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AI-IoT Integrated Framework for Real-time Soil Monitoring and Nutrient Prediction in Precision Agriculture

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Monitoring soil moisture and nutrient levels is crucial for increasing agricultural productivity. Traditional soil analysis methods are laborious and inadequate for real-time decision-making, leading to wasteful resource allocation, which can result in suboptimal crop yields and increased costs for farmers. This research introduces an AI-integrated IoT (AI-IoT) framework for real-time soil monitoring and nutrient forecasting in precision agriculture. The suggested system combines soil moisture and nitrogen (N), phosphorus (P), and potassium (K) sensors with a microcontroller, powered by an off-grid solar unit, facilitating deployment in remote agricultural settings. Sensor data are transferred to a cloud platform via the message queuing telemetry transport (MQTT) protocol, where machine learning algorithms evaluate the data to provide watering and fertilizer recommendations. The system underwent validation at two field sites in Tamil Nadu, India, spanning a duration of 30 days. Experimental findings indicate a prediction accuracy of 92% with minimal error rates, surpassing traditional models. The suggested methodology facilitates data-informed decision-making, minimizes resource depletion, and improves sustainable agriculture practices.

1. Introduction

The purpose of soil management is to improve crop productivity with minimal use of resources, such as water and fertilizers, so as to enhance efficiency and diminish environmental impacts.(1–3) This is particularly the case in developing countries like India where agriculture is a key sector for food security and economic stability.(1–3) Traditional soil testing methods are based on laboratory analysis, which is time-consuming and labour-intensive, and does not provide real-time information for decision-making at the field level. Consequently, farmers do not receive timely information on the soil nutrient status, moisture levels, and crop requirements, resulting in inefficient use of resources. Recent advances in IoT technologies have allowed the continuous monitoring of soil parameters using sensor-based systems.(4–7) However, most of the existing IoT solutions are restricted to data acquisition and visualization without predictive

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intelligence. As a result, farmers may over-apply water and fertilizers, which can negatively affect crop yield and sustainability.

The fusion of embedded systems, wireless sensor networks (WSNs), and IoT has profoundly transformed precision agriculture.[4,8,9] WSNs provide energy-efficient and scalable solutions for agricultural monitoring, and IoT-enabled systems have improved irrigation management and nutrient monitoring by using real-time sensing.[6,10,11] Furthermore, innovations such as paper-based soil testing devices,[12] smart fertilizers,[13] and compact nutrient analysers[14] have brought precision agriculture technologies closer to resource-constrained farmers. The integration of AI with IoT has further enhanced the predictive capabilities, allowing data-driven irrigation and fertilization decisions.[12,15] Machine learning (ML) techniques, especially ensemble models like random forest, have shown better performance in prediction tasks over traditional ones owing to their immunity against overfitting and better generalization.[11,15,16] Furthermore, cloud-assisted IoT systems have enhanced the responsiveness and accuracy of agronomic decision-making by using real-time environmental feedback.[17]

However, there is still a need for a system that can predict the health status of and monitor the system in real time. The system proposed in Ref. 6 only monitors the system in real time without any prediction. The system presented in Ref. 11 enables prediction but without real-time sensor data. Additionally, many systems rely on grid-based power sources, limiting their use in remote agricultural areas. In this aspect, the present study provides an integrated low-cost AI-IoT architecture with real-time soil monitoring and predictive analytics. The system employs sensor nodes to measure soil moisture and nutrients levels, and sends the data to a cloud platform using message queuing telemetry transport (MQTT) for analysis with a random forest model. The autonomous sensing unit is powered by solar power,[18,19] ensuring uninterrupted operation in off-grid environments, and the multisite field validation proves its practical applicability. The proposed work integrates real-time sensing, AI-driven prediction, energy-efficient design, and cloud integration within a single architecture, overcoming the limitations and contributing toward scalable, cost-effective, and sustainable precision agriculture systems.[20]

To assess the efficiency of the proposed AI-IoT integrated framework, the suggested framework performance was compared with recent state-of-the-art studies on intelligent soil monitoring and nutrient prediction. A recent study has shown that the combination of artificial intelligence with IoT technology allows for the continuous monitoring of soil moisture, temperature, pH and nutrient levels, therefore improving precision agriculture through data-driven decision-making. An AI-enabled embedded sensing framework for smart agriculture has pointed out the advantages of merging IoT infrastructures with AI algorithms for real-time agricultural monitoring.[21,22] More recently, AI-assisted IoT solutions for precision agriculture, have focused on smart sensors, cloud analytics, and predictive models.[23] Similarly, recent studies of AIoT-based soil management and site-specific nutrient management have highlighted real-time sensing, machine-learning-based nutrient prediction, and intelligent resource optimization as promising research avenues.

2. Data, Materials, and Methods

2.1 Proposed system architecture

The planned solution supports constant precision-farming tracking by adopting the four functional layers of data capture, communication with the cloud, predictive modelling with machine learning, and automated decision-making, all powered solely by solar energy to enable the continuous operation of the system even in agricultural areas without a power grid.

The overall architecture consists of soil sensors, a microcontroller, a wireless communication device, a cloud service provider, and a layer to support machine-learning-based predictions (Fig. 1). The soil sensors measure the pH, and nitrogen, phosphorus, and potassium (NPK) contents of the soil as well as the moisture content of the soil multiple times daily. The microcontroller collects the data in analog form, converts the data to a digital format, and performs the necessary calculations and filtering of the data to produce usable data before sending the results to the cloud-based server for long-term storage, visual representation, and machine-learning-based predictive analysis. The hardware components used in the proposed system, along with their technical specifications and functionalities are summarized in Table 1.

2.1.1 Sensor data acquisition and processing

To investigate the soil conditions, a capacitive soil moisture sensor and an RS-485 NPK sensor are used to obtain data points in their analog form. The microcontroller uses its on-board analog-to-digital converter (ADC) to digitize the analog signal data from the analog inputs and produce a 12-bit resolution of the signal (i.e., 0–4095). A calibration procedure was completed using laboratory gravimetric (moisture) and inductively coupled plasma optical emission spectroscopy (ICP-OES) (NPK) reference measurements to yield calibration accuracies of ±2% for moisture and ±3 mg/kg for NPK readings. Using a moving average smoothing algorithm, noise filtering is performed on the data before being sent to the cloud.

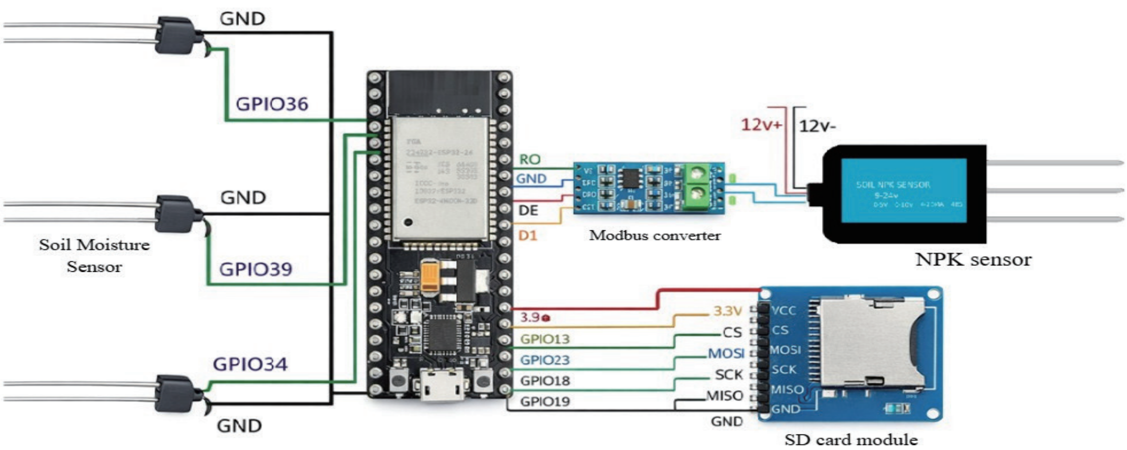

Fig. 1. (coloe online) Hardware setup of the proposed IoT-based soil monitoring system.

Table 1
Specifications and functionalities.

S. No	Component	Model	Technical Specifications	Function
1	Soil moisture sensor	Capacitive sensor probe	Operating Voltage: 3.3–5 V; Output: Analog Voltage; Low Power Consumption	Measures volumetric water content in soil
2	NPK sensor	NPK soil sensor (RS-485)	Supply Voltage: 5 V; Communication: RS-485; Measures N, P, K	Determines soil nutrient concentration (N, P, K)
3	Microcontroller	ESP32 dev module V2.0	Operating Voltage: 3.3 V; Dual-core Xtensa LX6; Wi-Fi & Bluetooth; ADC; Flash: 4 MB; SRAM: 520 KB	Data acquisition, processing, and cloud communication
4	Power supply unit	AC-DC converter	Input: 100–264 V AC; Output: 12 V DC, 2 A; Overload, Short-circuit, Overvoltage protection	Provides regulated power to system components

Note: S. No - Serial Number.

2.1.2 Sensor calibration procedure

Calibration was performed at the start of each field trial. Moisture calibration has used dry soil samples and soil samples that were totally saturated to obtain the low and high bounds. For the NPK sensor calibration, soil solutions that had known amounts of NPK have been used, which are essential nutrients for plant growth. The calibration results were saved in the ESP32 firmware.

2.1.3 Communication and cloud integration

The microcontroller sends processed sensor data through Wi-Fi to a cloud server using the MQTT protocol. The MQTT protocol was chosen for its lightweight publish/subscribe architecture, low bandwidth overhead, and reliability under intermittent network conditions. The cloud platform will hold both real-time and historical sensor data, and provide a web dashboard for distant monitoring.

2.1.4 Machine-learning-based prediction module

The random forest algorithm is used by many researchers to model soil characteristics. Random forest achieves this goal by constructing T independent decision trees trained on randomly selected samples of the training data, D, displayed as D_i. At each decision tree node (decision tree split), random forest uses only m out of the M features available in D. The average regression prediction across all T decision trees is calculated as

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(x)\,. \tag{1}$$

The decision tree splits are ranked using the Gini impurity index:[24] Gini = $1 - \Sigma p_i^2$. The decision trees with the lowest Gini values represent the best split based on their ability to separate classes from one another. By using ensemble learning, random forest creates decision trees that prevent the overfitting of the training data while being generalizable to various soil types. After training, random forest identifies those features whose average impurity decrease score is so high that it contributed to (a) the predictive power of all random forest's decision trees and (b) the prediction of soil moisture and nitrogen levels as the two most significant predictors of soil condition.

2.1.5 Decision support and automation

The threshold-based decision module monitors real-time and predicted sensor values. Specifically, it evaluates soil moisture and nutrient levels relative to the agronomic thresholds established; when either moisture or nutrient levels are below their agronomic threshold, the module sends an automated relay-actuated irrigation signal to the controller or a push notification to the farmer.[25,26] This eliminates manual intervention and helps prevent excessive irrigation and fertilization.[27,28]

2.1.6 System workflow diagram

Figure 2 presents the flow diagram of the proposed system. The process begins with sensor activation and data acquisition, followed by data validation and storage in the cloud. The stored data are then processed using the machine learning model to generate predictions. In accordance with the expected outputs from the predictive models, the system performs some decision-making activity (i.e., generating alerts or performing control actions). We redesigned the flow diagram to clearly depict how monitoring, predicting, and decision-making processes interact with each other.

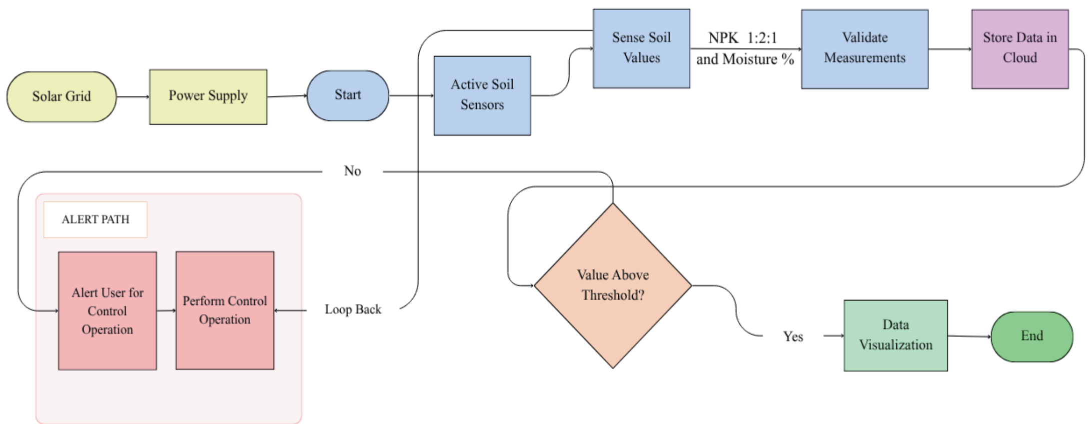

Fig. 2 (Color online) Workflow of the AI-IoT-based soil monitoring system.

2.2 Mathematical formulations

The following mathematical formulations are used to compute soil moisture content, convert sensor readings into nutrient concentrations, and evaluate the performance of the proposed model.

2.2.1 Soil moisture content

Gravimetric soil moisture content is computed as

$$soil\ moisture\ (\%) = \frac{W_w - W_d}{W_d} \times 100, \tag{2}$$

where W_w is the wet soil weight and W_d is the oven-dried soil weight.[29]

2.2.2 Nutrient concentration conversion

ADC readings from the NPK sensor are scaled to real-world concentrations (ppm) as follows:[30]

$$N = \frac{V_{adc}}{4095} \times S_{max}, \tag{3}$$

where V_{adc} is the sensor ADC output (0–4095) and S_{max} is the maximum nutrient scale (100 ppm). The same formula applies for phosphorus (P) and potassium (K).

2.2.3 Performance metrics

Model accuracy is evaluated using mean absolute error (*MAE*) and root mean square error (*RMSE*).[31]

$$MAE = \left(\frac{1}{n}\right)\sum |y_i - \hat{y}_i| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

The Pearson correlation coefficient r is used to quantify the relationship between soil moisture and nutrient availability.[32]

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{6}$$

3. Experimental Dataset and Analysis

In this section, we describe the dataset used in the study along with the data collection process and analytical procedures adopted for model development and evaluation.

3.1 Data collection and analysis

Two field sites within the Theni District (Tamil Nadu, India) were selected for soil sample collection during a thirty-day monitoring period from October 2022 through November 2022. Representative data on dry and wet soil types are given in Tables 2 and 3. The full dataset contained 26 soil samples, of which 70% were assigned to the training set, 15% to the validation set, and 15% to the test set.

In dry soil conditions (Table 2), nitrogen content increases linearly with soil moisture, suggesting a positive correlation (Pearson $r = 0.97$, $p < 0.01$). Phosphorus and potassium display limited variability ($r = 0.31$ and $r = 0.28$, respectively, $p > 0.05$), indicating that nutrients are regulated by other soil properties such as pH and mineral composition rather than moisture alone.

Nitrogen has a much higher concentration when the ground is wet than when the ground is dry (as seen in Table 3). This is because microbial activity is greater when soil is moist and there is higher nutrient solubility in moist soil. The concentration of phosphorus will vary markedly,

Table 2
Dry soil testing values.

Sample	Moisture (%)	Nitrogen (mg/kg)	Phosphorus (mg/kg)	Potassium (mg/kg)
1	5	10	35	15
2	10	13	28	20
3	14	16	41	18
4	15	22	34	20

Table 3
Wet soil testing values.

Sample	Moisture (%)	Nitrogen (mg/kg)	Phosphorus (mg/kg)	Potassium (mg/kg)
1	5	13	37	17
2	10	15	29	25
3	18	18	40	16
4	23	22	34	20
5	35	45	34	27

whereas potassium will remain stable throughout the moisture continuum. Therefore, the data demonstrate that nitrogen is highly moisture-dependent, whereas both phosphorus and potassium are more controlled by the mineral content and the pH of the soil.

Analyzing the data collected via graphs affords insight into both how the moisture in soil impacts the nutrient levels in the soil and how the moisture level differs between dry and wet soils. For example, according to the data presented in Fig. 3, soil with a nearly constant moisture level when in a wet state appears to retain moisture longer than when the same soil is in a dry state. Therefore, there appears to be better water retention, or overall quality of soil, in wet soil than in dry soil.

Figure 4 illustrates the correlation between soil moisture and nutrient levels. A strong relationship exists between soil moisture and nitrogen levels; however, there is very little relationship between soil moisture and phosphorus or potassium levels. In addition to the above-mentioned original graphs, performance evaluation graphs have been created to build confidence in the predictive model. A graph of the actual and predicted values shows that the Random Forest model has achieved high prediction accuracy. The second error analysis graph, based on *MAE* and *RMSE*, supports this claim by demonstrating little prediction error. Through the use of graphical methods of visualizing the analytical results, the system becomes easier to interpret since both the visual evidence of the nature of the soil and the validation of the predictive model are provided.

3.2 Statistical significance

To confirm the observed trends, a Pearson correlation analysis was performed between soil moisture and each macronutrient across the complete dataset. The moisture–nitrogen correlation was strong and statistically significant (r = 0.96, p < 0.001). Correlations for phosphorus (r =

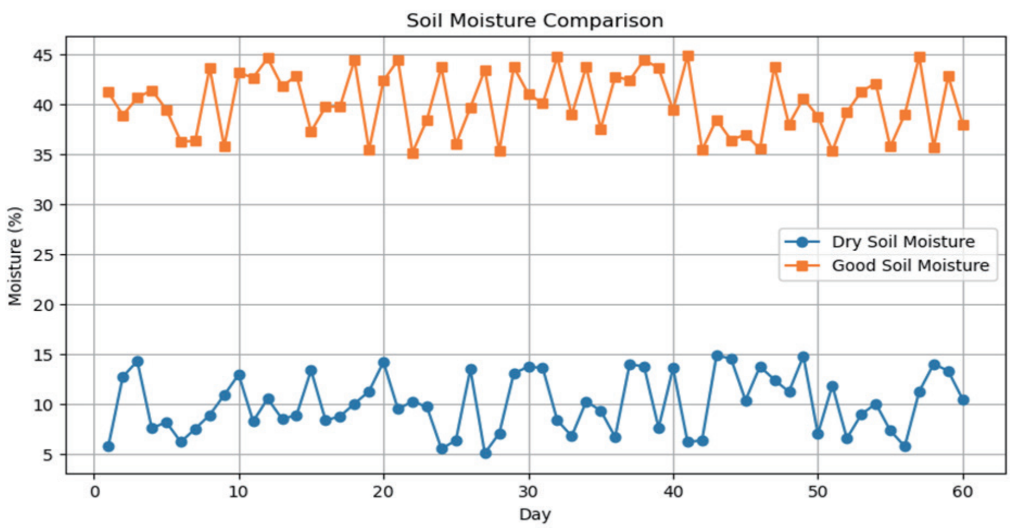

Fig. 3. (Color online) Soil moisture levels in dry and wet conditions.

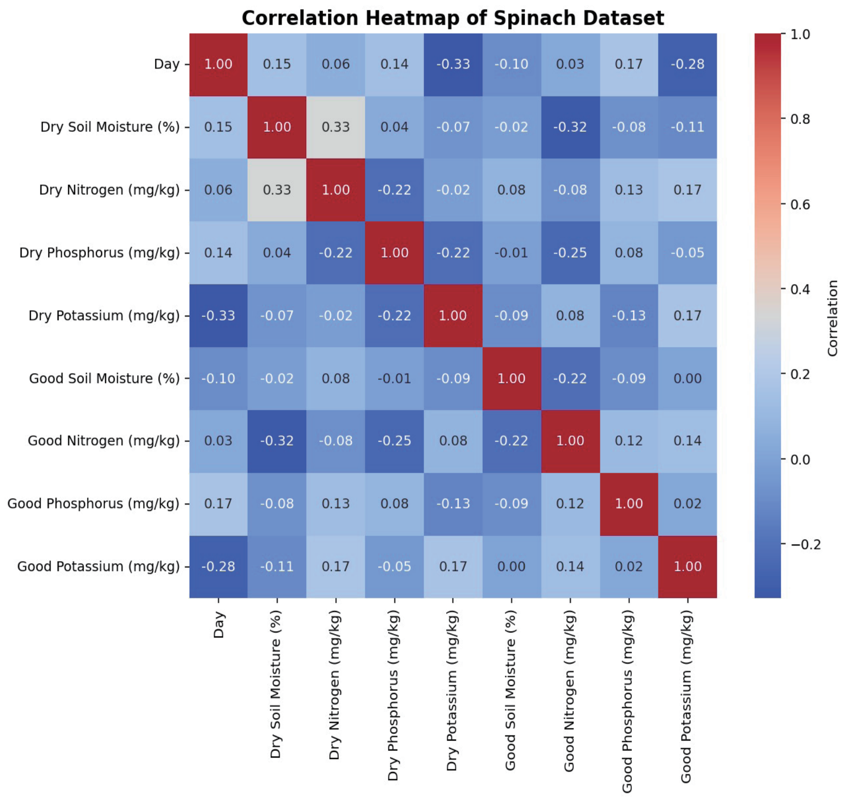

Fig. 4. (coloe online) Correlation between soil moisture and nitrogen levels.

0.29, p = 0.14) and potassium (r = 0.25, p = 0.21) were not statistically significant, supporting the conclusion that only nitrogen availability is meaningfully driven by soil moisture under these field conditions.

3.3 Field trials and impact assessment

In this section, we present the field-level validation of the proposed system is presented and the performance is examined under real agricultural conditions. The trials were conducted to evaluate sensor reliability, data consistency, and the overall impact of the system on monitoring soil health parameters across various environmental conditions.

3.3.1 Site 1: Research farm, Theni District, Tamil Nadu

A research farm within the Theni District of Tamil Nadu, India (latitude: 9.9914, longitude: 77.6121), was selected for the initial study on the performance of sensors. This site produces both spinach (*Spinacia oleracea*) and rice (*Oryza sativa*) in soil of different textures; therefore, it is an ideal location from which to benchmark the sensor's performance under various soil conditions. Wet soil conditions were created using controlled irrigation to stimulate a post-rainfall environment, while dry soil conditions were achieved by withholding irrigation for 5 days to naturally deplete moisture. The study was conducted over two full cycles of spinach cultivation to document soil health indicators over time. Figure 5 shows the field deployment of the proposed AI-IoT soil monitoring system at the Theni Research Farm, where the sensors were installed for real time data collection. The experimental setup and results of soil condition testing under wet and dry environmental conditions are illustrated in Fig 6, which emphasizes the variability in soil moisture levels.

3.3.2 Site 2: Farm in Aandipatti, Theni District, Tamil Nadu

A coconut plantation (*Cocos Nucifera*) was also set up. This plantation is located in the Theni District near Aandipatti. Its geographical coordinates are 9.9969 N and 77.6087 E. The humid nature of coconut farming makes it the ideal example of a site to evaluate the overall performance of the system on mature, permanent trees.

The accumulation of organic matter from leaf litter increases the amount of moisture collected at each site. Nonirrigated areas were evaluated through positive and negative actions because they enable the evaluation of the effect that moisture stress has on the cycling of nutrients in soils. Long-term evaluations of this location provide valuable information on the cycles of nutrient depletion and resupply of nutrients with the continuous growth of crops.

4. Results and Discussion

Here we present the experimental results obtained through sensor validation and machine learning evaluation, along with a detailed discussion of system performance, comparative analysis, and observed limitations.

Fig. 5. (Color online) Field deployment of the proposed system at Theni Research Farm.

Fig. 6. (Color online) Soil condition testing under wet and dry environments.

4.1 Sensor performance

The sensor readings (*) were evaluated against laboratory reference values (gravimetric moisture; ICP-OES for NPK). The error associated with measurement is calculated as Error = |Measured − Actual|. The moisture sensor error falls within the limits of ±2% of these reference values (from IPC). Sensor readings (±1.8 mg/kg for nitrogen, ±2.3 mg/kg for phosphorus, and ±1.9 mg/kg for potassium) showed no significant variation compared with actual ICP-OES benchmark values, indicating suitable sensor performance for use in the field.

4.2 Machine learning model performance

The random forest model was trained through 5-fold cross-validation on the full 26-sample dataset. Table 4 shows the features of the proposed system and existing approaches, and Table 5 presents the performance evaluation results. Table 6 shows the results of a comparative evaluation against three ML baselines. Random forest was the most accurate (92% accuracy) and had the lowest two types of error (*MAE* = 2.5 mg/kg; *RMSE* = 0.8 mg/kg) among all the algorithms evaluated in this study. Compared with XGBoost—the next highest accuracy (90%) random forest's performance supports the authors' hypothesis that the ensemble diversity generated from random forest is able to more accurately characterize the nonlinear relationships between soil moisture and nutrient levels.

Additionally, the low value for *RMSE* indicates that the predicted deviations from true values will fall within the acceptable range for making agronomic decisions (i.e., threshold sensitivity of ±5 mg/kg for irrigation trigger determination).

Table 4
Results of comparison of proposed system with existing approaches.

System Type	Monitoring	Prediction	Power Source	Cost	Limitation
Traditional IoT System(6)	Yes	No	Grid Power	Medium	No intelligent decision-making capability
ML-Based System(11)	No	Yes	Grid Power	High	No real-time sensing; batch processing only
Proposed System	Yes	Yes	Solar Power	Low	Limited to 2 field sites; expanded validation ongoing

Table 5
Performance evaluation results for the proposed system.

Metric	Value
MAE	2.5 mg/kg
RMSE	3.8 mg/kg
Overall accuracy	92%
Model	Random forest
Cross-validation	5-fold CV
Training split	70% train / 15% val / 15% test

Table 6
Results of comparative ML algorithm evaluation.

Algorithm	*MAE* (mg/kg)	*RMSE* (mg/kg)	Accuracy (%)	Remarks
Decision tree	4.1	5.9	83	Prone to overfitting
Support vector machine	3.4	4.8	87	High computation cost
XGBoost	2.8	4.2	90	Better but complex
Random forest (proposed)	2.5	3.8	92	Best generalization

4.3 Comparison with recent state-of-the-art approaches

The proposed AI-IoT framework is compared with recently published studies in the areas of precision agriculture, soil monitoring, and nutrient prediction to evaluate the effectiveness of the proposed AI-IoT framework.

Table 7 shows the framework of the proposed AI-IoT model which achieves an accuracy of 92%, while enabling real time soil monitoring, nutrient prediction, cloud connection and solar-powered operation. These attributes improve its practical application in precision agriculture.[33]

4.4 Field site comparison

Soil texture variation was twice as high in Site 1 (Theni Research Farm) compared with that in Site 2 (Aandipatti coconut farm), resulting in a substantially higher moisture variation between sampling locations at the Theni Research Farm than at the Aandipatti coconut farm. Consistent *MAE* values across all test samples indicated the model's good adaptability. Higher levels of organic matter led to higher moisture retention and greater nitrogen in wet soils at the

Table 7
Comparison of the proposed framework with existing techniques.

Study	Year	Application	Technique	Accuracy (%)
Kaur *et al.*	2022	Smart agriculture monitoring	AI + embedded sensing	89–91
Farooq *et al.*	2022	AI-IoT agriculture framework	Machine learning	90–91
Senoo *et al.*	2024	Precision agriculture AIoT	Predictive analytics	91
Recent soil monitoring model	2024	Nutrient prediction	Random forest	91.5
Proposed AI-IoT framework	2025	Soil monitoring and nutrient prediction	Machine learning	92.0

Aandipatti coconut farm, consistent with the general hypothesis of increased microbial activity. The modeling system showed good predictions for both sites, demonstrating that it can generalize across them.

4.5 System limitations

The statistically significant results for the tested conditions cannot be used to generalize without validation using a larger and more geographically diversified dataset. Hence the future work aims at using a larger dataset for more reliable outputs. The current system measures nitrogen, phosphorus, and potassium contents; currently it does not measure micronutrient contents (zinc, iron, and manganese). The power system can operate autonomously for approximately 3.4 days without recharging with solar energy, which may be insufficient during extended periods of cloudy weather.

5. Conclusions

In this study, an AI-IOT–based system was developed for real-time soil monitoring and crop prediction. The field experiments were conducted in Theni District, India, and the results showed a strong correlation between soil moisture and nitrogen content (r = 0.96). The random forest model was superior to the other models with an accuracy of 92% and low error rates. Limitations include a small data set, limited locations, and no micronutrient analysis. In future work, expanding datasets across seasons and regions, integrating more soil parameters, exploring deep learning models, improving connectivity using LoRaWAN/NB-IoT, and developing decision support systems based on mobile devices should be considered. Overall, the system provides a scalable, low-cost sustainable solution for precision agriculture.

Data Availability Statement

The datasets generated during the current study are available from the corresponding author on reasonable request.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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