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The Planning in Smart Agricultural Production with Artificial Intelligence

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Abstract

As the population grows and conflicts continue, we need to increase agricultural productivity to ensure food security. Artificial intelligence is now a key part of agricultural and Data-Driven Agricultural Management. It is helping to move modern farming toward smart farming. This leads to more crops, better products, and lasting growth. Today, we see significant progress in AI technologies and the Internet of Things being used for many farming tasks. The goal of this study is to demonstrate some of the modern ways that artificial intelligence can be used to plan smart agricultural production. Adding AI-powered systems to the farming planning process can help address problems with traditional farming and make the system more flexible and efficient. Digital technologies are now changing the agriculture industry in a big way.

Keywords: *smart agriculture, Artificial intelligence, agricultural planning*

Introduction

Agriculture is one of the most important industries working to solve these problems. It needs to grow in both number and quality. The agricultural industry also has to deal with workers leaving for better-paying jobs and farmers being older on average (Miyake et al., 2022). To solve these problems and meet the nutritional needs of the growing population, scientists and agricultural experts need to find more creative and long-lasting ways to grow food. To solve these problems, agricultural experts have come up with new ways to keep an eye on things, like variable-rate applications, remote sensing systems, global positioning systems, and optimal nutrient monitoring. All of these methods are part of precision farming or precision agriculture (PA). To get the most out of both quantity and quality while cutting down on waste, precision agriculture uses the right actions, such as fertilization or irrigation, in the right way, at the right place, and at the right time (Nowak, 2021). There is also a new idea called "smart agriculture," which uses AI and digital technology in farming (Zinke-Wehlmann & Charvát, 2021).

Artificial intelligence (AI), the Internet of Things, robotics, and big data are all types of information technology that are growing quickly. AI can help smart farming make predictive control models and make the best choices. Robotics can perform high-intensity work that people normally do, and the Internet of Things can collect and analyze large-scale environmental data (Ge et al., 2025). Ultimately, this will render the entire agricultural process secure, economical, and efficient (Yang et al., 2021). Data-driven AI has become the most important part of smart agriculture among these new technologies. Smart agriculture is the precise, automated, and intelligent management of agricultural production (Taha et al., 2025). It is important to use it because the world's population is growing, food security issues are rising, and the demand for high-quality agricultural goods is rising. The main purpose of this study is to show some of the new ways that smart agricultural planning is using AI. Through this review, we also seek to highlight some artificial intelligence technologies used in agriculture and their role in driving agricultural production.

Artificial Intelligence and smart agricultural production planning

The use of AI technology in agriculture has been the subject of much study in recent years, further supporting the industry's ongoing growth (Bai et al., 2025). AI seeks to enable robots to perform complex tasks such as learning, reasoning, perception, and decision-making by analyzing datasets, identifying patterns, and generating predictions about targets. It is widely used in domains such as social security, autonomous driving, smart healthcare, and industrial automation. AI technologies are changing agricultural production practices through data, algorithms, and equipment, rather than relying on traditional human-experience-based analysis and decision-making or on simple mechanical labor substitution. With applications in agricultural production management, soil and crop monitoring, pest and disease detection, yield prediction, and crop planning, food quality, climate-smart agriculture, supply chain optimization, autonomous farming equipment, mechanical equipment fault analysis, etc., these technologies address nearly every facet of agricultural production, including planting, cultivation, management, and harvesting. However, open, unstructured, and complex agricultural environments, limited and unevenly distributed high-quality annotated data, multi-source heterogeneous data fusion, and problems like inadequate generalization, poor interpretability, and insufficient real-time performance of AI models pose serious obstacles to the application of AI in agriculture (Ge et al., 2025).

Artificial intelligence (AI) contributes to agricultural sustainability by enabling precision crop management. By analyzing data from sensors, satellites, and drones, AI systems monitor crop health, soil quality, and weather conditions. These insights enable the optimization of irrigation, fertilizer, and pesticide applications, thereby reducing waste and minimizing environmental impact. Consequently, resource use becomes more efficient, leading to increased productivity and the conservation of soil and water (Ali et al., 2025). AI significantly advances sustainable agriculture by increasing efficiency, optimizing resource utilization, and facilitating data-driven decision-making within contemporary farming systems. The adoption of AI technologies, including machine learning, remote sensing, robotics, and the Internet of Things (IoT), enables precision agriculture and supports the progression toward Agriculture 5.0. This evolution seeks to improve productivity while reducing environmental impact (Taha et al., 2025). With predictive analytics and decision-support tools, farmers can spot crop diseases, pest problems, and climate risks early. This early detection enables them to act quickly and use fewer chemicals, helping protect biodiversity. AI monitoring systems also improve water management by indicating when crops need water and helping farmers plan irrigation, which is most important in areas with limited water (Ali et al., 2025).

AI models can predict crop yields, check soil health, and suggest the best crop types for local conditions. These tools help farmers grow more food sustainably, which is important as the world's population grows and the climate changes (Kumari et al., 2025). AI agricultural robots are a state-of-the-art use of robotics and artificial intelligence in contemporary agriculture. In the current era, AI agricultural robots are increasingly being adopted in agricultural production. Their substantial potential to improve food safety, reduce labor shortages, increase production efficiency, and safeguard the environment are the main causes of this development (Wang et al., 2023). Intelligent applications for field operations, particularly in planting, crop management, and harvesting, are now the focus of technical advancements in agricultural robots. Autonomous navigation technology has also become a core pillar of innovative agricultural robots (Ge et al., 2025). AI also supports climate-smart farming. By analyzing greenhouse gas emissions, soil carbon, and other environmental data, AI helps farmers choose methods that lower emissions and increase soil carbon storage. These practices support sustainable farming and align with global goals for food security and environmental protection (Ali et al., 2025). A four-layer intelligent agriculture system that includes cloud computing, edge computing, data transmission, and agricultural data collection was developed by Bu & Wang (2019). This technology enables real-time environmental monitoring, soil moisture and climate analysis, and automatic adjustments for irrigation and fertilizer dosing. Its adaptability to various working environments also makes it easier to incorporate existing expertise into new farming settings. To enhance plant growth conditions and provide real-time notifications to users, Mohamed et al. (2022) developed a fog cultivation system that primarily uses Arduino-based cooling fans to intelligently cool the lettuce root zone based on real-time temperature and humidity data from the surrounding environment.

Qureshi et al. (2025) explored plasma technology for microbial control and plant nitrogen fixation. They developed an The artificial intelligence of things (AIoT)-enabled system that automatically adjusts fertilizer content, spray cycles, and plasma composition to reduce resource use while maintaining crop yield. According to Judijanto et al. (2024), AI can reduce input usage by over 30% and increase productivity by up to 20% compared to traditional methods. The rigidity of conventional approaches is surpassed by technologies such as drones equipped with computer vision, IoT sensors, expert systems, and neural networks, which facilitate continuous monitoring and adaptive responses to changing soil, crop conditions, and climate (Shamshiri et al., 2018). Even with these benefits, using AI in farming poses challenges such as high startup costs, the need for technical skills, and difficulties obtaining sufficient data. Still, as technology improves and researchers, farmers, and policymakers work together, AI could help make farming more sustainable, resilient, and efficient (Ali et al., 2025).

AI technologies have extensive applications in smart agriculture, each offering unique advantages. Nonetheless, substantial challenges persist in their practical implementation (Ge et al., 2025). In the domains of AI detection, fault diagnosis of agricultural machinery, and crop condition forecasting, the majority of existing models rely heavily on large, labeled datasets and substantial computational resources to achieve satisfactory accuracy (She et al., 2024). However, due to the inherent complexity of agricultural environments, acquiring large-scale, balanced, and thoroughly annotated datasets is often costly, labor-intensive, and computationally demanding, thereby significantly limiting their applicability in real-world settings. Furthermore, AI models often lack interpretability, hindering agricultural producers' ability to understand the decision-making processes underlying them. This lack of transparency can undermine trust and confidence in the diagnostic and predictive outcomes generated by these models (Zhou et al., 2023). Future research could develop models capable of handling low-quality, imbalanced data, reducing computational demands, and enhancing generalization and stability under varying agricultural conditions. Exploring lightweight neural network architectures and optimization algorithms can reduce computational demands, enabling high-performance AI models to be directly deployed on agricultural machinery, drones, or field edge computing devices for real-time, online detection and diagnosis (Ge et al., 2025).

Given these advantages, the use of artificial intelligence technology offers significant benefits in agriculture, helping maximize production and improve the quality of agricultural products.

Conclusion

Through improvements in how people perceive, what they know, and how they make decisions, artificial intelligence has made modern farming much more effective. Finding crops, eliminating pests, making predictions, and sounding alarms for equipment are all things that it assists with. The application of artificial intelligence, particularly in the form of agricultural robots, is rapidly expanding as traditional farming methods become less common. The use of artificial intelligence is replacing traditional farming methods, but there are still issues that need to be resolved. To address these issues, we need to conduct further research and leverage technology.

Declarations

Ethical Approval Certificate

No need

Author Contribution Statement

Wadah Elsheikh: writing the original draft. Ilknur Ucak: supervision, conceptualization, review, and editing.

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Conflict of Interest

The authors declare no conflict of interest.

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