

AI-Driven Self-Adaptive Smart Irrigation System Using IoT, Computer Vision and Machine Learning

Ramya S Yamikar¹, Aravinda T V², Krishnareddy K R³, Ramesh B E⁴

¹Selection Grade Lecturer, Department of CS&E, Govt. Polytechnic, Harapanahalli, Karnataka, India

²Professor & HOD, Department of AI&ML, SJM Institute of Technology, Chitradurga, Karnataka, India

³ Professor & HOD, Department of CS&E, SJM Institute of Technology, Chitradurga, Karnataka, India

⁴ Professor, Department of CS&E, SJM Institute of Technology, Chitradurga, Karnataka, India

Emails: ramyasyamikar@gmail.com¹, tvaravinda@gmail.com², krkrishnareddy69@gmail.com³, ramesh.be@gmail.com⁴

Abstract

This paper presents an AI-driven self-adaptive irrigation framework integrating IoT sensing, computer vision, adaptive learning, and automated irrigation control. The proposed system continuously monitors soil moisture, temperature, humidity, water flow, and visual plant health conditions using ESP32-based sensing devices and ESP32-CAM image acquisition. Centralised FastAPI server performs feature extraction, environmental analysis and AI based irrigation decision making at the backend. The proposed system, compared with existing threshold-based conventional irrigation systems, dynamically adjusts irrigation behaviour based on feedback received from the environment and plant stress conditions.

Keywords: Index Terms— Smart Irrigation, IoT, ESP32, Machine Learning, Computer Vision

1. Introduction

The advancements in agricultural technology and a growing demand for technical irrigation are seeking intelligent systems that can adapt themselves and work with less dependency on humans. Traditional farming was initially taken over by conventional irrigation systems that used some pre-defined rules inferred by manual experiences. These systems often failed or were difficult to adapt for varied vegetation or changing environmental responses. The crops were either over-irrigated or under irrigated also witnessing inefficient water usage. Alarming concerns with respect to water scarcity and climate variability strongly stress the need for adaptive and intelligent irrigation frameworks that can independently make real-time decisions based on the actual plant and environmental conditions. Automated decision making can be achieved by closely analysing climatic indicators such as temperature, humidity, soil moisture, amount of irrigated water along with visual plant health indicators. This paper proposes a novel framework enclosing AI-driven self-adaptive irrigation system

that is smart enough to integrate ESP32-based IoT sensing, computer vision, FastAPI backend processing, and adaptive machine learning to generate dynamic intelligent irrigation decisions to improve irrigation efficiency, reduce manual intervention, and support healthy plant growth.

2. Literature Survey

Recent studies have demonstrated the growing importance of AI, IoT, and machine learning in smart agriculture and irrigation management. Elbasi et al. [1] highlighted the role of AI in agricultural automation and intelligent decision-making. Zhao et al. [2] and Chen et al. [3] showed that reinforcement learning techniques improve irrigation efficiency compared to traditional rule-based systems. IoT-based irrigation frameworks proposed by Esmail et al. [4] and Morchid et al. [5] enabled real-time environmental monitoring and automated irrigation control. Hoi et al. [6] discussed adaptive online learning methods, while Loh et al. [7] focused on multi-objective irrigation optimization for efficient water management.

3. System Architecture

3.1.Overall System Architecture

Fig. 1 illustrates the architecture of the proposed AI-driven self-adaptive irrigation framework. The system integrates IoT sensing, computer vision, backend intelligence, and automated irrigation control into a unified precision agriculture platform. The architecture is organized into sensing, communication, backend processing, visualization, and actuation layers[8] to support continuous monitoring and irrigation management intelligently.

3.2.Sensing Layer

The sensing layer is responsible for collecting environmental and plant-related information from the agricultural field. The ESP32 microcontroller is connected to the soil moisture, temperature, humidity and water flow sensors to get the real time environmental parameters. ESP32-CAM also takes pictures of plants periodically for visual health monitoring. The data obtained permits continuous monitoring of the conditions in the environment and contributes to the evaluation of an intelligent irrigation[9].

3.3.Collecting Data and Communication Level

The ESP32 node sends sensor readings and plant images to the FastAPI backend server through Wi-Fi communication and HTTP-based API requests. The sensing node and the backend system communicate with lightweight data exchange in JSON format. This communication architecture ensures reliable real-time monitoring while reducing processing overhead on the embedded hardware device.

3.4.Backend AI Decision Engine

The FastAPI backend serves as the centralized processing and decision-making unit of the proposed framework. Sensor readings and image frames are validated and stored in MongoDB collections for further analysis. Plant features such as leaf area, green index, curl index and stress regions if any are extracted from the stored images using image preprocessing techniques such as Gaussian Blur, CLAHE enhancement, HSV segmentation, and contour-based feature extraction. These extracted features along with environmental parameters are analysed to evaluate plant conditions and irrigation requirements.

3.5.Adaptive Irrigation Control Mechanism

The implemented model accomplishes adaptive irrigation management by regulating watering behaviour based on environmental variations and visual plant observations. Irrigation decisions are generated by considering plant responses also rather than just fixed moisture thresholds. Spotting of leaf curling due to excessive watering renders the system to alter moisture thresholds for efficient irrigation. This adaptive mechanism boosts irrigation accuracy and curtails needless water consumption.

3.6.Dashboard and Visualization Layer

The dashboard layer provides graphical visualization of sensor readings, irrigation status, water consumption, adaptive threshold behavior, and plant growth analysis. The monitoring interface enables users to observe environmental conditions and evaluate irrigation performance in real time[1].

3.7.Actuation Layer

The actuation layer consists of a relay module and irrigation pump controlled by the ESP32 microcontroller. Based on backend-generated irrigation commands, the relay activates or deactivates the pump to regulate water supply automatically. This automated control mechanism reduces manual intervention and supports efficient irrigation management.

3.8.Closed Loop Feedback Architecture

The proposed framework operates using a closed-loop feedback mechanism in which irrigation actions continuously influence future decision-making. Environmental updates and plant responses obtained after irrigation are analysed to refine irrigation behaviour over time. This continuous feedback process improves adaptability, irrigation precision, and overall system efficiency.

4. Methodology

The proposed framework follows a real-time intelligent irrigation workflow consisting of environmental sensing, image acquisition, backend processing, adaptive analysis, irrigation control, and performance evaluation. The methodology enables intelligent irrigation management through continuous monitoring and adaptive decision-making. As shown in Figure 1 AI-Driven Self-Adaptive Irrigation System Architecture Diagram

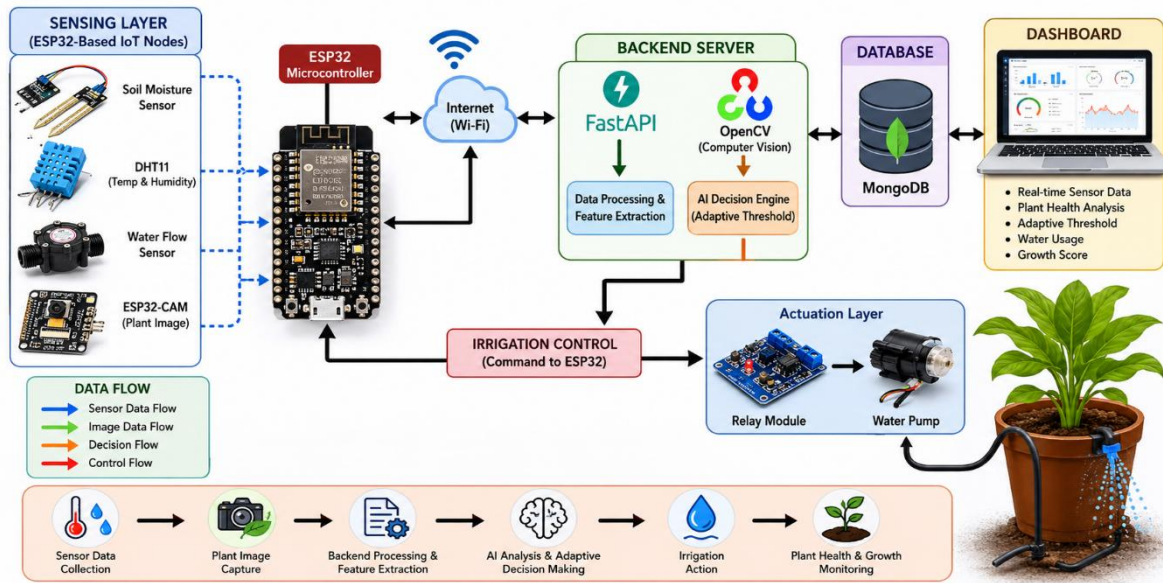


Figure 1 AI-Driven Self-Adaptive Irrigation System Architecture Diagram

4.1. Real-Time Environmental Data Collection

ESP32 is for sensing and actuation. Soil moisture sensor is used to sense the moisture in the soil and DHT sensor is used to sense the temperature and humidity prevailing. A water flow sensor is employed to measure the amount of water flown to the plant in each irrigation cycle. These sensor readings are sent to the backend server at regular intervals using Wi-Fi communication with JSON based API requests. This light weight architecture is characterized by continuous real time monitoring and scalability.

4.2. Plant Health Monitoring and Recording Images

The ESP32-CAM is used to capture images of the plants to analyse the health of the plants. The designed architecture is based on image-based plant health monitoring instead of pre-defined moisture thresholds. The acquired images are pre-processed using Gaussian Blur and CLAHE enhancement techniques for noise reduction and contrast enhancement. HSV-based segmentation and morphological operations precisely isolate required plant regions. Isolated plant regions are used to extract features like green intensity, leaf area, curl index, yellow stress regions, growth behaviour etc. These features can be used as visual cues for assessing healthy and unhealthy plant conditions. As

shown in Figure 2 Plant Image Captured by ESP32-CAM, Figure 3 HSV-Based Plant Segmentation



Figure 2 Plant Image Captured by ESP32-CAM



Figure 3 HSV-Based Plant Segmentation

4.3. AI-Based Decision Making and Backend Processing

The sensor data and images from the hardware are received by the API server at the backend. This data is first validated to filter out non-plant images, images with less significant change and pump dry run. After validation, the data is stored in the database and serves for further analysis. Adaptive decision making whether to irrigate the plant or not using the plant health indicators extracted in the second step along with sensor data takes place here in the third stage. Threshold-Based Irrigation Decision Algorithm and Hybrid Adaptive Irrigation Decision Algorithms are used to deliver intelligent decisions by the AI model. Over watering or under watering stress is also detected to aid AI in the making adaptive threshold judgements. The data collected and stored so far in the database serves as the dataset for further learning of the AI model.

4.4. Irrigation Control in a Closed Loop

In this stage, based on the decision whether to irrigate the plant or not, commands are issued to the hardware. Upon receiving the commands, relay module sets the pump on or off accordingly. If irrigated, the number of water pulses are measured and sent back to the backend server to calculate the quantity of water flown. This data is also stored in the database along with the timestamps so that any further choices pertaining to irrigation adaptation is ancillary to the healthy growth of the plant. All it forms is a closed loop to promote plant growth with no or reduced use of water.

5. Results And Discussion

The resulting self-adaptive irrigation system design, utilizing artificial intelligence, effectively displayed adaptive irrigation control via IoT-based sensing using ESP32 devices, backend programming using FastAPI, and image analysis via OpenCV. The experimental data collected during this project show that the system was able to monitor environmental conditions reliably, manage irrigation intelligently, and evaluate plant health more accurately based on changing field conditions.

5.1. Analyzing Threshold and Irrigation Adaptability

Evaluation of the irrigation threshold provides an assessment of the changes made by the irrigation

system on the irrigation threshold in response to plant conditions, which were identified through the observation of plant stress indicators (e.g., over-watering of plant material and leaf curling). Initially, the irrigation thresholds were at a normal level. After identifying plant stress indicators, the backend artificial intelligence (AI) system made automatic changes to the irrigation threshold in order to limit the amount of water applied to the plant. The adaptive threshold graph in Fig. 4 illustrates how irrigation behaviour was refined dynamically to improve irrigation efficiency during stress conditions. As shown in Figure 4 Adaptive Irrigation Threshold Graph

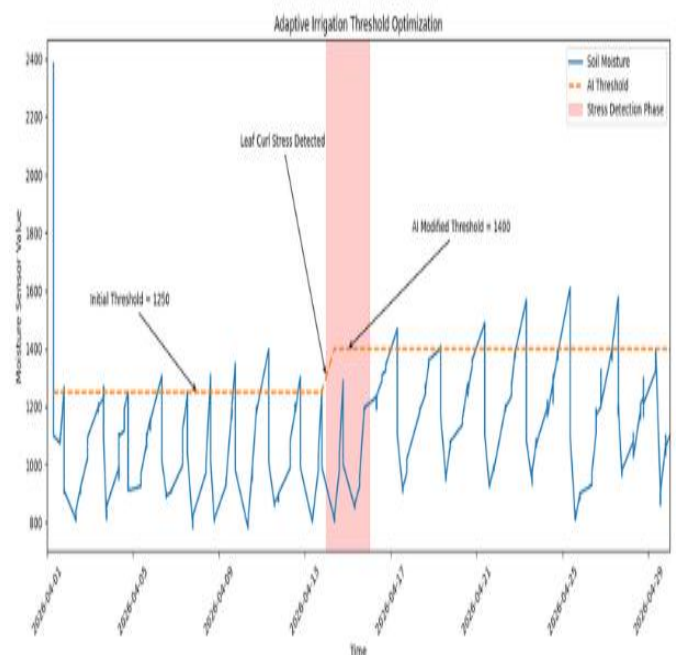


Figure 4 Adaptive Irrigation Threshold Graph

5.2. Water Usage Analysis

The water usage analysis shown in Fig. 5 demonstrates the reduction in unnecessary water consumption achieved by the proposed framework. During stress conditions, irrigation duration was reduced automatically to optimize water delivery. Compared to conventional fixed-threshold irrigation approaches, the proposed framework achieved better water conservation while maintaining stable plant conditions. Shown as Figure 5 Water Usage Graph with Stress Annotation

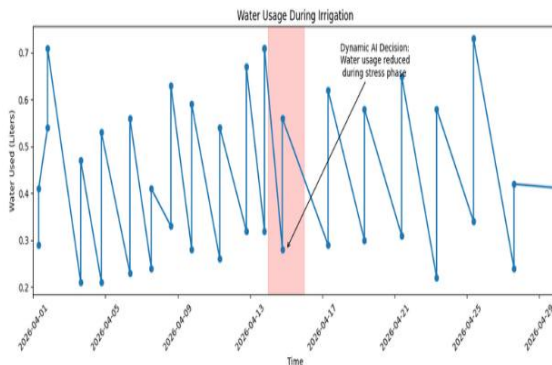


Figure 5 Water Usage Graph with Stress Annotation

5.3.Plant Growth Score Analysis

The plant growth score graph shown in Fig. 6 illustrates the variation in plant health over time using environmental monitoring and visual feature analysis. Growth score evaluation was performed using extracted plant features including green intensity, leaf area, and stress indicators. The graph indicates gradual improvement in plant growth stability after adaptive irrigation policies were introduced. Shown as Figure 6 Plant Growth Score Graph

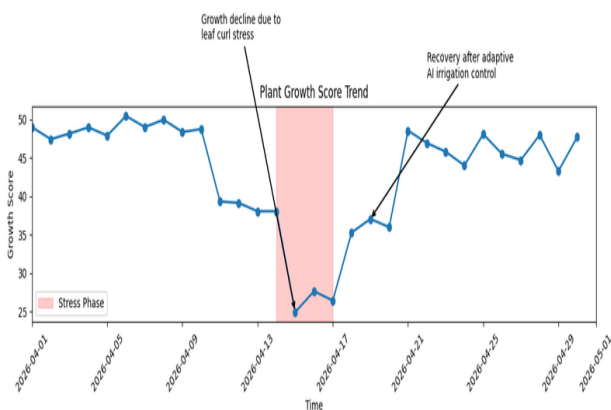


Figure 6 Plant Growth Score Graph

5.4.System Performance Metrics

As stated, above experiments exhibited improvements in irrigation efficiency, automation capability, water conservation, and stress detection accuracy. The novel architecture sustained reliable operation during continuous monitoring and irrigation activities. The performance evaluation

results in Table 1 indicate that combining IoT sensing, computer vision, and adaptive analysis improves irrigation management including plant stress detection compared to conventional rule-based irrigation systems.

Table 1 Experimental Performance Evaluation Results

Parameter	Observed Performance
Sensor Data Transmission Accuracy	95–98%
API Communication Success Rate	97%
Database Storage Reliability	96%
Image Processing Accuracy	88–92%
Irrigation Decision Accuracy	90–94%
Pump Response Accuracy	98%
Water Usage Optimization	Improved compared to fixed irrigation
System Stability	High during continuous operation

5.5.Comparison Between Traditional and Proposed System

Table 2 presents a comparative analysis between conventional irrigation systems and the proposed

adaptive irrigation framework. Traditional irrigation approaches mainly rely on fixed thresholds and static monitoring mechanisms, limiting their adaptability to changing environmental conditions. In contrast, the proposed framework integrates adaptive analysis, visual plant monitoring, and closed-loop irrigation control to improve irrigation efficiency and intelligent decision-making. As shown in Table 2. Comparative Analysis Between Conventional and Proposed Adaptive Irrigation Systems

Table 2 Comparative Analysis Between Conventional and Proposed Adaptive Irrigation Systems

Parameter	Traditional	Proposed
Decision Logic	Fixed Threshold	Adaptive AI
Plant Analysis	Moisture Only	Sensor + Vision
Learning	Static	Self-Adaptive
Water Usage	Moderate	Optimized

Conclusion

The suggested architecture for self-adaptive irrigation based on Artificial Intelligence integrates (1) IoT sensing and computer vision, (2) adaptive backend analysis, and (3) an intelligent precision agriculture system to support irrigation decision making. Incessant perceiving of climatic responses associated with plant traits turned out to be promising data for taking irrigation decisions to encourage well development of a plant. This design attempts to illustrate that AI can be made to make adaptive decisions without predefined learning using a huge dataset but by realizing the everyday data and decisions as the learning dataset. Even though this work proposes a universal learning technique that can be used to adapt to different plants without past training, multipurpose usage of this application can be realized in future by combining with plant specific trends. Edge and cloud deployments of such applications will help to blend the irrigation with intelligent technologies.

References

[1]. E. Elbasi, N. Mostafa, Z. Al-Arnaout, A. I.

Zreikat, E. Cina, G. Varghese, A. Shdefat, A. E. Topcu, W. Abdelbaki, S. Mathew, and C. Zaki, "Artificial intelligence technology in the agricultural sector: A systematic literature review," *IEEE Access*, vol. 11, pp. 171–202, 2023, doi: 10.1109/ACCESS.2022.3232485.

[2]. H. Zhao, L. Di, L. Guo, L. Lin, C. Zhang, E. Yu, and H. Li, "Optimizing irrigation scheduling using deep reinforcement learning," in *Proc. 2023 11th Int. Conf. Agro-Geoinformatics*, 2023, pp. 1–6, doi: 10.1109/Agro-Geoinformatics59224.2023.10233673.

[3]. M. Chen, Y. Cui, X. Wang, H. Xie, F. Liu, T. Luo, S. Zheng, and Y. Luo, "A reinforcement learning approach to irrigation decision-making for rice using weather forecasts," *Agricultural Water Management*, vol. 250, 2021, Art. no. 106838, doi: 10.1016/j.agwat.2021.106838.

[4]. A. A. Esmail, M. A. Ibrahim, S. M. Abdallah, and A. E. Radwan, "Smart irrigation system using IoT and machine learning methods," in *Proc. 2023 5th Novel Intelligent and Leading Emerging Sciences Conf. (NILES)*, 2023, pp. 85–90, doi: 10.1109/NILES59815.2023.10296736.

[5]. A. Morchid, M. El Bakkali, H. El Fadili, and A. Haqiq, "IoT smart irrigation for agricultural water security," *Sensors*, vol. 24, no. 7, 2024, Art. no. 2436, doi: 10.3390/s24072436.

[6]. S. C. H. Hoi, D. Sahoo, J. Lu, and P. Zhao, "Online learning: A comprehensive survey," *Neurocomputing*, vol. 459, pp. 249–289, 2021, doi: 10.1016/j.neucom.2021.04.112.

[7]. C. H. Loh, Y.-I. Chen, M. U. A. Rahman, and H. T. Nguyen, "Multi-objective decision support for irrigation systems based on skyline query," *Applied Sciences*, vol. 14, no. 3, 2024, Art. no. 1189, doi: 10.3390/app14031189.

[8]. Vinod Biradar et al. "Tuned improved SqueezeNet with texture pattern extractor based object recognition and distance estimation for navigating visually impaired persons", Accepted in "Computers and

Electrical Engineering”, Volume 130, Issue 1, pp. , Feb2026. ISSN .(Scopus IndexedQ1Journal), DOI:<https://doi.org/10.1016/j.compeleceng.2025.110813>

- [9]. Vinod Biradar, Dr. Karuna C. Gull, “Enhancing object detection for visually impaired integrating YOLOv8 with spiking EfficientDet”, Accepted in “Multimedia Tools and Applications”, Volume 84, Issue 1, pp. 43721-43749, 03may 2025. ISSN 2185-3118. (Scopus Indexed Q1 Journal), DOI:[10.1007/s11042-025-20872-5](https://doi.org/10.1007/s11042-025-20872-5)
- [10]. Vinod Biradar, Dr. Karuna C. Gull, “Multiple Object Detection and Tracking Using Deep Learning Framework with Non-Maximum Suppression”, Accepted in “International Journal of Intelligent Engineering and Systems”, Volume 18, Issue 1, pp. 105-116, Jan 2025. ISSN 2185-3118. (Scopus Indexed Q3 Journal), DOI:[10.22266/ijies2025.0229.09](https://doi.org/10.22266/ijies2025.0229.09)