Design and Implementation of an IoT-Based Smart Irrigation System for Sustainable Agriculture

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Abstract: This study presents the design, implementation, and evaluation of a low-cost IoT-based smart irrigation system aimed at promoting sustainable agriculture and serving as an educational platform for students. The system integrates a NodeMCU microcontroller with temperature, humidity, and soil moisture sensors to automate irrigation, temperature control, and air circulation. The development was carried out in two stages: laboratory prototyping and real-world testing in a custom-built mini-greenhouse. Experimental validation in a four-week cultivation cycle of arugula (Eruca sativa) showed that the system maintained optimal soil moisture levels, reduced water consumption by approximately 20% compared to manual irrigation and ensured uniform plant growth under stable environmental conditions. Remote monitoring and control were implemented using the Blynk platform, which provided reliable operation and a user-friendly interface suitable for agricultural and educational use. A significant educational impact was achieved, as students gained hands-on experience in IoT hardware–software integration, environmental data collection, and the fundamentals of AI-based predictive modelling. Future research will focus on integrating AI-driven predictive analytics, cloud computing, and additional automation features to develop a fully autonomous smart agriculture platform.

Keywords: IoT; precision agriculture; smart irrigation; sustainable farming; AI integration

1 Introduction

The growing global demand for food, driven by population growth and climate change, presents significant challenges to the agricultural sector. Agriculture accounts for approximately 70% of global freshwater withdrawals, and inefficient irrigation is a major contributor to water waste [1]. The need for sustainable water management and zero hunger has been emphasised in the Sustainable Development Goals (SDG 6 and SDG 2) [2]. Sustainable farming practices play a key role in overcoming these challenges by promoting efficient resource utilisation and reducing environmental impact. Recent advances in IoT and cloud-based technologies have enabled smarter and more efficient agricultural systems, significantly improved resource management and reducing operational costs [3].

Precision agriculture, powered by the Internet of Things (IoT) and wireless sensor networks (WSNs), has emerged as a transformative approach that allows efficient management of agricultural processes. IoT-based systems provide real-time data collection, advanced analytics, and automated decision making capabilities, allowing farmers to optimize water use, monitor soil health, and improve crop yields. By integrating cloud computing with the IoT, smart irrigation systems have become more adaptable and capable of providing real-time responses to changing environmental conditions [3]. These developments align with broader sustainability goals by minimizing resource waste and promoting environmentally friendly agricultural practices.

Artificial intelligence (AI) and machine learning (ML) have been increasingly integrated into smart agriculture, enabling predictive analytics and decision support systems. AI techniques improve irrigation scheduling by predicting soil moisture levels based on historical and real-time environmental data, improving agricultural productivity and sustainability. With the increasing availability of IoT-generated data, AI models can analyse climate conditions, automate irrigation processes, and reduce water consumption, making them indispensable tools in modern agriculture [4].

The system presented in this study integrates a NodeMCU microcontroller with temperature, humidity, and soil moisture sensors to automate irrigation, temperature control, and air circulation. Remote monitoring and control are implemented using a cloud-based platform, providing a user-friendly interface for real-time interaction. Beyond its technical implementation, the project was designed with a strong educational dimension. Students actively participated in all stages, from system design and hardware integration to testing and data analysis. This hands-on experience allowed them to acquire practical skills in embedded systems, environmental sensing, and the fundamentals of AI-based predictive modelling.

The system was developed and evaluated in two phases: a laboratory prototype phase and a real-world deployment phase within a custom-built mini-greenhouse. During the testing, the system demonstrated the ability to maintain stable environmental conditions, reduce water consumption compared to manual irrigation, and ensure uniform plant growth. Although existing solutions often rely on commercial grade components and focus on large-scale applications, this study aims to explore a more accessible and educationally valuable alternative through a student-built system validated in a real-world setting.

The results of this work highlight the potential for cost-effective IoT-based automation in agriculture, particularly for educational environments and small-scale farming. The environmental data further supports future research directions, including the integration of artificial intelligence, cloud computing, and predictive analytics for fully autonomous agricultural systems.

2 Literature Overview

Numerous studies have explored the use of IoT technologies in optimising agricultural inputs, with particular attention to irrigation systems, environmental monitoring, and automation. IoT and cloud-based technologies are often combined to support adaptive irrigation systems and real-time environmental monitoring [3]. These systems are further enhanced through artificial intelligence and machine learning, which enable predictive analytics and decision support mechanisms to optimise water use and improving crop yields [4].

A systematic review examined the role of sensors, controllers, and communication protocols in enhancing agricultural efficiency, identifying key challenges such as high initial costs, data reliability, and system scalability. Despite these limitations, the findings emphasise the potential of IoT to support sustainable farming practices [5].

Several studies have analysed the applications of smart drip irrigation and precision agriculture systems that are based on sensor-based automation to improve crop yields and reduce labour requirements [6]. However, the high implementation costs and infrastructure demands often limit their accessibility, especially for small-holder farmers.

A low-cost IoT-based weighing system was proposed to measure crop evapotranspiration using open-source components and real-time data transmission [7]. Although this approach improves irrigation accuracy, it relies on cellular networks and lacks local data storage, which may reduce reliability in remote or low-connectivity areas.

Further research has examined the integration of artificial intelligence, machine learning, and IoT for precision irrigation, pest control, and real-time monitoring [8]. These technologies can improve productivity and sustainability, but often require large datasets, advanced technical knowledge, and significant investment, creating barriers to widespread adoption particularly in developing regions. Similarly, the IoT combined with WSNs allows precise monitoring and efficient resource allocation [9], yet energy consumption, connectivity challenges, and unresolved data security issues remain persistent obstacles.

In addition to IoT-based solutions, innovations such as hydroponics, biochar and nanotechnology have been introduced to increase agricultural productivity and address environmental constraints [10]. Although these technologies offer benefits such as improved soil fertility and reduced environmental impact, their high costs and the need for specialised labour limit their broader implementation.

Although many studies confirm the advantages of smart irrigation systems, most focus on large-scale agricultural applications or controlled laboratory environments, often using expensive hardware. Few works explore low-cost systems developed by students or assess their relevance in educational contexts and small-scale urban agriculture. Furthermore, the educational potential of student participation in the design and implementation remains largely underexplored in the literature.

This study addresses the identified gaps by presenting a cost-effective smart irrigation system, developed by students and tested in real-world conditions in a custom-built mini-greenhouse. The system demonstrates its technical feasibility through automation of irrigation, temperature control, and humidity regulation. At the same time, it provides educational value by offering hands-on experience in IoT integration, environmental data analysis, and practical system implementation. In this way, the study contributes to the development of accessible and scalable technologies for smart agriculture, particularly those suitable for small-scale farming and educational settings.

3 Materials and Methods

This section describes the materials, hardware components and methodological approach used to design, develop and evaluate the IoT-based smart irrigation system. The development process was carried out in two stages: (1) laboratory prototyping, where the system architecture and control logic were designed and tested, and (2) real-world implementation in a custom-built mini-greenhouse, allowing validation of automated irrigation and environmental regulation under realistic conditions. The methods include hardware configuration, sensor integration, and environmental calibration, as well as experimental setup for evaluating the performance in terms of water efficiency and plant growth. The following subsections provide a detailed overview of the system architecture and experimental procedures.

3.1 System Architecture and Components

The smart irrigation system was initially developed in a controlled laboratory environment, where students, as part of the *Integration of Information Systems* course, designed and tested a prototype shown in Figure 1. This laboratory phase served as the foundation for subsequent real-world deployment, ensuring that sensor calibration, control logic, and hardware integration were fully functional before field implementation. The primary objective was to create an IoT-based system capable of continuously monitoring environmental parameters and automating irrigation, temperature control, and humidity regulation. The system development followed a project-based learning model in which students worked in teams to design, build and test each subsystem. Through this approach, they engaged in real-world problem solving, iterative debugging, and decision making processes that closely mirror professional engineering practice. The experience provided an authentic context for developing technical competencies in IoT and embedded systems while simultaneously fostering soft skills such as collaboration, initiative, and communication.

The core components of the system were:

- NodeMCU v3: Microcontroller with integrated ESP8266 Wi-Fi module, responsible for processing sensor data and controlling peripheral devices.
- DHT11 sensor: Digital temperature and humidity sensor selected for its simplicity and cost-effectiveness.
- Soil moisture sensor: Provided real-time soil moisture data to trigger irrigation events automatically.
- Relay module (4-channel): Controlled high-voltage devices such as the water pump, fan, and LED lighting.
- Water pump: Low power pump (80 L/h capacity) for uniform water distribution via plastic tubing.
- LED lighting: Full-spectrum lamp optimised for plant growth, ensuring low energy consumption.
- Fan: Maintained proper air circulation and stable humidity levels inside the mini-greenhouse.

As shown in Figure 1, the prototype integrated these components to validate sensor readings, automate irrigation based on soil moisture thresholds, and ensure safe switching of high-voltage devices. This phase was critical to verify the reliability of hardware–software communication prior to real-world deployment.

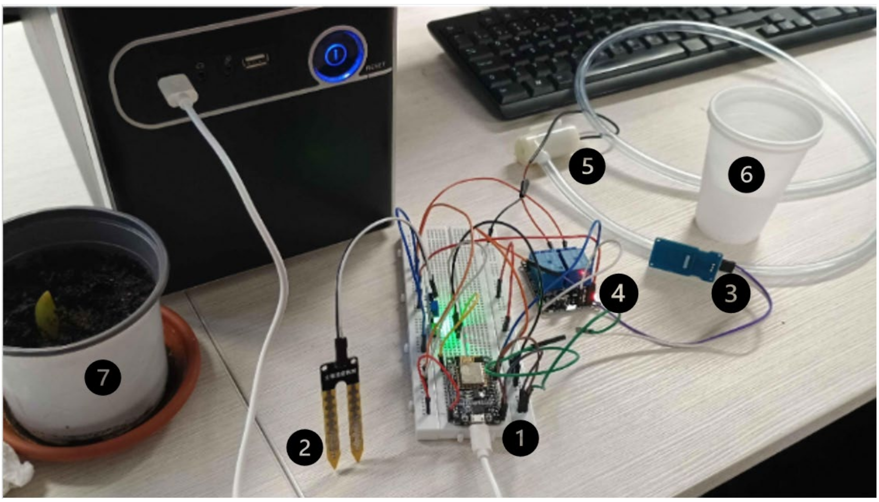

Figure 1
Prototype of the IoT-based smart irrigation system. (1) NodeMCU, (2) soil moisture sensor, (3) DHT11 sensor, (4) relay module, (5) water pump, (6) water reservoir, and (7) potted plant

3.2 Experimental Setup

After the prototype, the system was deployed in a custom-built mini-greenhouse designed for real-world testing. The structure was constructed from a wooden frame with insulated Lexan polycarbonate sheets, providing a stable microclimate for plant growth. The IoT components of the laboratory phase were integrated as follows:

- Real-time control: The NodeMCU processed data from DHT11 and soil moisture sensors to manage the water pump, fan, and lighting.
- Protective housing: The sensors were enclosed in protective casings to minimise the effect of temperature fluctuations and humidity on measurements, as shown in Figure 2. Sensor placement and protective housing were crucial for reliable operation under variable environmental conditions. This configuration enabled fully automated irrigation, temperature regulation, and air circulation in the greenhouse.
- Hardware stabilisation: Additional electrical components were added to the relay circuit to prevent unintended device activation during power fluctuations.

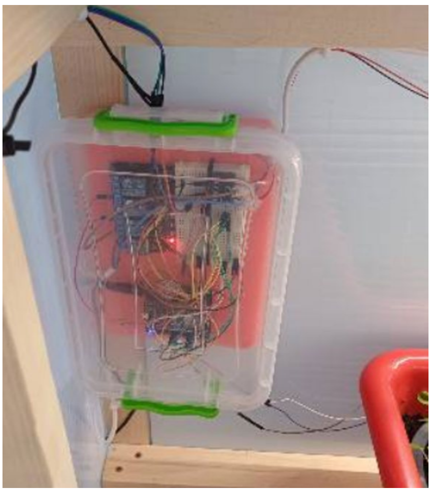

Figure 2

Sensor placement and protective housing ensured stable operation, despite environmental fluctuations

4 Results and Discussion

This section presents the results of the system's development and experimental validation, followed by a discussion of its performance and practical implications.

4.1 System Evaluation

The system was tested in the mini-greenhouse under real-world conditions for four consecutive weeks, during which arugula (*Eruca sativa*), a fast-growing leafy vegetable, was cultivated. The experimental validation was aimed at assessing the stability of IoT-based automation, its impact on water efficiency, and its ability to maintain optimal environmental conditions for plant growth.

To provide a structured overview of the observed results, the main performance parameters recorded during the testing period are summarised in Table 1. These results reflect the system's ability to maintain stable environmental conditions, optimise water usage, and support healthy plant growth.

Table 1
Key performance indicators of the IoT-based smart irrigation system

Parameter	Measured value	Remarks
Soil moisture range	25–35%	Maintained within ±5% variation of the set threshold
Irrigation frequency	8–10 times per week	Triggered based on real-time soil moisture readings
Irrigation duration	2–3 minutes per cycle	Adjusted dynamically by the control logic
Water consumption	9.2 L (automated) vs. 11.5 L (manual)	Approx. 20% reduction compared to manual irrigation
Plant growth	Average leaf length: 10.2 cm	Uniform development with no signs of water stress
System reliability	No hardware malfunctions	Stable operation ensured, despite occasional network issues

The recorded data confirm that the system achieved stable and efficient operation under real-world conditions. Automated irrigation responded reliably to environmental changes, reducing water consumption while ensuring consistent plant development. As illustrated in Figure 3, the cultivated arugula demonstrated uniform growth, confirming that the system maintained optimal environmental conditions throughout the test cycle. These results align with previous controlled-environment studies on arugula (*Eruca sativa*), where maintaining substrate volumetric water content (VWC) at approximately 0.30 m^3/m^3 was identified as optimal for balancing yield, water use efficiency, and quality parameters, while lower moisture levels (0.20 m^3/m^3) induced drought stress, reduced shoot growth, and decreased certain glucosinolate contents [11]. The experimental results validate that low-cost IoT-based automation can achieve significant water savings while maintaining plant health, making it suitable for small-scale agriculture and educational applications.

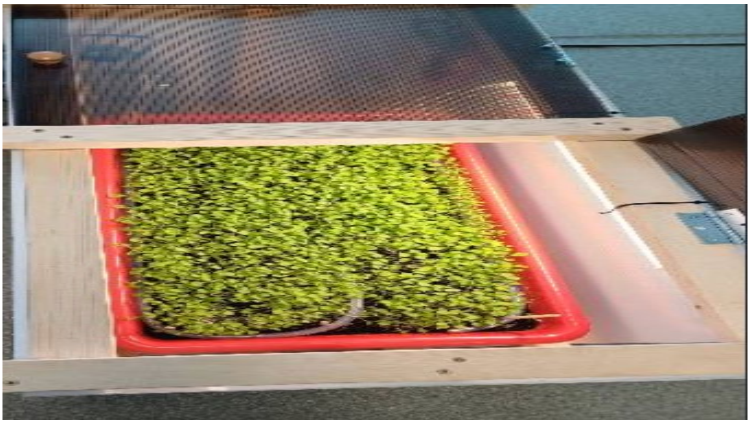

Figure 3
Arugula (Eruca sativa) cultivated in the IoT controlled mini-greenhouse; uniform growth and healthy foliage validate the effectiveness in real-world conditions

4.2 Software Development and Remote Monitoring

Remote monitoring and control functionalities were implemented using the Blynk platform, providing a user-friendly interface for managing the mini-greenhouse environment. The web interface (Figure 4) displayed real-time temperature, humidity, and soil moisture data, allowing manual or automated control of irrigation and ventilation. The clear visualisation of real-time data in the web interface makes the system suitable for use in student laboratories, where it can serve as a practical example for learning IoT-based environmental monitoring. The mobile application, as shown in Figure 5, offered convenient remote access, making the system practical for both farmers and hobby gardeners. The mobile interface provides an accessible way for students to experiment with remote control of IoT devices, strengthening their understanding of applied automation in smart agriculture.

The Blynk platform proved to be stable during the evaluation period. Timers and reconnection mechanisms successfully maintained system operation during occasional Wi-Fi interruptions, confirming its suitability for environments with variable network availability.

From a usability perspective, the software demonstrated high potential for educational and small-scale agricultural use. Its intuitive design enabled nontechnical users, such as hobby gardeners, to easily interact with the system, which supports broader adoption of low-cost IoT solutions in sustainable farming.

Figure 4
Blynk web interface displaying real-time temperature, humidity, and soil moisture data; enables manual or automated control of irrigation and ventilation

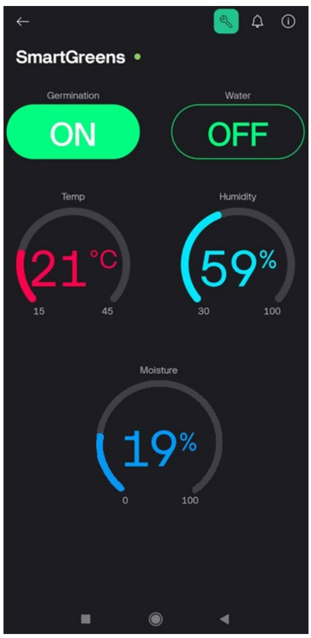

Figure 5
Blynk mobile interface for remote irrigation control; designed for user-friendly monitoring of temperature, humidity, and soil moisture by farmers and hobby gardeners

4.3 AI-driven Data Analysis and Predictive Modelling

The smart irrigation system continuously collects environmental data, providing a valuable dataset for further analysis. As these parameters are monitored in real-time, they form a time series dataset that can be used for predictive modelling. Recent studies demonstrate that AI-based approaches significantly enhance the accuracy of soil moisture prediction and irrigation planning using deep learning and machine learning models [12]. Several studies have demonstrated the potential of AI-driven approaches to improve agricultural efficiency [13-15].

In [16], researchers focused on predicting soil parameters, essential for agricultural productivity, using cost-effective machine learning techniques. Because the deployment of expensive soil sensors on a large scale is impractical, alternative methods were explored to predict soil moisture and temperature based on ambient humidity and temperature. The study collected 9,000 data points from an uncontrolled agricultural setting using inexpensive sensors. Various machine learning models were evaluated and XGBoost achieved the best performance, delivering high R^2 scores of 0.93 for soil moisture and 0.99 for soil temperature. These findings highlight the strong correlation between weather conditions and soil parameters. This demonstrates the potential for affordable agricultural automation.

A similar AI-based smart irrigation system is presented in [17], where machine learning was used to predict soil moisture levels based on temperature, humidity, and soil moisture data collected from IoT sensors. The system, developed through cloud computing, enables data extraction and analysis. Using a decision tree algorithm, it achieved 90% accuracy in predicting the required amount of water, leading to improved irrigation efficiency, increased farmer profits and improved sustainability.

In [18], researchers explored smart irrigation systems that optimise water use using real-time data and predictive analytics. The study emphasised the importance of applying machine learning techniques to improve irrigation efficiency by forecasting future soil water content within an IoT-enabled smart irrigation framework. These findings further support the integration of AI and IoT in resource-efficient precision agriculture.

Although the current phase of the project did not include the implementation of artificial intelligence techniques, the system was designed to support future integration of AI-driven analytics. During the real-world deployment in the mini-greenhouse, a significant amount of environmental data was collected, including time series measurements of temperature, humidity, and soil moisture. These data sets provide a valuable foundation for the application of predictive modelling and machine learning in the next phase of the project.

In the upcoming project stage, students will use this data set to explore AI-based approaches for predictive soil moisture estimation, irrigation scheduling, and environmental optimisation. Several key data science techniques are planned for application in the next phase of development. These include pre-processing of collected sensor data, exploratory analysis to identify trends, time series forecasting for irrigation planning, and the use of machine learning models to optimise scheduling. Table 2 outlines the main stages of the planned data analysis, along with the corresponding techniques and expected results. This structured approach will support the integration of predictive analytics in the next development phase.

Table 2
Planned stages of AI-based data analysis and predictive modelling

Stage	Techniques / Methods	Purpose
Data cleaning and preprocessing	Handling missing values, smoothing, normalization	Ensure accuracy and reliability of sensor readings
Exploratory data analysis (EDA)	Trend visualisation, correlation analysis, seasonal detection	Identify patterns and guide model selection
Predictive modelling	ARIMA, LSTM, SARIMAX	Forecast future soil moisture and environmental parameters
Machine learning regression	Random Forest, Gradient Boosting	Predict optimal irrigation schedules based on historical data
Optimization algorithms	Rule-based control, decision trees, adaptive thresholds	Minimise water usage while maintaining optimal plant growth

Beyond technical implementation, the project introduced students to interdisciplinary learning by integrating environmental data analysis with foundational data science techniques. By working with real sensor datasets collected from the mini-greenhouse, students gained experience in preparing, analysing, and modelling real-world time series data. This learning process provided a bridge between theory and application, reinforcing their understanding of AI principles in an agricultural context.

Through participation in these tasks, students not only apply theoretical knowledge, but also develop practical skills in data science, AI, and IoT integration. Working with real-world sensor data allows them to explore supervised and unsupervised learning techniques, adjust model parameters, and evaluate performance using metrics such as mean absolute error (MAE) and root mean square error (RMSE). This project bridges the gap between software development, machine learning, and agricultural automation, offering hands-on experience applying AI to real-world IoT systems. Future improvements could incorporate cloud-based data processing for AI-driven real-time irrigation control, optimising water use based on predicted weather and soil moisture trends.

Conclusions

The development and implementation of the IoT-based smart irrigation system demonstrated the potential of combining sensor technology, automation, and real-time monitoring to enhance agricultural efficiency. The system successfully automated irrigation, temperature control, and humidity regulation, which resulted in reduced water consumption and minimised human intervention. Real-time data collection and remote monitoring through the Blynk platform provided a scalable and user-friendly solution suitable for precision agriculture. A significant educational impact was achieved, as students participated in all stages of the project, including system design, hardware integration, testing, and data analysis. This hands-on experience allowed them to develop practical skills in IoT integration, environmental data collection, and the fundamentals of AI-based predictive modelling, helping them better understand the interdisciplinary nature of modern agriculture. Such experience directly contributes to strengthening their technical competencies, problem-solving abilities, and innovation, which are essential for future work in sustainable farming and smart city projects. Additionally, the system and associated datasets have been incorporated into regular coursework in the IoT laboratory, providing a reusable platform for future generations of students. Therefore, not only delivered immediate educational benefits but also laid the foundation for sustained curriculum enhancement through hands-on experiential learning. Future research will focus on the integration of AI-driven predictive analytics for real-time irrigation control, the use of cloud computing for faster decision making, and improving system adaptability to different agricultural environments. Additional improvements will include the use of weather forecast APIs satellite data. The incorporation of solar-powered components and automated nutrient delivery systems is also planned, which could transform the current system into a fully autonomous platform for smart agriculture.

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