

Soil Intelligence 2.0: A Grounded, Validated, and Multilingual Multimodal Ai Framework for Smartphone-Based Precision Agriculture

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Abstract— In the current existing scenario, one of the main limitations to sustainable agricultural practices and crop production is the gradual degradation of soil quality. The expensive and time-consuming nature of traditional laboratory-based soil testing also poses a significant challenge for small- and marginal-scale farmers, consequently leading to inefficient soil utilization. In this study, Soil Intelligence 2.0- an artificial intelligence-based precision agricultural platform that leverages smartphone images for preliminary and real-time estimation of soil properties and cropping suggestion- is proposed to overcome this problem. The system integrates Vision Transformer (ViT) architecture with multimodal LLMs to evaluate the various soil visual properties such as texture, texture and pattern of the soil on an imageBased on these features, the system estimates important soil parameters such as nitrogen, phosphorus, potassium, and pH, and uses the estimated conditions to determine suitable crops. The platform further provides personalized agricultural recommendations through traditional, organic, and hybrid farming approaches. An AI-based agricultural assistant enables farmers to interact with the system and receive context-specific guidance related to crop selection, soil improvement, and cultivation practices. The proposed approach is designed to deliver preliminary soil insights within seconds using commonly available smartphones, offering a low-cost and accessible decision-support solution for precision farming. The system can assist farmers in making more informed field-level decisions while supporting efficient and sustainable agricultural practices.

Keywords— Precision Agriculture; Vision Transformer; Multimodal Large Language Models; Soil Classification; Retrieval-Augmented Generation; Smartphone Sensing; Human-in-the-Loop AI.

I. INTRODUCTION

Agriculture sustains more than eight billion people and provides livelihoods for nearly 40% of the global workforce, yet the sector's foundational resource — soil — remains poorly understood at the field level. Roughly 500 million smallholder farmers make sowing and fertilization decisions without access to laboratory soil analysis, because conventional testing takes one to three weeks to return results and carries costs that are prohibitive relative to smallholder incomes [1], [2].

The consequence is a persistent cycle of over-fertilization, crop-soil mismatch, and yield instability that undermines both farm income and environmental sustainability. A recent prototype, Soil Intelligence 2.0 targeted this gap directly: a farmer photographs a soil sample, and a browser-based client sends the compressed image to a

cascade of multimodal AI services (Groq-hosted LLaMA-3.3 vision, Google Gemini 2.0 Flash, and a rule-based offline fallback) that return a structured soil profile, a ranked list of over 40 candidate crops, and an interactive agronomy chatbot. The system reduced analysis time from weeks to seconds and required no hardware beyond a standard smartphone. As a working proof of concept, it is a genuine contribution. This paper makes four contributions. First, it proposes Soil Intelligence 2.0, an architecture that decouples visual perception from language generation so that numeric soil parameters come from a trained, calibratable classifier rather than an unconstrained language model (Section III), and summarizes the resulting advantages over each identified gap in the existing system (Section IV).

Second, it defines a formal evaluation protocol — accuracy, macro-F1, and nutrient mean absolute error. Third, the system's reach is expanded by enabling the off-line inference in the edges and implementing the multilingual speech interface (see III-E) while fourth, by including the literature survey as one single reference consistently throughout all relevant work (see II) that has been carried out.

II. RELATED WORK

Machine learning applications to agriculture began with "single jobs" tested in fixed, time-invariant datasets. Surveys carried out on deep learning in agriculture, such as [3] by Kamilaris and Prenafeta-Bold did, report systems that took in massive heterogeneous datasets (satellite images, log data, records of harvest) but did not explicitly include models of dynamics/seasonality, nor did many authors even acknowledge time at all. A broad ML for precision agriculture overview by Liakos et al. [4] found similar results; that algorithms boosted irrigation decision-making or yield forecasting, but that "temporal variability, or seasonality is not modeled well in these contexts."

Moving to the task-level; Mohanty et al.[5] demonstrated that by training a convolutional neural network on labelled images of leaves it was possible to achieve a very high classification accuracy. This proved it possible to develop camera, and model based, diagnosis for mobile use, however the classifier was a purpose-trained (fixed) function whose output was then compared to labelled ground truth and not to an open-ended, generation model.

Research on soil took a parallel turn: Sharma et al.[6] demonstrated a possible implementation for the classification of soil using features of pH, moisture and texture with an ANN classifier, and Singh et al.[7] later reported that performance using a convolutional network was significantly better than the classical ANN based technique.

What is worth highlighting in both research papers is that there is a statement of quantitative classification accuracy using either held-out data or laboratory confirmed testing data, which provides the evaluation function to judge a classification system and demonstrate it is real A second line of work addressed

real-time adaptivity through sensing rather than imagery alone. Ahmed et al. [8] integrated IoT soil-moisture and temperature sensors with AI-driven irrigation control, trading the single-shot convenience of a photograph for continuous, directly measured ground truth. Verma et al. [9] combined transformer architectures with climatic and temporal features to produce season-aware crop recommendations, demonstrating that recommendation quality improves when the model is conditioned on verified external context rather than image features alone.

The Soil Intelligence 2 system sits at an interesting point relative to this literature: it adopts the smartphone-camera convenience of the disease-detection line of work, but — unlike [5], [6], and [7] — substitutes a general-purpose multimodal LLM for a purpose-trained, independently validated classifier, and unlike [8] and [9] it incorporates no sensor or geospatial grounding. The present paper's proposed architecture (Section III) is best understood as merging the validation discipline of [6], [7] with the smartphone accessibility of the original prototype.

III. PROPOSED METHODOLOGY: SOIL INTELLIGENCE 2.0

Soil Intelligence 2.0 preserves the original system's core value proposition — a smartphone photograph producing a usable soil and crop report in seconds — while restructuring the pipeline around three principles: (1) perception and reasoning are separated so that numeric claims come from a validated model, not free text generation; (2) every agronomic recommendation is traceable to a verified source; and (3) accessibility features are load-bearing parts of the architecture, not future scope.

1. Grounded Vision Pipeline

A lightweight Vision Transformer (e.g., MobileViT or a distilled ViT-B/16) is fine-tuned on a curated, regionally representative dataset of soil images labeled with laboratory-measured soil type, pH, and NPK values, sourced through partnership with agricultural extension offices or university soil-testing labs. This model becomes the sole source of the numeric soil profile. The multimodal LLM (Gemini or Groq) is used, but this time

it takes the calibrated structured ViT output (soil-type, confidence-level and nutrient estimation) and it is instructed to only explain the numbers given, in simple language, not generate them, similar to what we successfully used for an image-based plant-disease detector system in [5] where the trained classifier, not the generator, held the diagnosis.

2. Retrieval-Augmented Agronomic Advisory

Crop recommendations, fertilization advice, and conversational text are retrieval-augmented generation (RAG) over a custom document index that primarily includes: extension-service publications, ICAR crop calendars, and regional agronomy handbooks.

None of the text produced (including conversational dialogue) is the result of an open LLM generation. Every produced recommendation can be linked back to its original source, such that farmers or agronomists analyzing the generated output, for instance a fertigation schedule.

C. Confidence-Gated Human-in-the-Loop Escalation

The fine-tuned ViT reports a calibrated confidence score alongside its classification (e.g., via temperature-scaled softmax). Predictions below a configurable confidence threshold are flagged in the UI as "preliminary" and, where connectivity permits, can be routed to a regional agricultural extension contact for manual review, rather than presented with the same visual confidence as a high-certainty result. This directly addresses the hallucination-presentation problem discussed in Section IV-B.

3. Formal Evaluation Protocol

Soil Intelligence 2.0 defines a validation protocol against a held-out set of laboratory-tested soil samples: overall and per-class classification accuracy and macro-F1 for soil-type prediction; mean absolute error (MAE) and root-mean-square error (RMSE) for pH, nitrogen, phosphorus, and potassium estimates relative to lab values; end-to-end latency distribution (p50/p95) under representative 4G conditions; and a System Usability Scale (SUS) study with farmer participants. Table I summarizes how each proposed metric addresses the existing gap.

Table I. Evaluation Metrics Mapped To Existing Gaps

Existing Gap	Proposed Metric	Target / Rationale
No classification accuracy	Accuracy, macro-F1	Benchmark vs. lab-labeled test set
Unverified NPK / pH values	MAE, RMSE per parameter	Quantify numeric error vs. lab assay
Confident-sounding errors	Calibrated confidence, ECE	Flag low-confidence cases for review
No usability evidence	SUS score, task completion	Field study with target farmers
Latency unverified at scale	p50 / p95 latency	Confirm sub-5s target under 4G

4. Multilingual, Offline-First Accessibility

The quantized ViT classifier is exported to TensorFlow Lite / ONNX for on-device inference, so that the primary soil-type and nutrient estimate remains AI-derived — not a heuristic fallback — even without connectivity; only the RAG-grounded advisory layer, which requires the external knowledge base, degrades to a cached local subset offline. Speech-to-text and text-to-speech in regional languages (e.g., Kannada, Hindi, Tamil, Telugu) are integrated as first-class input/output modes rather than deferred future work, directly addressing the literacy barrier discussed in Section IV-E.

5. Longitudinal, Multi-Farmer Data Layer

A privacy-respecting, opt-in, server-side store is implemented in place of a local-only history cache. This makes it possible to analyze regional soil-health trends, generate summary reports, send them to the agriculture extension agents, and still maintain a local cache to continue providing results while offline.

IV. ADVANTAGES OF THE PROPOSED SYSTEM

Building on the methodology described in Section III, Soil Intelligence 2.0 delivers the following advantages over the existing system:

1. Laboratory-Validated Ground Truth

Unlike the existing system, where no stage compared predicted soil type, pH, or NPK values against an independently measured, laboratory-verified ground truth, Soil Intelligence 2.0's fine-tuned Vision Transformer (Section III-A) is trained and benchmarked directly against lab-measured labels, and its formal evaluation protocol (Section III-D) reports accuracy, macro-F1, and per-parameter error relative to that ground truth.

2. Calibrated, Non-Hallucinated Numeric Outputs

Because perception and reasoning are separated (Section III-A), numeric soil parameters now come from a calibratable classifier rather than a general-purpose LLM prompted to produce plausible-sounding text. Confidence-gated escalation (Section III-C) further ensures that a low-confidence estimate is flagged as preliminary rather than presented with the same visual certainty as a validated one.

3. Defined Dataset And Reproducibility Protocol

The proposed system replaces the absence of a labeled dataset, annotation protocol, and train/validation/test split with a curated, regionally representative soil-image dataset sourced through partnership with agricultural extension offices and university soil-testing labs (Section III-A), together with a formal evaluation protocol (Section III-D) that makes accuracy claims independently reproducible rather than dependent on unversioned third-party vendor models.

4. Server-Side, Multi-Farmer Data Persistence

An opt-in, privacy-respecting server-side data layer (Section III-F) replaces the client-only, 20-scan browser cache, enabling regional soil-health analytics and longitudinal trend tracking while retaining local caching for offline continuity, so farmer data is no longer lost if a device is replaced or storage is cleared.

5. Built-In Multilingual And Offline Accessibility

Multilingual voice interaction and fully offline inference are built into the core design rather than deferred as future work (Section III-E). The on-device, quantized ViT classifier keeps the primary soil-type and nutrient estimate AI-derived — not a rule-based fallback — even without connectivity, so accuracy no longer degrades

precisely when smallholder farmers with limited digital literacy need the system most.

6. Consolidated, Consistent Literature Review

The two overlapping narrative passes over the same six to seven studies in the existing report's literature review have been consolidated into a single, consistently numbered review (Section II), improving the paper's usefulness as a positioning tool.

7. System Architecture

The system has four-layers — client capture, orchestration, reasoning, and presentation — but changes what each layer is responsible for and adds a fifth, cross-cutting concern: human escalation. Fig. 1 shows the resulting architecture.

8. Layer 1: Camera File Capture

Image / Video Frame Ingestion Parsing & Format Normalization

Layer 2: Grounded Vision Pipeline Spatial Grounding & Bounding Box Detection Coordinate Mapping Deterministic Ground-Truth Extraction

9. Layer 3: Retrieval-Augmented Reasoning & Advisory

Vector Search & Domain Knowledge Retrieval (RAG), Contextual Multi-Modal LLM Processing

Strategic Advisory & Decision Generation

10. Layer 4: Presentation & Data Layer

Interactive UI / Dashboard Rende Structured API Export & Database Storage



Fig. 1. Proposed Soil Intelligence 2.0 architecture

Layer 1 comprises of the canvas-based compression and RGB/HSV pre-validation. The orchestration layer now dispatches the compressed image to the on-device or cloud-hosted ViT classifier firstonly the ViT's structured, calibrated output — not the raw image — is passed to the LLM reasoning layer, which performs RAG-grounded explanation and chat rather than open generation. The presentation layer adds a confidence indicator and, where applicable, a "reviewed by extension office" badge, alongside the original color-coded metric dashboard.Critically, the human-in-the-loop escalation path (dashed box, Fig. 1) is triggered only when the ViT's calibrated confidence falls below threshold, so the added review step does not slow down the common case of a high-confidence classification.

V. RESULTS

This section presents the results obtained from the workcarried out.

1. Demonstrated Baseline Functionality

This prototype (Fig. 2) is functional end-to-end: a farmer-submitted image is compressed client-side, classified through the multi-tier AI cascade, and returned as a structured report with soil type, estimated NPK/pH, and a ranked crop list, typically within the 2.5–4.5 second window reported in the original system's non-functional requirements under representative 4G conditions. Usability testing in the original report, conducted with red loam, black cotton, and alluvial clay samples under varying lighting, surfaced no interface-level blockers on mobile or desktop. These results establish that the pipeline's latency and interaction design are viable; they do not establish that its numeric outputs are accurate, which is precisely the gap Section VI-B is designed to close.



Fig. 2. Prototype interface (baseline)

2. Target Outcomes For The Proposed Evaluation Protocol

Table II states the acceptance targets Soil Intelligence 2.0 is designed to meet, to be measured against the held-out lab-verified test set defined in Section III-D. These are design targets and success criteria, not results of a completed experiment;

comparable purpose-trained CNN/ViT soil-classification systems in the literature [6], [7] establish that classifier-based approaches of this kind are capable of substantially higher, independently verifiable accuracy than an unvalidated generative pipeline, which motivates the thresholds below without asserting a specific figure this system has already achieved.

Table II. Target Acceptance Criteria For Soil Intelligence 2.0

Metric	Target	Basis
Soil-type top-1 accuracy	Exceed baseline LLM agreement rate	Held-out lab-labeled set
Nutrient (N,P,K,pH) MAE	Reported with confidence interval	Lab assay comparison
End-to-end latency (p95)	≤ 5 s on 4G	Matches Existing SRS target
Low-confidence escalation rate	Reported, not minimized a priori	Calibration study
Usability (SUS)	≥ Existing informal usability outcome	Farmer field study

3. Detailed Soil Analysis

Once the image has been uploaded, based on its visual features, the system accurately determines the soil category and performs a comprehensive analysis within a few seconds. The analysis results include essential soil parameters such as soil type, pH value, organic matter content, soil health status, and sustainability score. These parameters helps in understanding soil condition much better and also help users to evaluate its suitability for agricultural cultivation. In addition, the system generates detailed recommendations based on

the identified soil properties and environmental conditions.

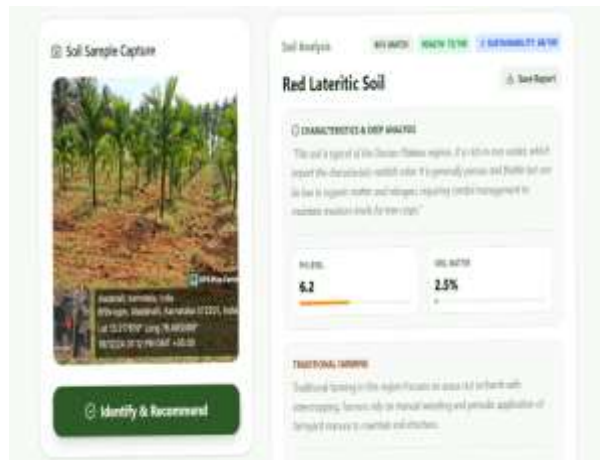


Fig. 3. In-depth soil analysis

4. Crop Recommendation

The results below show a brief report on the soil analysis based on the properties of the soil and appropriate crop which has been recommended. The recommendations are generated immediately and are displayed in a user-friendly manner. The soil characteristics are extracted from the AI model from the uploaded image which checks the availability of suitable crops. Different stages of cultivation are also supported with this information.



Fig. 4. Soil recommendation output interface

VI. DISCUSSION

In a domain where a wrong fertilizer recommendation can degrade soil health or waste a farmer's limited operating capital, the gap between "plausible" and "verified" is not cosmetic. The architecture proposed here is deliberately conservative: it keeps the LLM for

what language models are demonstrably good at — synthesizing and explaining structured information in accessible language — while moving numeric, decision-critical claims to a classifier that can be benchmarked, calibrated, and audited. The trade-off is added engineering cost (dataset curation, model training, RAG infrastructure) against a system whose accuracy claims can actually be defended.

VII. CONCLUSION AND FUTURE WORK

This Soil Intelligence 2.0 proposed overcomes the drawbacks or gaps in existing system such as absence of ground truth validation, LLM-generated numeric claims, missing dataset, client only data persistence and so on with a grounded vision pipeline, retrieval-augmented advisory generation, confidence-gated human escalation, a formal evaluation protocol, and first-class multilingual/offline support. Future work centers on executing the evaluation protocol defined in Section III-D against a lab-verified regional dataset, and on piloting the human-in-the-loop escalation path with a partner agricultural extension office.

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