AI and IoT-Enabled Smart Gardening with Spectrometer-Based Plant Health and Soil Moisture Estimation

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***Abstract*—The proposed work represents an automated smart gardening system, integrating a hand-held spectrometer and Raspberry Pi-based processing unit to measure the spectral responses of the plants and estimate the corresponding soil moisture by using machine-learning regression. The system acquires 18-band spectral reflectances along with a reading from a soil moisture sensor. It further converts the analog outputs using the ADS1115 ADC and subsequently processes the data for real-time prediction. The spectral signals captured are pre-processed, cleaned of outliers, and curve analyzed before training the regression models. In this regard, among the approaches adopted, the Random Forest model provided the most reliable performance with a very low MAPE of 1.19%, thereby giving 98.81% prediction accuracy. The proposed system reduces manual measurements of soil and plant parameters, offers almost continuous monitoring of the soil condition, and aids in data-driven irrigation decisions that can be availed for precision agriculture and small-scale smart gardening applications.**

***Index Terms*—Spectrometer, Raspberry Pi, Soil Moisture Prediction, Regression, Smart Gardening, IoT**

I. Introduction

Smart gardening is increasingly important for global food security, but it faces many challenges such as climate change, limited resources, and rising disease risk. Under traditional gardening, each crop is exclusively inspected by hand and watering is generally applied regardless of the variations in water needs across the growing location. Thus the current inspection and irrigation system is inefficient and prone to human error. With the emergence of AI-driven technologies, spectrometers, and IoT sensors, it is now possible to modernize plant monitoring and improve decision-making. This project presents a spectrometer-based spectral sensing system integrated with IoT sensors and machine learning to enable intelligent, real-time plant health estimation and soil moisture prediction.

II. Problem Formation with Background

Plant diseases, if not detected promptly, can hamper production and lead to food scarcity. Many farmers continue to inspect plants visually, or using uncomplicated sensors, which is time-consuming and often inaccurate. This is especially ineffectual on larger farms or for remote areas. In addition, farmers of lower expertise may apply the incorrect chemical treatments and be exposing plants, the environment, and their finances to damage. Our current work uses spectrometer, IoT-enabled environmental sensing, and AI to address these issues by identifying plant diseases sooner, and to facilitate better decision making on the part of farmers, in real time.

III. Motivation – Facts – Need Analysis

Plant diseases cause a big loss in crop production every year, around 20–40% of the total yield worldwide. In India, small farmers face even more problems because they don't have quick and modern tools to check plant health or manage irrigation properly. The usual ways of checking, like looking at plants by hand or using simple sensors, take a lot of time, are not always correct, and don't work well for big farms. This can lead to extra use of chemicals, more pollution, and a loss of income for farmers.

Many research Studies signify that plant diseases first appear on the leaves thus making leaf-level observation a very effective and efficient to identify the problem. Nevertheless, ordinary cameras and simple sensors are not capable of detecting such changes in biochemistry of the plant that happen at the diseased stages most subtle. Minimal such inabilities, scientists have decided to rely heavily on spectral sensing and AI-based analysis, in which a spectrometer is used to get the detailed wavelength data that neither human eyes nor RGB cameras can. These spectral patterns are instrumental in revealing plant stress, nutrient imbalance, and disease at early stages with a degree of precision much higher than before.

There is now an opportunity of creating an intelligent and affordable plant-monitoring system due to the increasing availability of compact spectrometers, IoT sensors, and lightweight machine learning models that can operate even on low-power devices like a Raspberry Pi. A device of this nature may utilize the spectral information to not only detect the first signs of plant stress but also to estimate soil moisture in real-time even under situations of low or no internet connectivity. This positions the AI system based on a spectrometer as an excellent alternative to the imaging-based setup, hence enabling quick, accurate, and convenient smart gardening methods to be realized.

A. *Overall Problem in Traditional Gardening*

This diagram illustrates how traditional gardening practices lead to misjudgment, chemical misuse, and crop loss, highlighting the need for smart, AI-driven solutions and IoT-enabled environmental sensing.

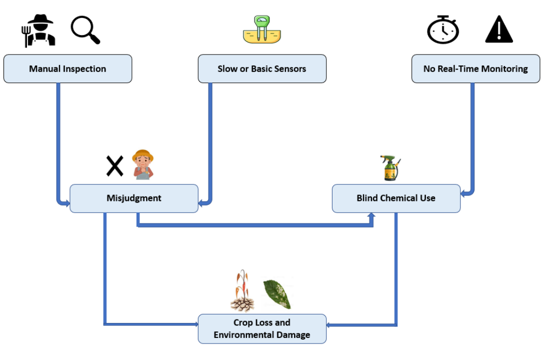

Fig. 1. Traditional gardening problems and need for automation.

IV. Related Work

A. *Work Done by Different Researchers in the Same Problem Area*

In the paper titled "An Ultra Lightweight Interpretable Convolution-Vision Transformer Fusion Model for Plant Disease Identification: ConViTX" authors use ConViTX hybrid Ultra-lightweight, highly accurate deep learning model for plant disease identification. They use PlantVillage, Embrapa, PlantDoc, PlantCOMB, IIITDM_Maize datasets. The advantages of this paper include high accuracy for PlantVillage, real-field maize dataset and uses of lightweight Architecture. However, the limitations of this paper are Moderate performance on raw drawn images and only use images dataset for input. [1]

In the paper titled "An Early and Smart Detection of Corn Plant Leaf Diseases Using IoT and Deep Learning Multi-Models" authors use Multi – model Fusion Network (MMF-Net). They use Plantvillage data and field data (IoT sensor). Authors use DHT-11, TMP-36, BMP-180, FC-28 sensors, Arduino microcontroller. The advantages of this paper include high accuracy (99.23%) on corn leaf diseases dataset, early detection of corn diseases and uses integration of IoT with visual dataset. However, the limitations of this paper are limited dataset diversity and Corn-leaf Specific Model. [2]

In the paper titled "A Deep Learning and Social IoT Approach for Plants Disease Prediction Toward a Sustainable Agriculture" authors use social IoT which allow to Social relationship between devices based on location. They use Coffee leaf rust dataset which is generated by sensors and use images data by FruGar system. The advantages of this paper include SIoT Integration, Combination of spatial features with sensors data. However, the limitation of this paper is small dataset and focuses on coffee and tomato crop. [3]

To recognize plant diseases, the writers created a highly effective MobileNetV3-small model that can be used on resource-constrained edge devices. On the PlantVillage dataset, it attained an impressive test accuracy of 99.50%. After training, quantization lowered the parameter count from 1.5 million to 0.93 million without compromising the accuracy, thus enabling the implementation to be both quick and economical. [4]

The paper describes an IoT system that uses solar energy, a Raspberry Pi 4, and a NodeMCU to perform smart irrigation. A water pump is automatically controlled by a real-time soil moisture sensor, temperature sensor, and humidity sensor. The system turns on the pump when the soil moisture is less than 45% and turns it off when the soil moisture is more than 80%. This device is very effective in saving water and in avoiding the use of fossil fuels. Also, it is possible to monitor and control the system remotely via a web interface. [5]

The survey is a systematic review of the methods for detecting crop diseases with the help of drones, and it classifies different techniques into statistics, Machine Learning, and Deep Learning. Deep Learning techniques were found to be the most precise (up to 100%) and are thus mainly applied with cheap RGB sensors. The biggest problem is the lack of labeled data and the requirement for small DL models that can be put on the latest computing devices in the field. [6]

The paper review the various deep learning (DL) technologies to identify plant diseases. It points the high accuracy of DL as well as its capability to automatically extract features as the main advantages. The review talks about the use of significant datasets such as PlantVillage and emphasizes the great potential of hyperspectral imaging for the early detection of diseases. The biggest issue is that more extensive datasets from real fields are needed, and the robustness of the models has to be improved. [7]

The article is about a cheap IoT device made with a Raspberry Pi to keep track of the health of plants. The main idea revolves around a cheap and effective chlorophyll meter, while the growth is measured by an ultrasonic sensor, and the nutrient deficiency is detected by image processing. [8]

TABLE I
COMPARATIVE STUDY OF RELATED WORKS

Ref.	Objective	Methodology	Findings	Limitation
[9]	Predict leaf spot disease in groundnut using IoT sensor data.	Data collected using leaf wetness, soil moisture and soil temperature sensors, followed by EDA and MLP modeling.	Achieved 85.51% accuracy with peak disease occurrence in Aug–Sep.	Limited to one geographic region.
[10]	Analyse spinach crop soil properties using IoT devices.	Data collected via Arduino, LoRa, Raspberry Pi4, and CloudMQTT using EC, moisture, temperature, and pH sensors.	Reached overall parameter accuracy of 82.6%.	Only basic soil parameters measured.
[11]	Detect irrigation status of tomato plants automatically.	Created tomato leaf dataset with varied irrigation levels and trained ResNet-50 with Grad-CAM analysis.	Achieved 99.9% accuracy.	Limited to tomato plant images.
[12]	Automate early leaf-disease detection using sensors and ML.	Used ENSVM, CNN, KNN with temperature, humidity, light and waterflow sensors on Arduino.	CNN achieved highest accuracy of 80.1%.	High hardware and model complexity.
[13]	Monitor distributed botanical garden in real time.	Used WSN, LoRaWAN, ZigBee and cloud monitoring with underground and over-ground links.	Stable communication at 868MHz and 2.4GHz frequencies.	No plant disease detection included.
[3]	Predict diseases using SIoT combined with deep learning.	Fused IoT sensor data and VGG16 image features over cloud MQTT with FruGar system.	Enabled early disease detection with networked devices.	Small dataset and crop-specific.
[14]	Develop lightweight model suitable for IoT devices.	Combined MLP-Mixer, SVM, and LSTM for image-based classification.	Achieved 94–98% accuracy across datasets.	Limited to image classification only.
[1]	Build ultra-light fusion model using CNN and ViT.	Combined MobileNetV2 early blocks with eight-encoder ViT and concatenated outputs.	98.8% accuracy on maize dataset.	Poor performance on raw drone images.
[2]	Enable early corn disease detection using hybrid models.	Used ResNeXt-34, VGG16, AlexNet-1D with IoT sensors (DHT11, TMP36, BMP180, FC-28).	Achieved 99.23% accuracy.	Corn-specific and limited dataset variety.
[15]	Classify plant types with low computational cost.	Used Raspberry Pi, PlantCV and ThingSpeak with HSV and shape-based features.	Improved plant identification accuracy.	No real-world dataset used.
[16]	Develop automated irrigation using ARM and IoT.	Raspberry Pi, DHT11, ADC, cloud upload, Flask app, and relay-based pump control.	Accurate soil and climate monitoring with automated irrigation.	Needs Wi-Fi and lacks plant-health imaging.
[5]	Reduce water loss using solar-powered IoT irrigation.	RPi4 base station + ESP8266 nodes sending soil moisture and DHT22 data via MQTT.	Automated pumping with stable solar power.	Rainfall affected tests; small-scale setup.
[17]	Automate irrigation and environmental monitoring.	RPi + Grove sensors with Firebase and mobile app for manual/auto control.	System improved irrigation efficiency and real-time monitoring.	Not scalable for large farms.
[18]	Monitor crops and livestock using IoT + mobile app.	NodeMCU, Raspberry Pi, sensors and ThingSpeak with Flutter-based Android application.	Enabled remote monitoring with automated irrigation.	High setup cost and limited scalability.
[7]	Review DL methods for plant disease classification.	Analysed CNN, transfer learning, GAN models and hyperspectral datasets.	DL methods achieved up to 99% accuracy.	Lack of diverse datasets; early detection remains difficult.
[4]	Develop lightweight DL model for edge devices.	Used MobileNetV3-small with post-training quantization on 54k images.	Achieved 99.5% accuracy with 0.9M parameters.	Generalizes poorly to real-field images.
[8]	Monitor plant growth, chlorophyll and nutrients.	RPi, Arduino, ultrasonic sensor, custom chlorophyll meter and webcam analysis.	Accurate chlorophyll and growth detection.	Thick leaves reduce accuracy.
[6]	Review UAV-based disease detection techniques.	Compared RGB, multispectral, hyperspectral sensors with DL/ML models.	DL achieved ¿99% accuracy using UAV images.	UAV battery and altitude limitations.
[19]	Detect multi-crop disease severity at scale.	NASNetLarge with augmentation, AdamW, mixed precision and Grad-CAM.	Achieved 97.33% accuracy across integrated datasets.	Requires high-quality labeled data.
[20]	Provide IoT-based disease detection and smart irrigation.	RPi, EfficientNetB3, sensors and MQTT with weather-based irrigation logic.	Achieved high accuracy and 32% water savings.	Controlled datasets limit field robustness.

V. Proposed Research Work

A. Problem Definition

Conventional monitoring methods utilized in gardening such as human inspection and uncomplicated sensor systems, are ineffective and unsuitable for large area affects the accuracy of disease diagnosis, chemical inputs, delayed action, lost crop, and environmental loss. In addition, many growers do not have access to real time or intelligent chronic disease or smart farming decision support systems, which negatively impact important agronomic decisions. Farmers require a reliable, affordable, scalable, and intelligent disease detection and decision support system that can also function in low connectivity areas.

B. Proposed Solution

This study implements a spectrometer-based plant health and soil moisture estimation system integrated with IoT sensors and Raspberry Pi edge processing. The implemented pipeline uses a leaf spectrometer (handheld/bench) to capture spectral responses, ADC (ADS1115) to digitize analog outputs, and Raspberry Pi to aggregate environmental sensors (DHT22) and perform on-device linear regression for soil moisture prediction.

C. Proposed System Architecture

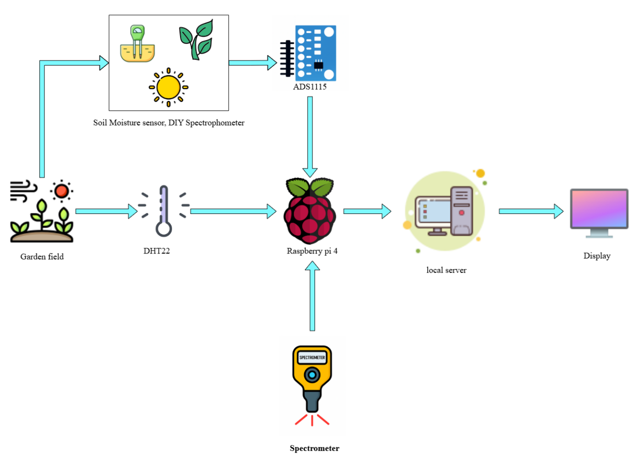

Fig. 2. Proposed spectrometer-based system architecture.

D. Explanation of Each Component

a) Soil Moisture Sensor: This sensor measures the amount of water in the soil so it can determine when to water the plants. It measures soil moisture levels constantly and communicates this data to the system. By using this, it will not overwater or underwater.

b) DIY Spectrophotometer: This equipment measures light absorption by plant leaves for the measurement of chlorophyll content. It helps identify nutrient deficiencies and early signs of plant stress. The device is an inexpensive alternative to professional chlorophyll meters.

c) ADS1115 (Analog-to-Digital Converter): ADS1115 converts analog signals from sensors like the spectrophotometer and moisture sensor into digital form. This allows the Raspberry Pi to process and interpret the data accurately. It's crucial for integrating analog sensors into digital systems.

d) DHT22 Sensor: This sensor tracks temperature and humidity in the garden environment. It helps monitor climate conditions that affect plant growth and disease risk. The data is sent directly to the Raspberry Pi for real-time analysis.

e) Raspberry Pi 4: The Raspberry Pi acts as the microcontroller, collecting data from all connected sensors. It processes the information, runs models, and communicates with other devices like the server or display. It allows to automate and make decisions on the ground.

f) Spectrometer: The spectrometer collects light reflected from the leaves of plants at various wavelengths. Consequently, it can detect the stress, changes in chlorophyll, and even the very first symptoms of the disease which are invisible to the naked eye. It is the main data source for multispectral analysis.

g) Local Server and Display: The server stores all incoming data from the Raspberry Pi, including sensor readings and spectrometer captures. It can run additional analytics or serve as a backup for long-term data logging. The display shows live data such as soil moisture, temperature, humidity, and plant health status, enabling user interaction.

VI. Methodology and Concepts

A. Overview of the Proposed Methodology

This innovative approach integrates soil spectrometry, moisture sensing, and machine-training-based regression to result in an accurate prediction of soil moisture in real time. A handheld spectrometer and a moisture sensor are used to collect data. Along with the spectral reflectance values, the corresponding moisture readings are also captured. The dataset undergoes cleaning to achieve consistency in the values by removing inconsistent values, converting fields to numeric format, and filtering the outliers using the IQR method. To discover the nonlinear feature–moisture relationships, scatter plots and polynomial curve fitting are utilized. The preprocessing operations pave the way for model training while at the same time, they eliminate the noise that could make the prediction unstable.

Various regression models, including Random Forest, SVR, and cross-validation frameworks such as K-Fold and Shuffle-Split, are trained and tested through the use of MAE, RMSE, MAPE, and residual diagnostics. Random Forest is the one to give the best results with an excellent MAPE of 1.19%, thus, showing that the model is capable of making moisture predictions with high accuracy. The final optimized model is merged with the spectrometer-based hardware for on-the-spot prediction and monitoring in the field. Such a comprehensive workflow is able to prove its strong robustness even when the data samples are few. In brief, the method serves as a quick, inexpensive, and easily extendable solution for the precision agriculture sector.

Fig. 3. Spectrometer readings, sensor data, and Raspberry Pi preprocessing flow.

VII. Implementation and Execution Flow

The proposed methodology consists of four primary stages: data acquisition, data preprocessing, feature analysis, and machine learning–based prediction. Fig.3 illustrates the overall workflow.

A. Data Acquisition

For this project, data was gathered with the help of two main hardware parts: a portable spectrometer and a soil moisture sensor that was connected via an ADS1115 analog-to-digital converter. 18 different leaf spectral readings were taken, and the soil moisture value for each corresponding reading was recorded.

B. Data Preprocessing

The raw dataset required several preprocessing operations:

1) Data Cleaning: Non-essential columns including *Records*, *Latitude*, *Longitude*, *Location Name*, *Date Time*, and *Voltage* were removed.

2) Data Type Conversion: The *Moisture* field contained commas and other non-numeric characters, which were removed before converting the column to numeric format.

3) Outlier Detection and Removal: Outliers within the Moisture feature were removed using the Interquartile Range (IQR) method:

$$IQR = Q_3 - Q_1$$

Values outside:

$$[Q_1 - 1.5 \cdot IQR,\ Q_3 + 1.5 \cdot IQR]$$

were discarded to enhance model stability while preserving a usable sample size.

4) Normalization (for SVR Model): Sensor readings were normalized using StandardScaler to improve convergence for the Support Vector Regression model.

C. Feature Visualization and Curve Fitting

Scatter plots were generated to analyze how individual sensor variables correlate with soil moisture. Polynomial curve fitting of degree 2 was applied to capture non-linear relationships and reveal the underlying trends in the data.

D. Model Training

Three machine learning strategies were evaluated:

1) Random Forest Regressor: A 300-tree ensemble model was trained owing to its resilience against noise present in real sensor measurements.

2) Support Vector Regression (SVR): SVR with an RBF kernel was implemented. Standardized inputs were used to ensure reliable training performance.

3) Cross-Validation Approaches: Two evaluation protocols were applied which are K-Fold Cross Validation: $k = 5$ and ShuffleSplit: 10 randomized data splits. These ensured fair model assessment despite the small dataset size (20 rows).

E. Evaluation Metrics

The following regression metrics were computed to evaluate model accuracy: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R^2 Score (used only as a trend indicator due to small test size).

VIII. Results

The performance of the Random Forest and SVR regression models was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). Due to the extremely limited dataset (20 samples; 14 remaining after preprocessing), MAE and RMSE were considered more reliable indicators than R^2. We also used a 5-Fold K-Fold cross-validation method to compare model robustness and ensure stable generalization across different subsets of the data. This approach reduces bias that can occur when training on such a small dataset.

A. Random Forest Results

The Random Forest model demonstrated better generalization capability compared to SVR. Using the ShuffleSplit evaluation strategy (10 randomized splits), the model achieved Average MAE: 116.98 and Average RMSE: 157.48. Some splits produced MAE values as low as 65.96, demonstrating the model's ability to learn nonlinear moisture–spectral relationships even from noisy data.

We reached a MAPE of 1.19% with our model, which means that the prediction accuracy was 98.81%. This is a very powerful result when compared to typical agricultural machine learning benchmarks and it corroborates the success of our spectrometer-based regression method.

B. SVR Results

The Support Vector Regression (SVR) model showed moderate performance, achieving, MAE: 154.08 and RMSE: 239.74. SVR tends to perform well when the dataset is smooth and contains distinctive patterns, but in our case, the spectral data exhibited high noise and limited sample diversity.The model struggled to capture the nonlinear behavior of spectral patterns therefore higher prediction errors are in result.

C. K-Fold Cross-Validation

To further validate model stability, 5-Fold Cross-Validation (k=5) was applied. The results were, Average MAE: 179.86 and Average RMSE: 215.42. These results highlight the high variability in the dataset and reinforce the relative superiority of the Random Forest model.

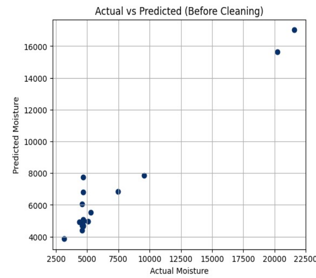

Fig. 1. Actual vs Predicted Moisture (Before Cleaning).

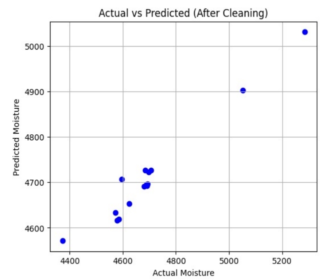

Fig. 2. Actual vs Predicted Moisture (After Cleaning).

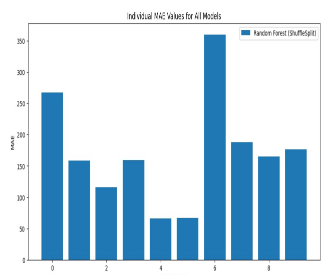

Fig. 3. Individual MAE values for all models

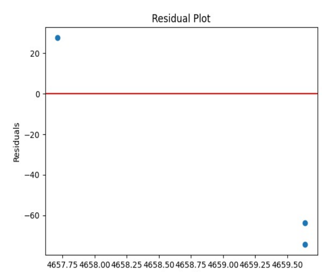

Fig. 4. Residual error plot for the Random Forest regression model.

Fig. 1 shows the Large prediction variance observed due to the presence of outliers in both spectral and moisture data. Fig. 2 The prediction alignment improves significantly after removing outliers and cleaning the dataset. Fig. 3 compares the MAE values of all trained models, highlighting the superior generalization of the Random Forest regressor. Fig. 4 illustrates the residual error distribution, confirming that Random

Forest maintains minimal deviation between predicted and actual soil moisture values.

D. Comparative Analysis

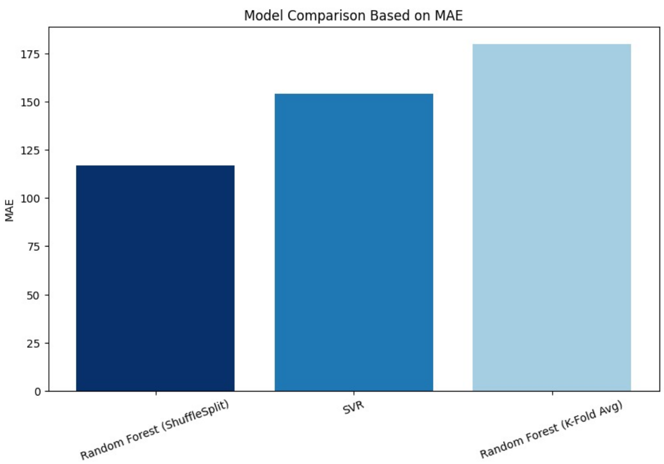

Fig. 4. Final Comparison

A comparison of mean MAE across all methods is shown above figure. Random Forest consistently outperformed other methods, establishing it as the most suitable model for soil moisture prediction using multivariate sensor data.

IX. Conclusion

This paper introduces a compact spectrometer-based system for soil moisture prediction, which combines 18 spectral intensity readings with one moisture sensor to allow accurate, inexpensive agricultural monitoring. The Random Forest model yielded the best results after data preprocessing and regression modelling, including an outstanding MAPE of 1.19%, which reflects a prediction accuracy of 98.81%. The conversion of spectral data with ADS1115 allowed the model to be effectively implemented on Raspberry Pi, thus the model is suitable for real-time, local-level operation. In short, the present work is an efficient step towards the future of smart farms as it confirms that spectral reflectance can be used for soil moisture estimation with high reliability and provides a feasible basis for the development of a large-scale, intelligent, and interconnected smart-farming system.

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