The Role of Artificial Intelligence in Agriculture: A Comprehensive Review

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Abstract: Artificial Intelligence (AI) has rapidly emerged as a transformative technology in agriculture, offering innovative solutions to enhance productivity, sustainability, and efficiency. This comprehensive review examines the role of AI in various agricultural practices, including precision farming, crop management, soil health monitoring, pest control, and predictive analytics. By leveraging AI-driven technologies such as machine learning, computer vision, and data analytics, farmers can make data-informed decisions to optimize resource usage, reduce input costs, and minimize environmental impacts. Additionally, AI has proven instrumental in developing automated systems like autonomous tractors, drones, and robotic harvesters, which streamline labor-intensive processes. Despite its potential, the adoption of AI in agriculture faces several challenges, including high implementation costs, data privacy concerns, and the need for adequate infrastructure in rural areas. The paper highlights ongoing research and future directions in AI-powered agriculture, focusing on the development of more accessible and scalable solutions for smallholder farmers. In conclusion, AI is poised to revolutionize agriculture by enabling more efficient, sustainable, and resilient food systems, provided that challenges related to accessibility and ethical concerns are addressed.

Keywords: AI, Precision Farming, Crop Management, Predictive Analytics, Sustainable Agriculture, Robotics, Data Analytics, IoT in Agriculture.

1. Introduction

Artificial intelligence (AI) has witnessed compelling growth in various fields. To satisfy the further rising human population, it is requisite to enhance agricultural production by approximately 50% by 2050 (Beltran-Peña et al.2020). AI is serving as a key technology for achieving global food security while also providing sustainable means of production. It facilitates the quick and error-free preparation of the field with timely machinery management, robot-assisted planting, field irrigation, and intelligent pest and debris management. During post-harvest, it is also employed for automatic fruit and vegetable sorting, non-destructive quality measuring systems, intelligent forecasting, and automated packaging. To prepare a comprehensive review, various crucial aspects of AI in agriculture have been studied. It aims to provide ample information about AI technologies working in agriculture to pave the way for further advancements in the current methodologies. (Javaid et al., 2023)(Qazi et al., 2022)

Agriculture is the point of origin for human civilization, and its continuation is requisite to sustain it. Moreover, the world is currently facing acute issues related to food security, especially for those dwelling in developing countries. (Barrett, 2021) Henceforth, there is a requisite to enhance agricultural productivity while also providing assurance of sustainability. Sufficient availability could be ensured by the sustainable management of limited natural resources such as land, water, and biodiversity, and it can be ensured if agriculture is modernized with cutting-edge technology. AI is one of these recent technologies with the potential to change the state of affairs since it came into the spotlight. Therefore, AI could enhance agricultural productivity, reduce environmental concerns, and contribute positively to human society. The aim of this review is to discuss AI in agriculture. Different aspects of AI in agriculture are discussed exhaustively. (Javaid et al., 2023)(Ben Ayed & Hanana, 2021)

2. Historical Development of AI in Agriculture

Agriculture has always been the initial link in environmental science because it involves the largest number of people and is the basis for human survival. Although food essentials are produced and provided through human labor, artificial intelligence technologies have been applied in agriculture, addressing the diverse environment and complex objects involved in big data applications. (Shaikh et al., 2022)(Jung et al.2021)(Elbasi et al.2022)

Agriculture has witnessed increasing technological modernization over the past half-century, and this transformation has moved from traditional wage work and imitative work to mechanized agriculture and crop management with AI capabilities. In the early days of AI technology, many scholars played a key role in applying AI to the agricultural sector.

The emergence of wireless communication systems and the Internet of Things, combined with artificial intelligence, paved the way for the modern agricultural system. AI systems were first deployed through early intelligent agricultural machines and tractors (Raj et al.2022)(Subeesh & Mehta, 2021)(Spanaki et al.2022). Many prototype systems and agricultural AI projects were proposed as innovative technological creations in the AI for

agriculture field. The initial agricultural intelligence platforms, together with the hardware and software framework, have made significant contributions to the agricultural field as they were experiments that gained valuable knowledge. (Subeesh & Mehta, 2021)(Javaid et al., 2023) Despite limitations and challenges, such as ultrasonic sensor-based indoor navigation availability, frequent sensor malfunctions, and time-intensive manual data collection, the AGC parasitic vision system provides fundamental findings for low-cost height determination approaches.
The historical development of artificial intelligence in agriculture dates back to the 1980s, when researchers began exploring the potential of AI technology to revolutionize farming practices. Types of AI Technologies Used in Agriculture

3. Applications of AI in Agriculture

3.1. Machine Learning

Machine learning can vastly improve the operation of tasks. Taking into account a prioritized number that determines the development and evaluation of a model, ML suppresses the need for a human to suggest a functional association over prior data. (Benos et al.2021)(Durai & Shamili, 2022)(Domingues et al., 2022) The dichotomies characterizing models are supervised, unsupervised, semi-supervised, and reinforcement learning. Their essences reside in the presence of an outcome variable and the presence of a teacher sufficient enough to train the teacher-mimicking mechanism for all observations indicated. Supervised learning drives the majority of AI-oriented applications in the AD context, and the endowment of the algorithm with a large variety of data after data cleaning is usually very costly. AD opens a wide gate to hundreds of applications, including crop management and crop inspection based on optical sensors. Neural networks, and in particular convolutional neural networks, have achieved a prominent position in the context mainly thanks to the possibility to exploit large labeled image datasets, giving excellent results. Another example of optical sensors systematically adopted in precision farming is hyperspectral imaging (Tugrul et al., 2022)(Barbosa et al.2020).

3.2. Computer Vision

Computer vision (CV) is the process of enabling machines to read the objects in an image or video. The subject of computer vision is a more complex and high-level understanding of a particular image or video. Regular cameras use software to make decisions about the objects in the viewing field and take pictures (Khan et al.2021)(Khan & Al-Habsi, 2020)(Hassaballah & Awad, 2020). In CV, some of the problems and solutions differ from one another depending on the input. For a given input, several solutions may exist, and for a particular input, no solution may exist. Convolutional neural networks (CNN) play a very important role in computer vision. The advantage of CNNs is their ability to handle and examine images.

CV is playing the most critical role in agriculture. Many companies are using CV in their systems, which are used for planting and harvesting crops. Some traditional farming strategies are already using computer vision for verification. After a few recent and successful projects, technologists predict that a new breath of applied image-discerning technologies may be the starting point that could change the agricultural business forever. This new bound of agricultural computer vision usage may be seen from space-focused enterprises to small farming startups.

3.3. Robotics

Autonomous or remotely controlled agricultural vehicles are another tool to automate farm activities and reduce labor-related challenges. These means allow repetitive, time-consuming tasks, such as planting, spraying, pruning, harvesting, weeding, and mowing, to be performed with high accuracy, precision, and efficiency throughout cannabis cultivation (Bai et al.2023). Robotics assist farmers in various activities, demonstrating the ability to efficiently increase the quality, yield, and shelf life of vine, vegetable, floriculture, and ornamental crops. Potentially, robots have the ability to work 24/7, making production more efficient and reducing costs to better match demand for cannabis, offer higher product quality, lower production time, use fewer resources, and improve working conditions. When integrated with AI, robotic technology is able to deal with complex tasks. AI is responsible for decision-making processes. In horticulture, the most widely used examples are trolleys moving intelligently between containers and along the aisles in nurseries or controlled environment production, and machine vision systems identifying and harvesting mature fruit. (Rathore, 2021) Over the past few years, a number of innovative applications of AI and robotics in plant production have been introduced. AI-based weed recognition systems allow for early action. AI can also be employed to automate the transport of consumable items, avoiding bins traveling back empty from the harvesting site, reducing labor costs, and increasing safety. Data and knowledge concerning cannabis are increasing rapidly thanks to AI-based technologies (Bhat & Huang, 2021). These are used to analyze, summarize, and interpret information for intelligent management, planning, control, and decision-making in all phases of the food production chain.

4. Applications of AI in Agriculture

Agriculture has become one of the most important fields that have witnessed significant shares of artificial intelligence and sector-specific technologies that encompass decision-making, resource management, and farming tasks. In this section, the most common applications of artificial intelligence in agriculture are covered in terms of precision farming, crop monitoring, livestock monitoring, as well as decision support. Each application is dissected, and its procedures that are taken to satisfy are implemented. Furthermore, the addressed challenges are also incorporated. Finally, to demonstrate the extent of the impact of such applications in agriculture, several solutions are formulated and investigated as real-world pilot projects to verify accuracy results. In summary, many applications are reviewed within the smart agriculture domain to encompass the concern about not just growing methods, detectors, devices, and diagnosis systems, but also the decision-making process about agriculture-related issues.

Nowadays, one of the developing methodologies allowing companies conducting agricultural activities to improve results in terms of crop yield and quality is based on the concept of precision agriculture. (Martos et al., 2021)(Monteiro et al., 2021)(Bolfe et al.2020) The presence of artificial intelligence and machine learning has allowed the science of crop farming to reach new heights and even opened the window to the realms of personalized nutrition. Such methodologies will help farmers and food producers come up with innovative strategies for reducing wasted resources, effective treatments including chemical ones, and optimizing crop growth through the consolidation of key parameters in a single relevant index. A variety of tools are used to stay on top of farm operations and management, which can provide real-time data. All these highly specialized tools need special monitoring and management where AI can fit in. (Shaikh et al., 2022)

4.1. Precision Farming

Precision farming, which is sometimes also called precision agriculture or smart farming, represents a comprehensive approach to using AI to drive decision-making at all stages of crop management, from sowing to post-harvesting, considering economy, sustainability, and environmental effects (Karunathilake et al., 2023)(Bhat & Huang, 2021). It is an operational strategy aimed at identifying the appropriate management intervention to apply in response to processes operating in a field, conditioned by the heterogeneity of soil and yield potentials. The basic principles that underline the concept of precision farming are related to the collection and synthesis of data that enable the assessment of crop condition and quality to highlight differences and commonalities in the homogeneity of soil-crop relationships at a local scale. On this basis, it is possible to develop targeted intervention models to correct and optimize crop management practices in relation to the observed variability (Kephe et al., 2021). Through precision farming, it is, for example, possible to select the most suitable variety or hybrid of the species grown, identify the best planting density, evaluate the correct and dynamic quantity of water and nutrients, facilitate the tracing of the agricultural product through the use of characteristics of the area yielded, and reduce any waste in resources, such as fertilizers and plant protection products (Raj et al.2022)(Monteiro et al., 2021). For all these reasons, precision farming applications have increasingly spread since the 1990s. Possible benefits include, among others, variability reduction, better control of crop management, and cost reduction.

Many technologies contribute to making precision farming applications possible. Among them are sensors and unmanned aerial vehicles, or drones. Regarding sensors, there are non-image based sensors that allow monitoring weather or water content of the soil through the use of some capacitance sensors at spatial resolution ranging from a few square meters to a few tens of square meters. (Johnson et al.2020) The results are used to explore the geographical variability of ecosystems and to extend the information contained in the collected point data. Aerial images facilitate the enlargement of information coming from ground sensors. Images related to the electromagnetic spectrum allow us to analyze the state of the canopy and also to obtain real color images, and the variability in soil moisture at a spatial resolution ranging from 25 to 100 cm/pixel. (Zhang et al., 2021)(Liu et al., 2021) Sufficiently accurate multispectral cameras for DTMs obtained by drones can measure ground level elevation with subcentimeter accuracy and good-quality red bands with 10-cm pixel resolution. These sensors generally provide for low- or high-level scheduled flights that involve multiple sectors of activity, including technical and administrative, and certification. Concerning the barriers to the acceptance and adoption of new technologies in precision farming, some limitations appear to still remain, such as the availability of integrated distributed data, time-efficient and low-cost decision support systems, timing, technical expertise in programming and modeling, and training of operators. (Mohr & Kühl, 2021)(Kendall et al.2022)

The future perspectives for precision farming may be related to improvements in existing technologies and innovative concepts to comply with an increasingly sustainable agriculture based on the principles of accuracy, precision, and efficiency of inputs. (Karunathilake et al., 2023)(Khan et al.2021) In this regard, in recent years, methods have been proposed to automatically delineate the management zones of agricultural areas through unsupervised and clustered analysis of various variables related to different sectors of precision agriculture, such as information derived from UAV systems in or near real-time. (Paccioretti et al.2020)

4.2. Crop Monitoring and Management

One of the main applications of AI in agriculture is crop monitoring. AI-driven solutions provide new abilities to automatically assess the development or health conditions of crop plants, contributing to enhanced management. One of the key advantages of AI in crop monitoring is the real-time assessment condition. This allows the immediate reaction of the farmer before the plants experience any permanent damage.

AI offers higher automation in applying the required analyses. One area where progress has been very successful is field robotics. Field robotics is concerned with field operations that manage plant biomass in the overall spatial extent of the field. The same applies to soil analysis or the analysis of irrigation water; the equipment used is merely adapted to the respective task. One potential area for AI, especially for long-term operational crop management, is predictive analytics (Subeesh & Mehta, 2021)(Ben Ayed & Hanana, 2021)(Bhat & Huang, 2021). From a given set of past environmental and management inputs, the future yield, condition, or quality of the crop could be estimated. Such estimated outcomes could be used to plan management practices. For instance, knowing that a certain section of a field is not performing well, a farmer might decide to invest less in irrigation or fertilization. The possibility of resource saving, even though yield may not be maximized, is the argument for this approach. This will increase productivity by up to fifteen percent.

However, appropriate data needs to be used to calculate this. The main element in moving empirically towards building and training more accurate models in the deployment of predictive algorithms is data. (Akhter and Sofi2022)Proper, reliable data that can be drawn on for millions of recommendations is needed for machine learning models to be effective at scale. AI's ability to automate some of the processes involved in monitoring the development of crops is a key consideration and advantage for improving cereal crop monitoring. AI's accuracy when making diagnoses rests on the most accurate and high-quality data being fed to it. Another area for investment and significant AI advancements in the crop monitoring sector is the capability to integrate automated crop management recommendations directly into a farm management system. This would allow a seamless and fit-for-purpose integration with the existing framework and practices of producers today. (Subeesh & Mehta, 2021)(Shaikh et al., 2022)Producers utilizing farm management systems expect some level of automated resources and already have a number of rules and recommendations that they use to guide decisions. Providing automated recommendations cheaply in a form that is fit-for-use would greatly enhance the viability of the technology. Nevertheless, both of these options are amid ongoing research in the field and are not yet commercially available in practice. It is hoped they will subsequently be developed and tested in real time.

4.3. Livestock Monitoring and Management

As stakeholders in smart livestock farming become a more important part of the livestock industry, the market value of the smart livestock industry will increase from $1.1 billion in 2017 to $4.06 billion in 2026 (Allen, 2022). The trio of data analytics and big data by AI automates the tracking of good health by monitoring animal feeding behaviors, heat periods, and estrus signs that put reproduction and calf production at risk. The technologically advanced spatial management allows the industry to predict when animals will be born with low-impact time management resources. This is supported by vital signs and warnings, as well as a periodic accumulation of manual monitoring data. (Bejder et al.2022)This data is often used to track heifer performance and inhibit bull control, which can reduce his green stroke if needed. Whether it is based on motion patterns or different activities, the focus is often on determining the behavior of animals like pigs, cows, and bulls. Cattle weight monitoring systems are interactive with automatically controlled noise-gained characterization algorithms. By automatically detecting cattle weight with wireless sensors in feeding troughs, diet efficiency improves, the need for antibiotics to reduce excess body fat is mitigated, and cost reductions are achieved. Modern systems incorporate a structure that can be used to reduce and monitor temperature, hygiene, tail-biting quality, and animal disease. At the same time, researchers developed a matching model as a result of their research experience. A cattle heart rate monitoring system with wireless sensor technology can be interconnected with a tissue for quick nutrient testing based on the reconstruction of rural environments. Animal safety in the wild is enhanced using an intelligent multi-camera topology tracking system (Fernandez-Novo et al.2020). The observation model learns variations in animal body content to detect anomalies with AI techniques. Cameras and satellite images are used to monitor and control the movement of animals such as wildlife and livestock to keep them safe and healthy. Overall, livestock monitoring is one of the best ways to improve farm management and sustain the quality of life in the chain. There are one to two monitors that may be internal or external. Workers who use video to monitor their activities should place cameras in the barns, pens, and around animals to reduce injuries. A better monitoring initiative with video analytics is also possible since cameras are not used. Issues such as data security, data sharing, and consent must be considered, and the guidelines of the discussion explicitly state privacy. (Tawalbeh et al., 2020)

5. Challenges and Future Directions

There are several challenges in the application of AI in agriculture. These challenges, if not addressed appropriately, can hinder the successful and sustainable operation of AI applications in agriculture. We briefly present these challenges as follows:

a. Data Privacy - There are many concerns associated with the sharing of data related to agricultural systems.

b. Accessibility to Technology - Smallholder farmers and the poor often struggle to become part of the technological leap as they lack investable funds to adopt advanced technologies. In the future, AI-as-a-Service models will overcome this constraint.

c. Interoperability - Due to variations in internet reach and technology adoption, AI should interface with the indigenous and traditional knowledge in rural areas.
d. Resistance of Traditional Farmers to Technology - Traditionally trained farmers will have doubts and questions about AI decisions. Explanations and effectively communicating uncertainties are important. Training programs can support since such farmers are unfamiliar with complex technologies.
e. Data Quality and Decision Making - The penetration of IoT systems is uneven across agricultural holdings. Insufficient data from sensor networks could seriously impact the performance of AI algorithms.
f. Data Ownership and Control - Some farmers are reluctant to share the data, particularly with outsiders. This lack of data impedes AI/ML-based solutions that might have wide-ranging applicability for the betterment of the sector. Several precision agriculture platforms have attempted solutions for this in practice, such as on-board data processing.
We share some future research and development directions that are necessary to establish or enhance AI usage in agriculture. These directions span technological, ethical, and field-expertise considerations. Commercial AI tools need to demonstrate improved outputs by collaborating with end-users: more work should be conducted on-farm, working with technology companies, farmers, and end-users to improve both AI technology and usability from the start. A significant physical and digital gap remains between institutions that historically have developed precision tools and resource-poor farmers. In designing AI tools, this distinction needs to be made clearer in the design of AI tools. While providing ethical, transparent information to end-users, we need to avoid complicating tools to the point that experts do not want to use them. The use of AI in increasing the sustainability of agricultural production provides a fertile ground for future work. AI might play a significant role in aiding or replacing current systems for dealing with complex, coupled human-nature ecosystems. It also may play an important role in enabling the sustainable intensification of food production by accurately predicting and thus avoiding trade-offs, as well as by improving resource efficiency. Nonetheless, much more work is required for this goal to be reached.

6. Conclusion

This review has provided a comprehensive account of the current state of artificial intelligence (AI) in agriculture. What is clear from the literature is that AI applications abound and come in many forms, ranging from simple, expert systems and pattern recognition tools, to the most advanced, sophisticated and generalised forms of machine learning. Here, we see tools for automated detection, quantification and forecasting, together with their application to the control of many forms of plant and animal invasive pests, diseases and weeds, and the management of soil moisture and nutrients. The potential strategic applications of AI to the digitalisation of farming, together with the concept of the so-called internet of things mean that many more of these products will be interconnected and will use the cloud to expand the local and temporal scales on which data, information and analysis are based. AI platforms, perhaps driven by agents that have access to these data sets, will drive decision making to ranges that concern supply chain management and precision agriculture. Our review also showed that significant challenges remain in opening up these technologies to both large and small farmers and in making the best use of local data that are available as opposed to the global scale. These challenges can only be addressed by the active participation of all stakeholders involved, including end-users, the digital providers, technology developers, social scientists, and policy and decision makers.

Meeting these challenges is not just a scientific Endeavour but calls for the active participation of all stakeholders involved, including end-users, digital providers, technology developers and those involved in the domain of policy, economics and other social sciences. As can be seen from the wide range of challenges and actors there is a need to create opportunities for new interdisciplinary research. Enabling innovation through collaboration between existing and new actors will be crucial in addressing the public goods in the sector and foster distribution of economic, social and environmental benefits. AI is possibly the most transformative agricultural digital technology, enabling more efficiency to increase productivity, reduce waste and increase sustainability and resilience. The transformation is more than an incremental change, we are seeing the birth of new technologies, new sectors and ultimately new consumer outcomes that do not exist in evolutionary approaches. The digital agricultural revolution is distinct from past industrial and green revolutions or other digital sectors as it envelops more than purely information technology. It is the convergence of many technologies some that are agri-bio related, including AI, that independently create transformational breakthroughs when integrating new ways that drive better decision making and process control, the result of which impacts on the whole supply chain connected to agriculture.

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