

AgriSense AI: A Multimodal Prompt-Engineered Framework for Intelligent Soil Analysis, Disease Detection and Crop Recommendation

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Abstract

The agricultural sector in developing nations faces persistent challenges stemming from limited access to technical expertise, language barriers, and a lack of real-time decision-support systems tailored to local conditions. This paper presents AgriSense AI, a browser-based multimodal artificial intelligence platform that integrates AI based soil image analysis, leaf-level plant disease detection, weather-contextual crop recommendation, multilingual advisory generation across ten Indian languages, and a conceptual privacy-aware federated learning component. The system employs a structured prompt engineering methodology to generate structured and machine-parseable JSON outputs from large language models, enabling reliable and machine-parseable agricultural advice. The proposed AgriSense AI framework utilizes the pretrained Qwen/Qwen3.6-27B multimodal model through the Groq API to perform image-based soil assessment and plant disease identification. For crop recommendation, the Llama 3.1 8B Instant model integrates the estimated soil parameters with real-time weather data obtained from the OpenWeatherMap API to generate suitable crop and farm management recommendations.

Experimental evaluation indicates that the proposed API-based framework can generate structured and comprehensive agricultural responses for soil assessment, plant disease analysis, and crop recommendation. The system integrates pretrained multimodal AI models with real-time weather information to provide farmer-oriented agricultural guidance. Its web-based design supports accessible AI-assisted agricultural decision-making and can be used across different devices and network environments.

Keywords: Smart Agriculture; Artificial Intelligence; Multimodal AI; Soil Image Analysis; Plant Disease Detection; Crop Recommendation; Large Language Models; Prompt Engineering; Groq API; Real-Time Weather Data; Multilingual Agricultural Advisory.

I. INTRODUCTION

Agriculture remains a vital sector of the Indian economy and plays an important role in supporting rural livelihoods and food security. However, many farmers continue to face challenges related to soil assessment, timely plant disease identification, suitable crop selection, changing weather conditions, language barriers, and limited access to expert agricultural guidance. These challenges can affect soil management practices, disease control, crop productivity, and overall farm decision-making.

Recent developments in artificial intelligence, multimodal learning, large language models, and cloud-based inference have created new opportunities for delivering accessible agricultural decision-support services. AI-based image analysis can support the assessment of soil characteristics and the identification of visible plant disease symptoms from images captured using smartphones. In addition, large language models can integrate agricultural information and generate farmer-oriented guidance in multiple languages. The integration of AI-based analysis with real-time weather information can further support context-aware crop and farm management recommendations.

However, developing an integrated agricultural platform requires the effective coordination of image-based analysis, structured AI responses, weather information, multilingual interaction, and user-friendly web deployment. Since unstructured language-model responses can be difficult to process and display consistently, the proposed system uses structured prompt engineering to generate machine-parseable JSON outputs for organized presentation within the application.

This paper presents AgriSense AI, a browser-based multimodal agricultural decision-support platform that integrates AI-based soil image analysis, image-based plant disease detection, weather-informed crop recommendation,

multilingual agricultural guidance, and farmer-oriented irrigation and fertilizer recommendations. The framework uses pretrained multimodal AI models through the Groq API and integrates real-time weather information obtained from the OpenWeatherMap API. The system is designed to provide accessible and practical AI-assisted agricultural support across different devices and network environments.

II. LITERATURE REVIEW

Traditional agricultural advisory systems relied on rule-based logic and farmer experience, which could not adapt to the nonlinear relationships among soil, weather, and crop variables [1], [2]. The shift toward AI and IoT-based smart agriculture has since enabled real-time, data-driven decision support across the crop lifecycle [3], [4].

For crop recommendation, classical ML models such as Decision Tree, Random Forest, and KNN have been widely applied to NPK, pH, and climatic datasets, generally achieving 85–99% accuracy [5], [6], [17]. Recent work has moved toward ensemble and Bayesian-optimized models to improve robustness across crop varieties [7], [8], and toward IoT-enabled monitoring pipelines that feed live sensor data into these classifiers [9].

Soil and fertilizer analysis research has combined regression models (PLSR, SVR, XGBoost) with field imaging or spectroscopic data to estimate nutrient levels and recommend fertilizer type more precisely than static tables [10]–[13]. IoT-assisted, context-aware fertilizer systems further personalize recommendations to real-time soil conditions [10].

Irrigation planning has evolved from threshold-based sprinkler control to AI-driven scheduling using evapotranspiration modelling, cloud-integrated IoT systems, and transformer architectures with sensor data fusion, which capture temporal and cross-feature dependencies better than CNNs or LSTMs [14]–[16], [21].

Explainability (XAI) has become central to farmer trust. SHAP and LIME are now routinely layered onto tree-based and deep tabular models (e.g., TabNet) to expose which features drove a given recommendation, addressing the black-box adoption barrier reported across studies [17]–[19].

Beyond the tabular pipeline covered by most existing systems, two adjacent threads are directly relevant to AgriSense AI: plant disease detection via CNN/vision-transformer image classification, which adds a visual diagnostic layer that purely sensor-driven systems lack [22], [23]; and federated learning, which allows collaborative model training across farms or regions without centralizing raw sensor data, addressing privacy and connectivity constraints in rural deployments [24]. Multilingual conversational assistants have also emerged as a usability layer, translating model outputs into accessible guidance for low-literacy farmers [25].

The recent work by Khaliq et al. proposed an AI-driven smart agriculture framework combining IoT sensors, Transformer-based Tabular Learning (TTL), Sparse Weighted Fusion Transformer (SwiFT), and TabNet with XAI, achieving 98.75% (crop), 99.13% (irrigation) and 99.3% (fertilizer) accuracy on sensor datasets, but requiring dedicated IoT hardware and fixed labelled datasets, and leaving disease detection, multilingual access, and federated learning as future work [20]. This gap directly motivates the design of AgriSense AI, which replaces physical sensor dependency with a single-image, cloud-AI pipeline usable on any internet-connected device.

III. PROPOSED METHODOLOGY

AgriSense AI was implemented using a client-server architecture. The frontend was built with React and Vite to provide an interactive user interface, while the backend consists of multiple Node.js/Express API services responsible for processing requests and generating recommendations. Authentication and data storage are handled through Supabase.

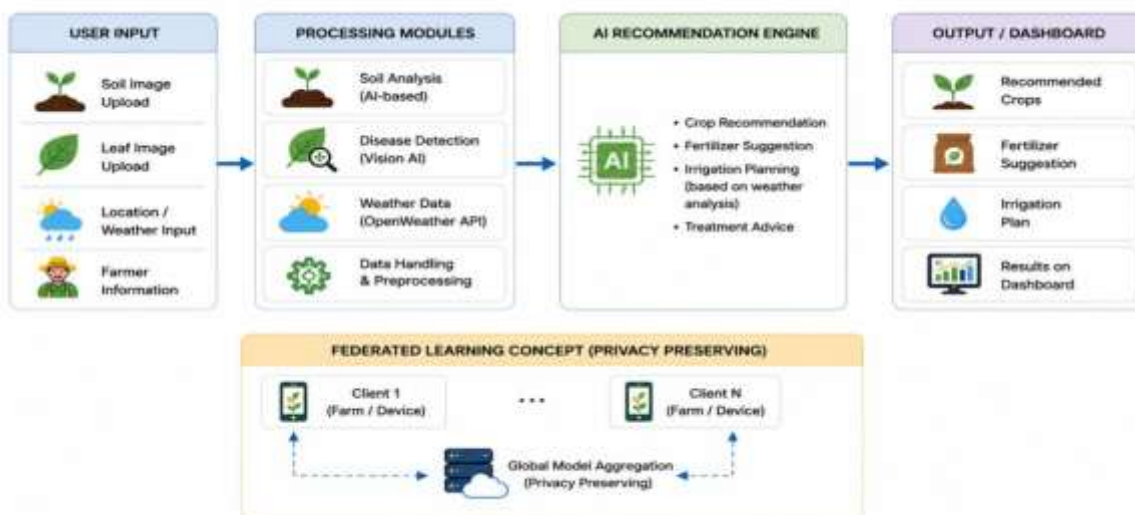


Fig 1: Methodology of the Proposed Model

A. System Modules

- 1) Soil Analysis Module: Accepts an uploaded soil image and returns soil type, estimated NPK values, pH, moisture, texture, colour, and a natural-language analysis.
- 2) Disease Detection Module: Accepts a leaf image and identifies the probable disease category along with treatment guidance.
- 3) Crop Recommendation Module: Combines soil and environmental information with AI-based reasoning — rather than a fixed classifier — to generate suitable crop suggestions.
- 4) Weather Intelligence Module: Retrieves real-time weather and forecast data through the OpenWeather API to support irrigation planning.
- 5) Federated Learning Simulation: Simulates multiple virtual farmer clients performing local updates that are aggregated into a global model across communication rounds, without exchanging raw client data, to demonstrate privacy-preserving collaborative learning.
- 6) Multilingual Interface: Supports multiple Indian languages to improve accessibility for users with different linguistic backgrounds.

B. AI Integration

Two Groq-hosted models are used: a multimodal vision-language model that analyzes soil and leaf images to estimate soil properties and detect disease categories, and a lightweight instruction-tuned language model (llama-3.1-8b-instant) used for text-based reasoning over soil and weather data to generate crop, irrigation, and fertilizer suggestions. Both are accessed via low-latency API calls, enabling near real-time recommendations without on-device model training or specialized hardware.

IV. RESULTS AND DISCUSSION

A. Experimental Setup and Evaluation Criteria

The proposed AgriSense AI framework was evaluated to examine the functional performance, reliability, response time, and completeness of the generated agricultural responses. The evaluation included soil image analysis, plant disease detection, API response testing, and module-wise functional verification. Since the proposed system uses pretrained AI models through cloud APIs rather than locally trained task-specific models, the evaluation focuses on application-level and API-level performance measures.

The soil analysis module was evaluated using soil images obtained from publicly available sources and images collected for system testing. The plant disease detection module was evaluated using plant leaf images from the PlantVillage dataset. The generated outputs were manually compared with the expected soil or disease categories associated with the test images. The Soil Analysis API was further evaluated based on HTTP response status,

successful response generation, required-field availability, and response time.

The evaluation measures used in this study include observed category-level accuracy, API success rate, average response time, and Field Completeness Score.

The soil analysis and plant disease detection modules were evaluated using labelled test images. The evaluation was conducted at the category level by comparing the AI-generated output with the expected soil or disease category associated with each test image.

For soil analysis, 21 test images were evaluated. The generated soil category matched the expected category for 15 images, while 6 results did not match. The observed category-level accuracy was calculated as follows:

Observed Category-Level Accuracy = (Correct Results / Total Test Samples) × 100 Observed Category-Level

$$\text{Accuracy} = (15 / 21) \times 100$$

$$\text{Observed Category-Level Accuracy} = 71.4\%$$

For plant disease detection, 10 leaf images were evaluated. The generated disease category matched the expected category for 7 images, while 3 results did not match. The observed category-level accuracy was calculated as follows:

Observed Category-Level Accuracy = (Correct Results / Total Test Samples) × 100 Observed Category-Level

$$\text{Accuracy} = (7 / 10) \times 100$$

$$\text{Observed Category-Level Accuracy} = 70.0\%$$

The results provide an initial application-level evaluation of the pretrained AI models integrated into the proposed system. The reported values represent the observed performance on the selected test samples and should not be interpreted as the general benchmark accuracy of the underlying pretrained models.

Module	Total Samples Tested	Correct Predictions	Incorrect Predictions	Observed category level Accuracy
Soil Analysis	21	15	6	71.4%
Disease Detection	10	7	3	70%

TABLE 1: Category-Based Evaluation Of The Proposed System

C. Soil Analysis API Functional Evaluation

The Soil Analysis API was functionally evaluated using 10 soil images. Each image was uploaded through the web application and processed using the cloud-based AI service. The returned response was examined based on the HTTP status code, successful response generation, availability of the required fields, and response time.

All 10 requests returned HTTP status code 200 and generated a structured response. The required fields evaluated in each response were soil type, confidence, NPK values, pH, moisture, texture, colour, and analysis. All required fields were present in the responses generated for the tested images. The results demonstrate the successful operation of the Soil Analysis API under the evaluated test conditions.

Test Image	HTTP status	Response received	Required fields	Response time	Result
Black Soil	200	yes	8/8	3.31s	Pass
Red Soil	200	yes	8/8	2.81s	pass
Silty Soil	200	yes	8/8	2.81s	pass
Loamy Soil	200	yes	8/8	3.78s	pass
Loamy Soil	200	yes	8/8	5.13s	pass
Sandy Soil	200	yes	8/8	3.57s	pass
Silt Soil	200	yes	8/8	3.82s	pass
Clay Soil	200	yes	8/8	4.63s	pass
Clay loam	200	yes	8/8	3.17s	pass
Silt soil	200	yes	8/8	3.78s	pass

Table 2: soil analysis API testing

API Success Rate

$$\text{API Success Rate} = \frac{\text{successful api \#}}{\text{Total API request}} \times 100$$

$$\text{API Success Rate} = \frac{10}{10} \times 100 = 100\%$$

All 10 soil images were successfully processed by the Soil Analysis API, resulting in an API success rate of 100%.

Average Response Time

$$\text{Average Response Time} = \frac{\text{Sum of All Response Times}}{\text{Num of Valid Response Times}} = \frac{36.81}{10} = 3.681 \text{ seconds}$$

≈ 3.68 seconds

The response time of the Soil Analysis API was measured for 10 test images. The total response time was 36.81 seconds. The average response time was calculated by dividing the total response time by the number of API requests. The obtained average response time was 3.68 seconds.

D. Comparison with the Base System

The proposed AgriSense AI framework differs from the base system primarily in its input method, model deployment strategy, and hardware requirements. The base system relies on physical IoT sensors and dataset-specific trained models, whereas the proposed system uses uploaded images and pretrained cloud-based AI models. The proposed browser-based architecture does not require dedicated sensor hardware for image-based soil and plant analysis. In

addition, the system integrates soil analysis, disease identification, weather retrieval, crop recommendation, irrigation guidance, and fertilizer suggestions within a unified application.

However, the evaluation results of the two systems should not be directly compared as equivalent model accuracies because they use different data sources, evaluation procedures, and system architectures.

Parameter	Base Paper	Current Project
1] Data acquisition	Physical IOT sensor data	user uploaded soil or plant image
2] hardware required	required	No required
3] Model approach	Dataset-specific trained model	Pretrained cloud-based AI models
4] Evaluation metric	Reported accuracy on the original dataset	Observed category-level evaluation and API-level metrics
5] Deployment requirement	Sensor-equipped environment	Browser-based web application
6] Accessibility	Dependent on installed hardware	Accessible through internet connected device
7] Recommendation generation	Based on the base-system design	Uses estimated soil data and weather information

Table 3: Caparison table

V. CONCLUSION

This study introduced **AgriSense AI**, a web-based intelligent agriculture framework developed to provide integrated support for soil assessment, plant disease identification, crop selection, and farm management. The proposed framework combines image-based analysis, pretrained multimodal artificial intelligence models, real-time weather information, structured prompt engineering, and multilingual advisory services within a single application. Unlike agriculture systems that depend on dedicated sensors and locally trained models, AgriSense AI allows users to access AI-assisted recommendations through an internet-connected device by uploading soil or plant images.

The evaluation confirmed that the developed system can generate structured agricultural responses and support the successful interaction of multiple AI and API-based modules. During the selected test evaluation, the soil analysis module obtained an observed category-level accuracy of **71.4%**, while the plant disease detection module obtained **70.0%**. In addition, all ten Soil Analysis API requests were completed successfully, resulting in a **100% API success rate**. The required output information was available in every tested response, and the average response time was approximately **3.68 seconds**. These findings demonstrate the functional reliability and practical feasibility of the proposed web-based framework under the evaluated test conditions.

The main contribution of AgriSense AI is the integration of multiple agricultural decision-support functions into an accessible and hardware-independent platform. The use of structured JSON outputs improves the consistency and usability of AI-generated information, while the integration of weather data supports more context-aware crop and farm management recommendations. Multilingual support further increases the potential usability of the system for users with different language preferences.

Although the obtained results demonstrate the feasibility of the proposed approach, the current evaluation was conducted using a limited number of test samples. Therefore, the reported category-level accuracies represent the observed performance of the integrated application and should not be considered general performance values for the underlying pretrained models. Future work can include testing with larger and more diverse real-field datasets, validating soil estimates using laboratory measurements, obtaining agricultural expert feedback, and improving the evaluation of crop, fertilizer, and disease recommendations. The conceptual federated learning component may also be extended into a fully implemented privacy-preserving learning framework. With these improvements, AgriSense AI can be further developed into a more reliable, scalable, and practically useful decision-support system for smart agriculture.

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