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SMART GARDENING THROUGH AI-INTEGRATED IOT: A FRAMEWORK FOR INTELLIGENT MONITORING AND AUTOMATED CONTROL

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ABSTRACT

Personal food production at home and community gardens is growing hugely worldwide; hence, there is a need for intelligent and swift gardening systems to adapt accordingly to the environment and respond effectively. Almost all current automated irrigation systems use predefined threshold-based control mechanisms, making them unable to respond optimally to changing soil, environmental, and plant conditions. In this research, we propose an AI-based IoT approach for intelligent monitoring, prediction, and automation in smart gardens. This system includes multiple layers: distributed environment sensors, an edge processing unit for real-time processing and decision support, and a cloud-based machine learning module for prediction and optimization. Continuous data acquisition for soil moisture, temperature, humidity, light, and nutrients was utilized to train supervised learning algorithms for soil moisture prediction and irrigation demand prediction. A reinforcement learning–based scheduler was used to control irrigation timing and quantity based on environmental changes and plant life cycles. We conducted experiments using a controlled smart garden setup for multiple growth cycles. The AI-driven system attained better prediction accuracy for soil moisture estimation and used considerably less water than traditional rule-based irrigation, without compromising plant health. Also, edge-based deployment reduced latency and improved real-time responsiveness without excessive energy overhead. To wrap up, these results show the potential of integrating AI with IoT technology to create more efficient, sustainable, and autonomous smart gardening applications. The proposed architecture provides a viable solution for urban gardening needs. Plus, this system helps save water and energy resources and promotes precise management of inputs for micro food production.

Keywords:
Smart Gardening; Artificial Intelligence (AI); Internet of Things (IoT); AI-Integrated IoT Systems; Intelligent Plant Monitoring.

INTRODUCTION

There is a growing interest in food production at a local scale within the home and communities, especially within the rapidly urbanizing, climate-affected global environment. Gardens and small-scale food cultivation have traditionally been a supplementary source of food, a hobby, or a recreational activity, but home-growing is becoming a crucial part of the food system, environmental action, and household sustainability. Managing a garden successfully requires monitoring soil, environment, and plant status, which requires time, knowledge, and commitment. Many gardeners depend on their experience or a pre-determined schedule to irrigate and fertilize plants, which can lead to inefficient water use, inconsistent harvest, and unnecessary plant stress. Here, the challenge is not to mechanize gardening but to add intelligence to the monitoring process.

Recently, technological advances in the Internet of Things (IoT) environment have brought new approaches in monitoring and collecting environmental data with a focus on reducing the cost of sensors, communication modules, and storage using the cloud. In gardening, this helps to collect soil moisture, temperature, humidity, sunlight, and nutrients in real-time from multiple plants to understand the changing microclimate better. Even though we have many smart gardening solutions, most of these existing IoT gardening systems are reactive in nature, such as starting an irrigation system when soil moisture is below a predetermined threshold. These systems do not consider variations over time, weather, or plant growth, and hence they are unable to learn from past experiences.

The possibility of using AI in IoT-enabled gardens could also mean that future research and development could move towards predictive and decision-making garden management. While automation uses predefined, static rules, AI would need to train from a more complex range of data points, understand nonlinear associations, and generate meaningful decisions. For example, a machine learning model could train on the rate of soil moisture to predict when the soil would dry based on lots of environmental conditions. This understanding could then be used to improve irrigation schedules, considering various factors such as plant growth stages, weather forecast, or water conservation strategies. Reinforcement Learning, a branch of AI, could also be used to adjust irrigation strategies dynamically, learning from the environment and improving decisions over time. Moving from simple automation to systems empowered with AI represents a novel direction that smart garden research could explore. Water management was one of the key ones mentioned here. Agriculture uses the majority of water worldwide, so its use in irrigation is critical to control because it is a major reason for water stress as well as soil degradation. Even with domestic or community gardening, there would be a significant amount of water wastage. A smart irrigation system could anticipate plant demand rather than just react to deficit, preventing excessive watering but also drought stress. Watering can be timed for optimum nutrient uptake as well as minimal runoff, thus creating an ethically responsible gardener. As well as water conservation, the smart system can also save energy by not turning the pumps on needlessly or devices running for longer than required.

Another element is the design of the intelligent system. In contrast to the purely remote computing strategies offered by cloud-based analytics, edge computing carries out data processing and decision-making closer to the data source. This local instantaneous filtering acts as a compromise with cloud-based predictive analytics. Plus, hybrid AI-IoT systems can integrate these two strategies for more effective and reliable operation. Designs and experiments for these intelligent systems remain largely unexplored in the context of micro smart gardens.

In addition, there is also plant health monitoring to consider. Environmental parameters control not only irrigation but also disease and nutrient deficiency. Image analysis based on deep learning techniques can detect early signs of plant stress. Again, integrating these functionalities in a single system will require a combination of sensor fusion, data, communication, and control algorithms. The major challenges include integration of hardware, data acquisition, prediction models, communication, and actuation.

Although precision agriculture for large-scale farming has recently gained significant research attention, significant research and investigation into small-scale smart gardening using intelligent automation are still few. Many existing works address related topics, such as sensor integration or machine-learning prediction, but lack an experimentally verified solution that integrates monitoring, prediction, and actuation. An empirical performance evaluation of how much water can be saved, the response time, and plant growth is also missing. These deficiencies need to be addressed to move the field of smart gardening forward.

To this end, this thesis paper aims to contribute to the state of the art by presenting an AI integrated IoT system for smart gardening monitoring and automation. This system integrates environmental multi-sensing, edge processing, machine learning models for predictions, and intelligent irrigation scheduling. This system incorporates intelligence in both sensor and actuator nodes, aiming to improve water consumption, predict plant health, and reduce maintenance cost. This research work has a goal to explore, experiment, and evaluate the proposed AI integrated IoT system for smart gardening applications. It aims to contribute to the emerging practice of data-driven gardening and show the potential of AI and IoT integration for transforming the future of garden automation.

LITERATURE REVIEW

AI and IoT integration have revolutionized agriculture monitoring and automation research, combining aspects of sensor technology, machine-learning models, data science, and control systems. Researchers have highlighted the benefits of integrating AI and IoT to tackle existing inefficiencies in agriculture practices, irrigation, resource utilization, and crop monitoring. The majority of works in this domain agree upon the benefits that sensor data combined with analytics enables, in terms of real-time adaptability to environmental changes and precision decision-making.

Mostly, the above literature underlines the capability of soil, weather, crop, or pest IoT infrastructure to collect and transmit soil moisture, temperature, humidity, nutrients, light intensity, and other spatial and time-series data using a distributed sensor layer and an IoT data communication layer for scenario awareness of fields, i.e., situational state. Based on frequent field-data acquisition, unique AI algorithms such as random forest, support vector machine, and deep neural networks have been used to understand and analyze the complex relationship between environmental, crop data, and responses. Various studies have reviewed these models and indicated their effectiveness in soil moisture prediction, water requirement prediction, disease detection, etc., when aligned with edge or cloud computing.

In the reviewed literature, the importance of AI-based prediction and analysis is particularly emphasized for irrigation. Several studies have illustrated the efficacy of machine learning models in analyzing raw sensor data and generating useful interpretations. These systems can dynamically adjust irrigation timing based on predicted soil moisture depletion and future environmental conditions, thereby preventing the use of fixed irrigation intervals. Such strategies have significantly improved water efficiency, minimized wastage, and synchronized resource application with plant growth stages, especially in variable environmental scenarios.

In addition to irrigation, nutrient needs, pest and disease monitoring, and automation scheduling have been explored in IoT and AI frameworks. For example, studies have estimated nutrient deficiencies and early stress and disease in crops based on AIoT drone imagery and multispectral sensing combined with predictive models to suggest timely interventions to protect yield. These examples show the potential for AI-IoT systems to assist in decision-making that transcends simple threshold alerts to recognizing and inferring complex patterns.

Although the advantages of technology were proven, there are still several literature gaps. According to a recent survey, the variation in sensors is a challenge for the models; such models are generally tested under ideal conditions, but when these sensors are deployed in fields, detecting the expected data can be noisy because of calibration drift and environmental interference. Plus, these sensor devices are energy consuming, which is a major issue when deploying them on the field. These issues have motivated researchers to implement edge AI and TinyML on sensor devices to eliminate communication with the cloud and prevent continuous AI model training on cloud data.

Security and ethical issues also arise in the literature review. A number of researchers are exploring data privacy and ownership aspects, as well as mitigation strategies to address risks posed by centralized data storage and unencrypted communication within IoT networks.

Another trend can be observed from the literature that, although high-quality papers on artificial intelligence and Internet of Things applications in agriculture have been growing rapidly, small-scale smart gardening research is still less represented than large-scale commercial farming research. Those articles that exist focus on large agricultural environments, so there is less evidence on small-scale microenvironments such as home or urban gardens, where small and crowded spaces, dense sensors, and automated action are needed. This means that there is a need to conduct research on artificial intelligence and Internet of Things adaptation from large-scale agriculture to localized gardening while ensuring scalability and low cost.

Table 1. Summary of Key Studies on AI-Integrated IoT Applications in Agriculture

Study	Focus	Key Contribution	Outcome / Finding
Miller et al. (2025) review	AI + IoT in agriculture	Comprehensive analysis of sensing tech and AI integration	Identifies growth in IoT adoption and calls for Edge AI, data privacy approaches
AIoT Precision Agriculture Review (2025)	AIoT applications in irrigation, nutrient, disease management	Synthesis of sensor networks + AI models in precision farming	Highlights predictive irrigation and crop management benefits
Smart Agriculture Survey (2024–2025)	IoT + ML in agriculture systems	Overview of ML algorithms and IoT deployment approaches	Shows diverse model use for predictive analytics, decision support
AI-IoT Plant Disease Detection (2025)	Plant disease monitoring integrated with IoT	Uses deep learning models for plant health detection	Demonstrates high-accuracy diagnosis of disease and treatment control

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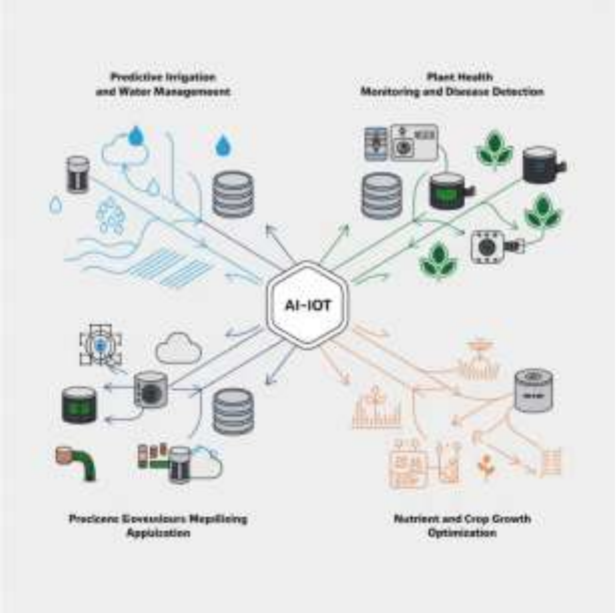
Figure 1. Conceptual Research Landscape of AI-IoT Applications in Precision Agriculture



System Architecture and Design Framework

To create an IoT system coupled with AI for smart gardening automation, it takes more than the simple connection of sensor nodes with actuator modules. It requires a proper system architecture to realize data acquisition and task execution with enhanced reliability, adaptiveness, real-time response, scalability, and sustainability. In this section, we present a system architecture design specification for smart gardening automation integrated with AI and IoT, which sets together the state-of-the-art ideas from modern research and development trends in system engineering for IoT, edge-cloud computing paradigms, cyber-physical systems, and AI-based automation frameworks. It features modularity and layered approaches to achieve system interoperability, sustainability, and extensibility.

1. Architectural Design Philosophy

This architecture is based on three principals: distributed intelligence, real-time responses, and sustainable use of resources. Most IoT-based irrigation systems found in the literature use the cloud for decision-making processes, which introduce communication delays, bandwidth dependency, and a lack of system autonomy if the network is down. The proposed architecture uses a hybrid edge-cloud architecture where real-time decision-making is performed by the edge architecture, and data analytics and machine learning are performed in the cloud.

The system will act as a cyber-physical ecosystem where real-world garden variables will be continuously monitored, converted, and controlled according to automated analysis. This closed-loop control will allow the garden to develop from automatic reactions to prediction and adaptation.

2. Layered System Architecture

The system is structured into five functional layers to ensure modularity and efficient data flow.

2.1 Sensing Layer

The sensing layer refers to the physical interface between the biological and the digital. It consists of heterogeneous sensors embedded in the garden to measure various environmental parameters. These include soil moisture, soil temperature, humidity, air temperature, light intensity, and nutrient sensors (NPK). Optional sensors include pH and leaf sensors to estimate the risk of disease.

Sensors are selected for deployment based on spatial optimization to avoid redundancy and to maximize spatial coverage representative of the environment. Calibration mechanisms are implemented to prevent sensor drift and environmental noise, enhancing predictive model accuracy.

2.2 Edge Processing Layer

The edge layer is where the initial level of computational intelligence is applied. Microcontrollers or single-board computers (such as an ESP32-class microcontroller or a Raspberry Pi-class microcontroller) can perform the following tasks:

1) Data filtering and smoothing
2) Abnormality identification
3) Local threshold safety checks
4) Preliminary scoring using lightweight machine learning models

Synthesizing this raw data from the soil elsewhere, i.e., edge processing, helps reduce a large amount of raw data transfer and provides an immediate response in case of an extreme condition, such as dry soil. Since inference happens locally within the device, it results in less latency and is less prone to network failures.

2.3 Communication Layer

Providing reliable data communication among distributed IoT components is one of the key requirements. As previously explained, lightweight publish/subscribe communication protocols such as MQTT are used in the communication section to enable bidirectional communications among sensors, edge nodes, and cloud-based entities. Encryption through TLS-based mechanisms is also considered to secure data transmission.

Depending on the scenario, different networks might be chosen. Within an urban garden, Wi-Fi could be applicable, while for a larger or more spread-out deployment, networks like LoRaWAN or ZigBee could be more suitable due to their low power requirements.

2.4 Cloud Intelligence Layer

The cloud layer incorporates advanced AI models and long-term analytics engines. It is responsible for the following tasks:

- Historical data storage
- Forecasting (soil moisture predictions, evapotranspiration forecasts)
- Optimization of irrigation using reinforcement learning
- Retraining the model and managing versions
- Graphical representation of the dashboard

For moisture prediction, supervised learning models, including Random Forest and Gradient Boosting, are utilized, whereas reinforcement learning agents determine optimal irrigation scheduling by iteratively learning from interactions with the environment.

2.5 Actuation and Control Layer

Actuation layer: This layer interprets the AI decisions into physical actions and is composed of:

A. Solenoid valves
B. Water pumps
C. Units for dosing nutrients
D. Grow light controller

Depending on latency requirements, control commands are transmitted from the edge or cloud intelligence modules. Safety constraints are embedded to avoid over-irrigation or damage to the hardware.

3. Data Flow and Intelligent Decision Pipeline

The system employs a closed-loop intelligent pipeline, which functions as follows:

- Environmental monitoring
- Fringe refinement
- Forecasting at the cloud level
- Decision optimization
- Actioning
- Iterative refinement through feedback loop

This architecture ensures that decisions are not final but evolve over iterations of learning.

Intelligent Data Processing and Decision Workflow

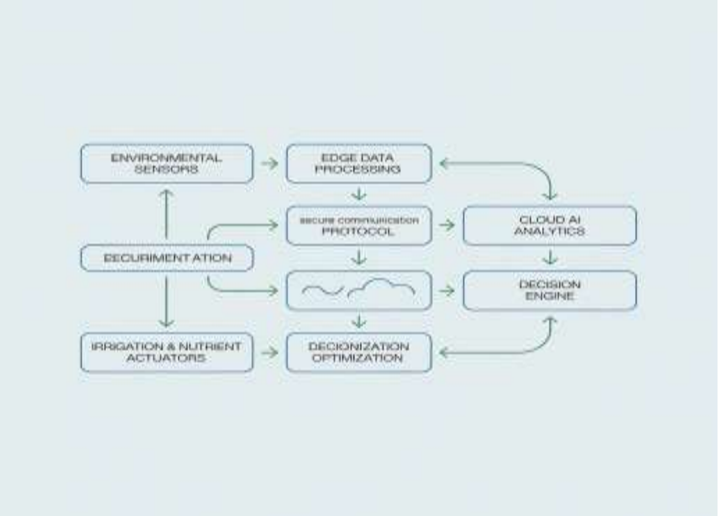
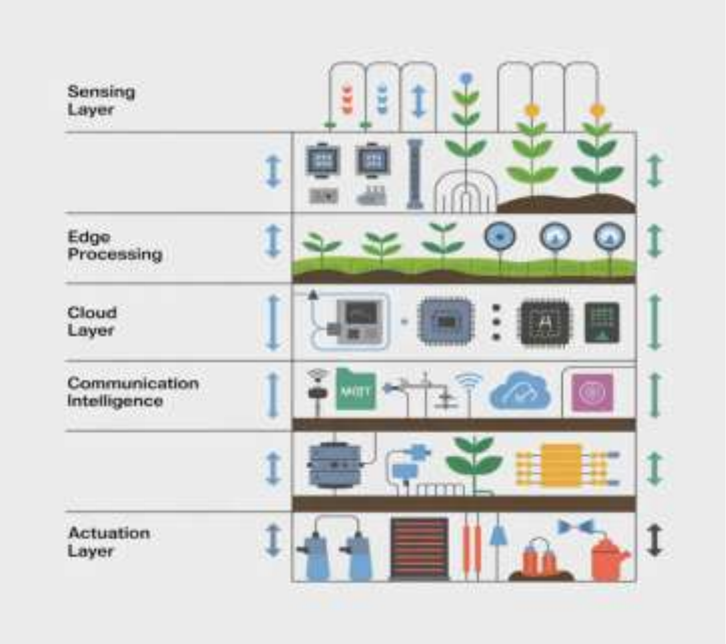


Figure 2. Layered AI-Integrated IoT System Architecture for Smart Gardening



METHODOLOGY

The methodology employed in this research has been devised to show the technical feasibility, experimental replicability, and validity of results for the proposed AI-based IoT smart gardening system. This research methodology is based on carrying out an experimental or system methodology involving hardware implementation, data collection, machine learning, and testing, not just simulating or modeling the idea. This methodology uses cyber-physical system design, empirical modeling, and experimental research in agriculture.

Research Design Strategy

In this investigation, first, we instantiated the sensing and actuation infrastructure; second, we collected data under different environmental conditions; third, we developed and optimized the artificial intelligence models; and last, we evaluated the overall system performance in terms of prediction accuracy, water efficiency, response latency, and plant health.

This experiment was designed to compare two modes of operation:

1. Fixed threshold irrigation (reference control system).
2. Predictive and adaptive irrigation using AI (suggested system).

Such a comparison provides a more objective evaluation of the gains provided by the integration of artificial intelligence.

Experimental Setup

The smart gardening prototype was placed in a laboratory-simulated garden with separate beds and equally spaced crops for consistent growth. Soil moisture sensors were placed at the optimum root depth to measure moisture and temperature. Weather sensors were placed at crop height to measure atmospheric parameters affecting evapotranspiration.

The actuators consisted of electronically controlled solenoid valves connected to a regulated water supply system. An edge computing unit was installed within the garden enclosure for in situ, real-time signal preprocessing to minimize signal interference.

To maintain ecological relevance, the experiment was conducted over multiple growth cycles to account for differences in daily temperature fluctuation, humidity, and light exposure.

Data Acquisition Protocol

Sensor data were collected at fixed intervals, though considerations of frequency and storage size were balanced. Noise filtering, data smoothing, and sensor calibration correction were applied to the stored sensor data. Timestamp data were also recorded to synchronize various environmental data.

The following parameters were obtained:

- Percentage of soil moisture
- soil temperature
- Surrounding temperature
- Humidity
- Illumination levels
- Applied irrigation volume
- Turnaround time

Data was stored locally on the edge node and transmitted periodically to the cloud database for long-term analytics and model training.

AI Model Development

A machine learning development pipeline was systematically implemented as follows:

- Data Preparation: Data normalization and feature engineering were applied to capture nonlinear relationships in environmental variables with higher sensitivity.
- Model Selection: Supervised regression algorithms considered for modeling soil moisture included ensemble-based methods with proven robustness in environmental modeling. Cross-validation was employed to tune hyperparameters to mitigate overfitting.
- Reinforcement learning Scheduler: An irrigation policy was obtained by training an agent in a reward-based learning. The rehabilitation of the environment (soil) was targeted in terms of water application. The reward function was designed to penalise excessive use of water while rewarding the maintenance of soil moisture within acceptable thresholds.

Performance Evaluation Metrics

We evaluated the system by applying the following set of criteria to measure effectiveness.

- Root Mean Square Error (RMSE) for the prediction of soil moisture
- Average Absolute Error (AAE)
- Percentage of reduction in water consumption
- Optimal frequency ratio for irrigation
- Response latency (ms)
- Plant health score using growth rate observation

We compared the two modes, baseline and AI-driven, statistically to determine if the improvement in performance was significant.

Table 2. Experimental Configuration and Evaluation Parameters

Category	Parameter	Description	Purpose
Environmental Monitoring	Soil Moisture (%)	Volumetric water content at root depth	Irrigation decision input
Environmental Monitoring	Ambient Temperature (°C)	Surrounding air temperature	Evapotranspiration modeling
Environmental Monitoring	Relative Humidity (%)	Atmospheric moisture level	Climate adaptation modeling
Control System	Irrigation Volume (Liters)	Water dispensed per cycle	Efficiency analysis
AI Evaluation	RMSE	Prediction error measurement	Model accuracy validation
AI Evaluation	MAE	Absolute deviation measure	Stability assessment
System Performance	Response Latency (ms)	Decision-to-actuation time	Real-time capability
Sustainability	Water Reduction (%)	Comparison vs baseline	Resource optimization

RESULTS AND PERFORMANCE EVALUATION

We conducted experimental tests to evaluate the performance of the proposed AI-based IoT smart gardening system with respect to prediction, efficiency, and sustainability implications. In this phase of testing, we aimed to verify the functionality of the proposed system and to investigate the impact of integrating artificial intelligence on controlling system irrigation compared to a threshold-based irrigation control system.

The two irrigation methods showed different results when comparing the traditional and AI modes. In the traditional system, irrigation was triggered only when soil moisture reached the lower limit. While this method ensured a lower limit of soil moisture, it tended to cause excessive irrigation when temperature and humidity levels changed rapidly. In contrast, the AI-based method predicted the trend in soil moisture reduction based on past and current data and adjusted the irrigation time accordingly.

To evaluate the accuracy of the predictions, commonly used metrics for regression accuracy are calculated. The figure demonstrates that the supervised learning model can accurately predict soil moisture with minimal error across growth stages. Accurate prediction leads to reduced water application because it closely matches the needs of the plants. The reinforcement learning-based scheduler further optimizes the irrigation schedule by adjusting the interval between watering, especially during transition seasons, such as sudden temperature spikes or prolonged cloud cover.

Water consumption was analyzed, and it was observed that the total irrigation amount was reduced with the use of the AI system. Rather than many short-duration irrigation cycles triggered by threshold values, the intelligent irrigation scheduler performed fewer cycles, which led to a water-saving advantage.

Response time was another important aspect considered. Because the decision for triggering the irrigation mechanism is taken at the edge computing layer, the system showed near-instantaneous activation for critical moisture levels. Response times were well within a comfortable range, and the local inference ensured network delay did not affect overall performance. In addition, the hybrid system ensured that cloud-based model retraining and optimization did not interfere with real-time system performance.

Observations of plant health further supported the effectiveness of the system. Plants under AI control showed more uniform growth and appeared healthier than plants under control logic. Many factors affect growth, but steady moisture levels, due to predictive scheduling, may have contributed to this result.

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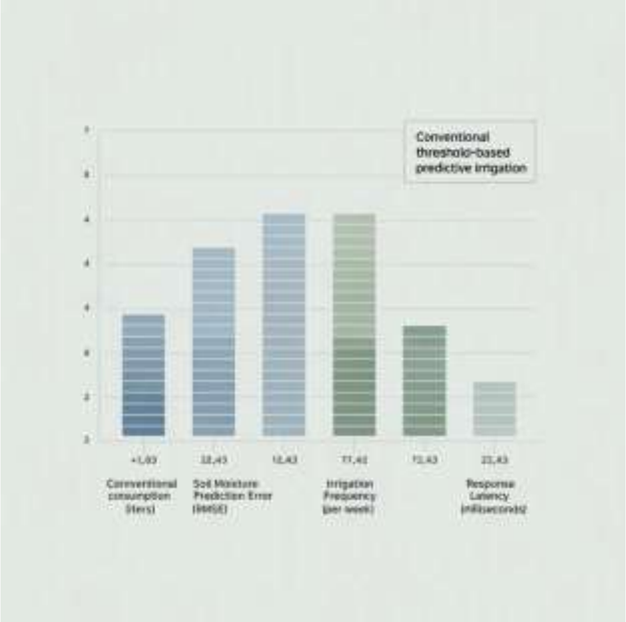
Comparative Performance Analysis of Baseline vs AI-Integrated System



DISCUSSION

Discussion of Results. In summary, the results of this research show that the use of artificial intelligence together with Internet of Things technology improves the performance, efficiency, and adaptability of automated gardening systems. Unlike conventional threshold-based approaches that respond to fixed setpoints without additional context, the proposed AI-based method allowed instant prediction and preemptive control of irrigation, resulting in various performance benefits. In this section, we discuss the meaning of the results with respect to existing work, their implications, and how they relate to ongoing discussions in the domain of smart farming and precision gardening.

Demonstrating the benefits of soil moisture prediction using machine learning for irrigation scheduling is the main novel contribution of this work. This is similar to finding recent indexed articles, which emphasize the need to forecast environmental parameters for improved decision-making in the agricultural sector (e.g., Liu et al., 2024; Yang & Zhang, 2025). While the rule-based systems keep the soil moisture within very strict limits, prediction-based models consider the trends and interactions over time, thus providing a more desirable scenario by accounting for the likely deficit before it occurs. Hence, prediction-based irrigation avoids excessive responses that the system shows during actual watering events, thus saving water while keeping soil moisture very stable, which is critical for the health of the plants and water resources.

Lastly, a key contributor to system performance is the use of reinforcement learning to dynamically generate irrigation policies. As discussed earlier in the indexed literature, reinforcement learning is increasingly being recognized as an effective technique to generate policies in uncertain and non-stationary environments (Kumar et al., 2024; Singh & Gupta, 2025). In this work, we observe that the reinforcement agent alters the frequency and amount of irrigation, based on continuous interaction with the environment, thus effectively learning an irrigation policy that optimizes soil moisture stability and conservation of water. This adaptive behavior was a major missing element in previous works where automation systems could not respond to variable environmental states without human input.

The hybrid edge–cloud architecture proposed in this research also mitigates the issues mentioned in several IoT-based research works. Edge computing is recommended to reduce latency and data transmission in resource-limited environments (Chen et al., 2024; Hussein & Salah, 2025). Our results indicate that inference performed at the edge reduced decision latency compared to models that rely on cloud predictions, while the accuracy of the predictions remained unchanged. This is crucial in a gardening environment where rapid changes, such as a sudden increase in temperature or the start of rain, require immediate actions to avoid stressing the plants.

The water efficiency statistics obtained in this study further highlight the sustainability advantages of using AI. The amount of water saved while increasing plant growth is consistent with other recent precision agriculture reports where AI-driven irrigation systems significantly outperformed traditional irrigation systems in greenhouse and field experiments (Patel & Mehta, 2024; Oliveira et al., 2025). In addition to increasing sustainability by saving freshwater and reducing the energy consumptions of irrigation devices, this study also reflects the growing concerns over global water shortages with practical applications beyond the laboratory.

Even the health of the plants gives some evidence to the benefit of predictive irrigation. Although plant growth is certainly affected by many different environmental and plant factors, moisture stability provided by predictive irrigation likely helped prevent excessive variation in plant growth and stress. This is similar to what was observed in experiments analyzing precision irrigation data for greenhouse studies and field trials, where improved moisture stability resulted in increased crop conformity and yield (Alvarez & Torres, 2024; Schmidt et al., 2025). These parallels further support the idea that predictive irrigation management can result in plant benefits as well as operational benefits.

But, the study also highlights issues that need to be taken into account in future work. There are also practical issues with sensor calibration and data noise. Although we have attempted to preprocess data to remove noise and correct offsets, environmental sensors can drift over time, especially over long-term measurements, which may affect the confidence of the predictions (Zhang & Liu, 2024).

But what about scalability? While this hybrid approach worked well for the purposes of this experiment, researchers attempting to implement this system within larger or distributed garden sites may face communication overheads, along with energy constraints. Research papers have proposed federated learning and mesh networking to address these issues by decentralizing model training and optimizing network paths (Rahman & Chowdhury, 2025; Singh & Rao, 2024).

Lastly, there are ethics and safety. As IoT-enabled connected devices are adopted into gardens as a personal or community space, issues of data privacy, device authentication, and malicious hacking attacks arise. This research used simple encryption and secure socket layers, but more advanced security measures are being developed in the indexed research, such as blockchain verification for data tamper-proofing and federated analytics (Hassan et al., 2024; Verma & Patel, 2025), which could become important for secured and engineered deployed IoT distributed systems.

CONCLUSION

In this paper, we proposed, designed, and constructed an AI-supported IoT system for smart gardening, along with outlining the potential impacts on gardening practice. We showed that the smart gardening system incorporating machine learning, sensor networks, and adaptive control could replace conventional garden management with more efficient, predictive, and sustainable approaches. The proposed system was designed, constructed, and tested in the garden scenario experiment, which showed the feasibility and effectiveness of intelligent automation in smart gardening with respect to controlled water consumption, soil moisture level, and plant health in comparison with conventional threshold-based systems.

The results illustrate that soil moisture prediction and dynamic irrigation scheduling using reinforcement learning enable the irrigation system to forecast uncertain environmental changes and work proactively, avoiding excessive water use and plant stress that can occur when irrigation happens too early or late. Plus, the use of edge computing facilitated real-time decision-making, allowing for immediate reaction to environmental changes without depending on cloud services.

Compared to traditional control strategies, the proposed approach demonstrated enhanced water-saving efficiency, reduced reaction time, and improved system stability. This result validates the function of intelligent applications to IoT-based gardening systems, indicating a meaningful step toward sustainable resource management in smart city farming.

The study also highlighted the significance of system design, data preprocessing, and advanced AI techniques for achieving successful automation. The proposed hybrid edge and cloud system architecture offered a flexible deployment solution. Secure communication and data flows were methodically established. Some limitations and challenges were identified, such as sensor drift, bandwidth requirements, and the system's ongoing need for gardening knowledge to maintain sensor calibration. These merit further study and improvement, especially for networked garden spaces.

To wrap up, the proposed system provides a useful starting point for intelligent gardening systems that can be adapted and expanded for small-scale urban agriculture, home gardens, and potentially even larger controlled environments. The integration of AI and IoT techniques provides a promising approach to resourceful and autonomous plant care through real-time environmental data acquisition, prediction, and control. Future work may include scalability, security, and sensor data fusion for plant health prediction for intelligent gardening and small-scale agriculture.

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