Pawar Ravi Santosh 2026, 14:5
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Ai-Based Smart Agriculture: A Review Of Edge Disease Diagnosis, Soil Nutrient Profiling And Reinforcement Learning For Precision Irrigation

Pawar Ravi Santosh[1]; Prof. M. R. Kumbhoje[2]; Prof. M. C. Kolse[3]; Prof. S. K. Said[4]
Department Of Artificial Intelligence And Data Science Jaihind College Of Engineering Pune, Maharashtra, India;

Abstract—Agriculture faces pressure from changing climate, water scarcity, soil degradation and crop diseases, while many farmers still decide when to irrigate, how much fertilizer to apply and how to treat diseases by experience alone. This paper reviews AI-based smart agriculture with an integrated, field-deployable perspective. It examines IoT sensing of soil moisture, temperature, humidity and nutrients; deep convolutional networks, including efficient architectures such as EfficientNet, for multi-class foliar disease diagnosis; machine learning for soil macronutrient (nitrogen, phosphorus, potassium) classification and fertilizer guidance; and machine learning and reinforcement learning for precision irrigation scheduling based on evapotranspiration and weather forecasts. Deployment on resource-constrained edge gateways using model quantization is discussed so that diagnoses and irrigation decisions do not depend on continuous internet access. A five-layer architecture comprising field sensing, edge intelligence, a farm decision engine, actuation and a farmer advisory application is proposed, together with research gaps, objectives, a comparison of AI components and challenges such as cost, data scarcity, connectivity, farmer adoption and sustainability. The review concludes that integrated AI systems can raise yields while saving water, fertilizer and pesticide.

Index Terms—Smart agriculture, precision farming, plant disease detection, EfficientNet, soil nutrient prediction, smart irrigation, reinforcement learning, edge AI

I. INTRODUCTION

Farmers must make many interdependent decisions each season: which crop to sow, when and how much to irrigate, which fertilizer to apply and how to respond to disease. In India, groundwater depletion, erratic monsoons and soil nutrient imbalance make these decisions harder. Wolfert *et al.* [1] described how big data and sensing are transforming farming into data-driven smart farming.

AI can support each of these decisions. Liakos *et al.* [2] reviewed machine learning in agriculture across crop management, water management, soil management and livestock, and Kamilaris and Prenafeta-Boldú [3] surveyed deep learning applications. Most systems, however, address a single problem. An integrated system that links disease, soil and water decisions on the farm is more useful to a farmer.

This paper reviews these components and proposes an integrated edge-based architecture.

II. RELATED WORK

Disease diagnosis. Mohanty *et al.* [4] showed that deep CNNs identify crop diseases from leaf images with high accuracy on curated data. EfficientNet [5] scales depth, width and resolution in a balanced way, giving high accuracy for its size and making it suitable for edge deployment after quantization [6].

Soil nutrients. Suchithra and Pai [7] classified soil nutrient levels and fertility from soil test data using optimized extreme learning machines, showing that machine learning can support fertilizer recommendations.

Irrigation. Goap *et al.* [8] built an IoT smart irrigation system that combined sensor data with weather forecasts and machine learning to predict soil moisture and schedule irrigation, reducing water use. Chen *et al.* [9] used reinforcement learning with weather forecasts for rice irrigation decisions and reported water savings

© 2026 Pawar Ravi Santosh ,This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly credited.

without yield loss. Sutton and Barto [10] provide the theoretical basis of the RL methods used.

Big picture. Wolfert *et al.* [1] identified data ownership, integration and business models as obstacles to smart farming adoption. Table @lit summarizes these works.

Ref.	Author(s) / Year	Technique / Approach	Key Contribution	Limitation / Gap
[4]	Mohanty et al., 2016	Deep CNN disease detection	High accuracy on leaf images	Lab-to-field gap
[5]	Tan and Le, 2019	EfficientNet scaling	High accuracy per parameter	General vision
[7]	Suchithra and Pai, 2020	ELM soil nutrient classification	Accurate fertility classes	Soil-test inputs
[8]	Goap et al., 2018	IoT + ML smart irrigation	Water savings with forecasts	Single crop setting
[9]	Chen et al., 2021	RL irrigation with forecasts	Water saved without yield loss	Rice-specific
[11]	Allen et al., 1998	FAO-56 evapotranspiration	Standard water demand method	Needs crop coefficients
[2]	Liakos et al., 2018	Review of ML in agriculture	Mapped ML applications	Review only
[1]	Wolfert et al., 2017	Review of big data in smart farming	Adoption barriers identified	Conceptual

TABLE I Summary of Literature Survey

III. PRELIMINARIES

1. Pillars Of Smart Agriculture

Fig. 1 organizes smart agriculture into four pillars: crop health, soil nutrition, water management and farm advisory, each with associated sensors and AI methods.

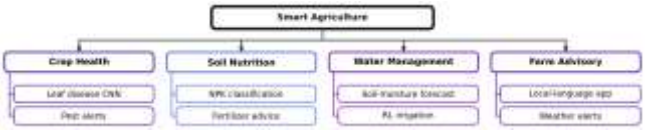


Fig. 1. Pillars of AI-based smart agriculture.

2. Crop Water Requirement

The FAO-56 method [11] estimates crop evapotranspiration as a reference rate multiplied by a crop coefficient that depends on growth stage. This physical estimate provides a baseline that AI-based irrigation can refine.

IV. PROBLEM STATEMENT AND OBJECTIVES

1. Identified Research Gaps

- **G1:** Disease, soil and irrigation systems are usually developed separately.
- **G2:** Models trained on laboratory images and foreign soils transfer poorly to Indian fields.
- **G3:** Many solutions require continuous internet access unavailable in rural areas.
- **G4:** Low-cost nutrient sensors are less accurate than laboratory tests.
- **G5:** Farmer-friendly interfaces in local languages are lacking.

2. Objectives Of The Review

- **O1:** To review AI methods for crop disease diagnosis, soil nutrient profiling and irrigation scheduling.
- **O2:** To examine edge deployment of agricultural AI models.
- **O3:** To propose an integrated five-layer smart agriculture architecture.
- **O4:** To compare AI components in data needs and benefits.
- **O5:** To identify challenges and future directions.

3. Proposed Framework

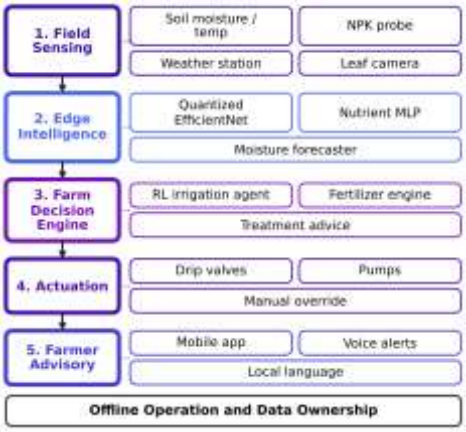


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed integrated edge-based smart agriculture architecture.

4. Field Sensing Layer

Soil moisture, temperature and humidity sensors, an NPK probe, a weather station and a smartphone or fixed camera for leaf images provide data.

5. Edge Intelligence Layer

A gateway runs a quantized EfficientNet for disease diagnosis, an MLP for nutrient classification and a soil-moisture forecaster, working offline when needed.

6. Farm Decision Engine Layer

A reinforcement learning agent decides when and how long to irrigate, a rule-and-model engine recommends fertilizer doses and disease treatments are suggested from an agronomic knowledge base.

7. Actuation Layer

Solenoid valves and pumps for drip irrigation are controlled automatically, with manual override.

8. Farmer Advisory Layer

A mobile app in the farmer's language shows field status, alerts and recommendations, with voice support.

V. WORKING METHODOLOGY

Fig. 3 describes the workflow. Crop water demand follows

$$ETc = Kc \cdot ET_0 \quad (1)$$

where ET_0 is reference evapotranspiration and Kc the crop coefficient. The irrigation agent receives reward

$$r = Yield_proxy - \lambda_w \cdot Water - \lambda_e \cdot Energy \quad (2)$$

and learns to keep soil moisture in the optimal band while minimizing water and energy use.

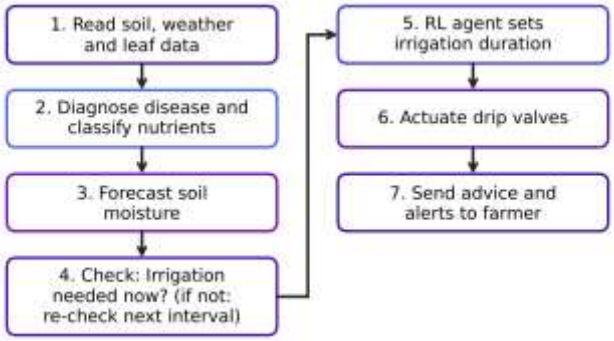


Fig. 3. Integrated smart farm decision workflow.

VI. DISCUSSION

1. Comparison Of Approaches

Table II compares AI components. Disease CNNs and soil-moisture prediction are mature, nutrient models depend on sensor accuracy, and RL irrigation is promising but needs careful validation.

Component	AI Method	Maturity	Main Benefit
Disease diagnosis	EfficientNet CNN	High	Early treatment
Nutrient profiling	MLP / ELM	Medium	Balanced fertilizer
Moisture forecasting	Regression / LSTM	High	Planned irrigation
Irrigation control	Reinforcement learning	Emerging	Water saving
Advisory	Rules + NLP	Medium	Farmer adoption

TABLE II Comparison of Smart Agriculture AI Components

2. Open Challenges And Future Work

Table III summarizes challenges. Future directions include drone and satellite crop monitoring, yield prediction, federated learning across farms, integration with government advisory services and market price forecasting.

Challenge	Mitigation
Cost for small farmers	Shared gateways; low-cost sensors
Data scarcity	Local datasets; transfer learning
Connectivity	Edge inference; offline mode
Sensor accuracy	Periodic lab calibration
Adoption	Local language; extension support

TABLE III Challenges and Mitigation

VII. CONCLUSION AND FUTURE WORK

AI can help farmers make better decisions about disease, nutrients and water. The reviewed literature shows accurate CNN-based disease diagnosis, machine-learning nutrient classification and water-saving smart irrigation with ML and RL. Integrating these components on low-power edge devices with farmer-friendly interfaces offers a practical path to higher yields and sustainable use of resources.

1. Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

REFERENCES

1. S. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, “Big data in smart farming—A review,” Agric. Syst., vol. 153, pp. 69–80, 2017.
2. K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, “Machine learning in agriculture: A review,” Sensors, vol. 18, no. 8, Art. no. 2674, 2018.
3. A. Kamilaris and F. X. Prenafeta-Boldú, “Deep learning in agriculture: A survey,” Comput. Electron. Agric., vol. 147, pp. 70–90, 2018.
4. S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” Front. Plant Sci., vol. 7, Art. no. 1419, 2016.
5. M. Tan and Q. V. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in Proc. Int. Conf. Mach. Learn. (ICML), 2019, pp. 6105–6114.
6. B. Jacob et al., “Quantization and training of neural networks for efficient integer-arithmetic-only inference,” in Proc. IEEE/CVF CVPR, 2018, pp. 2704–2713.
7. M. S. Suchithra and M. L. Pai, “Improving the prediction accuracy of soil nutrient classification by optimizing extreme learning machine parameters,” Inf. Process. Agric., vol. 7, no. 1, pp. 72–82, 2020.
8. A. Goap, D. Sharma, A. K. Shukla, and C. R. Krishna, “An IoT based smart irrigation management system using machine learning and open source technologies,” Comput. Electron. Agric., vol. 155, pp. 41–49, 2018.
9. M. Chen et al., “A reinforcement learning approach to irrigation decision-making for rice using weather forecasts,” Agric. Water Manage., vol. 250, Art. no. 106838, 2021.
10. R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction, 2nd ed. Cambridge, MA, USA: MIT Press, 2018.
11. R. G. Allen, L. S. Pereira, D. Raes, and M. Smith, “Crop evapotranspiration—Guidelines for computing crop water requirements,” FAO Irrigation and Drainage Paper 56, FAO, Rome, Italy, 1998.