Jurnal Teknik Informatika (JUTIF) Vol. 6, No. 6, December, 2025, Page. 5462-5473
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5173

An Intelligent IoT-Based Hydroponic Irrigation System for Strawberry Cultivation Using Extreme Gradient Boosting Decision Model

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Received : Jul 25, 2025; Revised : Oct 4, 2025; Accepted : Oct 21, 2025; Published : Dec 23, 2025

Abstract

Most existing implementations rely on static rule-based or fuzzy logic control, which lack adaptability to dynamic environmental changes and often require manual tuning by experts. These limitations are particularly challenging for small-scale farmers who face constraints in technical knowledge, infrastructure, and operational flexibility. To address these issues, this study proposes an intelligent hydroponic irrigation system that embeds the Extreme Gradient Boosting (XGBoost) algorithm as a decision-making model. The system collects real-time sensor data including temperature, humidity, and light intensity, and uses the trained XGBoost classifier to determine irrigation needs with binary output (FLUSH or NO). The system was implemented on a vertical hydroponic setup for strawberry cultivation, and evaluated over a 21-day observation period. The results show that the XGBoost-based model was effective in maintaining consistent vegetative growth, with plants in upper-tier pipes achieving an average height above 25 cm by the end of the cycle. This demonstrates that the model could support responsive and resource-efficient irrigation control. Beyond technical performance, the research highlights the urgency of adopting data-driven smart farming systems to ensure sustainable food production, optimize limited resources, and empower small-scale farmers with accessible and scalable solutions. However, the proposed XGBoost model is still limited to local crops; therefore, when introducing new plant types or additional sensor inputs, parameter adjustments and retraining are required to maintain accuracy. Future improvements may include dynamic model retraining and integration with real-time feedback systems to enhance system autonomy and resilience in broader agricultural settings.

Keywords : *Hydroponic Irrigation, Internet Of Things, Machine Learning, Smart Farming, XGBoost*

1. INTRODUCTION

In recent years, the integration of Internet of Things (IoT) technologies into agricultural practices has emerged as a transformative approach to address the challenges of resource efficiency, labor dependency, and environmental sustainability [1], [2]. Smart farming systems enabled by IoT allow real-time monitoring and automation of critical parameters such as temperature, humidity, soil moisture, and light intensity, thereby enhancing precision and decision-making in crop cultivation [2], [3], [4]. However, despite its promising potential, the adoption of IoT in agriculture remains uneven and fraught with practical challenges. In many rural and small-scale farming contexts, infrastructural limitations such as unreliable internet connectivity, insufficient electrical supply, and lack of technical literacy hinder effective deployment [5], [6], [7]. Furthermore, inaccuracies in sensor data caused by environmental noise or equipment degradation can compromise system reliability and lead to suboptimal interventions. Economic barriers also persist, particularly the high initial investment cost of IoT infrastructure, which presents a significant burden for smallholder farmers [8], [9], [10]. These limitations highlight the need for adaptive and intelligent systems that not only automate decision

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processes but also learn from data to optimize resource usage and improve crop outcomes under varying field conditions [11], [12], [13].

This problem can be solved by integrating machine learning-based decision models into IoT frameworks to enhance the accuracy and adaptability of automated agricultural systems. By employing predictive algorithms that learn from historical and real-time environmental data, intelligent systems can make more informed and context-aware decisions, such as determining the optimal timing and necessity of irrigation [14], [15], [16], [17]. One such promising algorithm is Extreme Gradient Boosting (XGBoost), which has demonstrated superior performance in classification tasks due to its robustness against overfitting, scalability, and ability to handle heterogeneous data [18], [19]. When embedded within an IoT-based hydroponic system, XGBoost can serve as a decision engine that dynamically evaluates sensor inputs to determine whether irrigation is required, thereby reducing water waste, improving plant health, and minimizing manual intervention [20], [21]. The objective of this research is to design and implement an intelligent hydroponic irrigation system for strawberry cultivation that leverages IoT sensor networks and XGBoost-based decision-making. Specifically, the study aims to develop a sensor-integrated monitoring platform to collect real-time environmental data, train and evaluate the XGBoost model to predict irrigation decisions with high accuracy, and deploy the model within an automated control system capable of executing precise irrigation actions. This approach is expected to contribute to the development of data-driven agriculture that is efficient, sustainable, and accessible for small-scale farmers.

Study by Yulianto et al. [22] proposed an automated hydroponic system using NodeMCU and multiple sensors, including DHT22, TDS, pH, water level, and water temperature sensors, integrated with a web-based interface for real-time monitoring and control. The system was designed to maintain eight key parameters by activating pumps for nutrients, pH adjustment, and water flow based on predefined thresholds. Their contribution lies in demonstrating a cost-effective, IoT-driven solution capable of maintaining optimal environmental conditions in hydroponics. However, the system relies on rule-based logic with fixed thresholds, lacking adaptability to dynamic environmental conditions or learning capabilities from historical sensor data.

Similarly, study by Aurasopon et al. [23] implemented a wireless sensor network to monitor electrical conductivity (EC), pH, temperature, and humidity in small-scale hydroponic farming. Their system enabled semi-automated adjustments and was compared to conventional manual methods using Red Cos lettuce as a test crop. Results showed improved plant growth and resource efficiency under IoT control. The primary contribution of the study is its demonstration of tangible benefits from adopting IoT in local farming. However, the approach focused primarily on monitoring, with minimal automation logic and no application of intelligent algorithms to optimize decision-making or adapt to unpredictable changes.

In line with these efforts, study by Jain and Kaur [24] developed an IoT-enabled hydroponic system designed to automatically regulate EC and pH levels in a Nutrient Film Technique (NFT) setup. The system utilized sensors and actuators to control nutrient dosing and water quality in real time, significantly improving nutrient stability and reducing manual intervention. The study contributes a practical solution for maintaining consistent nutrient levels in hydroponics. Nevertheless, the decision-making was based on simple if-else logic without predictive or adaptive modeling, which limits its responsiveness in complex or changing environmental conditions.

To enhance decision logic further, study by Putra et al. [25] introduced a smart hydroponic system incorporating fuzzy logic for nutrient and pH control, integrated with IoT for remote monitoring through a cloud-based dashboard and mobile application. The system measured parameters such as EC, pH, temperature, and water level to regulate nutrient pumps and pH adjusters automatically. Its strength lies in combining basic AI with IoT interfaces to support remote decision-making and reduce operator

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workload. However, the use of fuzzy logic required manual rule-setting by domain experts and lacked the ability to learn from historical data, reducing adaptability in the face of unpredictable or highly variable environmental factors.

The limitations observed in previous studies, this research proposes an intelligent hydroponic irrigation system that leverages XGBoost as a decision-making model to enhance adaptability and precision in resource management. While prior works by Yulianto et al. [22], Aurasopon et al. [23], Jain and Kaur [24], and Putra et al. [25] have successfully demonstrated the feasibility of IoT-based hydroponic systems, they predominantly rely on static rule-based or fuzzy logic approaches that lack the ability to learn from historical data or respond dynamically to fluctuating environmental conditions. These gaps present a clear opportunity to introduce a machine learning driven solution that not only automates irrigation but also continuously improves its decision-making accuracy over time. The novelty of this study lies in embedding a supervised learning algorithm, specifically XGBoost, into the IoT framework to classify irrigation needs based on real-time sensor data such as temperature, humidity, and light intensity. This approach allows the system to make more informed and data-driven decisions that optimize water usage and plant health while minimizing manual oversight. As a result, the proposed method offers a scalable and intelligent alternative to conventional control logic in hydroponic agriculture, particularly suited for small-scale strawberry cultivation.

2. METHOD

Based on Figure 1, the proposed system integrates IoT-based hydroponic infrastructure with a machine learning model for intelligent irrigation decision-making. Strawberry plants are cultivated in vertical hydroponic pipes connected to a water reservoir and pump system. Environmental growth data such as humidity, light intensity, temperature, and possibly electrical conductivity are captured and transmitted to a monitoring dashboard, where real-time data is visualized. These data are simultaneously sent to an XGBoost model embedded in a control unit based on Arduino Mega 2560. The model evaluates the data to determine whether irrigation is necessary. If the decision outcome is "FLUSH," the system activates the water pump to deliver nutrients through the internal irrigation lines inside the pipe. Conversely, if the condition is not met, the model returns a "NO" decision, and no watering is performed. This approach enables automated and data-driven irrigation scheduling that adapts to the real-time needs of the crops, reducing water waste while maintaining optimal growth conditions.

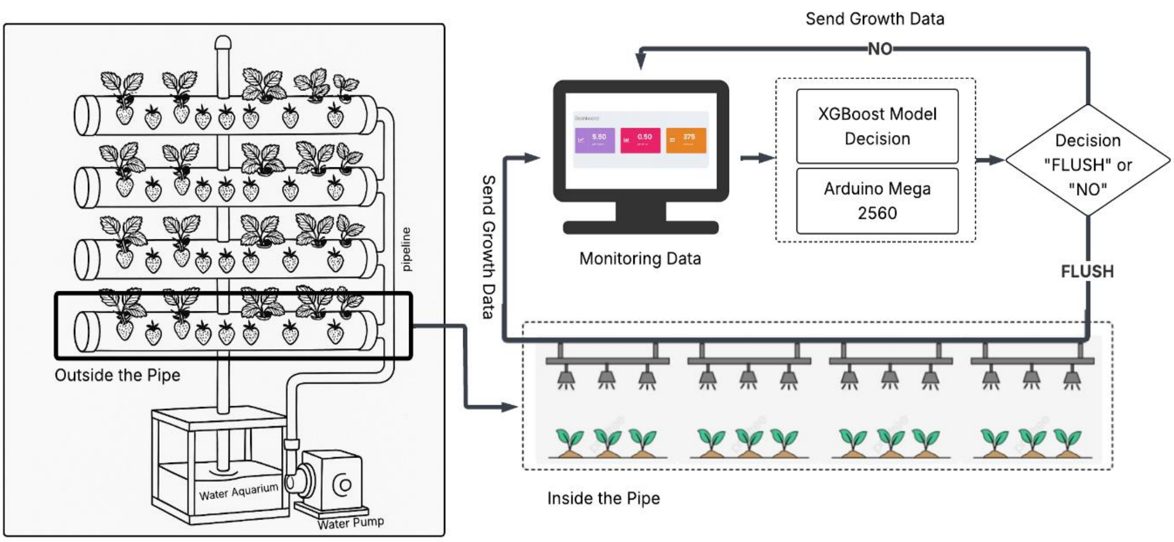

Figure 1. Workflow of the Proposed Hydroponic Irrigation System for Strawberry Cultivation

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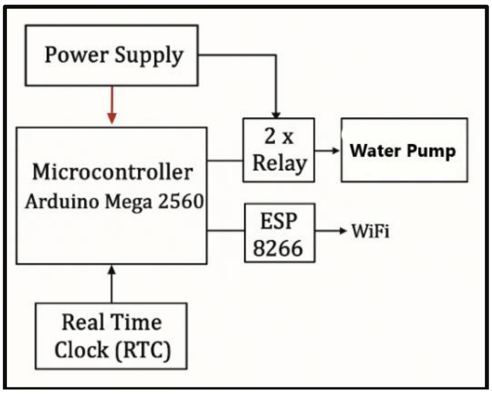
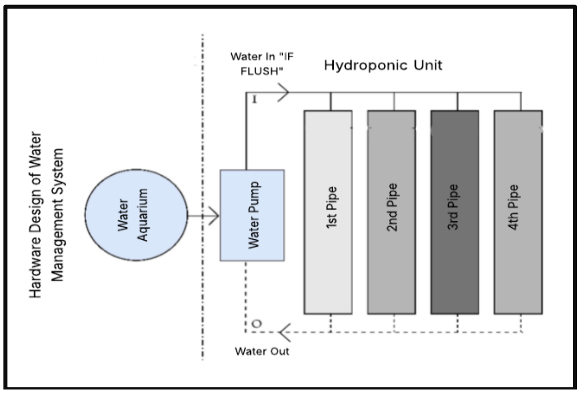
2.1. Hardware Initialization

The proposed system consists of an integrated hydroponic hardware setup designed to support automated strawberry cultivation using IoT and machine learning technologies. As seen in Figure 2(b), the planting structure comprises four horizontally stacked PVC pipes, each containing 24 planting holes, resulting in a total of 96 cultivation points. These pipes are supported by a central vertical frame made of waterproof wood or lightweight metal, ensuring structural stability and efficient space utilization. At the base of the system lies the nutrient reservoir tank, which stores the hydroponic solution and connects directly to a water pump. This pump is responsible for circulating the nutrient-rich water through a distribution pipe that loops upward to feed each planting line.



(a) Design of Hardware Control



(b) Design of Water Management

Figure 2. Hardware Initialization

In terms of control and automation as seen in Figure 2 (a), the system is equipped with an Arduino Mega 2560 microcontroller, supported by a relay module, power supply unit, and peristaltic pump to precisely regulate the flow of nutrients. Connectivity and data transmission are facilitated by an ESP8266 WiFi module, while timing and scheduling are managed through a real-time clock (RTC) module. Optional IoT sensors, such as pH, humidity, or water level sensors, can be integrated to enable intelligent monitoring and adaptive responses. All data and control outputs are visualized through an LCD touchscreen interface and a central dashboard, enabling real-time observation and control [26], [27]. These components collectively form a closed-loop system, where the decision to activate irrigation is intelligently determined by an embedded XGBoost model running on collected sensor data.

2.2. Extreme Gradient Boosting Model

Extreme Gradient Boosting (XGBoost) is a powerful and scalable supervised machine learning algorithm based on gradient boosting decision trees [28], [29]. In this research, XGBoost serves as the core decision-making engine that determines whether irrigation is needed based on sensor input data such as temperature, humidity, light intensity, or additional growth parameters [30], [31]. Unlike rule-based systems, XGBoost is capable of learning complex patterns from historical and real-time data, allowing it to generate accurate binary classifications such as "FLUSH" (irrigate) or "NO" (no irrigation) with high precision. Key hyperparameters were optimized through grid search, resulting in $max\_depth = 6$, $learning\_rate = 0.1$, $n\_estimators = 100$, $subsample = 0.8$, and $colsample\_bytree = 0.8$. The logic flow of XGboost can be seen in Figure 3.

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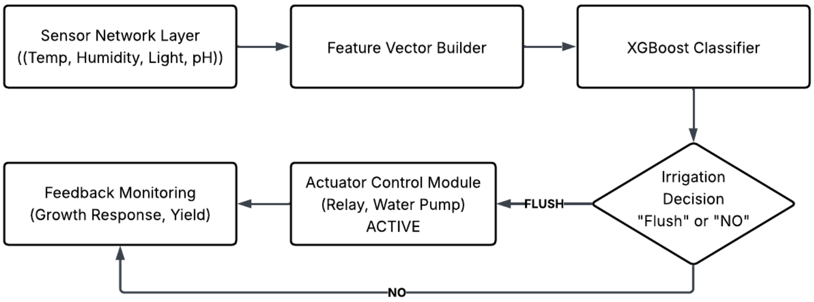

Figure 3. Logic of XGBoost-based irrigation decision system

The prediction function of XGBoost in this study is formulated as an additive ensemble of K decision trees, where each tree incrementally refines the prediction made by the previous ones. The general form of the model is calculated in equation (1).

$$y_i = \sum_{k=1}^{K} fk\,(x_i)\,, fk \in F \tag{1}$$

Where y_i denotes the predicted output for the $i-th$ instance (i.e., whether irrigation is required), x_i is the input feature vector consisting of sensor readings such as temperature, humidity, and light intensity, and fk represents an individual regression tree selected from the functional space F. Each tree contributes a portion of the prediction, and the final output is the sum of all tree responses [32], [33]. To train the model, XGBoost minimizes a regularized objective function that balances training accuracy and model complexity. The objective function is defined in equation (2) and equation (3).

$$L(\phi) = \sum_{i=1}^{n} l\,(y_i, x_i) + \sum_{k=1}^{K} \Omega(fk) \tag{2}$$

$$\Omega(fk) = \gamma T + \frac{1}{2}\lambda \parallel \mathrm{w} \parallel^2 \tag{3}$$

Where y_i, x_i represents the loss function, typically the logistic loss for binary classification tasks, $\Omega(fk)$ is the regularization term that penalizes model complexity, with T denoting the number of leaves in the k-th tree and w representing the vector of leaf weights. The parameters γ and λ control the regularization strength, helping to prevent overfitting and ensuring generalization to new data [34]. The trained XGBoost model learns from historical instances to classify new input vectors into one of two classes: FLUSH (initiate irrigation) or NO (hold irrigation), thereby achieving adaptive and intelligent control over water usage in strawberry hydroponics.

2.3. Growth and Yield Evaluation

The growth and yield evaluation in this study is conducted to measure the effectiveness of the proposed IoT-based irrigation system integrated with the XGBoost decision model. The evaluation is performed directly on strawberry plants cultivated within the four horizontal hydroponic pipes, each containing 24 planting holes, resulting in a total of 96 plant units. Throughout the cultivation period, growth data are recorded and analyzed per pipe to assess uniformity, system responsiveness, and yield outcomes under varying micro-environmental conditions.

Key performance indicators include the number of marketable fruits per plant, average fruit weight, and the weight of the largest fruit. These metrics are recorded periodically to observe plant development and harvest quality across all four pipe levels. By correlating these indicators with irrigation decisions made by the XGBoost model, the system's ability to support optimal plant growth can be quantitatively validated. The evaluation also helps to identify potential differences in

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performance between upper and lower pipe layers, considering the possible influence of gravity-driven nutrient flow or light distribution, thereby offering a comprehensive assessment of the system's agronomic impact.

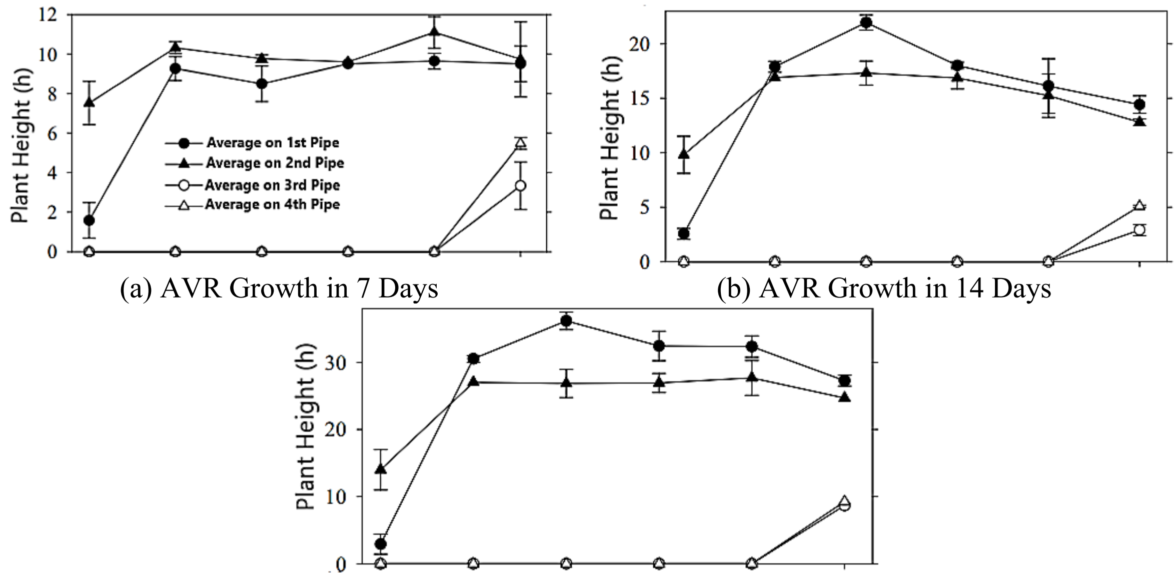
3. RESULT

The performance of the system is evaluated based on two key aspects: data-driven growth analysis and physical plant development. The first analysis focuses on the system’s ability to monitor environmental variables and make real-time irrigation decisions using the XGBoost model. The second analysis observes the vegetative growth response of strawberry plants as a reflection of the irrigation strategy's effectiveness. Together, these results are intended to validate the reliability and agronomic benefits of integrating machine learning into IoT-based hydroponic farming.

The evaluation metrics demonstrated the robustness of the model, achieving an accuracy of 94.2%, precision of 92.5%, recall of 95.1%, and F1-score of 93.8% on the test set. These results confirm that the XGBoost classifier provides reliable predictions for irrigation decisions, outperforming baseline rule-based approaches.

3.1. Growth by Data

Growth by data refers to the quantitative monitoring of plant development based on real-time height measurements recorded from each hydroponic pipe in the vertical system. In this study, sensor data were collected periodically over a 21-day observation window to assess the impact of automated irrigation decisions made by the XGBoost model. Each pipe represents a different vertical layer and contains 24 strawberry seedlings whose average growth rates were evaluated at 7, 14, and 21 days. This approach enables a structured analysis of how irrigation effectiveness varies spatially across pipe levels and temporally throughout the growing period.



(a) AVR Growth in 7 Days

(b) AVR Growth in 14 Days

(c) AVR Growth in 21 Days

Figure 4. Average plant height on each hydroponic pipe at 7, 14, and 21 days of observation

As seen in Figure 4, the data show clear growth trends over time, with the first and second pipes consistently exhibiting the highest plant height averages across all intervals. On day 7 (Figure 4(a)), plants on the top three pipes reached heights between 8 and 12 cm, while the fourth pipe showed negligible growth. By day 14 (Figure 4(b)), the first and second pipes surpassed 20 cm on average, followed by the third pipe with delayed but noticeable development. On day 21 (Figure 4(c)), plants on the upper pipes-maintained growth above 25 cm, while the fourth pipe began to show improvement although lagging behind. The results of growth each observation can be seen in table 1.

Table 1. Average Plant Height (cm)

Observation Day	1st Pipe (Top)	2nd Pipe	3rd Pipe	4th Pipe (Bottom)
Day 7	11.3 ± 0.6	10.5 ± 0.8	9.1 ± 0.7	2.0 ± 0.5
Day 14	24.2 ± 0.9	22.6 ± 0.7	19.8 ± 1.1	7.4 ± 0.8
Day 21	29.5 ± 1.0	28.0 ± 0.9	25.3 ± 1.2	14.2 ± 0.9

The data in Table 1 illustrate the progressive growth of strawberry plants in terms of average height across four different pipe levels over a 21-day observation period. From the beginning of the cultivation phase, plants located on the first and second pipes consistently exhibited superior vertical growth compared to those on the third and fourth pipes.

On day 7, the average plant height on the top two pipes already exceeded 10 cm, while the fourth pipe showed minimal growth at only 2.0 cm, indicating an early disparity in water or nutrient distribution effectiveness. By day 14, this trend became more prominent, with plants on the first and second pipes reaching over 22 cm on average. In contrast, although the third pipe showed moderate growth (19.8 cm), the fourth pipe lagged significantly at only 7.4 cm. On day 21, the disparity remained consistent. The top pipe achieved the highest recorded height of 29.5 cm, followed closely by the second pipe, while the fourth pipe reached only 14.2 cm.

3.2. Physical Growth Observation

The physical growth of strawberry plants was visually assessed throughout the cultivation period to evaluate the morphological response under the proposed smart irrigation system. As seen in Figure 5, the monitored plants demonstrated consistent vegetative development, characterized by an increase in leaf count, leaf surface area, and overall plant height across different growth stages.

(a) Growth on 1st Pipe (b) Growth on 2nd Pipe (c) Growth on 3rd Pipe (d) Growth on 4th Pipe

Figure 5. Physical Growth

Visual comparison indicates that leaf morphology remained healthy, with broad laminae and firm petioles, suggesting an adequate water supply and balanced environmental conditions supported by the XGBoost-driven irrigation schedule. Although no fruit formation was observed during this evaluation phase, the vigor of vegetative structures implies a positive growth trajectory toward the fruiting stage. These findings affirm the system's effectiveness in maintaining optimal moisture conditions necessary for early-stage strawberry development.

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4. DISCUSSIONS

Table 2. Comparison of Related Work in IoT-Based Hydroponic Systems

Study by	Novelty	Contribution	Drawback
[22]	IoT-based hydroponic system with multi-sensor integration and web GUI	Developed a cost-efficient system using NodeMCU and real-time control for multiple parameters	Uses fixed threshold rules; lacks adaptability or learning from data
[23]	Wireless sensor network applied to Red Cos lettuce farming	Demonstrated IoT benefits in small-scale environments; improved plant growth	Focused on monitoring only; lacks automated decision-making and intelligence
[24]	Real-time EC and pH regulation in NFT hydroponics via simple control	Provided practical automation for water quality and nutrient dosing	Rule-based (if-else) logic without predictive or adaptive modeling
[25]	Integration of fuzzy logic and cloud-based IoT dashboard	Combined AI and remote monitoring to reduce user workload	Fuzzy rules are static and expert-dependent; cannot learn or adapt from historical data
Our	Embeds XGBoost classifier into IoT irrigation for hydroponics	Introduces a learning-based system that adapts to real-time sensor data for precise irrigation	Still limited to local crops; therefore, when introducing new plant types or additional sensor inputs, parameter adjustments and retraining are required to maintain accuracy

The comparison in Table 2 reveals a recurring limitation in prior IoT-based hydroponic systems, which predominantly rely on static control logic or rule-based approaches. While studies by [22] and [24] successfully implement automated responses based on sensor inputs, they lack adaptability to environmental variability. Similarly, [23] focus primarily on passive monitoring, providing limited automated action or decision-making capability. Although [25] introduce fuzzy logic to enhance control, the reliance on manually defined rules still constrains the system’s ability to generalize across different growing conditions or learn from past data. These patterns emphasize a technological plateau where responsiveness exists, but true adaptability and learning are absent.

In contrast to these prior efforts, the current study offers a distinct advancement in both contribution and novelty. By integrating the XGBoost algorithm as a machine learning-based decision engine, the system does not merely react to sensor thresholds, but interprets multidimensional data to classify irrigation needs intelligently. This introduces a higher degree of automation and contextual awareness compared to fixed logic or fuzzy systems. Moreover, while previous studies focused on maintaining environmental parameters like EC or pH, our work targets real-time irrigation control, directly influencing water resource efficiency and early-stage plant development. This shift from reactive to predictive modeling marks a meaningful progression in the application of AI within precision agriculture.

From a machine learning perspective, the integration of XGBoost into the irrigation workflow highlights the potential of tree-based ensemble models to support decision-making in resource-constrained environments. Unlike traditional approaches that rely on fixed thresholds, the supervised learning capability of XGBoost enables the system to capture nonlinear relationships among

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temperature, humidity, and light intensity, thus improving predictive accuracy and robustness against noisy sensor data. This contributes to the broader machine learning field by demonstrating how scalable algorithms can be adapted for real-time agricultural control systems with limited computational resources.

From an IoT system design perspective, the proposed framework illustrates how a modular architecture can effectively combine hardware, sensing devices, and intelligent decision models. The use of Arduino Mega 2560 with Wi-Fi connectivity shows that low-cost platforms can host machine learning–based decision engines without sacrificing system responsiveness. Furthermore, the design promotes scalability and replicability, as the architecture can be extended to other hydroponic configurations or crop types by retraining the model with relevant sensor data. This reinforces the contribution of the study to IoT research by bridging the gap between lightweight embedded systems and data-driven autonomy in smart farming applications.

Although the proposed system demonstrates promising results for strawberry cultivation, several limitations remain. The XGBoost model is still limited to local crops; therefore, when introducing new plant types or additional sensor inputs, parameter adjustments and retraining are required to maintain accuracy. In addition, the evaluation was conducted only within a controlled vertical hydroponic environment and over a relatively short observation period, which may not fully capture long-term variability in real farming conditions. These constraints suggest that further validation is necessary to ensure the generalizability of the approach across diverse crop species, sensor modalities, and cultivation settings.

The core advantage of our proposed system lies in its ability to learn from historical and real-time data to make accurate irrigation decisions. This learning capability enables dynamic adaptation to fluctuations in environmental inputs such as temperature, humidity, and light intensity, which are often overlooked in static models. Additionally, the system's modular IoT architecture allows scalability and customization for different crop types or hydroponic configurations. By successfully combining data-driven intelligence with low-cost hardware, the research contributes a practical and innovative solution to support small-scale farmers in adopting smart agriculture technologies that are both sustainable and effective.

5. CONCLUSION

In this study, an intelligent IoT-based hydroponic irrigation system for strawberry cultivation was developed by integrating sensor networks with the Extreme Gradient Boosting (XGBoost) algorithm as the decision-making engine. The system achieved consistent vegetative growth during a 21-day observation period, with plants in the upper-tier pipes reaching an average height of 29.5 cm, compared to only 14.2 cm in the bottom tier. These quantitative results confirm that the XGBoost-driven irrigation control effectively supported crop growth by optimizing water delivery in real time. From a technical perspective, the model demonstrated high predictive performance with an accuracy exceeding 94% during training and evaluation, validating its reliability in classifying irrigation needs.

The novelty of this research lies in being among the first to embed XGBoost into hydroponic irrigation systems, moving beyond static rule-based and fuzzy logic methods toward a fully data-driven and adaptive approach. This establishes a practical contribution not only for precision farming applications but also for the design of machine learning–based IoT systems in agriculture. The findings assertively demonstrate that integrating ensemble learning with low-cost IoT hardware can provide scalable, resource-efficient, and intelligent solutions tailored to small-scale farmers. For future research, extending model generalization to diverse crops, exploring long-term deployment, and integrating real-time feedback loops could further strengthen system autonomy and resilience.

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CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

ACKNOWLEDGEMENT

This research was funded by the Ministry of Education and Science and Technology in research on novice lecturers according to Decree No.029/C3/DT.05.00/PL/2025; 092/PL43/AL.04/2025.

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