Collaborative Transdisciplinary Educational Approaches in AI

Adriana Mihaela Coroiu[a], Alina Delia Călin[b] and Horea-Bogdan Mureşan[c]

Faculty of Mathematics and Computer Science, Babeş-Bolyai University, Mihail Kogălniceanu, Cluj-Napoca, Romania

Keywords: AI, Machine Learning, Climate Change, Online Teaching, Transdisciplinary, Multidisciplinary.

Abstract: In this paper we present a transdisciplinary approach towards teaching and applying AI methods, to mitigate climate change related issues. The proposed method is a course with a student-centred approach, enabling collaborative experiential learning and multi-disciplinary exploration with specialists from different fields of expertise internationally. The study covered data collected through questionnaires, observations and evaluation, and was proven to stimulate creativity, motivation and innovation in using AI to effectively solve real-life problems, which is the aim of the course.

1 INTRODUCTION

One of the COVID-19 pandemic challenges and opportunities related to education was the requirement to shift entirely to online teaching. This required new and adapted methodologies to engage students in the online environments however, this also posed new opportunities of connection and cooperation.

The educational system focuses on several disciplines which are studied in depth, but often the bonding element between the subjects is missing or is very weak. Therefore, educators and researchers are still trying to figure out cross-domain solutions to real-life problems. Recent tendencies are towards new multi-domain or transdisciplinary and inter-disciplinary studies, such as studying natural sciences and the natural world as a whole from an integral approach, rather than studying only separate domains biology, geography, chemistry, physics and social science. From this perspective, a study has found that the lack of social science perspective on the issues of climate change is lacking in science textbooks (Morris, 2014). This means the approach is not stimulating the need to find sustainable solutions for the environment and green choices in the everyday life. A successful example of multidisciplinarity is neuroscience (Ruiter et al., 2012), looking at the nervous system from all perspectives (physiology, anatomy, molecular biology, developmental biology, cytology, computer science).

[a] https://orcid.org/0000-0001-5275-3432
[b] https://orcid.org/0000-0001-7363-4934
[c] https://orcid.org/0000-0003-4777-7821

Following this trend, the proposed computer science course presented here is titled ”Artificial Intelligence Models for Climate Change” and aims to bring together multiple disciplines related to natural sciences describing climate change issues and pollution to inform recent advances in computer science (artificial intelligence and machine learning, big data, sensors, data storage) in the search of new solutions for today’s real world problems. This also comes in line with our University’s initiative ”to go GREEN”, encouraging active participation to reduce pollution and find ingenious solutions to Global Warming and Climate Change.

From a teaching methodology perspective, applied in the field of computer science, recent studies have shown better educational outcomes in using collaborative learning and student-centred approaches (Lu et al., 2010) as opposed to teacher-centred methodologies (Dias Canedo et al., 2017).

These involve providing materials that students go through at their own pace, addressing more student feedback and questionnaires in going deep into the material (Griffiths et al., 2007) or using interactive audio-visual content (Lu et al., 2010). However, although these are not very new, the traditional teacher-centred methodologies are still preserved, although sometimes not as effective as desired.

Thus, this course was designed to use modern teaching approaches which are more student-centred, collaborative and critical thinking oriented, to increase motivation and engagement, as well as the overall learning experience of students.

Coroiu, A., Călin, A. and Mureşan, H.
Collaborative Transdisciplinary Educational Approaches in AI.
DOI: 10.5220/0011039500003182
In *Proceedings of the 14th International Conference on Computer Supported Education (CSEDU 2022) - Volume 2*, pages 260-267
ISBN: 978-989-758-562-3; ISSN: 2184-5026

2 ARTIFICIAL INTELLIGENCE MODELS FOR CLIMATE CHANGE - A NOVEL TEACHING APPROACH

Besides the multi and transdisciplinary characteristic of this course, combining multiple expertise on climate change and advanced artificial intelligence (AI) techniques, its novelty is also in the modern educational approach towards collaborative and experiential learning of students, teachers, and external experts in the field. Moreover, the evaluation methodology is also a reflective and collaborative one, involving also self-evaluation and inter-evaluation. While many have considered and researched a multidisciplinary approach of the climate change issues from an academic educational and research point of view, and have proven that this is very much needed for good solutions to arise, its success depends also on how this is managed (Briguglio and Moncada, 2019), for which reason the collaborative and experiential components play very important roles.

2.1 About the Course

The course was held for the first time in the academic year 2020-2021, second semester, addressing third year Bachelor's degree students who already had studied the basics of Artificial Intelligence course. There were 95 students enrolled from different specialisations: 54% Computer Science, 45% Mathematics and Computer Science, and 1% Mathematics), so backgrounds were a bit different among the participants.

The general aim of the course was to identify solutions for climate change using techniques and methods from Artificial Intelligence. The students would enhance these abilities in the 12-weeks course:

- Identify current issues related to climate change that could be addressed
- Model these identified problems
- Propose viable solutions in the form of software applications that can solve at least partly the identified problems

The best keywords to describe this course are: innovation, applicability, collaboration, development and transdisciplinarity.

2.1.1 Innovation and Applicability

The subjects addressed were still recent and full of challenges, both from the perspective of data sources involved in the analysed subject (Earth, Environment, Agriculture, Society) and from the point of view of the Artificial Intelligence Methods that can be applied. The implemented solutions were required to be robust, accurate with minimal compromise, and to have a positive impact on the health of the people and of the environment. Computer Science and Artificial Intelligence, through the mathematical device behind them and the existent tools, are able to provide useful and concrete solutions to real problems of society and humanity.

2.1.2 Collaboration and Development

The course was student-centred oriented and dynamic. We started from the state-of-the-art of research literature for each domain, then involving a specialist (invited to get more insight in the analysed issues) that presented a very concrete problem. Specialists and students have discussed the requirements and proposed solutions in the form of software applications that were developed during the labs. The laboratory involved group collaborative work between 4-6 students.

2.1.3 Transdisciplinar

As the name suggests, the course involved several domains. This component is also supported by the University resources, which allow us to invite specialists from other faculties or departments, even industry experts or NGOs activists internationally, to share their knowledge and expertise with students.

2.2 Platforms and Tools Utilised

The course was held in the context of online teaching imposed by the COVID19 pandemic, using the online platforms Moodle (for content sharing in terms of materials and theory, and evaluation), Microsoft Teams University platform or the Zoom platform (for open discussions, especially involving guest speakers, presentations sharing and feedback) and JupyterLab (an interactive development environment for developing the projects, using Python as programming language, machine learning, related packages for data pre-processing, model training and testing) (Perez and Granger, 2015). As an online development tool, including libraries (Tensorflow, Keras, ScikitLearn), it is well suited for collaborative programming and group projects, facilitating code sharing, but also models and obtained results.

2.3 Teaching Methodologies

As teaching methodology, the course is taking a shift towards student-centred approach through cooperative learning, inquiry based learning and experiential learning. Collaborative learning is performed from three perspectives: perspective teacher-student, perspective student-student and perspective student-specialist (specialist meaning a guest invited to share knowledge and expertise in a different field). The teacher's role starts with facilitating the introduction of new concepts of AI methodologies, but it mostly continues as a facilitator and delegator, involving critical thinking and discussions between students and external experts in various transdisciplinary fields related to climate change.

This is based on the approach toward innovation and cutting-edge research, aiming to stimulate creativity, interest, critical thinking and involvement in actual solving of real life problems that are close to the experience of a student. Reaching into the intrinsic motivation of students, will engage a much deeper learning approach (Baeten et al., 2010) and increased results, especially if they satisfied with the course overall. This can be achieved by selecting content that is of interest to them (which was performed in this case at the beginning of the course by using a questionnaire). The votes are distributes as such: 29.9% AI for Society, 25.3% AI for Agriculture, 23.7% AI for Earth, and 21.1% AI for Environment.

From this point of view, experiential learning is the basis not only from the learning during the course perspective, but also from an evaluation perspective, meaning students are asked to reflect on their work and their colleagues work and evaluate the innovation and performance of the solutions. Therefore, evaluation is also collaborative in this sense, between students, teacher and specialists in other fields.

Table 1: Research questions.

Questions for analysing a research paper:
1. What is the main problem addressed?
2. What was done before, and how does this paper improve on it?
3. What is the one cool technique/idea/finding that was learned from this paper?
4. What part was difficult to understand?
5. What generalisation or extension of the paper could be done?

The laboratory work is based on a kinestethic learning (involving hands-on experience). Group projects involve differentiated instruction based on specific aims of the chosen project and requirement, as well as based on the team capabilities, starting with literature review, debating possible improvements and how relevant are the results (the questions are presented in Table 1). It might involve also a level of expeditionary leaning (engaging with experts to learn even more on the subject, understand the problem and decide the action).

After identifying a relevant research paper and performing a critical analysis, the next challenge is finding relevant data (or collecting/generating it). We tried focusing on data collected in Romania or Europe, as research clearly shows that educational interventions are most successful when they focus on local, tangible, and actionable aspects of sustainable solutions (Anderson, 2012). This way, the aim was to engage students in a local tangible problem that they can solve with AI, emphasising their crucial role in it, but also to educate them to remember the issues of the environment beyond the computer science course, and keep a focused attitude towards protecting the environment within all aspects of their life. The final datasets used in the projects are from eleven different sources, as presented in Figure 1.

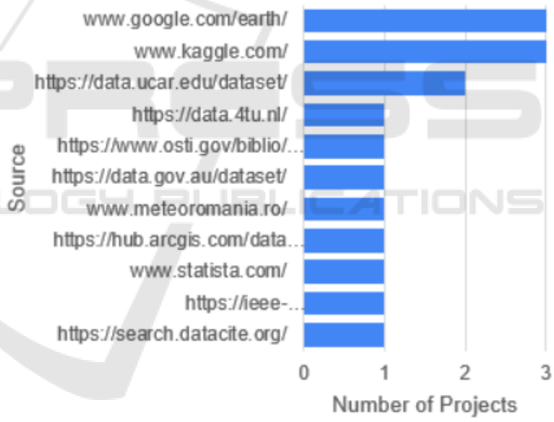

Figure 1: Datasets sources.

Next, the general steps required when applying artificial intelligence algorithms (as presented in detail in Section 2.5) were given as guidance for project development. This guidance was useful for the groups to work together and collaborate, especially as groups were mixed (more computer science oriented or more mathematical oriented background) to encourage communication and sharing of different perspectives, involving an important component of knowledge transfer between the team members of each group.

Group projects which are problem-based learning pose several advantages: the development of critical thinking and creative skills, the improvement of problem solving abilities, increased student motivation, better knowledge sharing in challenging situations and it is a form of experiential learning.

2.4 Subjects Addressed by the Course

Half of the course included technical content related to optimising AI methods (for example Features Selection/Extraction Techniques, Ensemble Learning Methods or Hyperparameter Techniques), and the other half involved a guest speaker in one of the interest domains voted by students about climate change, which are presented below.

2.4.1 Light Pollution

This presentation was performed by Mihai Cuibus, Software Engineer, member of the Romanian Society for Cultural Astronomy, and lead on the Light Pollution department. He brought to light a new topic with high impact which is still rarely discussed in our country, by presenting the impact of light pollution at a national/local level, as well as globally, for the human health, as well as for the natural world and its biodiversity. After discussing the different issues involved and possible solutions from a Computer Science point of view, some specific tasks were identified mostly related to image processing and analysis:

- Detecting light sources in an image
- Spectral analysis of an image (colour temperature)
- Predicting the extension of light pollution based on satellite images (such as Figure 2) and correlation with health issues related to light pollution for those regions; also correlation with air pollution on those areas
- Mapping the streets of a neighbourhood with a luxmeter or SQL or spectrometer and correlating these with existing maps
- Design of intelligent street lights that can be remotely controlled, function based on time of day, traffic intensity, or geographic location, adapting to the user behaviour to reduce light where it is not used, and automatic adjustment of the light intensity based on certain conditions

2.4.2 Sustainability and Society

This presentation was held by Sorina Avadanei, master student at the Anthropology Department from Durham University. She presented the complex problem of sustainability as a result of technological advancement and the people that intervene in the environment. She compared how people relate to this

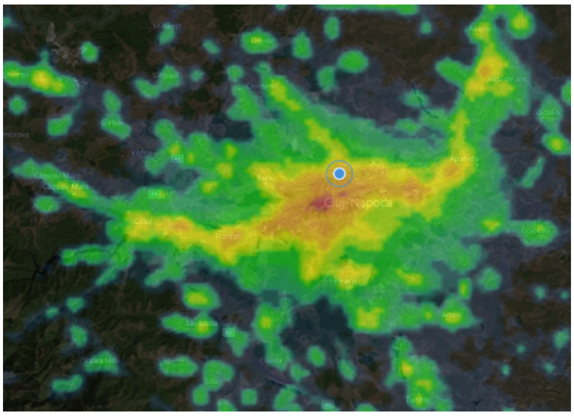

Figure 2: Light pollution sky map for Cluj-Napoca and surroundings generated in May 2021 using the new atlas of artificial of night sky brightness (Microsoft, 2021; Falchi et al., 2016). Warmer colours indicate a higher degree of light pollution.

in Romania or UK and presented some relevant ideas that can be tackled by Computer Science, such as developing an application which based on a map displays the closest recycling units to the user.

2.4.3 Agent Green

Agent Green is an NGO for the protection of the environment created in 2009 in Romania. The organisation investigated environment crimes and tries to expose them strategically, promoting solutions for biodiversity conservation and the assurance of a health environment for the future generations. Veronica Tulpan and Raluca Nicolae have been involved in the presentation, discussing their national projects, the actual stage of forests in Romania and the impact of uncontrolled deforestation on climate change. Other issues discussed were the increasing consumption of meat and the high impact of methane emissions from intensive breeding. The proposed ideas were

- Identifying deforestation areas and levels by using drone/satellite images
- Identifying the age of a tree based on the number of extracted samples
- Creating an app to encourage nature lovers to meet for planting trees, or perhaps extinguishing fires or exploring

2.4.4 Human Ecology and the Impact of Climate Change on Biodiversity

This presentation performed by Alexandru Stermin, Lecturer at the Faculty of Biology, highlighted the faculty's projects to protect the environment and identify methods that are able to automatise this process.

The solutions envisioned are:

- Identifying the area of separation between taiga / steppe based on the current images and comparing them with those existing for several decades, to identify changes in their structure (their retreat faster and faster to the north)
- Automatic identification of birds and framing in a certain species based on a picture / video taken
- Automatic analysis of information related to the total number of birds of a certain species (see Figure 3) and plants in a given area and prediction for the coming years (it was found that there are areas where bird populations and certain plants are constantly declining - also based on the harmful effects of humans on the environment)

Figure 3: Identifying and counting birds from images.

- Creating a mobile app that warns us how much harm we do to the environment through daily activity, for example: recording the sound of running water used for the duration of brushing teeth, or identifying the engine noise of a car for travel and providing notifications in real-time or at the end of the day related to the risk that our day represents for the environment.

2.4.5 Microsoft Initiatives for the Environment

This presentation performed by Rusen Daniel and Lucian Ungureanu was based on the Microsoft AI for Earth projects. They also mentioned the reasons for being a sustainable company, such as 100% recycling policy or garden roofs, and offered free credits access to students for Microsoft Azure.

2.5 Steps Required When Applying Artificial Intelligence Algorithms

1. **Understanding the Domain:** In order to make an informed decision on what AI algorithm is best for a given task, understanding the currently available data that can serve as input is mandatory. As an AI model processes data, it produces an output which can take several forms (array of probabilities, number, feature map etc.). Choosing an AI algorithm should take into consideration the provided output.
2. **Data Gathering:** Part of developing a good AI model is selecting appropriate data to train it on. The data should include samples for each category and, ideally, a balanced number of samples per category. In some cases, such datasets already exist, however, in all other cases the dataset must be built. To improve the quality of a dataset, a couple of techniques can be applied: data sensitisation and preprocessing (Famili et al., 1997; Perez and Wang, 2017). Data sensitisation involves identifying and eliminating data points that are not relevant to the studied problem or that contain invalid attributes. Preprocessing data refers to a number of algorithms that can enlarge the dataset by adding new data points generated based on the existing ones (eg. for image datasets, image flips and rotations can achieve this goal).
3. **Exploratory Data Analysis:** Regardless of how the dataset is obtained, overview information such as total count, count per class, minimum, maximum, average and standard deviation (where applicable) can help further understanding of dataset characteristics (Famili et al., 1997). The identification of existent correlations within the dataset can also help in simplifying the training process by reducing the amount of processed features.
4. **Determining the AI Algorithm:** Choosing the right algorithm to train a model requires careful consideration of available input data characteristics as well as target result type(Dey, 2016). If the desired outcome is to identify patterns in unlabelled data and grouping data points based on their feature, the go to method will be an unsupervised learning algorithm. Among the most widespread unsupervised learning algorithm is clustering, which attempts to partition a set of data points into clusters by minimising the distance between data points of the same cluster and by maximising the distance between data points of different clusters. Should labelled data be available, then supervised learning can be employed. This

class of machine learning algorithms can predict either a continuous value (regression) or can identify to which class/classes a data point belongs to (classification).

5. **Training the Model:** Once the dataset is obtained or created and the AI method is chosen, the training process can begin. It is recommended to split the dataset into three subsets: train - validation - test (Xu and Goodacre, 2018). The train subset will be used by the AI algorithm to adjust the model's weight such that the values of performance metrics (accuracy, loss, F1-score, etc) tend towards the optimum. The validation subset will be used at the end of a training epoch (ie. when the training algorithm has iterated over the entire train subset) to evaluate the current performance of the model. Based on this, hyper-parameters such as learning rate can be adapted during training, while a stagnation in performance can lead to an early stop of the process. The validation subset must be distinct from the train subset as it can easily indicate if the model is unable to generalise on new data, issue known as over-fitting.
6. **Evaluating the Model:** The test subset is not involved in training/validating the model and typically contains samples that are meant to represent "real-world" data points. As such, this subset is the most appropriate for evaluating the performance of the trained model and it serves as an indicator to how well can the model be used in a practical application.
7. **Validating, Visualising and Interpreting the Results:** To gain insight on the performance of a model, the evaluation results can be aggregated into tables and plotted on charts. This is a more "human readable" way to analyse data and makes it more simple to interpret it. The evolution over time of the performance of the model during training can help indicate if the training is too long (the model saturated early and no longer learns) or is too short (the model keeps improving every epoch). In the case of classifiers, a confusion matrix can quickly show if the model can distinguish properly between the classes, and if not, which are the classes that are considered very similar.
8. **Synthesising the Results:** Once results are organised, they can be summarised to form a conclusion. This should contain observations regarding the problem that the model solves side by side with other results from the literature. The key differences between the proposed method and the existing methods should be highlighted, with both advantages and disadvantages. Finally, further improvement directions can be suggested based on observed weaknesses of the model and new directions for expanding the model can be provided.

2.6 Course Evaluation Methods and Results

The final evaluation for the course involved:

- 30% Self-evaluation of the project team
- 30% Evaluation of the final project (involving a presentation and a demo or an application and a descriptive report)
- 30% Evaluation of the work by other teams
- 10% Activity during the semester at the lab

Each team had to evaluate their strategy of working, roles distribution, internal task assignment and development of solutions, and to propose a grades based on these aspects. The final project was based on an application and a descriptive report (describing the motivation, the problem to be solved, theoretical elements used, similar approaches in literature, presentation of the methodology chosen for the solution and the application), which was aimed at:

- solving a problem related to the climate change, environment, or pollution using one of the advanced AI methods presented;
- use the recommended steps in the solution development;
- be innovative and refer to the state-of-the-art published in the last 5 years and no later then this.

It was mandatory that each team will participate at the presentations of other teams, to reflect on other approaches, to ask questions and then to evaluate the team projects. Based on the average of the results for the team, the students should allocate to each of them (inside the team) a particular grade, thus obtaining the average which is the team's evaluation grade. In this way, they have the opportunity to correctly reflect the individual grade according to the implication within the project. They demonstrated a fair analysis, the results recompensing those students who worked harder than others.

The projects and solutions proposed by students are related to: drought and flooding prediction,air quality classification and prediction, fruit recognition from images, detecting plants and leaf diseases, animal monitoring by image recognition, storm detection, deforestation detection, forest fire prediction, intelligent plant irrigation, greenhouse monitoring, weather and temperature prediction, city metabolism analysis, care homes and orphanages classification based on needs and priorities, traffic prediction in Europe's big cities, and household electricity consumption.

The intelligent algorithms, models, methods and datasets involved are: LSTM, CNN, K-Means, Clusters, PCA, ANN, Regression, SVM, Random Forest, DeepWeeds, Inception-v3, ResNet-50, and the datasources presented previously in Figure 1.

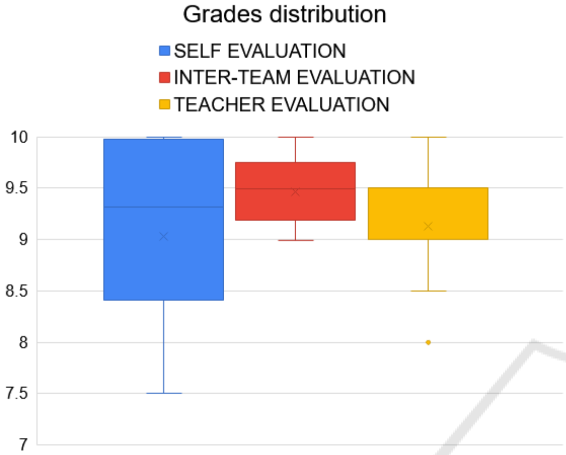

Figure 4: Distribution of grades for each component of the evaluation.

The grades obtained by each team are presented in Figure 4, including each component of the evaluation. Comparing the three types of team project evaluation (self-evaluation, inter-evaluation and teacher evaluation) as seen in Figure 5, we can observe that inter-evaluation and teacher evaluation are similar and have less variance, as opposed to self-evaluation, which has a high variance, and surprisingly, with a lower mean (9.02) then inter-evaluation mean (9.46) and teacher evaluation mean (9.12). This reflects the different expectation that each team had related to the project's success.

3 EVALUATION AND BENEFITS OF THE APPROACH

At the end of the semester, it seems that the main advantage of the course methodology was represented by the mixture of technical and non-technical presentations. On one hand, the presentations delivered by the external guests in different domains about environment issues were eye-opening for students. The process of being aware of unseen problems of earth and the environment brings a new perspective for most of them (they even mention "we didn't know about this issue ..."). On the other hand, the technical

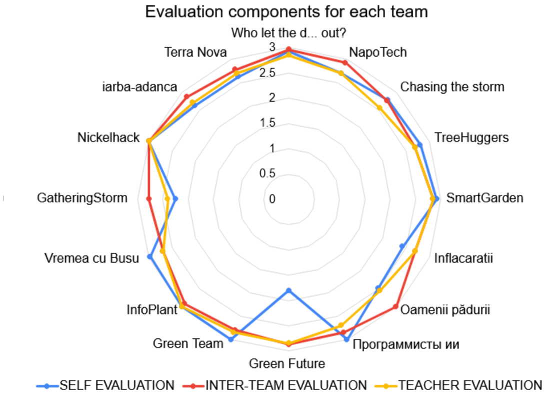

Figure 5: Self evaluation, inter-team evaluation and teacher evaluation for each project team.

presentations about literature and AI techniques clarified the main and useful ML approaches for finding solutions for such issues, offering a set of rules for an AI-based project.

At the end of the activity, the students were asked to provide antonymous feedback using Google forms. Most of them mentioned they learn a lot of new things from our guests. They express their gratitude for the opportunity and they mention that this discipline was one of the most interesting from this semester and they performed an awesome choice to enrol with this one. Regarding the evaluation process, they provided feedback that the idea of self-evaluation and the idea of evaluating other teams allow them to feel that their opinion is important and valuable. They also said that they were more confident in expressing interest in presentations and addressing questions.

In what concerns the project development, they appreciated they have worked for solutions than can be extended and used in real-life, and this was not only a school project. Some also mentioned that the discussions with the guests was introducing them to the industry context of working with the clients into a company, in order to figure out the requirements from a non-technical person and translate it into a computer science solution.

In terms of drawbacks, students highlighted that their main problem was that the course was held in the last semester of bachelor's degree, by which time they have already chosen their degree title, thus having limited time to invest in this course.

The students also emphasised that this was the third discipline in three years in which they were required to work in a team. In this sense, the idea of collaboration while also keeping in mind the individual task and the collective task was a real challenge and they were proud they succeed in it.

4 CONCLUSIONS

The presented approach of the course "Artificial Intelligence for Climate Change" was new into the faculty and for the students, but the feedback and the interest from both students and specialists invited show that the idea can be of success also in the next years.

To the best of our knowledge, this approach is unique among the universities of Romania, in particular, computer science faculties. Globally however, this program is implemented across several universities such as: AI for Social Good from Stanford, Climate Change and AI from Oxford and AI for the study of Environmental Risks from University of Cambridge.

In the scientific community there is a great interest for this topic, "AI for Good" being the largest conference to date (https://aiforgood.itu.int/). There are also working groups consisting of researchers and specialists to support the fight against climate change (Focus Group on Environmental Efficiency for Artificial Intelligence and other Emerging Technologies, Focus Group on AI for Natural Disaster Management, Focus Group on AI for Health, etc.).

As future work directions, our intention is to extend the list of specialists from different areas, increase the numbers of AI teachers and to organise some workshop during the laboratory work activity - engaging also experts from other fields to offer feedback in real-time for a new implemented feature.

ACKNOWLEDGEMENTS

The work presented became real with the help of supportive colleagues, extremely passionate guests, and highly involved students. Therefore we would like to express our gratitude to Professor Motogna Simona, Lecturer Alexandru Stermin and specialists Mihai Cuibus (Romanian Society for Cultural Astronomy), Veronica Tulpan and Raluca Nicolae (Agent Green), Sorina Avadanei (Durham University), Daniel Rusen and Lucian Ungureanu (Microsoft Romania).

The publication of this paper was supported by the 2021 Development Fund of the Babeş-Bolyai University (UBB).

REFERENCES

Anderson, A. (2012). Climate change education for mitigation and adaptation. *Journal of Education for Sustainable Development*, 6(2):191–206.

Baeten, M., Kyndt, E., Struyven, K., and Dochy, F. (2010). Using student-centred learning environments to stimulate deep approaches to learning: Factors encouraging or discouraging their effectiveness. *Educational Research Review*, 5(3):243–260.

Briguglio, L. and Moncada, S. (2019). The benefits and downsides of multidisciplinary education relating to climate change. *Climate Change and the Role of Education*, pages 169–187.

Dey, A. (2016). Machine learning algorithms: a review. *International Journal of Computer Science and Information Technologies*, 7(3):1174–1179.

Dias Canedo, E., Santos, G. A., and Andrade de Freitas, S. A. (2017). Analysis of the teaching-learning methodology adopted in the introduction to computer science classes. In *2017 IEEE Frontiers in Education Conference (FIE)*, pages 1–8.

Falchi, F., Cinzano, P., Duriscoe, D., Kyba, C. C., Elvidge, C. D., Baugh, K., Portnov, B. A., Rybnikova, N. A., and Furgoni, R. (2016). The new world atlas of artificial night sky brightness. *Science advances*, 2(6):e1600377.

Famili, A., Shen, W.-M., Weber, R., and Simoudis, E. (1997). Data preprocessing and intelligent data analysis. *Intelligent data analysis*, 1(1):3–23.

Griffiths, G., Oates, B. J., and Lockyer, M. (2007). Evolving a facilitation process towards student centred learning: A case study in computing. *Journal of Information Systems Education*, 18(4):459.

Lu, Z., Hou, L., and Huang, X. (2010). A research on a student-centred teaching model in an ict-based english audio-video speaking class. *International Journal of Education and Development Using ICT*, 6(3):101–123.

Microsoft (2021). Light pollution maps.

Morris, H. (2014). Socioscientific issues and multidisciplinarity in school science textbooks. *International Journal of Science Education*, 36(7):1137–1158.

Perez, F. and Granger, B. E. (2015). Project jupyter: Computational narratives as the engine of collaborative data science. *Retrieved September*, 11(207):108.

Perez, L. and Wang, J. (2017). The effectiveness of data augmentation in image classification using deep learning. *arXiv preprint arXiv:1712.04621*.

Ruiter, D. J., van Kesteren, M. T., and Fernandez, G. (2012). How to achieve synergy between medical education and cognitive neuroscience? an exercise on prior knowledge in understanding. *Advances in health sciences education*, 17(2):225–240.

Xu, Y. and Goodacre, R. (2018). On splitting training and validation set: A comparative study of cross-validation, bootstrap and systematic sampling for estimating the generalization performance of supervised learning. *Journal of Analysis and Testing*, 2.