AI-Based Crop Rotation for Sustainable Agriculture Worldwide

Julius Schöning
Faculty of Engineering and Computer Science
Osnabrück University of Applied Sciences
Osnabrück, Germany
Email: j.schoening@hs-osnabrueck.de

Mats L. Richter
Institute of Cognitive Science
Osnabrück University
Osnabrück, Germany
Email: matrichter@uni-osnabrueck.de

***Abstract*—Artificial intelligence (AI) and sustainability. Two words not commonly used in the context of crop rotation management. However, simple AI-based expert systems supporting farms' decision-making for optimizing crop rotation might be the key to solving most of the UN sustainable development goals worldwide. The essence of AI-based crop rotation and farm management is that it works with nature—not against it! Thus, the AI-based expert system needs to solve the multidimensional optimization tasks of maximizing the diversity of crops that match the local soil, local climate condition, the needs of the livestock, and any available machinery. Next to the option task, the expert system had to argue its decision-making basis since the goal is to get the most sustainable farming with the most profitable crop yield, not to get the largest yield. The expert systems' user interface (UI) should broaden thinking habits, opting for new sustainable farming perspectives. This paper will introduce both the technical architecture and the user-in-the-loop (UIL) principle of such an expert system. Since our system is still in the conceptional phase, we argue design decisions and address open research questions needed to implement such an expert system.**

***Index Terms*—sustainable agriculture, AI-based farming, expert system, crop rotation, user interface**

I. Introduction

How can farming cope with changing climate conditions and extreme weather events? One quite old answer might be even more intelligent crop rotation. The idea of crop rotation is old, and even our ancestors recognize that changing the kind of crops grown on the same field improves the yield and plants' health. The positive impacts of crop ration are also scientifically proven [1], [2].

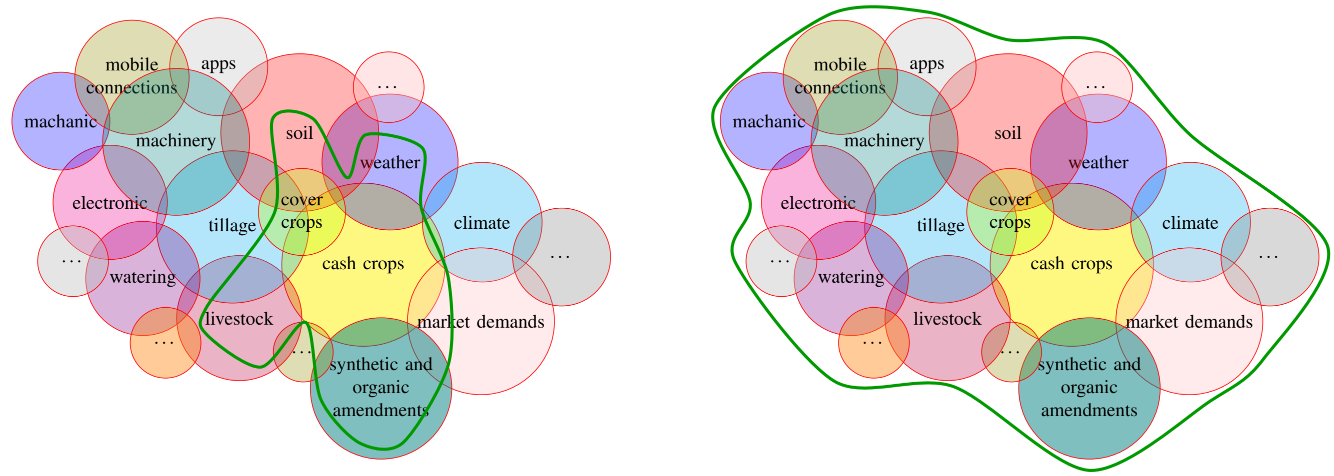
However, by the pressure to maximize profits, farmers are often trying to maximize the amount of yield per hectare and deviate from crop rotation growing similar crops one season after another on the same fields. In this worldwide trend, the crop rotation periods drastically shorten from seven-year to even growing crops in monoculture [2]. Putative from crop rotation will increase external inputs like chemical fertilizer, organic fertilizer, pesticides, and water. Next to the reduction of external inputs, crop rotation protects the land from erosion by rain and wind, since longer-term rotations, including pastures or grass-leys which absorb heavy rain events better as row crops like corn [3], [4].

The critical question is how agriculture provides food security and availability for the next decades and relieves farmers from the market forces producing higher yields year by year. In our opinion, an open-source AI-based crop rotation expert system is the solution, ensuring sustainable, profitable, and secure food production. This expert system provides support for the farmers in the decision-making on her/his farming strategies because the system provides short-, mid-, and long-term plans dynamically based on the implications of today's farming actions. Thus, the farmers can assess impacts of, e.g., a yield amount maximization in the current season to the profits in the next three years depending on all factors like the cost of chemical fertilizer and pesticides.

For introducing the first concepts, architecture, UI, and research question needed to be solved for the implementation of such an open-source AI-based crop rotation expert system, this paper first discusses the considered variables of the multidimensional optimization task crop rotation in Section II. Like any machine learning (ML) algorithm, AI is based on data; in Section III we discuss how data can be entered in the expert system in consideration of farmers' experiences and knowledge and without the use of comprehensive and expensive sensor networks. Through the UIL principle, farmers and AI go hand in hand. How UIL can give expert advice and why UIL has not already been used in the agriculture domain is evaluated in Section IV. The current technical architecture and first UI mockups for specific tasks are also sketched in this section. By outlining this possible architecture and UI, open research questions ranging from the domain of soil science via botany to the visualization and interaction with AI algorithms. Highlighting the interdependency of an open-source AI-based crop rotation expert system and the UN sustainable development goals, in Section V, we conclude this paper.

II. Crop Rotation, a Multidimensional Optimization Task

Why is crop rotation a difficult task? In theory, crop rotation should maximize the diversity of crops in a three to seven-year rotation, ensuring a balanced nutrient content of the soil [5]. The starting point of any crop rotation is the knowledge that crops are nitrogen hungry, phosphorous hungry, which are



(a) frame of attention (green line) usually considered for optimizing crop rotation management

(b) ideal frame of attention (green line) for optimizing crop rotation management

Fig. 1. Crop rotation—the big picture of a multidimensional optimization task, (a) dimensions inside the frame of attention currently considered for crop rotation management by little computer support, (b) dimensions that might be understood and approved by farmers with AI-based expert systems.

potassium hungry, and nitrogen-fixing. Up to this level, crop rotation, has only one dimension, the dimension of the cash crop, marked as the yellow circle in Fig. 1.

The next dimension is the soil. The optimization task becomes trickier with the soil since the crops like corn, wheat, grass, clover, carrots, oat, and triticale must match the local soil conditions. The market demands as the dimension strongly coupled with the profitability of the cash crops are the dimension needed for efficient crops rotation. The farmers also must consider the needs of the livestock available, the weather, the kind of cover crops, the available machinery, law regulations, subsidies, tillage, and many more dimensions.

The frame of attention a farmer considers by manual, i.e. without or with a little computer support, does not cover all dimensions possible, exemplary illustrated in Fig. 1 (a). By applying an AI-based crop rotation management system, ideally all these dimensions and their interdependencies are considered.

In the first development stage of the open-source AI-based crop rotation system, the dimensions: cash crops, market demands, soil, watering, cover crops, tillage, weather, climate, livestock, and synthetic amendments and their interdependencies will be considered. Significantly, the four dimensions: soil, watering, cover crops, and tillage are crucial in ensuring climate-resistant farming. The condition of the soil is one of the key values for sustainable agricultural production [1], [6].

In the second stage of development, the dimensions: machinery and energy consumption should be considered, but even for the first stage, there are non-existing open-source and free expert systems available. On the contrary, most data platforms for farming are firmly in the hands of vendors for agriculture machinery [7]. Consequently, solving the multidimensional optimization problem of crop rotation might not be available for small family-run farms.

III. Farmers' Experiences and Knowledge

In everyday life, more and more decisions are made on screens [8], even in agriculture, farmers relied on information, e.g., from online weather services. Nevertheless, in contrast

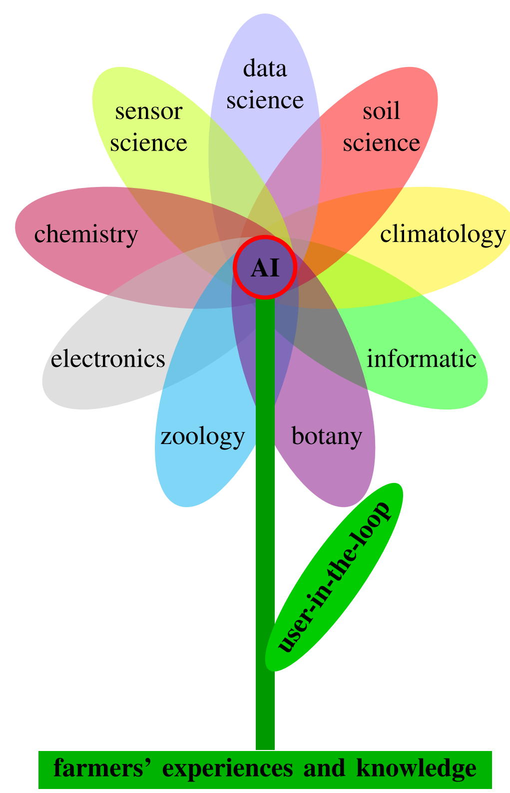


Fig. 2. AI-based expert systems need to incorporate interdisciplinary "bookish knowledge" combined with farmers' experiences for proposing explainable farming options which earn farmers' trust.

to other domains, the most important information is gained by framers' observations, experiences, and knowledge about her/his framing grounds. As illustrated in Fig. 2, the interdisciplinary "bookish knowledge" of the fields botany, zoology, soil science, climatology, chemistry, data science, sensor engineering, and informatics can be summarized easily by AI and ML algorithms into applicable knowledge bases, and ontologies [9]. The most challenging part, how to combine this "bookish knowledge" with farmers' practical and empirical knowledge. Like in Fig. 2 the flower stems, the principle interconnect "bookish knowledge" with farmers' experiences and knowledge.

Absorbing and process the farmers' experiences and knowledge about her/his fields and the current status of crop growth can be measured by comprehensive sensor networks [10] and be the use of guided questionnaires, like it is common for evaluation of soil structure [11], [12]. The way how smartphone apps like *Feldgefügeansprache* [12] interactively support the farmers is one way of ensuring that even farms worldwide will be capable of using a crop rotation expert system.

Digital nudging—or why an AI-based crop rotation expert system should be vendor-independent. Unfortunately, in more and more software products, users are often engaged in making buy-decision quite fast and in an almost automatic manner [8], [13]. These kinds of paternalism must be avoided. One way of doing so is to have an independent expert system, where any company might profit by, e.g., selling fertilizer, pesticides, sensor sets, and machinery.

IV. User-In-The-Loop of Sustainable Farming

With their very fast comprehension, experience, and analytical as well as reliable problem-solving techniques, humans could help AI achieve a broad breakthrough in sustainable farming. In this case, interaction with users requires a simple, consistent, and intuitive visualization technique so that even inexperienced users can understand and comprehend the algorithms and contribute their experiences to the algorithms in an appropriate, scalable dialogue.

The UIL principle is indispensable for a functioning human-machine cooperation. Thereby AI algorithms are the working horse of the expert system, and they are processing data from needed dimensions like weather, law regulations, amount, and qualification of employees as shown as in Fig. 3. If needed information is missing, the algorithms themselves must recognize it, and the algorithm to ask the farmer for assistance for filling this missing information, for instance, that the farmer needs to input the crop growth for a specific field. Consequently, the crop rotation expert systems are capable to generate short-, mid- as well as long-term crop rotation plans. Next to recommended farming action, all three plans contain estimations of yield, water, fertilizer, pesticides, and profit. By having plans of three different durations, impacts on specific farming actions, like switching to a no-tillage strategy

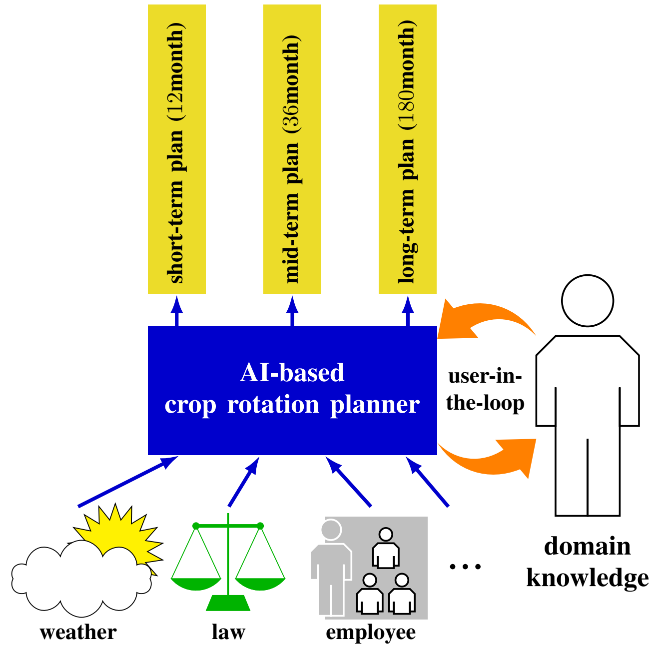


Fig. 3. High-level illustration of the user-in-the-loop principle for crop rotation. The expert systems need to provide a short, mid, and long-term plan for crop management, at last, for dynamically providing the possible implications of today's farming actions.

[14], and its ecological, economic and technological benefits become apparent.

For the worldwide applicability of the AI-based crop rotation expert system, the UIL principle is essential, ensuring that region-specific application of crop rotation concepts will be considered. In addition, the UIL principle avoids that data collected in another region of the world and based on other farm sizes are erroneously used for giving expert advice. Simplicity, i.e., providing AI-based systems without needing, e.g., mainframes, is quite important and challenging. Considering rural small-scale farmers in developing nations, where the crop rotation expert system might help achieve food security, it is still changing to access AI cloud services. Therefore, instead of developing a complex compute-intensive AI algorithm, the architecture design had to target lightweight artificial neural networks [15] that can be executed on smartphones and other devices.

A. Give Expert Advised

For full acceptance, the users and the AI of software need to work hand in hand, i.e., both must speak the same language [16]. Only in this way can human-machine cooperation succeed and the AI-based crop rotation expert system can integrate farmers visual impressions about soil, crop, and weed conditions into the computation of the rotation plan. Giving experts advice, appropriate forms of interaction must be developed, implemented, and tested. The working environment has to be considered since, for instance, touch screens are difficult to operate when driving in the field.

 The final publication is available at DOI 10.1109/GHTC53159.2021.9612460

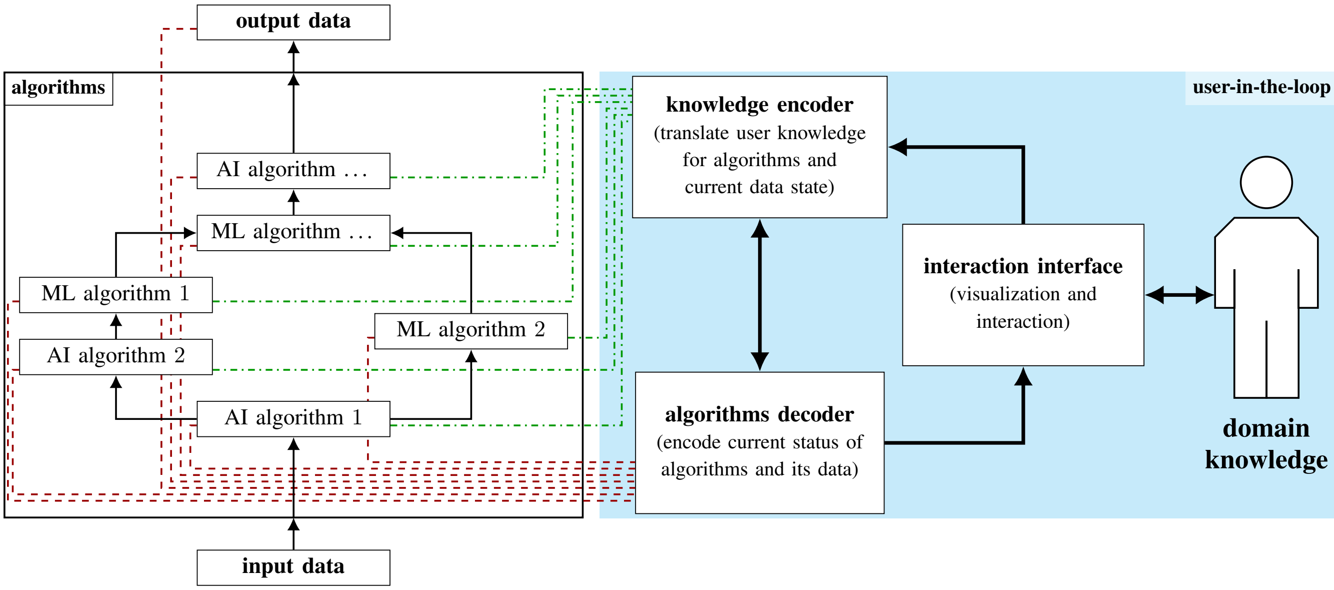


Fig. 4. The user-in-the-loop principle, simple idea but hard to realize to the fact that AI and ML algorithms solve problems in high dimensional space which must be visualized in such a way the expert user can interact with it.

Therefore, human-machine cooperation must take the context of use into account and allow interaction via auditory, visual, and haptic elements. Here, interaction methods such as voice or gaze control could play an important role.

A first conceptual sketch of how the technical implementation of the UIL process in conjunction with AI algorithms might look like is illustrated in Fig. 4. On the left side, the classical software part is shown. This software part executes hard-coded, trained processes in modern machines without feedback from the user. Integrating the expert and experiential knowledge of the users into the software, an algorithm decoder, and a knowledge encoder are required.

The algorithm decoder acts as a translation aid so that users with their very fast comprehension and analytical as well as reliable problem-solving techniques can understand the algorithm, including the data available at the current time. The result of the translation process is visual and auditory representations of the algorithms that users can see and comprehend.

If the users understand the current system state, they can communicate their experiences to the algorithms in an appropriate human-machine dialogue. The knowledge encoder handles this knowledge's feedback into a mathematically understandable representation back to the algorithms. Implementing the algorithm decoder and the knowledge encoder in conjunction with AI algorithms is still a young field of research.

B. Why hasn't the User Already Put in the Loop?

Putting the user in the loop sounds quite simple, but especially AI algorithms, as high-dimensional problem solvers, are still opaque boxes, which are neither self-evident nor human interpretable. Enabling the users to work closely with algorithms understandable simplified visualizations of interim results, as shown by Lundberg and Lee [17], are needed. These visualizations project the data into low visualizable subspaces and leverage the UIL principle within the agricultural domain. Nevertheless, mapping data from all dimensions illustrated in Fig. 1 to low visualizable subspaces is critical for expert systems because these drastic simplifications in the model go along with risking sub-optimal and miss-interpretations of the results [18]–[20]. Thus, the farmer as the expert will get a biased representation of the data and might question the advice given.

In agriculture, many farming actions are based on the farmers' senses. For instance, for evaluation of the soil structure, farmers' visual, olfactory, tactile senses are needed. Thus, the UI must provide an input mechanism ensuring a usable, easy input of data. A possible setup UI mockup for the task of evaluating the soil structure is illustrated in Fig. 5. For analyzing the soil structure, the farmer needs to dig out a spade-sized block down to a depth of approx. $30cm$. In the next step, by the use of her/his hands, the block start is broken up, and the details about the soil fragments are documented. For the digitization of this task, the UI must be entirely designed for hands-free operation. The recent developments in the visualization of intermediate results within AI algorithms, as well as the emerging usability of hands-free UIs, make the implementation of the UIL principle in the next few years possible.

V. Conclusion

With the emergence of usable hands-free UIs an easy and comfortable opportunity is given to incorporate farmers' experiences, knowledge, and observation into an expert system, without the need for expensive sensor sets. Solving the multidimensional optimization task of crop rotation, the "bookish

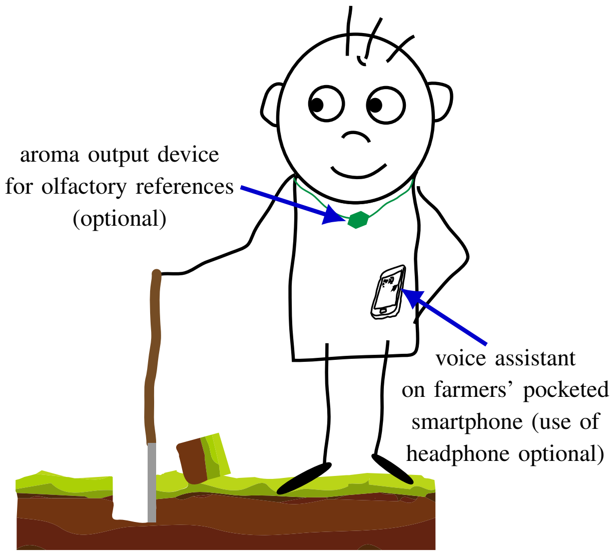


Fig. 5. UI mockup for the task of evaluating the soil structure. The UI uses a farmers' smartphone, where a voice assistant is used for guided input of the data. Thus, the farmer has her/his hands for performing the soil structure analysis. If needed, olfactory references can be created by an aroma output device, and visual references might be described in an auditory manner.

knowledge" is combined with farmers' experiences using the UIL principle. The UIL principle is proposing explainable farming actions which earn farmers' trust due to its explainability. Therefore, the introduced first concepts of an open-source AI-based crop rotation expert system might convince farmers to continuously revising her/his farm management. Since our open-source AI-based crop rotation expert system is not implemented yet, we cannot provide results in numbers, but by arguing our concepts and architectures in this early conceptional phase, we are addressing open research questions needed to implement such an expert system in the upcoming years.

Note the term open-source expert system, since current yield and farming data platforms are mostly vendor depended [7]. Therefore, the open-source expert system will lead to vendor-independent short-, mid-, and long-term corp rotation plans focusing on food security and soil quality of farmers' fields for the next decades.

Farming activities have mutual interaction with many UN sustainable development goals. For naming the most important ones only: zero hunger, clean water, responsible consumption and production, and climate actions. By concluding this paper, we are optimistic that an open-source AI-based crop rotation expert system will establish sustainable agriculture everywhere, since viable agriculture works with nature—not against it!

References

[1] S. Ouda, A. E.-H. Zohry, and T. Noreldin, *Crop Rotation*. Springer International Publishing, 2018 . doi: 10.1007/978-3-030-05351-2

[2] A. J. Bennett, G. D. Bending, D. Chandler, S. Hilton, and P. Mills, "Meeting the demand for crop production: the challenge of yield decline in crops grown in short rotations," *Biological Reviews*, vol. 87, no. 1, 2011 . doi: 10.1111/j.1469-185x.2011.00184.x

[3] S. P. Seibert and K. Auerswald, *Hochwasserminderung im ländlichen Raum*. Springer Berlin Heidelberg, 2020 . doi: 10.1007/978-3-662-61033-6

[4] P. Fiener and K. Auerswald, "Influence of scale and land use pattern on the efficacy of grassed waterways to control runoff," *Ecological Engineering*, vol. 27, no. 3, 2006 . doi: 10.1016/j.ecoleng.2006.02.005

[5] Earth Observing System. (2021, 6) Crop rotation: A way to boost your yields. [Online]. Available: https://eos.com/blog/crop-rotation-a-way-to-boost-your-yields/

[6] A. M. Bondarenko, L. S. Kachanova, A. V. Baryshnikov, and S. A. Novikov, "Technologies for the production and application of organic fertilizers in agriculture," in *The Challenge of Sustainability in Agricultural Systems*. Springer International Publishing, 2021, pp. 897–906 . doi: 10.1007/978-3-030-72110-7_98

[7] Bundesministerium für Wirtschaft und Energie. (2021, 6) Projekt: Agri-gaia. [Online]. Available: https://www.bmwi.de/Redaktion/DE/Artikel/Digitale-Welt/GAIA-X-Use-Cases/agri-gaia.html

[8] T. Mirsch, C. Lehrer, and R. Jung, "Digital nudging: Altering user behavior in digital environments," in *13. Internationalen Tagung Wirtschaftsinformatik (WI)*, 2017, pp. 634–648.

[9] D. O'Leary, "Using AI in knowledge management: knowledge bases and ontologies," *IEEE Intelligent Systems*, vol. 13, no. 3, pp. 34–39, 1998 . doi: 10.1109/5254.683180

[10] T. Rajasekaran and S. Anandamurugan, "Challenges and applications of wireless sensor networks in smart farming—a survey," in *Advances in Intelligent Systems and Computing*. Springer Singapore, 2018, pp. 353–361 . doi: 10.1007/978-981-13-1882-5_30

[11] The Royal Society. (2021, 6) Soil structure and its benefits. [Online]. Available: https://royalsociety.org/topics-policy/projects/soil-structure-and-its-benefits/

[12] Landwirtschaftsverlag Münster. (2021, 6) Apps für die feldgefügeansprache. [Online]. Available: https://www.dlg-mitteilungen.de/mediathek/apps/

[13] M. Weinmann, C. Schneider, and J. vom Brocke, "Digital nudging," *Business & Information Systems Engineering*, vol. 58, no. 6, pp. 433–436, 2016 . doi: 10.1007/s12599-016-0453-1

[14] R. Lal, D. Reicosky, and J. Hanson, "Evolution of the plow over 10,000 years and the rationale for no-till farming," *Soil and Tillage Research*, vol. 93, no. 1, pp. 1–12, 2007 . doi: 10.1016/j.still.2006.11.004

[15] M. L. Richter, J. Schöning, A. Wiedenroth, and U. Krumnack, "Should you go deeper? optimizing convolutional neural network architectures without training," *Under Review*.

[16] J. Schoning, X. Jiang, C. Menon, and G. Heidemann, "Content-aware 3d reconstruction with gaze data," in *2017 3rd IEEE International Conference on Cybernetics (CYBCONF)*. IEEE, 2017 . doi: 10.1109/cybconf.2017.7985769

[17] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *International Conference on Neural Information Processing Systems*, ser. NIPS'17. Red Hook, NY, USA: Curran Associates Inc., 2017, p. 4768–4777.

[18] I. E. Kumar, S. Venkatasubramanian, C. Scheidegger, and S. Friedler, "Problems with shapley-value-based explanations as feature importance measures," in *International Conference on Machine Learning (ICML)*, ser. Proceedings of Machine Learning Research, vol. 119. PMLR, 2020.

[19] J. Schöning and G. Heidemann, "Visual video analytics for interactive video content analysis," in *Advances in Intelligent Systems and Computing*. Springer International Publishing, 2018, pp. 346–360 . doi: 10.1007/978-3-030-03402-3_23

[20] P. Tanisaro, J. Schöning, K. Kurzhals, G. Heidemann, and D. Weiskopf, "Visual analytics for video applications," *it - Information Technology*, vol. 57, no. 1, pp. 30–36, 2015 . doi: 10.1515/itit-2014-1072