Subject Description Form

Subject Code	EIE4122 (for 42470, 42477)
Subject Title	Deep Learning and Deep Neural Networks
Credit Value	3
Level	4
Pre-requisite	**For 42477:** EIE3124: Fundamentals of Machine Intelligence **For 42470:** AMA2104 Probability and Engineering Statistics
Co-requisite/ Exclusion	Nil
Objectives	This course is for students who would like to equip themselves with cutting-edge AI knowledge and know-how to join the AI profession. Students will learn the foundations of deep learning and how to construct deep neural networks for real-world applications and AI systems. Students will also learn the trends in deep learning and deep neural networks.
Intended Subject Learning Outcomes	**Upon completion of the subject, students will be able to:** Category A: Professional/academic knowledge and skills 1. Understand the benefits of deep learning and deep neural networks. 2. Understand the basic theories in deep learning and deep neural networks. 3. Understand how deep learning and deep neural networks are applied in real-world applications and AI systems. Category B: Attributes for all-roundedness 4. Understand the creative process when designing solutions to a problem.
Subject Synopsis/ Indicative Syllabus	1. A High-Level Perspective of Deep Learning and Deep Neural Networks 1.1 What are neural networks and deep neural networks? 1.2 Relationship among AI, machine learning, deep learning, and DNNs 1.3 Neural networks: From shallow to deep 1.4 How DNNs learn from data? 1.5 Examples of real-life applications: Computer vision, speech, text analysis, and healthcare 2. Machine Learning 2.1 Vectors, matrices, tensors, and vector space 2.2 Random variables and probability distributions 2.3 Bayes theorem and its applications 2.4 Supervised learning versus unsupervised learning 2.5 Overfitting, underfitting, and dimension reduction 2.6 Gaussian mixture models and Support vector machines 3. From ANN to DNN 3.1 Biological Neurons versus artificial neurons 3.2 Perceptrons and multi-layer perceptrons 3.3 Relationship between MLP, GMM, and SVM 3.4 Why going deep? 3.5 DNN for classification and regression 4. Deep Architectures 4.1 Autoencoders and denoising autoencoders 4.2 Convolutional neural networks 4.3 Residual networks and DenseNet 4.4 Recurrent neural networks 4.5 Long short-term memory and gate recurrent unit

4.6 Sequence-to-sequence models
4.7 Transformer models and attention mechanism

5. Deep Learning
   5.1 Loss functions: MSE and cross-entropy (softmax) loss
   5.2 Gradient-based optimization: momentum and learning rate schedule
   5.3 Backpropagation
   5.4 Gradient vanishing
   5.5 Batch normalization and layer normalization
   5.6 Regularization: Dropout, weight decay, L1 and L2 regularization, data augmentation, and early stopping
   5.7 Representation learning: embedding and statistics pooling
   5.8 Adversarial learning
   5.9 End-to-end training

6. Software and Hardware Tools
   6.1 Software stack: CUDA, cuDNN, Tensorflow, PyTorch, and Keras
   6.2 Cloud platforms: Amazon EC2, Azure, Google Cloud, Nvidia GPU cloud, Alibaba Cloud, Google Colab, etc.
   6.3 Hardware: GPU, TPU, Nvidia Jetson

Teaching/Learning Methodology

Lectures: The subject matters will be delivered through lectures. Students will be engaged in the lectures through Q&A, discussions and specially designed classroom activities. The background theories on DL and DNNs will be accompanied by various real applications.

Tutorials: During tutorials, students will work on/discuss some chosen topics. This will help strengthen the knowledge taught in lectures.

Laboratory and assignments: During laboratory exercises, students will perform hands-on tasks to practice what they have learned. They will evaluate performance of systems and design solutions to problems. The assignments will help students to review the knowledge taught in class.

While lectures and tutorials will help to achieve the professional outcomes, the open-ended questions in laboratory exercises and assignments will provide the chance for students to exercise their creatively in problem solving.

Assessment Methods in Alignment with Intended Subject Learning Outcomes

Specific Assessment Methods/Tasks	**% Weighting**	**Intended Subject Learning Outcomes to be Assessed (Please tick as appropriate)**			
		1	**2**	**3**	**4**
1. Continuous Assessment (total: 50%)					
• Homework and assignments	15%	✓	✓	✓	✓
• Tests and Quizzes	20%	✓	✓	✓	
• Laboratory exercises	15%			✓	✓
2. Examination	50%	✓	✓	✓	✓
Total	100%				

Explanation of the appropriateness of the assessment methods in assessing the intended learning outcomes:

Assignment, homework, and laboratory exercises will require students to apply what they have learnt to solve problems. There will be open-ended questions that allow students to exercise their creativity in making design.

Examination and tests: They assess students’ achievement of the learning outcomes in a more formal manner.

Student Study Effort Expected	**Class contact (time-tabled):**	
	• Lecture	24 Hours
	• Tutorial/Laboratory/Practice Classes	15 Hours
	Other student study effort:	
	• Lecture: preview/review of notes; homework/assignment; preparation for test/quizzes/examination	36 Hours
	• Tutorial/Laboratory/Practice Classes: preview of materials, revision and/or reports writing	30 Hours
	Total student study effort:	**105 Hours**
Reading List and References	**Reference Materials:** 1. I. Goodfellow, Y. Bengio and A. Courville, *Deep Learning*, MIT Press 2016 2. M.W. Mak and J.T. Chien, *Machine Learning for Speaker Recognition*, Cambridge University Press, 2020. 3. C.M. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006. *4.* J. Langr and V. Bok, *GANs in Action*: *Deep Learning with Generative Adversarial Networks (GANs)*, Manning Publications, 2018. *5.* F. Chollet, *Deep Learning with Python*, Manning Publications, 2018.	
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