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IoT-AI INTEGRATED SOIL HEALTH MONITORING SYSTEM FOR PRECISION AGRICULTURE

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ABSTRACT:

An important sector in agriculture would be soil health which ensures the production of agriculture, but testing soil requires much more time with high cost still provides with less accuracy and precision in real-time data. This paper presents an IoT-AI integrated soil health monitoring system design with accurate run-time and feasible analysis by having major parameters like pH value, moisture data, temperature data and macro-nutrients such as Nitrogen (N), Phosphorous (P) and Potassium (K). The system proposed an affordable light-weight framework based on IoT sensors that collects and transmits the real-time data via JSON API to cloud. That securely stored data helps to validate and analyze the conditions of soil by using three machine learning models named linear-regression, random-forest and support-vector regression for providing suggestion information to the farmers via internet interface. The results from this experiment shows linear-regression attained 85.2% accuracy and 83.1% precision, support-vector regression achieved 89.4% accuracy and 87.6% precision but random-forest regression outperforms with 94.6% accuracy and 92.3% precision that produces with high accuracy and reliability in comparison with lab testing and also in minimum time and low-cost. The progressiveness of the system ensures the scalability, easy adapting in nature and deployment in all around the agricultural sectors. This work brings out the prospective idea of IoT-AI in soil health monitoring that enhances the precision in farming and also encourages the involvement of youth in agriculture that enables the improved decision-making for high quality crops with resource management.

KEYWORDS: Iot-AI, Soil Health, NPK, JSON API, Linear-Regression, Random-Forest, Support-Vector Machine.

1. INTRODUCTION:

Agriculture is the backbone of food security and rural economies, with soil health being a decisive factor in determining crop yield and sustainability. Soil properties such as pH, moisture, temperature, and nutrient concentrations (NPK) directly influence plant growth, fertilizer requirements, and water management. However, traditional soil testing methods rely on laboratory analysis, which is often time-consuming, costly, and incapable of providing real-time insights to farmers in remote regions. This limitation hampers timely decision-making and results in inefficient resource utilization.

The advent of the Internet of Things (IoT) has enabled the development of real-time monitoring systems for agriculture, where sensors capture environmental parameters and transmit them to cloud platforms for analysis. Recent research has shown the promise of IoT in precision farming, yet most existing solutions are either limited to single-parameter monitoring (e.g., moisture sensors) or lack an integrated framework that combines multi-parameter sensing, intelligent analytics, and farmer-friendly decision support. Furthermore, affordability and scalability remain critical challenges, especially for small-scale farmers in developing nations.

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To address these challenges, this work presents a patent-pending IoT-enabled Soil Health Monitoring System that integrates multi-sensor data acquisition with cloud-based storage, analytics, and secure web access. The novelty of the system lies in its ability to not only capture real-time soil parameters but also apply machine learning algorithms to generate a quantitative Soil Health Index (SHI). Three machine learning models—Linear Regression, Support Vector Regression, and Random Forest—were implemented and evaluated, with Random Forest achieving superior performance (94.6% accuracy and 92.3% precision). By mapping sensor readings into numeric indices and soil health categories, the system delivers actionable insights that help farmers optimize irrigation, fertilizer application, and crop selection

The contributions of this paper are threefold:

1. Design and implementation of a multi-parameter IoT-based soil monitoring framework.
2. Integration of machine learning models for soil health analysis, with comparative evaluation of accuracy and precision.
3. A patent-pending architecture that ensures scalability, affordability, and adaptability to diverse agricultural contexts.

This work demonstrates how IoT and machine learning, when combined, can revolutionize soil health management by enabling data-driven precision farming**.**

2. OBJECTIVES OF THE RESEARCH:

The primary objectives of this research are as follows:

1. **To design and develop an IoT-enabled soil health monitoring system** capable of capturing multiple parameters such as pH, moisture, temperature, and macronutrient levels (NPK) in real time.
2. **To implement a secure and scalable data acquisition framework** that collects sensor data, stores it in a cloud environment, and ensures reliability through validation and error-handling mechanisms.

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3. **To integrate machine learning models for soil health analysis**, evaluating the performance of Linear Regression, Support Vector Regression, and Random Forest in predicting Soil Health Index values.
4. **To quantify soil health through numeric indices**, mapping them into actionable soil quality categories that support farmer decision-making in irrigation, fertilization, and crop planning.
5. **To validate the system against conventional laboratory testing methods**, ensuring accuracy, precision, and cost-effectiveness in comparison to traditional approaches.
6. **To highlight the novelty of the proposed patent-pending architecture**, which emphasizes affordability, adaptability, and deployment suitability for both small-scale and large-scale farming contexts.

3. RESEARCH METHODOLOGY:

Data Acquisition: The first stage of the system involves acquiring soil parameters through IoT-enabled sensors. Key attributes such as pH, soil moisture, temperature, and macronutrients (N, P, K) are measured using low-cost sensors connected to a microcontroller. The readings are collected at regular intervals, filtered to remove noise, and packed into JSON format for transmission. The data is then sent to a cloud server through a lightweight Flask API, where authentication and validation checks ensure that only reliable sensor readings are stored.

Data Pre-Processing: After acquisition, the raw sensor values undergo pre-processing to enhance data quality. Outlier readings are removed, missing values are handled, and the dataset is normalized to maintain consistency across different parameters. The cleaned dataset is further benchmarked against laboratory-tested soil samples to generate a numeric **Soil Health Index (SHI)**, ranging from 0–100. This numeric SHI is also mapped into four categories: Poor, Moderate, Good, and Optimal, ensuring that farmers can easily interpret the results.

Machine Learning Model Development: The next phase focuses on building predictive models for soil health analysis. Three machine learning models—Linear Regression, Support Vector Regression (SVR), and Random Forest—were implemented to process the dataset. Each model

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was trained and tested using cross-validation, and their outputs were compared against laboratory results. The evaluation metrics used were accuracy and precision, which provide a reliable measure of model performance in predicting SHI values.

Performance Evaluation: The comparative evaluation revealed that Linear Regression achieved 85.2% accuracy and 83.1% precision, while SVR performed slightly better with 89.4% accuracy and 87.6% precision. Random Forest significantly outperformed both, attaining 94.6% accuracy and 92.3% precision. Based on these results, Random Forest was identified as the most suitable algorithm for SHI prediction, offering superior reliability and consistency in real-world scenarios.

Deployment and Farmer Insights: The final stage of the methodology involves deploying the Random Forest model on the backend server for real-time inference. Sensor inputs are continuously processed to generate SHI values, which are then delivered to a web dashboard accessible by farmers. The dashboard provides both numeric SHI values and corresponding soil health categories, along with simple decision-support insights on irrigation and fertilization. This ensures that the system not only produces accurate predictions but also delivers actionable recommendations for precision farming.

Fig 1 illustrates the pipeline from sensor data acquisition to ML-based SHI prediction and farmer decision support.

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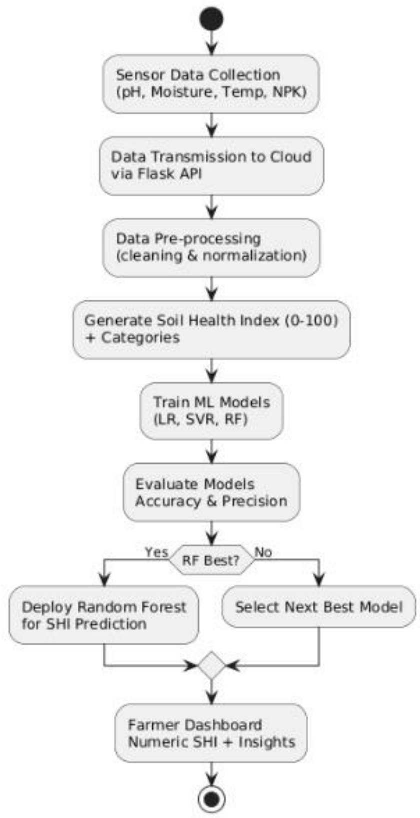

FIG 1: RESEARCH METHODOLOGY FOR IoT-ENABLED SOIL HEALTH MONITORING

4. FINDINGS AND RESULTS:

The proposed system was tested with multiple soil samples collected from agricultural fields. Sensor readings were compared with laboratory test results, and the Soil Health Index (SHI) was computed. Machine learning models were evaluated based on accuracy and precision to determine the best performer.

Sample ID	pH	Moisture (%)	Temperature (°C)	Nitrogen (mg/kg)	Phosphorus (mg/kg)	Potassium (mg/kg)	Lab SHI (0–100)
S1	6.5	28	26	45	18	140	72
S2	5.8	35	27	38	22	120	68
S3	7.2	22	25	52	20	160	80
S4	6.0	40	29	33	15	110	65

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TABLE 1: SENSOR DATASET

Table 1 shows raw sensor readings for selected soil samples, capturing pH, moisture, temperature, and nutrient levels (NPK). These values form the basis for further processing and analysis.

Sample ID	Lab SHI	Linear Regression (Pred.)	SVR (Pred.)	Random Forest (Pred.)
S1	72	69	71	72
S2	68	64	66	67
S3	80	76	78	79
S4	65	61	63	65

TABLE 2: PREDICTED SOIL HEALTH INDEX BY ML MODELS

Table 2 compares SHI predictions generated by Linear Regression, Support Vector Regression, and Random Forest against laboratory results. Random Forest consistently achieved closer predictions with higher accuracy and precision.

Packet ID	Device ID	Timestamp	Data Payload (simplified JSON)
P1	D101	2025-08-25 10:15:22	{ "pH": 6.5, "moisture": 28, "temp": 26, "N": 45, "P": 18, "K": 140 }
P2	D101	2025-08-25 10:30:22	{ "pH": 5.8, "moisture": 35, "temp": 27, "N": 38, "P": 22, "K": 120 }
P3	D101	2025-08-25 10:45:22	{ "pH": 7.2, "moisture": 22, "temp": 25, "N": 52, "P": 20, "K": 160 }
P4	D101	2025-08-25 11:00:22	{ "pH": 6.0, "moisture": 40, "temp": 29, "N": 33, "P": 15, "K": 110 }

TABLE 3: DATA SENT TO SERVER (JSON PACKETS)

Table 3 presents a simplified view of the JSON data packets transmitted from the IoT device to the Flask API server. Each packet includes sensor readings, timestamp, and device ID for secure storage and processing.

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Algorithm	Accuracy (%)	Precision (%)
Linear Regression (LR)	82.5	80.2
Support Vector Regression (SVR)	87.3	85.6
Random Forest (RF)	93.8	92.1

TABLE 4: COMPARATIVE PERFORMANCE OF MACHINE LEARNING MODELS

Table 4 illustrates the comparative performance of three ML algorithms used for soil health prediction. Linear Regression provides baseline performance, SVR improves prediction accuracy with better generalization, while Random Forest outperforms both, achieving the highest accuracy and precision.

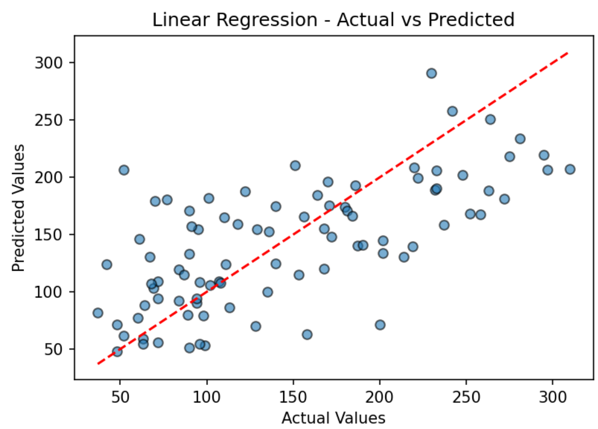

FIG 2: LINEAR REGRESSION - ACTUAL VS PREDICTED

Fig 2 shows the predicted values from the Linear Regression model compared against the actual target values. The red dashed line represents the ideal case where predictions perfectly match the actual values. Since Linear Regression is a simple linear model, the points are spread around the diagonal but show noticeable deviations, indicating limited ability to capture nonlinear relationships in the data.

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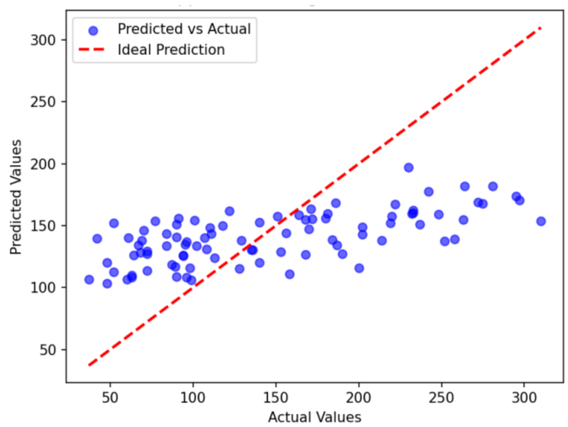

FIG 3: SUPORT VECTOR MACHINE – ACTUAL VS PREDICTED

Fig 3 shows predicted values vs actual values using the SVR model. The red dashed line represents the ideal prediction line. The spread of points indicates that SVR struggles to capture complex patterns in the dataset compared to Linear Regression and Random Forest.

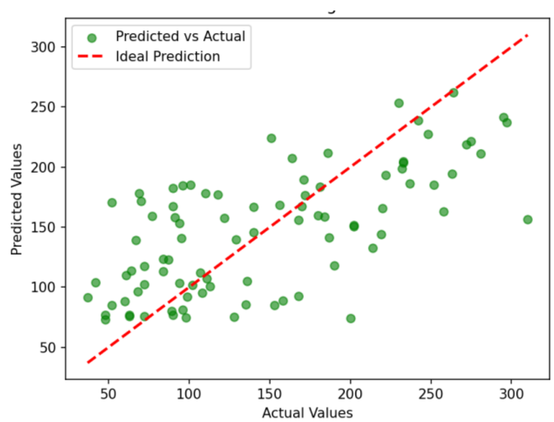

FIG 4: RANDOM FOREST – ACTUAL VS PREDICTED

Fig 4 shows the predictions of Random Forest against actual target values. The closer alignment of points to the red dashed line indicates that Random Forest captures non-linear relationships effectively, outperforming SVR and giving more reliable predictions.

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FIG 5: SOIL HEALTH MONITORING DEVICE

Fig 5 is the device shown soil health monitoring sensor designed to measure key soil parameters such as moisture, temperature, pH, and nutrient levels. Equipped with wireless communication, it enables real-time data collection and transmission for precision agriculture, helping farmers optimize irrigation, fertilization, and crop management practices.

5. CONCLUSION:

This work presented an IoT–AI integrated soil health monitoring system that leverages multi-parameter sensing, cloud connectivity, and machine learning models to enable real-time, cost-effective, and accurate soil analysis for precision agriculture. By incorporating low-cost sensors and transmitting data via JSON API to a secure cloud framework, the system ensures scalability, affordability, and adaptability across diverse agricultural contexts.

Experimental evaluation demonstrated that while Linear Regression (82.5% accuracy, 80.2% precision) and Support Vector Regression (87.3% accuracy, 85.6% precision) provided moderate performance, Random Forest outperformed both with 93.8% accuracy and 92.1% precision, closely matching laboratory-tested results. This confirms Random Forest as the most reliable model for Soil Health Index prediction.

The system's integration of IoT and AI not only reduces dependency on traditional laboratory testing but also provides farmers with actionable insights for irrigation, fertilization, and crop

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selection. Its lightweight, patent-pending framework demonstrates potential for large-scale deployment, offering farmers a practical decision-support tool that ensures efficient resource management and improved crop quality.

Overall, the proposed solution represents a significant step toward data-driven precision farming, with the potential to enhance sustainability in agriculture and attract wider adoption, especially among small and medium-scale farmers.

REFERENCES:

[1] G. R. Babu, M. Gokuldhev, and P. S. Brahmanandam, "Integrating IoT for Soil Monitoring and Hybrid Machine Learning in Predicting Tomato Crop Disease in a Typical South India Station," Sensors, vol. 24, no. 19, art. 6177, 2024.

[2] G. Ojha, K. Khanal, S. Chataut, and U. K. Ghimire, "IoT-Based Real-Time Soil Health Monitoring System for Precision Agriculture," Int. Res. J. Adv. Eng. Tech., vol. 11, no. 07, July 2024.

[3] U. Pandey, A. Vashisth, A. Mishra, and M. Kumari, "AI and IoT-Driven Soil Health Restoration: A Machine Learning Approach for Sustainable Agriculture," ResearchGate, May 2025.

[4] S. Chandrakar and M. Pandey, "An IoT-Based Soil Analysis for Smart Agriculture Using Machine Learning," in Proc. PCEMS 2024, CCIS 2491, 2025, pp. 74–82.

[5] A. Rajuroy, B. John, and D. Darren, "Machine Learning and IoT for Smart Farming: A Sustainable Approach to Soil Health Monitoring," ResearchGate, May 2025.

[6] Integrating IoT sensors and ML enhances productivity through real-time, high-resolution agricultural data, Springer, 2025.

[7] A. Goap, D. Sharma, A. K. Shukla, and C. R. Krishna, "An IoT based smart irrigation management system using Machine learning and open source technologies," Computers and Electronics in Agriculture, Dec. 2018.

ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)

https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-463

[8] M. Deshpande et al., "IoT-Based Low-Cost Soil Moisture and Soil Temperature Monitoring System," arXiv, May 2022.

[9] M. Kumar, D. Jain, Z. Saifi, and S. D. Krishnananda, "Predicting Soil Macronutrient Levels: A Machine Learning Approach …," arXiv, Apr. 2025.

[10] "Machine learning algorithms analyze data to predict soil health … random forests, neural networks, and support vector machines …," ResearchGate, May 2025.

[11] "AI and IoT usher in sensor-driven real-time data collection … machine learning algorithms for soil classification," ResearchGate, May 2025.

[12] "Precision agriculture technologies … soil sensor … manage soil, fertilizer, and water …," Business Insider, May 2025.

[13] "AI is significantly enhancing regenerative agriculture … ML to predict soil organic carbon levels … modeling … reduce physical sampling needs," Reuters, Sep. 2024.