CO-2:	Compare the optimization algorithms and high dimensional data using reduction techniques	-	2	-	-	-	-	-	-	2	-	-	-	-	-	2
CO-3:	Implement word2vec models and Convolution Neural Network models	-	3	-	2	-	-	-	-	3	-	-				2
CO-4:	Apply RNN and transfer learning to real world scenarios	-	3	-	2	-	-	-	-	3	-	-	-	-	-	3
CO-5:	Use deep learning models to solve real-world applications	-	3	-	2	-	-	-	-	3	-	-	2	-	-	3

Unit-1 - Introduction to Neural Networks — 15 Hour

Biological neuron, Motivation from biological neuron, McCulloch Pitts Neuron, Perceptron, Perceptron learning Algorithm, Representation power of a network of perceptrons, Activation functions-Sigmoid, tanh, ReLU, leaky ReLU, Sigmoid neuron, Gradient descent learning Algorithm, Representation power of multilayer Network of Sigmoid Neurons, Representation power of function: Complex functions in real world examples, Feedforward Neural Networks, Learning parameters, output and loss functions of FFN Networks, Backpropagation learning Algorithm, Applying chain rule across in a neural network, Computing partial derivatives w.r.t a weight

Unit-2 - Optimization — 15 Hour

Limitations of gradient descent learning algorithm, Momentum based gradient descent, Nesterov accelerated gradient descent, AdaGrad, RMSProp, Adam learning algorithm, Stochastic gradient descent, Mini-batch gradient descent, Bias Variance tradeoff, Overfitting in deep neural networks, Hyperparameter tuning, Regularization: L2 regularization, Dataset Augmentation and Early Stopping, Dimensionality reduction, Principal Component Analysis, Autoencoders, Relation between PCA and Autoencoders, Regularization in Autoencoders

Unit-3 - Word2vec and Convolutional Neural Networks — 15 Hour

One hot representation of words, Distributed representation of words, SVD for learning word Representations, Continuous bag of words model, Skip-gram model, Introduction to Convolution Neural Networks, Kernel filters, the convolution operation with Filters, padding and stride, Max pooling and non-linearities, Classic CNNs architecture- The ImageNet challenge, Alex Net architecture, ZFNet, The intuition behind GoogleNet Residual CNN-ResNet architecture, DenseNet Architecture.

Unit-4 - Recurrent Neural Networks — 15 Hour

Transfer Learning, Need for Transfer Learning, Applications of Transfer learning, Sequence Learning Problems, Recurrent Neural Networks, Backpropagation through time, Unfolded RNN, problem of exploding and vanishing Gradients, Seq to Seq Models, how gates help to solve the problem of vanishing gradients, Long-Short Term Memory architectures, dealing with exploding gradients, Gated Recurrent Units, Encoder-Decoder Models, and its applications.

Unit-5 - Attention models & Generative Adversarial Networks **15 Hour**

Language Modeling, Image Captioning, Machine Translation, Attention Mechanism, Attention over images, Hierarchical Attention, Monte Carlo Methods, Local Independencies in a Markov Network, Joint Distributions, the concept of a latent variable, Restricted Boltzmann Machines, RBMs as Stochastic Neural Networks, Unsupervised Learning with RBMs, Setting up a Markov Chain for RBMs, Generative Adversarial Networks-Architecture, Generative Adversarial Networks- Applications

Lab Experiments

Lab1: Apply MP Neuron and perceptron to solve a binary classification problem
Lab2: Apply sigmoid neuron to solve a real-world classification / regression problem
Lab3: Build a FFN Network to solve a multi-class classification problem
Lab4: Implement linear regression with stochastic gradient descent.
Lab5: Implement linear regression with stochastic mini-batch gradient descent and compare the results with previous exercise.
Lab 6: Optimizing neural networks using L2 regularization, Dropout, data augmentation and early stopping
Lab 7: Implement skip gram model to predict words within a certain range before and after the current word.
Lab 8: Implement LeNet for image classification
Lab 9: Implement ResNet for detecting objects.
Lab 10: Transfer learning implementation using VGG16 model to classify images.
Lab 11: Building a RNN to perform Character level language modeling
Lab 12: Build a LSTM network for Named Entity recognition.
Lab 13: Neural Machine Translation with attention.
Lab 14: Case study on Scene Understanding using RBMs
Lab 15: Case study on generating examples for Image dataset using Generative Adversial Networks

Learning Resources

1. *Ian Goodfellow, Yoshua Bengio, Aaron Courville, Deep Learning, MIT Press, 2016.*
2. *Stevens, Eli, Luca Antiga, and Thomas Viehmann. Deep learning with PyTorch. Manning Publications, 2020.*
3. *Eugene Charniak, Introduction to Deep Learning, MIT Press, 2018.*
4. *Charu C. Aggarwal, Neural Networks and Deep Learning, Springer, 2018.*
5. *Francois Chollet , Deep Learning with Python, Manning Publications, 2017*
6. *NPTEL course: Deep Learning, Prof. Mitesh M Khaprahttps://archive.nptel.ac.in/noc/courses/noc18/SEM2/noc18-cs41/*
7. *MIT Deep Learning and Artificial Intelligence Lectures: https://deeplearning.mit.edu*
8. *Stanford course CS231n: Deep Learning for Computer Vision: http://cs231n.stanford.edu*
9. *MIT's introductory course on deep learning methods: http://introtodeeplearning.com*

Learning Assessment

	Bloom's Level of Thinking	Continuous Learning Assessment (CLA)				Summative Final Examination (40% weightage)	
		Formative CLA-1 Average of unit test (45%)		Life-Long Learning CLA-2 (15%)			
		Theory	Practice	Theory	Practice	Theory	Practice
Level 1	Remember	15%	-	-	15%	15%	-
Level 2	Understand	25%	-	-	20%	25%	-
Level 3	Apply	30%	-	-	25%	30%	-
Level 4	Analyze	30%	-	-	25%	30%	-
Level 5	Evaluate	-	-	-	10%	-	-
Level 6	Create	-	-	-	-	-	-
	Total	100 %		100 %		100 %	

Course Designers

Experts from Industry	Experts from Higher Technical Institutions	Internal Experts
1. *Dr. Marriappan Vaithilingam, Senior Director of Engineering, Fresh works*	1. *Dr. Lathaparthiban, Pondicherry University*	1. *Dr.Athira M Nambiar SRMIST*