AI-DRIVEN CROP GROWTH PREDICTION USING RASPBERRY PI: A MULTIMODAL EDGE-AI FRAMEWORK FOR SMART AGRICULTURE

Banka Hruthik Sai, Dr. S. Sandhya Rani
Department of Electronics and Communication Engineering,
Jayamukhi Institute of Technological Sciences, Narsampet, Warangal, Telangana, India

ABSTRACT

The increasing demand for sustainable agricultural production has created a need for intelligent systems capable of continuously monitoring crop and environmental conditions and supporting timely management decisions. Conventional crop monitoring primarily relies on manual inspection and periodic measurements, which can be labour-intensive, subjective, and unable to capture short-term variations in crop and environmental conditions. This paper presents an AI-driven crop growth prediction framework integrating Internet of Things (IoT) sensing, computer vision, multimodal deep learning, edge computing, and remote monitoring using a Raspberry Pi 4. The proposed system acquires crop images through a camera module and simultaneously monitors soil moisture, temperature, relative humidity, nitrogen, phosphorus, potassium, and light intensity. The acquired multimodal observations are timestamped, preprocessed, and synchronized to establish corresponding image–sensor samples. A Convolutional Neural Network (CNN) extracts visual characteristics associated with crop development, while a Long Short-Term Memory (LSTM) network models temporal dependencies in environmental sensor measurements. The resulting visual and temporal representations are fused to classify four crop growth stages: germination, vegetative, flowering, and maturity. The framework further provides decision support for irrigation and nutrient management and supports lightweight AI inference on Raspberry Pi using optimized deployment frameworks. The reported comparative results indicate that the multimodal CNN+LSTM/GRU configuration can outperform individual image-only and sensor-only models. The proposed framework provides a low-cost and scalable foundation for edge-AI-enabled precision agriculture, smart irrigation, crop monitoring, and nutrient management.

Keywords: Artificial intelligence, crop growth prediction, Internet of Things, Raspberry Pi, convolutional neural network, LSTM, multimodal fusion, edge AI, precision agriculture, smart irrigation.

I. INTRODUCTION

Agriculture is essential for food security, rural livelihoods, and economic development. However, agricultural productivity is increasingly affected by water scarcity, climate variability, soil degradation, nutrient imbalance, and changing environmental conditions. These challenges have increased the need for technologies that can improve the efficiency of water, fertilizer, energy, and labour utilization. Precision agriculture provides an important technological approach for addressing these challenges by enabling agricultural decisions based on continuously collected field information. The integration of IoT, wireless sensors, computer vision, artificial intelligence, and edge computing has transformed agricultural monitoring from periodic manual observation toward continuous and data-driven decision-making. IoT sensors can continuously measure soil and environmental parameters, while cameras provide visual information about crop appearance. Machine learning and deep learning techniques can then identify relationships between these heterogeneous data sources and crop conditions. Previous research has demonstrated the application of machine learning to crop management, yield prediction, disease detection, weed identification, irrigation management, and soil analysis. Deep learning has become particularly important for agricultural image analysis. CNNs can automatically extract visual characteristics such as colour, texture, shape, and plant morphology. However, crop development is also inherently temporal. Environmental conditions collected over a sequence of observations can reveal trends that cannot be identified from a single

Doi:10.48047/ijiee.2026.16.2.61

measurement. LSTM networks are therefore appropriate for modelling temporal dependencies in environmental sensor data. The proposed work integrates these complementary sources of information through a multimodal CNN–LSTM/GRU architecture. The CNN processes crop images, whereas the LSTM/GRU analyses environmental sensor sequences. Their extracted features are combined to predict the crop growth stage. Raspberry Pi 4 is used as the central edge-computing platform for data acquisition, preprocessing, model inference, and IoT communication.

The major contributions of this work are:

1. Development of a Raspberry Pi-based multimodal agricultural monitoring system.
2. Integration of crop imagery with soil and environmental sensing.
3. Development of a CNN–LSTM/GRU architecture for multimodal crop growth-stage prediction.

II. RELATED WORK

IoT-based agriculture has become an important research area because it enables continuous monitoring of environmental and soil conditions. Agricultural IoT systems commonly incorporate soil-moisture, temperature, humidity, nutrient, weather, and light sensors connected to processing units and cloud or edge platforms. Smart irrigation is one of the major applications of IoT in agriculture. Soil-moisture information can be used to determine irrigation requirements rather than relying exclusively on fixed irrigation schedules. Previous studies have demonstrated the potential of IoT-based sensing and intelligent decision-support systems for improving water-management efficiency. Machine learning has also been extensively investigated in agriculture. Applications include crop-yield prediction, disease identification, weed detection, soil classification, irrigation management, and crop-quality assessment. Traditional machine-learning models such as Random Forest, Support Vector Machine, Decision Tree, and regression techniques have been used for agricultural prediction and classification. Deep learning has expanded agricultural intelligence, particularly in computer vision. CNN-based approaches can automatically learn complex visual characteristics from plant images and have been successfully applied to crop monitoring, plant phenotyping, disease detection, and related agricultural tasks. Despite these developments, several research challenges remain. Many systems focus on either environmental sensing or image analysis rather than integrating both modalities. Furthermore, high-performing deep learning models are frequently developed on powerful computing platforms, while comparatively fewer systems demonstrate complete multimodal processing and inference on low-cost edge devices. Another challenge is synchronization. Images and sensor observations may be generated at different sampling frequencies. Incorrect association between image observations and environmental measurements can reduce the effectiveness of multimodal learning. The proposed work addresses these issues by integrating crop images, environmental sensor sequences, multimodal deep learning, edge computing, and IoT monitoring into a unified framework. The uploaded project identifies edge-level multimodal fusion, computational optimization, synchronized sampling, and cross-season/cross-variety validation as important research considerations.

III. PROPOSED METHODOLOGY

The proposed system consists of six major stages Hardware and sensor integration, Multimodal data acquisition, Data preprocessing and synchronization, CNN–LSTM/GRU-based multimodal prediction, Edge-AI inference using Raspberry Pi and IoT-based visualization and decision support. The Raspberry Pi 4 acts as the central edge-processing platform. A camera captures crop images periodically, while sensors collect environmental and soil information. The acquired information is processed locally before the prediction results are transmitted to an IoT platform.

B. Hardware Configuration

The proposed hardware configuration consists of:

Component	Function
Raspberry Pi 4	Central processing and edge-AI inference
Camera Module v2/HQ Camera	Crop-image acquisition

Doi:10.48047/ijiee.2026.16.2.61

Soil-moisture sensor	Soil-water monitoring
DHT11/DHT22	Temperature and humidity monitoring
NPK sensor	Nitrogen, phosphorus, and potassium measurement
LDR/Digital Lux sensor	Light-intensity measurement
Wi-Fi	IoT/cloud communication
Power supply	System operation

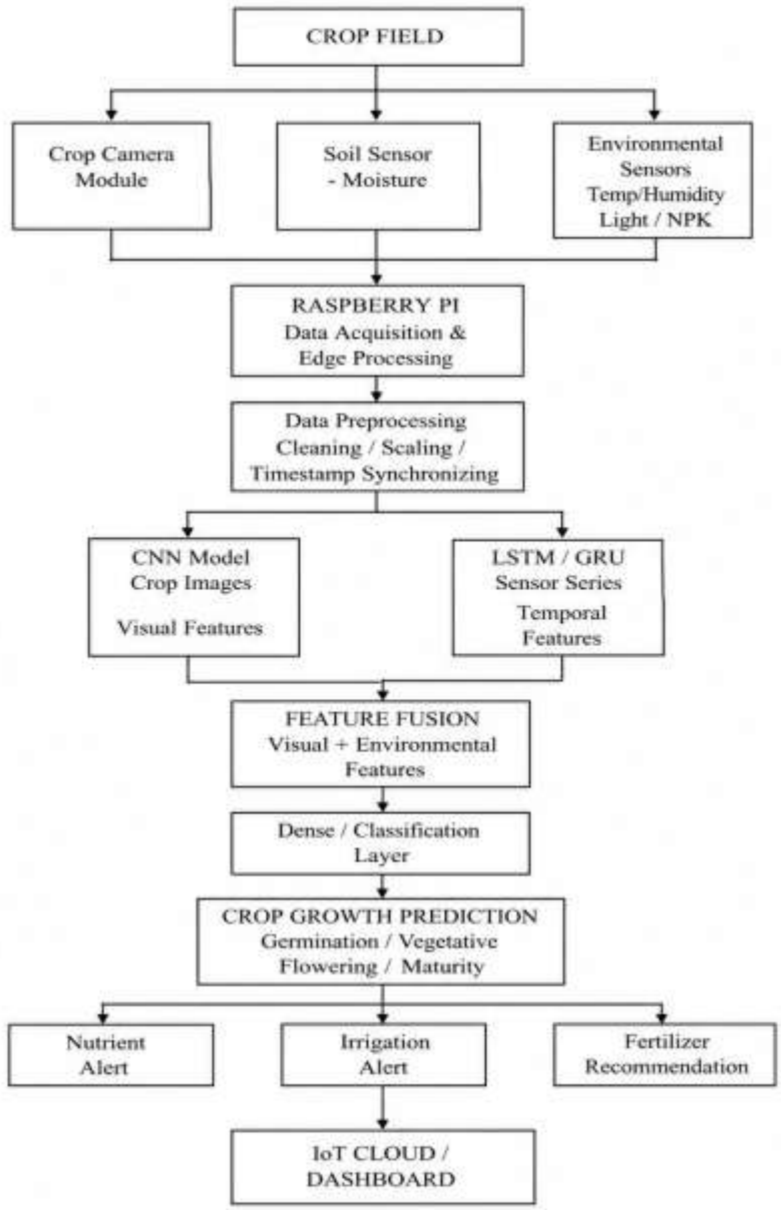

Figure 1 Overall System Architecture

C. Crop Image Acquisition

The camera module periodically captures crop images during the crop-development cycle. Each image is associated with a timestamp and a corresponding crop-growth label. The proposed growth-stage classes are Germination, Vegetative, Flowering, and Maturity. The images provide visual information about crop appearance, including colour, texture, structure,

Doi:10.48047/ijiee.2026.16.2.61

shape, canopy development, and other characteristics associated with plant growth.

D. Environmental Data Acquisition

The system continuously records Soil moisture, Temperature, Relative humidity, Nitrogen, Phosphorus, Potassium, and Light intensity.Every measurement is associated with a timestamp. This enables the environmental information to be synchronized with the crop images. The sensor configuration and environmental parameters are specified in the source project.

E. Data Preprocessing

Raw sensor data may contain missing observations, abnormal values, measurement noise, and different numerical ranges. Therefore, preprocessing is performed before model training. The preprocessing pipeline includes Data-quality checking, Missing-value handling, Sensor-data normalization, Timestamp assignment, Image resizing, Image normalization, Image augmentation, and Image–sensor synchronization.

Image augmentation can include rotation, horizontal flipping, translation, zooming, and brightness variation. These operations improve robustness to changes in camera orientation, illumination, and crop position. A major challenge in multimodal agricultural monitoring is the difference between image and sensor sampling frequencies. The proposed system uses timestamp-based synchronization. When a crop image is captured, the sensor observations collected within the selected temporal window are associated with that image. These measurements form the environmental sequence corresponding to the visual observation. This process produces a synchronized multimodal sample containing Crop image + Environmental sensor sequence + Growth-stage label. Such synchronization is important because the image and environmental measurements should represent approximately the same crop condition.

IV. PROPOSED CNN–LSTM/GRU MODEL

A. CNN-Based Visual Feature Extraction

The CNN branch receives the preprocessed crop image as input. Convolutional layers automatically learn visual representations from the image. The early layers learn relatively simple patterns such as edges, colour transitions, and textures. Deeper layers learn more complex characteristics associated with plant morphology, leaf structure, canopy development, and growth stage. The final CNN representation is used as the visual feature vector for multimodal fusion.

B. LSTM/GRU-Based Temporal Feature Extraction

The environmental sensor measurements form a time series. The LSTM/GRU branch processes this sequence to identify temporal patterns. For gradual changes in soil moisture, temperature, humidity, and light intensity may provide useful information about crop development. The recurrent network learns relationships among these measurements over time. The resulting temporal feature vector represents the environmental behaviour associated with the crop.

C. Multimodal Feature Fusion

The visual and temporal features are combined before the final classification stage. The CNN contributes information about Plant appearance, Leaf structure, Colour, Texture, Morphological development.

The LSTM/GRU contributes information about Soil-moisture trends, Temperature variations, Humidity patterns, Nutrient conditions, Light-intensity trends and Environmental changes over time.

The fused representation is processed through fully connected layers and a Softmax classification layer to determine the most probable crop growth stage. This architecture allows the system to use both what the crop looks like and what environmental conditions the crop has experienced.

Doi:10.48047/ijiee.2026.16.2.61

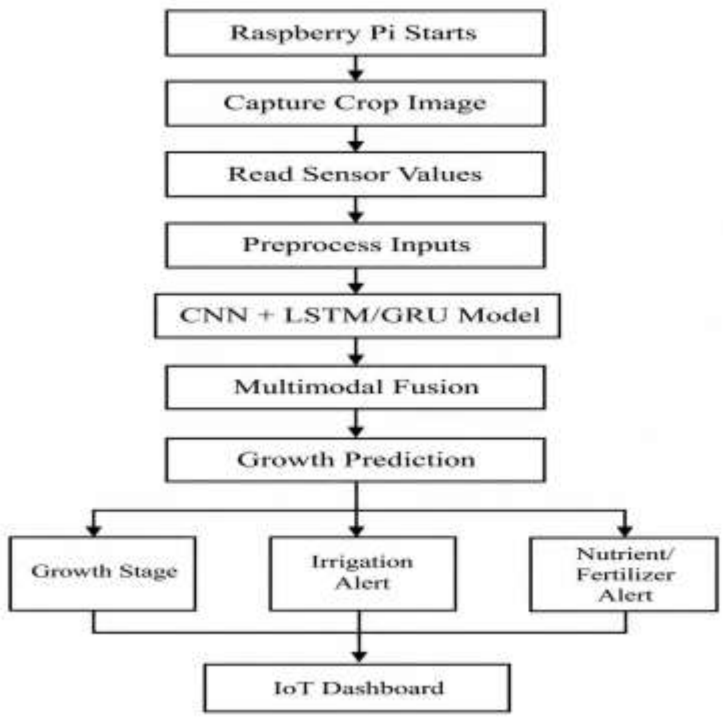

Figure 2 Real-Time Inference Pipeline

V. EXPERIMENTAL SETUP and RESULTS

A. Software Environment

The proposed AI pipeline can be implemented using Python and appropriate machine-learning and deep-learning libraries. The candidate model configurations include CNN, LSTM/GRU, CNN+LSTM/GRU. For Raspberry Pi deployment, lightweight inference frameworks such as TensorFlow Lite, PyTorch Lite, and ONNX can be considered.

B. Dataset Organization

The dataset consists of crop images and corresponding environmental sensor observations.

The data are divided into Training set used for Model parameter learning, Validation set for Hyperparameter selection and model monitoring and Test set for Final performance evaluation

Comparative Model Performance

Model	Input Data	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	Crop images	91.25	90.84	89.96	90.40
LSTM/GRU	Sensor time series	87.50	86.93	85.72	86.32
Proposed CNN+LSTM/GRU	Images + sensors	95.83	95.47	94.92	95.19

The reported results indicate that the proposed multimodal architecture provides the highest performance among the evaluated configurations. The CNN provides visual information, while the LSTM/GRU captures temporal environmental behaviour. Combining these complementary sources improves the representation available to the final classifier. The reported accuracy increases from 91.25% for the CNN to 95.83% for the multimodal model, while the sensor-only LSTM/GRU achieves 87.50%.

Doi:10.48047/ijiee.2026.16.2.61

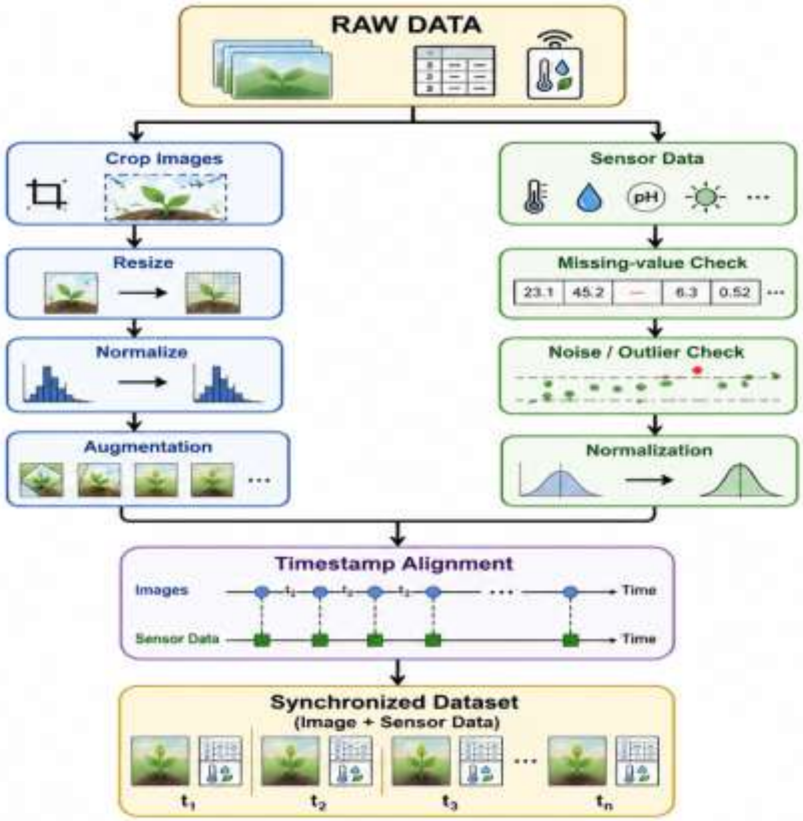

Figure 3 Image and sensor data preprocessing

Confusion Matrix Analysis

The reported confusion matrix for the proposed model is:

Actual / Predicted	Germination	Vegetative	Flowering	Maturity
Germination	29	1	0	0
Vegetative	0	29	1	0
Flowering	0	1	28	1
Maturity	0	0	0	29

The matrix shows that most samples are correctly classified. The majority of predictions occur along the diagonal, indicating strong class recognition.

C. Raspberry Pi Edge-Deployment Performance

The source reports the following edge-deployment measurements:

Parameter	CNN	LSTM/GRU	CNN+LSTM/GRU
Model size (MB)	8.42	6.87	14.36
Average inference time (ms)	18.6	15.8	27.4
RAM usage (MB)	142	128	186
CPU utilization (%)	38.5	34.2	46.8
Prediction latency (ms)	21.3	18.1	31.6

The multimodal architecture requires more computational resources than the individual models because it simultaneously processes visual and temporal information. Nevertheless, the reported inference latency indicates the potential feasibility of performing AI inference on a Raspberry Pi. Model optimization is therefore important for practical deployment. Quantization, pruning, reduced image resolution, lightweight CNN architectures, and optimized inference runtimes can be investigated to reduce computational requirements.

Doi:10.48047/ijiee.2026.16.2.61

Irrigation Decision Support

Soil moisture is continuously monitored to support irrigation decisions. The system considers the measured soil condition together with the predicted crop growth stage and environmental conditions.

The project provides representative cases:

Test case	Soil moisture (%)	Growth stage	Decision
1	28	Germination	Irrigation required
2	45	Vegetative	Maintain moisture
3	62	Flowering	No irrigation required

Nutrient Monitoring

The NPK sensor provides information about nitrogen, phosphorus, and potassium availability.

Representative cases reported in the project are:

Test case	N (mg/kg)	P (mg/kg)	K (mg/kg)	Growth stage	Recommendation
1	82	38	45	Germination	Maintain balanced NPK; moderate irrigation
2	125	52	68	Vegetative	Increase nitrogen availability; maintain adequate moisture
3	105	72	92	Flowering	Increase phosphorus and potassium; avoid excess nitrogen

The recommendation mechanism combines NPK measurements with the predicted crop-growth stage. The actual fertilizer recommendations should be calibrated according to crop-specific agronomic requirements rather than using fixed thresholds. The Raspberry Pi can transmit sensor observations and AI predictions to an IoT platform through Wi-Fi. The project considers platforms such as Firebase, MQTT-based systems, and ThingSpeak.

VI. CONCLUSION

This paper presented an AI-driven crop growth prediction framework integrating IoT sensing, computer vision, multimodal deep learning, edge computing, and remote monitoring using Raspberry Pi. The proposed system combines crop imagery with soil moisture, temperature, humidity, NPK, and light-intensity measurements to provide a comprehensive representation of crop and environmental conditions.

A CNN extracts visual characteristics from crop images, while an LSTM/GRU analyses temporal environmental information. The extracted features are fused to classify four crop growth stages: germination, vegetative, flowering, and maturity. The framework also incorporates irrigation and nutrient decision support and provides an IoT-based mechanism for remote monitoring. The reported comparative results indicate that the multimodal CNN+LSTM/GRU architecture achieves higher classification performance than the individual CNN and LSTM/GRU models. This demonstrates the potential value of combining visual and temporal environmental information for crop-growth assessment. The use of Raspberry Pi provides an edge-oriented architecture capable of performing local data processing and AI inference. Lightweight deployment frameworks can further improve the practicality of the system by reducing computational requirements. The proposed framework therefore establishes a foundation for intelligent and low-cost precision agriculture by integrating multimodal sensing, AI-based crop assessment, edge computing, irrigation support, nutrient monitoring, and IoT visualization. Future validation using larger datasets, multiple crop varieties, different seasons, and real field conditions will be necessary to establish the robustness, generalizability, and scalability of the proposed approach.

REFERENCES

[1] Food and Agriculture Organization of the United Nations, “Agricultural Water Management,” FAO, 2026.

[2] J. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, “Big Data in Smart Farming – A

Doi:10.48047/ijiee.2026.16.2.61

review," Agricultural Systems, vol. 153, pp. 69–80, 2017.
[3] "Internet of Things-enabled smart irrigation systems for precision water management: A systematic review," Agricultural Water Management, vol. 333, Art. no. 110615, 2026.
[4] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine Learning in Agriculture: A Review," Sensors, vol. 18, no. 8, p. 2674, 2018.
[5] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, 2018.
[6] Food and Agriculture Organization of the United Nations, "Climate Change," FAO, 2026.
[7] "Data-driven water need estimation for IoT-based smart irrigation: A survey," Expert Systems with Applications, 2023.
[8] "The application of machine learning techniques for smart irrigation systems: A systematic literature review," Smart Agricultural Technology, vol. 7, Art. no. 100425, 2024.
[9] "Artificial intelligence and IoT for water saving in agriculture: A systematic review," Smart Agricultural Technology, vol. 11, Art. no. 101008, 2025.
[10] "Artificial intelligence of things (AIoT) for precision agriculture: Applications in smart irrigation, nutrient and disease management," Smart Agricultural Technology, vol. 12, Art. no. 101629, 2025.
[11] M. N. Mowla, N. Mowla, A. F. M. S. Shah, K. M. Rabie, and T. Shongwe, "Internet of Things and Wireless Sensor Networks for Smart Agriculture Applications: A Survey," IEEE Access.
[12] S. Vinod Kumar, C. D. Singh, and K. Upendar, "Review on IoT Based Precision Irrigation System in Agriculture," Current Journal of Applied Science and Technology, vol. 39, no. 45, pp. 15–26, 2020.
[13] A. R. Kamienski et al., "Smart water management platform: IoT-based precision irrigation system," Sensors, 2019.
[14] A. Ojha, B. Misra, and N. K. Singh, "IoT-Based Smart Irrigation Systems: An Overview on the Recent Trends on Sensors and IoT Systems for Irrigation in Precision Agriculture," Sensors, 2020.
[15] A. L. Chandra, S. V. Desai, W. Guo, and V. N. Balasubramanian, "Computer Vision with Deep Learning for Plant Phenotyping in Agriculture: A Survey," 2020.
[16] U. Nawaz, M. Z. Zaheer, F. S. Khan, H. Cholakkal, S. Khan, and R. M. Anwer, "AI in Agriculture: A Survey of Deep Learning Techniques for Crops, Fisheries and Livestock," 2025.
[17] G. S. Kahar et al., "IoT and Sensor Networks for Smart Agriculture: Technologies, Applications, and Future Directions," International Journal of Agriculture Extension and Social Development, 2026.
[18] G. Patle et al., "A Comprehensive Review of Sensor Technologies and IoT Platforms for Precision Agriculture: Indian Context," 2026.
[19] "Recent advances in IoT-driven crop monitoring and precision irrigation: Technologies, models, and future challenges," Smart Agricultural Technology, 2026.
[20] S. Dutta, S. Gorain, S. Roy, and S. Banerjee, "Integrating IoT and communication technologies for smart and precision irrigation systems toward sustainable water management," Discover Internet of Things, vol. 6, Art. no. 82, 2026.

Doi:10.48047/ijiee.2026.16.2.61