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ENHANCING AGRICULTURAL PRODUCTIVITY THROUGH A SEMI-AUTONOMOUS IOT ROBOT IN SMART FARMING SYSTEMS

N. Yeasdani[1*], M. S. S. Bhuiyan[1], S. I. Ifte[2], Adnan[1], L. Mannan[1], A. I. B. Harun[1], M. H. Pranto[1], M. Hasan[1] and N. A. Chisty[1]

[1]Department of Electrical and Electronics Engineering, American International University Bangladesh (AIUB), Dhaka; [2]Department of Computer Science and Engineering, American International University Bangladesh (AIUB), Dhaka. Bangladesh

Abstract

In addressing the challenge of enhancing agricultural productivity in developing countries, this research introduces a semi-autonomous IoT robot designed to modernize traditional farming practices in regions like Bangladesh. The study explores whether such a robot can effectively integrate with existing farming practices and assesses its impact on agricultural productivity, resource optimization, and most importantly cost-efficiency. The literature reveals a push towards smart farming technologies, but their adoption in less affluent regions is hindered by cost and resource constraints. Employing a mixed-methods case study approach, the research developed and tested a robot equipped with an NPK sensor for detecting levels of nitrogen, phosphorus, and potassium in the soil, a water level indicator to measure flood water levels in millimeters, and a soil moisture sensor. These data were transmitted to the user's phone over the internet, allowing for remote monitoring of fertilizers and water levels. Additionally, the system included a remote-controllable water dispenser for irrigation and a fruit-picking mechanism for harvesting. The results indicated that all intended data collection was executed accurately, enabling users to remotely monitor soil conditions and effectively control the robot's actions. However, the initial cost of the robot may be slightly expensive for individual farmers, though mass production is anticipated to reduce the price to a level that is reasonably affordable for widespread adoption. However, limitations in sensor calibration for different soil types are acknowledged. Future research suggest exploring sensor calibration precision, extending system capabilities, and integrating predictive AI for a comprehensive agricultural solution.

Keywords: Agriculture, IoT, Sensor, Semi-autonomous, Smart farming, Web server

Introduction

Agriculture plays a pivotal role in shaping the economy and ensuring sustenance in many developing countries, including Bangladesh. Traditional agricultural practices in these regions often result in inefficiencies and suboptimal yields, highlighting the need for modernization. The emergence of smart farming, driven by technological

[*]Corresponding author: shahidulislamifte3@gmail.com

advancements, promises to enhance agricultural productivity. However, these state-of-the-art systems, while promising, often remain inaccessible to less affluent regions due to their high costs and resource requirements. The existing literature highlights various technological initiatives aimed at improving agricultural productivity. Studies such as those by (Oliveria *et al.,* 2020), and (Malavazi *et al.,* 2018), have introduced monitoring systems and agrovot robots, respectively, with a focus on weed management and autonomous operation in crops. While these solutions are innovative, they are often constrained by crop specificity and high costs. (Birrell *et al.,* 2020) also designed a robotic lettuce harvesting system, emphasizing precision in handling delicate vegetables. The importance of smart agriculture, employing technologies like AI, IoT, and robotics, is underscored by works like (Subeesh and Mehta, 2021), (Said Mohamed *et al.,* 2021), and (Ummadi *et al.,* 2022). These studies explore the automation and digitization of agriculture, emphasizing the potential of IoT and AI in developing smart farm machinery and real-time crop health monitoring. Furthermore, (Dhanaraju *et al.,* 2022), and (Krishnan *et al.,* 2020), delve into the convergence of robots, AI, IoT, and cloud computing in agriculture, underscoring the advancements in smart farming and precision agriculture. Recognizing this gap, our study aims to design, develop, and test a cost-effective, semi-autonomous IoT robot that seamlessly integrates with existing farming practices in developing regions like Bangladesh. This research is designed to perform tasks ranging from monitoring soil moisture levels to precise pesticide dispensing, ensuring real-time data transmission for immediate action.

Materials and Methods

Our proposed system hinges on the integration of key components, central to which is the Arduino Pro Mini, orchestrating various functionalities. Accompanying units include the Esp8266 and ESP32cam, essential for communication and imaging tasks, respectively. The system's acumen in environmental adaptation is enhanced by sensors such as an infrared sensor for navigational aid, NPK sensor for soil fertility, Soil moisture sensor, and Water level detector. A Robotic arm enables task-specific manipulations, while an LCD display offers immediate system feedback.

Arduino pro mini

This is a microcontroller board based on the ATmega328P. From the 14-digital input/output pins of the Arduino Pro Mini, 6 PWM pins can be used as outputs. It also has 6 analogue inputs, an onboard resonator, a reset button, and holes for mounting pin headers. In the prototype robotic vehicle, most and components devices were controlled by the Arduino Pro Mini (www.etechnophiles.com),

Node MCU Esp8266 and ESP32cam

It was used as a Wi-Fi module and microcontroller in this prototype. It was used to collect data using digital and analogue pins from various sensors (Joshi *et al.,* 2015). After calibrating those data points, the collected data was sent to the Arduino Pro Mini.It was used to stream data from the field with the help of external devices such as mobile phones or computers (Mehendale, 2022).

Sensors utilized in the system

NPK Sensor measures the levels of nitrogen, phosphorus, and potassium in the soil, providing values in milligrams per kilogram (mg/kg). Soil Moisture Detector (YL69) measures soil moisture, with readings ranging from 0 to 1023. Lower readings signify higher soil moisture content. Although the ideal metric is percentage, the sensor doesn't provide this directly. The readings vary with different soil types, necessitating initial manual calibration for each new soil context. The water level Indicator tool gauges flood water levels above the ground. Readings below 100 suggest minimal water presence. A reading around 300 indicates the water has reached half the sensor's height, set at 40mm. Values exceeding 500 denote water levels surpassing 40mm. These sensors collectively inform the system's responses, ensuring it reacts appropriately to various environmental conditions.

Block diagram

The whole working process of (Fig.1) IoT-based autonomous integrated smart farming system for agricultural farms system is mainly an IoT-based robotic vehicle..

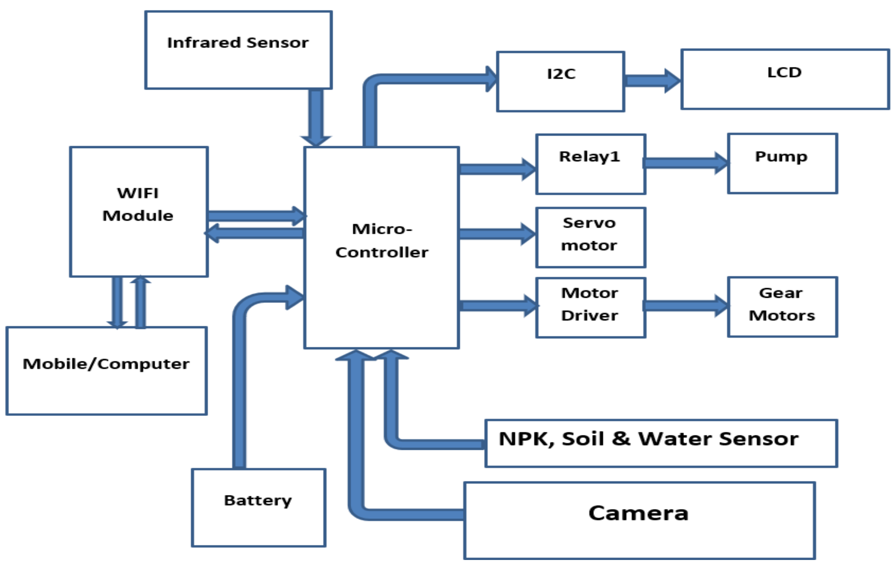

Fig. 1. System block diagram

In the schematic representation, several components are linked to a central microcontroller, encompassing elements like the I2C, LCD display, and relay module—the latter essential for regulating the pump's operations. The system incorporates two kinds of servo motors for diverse functionalities, particularly in maneuvering mechanical limbs, through a motor driver and a gear motor. The vehicle's motion is propelled by these motors, steered by inputs from various sensors monitoring soil nutrients, moisture, and water levels. Additionally, a camera is interfaced with the Arduino Pro Mini, while data communication is facilitated through a Wi-Fi module, enabling real-time data transmission to a central server and subsequent access via digital devices. The setup also includes infrared sensors to monitor road conditions and vehicle movement, providing a holistic overview of the system's operation as depicted in the comprehensive block diagram.

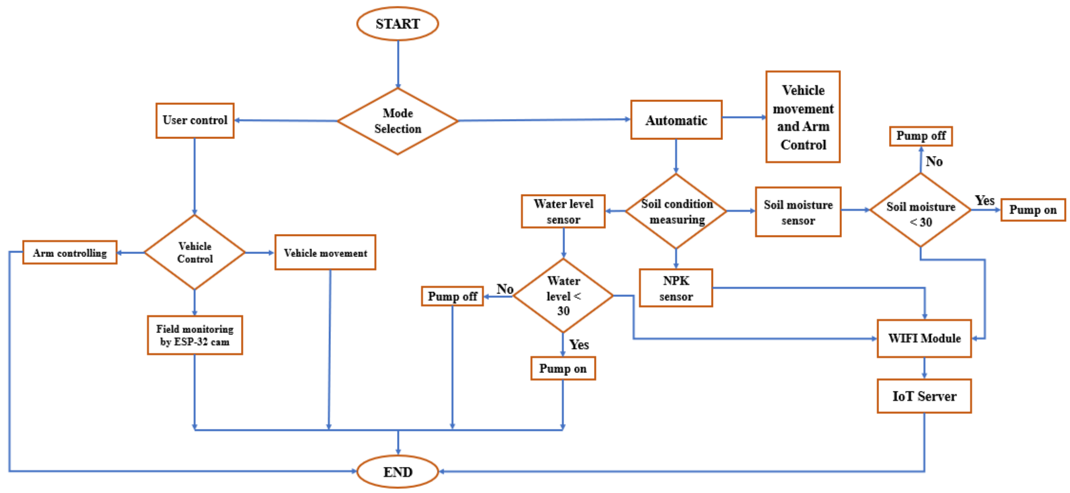

Fig. 2. Overall system flowchart

The flowchart presented illustrates the architectural blueprint of the proposed system, simplifying the detection framework to enhance comprehension of the project's operational mechanics. It details the process initiated by input data derived from the potentiometer readings, followed by the application of specific algorithms to manage water and fertilizer distribution. The system's versatility is evident, with the robotic vehicle's control shifting between manual and automatic. Specifically, a potentiometer reading of zero implies manual control via a local server, allowing user intervention. Conversely, a reading exceeding three hundred triggers the vehicle's autonomous function. This mode involves data transmission to the server for analysis, with particular attention to soil moisture levels. Should these levels fall below 30, the system autonomously activates the pump, ensuring adequate water supply without necessitating manual oversight. The foundation of the server underscores its role in overseeing and maintaining agricultural data storage. At the heart of this system is a Wi-Fi module, functioning as the primary microcontroller that bridges the sensor data with the server. Data storage is facilitated through the Blynk software, a specialized Internet of Things (IoT) platform that streamlines the creation of associated mobile and web applications (Serikul *et al.*, 2018). This innovative platform swiftly integrates IoT mobile applications for devices like iOS and Android with various hardware, including Arduino, ESP8266, and ESP32. Essential parameters such as NPK levels, soil moisture, and water levels are interfaced with the Wi-Fi module, enabling real-time monitoring. Users can conveniently access this crucial data via the Blynk server on personal devices like smartphones or computers, provided there is an internet connection between the user's device and the Wi-Fi module. Users can see the data from their mobile device or computer when the device and the automated vehicle WiFi module are connected to the internet. Without the internet, this procedure will not run.

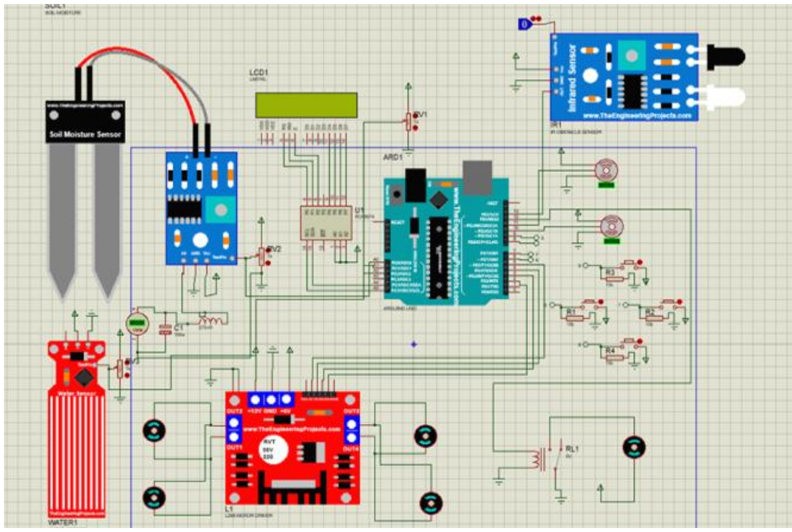

Fig. 3. Simulated diagram in Proteus

Software implementation

A simulation model was shown which the complete simulation model of this project is. Various sensors are used here, like soil, water, NPK, etc. No library is available for the NPK sensor Proteus. So, its work is shown by using a potentiometer as an alternative. The camera module is used in hardware. But since there is no camera in Proteus, only other activities are shown. Here, the display is connected through the display driver. And there are four buttons through which the car will be driven. Four motors are connected to the motor driver, and the vehicle will be controlled by pressing the buttons through the mobile server. As there is no Wi-Fi connection, the opposite button is shown as physically attached. Thus, the simulation model is created using Arduino Pro Mini by connecting each sensor. After designing the whole circuit in Proteus, the simulation was run to check whether it worked properly or not. In the simulation, soil and water levels were set to 29%. When the soil and water level value is less than 30%, the pump will be on, which means it will start pumping. These conditions were set in code on the microprocessor. So, the user can see that when soil and water values are 29%, the relay is on, which is pointed with an arrow, and the pump starts. LCD display shows that when the soil and water sensor value is 31%, the relay is OFF, and the pump stops. As there is no NPK sensor in the Proteus library, a potentiometer was used here instead of an NPK sensor, which represents the NPK sensor with the potentiometer. By changing the potentiometer value, the user can change the NPK sensor value.

In this project, four wheels were used to move a robotic vehicle. In the simulation, the four remote switches were used to control the wheels virtually. This remote switch is not connected to the circuit. These are connected virtually. Arduino cannot take 12V directly; that's why a motor driver was connected to it for controlling the wheels. Also, two voltmeters were connected to the wheels. When any of the remote switches are pressed, Arduino sends a signal to the motor driver, which regulates voltage, and the motor rotates. In the figure, the regulation voltage is shown as 3.75V on the voltmeter. In the simulation circuit, a switch was used to control the robotic arm and clamping. Two servo motors were used to control the robotic arm and clamp. The upper servo motor controls the robotic arm, and the lower servo motor controls the clamping. When the switch is pressed, the servo motors rotate and control the robotic arm and clamping. The 3D design of the prototype model for this project was designed with the help of Solid Work software. Solid works is a computer-aided design and engineering software for solid modeling.

Results and Discussion

This is the final implementation of the prototype robotic vehicle. Here, this prototype was designed the same as the 3D design, which was designed on Solid Work. It was implemented with four wheels, an Arduino Pro Mini, three sensors, a water pump, a robotic arm, and an ESP32cam.

Hardware results

In this research, the amount of fertilizer in the raw soil was measured using an NPK sensor, the moisture content of the soil was determined using a soil sensor, and the water level of the soil; particularly in the paddy field, which is constantly in need of water, was determined using a water level sensor. Three different fertilizers (nitrogen, potassium, and phosphorus) that are commonly used in the agricultural sector were used here. Urea is the most concentrated solid nitrogen fertilizer, a white, crystalline solid with a nitrogen content of 46%. The focus here will be on its use as a nitrogen fertilizer. Triple Super Phosphate, also known as TSP, is a widely used Phosphorus (P) source for several benefits. Triple Super Phosphate (TSP) has a phosphate content of 20%. So, TSP fertilizer was used for Phosphorus measuring purposes, and Potassium was used. For the measurement of the appropriate value of the NPK sensor, a mixture of soil was created with urea, TSP, and Potassium fertilizer. Since Urea contains nitrogen, TSP contains phosphorus, and Potassium fertilizer (Potash) contains potassium only, they are mixed together and tested. As these fertilizers do not have other elements that would obstruct the reading theoretically, the mixture is ideal for testing the NPK sensor's ability to sense all three components. After mixing, the sensor detected the amount of fertilizer in the soil, and then the user received or saw the result value on the LCD display and mobile device via the BLYNK server. This research was divided into the following eight cases to be tested.

Case 1 and Case 2 (raw- soil, soil with water)

In Case 1, a sample of soil from an area where no crops had been grown was tested. This soil had minimal moisture content, leading to low readings from both the water level sensor and the soil moisture sensor. As the soil was naturally low in Nitrogen (N), Phosphorus (P), and Potassium (K), the sensors reflected this with negligible values for these nutrients. In Case 2, the same soil sample was used, but with a significant change: water was added to it. This addition of water was crucial for allowing the NPK sensor to effectively measure the nutrient values in the soil. After adding water, the NPK sensor displayed values of 173 mg/kg for nitrogen (N), 51 mg/kg for phosphorus (P), and 70 mg/kg for potassium (K), as indicated on the LCD display and the BLYNK server.

The addition of water was essential in facilitating the sensor's ability to accurately assess the nutrient content of the soil.

Case 3 (fertilizer and water mixture with soil)

Here, fertilizer and water were mixed with the soil and measured with all three sensors. This time, the data on fertilizer and water amounts was taken only from the BLYNK server; that shows the mobile display. Since there was an issue, the LCD display has less capacity for counting and displaying digits. In this case, the value for Nitrogen, Phosphorus, and Potassium are 229 mg/kg, 143 mg/kg, and 196 mg/kg, as shown in the figure below. The water and soil sensor values were 53 and 24 percent, respectively.

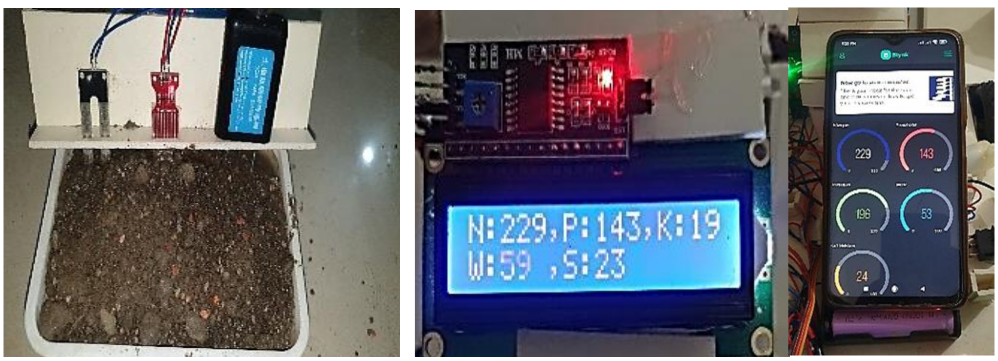

Fig. 4. Soil mixture with Fertilizer and Water (Real Data) a) Sensors connected to sample soil, b) Output values from sensors, c) Values displayed in mobile phone over internet

Case 4 (Live streaming with ESP 32 Cam)

In this scenario, a command was initiated to navigate the robotic vehicle toward a specified target, identified here as a fruit-bearing plant. Upon reaching the intended location, the integrated ESP-32 camera enabled live streaming of the plant's surface directly to a local server. However, accessing this live feed required adherence to certain prerequisites, most notably, the viewing device had to be connected to the same Wi-Fi network as the server. The vehicle was equipped with a specialized arm mechanism, designed for the precise task of grasping and relocating objects, demonstrating its utility in agricultural settings like this.

Case 5 (Picking fruit or vegetables)

In this specific case, sample fruit plants were used as a part of the robotic arm to pick up sample fruit. The following figure demonstrates how the robotic arm is harvesting sample fruits from the plant and placing them, with the assistance of clamps, in the box where they will be stored. Additionally, the entire harvesting process is manually controlled from a mobile device, allowing precise and targeted picking of fruits.

Case 6 (Vehicle moving)

This prototype vehicle is an automatic vehicle. It can move automatically in the field. An IR sensor was used for automatic movement. When the IR sensor detects an obstacle, it changes direction automatically. The figure below represents the vehicle movement. At first, the vehicle goes forward, but when the IR sensor senses the obstacle, the vehicle changes its direction automatically and turns right.

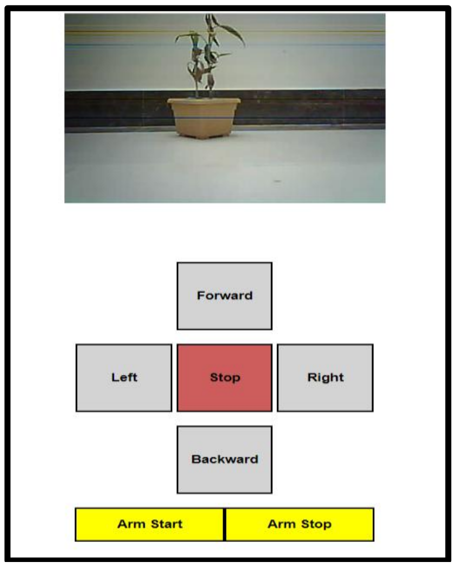

Fig. 5. View of Live Streaming with ESP 32 Cam

Case 8 (Irrigation system)

The proposed design model is engineered to autonomously irrigate the field, utilizing data derived from the soil via moisture and water level sensors. As the vehicle traverses the field, it employs these sensors to assess soil conditions. Specifically, if soil moisture falls below the 30 percent threshold, the system activates the water pump, triggering immediate irrigation. Conversely, if moisture levels exceed this preset limit, the system refrains from engaging the pump, thereby preventing unnecessary water usage. This mechanism ensures an efficient response to real-time soil moisture data, optimizing water resource management. When the soil moisture sensor detects a moisture level of 1 % as shown in the display, the water pump automatically runs and instantly provides water. But the pump will stop providing water when the moisture increases by up to 30 percent.

Results of comparison

In the first scenario, when the raw soil was measured, the values for nitrogen (N), phosphorous (P), and potassium (K) all came out to be zero. This is shown in above figures which also illustrates how the NPK sensor value rises when water is added to soil and the two are mixed together. It is possible to draw the conclusion that the NPK sensor cannot detect elements of fertilizer until water is mixed in with the soil first. When compared to Cases 1 and 2, Case 3's NPK, soil, and water level detector sensor values were higher after the addition of TSP, urea, and potassium fertilizer. The sensor data from the experiment in different cases is shown in the table below.

Table 1. Sensor data

Sensor name		Case 1	Case 2	Case 3
NPK	Nitrogen (N) (mg/kg)	0	173	229
	Phosphorus (P) (mg/kg)	0	51	143
	Potassium (K) (mg/kg)	0	70	196
Soil moisture (%)		1	1	53
Water Level (%)		12	0	24

The vertical axis in this bellow graph shows the quantity of each of the five soil components (water level, nitrogen, phosphorus, potassium, and soil moisture level), while the horizontal axis shows time. The data from the soil moisture sensor, water level detector, and NPK were stored on the BLYNK server. Through the BLYNK server, users can view this recorded data as a graph or chart. From there, users track how much the sensor value has increased or decreased and examine the sensor's value in this graph.

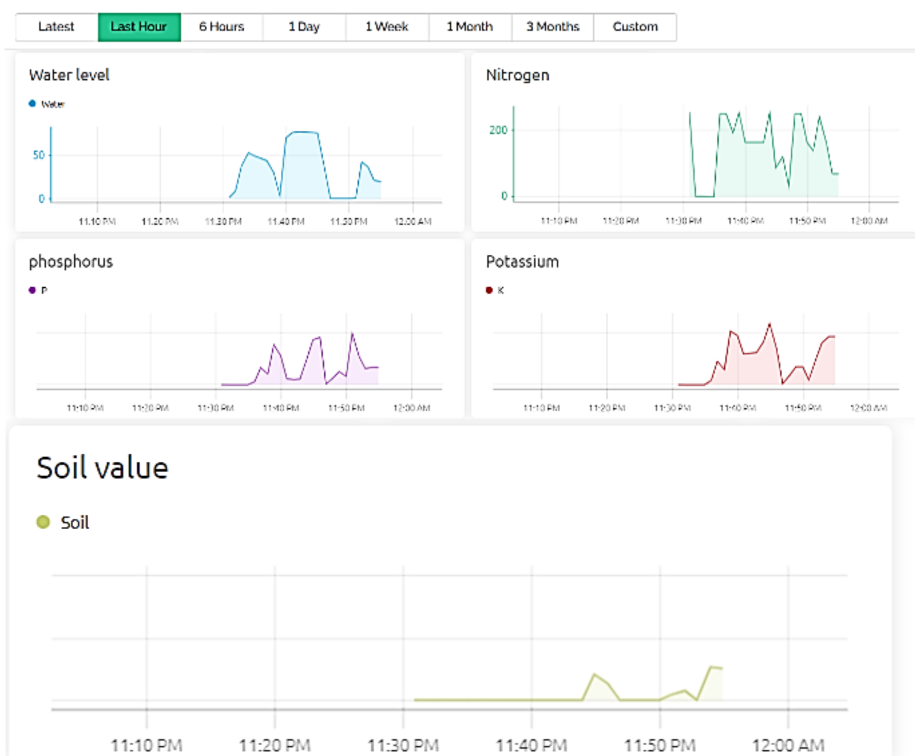

Fig. 6. Graph from BLYNK server

In-depth analysis of results

Our analysis began with an evaluation of soil's natural state (Case 1) and proceeded through various scenarios, each adding a new variable (water, fertilizers) and monitoring changes through the sensors. The most significant leap in nutrient values was observed in Case 3, where the integration of fertilizers and water dramatically altered the readings, underscoring the sensors' sensitivity and the soil's responsive nature.

Sensor efficiency and accuracy

The consistency observed in sensor readings across different cases establishes their reliability. However, the disparity between natural soil nutrient levels and those recorded post-fertilization indicates not just the impact of agricultural supplements but also the precision required in calibrating these sensors, particularly for varying soil types and conditions.

Real-time monitoring and responsiveness

The system's ability to transmit data for real-time analysis (as seen in the live streaming case) is crucial for immediate decision-making. The rapid response of the irrigation system and the robotic arm's successful field operations demonstrate the system's potential for timely interventions, directly influencing crop health and yield.

Automated navigation and task execution

The vehicle's navigation and obstacle detection, essential for its autonomous functions, were tested rigorously. Its successful maneuvering and task execution, even in non-uniform terrains, highlight its adaptability and functionality in real-world scenarios.

Sensor Accuracy (NPK Sensor Specifications)

- Measure Range: 0-1999mg/kg
- Accuracy: ±2% Full scale (F.s)
- Resolution: 1mg/kg (mg/l)

The NPK sensor's specifications indicate a high level of precision in nutrient measurement within the soil, essential for accurate agricultural adjustments. The consistency observed in sensor readings across different cases establishes their reliability in the field. However, the disparity between natural soil nutrient levels and those recorded post-fertilization highlights the impact of agricultural supplements and the precision required in sensor calibration, particularly for varying soil types and environmental conditions. The integration of our semi-autonomous IoT robot into farming practices marks a transformative approach to agriculture, with substantial implications for efficiency, productivity, and economic viability. By employing real-time data, the system optimizes resource use, potentially reducing water and fertilizer usage by a significant margin, thereby minimizing environmental impact and expenditure. This precision in resource distribution not only curtails waste but also fosters ideal crop-growing conditions, directly contributing to an expected rise in yields. Furthermore, the automation of mundane tasks alleviates labor requirements, decreasing human error and operational costs, which translates into enhanced overall productivity. Currently valued at Tk. 28,300, the initial cost of implementing this system might appear prohibitive for individual farmers. However, the project's true economic appeal lies in its scalability. As the technology is adapted for mass production, there's a realistic projection that costs could plummet substantially, rendering this innovative solution more accessible and financially feasible for widespread adoption, even within economically constrained regions. This transition not only democratizes advanced farming practices but also fortifies the agricultural sector against future challenges.

Conclusion

The findings of this study clearly expressed that the robot effectively monitors and controls farming activities in real-time, showcasing reliability and precision in collecting soil parameters. Notably, the system demonstrated its capability to accurately detect variations in nutrient levels and soil moisture, thereby optimizing resource use and aligning with sustainable practices. Comparing with previous studies, the robot's successful navigation and task execution in various field conditions confirm its adaptability and potential for broader application. However, the study acknowledges certain limitations, such as the need for precision in sensor calibration across different soil types. Therefore, a promising step towards revolutionizing smart farming in developing regions, providing a cost-effective and technologically advanced solution and significant contribution to future agricultural innovations.

Conflicts of Interest

The authors declare no conflicts of interest regarding publication of this paper.

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