Institute of Cyber-Physical Systems						
Name of the subject:	Code of the subject:	Credits:	Weekly hours:			
				lec	sem	lab
Deep Learning	NSXMG1EMNF		full-time	2	0	2
Responsible person for the subject: Dr. Mehdi Taassori			Classification:			
Subject lecturer(s):						
Prerequisites:						
Way of the assessment:	Exam					

Course description	
Goal:	The goal of this course is to provide students with a solid foundation in deep learning, covering both theoretical principles and practical applications. Students will learn how to design, train, and evaluate deep neural networks, understand the mathematical foundations behind key algorithms, and explore state-of-the-art architectures such as convolutional networks, recurrent networks, autoencoders, and generative models.
Course description:	This course introduces the fundamental concepts, architectures, and algorithms of deep learning. Topics include feedforward networks, optimization methods, regularization, convolutional and recurrent neural networks, autoencoders, and generative models. Emphasis is placed on both theory and practice: students will gain mathematical intuition about why deep learning methods work, as well as hands-on experience implementing and training models.

Lecture schedule

Education week	Topic
1.	**Introduction to Deep Learning** Overview of deep learning and its foundations. Why representations matter, depth via repeated composition, and the MNIST dataset as a running example.
2.	**Deep Feedforward Networks I** Basic structure and intuition of feedforward networks. XOR and non-linear separability. Activation functions (ReLU) and role of hidden units.
3.	**Deep Feedforward Networks II** Gradient-based learning and backpropagation. Cost functions and output units. Universal Approximation Theorem and the role of depth.
4.	**Regularization in Deep Learning** Motivation for regularization. Parameter norm penalties (L1, L2), dataset augmentation, and multi-task learning.
5.	**Advanced Regularization Techniques** Early stopping, ensemble methods (bagging), dropout, and adversarial training.
6.	**Optimization for Deep Networks I** Optimization basics: derivatives, second derivatives, Taylor approximation. Challenges in optimization: local minima, saddle points, and poor conditioning. First-order methods: SGD, momentum, Nesterov momentum. Adaptive methods: AdaGrad, RMSProp, Adam, AdamW. Second-order methods (Newton, BFGS, L-BFGS) and normalization techniques (batch, layer, instance, group normalization).
7.	**Convolutional Neural Networks (CNNs)** Foundations of convolution: sparse connectivity, receptive fields, parameter sharing. Core components: convolution, pooling, and invariance.
8.	**CNN Architectures and Applications** CNN architectures for classification, strided and padded convolutions, local vs fully connected layers, and applications to image recognition.

9.	**Sequence Modeling I (RNNs)** Foundations of sequence modeling. Recurrent neural networks (RNNs), unfolding computation graphs, training with teacher forcing.
10.	**Sequence Modeling II (Advanced RNNs)** Bidirectional RNNs, deep RNNs, encoder–decoder architectures, recursive networks, LSTMs, and gradient clipping.
11.	**Autoencoders** Autoencoder framework: encoder–decoder, stochastic and regularized autoencoders, sparse and denoising autoencoders. Theoretical perspectives (score matching, vector fields).
12.	**Deep Generative Models** Overview of generative models: Variational Autoencoders (VAE), GANs, and Diffusion Models (DDPM). Training strategies, strengths, and limitations.
13.	Written Exam & Lab Exam
14.	Written Exam (Retake) & Lab Exam (Retake)

Mid-term requirements

Conditions for obtaining a mid-term grade/signature	Lab/Programming Assignments , Written Exam, Homeworks A minimum of 51% must be achieved in Lab Exam, Written Exam and Homeworks to receive a signature.

Type of the replacement

Type of the replacement of written test/mid-term grade/signature	Students must take the signature retake exam if their lab grade, or written exam grade, or homework grades are below 51%.

Type of the exam (to be filled out only for subjects with exams)

Written and multiple-choice exam

Calculation of the exam mark (to be filled only for subjects with exams)

- Lab/Programming Assignments 40%
- Final Exam 60%
- The submission of homework on Moodle by the designated deadline is mandatory for all students.
- Attendance for lab sessions, lab exam, and exams is mandatory.
- If students exceed the allowed number of absences, they will be banned from the course.
- A minimum of 51% must be achieved in each exam to pass.

Final grade calculation methods:

0-50 points - Fail
51-69 points - Pass
70-79 points – Satisfactory
80-89 points - Good
90-100 points – Excellent

References

Obligatory:	Goodfellow, I., Bengio, Y., Courville, A. (2016). *Deep learning* (Vol. 1, No. 2). Cambridge: MIT Press.
Recommended:	Bishop, C. M., & Bishop, H. (2023). *Deep Learning: Foundations and Concepts*. Springer.
Other references:	Prince, S. J. D. (2023). *Understanding Deep Learning*. MIT Press, Cambridge, MA.