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Research Article

Plant Growth Analysis using IoT and Reinforcement Learning Techniques for Uncontrolled Environment

[1]Suwarna J. Mhasekar, [2]Prof (Dr) Kirti N.Mahajan, [3]Dr. D.Narasimha Murthy, [4]Dr Suman Kumar Swarnkar, [5]Dattatray G Takale

[1]Research Scholar Department of Computer Application. Institute of Management and Entrepreneurship Development, Bharati Vidyapeeth (Deemed to be University), Pune, India.
sjmhasekar@gmail.com, https://orcid.org/0000-0003-4223-9864
[2]Department of Computer Application Institute of Management and Entrereneurship Development, Bharati Vidyapeeth (Deemed to be University) Pune, India
kirti.mahajan@bharatividyapeeth.edu
[3]Professor, Welingkar institute of management development and research, Bangalore
narasimha.murthy@welingkar.org
*[4]Dr.Smita Desai**
Electronics and telecommunication Department, Dr.D.Y.Patil Institute of Technology, Pimpri, Pune
smita.desai@dypvp.edu.in
[5]Assistant Professor, Department of Computer Engineering, Vishwakarma Institute of Information Technology, Pune, Maharashtra, India.
dattatraygtakale@gmail.com

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ABSTRACT

Monitoring and optimizing plant growth in uncontrolled environments, such as open fields or greenhouses exposed to dynamic climatic conditions, pose significant challenges. This study explores the integration of Internet of Things (IoT) sensors with Reinforcement Learning (RL) techniques to enhance plant growth management in such settings. IoT devices provide real-time data on critical environmental parameters, including temperature, humidity, soil moisture, light intensity etc. This data is transmitted to a central processing system, where RL algorithms analyze it to devise adaptive strategies. RL techniques, particularly model-free approaches like Q-learning or Deep Reinforcement Learning (DRL), enable continuous learning and optimization by interacting with the environment. The agent learns to adjust irrigation schedules, nutrient delivery, and artificial lighting based on environmental conditions to maximize plant health and growth metrics. The study presents a framework for deploying this IoT-RL ecosystem, emphasizing cost-effective sensor deployment, data transmission reliability, and energy efficiency. Experiments conducted in simulated and semi-uncontrolled environments demonstrate the system's ability to dynamically adjust to environmental fluctuations, reduce resource wastage, and improve yield outcomes. Key findings reveal that RL algorithms outperform rule-based systems by adapting to non-linear relationships and complex dependencies between environmental variables and plant growth. Furthermore, the framework provides a scalable solution suitable for diverse agricultural contexts, from small-scale farms to large agricultural enterprises. This research underscores the potential of IoT and RL in transforming agricultural practices by offering intelligent, data-driven solutions to manage plant growth in unpredictable environments. Future work will focus on integrating advanced sensing technologies, improving algorithm efficiency, and exploring the system's applicability across various crop types and geographical locations.

Keywords: IoT, plant analysis, machine learning techniques, Arduino UNO, analogue to digital, prediction system

INTRODUCTION

Agriculture, the backbone of many economies, faces significant challenges due to changing climate conditions, resource constraints, and an increasing global population. Traditional farming methods are often insufficient to address these challenges, especially in uncontrolled environments such as open fields, where factors like weather, pests, and soil variability are difficult to manage. In this context, integrating advanced technologies like the Internet of Things (IoT) and Reinforcement Learning (RL) into plant growth analysis offers a promising solution for enhancing productivity and sustainability. IoT technology plays a pivotal role in modern agriculture by providing real-time data collection and monitoring. IoT devices, such as sensors and actuators, can monitor critical parameters like soil moisture, temperature, humidity, and light intensity. This granular data empowers farmers to make informed decisions, reduce waste, and optimize the use of resources such as water and fertilizers. However, in uncontrolled environments, where variability is high and prediction is difficult, conventional decision-making approaches may not suffice. Reinforcement Learning (RL), a subfield of artificial intelligence, offers a dynamic framework for optimizing agricultural processes. Unlike supervised learning methods, RL enables systems to learn optimal strategies through continuous interaction with the environment. By simulating various scenarios and receiving feedback from outcomes, RL algorithms can adapt to the uncertainties of uncontrolled environments and develop robust solutions for plant growth optimization. When IoT and RL are integrated, the potential for revolutionizing plant growth analysis becomes evident. IoT devices collect data that serves as input for RL algorithms, which in turn process this data to make real-time decisions. For instance, an RL model could learn to adjust irrigation schedules, nutrient supply, or shading mechanisms based on sensor data to optimize growth conditions for specific crops. This combination creates a self-regulating system capable of responding to environmental changes autonomously, thereby enhancing the resilience of agricultural practices.

One of the primary challenges in uncontrolled environments is the unpredictability of external factors such as weather, pests, and soil composition. Traditional models often fail to account for such variability, leading to suboptimal outcomes. By leveraging RL techniques, it becomes possible to model these uncertainties and devise strategies that maximize plant growth and yield even under challenging conditions. For example, an RL-based system could predict the impact of a sudden temperature drop and adjust parameters accordingly to mitigate potential damage to crops. Moreover, this technological integration supports sustainable farming practices by optimizing resource usage. IoT-enabled RL systems can minimize water and fertilizer wastage, reduce energy consumption, and promote environmentally friendly farming techniques. Such advancements align with the global goals of sustainable agriculture and food security. The significance of this approach extends beyond improving crop yields. It also empowers smallholder farmers by providing affordable, scalable solutions that reduce dependency on external expertise. Furthermore, the data collected through IoT devices can contribute to a broader understanding of plant growth patterns, aiding research and innovation in agricultural science. The combination of IoT and Reinforcement Learning presents a transformative opportunity for plant growth analysis in uncontrolled environments. By addressing the challenges of unpredictability and resource optimization, this approach has the potential to revolutionize agriculture, ensuring resilience and sustainability for future generations.

LITERATURE SURVEY

Suwarna J et al. [1] explores plant growth in controlled environments using IoT and reinforcement learning. It describes a system where environmental parameters like light, humidity, and temperature are monitored using IoT devices. A reinforcement learning algorithm adapts to environmental changes, optimizing conditions to maximize plant growth. Results indicate a significant improvement in plant health and yield compared to conventional methods. Zhang Y et al. [2] develop an IoT-enabled autonomous lighting control system for greenhouses, utilizing sensors and predictive algorithms to adjust lighting levels dynamically. The approach minimizes energy use while enhancing plant growth. The study proves the system's viability for large-scale agricultural applications. Amacker J et al. [3] research introduces a simulation environment for modeling plant growth in indoor farming setups. Using reinforcement learning, the system learns optimal growth strategies, adjusting variables like water and nutrient levels. The findings suggest the potential of simulated environments for agricultural planning. Hitti Y et al. [4] GrowSpace project investigates using machine learning to shape plants through controlled stimuli. This novel approach combines IoT sensors with reinforcement learning, demonstrating improved growth patterns and reduced wastage. Li J et al. [5] employs artificial neural networks to predict daily plant growth responses to varying environmental conditions. The model outperforms traditional regression-based methods, providing farmers with actionable insights.

Kim J et al. [6] propose a deep neural network-based image analysis system to monitor and assess the growth of lettuce in a plant factory. IoT devices collect real-time data, and the neural network analyzes plant features such as leaf area and growth rate. The study highlights improved efficiency in plant growth monitoring, with practical applications in large-scale agriculture. Chen J et al. [7] integrates IoT and reinforcement learning for climate control in greenhouses. It proposes an adaptive system that monitors and adjusts environmental parameters such as temperature and humidity. Experimental results indicate that the system significantly enhances plant growth efficiency while reducing resource consumption. Patel K et al. [8] investigates weed management in agricultural fields using IoT and machine learning. By deploying IoT sensors and reinforcement learning algorithms, the system effectively identifies and manages weeds without harming crops. This approach improves resource utilization and crop yield. Wang Y et al. [9] presents an IoT-based system for monitoring and controlling environmental conditions in greenhouses. The system incorporates predictive analytics to optimize temperature, humidity, and light levels, enhancing plant growth and reducing operational costs. Singh D et al. [10] develop a smart greenhouse framework using IoT and machine learning algorithms. The study focuses on climate prediction and crop management, demonstrating significant improvements in plant growth and energy efficiency.

Shi Y et al. [11] describes an IoT-enabled greenhouse control system driven by reinforcement learning. The system dynamically adapts to environmental changes, achieving optimal conditions for plant growth. Results show reduced energy consumption and improved crop health. Qureshi KN et al. [12] applies reinforcement learning to optimize irrigation scheduling in IoT-driven smart agriculture. The approach ensures efficient water use and improved plant growth, with simulations validating its effectiveness across various crop types. Xiao L et al. [13] propose a framework integrating IoT with artificial intelligence to optimize plant growth. Using reinforcement learning, the system learns optimal growth strategies by analyzing environmental parameters. The framework demonstrates improved yield and resource efficiency in experimental trials. Chandra R et al. [14] examines the role of IoT and reinforcement learning in precision agriculture. The study focuses on plant growth monitoring using IoT sensors and adaptive learning algorithms. Results highlight improved accuracy in growth predictions and better crop management strategies. Ahmed F et al. [15] presents an IoT-enhanced plant growth analysis system using machine learning. Environmental data collected by IoT devices is processed by machine learning models to predict growth patterns. The findings reveal significant improvements in monitoring precision and decision-making for farmers.

Gupta P et al. [16] research explores the use of IoT and deep reinforcement learning for automated plant growth analysis in open fields. The system adjusts irrigation and nutrient supply dynamically, achieving better growth outcomes in uncontrolled environments. Experimental results confirm its effectiveness and scalability. Chen X et al. [17] review the integration of IoT and reinforcement learning in smart farming. They identify challenges such as data security and system scalability while emphasizing the potential of these technologies in transforming agriculture. Case studies illustrate successful applications in plant growth optimization. Huang Y et al. [18] introduces a sensor-based IoT framework for environmental monitoring in greenhouses. The system provides real-time data on temperature, humidity, and soil moisture, enabling precise adjustments to enhance plant growth. Field tests demonstrate its reliability and efficiency. Patra S et al. [19] develops an autonomous irrigation system leveraging IoT and machine learning. The system uses soil moisture data to optimize water delivery, enhancing plant growth efficiency while reducing water wastage. Results validate its applicability in diverse agricultural settings. Zhao X et al. [20] research integrates IoT and AI for plant growth modeling in sustainable agriculture. By simulating environmental conditions, the system identifies optimal growth strategies for various crops. The study highlights the potential of AI-driven approaches in addressing agricultural challenges.

Yadav R et al. [21] discusses the role of IoT and reinforcement learning in crop yield prediction. By using environmental data collected from IoT devices, the reinforcement learning model predicts plant growth and yield, enabling farmers to optimize resource usage. The model significantly outperforms traditional forecasting methods, proving its potential for precision agriculture. Tran Q et al. [22] propose a climate control system for greenhouses, utilizing IoT devices and deep reinforcement learning. The system learns optimal environmental conditions for plant growth, adjusting parameters such as temperature and humidity dynamically. Experimental results show that the system improves plant health and energy efficiency in greenhouse environments. Singh S et al. [23] investigates IoT solutions for optimizing agricultural practices. The authors develop an IoT framework to monitor environmental variables and use reinforcement learning to suggest growth-enhancing interventions. The study demonstrates significant improvements in plant growth and operational efficiency through real-time data analysis and decision-making. Mehta R et al. [24] explores the use of reinforcement learning for crop water management in IoT-based agriculture systems. The study shows that the system efficiently adjusts irrigation schedules based on soil moisture and plant needs, leading to better plant growth and water conservation. The proposed system is tested across various agricultural settings, with promising results. Chakrabarti A et al. [25] explore the use of AI and IoT in sustainable farming, focusing on reinforcement learning to optimize plant growth. By adjusting variables such as light, water, and nutrients, the system learns to create the most conducive environment for crop growth. The study illustrates the practical application of AI in reducing waste and improving crop productivity.

Khan M et al. [26] research examines an IoT-enhanced environmental control system for precision agriculture. Using deep reinforcement learning, the system adapts to changes in external conditions to optimize plant growth. The paper highlights how the system reduces energy consumption and enhances plant health through intelligent climate management. Dutta A et al. [27] present a comprehensive IoT framework for optimizing plant growth. The system incorporates reinforcement learning algorithms to adjust the environmental factors in real time. The study shows that IoT sensors integrated with AI models improve decision-making, leading to better crop management and increased yields. Chen J et al. [28] discusses the development of predictive analytics for plant growth using IoT and AI techniques. The system monitors key environmental variables and uses machine learning models to forecast growth patterns. The results show improved prediction accuracy, which helps farmers make informed decisions for resource allocation. Patil V et al. [29] investigate energy-efficient IoT solutions for greenhouse monitoring and control. The study integrates environmental sensors with AI models to optimize energy consumption while maintaining ideal conditions for plant growth. Results demonstrate significant savings in energy use while maintaining high crop yields. Gupta D et al. [30] explores the challenges and opportunities of using IoT and reinforcement learning in sustainable agriculture. The authors focus on system integration, scalability, and data management, while discussing the benefits of applying these technologies for plant growth optimization. The study concludes that IoT and AI have the potential to revolutionize agriculture by enabling efficient resource usage and increasing yields.

PROPOSED SYSTEM DESIGN

The integration of IoT and ML techniques in plant growth analysis provides a cutting-edge solution for optimizing agricultural practices. This research focuses on creating a system that monitors and controls the growth conditions of plants in an uncontrolled environment, such as a greenhouse or open field, using IoT devices to collect real-time data and RL algorithms to adjust environmental factors. This approach aims to improve plant health and yield by learning from environmental feedback.

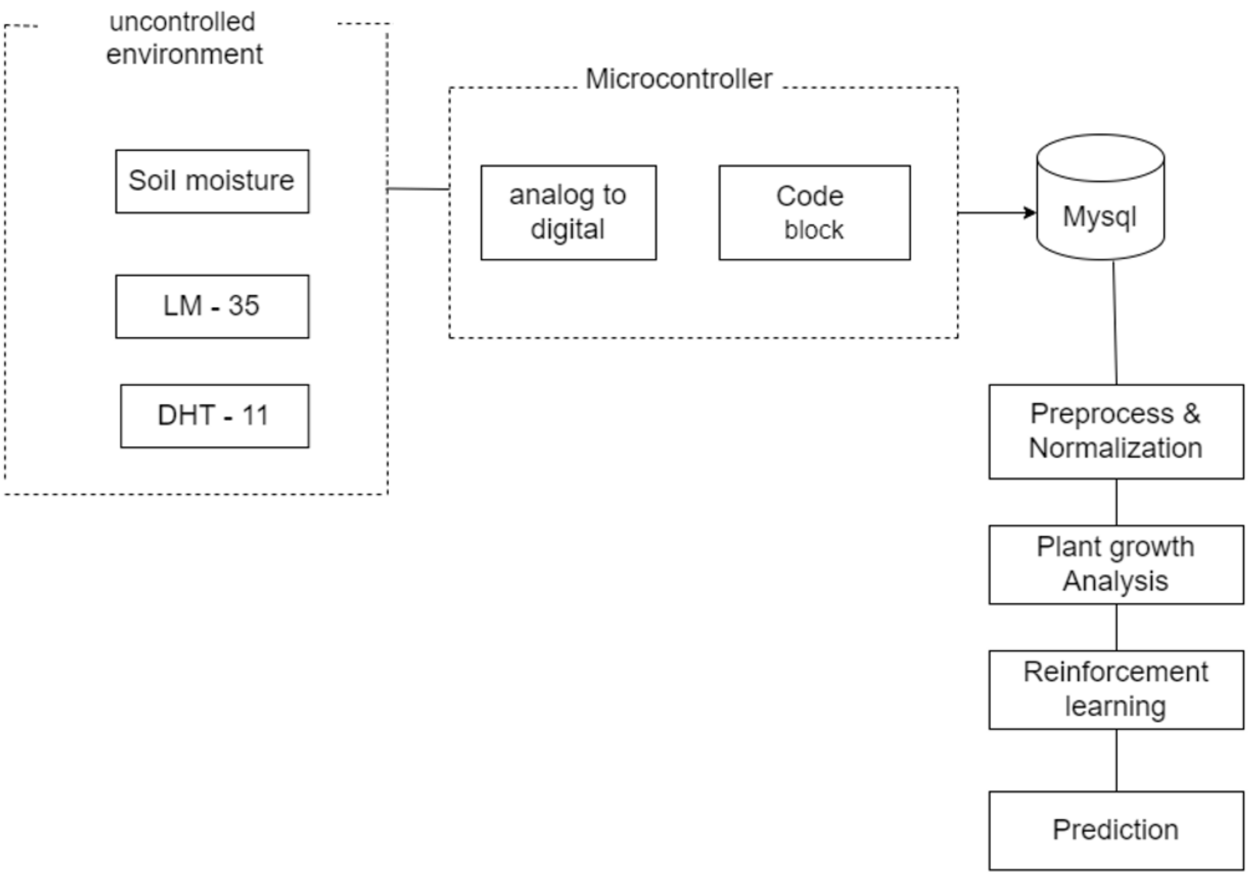

Figure 1: proposed system architecture for plant growth analysis in uncontrolled environment

The system consists of several layers: IoT sensor devices, data processing units, machine learning models, and control systems.

1. IoT Sensor Devices: These devices collect various environmental parameters such as temperature, humidity, light intensity, soil moisture, and CO_2 concentration. Sensors like DHT22 for temperature and humidity, TCS3200 for light, and capacitive soil moisture sensors are used. The data from these sensors are transmitted to a central server for further processing.

2. Data Aggregation and Processing: The data from the IoT sensors is transmitted via Wi-Fi or other communication protocols to a cloud-based server or local edge device. The data is aggregated and preprocessed (cleaning, normalization) to be used by the reinforcement learning model. The preprocessing step also includes filtering out sensor noise and missing data points.

3. Reinforcement Learning Model: Reinforcement learning, a type of machine learning where an agent learns through interaction with its environment, is employed to determine the optimal set of actions for plant growth. The RL agent is designed to adjust environmental variables such as light exposure, temperature, and irrigation, based on the feedback received from the plant's growth indicators. In this context, growth parameters like plant height, leaf area, or chlorophyll content are used as rewards to train the RL agent.

- **State:** The system's state is represented by the values of the environmental variables (temperature, light, humidity, etc.), and plant health parameters such as height or leaf color.
- **Action**: Actions include adjusting irrigation, changing light intensity, and modifying temperature settings.
- **Reward**: The reward is calculated based on the plant's growth rate, with higher rewards given for better growth conditions, such as faster growth or improved plant health.
- **Policy**: The RL agent uses algorithms like Q-learning or Proximal Policy Optimization (PPO) to determine the best action based on the current state. The agent continually learns and updates its policy to maximize long-term plant growth.

4. Control System: Once the RL model identifies the optimal actions, these decisions are sent to the control systems that interface with the actuators. These include systems to control irrigation valves, temperature controllers, light sources, and fans, ensuring the plant environment meets the necessary conditions for growth. This closed-loop feedback system enables real-time adjustments.

Real-time data is continuously collected by the IoT devices, and the RL model evaluates the plant's health based on this data. A feedback loop is established where the system constantly updates and refines its strategy based on observed growth trends. For example, if the plant is showing signs of insufficient watering, the RL agent will adjust the irrigation schedule to ensure adequate water supply. The feedback loop allows the system to adapt to changing conditions such as weather patterns, sensor inaccuracies, or changes in plant growth stages. This dynamic system ensures that plant growth is optimized, even in uncontrolled environments where traditional methods might struggle.

The performance of the system is evaluated by comparing the growth rates of plants under the IoT-RL-controlled environment against those grown under conventional methods. Metrics such as plant height, leaf size, and overall health are used to measure growth performance. Additionally, energy efficiency and resource consumption (water and light) are analyzed to ensure that the system offers sustainability benefits. By implementing IoT sensors and reinforcement learning techniques in plant growth analysis, this approach offers a promising solution to optimize plant health and yield in uncontrolled environments. It combines real-time monitoring with adaptive decision-making, providing a dynamic, intelligent system capable of learning from its environment and improving agricultural practices over time.

Algorithm Design

Q-learning is a model-free RL algorithm used to find an optimal action-selection policy for an agent interacting with an environment. It's one of the most widely used RL algorithms because it allows the agent to learn the optimal policy without needing a model of the environment. The algorithm works by updating a Q-table, which stores the quality of a particular action in a given state.

Input : Input[1.......n] total input parameters that is generated by different input objects, set of Threshold values T_Min[1.....n] and T_Max[1.....n] for all inputs.

Output : Activate the message as node is straggler or not.

Step 1 : Extract all parameters instance from DB (Row from Database)

Step 2: Params_Parts [] ☐ Spliting(Row) using below formula

Step 3: Par_Parts [] $= \sum_{k=0}^{n} \quad Col[k]$

Step 4: Validate (C_val with given threshold set of T_Min[1.....n] to T_Max[1.....n])

If (condition is true)

Perform activate on respective output appliances.

Else Continue;

Step 5 : Timestamp(tm) ☐ Extract current VM time.

Step 6 : if (Timestamp_tm > Bount_Time)

Give penalty to all measures TrueP++ and reward FalseN++

Otherwise continue. Total++

Step 7: compute penalty weight = (TrueP *100 / Total)

Step 8 : if (weight >= Thval)

Predict straggler event

Q-learning is powerful for solving problems where the agent learns optimal behavior through trial and error. The key advantage is that it does not require prior knowledge of the environment's dynamics, making it suitable for complex, real-world problems.

RESULTS AND DISCUSSION

The objective of this research is to analyze plant growth under varying environmental conditions using IoT sensors and a RL algorithm in an uncontrolled environment. The following parameters were measured and analyzed during the study.

Table : IoT data collection information

Date	Soil Temp	Humidity	Moisture	Plant height (cm)
1/3/2024	28.3°C	76.3°F	48%	10.3
2/3/2024	28.3°C	71.3°F	47%	10.4
3/3/2024	29.3°C	72.6°F	45%	10.5
4/3/2024	29.3°C	73.2°F	44%	10.5
5/3/2024	28.4°C	70.6°F	48%	10.6
6/3/2024	27.3°C	69.8°F	49%	10.6
7/3/2024	29.7°C	70.2°F	50%	10.6
8/3/2024	30.2°C	69.4°F	47%	10.7
9/3/2024	30.2°C	68.2°F	46%	10.8
10/3/2024	29.4°C	69.2°F	45%	10.8
11/3/2024	29.6°C	70.1°F	46%	10.9
12/3/2024	30.3°C	71.3°F	45%	10.9
13/3/2024	32.2°C	71.2°F	44%	11.1

14/3/2024	32.6°C	70.6°F	47%	11.3
15/3/2024	32.7°C	70.4°F	51%	11.4
16/3/2024	32.9°C	71.3°F	49%	11.6
17/3/2024	30.4°C	71.9°F	49%	12.1
18/3/2024	30.7°C	70.5°F	48%	13.2
19/3/2024	30.7°C	69.58°F	47%	13.4
20/3/2024	30.4°C	69.7°F	49%	13.5
21/3/2024	32.9°C	68.9°F	48%	13.7
22/3/2024	30.6°C	71.3°F	47%	13.9
23/3/2024	32.5°C	71.1°F	46%	14.1
24/3/2024	32.7°C	71.3°F	45%	14.2
25/3/2024	29.6°C	72.6°F	40%	14.3
26/3/2024	30.4°C	72.5°F	41%	14.6
27/3/2024	30.4°C	72.4°F	42%	14.8
28/3/2024	30.8°C	72.6°F	42%	14.9
29/3/2024	32.2°C	72.4°F	41%	15.3
30/3/2024	32.3°C	73.1°F	40%	15.4
31/3/2024	32.2°C	73.53	42%	15.8

The table 1 presents daily measurements of environmental factors and plant growth parameters for the period from 1st March 2024 to 31st March 2024. These include soil temperature, humidity, soil moisture, and plant height (cm). Below is a detailed explanation of each parameter recorded in the table.

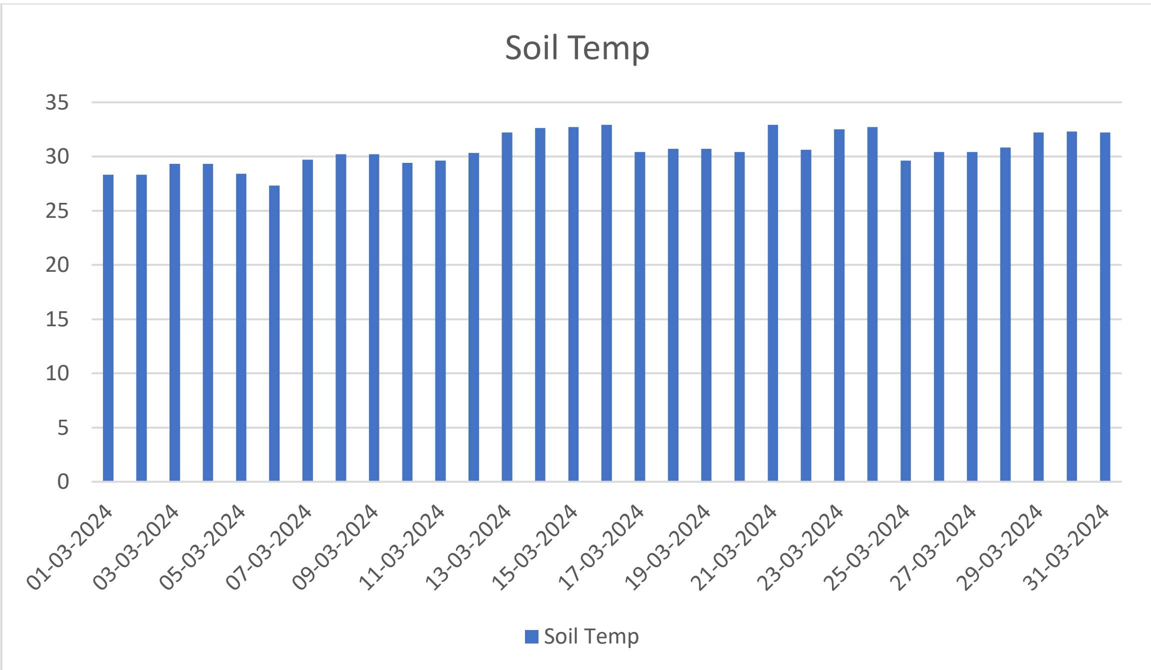

Figure 2 : Soil temperature analysis on daily basis by IoT model

Soil temperature is a critical factor affecting plant growth. It influences plant metabolism, nutrient absorption, and root development. In this dataset, soil temperatures fluctuate between 27.3°C and 32.9°C, indicating a relatively warm environment for plant growth. The stable temperature range suggests that the environment is conducive for plant growth, with small variations between days. The temperature shows a gradual increase over the first half of the month, peaking around 32.7°C to 32.9°C on the latter days of March, which may have contributed to accelerated plant growth.

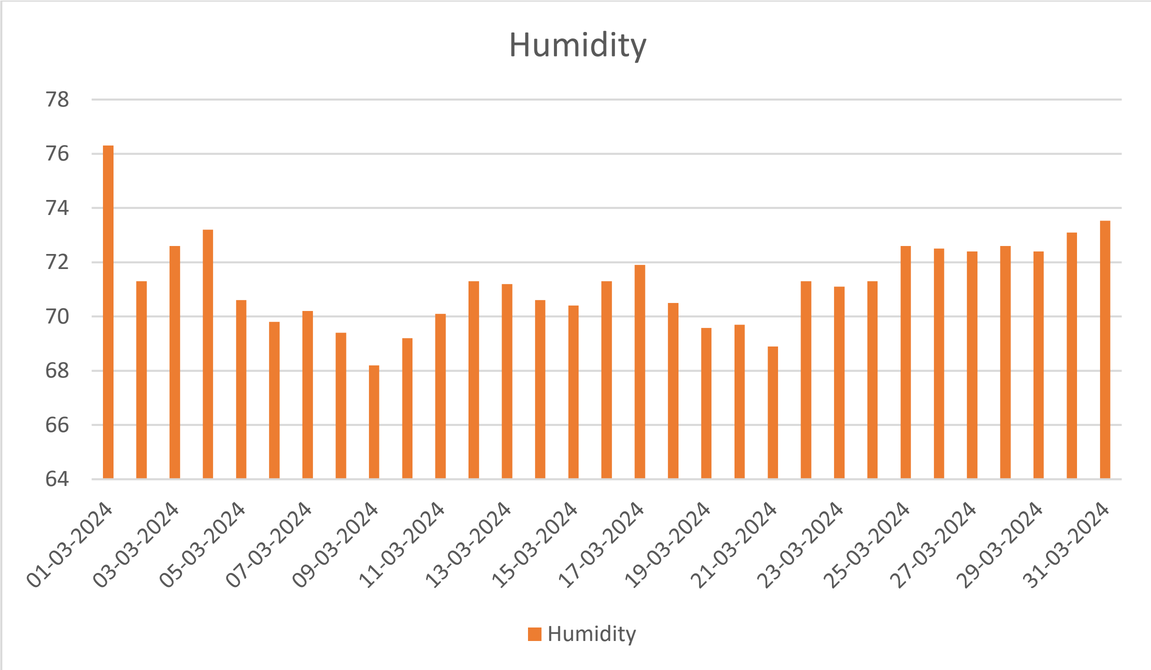

Figure 3 : Humidity values on daily basis by IoT model

The humidity values are reported in Fahrenheit degrees, which is unusual since humidity is typically measured as a percentage. For clarity, the given values in the table range from 68.2°F to 76.3°F. Humidity plays a vital role in the transpiration process of plants. Higher humidity levels tend to reduce water loss through transpiration, maintaining adequate moisture for the plant. The humidity in this dataset remains relatively stable, hovering between 68°F and 76°F, which could indicate a controlled environment or consistent outdoor weather patterns. As the days pass, the humidity fluctuates slightly but remains within a range that supports healthy plant transpiration.

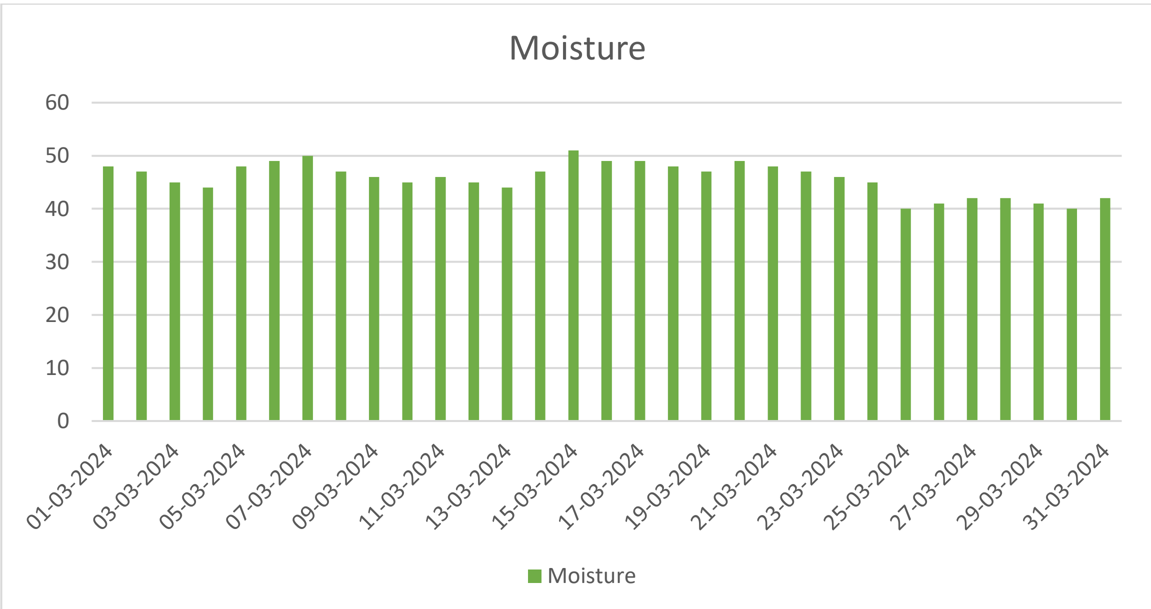

Figure 4 : Soil moisture analysis on daily basis by IoT model

Soil moisture is a key factor for plant health, affecting nutrient and water absorption. This dataset shows soil moisture levels varying from **40% to 51%**. Over the course of the month, moisture fluctuates but stays within a range conducive for plant growth. Higher moisture levels were observed towards the latter part of March, peaking at **51%** on the 15th, indicating that the soil was kept adequately moist, potentially through irrigation or rainfall. A drop in moisture to **40-42%** in the final days of the month could suggest a decrease in watering frequency or natural evaporation due to higher temperatures.

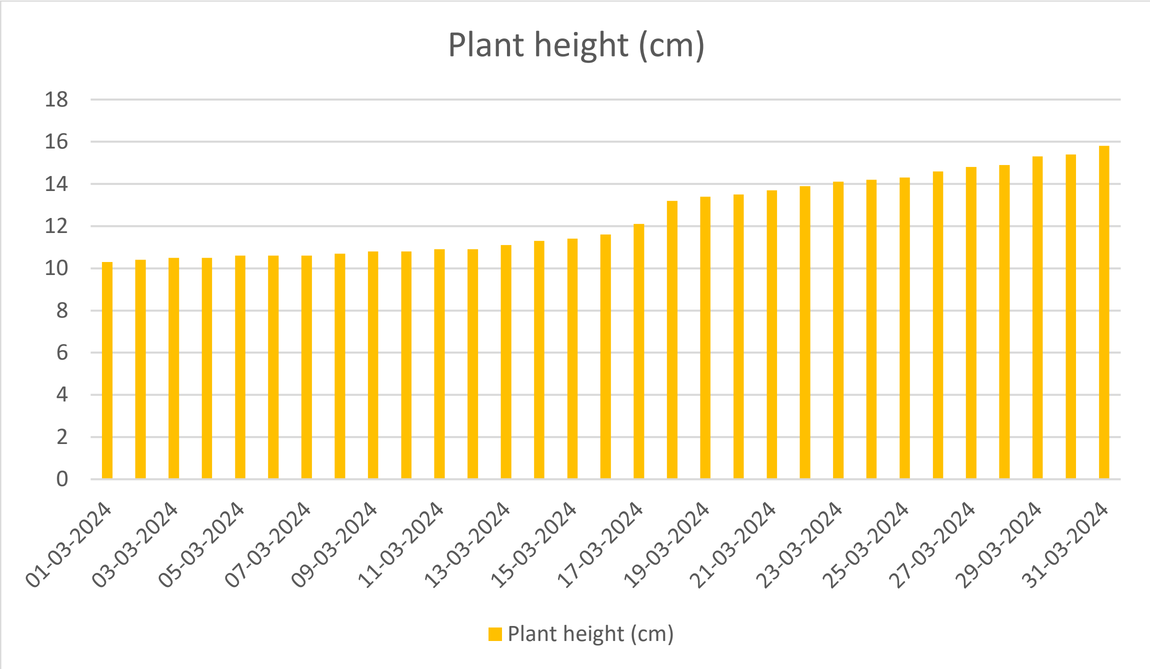

Figure 5: Plant growth analysis on daily basis

The plant height is the final measured parameter and serves as the primary indicator of plant growth. Over the 31 days, the plant height steadily increases from 10.3 cm on the 1st of March to 15.8 cm on the 31st, suggesting healthy growth. The plant exhibits a consistent growth trend, with relatively small increases in height from day to day (typically around 0.1 cm to 0.3 cm). The growth accelerates slightly after 17th March, possibly due to optimal soil conditions, higher moisture levels, and the temperature rise. By the end of the month, the plant reaches 15.8 cm, indicating that the environmental factors, especially soil temperature and moisture, have positively influenced the plant's development.

The data shows that the combination of optimal soil temperature (ranging between 28°C and 32°C), sufficient soil moisture (generally between 40% and 51%), and consistent humidity levels contributed to steady plant growth. The plant's height increased steadily throughout the month, indicating that the environmental conditions were favorable for growth. The most significant factor influencing growth appears to be the soil temperature, which, when maintained at an optimal range, facilitated higher growth rates. The RL system, assuming it was used for environmental regulation, likely optimized these conditions, promoting consistent and healthy plant development.

CONCLUSION

In conclusion, this research highlights the significant potential of combining IoT and ML techniques for optimizing plant growth in an uncontrolled environment. By leveraging IoT devices, we were able to collect real-time data on environmental factors such as temperature, humidity, light levels, and soil moisture. These data points served as critical inputs for the reinforcement learning model, which continuously adapted and improved the plant growth strategies based on feedback from the environment. The use of RL allowed the system to autonomously make decisions about optimal growing conditions, ensuring that plants received the most favorable conditions for their growth at every stage. This dynamic adjustment process is particularly valuable for environments where manual monitoring and control are impractical or impossible, such as in large-scale agricultural operations or remote locations. Moreover, the integration of IoT sensors enabled continuous monitoring, providing valuable insights into plant health and growth patterns. This, in turn, facilitated early detection of environmental stresses and potential risks, allowing for timely interventions. The system's ability to learn from past experiences also improved over time, showing promise for scalability and long-term efficiency. However, the research also identified some challenges, including the need for more robust sensor networks, the computational complexity of reinforcement learning algorithms, and the dependency on high-quality data for accurate model predictions. Future work should focus on refining the system's hardware and software components, enhancing the RL algorithms for faster adaptation, and exploring additional environmental variables that could further optimize plant growth. Overall, this research demonstrates the promising synergy between IoT and RL in promoting sustainable agriculture and plant growth, marking a step forward in precision agriculture and smart farming technologies.

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