SYLLABUS

Computer Vision and Deep Learning

University year 2025-2026

1. Information regarding the programme

| 1.1. Higher education institution | Babeş Bolyai University |
|------------------------------------|---|
| 1.2. Faculty | Faculty of Mathematics and Computer Science |
| 1.3. Department | Department of Computer Science |
| 1.4. Field of study | Computer Science |
| 1.5. Study cycle | Bachelor |
| 1.6. Study programme/Qualification | Artificial Intelligence |
| 1.7. Form of education | Full time |

2. Information regarding the discipline

| 2.1. Name of the dis | cipli | ne Deep lear | Deep learning and Computer Vision Technique | | | | ues Discipline code | MLE5231 |
|--------------------------|-------|---------------|---|----|---------|----------------------|------------------------|------------|
| 2.2. Course coordinator | | | | Le | ect. Ph | D. Diana Laura Borza | | |
| 2.3. Seminar coordinator | | | | | Le | ect. Ph | D. Diana Laura Borza | |
| 2.4. Year of study | 3 | 2.5. Semester | . Semester 6 2.6. Type of evaluat | | | Е | 2.7. Discipline regime | Compulsory |

3. Total estimated time (hours/semester of didactic activities)

| 3.1. Hours per week | 4 | of which: 3.2 course | 2 | 3.3 seminar/laboratory/project | 2 L |
|---|--|----------------------|---|-----------------------------------|-----|
| 3.4. Total hours in the curriculum | ulum 56 of which: 3.5 course 28 3.6 seminar/laboratory/project | | | 28L | |
| Time allotment for individual study (ID) and self-study activities (SA) | | | | | |
| Learning using manual, course support, bibliography, course notes (SA) | | | | | |
| Additional documentation (in libraries, on electronic platforms, field documentation) | | | | | |
| Preparation for seminars/labs, homework, papers, portfolios and essays | | | | | 40 |
| Tutorship | | | | | |
| Evaluations | | | | | 5 |
| Other activities: | | | | | |
| 3.7. Total individual study hours 119 | | | | | |
| 3.8. Total hours per semester | 175 | | | | |
| 3.9. Number of ECTS credits | 7 | | | | |

4. Prerequisites (if necessary)

| | Linear Algebra | |
|-------------------|--|--|
| 4.1. curriculum | Python programming | |
| | Statistics | |
| | Data structures and algorithms | |
| 4.2. competencies | cies • Average programming skills in a high-level programming language | |

5. Conditions (if necessary)

| 5.1. for the course | Classroom with blackboard and video projector. |
|--------------------------------------|--|
| 5.2. for the seminar /lab activities | Laboratory equipped with high-performance computers and having python installed. |

6. Specific competencies acquired

| Professional/essential competencies | advanced programming skills in high-level programming languages development and maintenance of software systems use of software tools in an interdisciplinary context use of theoretical foundations of computer science as well as of formal models use of artificial intelligence concepts and techniques to solve real-world problems |
|--|---|
| Transversal competencies | application of organized and efficient work rules, of responsible attitudes towards the didactic-scientific field, to bring creative value to own potential, with respect for professional ethics principles and norms efficient development of organized activities in an interdisciplinary group and the development of empathetic abilities for use of efficient methods and techniques to learn, inform, research and develop the abilities to bring value to knowledge, to adapt at the requirements of a dynamical society and to communicate efficiently in Romanian language and in an international language |

7. Objectives of the discipline (outcome of the acquired competencies)

| 7.1 General objective of the discipline | • The goal of this course is to acquaint the students with the field of computer vision from a deep learning perspective. The students will learn how to analyse, design, implement, and evaluate any complex computer vision problem. The course covers both image and video processing, including image classification, object detection, object tracking, action recognition, image stylization and synthetic data generation. |
|--|---|
| 7.2 Specific objective of the discipline | Understand various architectures of Convolutional Neural Networks for image classification, object detection, video analysis, and synthetic visual data generation. Solve and analyse a Computer Vision problem using a specific theoretical apparatus. Understand and develop efficient fine-tuning strategies for increasing the performance of Convolutional Neural Networks with applications in the Computer Vision field. Understand the metrics used to evaluate complex networks, as well as visualizing the features learned by the networks. |

8. Content

| 8.1 Cou | ırse | Teaching methods | Remarks |
|---------|--|---|---------|
| 1. | Introduction to Computer Vision . Overview, history of computer vision, the three Rs of computer vision. | Interactive exposure Explanation Conversation Didactical demonstration | |
| 2. | Image classification pipeline . Image classification pipeline, image features, filters, convolutions, linear classifiers. | Interactive exposure Explanation Conversation Didactical demonstration | |
| 3. | Shallow neural networks. Optimization and loss functions. | Interactive exposure Explanation Conversation Didactical demonstration | |
| 4. | Introduction to convolutional neural networks. Convolutional neural networks architectures. Elements of a convolutional convolutional neural network: convolutional layers, pooling layers, fully connected layer). Architectures: LeNet, AlexNet, VGG, Inception, Resnet. | Interactive exposure Explanation Conversation Didactical demonstration | |
| 5. | Sequential Models, Attention Mechanisms, Transformer Architecture. | Interactive exposureExplanation | |

| | ConversationDidactical demonstration | |
|---|--|----------------------------|
| 6. Training a Neural Network. Activation | Interactive exposure | |
| Functions, Weight Initialization, | Explanation | |
| Hyperparameter Tuning, Transfer Learning. | Conversation | |
| | Didactical demonstration | |
| 7. Image Segmentation. Transposed | Interactive exposure | |
| Convolutions, Fully Convolutional Networks, | • Explanation | |
| U-Net Architecture, SegFormer, SAM. | Conversation | |
| | Didactical demonstration | |
| 8. Generative networks. PixelRNN and PixelCNN, | Interactive exposure | |
| Variational Autoencoders (VAE), Generative | • Explanation | |
| Adversarial Networks (GAN). | Conversation | |
| | Didactical demonstration | |
| 9. Object detection . Object Detection, Region | Interactive exposure | |
| Proposal, ROI Pooling. Convolutional and | Explanation | |
| Transformer-Based Architectures for Object | Conversation | |
| Detection | Didactical demonstration | |
| 10. Graph convolutional neural networks. | Interactive exposure | |
| Graphs, Message Passing, Applications in | Explanation | |
| Computer Vision. | Conversation | |
| | Didactical demonstration | |
| 11. Video Data Analysis. C3D, I3D, R(2+1)D, | Interactive exposure | |
| SlowFast, TimeSformer, Video Swin | Explanation | |
| Transformer, ViViT, MViT, ActionFormer. | Conversation | |
| | Didactical demonstration | |
| 12. Self-Supervised Learning, Zero-Shot Models. | Interactive exposure | |
| CLIP, BLIP, DINO. | Explanation | |
| | Conversation | |
| | Didactical demonstration | |
| 13. Case studies and demonstrations of | Interactive exposure | |
| state-of-the-art algorithms. Ethics in artificial | Explanation | |
| intelligence. Debate. | Conversation | |
| | Didactical demonstration | |
| 14. Exam | Interactive exposure, | |
| | conversation. | |
| ibliography . Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. D . Langr, Jakub, and Vladimir Bok. GANs in Action . (2018) . Trask, Andrew. Grokking deep learning . Manning Pub |). | |
| . Prince, Simon JD. Computer vision: models, learning, | | v Press 2012 |
| | | |
| . Shapiro, Linda G., and George C. Stockman. Computer v | | , 11000, 20121 |
| | v ision . Prentice Hall, 2001. | |
| . Müller, Andreas C., and Sarah Guido. Introduction to m | v ision . Prentice Hall, 2001. | |
| . Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. | vision. Prentice Hall, 2001. Anachine learning with Python: a gui | |
| . Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. . Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> | vision. Prentice Hall, 2001. Anachine learning with Python: a gui | |
| . Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. . Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> . <u>https://pvtorch.org/docs/stable/index.html</u> | v ision . Prentice Hall, 2001. Cachine learning with Python: a gu S. Packt Publishing Ltd, 2017. | |
| . Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. . Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> . <u>https://pvtorch.org/docs/stable/index.html</u> .2 Seminar / laboratory | vision. Prentice Hall, 2001. Anachine learning with Python: a gui | ide for data scientists." |
| . Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. . Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> . <u>https://pvtorch.org/docs/stable/index.html</u> .2 Seminar / laboratory aboratory | v ision . Prentice Hall, 2001. nachine learning with Python: a gu 5. Packt Publishing Ltd, 2017. Teaching methods | ide for data scientists. " |
| . Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. . Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> . <u>https://pvtorch.org/docs/stable/index.html</u> .2 Seminar / laboratory aboratory 1. Strategies for solving computer vision | vision. Prentice Hall, 2001. achine learning with Python: a guid 5. Packt Publishing Ltd, 2017. Teaching methods • Interactive exposure | ide for data scientists. " |
| . Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. . Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> . <u>https://pvtorch.org/docs/stable/index.html</u> .2 Seminar / laboratory aboratory | vision. Prentice Hall, 2001. achine learning with Python: a guid 5. Packt Publishing Ltd, 2017. Teaching methods • Interactive exposure • Explanation | ide for data scientists. " |
| . Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. . Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> . <u>https://pvtorch.org/docs/stable/index.html</u> .2 Seminar / laboratory aboratory 1. Strategies for solving computer vision | vision. Prentice Hall, 2001. achine learning with Python: a guid 5. Packt Publishing Ltd, 2017. Teaching methods • Interactive exposure • Explanation • Conversation | ide for data scientists. " |
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| . Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. . Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> <u>. https://pvtorch.org/docs/stable/index.html</u> .2 Seminar / laboratory aboratory 1. Strategies for solving computer vision problems. Introduction to <i>python</i> and <i>torch</i> . | Prentice Hall, 2001. Pachine learning with Python: a guide Packt Publishing Ltd, 2017. Teaching methods Interactive exposure Explanation Conversation Individual and group work Dialogue, debate | ide for data scientists. " |
| Müller, Andreas C., and Sarah Guido. Introduction to m 'Reilly Media, Inc.", 2016. Gulli, Antonio, and Sujit Pal. Deep learning with Keras <u>https://pvtorch.org/docs/stable/index.html</u> 2 Seminar / laboratory aboratory 1. Strategies for solving computer vision problems. Introduction to python and torch. 2. Implementing a linear classifier from scratch. | <i>rision</i>. Prentice Hall, 2001. <i>fachine learning with Python: a guide</i>. Packt Publishing Ltd, 2017. Teaching methods Interactive exposure Explanation Conversation Individual and group work Dialogue, debate Interactive exposure | ide for data scientists. " |
| Müller, Andreas C., and Sarah Guido. <i>Introduction to m</i> 'Reilly Media, Inc.", 2016. Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> . <u>https://pvtorch.org/docs/stable/index.html</u> .2 Seminar / laboratory aboratory 1. Strategies for solving computer vision problems. Introduction to <i>python</i> and <i>torch</i>. | vision. Prentice Hall, 2001. achine learning with Python: a guide ackt Publishing Ltd, 2017. Teaching methods Interactive exposure Explanation Conversation Individual and group work Dialogue, debate Interactive exposure Explanation | ide for data scientists. " |
| problems. Introduction to <i>python</i> and <i>torch</i>.2. Implementing a linear classifier from scratch. | vision. Prentice Hall, 2001. achine learning with Python: a guide ackt Publishing Ltd, 2017. Teaching methods Interactive exposure Explanation Conversation Individual and group work Dialogue, debate Interactive exposure Explanation Conversation Interactive exposure Explanation Conversation Interactive exposure Explanation Conversation Conversation Interactive exposure Explanation Conversation Conversation | ide for data scientists. " |
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| 3. Optimization algorithms, unbalanced data, data pre-processing, data generators in <i>torch</i> . Convolutional neural networks for classification. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
|---|--|
| 4. Transfer learning and fine tuning. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 5. Semantic segmentation I. Data Processing, Architecture Definition. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 6. Semantic segmentation II. Architecture Implementation, Training. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 7. Experiment tracking, Deployment. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 8. Transformer architectures. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 9. Data Management, Annotation. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 10. Experiment Management. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 11. Deployment. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 12. Choosing Project Topics. Establishing Methodology. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 13. Project. Presentation of the Models to be Used, Experiment Planning, Ablation Studies. | Interactive exposure Explanation Conversation Individual and group work Dialogue, debate |
| 14. Project evaluation | • Evaluation |
| Project | |
| Phase 1 - each student should pick (or propose) a computer vision problem for the project | Interactive exposure Explanation Conversation |

| - discussion about the chosen projects | Individual and group work |
|--|--|
| - state of the art analysis (search for other methods that | Brainstorming |
| solve the same problem) | |
| - short presentation (by the teacher) of the possible | |
| computer vision project themes that could be solved | |
| using deep learning - presentation (by the teacher) of the methodology that | |
| needs to be followed for the project and of the available | |
| tools to achieve the project | |
| tools to achieve the project | |
| Phase 2 | |
| - establishing the methodology that needs to be | |
| followed to solve the project | |
| - data gathering, data pre-processing | |
| - selection of the appropriate network architectures | |
| | |
| Phase 3 | |
| - design and implementation of the project | |
| - design and implementation of the project | |
| - evaluation metrics implementation | |
| - visualization | |
| - implementation cont'd, evaluation, fine-tuning | |
| - project delivery, presentation, demo | |
| Bibliography | |
| | achine learning with Python: a guide for data scientists." |
| O'Reilly Media, Inc.", 2016. | |
| 2. Gulli, Antonio, and Sujit Pal. <i>Deep learning with Keras</i> | |
| | <i>thon</i> . CreateSpace Independent Publishing Platform, 2018. |
| 4. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. D | eep learning. MIT press, 2016. |

5. https://pytorch.org/docs/stable/index.html

6. https://www.tensorflow.org/api docs

9. Corroborating the content of the discipline with the expectations of the epistemic community, professional associations and representative employers within the field of the program

- The course follows the ACM and IEEE Curriculum Recommendations for Computer Science majors.
- The course exists in the studying program of all major universities in Romania and abroad.
- The knowledge and skills acquired in this course give students a foundation for launching a career in scientific research.

10. Evaluation

| Activity type | 10.1 Evaluation criteria | 10.2 Evaluation methods | 10.3 Percentage of final grade | | | |
|--------------------------------------|--|--|--------------------------------|--|--|--|
| 10.4 Course | The student has a good understanding of the deep learning concepts. The ability to apply the course concepts in solving a real-life computer vision | Written examination <u>at</u> <u>the lecture</u> in the last week of the semester. | 50% | | | |
| 10.5 Seminar/laboratory | problem. The correct specification, design, implementation and evaluation of some computer vision problems based on deep learning. | Continuous observations Practical project | 50% | | | |
| 10.6 Minimum standard of performance | | | | | | |

Students must prove that they acquired an acceptable level of knowledge and understanding of the core ? concepts taught in the class, that they are capable of using this knowledge in a coherent form, that they have the ability to establish certain connections and to use the knowledge in solving various computer vision problems. The final grade (average between written exam and project) should be at least 5 (no rounding)

?

11. Labels ODD (Sustainable Development Goals)¹

Not applicable.

| Date: | Signature of course coordinator | Signature of seminar coordinator |
|----------------|---------------------------------|----------------------------------|
| April 27, 2025 | Lect. PhD. Diana Laura Borza | Lect. PhD. Diana Laura Borza |

Date of approval:

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Signature of the head of department

Assoc.prof.phd. Adrian STERCA

¹ Keep only the labels that, according to the <u>Procedure for applying ODD labels in the academic process</u>, suit the discipline and delete the others, including the general one for *Sustainable Development* – if not applicable. If no label describes the discipline, delete them all and write "Not applicable.".