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Bioinformatics-Driven Automation in Hydroponics: Nutrient Management System and Growth Prediction Model

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Abstract

Effective nutrient management is needed for hydroponic farming. Herein, a bioinformatics-driven automation system that incorporates growth prediction models, automated dosing of nutrients, and real-time analysis of sensor data for optimal plant growth is introduced. For control and monitoring in real-time, a microcontroller is coupled with calibrated TDS, pH, and EC sensors. TDS differentials are used to predict nutrient uptake, and a pH- and EC-based regression model is employed to predict plant height. The technique was validated using a range of plants like tomatoes, lettuce, and beans. Without relying on IoT infrastructure, the outcome is higher nutrient efficiency and accurate height prediction, offering a scalable and cost-effective alternative to existing systems.

Keywords: Hydroponics, Automation, Nutrient Management, Data Synthesis, Regression Model.

1. Introduction

Hydroponics, which grows crops without soil by using nutrient solution water, is one of the newest agricultural techniques. It is also growing in popularity because it uses less land and water and yields high-quality results under controlled conditions. Hydroponic systems are often automated using cloud technology, which depends on constant internet access, requires

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recurring subscription fees, and raises concerns about data privacy. These limitations pose serious challenges for small-scale farmers, schools, and places with inconsistent internet access. The majority of today's IoT-based hydroponic systems rely on remote servers to process sensor data and make decisions. This reliance limits the system's ability to scale in resource-constrained environments and exposes it to outages. Additionally, these systems usually neglect sensor calibration, leading to inaccurate monitoring and less-than-ideal conditions for plant growth. In addition, most commercially available automated solutions are rigid in terms of customization or integration into open-source ecosystems. To overcome this limitation, the proposed work introduces a low-cost offline-capable hydroponics automation system. Important parameters like EC, pH, temperature, and humidity are tracked by the system using microcontrollers and locally calibrated sensors.

It differs from the other models in that it forecasts plant height growth without the use of cloud computing by utilizing machine learning algorithms, particularly regression-based prediction. Through the use of an Excel interface, local data control and real-time information processing are made possible, promoting openness and usability in the field or classroom. This paradigm produces accessibility, dependability, and educational value by forgoing cloud connectivity requirements and providing adaptable hardware and software modules. In the context of smart farming, it aims to demonstrate how technology can be made affordable to support intelligent agricultural decision-making and serve as a useful tool for both practitioners and students.

2. Literature Survey

Several automated hydroponic systems have been proposed using various control techniques. For instance, nutrient dosing systems based on predictive control using pH and EC thresholds have been reviewed in [1]. The importance of sensor calibration in ensuring nutrient accuracy is highlighted in [2]. Regression-based plant growth prediction models are presented in [3] and regression techniques for sensor calibration in hydroponics are demonstrated in [4]. However, most of these models depend on IoT and cloud infrastructure. Our proposed model addresses this gap by offering a low-cost, offline solution with real-time Excel-based feedback. The recent developments in automated hydroponic systems have been largely facilitated by the incorporation of Internet of Things (IoT) technologies, making precision agriculture possible in controlled environments. Sadek and Shehata [5] introduced a smart greenhouse system in

Egypt that utilizes IoT-capable hydroponics and aeroponics systems with an emphasis on effective water utilization and climate resilience to maximize crop yield. Their research emphasizes the significance of IoT automation within dry areas where conventional farming is limited. Niswar [6] also designed an IoT-based automated indoor hydroponic system, outlining sensor integration for real-time control and monitoring of water flow, fertilizer content, and climate conditions. His research provides evidence of the applicability of steady, high-efficiency crop yield in urban and space-limited environments. Corroborating this, Prasetia et al. [7] analyzed the effect of grow light automation based on IoT on the growth of plants in hydroponics, determining that advanced lighting control directly enhances vegetative growth and energy efficiency. Scaling up from modest uses, Dennison et al. [8] investigated how automation and robotics can scale hydroponics and aquaponics up to commercially sound large-scale systems, highlighting scalability, lower labor, and data-based optimization as major advantages. Together, these studies demonstrate how intelligent automation restructures soilless cultivation to be more sustainable, resilient, and attuned to challenges of future food production.

3. Novelty and Contributions

This system introduces multiple novel aspects:

- It avoids dependence on IoT/cloud infrastructure by using real-time Excel data streaming.
- Calibration-based nutrient dosing enhances precision in small-scale systems.
- Regression modelling for plant height based on real-time EC and pH is uniquely integrated.
- The approach is cost-effective and replicable using off-the-shelf components and open-source platforms.

4. System Architecture

4.1 Block Diagram

Figure 1 illustrates how the Arduino Uno microcontroller, which serves as the automation system's central processing unit, interfaces with a variety of sensors and actuators. The three main components are a temperature sensor that detects temperature changes in the nutrient solution, a total dissolved solids (TDS) sensor that measures the concentration of nutrients in the solution, and a pH sensor that tracks acidity levels and automatically modifies them using solenoid valves.

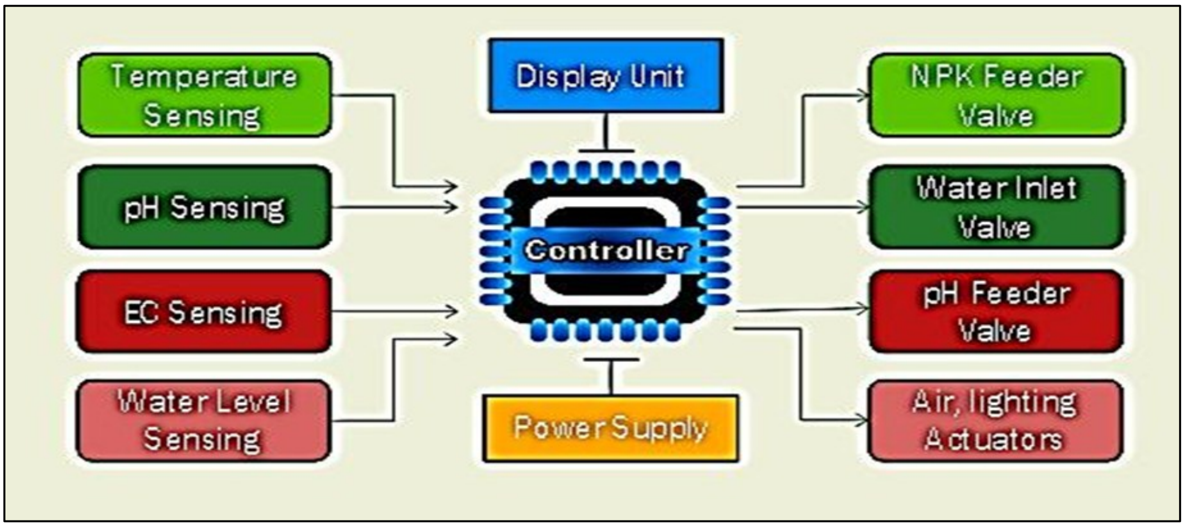

Figure 1. Block Diagram

A water level sensor ensures there is enough water for plants to grow. Water levels, pH correction solutions, and nutrients are managed by solenoid valves and relays. Real-time hydroponic condition status is shown on an LCD screen.

4.2 Nutrient Requirements

An Arduino Uno microcontroller serves as the central processing unit of the automation system; Figure 1 illustrates how it interfaces with a variety of sensors and actuators. The three main parts are a temperature sensor that detects temperature changes in the nutrient solution, a total dissolved solids (TDS) sensor that measures the concentration of nutrients in the solution, and a pH sensor that tracks acidity levels and automatically manipulates them using solenoid valves.

4.3 pH Monitoring and Adjustments

For nutrients to be absorbed, the pH range between 5.5 and 6.5 must be maintained. If the pH is higher than 6.5, it should be lowered with phosphoric or citric acid; if it is lower than 5.5, it can be raised with potassium hydroxide or bicarbonate. Frequent monitoring guarantees that plants receive nutrients effectively and without toxicities or deficiencies.

4.4 Water Intake and EC Management

Water intake and Electrical Conductivity (EC) are key factors in hydroponic plant growth. Beans require an EC range of 1.5 - 2.2 dS/m and the water requirement is approximately 3-5 liters per plant per week. While beans were selected for detailed nutrient and water requirement modelling due to their widespread usage and sensitivity to EC, the system was tested on lettuce and tomato as well. Their respective water needs fall within 3–6 liters per plant per week, but beans are used here as the benchmark species for quantitative analysis.

4.5 Automated Nutrient Dosing System

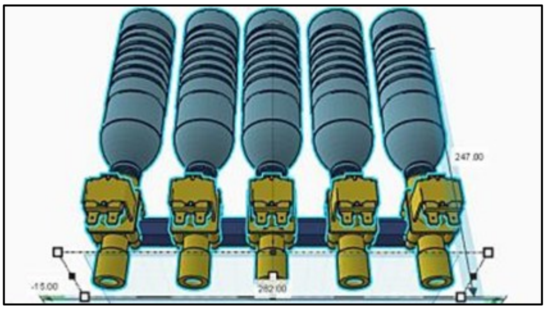

Figure 2. Gravity Feeder

A 3D model, depicted in figure 2, is used to design an automated dosing system that uses solenoid valves and gravity-based feeders to maintain precise nutrient levels. By using sensors to continuously check pH, EC, and water levels, this system modifies nutrient concentrations in real time. By ensuring precise and effective dosing, a threshold-based control algorithm minimizes nutrient waste and the need for human intervention.

5. Simulation and Implementation

5.1 Proteus Simulation

Proteus Simulation ensures the circuit functionality with their library modules as shown in figure 3.

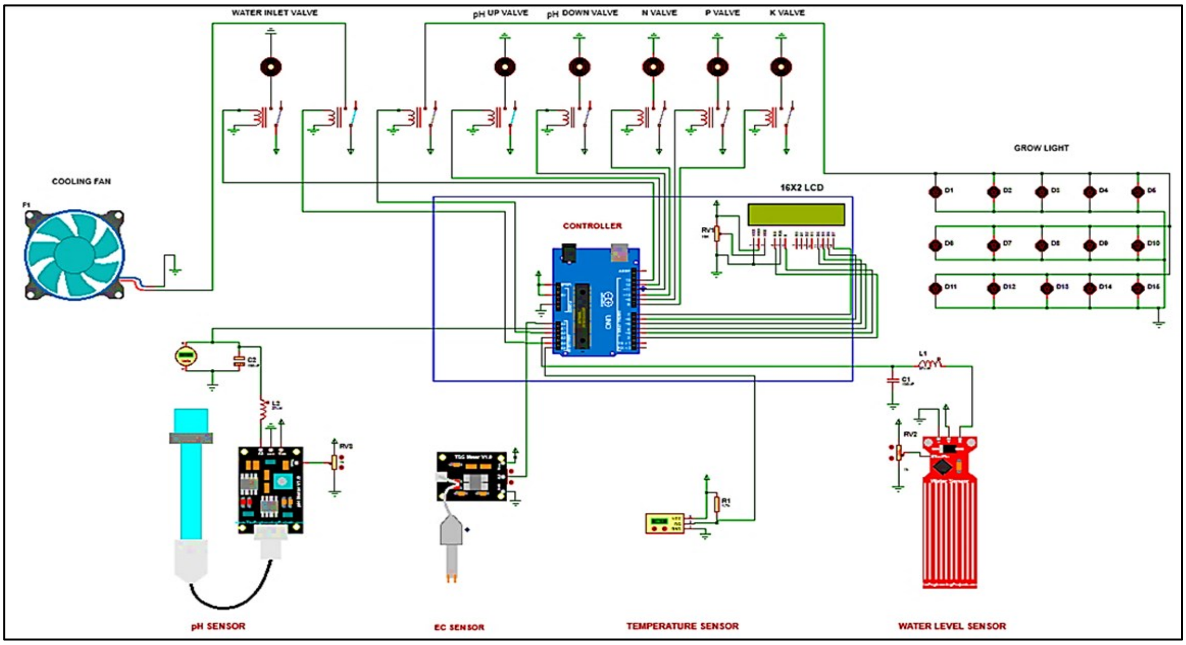

Figure 3. Schematic in Proteus

5.2 Data Visualization in MS Excel

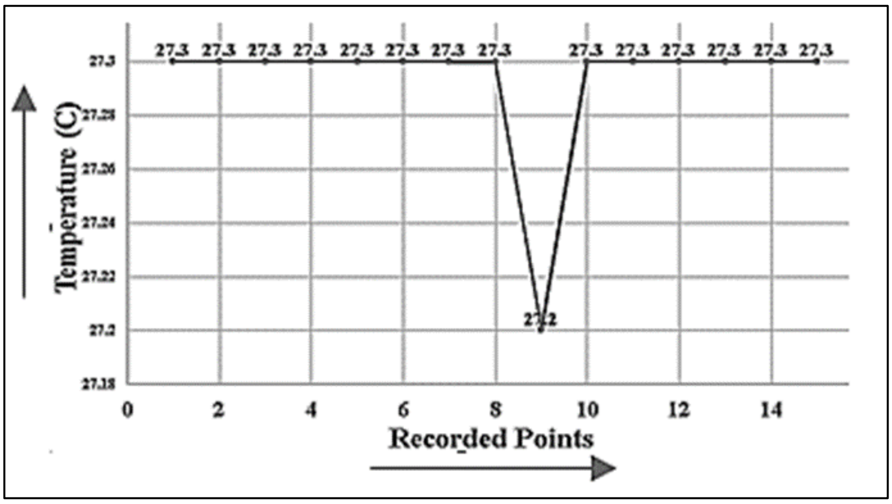

Figure 4. Temperature Level in Nutrient Reservoir

The temperature graph in the hydroponic system shown in figure 4 indicates a consistent temperature of around 27.3°C, with a sudden drop at a specific point before returning to stability. This anomaly could indicate an external environmental factor, a fluctuation in the system's cooling or heating mechanisms, or a momentary sensor error. In hydroponic cultivation, maintaining a stable temperature is crucial for optimal plant growth, as sudden deviations can affect nutrient uptake efficiency and overall plant health. Automated monitoring systems integrated with real-time data analysis can help detect and correct such fluctuations, ensuring a stable environment for plant development. This analysis reinforces the importance of automation and data-driven control in hydroponic systems to maintain optimal growth conditions.

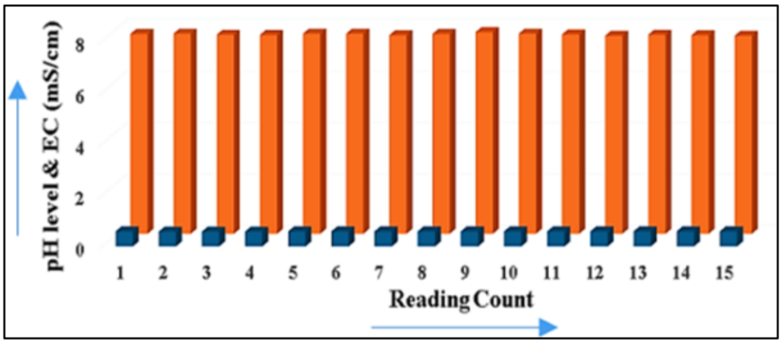

Figure 5. pH and EC Level

Figure 5 shows the bar graph that illustrates the relationship between EC and pH in the hydroponic system. While EC values indicate the amount of dissolved nutrients in hydroponic systems, pH stability ensures maximum nutrient absorption. Plants experience nutrient toxicity when EC values are too high, and deficiencies when EC values are too low. Similarly, a pH imbalance hinders the uptake of nutrients and consequently affects the growth of plants. The system is maintained in the ideal range for plant health and yields through routine inspections and automated adjustments. Series 1's blue bars display pH values, while Series 2's orange bars display EC values. Over the 15 points that were recorded, the data appear to be stable with little fluctuation. Such stability suggests that the required equilibrium is being maintained by the auto-nutrient dosing system.

5.3 Real-Time Implementation

Figure 6 illustrates how the control panel combines multiple parts to operate automated hydroponic systems. The microcontroller reads environmental parameters like pH, EC, temperature, and water levels by processing data from several sensor modules. Relay modules handle different system functions like water inlet and nutrient dosing, while LCD modules allow for real-time data display. Glass fuses offer safety by protecting the system from electrical failure. Different color-stack light systems indicate normal operation, alert conditions, and critical failure. With minimal assistance from humans, this system offers enhanced dependability and efficient automated control.

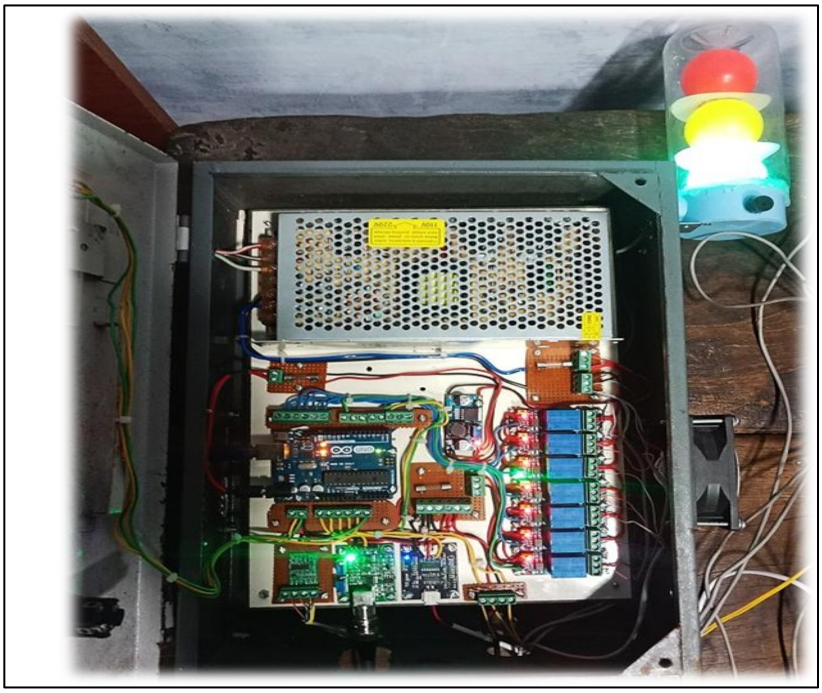

Figure 6. Control Panel

5.4 Sensor Calibration

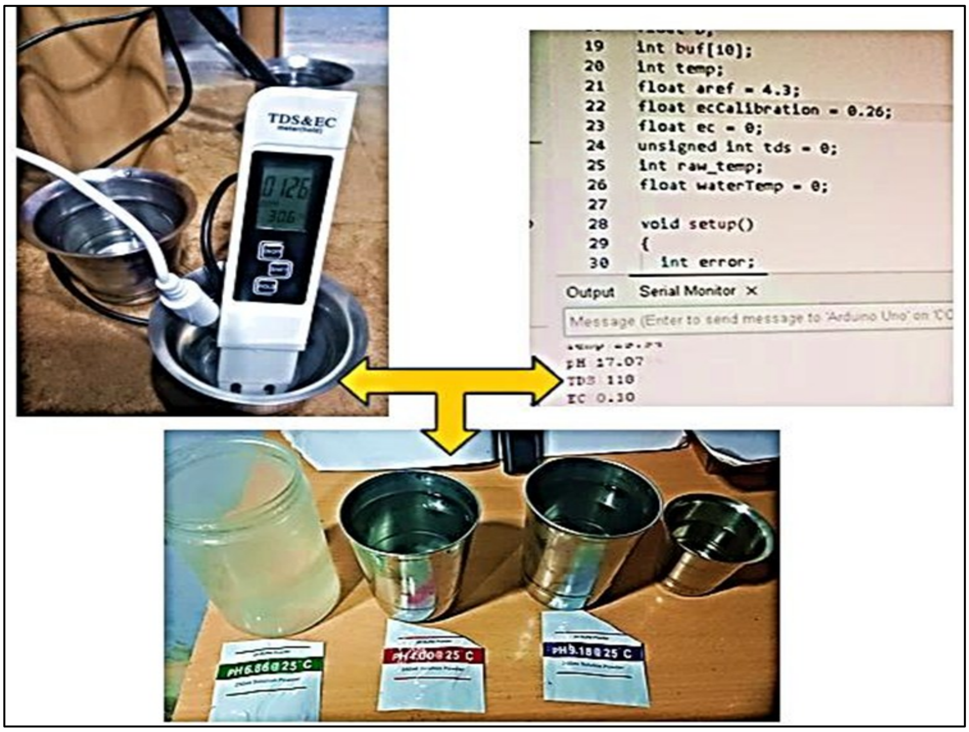

Figure 7. Calibration with Buffer Solution

The image shown in figure 7 is a TDS and EC meter reading conductivity levels in different solutions as the serial monitor displays real-time readings from the sensor. Calibration takes place using known reference solutions as indicated by the marked pH buffers (pH 6.86, 4.00 and 9.18 at 25°C). The EC calibration offset of 0.26 is coded to compensate for variations. Calibration was done using standard pH buffer solutions (pH 4.00, 6.86, 9.18 at 25°C) and EC calibration solutions with known electrical conductivity values. The EC and TDS sensors were dipped in the reference solutions, and live readings were noted through the Arduino serial monitor. Calibration offsets (e.g., EC offset = 0.26) were applied to the firmware to compensate for deviations. This helped to provide a high degree of precision while dosing nutrients. Regular recalibration was done on a weekly basis to compensate for sensor drift. This process ensures precise and reliable information from the sensors regarding automated nutrient dosing and hydroponic system surveillance.

5.5 Data Synthesis

Current Data

4	Time	TDS (PPM)	EC (MS)	TEMPERATURE (C)	NUTRIENT SOURCE (Kg)	pH
5	11:58.2	305	0.58	27.3	0.01	7.69

Historical Data

7	Time	TDS (PPM)	EC (MS)	TEMPERATURE (C)	NUTRIENT SOURCE (Kg)	pH	NUTRIENT UPTAKE (TDS)
8	11:06.2	304	0.58	27.3	0.01	7.76	304
9	11:09.9	303	0.57	27.3	0.02	7.77	303
10	11:13.7	303	0.57	27.3	0.02	7.73	303
11	11:17.4	303	0.57	27.3	0.02	7.72	#VALUE!
12	11:21.1	305	0.58	27.3	0.03	7.77	0
13	11:24.8	304	0.58	27.3	0.03	7.77	304
14	11:28.5	304	0.58	27.3	0	7.71	#VALUE!
15	11:32.2	304	0.58	27.3	0.01	7.76	0
16	11:36.0	304	0.58	27.2	0.01	7.83	1
17	11:39.7	304	0.58	27.3	0.01	7.77	1
18	11:43.4	305	0.58	27.3	0.02	7.74	2
19	11:47.1	305	0.58	27.3	0.02	7.69	0
20	11:50.8	304	0.58	27.3	0.01	7.73	0
21	11:54.5	305	0.58	27.3	0	7.71	1
22	11:58.2	305	0.58	27.3	0.01	7.69	1

Figure 8. Data streamer in MS Excel

It facilitates real-time data analysis, visualization, and error identification (e.g., #VALUE! errors in nutrient uptake calculations), enhancing decision-making for hydroponic nutrient management, as illustrated in figure 8.

By comparison, the low-cost non-IoT data logging option would entail manual measurement with conventional instruments such as handheld TDS and pH meters, and thermometers with calibrated vessels for nutrient determination. Data would be keyed into a physical logbook or spreadsheet, saving hardware expenses at the cost of human error and lag in trend analysis. Although fine for small-scale production, manual logging is not self-contained or capable of real-time feedback, rendering it unsuitable for dynamic hydroponic system adjustments. Therefore, automated streaming in Excel increases accuracy and real-time response.

6. Results

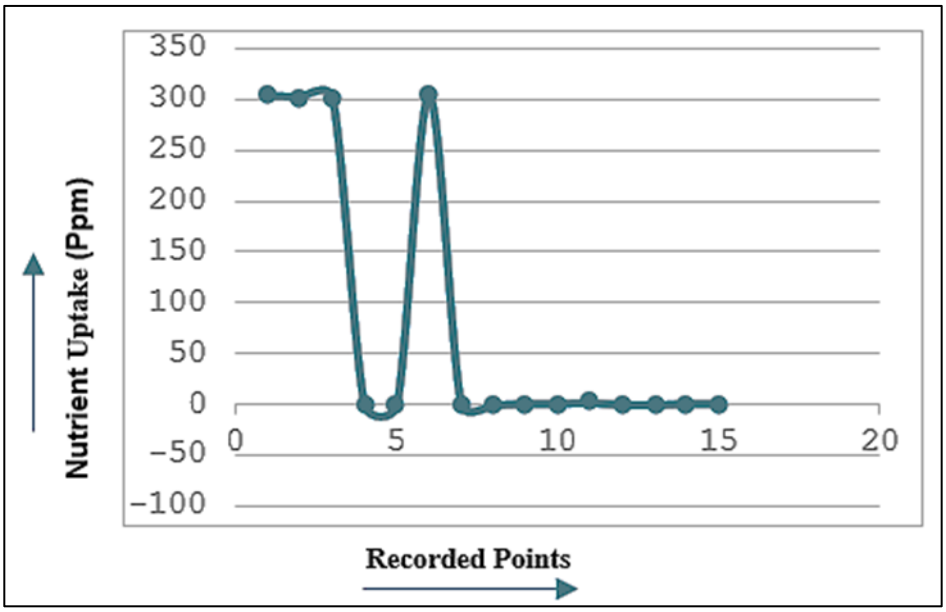

Figure 9. Nutrient Uptake

The formula =B22-B15, which computes the difference in TDS between two time points, is used to determine the nutrient uptake correlation in this data streaming setup (see figure 9). This approach makes the assumption that a gradual decrease in TDS indicates that plants are absorbing nutrients. The system is able to estimate current trends in nutrient consumption by comparing historical data points. The nutrient uptake correlation for the given data is determined using the formula:

$$U(t)=TDS(t1)-TDS(t2) \quad (1)$$

where,

t1- Previous Time Stamp

t2-Current Time Stamp

To refine this approach, rate of nutrient uptake can be estimated using the formula:

$$d(TDS)/dt = (TDS(t2) - TDS(t1))/(t2 - t1) \tag{2}$$

$$H = (-0.969 \times EC) + (0.0763 \times pH) + 1.909H \tag{3}$$

above equation is in a multiple linear regression form given by,

$$Y = \beta 1X1 + \beta 2X2 + CY \tag{4}$$

where,

Y- Predicted Plant Height (cm)

X1- Electrical Conductivity

X2- pH Level

β1, β2- Regression coefficients

CY- Constant offset (baseline height)

predicts plant height based on EC and pH levels in a hydroponic system.

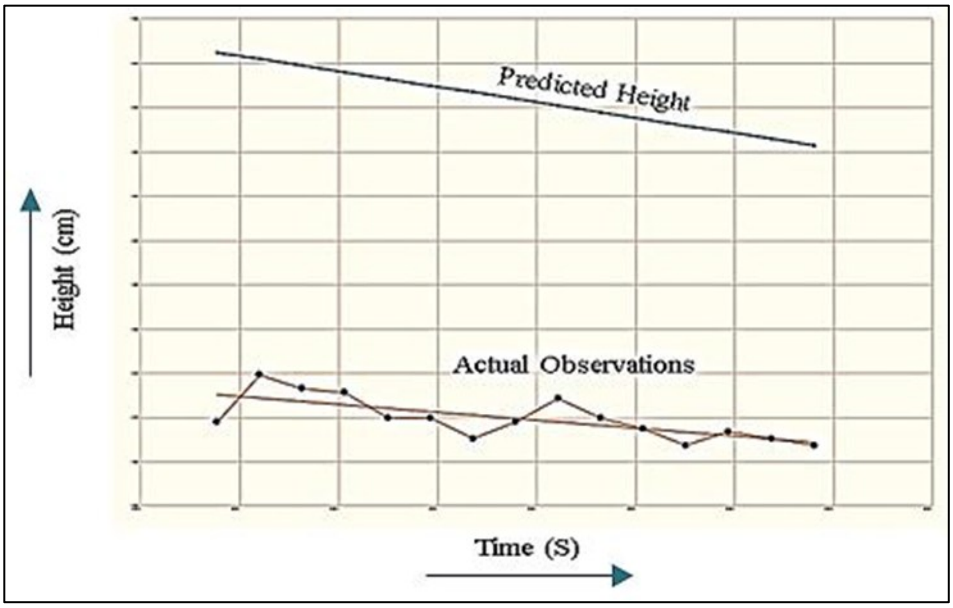

Figure 10. Regression Model

The regression model depicted in figure 10 is used to implement the plant height prediction model. Higher EC values are associated with a decrease in plant height, possibly as a result of osmotic stress brought on by an excess of nutrients, according to the negative coefficient for EC (-0.969) pH, on the other hand, has a small positive influence (0.0763), meaning that small changes in pH have very little effect on variations in height.

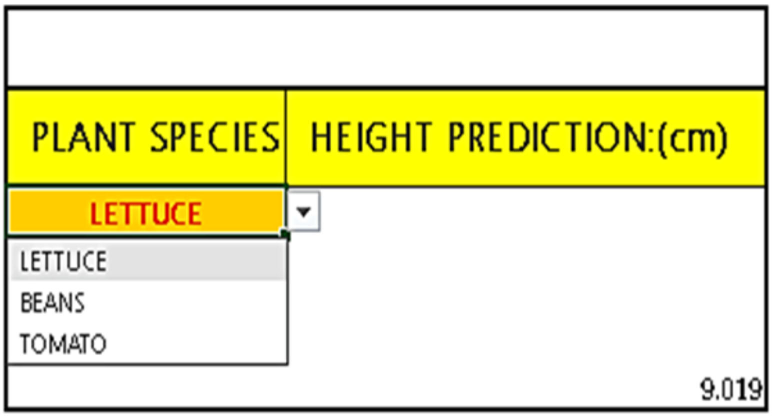

Figure 11. Multiple Species Height Prediction

Figure 11 illustrates how Multiple Species Height Prediction uses a linear regression model to predict plant height (H) in relation to electrical conductivity (C) and nutrient uptake (F).

The general form of the model is:

$$H=aF+bC+c \tag{5}$$

where,

a, b-Regression coefficients

c-Constant offset

7. Limitations and Future Scope

Despite being a low-cost offline solution system, it occasionally needs manual calibration to ensure accuracy. Furthermore, the lack of remote access makes it impossible to perform remote diagnostics in real-time. For this reason, the proposed hydroponic monitoring and prediction system will open the door for data-driven agriculture to offer real-time insights into plant height estimation and nutrient uptake. Combining current machine learning algorithms, like neural networks and decision trees, could lead to further advancements in the future by lowering the error rates in height predictions and nutritional correlations within the system.

Precision farming will become a more cost-effective and scalable option as the system is scaled up with cloud analytics and IoT-based remote monitoring. Additionally, using computer vision and multispectral imaging can produce a more accurate plant health status and potentially aid in preventative measures. By optimizing resource efficiency for increased crop production, these essential innovations will further expand system flexibility and usher in a new era of intelligent hydroponics.

8. Conclusion

This study effectively illustrates a data-driven method for utilizing electrical conductivity monitoring and nutrient uptake correlation to predict plant height in a hydroponic system. Based on real-time sensor data, we have estimated the height of several plant species (lettuce, beans, and tomatoes) by implementing a regression-based model, an effective, scalable, and economical solution for plant growth monitoring is ensured by the combination of sensors and automated data streaming in Excel. In contrast to conventional IoT-based models, this method maintains high accuracy and adaptability while lowering infrastructure costs. Furthermore, by determining the most efficient patterns of nutrient absorption, the nutrient uptake correlation technique aids in optimizing the growth environment. Precision agriculture is made possible by this, maximizing plant health and yield while reducing resource waste.

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