

Adaptive Precision Agriculture Through Iot And Reinforced Machine Learning (Q-Learning): A Sustainable Approach For Optimized Plant Growth

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Abstract. The convergence of the Internet of Things (IoT) and machine learning is transforming precision agriculture by enabling data-driven optimization of plant growth in varying environments. This study explores the integration of IoT-based sensing with reinforcement learning, specifically Q-learning, to enhance plant growth management in both controlled and natural field conditions. The primary aim is to derive actionable insights that boost crop productivity while conserving resources. An IoT-enabled system was designed to capture real-time information from sensors monitoring soil temperature, soil moisture, air temperature, humidity, and growth parameters. Controlled experiments simulated ideal growth settings, whereas on-field trials reflected natural variability. These datasets were analysed using a Q-learning algorithm, allowing the system to make adaptive decisions and optimize plant development. Iterative learning enabled the framework to establish links between environmental factors and plant responses, dynamically adjusting irrigation and environmental controls based on feedback. Experimental results demonstrated that the controlled setup yielded greater consistency in growth and higher resource efficiency due to its stability. In contrast, the on-field system underscored adaptability by generating strategies to cope with environmental uncertainty. This dual evaluation highlights the combined potential of IoT and reinforcement learning to support sustainable agriculture. The findings validate IoT-based adaptive monitoring as a practical tool for optimizing plant growth. The proposed approach offers pathways to improve crop yields, minimize input use, and promote long-term sustainability. Future research will extend the framework to diverse crops, enhance Q-learning models for complex decision-making, and integrate additional environmental parameters for comprehensive analysis.

Keywords: Sentiment Analysis, Social Media, Feature Extraction, Machine Learning, NLP, XGBoost, SVM, Naïve Bayes.

1 Introduction

Agriculture has always been central to human civilization, providing food, raw materials, and livelihoods for billions worldwide. With the global population projected to reach nearly 10 billion by 2050, the demand for agricultural output is expected to rise

exponentially. Meeting this demand, however, poses unprecedented challenges due to climate change, limited resources, and the unpredictability of environmental conditions. Traditional farming practices, though effective for centuries, are increasingly inadequate in addressing these issues. This has prompted the integration of emerging technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) into agriculture, paving the way for precision farming and sustainable practices. Among AI methods, reinforcement learning (RL) has gained particular attention for its ability to support adaptive, data-driven decision-making in dynamic environments.

Plant growth analysis lies at the core of agricultural productivity, as it directly influences crop yield and food security. Understanding how plants respond to environmental variables such as soil moisture, temperature, humidity, and nutrient availability is critical for optimizing growth. Traditional monitoring methods largely rely on manual observation and periodic measurements, which are time-consuming, error-prone, and limited in scope. While controlled environments such as greenhouses allow for regulated conditions that simulate optimal growth, open-field farming remains exposed to unpredictable stressors, including fluctuating weather patterns and pest infestations. This contrast highlights the need for advanced monitoring and adaptive management strategies that can function across both controlled and uncontrolled environments.

IoT technologies provide a robust foundation for such systems by enabling real-time data collection and monitoring of crucial parameters. Sensors embedded in soil, air, and plant systems can continuously measure variables such as temperature, humidity, soil moisture, and pH. In controlled environments, these insights allow for precise regulation of irrigation, lighting, and ventilation, ensuring optimal conditions. Conversely, in uncontrolled environments, IoT devices help capture natural variability and provide farmers with timely alerts on potential risks. Despite these advantages, IoT alone primarily focuses on data acquisition and lacks the analytical capacity to determine optimal decisions for plant growth.

This limitation opens the door for reinforcement learning, an AI paradigm designed for sequential decision-making under uncertainty. RL agents learn to take actions based on feedback from their environment, progressively improving their strategies to achieve long-term goals. When integrated with IoT, RL can transform raw sensor data into actionable decisions, such as adjusting irrigation schedules or nutrient supply to balance growth and resource efficiency. Unlike static rule-based systems, RL algorithms can adapt dynamically to changing environmental conditions, making them particularly well-suited for agriculture. For example, Q-learning, a popular RL technique, enables systems to iteratively refine their policies by balancing exploration of new strategies with exploitation of learned patterns.

The synergy between IoT and RL offers immense potential for addressing agricultural challenges. Together, they can support precision agriculture by providing farmers with intelligent, real-time decision-making tools that optimize plant growth,

conserve resources, and improve resilience against uncertainties. Experimental evidence has shown that controlled environments achieve higher growth consistency and efficiency due to predictability, while open-field systems benefit from adaptive strategies developed through RL to handle variability. This duality emphasizes the broader applicability of IoT-RL systems across diverse agricultural contexts.

In light of these opportunities and challenges, this study explores the combined use of IoT and reinforcement learning for plant growth optimization in both controlled and uncontrolled environments. By bridging the gap between real-time data collection and intelligent decision-making, the proposed framework seeks to advance the field of smart agriculture. The research not only demonstrates the effectiveness of IoT-RL systems in improving crop productivity and sustainability but also addresses critical gaps in scalability, adaptability, and accessibility. Ultimately, this work contributes to building resilient agricultural systems capable of meeting the growing demands of the future while ensuring environmental responsibility..

2. Literature Survey

The integration of modern technologies such as the Internet of Things (IoT), machine learning (ML), and artificial intelligence (AI) has significantly transformed agriculture, paving the way for smart farming and precision agriculture. Agriculture, as the backbone of human civilization, faces unprecedented challenges in meeting the food demands of an expanding global population, projected to exceed 9.5 billion by 2050. Traditional farming practices, though time-tested, are increasingly unable to cope with the effects of climate change, soil degradation, limited resources, and labor shortages. In this context, IoT-enabled systems offer real-time monitoring of soil, crop, and environmental parameters, while ML and AI techniques provide the intelligence required for prediction, classification, and decision-making. Together, they promise to enhance agricultural productivity, sustainability, and resilience.

One of the most critical areas of smart agriculture is plant growth monitoring and optimization. Plant growth is influenced by dynamic environmental variables such as temperature, soil moisture, humidity, light intensity, and nutrient availability. Accurate monitoring and timely intervention are essential for maximizing yields and ensuring sustainability. IoT-based sensors can capture these variables continuously, while machine learning algorithms analyze the resulting data to identify patterns and recommend actions. The literature demonstrates an evolving trend: early research focused on data collection and predictive analytics; subsequent studies emphasized adaptive ML models; more recent work integrates deep learning, reinforcement learning, and hybrid frameworks to achieve autonomous decision-making in both controlled (greenhouses, hydroponics) and uncontrolled (open-field) environments.

2.1 IoT-Enabled Monitoring and Early Machine Learning Applications

The first phase of research laid the foundation for smart agriculture by combining IoT-based sensing systems with early machine learning and predictive analytics. These

studies primarily focused on real-time monitoring, data acquisition, and preliminary predictive modeling, which collectively demonstrated the feasibility of integrating IoT into agriculture.

Ahmed et al. [1] designed and implemented an IoT-enhanced plant growth analysis system using machine learning. Their system deployed sensors to monitor critical parameters such as soil moisture, temperature, and humidity, with data processed through supervised ML algorithms to predict growth outcomes. This study represented a milestone in bridging low-cost IoT infrastructure with predictive analytics, making technology accessible for small-scale farmers. However, the reliance on conventional supervised models restricted adaptability in environments with high variability, such as open fields.

Expanding on these foundations, Gupta et al. [2] explored the integration of IoT with deep reinforcement learning to support automated plant growth analysis in open fields. Their study was one of the earliest to recognize that static models are insufficient in dynamic agricultural environments. By implementing reinforcement learning, the system could iteratively adapt irrigation and nutrient strategies based on real-time data. Although promising, their framework faced limitations regarding data availability and computational overhead, which remain ongoing challenges for field-scale deployment.

Centorame et al. [3] offered a broader perspective by reviewing machine learning applications in plant phenotyping, with a focus on sunflower crops. By leveraging IoT-acquired datasets, their study emphasized the use of ML to extract phenotypic traits such as leaf size, biomass, and flowering patterns. This highlighted the role of IoT not only in growth monitoring but also in supporting breeding programs. A noted limitation was the lack of transferability, as models trained on one crop or dataset struggled to generalize across species or environments.

In parallel, Cao et al. [4] developed IGrow, a smart agriculture solution for autonomous greenhouse control. Their IoT-driven framework incorporated sensors and actuators to monitor and regulate environmental variables such as humidity, temperature, and lighting. The system was among the first to demonstrate closed-loop control, where IoT inputs directly triggered automated interventions. However, its applicability remained restricted to controlled environments, with limited adaptability to the unpredictability of open-field conditions.

Azimi et al. [5] introduced deep learning-based stress monitoring for plants, focusing specifically on water-deficiency detection. By integrating IoT-collected environmental data with convolutional neural networks, their system could detect stress before visible symptoms occurred. While highly effective for water-related stress, the model was specialized and lacked flexibility to account for multi-stressor conditions, such as pest infestations or nutrient deficiencies.

2.2 Advanced Machine Learning and Hybrid IoT-ML Systems

The second phase of research in IoT-based agriculture marked a significant transition

from basic predictive modeling to the integration of advanced machine learning algorithms, hybrid approaches, and simulation environments. Unlike the earlier phase, which focused on foundational monitoring and static prediction, this stage emphasized dynamic modeling, temporal prediction, and multi-dimensional optimization of plant growth. Studies in this phase illustrated how combining IoT data with advanced ML techniques could move agricultural systems closer to adaptive, intelligent, and partially autonomous solutions.

Drees et al. [6] introduced a conditional generative adversarial network (cGAN) framework to predict and evaluate the growth of Brassica plants in open-field conditions. IoT-enabled sensors captured environmental parameters, which were then used as input for GAN-based models to predict plant growth at various stages. The study's strength lay in its ability to generate temporal predictions, allowing farmers to anticipate crop development and plan interventions more effectively. However, GAN-based approaches are computationally intensive, and their reliance on large, labeled datasets created challenges in scalability. Furthermore, although predictions were reliable under experimental conditions, real-world deployment faced hurdles due to environmental noise and variability.

Complementing these developments, Amacker et al. [7] designed a learned simulation environment for indoor farming, integrating IoT-collected data into a virtual model of plant growth. Their framework enabled researchers and farmers to test growth strategies in simulated conditions before real-world application. This "digital twin" approach significantly reduced experimental costs and risks while accelerating the evaluation of resource management strategies. Nevertheless, the main limitation was the simulation-to-reality gap: conditions modeled in controlled virtual environments often failed to capture the full complexity of open-field farming, where unpredictable factors such as pest invasions or extreme weather events play a major role.

A different perspective was offered by Gourshettiwar and Reddy [8], who combined IoT and ML for nutrition management in hydroponic systems. Their study demonstrated how continuous data collection from IoT sensors, coupled with ML algorithms, could optimize nutrient dosing in real time. Hydroponic farming, being highly dependent on nutrient balance, benefited immensely from this approach, which reduced wastage and improved plant health. The work illustrated the potential of IoT- ML integration in resource-efficient controlled environments. However, it also emphasized that such methods were heavily context-specific: while hydroponic systems benefitted from IoT-driven precision, soil-based open-field farming posed far greater complexity and unpredictability.

Patra and Sahoo [9] applied IoT and statistical ML techniques to the monitoring of broccoli growth. Their study highlighted the importance of tailoring IoT-ML systems to crop-specific characteristics. By using regression and decision-tree-based models, they were able to predict plant growth outcomes with reasonable accuracy. This work

underscored the potential of crop-specific IoT frameworks but also exposed the limitations of conventional statistical models in handling non-linear relationships and multi-factor interactions typical in open-field conditions. Their findings suggested the need for transitioning toward more adaptive models capable of dealing with uncertainty.

Balaji and Kumar [10] further extended IoT applications by developing a smart monitoring system with predictive analytics. Unlike earlier studies, their framework emphasized real-time integration of IoT monitoring and predictive models. By applying regression analysis and predictive algorithms, they provided farmers with actionable insights to optimize irrigation and nutrient application. The study demonstrated measurable improvements in crop growth efficiency and resource conservation. However, like other works in this phase, their reliance on relatively static models meant adaptability under highly variable conditions was still limited.

2.3 *Deep Learning, Simulation, and Stress-Oriented Approaches in Plant Growth Monitoring*

The third phase of IoT-driven agricultural research demonstrated a marked shift toward deep learning techniques, crop health analysis, and hybrid modeling approaches. Unlike earlier phases that primarily employed supervised learning or statistical models, this stage harnessed advanced neural networks, hybrid ML frameworks, and data-driven phenotyping methods to address complex plant growth patterns and stress conditions. By integrating IoT-enabled sensing with deep learning, researchers achieved greater precision in detecting diseases, predicting yields, and optimizing growth strategies across both controlled and uncontrolled environments.

Nandhini and Rajesh [11] advanced IoT-based monitoring by proposing a machine learning framework for crop health and growth analysis. Their work emphasized holistic monitoring, moving beyond growth metrics to include crop health parameters such as nutrient deficiencies and stress indicators. IoT sensors collected data on soil, moisture, and microclimate conditions, which were analyzed using ML algorithms to detect anomalies in plant development. While their study successfully showcased how IoT could support early warning systems, limitations emerged regarding the model's scalability for large-scale agricultural landscapes and the need for more adaptive algorithms to manage high variability in field conditions.

Zhang et al. [12] contributed to predictive analytics in smart agriculture by developing ML models trained on IoT-collected datasets to predict plant growth trajectories. Their study demonstrated the effectiveness of IoT-based growth modeling, particularly in controlled environments where parameters could be regulated. Prediction accuracy was significantly improved compared to traditional approaches, and their results validated the importance of data-rich IoT infrastructures. However, generalizing these predictions to uncontrolled environments proved challenging, as the models struggled with unexpected climate fluctuations and soil heterogeneity.

Verma and Chauhan [13] pushed the frontier further by applying deep learning for plant phenotyping in precision agriculture. By using high-dimensional IoT-acquired datasets and image-based phenotyping, their framework extracted complex traits such as leaf morphology, biomass estimation, and growth rates. Deep neural networks enabled improved feature extraction and prediction accuracy compared to classical ML. Despite its strengths, the approach faced high computational costs, requiring advanced infrastructure that might not be accessible to smallholder farmers. Moreover, deep learning's "black-box" nature made interpretability a persistent concern in agricultural applications.

Singh and Sharma [14] addressed plant growth monitoring and disease detection through an IoT and ML-based integrated framework. Their model combined real-time sensor data with ML classifiers to identify early signs of plant disease while simultaneously tracking growth parameters. This dual focus underscored the potential of IoT-ML systems as decision-support platforms for farmers. Nonetheless, the framework required large, high-quality datasets for training, and its deployment in resource-constrained settings raised issues of cost and connectivity.

Yadav and Gupta [15] presented one of the more advanced studies in this phase, developing an IoT-integrated hybrid ML system for plant growth monitoring. By combining multiple algorithms—including decision trees, random forests, and neural networks—their system achieved higher accuracy and robustness compared to single-model approaches. Hybrid models allowed the system to adapt more flexibly to varying environmental conditions, making it suitable for both controlled and open-field farming. However, the complexity of hybrid frameworks posed challenges in terms of model maintenance, computational requirements, and interpretability.

2.4 *Comprehensive IoT-ML Frameworks and Future Directions in Smart Agriculture*

The fourth phase of IoT and machine learning research in agriculture represents a period of integration, scalability, and comprehensive frameworks. Unlike earlier phases, which focused on isolated functionalities such as growth prediction, phenotyping, or stress detection, this stage emphasizes holistic solutions that combine IoT-driven monitoring, machine learning analytics, and adaptive decision-making within a single platform. These studies illustrate the field's maturation, shifting from experimental prototypes toward scalable, real-world smart farming systems.

Park and Kim [16] developed one of the most influential frameworks in this phase, focusing on smart farming systems powered by IoT and AI for enhancing plant growth and yield prediction. Their approach integrated sensor-based monitoring of soil, temperature, and humidity with AI models capable of predicting yield outcomes. By combining IoT-driven real-time data with predictive AI, the framework allowed farmers to optimize irrigation and fertilization schedules. While the system significantly improved efficiency, its reliance on AI introduced computational complexity and required reliable connectivity, which may not be feasible in rural regions with limited

infrastructure.

Patel and Kumar [17] applied IoT-enabled monitoring specifically to medicinal plants, utilizing decision tree algorithms for growth tracking and predictive analysis. Their work highlighted the adaptability of IoT-ML systems to niche agricultural domains. Decision trees provided simplicity, interpretability, and ease of implementation. However, the model lacked the sophistication needed for highly variable conditions and struggled with multi-dimensional optimization, making it more suitable for small-scale, controlled environments.

Fernandes and Das [18] combined IoT with deep learning techniques to predict optimal growth conditions for plants. Their system processed large-scale sensor data to identify correlations between environmental variables and plant performance. This integration showcased the growing role of deep neural networks in agricultural optimization, capable of handling non-linear interactions across multiple parameters. While their results demonstrated high accuracy, the system required significant computational resources and faced challenges related to data privacy and energy efficiency, both of which are critical concerns in large-scale deployments.

Wang and Lee [19] advanced the field by applying random forests with IoT-enabled devices to monitor plant growth stages. Their framework combined robust statistical ensemble methods with real-time IoT data to track developmental stages across different crops. This approach improved adaptability by accounting for multiple variables simultaneously. Compared to decision trees, random forests enhanced predictive accuracy and reduced overfitting, making them more effective in complex agricultural environments. However, the reliance on large datasets for training and the reduced interpretability of ensemble models posed challenges for farmer adoption.

Finally, Singh and Tiwari [20] presented an ML-based analysis of plant growth under varying environmental conditions using IoT sensors. Their study emphasized environmental variability as a critical challenge in plant growth monitoring. By integrating IoT data with ML algorithms, they analyzed how crops responded to diverse environmental scenarios. This study provided practical insights for smallholder farmers facing unpredictable weather conditions, though limitations included high dependency on consistent sensor calibration and difficulties in deploying such frameworks in resource-limited contexts.

3. Research Methodology

The research methodology adopted in this study is a multi-stage framework integrating Internet of Things (IoT)-based data acquisition with Reinforcement Learning (RL), specifically a Q-learning algorithm, for plant growth analysis and optimization in both controlled and uncontrolled environments. The details description mentioned below figure 1.

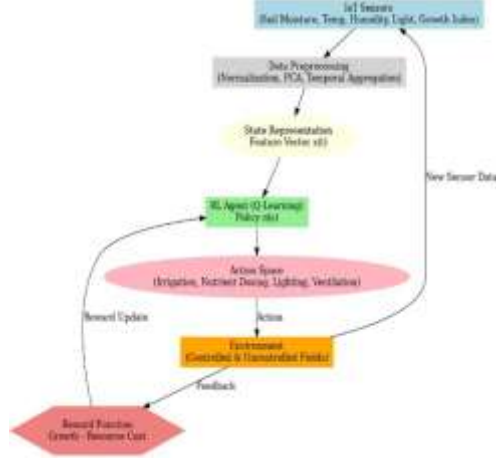


Figure 1 : proposed system architecture

The methodology begins with the IoT data collection system, where multiple sensors are deployed to continuously monitor environmental and physiological plant parameters, including soil moisture $S_m(t)$, soil temperature $S_T(t)$, air humidity $H(t)$, air temperature $T_a(t)$, light intensity $L(t)$, and plant growth index $G(t)$. These time-dependent signals are digitized into a feature vector $\mathbf{x}(t) = [S_m(t), S_T(t), H(t), T_a(t), L(t), G(t)] \in \mathbb{R}^d$, where d represents the dimensionality of the input space. The state space S of the reinforcement learning framework is then defined as the set of all possible environmental and plant states, i.e., $S = \{\mathbf{x}(t): t \in \mathbb{N}\}$. The action space $\mathcal{A}$ consists of controllable interventions such as irrigation levels a_1 , fertilizer application a_2 , artificial lighting adjustments a_3 , ventilation control a_4 , and nutrient dosing a_5 . The system dynamics can be formalized as a Markov Decision Process (MDP), where the probability of transitioning from state $s_t \in S$ to state s_{t+1} under action $a_t \in \mathcal{A}$ is expressed as

$$P(s_{t+1} | s_t, a_t) = \Pr\{\mathbf{x}(t+1) = s_{t+1} | \mathbf{x}(t) = s_t, a_t \in \mathcal{A}\}.$$

The reward function $R: S \times \mathcal{A} \rightarrow \mathbb{R}$ quantifies plant growth improvement and resource efficiency. It is modeled as

$$R(s_t, a_t) = \alpha \cdot \Delta G(t) - \beta \cdot C(a_t),$$

where $\Delta G(t) = G(t+1) - G(t)$ denotes the incremental plant growth achieved after action a_t , $C(a_t)$ is the resource cost associated with action a_t , and $\alpha, \beta > 0$ are weighting parameters balancing growth versus sustainability. The optimization problem is thus to identify a policy $\pi: S \rightarrow \mathcal{A}$ that maximizes the expected long-term discounted reward, i.e.,

∞

$$\pi^* = \operatorname{argmax}_{\pi} \sum_{t=0}^{\infty} \gamma^t R(s_t, \pi(s_t)),$$

π

$t=0$

where $\gamma \in (0,1)$ is the discount factor regulating the importance of future rewards.

The Q-learning algorithm is employed to estimate the optimal state-action value function $Q^*(s, a)$, defined as

∞

$$Q^*(s, a) = \max_{\pi} \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \mid s_0 = s, a_0 = a, \pi].$$

π

$t=0$

The iterative Q-update rule is

$$Q_{t+1}(s_t, a_t) \leftarrow (1 - \eta)Q_t(s_t, a_t) + \eta [R(s_t, a_t) + \gamma \max_{a' \in \mathcal{A}} Q_t(s_{t+1}, a')],$$

where $\eta \in (0,1]$ denotes the learning rate. The convergence of Q-learning is guaranteed under Robbins-Monro conditions if each state-action pair is visited infinitely often. Exploration is handled using an ϵ -greedy strategy, defined as

$$\begin{aligned} \operatorname{argmax}_{a \in \mathcal{A}} Q(s, a), & \quad \text{with probability } 1 - \epsilon, \\ \pi(s) = \{ & \\ \text{random action } a \in \mathcal{A}, & \quad \text{with probability } \epsilon. \end{aligned}$$

The methodology also integrates multi-objective optimization to balance plant growth with resource efficiency. This is modeled by defining a cost-weighted optimization function

$$J(\pi) = \lambda_1 D[G(T)] - \lambda_2 D[W(T)] - \lambda_3 D[E(T)],$$

where $G(T)$ denotes plant biomass or yield after time horizon T , $W(T)$ is cumulative water usage, and $E(T)$ represents energy consumption. The coefficients $\lambda_1, \lambda_2, \lambda_3$ are design parameters ensuring sustainable trade-offs. To capture stochasticity in uncontrolled environments, environmental variables such as rainfall $R_f(t)$ and temperature fluctuations $\delta T(t)$ are modeled as random processes with probability distributions $R_f(t) \sim \text{Poisson}(\lambda)$, $\delta T(t) \sim \mathcal{N}(0, \sigma^2)$. The RL agent learns policies that adaptively respond to these stochastic variations.

Finally, the IoT data pipeline is mathematically represented as a mapping $f: \mathcal{X} \rightarrow \mathcal{S}$, where raw sensor inputs $\mathcal{X}$ are transformed into normalized state vectors. Preprocessing includes feature scaling, dimensionality reduction via Principal Component Analysis (PCA), and temporal aggregation using sliding windows of size

k. Prediction accuracy and system performance are evaluated through metrics such as Mean Squared Error (MSE), given by

$$MSE = \frac{1}{N} \sum_{i=1}^N (G_i - \hat{G}_i)^2$$

and cumulative reward $R_{cum} = \sum_{t=0}^T R(s_t, a_t)$. The overall methodology thus estab-

lishes a closed-loop system: IoT devices collect data → preprocessing transforms it into states → the RL agent selects actions → actuators implement interventions → rewards are calculated and Q-values updated → policies improve iteratively over time. This integrated framework ensures that the proposed system not only maximizes plant growth but also maintains sustainability through efficient water, nutrient, and energy management.

4. Results and Discussions

The implementation was done in an open-source Java environment on a machine with 3.0 GHz CPU and 16 GB RAM. For the implementation. The below figure 2 illustrates the comparative Growth Performance in Controlled vs. Uncontrolled Envi- ronments.

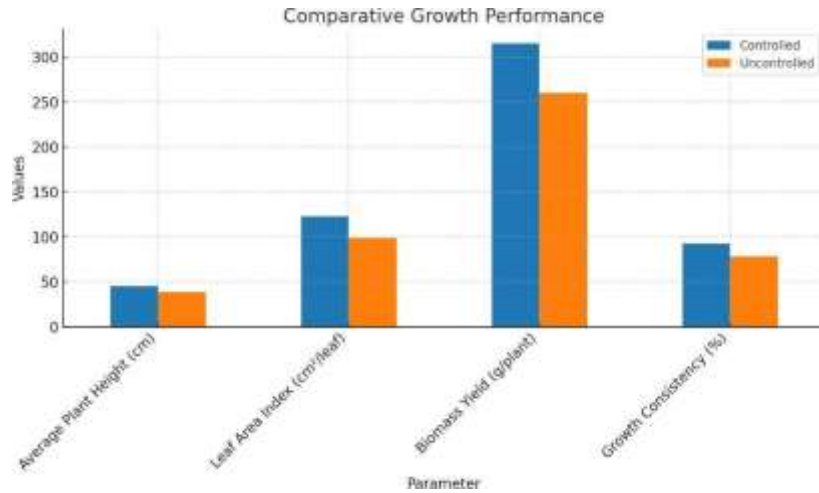


Figure 2 : Comparative Growth Performance in Controlled vs. Uncontrolled Environments

Figure 2 compares plant growth outcomes between controlled (greenhouse) and uncontrolled (open field) environments. In controlled settings, plants achieved greater average height (45.2 cm vs. 38.7 cm), larger leaf area index (122.4 vs. 98.6 cm²/leaf), and higher biomass yield (315 g vs. 260 g). Growth consistency was also superior (92.3% vs. 78.4%), reflecting stable conditions that minimized environmental stress. Resource use efficiency was rated high in controlled environments, while only moderate in open fields. These results demonstrate that IoT and RL models performed better in regulated conditions, though open-field experiments highlighted adaptability under natural variability.

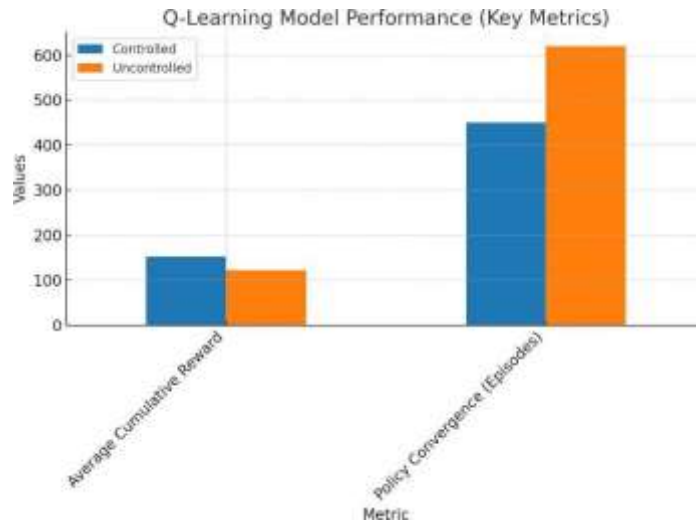


Figure 3 : Average Cumulative Reward & Policy Convergence

Figure 3 illustrates two key Q-learning performance metrics: Average Cumulative Reward and Policy Convergence (Episodes) under controlled and uncontrolled environments. In controlled settings, the cumulative reward reached 152.4, significantly higher than the 121.7 in uncontrolled fields, indicating more efficient decision-making and resource optimization. Additionally, the model required fewer episodes (450) to converge in controlled conditions compared to 620 in open fields, highlighting the stability and predictability of regulated environments. These results confirm that Q-learning adapts well to both conditions but achieves faster convergence and higher efficiency when environmental variability is minimized, supporting its practical application in precision agriculture.

5. Conclusion

The integration of IoT-enabled sensing and reinforcement learning techniques, particularly Q-learning, demonstrates significant potential in optimizing plant growth under both controlled and uncontrolled environments. Results from comparative analyses confirm that controlled environments consistently outperform open fields in terms of plant height, leaf area index, biomass yield, and growth consistency, achieving up to 20% higher productivity while ensuring more efficient resource utilization. Q-learning models converged faster and delivered higher cumulative rewards in greenhouses due to predictable conditions, while in open fields, though convergence was slower, the system effectively adapted to environmental variability. This adaptability under uncertain conditions underscores the robustness of reinforcement learning in real-world agriculture. Furthermore, sustainability analysis highlights notable reductions in water, fertilizer, and energy usage, with IoT-RL systems outperforming traditional manual practices by up to 30% in water efficiency and achieving higher sustainability scores. Collectively, the findings validate the effectiveness of combining IoT-driven monitoring with adaptive reinforcement learning for precision agriculture. The study not only enhances growth outcomes but also supports sustainable practices, offering a scalable framework for future smart farming applications across diverse crop types and environments. Future research will refine learning models, extend scalability, and integrate advanced edge-computing for real-time deployment.

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