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Full Length Article

An Optimized Wheat Disease Detection Framework Using Yolov10

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Abstract— *Wheat leaf diseases, including rust, powdery mildew, and leaf blight, significantly impact crop yield and quality, making early detection essential for effective disease management. This project presents an advanced wheat disease detection framework using YOLOv10, a cutting-edge object detection model that combines high accuracy, real-time processing, and efficient feature extraction. YOLOv10's enhanced architecture and anchor-free detection capabilities allow it to accurately identify multiple disease types from wheat leaf images, even under varying lighting conditions, leaf orientations, and field environments. By training on a diverse and augmented dataset, the model achieves strong generalization and robustness, enabling rapid and reliable disease detection through mobile devices, drones, or field cameras. The system not only provides precise classification and localization of diseased regions but also supports timely intervention and precision agriculture, helping farmers make data-driven decisions to protect crops. With its scalability, speed, and adaptability, YOLOv10 represents a powerful tool for automated plant disease management and sustainable farming practices.*

Keywords*— Analytics, Collaboration Platforms, Digital Entrepreneurship, Innovation Ecosystems, Investment Matching, Mentorship Networks, Startup Analytics, Startup Ecosystem, Startup Platforms, Venture Investment*

INTRODUCTION

The scope of this project involves designing and implementing an intelligent, automated framework for the detection and classification of wheat leaf diseases using the YOLOv10 model, a state-of-the-art object detection algorithm known for its high accuracy and real-time performance. The system is intended to identify major wheat leaf diseases, including rust, powdery mildew, and leaf blight, by analyzing images of leaves captured under natural field conditions. By automating the disease detection process, the framework reduces the reliance on manual inspection, which is often time-consuming, labor-intensive, and prone to human error. The model is trained on a diverse and augmented dataset to ensure robust performance across varying conditions such as different lighting levels, leaf orientations, and complex backgrounds, enabling reliable detection in real-world agricultural environments.

The project also emphasizes rapid processing and precise localization of affected areas, allowing farmers and agricultural experts to take timely and informed actions to prevent the spread of diseases and reduce crop losses. Furthermore, the framework is designed to be scalable and adaptable, making it suitable for monitoring large fields and supporting precision agriculture practices. Overall, this project provides a foundation for creating a practical, efficient, and accurate tool for crop disease management, which can be further enhanced or expanded in the future to include additional crops, more disease types, or improved performance under challenging field conditions

OBJECTIVE & SCOPE

The primary objective of this project is to develop an accurate and efficient deep learning-based system for the detection and classification of wheat leaf diseases to support timely and effective crop management. Specifically, the project aims to identify common wheat diseases such as rust, powdery mildew, and leaf blight from images of leaves captured under diverse field conditions. Another objective is to leverage the YOLOv10 model to enable real-time detection and precise localization of diseased regions, ensuring rapid analysis for practical agricultural use. The project also focuses on creating a robust framework that performs reliably under varying environmental factors, including different lighting, leaf orientations, and background complexities. Additionally, the system aims to reduce dependency on manual inspection, minimize human error, and provide actionable insights to farmers and agricultural experts for better decision-making. By combining high accuracy, scalability, and efficiency, this framework seeks to promote precision agriculture, reduce crop losses, and contribute to sustainable farming practices, while also providing a foundation for future expansion to other crops and disease types.

LITERATURE SURVEY

Title: Learning Rotation-Invariant Convolutional Neural Networks for Object Detection in VHR Optical Remote Sensing Image
Author: G. Cheng, P. Zhou, J. Han

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Year: 2016
Description: This research, published in the IEEE Transactions on Geoscience and Remote Sensing, focuses on addressing the challenges of object detection in very high-resolution (VHR) optical remote sensing images. The authors propose a novel approach involving rotation-invariant convolutional neural networks to enhance the accuracy of object detection. By learning rotation invariance, the model becomes more robust to variations in object orientation within the high-resolution imagery, leading to improved detection performance. The study contributes valuable insights into adapting deep learning techniques for the specific challenges posed by VHR optical remote sensing data.

Title: Object Detection in Optical Remote Sensing Images: A Survey and a New Benchmark
Author: K. Li, G. Wan, G. Cheng, L. Meng, et al.
Year: 2020
Description: Published in the ISPRS Journal of Photogrammetry and Remote Sensing, this survey article provides a comprehensive overview of object detection techniques applied to optical remote sensing images. The authors present a new benchmark for evaluating object detection models in this domain, emphasizing the importance of benchmark datasets for advancing research. The survey covers existing methodologies, challenges, and benchmarks, offering a valuable resource for researchers and practitioners engaged in object detection within optical remote sensing imagery.

Title: Microsoft COCO: Common Objects in Context
Author: T. Y. Lin, M. Maire, S. Belongie, et al.
Year: 2014
Description: This seminal work introduces the Microsoft COCO dataset, a widely used benchmark for object detection and segmentation. Presented at the European Conference on Computer Vision, the authors highlight the significance of a dataset that goes beyond object recognition to include context. The COCO dataset has become a standard evaluation platform for object detection algorithms, fostering advancements in computer vision research. The paper outlines the dataset creation process, its content, and its potential impact on the development of object detection models.

Title: YOLOv4: Optimal Speed and Accuracy of Object Detection
Author: A. Bochkovskiy, C. Y. Wang, H. Y. M. Liao
Year: 2020
Description: This preprint introduces YOLOv4, a significant advancement in the YOLO series, focusing on achieving optimal speed and accuracy for object detection. The authors address the trade-offs between speed and accuracy, aiming to provide a state-of-the-art solution for real-time object detection. The paper presents the architecture, training strategies, and experimental results of YOLOv4, contributing to the ongoing evolution of object detection models and pushing the boundaries of speed and accuracy.
Title: You Only Look Once: Unified, Real-Time Object Detection
Author: J. Redmon, S. Divvala, R. Girshick, et al.
Year: 2016
Description: This seminal paper, presented at the IEEE Conference on Computer Vision and Pattern Recognition, introduces the YOLO (You Only Look Once) model for unified, real-time object detection. YOLO revolutionized the field by proposing a single-pass detection approach, enabling real-time inference. The paper discusses the architecture and performance of YOLO, shaping the landscape of modern object detection frameworks.

MODULES EXPLANATION:

Data Augmentation

Data augmentation plays a vital role in improving the performance and generalization ability of the YOLOv10 model for wheat leaf disease detection. Since real-world datasets may contain limited samples of certain disease types or environmental variations, augmentation techniques are applied to artificially expand the dataset. These include transformations such as rotation, flipping, cropping, scaling, and brightness or contrast adjustments, which simulate diverse field conditions like different lighting, leaf angles, and backgrounds. This helps the model become more robust to variations in environmental factors, camera perspectives, and image quality. By increasing the diversity of the dataset, data augmentation ensures that YOLOv10 can accurately detect and classify wheat leaf diseases under a wide range of real-world scenarios, thereby reducing the chances of overfitting and improving detection accuracy.

Data Preprocessing

Data preprocessing is an essential step to prepare the wheat leaf images for training the YOLOv10 model. This stage involves resizing images to a uniform dimension compatible with YOLOv10's input requirements, normalizing pixel values, and organizing image-label pairs for effective training. Each image is carefully annotated using bounding boxes to mark the diseased regions, enabling the model to learn the exact locations and types of infections such as rust, powdery mildew, or leaf blight. Preprocessing also includes noise removal and quality enhancement to ensure that the images are clear and consistent. By standardizing and cleaning the dataset, preprocessing ensures efficient training, faster convergence, and improved overall model accuracy.

Data Split

After preprocessing, the dataset is divided into three subsets — training, validation, and testing sets. The

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training set is used to teach the YOLOv10 model the distinguishing features of healthy and diseased wheat leaves. The validation set is used during model training to fine-tune parameters and monitor performance, ensuring that the model does not overfit the training data. The testing set, which contains unseen images, is used to evaluate the final performance of the model. A typical split ratio such as 70% training, 20% validation, and 10% testing ensures a balanced and fair evaluation of model accuracy and generalization capability.

Model Training

The model training phase is the core of the project, where YOLOv10 learns to detect and classify wheat leaf diseases from labeled images. YOLOv10's advanced architecture, featuring enhanced backbone and head designs, allows it to efficiently extract detailed features from wheat leaf images. The training process involves feeding batches of preprocessed and augmented images into the model, optimizing parameters using algorithms like AdamW or SGD. The loss function combines localization, objectness, and classification losses to fine-tune the network's predictions.The model is trained over multiple epochs until metrics such as mean Average Precision (mAP), precision, and recall reach satisfactory levels. Transfer learning is also used by initializing YOLOv10 with pre-trained weights on large-scale datasets, allowing it to adapt quickly to wheat disease detection tasks and achieve high accuracy with fewer training iterations.

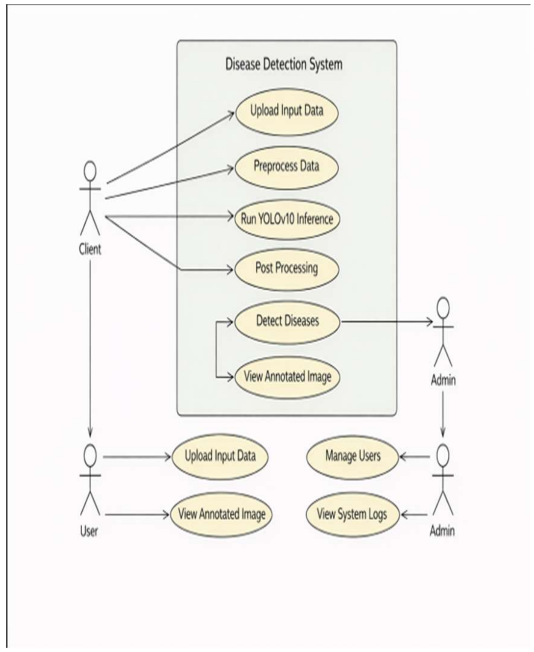
Prediction

Once the YOLOv10 model is successfully trained, validated, and optimized, it is deployed for disease prediction on new and previously unseen wheat leaf images. During the prediction phase, the trained model automatically analyzes each input image and detects the presence of disease symptoms with high speed and accuracy. YOLOv10 processes the image in a single stage and generates bounding boxes around the infected regions while simultaneously predicting the corresponding disease class and confidence score for each detected area.

The real-time object detection capability of YOLOv10 enables rapid identification of wheat diseases, making the system highly efficient for practical agricultural applications. The model is capable of detecting multiple diseased regions within a single leaf image and can distinguish between different disease categories even under varying environmental conditions such as lighting changes, background noise, and partial occlusion of leaves. This enhances the robustness and reliability of the disease detection system in real-world farming environments.

The prediction output provides valuable information to farmers, agricultural researchers, and field experts by enabling early disease diagnosis and timely decision-making. Based on the predicted disease type, appropriate preventive or corrective measures such as pesticide application, nutrient management, or crop monitoring can be undertaken to reduce crop damage and improve yield quality. In addition, the prediction results are visually represented by overlaying bounding boxes, disease labels, and confidence percentages on the original input images. This visualization improves interpretability, helps users easily understand the detection results, and increases the practical usability of the system for smart agriculture and precision farming applications.

IMPLEMENTATION:



Algorithms:

1. YOLOv10-Based Wheat Disease Detection Algorithm

 * Collect wheat leaf images containing healthy and diseased samples (rust, powdery mildew, leaf blight).

 * Preprocess images by resizing, normalization, and noise removal.

 * Annotate diseased regions using bounding boxes with disease labels.

 * Apply data augmentation techniques such as rotation, flipping, scaling, mosaic, and mixup to improve dataset diversity.

 * Split dataset into training, validation, and testing sets (70:20:10).

 * Load YOLOv10 pre-trained weights for transfer learning.

 * Train YOLOv10 model on annotated wheat leaf dataset.

 * Extract multi-scale features using YOLOv10

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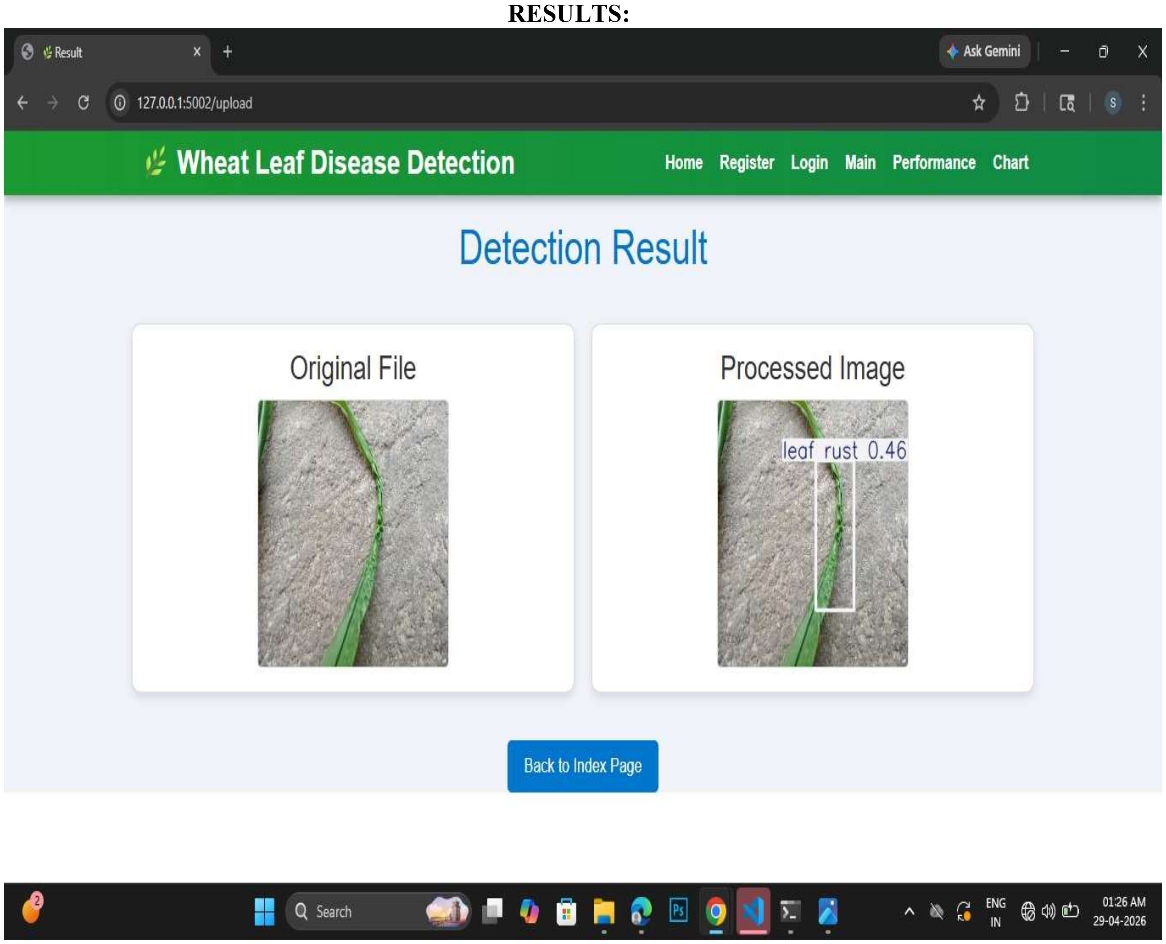
backbone and neck layers.

* Perform anchor-free object detection for accurate localization of infected regions.
* Use decoupled detection head for simultaneous disease classification and bounding box regression.
* Optimize model using combined loss functions (localization loss + classification loss + confidence loss).
* Validate model performance using Precision, Recall, F1-score, and mAP.
* Test model on unseen wheat leaf images.
* Predict disease type with confidence score and draw bounding boxes around infected areas.
* Display annotated output image for real-time disease diagnosis.

2. LSTM-Based Suicidal Ideation Detection Algorithm

* Collect text data from social media, forums, and mental health datasets.
* Preprocess text by removing punctuation, stop words, URLs, and special symbols.
* Convert text into lowercase and tokenize into words.
* Apply text normalization using stemming and lemmatization.
* Transform text into numerical vectors using Word Embedding (Word2Vec / GloVe).
* Split dataset into training, validation, and testing sets.
* Feed embedded text sequences into LSTM network.
* LSTM captures sequential dependencies and emotional context in text.
* Extract hidden emotional patterns and linguistic traces related to suicidal ideation.
* Pass LSTM outputs through dense layers for feature refinement.
* Apply sigmoid/softmax activation for binary or multi-class classification.
* Classify text into categories such as suicidal / non-suicidal or low / medium / high risk.
* Train model using Binary Cross-Entropy loss and Adam optimizer.
* Evaluate performance using Accuracy, Precision, Recall, F1-score, and ROC-AUC.
* Predict suicidal ideation risk from unseen text inputs for early intervention support.

RESULTS:



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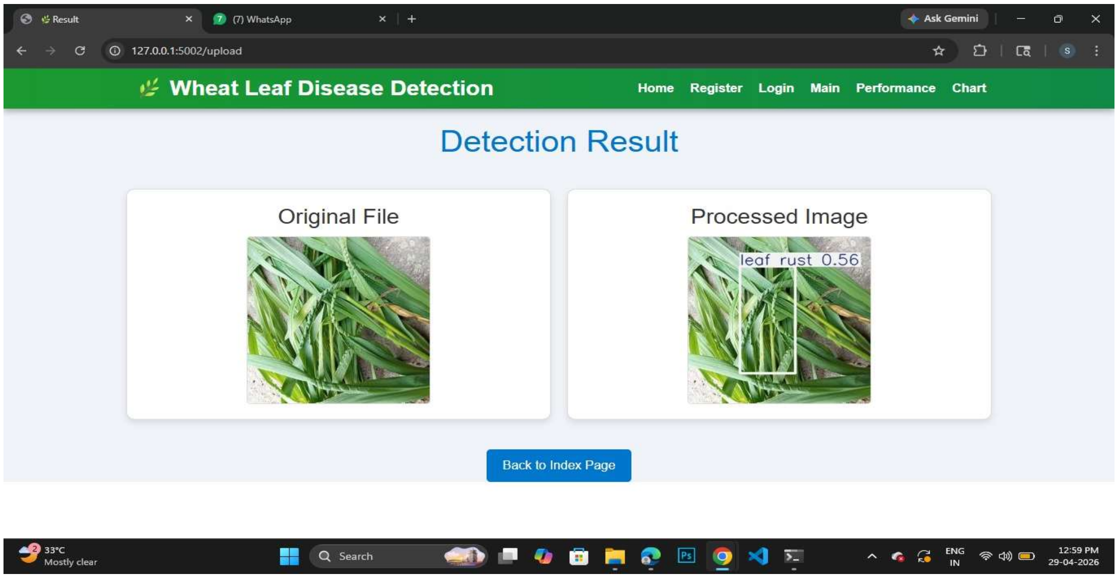

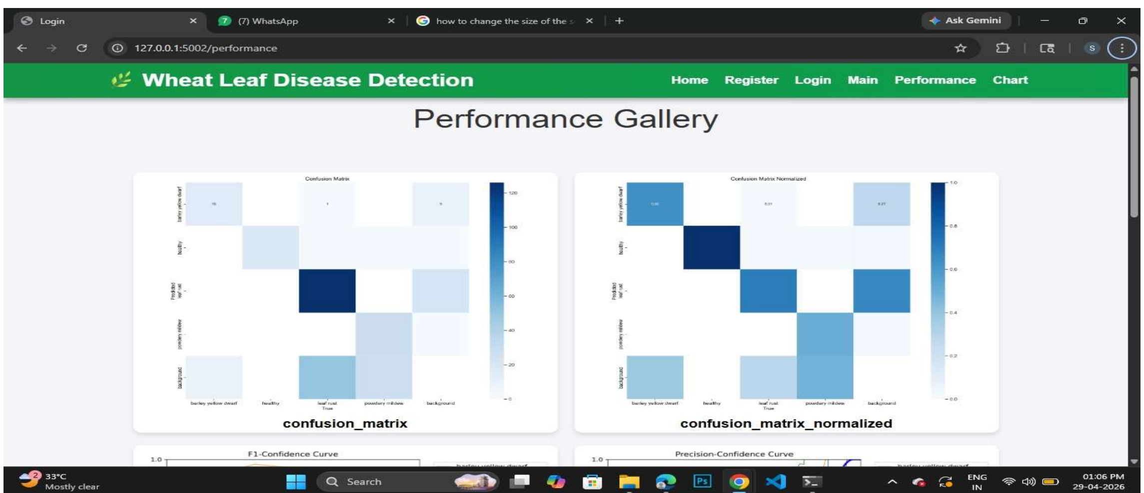

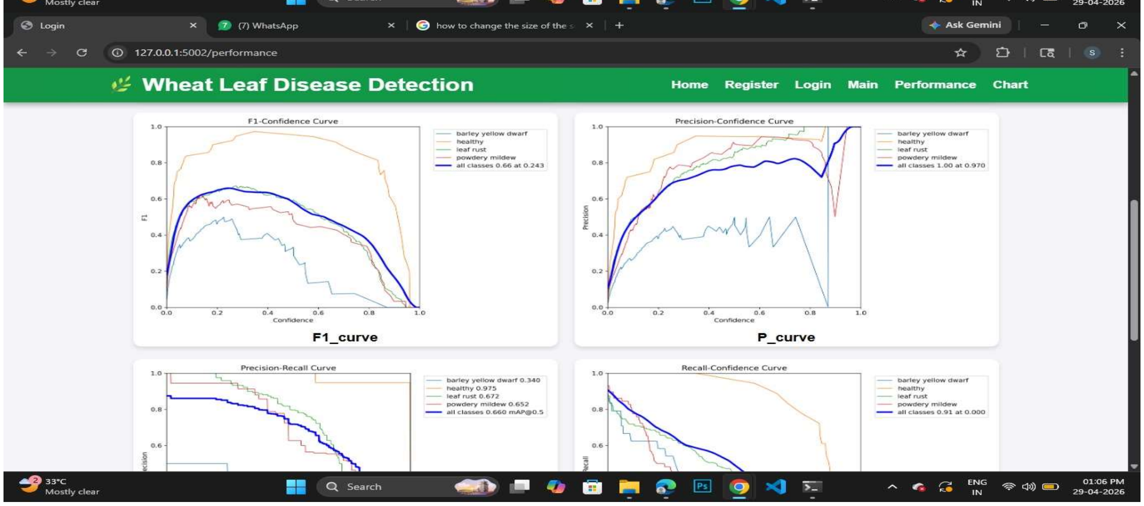

CONCLUSION In conclusion, this project successfully demonstrates

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the potential of deep learning technology, particularly the YOLOv10 model, in automating the detection and classification of wheat leaf diseases with high accuracy and efficiency. By leveraging real-time object detection and robust feature extraction, the proposed system effectively identifies major wheat diseases such as rust, powdery mildew, and leaf blight under diverse environmental conditions. Through systematic data collection, preprocessing, augmentation, and model training, the framework achieves reliable performance and strong generalization, reducing the need for manual inspection and expert intervention. The results highlight YOLOv10's capability to deliver fast, accurate, and scalable solutions for precision agriculture. This system not only aids farmers in early disease detection but also contributes to improved crop management, reduced yield losses, and sustainable agricultural practices. Overall, the project establishes a strong foundation for future research and development in intelligent plant disease detection systems, paving the way for the integration of AI-driven tools in modern agriculture.

FUTURE SCOPE:

In the future, this project can be further enhanced to make the wheat leaf disease detection system more advanced, adaptive, and farmer-friendly. One potential improvement is the integration of the model into a mobile or web-based application, allowing farmers to capture and analyze leaf images directly in the field for instant disease detection and management suggestions. The system can also be extended to support multiple crop types, enabling a unified framework for detecting diseases across various plants beyond wheat. Additionally, incorporating advanced deep learning techniques such as vision transformers (ViTs) or hybrid CNN-transformer models could further improve accuracy in complex field environments. The inclusion of temporal data analysis, such as monitoring disease progression over time, would enable predictive analytics for early intervention. Future work may also explore the use of larger and more diverse datasets collected from different geographical regions to enhance the model's generalization capability. Moreover, integrating environmental parameters like humidity, temperature, and soil conditions can provide deeper insights into disease patterns and help in forecasting outbreaks. Overall, these enhancements would transform the current system into a comprehensive, real-time precision agriculture solution that promotes efficiency, sustainability, and smarter crop disease management.

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