Journal of Research and Innovation in Technology, Commerce and Management
Vol. 3 Issue 9, September 2026, pp. 39082-39088
ISSN: 3049-3129 (Online)
ICAIISD–2026

Smart Agriculture Using Artificial Intelligence and IoT: Enhancing Crop Monitoring, Irrigation, and Decision-Making

Kushmitha S
Computer Science and Engineering
Sheshadripuram Institute of Technology, Mysuru, Karnataka
Email: kushmithas2006@gmail.com

Sneha N
Computer Science and Engineering
Sheshadripuram Institute of Technology, Mysuru, Karnataka
Email: snehapradhan.official@gmail.com

Sahana B.R.
Computer Science and Engineering
Sheshadripuram Institute of Technology, Mysuru, Karnataka
Email: sahana.br@sitmysore.ac.in

Cite as: Kushmitha S, Sneha N, & Sahana B.R. (2026). Smart Agriculture Using Artificial Intelligence and IoT: Enhancing Crop Monitoring, Irrigation, and Decision-Making. Journal of Research and Innovation in Technology, Commerce and Management, Vol. 3(Issue 9), 39082–39088.
https://doi.org/10.5281/zenodo.22790399

DOI: https://doi.org/10.5281/zenodo.22790399

Abstract—Agriculture is increasingly challenged by irregular rainfall, water scarcity, changing climatic conditions, rising labor requirements, crop diseases, and the need to improve productivity without increasing the unnecessary use of natural resources. Traditional agricultural practices often depend on periodic manual observation and fixed schedules for irrigation and field management. These methods may not provide an accurate representation of continuously changing soil and crop conditions. The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) provides an opportunity to develop intelligent agricultural systems capable of continuously sensing field conditions, analysing data, predicting future requirements, and supporting farmers in timely decision-making. This paper presents an expanded smart agriculture framework focused on three major functions: crop monitoring, precision irrigation, and intelligent decision support. The proposed system collects data from soil-moisture, temperature, humidity, light, and other environmental sensors through IoT-enabled devices. The collected information is transmitted through a communication network to an edge gateway or cloud platform, where it is cleaned, stored, and analysed. AI and machine-learning techniques are then used to identify patterns, estimate irrigation requirements, detect abnormal conditions, classify crop-related observations, and generate recommendations.

Vol. 3 Issue 9, September 2026, pp. 39082-39088

ISSN: 3049-3129 (Online)

The framework also supports automatic or semi-automatic control of irrigation equipment while preserving farmer oversight. The paper explains the architecture, workflow, data-processing methodology, AI techniques, evaluation parameters, advantages, implementation challenges, and future research opportunities. The proposed approach demonstrates how continuous sensing and intelligent analysis can transform agricultural management from reactive manual observation into a more precise, data-driven, and resource-aware process.

Keywords—Smart agriculture; Artificial Intelligence; Internet of Things; crop monitoring; precision irrigation; machine learning; decision support; sensor networks.

I. INTRODUCTION

Food production depends heavily on the timely availability and proper management of water, soil nutrients, climatic conditions, and crop health. However, agricultural environments are dynamic. Soil moisture can change rapidly because of evaporation, rainfall, irrigation, and crop water uptake. Temperature and humidity vary during the day, while pests and diseases may develop before visible symptoms are noticed during manual inspection. Therefore, farmers must frequently make decisions under uncertainty.

The rapid development of IoT technology makes it possible to place connected sensors and devices directly in agricultural fields. These devices can observe environmental and soil-related parameters at regular intervals and communicate the measurements to a central platform. Instead of relying only on occasional observation, the farmer can obtain a continuous record of field conditions. Nevertheless, large volumes of sensor data are useful only when they can be interpreted effectively.

Artificial Intelligence provides the analytical capability required to convert raw agricultural data into meaningful information. Machine-learning algorithms can learn relationships between environmental variables and agricultural outcomes, while computer-vision models can analyse crop images. AI can also identify abnormal sensor patterns, forecast future conditions, and recommend appropriate actions. The combination of IoT for data acquisition and AI for interpretation therefore forms the foundation of smart agriculture. The purpose of this paper is to present a detailed research framework for integrating AI and IoT in crop monitoring, irrigation management, and agricultural decision-making. The proposed framework is designed as a complete pipeline beginning with sensing and ending with recommendations or physical actions such as valve control.

II. PROBLEM STATEMENT AND OBJECTIVES

In conventional farming, irrigation decisions are frequently based on fixed time schedules, visual inspection, previous experience, or general weather expectations. Although these practices may be effective in familiar conditions, they may lead to over-irrigation, under-irrigation, unnecessary energy consumption, or delayed responses when field conditions change. Large farms create an additional challenge because conditions may differ significantly from one area to another. Another difficulty is the separation of information sources. Soil readings, weather observations, crop images, irrigation history, and farmer knowledge may exist independently. A smart agricultural system should integrate these sources and provide a unified interpretation rather than simply displaying isolated values. The main objectives are: to collect real-time agricultural data using IoT devices; to monitor soil and environmental conditions continuously; to analyse historical and current observations using AI; to estimate crop water requirements; to detect unusual conditions and generate alerts; to provide interpretable recommendations; and to evaluate the technical and agricultural performance of the complete system.

III. LITERATURE AND TECHNOLOGICAL BACKGROUND

Smart farming combines sensing, communication, data storage, analytics, automation, and human decisionmaking. A typical IoT deployment

contains sensor nodes, a communication layer, a gateway, a processing platform, and an application interface. Sensor nodes may measure soil moisture, air temperature, relative humidity, light intensity, rainfall, pH, electrical conductivity, or other crop-specific parameters. Communication technology must be selected according to field size, distance, power availability, and network coverage. Short-range technologies can be useful in small or greenhouse environments, whereas long-range low-power communication can be more suitable for distributed agricultural areas.

The gateway collects sensor observations and forwards them to local or cloud-based services. AI techniques used in agriculture include regression, classification, clustering, anomaly detection, time-series forecasting, and deep learning. Regression can estimate continuous outputs such as future soil moisture. Classification can assign observations to categories such as normal or stressed conditions. Unsupervised approaches can discover patterns without complete labels. Deep learning can analyse images when sufficiently representative training data are available.

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed architecture is organized into five functional layers. The sensing layer contains distributed sensor nodes and optional imaging devices. Each node records selected parameters according to the needs of the crop and field. The communication layer transfers these observations to a gateway using an appropriate network protocol. The processing layer performs timestamping, validation, filtering, and storage. Data quality is important because faulty sensors, temporary communication failures, and environmental interference can create missing or unrealistic readings.

Preprocessing may include removing duplicates, detecting impossible values, interpolating carefully selected missing observations, and normalizing features for machinelearning models. The intelligence layer contains AI models and decision logic. A prediction model can estimate future moisture conditions, while anomaly detection can identify unusual sensor behavior. The decision engine combines model output with configurable agronomic rules and safety constraints. The application layer provides dashboards, notifications, historical charts, and manual control options.

The overall workflow can be represented as: Field Sensors and

Cameras → Communication Network → Edge Gateway or Cloud → Data Preprocessing and Storage → AI Analysis → Decision Engine → Dashboard, Alerts, or Irrigation Actuator. This separation allows each layer to be improved without redesigning the entire system.

V. CROP MONITORING USING AI AND IOT

Crop monitoring begins with the systematic collection of measurements from the agricultural environment. Soilmoisture sensors provide an indication of water availability near the root zone, while temperature and humidity help explain evaporation and plant stress. Light measurements can provide additional context for greenhouse or controlled environments. Cameras can capture visible information about leaves, fruits, or crop rows.

Raw sensor values should not automatically be treated as correct. A sudden extreme value may indicate a real event, a disconnected sensor, or measurement noise. For this reason, the system can compare current observations with recent history, neighboring sensors, and physically reasonable ranges. AI-based anomaly detection can complement fixed threshold rules.

For image-based monitoring, the system can use labelled crop images to train a classification model. Depending on the available dataset, the model may identify healthy and potentially affected visual conditions. However, image models must be validated for the crop variety, lighting conditions, camera quality, and local environment. A prediction should be presented as a decisionsupport signal, particularly when model confidence is low.

VI. PRECISION IRRIGATION STRATEGY

Precision irrigation aims to apply water when and where it is required. Instead of activating

Vol. 3 Issue 9, September 2026, pp. 39082-39088

ISSN: 3049-3129 (Online)

irrigation only at predetermined times, the proposed system evaluates the current soil condition together with environmental variables and recent irrigation history. A basic implementation can use crop-specific threshold ranges. When soil moisture falls below a lower limit and no sufficient rainfall is expected, the system can recommend irrigation.

A more advanced implementation uses forecasting. Historical moisture readings, temperature, humidity, rainfall, time of day, and irrigation events can be transformed into features. A machinelearning model estimates the expected future moisture state or water requirement. The decision engine then considers the prediction together with operational constraints.

Automation must include safeguards. A valve should not remain open indefinitely because of a sensor or communication failure. Maximum irrigation duration, minimum delay between cycles, manual override, event logging, and fallback rules are therefore important. In practical deployment, the farmer should be able to inspect recommendations and override automatic control.

VII. ARTIFICIAL INTELLIGENCE TECHNIQUES

A. Regression and forecasting: Regression models estimate continuous agricultural variables. For example, a model can predict soil moisture after a specified period or estimate an irrigation requirement. Model performance can be compared using Mean Absolute Error and Root Mean Square Error.

B. Classification: Classification assigns an input to a

predefined category. Agricultural examples include normal versus abnormal conditions or image categories representing different visible crop states. Accuracy alone may be insufficient when classes are imbalanced; precision, recall, and F1-score should also be considered.

C. Anomaly detection: Sensor networks can generate unusual observations because of equipment failure, communication problems, or genuine environmental events. Isolation-based approaches, statistical methods, and neural models can help identify observations requiring verification.

D. Computer vision: Convolutional neural networks and related visual models can extract features from crop images. Their usefulness depends strongly on image quality, diversity, correct labels, and validation on data different from the training set.

E. Hybrid decision systems: Machine-learning predictions can be combined with expert rules. This approach can improve interpretability and prevent recommendations that violate operational or safety constraints.

VIII. DATA PROCESSING AND METHODOLOGY

The research methodology begins with requirement analysis. The selected crop, field size, sensor variables, sampling frequency, communication method, and intended decisions are defined before deployment. Sensors are then calibrated and tested. During data collection, every observation should contain a timestamp and device identifier.

Data preprocessing handles missing values, noise, duplicate records, and outliers. Feature engineering can include rolling averages, recent changes, weather variables, irrigation history, and crop-growth-stage information. For machine learning, the dataset should be separated into training, validation, and testing stages. Time-dependent agricultural data should be split carefully to avoid using future information when evaluating earlier observations.

Multiple candidate models can be compared before deployment. After deployment, predictions and decisions should be logged. The observed result after irrigation or an alert can be used as feedback. Periodic retraining may be necessary because agricultural conditions vary across seasons and locations.

Vol. 3 Issue 9, September 2026, pp. 39082-39088

ISSN: 3049-3129 (Online)

IX. EVALUATION METRICS

Evaluation must address both the AI model and the complete agricultural system. Regression tasks can use MAE, RMSE, and coefficient of determination. Classification tasks can use accuracy, precision, recall, F1-score, and a confusion matrix. IoT performance can be measured through sensor availability, data completeness, communication latency, packet delivery, battery life, and system uptime.

Agricultural effectiveness can be evaluated by comparing water consumption, number of irrigation cycles, response time, and cropcondition indicators against a baseline method. A useful research experiment should therefore compare the proposed system with conventional fixedschedule irrigation or manual monitoring under similar conditions. This makes it possible to distinguish technical model performance from actual operational benefit.

X. ADVANTAGES AND APPLICATIONS

The proposed system can provide continuous awareness of field conditions and reduce the delay between observation and response. Precision irrigation can potentially reduce unnecessary water use, while AI-based analysis can prioritize locations requiring attention. Applications include greenhouse monitoring, open-field crop monitoring, localized irrigation, soil-condition tracking, environmental logging, crop-image analysis, and mobile decision dashboards. The same architecture can be adapted to different crops by modifying sensor selection, decision rules, and model training data.

XI. CHALLENGES AND LIMITATIONS

Low-cost sensors may drift over time and require maintenance. Agricultural communication networks may experience limited coverage or interference. Batterypowered devices must balance sampling frequency with energy consumption. AI models are limited by the data used for training. A model developed for one climate, crop variety, or soil type may not perform equally well elsewhere. Data imbalance, insufficient labels, and seasonal variation can reduce reliability.

Cybersecurity and privacy are also important because connected devices and cloud services increase the system's attack surface. Authentication, secure communication, access control, and reliable backups should therefore be considered during implementation.

XII. FUTURE SCOPE

Future systems can combine ground sensors with satellite, drone, and weather information to create a more complete representation of agricultural conditions. Edge AI can reduce communication requirements and support faster local decisions. Explainable AI can help farmers understand why a recommendation was generated. Federated learning may allow models to learn from distributed farms without centralizing all raw data. Digital twins can support simulation, while reinforcement learning may be investigated for irrigation policies operating under carefully defined safety constraints.

Long-term field experiments across multiple seasons, crops, and geographical regions remain essential. Such studies can determine whether an intelligent system remains reliable outside controlled test conditions and whether its benefits justify deployment and maintenance costs.

XIII. CONCLUSION

AI and IoT together provide a practical technological foundation for smart agriculture. IoT devices make continuous observation possible, while AI transforms raw measurements into predictions, classifications, anomaly alerts, and decision-support recommendations. The proposed framework connects crop monitoring, precision irrigation, and decision-making within a single pipeline.

The effectiveness of such a system depends on more than algorithm accuracy. Reliable sensing, careful data preprocessing, secure communication, interpretable recommendations, safety controls, and field validation are equally important. A welldesigned human-centered system can assist rather than replace agricultural

expertise and can support more timely, resource-aware management decisions.

AI DISCLOSURE STATEMENT

AI tools were used to assist with language editing, document formatting, and preparation of the submission layout. The authors remain responsible for the originality, technical accuracy, interpretation, and final content of the manuscript.

REFERENCES

[1] S. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, "Big data in smart farming: A review," Agricultural Systems, vol. 153, pp. 69–80, 2017.

[2] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, 2018.

[3] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," Sensors, vol. 18, no. 8, 2018.

[4] C. Verdouw, A. J. M. Beulens, A. Trienekens, and J. Wolfert, "Virtualization of food supply chains with the Internet of Things," Journal of Food Engineering, vol. 176, pp. 128–136, 2016.

[5] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things: A vision, architectural elements, and future directions," Future Generation Computer Systems, vol. 29, no. 7, pp. 1645–1660, 2013.

[6] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E.-H. M. Aggoune, "Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk," IEEE Access, vol. 7, pp. 129551–129583, 2019.

[7] M. Elijah, S. Rahman, I. Orikumhi, C. Leow, and M. Hindia, "An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges," IEEE Internet of Things Journal, vol. 5, no. 5, pp. 3758– 3773, 2018.

[8] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A survey on the role of IoT in agriculture for the implementation of smart farming," IEEE Access, vol. 7, pp. 156237–156271, 2019.

[9] P. K. R. Maddikunta, Q.-V. Pham, P. B. Prabadevi, N. Deepa, K. Dev, T. R. Gadekallu, R. Ruby, and M. Liyanage, "Industry 5.0: A survey on enabling technologies and potential applications," Journal of Industrial Information Integration, vol. 26, 2022.

[10] D. C. Rose and J. Chilvers, "Agriculture 4.0: Broadening responsible innovation in an era of smart farming," Frontiers in Sustainable Food Systems, vol. 2, 2018.

[11] S. Fountas, G. Carli, C. G. Sørensen, Z. Tsiropoulos, T. Cavalaris, V. Vatsanidou, B. Liakos, M. Canavari, J. Wiebensohn, and B. Tisserye, "Farm management information systems: Current situation and future perspectives," Computers and Electronics in Agriculture, vol. 115, pp. 40–50, 2015.

[12] M. Shamshiri, C. Weltzien, I. H. P. Morton, K. J. Ahmad, D. Parajuli, and R. J. J. M. J. P. van Henten, "Research and development in agricultural robotics: A perspective of digital farming," Biosystems Engineering, vol. 149, pp. 1–16, 2016.

[13] A. Tzounis, N. Katsoulas, T. Bartzanas, and C. Kittas, "Internet of Things in agriculture, recent advances and future challenges," Biosystems Engineering, vol. 164, pp. 31–48, 2017.

[14] C. Zhang, W. S. Potdar, and L. Liu, "Internet of Things applications in smart agriculture: A review," Computers and Electronics in Agriculture, vol. 202, 2022.

[15] J. M. Barbedo, "A review on the main challenges in automatic plant disease identification based on visible range images," Biosystems Engineering, vol. 144, pp. 52–60, 2016.

[16] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, 2016.

[17] E. R. Hunt and R. Daughtry, "What good are unmanned aircraft systems for agricultural

remote sensing and precision agriculture?" International Journal of Remote Sensing, vol. 39, no. 15–16, pp. 5345–5376, 2018.

[18] M. A. Mulla, "Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps," Biosystems Engineering, vol. 114, no. 4, pp. 358–371, 2013.

[19] R. Gebbers and V. I. Adamchuk, "Precision agriculture and food security," Science, vol. 327, no. 5967, pp. 828–831, 2010. [20] J. R. Evans and W. M. L. Sadler, "Methods and technologies to improve efficiency of water use," Water Resources Research, vol. 44, 2008.