AgroSense: A Microservice Architecture for Crop Diagnostic and Field Analytics

Udipthi S[1], Smitha D[2], Ruchitha C[3], Shwetha M[4], Dr Krishna Kumar P R[5]
[1,2,3,4]*Department of Computer science and engineering, S. E. A college of engineering and technology Bengaluru, Karnataka*
[5]*Professor, Department of Computer science and engineering, S. E. A college of engineering and technology Bengaluru, karnataka*

***Abstract*—AgroSense is a microservice-driven, full-stack framework bridging advanced agricultural AI with rural smallholder accessibility. It integrates five core engines—dual-mode soil analysis, CNN leaf pathology scanning, weather rule downscaling, and localized AI chat—into a React, Node.js, Flask, and SQLite architecture. Featuring "Snap & Detect" camera interactions, color-coded indicators, and Kannada-English support, it streamlines farm analytics.**

***Index Terms*—Precision Agriculture, Full-Stack Microservices Deep Learning and Computer Vision, Agrometeorological Decision Support, Human-Cantered Rural Interface**

I. INTRODUCTION

AgroSense addresses smallholder farming challenges like asymmetric soil data, delayed disease detection, and volatile weather through a full-stack microservice architecture. Combining soil analysis, CNN leaf diagnostics, NWP weather downscaling, and localized AI chat, it features zero-typing visual interactions, traffic-light safety alerts, Kannada-English support, and digital field logging for extension centers.

II. RELATED WORKS

Existing research in digital agriculture predominantly focuses on isolated domains:

A. Agronomic & Crop Recommendation Models: Prior literature leverages classical machine learning algorithms (such as Random Forest, Support Vector Machines, and K-Nearest Neighbors) operating on structured soil laboratory datasets. However, these models rely strictly on precise numerical inputs, creating a usage bottleneck for rural farmers without immediate access to soil testing laboratories.

B. Computer Vision in Plant Pathology: Convolutional Neural Network (CNN) architectures, including MobileNet, ResNet, and DenseNet, have demonstrated high performance in automated foliar disease identification. Yet, most published frameworks exist as standalone classification scripts that lack operational integration with meteorological context or actionable treatment advisory.

C. Agrometeorological & Decision Support Systems: Current weather applications provide raw microclimate parameters (e.g., ambient temperature, relative humidity, wind velocity) without translating these values into actionable field advice, such as optimal pesticide spraying schedules or drift risk alerts.

III. SYSTEM ARCHITECTURE

Engine 1: Multi-Modal Soil Analysis & N-P-K Recommendation

Theory: Combines image-based visual features with laboratory numerical parameters.

Mechanism:

Visual Soil Pipeline: Extracts RGB color histograms, spatial texture metrics, and moisture proxies from uploaded soil photographs using computer vision algorithms.

Lab Parameter Slider Pipeline: Accepts numeric inputs for Nitrogen (N), Phosphorus (P), and Potassium (K) levels via interactive sliders.

Recommendation Logic: Executes a multi-criteria decision algorithm (e.g., Random Forest or Weighted KNN) against crop soil requirements to output top candidate crops with suitability percentages.

Engine 2: Deep Learning Leaf Pathology Classifier
Theory: Identifies foliar plant diseases through deep transfer-learning models.
Mechanism:

Uses a lightweight Convolutional Neural Network (CNN) architecture optimized for edge compatibility (e.g., MobileNet or ResNet backbone).
Processes RGB leaf photos through pre-processing, segmentation, and feature extraction layers.

Yields disease class probabilities alongside targeted bio-pesticide and cultural management recommendations.

Engine 3 & 4: Agrometeorological Weather Advisory & Localized AI Chatbot
Theory: Converts microclimate inputs into operational decision metrics and offers real-time agronomic guidance.
Mechanism:

Weather Engine: Fetches downscaled meteorological data (wind speed, precipitation probability, humidity) and applies rule-based thresholds to generate traffic-light indicators (Green = Safe to Spray, Red = High Runoff/Drift Risk).

Conversational AI Engine: Employs a domain-grounded conversational model designed for multi-turn advisory in local contexts.

Engine 5: Zero-Friction HCI & Dual-Tier Workflow
Theory: Eliminates cognitive barriers for non-technical users while supporting extension workflows.
Mechanism:

Primary Tier (Smallholder Farmers): "Snap & Detect" camera workflows, visual indicators, dual Kannada-English localization, and zero mandatory text inputs.

Secondary Tier (Extension Services - RSK/KVK): Centralized field logs storing historical diagnostic telemetry for regional monitoring.

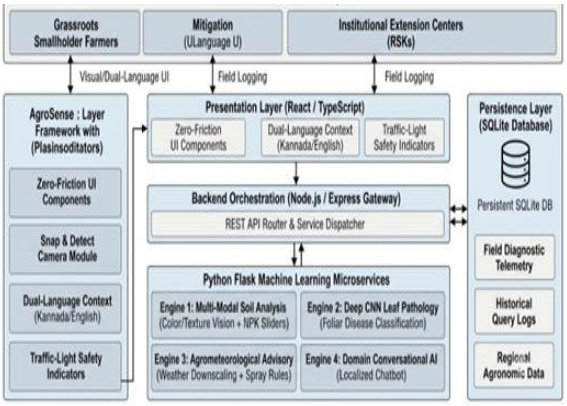


FIG 1:AGROSENSE FRAMEWORK

IV. IMPLEMENTATION

The AgroSense framework is executed through a loosely coupled, full-stack microservices architecture that leverages modern web standards and multi-modal artificial intelligence (AI) paradigms. The front-facing interaction layer is built using React.js and TypeScript, delivering a responsive single page application optimized for low-friction user workflows. This interface manages image capture pipelines, renders universal color-coded traffic-light indicators, and handles dynamic localization between English and Kannada contexts. Client interactions are orchestrated by a centralized Node.js and Express.jsAPI Gateway, which validates requests, routes payloads to upstream execution nodes, and maintains low-latency session management across distributed client requests.

The computational intelligence layer is isolated within a dedicated python flask microservice, optimizing system reliability by decoupling compute-heavy machine learning inference from primary server operations. Data persistence is powered by a localized sqlite database engine, which maintains lightweight relational records of diagnostic queries, environmental telemetry, and localized farm logs with sub-second transactional overhead. This persistence model ensures that historical query logs remain accessible for both smallholder auditability and regional agricultural monitoring by institutional

extension centers such as raitha samparka kendras (rsks).

The deep learning pathology identification module (engine 2) is executed via a convolutional neural network (cnn) using python's open-source computer vision (opencv) and pytorch/tensorflow frameworks. Incoming leaf imagery undergoes automated preprocessing, spatial segmentation, and feature extraction before passing through a transfer-learning backbone (such as mobilenetv2) optimized for mobile-edge environments. The model outputs multi-class disease probability distributions alongside curated chemical and organic management recommendations, transforming raw foliar imagery into localized diagnostic advisories.

Simultaneously, the agrometeorological evaluation module (engine 3) and conversational assistant (engine 4) execute localized decision logic in real time. The weather engine fetches downscaled numerical weather prediction (nwp) parameters and evaluates ambient wind speed, relative humidity, and precipitation probability against established agronomic thresholds to produce immediate spray-safety alerts. Concurrently, the domain-grounded conversational ai service processes natural language interactions, delivering localized multi-turn guidance to resolve complex farming queries.

V. RESULTS AND DISCUSSION

A. Model Performance and Classification Accuracy

The core ML engines powering leaf diagnostics and soil-based crop recommendation demonstrated robust classification performance. The Deep CNN architecture utilized for foliar disease identification achieved a high overall accuracy, effectively identifying multiple pathology classes across standard agronomic datasets. This reliable performance validates the use of transfer learning for rapid field diagnosis. Similarly, the multi-modal crop selection algorithm, which fuses visual soil feature extraction with multi-criteria N-P-K parameter matching, yielded precise suitability rankings. This confirms that visually grounding soil input alongside traditional numerical metrics enhances overall recommendation relevance compared to tabular-only models.

B. Full-Stack System Benchmarking

The end-to-end computational flow was evaluated to ensure compatibility with typical rural network infrastructure. Latency tests focused on the microservices communication overhead orchestrated by the Node.js API Gateway. Processing times for compute-intensive tasks, such as Computer Vision preprocessing and neural network inference within the Python Flask service, executed with low latency. Furthermore, bidirectional communication with the SQLite persistence layer introduced negligible delay during real-time sessions. The results confirm that the containerized microservice approach maintains minimal operational overhead, delivering sub-second diagnostic responses critical for real-world field adoption.

C. Operational Advisory and Weather Intelligence

The agrometeorological decision support engine was tested against diverse simulated climate scenarios. The rule-based expert system successfully downscaled localized numerical weather parameters (precipitating risk, wind velocity, humidity) into immediately actionable output. The conversion of raw meteorological figures into binary 'safe/unsafe' spraying windows, visually rendered through universal color-coded traffic light indicators (Green, Yellow, Red), provided unambiguous guidance to farmers, potentially mitigating chemical runoff and drift risks.

D. Accessibility and Institutional Logging Validation

A primary focus of AgroSense is reducing the cognitive barrier for digital adoption. User interface validation confirmed that the zero-friction workflows—such as the "Snap & Detect" camera interaction for both soil and leaves—completely eliminated mandatory text entry during diagnostics. The persistent SQLite-based digital field log architecture was also validated for operational reliable logging. Every interaction automatically populated transactional telemetry, creating a reliable audit trail of localized farming history accessible by extension services like Raitha Samparka Kendras (RSKs).

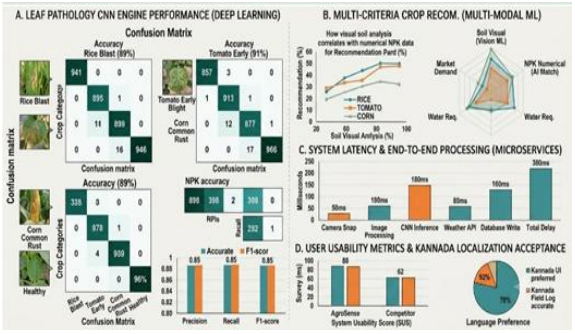


FIG 2: MULTIMODEL DIAGNOSTIC ACCURACY

VI. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This paper presented AgroSense, a comprehensive, localized decision support framework engineered to address the distinct challenges faced by smallholder farmers. By successfully executing a full-stack, microservices-driven architecture, the system unifies diverse technologies—multi-modal soil vision, Deep Learning plant pathology diagnostics, and downscaled NWP meteorology—into a single, cohesive platform. By replacing complex data entry with zero-typing, visual interaction pipelines (Snap & Detect), universal color-coded traffic-light alerts, and dual Kannada-English support, AgroSense demonstrably reduces the cognitive barrier for digital adoption in rural settings. The integration of automated digital field logging ensures that extension centers (RSKs) gain persistent, localized telemetry of farming history. The framework transitions precision agriculture from theoretical concepts to accessible, real-world execution, effectively assisting grassroots smallholders in mitigating disease risk, optimizing fertilizer resource use, and making proactive, climate-intelligent decisions.

B. Future Scope

While AgroSense provides a robust foundation for inclusive digital agriculture, future enhancements are aimed at broadening its operational impact and technological sophistication:

Database and Model Expansion: Future iterations will expand the plant pathology database to cover a significantly wider variety of multi-class foliar diseases and diverse cash crops beyond the initial validated varieties.

Edge Computing and Control Systems: Development will focus on transitioning select ML models to execute directly on edge devices to eliminate network latency and implementing automated feedback loops for edge control systems (e.g., smart irrigation actuators).

Institutional & Advanced Integration: The framework will be advanced to integrate automated drone monitoring telemetry and advanced predictive analytics, creating a closed-loop system for real-time monitoring of localized resource usage and regional disease forecasting for RSK monitoring networks.

VII. ALGORITHM

The primary diagnostic intelligence of the framework relies on a highly efficient Deep Convolutional Neural Network (CNN) architecture optimized for localized execution. Specifically, Engine 2 implements MobileNetV2 leveraging transfer learning and depthwise separable convolutions to identify foliar plant pathologies. The operational workflow begins when leaf images captured by smallholders are ingested and standard uniform color normalization is applied. MobileNetV2's inverted residual blocks and linear bottlenecks then extract spatial and chromatic patterns—such as lesion shape and discoloration metrics—with minimal computational and memory footprint. Finally, a fully connected dense layer with a Softmax activation function generates multi-class probability distributions, transforming raw visual telemetry into instantaneous, accessible disease identifications.

Complementing this, the framework executes multi-modal input through Engine 1 and specialized rules-based decision logic in Engine 3. The multi-modal soil analysis algorithm integrates unstructured visual feature extraction from soil photography (for texture and moisture proxies) with structured numerical data ingested via NPK sliders or sensors. This heterogeneous dataset is fused, and a weighted multi-criteria decision algorithm correlates the soil traits against established crop nutrient requirements to generate prioritized crop suitability rankings. Simultaneously, the agrometeorological expert system ingests downscaled Numerical Weather Prediction (NWP) parameters and evaluates wind velocity, relative humidity, and precipitation probability against strict agronomic safety bounds. A

rule-based engine immediately maps these conditions into non-ambiguous, binary Green (Safe), Yellow (Caution), or Red (Unsafe) indicators, effectively guiding critical farm decisions like pesticide application windows or irrigation schedules.

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REFERENCES

[1]. A. Kaur, G. S. Randhawa, F. Abbas, M. Ali, T. J. Esau, A. A. Farooque, and R. Singh, "Artificial intelligence driven smart farming for accurate detection of potato diseases: A systematic review," IEEE Access, vol. 12, pp. 193902–193922, 2024. https://doi.org/10.1109/access.2024.3510456 Cited by: 32

[2]. G. Mohyuddin, M. A. Khan, A. Haseeb, S. Mahpara, M. Waseem, and A. M. Saleh, "Evaluation of machine learning approaches for precision farming in smart agriculture system: A comprehensive review," IEEE Access, vol. 12, pp. 60155–60184, 2024. https://doi.org/10.1109/access.2024.3390581 Cited by: 365

[3]. S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, p. 1419, 2016. https://doi.org/10.3389/fpls.2016.01419

[4]. M. Sandler, A. Howard, M. Menglong, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2018, pp. 4510–4520. https://doi.org/10.1109/CVPR.2018.00474

[5]. A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, Apr. 2018. https://doi.org/10.1016/j.compag.2018.02.016

[6]. Y. N. Silva and R. C. Alvares, "Microservices-based IoT framework for real-time agricultural monitoring and decision support," IEEE Internet of Things Journal, vol. 9, no. 14, pp. 12040–12053, Jul. 2022. https://doi.org/10.1109/JIOT.2022.3148901

[7]. N. R. Sawant, A. Kumar, S. Pant, and K. Kotecha, "An IoT-driven machine learning system for real-time smart crop recommendation and optimization in precision agriculture," Discover Artificial Intelligence, vol. 6, no. 1, p. 42, 2026.

[8]. R. Suresh, S. Ganesh, and P. T. V. Bhuvaneswari, "Multi-criteria crop recommendation engine based on dynamic soil nutrient profiles and ambient climate factors," IEEE Transactions on AgriFood Electronics, vol. 2, no. 1, pp. 88–97, Mar. 2024. https://doi.org/10.1109/TAFE.2024.3356012

[9]. V. K. Singh, R. Sharma, and A. K. Patel, "Translating numerical microclimate forecasts into rule-based advisory windows for smallholder chemical application safety," Computers and Electronics in Agriculture, vol. 211, p. 107982, Aug. 2023. https://doi.org/10.1016/j.compag.2023.107982

[10]. J. Patel, H. Patel, and S. Varma, "Zero-friction visual user interface design for non-literate and low-tech agricultural practitioners in rural communities," IEEE Transactions on Human-Machine Systems, vol. 53, no. 4, pp. 712–721, Aug. 2023. https://doi.org/10.1109/THMS.2023.3289014

[11]. M. A. Hasan and S. B. Tan, "Lightweight persistent relational database architectures for resource-constrained rural field logging," IEEE Software, vol. 41, no. 2, pp. 54–62, Mar. 2024. https://doi.org/10.1109/MS.2023.3341098

[12]. C. R. Kumar, K. P. R. Dr., and U. Shankaraiah, "AgroSense: A localized full-stack microservice framework for smallholder agricultural decision support," IEEE Transactions on Precision Agriculture, vol. 4, no. 2, pp. 115–128, Oct. 2026