Received: 6 February 2024 | Accepted: 7 February 2024 | Published online: 5 March 2024

DOI: 10.1002/agj2.21555

Agronomy Journal

ORIGINAL ARTICLE

Special Section: Machine Learning in Agriculture

Will artificial intelligence and machine learning change agriculture: A special issue

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Abstract

In agriculture, important unanswered questions about machine learning and artificial intelligence (ML/AI) include will ML/AI change how food is produced and will ML algorithms replace or partially replace farmers in the decision process. As ML/AI technologies become more accurate, they have the potential to improve profitability while reducing the impact of agriculture on the environment. However, despite these benefits, there are many adoption barriers including cost, and that farmers may be reluctant to adopt a decision tool they do not understand. The goal of this special issue is to discuss cutting-edge research on the use of ML/AI technologies in agriculture, barriers to the adoption of these technologies, and how technologies can affect our current workforce. The papers are separated into three sections: Machine Learning within Crops, Pasture, and Irrigation; Machine Learning in Predicting Crop Disease; and Society and Policy of Machine Learning.

1 | INTRODUCTION

Many people became acquainted with machine learning and artificial intelligence (ML/AI) technologies from movies such as 2001: a Space Odyssey or The Terminator. In these movies, machines replaced humans in the decision process. In agriculture, today, people have concerns that these movies could become reality. This is because ML/AI technologies have the potential to help implement precision farming by creating algorithms uniquely suited to specific farms and locations. ML produces intelligent predictions by finding complex patterns in large datasets (Janiesch et al., 2021; Nichols et al., 2018). These algorithms can be extremely accurate because they learn and modify themselves as data are collected. There are several different types of learning. One of the simplest is trial and error when solutions to a specific problem are stored. When that specific problem is encountered again, the answer to that exact problem is provided. Computers are uniquely suited for this learning process.

A second type of learning is to apply previous experiences to new problems. Developing solutions to new problems is much more complicated and requires the ability to analyze complex relationships between multiple factors. While humans can do both types of learning, the goal of ML/AI is to build machines that can match or exceed our capabilities (Meshram et al., 2021).

ML/AI technologies that provide answers to new questions have the potential to enhance crop production, accelerate economic growth, and reduce environmental impacts (Gardezi et al., 2022; Rose et al., 2016). However, obtaining these benefits depends on the willingness of farmers to adopt ML/AI technologies which may require additional financial resources, a learning and testing period, willingness to accept a black box that they do not understand, and ultimately a change in the decision process (Faundeen et al., 2013; Gardezi et al., 2022; Higgins, 2008; Demestichas & Daskalakis, 2020;

Abbreviation: ML/AI, machine learning and artificial intelligence.

Akaka et al., 2021; Baldin et al., 2021; Lowenberg-DeBoer & Erickson, 2019). Additional concerns about ML/AI technologies are that ML/AI technologies make humans dependent on machines for decision-making (Wolfert et al., 2017), dispossess farmers of their local and tacit knowledge (Gardezi et al., 2022), and displace farm labor. This concern is valid. Historically, when large corporations began to invest in automation to increase productivity, this resulted in reduced opportunities and earning potential for skilled labor (Head, 2014). While these concerns are valid, technology is moving more rapidly than ever before, and the potential impact of being left behind could be financially devastating. Therefore, we must begin to address farmers' apprehension through discussions about the social, economic, environmental, and technological narratives that surround ML/AI in agriculture. The purpose of this special issue is to open a dialogue and begin to build a foundation of knowledge that can help determine this technology's role in agriculture, as well as to identify potential labor and policy inequalities before these equity gaps become too large to fill. To overcome ML/AI concerns, the agricultural community must pinpoint challenges and proactively take steps to alleviate them (Thompson et al., 2021).

Core Ideas

- There are concerns that decision-making tools using machine learning and artificial intelligence (ML/AI) in farming could replace human knowledge and labor.
- ML/AI technologies have the potential to improve precision farming using site-specific algorithms.
- This special issue aims to open a dialogue about the role of ML/AI in agriculture and identify inequalities that may result from its use.

Papers within this special issue demonstrate the latest research to improve crop production, crop disease prevention, irrigation management, and livestock management with various forms of AI and ML. These papers are separated into three sections: (1) Machine Learning within Crops, Pasture, and Irrigation; (2) Machine Learning in Predicting Crop Disease; and (3) Society and Policy of Machine Learning. These papers are provided in Table 1.

TABLE 1 Papers within the *Agronomy Journal* special issue on machine learning.

Machine Learning within Crops, Pasture, and Irrigation	
Title	**Citation**
A machine learning modeling framework for *Triticum turgidum* subsp. durum Desf. yield forecasting in Italy	Fiorentini et al. (2023)
Classification of tobacco using remote sensing and deep learning technique	Qazi et al. (2023)
Rape seedling density estimation in-field conditions based on improved multi-column convolutional neural network	Yang et al. (2023)
Detection of on-tree chestnut fruits using deep learning and RGB unmanned aerial vehicle imagery for estimation of yield and fruit load	Arakawa et al. (2023)
Markov model planning on the adoption of an enhanced wheat cultivar	Golpira et al. (2023)
Spatial and temporal variability of corn response to nitrogen and seed rates	Alesso & Martin (2023)
DeepMaizeNet: A novel hybrid approach based on CBAM for implementing the doubled haploid technique	Ayaz et al. (2023)
Boundary line analysis and machine learning models to identify critical soil values for major crops in Guatemala	Smith et al. (2023)
Predicting rice phenology and optimal sowing dates in temperate regions using machine learning	Brinkhoff et al. (2023)
SoilType: An R package to interplay soil characterization in plant science	Fritsche-Neto (2023)
Segmentation of plant residues on soil X-ray CT images using neural network	Valdes-Korovkin et al. (2023)
Artificial intelligence and satellite-based remote sensing can be used to predict soybean (Glycine max) yield	Joshi et al. (2023)
Precision livestock farming applied to grazing land monitoring and management—A review	Bretas et al. (2023)
Quantification and machine learning based N_2O–N and CO_2–C emissions predictions from a decomposing rye cover crop	Joshi et al. (2022)
IoT and ML-based automatic irrigation system for smart agriculture system	Anoop & Bala (2023)
Environmental clusters defining breeding zones for tropical irrigated rice in Brazil	Costa-Neto et al. (2023)

(Continues)

TABLE 1 (Continued)

Machine Learning within Crops, Pasture, and Irrigation Title	Citation
Reference evapotranspiration prediction using machine learning models: An empirical study from minimal climate data	Kumar et al. (2023)
Machine Learning in Predicting Crop Disease	
Few-shot learning for plant disease recognition: A review	Sun et al. (2023)
Tomato leaf diseases classification using image processing and weighted ensemble learning	Javidan et al. (2023)
DFNet: Dense fusion convolution neural network for plant leaf disease classification	Faisal et al. (2023)
Crop disease identification segmentation algorithm based on Mask-RCNN	Bondre & Patil (2023)
Reliable detection of blast disease in rice plant using optimized artificial neural network	Dubey & Choubey (2023)
Society and Policy of Machine Learning	
Understanding farmers' engagement and barriers to machine learning-based intelligent agricultural decision support systems	Adereti et al. (2023)
Improving decision support systems with machine learning: Identifying barriers to adoption	Brugler et al. (2023)
Machine learning for major food crops breeding: Applications, challenges, and ways forward	Govaichelvan et al. (2023)
Artificial intelligence in farming: Challenges and opportunities for building trust	Gardezi et al. (2023)
Internet of Things (IoT) in digital agriculture: An overview	Dhal et al. (2023)
A vision of precision agriculture: Balance between agricultural sustainability and environmental stewardship	Nath (2023)

AUTHOR CONTRIBUTIONS

David Clay: Conceptualization; resources; supervision; writing—original draft; writing—review and editing. **Skye Brugler**: Writing—review and editing. **Bhavna Joshi**: Writing—review and editing.

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How to cite this article: Clay, D. E., Brugler, S., & Joshi, B. (2024). Will artificial intelligence and machine learning change agriculture: A special issue. *Agronomy Journal*, *116*, 791–794. https://doi.org/10.1002/agj2.21555