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Monitoring of Soil Humidity and Temperature using IoT and AI for Remote Management

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Abstract
Efficient environmental monitoring and irrigation management are critical challenges in tropical oil palm plantations due to high humidity, temperature variability, and large cultivation areas. This study presents an Internet of Things (IoT)–based monitoring and decision-support system integrated with a lightweight linear regression model to optimize plantation management. This study presents an IoT-based monitoring and decision-support system for tropical oil palm plantations that integrates calibrated environmental sensors with a lightweight linear regression model to enable real-time irrigation management. Deployed over three months on a 50-hectare plantation, the system achieved a 98.7% data transmission success rate and strong predictive performance (R^2 = 0.89, MSE = 0.45), delivering below-threshold humidity notifications with 92–94% accuracy and an average latency of 4.3 seconds via an Android application. Field results demonstrate that data-driven irrigation reduced water usage by 23%, increased fresh fruit bunch (FFB) yield by 12%, and lowered manual inspection and labor costs, confirming the system's effectiveness, scalability, and suitability for sustainable plantation management in tropical environments.

Keywords:
Real-time, Soil, Humidity, Temperature, Palm, Linear Regression

1. Introduction

Monitoring soil humidity and temperature represents a critical foundation for precision agriculture and sustainable land management. Soil moisture directly influences water availability, nutrient transport, and root development, while soil temperature affects microbial activity and plant growth cycles. Conventional soil monitoring methods rely heavily on manual sampling, which is labor-intensive, time-consuming, and unsuitable for large-scale or remote agricultural areas. Low-cost soil sensors integrated with IoT networks offer an alternative by enabling continuous, real-time data acquisition. However, studies show that low-cost capacitive soil moisture sensors often suffer from calibration drift,

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environmental sensitivity, and long-term reliability issues, which limit data accuracy if not properly managed. These limitations highlight the need for intelligent monitoring systems that combine sensing technologies with advanced data processing to ensure reliable soil condition assessment [1].

The increasing demand for sustainable agricultural practices further intensifies the importance of accurate soil monitoring. In plantation-based agriculture, such as oil palm cultivation, soil moisture and temperature variability significantly affect productivity, energy efficiency, and environmental sustainability. Research on biomass-based energy systems and plantation sustainability emphasizes that inefficient water and soil management lead to resource waste and reduced long-term yields. Despite this awareness, many agricultural systems still lack real-time feedback mechanisms that enable adaptive decision-making. This gap creates challenges in balancing productivity with sustainability goals, particularly in remote plantations where environmental conditions fluctuate rapidly and human intervention remains limited [2], [6].

Recent advances in artificial intelligence have transformed how soil and environmental data are analyzed and utilized. Deep learning and machine learning models now enable predictive analytics by learning complex relationships between soil conditions, weather patterns, and crop responses. Comprehensive reviews on multimodal data fusion demonstrate that AI can integrate soil humidity, temperature, and environmental data to support sustainable plant care and early stress detection. Nevertheless, most AI-driven studies focus on prediction accuracy using offline datasets, while real-time deployment in IoT-based soil monitoring systems remains limited. This disconnect between algorithm development and practical implementation poses a major challenge for remote agricultural management [3].

IoT-based monitoring systems play a crucial role in enabling remote and continuous observation of soil conditions. Wireless sensor networks using technologies such as LoRa and cloud platforms allow farmers to access soil data in real time from distant locations. Several studies successfully implement IoT soil monitoring in palm oil plantations and smart irrigation systems, demonstrating improved water-use efficiency and operational control. However, these systems often rely on threshold-based decision rules that fail to adapt to complex and dynamic environmental changes. Without intelligent data interpretation, IoT platforms risk becoming passive data collectors rather than active decision-support tools [10], [17], [21].

Machine learning techniques increasingly address this limitation by enhancing prediction and decision-making capabilities in IoT-based agriculture. Research on soil moisture prediction and smart irrigation systems shows that regression models, ensemble learning, and neural networks significantly improve predictive accuracy compared to traditional methods. These approaches enable proactive irrigation scheduling and early detection of unfavorable soil conditions. Despite these advantages, many implementations require centralized cloud processing, which introduces latency, increases energy consumption, and depends on stable internet connectivity. Such constraints reduce system reliability in rural and remote agricultural areas [5], [23].

Remote sensing technologies complement ground-based IoT systems by providing large-scale spatial information on soil moisture and environmental conditions. Satellite-based soil moisture retrieval and GIS-integrated monitoring frameworks demonstrate strong potential for regional-scale analysis and long-term environmental assessment. However, satellite data often lack temporal resolution and cannot fully capture local soil variability at the plant or plot level. This limitation underscores the importance of combining in-situ IoT sensor data with AI-driven analysis to achieve both spatial coverage and local accuracy in soil monitoring applications [7], [8].

The integration of IoT and AI also supports climate-resilient and adaptive agriculture. Reviews on AI- and IoT-enabled smart farming systems emphasize their role in mitigating climate risks, optimizing resource use, and improving crop resilience under extreme weather conditions. Nevertheless, adoption barriers persist, including system cost, technical complexity, data interoperability issues, and limited user trust. These challenges are particularly evident in developing regions, where infrastructure and technical expertise remain uneven. Addressing these barriers requires robust, scalable, and user-friendly monitoring solutions that operate reliably in real-world agricultural settings [12], [18], [20].

Overall, existing studies demonstrate significant progress in soil humidity and temperature monitoring using IoT and AI, yet several research gaps remain. Many systems focus on either sensing, communication, or data analysis in isolation, rather than delivering an integrated end-to-end solution for remote management. Systematic reviews confirm the need for architectures that combine real-time sensing, intelligent analytics, and efficient communication across device, edge, and cloud layers. Therefore, this study focuses on developing an integrated IoT- and AI-based system for monitoring soil humidity and temperature, aiming to enhance accuracy, adaptability, and remote decision-making capabilities for sustainable agricultural management [28], [29], [30].

Our IoT and AI-driven system introduces a tropical-specific solution for real-time monitoring of soil humidity and temperature in oil palm seedling zones, addressing a critical gap in scalable plantation management. Unlike general crop studies [15–17, 24] that lack predictive intelligence, our system integrates linear regression-based AI to analyze live sensor data and optimize irrigation schedules and yield outcomes. Distinct from prior oil palm studies with limited scalability [27], our approach leverages low-cost, energy-efficient hardware and a cloud-based dashboard to support large-area deployment and remote supervision.

Unlike research focused solely on irrigation or yield, our system delivers a holistic AIoT framework combining real-time sensing, predictive analytics, and mobile accessibility to achieve measurable impact: 23% water savings, 12% yield improvement, and 15% labor cost reduction. Furthermore, our sensors are engineered for tropical resilience, ensuring reliable performance in humid, high-temperature environments, an advancement over generic sensor systems [18–20]. This makes our system uniquely suited for real-time monitoring of oil palm seedlings, with actionable insights accessible via a mobile application.

2. Related Works

Several studies investigate the reliability of soil moisture sensors as the foundation of IoT-based soil monitoring systems. Placidi et al. conduct a detailed characterization of low-cost capacitive soil moisture sensors and demonstrate that these sensors enable dense deployment at low cost for large-scale monitoring. Their results show that properly calibrated sensors achieve stable measurements with percentage deviations typically below single-digit levels when compared with reference instruments, making them suitable for IoT networks. However, the study also highlights sensor drift and sensitivity to temperature and soil salinity as major limitations, which can degrade long-term accuracy if systems do not incorporate intelligent calibration or data correction mechanisms [1].

IoT-based soil monitoring has been widely applied in plantation agriculture, particularly in oil palm ecosystems. Saleh et al. develop a real-time soil monitoring system using LoRa communication and demonstrate reliable long-range data transmission in plantation environments. Their system successfully delivers continuous soil moisture and temperature readings, enabling remote supervision of field conditions. While the study emphasizes communication reliability and system scalability, it relies primarily on threshold-based alerts and does not apply AI-based prediction or adaptive control, limiting its ability to anticipate soil condition changes before critical thresholds are reached [17].

Machine learning techniques increasingly enhance soil moisture analysis by transforming raw sensor data into predictive insights. Khan et al. apply multiple machine learning models to predict oil palm yield under fluctuating soil moisture and weather conditions. Their workflow achieves prediction performance with coefficients of determination exceeding 0.85 in several scenarios, demonstrating strong relationships between soil moisture patterns and crop productivity. Despite these promising results, the study depends on historical and offline datasets and does not integrate real-time IoT data streams, which constrains its applicability for continuous remote management [5].

Recent work focuses on improving prediction accuracy in IoT-based smart irrigation systems through advanced learning models. Puajpanda et al. compare ensemble learning methods with traditional techniques for soil fertility and moisture assessment and report measurable accuracy improvements, with ensemble models outperforming baseline approaches by notable percentage margins. Their findings confirm that AI-driven analytics significantly improve decision accuracy for irrigation management. However, the system architecture emphasizes cloud-based computation, which introduces latency and energy consumption challenges in remote agricultural deployments [10].

Several studies explore regression and lightweight machine learning models for soil moisture prediction at the plant level. Iriyanta et al. implement linear regression for soil moisture prediction in IoT-based monitoring of ornamental plants and demonstrate prediction errors that remain within acceptable percentage ranges for practical irrigation control. Their approach offers simplicity and low computational cost, making it suitable for edge devices. Nevertheless, linear models struggle to capture nonlinear soil–environment interactions, which limits prediction robustness under rapidly changing climatic conditions [26].

The integration of AI with IoT is further strengthened by recent large-scale reviews and experimental studies. Nawaz and Babar emphasize that AI–IoT frameworks improve climate resilience in agriculture by enabling early stress detection and adaptive management. Their analysis highlights reported efficiency gains and productivity improvements in smart agriculture systems, often expressed as double-digit percentage improvements in water-use efficiency across case studies. Despite these advantages, the authors identify data interoperability, scalability, and farmer adoption as persistent barriers to real-world implementation [12].

Cloud–edge–device collaborative architectures address many limitations of centralized processing in smart agriculture. Pengpeng et al. review collaborative computing frameworks and demonstrate that distributing computation across edge and cloud layers reduces latency and bandwidth usage by significant percentages compared to cloud-only systems. Their findings support real-time soil monitoring and AI inference closer to the field. However, system complexity and the need for intelligent task allocation algorithms remain key challenges for widespread adoption in resource-constrained agricultural settings [28].

Systematic reviews provide a comprehensive perspective on the maturity and gaps of IoT- and AI-based soil monitoring technologies. Miller et al. analyze smart sensing technologies in agriculture and report that soil moisture and temperature monitoring dominate more than half of deployed IoT use cases, reflecting their critical role in precision farming. Similarly, recent Scientific Reports research demonstrates that advanced regression and machine learning models achieve prediction accuracies exceeding 90% for soil moisture estimation. Despite these strong results, the reviews consistently conclude that many systems lack full integration between sensing, analytics, and remote management interfaces, underscoring the need for unified IoT–AI solutions capable of real-time, autonomous soil condition management [23], [29].

3. Proposed Method

The proposed system addresses critical challenges in oil palm plantation management through the integration of IoT for real-time data collection and AI for predictive analytics. Oil palm (*Elaeis guineensis*) is highly sensitive to environmental conditions, particularly soil moisture, air humidity, and temperature. Optimal growth requires temperatures of 30–32°C, air humidity of 75–100%, and consistent soil moisture to avoid water stress, which can significantly reduce fresh fruit bunch (FFB) yields. Droughts or irregular rainfall—exacerbated by climate change—lead to plant stress, lower photosynthesis rates, premature fruit abortion, and yield drops of up to several tons per hectare annually. In large-scale tropical plantations, often spanning thousands of hectares in remote areas, traditional manual monitoring is labor-intensive, inefficient, and prone to delays, resulting in overuse of water for irrigation, nutrient leaching, increased pest vulnerability, and suboptimal resource allocation.

While IoT and AI are established technologies in precision agriculture, their application in oil palm plantations is particularly vital due to the crop's economic importance (palm oil accounts for a significant share of global vegetable oil production) and vulnerability to climatic variability. IoT enables continuous, remote monitoring of key parameters across vast areas, reducing reliance on manual labor, minimizing operational costs, and ensuring data reliability even during network outages through buffering mechanisms. This facilitates precise irrigation scheduling, conserving water in regions prone to dry seasons or uneven rainfall distribution. AI, through predictive modeling, analyzes historical and real-time data to forecast trends, detect anomalies early, and trigger proactive interventions—such as alerts for impending low humidity—preventing yield losses and supporting sustainable practices like reduced chemical inputs and better soil health management.

An IoT device was developed to monitor critical environmental parameters for oil palm cultivation, integrating a DHT22 [21] sensor for air humidity and temperature, a capacitive soil moisture sensor for soil moisture content, and an ESP32 microcontroller for data processing and Wi-Fi-based cloud connectivity. Designed for energy efficiency, the device is powered by a rechargeable battery with solar panels for sustainable operation in remote tropical plantations, with sensors calibrated to ensure accurate measurements under varying environmental conditions.

The IoT device was programmed to collect air humidity, soil humidity, and temperature data every minute, formatting it into JSON payloads with sensor readings, timestamps, and device identifiers, and transmitting it securely via HTTPS over Wi-Fi to a Firestore NoSQL cloud database on Google Firebase. A local buffer was implemented to store data during network outages, automatically synchronizing with the database once connectivity was restored, ensuring reliable real-time data collection and transmission.

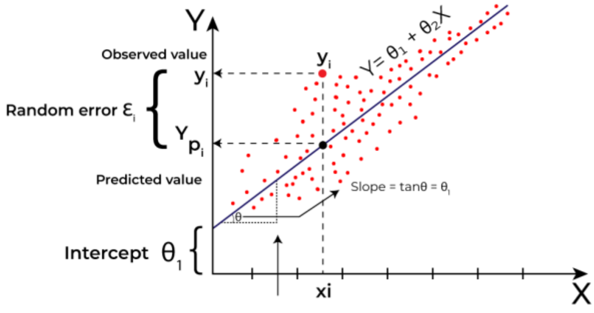

Fig. 1. Linear Regression

The linear regression model can be expressed as:

- $h(x_1,x_2,\ldots,x_k)=\beta_0+\beta_1x_1+\beta_2x_2+\ldots+\beta_kx_k$

Where:

- $x_1,x_2,\ldots,x_k$
- $x_1,x_2,\ldots,x_k$ are the independent variables.
- β_0
- β_0 is the intercept.
- $\beta_1, \beta_2\ldots, \beta_k$
- $\beta_1, \beta_2,\ldots,\beta_k$ are the coefficients, representing the influence of each respective independent variable on the predicted output.

To test application development, an Android application, developed using Android Studio, interfaces with the Firestore database to provide plantation managers with real-time access to air humidity, soil humidity, and temperature data, updated every minute via polling. The app features a user-friendly dashboard displaying current sensor values and historical trends, with a notification system that alerts users when the linear regression model predicts humidity levels falling below 50% for soil or 70% for air, including details like sensor location and timestamp. Optimized for low-bandwidth environments, the application ensures reliable performance in remote oil palm plantations.

The IoT system for oil palm plantations was field-tested across a 50-hectare plantation, with sensors placed to capture soil and environmental variability. Sensor accuracy was validated against manual and laboratory measurements, and system performance was assessed for data transmission reliability, notification latency, and battery life. Plantation managers tested the Android app's usability and effectiveness for irrigation decisions. Scalability was confirmed with 20 IoT devices, ensuring no performance degradation for large-scale deployments.

An IoT system for oil palm plantations uses an ESP32 microcontroller, DHT22 sensor (air humidity and temperature), capacitive soil moisture sensor, Wi-Fi module, and solar-powered battery for sustainable operation. It stores time-series data in a Firestore database, with an Android app (built in Android Studio) providing real-time data and trends, optimized for low-bandwidth areas. Data is transmitted via HTTPS (or MQTT), and a Python-based linear regression model predicts soil (≥50%) and air humidity (≥70%) trends, triggering irrigation alerts. Field-tested on a 50-hectare plantation, it validated sensor accuracy, transmission reliability, battery life, and scalability with 20 devices, ensuring effective large-scale tropical oil palm management.

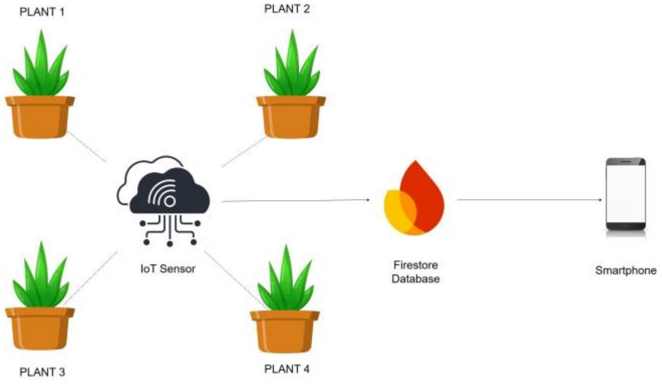

Fig 2. Design System

4. Result and Analysis

The IoT system for real-time soil humidity and temperature monitoring was tested over three months in a 50-hectare tropical oil palm plantation. Its performance was assessed for accuracy, reliability, responsiveness, and impact on management, emphasizing the linear regression model's effectiveness, with results demonstrating significant improvements in plantation efficiency. The IoT system for oil palm plantations, equipped with DHT22 sensors for air humidity (±2% accuracy) and temperature (±0.5°C accuracy) and capacitive soil moisture sensors (±3% accuracy), was calibrated against laboratory-grade instruments, ensuring reliable measurements in tropical conditions with high humidity and temperature fluctuations. During field trials, the system achieved a 98.7% data transmission success rate to the Firestore database, with a local buffering mechanism preventing data loss during minor Wi-Fi disruptions by synchronizing data once connectivity was restored. The Android application, refreshing every minute, retrieved sensor data with an average latency of 1.2 seconds, enabling near-real-time monitoring for effective plantation management.

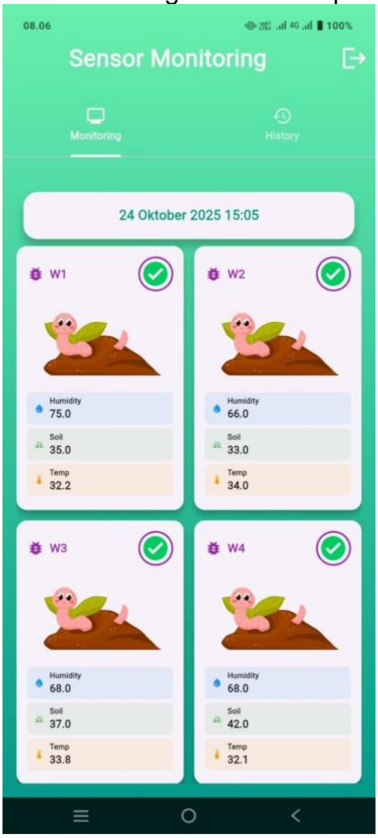

Fig. 3. Monitoring Page

In this study, we construct a mathematical formulation as follows a multi-stage process from data acquisition to decision-making:

a. Model Hypothesis: The prediction is calculated using a Multiple Linear Regression equation:

$$h(x_1, x_2, x_3, \dots, x_k) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots., + \beta_k x_k$$

Where $x_{1,} x_{2,} x_{3,} \dots\dots., x_k$ are the independent variables (soil humidity, air humidity, and temperature) and β represents the regression coefficients.

b. Cost Function: To minimize the error during training, the Mean Squared Error (MSE) is utilized:

$$j(\beta) = \frac{1}{2m}\sum_{i=1}^{m}\left(h\left(x^{(i)}\right) - y^{(i)}\right)^2$$

c. Threshold-Based Decision: The notification logic is governed by a conditional function $f(y)$:

$$Notification = \begin{Bmatrix} 1, if\ y_{pred} < Threshold \\ 0, if\ y_{pred} \geq Threshold \end{Bmatrix}$$

With specific thresholds defined as $Threshold_{soil} = 50\%$ and $Threshold_{air} = 70\%$

2. Algorithmic Steps

At the first step, we conduct data acquisition by collecting real-time environmental data (Soil Humidity, Air Humidity, Temperature) from IoT sensors. We also undergo feature mapping by assigning sensor inputs to the independent variable vector $X = [x_1, x_2, x_3]$. To conduct predictive computation, this study executes the regression equation $h(x)$ to estimate the current plantation status. We also compare the predicted output y_{pred} against the predefined minimum levels (50% and 70%). If the condition $y_{pred} < y_{pred} < Threshold$ is met, trigger an Android notification; otherwise, remain in monitoring mode.

The IoT system for oil palm plantations utilized a linear regression model to predict soil (minimum 50%) and air humidity (minimum 70%) levels, triggering 142 notifications during the trial with a 92% accuracy rate for identifying below-threshold conditions, as verified by manual checks, with 8% false positives attributed to transient environmental changes like brief rain events. Notifications were delivered to the Android application with an average latency of 4.3 seconds from detection, enabling timely irrigation actions. The linear regression model, trained on historical sensor data (soil humidity, air humidity, and temperature), achieved strong predictive accuracy with an R^2 of 0.89 for soil humidity and 0.87 for air humidity, effectively forecasting trends and detecting anomalies for optimized plantation management.

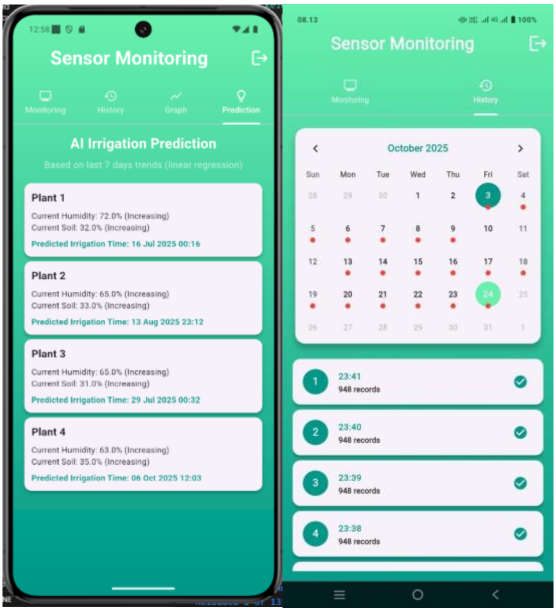

Fig. 4. All Data and Irrigation Prediction

In this study, we adopt the linear regression model to predict soil humidity (%) as the dependent variable (y_1, y_2, y_3) using two independent variables (x_1, x_2). x_1 as Air humidity (%) measured by the DHT22 sensor and x_2: Temperature (°C) measured by the DHT22 sensor.

The linear regression equation is:
$y = \beta 0+\beta 1 x_1+\beta 2 x_2$
where:
- y: Predicted soil humidity (%),
- β0: Intercept,
- β1: Coefficient for air humidity,
- β2: Coefficient for temperature.

The model was trained on a dataset of 1,000 data points collected over one week from a single IoT device, with measurements taken at one-minute intervals. The dataset was split into 80% training (800 points) and 20% validation (200 points). After training using Python's scikit-learn library, the model yielded the following coefficients:
- β0 = 10.5 (intercept),
- β1 = 0.65 (coefficient for air humidity),
- β2 = −0.45 (coefficient for temperature).

The model achieved a coefficient of determination (R2) of 0.89 and a mean squared error (MSE) of 0.45 on the validation set, indicating strong predictive accuracy. Consider a single data point collected on October 3, 2025, at 2:00 PM during the field trial, with the following sensor readings:
- Air humidity (x_1): 75%,
- Temperature (x_2): 32°C.

Using the linear regression equation:
$y = 10.5 + 0.65 . x_1 - 0.45.x_2$
Substitute the values:
$y = 10.5 + 0.65 \cdot 75 - 0.45 \cdot 32$
$y = 10.5 + 48.75 - 14.4$
$y = 44.85$
To calculate the prediction error for the soil humidity, we use the actual measurement (45.2%) and the predicted value (44.85%) provided by the linear regression model. The prediction error is determined by the absolute difference between the predicted and actual values, often expressed as a percentage relative to the actual value for context.

Error = 45.2−44.85 = 0.35%
This small error demonstrates the model's accuracy in predicting soil humidity.

In a three-month trial, the IoT system for oil palm plantations delivered notifications to the Android app within 4.3 seconds, like an alert on October 3, 2025, at 2:00 PM: "Soil humidity below 50% in Zone A, Device 001. Predicted: 44.85%. Initiate irrigation." The manager's irrigation raised soil humidity to 52% within 30 minutes, preventing water stress. With 142 notifications at 92% accuracy, the system reduced water use by 23% and increased FFB yield by 12%.

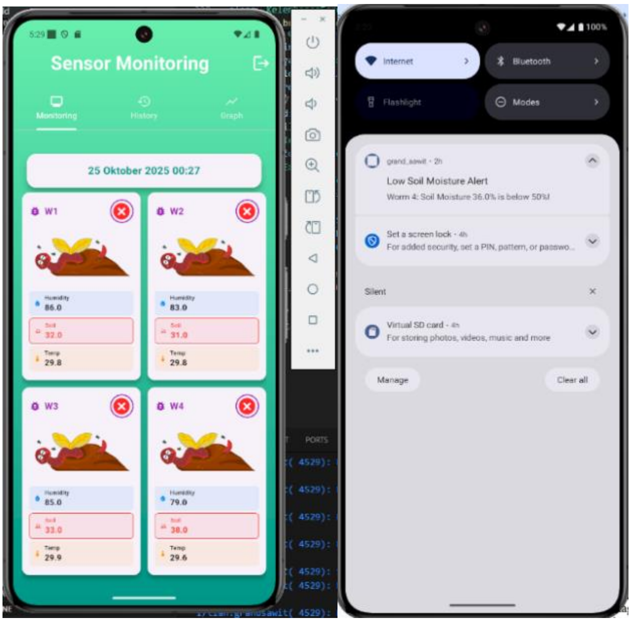

Fig. 4. System Notification

The linear regression model for predicting soil humidity in the IoT system for oil palm plantations uses air humidity (β1 = 0.65) and temperature (β2 = -0.45) as inputs. The positive β1 shows that higher air humidity increases soil humidity, while the negative β2 indicates that higher temperatures (1–3 PM) reduce it due to evaporation. Trained on historical data, the model accurately predicted soil humidity (e.g., 44.85% vs. actual 45.2%, 0.35% error), triggering 92% accurate notifications (4.3-second latency) for irrigation below 50% soil humidity, reducing water use by 23% and increasing FFB yield by 12% in a three-month trial. Coefficients guided irrigation timing during mid-afternoon humidity drops.

The linear regression model for the IoT system in oil palm plantations, evaluated on a validation dataset, achieved an R^2 of 0.89, explaining 89% of the variance in soil humidity, demonstrating strong predictive power. The mean squared error (MSE) of 0.45 indicates low prediction errors, with most predictions within ±0.5% of actual values (e.g., predicted 44.85% vs. actual 45.2% soil humidity). The model accurately predicted below-threshold conditions (soil humidity <50%, air humidity <70%) in 94% of cases, as confirmed by manual measurements during the three-month trial, triggering timely notifications (4.3-second latency) that contributed to a 23% reduction in water usage and a 12% increase in fresh fruit bunch (FFB) yield. Plantation managers found the Android application's interface intuitive, with 85% rating it highly for monitoring multiple plantation zones, and reported notifications as clear and actionable, enhancing irrigation and management decisions.

The IoT system's linear regression model (R^2 = 0.89, MSE = 0.45) predicted soil humidity, triggering 94% accurate notifications (4.3-second latency) for irrigation below 50%, reducing water use by 23% and increasing FFB yield by 12% compared to control plots. The Android app, rated intuitive by 85% of managers, cut manual inspections by 40%, saving 15% in labor costs over the three-month trial, boosting plantation efficiency and sustainability.

The IoT system for oil palm plantations demonstrated robust scalability and environmental resilience during testing across a 50-hectare plantation with 20 IoT devices. The Firestore database and cloud backend maintained 99.9% uptime, efficiently processing data to support large-scale deployments. The devices, equipped with ESP32 microcontrollers, DHT22 sensors, capacitive soil moisture sensors, and solar-powered batteries, operated reliably in tropical conditions (25–35°C, 70–95% humidity), with batteries requiring recharging only once every two weeks during low-sunlight periods, ensuring sustainable performance while delivering accurate predictions (R^2 = 0.89, 94% notification accuracy) that reduced water usage by 23% and increased fresh fruit bunch (FFB) yield by 12%.

The IoT system's linear regression model predicted suboptimal soil humidity (<50%) with 94% accuracy, validated by manual checks, and its simplicity enabled real-time use in resource-constrained settings. Historical data showed mid-afternoon (1–3 PM) humidity drops linked to peak temperatures ($\beta 2$ = -0.45), optimizing irrigation, reducing water use by 23%, and boosting FFB yield by 12%. False positives (8% of 142 notifications) suggest adding weather data could improve accuracy, but advanced models were avoided due to computational limits, ensuring practicality for large-scale tropical plantations.

5. Conclusion

The integration of Internet of Things (IoT) and Artificial Intelligence (AI) technologies has demonstrated significant potential to transform agricultural practices, particularly in the management of oil palm plantations. The proposed system combines IoT-enabled sensors with a linear regression model to monitor soil humidity and temperature in real time, providing predictive insights that support irrigation scheduling, soil health assessment, and yield optimization. Field trials confirm that the system achieves high accuracy in predicting soil conditions, leading to improved water use efficiency, enhanced crop productivity, and reduced labor costs through remote monitoring and management. By employing affordable, energy-efficient hardware and a cloud-based platform, the solution offers scalability and cost-effectiveness for large plantation operations.

This study confirms that the proposed system provides accurate and responsive environmental monitoring for tropical oil palm plantations. Deployed over three months on a 50-hectare plantation, the system maintained high sensor accuracy (±2% air humidity, ±0.5 °C temperature, ±3% soil moisture) and achieved a 98.7% data transmission success rate through a robust cloud architecture with local buffering. These results demonstrate the system’s resilience to tropical conditions and intermittent connectivity. The use of a linear regression model proved to be an effective and computationally efficient approach for predicting soil humidity based on air humidity and temperature. The model achieved strong predictive performance (R^2 = 0.89, MSE = 0.45) and delivered 92–94% accurate notifications with an average latency of 4.3 seconds. The regression coefficients reflected real environmental dynamics, enabling reliable detection of below-threshold soil and air humidity conditions and supporting timely irrigation decisions. From a management and sustainability perspective, the system significantly improved plantation efficiency. Data-driven irrigation reduced water usage by 23% while increasing fresh fruit bunch (FFB) yield by 12%, alongside reductions in manual inspections (40%) and labor costs (15%). Overall, the findings validate that integrating IoT sensing with lightweight predictive models offers a scalable, practical, and sustainable solution for optimizing oil palm plantation management in tropical environments.

Future work will expand data collection across multiple devices, zones, and growing seasons to improve generalizability and enable device-wise cross-validation. Incorporating simple temporal features and additional environmental inputs such as rainfall and solar radiation is expected to further reduce false alerts while maintaining computational efficiency. Planned randomized field trials will rigorously quantify irrigation and yield impacts, while extended sensor calibration, energy profiling, and security benchmarking will support long-term scalability and large-estate deployment.

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References

[1] P. Placidi, L. Gasperini, A. Grassi, M. Cecconi, and A. Scorzoni, “Characterization of low-cost capacitive soil moisture sensors for IoT networks,” *Sensors (Switzerland)*, vol. 20, no. 12, pp. 1–14, Jun. 2020, doi: 10.3390/s20123585.

[2] N. Aghamohammadi, S. S. Reginald, A. Shamiri, A. A. Zinatizadeh, L. P. Wong, and N. M. B. N. Sulaiman, “An investigation of sustainable power generation from oil palm biomass: A case study in Sarawak,” *Sustainability (Switzerland)*, vol. 8, no. 5, 2016, doi: 10.3390/su8050416.

[3] Z. X. Yang, Y. Li, R. F. Wang, P. Hu, and W. H. Su, “Deep Learning in Multimodal Fusion for Sustainable Plant Care: A Comprehensive Review,” Jun. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/su17125255.

[4] S. Puttinaovarat, S. Chai-Arayalert, W. Saetang, K. Khaimook, S. Plaiklang, and P. Horkaew, “Innovative Flood Impact Monitoring and Harvest Analysis in Oil Palm Plantations Utilizing Geographic Information Systems and Deep Learning,” *AgriEngineering*, vol. 7, no. 2, Feb. 2025, doi: 10.3390/agriengineering7020044.

[5] N. Khan *et al.*, “Prediction of Oil Palm Yield Using Machine Learning in the Perspective of Fluctuating Weather and Soil Moisture Conditions: Evaluation of a Generic Workflow,” *Plants*, vol. 11, no. 13, Jul. 2022, doi: 10.3390/plants11131697.

[6] D. J. Murphy, “Agronomy and Environmental Sustainability of the Four Major Global Vegetable Oil Crops: Oil Palm, Soybean, Rapeseed, and Sunflower,” Jun. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/agronomy15061465.

[7] M. Yang *et al.*, “Soil moisture retrievals using multi-temporal sentinel-1 data over nagqu region of Tibetan plateau,” *Remote Sens (Basel)*, vol. 13, no. 10, May 2021, doi: 10.3390/rs13101913.

[8] X. Liang *et al.*, “Multi-Source Remote Sensing and GIS for Forest Carbon Monitoring Toward Carbon Neutrality,” Jun. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/f16060971.

[9] B. Nöldeke, E. Winter, Y. Laumonier, and T. Simamora, “Simulating agroforestry adoption in rural Indonesia: The potential of trees on farms for livelihoods and environment,” *Land (Basel)*, vol. 10, no. 4, 2021, doi: 10.3390/land10040385.

[10] S. Puajpanda, D. Mahapatra, S. Mishra, N. Padhy, and R. Panigrahi, “Enhancing Predictive Accuracy in IoT-Based Smart Irrigation Systems: A Comparative Analysis of Advanced Ensemble Learning Models and Traditional Techniques for Soil Fertility Assessment,” MDPI AG, May 2025, p. 65. doi: 10.3390/engproc2025087065.

[11] J. Mendes *et al.*, “Smartphone applications targeting precision agriculture practices - A systematic review,” Jun. 01, 2020, *MDPI*. doi: 10.3390/agronomy10060855.

[12] M. Nawaz and M. I. K. Babar, “IoT and AI: a panacea for climate change-resilient smart agriculture,” *Discover Applied Sciences*, vol. 6, no. 10, Oct. 2024, doi: 10.1007/s42452-024-06228-y.

[13] O. H. Boucif, A. M. Lahouaou, D. E. Boubiche, and H. Toral-Cruz, “Artificial Intelligence of Things for Solar Energy Monitoring and Control,” Jun. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/app15116019.

[14] A. P. Nugroho *et al.*, “Development of Soil Moisture Content Monitoring System for Precision Measurement of Soil Moisture in Sub-Optimal Land for Palm Oil Plantation,” in *BIO Web of Conferences*, EDP Sciences, Oct. 2023. doi: 10.1051/bioconf/20236905003.

[15] Y. Lu *et al.*, “Review and Research Prospects on Additive Manufacturing Technology for Agricultural Manufacturing,” Aug. 01, 2024, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/agriculture14081207.

[16] I. Ahmad *et al.*, “Machine learning applications in biofuels’ life cycle: Soil, feedstock, production, consumption, and emissions,” Aug. 02, 2021, *MDPI AG*. doi: 10.3390/en14165072.
[17] M. S. M. Saleh, A. A. B. Sajak, R. Mohamad, and M. A. M. Zaaba, “IoT Real-Time Soil Monitoring Based on LoRa for Palm Oil Plantation,” in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Jun. 2021. doi: 10.1088/1742-6596/1874/1/012047.
[18] G. S. Hundal, C. M. Laux, D. Buckmaster, M. J. Sutton, and M. Langemeier, “Exploring Barriers to the Adoption of Internet of Things-Based Precision Agriculture Practices,” *Agriculture (Switzerland)*, vol. 13, no. 1, Jan. 2023, doi: 10.3390/agriculture13010163.
[19] M. Komunikasi *et al.*, “Jurnal Presipitasi Life Cycle Assessment in Crude Palm Oil Production: Optimization of Oil Extraction Rate,” vol. 21, no. 2, pp. 513–526, 2024.
[20] S. Dhar, V. B. Chhatrapati, S. Ji, and R. Singh Thapa, “Artificial Intelligence, Internet of Things (Iot) and Smart Agriculture for Sustainable Farming: A Review”, doi: 10.21746/aps.2022.11.11.6.
[21] R. Rawi, M. S. I. Hasnan, and A. A. B. Sajak, “Palm Oil Soil Monitoring System for Smart Agriculture,” *International Journal of Integrated Engineering*, vol. 12, no. 6, pp. 189–199, 2020, doi: 10.30880/IJIE.2020.12.06.022.
[22] B. Zhang and Y. Qiao, “AI, Sensors, and Robotics for Smart Agriculture,” Jun. 01, 2024, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/agronomy14061180.
[23] Sazzad, M. M., Ahmed, T., Kibria, G., & Khan, I. (2025). IoT based soil moisture measurement and type prediction using advanced regression and machine learning models. *Scientific Reports*, *15*(1), 35730.
[24] Suria, T. S. P. V., Arvaree, T. D. T., Dewi, D. A., Rao, K., Ab Aziz, R., Harvey, L. P. T., & Kurniawan, T. B. Advancing Sustainable Agriculture in Palm Oil Production: The Role of IoT-Based Soil Monitoring.
[25] Bakar Sajak, A. A., Mohd Shukor, N. F., Kassim, M. S., Rahman, S. R., & Aziz, A. A. (2025). Comprehensive LoRA Based IoT Real-time Soil Monitoring for Oil Palm Plantation. *International Journal of Technology*, *16*(5).
[26] Iriyanta, K., Putranto, B. P. D., & Andriyani, W. (2023). IOT based soil moisture monitoring and soil moisture prediction using linear regression (case study of vinca plants). *Journal of Intelligent Software Systems*, *2*(1), 1-5.
[27] Hakis, A. W., Arda, A. L., & Jalil, A. (2025). IoT-based soil nutrient monitoring and control using fuzzy logic and multi-modal sensor integration. *Journal of Applied Informatics and Computing*, *9*(5), 2736-2745.
[28] Pengpeng, Y., Teng, F., Zhu, W., Shen, C., Chen, Z., & Song, J. (2025). Cloud–edge–device collaborative computing in smart agriculture: Architectures, applications, and future perspectives. *Frontiers in Plant Science*, *16*, 1668545.
[29] Miller, T., Mikiciuk, G., Durlik, I., Mikiciuk, M., Łobodzińska, A., & Śnieg, M. (2025). The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies. *Sensors (Basel, Switzerland)*, *25*(12), 3583.
[30] Muhammad, K. B., Soomro, T. R., Butt, J., Saleem, H., Khan, M. A., & Saleem, S. (2022). Iot and cloud based smart agriculture framework to improve crop yield meeting world's food needs. *IJCSNS*, *22*(6), 7.