



IoT-Based Soil Health Monitoring and Seed Variety Recommendation System: A Review of Sensing, Machine Learning and Recommendation Methods

**Khandagale Aakanksha Ajit, Prof. Bangar Abhishek Popat,
Prof. Bhosale Sachin Bajirao, Dr. A. A. Khatri**

Dept. of Computer Engineering
Jaihind College of Engineering, Pune, India

Abstract. IoT-based soil sensing combined with machine learning (ML) can already recommend a suitable crop from soil and weather readings, with reported classification accuracies from about 91 % to over 99 %, but none of the five reviewed systems recommends a seed variety. Soil health governs productivity, yet farmers still rely on infrequent laboratory tests and general advice, which delay decisions and ignore field-level variation. This paper presents a focused narrative review of five studies from IEEE, Elsevier and Springer venues (2022–2025) that combine low-cost sensors, wireless or cloud transmission and ML-based crop or fertilizer recommendation. The review covers sensing hardware (NPK, pH, moisture, temperature and humidity sensors, and visible-infrared spectroscopy), ML methods (random forest, classifier comparisons, neural networks), and IoT architectures built on Arduino, ESP32, MQTT and cloud platforms. Common weaknesses are small or open (non-field) datasets, limited validation across seasons and regions, recommendations that stop at crop level, and little reporting of sensor calibration or drift. The paper contributes a comparative analysis, a list of research gaps, and research directions toward variety-level recommendation that uses soil data, climate and variety traits.

Keywords: Soil Health Monitoring, Internet of Things, Machine Learning, Crop Recommendation, Seed Variety Recommendation, Precision Agriculture, Smart Farming

I. Introduction

Crop yield depends on matching soil condition (nutrients, pH, moisture, temperature) to the crop and the seed that is sown, and repeated cultivation of the same crop depletes soil nutrients [5]. Traditional practice relies on occasional laboratory analysis and general recommendations, which are slow, costly and rarely specific to a single field [1].

Two technologies change this. Low-cost sensors on microcontrollers such as Arduino and ESP32 measure soil parameters in the field and send them over MQTT or other wireless links to a cloud server [1], [3]. ML models then turn those readings into a crop, fertilizer or irrigation recommendation [2], [4].

Existing systems stop at crop-level advice. Choosing a seed variety (for example a drought-tolerant or short-duration variety of one crop) needs extra inputs such as variety traits, sowing season and local climate. This review therefore asks three questions: which sensing and IoT designs are used for soil health monitoring, how well do the ML methods perform, and how far are current systems from variety-level recommendation?



II. Review Methodology and Literature Selection Criteria

Publisher and repository records (IEEE Xplore, Elsevier/ScienceDirect via DOAJ, Springer, institutional repositories) were searched in October 2026 with combinations of: IoT, soil health, soil nutrient monitoring, crop recommendation, fertilizer recommendation, machine learning, precision agriculture and seed variety.

Inclusion criteria: (i) peer-reviewed journal, conference or book-chapter publication from IEEE, Elsevier or Springer; (ii) published 2022–2025; (iii) an IoT or sensor-based soil data pipeline; (iv) an ML recommendation or prediction component.

Exclusion criteria: (i) simulation-only studies with no sensor data; (ii) non-indexed or preprint sources; (iii) papers without an accessible abstract or publication record.

Five studies met these criteria and are analysed in detail. Two further sources (a 2024 MDPI conference paper and a Bentham Science chapter) are cited for context only. This is a narrative review: only abstracts and publisher records were available, so reported figures are as stated by the authors and were not independently reproduced.

III. Literature Review

Sensing and IoT Hardware. Islam et al. [1] built a device with FC-28 (moisture), DHT11 (temperature and humidity) and JXBS-3001 (nutrient) sensors that sends data to a server over MQTT. Saha et al. [2] measure seven parameters (N, P, K, pH, moisture, air temperature, humidity) on a portable unit that uploads to a cloud platform. Jaja et al. [3] replace chemical probes with a visible-infrared spectroscopy sensor for NPK, integrated on an ESP32 node. Sreehari et al. [5] use an Arduino with pH, temperature and moisture sensors and add actuators that act on the readings.

ML for Recommendation. Islam et al. [1] generate a high-yielding crop list plus fertilizer names and amounts, and store applied fertilizers and treatments in a database. Saha et al. [2] compare several classification algorithms to pick the most accurate, and validate on indoor and outdoor samples. Jaja et al. [3] train a random forest on NPK data and report 91.1 % overall accuracy. A study at IISA 2023 [4] applies several state-of-the-art models to an open multi-class dataset and finds that random forest outperforms the others. Sreehari et al. [5] predict a suitable crop from sensor values and switch actuators accordingly.

Context from Other Work. A 2024 conference study reports 99.77 % accuracy with Gaussian naive Bayes on a crop and soil-nutrient task [6], and a Bentham Science book chapter reports 99.33 % for an MLP classifier and 98.67 % for a CNN [7]. Such near-perfect figures should be read with caution because they come from curated tabular datasets, not multi-season field trials.

Seed Variety. None of the five studies [1]–[5] recommends a variety within a crop. Their output is a crop name and, in [1] and [2], a fertilizer suggestion. Variety-level recommendation is therefore an open problem rather than a reviewed capability.

IV. Comparative Analysis of Existing Studies

Table I summarises the five primary studies. Accuracy values are not directly comparable because datasets and validation differ. Entries come from abstracts and publisher records; “not stated” means the abstract gives no figure.



Table 1 Comparison of Representative Iot-Based Soil Monitoring and Recommendation Studies

Ref., venue, year	Sensors / ML	Output / reported result	Limitation
Islam et al. [1] J. Agric. Food Res., 2023	FC-28, DHT11, JXBS-3001; MQTT; ML method not stated	Crop list, fertilizer and amount; no accuracy in ab- stract	Crop level only; no accu- racy figure
Saha et al. [2] IEEE CSNT, 2024	N, P, K, pH, moisture, tem- perature, humidity; cloud; several classifiers compared	Crop and fertilizer; indoor and outdoor validation	Accuracy not stated in ab- stract
Jaja et al. [3] EAI/Springer, in press	Vis-IR NPK sensor; ESP32; random forest	Crop; 91.1 % overall accu- racy	NPK only; crop level
IISA 2023 study [4] IEEE IISA, 2023	IoT data, open dataset; sev- eral models	Crop; random forest best (figure not stated)	Open dataset, not own field data
Sreehari et al. [5] IEEE ICOEI, 2022	Arduino; pH, temperature, moisture; actuators; ML	Crop plus actuator control; no accuracy in abstract	Small prototype; crop level

V. Research Challenges and Identified Gaps

- **No variety-level recommendation.** All five studies output a crop, and sometimes fertilizer [1]–[5].
- **Data quality.** Some work relies on an open crop dataset [4] or small prototypes, and the abstracts report no multi-season, multi-region trials.
- **Sensor reliability.** Low-cost probes such as the DHT11 and FC-28 are sensitive to soil type and drift over time. The abstracts do not describe calibration against laboratory analysis.
- **Incomplete soil health indicators.** Most systems read NPK, pH, moisture and temperature, and omit organic carbon, salinity (EC) and microbial indicators.
- **Weak reporting.** Several abstracts give no accuracy, and none describe uncertainty, explainability or farmer-facing evaluation.
- **Deployment.** Power, rural connectivity and long-term field operation are rarely addressed.

VI. Proposed Research Directions

- Build a field dataset linking soil readings, weather, sowing date and **variety-level yield outcomes**, with laboratory soil tests as reference labels.
- Add a variety-matching layer: crop-level recommendation first, then ranking of varieties by traits (duration, drought or salinity tolerance, disease resistance) against local soil and forecast climate.
- Calibrate sensors against laboratory results and compensate for temperature and soil type.
- Validate with grouped splits (by field and season) rather than random splits, and report uncertainty.
- Use edge inference for offline operation with cloud sync, plus a local-language mobile or voice interface for farmers.
- Add explainable recommendations (why this variety, and what soil amendment would change the ranking).

Fig. 1 shows a conceptual architecture that follows from these directions. It is derived from the reviewed systems and has not been experimentally validated.

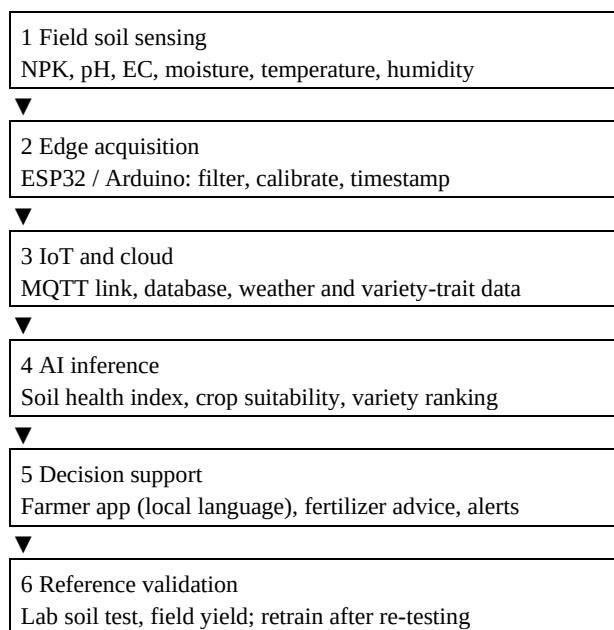


Fig. 1. Proposed conceptual architecture for IoT-based soil health monitoring and seed variety recommendation (conceptual, not experimentally validated)

VII. Conclusion and Future Scope

IoT sensing with ML can recommend crops and fertilizers from soil data in low-cost prototypes, with reported accuracies of 91.1 % in a field-sensor study [3] and above 98 % in dataset-based studies [6], [7]. However, the five reviewed studies stop at crop level, rely on small or open datasets, and say little about calibration, uncertainty or long-term field use. Future work should build field datasets with variety-level yield outcomes, calibrate low-cost sensors against laboratory tests, validate across seasons and regions, and add a variety-ranking layer that matches soil and climate to variety traits.

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