BioThink, Vol -2, Issue -2
ISSN: 3048-7943

Advancing Crop Management with Artificial Intelligence: A Comprehensive Review of Innovations, Challenges, and Future Prospects

[1]Sanjeev Khan, [2]Shivani, [3]Nutan Pathania, [4]Nitesh Kumar and [5]Pawan Kumar

[1,2-]Department of Data Science and Artificial Intelligence, [4]Department of Biosciences,
[3,5-]Department of Computer Science, Himachal Pradesh University, Summerhill, Shimla, India
Corresponding author email: sanjeevkhan.hpu@gmail.com

1. Introduction

1.1 Importance of Efficient Crop Management for Global Food Security

Agriculture is critical to human survival, as it provides food, fiber, and raw materials for industrial applications. With the number of people worldwide expected to surpass 9.7 billion by 2050, the world faces a critical desire for boosting yields from agriculture while maintaining environmental sustainability. (Sharma & Shivandu, 2024). Traditional farming practices rely primarily on human labor, historical knowledge, and reactive problem-solving, rendering them ineffective in dealing with modern agricultural concerns featuring change in the climate, soil degradation, and dropping water resources (Aijaz *et al.*, 2025). AI-based technologies provide a data-driven approach to optimizing agricultural practices, leading to higher productivity with reduced resource input (Elbasi *et al*., 2023). The unpredictability of climate conditions has further complicated global food production, resulting in reduced yields and increased crop losses. Artificial intelligence approaches, including predictive statistical analysis and machine learning models, help farmers anticipate weather patterns, optimize irrigation schedules, and manage pests more effectively (Gardezi et al., 2023). Efficient crop management strategies are essential for meeting global food demands, reducing environmental impact, and ensuring that smallholder farmers can compete in an increasingly technology-driven agricultural industry (Aylak, 2021).

1.2 Role of AI in Transforming Traditional Farming Practices

Artificial intelligence has the ability to transform traditional farming by incorporating data analytics, automation, and robotics into agricultural workflows. Conventional farming is based on conventional agricultural practices, which frequently result in excessive fertilizer use, inadequate irrigation, and substantial post-harvest losses (Aijaz et al., 2025). AI-powered precision agriculture facilitates continuous tracking of soil conditions, health of crops, and environmental variations, allowing farmers to make data-driven decisions that improve yield and sustainability.(Sharma & Shivandu, 2024). For instance, powered by AI drones outfitted with primarily multispectral photographing sensors may analyze crop health by detecting early signs of nutrient deficiencies or disease outbreaks. AI-driven robotic systems also automate labor-intensive tasks such as planting, weeding, and harvesting, reducing dependency on human labor while improving operational efficiency (Elbasi et al., 2023). These advancements minimize resource wastage and enhance overall agricultural efficiency, making AI an indispensable tool for modern farming (Gardezi et al., 2023).

2.3 Scope of the Review and Research Questions

This review intends to examine the consequences of artificial intelligence in managing crops, with an emphasis on its applications in precision agriculture., pest detection, yield forecasting, smart irrigation, and supply chain management. The study also identifies challenges associated with AI implementation and discusses potential solutions. The primary research questions guiding this review include:

1. How does AI improve precision farming and optimize resource utilization?
2. What AI techniques are most effective for pest and disease detection?
3. How do AI-driven models enhance crop yield prediction and monitoring?

4. How does AI contribute to smart irrigation and sustainable water management?
5. What challenges hinder AI adoption in agriculture, and how can they be addressed?

Table 1: Comparison of Traditional vs. AI-Driven Crop Management Practices

Feature	Traditional Crop Management`	AI-Driven Crop Management
Making Choices	Following historical information, farmer experience, & general guidelines.	Insights generated by continuous tracking, automated analysis, and machine learning mathematical algorithms. (Chen et al.,2023)
Resource Management	Uniform application of resources (water, fertilizer, pesticides) across the field.	Precise and variable-rate application of resources based on specific crop and soil needs (Malhotra & Firdaus, n.d.).
Pest and Disease Management	Manual inspection and calendar-based application of pesticides.	Early detection of pests and diseases through image recognition and AI-powered diagnostics, leading to targeted interventions and reduced chemical use (Malhotra & Firdaus, n.d.).
Yield Prediction	Based on historical averages and visual assessment.	Predictive models forecast yield by taking into account elements such as climate conditions, soil condition, and crop health.(Malhotra & Firdaus, n.d.).
Labor	Labor-intensive, with significant manual work required.	Increased automation through AI-powered robots and systems, reducing labor dependency (Majeed et al., 2024).
Data Collection & Analysis	Limited data collection, with manual record-keeping.	Continuous data collection from various sources (sensors, drones, satellites), enabling comprehensive analysis and informed decision-making (Chen et al., 2023).
Environmental Impact	Higher potential for environmental damage due to over-application of resources.	Reduced ecological impact through better resource utilization and less chemical treatment (Malhotra & Firdaus, n.d.).

2. AI Applications in Crop Management

2.1 AI for Precision Farming

Precision farming uses AI to improve decision-making by giving farmers immediate information about the health of the soil, plant conditions, and atmospheric conditions. Traditional farming methods apply fertilizers, pesticides, and irrigation uniformly across fields, often leading to resource wastage and environmental damage. AI-driven precision farming enables site-specific management, where inputs are optimized based on soil characteristics and crop requirements (Sharma & Shivandu, 2024).

2.1.1 AI-powered Soil Health Analysis

Soil health is vital for predicting the yield of crops, and artificial intelligence-based assessment of soil allows farmers to monitor nutrient levels, pH balance, and moisture content more effectively. AI models process data collected from soil sensors, satellite imagery, and historical records to generate precise soil fertility maps. These insights allow farmers to make data-driven decisions about fertilization and crop selection, ultimately improving yield and reducing input costs. Algorithms developed using machine learning will recognize early indications of soil degradation, helping to manage possible problems before they harm crop health. (Aijaz et al., 2025).

2.1.2 Variable Rate Application (Fertilizers, Pesticides, Irrigation)

Artificial Intelligence (AI) variable rate application (VRA) AI facilitates VRA of water, fertilizers, and pesticides by applying inputs only where necessary. AI-driven sensors and drones gather information about soil type and plant health and enable precise treatment. This technique minimizes overuse of chemicals, reduces the environmental footprint, and increases cost-effectiveness. AI-based irrigation systems, for instance, scan real-time weather and soil moisture levels to determine water distribution, avoiding overwatering and drought stress.

This precision application not only conserves resources but also promotes sustainable farming practices (Kowalska & Ashraf, 2023).

Table 2: AI Techniques Used in Precision Farming and Their Benefits

AI Technique	Description	Benefits	Example Applications
Machine Learning	Algorithms that learn from data to make predictions or decisions without explicit programming.	Improved accuracy, adaptability, and efficiency in various farming tasks (Benos et al., 2021).	Yield prediction, disease detection, and soil analysis (Majeed et al., 2024).
Computer Vision	AI that enables machines to "see" and interpret images.	Automated monitoring, early detection of anomalies, and precise targeting of interventions (Mishra & Mishra, n.d.).	Weed identification, crop health monitoring, and fruit counting.
Expert Systems	AI systems that use rule-based reasoning to provide expert-level advice and decision support.	Improved decision-making, allocation of resources, and crop management procedures. (Dawn et al., 2023).	Irrigation scheduling, pest control recommendations, and fertilizer management.
Robotics	Autonomous machines capable of performing physical tasks in the field.	Increased efficiency, lower labor costs, and more precision in farming operations (Mishra & Mishra, n.d.).	Automated planting, weeding, harvesting, and spraying.

2.2 AI in Pest and Disease Detection

AI significantly enhances pest and disease detection by using advanced imaging techniques and predictive models to identify threats before they cause extensive damage. Traditionally, pest monitoring relied on manual field inspections, which were time-consuming and often inaccurate. AI-based solutions improve this process by automating disease identification and enabling timely intervention (Malhotra & Firdaus, 2023).

2.2.1 Image Recognition for Early Pest/Disease Identification

Artificial intelligence-powered image recognition systems evaluate plant photos using machine learning models like Convolutional Neural Networks (CNNs) & detect signs of disease or pest infestations.

These models compare visual symptoms with large datasets of pre-identified cases, providing farmers with real-time alerts and treatment recommendations. Drones and ground-based cameras equipped with AI further enhance this process by continuously scanning fields for abnormalities, allowing for immediate action to be taken (Schaefer, 2023).

2.2.2 AI-Based Predictive Models for Outbreak Forecasting

AI-based predictive models use climate data, historical pest patterns, and real-time environmental factors to forecast potential outbreaks. These models assess conditions such as humidity, temperature, and rainfall, which influence pest populations and disease spread. By offering early warnings, AI enables farmers to take preventive actions, reducing reliance on reactive pesticide applications. AI-integrated IoT sensors also contribute by detecting pest activity and soil nutrient imbalances, ensuring timely intervention (Harinath et al., 2024).

2.3 AI for Yield Prediction and Crop Monitoring

AI enhances crop yield prediction by analyzing various factors, including weather conditions, soil health, and plant growth stages. By leveraging machine learning and remote sensing technologies, AI enables accurate forecasting and early detection of potential yield limitations, helping farmers make informed decisions to maximize production (Ghosh et al., 2024).

2.3.1 Machine Learning Models for Yield Forecasting

Machine learning models use vast datasets, including historical weather records, soil properties, and crop performance metrics, to predict harvest yields. These models incorporate real-time sensor data, improving accuracy and enabling proactive adjustments in farm management. Advanced AI techniques such as deep learning refine yield predictions by identifying complex patterns in agricultural data, helping optimize planting schedules and resource allocation (Singh et al., 2023).

2.3.2 Satellite and Drone-Based Crop Health Monitoring

Artificial intelligence-enabled satellites and drones track the health of crops through high-resolution imaging and interpretation of vegetation indexes like NDVI (Normalized Difference Vegetation Index). These instruments identify stress symptoms, nutrient deficiency, and infestation, enabling early treatment. AI software analyzes this imagery to produce real-time field maps that enable farmers to target affected patches more effectively. This monitoring ensures lower yield losses and optimal growing conditions throughout the season (Saikanth et al., 2023).

2.4 Leveraging AI for Efficient Water Management in Smart Irrigation Systems

AI is crucial to optimizing water in agriculture by compiling real-time input from soil sensors, weather models, and the needs of plants. This enhances water distribution such that wastage is minimized yet the crops retain the best amount of hydration necessary (Wang & Chen, 2023).

2.4.1 AI-Driven Water Usage Optimization

AI-powered systems for irrigation analyze the moisture content of the soil and weather conditions to determine accurate water needs for each region of a field. By automating irrigation schedules, these systems prevent overwatering and under-irrigation, reducing water waste and ensuring sustainability. AI algorithms also factor in evapotranspiration rates, adjusting water delivery accordingly to maintain optimal soil conditions (Sachan et al., 2023).

2.4.2 IoT and AI Integration for Automated Irrigation

IoT-enabled irrigation systems use AI to automate water distribution based on real-time field data. Sensors measure soil hydration levels, while AI processes this information to control irrigation valves remotely. This technology minimizes manual labor while enhancing water conservation. AI-integrated weather prediction models further optimize irrigation strategies by forecasting rainfall patterns, ensuring that water is applied only when necessary (Ghosh et al., 2024).

2.5 AI in Supply Chain and Post-Harvest Management

AI contributes to agricultural supply chain efficiency by improving demand forecasting, optimizing logistics, and reducing post-harvest losses. Traditional supply chains often suffer from inefficiencies due to unpredictable market demand and perishable produce. Solutions based on artificial intelligence Address these difficulties with real-time data and advanced decision-making tools (Dawn et al., 2024).

2.5.1 AI-Driven Demand Prediction and Streamlined Logistics Management

AI models use previous sales data, weather factors, and customer behavior to anticipate market demand accurately. This forecasting helps farmers and distributors plan harvest schedules, reducing the risk of overproduction or shortages. AI also enhances logistics management by optimizing transport routes and storage conditions, ensuring that fresh produce reaches markets efficiently. By minimizing delays and spoilage, AI-driven logistics improve profitability and sustainability (Sanyal et al., 2024).

2.5.2 Reducing Food Waste through Intelligent Supply Chain Management

Post-harvest losses are a significant challenge in agriculture, often resulting from improper storage, transportation, and handling. AI solutions address these issues by monitoring temperature, humidity, and storage conditions in real time. Smart warehouse systems equipped with AI detect produce deterioration and suggest redistribution strategies to minimize waste. Additionally, AI-powered markets connect producers directly to consumers, removing the need for intermediaries and assuring fair pricing (Abdelhamid et al., 2023).

3. Current Challenges and Limitations

3.1 Data Scarcity and Quality Issues in Agriculture

AI models require large datasets to function accurately, yet agricultural data is often fragmented, inconsistent, and limited in availability. Most small-scale farmers do not have access to structured digital records, making it difficult to develop AI models that accurately predict crop growth patterns, disease outbreaks, and yield forecasts (Sharma & Shivandu, 2024).

One major problem is the variability in agricultural conditions across regions, including differences in soil types, climate, and farming techniques. Artificially intelligent models trained on data gathered in one place may not generalize well to others, leading to inaccurate predictions and unreliable recommendations (Aijaz et al., 2025). Additionally, a lack of centralized data-sharing platforms limits collaboration between researchers, agribusinesses, and policymakers. Many agricultural companies hold proprietary data, making it inaccessible to farmers who could benefit from AI-driven insights (Elbasi et al., 2023).

To address this issue, governments and agricultural organizations should create open-source databases where farmers and researchers can share and access data. The integration of IoT sensors, satellite imagery, and cloud computing can also enhance real-time data collection, improving AI model accuracy (Gardezi et al., 2023).

3.2 High Costs and Technology Accessibility for Small-Scale Farmers

AI implementation in agriculture requires significant investment in infrastructure, including IoT devices, drones, automated irrigation systems, and cloud computing services. These technologies are often expensive, making them inaccessible to small-scale farmers who lack the financial resources to adopt AI-driven solutions (Aylak, 2021).

Additionally, most AI-powered agricultural tools require internet connectivity and digital literacy, which are often lacking in rural farming communities. Farmers may struggle to integrate AI solutions into their traditional practices due to limited technical knowledge and inadequate training programs (Sharma & Shivandu, 2024).

Developing cost-effective AI models tailored for small-scale farmers can help bridge this gap. Governments and corporate parties should offer monetary incentives, such as subsidies and grants, to encourage AI adoption in low-income farming communities. Moreover, user-friendly mobile applications with AI-based recommendations can help farmers leverage AI without requiring extensive technical expertise (Aijaz et al., 2025).

3.3 Navigating Ethical and Environmental Challenges in AI-Powered Agriculture

The inclusion of artificial intelligence in agriculture raises ethical concerns regarding data ownership, farmer autonomy, and job displacement. Large agritech corporations often develop AI-driven platforms, leading to centralized control over agricultural data. This creates a risk where small-scale farmers lose control over their farm data, making them dependent on external entities for insights and recommendations (Elbasi et al., 2023).

Another major concern is the potential displacement of agricultural workers owing to greater technology. AI-powered machinery, like self-driving tractor and robotic reapers, eliminates the need for human labor, which may result in loss of employment, especially in developing nations where agriculture employs a significant portion of the workforce (Gardezi et al., 2023)

Environmental concerns also arise as AI-driven agriculture increases energy consumption due to the operation of IoT devices, data centers, and automated equipment. Additionally, over-reliance on AI-based recommendations may reduce farmers' traditional knowledge and adaptive decision-making skills. It is critical to build AI solutions that complement rather than replace human expertise, while ensuring that ethical implications are addressed (Aylak, 2021)

3.4 Lack of Standardized AI Frameworks for Agriculture

The absence of standardized AI frameworks and regulatory guidelines complicates the widespread adoption of AI in agriculture. Different AI models use varied data formats, making it difficult to integrate multiple AI tools within a single farming system (Sharma & Shivandu, 2024).

Moreover, there is no universal benchmark for evaluating AI models in agriculture. Without standardized validation protocols, farmers and agronomists may struggle to determine the reliability of AI-driven recommendations (Aijaz et al., 2025).

To address these challenges, policymakers should develop global AI regulations specific to agriculture, ensuring interoperability between AI tools and setting ethical guidelines for AI-driven decision-making. Standardized data-sharing protocols and AI certification programs can help build trust among farmers and stakeholders (Elbasi et al., 2023).

Table 3: Key Challenges in AI-Based Crop Management and Proposed Solutions

Challenge	Description	Proposed Solutions	Potential Benefits of Solutions
Data Scarcity and Quality	Limited access to excellent, labeled information for training AI models. (Schaefer 2023)	Develop data sharing initiatives, invest in data collection infrastructure, use data augmentation techniques.(Schaefer, 2023)	Improved model accuracy, broader applicability, and reduced reliance on expensive manual data collection.(Schaefer, 2023)
Technology Costs and Accessibility	High costs of hardware, software, and expertise required to implement AI	Promote open-source AI platforms, develop affordable AI-powered tools, provide	Increased adoption by small-scale farmers, reduced technology gap, and

	solutions.(Elbasi et al., 2023).	training and education programs.(Schaefer, 2023)	democratized access to AI benefits.(Aijaz et al., 2025)
Ethical and Environmental Concerns	Data privacy breaches, algorithmic bias, and negative environmental repercussions are all possible (Aijaz et al., 2025).	Establish ethical rules and legislation, create transparent and explainable AI models, and encourage sustainable AI activities.	Enhanced public trust, reduced risks of unintended consequences, and alignment with environmental goals..(Aijaz et al., 2025)
Lack of Standardization	Absence of standardized data formats, protocols, and evaluation metrics.(Sharma & Shivandu, 2024).	Establish industry-wide standards, promote interoperability of AI systems, develop benchmark datasets for performance evaluation.	Facilitated collaboration, accelerated innovation, and improved comparability of AI solutions.(Ryan et al., 2023)
Lack of Farmer Knowledge and Training:	Insufficient knowledge among farmers of AI capabilities (Schaefer, 2023)	Develop Extension programs and demonstration farms to demonstrate AI benefits	Increased adoption and effective use of AI (Ryan et al., 2023)

4. Future Directions and Research Opportunities.

AI in agriculture is still evolving, and emerging technologies are expected to play a critical role in determining the future of smart farming. Future research should focus on improving AI's efficiency, accessibility, and integration with other digital tools. Key areas include AI's synergy with IoT and blockchain, climate-resilient farming techniques, affordable AI solutions for smallholders, and policies ensuring responsible AI adoption.

4.1 AI Integration with Blockchain, IoT, and Digital Twins for Smart Agriculture

AI is becoming more and more integrated with IoT devices, blockchain, and digital twin technologies for better decision-making and greater agricultural operation transparency. IoT sensors feed real-time soil moisture, temperature, and plant health data that AI algorithms parse to optimize watering, pest control, and fertilizer application schedules (Sharma & Shivandu, 2024). Blockchain technology improves the ability to track and safety of agricultural transactions.It ensures that data related to crop quality, supply chain logistics, and farm productivity remains tamper-proof and accessible to all stakeholders. This technology helps combat food fraud, optimize inventory management, and improve financial transactions in agriculture (Motta et al., 2020). Digital twins, virtual replicas of farms or fields, simulate agricultural conditions and predict future outcomes based on AI models. These simulations help farmers test different strategies, such as crop rotations or irrigation techniques, without implementing them in real life. The integration of artificial intelligence with these digital instruments has the possibility to increase productivity as well as sustainability in agriculture (Patelli & Mandrioli, 2020).

4.2 AI-Powered Climate-Resilient Farming Techniques

Climate change presents substantial problems to agriculture, making it critical to develop AI-powered solutions that assist crops in adapting to adverse weather conditions. AI can assist in breeding climate-resilient crops by analyzing vast genetic datasets and identifying traits that improve drought tolerance, heat resistance, and disease resilience (Rai, 2022). Machine learning models can predict weather patterns and recommend adaptive farming techniques. For instance, Artificial intelligence-based irrigation can maximize water use according to soil moisture content and forecasted rainfall to avoid water shortages while providing crops with sufficient water (Hafeez et al., 2023). Furthermore, precision agriculture facilitated by AI decreases greenhouse gas emissions through optimizing fertilizer application and preventing unnecessary applications of herbicides and pesticides. Such approaches not only enhance sustainability but also protect biodiversity and soil health (Smart et al., 2011).

4.3 Developing Cost-Effective AI Solutions for Smallholder Farmers

AI uptake is still low in small-scale farms because of exorbitant costs and infrastructure needs. To overcome this, researchers are developing cost-effective, low-energy AI technologies suited for smallholder farmers. An emerging option is the implementation of mobile-based AI applications offering real-time data on crop health, soil type, and weather forecasts through basic smartphone interfaces (Talaviya et al., 2020). Additionally, community-based AI models are being explored, where farmer cooperatives share AI-powered resources such as drones and IoT sensors. Government subsidies and financial incentives can further facilitate the adoption of AI among small farmers, ensuring that they benefit from technological advancements without facing economic barriers (Gardezi et al., 2023).Research is also being directed towards creating energy-efficient AI algorithms that can operate on low-power devices, reducing dependence on expensive cloud computing infrastructure and ensuring widespread adoption of AI in agriculture (Aylak, 2021).

4.4 Policies and Frameworks for Responsible AI Implementation

Ethical AI application in farming needs regulatory measures that uphold fairness, openness, and data security. AI farming solutions create an enormous amount of data, thus creating a threat to data privacy and ownership. Regulations need to be created that safeguard the rights of farmers but encourage ethical data-sharing behavior (Nolan, 2024). Additionally, AI bias in predictive models can lead to inequalities in resource allocation, favoring large-scale farms over smallholders. To mitigate this, policymakers should enforce guidelines on AI fairness and encourage the development of diverse datasets that represent different farming environments (Tomar & Melkania, 2024). International cooperation is essential to create standardized AI regulations that enable cross-border data sharing and technology exchange. Public-private partnerships can further accelerate AI innovation while ensuring that it aligns with sustainability goals and ethical standards (Birner et al., 2021).

Table 4: Emerging AI Trends in Crop Management and Their Potential Impact

Emerging AI Trend	Description	Potential Impact	Challenges & Opportunities
AI-powered Robotics and Automation	Autonomous robots performing tasks like planting, weeding, harvesting, and spraying (Mishra & Mishra, n.d.).	Improved productivity, lower cost of labor, and better precision (Dawn et al., 2023)	High initial investment, need for specialized training, ethical concerns about job displacement.
AI-driven Digital Twins	Crops, fields, or entire farms can be represented virtually for simulation and optimization purposes.	Better decision-making, enhanced utilization of resources, and risk reduction (Smith, 2018)	Data integration challenges, model complexity, and need for accurate calibration.
AI and Blockchain Integration	Combining AI with blockchain technology for secure and transparent supply chain management.	Enhanced traceability, reduced fraud, and improved food safety (Dawn et al., 2023).	Interoperability issues, scalability concerns, and regulatory uncertainties.
AI for Climate-Smart Agriculture	Using AI to develop climate-resilient crops, optimize water usage, and reduce greenhouse gas emissions (Mathur, 2023).	Increased food security, reduced environmental impact, and enhanced sustainability.	Data availability challenges, model complexity, and need for interdisciplinary collaboration.
Edge AI in Agriculture	Deploying AI models and processing data directly on edge devices (e.g., sensors, drones) in the field.	Reduced latency, improved data privacy, and enhanced real-time decision-making.	Limited computing resources, power constraints, and security vulnerabilities.

5. Conclusion

5.1 Summary of Key Findings

This paper emphasizes AI's transformative role in current crop management, highlighting its promise for precision farming, pest detection, yield prediction, irrigation control, and supply chain optimization. Farmers can use AI-powered tools to make data-driven decisions that increase productivity, minimize resource waste, and promote sustainability. However, barriers such as data scarcity, high costs, ethical concerns, and the lack of standardized AI frameworks continue to limit widespread adoption. Future advancements should focus on integrating AI with IoT, blockchain, and digital twins to enhance agricultural efficiency while developing cost-effective solutions tailored for smallholder farmers (Aijaz et al., 2025; Sharma & Shivandu, 2024).

5.2 Implications for Farmers, Researchers, and Policymakers

For farmers, AI offers precision tools that improve crop management, but affordability remains a key challenge. Governments and cooperative models must facilitate access to AI-driven technologies, ensuring that small-scale farmers benefit from advancements. Researchers should prioritize the development of region-specific AI models and explore synergies between AI, climate-resilient agriculture, and emerging technologies to enhance sustainability. Policymakers need to establish ethical guidelines, fair data-sharing protocols, and incentives for AI adoption, particularly in underdeveloped regions, to create an inclusive agricultural ecosystem.

References

Aijaz, N., Lan, H., Raza, T., Yaqub, M., Iqbal, R., & Pathan, M. S. (2025). Artificial intelligence in agriculture: Advancing crop productivity and sustainability. *Journal of Agriculture and Food Research, 101762.* https://doi.org/10.1016/j.jafr.2025.101762

Ayed, R. B., & Hanana, M. (2021). Artificial intelligence to improve the food and agriculture sector. *Journal of Food Quality, 2021*, 1–7. https://doi.org/10.1155/2021/5584754

Bock, C. H., Barbedo, J. G. A., Del Ponte, E. M., Bohnenkamp, D., & Mahlein, A. (2020). From visual estimates to fully automated sensor-based measurements of plant disease severity: status and challenges for improving accuracy. *Phytopathology Research, 2(1).* https://doi.org/10.1186/s42483-020-00049-8

De Oliveira, R. C., & De Souza E Silva, R. D. (2023). Artificial intelligence in agriculture: Benefits, challenges, and trends. *Applied Sciences, 13(13),* 7405. https://doi.org/10.3390/app13137405

Elbasi, E., Mostafa, N., AlArnaout, Z., Zreikat, A. I., Cina, E., Varghese, G., Shdefat, A., Topcu, A. E., Abdelbaki, W., Mathew, S., & Zaki, C. (2022). Artificial intelligence technology in the agricultural sector: A systematic literature review. *IEEE Access*, *11*, 171–202. https://doi.org/10.1109/access.2022.3232485

Gambhire, A., & Mohammad, B. N. S. (2020). Use of artificial intelligence in agriculture. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3571733

Gardezi, M., Joshi, B., Rizzo, D. M., Ryan, M., Prutzer, E., Brugler, S., & Dadkhah, A. (2023). Artificial intelligence in farming: Challenges and opportunities for building trust. *Agronomy Journal*, *116(3),* 1217–1228. https://doi.org/10.1002/agj2.21353

Goap, A., Sharma, D., Shukla, A., & Krishna, C. R. (2018). An IoT-based smart irrigation management system using machine learning and open-source technologies. *Computers and Electronics in Agriculture*, *155*, 41–49. https://doi.org/10.1016/j.compag.2018.09.040

Jarroudi, M. E., Kouadio, L., Delfosse, P., Bock, C. H., Mahlein, A., Fettweis, X., Mercatoris, B., Adams, F., Lenné, J. M., & Hamdioui, S. (2024). Leveraging edge artificial intelligence for sustainable agriculture. *Nature Sustainability*, *7(7),* 846–854. https://doi.org/10.1038/s41893-024-01352-4

Liu, S. Y. (2020). Artificial intelligence (AI) in agriculture. *IT Professional*, *22(3),* 14–15. https://doi.org/10.1109/mitp.2020.2986121

Schaefer, L. (2023). An emerging era of artificial intelligence research in agriculture. *Journal of Robotics Spectrum, 36–46.* https://doi.org/10.53759/9852/jrs202301004

Storm, H., Seidel, S. J., Klingbeil, L., Ewert, F., Vereecken, H., Amelung, W., Behnke, S., Bennewitz, M., Börner, J., Döring, T., Gall, J., Mahlein, A., McCool, C., Rascher, U., Wrobel, S., Schnepf, A., Stachniss, C., & Kuhlmann, H. (2024). Research priorities to leverage smart digital technologies for sustainable crop production. *European Journal of Agronomy*, *156*, 127178. https://doi.org/10.1016/j.eja.2024.127178