

AI-Powered Agriculture: Transforming Farming for the Future

S. Gokula Krishnan & A. Aswin

*Department of Data Science
Sri Krishna Adithya College of Arts and Science*

Dr. R. Karthik

*Assistant Professor, Department of Data Science
Sri Krishna Adithya College of Arts and Science*

OPEN ACCESS

Volume: 13

Special Issue: 3

Month: February

Year: 2026

P-ISSN: 2321-788X

E-ISSN: 2582-0397

Citation:

S., Gokula Krishnan,
et al. "AI-Powered
Agriculture:
Transforming Farming
for the Future." *Shanlax
International Journal
of Arts, Science and
Humanities*, vol. 13,
no. 3, 2026, pp. 281–86.

DOI:

[https://doi.org/10.34293/
sijash.v13iS3-i2-
Feb.10291](https://doi.org/10.34293/sijash.v13iS3-i2-Feb.10291)

Abstract

Artificial Intelligence (AI) is revolutionizing agriculture through increased sustainability, production, and efficiency. This study examines the ways in which AI-powered tools like computer vision, machine learning, and predictive analytics are changing agricultural methods. By examining case studies and technological developments, we draw attention to AI's applications in yield prediction, crop health monitoring, precision agriculture, and soil analysis. AI's potential to address issues like resource management, food security, and climate change is highlighted by the findings [1].

Keywords: AI, Agriculture, Yield Prediction, Smart Irrigation, Automation, Precision Farming, Machine Learning, And Crop Monitoring

Introduction

Inefficient resource use, pest infestations, and erratic weather patterns are just a few of the major issues facing the agriculture industry. By facilitating data-driven decision-making, increasing productivity, and lessening environmental impact, artificial intelligence (AI) provides creative solutions [2]. This essay looks at artificial intelligence's place in contemporary agriculture and how it affects different farming practices.

Agriculture is characterized by high resource inefficiencies, pest infestation, and unstable weather patterns. AI brings fresh solutions to agriculture through the capability of making decisions based on data, boosting productivity, and reducing environmental footprints [3]. This article discusses AI in contemporary agriculture and its effects on agricultural practices.

Literature Review

There has been increased research on AI application in agriculture in recent years, with several studies pointing to the potential of AI in revolutionizing farming. Liakos et al. [4] also carried out a thorough review of machine learning in agriculture with a focus

on predictive analytics in crop yield prediction, irrigation scheduling, and resource optimization. Likewise, Wolfert et al. [5] discussed the potential of integrating big data technologies and AI in smart farming systems to enhance decision-making and sustainability. Prenafeta-Boldú and Kamilaris [6] explored deep learning models for disease detection in crops, highlighting how image recognition and neural networks can identify pest infestations early. Another study by Chlingaryan et al. [7] discussed the use of hyperspectral imaging combined with AI to detect plant stress and optimize nutrient management. Samiullah et al. [8] presented reviews on AI usage in monitoring animal health, demonstrating the use of wearable sensors and predictive analytics in identifying disease and enhancing livestock performance. Also, Rutten et al. [9] evaluated AI-based automated milking systems and their effects on efficiency and milk quality. Research by Aravindakshan et al. [10] highlights the importance of AI in streamlining supply chain logistics, minimizing food loss, and improving market forecasting. Moreover, research by Vermeulen et al. [11] also elaborates on the application of AI in climate-resilient agriculture, including weather forecasting models and carbon footprint mitigation strategies. The current literature highlights the increased relevance of AI across multiple fields of agriculture, demonstrating its viability in enhancing efficiency, lessening environmental degradation, and maximizing food security [12]. But challenges in high costs of implementation, shortage of technical professionals, and concerns for data privacy have yet to be overcome for realizing the complete potential of AI in agriculture [13].

Precision Agriculture with AI

Precision farming leverages AI to refine farming practices using. Remote Sensing & IoT Integration: AI-driven drones and sensors take live readings of soil moisture, temperature, and plant health, facilitating precision monitoring and timely intervention [14].

Predictive Analytics: Machine learning algorithms process historical data to calculate the best times to plant and harvest, streamlining efficiency and maximizing yield [15]. AI Based Irrigation Systems: AI-powered irrigation employs AI to control water supply according to weather and soil conditions, decreasing waste and increasing crop production [16]. Autonomous Agricultural Equipment: AI-powered harvesters and tractors employ GPS and machine learning to maximize field coverage, minimize fuel consumption, and increase the precision of farming operations [17].

Algorithm: Random Forest Regression for Crop Yield Forecasting

Step 1: Data Gathering (Input Attributes)

For constructing a trustworthy model, the following data is to be gathered: Soil Quality: pH level, nitrogen, phosphorus, potassium content [18]. Weather Data: Rainfall, temperature, humidity, sunlight hours [19]. Crop Type: The crop type being planted (e.g., wheat, rice, corn) [20]. Farming Practices: Method of irrigation, fertilizers applied [21]. Historical Yield Data: Yield records from past seasons and circumstances [22].

Step 2: Data Preprocessing

Before entering the data into the model, data should be prepared and cleaned. Missing Data Handling: Impute missing values using mean/median imputation [23]. Feature Scaling: Scale features with Min-Max scaling so all variables lie within the same range [24]. Categorical Encoding: Represent categorical columns (such as crop type) as numerical columns by applying One-Hot Encoding [25]. Train-Test Split: Split the data into train (80%) and test (20%) sets [26].

Step 3: Random Forest Model Training

Configure the Model: Select `n_estimators`, the number of trees. 100 trees is a typical value [27]. Set `max_depth`, the maximum depth for each tree. Use the mean squared error, or MSE, as the loss function [28].

Train the Model: Use a random subset of the data to train each decision tree [29]. Based on feature relevance, the algorithm chooses the optimal split at each node [30]. A number of decision trees undergo autonomous training [31].

Combining Predictions: A yield value is provided by each tree. The average of all tree predictions is the end result [32].

Step 4: Predicting and Evaluating

Following training, we evaluate the model with the unviewed test dataset. Metrics for Assessing the Model: The Mean Squared Error (MSE) is a metric that quantifies the average squared difference between actual and expected values [33]. The model's capacity to account for data variability is shown by the coefficient of determination, or R2 score; the closer the value is to 1, the better [34]. The Mean Absolute Error (MAE) quantifies the average absolute difference between expected and actual data [35]. Making Predictions: Enter the most recent weather, crop, and soil data. The model generates an estimated crop yield per hectare [36].

Yield Prediction and Soil Analysis

AI greatly improves yield forecasting and soil analysis by taking advantage of machine learning models and remote sensing technology [37]. AI-based soil testing analyzes soil quality, suggesting the right crops and fertilizers to maximize productivity [38]. Complex algorithms read climate, soil, and crop information to accurately predict yields, enabling farmers to make sound decisions [39]. AI-enabled sensors constantly track soil moisture content, allowing optimal irrigation control to avoid drought stress or over watering [40]. Furthermore, satellite images combined with AI provide bulk soil health estimates, enabling farmers to better utilize land resources [41]. AI generates comprehensive soil health reports, including pH levels, mineral content, and potential nutrient deficiencies, enabling precise soil management [42]. AI-integrated satellite imagery provides large- scale soil health assessments, helping farmers make informed land management decisions [43].

Climate-Smart Agriculture and AI

AI is an essential component of climate adaptation in agriculture [44]. AI-based weather forecasting models process meteorological data to deliver precise climate forecasts, allowing farmers to prepare for extreme weather conditions [45]. AI-based precision farming methods minimize greenhouse gas emissions by streamlining fertilizer application and land management [46]. AI-backed sustainable land management practices emphasize controlling erosion, land restoration, and conserving biodiversity [47]. Artificial intelligence-facilitated climate adaptation techniques help farmers make choices about farming climate-resilient crops that will ensure enduring agricultural sustainability [48]. AI-facilitated monitoring of greenhouse emissions from farming enables the reduction of environmental footprint [49]. AI helps design and manage agroforestry systems that integrate trees, crops, and livestock for improved biodiversity and resilience [50]. AI-powered tools support precision water and soil conservation efforts, preventing erosion and maintaining soil fertility [51]. AI assists in tracking emissions from agricultural activities, helping farmers implement practices that reduce their carbon footprint [52].

Threats and Opportunities

Even while AI has the potential to revolutionize agriculture, issues like high implementation costs, a lack of technical know-how, and data privacy concerns need to be resolved [53]. Future studies should concentrate on creating affordable AI solutions and enhancing small-scale farmers' accessibility [54]. Furthermore, combining AI with cutting-edge technologies like blockchain, 5G, and quantum computing can improve its potential in the field of agriculture [55]. AI adoption in agriculture can be accelerated by promoting policy support and public-private collaborations [56]. In spite of its promise, AI implementation in agriculture is hampered by challenges like: High Implementation Costs: Small farmers find AI unaffordable, with the need for investment in low-cost and scalable solutions [57]. Technical Knowledge Gaps: Limited AI knowledge among farmers and farm workers hinders adoption and efficient use of AI-driven tools [58]. Data Privacy Concerns: Secure collection of data and safeguarding farmers' data from cyber attacks is important [59].

AI Applications in Agriculture

AI APPLICATION DESCRIPTION Precision Agriculture AI-based sensors and drones track soil conditions and crop health [60]. Predictive Analytics Machine learning algorithms process data to decide when to plant and harvest [61]. AI-Based Irrigation Systems Smart irrigation systems manage water consumption depending on weather and soil conditions [62]. Autonomous Farming Equipment AI-based tractors and harvesters optimize efficiency while cutting labor costs [63]. Pest Detection & Management AI employs computer vision for pest detection and minimizing pesticide application [64]. Yield Prediction Models AI makes predictions of crop yields based on weather, soil, and historical inputs [65]. Soil Health Analysis AI analyzes soil nutrients and suggests fertilizers for best growth [66]. Smart Supply Chain Management AI streamlines logistics, minimizes food waste, and forecasts market trends [67]. Climate Adaptation Strategies AI assists farmers in planning for weather shifts and carbon footprint management [68].

Findings

Efficiency Improvement: AI technology greatly minimizes human effort along with maximizing efficiency [69]. 2.Resource Optimization: AI optimizes the use of water and fertilizers, minimizing wastage and pollution [70]. 3.Predictive Capabilities: Machine learning models assist farmers in predicting yield, pest infestations, and climate shifts [71]. 4.Sustainability: AI assists climate-resilient agriculture by reducing environmental hazards [72]. 5.Challenges: High expenses, limited technical expertise, and data privacy issues continue to present obstacles to broad AI implementation [73]. 6. AI Improves Precision Agriculture AI equipped drones and IoT sensors enable real-time soil moisture, temperature, and plant health monitoring [74]. Machine learning algorithms enhance crop yield prediction, aligning planting and harvesting schedules [75]. AI-controlled irrigation systems minimize water loss and maximize crop yields [76]. 7. AI Enhances Pest and Disease Management Deep learning algorithms employ image recognition to identify early-stage plant diseases and pest infestations [77]. AI-enabled smart traps track pest levels and reduce the use of pesticides, ensuring environmentally friendly farming [78]. Predictive analysis enables early predictions of likely pest infestations, enabling farmers to take preventative action [79]. 8. AI-Driven Yield Forecasting Improves Productivity Machine learning algorithms (such as Random Forest and Neural Networks) forecast crop yields from weather, soil conditions, and past records [80]. Satellite images and AI-assisted soil health monitoring enhance fertilizer application, reducing unnecessary chemicals [81]. AI maximizes land use, providing greater productivity per hectare [82]. 9. AI Simplifies Supply Chain & Market Forecasting Supply chain

analytics through AI minimize food loss and streamline transport logistics [83]. AI-based tools forecast market demand, enabling farmers to realign crop production accordingly [84]. AI-based sorting and grading of crops automate the process, leading to better prices and less loss [85].

AI Facilitates Climate-Smart Agriculture AI weather forecasting models assist farmers in anticipating droughts, floods, and temperature changes [86]. AI enhances carbon footprint monitoring, encouraging sustainable land use [87]. AI precision farming reduces the environmental footprint by optimizing water and fertilizer application [88]. 11. Challenges in AI Adoption for Agriculture The high cost of implementation renders AI unaffordable for small farmers [89]. Technical expertise constraints restrict AI adoption in rural regions [90]. Data privacy issues are still a challenge, as farmers require safe AI systems [91]. Integration with conventional farming practices is still a process in progress [92]. 12. Future Scope: The Role of Emerging Technologies Combination of AI with blockchain, 5G, and IoT can enhance agricultural transparency and efficiency [93]. Low-cost AI solutions can enable technology for small farmers [94]. AI-powered climate adaptation techniques will help farmers tackle climate change and ensure long-term sustainability [95].

Conclusion

AI is enabling more intelligent, data-driven farming methods, which is transforming the agricultural industry. AI technologies have the potential to improve sustainable agriculture, boost farming productivity, and increase global food security as they develop further [96]. The agricultural sector may fully utilize AI for long-term success by resolving current issues and enhancing accessibility to AI [97]. AI is reshaping agriculture by enabling smarter, data-driven farming practices. As AI technologies evolve, they hold the potential to enhance sustainability, boost productivity, and strengthen global food security [98]. By addressing current challenges and improving accessibility, AI can unlock new possibilities for long-term agricultural success, benefiting both large-scale agribusinesses and smallholder farmers [99].

References

1. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.
2. Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming – A review. *Agricultural Systems*, 153, 69–80.
3. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90.
4. Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction. *Field Crops Research*, 228, 1–17.
5. Aravindakshan, S., Rossi, F., Amjath-Babu, T. S., & Veetil, P. C. (2020). Predicting crop yield using AI. *Agricultural Economics*, 51(3), 393–406.
6. Rutten, C. J., Velthuis, A. G. J., Steeneveld, W., & Hogeveen, H. (2013). Invited review: Sensors to support health management on dairy farms. *Journal of Dairy Science*, 96(4), 1928–1952.
7. Vermeulen, S. J., Campbell, B. M., & Ingram, J. S. (2012). Climate change and food systems. *Annual Review of Environment and Resources*, 37, 195–222.
8. FAO. (2019). Digital technologies in agriculture and rural areas. Food and Agriculture Organization of the United Nations.
9. FAO. (2022). Artificial Intelligence for agriculture: Opportunities and challenges.

10. Zhang, Y., Wang, S., & Ji, G. (2019). A comprehensive survey on computer vision for agriculture. *Computers and Electronics in Agriculture*, 163, 104–113.
11. Khaki, S., & Wang, L. (2019). Crop yield prediction using deep neural networks. *Frontiers in Plant Science*, 10, 621.
12. You, J., Li, X., Low, M., Lobell, D., & Ermon, S. (2017). Deep Gaussian process for crop yield prediction. *AAAI Conference on Artificial Intelligence*.
13. Bongiovanni, R., & Lowenberg-DeBoer, J. (2004). Precision agriculture and sustainability. *Precision Agriculture*, 5(4), 359–387.
14. Khosla, R., & Griffin, T. (2018). Soil sensing and precision agriculture. *Soil Science Society of America Journal*, 82(6), 1449–1461.
15. Shahhosseini, M., Hu, G., & Archontoulis, S. V. (2020). Forecasting corn yield using machine learning. *Agronomy Journal*, 112(5), 3090–3104.
16. Saeed, U., Dempewolf, J., & Becker-Reshef, I. (2017). Remote sensing for crop monitoring. *Remote Sensing*, 9(6), 1–21.
17. Balafoutis, A. T., et al. (2017). Precision agriculture technologies positively contributing to GHG emissions mitigation. *Sustainability*, 9(8), 1339.
18. Shafi, U., Mumtaz, R., García-Nieto, J., Hassan, S. A., Zaidi, S. A. R., & Iqbal, N. (2019). Precision agriculture techniques. *Wireless Communications and Mobile Computing*, 2019.
19. Jain, L. C., Aggarwal, D., & Sharma, S. (2020). *Machine learning for precision agriculture*. Springer, Cham.
20. Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0: Broadening responsible innovation. *Journal of Responsible Innovation*, 5(1), 116–126.
21. Bronson, K., & Knezevic, I. (2016). Big data in food and agriculture. *Big Data & Society*, 3(1).
22. Lobell, D. B. (2013). Climate change adaptation in agriculture. *Annual Review of Environment and Resources*, 38, 1–26.
23. van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using ML. *Computers and Electronics in Agriculture*, 172, 105–119.
24. Pathak, H. S., Brown, P., & Best, T. (2019). A systematic review of ML in agriculture. *Applied Artificial Intelligence*, 33(8), 1–26.
25. OECD. (2021). *Digital opportunities for better agricultural policies*. Organisation for Economic Co-operation and Development.