SYLLABUS
Academic year 2024-2025

Dean,
Prof. dr. eng. Vasile-Ion Manta

1. Program data

1.1 Higher education institution	"Gheorghe Asachi" Technical University of Iași
1.2 Faculty	Automatic Control and Computer Engineering
1.3 Department	Computers
1.4 Field of studies	Computers and Information Technology
1.5 The cycle of studies[1]	Master
1.6 Study program	Artificial Intelligence

2. Subject data

2.1 Name of the subject / Code	**Fundamentals of Machine Learning** *(Fundamentele învățării automate)* / **AI.101**						
2.2 Course coordinator	Lect. dr. eng. Marius Gavrilescu						
2.3 Application instructor	Assist. drd. eng. Codruț-Georgian Artene, Lect. dr. eng. Ștefan Achirei						
2.4 Year of study[2]	1	2.5 Semester[3]	1	2.6 Type of assessment[4]	exam	2.7 Type of subject[5]	DA

3. Estimated total time of daily activities (hours per semester)

3.1 Number of hours per week	4	3.2 lectures	2	3.3a sem.		3.3b laboratory	1	3.3c project	1
3.4 Total hours in curriculum[6]	56	3.5 lectures	28	3.6a sem.		3.6b laboratory	14	3.6c project	14

Distribution of the time fund[7]	No. hours
Study by textbook, course support, bibliography and notes	30
Additional documentation in the library, on specialist electronic platforms and in the field	40
Preparation of seminars/labs/projects, assignments, reports and portfolios	20
Tutorial[8]	
Examinations[9]	4
Other activities:	

3.7 Total hours of individual study[10]	94
3.8 Total hours per semester[11]	150
3.9 Number of credits	6

4. Prerequisites (where applicable)

4.1 curriculum[12]	
4.2 competences	

5. Conditions (where applicable)

5.1 conducting the lectures[13]	• Video projector
5.2 conducting the seminar / laboratory / project[14]	• Laboratory room with computers and Internet access • The Visual Studio programming environment (academic license)

[1] *Bachelor / Master*
[2] *1-4 for Bachelor's, 1-2 for Master's*
[3] *1-8 for Bachelors, 1-3 for Masters*
[4] *Exam, colloquium or VP A/R – from the curriculum*
[5] *DF - fundamental subject, DID - subject in the field, DS - specialized subject or DC - complementary subject - from the education plan*
[6] *It is equal to 14 weeksx number of hours from point 3.1 (similar for 3.5, 3.6abc)*
[7] *The lines below refer to the individual study; the total is completed at point 3.7.*
[8] *Between 7 and 14 hours*
[9] *Between 2 and 6 hours*
[10] *The sum of the values on the previous lines, which refer to the individual study.*
[11] *The sum of the number of hours of direct teaching activity (3.4) and the number of hours of individual study (3.7); must be equal to the number of credits allocated to the subject (point 3.9)x 25 hours per credit.*
[12] *Mention the subjects that must be passed previously or equivalent*
[13] *Blackboard, video projector, flipchart, specific teaching materials, etc.*
[14] *Computing technique, software packages, experimental stands, etc.*

6. Specific competences accumulated[15]

		Number of credits assigned to the subject[16]: **6**	Distribution of credits per competences[17]
Professional competences	CP1	Knowledge of advanced concepts of computer science and information technology and the ability to work with these concepts.	1.1
	CP2	Scientific and practical research in the field of artificial intelligence.	1.1
	CP3	Design and development of artificial intelligence systems.	1.1
	CP4	Problem solving using artificial intelligence methods and techniques.	1
	CP5	Utilization of artificial intelligence tools and technologies.	1
	CP6		
	CPS1		
	CPS2		
Transversal competences	CT1	Legislation compliant application of the intellectual property rights and of the principles, norms and values of the professional ethics code within their own strategies for rigorous, effective and responsible work.	0.1
	CT2	Application of communication techniques and effective group work; developing empathic interpersonal communication skills and assuming leadership roles/functions in a multi-specialized team.	0.3
	CT3	Creating opportunities for continuous training and the effective utilization of learning resources and techniques for personal development.	0.3
	CTS		

7. Objectives of the subject (resulting from the grid of specific competences accumulated)

7.1 General objective of the subject	Providing students with a comprehensive understanding of the core concepts, techniques, and applications within the field of machine learning. The lecture aims to offer a structured exploration of key topics such as supervised and unsupervised learning, model training and evaluation, feature engineering, and the underlying algorithms. Students are expected to gain significant knowledge and insight into the field of machine learning, enabling them to apply the corresponding algorithms and techniques to real-world problems.
7.2 Specific objectives	• Provide a clear understanding of fundamental machine learning concepts, including supervised and unsupervised learning, key algorithms, and their applications in various domains. • Understanding the process of training machine learning models, covering topics such as data preprocessing, model selection, and performance evaluation metrics • Illustrate the importance of feature engineering in enhancing model performance, emphasizing techniques to preprocess and select relevant features for improved predictive modeling. • Examine commonly used machine learning algorithms, such as linear regression, decision trees, and clustering methods, outlining their strengths, weaknesses, and applicability for various classification and regression problems. • Incorporate practical examples and demonstrations, enabling students to implement basic machine learning models and to apply them in real-world scenarios.

8. Contents

8.1 Course[18]	Teaching methods[19]	Remarks
1. Introduction Definitions; key concepts; fundamentals; types of machnie learning methods	Lectures via Powerpoint presentations,	

[15] *Competencies from the G1 and G1bis Grids of the study program, adapted to the specifics of the subject, for which credits are allocated (www.rncis.ro or the faculty website)*

[16] *From the education plan*

[17] *The credits allocated to the subject are distributed on professional and transversal competences according to the specifics of the subject*

[18] *Chapter and paragraph headings*

[19] *Exposition, lecture, blackboard presentation of the studied issue, use of video projector, discussions with students (for each chapter, if applicable)*

(supervised, unsupervised); examples of real-world applications; course overview. **2. Supervised Learning** Principles, definitions; classification vs regression; fundamental methods: linear regression, logistic regression, naïve bayes, decision trees, gradient boosting. **3. Unsupervised Learning** Principles, definitions; fundamental methods: K-Means, hierarchical clustering, expectation-maximization, DBSCAN; dimensionality reduction (PCA, t-SNE); anomaly detection. **4. Feature Engineering** Introduction, definitions; preprocessing techniques (standardization, normalization, encoding); feature selection; feature extraction. **5. Ensemble Methods** Introduction to ensemble methods; bagging; boosting; stacking. Case study: Random Forests. **6. Deep Networks I** Artificial neural networks: fundamentals; fully-connected architectures; forward and backpropagation; activation functions: sigmoid, tanh, ReLU, L-ReLU, ELU. Modern optimization methods: SGD, RMSProp, Adam, AdaGrad. **7. Deep Networks II** Convolutional neural networks; types of layers; convolution and correlation; training fundamentals; frequently-used architectures: U-Net, VGGNet, ResNet. **8. Deep Networks III** Recurrent neural networks: definitions, principles, description of recurrency in network layers; Long Short-Term Memory (LSTM); Gated Recurrent Units (GRU). **9. Encoder-decoder Models** General encoder-decoder layout; reccurency-based sequence-to-sequence architectures; attention mechanisms. **10. Transformer Neural Networks** Basic concepts; overview of a single-head architecture; general structure of encoder and decoder; self-attention in transformers. Generative models: Generative pretrained transformers (GPT), BERT, CLIP, DALL-E. **11. Overfitting and Regularization** Overfitting definition, reasons, negative effects; regularization techniques (L1, L2, dropout; early stopping). **12. Hyperparameter Optimization** Introduction, motivation; popular methods: grid search, random search, hyperband. **13. Evaluation of Machine Learning Models** Evaluation metrics: accuracy, precision, recall, F1-score; cross-validation. bias-variance tradeoff. **14. Transfer Learning** Traditional machine learning vs transfer learning; role of pre-trained models; inductive and transductive transfer learning; fine-tuning, feature extraction, and domain adaptation methods.	explanations and discussions	
Course references: [1] T. Jiang, J. L. Gradus, and A. J. Rosellini, “Supervised Machine Learning: A Brief Primer,” Behavior Therapy, vol. 51, no. 5, pp. 675–687, Sep. 2020, doi: 10.1016/j.beth.2020.05.002. [2] J. E. van Engelen and H. H. Hoos, “A survey on semi-supervised learning,” Machine Learning, vol. 109, no. 2, pp. 373–440, Nov. 2019, doi: 10.1007/s10994-019-05855-6.		

[3] G. James, D. Witten, T. Hastie, R. Tibshirani, and J. Taylor, “Unsupervised Learning,” An Introduction to Statistical Learning, pp. 503–556, 2023, doi: 10.1007/978-3-031-38747-0_12.
[4] G. Matteucci, E. Piasini, and D. Zoccolan, “Unsupervised learning of mid-level visual representations,” Current Opinion in Neurobiology, vol. 84, p. 102834, Feb. 2024, doi: 10.1016/j.conb.2023.102834.
[5] E. Hancer, B. Xue, and M. Zhang, “A survey on feature selection approaches for clustering,” Artificial Intelligence Review, vol. 53, no. 6, pp. 4519–4545, Jan. 2020, doi: 10.1007/s10462-019-09800-w.
[6] X. He, K. Zhao, and X. Chu, “AutoML: A survey of the state-of-the-art,” Knowledge-Based Systems, vol. 212, p. 106622, Jan. 2021, doi: 10.1016/j.knosys.2020.106622.
[7] I. D. Mienye and Y. Sun, “A Survey of Ensemble Learning: Concepts, Algorithms, Applications, and Prospects,” IEEE Access, vol. 10, pp. 99129–99149, 2022, doi: 10.1109/access.2022.3207287.
[8] X. Dong, Z. Yu, W. Cao, Y. Shi, and Q. Ma, “A survey on ensemble learning,” Frontiers of Computer Science, vol. 14, no. 2, pp. 241–258, Aug. 2019, doi: 10.1007/s11704-019-8208-z.
[9] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, “A survey of the recent architectures of deep convolutional neural networks,” Artificial Intelligence Review, vol. 53, no. 8, pp. 5455–5516, Apr. 2020, doi: 10.1007/s10462-020-09825-6.
[10] Y. Han, G. Huang, S. Song, L. Yang, H. Wang, and Y. Wang, “Dynamic Neural Networks: A Survey,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 11, pp. 7436–7456, Nov. 2022, doi: 10.1109/tpami.2021.3117837.
[11] A. Saxe, S. Nelli, and C. Summerfield, “If deep learning is the answer, what is the question?,” Nature Reviews Neuroscience, vol. 22, no. 1, pp. 55–67, Nov. 2020, doi: 10.1038/s41583-020-00395-8.
[12] R. Miikkulainen et al., “Evolving deep neural networks,” Artificial Intelligence in the Age of Neural Networks and Brain Computing, pp. 269–287, 2024, doi: 10.1016/b978-0-323-96104-2.00002-6.
[13] M. H. Farrell, T. Liang, and S. Misra, “Deep Neural Networks for Estimation and Inference,” Econometrica, vol. 89, no. 1, pp. 181–213, 2021, doi: 10.3982/ecta16901.
[14] J. A. Livezey and J. I. Glaser, “Deep learning approaches for neural decoding across architectures and recording modalities,” Briefings in Bioinformatics, vol. 22, no. 2, pp. 1577–1591, Dec. 2020, doi: 10.1093/bib/bbaa355.
[15] Y. Ji, H. Zhang, Z. Zhang, and M. Liu, “CNN-based encoder-decoder networks for salient object detection: A comprehensive review and recent advances,” Information Sciences, vol. 546, pp. 835–857, Feb. 2021, doi: 10.1016/j.ins.2020.09.003.
[16] C. Chen, D. Han, and J. Wang, “Multimodal Encoder-Decoder Attention Networks for Visual Question Answering,” IEEE Access, vol. 8, pp. 35662–35671, 2020, doi: 10.1109/access.2020.2975093.
[17] K. Han et al., “A Survey on Vision Transformer,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 1, pp. 87–110, Jan. 2023, doi: 10.1109/tpami.2022.3152247.

[18] E. Arkin, N. Yadikar, X. Xu, A. Aysa, and K. Ubul, “A survey: object detection methods from CNN to transformer,” Multimedia Tools and Applications, vol. 82, no. 14, pp. 21353–21383, Oct. 2022, doi: 10.1007/s11042-022-13801-3.
[19] C. F. G. D. Santos and J. P. Papa, “Avoiding Overfitting: A Survey on Regularization Methods for Convolutional Neural Networks,” ACM Computing Surveys, vol. 54, no. 10s, pp. 1–25, Jan. 2022, doi: 10.1145/3510413.
[20] N. Syam and R. Kaul, “Overfitting and Regularization in Machine Learning Models,” Machine Learning and Artificial Intelligence in Marketing and Sales, pp. 65–84, Mar. 2021, doi: 10.1108/978-1-80043-880-420211004.
[21] B. Bischl et al., “Hyperparameter optimization: Foundations, algorithms, best practices, and open challenges,” WIREs Data Mining and Knowledge Discovery, vol. 13, no. 2, Jan. 2023, doi: 10.1002/widm.1484.
[22] L. Yang and A. Shami, “On hyperparameter optimization of machine learning algorithms: Theory and practice,” Neurocomputing, vol. 415, pp. 295–316, Nov. 2020, doi: 10.1016/j.neucom.2020.07.061.
[23] L. Zhang and X. Gao, “Transfer Adaptation Learning: A Decade Survey,” IEEE Transactions on Neural Networks and Learning Systems, vol. 35, no. 1, pp. 23–44, Jan. 2024, doi: 10.1109/tnnls.2022.3183326.
[24] K. Zhou, Z. Liu, Y. Qiao, T. Xiang, and C. C. Loy, “Domain Generalization: A Survey,” IEEE Transactions on Pattern Analysis and Machine Intelligence, pp. 1–20, 2022, doi: 10.1109/tpami.2022.3195549.

8.2a Seminar	Teaching methods[20]	Remarks
8.2b Laboratory	**Teaching methods[21]**	**Remarks**
1. Supervised classification Training and tuning a traditional classification method on a small data set. Evaluation of accuracy, precision. **2. Unsupervised classification** Applying a popular clustering method to a small data set. Evaluation of clustering quality (i.e. silhouette score for K-Means) **3. Regression** Applying a conventional regression model (linear / polynomial) to a small data	General and individual explanations, individual computer work.	

[20] *Discussions, debates, presentation and/or analysis of papers, solving exercises and problems*
[21] *Practical demonstration, exercise, experiment*

set. Evaluation of resulting model (i.e. coefficient of correlation / determination). **4. Feature extraction** Using various techniques to compute / learn features from text and image-based data. Experimenting with the features using previously-studies classification and regression models. **5. Deep Networks** Designing/training a neural network-based classification model. Performing hyperparameter tuning, cross-validation, evaluation of accuracy. **6. Encoder/Decoder models** Designing a simple generative encoder and decoder, applying it to a text-based data set. Experimenting with various types of texts, evaluating the quality of the generated data. **7. Transfer learning** Fine-tuning of a pretrained model. Adapting a general-purpose pretrained model to a specific problem.		
8.2c Project	Teaching methods[22]	Remarks
The project involves developing, training and evaluating a classification/refgression model for solving a real-world problem. Stages: **1. Establishing the finer details of the problem to be solved. Searching for representative data sets.** **2. Preprocessing and filtering the data, removal of noise / irrelevant outliers, early experiments with simple classifiers/regressors.** **3. Establishing the classification/regression method to be used. Experimenting with and testing candidate methods.** **4. Training the best-suited method, fine tuning, cross-validation and hyperparameter search.** **5. Final evaluation of the model, documentation of the method and results.**		

Applications (laboratory / project) references:

[1] G. Matteucci, E. Piasini, and D. Zoccolan, “Unsupervised learning of mid-level visual representations,” Current Opinion in Neurobiology, vol. 84, p. 102834, Feb. 2024, doi: 10.1016/j.conb.2023.102834.

[2] Y. Ji, H. Zhang, Z. Zhang, and M. Liu, “CNN-based encoder-decoder networks for salient object detection: A comprehensive review and recent advances,” Information Sciences, vol. 546, pp. 835–857, Feb. 2021, doi: 10.1016/j.ins.2020.09.003.

[3] N. Syam and R. Kaul, “Overfitting and Regularization in Machine Learning Models,” Machine Learning and Artificial Intelligence in Marketing and Sales, pp. 65–84, Mar. 2021, doi: 10.1108/978-1-80043-880-420211004.

[4] J. E. van Engelen and H. H. Hoos, “A survey on semi-supervised learning,” Machine Learning, vol. 109, no. 2, pp. 373–440, Nov. 2019, doi: 10.1007/s10994-019-05855-6.

[5] I. D. Mienye and Y. Sun, “A Survey of Ensemble Learning: Concepts, Algorithms, Applications, and Prospects,” IEEE Access, vol. 10, pp. 99129–99149, 2022, doi: 10.1109/access.2022.3207287.

[6] G. James, D. Witten, T. Hastie, R. Tibshirani, and J. Taylor, “Unsupervised Learning,” An Introduction to Statistical Learning, pp. 503–556, 2023, doi: 10.1007/978-3-031-38747-0_12.

[7] Y. Han, G. Huang, S. Song, L. Yang, H. Wang, and Y. Wang, “Dynamic Neural Networks: A Survey,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 11, pp. 7436–7456, Nov. 2022, doi: 10.1109/tpami.2021.3117837.

[8] K. Zhou, Z. Liu, Y. Qiao, T. Xiang, and C. C. Loy, “Domain Generalization: A Survey,” IEEE Transactions on Pattern Analysis and Machine Intelligence, pp. 1–20, 2022, doi: 10.1109/tpami.2022.3195549.

[9] C. Chen, D. Han, and J. Wang, “Multimodal Encoder-Decoder Attention Networks for Visual Question Answering,” IEEE Access, vol. 8, pp. 35662–35671, 2020, doi: 10.1109/access.2020.2975093.

[10] L. Zhang and X. Gao, “Transfer Adaptation Learning: A Decade Survey,” IEEE Transactions on Neural Networks and

[22] *Case study, demonstration, exercise, error analysis, etc.*

Learning Systems, vol. 35, no. 1, pp. 23–44, Jan. 2024, doi: 10.1109/tnnls.2022.3183326.
[11] T. Jiang, J. L. Gradus, and A. J. Rosellini, “Supervised Machine Learning: A Brief Primer,” Behavior Therapy, vol. 51, no. 5, pp. 675–687, Sep. 2020, doi: 10.1016/j.beth.2020.05.002.
[12] R. Miikkulainen et al., “Evolving deep neural networks,” Artificial Intelligence in the Age of Neural Networks and Brain Computing, pp. 269–287, 2024, doi: 10.1016/b978-0-323-96104-2.00002-6.
[13] C. F. G. D. Santos and J. P. Papa, “Avoiding Overfitting: A Survey on Regularization Methods for Convolutional Neural Networks,” ACM Computing Surveys, vol. 54, no. 10s, pp. 1–25, Jan. 2022, doi: 10.1145/3510413.
[14] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, “A survey of the recent architectures of deep convolutional neural networks,” Artificial Intelligence Review, vol. 53, no. 8, pp. 5455–5516, Apr. 2020, doi: 10.1007/s10462-020-09825-6.
[15] G. Matteucci, E. Piasini, and D. Zoccolan, “Unsupervised learning of mid-level visual representations,” Current Opinion in Neurobiology, vol. 84, p. 102834, Feb. 2024, doi: 10.1016/j.conb.2023.102834.
[16] J. A. Livezey and J. I. Glaser, “Deep learning approaches for neural decoding across architectures and recording modalities,” Briefings in Bioinformatics, vol. 22, no. 2, pp. 1577–1591, Dec. 2020, doi: 10.1093/bib/bbaa355.
[17] A. Saxe, S. Nelli, and C. Summerfield, “If deep learning is the answer, what is the question?,” Nature Reviews Neuroscience, vol. 22, no. 1, pp. 55–67, Nov. 2020, doi: 10.1038/s41583-020-00395-8.
[18] K. Han et al., “A Survey on Vision Transformer,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 1, pp. 87–110, Jan. 2023, doi: 10.1109/tpami.2022.3152247.
[19] X. He, K. Zhao, and X. Chu, “AutoML: A survey of the state-of-the-art,” Knowledge-Based Systems, vol. 212, p. 106622, Jan. 2021, doi: 10.1016/j.knosys.2020.106622.

9. Corroboration of the contents of the subject with the expectations of representatives of the epistemic community, professional associations and representative employers in the field related to the program[23]

The course plays an important role in connecting various related courses within the fields of computer science and data science. It serves as a foundational bridge between statistical analysis, programming, and advanced artificial intelligence courses. Understanding the fundamentals of machine learning is essential for students pursuing specializations in data science, computer graphics, natural language processing etc. Its interdisciplinary nature establishes connections with mathematics, statistics, and computer engineering courses, therefore faclitating the understanting of important aspects within the related fields. In terms of the labor market, proficiency in machine learning is increasingly becoming a sought-after skill by employers across multiple industries. As organizations continue to process increasingly-complex data, the ability to implement and optimize machine learning models becomes a valuable asset. Graduates equipped with a solid understanding of the fundamentals of machine learning are well-positioned for roles ranging from data scientists and machine learning engineers to analysts, thus enhancing their competitiveness and employability in the dynamic job market.

10. Evaluation

Type of activity	10.1 Evaluation criteria	10.2 Evaluation methods		10.3 Weight in the final grade
10.4a Exam	Acquired theoretical and practical knowledge (quantity, correctness, accuracy)	Periodic tests[24]:		50% (minimum 5)
		Homework:		
		Other activities[25]:		
		Final evaluation:	100%	
10.4b Seminar				
10.4c Laboratory	Knowledge of related techniques, ability to use dedicated frameworks, evaluation and interpretation of results	• Practical demonstrations • Oral answers • Written questionnaires		50% (minimum 5)
10.4d Project	The quality of the project and the documentation, ability to defend the project coherently.	• Presentation and/or defence of the project • Quality and relevance of answers to questions		
10.5 Minimum performance standard[26]: grade 5 in the exam and applications (the average between laboratory and project)				

Date of completion,	Signature of course coordinator,	Signature of application instructor,
5 December 2023	Lect. dr. eng. Marius Gavrilescu	Assist. drd. eng. Codruț-Georgian Artene, Assist. dr. eng. Ștefan Achirei

[23] *The connection with other subjects, the usefulness of the subject on the labor market*
[24] *The number of tests and the weeks in which they will be held will be specified.*
[25] *Scientific circles, professional competitions, etc.*
[26] *The minimum performance standard from the competences grid of the study program is customized to the specifics of the subject, if applicable.*

Date of approval in the department,
7 December 2023

Director of department,
Assoc. prof. dr. eng. Andrei Stan