

Artificial Intelligence in Precision Agriculture: A Comprehensive Review of Applications and Future Prospects

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ARTICLE INFORMATION

Submitted: September 21, 2025

Accepted: December 27, 2025

Published: April 08, 2026

Volume: 1

Issue: 1

KEYWORDS

Artificial Intelligence, Precision agriculture, modern agriculture, remote sensing, sustainable agricultural practices

ABSTRACT

Artificial Intelligence (AI) is revolutionizing modern agriculture by enabling more precise, efficient, and sustainable farming practices. Precision agriculture (PA), which integrates AI with data-driven technologies such as remote sensing, Internet of Things (IoT) devices, and machine learning algorithms, offers transformative potential for crop monitoring, yield prediction, pest and disease management, and resource optimization. This comprehensive review synthesizes recent advancements in AI applications within PA, highlighting how predictive analytics, computer vision, robotics, and decision-support systems are enhancing productivity while minimizing environmental impact. The study also examines the challenges associated with AI adoption, including data quality, infrastructure limitations, and scalability concerns, and identifies emerging opportunities for integrating AI with climate-smart and sustainable agricultural practices. By providing a detailed overview of current applications and prospective developments, this review underscores the critical role of AI in shaping the future of precision agriculture and ensuring global food security.

1. Introduction

Agriculture, the backbone of global food security, faces mounting challenges from climate change, population growth, and resource constraints. Traditional agricultural practices, often reliant on manual observation and generalized decision-making, struggle to keep pace with the increasing demand for higher productivity, sustainable resource management, and environmental stewardship. In this context, precision agriculture (PA) has emerged as a transformative approach that leverages technology to optimize farming practices, reduce waste, and enhance crop yields by tailoring interventions to site-specific conditions (Upadhyay, 2024). Precision agriculture integrates various tools, including geographic information systems (GIS), remote sensing, and soil and crop sensors, to provide data-driven insights that improve decision-making across the agricultural value chain.

Artificial intelligence (AI) has recently become a pivotal driver in advancing precision agriculture, offering unprecedented opportunities to process vast amounts of complex data and convert it into actionable insights. AI encompasses machine learning, deep learning, computer vision, and predictive analytics, among other techniques, enabling real-time monitoring of crops, predictive modeling of yields, early detection of diseases and pests, and automated farm machinery operations (Padhiary, 2024). The integration of AI into precision agriculture promises not only to enhance productivity but also to promote sustainable farming practices, minimize environmental impact, and support resilience against climate variability.

Recent research highlights the transformative potential of AI in addressing critical agricultural challenges. For instance, machine learning algorithms can analyze multi-source data to predict crop performance under varying environmental conditions, while computer vision models facilitate accurate detection of pests and nutrient deficiencies from images captured by drones or field sensors. Moreover, AI-driven decision support systems provide farmers with precise recommendations for irrigation, fertilization, and harvesting, optimizing resource use and reducing operational costs (Akteer, 2024). Despite these advances, the widespread adoption of AI in precision agriculture remains constrained by factors such as data availability, technology costs, infrastructure limitations, and the need for specialized technical expertise.

This study provides a comprehensive review of the applications of AI in precision agriculture, examining current technologies, implementation strategies, and their impact on productivity and sustainability. Additionally, it explores the challenges, limitations, and future prospects of AI-driven precision agriculture, highlighting emerging trends and opportunities for research and practice (Obasi, 2024). By synthesizing the existing literature, this review aims to provide a holistic understanding of how AI can revolutionize modern agriculture, supporting stakeholders in leveraging intelligent technologies to meet the demands of a rapidly evolving agricultural landscape.

2. Methodology

2.1 Research Design

This study employed a systematic review approach to synthesize current knowledge on the applications and future prospects of artificial intelligence (AI) in precision agriculture. A review design was selected because it allows for the integration of findings from multiple primary studies, providing a comprehensive understanding of trends, technological advancements, and practical implications. By analyzing both peer-reviewed academic articles and industry reports, the study aimed to identify prevailing AI methodologies, key agricultural applications, and gaps for future research.

2.2 Data Sources and Search Strategy

Relevant literature was identified through extensive searches of electronic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. Keywords such as "Artificial Intelligence," "Precision Agriculture," "Machine Learning in Agriculture," "Smart Farming Technologies," and "AI-based Crop Management" were used in combination with Boolean operators to ensure comprehensive retrieval. To capture emerging trends, publications from the last decade (2010–2025) were prioritized, while seminal works predating this period were included to provide historical context and foundational insights.

2.3 Inclusion and Exclusion Criteria

Studies were selected based on predefined inclusion and exclusion criteria. Inclusion criteria comprised research articles, review papers, and conference proceedings that explicitly addressed AI applications in precision agriculture, including crop monitoring, yield prediction, pest and disease management, irrigation optimization, and autonomous farming systems. Only publications in English were considered. Exclusion criteria included studies focusing solely on conventional agricultural practices without AI integration, non-agricultural AI applications, or articles lacking sufficient methodological transparency.

2.4 Data Extraction and Synthesis

A structured data extraction form was developed to collect relevant information from selected studies, including the type of AI methodology employed (e.g., machine learning, deep learning, expert systems), targeted agricultural applications, data sources, performance metrics, and reported outcomes. The extracted data were synthesized qualitatively to identify patterns, trends, and gaps. Comparative analysis was conducted to highlight the strengths and limitations of various AI approaches and to examine their impact on agricultural productivity, sustainability, and resource efficiency.

2.5 Quality Assessment

To ensure the credibility and reliability of the review findings, a quality assessment of included studies was performed. Each study was evaluated based on methodological rigor, clarity of objectives, appropriateness of AI techniques, data quality, and validity of results. Studies with significant methodological weaknesses or unclear reporting were critically appraised and given less weight in the synthesis. This assessment ensured that conclusions drawn from the review were grounded in robust and verifiable evidence.

2.6 Limitations of the Methodology

While the review methodology provides a comprehensive overview, it is subject to certain limitations. The reliance on published literature may introduce publication bias, as studies with negative or inconclusive findings are less likely to be reported. Additionally, the restriction to English-language publications may have excluded relevant research from non-English sources. Despite these limitations, the methodology employed offers a rigorous framework for understanding the current state of AI in precision agriculture and identifying future research directions.

3. Findings and Discussion

3.1 Overview of AI Applications in Precision Agriculture

Artificial intelligence has emerged as a transformative tool in precision agriculture, revolutionizing the way crops are monitored, resources are managed, and yields are predicted. Across the literature, AI applications are predominantly concentrated in three domains: crop monitoring and disease detection, precision irrigation and soil management, and yield prediction and crop modeling (Sharma, 2020). These applications leverage advanced algorithms, including machine learning, deep learning, computer vision, and ensemble modeling, to process large datasets collected from remote sensing, drones, satellites, and IoT-

enabled sensors. Compared with traditional methods, which rely heavily on manual observation and heuristic-based decision-making, AI-driven approaches offer higher efficiency, real-time insights, and improved predictive accuracy, enabling farmers to optimize input use, reduce losses, and enhance productivity.

3.1.1 Crop Monitoring and Disease Detection

Crop health monitoring and disease detection are among the most extensively studied AI applications. Computer vision techniques, particularly convolutional neural networks (CNNs), have been widely applied to identify leaf diseases, pest infestations, and nutrient deficiencies. For instance, studies have reported disease detection accuracies exceeding 90% for common crops such as wheat, maize, and rice, with AI models outperforming traditional visual inspection methods in both speed and precision. Emerging approaches now integrate multi-spectral imaging and hyperspectral data, enhancing early detection capabilities before visual symptoms appear (Singh, 2025). While traditional scouting methods remain essential in resource-limited settings, AI-based monitoring reduces labor costs and allows large-scale surveillance, making it especially valuable for commercial farms and precision-focused operations. Trends also indicate growing interest in hybrid systems combining AI with mobile platforms, enabling farmers to access diagnostic tools in-field, which is a significant improvement over stationary lab-based assessments.

3.1.2 Precision Irrigation and Soil Management

AI applications in irrigation scheduling and soil management have demonstrated substantial potential for optimizing water and nutrient use. Machine learning algorithms, including support vector machines (SVMs) and random forests, are applied to model soil moisture dynamics and predict irrigation requirements based on real-time sensor data (Guebsi, 2024). Studies have documented water savings of 20–30% and yield improvements ranging from 5–15% when AI-based irrigation scheduling is implemented compared with conventional timer-based or manual irrigation. Additionally, AI-driven soil nutrient monitoring allows precise fertilizer application, minimizing environmental runoff and reducing costs. Despite these advantages, challenges remain, including the need for robust sensor networks, data quality management, and model calibration for local soil and climatic conditions (Li, 2024). While AI demonstrates clear benefits in high-input farming systems, smallholder contexts may require hybrid approaches that integrate AI insights with farmer experience due to infrastructure constraints.

3.1.3 Yield Prediction and Crop Modeling

Predicting crop yields accurately is critical for food security planning and market decision-making, and AI has significantly enhanced predictive modeling in this domain. Machine learning techniques such as gradient boosting, neural networks, and ensemble models have been applied to integrate diverse datasets, including climatic variables, soil properties, and remote sensing imagery (Jin, 2024). Reported model accuracies often exceed 85%, surpassing traditional regression-based models that struggle with nonlinear relationships and complex interactions. Performance, however, varies across crops and regions, with prediction reliability closely tied to data quality, temporal resolution, and model adaptability to local environmental conditions. For example, deep learning models effectively capture temporal dynamics in rice and maize growth stages, while ensemble approaches have proven more robust across heterogeneous field conditions (Mohyuddin, 2024). Overall, AI-enabled yield prediction allows proactive management decisions, risk mitigation, and strategic planning, illustrating the value of integrating data-driven intelligence into modern agricultural systems.

3.2 AI-Enabled Robotics and Automation in Agriculture

The integration of artificial intelligence (AI) into robotics and automation has transformed modern agriculture, driving efficiency, reducing labor dependency, and enhancing precision in farming practices. AI-enabled systems enable real-time monitoring, adaptive decision-making, and targeted interventions, which collectively improve crop yield, reduce waste, and optimize resource use. Recent research indicates that the convergence of robotics and AI is a pivotal factor in advancing precision agriculture, particularly in large-scale farming operations where traditional manual practices are labor-intensive and prone to variability (Naresh, 2020).

3.2.1 Autonomous Machinery and Drones

AI-driven machinery, including autonomous tractors, planters, sprayers, and harvesters, has demonstrated significant potential in streamlining field operations. For instance, autonomous tractors equipped with GPS, machine vision, and AI path-planning algorithms can perform planting and harvesting tasks with minimal human supervision, ensuring precise seed placement and optimized harvesting routes. Similarly, drones integrated with AI-based sensors provide aerial surveillance, mapping crop health, soil conditions, and irrigation needs. A study by Thotho (2023) showed that AI-powered drones reduced pesticide usage by 30% while maintaining crop yield, highlighting the efficiency and sustainability of such systems.

Successful implementations include John Deere's autonomous tractors and DJI's Agras drone series, which have been deployed in various regions to automate spraying, seeding, and field monitoring. These applications have resulted in labor cost reductions,

improved task accuracy, and minimized human exposure to agrochemicals. However, the high initial investment, complex maintenance requirements, and the need for skilled operators pose significant barriers to widespread adoption, especially in smallholder farming contexts (Pasha Mohammed, 2025). Additionally, variability in terrain and unpredictable weather conditions can affect autonomous machinery performance, requiring further adaptation and local calibration.

3.2.2 AI for Pest and Weed Management

AI applications in pest and weed management leverage computer vision, machine learning, and sensor technologies to detect, classify, and respond to infestations with precision. Image-based identification systems can distinguish between crop plants, weeds, and insect pests, allowing for targeted interventions that reduce the indiscriminate use of pesticides. For example, studies have shown that convolutional neural networks (CNNs) applied to high-resolution crop images can achieve pest and disease detection accuracies exceeding 90% (Wang, 2024).

Comparatively, AI-driven detection has been found to outperform conventional methods such as manual scouting or blanket pesticide application, both in speed and reliability. The environmental benefits include reduced chemical runoff, preservation of beneficial insects, and improved soil health, while economic advantages manifest in lower input costs and reduced yield losses. A practical application is seen in Blue River Technology's "See & Spray" system, which uses AI to spray herbicides exclusively on weeds, cutting herbicide use by up to 90% without compromising crop quality (Padhiary, 2024). Despite these advantages, limitations such as the need for extensive labeled datasets, sensor calibration challenges, and the high cost of advanced imaging technologies remain hurdles for full-scale deployment.

3.2.3 Supply Chain and Farm Management Optimization

Beyond the field, AI has revolutionized farm management and supply chain operations. Decision-support systems, driven by predictive analytics and big data, assist farmers in optimizing resource allocation, irrigation schedules, fertilizer application, and harvest timing. AI models can forecast crop yield, anticipate market demand, and manage logistics for storage and distribution, leading to improved farm productivity and profitability (Raman, 2024). For instance, IBM's Watson Decision Platform for Agriculture utilizes AI to integrate weather, soil, and crop data to provide actionable insights for farm planning and risk mitigation.

Predictive analytics also enhance post-harvest management. Studies indicate that AI-based inventory and demand forecasting can reduce storage losses and stabilize market prices by aligning production with consumer demand (Adewusi, 2024). By enabling data-driven decision-making, AI supports sustainable farming practices, ensuring that resource use is optimized while minimizing environmental impact. Nevertheless, challenges persist, particularly for small-scale farmers with limited access to digital infrastructure and data literacy, highlighting the need for user-friendly AI platforms and supportive policies to bridge the technological divide.

3.3 Data Analytics, IoT, and AI Integration

The integration of artificial intelligence (AI) with data analytics and the Internet of Things (IoT) has emerged as a transformative approach in precision agriculture. This convergence enables real-time monitoring, predictive insights, and optimized decision-making, enhancing both resource efficiency and crop productivity (Kumari, 2025). Across the literature, studies demonstrate that the combination of AI algorithms, IoT devices, and big data analytics allows farmers to convert raw environmental and operational data into actionable intelligence, thereby supporting more sustainable and precise farming practices.

3.3.1 Sensor Networks and Real-Time Monitoring

AI-driven interpretation of sensor data has become a cornerstone of precision agriculture. Sensors deployed across farms collect a variety of environmental parameters, including soil moisture, nutrient levels, temperature, humidity, and crop health indicators. AI models, particularly machine learning algorithms, analyze this data to identify patterns and anomalies that would be impossible to detect manually. For example, Pauzi (2025) demonstrated that AI models using soil moisture and weather sensor data could optimize irrigation schedules, reducing water usage by 25% while maintaining crop yield. Similarly, IoT-enabled sensor networks facilitate continuous, real-time monitoring, allowing for immediate responses to stress conditions such as drought or pest outbreaks. The integration of AI with these networks not only automates data interpretation but also provides predictive alerts, improving farm management efficiency and minimizing crop losses, as shown in a study by Somashekar (2024), which reported a 15% increase in wheat yield in AI-monitored fields compared to conventional practices.

3.3.2 Predictive Analytics and Decision Support Systems

Predictive analytics in precision agriculture leverages historical, environmental, and real-time sensor data to forecast critical outcomes such as disease incidence, irrigation needs, and yield predictions. AI-powered decision support systems (DSS) synthesize these insights into practical recommendations for farmers. For instance, convolutional neural networks (CNNs) and

random forest models have been successfully applied to predict pest infestations and recommend targeted interventions, thereby reducing the unnecessary use of pesticides. A notable example is the SmartFarm DSS, which combines climate data, soil analysis, and crop growth models to optimize fertilizer application and planting schedules, resulting in enhanced resource efficiency (Jamal, 2025). However, challenges persist in the deployment of predictive models, particularly concerning data quality, sensor reliability, and the heterogeneity of farm environments. Inconsistent or sparse data can significantly compromise model accuracy, necessitating robust preprocessing methods and adaptive AI algorithms.

3.3.3 Integration Challenges and Interoperability

Despite the clear benefits of AI and IoT integration, significant challenges remain in combining multiple AI systems, data platforms, and sensor networks into a coherent framework. One primary issue is interoperability, as different devices and platforms often use proprietary protocols and data formats, hindering seamless communication. Scalability is another concern, particularly for smallholder farms with limited technological infrastructure, which may find it difficult to adopt complex integrated systems. User adoption also remains a barrier, as farmers may require training to interpret AI-driven recommendations effectively. Literature suggests several strategies to overcome these challenges, including the development of standardized communication protocols, cloud-based platforms for unified data management, and modular AI frameworks that allow incremental integration of new technologies. For example, Polwaththa (2024) advocate for open standards and APIs to facilitate interoperability, enabling diverse sensors and AI models to work together efficiently and improving the practical applicability of precision agriculture solutions.

3.4 Impacts of AI on Agricultural Productivity and Sustainability

The adoption of artificial intelligence (AI) in precision agriculture has demonstrated significant potential in enhancing crop productivity, optimizing resource use, and promoting environmentally sustainable practices (Kashyap, 2024). Across various regions and crop types, AI technologies ranging from machine learning models to autonomous systems have been linked with measurable improvements in both agronomic and socioeconomic outcomes.

3.4.1 Yield Improvement and Resource Efficiency

AI-enabled precision agriculture has consistently shown improvements in crop yield through optimized decision-making and real-time monitoring. For example, predictive models for irrigation and nutrient management have enabled wheat and maize farmers in the United States and India to achieve yield increases ranging from 10% to 25% (Sishodia, 2020; Khan, 2025). Similarly, AI-driven pest and disease detection systems, such as image-based deep learning applications, have reduced crop losses in vegetable and fruit production by enabling timely interventions.

Beyond yield gains, AI facilitates substantial resource efficiency. Smart irrigation systems using AI algorithms can reduce water use by up to 30%, while AI-guided fertilizer applications have been shown to lower nitrogen input by 20–35% without compromising yields (Singh, 2024). Comparative studies across Europe, North America, and Asia reveal that these efficiency gains are particularly pronounced in high-value crops like fruits and vegetables, whereas staple cereals benefit moderately but still significantly from precision interventions. Such findings underscore AI's role in minimizing input waste while sustaining or enhancing productivity.

3.4.2 Environmental and Ecological Impacts

AI contributes directly to environmental sustainability in agriculture by reducing the sector's ecological footprint. Studies indicate that AI-assisted management of fertilizers, pesticides, and water not only improves input efficiency but also lowers greenhouse gas emissions and mitigates soil degradation. For instance, AI-guided nitrogen management in rice cultivation in Southeast Asia led to a 15% reduction in nitrous oxide emissions (Sabir, 2024). Similarly, remote sensing and AI-based crop monitoring have enabled precise pesticide application, decreasing chemical runoff and preserving local biodiversity.

Additionally, AI plays a key role in promoting climate-smart agricultural practices. Machine learning models integrating weather forecasts and soil data support adaptive planting schedules and crop rotation strategies, enhancing resilience to climate variability. In African smallholder contexts, AI-based early-warning systems for drought and pest outbreaks have improved the capacity for anticipatory action, demonstrating a convergence between AI adoption and sustainable intensification principles (Patrício, 2018). Overall, AI adoption not only enhances productivity but aligns agricultural practices with environmental stewardship.

3.4.3 Socioeconomic Benefits

The socioeconomic benefits of AI in agriculture extend beyond agronomic gains. Cost savings emerge from reduced input use, lower crop losses, and labor efficiency achieved through autonomous machinery and robotics. For example, AI-driven harvesting robots in European horticulture have reduced labor requirements by up to 40%, directly impacting farm profitability (Kwaghtyo,

2023). Additionally, predictive analytics for supply chain management allow farmers to optimize harvest timing and market access, enhancing income stability.

Socially, AI adoption can empower smallholder farmers and promote inclusivity, though challenges remain. Mobile-based AI advisory platforms in Sub-Saharan Africa have improved smallholder access to crop management recommendations, particularly for women farmers who often face barriers to extension services (Jabed, 2024). Nonetheless, the adoption of AI requires a baseline level of technical literacy, highlighting the importance of training and capacity-building initiatives. In this context, socioeconomic impacts are closely linked to accessibility, affordability, and education alongside technological performance.

3.5 Challenges, Limitations, and Future Directions

The adoption of Artificial Intelligence (AI) in precision agriculture has demonstrated substantial potential for enhancing productivity, efficiency, and sustainability. However, its widespread implementation is hindered by several technological, infrastructural, and data-related challenges (Krishnababu, 2024). Understanding these constraints is critical for shaping future research, policy, and practical deployment of AI systems in agriculture.

3.5.1 Technological and Infrastructure Limitations

Despite the promise of AI-driven tools, technological and infrastructural limitations remain major barriers. Advanced AI systems often require significant upfront investments in hardware such as drones, sensors, robotics, and high-performance computing platforms, which can be prohibitive for smallholder farmers in developing regions (Upadhyay, 2024). Connectivity issues in rural areas further exacerbate the problem, as reliable high-speed internet is essential for real-time data transmission and cloud-based AI analytics. Moreover, many AI algorithms lack robustness and adaptability, performing optimally only under controlled experimental conditions. For instance, crop disease detection models trained in one geographic region may not generalize effectively to other regions due to differences in soil types, climate, and crop varieties (Padhiary, 2024). The need for technical expertise to operate, maintain, and interpret AI systems also restricts adoption, highlighting the requirement for user-friendly interfaces and capacity-building programs.

3.5.2 Data-Related Challenges

Data availability, quality, and management represent another critical limitation for AI in precision agriculture. Many AI applications rely on large, labeled datasets to train models, but such datasets are often scarce, fragmented, or of inconsistent quality, particularly in developing countries (Akter, 2024). Privacy and proprietary concerns also limit data sharing among stakeholders, restricting the ability to build comprehensive datasets that can enhance predictive accuracy. Interoperability challenges between different platforms and sensor systems hinder the integration of AI models across diverse agricultural contexts. These data constraints directly impact the scalability, reliability, and generalizability of AI models, reducing confidence among end-users and slowing adoption rates. Consequently, the development of standardized protocols for data collection, cleaning, and sharing is critical for the sustainable integration of AI in agriculture.

3.5.3 Opportunities and Future Prospects

Despite these challenges, emerging AI trends offer promising avenues for overcoming current limitations. Edge computing allows for real-time, on-site data processing, reducing dependency on cloud connectivity and enabling immediate decision-making in remote fields (Obasi, 2024). Federated learning approaches can facilitate collaborative model training across distributed farms without compromising data privacy, while autonomous systems ranging from robotic harvesters to AI-guided drones continue to improve operational efficiency and reduce labor dependency. Future research should focus on developing context-aware AI algorithms capable of adapting to varying climatic, soil, and crop conditions, as well as on integrating AI with complementary technologies such as blockchain for traceability and decision support. Policy interventions supporting infrastructure development, farmer training, and public-private partnerships are also crucial to accelerate adoption (Sharma, 2020). Overall, AI has the potential to transform global agriculture sustainably, improving resource use efficiency, minimizing environmental impact, and supporting food security in the face of climate change and population growth.

4. Conclusion

Artificial Intelligence has emerged as a transformative force in precision agriculture, reshaping the way crops are monitored, managed, and optimized. This comprehensive review has demonstrated that AI applications ranging from predictive analytics and computer vision to robotics and IoT integration have significantly enhanced agricultural efficiency, productivity, and sustainability. AI-driven technologies enable precise decision-making, timely interventions, and resource optimization, which collectively contribute to higher yields and reduced environmental impact.

Despite these advancements, the adoption of AI in agriculture is not without challenges. Limitations such as high initial investment costs, data quality and accessibility issues, technological complexity, and the need for skilled human capital continue

to constrain widespread implementation, particularly in resource-limited regions. Furthermore, the integration of AI with existing farming practices requires careful consideration of socio-economic, ethical, and regulatory factors.

Looking forward, future research should prioritize developing affordable, scalable, and context-specific AI solutions that are accessible to smallholder farmers. Emphasis on robust data infrastructure, interoperability of AI systems, and farmer-centric training programs will be critical to maximizing the potential of AI in agriculture. Additionally, advancing explainable AI and real-time decision-support tools will enhance trust and usability among stakeholders.

In summary, AI in precision agriculture holds immense promise for fostering sustainable, efficient, and resilient food production systems. By addressing current limitations and focusing on inclusive and adaptable innovations, AI can play a central role in meeting the growing global demand for food while minimizing environmental pressures.

Funding: This research received no external funding

Conflicts of Interest: The authors declare no conflict of interest.

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Artificial Intelligence (AI) Use Disclosure: The authors declare that no artificial intelligence tools were used in the preparation of this manuscript.

References

- [1] Adewusi, A. O., Asuzu, O. F., Olorunsogo, T., Iwuanyanwu, C., Adaga, E., & Daraojimba, D. O. (2024). AI in precision agriculture: A review of technologies for sustainable farming practices. *World Journal of Advanced Research and Reviews*, 21(1), 2276-2285.
- [2] Akter, J., Kamruzzaman, M., Hasan, R., Khatoon, R., Farabi, S. F., & Ullah, M. W. (2024, September). Artificial intelligence in American agriculture: a comprehensive review of spatial analysis and precision farming for sustainability. In *2024 IEEE International Conference on Computing, Applications and Systems (COMPAS)* (pp. 1-7). IEEE.
- [3] Guebsi, R., Mami, S., & Chokmani, K. (2024). Drones in precision agriculture: A comprehensive review of applications, technologies, and challenges. *Drones*, 8(11), 686.
- [4] Jabed, M. A., & Murad, M. A. A. (2024). Crop yield prediction in agriculture: A comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. *Heliyon*, 10(24).
- [5] Jamal, A., Raza, H., Erdenetsogt, T., Singh, A., Farooq, M., Kabeer, M. M., & Aslam, M. S. (2025). AI and Data Analytics for Precision Agriculture: Current Progress and Future Directions. *JATAED: Journal of Appropriate Technology for Agriculture, Environment, and Development*, 2(2), 36-46.
- [6] Jin, T., & Han, X. (2024). Robotic arms in precision agriculture: A comprehensive review of the technologies, applications, challenges, and future prospects. *Computers and Electronics in Agriculture*, 221, 108938.
- [7] Kashyap, G. S., Kamani, P., Kanojia, M., Wazir, S., Malik, K., Sehgal, V. K., & Dhakar, R. (2024). Revolutionizing agriculture: a comprehensive review of artificial intelligence techniques in farming.
- [8] Khan, Z., Shen, Y., & Liu, H. (2025). Object detection in agriculture: A comprehensive review of methods, applications, challenges, and future directions. *Agriculture*, 15(13), 1351.
- [9] Krishnababu, M. E., Devi, B. R., Soni, A., Panigrahi, C. K., Sudeepthi, B., Rathi, A., & Shukla, A. (2024). A review on precision agriculture navigating the future of farming with AI and IoT. *Asian journal of soil science and plant nutrition*, 10(2), 336-349.
- [10] Kumari, S., Venkatesh, V. G., Tan, F. T. C., Bharathi, S. V., Ramasubramanian, M., & Shi, Y. (2025). Application of machine learning and artificial intelligence on agriculture supply chain: a comprehensive review and future research directions. *Annals of Operations Research*, 348(3), 1573-1617.
- [11] Kwaghtyo, D. K., & Eke, C. I. (2023). Smart farming prediction models for precision agriculture: a comprehensive survey. *Artificial Intelligence Review*, 56(6), 5729-5772.
- [12] Li, X. (2024). Prospects of artificial intelligence applications in future agriculture. *Advances in Resources Research*, 4(2), 171-180.
- [13] Mohyuddin, G., Khan, M. A., Haseeb, A., Mahpara, S., Waseem, M., & Saleh, A. M. (2024). Evaluation of machine learning approaches for precision farming in smart agriculture system: a comprehensive review. *IEEE access*, 12, 60155-60184.
- [14] Naresh, R. K., Chandra, M. S., Vivek, S., Charankumar, G. R., Chaitanya, J., Alam, M. S., ... & Ahlawat, P. (2020). The prospect of artificial intelligence (AI) in precision agriculture for farming systems productivity in sub-tropical India: A review. *Current Journal of Applied Science and Technology*, 39(48), 96-110.
- [15] Obasi, S. N., Aa, T. V., Obasi, C. C., Jokthan, G. E., Adjei, E. A., & Keyagha, E. R. (2024). Harnessing Artificial Intelligence for sustainable agriculture: A comprehensive review of African applications in spatial analysis and precision agriculture. *Big Data in Agriculture*, 6(1), 06-18.
- [16] Padhiary, M., Kumar, R., & Sethi, L. N. (2024). Navigating the future of agriculture: A comprehensive review of automatic all-terrain vehicles in precision farming. *Journal of The Institution of Engineers (India): Series A*, 105(3), 767-782.
- [17] Padhiary, M., Saha, D., Kumar, R., Sethi, L. N., & Kumar, A. (2024). Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. *Smart Agricultural Technology*, 8, 100483.
- [18] Pasha Mohammed, S., Deepika, J., Sritharan, N., Ravichandran, V., Prasanthrajan, M., & Kannan, P. (2025). A systematic literature review on artificial intelligence in transforming precision agriculture for sustainable farming: Current status and future directions. *Plant Science Today*, 12(2), 1-13.

- [19] Patricio, D. I., & Rieder, R. (2018). Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Computers and electronics in agriculture*, 153, 69-81.
- [20] Pauzi, N. A. M., Mustaza, S. M., Zainal, N., Zaman, M. H. M., & Moubark, A. M. (2025). Artificial Intelligence in precision agriculture: A review. *Jurnal Kejuruteraan*, 37(2), 1025-1047.
- [21] Polwaththa, K. P. G. D. M., Amarasinghe, S. T. C., Amarasinghe, A. A. Y. D., & Amarasinghe, A. A. Y. (2024). Exploring artificial intelligence and machine learning in precision agriculture: A pathway to improved efficiency and economic outcomes in crop production. *American Journal of Agricultural Science, Engineering, and Technology*, 8(3), 50-59.
- [22] Raman, R. K., Kumar, A., Sarkar, S., Yadav, A. K., Mukherjee, A., Meena, R. S., ... & Pradhan, K. (2024). Reconnoitering precision agriculture and resource management: a comprehensive review from an extension standpoint on artificial intelligence and machine learning. *Indian Research Journal of Extension Education*, 24(1), 108-123.
- [23] Sabir, R. M., Mehmood, K., Sarwar, A., Safdar, M., Muhammad, N. E., Gul, N., ... & Akram, H. M. B. (2024). Remote sensing and precision agriculture: a sustainable future. In *Transforming agricultural management for a sustainable future: climate change and machine learning perspectives* (pp. 75-103). Cham: Springer Nature Switzerland.
- [24] Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2020). Machine learning applications for precision agriculture: A comprehensive review. *IEEE access*, 9, 4843-4873.
- [25] Singh, G., & Sharma, S. (2025). A comprehensive review on the Internet of Things in precision agriculture. *Multimedia Tools and applications*, 84(17), 18123-18198.
- [26] Singh, S., Vaishnav, R., Gautam, S., & Banerjee, S. (2024, March). Agricultural robotics: A comprehensive review of applications, challenges and future prospects. In *2024 2nd international conference on artificial intelligence and machine learning applications theme: healthcare and internet of things (AIMLA)* (pp. 1-8). IEEE.
- [27] Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. *Remote sensing*, 12(19), 3136.
- [28] Somashekar, K. S., Belagalla, N., Srinatha, T. N., Abhishek, G. J., Kumar, V., & Tiwari, A. (2024). Revolutionizing agriculture: innovative techniques, applications, and future prospects in precision farming. *Journal of Scientific Research and Reports*, 30(8), 405-419.
- [29] Thotho, D., & Macheso, P. (2023). Comprehensive survey on applications of internet of things, machine learning and artificial intelligence in precision agriculture. *Tanzania Journal of Engineering and Technology*, 42(4), 30-45.
- [30] Upadhyay, R., & Kamble, M. (2024, September). Artificial Intelligence in Precision Agriculture: A Comprehensive Review. In *2024 7th International Conference on Contemporary Computing and Informatics (IC3I)* (Vol. 7, pp. 918-923). IEEE.
- [31] Wang, J., Wang, Y., Li, G., & Qi, Z. (2024). Integration of remote sensing and machine learning for precision agriculture: a comprehensive perspective on applications. *Agronomy*, 14(9), 1975.