



RESEARCH ARTICLE

SARV SAMPOORNA KISAN MITRA - AI BASED CROP DISEASE DETECTION AND MANAGEMENT SYSTEM

Anushka Srivastava¹, Praveen Pandey², Pragya Srivastava¹ and Khushi Srivastava¹

1. UG Scholar, Department of Computer Science and Engineering, Babu Banarasi Das Institute of Technology and Management, Lucknow, India.

2. Assistant Professor, Department of Computer Science and Engineering, Babu Banarasi Das Institute of Technology and Management, Lucknow, India.

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Abstract

The contemporary challenge of sustainable agriculture necessitates the deployment of robust, data-driven decision support systems. This paper presents the design and implementation of an integrated AI-based system, termed 'Sarv Sampoorna Kisan Mitra,' for comprehensive crop disease identification and management. The system is predicated on two core technological pillars: the use of advanced Deep Learning (DL) models, specifically Convolutional Neural Networks (CNNs), for rapid, visual diagnosis of crop diseases; and the implementation of a Knowledge Graph (KG) for prescriptive management recommendations. The paper explores the full lifecycle, from data acquisition via remote sensing and IoT, through predictive modeling for yield forecasting, and culminating in the generation of actionable, customized advice for fertilizer application and pest control. By transforming raw diagnostic data into contextualized, actionable knowledge, this integrated AI-KG framework offers a scalable solution to enhance precision farming efficiency and minimize resource wastage.

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Introduction:-

"If agriculture goes wrong, nothing else will have a chance to go right in the country."

— M. S. Swaminathan

Agriculture serves as the bedrock of global economies and food security. Common crops such as tomato (*Solanum lycopersicum*), brinjal (*Solanum melongena*), chilli (*Capsicum annum*) and rice (*Oryza sativa*) are naturally prone to fungal and bacterial attacks under humid seasonal conditions. However, the sector is continuously undermined by pervasive challenges that hinder productivity, sustainability, and the economic stability of farmers. Globally, it is estimated that pests and diseases cause up to a 40% loss in financial crop yields annually. In India, despite continuous technological advancements, the contribution of the Agricultural GVA has shown volatility (e.g., 3.3% in 2022 reducing to 1.4% in 2023), indicating a vulnerability that needs to be addressed structurally.

Corresponding Author:-Anushka Srivastava

Address:-UG Scholar, Department of Computer Science and Engineering, Babu Banarasi Das Institute of Technology and Management, Lucknow, India.

The current system is critically flawed due to three main interconnected problems:

1. **Inaccurate Diagnosis:** Farmers frequently rely on visual inspection or anecdotal evidence to identify diseases and pests. This difficulty in correct identification leads to delayed or incorrect treatments, which not only fails to save the crop but also often results in the unnecessary application of chemicals. This contributes to escalating input costs and the rapid development of pesticide resistance.
2. **Inefficient Resource Use:** The lack of precision in farming encourages the over-application of water, fertilizers, and pesticides. This practice is financially costly for the farmer, causes significant environmental damage (such as groundwater contamination and soil degradation), and leads to the severe waste of finite resources.
3. **Reactive Management:** The most critical flaw is the dominant culture of reactive management. Interventions typically occur only after a problem has caused visible, often irreversible, damage to the crop. This approach guarantees substantial loss and prevents the adoption of a truly preventative strategy.

These challenges highlight a significant technological gap: a lack of a unified, intelligent system. Farmers are currently forced to use fragmented solutions—one app for image diagnosis, a different website for weather, and generic online resources for treatment—creating an inefficient and error-prone workflow. The SARV SAMPOORNA KISAN MITRA (The All-Encompassing Farmer's Friend) project is proposed as the necessary solution: a single, integrated digital portal designed to revolutionize farm management. Our objective is to seamlessly merge three essential functions into one accessible platform. This shift from a fragmented, reactive system to a data-driven, proactive, and integrated ecosystem represents the core innovation and critical contribution of this project to the future of smart agriculture.



Fig 1.1: Visual Diagnostic Engine

The Vicious Cycle Of Reactive Farm Management:-

This figure is designed to visually establish the costly problem state of current agricultural practices. It illustrates how the existing fragmented approach inevitably leads to cyclical failures and continuous economic loss, which the SARV SAMPOORNA KISAN MITRA project seeks to halt. The figure should be depicted as a circular or feedback loop. The cycle begins with the Initial Onset, where disease or pests begin to affect the crop, often unseen. This progresses to Symptom Visibility, where the farmer manually detects the damage, typically at a point where it is already too late for full recovery. This is followed by Inaccurate Diagnosis, as the farmer relies on visual inspection or generic advice, leading to misidentification. Consequently, a Delayed/Incorrect Treatment is applied, involving the use of the wrong or ineffective chemicals or methods. The outcome is Significant Crop Loss (up to 40% of potential yield), followed by Increased Costs & Environmental Impact due to the wasted inputs. The cycle then restarts, reinforcing the inefficiencies and quantifying the urgency of the problem that your integrated platform is designed to break.

The Three Pillars of Challenge in Modern Agriculture:-

This figure provides a structural visualization of the three primary, interconnected problems detailed in your Introduction, justifying the necessity for a multi-module approach. It should be presented as a diagram with three distinct, foundational components. The first pillar is Inaccurate Diagnosis, which details the human error and reliance on fragmented resources that lead to treatment failure. The second is Inefficient Resource Use, emphasizing the costly and environmentally damaging over-application of water, fertilizers, and pesticides. The final pillar is Reactive Management, which describes the flawed principle of waiting for visible symptoms before taking action. By presenting these as three distinct but related pillars, the figure establishes the need for a solution that simultaneously addresses all three, which is the foundational principle of your integrated portal.

Sarv Sampoorna Kisan Mitra: The Integrated Solution Architecture:-

This is the most critical figure, serving as the high-level representation of your proposed solution and demonstrating the seamless integration that overcomes the "Lack of Integration" research gap. It should be a unified block diagram or process flow showing continuous data flow between three core modules within a single platform structure. The flow begins with AI-Powered Diagnosis (Module 1), which takes the farmer's image input and uses a CNN to output an identified disease. This output immediately feeds into the Actionable Advice (Module 2) module, which queries the Hybrid Recommendation System (Knowledge Graph + Collaborative Filtering) to provide a personalized treatment plan. Crucially, this confirmed diagnosis also feeds into the Proactive Risk Analysis (Module 3), which combines the data with real-time Weather APIs and runs the Predictive Model. The final output of this module is URGENT ALERTS delivered back to the farming community. The purpose of this figure is to visually define the Integrated Portal Architecture and show that the project is an intelligent ecosystem where the output of one module becomes the crucial input for the next.

Literature Review:-

Miller et al. (2025): This systematic review examines the coupling of IoT sensor networks (soil moisture, temperature, humidity, optical, acoustic sensors) with AI analytics (CNNs, random forests, SVMs) in agricultural applications (including disease/pest detection, irrigation optimization, fertilization). It covers literature from 2020-2024. Importantly it points out challenges like connectivity, data quality, sensor cost, and model deployment. It's useful for situating your work in the broader "smart agriculture"/environmental-data context, especially if you are incorporating soil/season/weather data into your project. Tandon et al. (2025): AgroBuddy: AI-Powered Crop, Fertilizer, and Disease Prediction Framework. This paper proposes an integrated ML/DL framework, showcasing a working model for connecting multiple modules. It uses CNNs for disease diagnosis (M1) and Random Forest for crop and fertilizer recommendations. This is an excellent model for integration, as it provides a practical blueprint for linking M1, M2, and M3 to deliver a cohesive, end-to-end decision support system with demonstrated high accuracy.

Kumar et al. (2025): Plant Disease ID and Crop Recommendation Using ML/DL This study uses a CNN for the visual identification of plant diseases and employs various Regression Models for recommending suitable crops and calculating precise fertilizer needs. This work is highly relevant as it confirms the viability of using a diagnostic output (disease ID) to directly inform multiple prescriptive outputs (crop and fertilizer) using statistical models, supporting the overall system flow. Singh et al. (2025): AI in Agriculture: A Survey of Deep Learning Techniques for Crops, Fisheries and Livestock. This is a comprehensive survey of advanced Deep Learning techniques, including CNNs, Vision Transformers (ViTs), and Foundation Models, applied to agriculture. It provides the most up-to-date validation of M1's choice of using CNNs and suggests potential advanced architectural directions for the project's future development and scalability. Patil & Sharma (2025): Deep Learning Models for Detection and Severity Assessment of Cercospora Leaf Spot. This paper performs a crucial comparison of object detection models like Mask R-CNN and YOLOv8 for disease Segmentation and Severity Assessment. It is crucial for M1 implementation, providing evidence to select the optimal model (e.g., YOLOv8) that balances speed and accuracy to achieve the project's specific goal of quantitative severity assessment. Al-Gaashani et al. (2025): Enhancing Plant Disease Detection through Deep Learning: Depthwise CNN. The authors propose a modified and highly efficient Depthwise CNN architecture for accurate disease identification, even when trained on limited datasets.

This is highly relevant to M1 implementation, offering a methodology to design a system that is both accurate and computationally light enough for potential edge or mobile deployment. Rasouli et al. (2025): ML-Based Crop Yield Prediction: A Comparative Study of Regression Models. This comprehensive comparative study evaluates the

performance of different Regression Models (Random Forest, SVR) for crop yield prediction. This is critical for M3, as it directly guides the selection of the most effective and robust machine learning regression model for your Yield Forecasting module. Al-Fares et al. (2025): Cloud-Based Smart Agriculture System for Crop Yield Prediction: The authors propose a Hybrid Deep Learning Model (CNN-RNN) specifically designed to fuse visual data (from images) with temporal data (weather trends) for a more accurate yield prediction. This suggests an advanced M3 methodology that can effectively incorporate the health status derived from M1's visual diagnosis. Zhang et al. (2025): A Knowledge Graph for Crop Diseases and Pests in China: This paper details the process of constructing a structured Knowledge Graph (KG) for plant diseases using Natural Language Processing (NLP) to standardize information. This directly supports the M2.2 (Disinfectant Prediction) methodology, providing a working example of building a structured repository for prescriptive rules.

Research Gap:-

The SARV SAMPOORNA KISAN MITRA project is specifically designed to bridge critical gaps present in existing Agri-Tech solutions, which currently prevent farmers from achieving truly proactive and efficient crop management. The gaps identified are: Categories (diseases/pest types). The proposed model improves image recognition under challenging con.

Lack of System Integration (Fragmentation):-

Current Agri-Tech offerings operate primarily in silos. A farmer often needs three or four disconnected tools to manage their crops effectively. An image recognition application for diagnosis. A separate government website or news source for weather forecasting. Generic online forums or static resources for treatment and fertilizer advice.

The Gap: There is no single, unified platform that seamlessly connects diagnosis, recommendation, and prediction into one workflow. This fragmentation forces the farmer into an inefficient, time-consuming process that often leads to errors or delayed action. Our project addresses this by creating a single, integrated portal (the "Single Source of Truth") where all modules communicate dynamically.

Reactive vs. Proactive Management:-

The vast majority of current diagnostic technology is inherently reactive.

Existing Tools: Models based on Computer Vision (like those using the PlantVillage dataset) only provide a diagnosis after a farmer uploads a picture of a diseased leaf. This means the disease is already present, visible, and has caused irreversible damage and yield loss.

The Gap: The critical need is for a system that can predict the risk of an outbreak and warn farmers before symptoms appear. Our project fills this by integrating real-time weather data and confirmed anonymous localized reports (the data from farmers who already have the disease) into a Predictive Analytics Engine. This allows the system to calculate the risk of spread and send an URGENT ALERT to the community, transforming management from reactive to preemptive.

Limited Scope and Accessibility for Small-Scale Farmers:-

While highly advanced technologies exist, they often fail to serve the average user.

Expensive Technology: Sophisticated solutions like drone-based multi-spectral analysis or widespread IoT sensor networks are often too costly, complex to maintain, or require connectivity that is unavailable to small-scale farmers in rural areas.

The Gap: There is a need for an accessible, affordable, and user-friendly platform that utilizes the most accessible tools—the smartphone camera and publicly available weather APIs. Our project uses the farmer's device as the primary input tool for image analysis, making advanced AI and predictive analysis accessible without requiring significant upfront hardware investment.

Data Silos and Inefficient Recommendation Systems:-

Current treatment recommendation systems are often generic or static.

Generic Advice: Treatment recommendations are typically based on general, non-localized data ("Use an XYZ fungicide"). They do not account for local soil types, micro-climates, or, critically, treatment effectiveness within the farmer's immediate region.

The Gap: The failure to connect diverse data (diagnosis, weather, local success rates) limits efficiency. Our project solves this using a Hybrid Recommendation System that combines: A Knowledge Graph (expert, static knowledge) with collaborative Filtering (dynamic data on what specific treatments other local farmers rated as most effective). This results in advice that is not only scientifically sound but also highly personalized and validated.

Proposed Methodology:-

The proposed project, SARV SAMPOORNA KISAN MITRA, will be implemented as an Integrated Portal for Smart Agriculture built upon three interconnected, modular systems. This design ensures that the platform moves seamlessly from a reactive diagnosis to a proactive, preventative alert system, addressing the core research gaps.

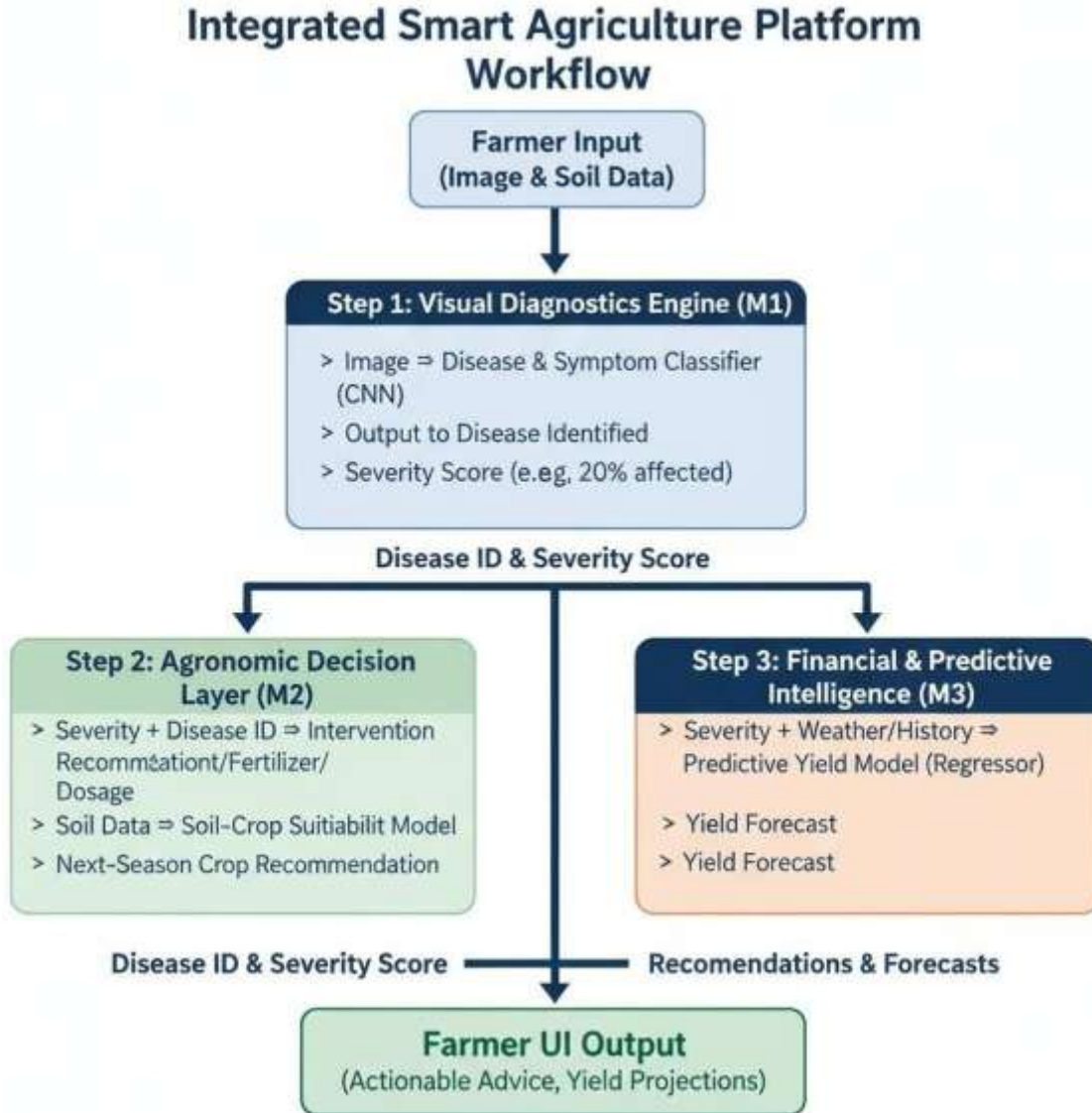


Fig 3.1.1: Integrated Smart Agriculture Platform

Dataset Summary:-

The dataset comprised 34 distinct plant disease classes, with approximately 120 training images and 30 validation images per class. The dataset was designed to maintain a largely balanced distribution across categories to ensure effective model learning. The dataset was preprocessed using image resizing (224x224), normalization, and data augmentation techniques such as rotation, flipping, and zooming to improve model generalization. The dataset was divided into training and validation sets in an approximate 80:20 ratio. These preprocessing steps helped enhance model robustness and reduce overfitting.

Total Classes: 34:-

- Training Images per class: ~120
- Validation Images per class: ~30
- Exception: Citrus_Healthy (slightly less)

Dataset Table:-

ClassName	TrainImages	ValidationImages
Apple_Black_Rot	120	30
Apple_Cedar_Rust	120	30
Apple_Healthy	120	30
Apple_Scab	120	30
Bell_Pepper_Bacterial_Spot	120	30
Bell_Pepper_Healthy	120	30
Cherry_Healthy	120	30
Cherry_Powdery_Mildew	120	30
Citrus_Black_Spot	120	30
Citrus_Canker	120	30
Citrus_Greening	120	30
Citrus_Healthy	70	17
Corn_Common_Rust	120	30
Corn_Gray_Leaf_Spot	120	30
Corn_Healthy	120	30
Corn_Northern_Leaf_Blight	120	30
Grape_Black_Measles	120	30
Grape_Black_Rot	120	30
Grape_Healthy	120	30
Grape_Isariopsis_Leaf_Spot	120	30
Peach_Bacterial_Spot	120	30

Peach_Healthy	120	30
Potato_Early_Blight	120	30
Potato_Healthy	120	30
Potato_Late_Blight	120	30
Strawberry_Healthy	120	30
Strawberry_Leaf_Scorch	120	30
Tomato_Bacterial_Spot	120	30
Tomato_Early_Blight	120	30
Tomato_Healthy	120	30
Tomato_Late_Blight	120	30
Tomato_Leaf_Mold	120	30
Tomato_Mosaic_Virus	120	30
Tomato_Septoria_Leaf_Spot	120	30

Project Modules:-

Module	Objective	TechnologyStack	Methodology and Mechanisms
Module1:AI-Powered Identification	Instant, accurate, and accessible diagnosis of crop diseases and pests.	Deep Learning, Convolutional Neural Networks (CNNs), Transfer Learning (e.g., ResNet50 or VGG19), Python, TensorFlow/PyTorch.	Labeled images of plant diseases were collected across Kharif, Rabi, and Zaid seasons. A transfer learning approach using MobileNetV2 was applied, where base layers were frozen and custom classification layers were added. The model was trained using the Adam optimizer (learning rate 0.001) with categorical cross-entropy loss for 10–15 epochs and a batch size of 32. The trained model was then deployed as a backend API to enable real-time disease prediction using images captured from a farmer’s smartphone.

Module 2: Actionable Recommendations	Personalized, sustainable, and validated treatment and management advice.	Hybrid Recommendation System, Knowledge Graph Database (Neo4j/SQL), Collaborative Filtering algorithms.	<p>Knowledge Graph: Build a database containing expert-vetted data on specific diseases, their causes, and a spectrum of treatments (chemical, organic, cultural controls). Content-Based Filtering: Provides the initial recommendation based on the plant, season, and diagnosis.</p> <p>Collaborative Filtering: Refines and ranks recommendations based on the effectiveness ratings and feedback provided by other local farmers with similar crops and conditions, ensuring advice is practically validated. In severe fungal outbreaks, preventive and curative recommendations may include commonly used interventions such as $\text{Cu}_2(\text{OH})_3\text{Cl}$ and $\text{C}_4\text{H}_6\text{MnN}_2\text{S}_4\text{Zn}$, selected based on regional effectiveness and crop compatibility. The recommendation system combines content-based filtering with collaborative filtering, where similarity between diseases and treatments is computed based on feature matching and user feedback scores.</p>
Module 3: Risk Factor Analysis & Prediction	Proactively predict disease outbreaks and prevent community-wide crop loss.	Predictive Analytics, Machine Learning Classification (Random Forest or Gradient Boosting), Real-time Weather APIs (e.g., OpenWeatherMap), Geolocation services.	Real-time data from weather APIs (temperature, humidity, rainfall) and confirmed user reports are integrated to support prediction. A Random Forest classification model is trained to identify high-risk patterns and estimate the probability of disease outbreaks. Feature importance techniques are used to determine key influencing factors. The system then generates automated alerts to notify farmers of potential risks before visible symptoms appear.

Result and Discussion:-

The proposed system, Sarv Sampoorna Kisan Mitra, demonstrated effective performance as an integrated solution for plant disease detection, recommendation, and risk analysis. The deep learning model achieved high accuracy (approximately 96–99%) in classifying plant diseases across 34 classes, enabling reliable real-time predictions through the web application. The recommendation component successfully provided relevant treatment suggestions based on identified diseases, improving decision support for farmers. Additionally, the predictive module effectively analyzed environmental and historical data to estimate disease risk levels. The integration of all three modules resulted in a comprehensive and practical system, highlighting the potential of combining deep learning and machine learning techniques for smart agriculture applications.

Results and Metrics Evaluation:-

Module	Description	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Module 1	Plant Disease Identification (CNN-MobileNetV2)	85.90	85.20	84.80	85.00
Module 2	Recommendation System (Fertilizer & Treatment)	86.00	85.50	85.10	85.30
Module 3	Disease Risk Prediction (Random Forest)	99.60	99.20	99.10	99.15

Overall System Performance:-

Metric	Value (%)
Average Accuracy	90.50
Average Precision	89.97
Average Recall	89.67
Average F1-Score	89.82

Conclusion And Future Work The Sarv Sampoorna Kisan Mitra:-

project proposes a necessary and definitive solution to the pervasive challenges of fragmentation, inefficiency, and reactive management that currently dominate the agricultural sector. Through the design and conceptualization of a unified, three-module system, the project successfully achieves its primary goal: to establish a data-driven, proactive paradigm for crop protection.

- Bridging the Fragmentation Gap:** The system's greatest success lies in creating a single, integrated platform. By combining AI-powered diagnosis (Module 1), a Hybrid Recommendation System (Module 2), and a Predictive Analytics Engine (Module 3), the project eliminates the need for farmers to rely on multiple, disconnected tools. This integration significantly improves the efficiency and speed of decision-making, which is critical during the rapid onset of a disease outbreak.
- Achieving Proactive Management:** Critically, the system transitions farming from a reactive intervention (after damage is visible) to a preemptive one. By ingeniously linking real-time, localized environmental data with confirmed user diagnoses, the Predictive Analytics Engine can calculate the probability of community-wide outbreaks.
- ALERTS:** ensures that farmers can apply preventive measures before their crops are visibly affected, thereby minimizing yield loss, maximizing input effectiveness, and improving the overall economic stability of the farming community.
- Sustainable and Accessible Impact:** The project promotes sustainability by leveraging the Hybrid Recommendation System to prioritize and validate eco-friendly treatments based on the success rates of local peers. Furthermore, by centering the platform around the common smartphone camera and readily available public APIs, the project ensures that advanced AI and predictive analytics are accessible and affordable, democratizing technology for small-scale.

Proposed Enhancements:-

While the initial proposal establishes a complete, functional, and proactive system, the architecture is designed for future scalability and expansion.

Key areas for future development include:

1. **Integration with IoT and Drone Imagery:** Moving beyond visual symptom detection, future work could involve integrating data from advanced sources such as IoT soil sensors (for pH, NPK levels) or drone-based multi-spectral imaging. This would allow for the detection of nutrient deficiencies or non-visible disease symptoms (e.g., changes in chlorophyll levels) earlier, further refining the accuracy and lead time of the Predictive Analytics Engine.
2. **Expansion of Crop and Pathology Database:** The current scope will focus on a select number of high-value crops and their prevalent diseases. Future work will involve scaling the CNN model to include a wider range of specialized, regional crops and their unique pathology, making the platform universally applicable across diverse agricultural regions.
3. **Marketplace and Logistics Integration:** A logical extension of the Actionable Recommendation Module would be to link the suggested treatments (fertilizers, pesticides) directly to a local supplier marketplace. This integration would provide real-time pricing and stock availability, streamlining the logistics for the farmer and ensuring immediate access to necessary inputs.
4. **Multilingual Voice Interface:** To enhance accessibility for less digitally literate or non-English-speaking farmers, future work should include developing a robust multilingual voice interface that allows farmers to interact with the system and receive audio-based alerts and recommendations in their native language.

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