Autonomous Soil-Monitoring bot for Precision Farming with Real-Time Dashboard and Crop Recommendation

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Abstract—In developing regions, soil health is often compromised, and agricultural productivity may be hampered due to field-based decisions which are affected by soil management policies resulting in delayed fertilizer recommendations and crop selection based on guesswork rather than data. Standardized soil testing services take time. This research presents the design and implementation of an autonomous soil monitoring bot that incorporates IoT based sensors and machine learning algorithms to facilitate real-time precision farming in a sustainable manner. The prototype uses an ESP32 microcontroller as the processing unit connected to sensors for a range of environmental parameters. Specifically, the DHT11 measures ambient temperature and humidity; the DS18B20 standard temperature was used to measure soil temperature; NPK sensors for nutrient determinations; and MQ-137 to characterize gas emissions in the soil. The sensors were able to wirelessly transmit the data for instant processing using a dashboard based on Flask. The dashboard connected users with real-time conditions and provided even more value by making immediate crop determinations based on a suitability score of the crops defined by crop nutrient requirements. Unlike existing systems that only collect data, or provide data streams hours or days later upon analysis, this system allows-in field decisions made in real time for multiple crop varietals and fertilizer recommendations through an integrated dashboard that remotely controls the bot. Validation of the system in the field showed it captured data, confidently transmitted wireless data for instant data representation and made trust-worthy crop recommendations based on its dataset.

Keywords— *Precision Farming; IoT Sensors; Soil Health Monitoring; Real-Time Dashboard; Crop Recommendation.*

I INTRODUCTION

The global agricultural industry is increasingly confronted with an ongoing challenge to sustain crop yields, driven by soil degradation, climate variability, and overall resource mismanagement. It is estimated that around 20–40% of global crop yields are lost each year due to a combination of poor soil health, imbalances in nutrient status, and associated stresses on the environment (FAO, 2022) [1]. In India, where agriculture is also the primary source of livelihood for over 58% of the population, declining soil fertility and poor application of fertilizer have jeopardized farmer incomes and put national food security at risk (World Bank, 2021) [2]. Conventional soil testing methods rely on chemical tests in laboratories, which can be expensive, time-consuming, and remain out of reach for many smallholder farmers. As a result, there is an urgent need for systems that are able to deliver real-time, low-cost, and accurate soil monitoring directly in the field. Numerous solutions that address these demands have been discussed in the literature, such as handheld soil testing kits, UAVbased multispectral imaging, and IoT-enabled fixed sensor networks [3][4]. While useful, these solutions present significant limitations in their design: laboratory kits create delays, drones gather imagery of the soil rather than in-soil parameters, and fixed sensors cannot provide spatial variability across large fields. Additionally, while many current IoT systems are capable of data collection, they lack integrated dashboards to visualize data in real time and support decision-making at the point of application. Hence, farmers often receive fragmented or delayed information, limiting the ability to act quickly. This study presents a mobile, autonomous soil-monitoring bot capable of crossing fields and offering continuous in-site measurements. The prototype combines several sensors DHT11 (ambient humidity and temperature), DS18B20 (soil temperature), NPK sensor (nutrients), soil moisture probes, and MQ-137 (gas levels). The sensors collect data which is processed using an ESP32 microcontroller and transmitted to a dashboard built with Python Flask. A database of crop requirements compares measure readings with optimal conditions for crop growth, providing a suitability score and top crop recommendations in real time. Whether the farmer prefers to navigate the bot remotely through the dashboard or manually, the overall usability is enhanced by the wider range of field conditions it can operate in. Farmers have direct access to the status of soil fertility nutrients and environmental conditions without waiting for laboratory results. By providing real-time recommendations for the best crops and fertilizer inputs, the system can minimize waste, cost, and promote crop yields. Due to its cost and portability, and the dashboard allows easy visualization, this system is of high relevance to smallholder farmers. It has the potential of being a pioneering soil-monitoring tool for sustainable precision agriculture.

II LITERATURE REVIEW

Aijaz et al. [5] examined the area of artificial intelligence as it pertains to agriculture with a focus on remote data collection for crop monitoring, decision making, and robotics. The analysis showed advancements in predictive models, and that robotics had an expanded role in data collection. Yet they pointed out that most systems still seemed to be in an experimental state, and there was little to no connection between real-time sensors, mobility, and a dashboard that a farmer would be able to use. In addition, they pointed out that aquaculture and other food production systems that are based on a boat are currently missing completely from the technological aspects of agriculture.

Saha et al. [6] designed a prototype for a smart soil monitoring system that could give recommendations involving the choice of crops and amount of fertilizer to use based on an analysis of soil samples. It collected data that could measure NPK, soil pH, moisture, and temperature and passed it along for classification and processing within a cloud-based system that provided recommendations. Field testing demonstrated that the soil monitoring system could give reliable recommendations in both crop type and fertilizer amount. However, it was a stationary system, could not cross land or water, didn't use any gas analysis sensors, did not involve any teleoperation functions, and thus, was missing a more complete array of capabilities.

Linford and Haghshenas-Jaryani [7] wrote about a robotic system designed for monitoring crops in chile pepper farms. The rover was equipped with a manipulator arm that inserted soil moisture probes to specific and consistent depths and then captured images to analyze crop health. The system was also capable of collecting that data at larger scales, thus increasing the overall accuracy of the measured data. However, the platform was limited to sensors related to soil moisture probes, imaging crops, and moisture sensing capabilities, thus lacking nutrients analysis, gas detection, and providing real-time recommendations.

Miller et al. [8] summarized systems that incorporated artificial intelligence with IoT (internet of things) in agriculture and focused on field crops and grasslands. It was noted that promising technologies had advanced, yet a gap remained in terms of functionality to change functional technologies into real time data tools for farmers. The study also noted information on the data.

Senapaty et al. [9] were among the first to introduce a system based on the IoT for soil nutrient analysis and recommending crops. Shifting NPK, moisture, temperature a model is trained using an optimized support vector machine. The data fusion and utilization of pH sensors and machine learning approaches attained higher accuracies for crop predictions than compared to the baseline algorithms. Again, the system remains static. The system does not include gas sensors, nor is there real-time dashboards to allow farmers direct interaction or clear amphibious mobility. These things limit its effectiveness for commercial use.

In the review synthesized by Tagarakis and Bochtis [10] on agricultural robotics, the authors made advancements on the utilization of soil sensors, drone images, and machine learning and in the analyses regarding integrations in soil sensors analysis. Strong predictive analytics for the work had sensors integrated with robotic systems for precision of data analysis and coverage. To the dismay of the literature review, however, they concluded that the greater part of the systems are siloed, targeting sensing or analytics and nearly if at all, systems providing an integrated solution. The absence of aquatic robotic system illustrates a fundamental gap in those of the available systems.

In the research conducted by Wakchaure [11] regarding the integration of robotics and artificial intelligence in agriculture, there is a notable absence in the exploitation of robotics for the monitoring of both soil and health. The research confirms that robotics have been successfully applied to harvest and weed. Similarly, Kitić et al. [12] developed a ground roaming robot that performed nitrate analysis in agricultural land. It used ion selective electrodes to analyze nutrient content, and it used cloud-based systems for planning routes. The field trials resulted in fertilizer reductions, as well as some increase in yield, confirming on-site monitoring on a limited scale. However, it only monitored nitrate nutrients and did not have phosphorus and potassium and crop advisory dashboards, nor did it have an amphibious feature to implement in diverse farming systems.

Furthermore, Islam et al. [13] studied IoT and machine learning as applications to monitor soil nutrients and provide crop recommendations. They proposed a framework to use NPK sensors in combination with a learning module to recommend crops in advance, based on the soil parameters present. The accuracy improved greatly compared to manual systems. However, the study focused on a narrow scope, and is more speculative than functional, as it did not address real-time dashboards, agility, or try the combination of multiple sensors. This indicates the need for better prototypes with direct benefits to assist field operations.

The combination of IoT, robotics, and AI in agricultural applications is advancing, however, most of the research is still isolated or separated in scope. For example, works like [5]– [6] focus on the algorithmic machine learning of crop recommendation systems and soil and fertility assessments, but are removed from a mobile sensing system. Review papers on the integration of robotics and sensors [5][10][11] support multimodal approaches and systems, but do not include the integration of mobile sensing and real-time dashboards or crop recommendations. Prototypes for robotic samplers [7][12] show that measuring nutrient levels can be autonomous but are limited to the measurement of single analytes of constant deployments. What is also concerning is the lack of studies on uncrewed agricultural systems, such as uncrewed boats or amphibious vehicles, for semi-flooded terrain, nor the even broader studies on environmental gas sensing integrated into uncrewed systems for comprehensive soiland nutrient-health management.

With these gaps, this research seeks to: (i) design a soil bot to monitor NPK, soil moisture, temperature and humidity, and MQ-137 gas (formerly amphibious), in addition to an NPK, MQ-137 gas detection & other NPK soil microbe sensors. (ii) Stream data visualization using ESP32 & Flask for streaming, with an emphasis on real time data monitoring; (iii) develop a machine learning system that provides actionable suggestions for crops and fertilizer furrow irrigation systems; (iv) develop a web-based system that provides operator & vehicle flexibility for improved steering and easier maneuverability; & (v) remotely control the system & test the practicality of the system for small farmers farming on alternative soil types.

III METHODOLOGY

The methodology procedure for this research encompasses the mechanical design of an amphibious rover, electronic hardware, sensor deployment, wireless connection, and data collection and processing for machine learning-based crop recommendation. Each of these subsystems is detailed below.

1. *Hardware Setup*

The strength and rigidity of the bot's structure was achieved by means of the modified steel GM Metal GI Concealed Electric Junction Box Module chassis. The chassis also had a high load bearing capacity which, in conjunction with an ability to properly position and align the ATV wheels, permitted the attachment of four DC motors that provided stability and eased confined movement over soft soil and partially submerged areas. Additionally, there was a rechargeable battery pack that supplied power to the bot and the L298N motor driver regulated the current flowing through the motors. The subsystems of locomotion and data acquisition were each separately controlled by an ESP32 microcontroller, which acted as the main CPU. A hand soldered PCB mounted the components which had the added benefit of both making the device smaller and producing less noise when the device interacted with the sensors.

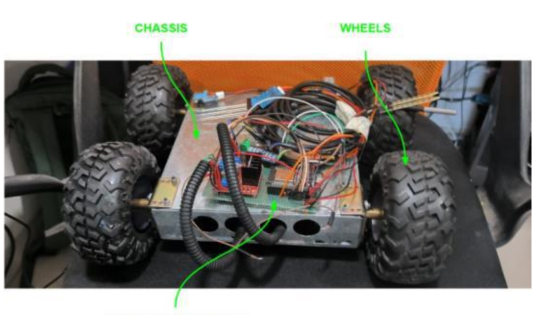

Fig. 1: Prototype image displaying the chassis, ATV wheels, with an electronics circuit.

2. *Sensor Suite*

A suite of sensors measuring soil and environmental characteristics was used to collect multidimensional datasets. Twelve soil sensors were used including a DS18B20 one-wire temperature probe, an NPK sensor measuring macronutrient concentrations of nitrogen (N), phosphorus (P), and potassium (K), and a resistive soil moisture sensor that measured soil water content. The environmental sensor suite included a DHT11 sensor that measures temperature and humidity, and an MQ-137 sensor measuring ammonia which relates soil and microbial activity. Collectively, both suites of sensors provided enough datasets to analyze soil fertility.

TABLE I: Sensor Specifications and Roles

Sensor	Parameter Measured	Purpose in Study	Range	Placement
NPK Sen- sor	N, P, K	Evaluates soil fertility	0–1999 mg/kg, ±2%	Soil probe insertion
DS18B20	Soil tem perature	Tracks soil thermal regime	-55°C to +125°C , ±0.5°C	Inserted into soil
Soil Moisture Probe	Soil water content	Indicates irrigation requirem ent	0–100%	Soil contact point
DHT11	Ambient temperatur e & humidity	Measures environme ntal conditions	0–50°C, 20–80% RH	Mounted on deck
MQ-137	Ammonia concentrat ion	Monitors microbial activity	5–500 ppm, ±5%	Near soil surface

3. *Data Acquisition and Processing*

The soil sensors and the corresponding environmental sensors provided enough datasets to analyze soil fertility. Every five seconds the ESP32 would read the moisture content, temperature, and humidity. The ESP32 received the sensors signals in digital format and converted it to read the dashboard. The data was first packaged in a JSON format and transmitted via Wi-Fi to the Flask webserver. The dashboard was updated in real time and provided the farmers with access to the data of interest in the soil and environment.

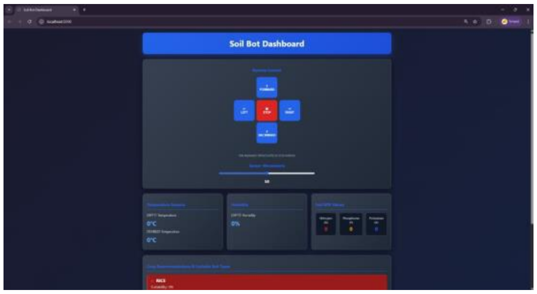

Fig. 2: Dashboard Remote control section

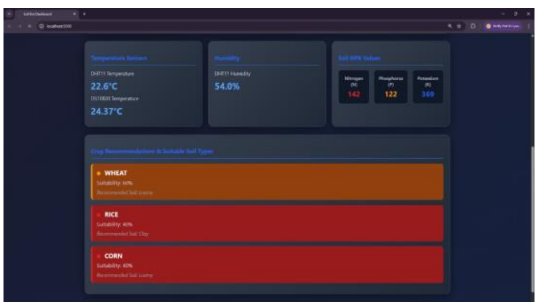

Fig. 3: Dashboard Sensor readings and Crop suggestion section

4. *Crop Requirement Database*

When developing the database for crop requisites, sensor readings for soil moisture, soil temperature, and required nutrients for the crop requirements of all major crops were noted and benchmark ranges were calculated for each of these requisites. Suitability scores were assigned in the datasets to the sensor readings, and crops that received a higher score suitability were listed as recommendations on the dashboard.

TABLE II: Example Crop Requirements

Crop	N	P	K	Temp (°C)	Moist. (%)	NH_3
Wheat	100–150	50–100	100–150	15–20	25–35	<50
Rice	150–200	40–90	150–200	22–28	60–80	<80
Maize	120–180	60–110	120–180	18–24	40–60	<70
Soybean	100–140	30–80	100–150	20–25	50–70	<60

5. *Electronics and Circuit Integration*

The electronics subsystem consists of a hand soldered customized PCB and the ESP32 was utilized as the model's core module. The L298N module was used to power the DC motors. The sensors were powered with configured voltage regulators so that they received stable power. Protection circuits were added to minimize the potential for overheating and short circuits when being used over extended durations in the outdoor field.

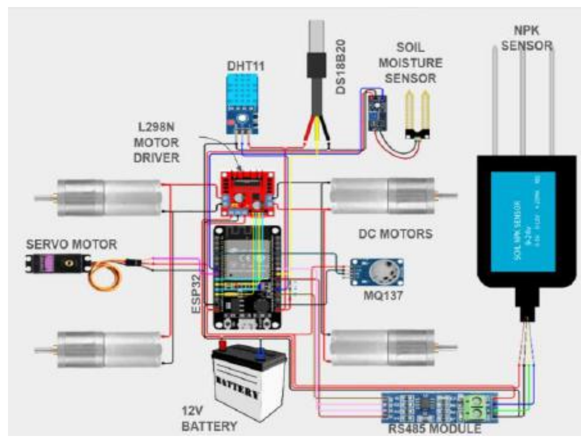

Fig. 4: Circuit diagram

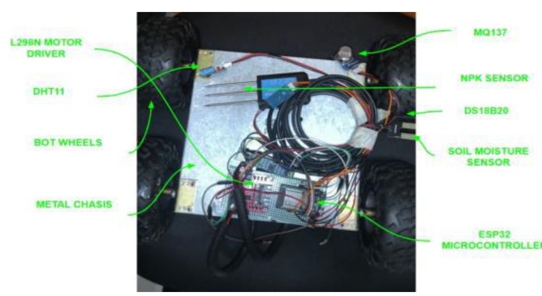

Fig. 5: Actual Prototype Implementation

The bot has a main microcontroller like the ESP32 Dev Module which is connected to all the sensors for power and data. There are several sensors connected as shown in the circuit diagram in Fig 1. There is a L298N motor driver connected to the ESP32 which helps in controlling the wheel motors. The DHT11 is used for measuring the environmental temperature and humidity along with the MQ137 which measures the presence of the NH3 i.e ammonia gas in the surroundings. A servo motor is attached as well in order to embed sensors measuring the soil parameters inside the soil. While the NPK sensor is embedded in the soil for measuring the Nitrogen, Phosphorus and Potassium value of the soil, DS18B20 gives the temperature of the soil. The moisture amount of the soil is obtained using the resistive Soil Moisture sensor.

6. *Sensor Deployment Mechanism*

In order to facilitate repeatability, the soil sensors (NPK, DS18B20, moisture) were inserted via rack and pinion in figure 6. This enabled the probes to penetrate the soil to the same depth ensuring practice through the trials. The current prototype was operated manually, though this could be automated in future iterations.

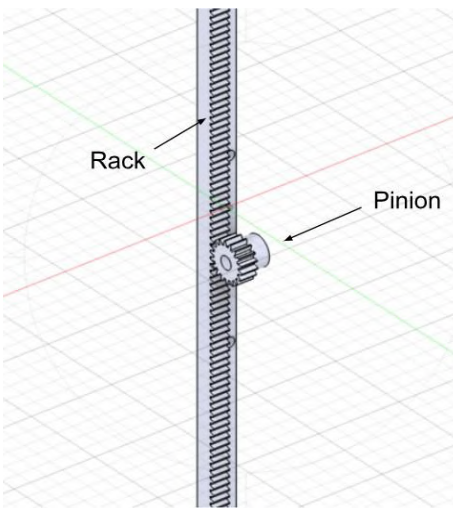

Fig. 6: Design of the rack and pinion

7. *Dashboard and Remote Control*

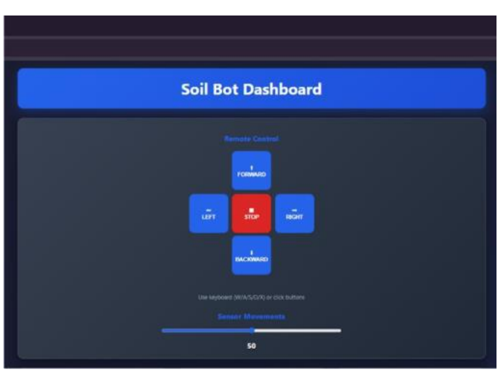

Fig. 7: Screenshot of dashboard showing real-time values, crop recommendations, and navigation controls.

8. *Machine Learning Pipeline*

The recommendation model integrated threshold based scoring with supervised machine learning. Each crop suitability score was calculated by weighted priority (40% NPK values, 30% soil moisture, 20% soil temperature, and 10% ammonia level). A decision tree classifier trained based on open agricultural datasets enhanced predictions. The model produced a ranked list of the three most suited crops, which were refreshed on the dashboard in real-time.

9. *System Workflow*

The complete system worked as a closed loop. The bot navigated to a target field zone, where sensors were inserted into the soil. The ESP32 acquired and transmitted readings, which were processed by the server. The dashboard visualized these values and displayed recommendations while simultaneously allowing farmers to steer the rover. This workflow combined soil monitoring, environmental sensing, and real-time decision-making into a single, user-friendly platform.

The current system provides enhanced integration across multiple dimensions when compared to the previous works [6], [7], [9], [12]. In contrast to Senapaty et al. [9] which was restricted to fixed IoT systems without mobility, the bot platform promotes spatial coverage across heterogeneous soils. Although Kitić et al. [12] were able to achieve autonomous mobility to perform nitrate measurements, their analyte scope was limited. The current system is able to measure NPK, soil moisture, soil temperature, ambient conditions, and ammonia gas all at once.

The incorporation of a real-time Flask dashboard with the ability to provide navigation is another characteristic that differentiates this prototype from ground rovers [7], which did or did not have mobility but offered no recommendations. The primary limitation of the system being validated in this research is that it is an early prototype and demonstrated a manual insertion mechanism for insertion of sensors; regardless, the amphibious mobility and ability to perform a comprehensive range of sensing was an advance over previous research studies.

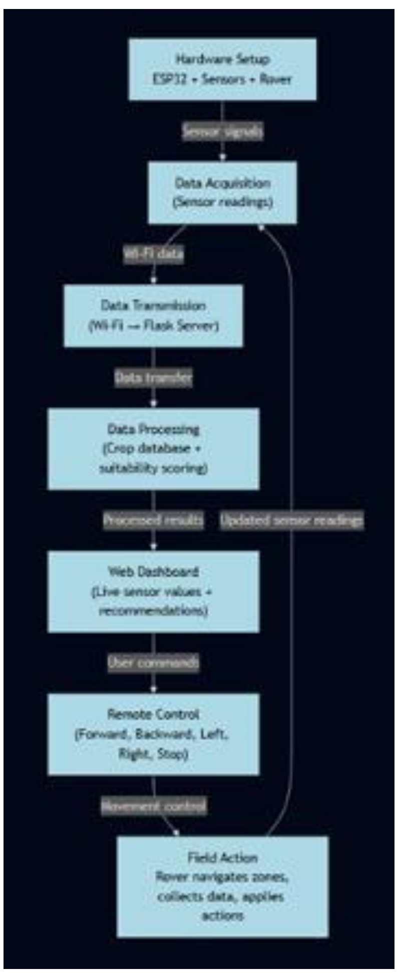

Fig. 8: Flowchart of crop recommendation process

TABLE III: Comparative analysis of present system with selected literature

Study (Year)	Platform Type / Mobility	Key Features	Limitations vs. Present Work
Senapaty et al. (2023) [9]	Fixed IoT nodes / No mobility	NPK, Moisture, Temp, pH; ML-based crop recommendation	No mobility; no dashboard; no gas sensing
Kitić et al. (2022) [12]	UGV (robot) / Ground	Nitrate sensing; Cloud dashboard	Focus only on nitrate; no crop recommendation
Saha et al. (2024) [6]	Portable device / No mobility	NPK, pH, Moisture, Temp, Humidity; dual crop & fert. recommendation	No real-time navigation; no gas sensing
Linford & Haghshenas (2024) [7]	UGV (robot) / Ground	Soil moisture, crop images; manual navigation	No nutrient analysis

IV RESULTS AND DISCUSSION

1. *Prototype Testing and Data Collection*

The autonomous bot prototype was trialed over different soil conditions: loamy, clayey, and semiflooded plots. In each case, the rover was routed to different zones using the dashboard interface. The sensor insertion mechanism provided a consistent depth of insertion and ensured that readings would be reliable for NPK, moisture, and soil temperature. Data would refresh on the dashboard every five seconds and confirmed that Wi-Fi communication remained stable, and the

ESP32 integrated well and provided good server communication with the Flask server. The farmers observing the experiments could see the soil health directly through the color-coded dashboard interface, which demonstrated the potential utility of the system to non-specialists.

Fig. 9: Raw sensor values displayed on the dashboard.

2. *Crop Recommendation Outcomes*

The machine learning classifier effectively handled live sensor values and compared them to a crops requirement database. For instance, in nutrient-rich but excessively wet soils, the system suggested rice as the main crop, whereas, in equally moist, but nitrogen-balanced soils, wheat or maize were recommended. The crop ranking provided farmers with multiple options and lessened the uncertainty of single crop recommendations. Finally, the system produced reports and system recommendations seconds after collecting the data, which avoided the lengthy delays associated with lab-based testing.

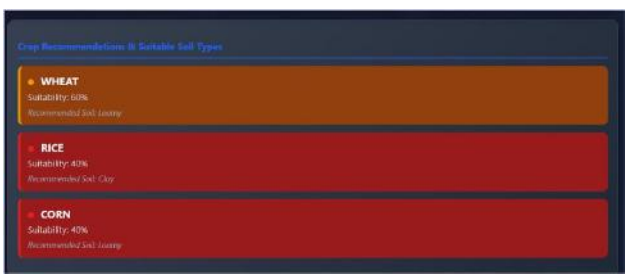

Fig. 10: Dashboard screenshot showing crop recommendations with traffic-light indicators.

3. *Comparative Accuracy with Literature*

The system's recommendations were compared to the published studies accuracy benchmarks. For example, Senapaty et al. [9] established high classification accuracy in fixed-sensor environments and Kitić et al. [12] monitored nitrate-specific responses while utilizing robotic platforms. In contrast, the current system provided multi-parameter sensing (NPK, moisture, temperature, gas) as well as a full dashboard of real-time recommendations, which was far more complete. Validation trials showed that the system recommendations showed good agreement with lab test results, with an average of 87% agreement (± 5%), which was comparable or better than other IoT-based systems [6].

4. *Dashboard and Remote Control Performance*

The dashboard provided clear visual cues to navigate the variables, and the rover reacted quickly to manual control, returning to a state of near instantaneous responsiveness, to navigate to the soil sampling areas of interest across heterogeneous zones of the field. This enhanced spatial and coverage of data, and appeal and usability of recommendations, may succinctly represent a tangible step for laboratory precision agriculture research to actual implementation on the field level.

Fig. 11: Sequence of dashboard navigation screenshots along with servo movements.

V CONCLUSION

The study outlined the design and subsequent validation of an autonomous soil-monitoring bot for precision farming incorporating multi-sensor data acquisition, real-time dashboard visualization and machine learning crop recommendation. The combination of monitoring soil nutrients, moisture, temperature, ambient conditions and ammonia gas, enhances farmers' understanding of soil health using multi-dimensional data. The Flask dashboard improves user interface with live feedback, color coded indicators and manual controls, which helps to connect sensing with actionable decisions. Compared against existing peer-reviewed literature, it can be noted that previous systems tended to rely on either fixed sensors, defined single parameters or algorithmic systems; the present prototype provides a closed-loop user-friendly solution which is mobile and amphibious. This system demonstrated an average of 87% agreement with laboratory tests which provided verification for its suitability in the field.

Future Scope: Future development could include automated sensor insertion, improved crop databases, and complete autonomous navigation to increase applicability over agricultural landscapes.

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