The potential of Explainable Artificial Intelligence in Precision Livestock Farming

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Abstract

In the discussion on the increasing demand for food, which is to be met by efficient and sustainable increases in productivity, animal welfare is becoming increasingly important. Animal health issues must be identified to prevent epidemics that significantly impact the economic performance of farms or even cause societal harm.

The use of cutting-edge technologies (IoT, sensors, Big Data processing, etc.) is increasingly enabling early intervention in livestock farming to curb productivity losses through real-time monitoring, alerts, and decision support. The ubiquity of these technological solutions has enabled stakeholders to create more robust agricultural supply chains, that deliver sustainable nutrition for a growing population. However, the increasing use of Artificial Intelligence (AI), which is responsible for many of the current breakthroughs in Precision Livestock Farming (PLF) and agriculture in general, has meant that modern decision-support solutions have increasingly transitioned toward black box systems. It has become apparent that a gap exists between efforts to develop more advanced machine learning models, and the growing demands for ethical assessment and transparency in agriculture decision-making.

Explainable Artificial Intelligence (XAI) is one such solution that could prove effective in overcoming the current limitations of black-box models, by allowing the decision-making process of such models to be explored. Through a literature review, we evaluate the potential of XAI in various agricultural use cases and demonstrate the potential benefits of its application to precision livestock management.

Keywords: Artificial Intelligence (AI), explainability, animal welfare, farm management, monitoring.

Introduction

In agriculture, Artificial Intelligence (AI) has attracted great interest in both research and industry. AI is commonly defined as “simulated human intelligent behavior such as learning, judgment, and decision-making” (Caiming Zhang, 2021). In line with this definition, AI has enabled breakthroughs that until recently could only be achieved by humans.

Its ability to provide high accuracy classification and decision support has enabled breakthroughs in Precision Livestock Farming (PLF), Smart Farming, and many optimization and monitoring tasks. The addition of cheap Internet-of-Things (IoT) technology has further enhanced the abilities of AI, enabling large volumes of unstructured data to be collected with relatively little effort.

In this context, ML has helped distinguish AI from other traditional methods, such as the use of threshold and rule-based modelling. In contrast to these, ML offers the ability to make predictions as well as aiding in important decisions for livestock farms based primarily on learning models from real-world data, enabling actionable information and knowledge to be extracted from the ever-increasing and diverse pool of available data sources (e.g., image, video, sound, text, etc.) (Unal, 2020). The ability of ML algorithms to learn directly from firsthand observation has translated into reduced costs, labor optimization, and better-improved decision-support for the farming community.

These benefits have been exemplified by the application of AI in the form of ML and now Deep-learning (DL) in PLF, which has provided timely and comprehensive knowledge to farmers through animal monitoring, behavior classification, disease prediction, and personalized management-support (J. Pomar *et al.*, 2011; Mathieu Marsot *et al.*, 2020). Although the adaptation of AI in agriculture has provided considerable breakthroughs, it is not without challenge or opposition. From being considered unreliable and impractical in critical applications, to even delivering irreversible wrong results, due to the black box nature of the involved algorithms, assessing such characteristics is often impractical.

As AI research focuses increasingly on improving the accuracy models at the expense of increased complexity (Gunning, 2016), it is sometimes difficult to find application of the technology in socially sensitive domains, due to the ethical concerns of unexplainable decision processes. To address some of these issues and encourage the use of AI technologies, we have proposed the use of Explainable Artificial Intelligence (XAI), which attempts to explain and interpret highly complex machine learning models. Although commercialization of XAI in agriculture is still a challenge, there have been several attempts to create working XAI solutions (i.e., SHAP, LIME, CXplain) that can explain a wide range of AI models. XAI-techniques such as LIME, taking a human-centric focus, seeks to justify machine decisions by describing the model within a few critical use cases (Gunning, 2016). Therefore, this paper explores the main issues that arise in the application of AI in the livestock supply chain.

To this end, we use a literature review to create an initial set of exemplary use cases that highlight the trust requirements in AI-based PLF. The resulting use cases will then be used to explore the inclusion of explainability, to demonstrate how the use of XAI in PLF-AI is a prerequisite for building trust with the agricultural community.

Material and methods

This paper follows the PRISMA framework to conduct a thorough review of the available literature to identify the aspects of livestock farming in which AI has made an improvement and what AI technologies are currently being used, as well as discover if there are already any cases where explainability is being used to solve problems (i.e., ethical assessment, fidelity, reliability in technology) in agriculture. In this context, the following issues will be analyzed: i) How does XAI affect the interaction between the human factor in the farming communities and the technologies they use; ii) How can we improve AI-models and overcome their failures when using them in critical decision processes; iii) To what extent does the use of machine learning affect animal welfare and challenges. The assessment of these questions will be made through exploring the different directions of AI in agriculture, which are currently being researched. Furthermore, a guideline of possible use-cases of how AI can be supplemented by XAI can be implemented in livestock farming to overcome the limitations imposed by complex AI models and the difficulties that their application in the industry faces. The most popular topics in agricultural-AI will be discussed and through them an analysis of impact will be derived.

Results and Discussion

Overview

A review of current AI research in precision livestock farming identified the following terms, which give an overview of Agri-AI applications and key research directions. The phrase "Smart Farming" is used in a broad sense to refer to the application of information technology or AI in agriculture. A sub-area of smart farming is the application of these technologies in livestock farms, which is referred to as precision livestock farming. For the use of AI in precision livestock farming, we have identified three main areas: animal monitoring, sustainability, and farm management. In animal monitoring, the monitoring of behavior, feeding, and constant body measurements are included. These dependencies are as shown in Figure 1.

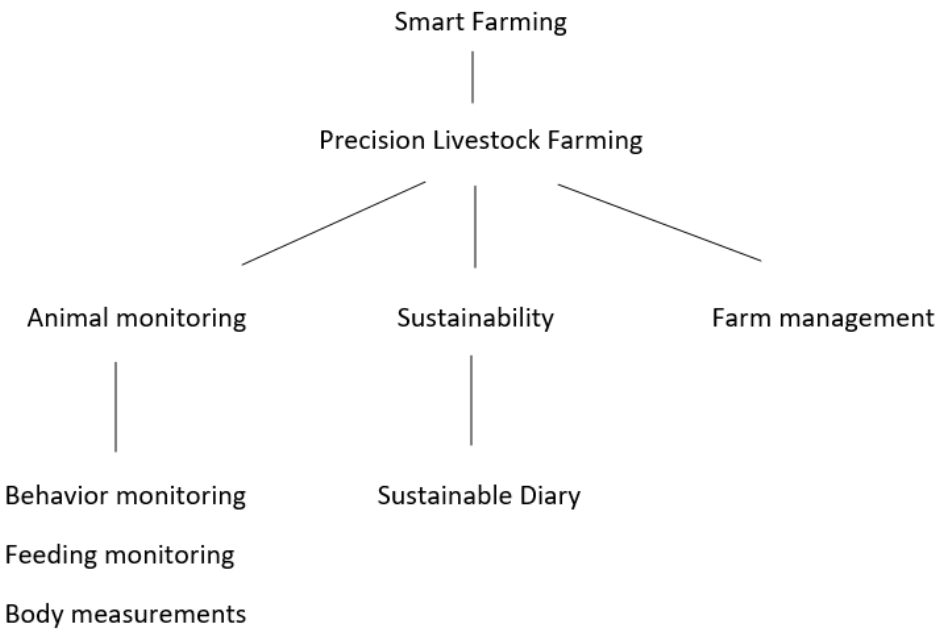

Figure 1: Core application areas of Agri-AI in precision livestock farming

Classification of behavior in livestock can be used to conduct performance classification which results in optimal management of resources (Reza Arablouei *et al.*, 2021). Since extensive monitoring via human labor can be considered almost impossible, the use of AI methods and IoT technologies to collect, process, and interoperate animal behavior is an extremely efficient and attractive substitute in livestock enterprises. Another key issue that AI adoption can address is deep learning-based face recognition and tracking, enabling remote identification that can replace chip implants, which can be costly and labor intensive to attach (Mathieu Marsot *et al*., 2020). Animal identification is an important procedure used for the personalized management of individual animals, especially in areas such as behavior assessment, disease detection, performance monitoring, and certification (e.g., Farm-to-Fork, etc.) (Mathieu Marsot *et al*., 2020).

Example use cases we have identified in machine learning applications for health assessment. One use-case that demonstrates how ML can be used for the classification of feeding behavior and, by extension, the health assessment of pigs utilizing pattern recognition and signal processing (José O. Chelotti et al., 2018; Berckmans et al., 2017). Research on such topics has clearly shown that physiological variables, if assessed correctly can provide valuable indicators for welfare issues (B. B. Odevci, 2021). By leveraging AI and its sub-domains ML and DL, models can be created that not only allow monitoring and classification of these variables, but also predict their future value. However, using these predictions to aid in farm management comes with several challenges, which will be discussed in the following section.

<u>Challenges</u>

Complex systems where processes and entities are not well understood need inter-disciplinary knowledge. Many of the methods used in agricultural applications of AI are "black-box" models which offer a high accuracy rate but with the trade-off of being non-transparent regarding their internal logic and decision-making process. Explainable Artificial Intelligence can tackle this problem by offering solutions which bridge such an interdisciplinary gap. XAI is a technology that creates a good cross-domain environment where domain experts can be incorporated directly into the model evaluation and validation processes. Precision Livestock Farming is a good example of a field that includes many researchers and professionals from differing backgrounds and thus could benefit greatly from a technology that initiates better understanding and transparency of models for all parties involved.

If the potential of AI is to be fully realized in the PLF community, there should be a certain level of trust built between the stakeholders and the technology that they are using. According to Steeneveld W. et al. (2017), farmers are hesitant to incorporate new technologies into their practices unless they are in more mature stages of development and fully reliable. AI has difficulty being applied in farming communities unless it fully addresses user concerns. Developing XAI systems that give full transparency in their decision-making processes offers more certainty and justified reliability (Marco Tulio Ribeiro *et al*., 2016) to the people who are using them. Since model trust, reliability, and fidelity are the main obstacles to the adoption of more Machine Learning technologies in agriculture, use-cases from other domains that successfully utilize XAI to achieve AI-integration could serve as a template for agriculture (Tjoa *et al*., 2021).

Therefore, a literature review on the implementation of XAI in non-agricultural domains was conducted. This review found that in human medicine and manufacturing the three most common applications of explainable artificial intelligence are used, namely environmental sustainability, diagnosis of disease, and classification. XAI is used for assessing environmental parameters and explaining the effect of phenomena on environmental sustainability. The next main utilization of XAI is in the field of health, more precisely in explaining the results of a diagnosis. XAI is commonly used for the classification of different events or objects, but the most relevant application to livestock can be found in research on behavior classification. Table 1. shows the three main topics where XAI has been successful in solving issues when adopting AI in decision critical systems.

Table 1: Explainable Artificial Intelligence applications

Application	Domain
Environmental Sustainability	Manufacturing
Diagnosis of Disease	Medical
Classification	Manufacturing, Medical

In nearly all the reviewed agricultural literature, the problems outlined, and solutions presented clearly lack the involvement of XAI.

The need to improve decision-making in the healthcare field can be exemplified in (Lamya *et al.*, 2019), where XAI is used to assist in making a diagnosis and prescribing medicine for breast cancer. They argue that this approach enables the user to understand the decision-making process of the AI model and how it diagnoses cancer, with it being suggested that the user could verify the model's decision by comparing output against their own personal knowledge. In a study by Sappagh et al. (El-Sappagh *et al.*, 2021), an explainable AI model is proposed that promises to overcome the difficulty of adopting machine learning systems for Alzheimer's disease detection in clinical practices. Looking at other critical domains, XAI is used to bridge the gap between the research efforts toward improving AI models and their implementation in practice. AI models face many issues and although accurate, are not seen as the most reliable tool, this is illustrated by examples identified in the aviation sector, where the introduction of composite components has led to a considerable increase in the amount of time needed to classify defects in the production line, here Neural Networks are suggested to help increasing efficiency. However, understanding the features which contribute to model decision itself can provide valuable knowledge, therefore more interpretable models are proposed (Meister *et al.*, 2021) as a method to increase Neural Networks utilization in practice, providing both a method to evaluate and investigate learned patterns.

While in many other sectors, due to the importance of explainability, XAI has been the answer to several issues, in farming enterprises AI-models that have been implemented or proposed are accompanied with almost no explanation about their predictions or how they work. The relevance of model explainability in livestock farming can be seen in several concrete use-cases that deal with crucial farming management decisions, methods like deep learning and artificial neural networks alone cannot be used in these cases because they are difficult to evaluate.

To illustrate the potential benefits of XAI, two PLF use-cases were derived based on XAI examples found in the medical and environmental domains.

1. **Explanation in culling decisions:** there are many examples (Anna Markella Antoniadi *et al.*, 2021; Tjeerd A.J. Schoonderwoerd *et al.*, 2021) in the medical domain where XAI-driven solutions have been proposed for critical decision-making processes. Model validation is a requirement that is currently lacking in the adaptation of machine learning systems in farming decisions. In PLF this could be meaningful when utilizing AI for high-cost decisions such as culling, which are complex and ambiguous in nature, requiring a model with high reliability and logical coherence (Saleh Shahinfar *et al.*, 2014).
2. **Feed intake monitoring:** animal nutrition is a key factor in environmental sustainability (A. Cerisuelo *et al.*, 2020). Feeding ingredients determine the environmental impact, performance, and health of animals, but precise results on how ingredients impact such KPIs can only be measured by collecting continuous data on farms using sensors as well as software that predicts outcomes based on this information. By using explainable AI based personalized feeding systems, the negative impact on the environment can be reduced by increasing the digestibility of feedstuffs or controlling gut health. XAI offers the opportunity to see which features have been the most influential in decision-making and explain for example the tradeoff of cost and environmental impact of selection and management of feedstuffs.

Another challenge that hinders the wide-spread adoption of AI in agriculture is that it is not perfect, if the model is fed with bad data it could lead to wrong correlations and invalid decisions. Mistakes in this aspect can be very costly and make the systems unreliable. Bias detection is something that can be achieved using XAI (Iam Palatnik De Sousa *et al.*, 2021), by identifying bias in a model XAI has the potential to allow the domain expert to assert any failure mode and minimize any potential damage that might arise from applying incorrect findings. In this approach, the user has an oversight over the decision-making process of these AI systems.

Conclusions

XAI can be a viable solution for precision livestock farming, as it has the potential to solve many of the limitations proposed by AI and even encourage the application of AI in agriculture by building trust among stakeholders. In this paper, we provide an overview of major issues of Agri-AI today, the challenges and limitations that AI poses due to its complexity and non-transparency, and how XAI can be used to solve many of these problems. XAI improves the interaction between users in the agricultural community and artificially intelligent machines by building trust and reliability. Offering reliability through explanations of "black-box models", exploiting the capacity of explainability to aid the creation of more complete models that do not lead to unexpected or undesirable results in, while enabling model validation, which is currently missing in the agricultural domain, create some of the foundational reasons why XAI can hold great potential to improve aspects of PLF.

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