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Application note

AI for crop production – Where can large language models (LLMs) provide substantial value?

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ABSTRACT

Since the launch of the “Generative Pre-trained Transformer 3.5”, ChatGPT by Open, artificial intelligence (AI) has been a main discussion topic in public. Especially large language models (LLM), so called “intelligent” chatbots, and the possibility to automatically generate highly professional technical texts get high attention. Companies, as well as researchers, are evaluating possible applications and how such a powerful LLM can be integrated into daily work and bring benefits, improve their business or to make the research outcome more efficient.

In general, underlying models are trained on large datasets, mainly on sources from websites, and online books and articles. In combination with information provided by the user, the model can give an impressively fast response. Even if the range of questions and answers look unrestricted, there are limits to the models.

In this paper, possible use cases for agricultural tasks are elucidated. This includes the textual preparation of facts, consulting tasks, interpretation of decision support models in plant disease management, as well as guides for tutorials to integrate modern digital techniques into agricultural work. Opportunities and challenges are described, as well as limitations and insufficiencies. The authors describe a map of easy-to-reach topics in agriculture where the integration of LLMs seems to be very likely within the next few years.

1. Current global issues in agricultural practice

Agriculture has always been in a constant state of change in order to become more economically efficient and to overcome changing agronomic challenges such as plant diseases or weather extremes. Many aspects of further development today have a different, new focus due to different driving forces. The sector has been assigned the responsibility of meeting stringent environmental protection standards and ensuring sustainability. It is also crucial to increase its recognition in society, such that the many different job opportunities in the sector are more visible and attractive. This is also crucial to ensure that the many different job opportunities in agriculture are responsive and interesting to future generations. Nowadays, the farmer must be an allrounder for plant growth, plant protection, animal feeding, economy, legislation etc. (Kuska et al., 2022) – such an allrounder is rare. Usually, employees on farms work as experts on specialised tasks, but the number of employees on the farms is shrinking due to many reasons (Yoon et al., 2021). This reduces the possible time for employee training and for the testing of new ideas or research news. Finally, farmers are spending the most time in their daily business as usual to ensure their economic stability.

Adoption of innovations in agriculture is a multifaceted process. One facet is the risk profile of the innovation. The perceived risk of an innovation will be related to its complexity and the adopter’s ability to understand it. The farmer and farm employees need to be specially trained for new applications and need a high commitment to the new digital technologies. At this point, LLMs can be a beneficial explainer, trainer for digital agriculture. For example: machine learning methods specific for sensor-based techniques, such as in digital plant pathology, plant phenotyping and remote sensing monitoring, have developed rapidly. As a result, the techniques have experienced rapid innovation from basic research to their practical application in precision agriculture (summarized in Mahlein et al., 2022). Nevertheless, the outputs are highly mathematical and lack easy access in terms of understanding and interpretation. Large Language Models (LLMs) specifically are capable of opening easy access to machine learning results, suitably edited even for non-experts. The first experiences with a LLM may be challenging,

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but the large potential will become apparent rapidly. In general, digitalization is linked to the emergence of transformative technologies for advantages related to productivity and environmental considerations, which will change farmers' identity, skills, and work, while identified in different queries that the social consequences received comparatively get less attention (Rijswijk et al., 2021; Zolkin et al., 2021; Barrett & Rose, 2020). In addition, a well build infrastructure is needed to introduce agriculture 4.0, which must be promoted by policy (Silveira et al., 2023).

2. What are the application fields for such a model and where may its integration first take place?

In public discussions, the current most recognized field of application of a LLM is in explaining the legal basis of farming. It represents one of the current main topics which are related to new legislations to fight climate change e.g. the Farm to Fork strategy in Europe, but it also shows a real existing use case of a LLM to support the farmer. LLMs can effectively explain legal documents, including the application of specific regional regulations, to clarify the legal implementation of a particular task, such as a plant protection measure, in a way that is easy to understand. This is possible because the LLM is using probabilistic tokenization, which compresses the "datasets" (i.e. text, Chang et al., 2023). In the case of highly sophisticated LLMs such as GPT-3, data cleaning has been carried out, as well as reinforcement learning from human feedback. This finetuning process ensures that the model provides answers that are more easily understandable and that the probabilistic output is correct. As an example, the authors asked GPT-3.5 about the "Plant Protection Application Regulation" in Germany. It is a 23-page regulation under the Plant Protection Act with complex and cross-referenced interrelationships. GPT-3.5 answers specific requests about the regulation in a few bullet points, which are all understandable, and the cross-referenced interrelationships are already unlocked. Such good explanations are also provided for other laws, even for legislative proposals such as the 89-page "Regulation of the European Parliament and of the Council on the sustainable use of plant protection products and amending Regulation (EU) 2021/2115". Recent investigations by Stoyanov et al., 2023 are implementing a LLM into ZEMEL, a smart crop production environment in Bulgaria, so that project funded farmers can easily get into account the legislations that are related to the different programs. Unfortunately, laws are often changed, which also requires repeated learning of the LLM to be able to accurately give the correct and legally valid answer. This needs a high human effort and a high economic investment for a high-quality model.

However, the author's literature research uncovers four big use cases for LLMs in agriculture. Starting with a) consulting and assistance, b) automated documentation, c) explanation and education, d) interpretation of ML results and forecasts (Fig. 1).

Consulting and assistance cover the idea of agricultural recommendations. This can help to find the right time point, the right action, and the right tool to increase the chance of high yield in the field. A substantiation of performance is indicated by field studies with GPT for technical advice for cassava farmers in Nigeria (Tzachor et al., 2023).

Automated documentation describes the process of translation of machine-readable data from farm management systems and machine trackers to human readable text. *Explanation and education* target the automated generation of handbooks, tutorials, videos and books for self-studies. This is highly recommended when using digital tools which often need a less technical and a more understandable way of introduction. Finally, the *interpretation of ML results and forecasts* is to give direct decision support, or a context-based interpretation (Fig. 1).

3. Current development of LLMs for agricultural value chain

Latest developments show that for topic experts, LLMs are improved search engines since they are more specific and focused (Arcila, 2023). For agriculture, this implies that LLM will improve farmer consultation by providing all necessary information e.g. crop cultivation, breeding, machines, or phytopathology to an advisor or to the farmer directly (Fig. 1). The prerequisite for this, however, is properly processed databases that contain validated information. Especially, because the output of LLMs is largely probabilistic, and current systems differ in their performance (Yadav and Kaushik, 2023). Agriculture consultation requires complex input, as it is dependent not only on abiotic factors such as measurable weather but also on soil quality/species and specific farm management. The model systems of the future must be even more capable of recording the user's individual information and classifying and characterizing it correctly. For this purpose, many user profiles must be created in which also further professions inside agriculture are included. Therefore, many start-ups, consulting, and even private persons are already using the possibility of non-code chatbot development (Arawjo et al., 2023), to develop topic specific chatbots. Such systems bring common models for text embedding work, like Word2Vec or BERT, and also the basis for retrieval augmented generation, into an almost "drag-and-drop" system. However, the evaluation and debugging of the LLM is still a hand-crafted work and needs high human effort. The

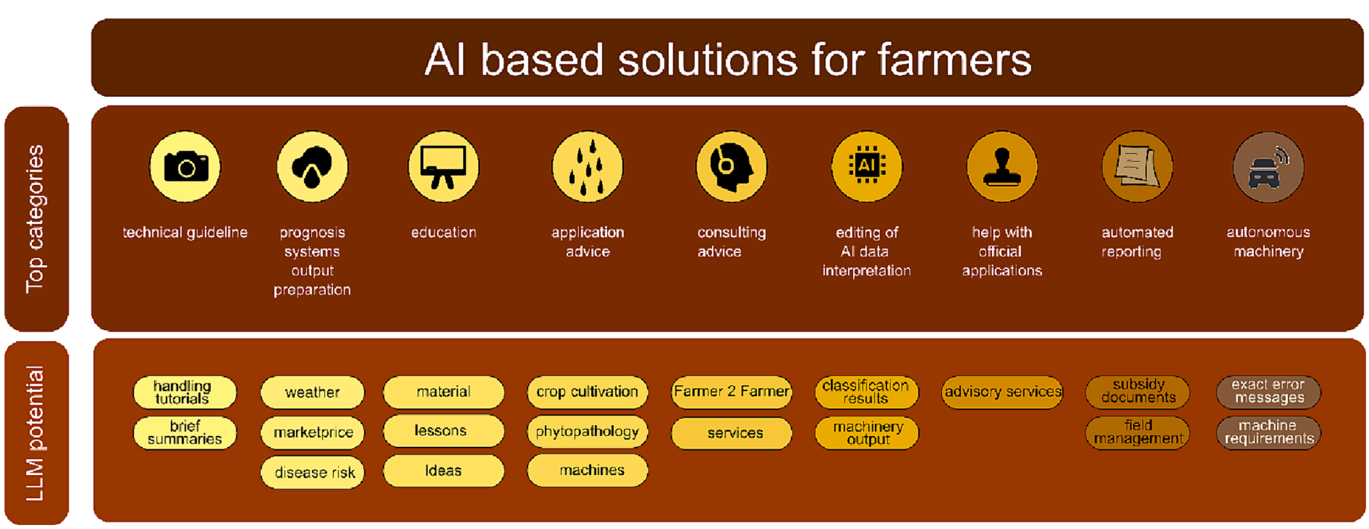

Fig. 1. Fields of application of Large Language Models in agriculture, which currently can be used or will be available soon. Biggest potential is seen in automated reporting, technical guidelines, the textual processing of prognosis system output, application decision support, application and consulting advice, textual processing of AI data interpretation results as well as help and advice for use of official applications.

higher the topic specialization (e. g. instructions for repairing the loading strip in a sugar beet loading mouse), the more experts are needed who, know and can implement a precise workflow in detail. This, in a somewhat meta situation, allows the LLM to train new experts in this field or to create teaching materials (Fig. 1). But to overcome this topic complexity can only be solved using publicly accessible databases, e.g. for consulting.

This also shows the limits of such a system. The much-promised functionality of predictions, such as market forecasts, can only be based on the learned market models. In particular, since numerical data from LLM cannot be used directly without further modification of the information. The idea of using a general data-driven learning approach to get new insights on data, or even the prediction model itself, is currently not available. The interpretation of prediction models can nevertheless be supported.

4. What must be developed to increase the impact and trust of LLMs in agricultural practice?

In order to increase the trust in LLMs, the generated output could be monitored for insufficient information and the resulting impossibility of the system to produce a valid answer. In this context, the LLM output provenance must be shown. Commonly it is unclear which data are used to generate the output. The reliability of the output is not necessarily linked to the reliability of the input, and vice versa. This is especially notable for the low-performing multilingual extension. While translations are rather simple as word families are similar across different languages, dialects, and technical terms, their transfer to the demands of agriculture is rather complex. This does not include the challenge of transferability, which must be added. Recommendations and conclusions in one language may be conclusive and valid for one specific geographic region but its translation and thus, transfer to another region with different geographical, legal, and agronomic conditions is not necessarily right. A reproduction of the processed data sources could be helpful and would increase confidence in the model. This would also support a non-trained farmer or operator to guide the LLM for more precise results. Nevertheless, it is still an open point that needs discussion and evaluation, especially not to fall in a total dependency on the leading "tech companies".

One application to make LLMs more usable in daily work life is to use LLMs as an Open-Ended Decoder for vision-centric tasks (Wang et al., 2023). This enables natural language description of pictures, diagrams or charts. The reverse of this is also possible. Text-to-image diffusion models (Zhang et al., 2023) include a visual interpretation of the written text and thus enable automatically generated examples for text paragraphs. The first step here is the publication of GPT-4V (see https://openai.com/).

LLM is not all you need (Gozalo-Brizuela et al., 2023) as further developments and progress in AI, especially generative approaches, will enable many new opportunities for automation. These systems could be provided to farmers, allowing them to automatically create agriculture maps, field overviews, documentation, or commands for agriculture machines and equipment by simply using context relevant prompts. The reduced development and training of AI models through such AI-driven solutions is beneficial, but the decision recommendations have to be based on the environment since a decision can be right at one place but wrong at another, all this with regard to plant biology and legislation rules. Reviewed by Maraveas et al., 2022, "*bioinspired intelligent algorithms for agricultural applications*" shows that tailored combinations of algorithms can give more accurate feedback. They propose that therefore the exploitation and the exploration of an algorithm must be described and comprehensible because currently there are no defined global guidelines. Such a common agreement in addition can improve AI development and the possibilities to include specific sources of agricultural knowledge and good agricultural practices which are needed, e.g. weather, sowing time, crop variety, and soil. In addition, global guidelines and the commitment to them could overcome the lack of agricultural data, because currently the data is often protected and cannot be shared to other systems or outside specific companies. It also ensures the farmer stays in charge of their own data. Approaches for a trusted data integration without the risk of eroding property claims are today described but not implemented (Paulus & Leiding, 2023).

Besides economical aspects, technical ones will decide how fast and in what way these models will be developed. The current success of LLMs, such as ChatGPT, are due to the high investments made by large tech-companies, for whom the monetization of such models and return of investment is the primary focus. However, national initiatives, such as OpenGPT-X (https://opengpt-x.de/) are also required to fund research for further progress towards accessible models for agriculture purposes. This can also ensure fair development of LLMs, e.g. a last layer rule for non-discrimination, kindness, etc. (Hacker et al., 2023). The output of an agricultural chatbot needs to cover further rule sets (Fig. 2). Currently remaining challenges that need to be addressed in future work are the question of multilinguality and thus regional applicability; trust in input data and data provenance, accompanied by the question of data property; the integration of text to image and image to text encoding; as well as the factual verifiability (Fig. 2).

5. Conclusion

The digital transformation and automation of agriculture have gained momentum in recent decades. The current progress in AI, and especially development like LLMs, can help to accelerate automation in agriculture. The authors try to give an overview of where to expect possible application scenarios for the integration of LLMs into practical agriculture work tasks. In addition, required changes of the "moderator stage" in LLMs need to be adapted regarding environmental knowledge, legislation, climate, and good agronomic practice.

Specialized LLMs for agriculture or crop protection will provide better consulting, explanation, interpretation, and decision recommendations. LLMs will help to make field monitoring much more interpretable, by transferring images and sensor measurements into a coherent and understandable human language. Nevertheless, a deep integration into agriculture can only succeed if it is ensured that the data behind these models is location-dependent, rely on real observations, and is up-to-date. The latter aspect will be crucial to ensure such systems always return reliable, trustworthy, and correct output, especially if LLMs are used as an agriculture search engine or recommendation supplier. But for a successful integration of LLMs in real-world

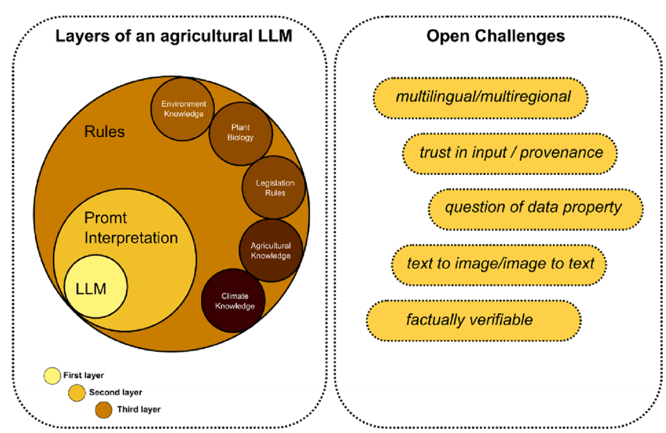

Fig. 2. Large Language Models are based on a trained language model. A prompt interpretation layer adds the human usability, while a mentoring step implements rules for communication. While chatbots integrate rules for non-discriminative and gentle communication, agricultural chatbots need to integrate agricultural knowledge based on rules, biology, environment and good practical use of farmers.

agriculture, it is also essential to have knowledgeable and skilled farmers (operators), who can interpret the LLMs outputs and guide the system to proper results.

CRediT authorship contribution statement

Matheus Thomas Kuska: Writing – original draft, Methodology, Conceptualization. **Mirwaes Wahabzada:** Writing – original draft, Methodology, Formal analysis. **Stefan Paulus:** Methodology, Conceptualization, Supervision, Visualization, Writing – original draft.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Stefan Paulus reports financial support was provided by German Research Foundation and the BLE/BMEL according to the information in the funding section. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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