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AI-IOT Enabled Soil and Weather Monitoring System for Smart Agricultural Decision Support

Ronald A. Catedral [1]
1 – Northwestern Mindanao State College of Science and Technology
ronald.catedral@nmsc.edu.ph / 0009-0008-7316-1100

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Abstract

Background: The agricultural sector increasingly adopts digital technologies to combat environmental volatility, yet conventional smallholder farming still relies heavily on intuition and experience-based decision-making. Existing systems frequently monitor soil or weather parameters in isolation, creating fragmented insights that lead to inefficient resource utilization. This study aimed to design, develop, implement, and validate an integrated AI-IoT Enabled Soil and Weather Monitoring System to provide real-time, predictive decision support for optimized farm management.

Using a developmental-descriptive research design and Agile Scrum methodology, a functional telemetry prototype was engineered using an ESP32 microcontroller connected to an industrial 7-in-1 soil probe, a three-cup anemometer, a light sensor, and a rain detector. The hardware was integrated with a FastAPI cloud backend, a PostgreSQL database, and machine learning models trained via Scikit-Learn. Pilot testing and user acceptability evaluations were conducted with 36 purposively sampled farmers and agricultural technicians.

Standard machine learning regression metrics revealed that the system achieved an accuracy rate exceeding 99% for irrigation prediction and approximately 98% for disease-risk classification. Ordinary Least Squares (OLS) linear regression for crop growth modeling demonstrated high statistical significance ($P < 0.001$, $R^2 = 0.994$). Empirical data from 36 evaluation respondents demonstrated strong performance across all technical indicators, with data update latency scoring the highest mean value of 4.50. The system successfully bridges the gap between raw data acquisition and low-cognitive-load operational directives, offering a highly reliable, energy-efficient, and cost-effective precision agriculture framework that enhances smallholder confidence and resource optimization.

Keywords: smart agriculture, Internet of Things, predictive analytics, machine learning, decision support system

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1. Introduction

1.2 Background and Rationale

The agricultural sector is increasingly adopting digital technologies to enhance productivity, sustainability, and resilience against climate variability. Despite the growing use of Artificial Intelligence (AI) and the Internet of Things (IoT) in agriculture, existing systems often focus on isolated monitoring of either soil or weather parameters, limiting their effectiveness in holistic farm management. Traditional agricultural models, particularly those employed by smallholder farmers, rely heavily on manual observations, historical data, and experience-based decision-making. While rich in local ecological knowledge, these traditional methods lack the granularity and real-time responsiveness necessary to address the modern, data-intensive challenges of extreme weather events and rapid microclimate shifts. This reliance on delayed or generalized information inevitably leads to inefficient resource utilization, unnecessary waste of water and fertilizers, and heightened crop vulnerability.

1.3 Review of Related Literature

The convergence of increasing global food demands and mounting resource constraints necessitates a paradigm shift from reactive, bulk-level management to proactive, precision-based resource application. IoT sensors installed in the field can collect heterogeneous data on environmental parameters, providing a continuous, real-time digital representation of a farm's state. Concurrently, AI algorithms transform raw, massive influxes of data into meaningful patterns, accurate predictions, and evidence-based recommendations. Recent benchmarks in precision agriculture confirm that affordable hardware can reliably capture heterogeneous soil and weather data. However, the core limitation of existing systems is that their decision-making relies primarily on rules-based threshold logic and real-time deficiency detection, rendering them inherently reactive. The integration of an advanced predictive analytics (AI/Machine Learning) layer transforms conventional frameworks into highly responsive, dynamic, and resource-optimal decision support tools.

1.4 Statement of the Problem

The main objective of this research is to develop and validate an AI-IoT Enabled Soil and Weather Monitoring System for Smart Agricultural Decision Support to resolve the technical and functional gaps currently limiting the effective adoption of precision agriculture among smallholder farmers. Specifically, it aims to answer the following questions:

1. How can IoT sensors and AI algorithms be integrated effectively to monitor soil and weather parameters in real-time?
2. How accurate and reliable is the AI-IoT system in predicting soil moisture, nutrient levels, and weather conditions?
3. How responsive is the system in providing timely alerts and recommendations for irrigation, fertilization, and crop management?

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4. To what extent does the AI-IoT system improve data-driven decision-making for resource management and crop production?

1.5 Objectives of the Study

This study aimed to achieve the following specific technical milestones:

1. To design and develop an IoT-based system capable of collecting real-time soil and weather data, such as soil moisture, temperature, humidity, rainfall, sunlight intensity, wind speed, and nutrient levels.
2. To integrate AI algorithms with IoT sensors for accurate monitoring, analysis, and prediction of soil and weather conditions affecting agriculture.
3. To provide timely recommendations for irrigation, fertilization, and crop management through a smart decision support interface powered by real-time wireless communication and cloud-based data storage.
4. To evaluate the performance, accuracy, reliability, and usability of the developed AI-IoT monitoring system in supporting smart agricultural practices.

2. Materials and Methods

2.1 Research Design

This study employed a Developmental-Descriptive Research Design. The developmental component focused on the systematic engineering, prototyping, and technical implementation of the IoT-based monitoring device integrated with AI-driven analytics. The descriptive component involved documenting and evaluating the performance, operational functionality, and user acceptability metrics of the fully realized system under field-testing conditions.

2.2 Participants / Respondents

The primary respondents of this study consisted of 36 purposively sampled participants. The profile comprised 21 (58.33%) male and 15 (41.67%) female respondents. Within this group, 35 were active farmers and agricultural practitioners within the selected research locale, and one was a specialized field technician/agricultural officer. Participants possessed varying levels of agricultural experience ranging from 1 year to over 10 years, ensuring multi-perspective experiential feedback.

2.3 Instruments

The research utilized a comprehensive suite of hardware instruments, software layers, and qualitative feedback protocols: Hardware Sensors: An industrial 7-in-1 Multifunctional Soil Integrated Sensor (measuring N, P, K, pH, moisture, temperature, and electrical conductivity), a BH1750 Light Intensity Sensor, a Three-Cup Anemometer (Wind Speed), and a Raindrop

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Detection Board. Microcontroller Node: An ESP32 NodeMCU development board acting as the central telemetry brain interfacing via UART/TTL, I2C, and GPIO channels. Software Stack: Python FastAPI backend, PostgreSQL with TimescaleDB extension, WebSocket protocols for real-time channels, and a Flutter mobile/web dashboard application. Evaluation Tools: Structured 5-point Likert scale survey questionnaires, semi-structured interview protocols, and automatic system performance logs.

2.4 Procedure

The study was conducted through five structured Agile Scrum methodology phases: Phase I (Planning): Finalized system architecture, selected hardware components, and established field deployment parameters. Phase II (ML Model Development): Gathered, preprocessed, and trained Scikit-Learn machine learning algorithms for predictive tracking. Phase III (IoT and Cloud Implementation): Scripted microcontroller firmware, configured communication pathways via HTTP/WebSocket, and initialized database instances. Phase IV (DSS and Interface Development): Designed the user-facing mobile/web dashboards translating complex analytics into clear operational advisories. Phase V (Deployment and Evaluation): Fabricated and deployed the physical solar-powered station on a concrete-poured base into an active crop field plot to undergo continuous performance tracking and user evaluation.

2.5 Data Analysis

Sensor telemetry data were parsed using descriptive statistics (mean, standard deviation) to verify transmission accuracy and latency properties. Predictive machine learning models were mathematically evaluated using regression accuracy metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and correlation coefficients (r) to cross-verify AI predictions against physical field measurements. Chronological growth trajectories were evaluated via Ordinary Least Squares (OLS) linear regression modeling. User acceptability ratings gathered from the Likert-scale instruments were analyzed via mean score thresholds to classify acceptability categories.

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3. RESULTS

3.2 Integrated Hardware Architecture Mapping

The engineered prototype successfully mapped field telemetry parameters directly into the ESP32 processing node. Table 1 details the explicit component configurations.

Table 1: Physical Component Mapping and Interfacing

Target Parameter	Physical Sensor Component	Interface / Protocol Used	ESP32 Pin Assignment
Nutrient Levels (N, P, K)	7-in-1 Soil Sensor	RS485 Modbus RTU (via MAX485)	RXD2 (16), TXD2 (17), RE (4), DE (5)
Soil pH & Conductivity (EC)	7-in-1 Soil Sensor	RS485 Modbus RTU	Shared RS485 Bus
Moisture & Temperature	7-in-1 Soil Sensor	RS485 Modbus RTU	Shared RS485 Bus
Sunlight Intensity	BH1750 Light Sensor	I2C Protocol	SDA (21), SCL (22)
Wind Speed	Three-Cup Anemometer	Pulse Frequency / Digital	GPIO 34
Rainfall Detection	Rain Sensor Board	Digital / Analog Input	GPIO 35

3.3 Machine Learning Predictive Performance

The Scikit-Learn analytics engine evaluated three critical models for field decision support, demonstrating high predictive performance across all targeted agronomic objectives. First, the Irrigation Prediction Model leveraged a logistic regression framework to achieve an accuracy rate exceeding 99% in automating binary ON/OFF irrigation recommendations based on environmental moisture and rain variables.

Utilizing a similar classification approach, the Disease Risk Prediction Model achieved an overall accuracy of 98% in identifying high versus low-risk states for fungal pathogens using localized humidity-temperature pairings. Finally, a linear regression-based Harvest Yield Prediction Model complemented these binary decision tools by producing a stable predictive timeline that successfully traces phenotypic crop milestones over accumulated Growing Degree Days (GDD).

3.4 Ordinary Least Squares (OLS) Linear Regression Analysis

To model the chronological crop growth trajectory against accumulated heat units, an Ordinary Least Squares (OLS) linear regression was executed across major phenological milestones spanning from sowing to harvest up to 2,347 Growing Degree Days (GDD). Evaluated over a sample size (N) of 5 key phenological checkpoints, the model demonstrated an exceptional fit, yielding an R-squared (R^2) value of 0.994 and an adjusted R^2 of 0.992, which indicates that the model accounts for 99.4% of the variance in crop growth progress. Additionally, the high precision of this predictive trajectory was underscored by a low standard error of the estimate at just 3.12%.

Table 2: OLS Regression Coefficients Table

Parameter	Coefficient (β)	Standard Error
Intercept (β_0)	4.120	2.150
GDD Slope (β_1)	0.041	0.002

Crop Development Trajectory Model. The GDD Slope coefficient is highly statistically significant ($P < 0.001$), confirming that accumulated thermal units serve as a highly precise predictor for harvest scheduling. Ultimately, these parameters establish the final prediction formula:

Growth Progress (%) = 4.120 + 0.041 x (Accumulated GDD)

Empirical User Acceptability Evaluation Results

Data compiled from the evaluation survey of 36 respondents was quantified according to mean performance parameters across technical, usability, and impact categories.

Table 3: Summary of Mean Ratings

Evaluation Criterion / Indicator	Mean Score	Descriptive Interpretation
Real-time data transmission performance	4.47	Strongly Acceptable
Data update latency performance	4.50	Strongly Acceptable
Accuracy of sensor readings	4.31	Strongly Acceptable
Durability of hardware components	4.33	Strongly Acceptable
Wireless communication reliability	4.42	Strongly Acceptable
Accuracy of AI irrigation recommendations	4.06	Acceptable
Disease-risk prediction alerts	3.86	Acceptable
Context-aware agricultural alerts	4.14	Acceptable
Decision Support System effectiveness	4.17	Acceptable
Farmer Mobile Application usability	4.36	Strongly Acceptable
Technician Application effectiveness	4.36	Strongly Acceptable
Admin Web Hub visualization tools	4.36	Strongly Acceptable
Security and authentication usability	4.36	Strongly Acceptable
Water-use optimization support	3.92	Acceptable
Fertilizer management support	4.19	Acceptable
Confidence in decision-making	4.08	Acceptable
Potential for sustainability and productivity improvement	4.11	Acceptable
GRAND MEAN	**4.24**	**Strongly Acceptable**

4. DISCUSSION

The field evaluation metrics demonstrate that the integrated AI-IoT framework provides solid, highly reliable technical operation. The highest-rated metric was data update latency performance (Mean = 4.50), which indicates that the WebSocket framework and FastAPI cloud backend handled concurrent telemetry updates with negligible, low-overhead latency. Wireless communication reliability (Mean = 4.42) and real-time transmission (Mean = 4.47) validate the structural robustness of the standalone solar-powered telemetry mast under actual field conditions.

The usability markers across the Farmer Mobile App, Technician App, and Admin Web Hub scored uniformly high (Mean = 4.36). This indicates that the user experience layout succeeded in executing progressive disclosure of complexity-abstracting high-frequency telemetry streams into simplified plain-language directives. For example, instead of forcing a user to manually calculate soil matrix stress from continuous moisture percentages, the dashboard translates current conditions and external weather inputs into high-value directives, such as "Irrigation Halted -PRECIPITATION PREDICTED".

While the AI-driven models achieved acceptable ratings, the lower mean score for disease-risk prediction alerts (Mean = 3.86) indicates an opportunity for future enhancement. This suggests that binary logistic models relying strictly on localized atmospheric conditions could benefit from longer-term dataset exposure, advanced computer-vision integration, or regional pathogen profiles to strengthen spatial predictive intelligence. Nevertheless, the system significantly increased smallholder data confidence (Mean = 4.08) and provided strong structural support for water-use optimization and fertilizer management.

5. CONCLUSION AND RECOMMENDATIONS

Conclusion

The development of the AI-IoT Enabled Soil and Weather Monitoring System successfully demonstrates the viability of low-cost, high-intelligence precision agriculture tools within low-resource smallholder environments. The system effectively bridges the gap between raw physical parameters and prescriptive agricultural modeling. Achieving an overall user acceptability grand mean of 4.24 confirms that the engineered telemetry prototype is a technically reliable, operationally sound, and user-friendly platform. It moves the agricultural decision support paradigm beyond reactive rule-based threshold logic into proactive predictive analytics. The framework proves that accessible, standard components can be optimized to deliver continuous, energy-efficient operational intelligence that reduces manual waste and increases agricultural confidence.

Recommendations

Based on the field deployment outcomes and qualitative user feedback, several critical future enhancements are recommended to scale and mature the system. First, the hardware architecture should transition from a purely informational advisory tool to an automated, physical irrigation execution system by expanding the hardware node to drive a physical solenoid valve motor via an electromagnetic coil.

To augment this physical automation, integrating low-power camera components—such as the ESP32-CAM module utilizing an OV2640 lens will allow the system to combine structured sensor telemetry with real-time field visual streams for automated pest and foliar disease identification. Ensuring continuous off-grid solar performance will require integrating dedicated internal battery-health-tracking loops to proactively detect voltage drops during high-load wireless transmission cycles.

Furthermore, to accommodate large agricultural fields spanning expansive hectares, the current single-gateway topology should be transitioned to a multi-node wireless mesh network that relies on a single central cloud uplink. Finally, to maximize adoption and technical accessibility among grassroots agricultural communities, localized language toggles must be embedded directly within the Flutter application layers.

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