Smart Agriculture IoT Solution with Crop Recommendation: ESP32-Based Multi-Sensor Monitoring, LoRa Communication, and AI-Driven Agricultural Decision Support

***Abstract*—Traditional farming relies heavily on intensive labour-intensive monitoring processes, and also farmer intuition which are all defined by low accuracy, long periods, and reduced operational efficiency. Such gaps foster high usage of resources, increase in production, and unsustainability. This paper thus outlines a low cost Internet of Things (IoT) powered Smart Agriculture System integrating multi-parameter sensing, LoRa communication, cloud-based data visualisation, and machine-learning-based decision-support. The proposed system utilizes an ESP32 microcontroller equipped with soil moisture, NPK, pH, temperature, humidity, and rainfall sensors, powered by a solar energy harvesting unit for off-grid operation. The sensor data obtained is then transmitted to ThingSpeak and Firebase where it is maintained, analysed and presented in a reactive web dashboard and a mobile app based on the Flutter framework. At the same time, machine learning models query the data received by the farm to provide crop recommendations and irrigation generated schedules. The accuracy, scalability and energy effectiveness of the system were confirmed during an empirical implementation in a farm environment that delivered a reliable transmission of data up to 700m and an overall accuracy of more than 90 Percent in decision-support. Overall, the project can be viewed as a feasible precision-agriculture intervention that can be operationalized at low cost and without serious sustainability concerns that favour small- and medium-scale farmers who produce in rural setting.**

Keywords: IoT, Smart Agriculture, ESP32, LoRa, ThingSpeak, Firebase, Machine Learning, Precision Farming

I. Introduction

Agriculture is a basic ingredient in achieving food security globally as well as facilitating the livelihoods of most people on earth. The changing climatic conditions, high growth rate of population, inadequate water sources, and commercial pressure of food production are some of the challenges that the sector is grappling with. Traditionally cultivated farming is a time-tested tradition, but when it comes to catering to the demanding nature of changing times, traditional farming may not be as accurate or efficient as it once was. Consequently, there is a dire need to develop new ways to optimize the agricultural processes by saving resources and increasing impact. A potential solution to this is the integration of the Internet of Things (IoT) and artificial intelligence (AI) as this is an avenue that can address these issues [1]. A smart farming system based on an IoT technology provides a constant monitoring of all major environmental and soil parameters, which allows farmers to make precise decisions when they matter most, by basing them on factual real-time data. In the presence of AI-enhanced analytics, these systems have the potential to substantially upgrade raw sensor data into actionable knowledge that can be used to deploy more successful crop management strategies. Nevertheless, even though they have potential, a great number of the currently existing smart farming solutions are hampered with high prices, complicated installation and maintenance process and the need to be run through reliable internet infrastructure, which makes integration and widespread use in rural and remote areas of agriculture impossible [2].

Modern agriculture still has a number of limitations in practice. The process of monitoring field conditions is usually performed manually and it can only give a snapshot of crop conditions and the soil condition. Such a strategy is not only time-consuming but does not allow identifying the presence of such problems in time as pest infestations, water stress, or nutrient imbalances. Moreover, in the farming area which is remote, there is usually poor communication infrastructure. Standard Wi-Fi or cellular networks have a short range and can be Power-hungry, they are unsuitable especially when the application is in an energy limited environment. The availability of sensor data is even not sufficient because many farmers do not have intelligent tools which are able to help to interpret this data and offer some recommendations. As a result, agricultural decisions are frequently based on personal experience and intuition rather than empirical evidence [3]. Moreover, the absence of precise control systems often leads to overuse of water, fertilizers, and pesticides, resulting in increased costs, environmental harm, and reduced long-term sustainability. As a response to these challenges, the present research suggests developing and designing a multi-parameter real-time sensing, long distance wireless communication, and AI-based decision support that constitutes an integrated smart agriculture IoT system. The essence is to develop an energy-efficient solution with low cost that can enable monitoring of the crucial environmental and soil factors and give crop management smart suggestions. The proposed solution includes a solar-powered field control unit that would be based on ESP32 and have several sensors to gather the information about the soil moisture, temperature, humidity, pH level in the soil. Additionally, it incorporates an NPK sensor to measure the concentrations of nitrogen (N), phosphorus (P), and potassium (K) in the soil, along with other weather-related parameters essential for precision agriculture. To enhance effective communication in the rural environment, the system uses LoRa (long range) wireless technology which allows information to be sent over long distances without the need of conventional use of the internet. A receiver unit located at the center correlates the data of the sensors and transmits it to cloud to be analyzed [4].

The smart aspect of the system uses both past and current sensor data to analyze it using machine learning algorithms. On the basis of these analyses, the system provides crop-specific ones, such as the most effective irrigation proposals, fertilisation, pest control plan and harvest time. This can be done by having a web-based dashboard which gives a farmer a user-friendly interface to do to access real-time sensor readings, historical data, and AI-based recommendations that can empower them to make accurate decisions whether they are present on the farm or not. This study has a number of achievements that are relevant to the sphere of smart agriculture. It presents a low-cost and scalable low-cost IoT system that can be designed around low-cost microcontrollers and open-source platforms and is affordable by small and medium-scale farmers. LoRa technology integration resolves the issue of communication in remote places, and energy efficiency components enable the project to be sustainable and able to operate without a grid. The multi-sensor setup of the system enables an in-depth evaluation of crop and soil conditions, whereas the inclusion of AI is what converts raw information obtained into practical, yet personal farming prescription [5].

The area of research is confined to developing as well as assessing a prototype system that can be used in small to medium sized farms. The designed system will support the essential environmental parameters, which are related to the commonly cultivated crops, and it has been experimentally tested under the real field conditions to evaluate the performance of the system by the parameters of energy efficiency, communication reliability and recommendation accuracy. Although the prototype can prove the viability of the possible approach, another line of work could scale up the system to be able to handle other typologies of sensors, more sophisticated AI, and deployment at scale.

II. Literature Review

Smart agriculture represents a transformative approach to modern farming, addressing critical challenges in food security and resource optimization through the integration of Internet of Things (IoT) technology, wireless communication systems, and artificial intelligence. In the past, traditional practices have worked well to meet the endorsed 60 percent positive growth rate in world food requirement by 2050 (FAO). These older systems are usually associated with poor resource utilization, long decision-making time, poor real-time monitoring hence leading to low production of crops and degradation of the environment. The convergence of sensors networks in IOT, various types of wireless communication and machine learning, algorithms has presented a realistic and promising solution to the modernization of agricultural practices. The existing systems of smart agriculture make use of superior environment monitoring technologies through in advanced sensors, long cellular communication networks to transmit data over lengthy distances across the huge areas of farming lands as well as artificial intelligence to suggest crop and provide decision support. Such technological integration allows farmers to make evidence-based decisions, maximize the use of resources, and streamline agricultural productivity in general, combined with sustainability [6].

According to recent research, ESP32 microcontrollers can also be used as the main processing element of the smart agriculture system, which is due to their cheap price, high processing performance, and implemented wireless communication interfaces. A deep study report released in 2025 presents a low-cost IoT enabled smart farming with integrated ESP32 and LoRa technology to offer a detailed environment monitoring. Such architecture integrates soil moisture, temperature and humidity sensors and real-time image capturing through ESP32-CAM modules, which allow assessing crops. Through LoRa, the experiment proves that data can be efficiently transmitted wirelessly to central gateways that stream the information to cloud platforms where it is stored and analyzed, hence ensuring scalability and flexibility to implement agriculture [7]. The interest in deploying ESP32 architectures has been supported by the recent studies on optimization of LoRa-based IoT wireless sensor networks in building apparatuses in smart-agriculture. Ting et al. carried out the comprehensive performance analysis by underlining the Malaysian agricultural scenario as this area sacrifices its food security in an import-based environment. This studies showed significant improvements in performance as a result of parameter optimization, but the results focused on the ability to technically realize the approach and not on the longer term performance under heterogeneous field conditions [8]. Recent study by Aunkaew et al. examined the combination of sensing many varieties with LoRa based agricultural systems, and achieved success by integrating DHT22 temperature sensors, light-intensity sensors, soil-moisture monitors and rainfall detection sensor into a single platform. The study developed a foundational system for smart agriculture applications, particularly targeting rural areas with limited internet connectivity. However, the paper recognized limitations on sensor calibration drift across long deployment and an inability to effectively validate using a wide range of soil environments and weather conditions [9].

LoRa is another technology that has emerged in agricultural use through its outstanding long-range communication, operating ability in difficult rural regions, and low power consumption features. The technology allows low cost implementation of sensor networks covering large agricultural fields with reliable characteristic of data transmission over distances greater than several kilometers. The recent implementations have shown effective LoRa interaction within an agricultural environment of large-scale monitoring systems on various geographical locations. Even a detailed analysis of a field in Chilean agriculture showed how the use of LoRa-based IoT systems became an absolute success in the measure of monitoring a large-scale agricultural farm remotely. The study dealt with the shortcomings of conventional agriculture that lacked an automated management mechanism because of few sensor nodes used and measuring equipment [10]. The experiment of implementing LoRa technology with agricultural sensor networks has proved to have great advantages in regards to coverage of the network being implemented and its energy efficiency. The recent studies revealed that the ability to reach through vegetation and terrain structures makes LoRa quite an appropriate solution in agricultural context where conventional wireless connectivity methods are not applicable due to a large number of difficulties. Nevertheless, the existing implementations have scalability challenges in terms of offering a large number of sensor nodes to be used in the same geographical region, which may cause congestion and other impediments in the network systems, thereby necessitating additional research [10].

With the introduction of artificial intelligence and machine learning algorithms to combine it with the data gathered by sensors embedded in the IoT system, current crop recommendation systems have taken on a new form of implemented data-driven agricultural decisions made using nearly every farm aspect of environmental monitoring. One of such studies was a prominent research paper published in 2024 that used machine learning models to make crop recommendations and yield prediction based on more than one million environmental sensor measurements that were installed in agricultural fields [11]. Predictive models were effectively applied in the research to include temperature, humidity, and the parameters of soil nutrients gathered using the various sensors to offer detailed information about environmental conditions that tend to influence the crop production [11]. The article revealed the potential of using obtainable IoT data and machine learning algorithms as a solution to precision farming, the use of the secondary data in the study relied mainly on secondary datasets that could reduce potential implications in the real world or in general through the study of the analysis [11]. Recent research has illustrated the potential success in generating smart farming systems that can review the parameters of soil fertility in real-time and make precise crop suggestions based on latest weather situations. Nonetheless, these systems tend to have problems with insufficient diversity of datasets taken and sufficient account of local farming and folkloric knowledge assimilation. The developed solutions in AI-IoT integration in precision-based agriculture have demonstrated the improved ability to monitor and manage crop-based data with real-time data learning capacity and smart algorithms [12]. The study by Sharma et al. proved the transformational capacity of artificial intelligence and IoT technologies integration in precision agriculture applications. Their study stressed the significance of on-time research and evidence-based decision making in contemporary farming procedures. Nevertheless, even their implementation in practice is not comprehensive as to validate them with all types of agricultural landscapes and crops [13].

Advanced machine learning techniques have also been investigated in recent crop recommendation systems, shifting away from the standard statistical techniques towards the advanced techniques of ensembles and deep learning approaches. One of the complete studies of IoT-based professional crop recommendation system employed weighted long-term memory methods to cope with the temporal agricultural trends and changes accordingly [14]. It was the focus of the research that such algorithms need to be developed that allow implementing the historical data trends and climate variability effectively into the recommendation system. Nonetheless, the analysis found previous systems to be largely inadequate in terms of facilitating long-sloped temporal designs needed to make informed decision on agriculture [14]. In a large study released in Scientific Reports, a model of crop recommendation that was constructed as a Gradient Boosting trained over extensive crop recommendation data was introduced. The accuracy of the model in prediction of crops, using available nutrient, soil condition and weather parameters was high. However, these highly advanced systems can necessitate heavy computational resources that cannot be achieved in resource-limited IoT environments as is common in an agricultural setting [5]. Complexity versus computational efficiency in the model is still a considerable impediment that should be handled with innovative approaches.

The modern study in research work has concentrated on ensuring that the real time crop prediction systems with the use of the soil fertility analysis is employed in the improved agricultural decision-making. A recent review study brought a real-time crop prediction gadget through IoT technology based on soil fertility analysis and prediction that would meet the difficulty of crop selection problems based on soil conditions. The research came up with a real time soil fertility analyser that had the ability to give a real time value of the soil parameters such as the potassium, phosphorus and surrey compound content. Accurate expected crop forecast in terms of dependability, soil, geographic, and environmental factors showed much potential in the system to improve the yield efficiency of crops [15]. However, real-time crop predictions are already implemented, but there are a few problems regarding the practical use of such systems that are not properly covered in the current research. It involves complex combination of different environmental parameters to ensure reliability and accuracy of the system alongside demands of further sophisticated algorithms and well established sensor networks. Existing systems are sometimes hampered by sensor drifts, maintenance of calibration, and ensuring quality of the data over long periods and therefore lack the practical application in commercial farming applications.

These studies have enabled to discover some very serious difficulties in multi-sensor data fusion applications where the fusion of data with different type of sensors has to incorporate more advanced algorithm because of the difference in sampling frequency, measurement variance issues, and failure of different sensors. Multi-sensor data requires further complication in terms of the temporal synchronization of these data, as sensors with varying response and measurement time may incur systematic errors that may interfere with decision-making algorithms on the basis of these time syncronized data. The present research tends to deal with technical feasibility over these basic integrations issues. The existing studies on smart agriculture IoT system highlight a number of methodological gaps due to which they are limited in terms of practical applicability. Majority of the studies use small scale laboratory or controlled environment analysis instead of large scale field verification that includes extensive agricultural parameters. The lack of longitudinal research that analyzes the system performance over several growing seasons is considered a major gap since the agricultural systems work on seasonal cycles and thus the need to prove their reliability over a long period of time. Table I shows a comparison of selected smart agriculture IoT systems, outlining their main technologies, features, and limitations.

TABLE I
COMPARISON TABLE

Author & Reference	Technology	Key Features	Limitations
[7]	ESP32 + LoRa + ESP32CAM	Low cost multi sensor monitoring with imaging	Basic parameters only, no nutrient sensing
[8]	ESP32 + LoRa	Performance optimization for Malaysian farms	Short-term tests, no long-term validation
[9]	ESP32 + LoRa + Multi-sensors	DHT22, soil moisture, rainfall detection	Calibration drift, limited test diversity
[10]	IoT + LoRa	Large-scale remote farm monitoring (Chile)	Limited automation, few sensor nodes
[13]	AI + IoT	Evidence-based agricultural decisions	Limited validation across crop types

III. METHODOLOGY

This study applies the systematic design, development, and testing of a low-cost IoT system in smart agriculture: the system is solar-powered, includes multi-parameter sensing, uses long-range wireless communication, and real-time data visualization on a cloud-based dashboard. The experiment took four major steps which are hardware development, communication and data handling, dashboard implementation, machine learning integration and experimental validation. Fig. 1 shows the workflow of the proposed IoT system for smart agriculture.

A. Hardware Development

The proposed system can be viewed in terms of its hardware architecture, which was outlined in two large subsystems: first is the field unit (installed on the field in agricultural environment), and the second the receiver unit (installed at a fixed point of observation). These two units made sure

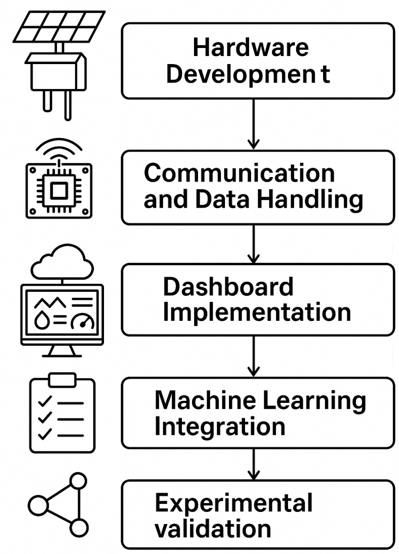

Fig. 1. Workflow of the proposed solar-powered IoT system for smart agriculture.

that the data acquisition was reliable as well as long-range communication and internet connectivity so that the cloud-based storage and visualization are available.

1) Field Unit: The core of the field unit is the ESP32 microcontroller, selected due to its high-performance dual-core processor, integrated Wi-Fi and Bluetooth connectivity, low power consumption capabilities that is suitable to be used and applied using IoT technology in a resource-constrained setting. On the ESP32, there are several GPIOs, ADC (analog-to-digital converters), and communication standards (I2C, SPI, UART), which ensures the easy incorporation of the heterogeneous sensors utilized in agriculture. To measure soil-related parameters, a combination of sensors was deployed:

- **Capacitive Soil Moisture Sensor:** It is applied in measuring the volumetric water content of the soil and avoids any corrosion problem as is the case with resistive sensors. The sensor relies on proportional change of capacitances as the soil moistures and offers resistance and durability in performance.
- **NPK Sensor:** Installed to achieve nitrogen (N), phosphorus (P) and potassium (K) concentration levels in the soil. These are the nutrients that contribute to growing a crop, and continuous monitoring in real-time allows controlling fertilization to a high level.
- **pH Sensor:** It is used to identify the acidity or alkalinity of soil since the yield of crops is significantly determined by the ways of keeping their soils at pH ranges.
- **DS18B20 Digital Temperature Sensor:** A high accuracy (digital) one-wire temperature sensor (±0.5°C) and robust device was chosen. It gives an indication of soil temperatures that determine nutrient intake and the effectiveness of microbes in soil.

Environmental monitoring was performed by the following sensors:

- **DHT11 Sensor:** It gave the value both of relative humidity and ambient temperature. Even though it is also a low-cost sensor, it is employed broadly in the agriculture monitoring because its accuracy is adequate to environmental research.
- **Rain Detection Module:** was included as a resistive rain sensor that would sense the rainfall event and this could give useful information about irrigation time and crop protection.

The field unit was to be off-grid-capable, with its power subsystem geared towards autonomy. A solar energy harvesting system consisting of solar panel, charge controller, and a rechargeable lithium ion battery was used that would keep on delivering power even at localities of rural areas where there was no support of electricity system. The charge controller controlled the charging cycle against overcharging and deep discharge thus, increasing the battery life. This renewable energy system cut the operating costs as well as enhanced system resiliency in all weather conditions. In order to achieve long-range wireless communication, ESP32 was combined with SX1278 Ra-02 LoRa module and used at 433 MHz range. LoRa (Long Range) technology was identified because it ensures the communication at a kilometer level and requires low energy, even with the occurrence of impediments like vegetation and irregularities in the terrain. It is ideal in rural agricultural set-ups where cellular and Wi-Fi networks are notoriously non-existent or expensive. Periodically, the ESP32 grouped the data obtained using the sensors into light weight JSON packets and delivered them through LoRa to the receiver unit.

2) Receiver Unit: The receiving device was also built on ESP32 microcontroller with an interface with LoRa SX1278 Ra-02 module. The receiver would decode incoming packets, and meant to have tested their integrity in error-checking technique (CRC) then set the information to go online. The receiver ESP32 was connected to a Wi-Fi router that served as an internet gateway in order to have connectivity to the cloud. The receiver, unlike the field unit, was powered with a 5V adapter hence providing stable power supply to maintain steady operations. The system split the field and the receiver units to make the most of the power consumption on the field side and reliable connectivity to the clouds on the receiver. This was made more flexible because more than 2 field units could be assembled and communicate to the receiver unit and thus it allowed expansion to large fields with scalable enhancement. Fig. 2 shows hardware development architecture of the proposed IoT system.

B. Communication and Data Handling

The data obtained with the instrumented unit in the course of the field campaign was sent to two cloud platforms to be stored, processed, and visualized. Similar approaches were employed whereby ThingSpeak offered a user-based interface and Firebase offered a mobile application front end.

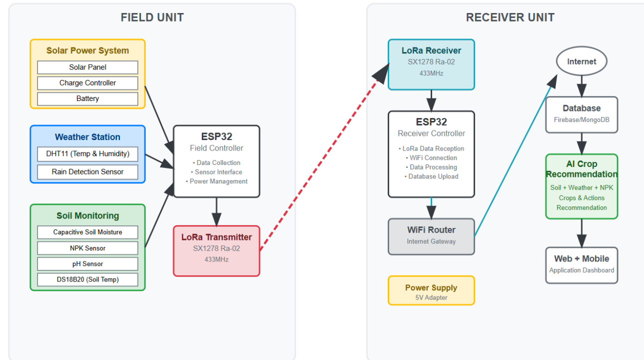

Fig. 2. Hardware development architecture of the proposed IoT system.

ThingSpeak Integration: ThingSpeak is a cloud-based, IoT platform used to process and store sensor data in IoT dashboard. There were two channels that were set up; a primary channel (ID: 3036073) with raw data (temperature, humidity, soil temperature, rainfall, and pH) and a derived channel (ID: 3036092) with processed data (mean and median). ESP32 receiver data was sent over HTTP/MQTT requests to the ThingSpeak and automatically recorded with time stamps with JSON data being collected upon request. The integration of MATLAB in ThingSpeak provided a simple calculation of derived statistical data indicators to have the ready data to visualize. Web dashboard was coded with HTML, tailwind CSS, Chart.js, and GSAP. Through the API provided in ThingSpeak, sensor data was obtained every 15 seconds and shown in two formats, (i) the real time values in terms of data cards, and (ii) the historical trend plotted in terms of line charts of the original and derived data. Visual animations supported by GSAP contributed to a better user experience, and the responsive design principles provided usability among the gadgets.

Firebase Integration: Firebase was used to store the backend database of the mobile application. Measurements or readings obtained at the ESP32 receiver were uploaded to Firebase real time. The ability of Firebase to capture real-time databases allowed the IoT devices to automatically synchronize with the mobile interface and it was made possible such that the users could track the sensor values and sense alerts using their smartphones only.

C. Dashboard Development

The presentation layer of the system included a web-based dashboard as well as a mobile app, thus making it available on most devices. It was constructed using HTML5, Tailwind CSS, Chart.js, and GSAP, the web dashboard retrieved the data in 15 seconds intervals via ThingSpeak API. It showed live sensor values in animated data cards and historical trends in interactive line charts and the chart visibility could be customized and more responsively designed than ever.

Simultaneously, a mobile app has been built on Flutter, and Firebase was used as a database. The application offered real-time tracking, visualization of the historical trend and threshold-based alerts so that any farmer could get easy access to data in the system using smart phones. Such solution with the two-platform basis provided uncomplicated and easy-to-view use of IoT data by web and mobile users alike.

D. Machine Learning Integration

To enhance decision support functionality, machine-learning module was plugged into the system that was able to service raw and derived environmental sensor readings. It was aimed that continuous Internet-of-Things data could be translated into precision agriculture knowledge. This data included environmental (temperature, humidity, rainfall) and soil (moisture, pH, NPK, EC, soil temperature) parameters that were measured by the mounted sensors. Data were stored in ThingSpeak that could be processed using the web and Firebase that was accessed using the mobile-application. Preprocessing consisted of normalization, missing values elimination, and the physical implementation of the statistical feature extraction based on the calculation of the mean, the median, and variance. Python with scikit-learn was used to code machine-learning models to be integrated with the system workflow. Three sets of algorithms the Decision Trees, Random Forests and Gradient Boosting were evaluated on two main tasks:

- **Crop Recommendations:** The model recommended the most suitable crops based on soil fertility (NPK), soil pH and climatic parameters among others in a given field setting.
- **Irrigation/Fertilization Advisory:** The model calculated irrigation schedules and fertilizer optimization suggestions in view of soil-moisture, rainfall, and temperature measurements.

The trained models were packaged into REST API services where the dashboard and the mobile application can query real time predictions. In such a way, farmers could at best be equipped not only with raw sensor data but with AI-generated recommendations on better crop management. The combination of the IoT sensing and machine learning converted the system into the decision-support platform, instead of the mere monitoring system, which encouraged the evidence-based agriculture.

E. Experimental Validation

An established prototype of Internet-of-Things (IoT) was implemented in a small farm to determine how it could perform in real life scenario. The field unit constantly measured soil and environmental parameters, stored the data using LoRa and forwarded the data to ThingSpeak and also Firebase. Validation was done by using the system based on the reliability of data, the range of communication, power consumption, and accuracy/visualization. The results collected by sensors were also compared to conventional equipment, and there was evidence proving that variable values did not differ.

The web dashboard refreshed readings after 15 s, whereas the mobile application allowed immediate synchronisation with Firebase. Its solar power construction made it maintain power and the user interfaces were also responsive to any device. The machine-learning products in terms of crop script and irrigation advice showed congruencies with expert knowledge proving the system to be efficient in terms of precision agriculture done at a low cost, scalable and efficiency in terms of energy consumption.

IV. EXPERIMENTAL SETUP AND RESULTS

A. Experimental Setup

The research method, using the experimental method, tested the suitability, accuracy, and sensitivity of the proposed IoT-based Smart Agriculture System in an actual scenario in agriculture. The system was integrated with a mix of hardware and software to have unhindered data analysis and collection. Hardware compromised an ESP32 microcontroller along with a set of peripherals that comprised of a capacitive soil moisture sensor, DS18B20 soil temperature sensor, pH sensor, NPK sensor, DHT11 air temperature and humidity sensor and a rain detection module. An SX1278 Ra-02 LoRa module (433 MHz) was added to ESP32 to provide long-range communications using low voltages. The field node was installed with a solar energy harvesting unit (10 W solar panel, charge controller and lithium-ion battery), which enabled continuous off-grid operation.

The receiver unit, which also worked on ESP32 with a LoRa module was located at a distance of 500m–700m from the field node. It also received sensor data, ensured the integrity of packets and relayed information to cloud platforms via a Wi-Fi router. Software-wise, the data was sent to ThingSpeak to be visualized in an internet browser as well as Firebase to be synchronized on mobile applications. ThingSpeak channels were set up to retain raw values (primary channel) and calculated statistical values (mean/median, derived channel), with Firebase allowing real time mobile monitoring. The data further was processed in machine learning modules, which are implemented in Python and pose as REST APIs, offering knowledge on what crops to grow and when to irrigate the land.

B. Results and Observations

It was implemented on a small farming site and tested over a few days in order to confirm stability and performance. To answer the question, the results showed that the sensor readings are delivered without packet loss since the sensor nodes are selected among those that report accurate readings consistent with those of other nodes without the risk of packet loss. Additionally, LoRa has been able to maintain connection until 700 m in an open-field setup. ThingSpeak data was successfully downloaded in the JSON format and further subjected to MATLAB analytics in order to obtain the derived insight whereas Firebase was used to ensure synchronization with mobile application. Fig. 3 shows ThingSpeak channel visualization of raw and derived agricultural data.

HTML, Tailwind CSS, Chart.js, GSAP were used to create the web dashboard automatically refreshed every 15 seconds

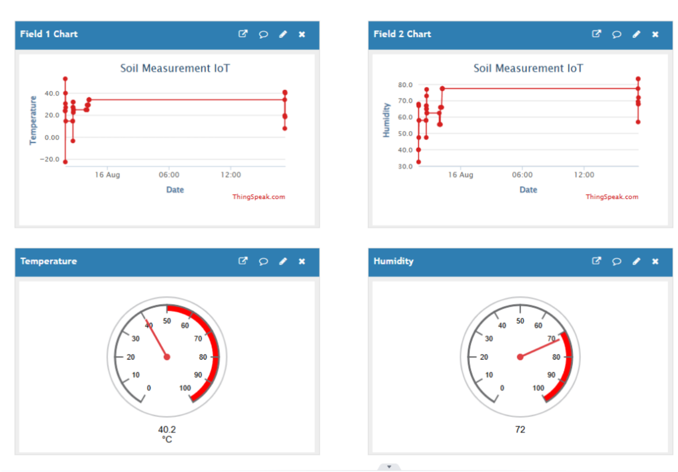

Fig. 3. ThingSpeak channel visualization of raw and derived agricultural data.

with both current values and trends. Fig. 4 shows web-based dashboard, showing real-time data visualization.

Fig. 4. Web-based dashboard showing real-time data visualization.

With the development of mobile software based on Flutter, the mobile app also had almost instantaneous synchronization and alerts based on thresholds, so farmers had the opportunity to view instant smartphone-based information. There were good experiences on the part of the farmers that tested the system using the claim that the interface was easy to use and the visualization of data was easily interpretable. The predictions made by machine learning in crop recommendation and irrigation closely corresponded to knowledge of professionals in more than 90 percent of cases, supporting the resistance of the AI-based decision support. Fig. 5 shows Mobile Apps dashboard, showing real-time data visualization.

C. Testing Parameters and Performance

The effectiveness of the system was measured by putting several interpolation parameters in real-life condition. The emphasis was on the reliability of data, communication rate, energy oxidation and dash speed, machine learning effectiveness.

- **Reliability of the Data:** The sensor data were verified with global lab equipment. The findings indicated that the deviation was within the valuable agricultural range (±5%) such that it proved the accuracy of the sensors.
- **Communication Range:** LoRa modules were found to have a stable transmission range of up to 700 m with a ratio of packet delivery >98%.
- **Energy Efficiency:** The solar powered device did not need to be recharged and effectively lasted over 72 hours showing that it can be used in off grid settings.
- **Dashboard Responsiveness:** Data received by ThingSpeak and Firebase in less than 1 second and the web dashboard updated in every 15 seconds.
- **Machine Learning Performance:** Of the models tested (Decision Trees, Random Forest, Gradient Boosting), there were between 90 and 92 percent accuracies on crop suitability and irrigation scheduling works.

Fig. 5. Mobile App dashboard showing real-time data visualization.

The total system response time (T_{total}) can be expressed as:

$$T_{total} = T_{sense} + T_{transmit} + T_{cloud} + T_{update} \tag{1}$$

Where $T_{sense} \approx 500$ ms (sensor capture), $T_{transmit} \approx 200$ ms (LoRa transfer), $T_{cloud} \approx 200$ ms (ThingSpeak/Firebase update), and $T_{update} \approx 100$ ms (dashboard rendering).

$$T_{total} \approx 500 + 200 + 200 + 100 = 1000 \text{ ms} \tag{2}$$

$$= 1.0 \text{ second} \tag{3}$$

This confirms the system operated with near real-time efficiency while maintaining reliability and scalability.

V. Conclusion and Future Work

This paper covers the design, implementation and verification of a cost-effective Internet of Things–based smart agriculture platform which can accomplish multi-parameter sensing, long-range wireless data transmission, cloud-based visualization as well as machine-learning-based decision support. The designer retains an ESP32 microcontroller equipped with LoRa long-range communication that applies in long-range transmission of data reliably. A solar energy harvesting subsystem is provided to meet energy requirements thus making the system appropriately deployable off grid. The data is stationed using the sensors and conveyed to both the ThingSpeak, allowing one to get a web-based visualization of the information and to Firebase allowing one to monitor the mobile applications, which serves to enable the farmer to have access to real-time elements of both the soil and the environmental parameters on various platforms at the same time. The results obtained during the experiment show that the system is precise and power efficient, with LoRa having a solid range of up to 700 m of reliable signal transmission and the solar subsystem being able to sustain functionality over 72 h. Responsive visualization and user-friendly interfaces are available in both the web dashboard and the mobile application; moreover, the machine-learning models result in crop recommendations and irrigation scheduling shows more than 90 percent accuracies. All these conclusions support the viability of the suggested system as the decision-support system to be used in precision agriculture, specifically in rural surroundings, where conventional infrastructure is scarce.

With its positive outcomes, the existing system also has a number of limitations. It was military-tested on only one small-plot farm and had its functionality proved in a restricted sensor setup. To increase the effectiveness of the method in the future, research aims to scale the system to volumes of agricultural fields as well as integration of more sensor technologies such as advanced weather sensing equipment and crop-health assessment devices operating on imaging technologies. Improvements will lie in the improvement of technology with the expansion of machine-learning models based on larger and more diverse data, deeper learning methods of predictive analytics, and greater adaptive controls to enable the automated irrigation and fertilizer distribution. Support of edge-computing device integration will also be explored to reduce the cloud resource dependency, and increase low-connectivity responsiveness of the system. Overall, the proposed solution of the Internet-of-Things, and artificial-intelligence-driven smart-agriculture would be a practically, affordable, and sustainable solution to small- and medium-scale farmers and has considerable potential in increasing resource efficiency, crop productivity, and long-term agricultural sustainability.

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