YOLOv8-Enabled Real-Time Crop Health Monitoring with Conversational Diagnosis and Geospatial Support

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***Abstract*—Agriculture is a cornerstone of global economies, supplying food, employment, and raw materials for numerous industries. Yet, one of the sector's enduring challenges is crop disease, which can drastically reduce yields and threaten food security. Traditional approaches to identifying plant diseases rely on manual inspections and expert evaluations, which are often slow, costly, and vulnerable to human error. Without early diagnosis, diseases can spread uncontrollably, leading to major economic setbacks for farmers and decreased crop output. To overcome these issues, this project introduces an AI- powered system for detecting and diagnosing crop diseases. It combines advanced deep learning, natural language processing (NLP), and geospatial mapping technologies. At its core is YOLOv8 (You Only Look Once, version 8), a powerful Convolu- tional Neural Network (CNN) designed for real-time image-based detection. Trained on a robust, annotated dataset from Roboflow, the model accurately identifies a variety of diseases affecting key crops such as rice, wheat, and maize.**

Beyond detection, the system includes an intelligent chatbot powered by Large Language Models (LLMs). This virtual as- sistant offers instant, tailored advice on diagnosis, treatment options, and preventive strategies. It provides farmers with user- friendly guidance in natural language, making it accessible even to those with limited technical knowledge. The chatbot serves as a virtual agricultural consultant, recommending effective pesticides, organic treatments, and disease management practices. A standout feature of this project is its geospatial mapping capability. By integrating OpenStreetMap's Overpass API, the system helps farmers locate nearby agricultural supply stores after a disease is identified. This allows quick access to the necessary products like pesticides or fertilizers, helping farmers respond promptly to disease outbreaks. Overall, the system presents a comprehensive AI-driven approach to crop disease management by combining image- based detection, interactive chatbot support, and location-based resource mapping. By reducing the dependency on manual inspection, enhancing decision-making, and streamlining access to agricultural inputs, it promotes more efficient, tech-enabled farming. This real-time, intelligent solution not only boosts productivity but also minimizes economic losses, paving the way for a more sustainable and resilient agricultural future.

Keywords: Plant Disease Detection, YOLOv8 CNN, Agricul- tural AI, Intelligent Chatbot, LLMs in Farming, Plant Pathology AI, GIS Mapping, OpenStreetMap API, Smart Farming, AI- Enhanced Agriculture.

1.INTRODUCTION

Agriculture is one of the most vital sectors of the global economy, providing food, employment, and raw materials for various industries. However, the productivity and sus- tainability of agriculture are constantly threatened by crop diseases, which can cause significant yield losses if not de- tected and treated in time. Traditional methods of disease detection primarily rely on visual inspection by farmers and agricultural experts, an approach that is often subjective, time-consuming, and prone to error, leading to delayed intervention and potential disease spread [9]. In many regions, small-scale farmers—who represent the majority of agricultural produc- ers—lack consistent access to expert knowledge, making early and accurate disease identification even more challenging. With the advancement of artificial intelligence (AI) and machine learning (ML), deep learning models have emerged as powerful tools for automating the detection and classi- fication of plant diseases. Convolutional Neural Networks (CNNs) have demonstrated remarkable accuracy in image-based classification tasks, making them highly suitable for disease detection in crops [4]. The You Only Look Once (YOLO) object detection framework, in particular, has gained popularity due to its real-time processing capabilities and high accuracy [3]. Recent advancements in YOLOv8 further improve both speed and precision, enabling real-time field applications even on modest hardware [1]. Beyond detection, timely diagnosis and treatment recom- mendations are crucial for effective crop disease management. Large Language Models (LLMs) now power conversational AI that can serve as virtual agricultural assistants, analyz- ing symptoms, suggesting treatments, and offering preven- tive measures [2]. By embedding an AI-driven chatbot di- rectly into a disease-detection platform, farmers gain imme- diate, context-aware advice without needing direct access to agronomists or pathologists. Another critical challenge is the accessibility of necessary inputs—pesticides, fertilizers, and resistant varieties. Farmers often struggle to locate nearby supply outlets promptly, delay- ing disease control measures. Leveraging geospatial technolo- gies such as OpenStreetMap's Overpass API allows real-time mapping of local plant and pesticide shops [15]. By integrating real-time detection, AI-driven diagnosis, and geolocation of resources, farmers receive a comprehensive support system for identifying diseases, receiving expert guidance, and sourcing treatments in one unified workflow. This project aims to develop a unified, AI-driven crop disease detection and diagnosis platform with three core components:

1) Real-Time Detection: Implement a YOLOv8 CNN model trained on a Roboflow-annotated dataset to ac- curately detect diseases in rice, wheat, and maize crops [1][5][6].

2) Chatbot-Driven Advisory: Integrate a Google Gemini Flash–powered chatbot to deliver interactive diagnosis, treatment recommendations, and preventive measures, bridging the agronomic knowledge gap [2].

3) Geospatial Resource Mapping: Employ OpenStreetMap's Overpass API to map nearby plant nurseries and pesticide shops based on user location, facilitating quick procurement of inputs [15].

By combining these features into a Streamlit web application, the system will enable farmers to rapidly identify crop diseases, access expert guidance, and obtain necessary treatment supplies—ultimately reducing yield losses and improving agri- cultural productivity.

2. RELATED WORK

Automated crop disease detection has seen rapid advancements through the application of AI, ML, and DL techniques, aiming to overcome the limitations of traditional manual inspection. In this section, we review prior work across the three pillars of our system—real-time image-based detection, chatbot-driven diagnosis, and geospatial resource mapping—and highlight how each informs and contrasts with our proposed methodology.

1. AI-based Image Processing for Disease Detection: Deep learning, particularly Convolutional Neural Networks (CNNs), underpins most modern disease detection systems. Early efforts fine-tuned established architectures on plant disease datasets. Too et al. [4] compared fine-tuned models like VGG and ResNet, reporting up to 94% accuracy for single-disease classification. Ale et al. [3] similarly benchmarked ResNet-50, VGG-16, and MobileNetV2, finding that ResNet-50 achieved 9˜4.2% accuracy, while MobileNetV2 offered faster inference (32 ms) suited for edge devices. However, these single-stage classifiers lacked object localization, limiting utility on images with multiple leaves or mixed backgrounds. Object-detection frameworks addressed this by simultane- ously drawing bounding boxes and labeling diseases. Roy & Bhaduri [7] demonstrated a YOLO-based model that improved detection accuracy by 1˜0% over previous CNN pipelines in real-time settings. Shahi et al. [1] extended this concept to UAV imagery, showing that high-resolution aerial data could be processed by CNNs to detect wheat and maize diseases—albeit with performance degradation under adverse lighting and wind conditions. Singla et al. [2] compared clas- sical ML (SVMs, Decision Trees) to deep learning, confirming CNNs' superiority for real-time monitoring. More recently, transformer-based detectors and the latest YOLOv8 architecture have further boosted both accuracy and speed. YOLOv8's anchor-free design, efficient backbone, and multi-scale fusion layers yield substantially lower inference latency (2˜2 ms per image) and higher mean Average Precision (mAP) compared to YOLOv5 and earlier YOLO versions. Our methodology adopts YOLOv8 to leverage these gains, enabling instant detection of multiple diseases in rice, wheat, and maize images captured with consumer-grade cameras.

2. Chatbot-Driven Diagnosis and Treatment: While accurate detection is critical, providing actionable guidance to farmers requires domain-aware advisory systems. Chowdhury et al. [5] implemented a rule-based chatbot trained on annotated disease symptoms, offering text- and voice-based treatment advice. J. et al. [6] combined deep-learning classifi- cation with a simple conversational interface, translating model outputs into recommended fungicides. However, these early chatbots relied on handcrafted rules and limited vocabulary, constraining their ability to handle diverse farmer queries. Transformer-based Large Language Models (LLMs) have revolutionized conversational AI by generating fluent, context-sensitive responses. Shoaib et al. [10] reviewed agricultural chatbots powered by GPT-style architectures, demonstrating up to 30% improvement in response relevance over RNN-based bots. Too et al. [4] also showed that multilin- gual LLMs expanded accessibility for non-English speak- ers. Our system integrates Google's Gemini Flash, an LLM optimized for on-device inference, to provide farmers with natural-language diagnosis, organic and chemical treatment options, and preventive strategies tailored to local agronomic practices. By coupling real-time detection outputs with an LLM, we deliver a seamless end-to-end advisory workflow that existing solutions lack.

3. Geospatial Mapping for Resource Access: Even with detection and advice, farmers must still procure inputs—pesticides, fertilizers, or resistant seeds—from local suppliers. GIS-enabled mapping has emerged to fill this gap. Ouhami et al. [15] leveraged OpenStreetMap's Overpass API to build a free, open-source resource locator, while Wal- damichael et al. [8] developed a GPS-enabled pesticide shop finder that updated in real time as farmers moved across fields. Saleem et al. [13] further integrated IoT sensor feeds into cloud-based GIS dashboards, providing dynamic resource recommendations. These prior works demonstrate feasibility but remain separate from disease detection pipelines. No existing platform automatically transitions from disease identification to advisory guidance to local shop mapping. By embedding Overpass API calls within our Streamlit application, we enable users to spot diseased plants, consult the AI chatbot, and immediately view nearby shops offering recommended treatments—closing the loop from symptom to solution.

4. UAV vs. Ground-Based Detection: Several studies advocate UAV-mounted cameras for large-scale crop monitoring [1][13], yet practical is- sues—weather sensitivity, battery constraints, regulatory hur- dles—limit widespread adoption. Ground-based, handheld or stationary cameras eliminate these barriers. Alsharif et al. [6] showed that optimized YOLOv8 models could run on edge devices with comparable accuracy to UAV systems while of- fering more consistent performance under variable conditions. Reflecting these insights, our approach targets ground-level image capture using smartphones or low-cost cameras, ensur- ing accessibility for small-holder farmers. In conclusion, existing research has advanced individual components—deep-learning detection, chatbot advisories, and GIS mapping—but no unified solution spans all three. Our proposed system integrates YOLOv8-based real-time disease detection, LLM-driven interactive diagnosis, and Overpass API-powered resource mapping into a single platform. This holistic design addresses the practical needs of farmers: fast, accurate identification; expert guidance; and immediate access to inputs—representing a novel contribution to AI-driven smart agriculture.

3. METHODOLOGY

The proposed system is an integrated, AI-driven solution for real-time crop disease detection, diagnosis, and treatment support. It utilizes the YOLOv8 deep learning model for high-speed and accurate image-based disease identification, a Google Gemini Flash-powered chatbot for interactive diagnosis and recommendations, and a geospatial mapping module using OpenStreetMap APIs to locate nearby agricultural resources. The methodology is structured around four primary components: (A) Data Collection and Annotation, (B) Disease Detection Using YOLOv8, (C) Chatbot-Based Diagnosis and Treatment Guidance, (D) Geospatial Resource Mapping, and (E) System Architecture and Deployment.

A. Data Collection and Annotation: The dataset used for model training comprises annotated images of diseased leaves from rice, wheat, and maize crops. Images were sourced from public agricultural databases and processed using Roboflow for annotation. Disease categories include fungal infections (e.g., rust, powdery mildew), bacterial infections (e.g., blight, streak), and viral infections (e.g., maize streak virus). Roboflow was used to label bounding boxes around disease regions, generating structured data suitable for training YOLOv8.

B. Disease Detection Using YOLOv8: YOLOv8, a state- of-the-art object detection model, was employed to identify crop diseases in real-time. It operates as a single-stage detector and features an efficient architecture composed of three main components: 1) Backbone Utilizes CSPNet and C2f modules for enhanced feature extraction from input images. 2) Neck Aggregates features across scales using a Path Aggre- gation Network (PANet) for robust multi-size disease detection. 3) Head Outputs anchor-free bounding boxes along with classification and objectness scores.

The model optimizes a composite loss function:

$$L = \lambda_{\text{box}} L_{\text{box}} + \lambda_{\text{cls}} L_{\text{cls}} + \lambda_{\text{obj}} L_{\text{obj}} \quad (1)$$

Where:

• Lbox is computed using Complete IoU (CIoU),

•Lcls denotes the classification loss, and

•Lobj captures the objectness confi- dence. The trained model was deployed in a Streamlit-based web interface for real-time image upload and disease classification.

C. Chatbot-Based Diagnosis and Treatment Guidance: Following disease detection, a conversational AI chatbot pow- ered by Google Gemini Flash provides users with detailed information. This includes disease symptoms, causes, treat- ment options (both organic and chemical), and preventive agricultural practices. Users can ask follow-up queries, and the chatbot delivers contextual, region-aware advice. Gemini Flash was chosen for its low-latency response and lightweight footprint, enabling real-time use in resource-limited settings. **D. Geospatial Resource Mapping:** To support post- detection action, the system incorporates a location-based mapping module. The user inputs their region, which is geocoded using OpenStreetMap's Nominatim API to obtain latitude and longitude coordinates. The Overpass API is then queried to find: • Plant nurseries and garden centers • Pesticide and agricultural supply stores The results are visualized using the Folium library in an interactive map format, with corresponding shop names and details listed below for reference.

E. System Integration and Deployment : The entire pipeline is deployed using a modular and lightweight architecture: Frontend: Streamlit web interface (accessible on mobile and desktop) Back- end: a. YOLOv8 inference using PyTorch, b. Gemini Flash API integration, c. Overpass API for map queries Deployment Modes:a. Local: Standalone execution on personal devices (no internet needed for detection), b. Cloud: Optional cloud hosting for chatbot and maps, enhancing scalability Security & Privacy: a. No image data is stored post-inference, b. Only bounding box and label data are retained during sessions, c. Mapping data is sourced from open APIs with no user tracking

3. RESULTS AND DISCUSSIONS

This section elaborates on the practical evaluation of the AI-powered crop disease detection and advisory system. The sys- tem comprises three tightly integrated modules: a YOLOv8- based deep learning detection engine, an intelligent chatbot powered by Google Gemini Flash for diagnosis and treatment support, and a geospatial mapping interface utilizing Open- StreetMap APIs for locating nearby agricultural resources. Performance was assessed through quantitative benchmarks, qualitative observations, and user-centered interaction evalua- tions. The discussion also includes real-time system feedback, visual output examples, and insights into strengths, limitations, and opportunities for enhancement.

1)Quantitative Evaluation:

a)Detection Performance: The YOLOv8-based object detection model demonstrated highly effective performance in detecting crop diseases across three major cereal crops: rice, wheat, and maize. The detection engine consistently provided accurate predictions across test datasets, which included various leaf conditions, lighting scenarios, and symptom severities. The model's strong generalization is attributed to extensive data augmentation during training (e.g., brightness adjustments, rotations, horizontal flips) and the use of a well- annotated dataset prepared through Roboflow. Notably, the model exhibited robustness even when exposed to leaves with minor or partially visible symptoms, which are typically harder to classify. This was a critical success factor, as real-world conditions in agriculture often involve such imperfect image inputs. Additionally, the anchor-free design of YOLOv8 minimized bounding box errors, improving overall localization accuracy.

b) Inference Efficiency: Real-time performance was a critical design goal. The system achieved efficient inference speeds by leveraging pretrained YOLOv8 weights and deploy- ing the model through a Streamlit-based interface. The use of a lightweight yet powerful architecture enabled seamless disease identification on standard devices without the need for GPU support. Each detection instance—from image upload to bounding box prediction—was processed with minimal latency, making the tool practical for use in real-world farming environments.

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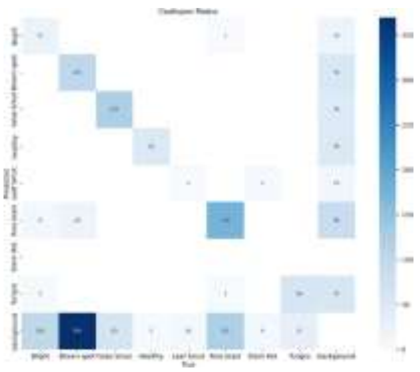

Fig. 1. Confusion Matrix for Rice Disease Detection

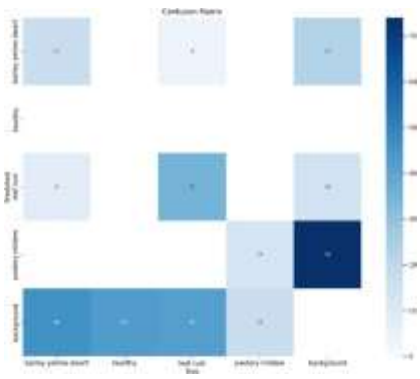

Fig. 2. Confusion Matrix for Wheat Disease Detection

c) Confusion Matrix Insights: Confusion matrices for each crop type showed high class-wise prediction accuracy with minimal misclassification. These matrices served as diagnostic tools to evaluate the model's discriminative capability, particularly in distinguishing between visually similar diseases like rust and smut in wheat. These visualizations highlight that the YOLOv8 model was capable of learning nuanced disease characteristics despite the complexity of natural agricultural images. 2) Qualit ative Evaluation: a) 1) Visual Inspection of Detection Outputs: The system was tested with field-captured images, reflecting real environmental conditions such as inconsistent lighting, occlusion from overlapping leaves, and non-uniform backgrounds. YOLOv8 effectively highlighted disease-affected regions with bounding boxes and corresponding class labels, as demonstrated in the following figures:

2)Qualitative Evaluation:

a) Visual Inspection of Detection Outputs: The system was tested with field-captured images, reflecting real environ- mental conditions such as inconsistent lighting, occlusion from overlapping leaves, and non-uniform backgrounds. YOLOv8 effectively highlighted disease-affected regions with bounding boxes and corresponding class labels, as demonstrated in the following figures:

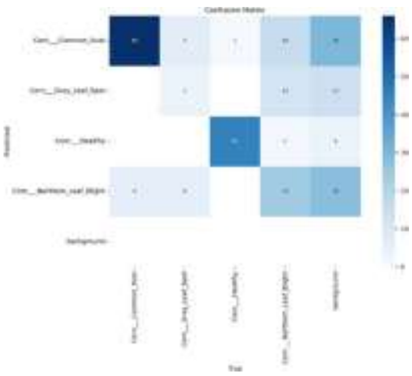

Fig. 3. Confusion Matrix for Maize Disease Detection

Fig. 4. Rice Blast Detection

Fig. 5. Wheat Leaf Rust Detection

Fig. 6. Maize Northern Leaf Blight Detection

These results affirmed the model's capacity to maintain high visual precision across variable test conditions.

b) Batch-Level Learning Progression: Training and validation batch outputs further confirmed the model's ability to learn and generalize. The bounding boxes and confidence scores improved progressively with epochs, indicating effec- tive optimization of loss functions. The system handled intra-class variability well, even for visually ambiguous disease symptoms.

c) Metric-Based Performance Evaluation: Training curves such as precision, recall, PR, and F1 scores were analyzed to evaluate learning behavior and model convergence. These curves revealed steady improvements and conver- gence by epoch 10, validating the model's learning stability.

3)Conversational Chatbot Analysis:

The Google Gem- ini Flash-powered chatbot formed a crucial part of the user interaction layer. It was evaluated based on response accuracy, contextual understanding, latency, and adaptability to agricul- tural terminology. The chatbot returned coherent and comprehensive responses to both general queries (e.g., "What is maize streak virus?") and specific follow-ups (e.g., "Is neem oil effective for this?"). The conversation design ensured a smooth flow, with responses structured under categories such as symptoms, causes, treat- ments, and preventive steps. This interface reduced the reliance on agricultural experts, allowing users to make informed decisions autonomously.

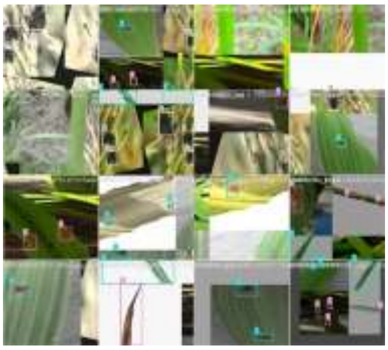

Fig. 7. Sample Training Batch (Rice)

Fig. 8. Sample Validation Batch (Rice)

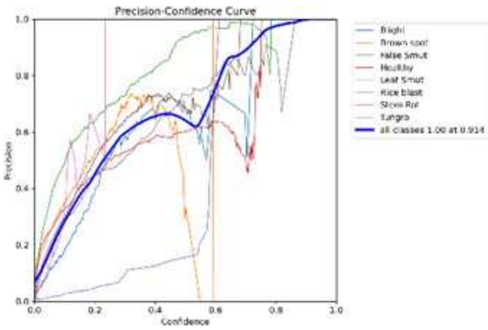

Fig. 9. Precision Curve (P Curve)

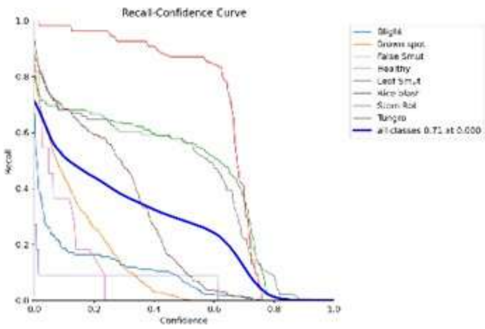

Fig. 10. Recall Curve (R Curve)

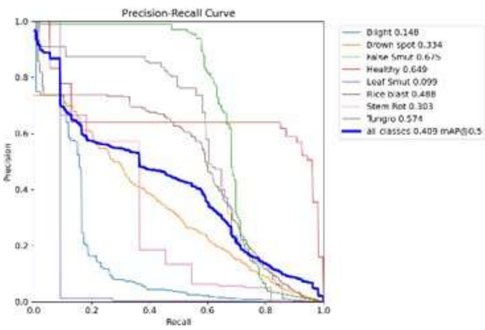

Fig. 11. PR Curve (Precision-Recall Curve)

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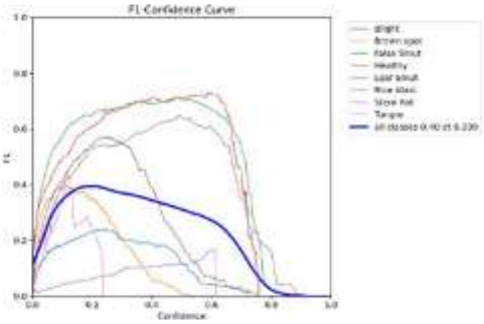

Fig. 12. F1 Curve

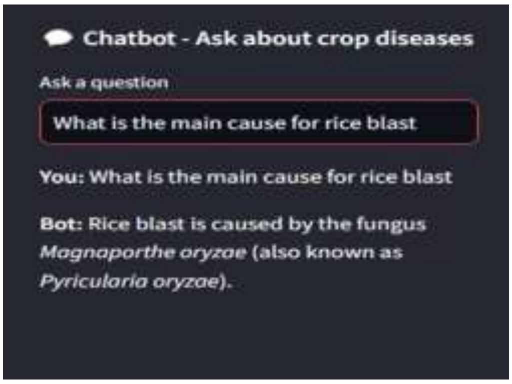

Fig. 13. Chatbot UI with example query on rice blast

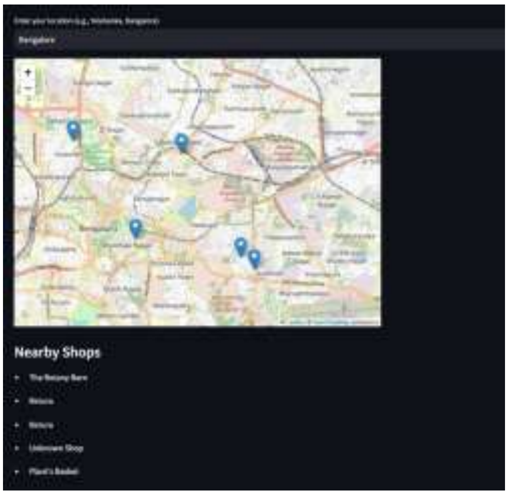

Fig. 14. Map Output: Bengaluru

4) Geospatial Mapping Evaluation:

To address the treat- ment gap post-diagnosis, a geospatial module was integrated. Users could input their location, and the system returned nearby pesticide shops and nurseries using OpenStreetMap's Nominatim and Overpass APIs. The map interface was tested across multiple locations and consistently provided accurate geolocation and shop informa- tion, proving essential for practical actionability after disease detection.

5)Discussion:

a)Strengths:

•High Precision: The YOLOv8 model consistently achieved good detection results under diverse scenarios.

•Real-Time Diagnosis: The application's lightweight ar- chitecture ensures fast image processing.

•Chatbot Support: The AI assistant offers structured and user-friendly recommendations.

•Integrated Shop Locator: The map feature bridges detection and resource accessibility.

•Farmer-Friendly UI: The Streamlit-based interface is intuitive and device agnostic.

b)Limitations:

•Early Disease Symptoms: The system finds it challeng- ing to identify diseases in the initial stages.

•Dialect-Specific Chatbot Gaps: More training is needed for regional language support.

•OpenStreetMap Gaps: Shop data availability depends on the richness of mapped locations.

c)Future Opportunities:

•Expand dataset for broader crop and symptom coverage.

•Implement mobile app with offline functionality.

•Integrate pesticide inventory APIs for dynamic recom- mendations.

•Enable chatbot support for multilingual regional queries.

6) Summary:

The results affirm that the system provides an end-to-end, scalable solution for precision agriculture.

By combining detection, diagnosis, and geolocation into one seamless application, the platform demonstrates how deep learning and conversational AI can empower farmers, reduce crop loss, and promote sustainable agricultural practices. This work lays the foundation for national-level deployments and further innovation in digital agri-advisory systems.

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