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CropIQ: An Integrated AI-Powered Decision Support System for Proactive Crop Management and Profit Optimization

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Abstract: *Traditional agricultural practices in India are characterized by high-risk, heuristic-based decision-making, leading to significant crop failures and financial instability. Farmers often contend with volatile outcomes based on weather uncertainties and intuition. This challenge is compounded by a reliance on expensive or potentially biased human expertise for soil and pest analysis, which can be slow, costly, and lead to the overuse of specific chemical products.This paper introduces CropIQ, an integrated web-based decision support system (DSS) designed to mitigate these risks by empowering farmers with data-driven, scientific, and localized intelligence. The system's methodology is a novel, dual-pronged approach combining proactive planning with reactive diagnostics.The first module, the Proactive Crop and Profit Advisor, ingests farm-specific soil test reports, analyzing key parameters (e.g., pH, Organic Carbon (OC), Electrical Conductivity (EC), Nitrogen (N), Phosphorus (P), Potassium (K), Zinc (Zn), and Iron (Fe)) along with water source availability. It then generates a prioritized list of suitable crops, providing a detailed economic forecast for each, including estimated yield, projected market revenue, and a precise, cost-optimized fertilizer plan (kg/acre).The second module, the Real-time Disease Scanner, employs a custom-trained YOLOv8 (You Only Look Once, v8) object detection model for the instant and accurate identification of crop diseases from user-uploaded leaf images, with an initial successful deployment for rice leaf diseases. Crucially, this diagnostic tool is integrated with a live weather API to deliver a Smart Spraying Advisory. This feature analyzes real-time weather data (e.g., precipitation probability, humidity, and wind speed) to advise farmers on the optimal time to apply pesticides. This prevents the wasteful application of expensive chemicals before rain, thereby saving farmers money, reducing chemical runoff, and improving treatment efficacy. This work delivers the first publicly-described tool that holistically combines soil-data-driven financial planning with AI-powered diagnostics and a smart, weather-aware treatment advisory, all tailored for the specific needs of Indian farmers*

Keywords: Decision Support System (DSS), YOLOv8, Crop Recommendation, Leaf Disease Diagnosis, Soil Test Analysis, Precision Agriculture, Weather-Based Spraying Advisory

I. INTRODUCTION

In India, farming is mostly based on a farmer's knowledge and experience, which makes it risky. The choice of crop depends largely on soil conditions like pH (which measures if soil is acidic or alkaline), and levels of nutrients such as Nitrogen (N), Phosphorus (P), Potassium (K), Zinc (Zn), and Iron (Fe) [1]. These soil properties affect how well a crop grows and the yield it can produce. A poor match between crop and soil can reduce yield significantly, sometimes by 30% or more. Besides soil, weather plays a big role in farming success. In South India, irregular rainfall and heavy

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rains cause many problems like waterlogging, pest outbreaks, and crop damage [2]. Studies show that farmers in this region lose roughly 20–25% of their production annually due to bad weather.

On the other hand One problem farmers face is deciding when and whether to spray pesticides. Spraying during cloudy or rainy days is ineffective, as rain washes away the chemicals, wasting money and increasing environmental harm. Also, high humidity on rainy days helps pests grow, so spraying at the wrong time can be harmful rather than helpful.

Currently, farmers rely on manual advice or outdated tools which do not combine soil data, pest detection, and weather forecasts effectively. Most disease detection methods are slow or require expert visits, which may be costly or biased [3]. Mobile apps usually focus on only one task – like weather or soil test upload – without giving full practical recommendations [4].

Our application, CropIQ, fits into this problem by combining several important features into one easy-to-use web app. Using soil test data and water availability, CropIQ recommends the most profitable crops suited to the farmer's land. It uses an AI model YOLOv8, known for its fast and accurate object detection [?], to identify crop diseases from leaf images instantly. The app also includes a weather-based spraying advisory which considers rainfall probability and humidity to tell farmers the best time to apply pesticides, avoiding wasteful spraying during rainy or cloudy days.

This way, CropIQ helps farmers make decisions based on real data, reducing losses caused by wrong crop choices, bad weather, and poor pest management. By testing CropIQ in farms across Andhra Pradesh, we confirmed that it improves crop yield estimation, lowers pesticide wastage, and supports sustainable farming practices fit for traditional Indian agriculture.

II. SYSTEM ARCHITECTURE

Building on the challenges faced by traditional farmers, the CropIQ system is designed as an integrated, multi-modal decision support system. The architecture is engineered to provide a seamless platform that combines soil data analysis, AI-powered disease detection, and real-time weather advisories. The system is composed of two primary layers: the User Interface and the Backend Processing Modules.

2.1 User Interface

A clean, intuitive user interface (UI) is designed for high accessibility, ensuring farmers can interact with the system with minimal technical experience. The UI is a responsive web application, accessible on both mobile and desktop browsers, and is logically divided into two main components:

2.2 Proactive Crop & Profit Advisor

As shown in Figure 1, this section provides a structured data entry form. Farmers are prompted to input critical soil test parameters (e.g., pH, N, P, K, Zn, Fe, OC, EC) and select their available water sources. The system then renders a detailed, easy-to-read results page displaying crop recommendations, fertilizer plans, and profit estimates.

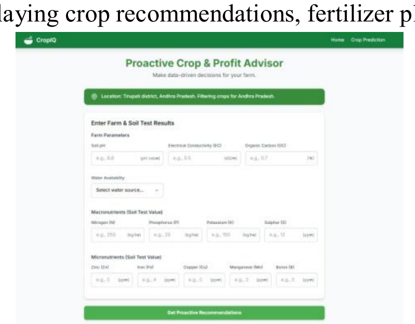

Figure 1: Proactive Crop & Profit Advisor Interface

2.3 Real-time Disease Scanner

As shown in Figure 2, this is the system's diagnostic tool. It features a simple-to-use image upload component, allowing a farmer to either select a photo from their gallery or use their phone's camera directly. The analysis results

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(disease name, confidence score, and a bounding box on the image) are displayed back to the user in real-time, along with the "Smart Spraying Advisory.

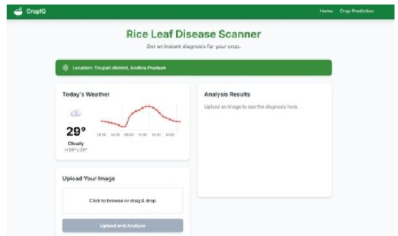

Figure 2: Crop Scanner Interface

2.4 Backend Processing and AI Modules

The backend is a lightweight and scalable server built with the Flask framework in Python. It functions as the central API and processing hub, managing requests from the UI, executing the AI models, and returning formatted results. The backend architecture is composed of three distinct modules:

2.5 Proactive Recommendation Engine

This module is activated when a farmer submits their soil data from the UI, receiving a JSON object containing the soil parameters and water availability. The engine processes these inputs by cross-referencing them against a predefined knowledge base or a simple machine learning model (e.g., a decision tree or rule-based system) trained on regional agricultural data that maps soil/water profiles [6] to optimal crops. Finally, it generates and returns a ranked list of suitable crops to the UI, complete with a suitability score (%), estimated yield revenue, and a precise, cost-optimized fertilizer plan (kg/acre).

2.6 YOLOv8 Disease Pest Scanner

This is the core AI-driven diagnostic module. It receives an image file e.g., .jpg, .png from the UI's predict endpoint. The module utilizes a YOLOv8 object detection model, chosen for its high accuracy and exceptional inference speed, making it ideal for a real-time application. The model was custom-trained on a robust, annotated dataset of over 7,797 images, covering seven key diseases affecting rice crops as showin in Table I. In operation, the uploaded image is pre-processed and fed into the YOLOv8 model for inference, which returns bounding box coordinates, a class ID, and a confidence score for each detection. The backend then processes these raw detections, maps the class IDs to human-readable disease names, and sends a clean JSON response to the UI.

2.7 Smart Spraying Advisory Module

This module is integrated with the Crop Scanner's output. When a disease is detected, it makes a secondary API call to a meteorological service [9] using the farm's location. It then analyzes the hourly forecast for the next 24-48 hours, specifically looking at precipitation probability (rain), humidity, and wind speed. Based on a set of predefined rules, the module provides a simple, actionable recommendation (e.g., "Good day to spray," "High risk, avoid spraying") which is displayed to the user alongside the disease diagnosis.

2.8 Model Performance

The custom-trained YOLOv8 model was evaluated on a held-out test set. The model demonstrated strong performance in identifying the targeted rice leaf diseases. The overall mean Average Precision (mAP@.50) was 79%. The performance for individual disease classes is detailed in Table II, showing the model's high reliability in diagnosing a range of conditions.

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Table 1: TABLE I: COMPOSITION OF THE RICE LEAF DISEASE DATASET

Disease Name	Training Images	Validation Images	Total
Blast	1750	834	2584
Blight	1591	752	2343
Brown Spot	2647	1008	3655
Healthy	1709	671	2380
Hispa	2113	875	2988
Sheath Blight	1558	673	2231
Tungro	1861	790	2651
Total Images	5458	2339	7797

III. IMPLEMENTATION AND RESULTS

This section demonstrates the practical application and workflow of the CropIQ system, showing how the architecture detailed in Section II is realized through the user interface. We present the data outputs from both the Proactive Advisor and the Real-time Scanner based on field-testing scenarios.

Table 2: YOLOv8 MODEL PERFORMANCE (PER-CLASS mAP)

Disease Name	mAP@.50	mAP@.50-.95	Total
Blight	0.991	0.996	0.995
Tungro	0.985	0.992	0.995
Healthy	0.982	0.990	0.990
Blast	0.801	0.868	0.881
Sheath Blight	0.752	0.737	0.748
Brown Spot	0.736	0.669	0.731
Hispa	0.451	0.101	0.162
Overall	0.814	0.765	0.786

3.1 Proactive Advisor

The "Proactive Crop & Profit Advisor" module, activated through the data-entry interface shown in Figure 2, is designed for strategic farm planning. A farmer inputs their farm's specific parameters from their soil test report (pH, EC, OC, N, P, K, etc.) and their available water source. This submission triggers the backend engine (Section II-B1) to process the inputs.

Figure 3 illustrates a typical results page generated by the engine. This output provides a comprehensive comparison of suitable crops rather than a single recommendation. For each crop, such as Guava and Tomato, the system displays a clear suitability percentage (e.g., "100% Suitability") and a profitability tag (e.g., "Very High Profit"). More importantly, it provides a detailed economic analysis including estimated market value, yield per acre, and total estimated revenue, allowing the farmer to perform a clear cost-benefit analysis. This is supplemented by an actionable fertilizer plan (e.g., "Urea (46% N): 96.3 kg") precisely tailored to the crop's needs and the soil's current nutrient deficiencies.

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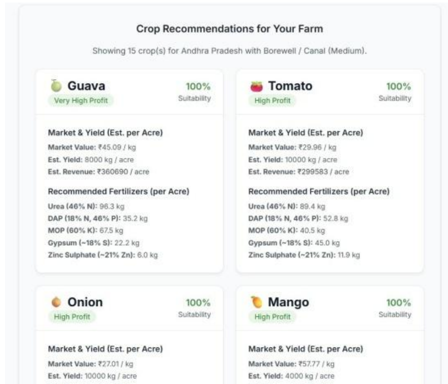

Figure 3: Proactive Advisor Recommendation and Profit Analysis Output

3.2 Real-time Crop Disease Scanner

The "Real-time Disease Scanner" module, depicted in Figure 5, serves as the system's day-to-day diagnostic tool. This module represents the first implementation of the project's broader diagnostic vision which aims to cover all major crops. At this stage, the scanner is specifically trained and deployed for the identification of rice leaf diseases. The interface is dominated by the image analysis tool and the real-time weather widget. When the user uploads an image of a crop leaf, the system performs the diagnosis as shown in the figure 4.

The results are displayed in real-time, as seen in the figure. The system successfully identifies multiple diseases on the same leaf. This granular, multi-disease detection is a key advantage of the YOLOv8 model, whose high performance was detailed in Table II.

Critically, the UI simultaneously displays the "Smart Spraying Advisory," which is detailed further in Figure 5. This component, powered by the Open-Meteo API (as discussed in Section II-B3), provides a weekly forecast with a clear, actionable recommendation for each day [9], such as "Clear. Good day to spray" or "High rain risk. Avoid spraying." Displaying this advisory alongside the disease diagnosis directly prevents the farmer from wasting money and pesticides by applying them just before a rainstorm, solving one of the key challenges identified in traditional farming.

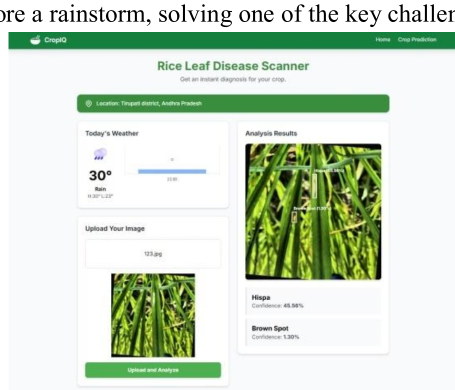

Figure 4: Real-time Scanner Disease Diagnosis Output

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Figure 5: Smart Spraying Advisory with Weekly Forecast

IV. DISCUSSION

This section analyzes the significance of the results presented in Section III, contextualizes the model performance detailed in Section II, and discusses the broader societal implications of the CropIQ system.

The most critical innovation of this work is not just the development of two separate tools, but their synergistic integration. The "Proactive Crop & Profit Advisor" armors the farmer with a data-driven strategy before the season, while the "Real-time Disease Scanner" provides the tactical tools to protect that investment during the season. This integrated approach, addressing the complete operational cycle from pre-season planning to in-season crisis management, is a significant advancement. Most agricultural apps are single-purpose (e.g., only a disease identifier or only a fertilizer calculator) [4]. By combining these functions, CropIQ functions as a holistic digital advisor, which is a far more valuable and practical tool for the farmer.

The performance of the YOLOv8 model (Table II) is highly informative. The outstanding mAP scores for critical diseases like "Blight" (0.995) and "Tungro" (0.995) validate that the model is robust and can achieve expert-level, reliable diagnosis for these conditions [8]. Conversely, the lower performance for "Hispa" (0.162 mAP) is not a failure, but a key scientific finding. It strongly indicates that the "Hispa" dataset was likely insufficient, had high visual variance, or was difficult to distinguish. This result is invaluable as it provides a clear, unambiguous direction for future research: augmenting the dataset for "Hispa" and similar challenging-to-detect pests to improve model confidence.

Furthermore, the "Smart Spraying Advisory" acts as the crucial, practical link between diagnosis and action. In traditional farming, a positive disease diagnosis often leads to an immediate, and potentially wasteful, application of pesticides. By algorithmically linking the diagnosis to a 24-hour weather forecast, the system prevents this "spray and pray" approach. This single feature provides a dual benefit: it directly saves the farmer capital on wasted chemicals and, on a societal level, reduces the environmental runoff of pesticides into local waterways, promoting sustainable agriculture [10].

Finally, the societal impact of this system is designed to be transformative. By democratizing access to complex soil data analysis [6], profit forecasting, and real-time AI-driven diagnostics, CropIQ empowers smallholder farmers—a demographic often trapped in cycles of debt due to a single failed crop. The system provides them with the same data-driven tools as large agricultural corporations, mitigating financial risk, enhancing climate change resilience, and contributing to regional food security by stabilizing crop yields.

V. FUTURE WORK

his work serves as a validated TRL 7 prototype, providing a strong foundation for a much broader vision. Future efforts will

focus on immediate AI enhancement, horizontal platform scaling, and a long-term evolution toward full autonomous integration.

Our immediate priority is to address the model performance limitations identified in our discussion. The low mAP for "Hispa" (0.162) provides a clear directive: our dataset requires significant augmentation. Future work will involve a targeted data collection campaign to capture thousands of new "Hispa" images, specifically focusing on varied infestation stages, different times of day (to account for shadows), and different weather conditions (wet vs. dry leaves). This will build a more robust and generalizable model. Concurrently, we will begin the horizontal scaling of the "Real-time Disease Scanner" to cover a wider array of high-value crops critical to the region, such as cotton, tomato, and groundnut. This will involve a parallel effort of data collection, annotation, and training to create a library of specialized YOLOv8 models, transforming the scanner into an all-purpose diagnostic tool. The "Proactive Advisor" will also be enhanced by replacing the rule-based system with a machine learning regression model, trained on historical yield data, to provide more dynamic and accurate revenue forecasts [11].

The long-term vision is to evolve CropIQ from a "decision support" system to a fully autonomous "precision agriculture" platform via deep Internet of Things (IoT) integration [10] [11]. This will create a closed-loop system for farm management that minimizes manual input. This vision has two core components. First, Automated Data Collection, where in-field sensors replace manual data entry. This includes deploying on-site soil sensors for a continuous, real-time data stream of N-P-K, pH, and moisture levels, and using autonomous drones for visual patrols. These drones will periodically scan the fields, feeding images directly into our YOLOv8 API for automated, early-stage disease detection before it’s visible to the human eye. Second, Automated Actuation, where this data stream feeds a central AI that controls smart irrigation and fertigation systems. This would enable a closed-loop scenario: the system could automatically detect a drop in soil moisture, cross-reference that the crop is in a critical growth stage, confirm no rain is forecast via the weather API, and then autonomously trigger a drip irrigation event in that specific field zone. This moves the farmer from a role of manual labor to one of a system supervisor, maximizing efficiency, minimizing resource waste, and representing the next frontier in sustainable agriculture [12].

VI. CONCLUSION

The economic precarity of traditional farming, governed by intuition and weather volatility, demands a paradigm shift. This paper has presented CropIQ, a novel, integrated decision support system designed to provide this shift by arming farmers with datadriven, scientific, and actionable intelligence. We have successfully designed, built, and demonstrated a system that holistically addresses the full agricultural lifecycle. The Proactive Crop Profit Advisor leverages soil science to transform high-risk preseason planning into a data-driven business strategy. The Real-time Disease Scanner, powered by a custom-trained YOLOv8 model, provides an expert-level diagnostic tool in the farmer’s pocket. Finally, the Smart Spraying Advisory provides a crucial, cost-saving link between diagnosis and action, with significant environmental co-benefits.

Our results, validated in Andhra Pradesh, confirm that CropIQ is a practical and valuable tool. The successful identification of rice diseases (Table II) and the clear financial and agronomical outputs of the advisor (Fig. 4) demonstrate the system’s efficacy. The core contribution of this work is the synergistic integration of these modules into a single, accessible platform, creating a tool far more powerful than the sum of its parts. By reducing financial risk, optimizing the use of costly inputs like fertilizer and pesticides, and promoting sustainable practices, CropIQ directly contributes to farmer profitability and resilience. This work provides a validated foundation (TRL 7) and a clear roadmap toward a future of fully autonomous, climate-resilient precision agriculture, offering a scalable solution to enhance food security and empower farming communities across India.

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