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AgroSense II: Smart Plant Disease Detection and Treatment Recommender

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Abstract: Plant diseases are one of the major causes of crop loss and reduced agricultural productivity worldwide. Farmers, especially in rural regions, often struggle to identify diseases at an early stage due to limited access to expert support and modern agricultural tools. Traditional diagnosis methods depend on manual observation, which is time-consuming and prone to errors in large-scale farming. This paper presents AgroSense-II: AI-Powered Plant Disease Detection and Treatment Recommender, a unified web-based platform that integrates machine learning-based disease prediction, treatment recommendation, analytics dashboards, and historical record management into a single lightweight framework. The system employs a Random Forest classifier trained on agricultural datasets, a FastAPI-powered backend, ReactJS frontend, and MongoDB for data storage. By combining these technologies into one deployable architecture, AgroSense-II helps farmers identify diseases faster, receive actionable treatment guidance, and make smarter crop management decisions without depending on expensive hardware infrastructure.

Keywords: Plant Disease Detection, Precision Agriculture, Machine Learning, Random Forest Classifier, Smart Farming, FastAPI, ReactJS, MongoDB, Crop Monitoring, Treatment Recommendation.

I. INTRODUCTION

Agriculture remains one of the foundational pillars of food security and economic stability across the globe. Yet, despite its importance, the agricultural sector continues to face significant threats from plant diseases that silently destroy crops before farmers can even detect them. A large percentage of crop losses each year can be attributed to fungal infections, bacterial diseases, nutrient deficiencies, and persistent environmental stress conditions. The consequences go far beyond individual farms, affecting food supply chains, rural livelihoods, and national economies.

Traditional disease diagnosis largely depends on the physical observation of plant symptoms by agricultural experts or extension workers. While this approach has served farming communities for decades, it is far from ideal. Experts are not always accessible, particularly in remote or rural areas, and even experienced observers can misidentify diseases, especially in the early stages when symptoms are subtle. By the time a disease is correctly diagnosed and treatment is initiated, significant crop damage may have already occurred.

The rapid advancement of machine learning and artificial intelligence has opened a new horizon for intelligent agricultural systems. These technologies make it possible to analyze complex agricultural parameters and generate accurate predictions in real time, without the need for physical expert visits. By training models on well-curated datasets containing crop attributes and environmental variables, systems can identify disease patterns that may not be visible to the naked eye.

The proposed AgroSense-II: AI-Powered Plant Disease Detection and Treatment Recommender directly addresses these challenges. The platform combines disease prediction using a Random Forest machine learning model, contextual treatment recommendations, analytics dashboards, and prediction history management into a single, deployable web-based architecture. Built on FastAPI for backend processing and ReactJS for the user interface, the system is designed to be accessible, lightweight, and practical for real-world agricultural use — with no dependency on expensive IoT hardware or advanced technical expertise from the user's side.

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This paper is organized as follows: Section II reviews related literature, Section III identifies the research gaps addressed by this work, Section IV describes the proposed framework and system architecture, Section V outlines practical applications, Section VI discusses future work directions, and Section VII concludes the paper.

II. LITERATURE SURVEY

Mohanty et al. [1] proposed a CNN-based approach for plant disease detection from leaf images, achieving high accuracy but requiring heavy computation impractical for low-resource farms. Ferentinos [2] further advanced image-based disease classification using deep learning, though without treatment guidance or user interfaces. A comprehensive IEEE survey [3] on smart farming reviewed ML approaches across crop monitoring and yield prediction, yet most systems demanded costly IoT infrastructure beyond the reach of small-scale farmers. Zhang et al. [4] developed an IoT-based monitoring system collecting real-time environmental data via physical sensors, but the hardware dependency increased deployment costs and lacked treatment recommendations. Recent ML-based crop protection research [5] demonstrated strong disease prediction using agronomic parameters, however these systems were not paired with user-facing interfaces or deployment-ready architectures. Agricultural decision support systems [6] represent the emerging intersection of AI and farm management, yet most lack integrated treatment recommendations, scalability, and accessibility for non-technical users. AgroSense-II addresses all these gaps by combining a lightweight Random Forest model, full-stack implementation with ReactJS, FastAPI, and MongoDB, along with treatment guidance, analytics visualization, and history management into one accessible, hardware-free web platform.

TABLE I COMPARISON OF LITERATURE SURVEY PAPERS

Reference	Focus Area	Key Strength	Limitation	AgroSense-II Improvement
Mohanty et al. (2016)	Deep Learning Plant Disease Detection	High accuracy using CNN	Requires high-end hardware	Lightweight ML with tabular data
Ferentinos (2018)	CNN-Based Disease Classification	Effective image-based recognition	No treatment recommendation	Integrated prediction + treatment
IEEE Smart Farming (2021)	AI-Based Precision Agriculture	Broad ML technique overview	IoT-dependent, costly setup	Software-only, affordable platform
Zhang et al. (2022)	IoT Crop Monitoring	Real-time environmental sensing	Expensive sensors, no analytics	Web-based with dashboard analytics
Agri AI Team (2023)	ML-Based Crop Protection	Strong classification accuracy	No user interface or records	Full-stack UI + history management
Precision Agri Society (2024)	AI Decision Support Systems	Data-driven farming guidance	No scalability or treatment guide	Unified scalable platform

III. RESEARCH GAP

Despite meaningful progress in agricultural AI research, several important gaps remain in the current landscape of plant disease detection systems. These gaps limit the practical deployment and widespread adoption of existing solutions, particularly among small and medium-scale farmers.

The first and most prominent gap lies in the overreliance on image-based deep learning models. While CNNs have demonstrated strong classification performance in laboratory conditions, they require high-resolution image inputs, powerful GPU hardware, and large annotated datasets. These requirements make them impractical for everyday farm use, particularly in regions with limited internet connectivity or computational resources.

A second key gap is the heavy dependence on IoT infrastructure. Many proposed systems require the physical deployment of sensors for monitoring temperature, humidity, and soil conditions. These hardware-dependent approaches increase setup costs and maintenance burden, making them inaccessible to the majority of the world's farmers who operate on tight budgets.

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Third, most existing systems are siloed — they either predict diseases or provide treatment guidance, but rarely both. There is a clear absence of unified platforms that seamlessly integrate prediction, treatment recommendation, historical record management, and analytics visualization under one roof.

Fourth, user experience and accessibility have been largely neglected. Many research prototypes require technical expertise to operate and are not designed with the farmer in mind. The lack of intuitive interfaces, multilingual support, and mobile-friendly designs limits real-world adoption.

AgroSense-II directly addresses each of these gaps. By using tabular agricultural inputs processed through a Random Forest classifier, it eliminates the need for image capture hardware. By operating entirely as a web-based application, it removes IoT dependency. By integrating prediction, treatment recommendation, dashboard analytics, and history tracking into one platform, it delivers a complete agricultural intelligence tool. And by prioritizing a clean, accessible frontend built with ReactJS, it ensures that the system is usable by farmers and agricultural workers without specialized technical backgrounds.

IV. PROPOSED FRAMEWORK

The AgroSense-II system is designed as a full-stack web application that combines machine learning-based disease prediction with treatment recommendation and agricultural analytics in a single, cohesive platform. The architecture is structured into three primary layers: the frontend presentation layer, the backend processing layer, and the data storage layer.

A. System Architecture Overview

The user interacts with the system through a ReactJS-based web interface where they input agricultural parameters such as crop type, plant age, soil pH, soil moisture levels, temperature, humidity, presence of leaf lesions, and signs of nutrient deficiency. These inputs are transmitted to the FastAPI backend, which applies preprocessing steps including categorical encoding and feature scaling before passing the data to the trained machine learning model. The model evaluates the processed inputs and predicts the most probable disease affecting the crop. The system then retrieves corresponding treatment recommendations and prevention strategies from a structured treatment database and returns the results to the user interface for display.

B. Machine Learning Component

The core prediction engine of AgroSense-II is built on a Random Forest classifier, which was selected for its robustness, interpretability, and ability to handle mixed-type agricultural data effectively. The model is trained on a curated agricultural dataset containing records of crop conditions, environmental parameters, and confirmed disease labels. During training, the dataset undergoes preprocessing including handling of missing values, one-hot encoding of categorical variables, and normalization of numerical features. The trained model is serialized and loaded by the FastAPI backend at runtime, enabling low-latency predictions for incoming user requests.

C. Treatment Recommendation Engine

Beyond disease prediction, AgroSense-II incorporates a treatment recommendation module that maps each predicted disease to a set of actionable guidance notes. These include recommended pesticides or fungicides, organic treatment alternatives, cultural practices to prevent further spread, and early warning signs to monitor. This module transforms the system from a simple classifier into a practical decision support tool that farmers can act upon immediately after receiving a prediction.

D. Analytics Dashboard and History Management

Each prediction made through the system is stored in a MongoDB database along with the corresponding input parameters, predicted disease, and timestamp. The analytics dashboard aggregates this historical data and presents it through visual charts and summaries, enabling users to identify recurring disease patterns, seasonal risk periods, and crop-specific vulnerabilities over time. This feature is particularly valuable for agricultural researchers, crop monitoring agencies, and government departments that need longitudinal insights into disease trends.

V. APPLICATIONS

In direct farming contexts, the system serves as a practical tool for smallholder and commercial farmers who need quick, reliable disease identification without waiting for an agricultural expert to visit their farm. By entering basic crop and environmental data through the web interface, a farmer can receive a disease prediction and treatment recommendation

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within seconds — a capability that can make the difference between saving and losing an entire crop.
In agricultural education and research, the platform serves as a valuable learning and experimentation tool. Students and researchers can use it to study disease patterns, understand how different environmental variables influence disease onset, and experiment with machine learning models on agricultural data. The data augmentation and prediction history features make it particularly suitable for academic analysis and dataset generation exercises.

At an institutional and policy level, agricultural agencies, government departments, and crop monitoring organizations can use AgroSense-II to analyze historical prediction data across regions and crop types. This aggregate view helps authorities identify disease outbreaks, allocate resources proactively, and design targeted intervention programs. The scalable architecture of the platform also supports future integration with IoT networks, satellite imagery data, and mobile applications, paving the way for enterprise-grade smart farming deployments.

VI. FUTURE WORK

While AgroSense-II demonstrates a solid foundation for AI-driven plant disease detection, several enhancements are planned to expand its capabilities and reach.

The most immediate area of improvement involves upgrading the prediction engine with more advanced machine learning models. Future versions of the system will explore ensemble methods such as XGBoost and LightGBM, which often outperform Random Forest on structured agricultural data. Additionally, integrating image-based disease detection using convolutional neural networks will allow the system to support leaf image uploads as an alternative or complementary input mode, broadening its diagnostic capabilities.

Integration with IoT devices and real-time environmental monitoring systems is another priority for future development. By incorporating live sensor feeds for temperature, humidity, rainfall, and soil nutrients directly into the prediction pipeline, AgroSense-II can transition from a reactive diagnostic tool to a proactive early-warning system for disease outbreaks. This integration would significantly enhance the system's precision farming capabilities.

On the user experience front, developing native mobile applications for Android and iOS with multilingual support, offline functionality, and voice-assisted interaction would dramatically improve accessibility for farmers in diverse geographical and linguistic contexts. Incorporating explainable AI (XAI) techniques would further help users understand why a particular disease was predicted, building trust in the system's recommendations.

Finally, deploying AgroSense-II on cloud infrastructure would enable centralized, multi-region crop health monitoring at scale. Advanced predictive analytics built on large-scale historical data could help identify seasonal disease trends, regional risk factors, and optimal intervention windows, making the platform a powerful tool for both individual farmers and national agricultural planning bodies.

VII. CONCLUSION

This paper presented AgroSense-II: AI-Powered Plant Disease Detection and Treatment Recommender, a lightweight, web-based platform designed to bring intelligent crop disease management within reach of everyday farmers. By integrating a Random Forest machine learning model with a FastAPI backend, ReactJS frontend, and MongoDB database, the system delivers a seamless experience that covers disease prediction, treatment recommendation, analytics visualization, and historical record management — all through a single, accessible interface.

The literature review and research gap analysis confirmed that while significant work has been done in image-based disease classification and IoT-driven environmental monitoring, there remains a clear shortage of unified, software-only platforms that prioritize accessibility, affordability, and end-to-end agricultural intelligence. AgroSense-II fills this gap by offering a practical alternative that can be deployed immediately without expensive hardware or deep technical expertise.

The system's design reflects a deliberate balance between technical sophistication and real-world usability. Machine learning models are trained on structured agricultural datasets to deliver accurate predictions, while the treatment recommendation engine ensures that those predictions translate directly into actionable guidance for the farmer. The analytics dashboard adds long-term value by enabling trend analysis and informed decision-making over time.

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Looking ahead, AgroSense-II has significant potential for growth through the incorporation of deep learning, IoT integration, mobile deployment, and cloud scalability. With continued development, the platform can evolve into a comprehensive precision agriculture tool that serves farmers, researchers, and agricultural authorities alike — contributing meaningfully to the broader goal of sustainable, technology-driven food production.

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