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Review On Solar-Powered Smart Agriculture Monitoring and Crop Prediction System

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Abstract—Smallholder agriculture often relies on manual observation and uncalibrated soil assessment, which leads to inefficient resource management, improper fertilization, and unsuitable crop selection. Internet of Things (IoT) technologies have lowered the cost of field monitoring, but many existing systems only visualize sensor data and do not turn measurements into actionable agricultural recommendations. To address this limitation, this paper presents an end-to-end, solar-powered smart agriculture monitoring and decision-support system built around an ESP32 microcontroller edge node. The system continuously monitors five parameters: soil moisture, air temperature, relative humidity, ammonia (NH_3), and methane (CH_4). The firmware averages 10 samples of each analog sensor reading and applies a two-point linear calibration to the soil moisture sensor. The processed data are transmitted over two concurrent Wi-Fi paths: to the Blynk IoT platform every 3 seconds for real-time monitoring, and to a Flask REST server every 15 seconds as JSON payloads. At the server, a Decision Tree machine learning model, trained on an agricultural dataset of 50 crop varieties, analyzes the sensor data to estimate the expected crop yield percentage and to generate a ranked list of suitable crops. Sensor data and prediction results are logged in an SQLite database and displayed on an auto-refreshing web dashboard, and the predictions are also sent to Blynk virtual pins for remote mobile access. A photovoltaic solar panel, a charge controller, and a rechargeable lithium-ion battery power the node, allowing autonomous operation. The proposed architecture combines field-level sensing, wireless communication, cloud monitoring, database management, and machine learning-based prediction into an affordable, energy-independent decision-support framework for precision agriculture.

Keywords—Precision agriculture, Internet of Things, ESP32, Decision Tree, crop recommendation, yield prediction, solar energy harvesting.

I. INTRODUCTION

Global food security depends on agricultural productivity, yet traditional farming in many smallholder regions relies heavily on manual monitoring, uncalibrated visual soil inspection, and empirical irrigation schedules. These practices frequently cause improper fertilizer application, over-irrigation or under-irrigation, unscientific crop selection, and reduced yields. Resource-constrained farmers also lack quantitative, real-time tools for tracking soil health and ambient microclimate conditions, which leaves crop yields exposed to unpredictable climate variability, rapid nutrient leaching, and long-term land degradation.

Precision farming addresses these problems by interfacing low-cost IoT microcontrollers, such as the ESP32, NodeMCU, ESP8266, and Raspberry Pi, with environmental sensors that capture soil moisture, ambient temperature, and relative humidity. These field nodes send telemetry over Wi-Fi, MQTT, or cellular links to cloud IoT platforms such as Blynk, Ubidots, and Adafruit IO, which enables remote visualization on mobile dashboards and threshold-based actuator responses. In parallel, supervised machine learning models, including Decision Trees, Random Forests, LightGBM, and deep



attention networks, are trained on historical agronomic datasets to support crop recommendation and yield forecasting. To remove the dependence on unreliable rural power grids, electronic field assemblies are increasingly paired with photovoltaic modules, charge controllers, and rechargeable batteries for continuous off-grid operation.

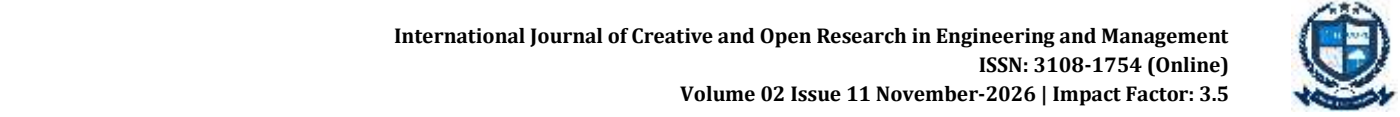
Despite these advances, the published literature shows several persistent limitations. Most field-deployed IoT monitoring platforms stop at raw data visualization or static threshold control, such as switching on a pump when soil moisture falls below a fixed percentage. This creates a "decision gap" in which farmers receive no predictive guidance on crop selection. Machine learning models for crop selection and yield prediction are typically trained offline on clean, curated public datasets and remain disconnected from live field hardware, so they are never exposed to sensor noise, calibration drift, or out-of-distribution values. Conventional field nodes also concentrate on macro-climate and soil moisture parameters and often omit trace atmospheric gases such as ammonia (NH_3) and methane (CH_4), which can provide additional information on nitrogen volatilization, fertilizer-related processes, and anaerobic soil conditions. Finally, published solar-powered sensor nodes often give limited information on verified daily watt-hour energy balances and on the sleep duty-cycling strategies needed for reliable operation during extended periods of low solar availability.

These limitations call for an integrated edge-to-cloud architecture that links real-time, multi-parameter field sensing with interpretable server-side analytics and practical off-grid energy management. Smallholder farmers need an affordable decision-support platform that converts raw sensor streams into transparent, actionable guidance, specifically a predicted crop yield percentage and a ranked list of suitable crops. Trace gas monitoring (NH_3 and CH_4), together with standard soil moisture and microclimate parameters, provides additional diagnostic information for assessing field conditions, including excessive moisture and potentially anaerobic environments. In addition, an interpretable model such as a Decision Tree, connected directly to live IoT telemetry, allows lightweight and rapid predictions and offers a model structure that agronomists and farmers can examine.



Fig. 1. Solar-Powered smart agriculture monitoring system in a crop field

To meet this need, this paper presents a solar-powered smart agriculture monitoring and crop prediction system centred on an ESP32 microcontroller edge node. The field node continuously measures five environmental parameters: capacitive soil moisture, air temperature, relative humidity, NH_3, and CH_4. Before transmission, the firmware averages 10 samples on each analog channel and applies a two-point linear calibration to the soil moisture probe. Telemetry then follows a dual-path Wi-Fi protocol: readings are uploaded to the Blynk cloud every 3 seconds for live gauge display on a mobile device, while structured JSON payloads are sent to a Flask REST server every 15 seconds. At the server, a Decision Tree model trained on an agricultural dataset of approximately 50 crop varieties evaluates the incoming telemetry, predicts the expected crop yield percentage, and outputs a ranked list of suitable crops. The prediction records are stored in an SQLite



database and shown on an auto-refreshing web dashboard. The complete edge assembly is powered independently by a photovoltaic solar panel, a solar charge controller, and a rechargeable lithium-ion battery.

Compared with existing approaches, this work makes the following contributions. First, it provides an affordable multi-parameter sensing suite based on an ESP32 edge node, which includes trace gas monitoring (NH_3 and CH_4) alongside standard microclimate variables to give additional information on soil and environmental conditions. Second, it uses a decoupled dual-path telemetry architecture that keeps real-time visualization on the Blynk mobile dashboard separate from server-side machine learning inference and data logging through Flask and SQLite. Third, it translates live field sensor streams into interpretable Decision Tree predictions of crop yield percentage and ranked crop suitability. Fourth, it includes a photovoltaic harvesting subsystem with battery storage, intended to support autonomous operation in remote agricultural fields with limited access to grid electricity.



Fig. 1. Prototype of the solar powered ESP32 Field Node

II. LITERATURE SURVEY

In [1], Sudheer et al. presented an ESP32-based smart agriculture system for irrigation and real-time monitoring. The system used soil moisture, DHT11 temperature and humidity, rain, and water-level sensors, with threshold-based pump control and wireless cloud logging. Although it responded quickly with automated irrigation, it offered no predictive crop selection or learning-based decision support.

In [2], Mohiuddin, Islam, and Shanjida developed an IoT-based irrigation and monitoring system using an ESP32, soil moisture, sunlight, and DHT11 sensors, and the Ubidots platform. The system provided live monitoring and automated irrigation, but crop recommendation and predictive yield analysis were outside its scope.

In [3], Al Mamun et al. implemented an IoT-enabled, solar-powered irrigation framework using a Raspberry Pi 4 and an ESP8266. Soil and microclimate measurements were used for pump scheduling and water management. The study reduced water wastage, but it included no crop recommendation or predictive yield logic.

In [4], Correa-Quiroz, Toribio-Barrueto, and Castro-Vargas developed an ESP32-based drip irrigation and climate-monitoring system for greenhouses. They demonstrated stable multi-sensor monitoring and responsive irrigation control. However, the system was tested only in a controlled greenhouse environment and did not use machine-learned crop selection.

In [5], Shahab et al. presented an IoT-driven agricultural platform that combined multi-probe soil measurements of temperature, moisture, EC, pH, and NPK with an ESP32 and an AI-supported mobile interface. The work showed the value of multi-parameter soil monitoring, but the cost of the chemical probes and the absence of trace-gas sensing are limitations.



In [6], Tsioropoulos et al. compared battery-powered and photovoltaic-powered wireless sensors for soil-water monitoring. The solar-powered node-maintained energy availability over long deployments, whereas battery-only operation did not, which demonstrates the importance of renewable energy harvesting for autonomous field nodes.

In [7], Khalid et al. developed a solar-powered smart agriculture system using a NodeMCU ESP32, a DHT11, soil moisture sensing, Blynk, and Google Sheets. They demonstrated practical solar operation and remote logging, but did not include predictive crop analytics.

In [8], Dobrilovic et al. evaluated lightweight machine learning methods on solar-powered edge sensor devices. Decision Trees, KNN, and SVM were considered for solar-panel performance estimation, showing that lightweight models can run on constrained platforms. The work did not, however, address the agricultural decision-support problem.

In [9], Turgut, Kök, and Özdemir proposed AgroXAI, an explainable AI-based crop recommendation framework, and compared several models, including Decision Trees and Random Forests. Tree-based methods provided interpretable decision structures, but the study relied on offline datasets rather than live physical field measurements.

In [10], Bouni et al. investigated integrated IoT and machine learning approaches to crop recommendation and yield prediction, using temperature, humidity, pH, NPK, and rainfall with tree-based and boosting models. They reported strong predictive performance, but their data were secondary and were not collected from a deployed multi-gas IoT node.

In [11], Singh and Sharma proposed a cloud-based crop recommendation model that combines tree-based learning with attention mechanisms. They showed the usefulness of cloud analytics and automated recommendations, but the work did not include live NH_3 and CH_4 field sensing.

In [12], Senapati, Ray, and Padhy developed a machine learning decision-support system for crop recommendation with an emphasis on explainability. The system supports transparent rule-based recommendations, but it relied mainly on manually supplied or prepared data rather than continuous live sensor streams.

In [13], Das et al. used ESP32 sensing with Random Forest and LSTM models and a Blynk/Flask architecture for soil-related prediction and agricultural control. Their work supports the value of a dual communication and inference architecture, but it did not include NH_3 and CH_4 sensing or a detailed solar energy audit.

In [14], Baba et al. investigated crop yield prediction using a multi-parameter soil probe, an ESP32, and a Flask-based machine learning server. They showed the value of live sensor data for yield prediction, but the study was limited to a single crop.

In [15], Ghule and Patil presented an intelligent smart-farming framework that combines IoT and machine learning for precision agriculture. The study further supports the integration of sensing and analytics for agricultural decision support.

In [16], Emon et al. integrated IoT, machine learning, and environmental sensors using ESP32-family devices. Their work included methane sensing and cloud-based analysis, but a verified solar energy subsystem was not central to it.

In [17], Chantima et al. proposed hybrid intelligence for field-scale soil analysis and crop advisory using embedded sensors and machine learning. The work demonstrates the value of



combining embedded observations with analytical models for field-level recommendations.

In [18], Musa, Sugeru, and Wibowo reviewed wireless sensor networks and NPK sensing for precision agriculture. They highlighted sensor error, calibration drift, and deployment cost as important considerations for low-cost agricultural instrumentation.

In [19], Molleman et al. evaluated a metal-oxide semiconductor (MOS) gas sensor for measuring methane emissions from agriculture. They demonstrated the potential of low-cost MOS sensing for methane monitoring, but did not combine it with a complete multi-parameter IoT crop analytics platform.

In [20], Parsiegel et al. investigated a virtual MOS sensor array for ammonia monitoring in agricultural environments. They demonstrated localized ammonia monitoring with low-cost sensing technology, although their scope was limited to a single gas.

In [21], Abdelmoneim et al. studied the calibration of low-cost capacitive soil moisture sensors connected to an ESP32. The variation they observed between probes shows the importance of individual calibration for reliable field deployment.

In [22], Saha et al. combined satellite remote sensing, crop prediction, and solar-powered irrigation. Remote sensing provides valuable spatial information, but cloud cover and satellite revisit intervals limit its ability to replace continuous root-zone and atmospheric measurements.

In [23], Ouhami, Hafiane, and Canals surveyed computer vision, IoT, and data-fusion methods for agricultural monitoring. They emphasized data-level, feature-level, and decision-level fusion, and identified sensor noise, sampling mismatch, and missing data as continuing challenges.

Research Gap

The reviewed studies demonstrate the potential of IoT sensing, solar energy, machine learning, trace-gas monitoring, and remote sensing for individual components of crop production, but these elements are typically treated as isolated features. A complete field-to-decision pipeline that combines live five-parameter sensing, trace-gas observations, cloud visualization, interpretable machine learning, and renewable-energy operation remains a practical gap. The proposed system addresses this gap through an ESP32 field node, dual-path telemetry, Decision Tree analytics, and a solar-plus-battery power subsystem.

III. SYSTEM OVERVIEW

The proposed system consists of an ESP32-based field node, two parallel Wi-Fi telemetry paths, a server-side analytics unit, and a photovoltaic power subsystem. Fig. 1 shows the overall architecture.

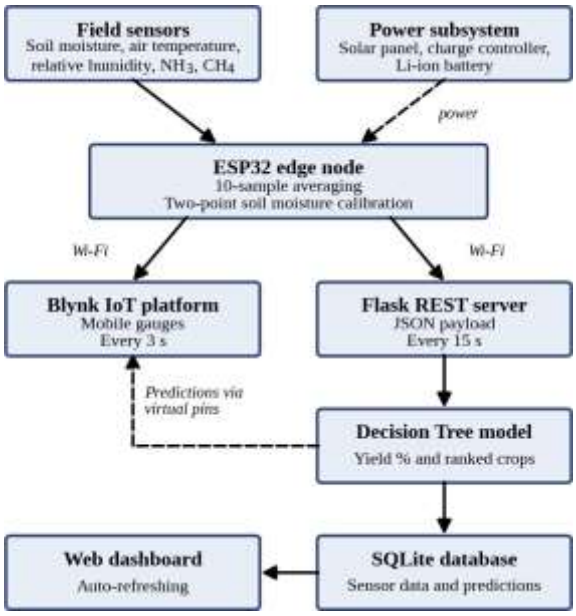


Fig. 2. Proposed system block diagram.



A. Field Node and Sensing

The field node is built around an ESP32 microcontroller and measures five parameters: capacitive soil moisture, air temperature, relative humidity, NH_3, and CH_4. For the analog sensor channels, the firmware computes the arithmetic average of 10 samples to reduce momentary noise. A two-point linear calibration is applied to the soil moisture sensor.

B. Dual-Path Wi-Fi Telemetry

The processed data are sent over two concurrent Wi-Fi paths. In the first path, the readings are uploaded to the Blynk IoT platform every 3 seconds for real-time monitoring on a mobile dashboard. In the second path, the node sends JSON payloads to a Flask REST server every 15 seconds. Separating the two paths keeps the real-time display independent of server-side inference and logging. The prediction outputs are also returned to Blynk virtual pins for remote mobile access.

C. Server-Side Prediction and Data Management

At the server, a Decision Tree model analyzes the five-parameter feature vector. The model was trained on an agricultural dataset covering approximately 50 crop varieties, and it estimates the expected crop yield percentage and a ranked list of suitable crops. Sensor data and prediction results are logged in an SQLite database and shown on an auto-refreshing web dashboard.

D. Solar Power Subsystem

The edge node is powered by a photovoltaic solar panel connected through a charge controller to a rechargeable lithium-ion battery. This arrangement is intended to allow autonomous operation in fields without a stable grid supply. The power-related limitations of the present design are discussed in Section V.

IV. APPLICATIONS

A. Precision Agriculture

Precision agriculture is the use of field-based measurements and digital technologies to support agricultural decision-making. Unlike traditional practice, which often relies on fixed crop calendars or regional assessments, it uses data gathered in the field to inform management decisions. Soil moisture, temperature, and relative humidity are examples of parameters used to assess the state of the agricultural environment. In this work, the field node uses an ESP32 to measure soil moisture and microclimate parameters periodically. Ammonia and methane sensing add environmental information that can support crop-related decisions beyond what the conventional parameters provide.

B. Soil Condition Monitoring

Soil condition monitoring involves determining the nature of the soil environment, which informs agricultural decisions. Moisture monitoring gives information on the water status of the field, while other factors, such as gas content, can be used to infer further information about field conditions. For instance, capacitive soil moisture sensing combined with ammonia and methane sensing can give a more comprehensive assessment of the field than moisture monitoring alone. The sensing node can therefore monitor soil conditions continuously and report the information to the user through the Blynk platform for further analysis.

C. Irrigation Management

Irrigation management is essential for crop production because it involves supplying water to the field according to crop needs. In contrast to periodic irrigation on a fixed schedule, smart irrigation uses field measurements to determine the water status of the field and makes decisions



accordingly. The moisture sensor can be used to monitor soil water content and to determine the need for irrigation. The present system transmits moisture measurements to the Blynk platform every three seconds, where they can be used to visualize the field condition. Combined with temperature and relative humidity measurements, these data can inform irrigation decisions.

D. Crop Yield Estimation and Prediction

Crop yield estimation is a significant aspect of precision agriculture because the information can support various management decisions. Crop yield prediction uses a set of parameters to estimate the potential yield of a given crop. The data from the sensing node form an environmental feature vector that can serve as the input to a crop yield model. In this work, the five-parameter environmental input vector is used with a Decision Tree algorithm, which provides an estimate of the crop yield percentage. Combined with other information, the yield estimate can support decisions related to agricultural production.

E. Environmental Microclimate Monitoring

The microclimate of an agricultural field can vary because of a number of factors, some related to the crop and others to the local environment. Temperature and relative humidity are critical parameters for assessing the field microclimate. Using the environmental sensor, the present system can monitor the temperature and relative humidity of the field continuously. Unlike approaches that rely on external weather reports, this system determines the microclimate of the field locally from the sensor data.

F. Early Identification of Agricultural Stress

Changes in environmental parameters can indicate agricultural stress and can inform management decisions. For instance, fluctuations in soil moisture can indicate water stress, whereas changes in methane and ammonia levels can provide information about the fertilizer status of the field. The data captured by the sensing node can therefore be used to identify agricultural stress at an early stage, enabling timely interventions to avoid losses.

G. Farmer Decision Support and Remote Monitoring

Farmer decision-making benefits when field measurements are processed into actionable information. Sensor data often need to be interpreted before they can be used, especially when multiple parameters are involved. The Decision Tree algorithm allows the system to provide decision support by processing sensor data into a crop suitability ranking and an estimated crop yield, which the farmer can use for purposes such as crop selection and yield forecasting. In addition, the Blynk platform enables remote monitoring of the field by visualizing the sensor data in real time. The server-side processing and web dashboard offer a further route for remote monitoring and decision-making alongside the mobile dashboard.

V. CHALLENGES

A. Sensor Accuracy and Calibration Drift

Low-cost field sensors, particularly capacitive soil moisture sensors and metal-oxide semiconductor (MOS) gas sensors, are prone to nonlinearity, manufacturing tolerances, baseline drift, and cross-sensitivity to temperature and humidity. These characteristics make accurate field measurement difficult and reduce the quality of the data used by the Decision Tree crop yield model. In particular, raw analog-to-digital converter (ADC) values may saturate at the maximum value of 4095, which skews the soil moisture estimates, and baseline offset in the gas sensors can lead to unreliable methane and ammonia estimates. These inaccuracies affect the



integrity of the five-parameter feature vector used as the model input.

One approach is to carry out a two-point calibration of the capacitive soil moisture sensors using known dry and wet references. Similarly, MOS gas sensors require appropriate burn-in and calibration against reference concentrations before deployment.

B. Out-of-Distribution Data and Model Generalization

Another challenge is out-of-distribution data, particularly for the gas sensors. Because the Decision Tree model was trained on synthetic data, its behavior is unpredictable when it encounters real-world measurements that fall outside the typical ranges of the training set. Real-world gas sensor readings in the range of 147–364 would produce stagnant predictions from the Decision Tree, since the model would reach a leaf node with no further decision rules to apply. In other words, the model would fail to differentiate between different field measurements and would give similar crop yield predictions.

To address this, input schema validation can be implemented on the server to reject requests that do not conform to the expected input ranges. In addition, the model can be retrained using empirical data gathered over multiple seasons with the IoT node under investigation.

C. Power Consumption and Energy Autonomy

The always-on Wi-Fi-enabled microcontroller and the heating elements of the MOS gas sensors result in high power consumption that may exceed the capacity of a small solar panel to charge the battery on a daily basis. This limits the operational lifetime of the system, since the battery could run out after several days of deployment.

One approach is to implement a duty-cycling strategy that places the microcontroller in deep-sleep mode after the sensor readings have been transmitted. Specifically, the microcontroller can be configured to wake up every 15 minutes, take a reading, and return to sleep after 15 seconds. This strategy would reduce power consumption while maintaining acceptable performance.

D. Environmental Noise and Trace Gas Cross-Sensitivity

In situ trace gas monitoring is subject to momentary power supply fluctuations, wind gusts, changes in relative humidity, and cross-sensitivity to various chemicals in the air. These effects can influence the measurements of the MOS gas sensors and, in turn, affect the five-parameter feature vector used as the input to the Decision Tree crop yield model. Fluctuations in the ADC of the microcontroller or momentary increases in trace gas concentration can trigger false readings and affect the model output.

One approach is to apply noise reduction at the sensor level; in this system, ten-sample arithmetic averaging of the ADC measurements reduces the influence of environmental noise. Similarly, range checking on the server can be used to detect and remove momentary outliers.

E. Communication and Network Limitations

Rural networks often have low bandwidth and limited coverage, which can cause intermittent communication link failures, particularly when the IoT node is far from the communication tower. These limitations can affect the transmission of HTTP JSON data to the server, where the data are used for visualization, model inference, and logging. First, intermittent link failures can compromise model inference and logging, particularly when the connection fails midway through a data transfer. Second, the inability to establish a stable connection can



affect the display of sensor data on the mobile dashboard.

One approach is to decouple the mobile dashboard from the model inference and logging process by using separate communication channels for the two processes, as is done in the proposed dual-path architecture.

VI. CONCLUSION

This paper presented the design and implementation of an autonomous, solar-powered smart agriculture monitoring and decision-support system based on an ESP32 microcontroller edge node. Smallholder farming systems can benefit from precision agriculture solutions that support informed decision-making. However, a decision-making gap exists, because many IoT devices measure field conditions without directly supporting crop-specific decisions. This work proposed an autonomous system that supports agricultural decision-making at the farm level. In particular, the system was designed to provide crop suitability and yield estimates based on five environmental parameters: capacitive soil moisture, temperature, relative humidity, NH_3, and CH_4. It uses a dual-path wireless telemetry architecture that provides real-time sensor visualization on the Blynk platform and also supplies the input vector to a server-side Decision Tree machine learning model. Using an agricultural dataset that covers 50 crop types, the model was trained to estimate the expected crop yield percentage and to generate a list of suitable crops from the five-parameter feature vector. The outputs are presented to the farmer through the monitoring interface and the web dashboard.

The proposed system combines several aspects of precision agriculture, including low-cost multi-parameter sensing, wireless monitoring, and machine learning-based decision support. The ESP32-based sensing node offers an affordable way to acquire multiple environmental parameters. Sharing sensor data on the Blynk platform and providing model-based crop yield estimates supports farm-level decision-making. The Decision Tree provides an interpretable machine learning model that avoids the computational complexity of higher-level models. In addition, the photovoltaic panel and battery provide an alternative to grid power, allowing the system to operate in areas that lack a stable electricity supply.

Nevertheless, the proposed system has several limitations that require further investigation. First, the behaviour of the machine learning model is unpredictable when it is presented with out-of-distribution data, particularly when uncalibrated gas sensors are used. In this case, the Decision Tree would assign similar crop yield percentages to fields with significantly different environmental characteristics, which reduces the precision of decisions. Second, individual calibration of the capacitive soil moisture sensors is required to address the nonlinearity and manufacturing tolerances that limit the accuracy of soil moisture measurements. Third, the high power consumption of the Wi-Fi module and the MOS gas sensor heating elements calls for a duty-cycling strategy to ensure continuous operation.

Future work will focus on these limitations. Individual two-point calibration of the capacitive soil moisture sensors against reference measurements will be carried out to improve moisture accuracy. The response characteristics of the MOS gas sensors will be characterized using Rs/Ro measurements to enable calibrated estimation of trace gas concentration. The Decision Tree model will be retrained using empirical data gathered over multiple field seasons to improve its generalization to out-of-distribution data. Future work may also explore the use of solenoid valves to implement a closed-loop irrigation system that responds to the specific needs of the farmer's crop.

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