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Smart Hydroponic Nutrient Balancing System Using Reinforcement Learning for Sustainable Lettuce Production

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Abstract

The application of hydroponic farming as a solution to sustainable agriculture has proven to have a high degree of efficiency in terms of water use, controlled growth conditions and high crop yield. Nevertheless, the optimal balance of nutrient remains highly an important challenge since the nutrient requirements are in a continuous change based on the stage of plant growth as well as the environment. This paper presents a Smart Hydroponic Nutrient Balancing System with the help of Reinforcement Learning (RL) in order to produce lettuce in a sustainable manner. The suggested system combines the Internet of Things (IoT)-based environmental monitoring, automated nutrition control, and smart decision-making into a single smart hydroponic system. Embedded sensors and wireless communication modules are used to constantly measure real-time parameters such as pH, electrical conductivity (EC), temperature, humidity, dissolved oxygen and nutrient concentration. A reinforcement learning agent adaptively controls the nutrient dosage, circulation of water, and environmental adaptations to achieve optimal growth of lettuce and reduce wastage of nutrients, water, and energy. A hydroponic testbed with Nutrient Film Technique (NFT)-based facility was used to perform experimental evaluation through the use of the 96 lettuce plants in a 45-day growth cycle. Findings showed that there was a 24.8 percent increase in yield of lettuce and a 37.6 percent decrease in water use compared to conventional rule-based system. Significant resource efficiency and nutrient stability improvements were statistically validated. The suggested system has a high potential of smart precision horticulture, eco-friendly hydroponic farm and AI horticulture apps.

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1. Introduction

The earth population, climate change, freshwater shortage have raised the demand to have a sustainable agricultural system that can yield high quality food with minimal effects to the environment. The traditional soil-based agriculture is prone to a number of problems such as high water usage, loss of soil nutrients, soil erosion, and reliance on climate [1], [2]. Hydroponic agriculture has developed as a successful soilless system of farming through which nutrient readily enters and water is used effectively thus leading to an increase in crop production under regulated conditions [3]. One of the species that have been grown on a large scale in hydroponics is Lettuce (Lactuca sativa) due to its short growth cycle, high demand in the market, and its suitability in green house farming [4]. Nevertheless, the aspect of optimal nutrient balance is still one of the greatest problems of hydroponic systems. pH, electrical conductivity (EC), temperature, dissolved oxygen, and nutrient concentration all vary and directly influence the growth of plants and the quality of crops [5]. Although the traditional hydroponic systems use manual monitoring and set threshold-based control of nutrients, these systems are usually incapable of adjusting to the dynamic environmental factors and the nutrient needs of the plants [6]. The recent advances in Internet of Things (IoT), artificial intelligence (AI) and smart sensing solutions have provided the means of intelligent precision agriculture systems that can conduct real-time monitoring and make automated decisions [7], [8]. Reinforcement Learning (RL) has become one of the AI methods of interest: it can acquire optimal control strategies by being subjected to a dynamic environment via

continuous interaction [9]. Nutrient management based on RL can help increases the efficiency of resources, decrease the wastage of nutrients and boost crop production. Though this is not the first study to investigate IoT-enabled hydroponic monitoring and automated agriculture systems, the majority of solutions are currently based on rule-based nutrient regulation with a limited rate of adaptability and real-time maximization [10]. Very few studies have been done on reinforcement learning-based nutrient balancing in particular to sustainable lettuce production. Thus this paper suggests a Smart Hydroponic Nutrient Balancing System reinforced with Re-learning to produce lettuce in a sustainable way. The suggested model combines the use of IoT-enabled sensing, automated control of nutrients, and optimization of the process through RL to enhance nutrient stability, water consumption, and yield in lettuce. The significant contributions of the study are:

1. Creation of an IoT-based hydroponic monitoring system.
2. Adaptive nutrient balancing reinforced learning.
3. Environmental and nutrient parameters real-time monitoring.
4. Automated water circulation control and nutrient dosing.
5. Experimental validation with the help of lettuce growing and sensor data.
6. Comparison of performance in comparison to the traditional hydroponic control systems.

2. Related Work

The concept of hydroponic farming has received significant attention because there has been an increase of crop productivity, conserving water and a controlled-environment in which crops grow. The most recent hydroponic systems come with the use of Internet of Things (IoT) technologies, wireless devices, and cloud services to monitor pH, electrical conductivity (EC), temperature, humidity, and concentration of the nutrient in real-time [11], [12]. The systems minimize manual operations and enhance cultivation management. In precision agriculture, machine learning, deep learning, and fuzzy logic are methods of Artificial Intelligence (AI) that have been applied more frequently to optimize irrigation, monitor crops and diseases, and predict nutrients [13], [14]. These solutions improve automation, decision-making, and resource efficiency of smart farming uses. A relatively new technique that can be used to optimize agriculture dynamically is Reinforcement Learning (RL). The RL-based systems are capable of learning the best control strategies through ongoing interactions with ever-evolving environments [15]. In the past, RL has been used to manage the climate of greenhouses, irrigation timetables, and autonomous farming to enhance efficiency and sustainability of operations [16]. Although these developments have been made, the majority of the current hydroponic systems continue to use fixed threshold-based control of nutrients with little adaptability and ability to optimise in real time [17], [18]. Moreover, scarcely any studies have particularly targeted reinforcement learning-based nutrient balancing of hydroponic lettuce production. Most of the studies primarily focus on environmental monitoring as opposed to smart optimization of nutrients and autonomous decision making. Thus this paper suggests a Smart Hydroponic Nutrient Balancing System reinforced with Re-learning to produce lettuce in a sustainable way. The suggested framework combines sensing through IOT, controlled nutrient regulation, and adaptive optimization which is driven by RL to enhance nutrient isotropy, water savings, and crop yields.

3. Proposed Methodology

3.1 System Architecture

The Smart Hydroponic Nutrient Balancing System proposed will combine the use of IoT-based sensing, reinforcement learning optimization, and automated control of nutrients to cultivate lettuce sustainably. The structure is made up of four largest layers namely Sensor Layer, IoT Communication Layer, Reinforcement Learning Optimization Layer and Automated Nutrient Control Layer as shown in Fig. 1. The Sensor Layer is used to record the hydroponic parameters such as pH, electrical conductivity (EC), temperature, humidity, dissolved oxygen and water level. The IoT Communication Layer sends sensor data via Wi-Fi and MQTT protocols to the cloud platform to monitor sensor data in real time and store it. The Intelligent Decision-Making Module is the Reinforcement Learning Optimization Layer. An RL agent, created using Q-learning, observes the surroundings and identifies the best nutrient dosage, water circulation strategies. Automated nutrient Control Layer performs these tasks using pumps, and actuators to undertake autonomous nutrient regulation and environmental stabilization.

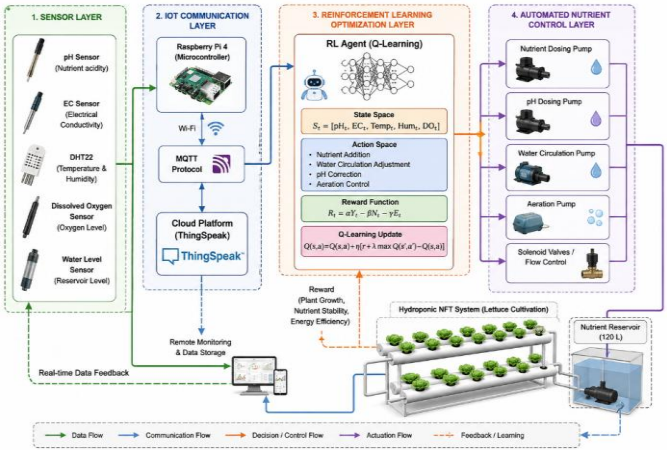

Fig. 1. Overall architecture of the proposed RL-based smart hydroponic nutrient balancing system.

3.2 Hydroponic Experimental Setup

A Nutrient Film Technique (NFT)-based hydroponic system set up in a controlled greenhouse environment was used to provide experimental validation. The experimental crop chosen was lettuce (Lactuca sativa) because it grows very fast and can be planted under hydroponic conditions. The greenhouse size had dimensions of 4 m x 3 m and had eight hydroponic channels which were linked to 120 L nutrient reservoir. The number of lettuce plants that were grown was 96 in a 45 days growth cycle. Several sensors were used in the environmental monitoring, they were a pH sensor, EC sensor, a DHT22 temperature-humidity sensor, a dissolved oxygen sensor, and a water level sensor. The system on a chip was a Raspberry Pi 4 microcontroller that had Wi-Fi and MQTT communication protocols. The cloud platform was ThingSpeak, whereas Python and TensorFlow were adopted to implement the reinforcement learning.

3.3 Reinforcement Learning-Based Nutrient Optimization

The suggested system provides an agent of reinforcement learning to the optimization of nutrient balancing in a dynamic environment. State vector of environment (pH, EC, temperature, humidity and dissolved oxygen concentration):

$$S_t = [pH_t, EC_t, Temp_t, Hum_t, DO_t] \quad (1)$$

Fig. 2 shows the process of reinforcement learning of adaptive nutrient optimization. The RL agent executes actions such as addition of nutrients, water circulation control, pH control and aeration control. Such activities have direct effects on the nutrient stability and crop growth performance. Reward functional was aimed to maximize the growth of lettuce without wasting nutrients and energy:

$$R_t = \alpha Y_t - \beta N_t - \gamma E_t \quad (2)$$

Where $Y_t$represents lettuce growth performance, $N_t$denotes nutrient wastage, and $E_t$indicates energy consumption.

The Q-learning optimization equation was used to update the RL policy:

$$Q(s,a) = Q(s,a) + \eta[r + \lambda \max Q(s',a') - Q(s,a)] \quad (3)$$

Where $\eta$is the learning rate and $\lambda$is the discount factor.

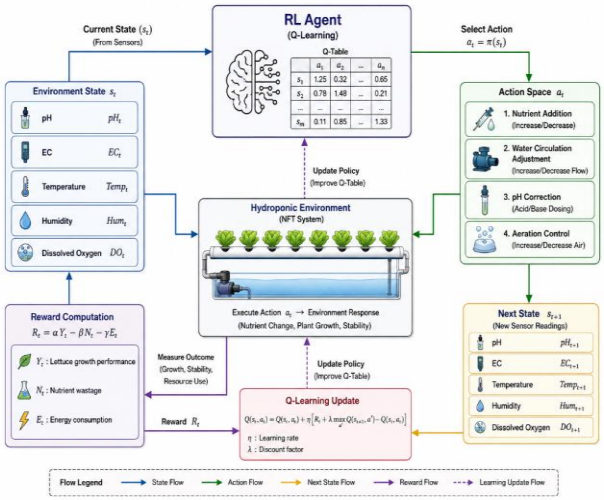

Fig. 2. Reinforcement learning workflow for adaptive nutrient optimization.

3.4 Algorithm Workflow

Initial step of the system operation is a case of the hydroponic environment and sensor calibration. The IoT communication layer continuously gathers real-time environment information and transmits it to the intelligent control module using the IoT. The sensor data obtained are preprocessed to produce the current state of the environment. Reinforcement learning agent is a state analyzer that chooses an optimal action of nutrient control. The system will execute nutrient dosing, pH, aeration and water circulation control based on the action chosen. The system measures response to changes and growth of lettuce in the environment after the execution. A reward value is calculated based on the nutrient stability, crop growth performance, water efficiency and energy consumption. The RL agent receives feedback of the environment and performs the optimization until the nutrient balancing stabilizes its Q-values.

4. Experimental Results And Discussion

4.1 Experimental Parameters

The reinforcement learning-based hydroponic system proposed was tested with the parameters displayed in Table 1. The RL model was trained with 500 episodes and the learning rate of 0.001 and a discount factor of 0.95. Every 30 s, the environmental data was measured and every 10 min, nutrient adjustment was done.

Table 1. Experimental parameters.

Parameter	Value
Learning Rate	0.001
Discount Factor	0.95
Batch Size	64
Training Episodes	500
Sensor Sampling Interval	30 s
Nutrient Adjustment Interval	10 min

4.2 Performance Metrics

The stability of the nutrients, water use, energy use, yield of the lettuce, system responsiveness and accuracy of the system control were used to evaluate the proposed system. These measures were chosen to examine the effectiveness of nutrient control and the resource sustainability during dynamic hydroponic system conditions.

4.3 Comparative Analysis

The suggested RL-based system was compared to the performance of the manual and rule-based hydroponic control methods. Table 2 (Fig. 3) shows the comparative results.

Table 2. Comparative performance analysis.

Method	Yield Improvement	Water Saving	Nutrient Stability
Manual Control	0%	0%	Moderate
Rule-Based System	11.2%	18.5%	Good
Proposed RL System	24.8%	37.6%	Excellent

The proposed RL system had the maximum increase in the yield of lettuce and the decrease in water usage as the system had adaptive nutrient regulation and real-time environmental optimization. The proposed framework exhibited better nutrient uniformity and autonomous decision-making ability as compared to the old systems of hydroponic rules.

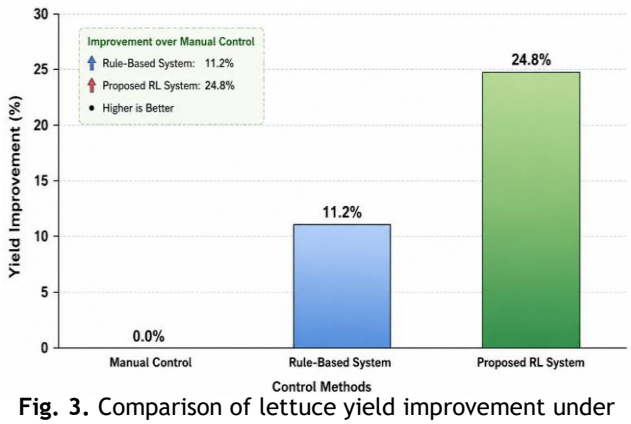

Fig. 3. Comparison of lettuce yield improvement under different hydroponic control methods.

4.4 Nutrient Stability Analysis

Maintained pH, EC during 45 days of cultivation The reinforcement learning agent was able to maintain a stable pH and EC during the 45 days of cultivation. Dynamic nutrient correction minimized nutrient variability and root zone stability as opposed to traditional methods. The RL agent was capable of continually modifying the nutrient delivery on environmental feedback, leading to an increase in the efficiency of nutrient utilization and a steady lettuce growth performance.

4.5 Resource Efficiency Evaluation

The suggested system saved a lot of water and avoided nutrient wastage by making optimal use of schedules of nutrient delivery and the work of the pump. The automated control of the nutrient reduced the unwarranted circulation and energy consumption. The experimental findings proved the possibility to significantly reduce the use of water to 37.6 percent relative to the conventional hydroponic systems, which is in favor of the concept of sustainable hydroponic farming and applications of precision horticulture.

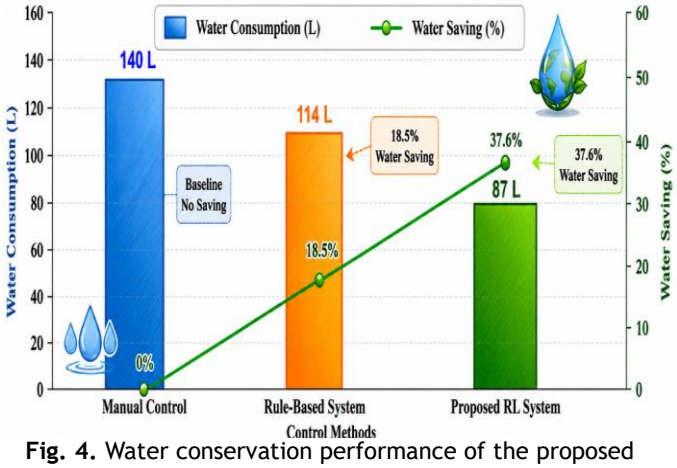

Fig. 4. Water conservation performance of the proposed hydroponic nutrient balancing system.

4.6 Statistical Validation

The improvements in the proposed system were statistically validated to have significance. The p-values are shown in table 3.

Table 3. Statistical validation results.

Metric	p-value
Yield Improvement	0.003
Water Conservation	0.007
Nutrient Stability	0.005

The p-values obtained were less than 0.05 and this established statistically significant increases in the yield of lettuce, water conservation and stability of the nutrients in comparison with the normal hydroponic nutrient management system.

5. Advantages Of The Proposed System

The hydroponic system suggested is reinforced by learning of the reinforcement type, which has multiple benefits to the sustainable production of lettuce. The structure allows the optimization of nutrients on a real-time adaptive basis by constantly changing the quantity of nutrients delivered depending on environmental conditions and plant needs. This

enhances stability of nutrients and crop yield as opposed to traditional fixed-threshold systems. It also minimizes waste of water and nutrients to water with smart dosing of nutrients and auto circulation. Constant control of pH, EC and dissolved oxygen enhances the efficiency of resource utilization, as well as promotes sustainable farming. The other significant benefit is enhanced uniformity in the growth of lettuce. Regulated environmental conditions in the stable environment ensure that the root-zone environment is favourable to the crop, leading to similar growth of the crops and increased biomass. Intelligent autonomous control with little human intervention is possible with the integration of IoT communication, cloud monitoring, and reinforcement learning. This enhances efficiency in operations and lessens on the manual observation work by hydroponic farming systems. Moreover, the suggested architecture can be used to scale to commercial hydroponic use due to the modular nature of the design to add more sensors, cultivation channels, and cloud services. In general, the given framework will contribute to the sustainable precision horticulture with the help of intelligent automation, effective management of resources, and AI-based optimization of hydroponics.

Conclusion

This paper introduced the Smart Hydroponic Nutrient Balancing System based on the reinforcement learning to produce lettuce sustainably. The framework developed was a combination of IoT-based sensing, optimization of reinforcement learning, monitoring on the cloud, and automated control of nutrients in one smart hydroponic architecture. The adaptive nutrient balancing and intelligent control was made possible by real-time monitoring of the environment and nutrient parameters. The experiment showed that the nutrient stability, growth of lettuce, water saving and efficiency of operations were improved considerably, in comparison to conventional hydroponic control methods. Reinforcement learning agent was successful in optimizing nutrient dosing and circulation plans to meet the dynamic environmental conditions leading to better crop growth consistency and less wastage of resources. The suggested system helps in innovative horticulture, precision farming, and AI-based hydroponic farm implementations. Moreover, the modular IoT architecture is capable of providing scalability to commercial hydroponic systems. Although there are positive outcomes, the framework has some drawbacks such as sensor reliance and computation cost in the process of reinforcement learning training. The future studies can be based on deep reinforcement learning incorporation, multi-crop hydroponic optimization, Edge-AI implementation, renewable energy-equipped hydroponics, and simulating a greenhouse through a digital twin to provide high-resolution applications to precisely control the agricultural industry.

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