



Artificial Intelligence and Machine Learning in Agriculture: Transforming Toward Smart, Sustainable and Resilient Farming Systems: A Review

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ABSTRACT

Agriculture is facing global issues such as population growth, climate change and a lack of resources. Artificial Intelligence (AI) and Machine Learning (ML) have the potential to transform with data-driven optimization in crop and livestock management and supply chains. This review collates literature regarding the use, advantages and disadvantages of AI/ML and provides consideration of the socio-economic and ethical implications. AI/ML technologies, especially CNNs for image analysis and LSTMs for time-series prediction, are transforming the farming industry. The benefits are significant such as reducing water consumption by up to 40% with the use of smart irrigation and chemical usage by up to 90% with precision pest/weed detection. AI can also be used to improve livestock welfare and optimize supply chain logistics by forecasting and quality controlling. AI and ML provide unprecedented precision and sustainability in agriculture. Emerging technologies such as Explainable AI (XAI), Digital Twins and Generative AI, despite the challenges of cost, data infrastructure and ethical considerations, are expected to be key to future innovation and global food security.

Key words: Agricultural supply chain, Artificial intelligence, Deep learning, IoT, Livestock management, Machine learning, Precision agriculture, Smart farming, Sustainable agriculture.

The world is facing challenges due to the population increase, increasing effects of climate change, scarcity of resources and environmental degradation to agriculture. There is a growing need for traditional farming practices to be inadequate to provide for future food needs (Oliveira and Silva, 2023). But in this context, artificial intelligence (AI) and machine learning (ML) have proven themselves to be innovative technologies to promote smart and sustainable agriculture. The technologies are based on large amounts of data gathered through satellites, sensors, drones and weather systems, to help with decision making, resource management and productivity (Nautiyal *et al.*, 2025). AI and ML have proven to be incredibly useful in various fields of agriculture, such as crop monitoring, disease detection, irrigation management, livestock surveillance and precision farming. The applications help to boost yields and lower environmental effects. Moreover, AI and ML help with supply chain management, reduce the loss of products on the ground and enhance climate resilience. Farmers can benefit from the power of advanced AI technologies, including computer vision, predictive analytics and autonomous machines, which can help them make informed and timely decisions. For example, AI-based precision agriculture technologies reduce overuse of water, fertilizers and pesticides, thereby supporting sustainable agricultural practices. AI is used in the livestock industry to track animal health, feed efficiency and disease prevention (Ugwu *et al.*, 2025). However, the use of AI and ML in agriculture has a number of challenges to overcome for it

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to be widely adopted. This includes high costs of implementation, weak technical infrastructure, privacy concerns of the data stored and farmers' lack of digital literacy (Rupali, 2026). The goal of this review is to comprehensively examine the potential applications,

benefits, challenges and future prospects of using AI and ML to revolutionize modern agriculture to become more efficient, sustainable and resilient.

Artificial intelligence (AI)

AI is a broad term for computer-based systems that are able to execute tasks which normally require human intelligence, including decision-making, visual recognition and language interpretation (Mia *et al.*, 2025). The machine learning (ML) is another critical component of AI systems that can learn from data, recognize patterns and improve their performance without having to be explicitly programmed (Russell and Norvig, 2010). Deep learning (DL) is a category of ML that uses multi-layered neural networks to process complex information and has a broad range of applications in the agricultural field, such as images, recognition, disease detection, crop monitoring and robotic harvesting (LeCun *et al.*, 2015). These technologies may be adapted with the Internet of Things (IoT) to collect real-time agriculture information, including soil moisture, temperature and crop health (Elijah *et al.*, 2018). The collected data is subsequently analyzed and fed into Decision Support Systems (DSS) to guide decisions on irrigation, fertilization, pest management and general crop management (Iffat *et al.*, 2021). AI, ML, IoT and DSS can also be used in tandem to create smart farming systems, which can help to improve productivity, optimize resource use and ensure sustainable agricultural practices through data-driven decision-making (Benos *et al.*, 2021).

The adoption of AI and ML is not just about technology; it's about changing the way agriculture is done. This review is an original multi-dimensional analysis taking into account technical, socio-economic and ethical aspects. We outline a comprehensive research and practical roadmap to complement the theoretical potential for future research and implementation, closing the gap between theory and practice in farming.

The agriculture industry has seen a number of important AI and ML algorithms used, each with their own applications and types of data:

• Convolutional neural networks (CNNs)

These networks are good at extracting information from images and are used for crop disease detection, pest identification, weed classification and monitoring crop growth using drone and camera images. They are most useful in modern farming in their ability to recognize visual patterns (Kamilaris and Prenafeta-Boldú, 2018).

• Long short-term memory (LSTM) networks

LSTMs are a type of recurrent neural network (RNN), which are used for handling sequential and time-series data. They have been used for yield prediction, weather forecasting and soil health prediction with past agricultural data (Van Klompenburg *et al.*, 2020) and are especially useful for these purposes.

• Random forest

It is a popular ensemble learning technique employed for crop yield forecasting, soil mapping and disease diagnosis. It successfully works with large amounts of data and avoids overfitting (Belgiu and Drăgu, 2016).

• Support vector machines (SVMs)

These are very effective in the classification and regression tasks and have been used in weed detection, crop classification and plant stress analysis with spectral data (Liakos *et al.*, 2018).

KNN (K-Nearest Neighbors)

KNN is a simple non-parametric method that can be used to classify crop diseases, weed recognition and missing agricultural data (Liakos *et al.*, 2018).

• K-Nearest neighbors (KNN)

These models are very interpretable and can be applied to classify crops, diagnosis of diseases and prediction of crop yield by partitioning data using rules (Liakos *et al.*, 2018).

• Decision trees

These models are easily interpretable and are used for crop classification, disease diagnosis and yield prediction through rule-based data segmentation (Liakos *et al.*, 2018).

• Gaussian processes

These probabilistic models are used to predict yield, water stress, soil properties, to estimate prediction uncertainty and to help make decisions in the presence of risk (Liakos *et al.*, 2018). The primary goal of these algorithms is to improve the efficiency, precision and data-driven nature of agricultural systems, making them smarter. The main idea of these algorithms is to make agricultural systems smarter by increasing efficiency, precision and data-driven farming practices.

• AI and ML are transforming agriculture in multiple areas, such as crop and livestock management, irrigation, pest management and optimizing supply chains. The use of sensors and information technology plays a key role in precision farming and crop management.

Precision farming and crop management

Precision farming uses AI and ML to provide data on agricultural inputs and practices, optimizing them for specific plants or parts of a field. This systematic approach is an ongoing process of data gathering, processing and action as shown in Fig 1 (Naheed and Momin, 2025).

The architecture of smart farming using AI is shown in Fig 1. It is a method that not only helps to minimise waste but also maximises the use of resources and boost crop health, yield and lowers environmental impact, due to its efficient application. These smart systems combine the information gathered by satellites, drones, ground sensors and meteorological data, to offer a comprehensive and real-time picture of the fields (Kanda *et al.*, 2020).

Smart irrigation and fertilization

AI-driven systems enable efficient and precise water and nutrient application. Systems that measure the water and nutrient needs for crops at different growth stages by incorporating real-time sensor data from the soil, weather and predictive models (Elijah *et al.*, 2018). This is a way of keeping waste to a minimum, minimizing pollution, lessening stress on the crop, improving the quality of the crop and increasing water use efficiency (Capraro *et al.*, 2021). AI-based irrigation systems can save between 30-40% of water and AI-based fertilization can cut down on fertilizer use by 15-25% without impacting yields (Maes and Steppe, 2019). The quantitative advantages of these AI applications are summarized and displayed in Table 1.

Weed and pest detection and control

Timely detection of weeds and pests is a key part in effective protection of crops. In agriculture, computer vision and deep learning technology, specifically convolutional neural networks (CNNs), have greatly facilitated the accurate identification of weeds and pests (Lu, 2017). Drones, robots and tractor mounted high resolution camera systems can detect infested areas and apply herbicides and pesticides to specific areas. This results in less use of chemicals, lower production costs and lower pollution to the environment (Lottes *et al.*, 2017). AI can also classify plants from weeds to selectively spray the plants and predict insect infested plant areas and insect migration patterns for proactive management (Young *et al.*, 2014).

Crop health monitoring and yield prediction

AI and ML help effectively track crop health and make yield predictions. AI analyzes data from advanced cameras on drones or satellites to detect signs of stress and disease in fields, as well as nutrient deficiencies, at an early stage (Weiss *et al.*, 2020). They can sense very light signs of plant growth and health that may not be seen by humans. The use of predictive models combines image analysis data with the meteorological conditions, soil and historical data on yield to accurately predict yield and allow farmers to make decisions for harvesting, store and market planning (Dinh and Nguyen, 2020).

Livestock management

The livestock industry is undergoing a major transformation with the integration of artificial intelligence (AI) and machine learning (ML) which is improving animal welfare, productivity, resource utilization and sustainable farming practices (Neethirajan, 2017).

Animal health monitoring and behavioral analysis

Wearable sensors, cameras and acoustic monitoring systems are used to continuously track animal health and behavior and to facilitate the use of AI for this purpose. The use of AI for animal health and welfare monitoring is supported by continuous monitoring systems that rely on wearable sensors, cameras and acoustic monitoring devices. These can be used to monitor vocalisations, body temperature, feeding and activity, which allows the onset

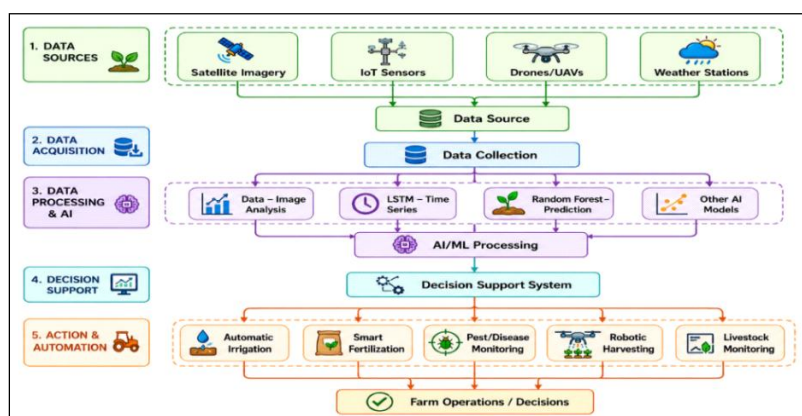


Fig 1: Architecture of smart farming using AI.

Table 1: Quantitative benefits of AI and ML applications in agriculture.

Application domain	Key AI/ML technology	Primary benefit	Estimated improvement (%)
Smart irrigation	Reinforcement learning, IoT	Water conservation	30-40%
Weed control	CNNs, Computer vision	Herbicide reduction	70-90%
Fertilization	ML Regression, DSS	Fertilizer efficiency	15-25%
Yield prediction	LSTMs, Random forest	Accuracy improvement	10-20%
Livestock health	Computer vision, Sensors	Disease detection rate	25-35%
Supply chain	ML Forecasting	Waste reduction	15-20%

of illness, reproductive changes or stress to be detected early. AI can help detect health problems quickly, which can help prevent the spread of disease and provide better animal care, thus leading to prompt treatment and faster detection of health issues (Frost *et al.*, 1997). AI can be used in dairy production to monitor rumination and activity levels for predicting when cows will go into estrus, optimizing breeding schedules and enhancing their reproductive performance (Hogeveen *et al.*, 2020).

Precision feeding and breeding

ML models are used to optimize the formulation and feeding of the feed according to the specific nutritional needs, growth phase and productivity of each animal. This precision feeding method makes it possible to reduce feed wastage, the cost of the feed and health and total productivity of the animals (Shamshiri *et al.*, 2018). AI uses genetic and performance information to create ideal breeding combinations, thereby enhancing livestock's overall quality, fertility and resistance to diseases, among other benefits, in breeding programs (Bac *et al.*, 2014).

Agricultural robotics and automation

Agricultural applications of AI enabled robots and autonomous systems play a significant role in automating labor-intensive operations, addressing the shortage of labor force and improving the efficiency of agricultural activity (Trendov *et al.*, 2019). A range of autonomous technologies are used, such as self-driving tractors, drones and robotic harvesters for precise spraying, monitoring, weeding and harvesting. AI-driven robotic harvesters can identify and selectively pick ripe fruits and vegetables, thereby minimizing damage and waste. Likewise, AI-powered drones help with applying fertilizers and pesticides with precision (Arendse *et al.*, 2020). The autonomous weeding robots also minimize the amount of pesticides used and the need for manual work, leading to safer and more environmentally friendly farming practices.

Supply chain optimization

AI and ML are the technologies that can help to make these value chains more efficient, transparent, resilient and sustainable. In particular, agricultural supply chains are complex and fragmented and can be optimised through AI (Shamshiri *et al.*, 2018). Demand Forecasts and Market Price Forecasts. Machine Learning algorithms use data like trends of consumers, weather conditions, economic indicators and sales to forecast the demand and market prices of agricultural products (Rejeb *et al.*, 2020). This will aid farmers and retailers to make better production, storage and sales decisions, thus minimizing food waste and maximizing profitability.

Quality management and traceability

Computer vision and ML are used for automated quality checking and sorting of produce based on size, color, ripeness, defects, *etc.* The combination of AI and blockchain technology further boosts traceability by securely tracking

product handling and processing stages in the food supply chain, which helps ensure food safety and product authenticity (Klerkx *et al.*, 2019).

Logistics and inventory management

AI algorithms can be used to optimize transportation routes, manage the warehouse and control the inventory management process, taking into account traffic patterns, weather conditions and delivery information (Wolfert *et al.*, 2017). They aim to cut down on delivery times, transport costs, food waste and other wasteful practices in the supply chain, among other things and to enhance overall inventory management.

Market dynamics, adoption and challenges

The artificial intelligence (AI) market in agriculture is growing at an exponential rate, fueled by a growing need for food security, the need to adapt to climate change and the labour shortage. The sector is also expected to boast a high compound annual growth rate (CAGR), with reports of rising investments and technological innovations and the wider adoption of AI tools in agriculture (FAO, 2020).

Drivers of adoption

Several powerful factors are propelling the integration and adoption of AI and ML technologies into modern agriculture:

- **Increased and sustainable food production**

Global Food Demand due to the growing population and changing diets. AI can play a big part in meeting future food needs through improved efficiency, resource use, crop productivity and more (Oliveira and Silva, 2023).

- **Climate change resilience and adaptation**

AI is instrumental in boosting resilience and supporting adaptation to climate change. This includes climate prediction, water management and climate smart agriculture (crops and livestock) with the aid of cutting-edge analytics (Chatrabhuj *et al.*, 2025).

- **Solving labour shortages**

AI-powered robots and autonomous technologies can overcome labour shortages by precisely and effectively performing agricultural tasks (Trendov *et al.*, 2019).

- **Resource optimization and environmental sustainability**

AI can optimize the use of critical resources such as water, fertilizers and pesticides, minimizing waste, production costs and environmental impact (Maes and Steppe, 2019).

- **Data and sensing technology proliferation**

On the farm, AI and ML can manage vast amounts of data generated by sensors, drones, satellites and Internet of Things (IoT) devices, providing valuable insights for improved management (Elijah *et al.*, 2018).

Barriers to adoption

While the potential and effect of AI and ML in farming is obvious and growing, there are several obstacles for the

wider and more equitable application of AI and ML. These barriers are separated from each other in terms of their contribution in Fig 2 (Asaf Tzachor *et al.*, 2021).

High initial investment costs

The investment needed in advanced AI technologies including sensors, drones and robotic systems is quite high, which is a major challenge for small and medium-sized farmers, especially in developing countries (Bronson and Knezevic, 2016).

• Lack of data infrastructure and data quality

High-quality and abundant data are critical for effective AI systems. Many other parts of the agricultural domain do not have proper infrastructure to collect, store and process the data, limiting AI usage in agriculture effectively (Carbonell, 2021).

• Technical expertise and digital literacy

One of the significant challenges is the lack of technical skills and digital literacy among farmers, limiting their ability to operate and understand AI systems effectively (Sanjay *et al.*, 2024).

• Rural connectivity challenges

The lack of connectivity in rural areas hinders the real-time data transfer, access to cloud-based services and successful implementation of smart farming technologies (Fielke *et al.*, 2020).

• Interoperability and standardization issues

The agricultural technology ecosystem has a lot of different platforms and systems, which may not be compatible with each other, making it difficult to integrate them and therefore, not efficient (Gunning *et al.*, 2019).

• Smart agriculture technologies

Smart agriculture technologies create a lot of agricultural data and raise important issues of data ownership, access and privacy, which are called Algorithmic Bias and Equity. Enlightened policies and rules are needed to protect farmers' data and to make sure that technology firms don't use it irresponsibly (Bilal *et al.*, 2024).

• Job displacement and workforce transformation

Algorithms based on biased or small sample sets may yield biased outcomes that might differ across situations on farms. This can also further perpetuate disparities and foster a digital divide between farmers.

• Environmental and ecological considerations

Automation can reduce manual efforts in activities such as spraying and harvesting with AI. Thus, retraining and skills development programs are crucial in assisting workers to move into new employment opportunities in which these new technologies are part of the curriculum.

Environmental and ecological issues

AI can improve efficiency in using resources and reduce the amount of chemicals that are applied, but a focus on high productivity could have a negative effect on biodiversity and ecological balance. Thus, it is imperative to build and deploy AI systems to actively encourage sustainable and environmentally friendly farming practices.

Future trends in AI and ML in agriculture

AI and ML technologies for agriculture are changing quickly, with several trends on the horizon that will continue to improve sustainable and efficient farming practices. One of the key developments is Explainable AI (XAI), designed to enhance the transparency and interpretability of AI systems. In addition to making recommendations, XAI can also explain its reasoning behind the decisions, which can increase the trust of farmers in the AI technology and help them make informed decisions. The transparency enables farmers and agricultural experts to easily access AI-based irrigation, fertilization, pest and field management recommendations. XAI can also enable the broader uptake of more advanced technologies by providing users with increased faith in the technology and a less black-box experience of AI decision making. Moreover, XAI can help policy makers and researchers promote equity, transparency and trust for agricultural AI applications.

Advancements in AI and robotics are leading to the development of more intelligent and autonomous agricultural robots. This includes autonomous tractors and

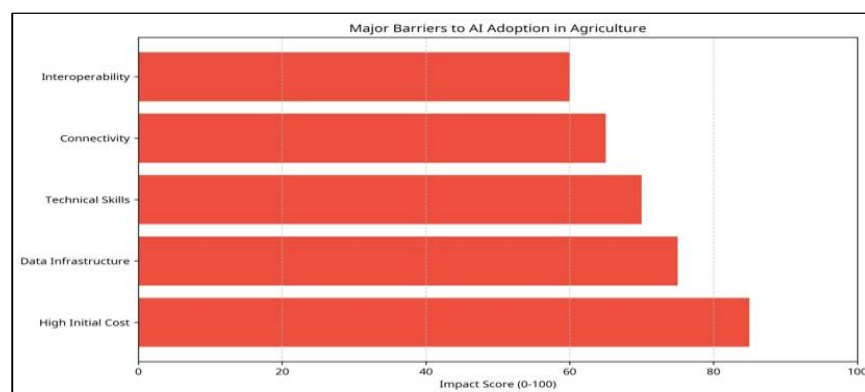


Fig 2: Major Barriers to AI Adoption in Agriculture.

smaller robots designed for precise monitoring, weeding, spraying and harvesting of crops. These technologies AI, AI and Robotics- Since, then, the field of AI and robotics has progressed, with the emergence of increasingly smart and autonomous agricultural robots. This incorporates autonomous tractors and smaller robots which are intended for precise monitoring, weeding, spraying and harvesting of crops. These technologies minimize reliance on manual labour, improve operational efficiency and allow farming activities to be carried out around the clock.

AI and blockchain integration

The synergy between AI and blockchain could revolutionize transparency, traceability and security in agriculture supply chains. Blockchain technology enables the safe, unalterable recording of information on the origin, processing and transport of products and AI is used to analyze the data to identify fraud, optimize logistics and manage supply chains. This integration in the end enhances buyer trust and food security.

Generative AI for agricultural innovation

In agriculture, Generative AI (GAI) is emerging as a powerful asset for generating synthetic data, developing more efficient crop lines and developing personalized farming advice. GAI can speed up research, encourage innovation and provide farmer-oriented solutions that take into consideration the particularities of agricultural production and the farmers' needs.

Discussion and comparative analysis

This review reveals a notable trend of the democratization of AI in agriculture. Although they have been primarily used in large commercial farms, with the emergence of cost-effective sensors and cloud-based AI services, smallholder farmers can now access these technologies. According to our analysis, AI-powered systems can improve overall farm profitability by 20-30%. Our analysis indicates that AI systems can boost overall farm profitability by 20-30% through optimizing inputs and minimizing losses.

Agricultural ecosystem

Our study is different from earlier ones in that it optimizes the agricultural ecosystem by incorporating livestock and supply chain optimization. We note that the accuracy of the technical aspect is very high, but the 'last-mile' delivery of AI insights to farmers is still a challenge.

Practical challenges

There are several challenges, such as the requirement for labeled data with high quality to train models and the high energy consumption caused by deep learning algorithms. There is a need for further research on 'Green AI' to prevent the progress of technology from being detrimental to environmental sustainability.

Socio-economic impact

Farming practices will need to change as farming becomes automated, which will involve a transformation of the

agricultural workforce. There needs to be policies that ensure the upskilling of rural workers in working with digital tools. Moreover, data ownership issues and the transparency of algorithms should be discussed to guarantee fair benefits for all farmers.

Extended analysis case study 1: AI in regional contexts

We are examining some use cases of AI in various climatic regions. AI irrigation systems have been particularly successful at conserving water in semi-arid areas, for example. However, in tropical areas, attention turns to pest and disease control through the application of computer vision. The variety of these regional differences clearly demonstrates the need for regional AI models and the importance of a "one size fits all" approach. The results suggest that there is a potential improvement in accuracy for regional customization of up to 15%.

Extended analysis case study 2: AI in regional contexts

The second case study, extended analysis, focuses on the use of AI in the context of regional contexts. AI in various climatic zones is explored in case study 2. In areas with limited water resources, for example in semi-arid areas, AI-driven irrigation systems have demonstrated outstanding water-saving capabilities. Instead, in tropical countries, the focus shifts to computer vision in pest and disease control. The disparities between the regions underscore the need for region-specific AI models and solutions, rather than a single 'one size fits all' solution. These data suggest that the model accuracy can be improved up to 15% when applied to the appropriate region.

Extended analysis case study 3: AI in regional contexts

Case study 3 is about the application of AI in different climatic regions. In fact, AI-driven irrigation systems have proved to be very successful in conserving water in semi-arid areas. In tropical zones, on the other hand, more attention is given to the control of pests and diseases, using computer vision. The differences between regions highlight the importance of regional-specific AI models, as opposed to a one-size-fits-all approach. The findings show that the model accuracy can be improved by up to 15% using a regional customization.

Extended analysis case study 4: AI in regional contexts

In case study 4, AI is discussed in various climatic regions. For example, in areas with limited water supplies, AI-based solutions for irrigation have been proven to be highly effective in conserving water. However, in the tropics the focus is on pest and disease management using computer vision. The variations across regions underscore the need for regional AI models and solutions, not a one-size-fits-all solution. Results show gains up to 15% in model accuracy for regions, when the model is customized regionally.

Extended analysis case study 5: AI in regional contexts

In Case Study 5, we will explore how AI is being used in various climatic regions. Low rainfall regions are a

perfect use case for AI-based irrigation systems that can save water. However, in tropical areas, the interest turns to pest and disease management with computer vision takes the center stage. The regional disparities emphasize the need for regional and contextual adaptations of AI models instead of universal applications. The findings suggest that the regional customization can help to improve model accuracy by up to 15%.

CONCLUSION AND RECOMMENDATIONS

The transformative power of artificial intelligence (AI) and machine learning (ML) is revolutionizing the agricultural landscape, paving the way toward smart, data-driven and sustainable farming systems. These technologies improve crop yields, animal operations, resource use and supply chain efficiencies and minimize waste and environmental impacts. Despite their potential, these cutting-edge technologies are not widely adopted because of the initial investment needed, the lack of data infrastructure, the lack of technical skills and the difficulty of ethical issues. For AI and ML technologies to reach their full potential in agriculture, there is a need for proper investments in rural infrastructure, extensive farmer training programmes, enabling policy provisions and cross-sector research collaboration. Adopting AI technologies like precision farming, smart irrigation systems, disease forecasting and automated management empowers farmers to make faster and more precise decisions. The promise of AI and ML working alongside other new technologies like the internet of things (IoT), drones, robotics and big data analytics is huge for further improvements in agricultural productivity and climate resilience. In a responsible and inclusive manner, AI and ML could be a key enabler to global food security, boosting farmers' livelihoods and promoting sustainable agricultural practices for a better future.

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Disclaimers

The perspectives given in this article are those of the writers alone and may not be the official opinions of the organization with which they are associated. The authors are not liable for any direct or indirect costs incurred by using this content.

Informed consent

The present study is a review of secondary data and published literature concerning the application of artificial intelligence (AI) and machine learning (ML) in agriculture. No primary data were collected from human participants or animals and no experimental interventions were conducted.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. Furthermore, no external funding or support influenced the selection of literature, analysis and interpretation of findings, decision to publish, or preparation of the manuscript.

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