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Web-Based AI Plant Disease Detection and Treatment Recommendation System using Deep Learning

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ABSTRACT: Agriculture remains a fundamental pillar of food security and economic sustainability, particularly in developing countries where a large proportion of the population depends on farming for their livelihood. One of the major challenges faced by the agricultural sector is the occurrence of plant diseases, which significantly reduce crop yield, degrade product quality, and lead to substantial economic losses. Plant diseases caused by fungi, bacteria, viruses, and pests often spread rapidly, and delayed identification can result in large-scale crop damage. Therefore, early and accurate detection of plant diseases is crucial for effective disease management and sustainable agricultural practices.

Traditional methods of plant disease identification primarily rely on manual inspection by agricultural experts or laboratory-based diagnostic techniques. Although these methods can provide reliable results, they are time-consuming, labor-intensive, and often inaccessible to small-scale farmers, especially in rural and remote regions. In many cases, farmers lack immediate access to expert guidance, leading to improper disease diagnosis and the excessive or incorrect use of pesticides. Such practices not only reduce crop productivity but also pose serious environmental and health risks. These limitations highlight the need for automated, accessible, and cost-effective plant disease diagnosis solutions.

Recent advancements in artificial intelligence (AI), particularly in deep learning and computer vision, have enabled significant progress in automated image-based plant disease detection. Convolutional Neural Networks (CNNs) have demonstrated strong capability in learning discriminative visual features from plant leaf images and achieving high classification accuracy across multiple crop species and disease categories. Transfer learning using pretrained models has further improved performance while reducing training time and computational requirements. However, many existing deep learning-based systems focus mainly on disease classification accuracy and often overlook practical deployment challenges, computational efficiency, and decision-support functionalities required for real-world agricultural applications.

Moreover, most current approaches provide only disease labels as output, without offering actionable treatment recommendations or assessing the reliability of predictions. In real-world scenarios, farmers require not only disease identification but also guidance on appropriate organic and chemical control measures to take timely action. The absence of confidence estimation and uncertainty handling in many automated systems can lead to misleading predictions, which may result in inappropriate treatment decisions and further crop damage. Additionally, heavy deep learning architectures often limit the feasibility of deploying such systems in web-based or resource-constrained environments.

To address these challenges, this work proposes a web-based intelligent plant disease detection and treatment recommendation system that integrates deep learning and machine learning techniques. A lightweight pretrained CNN model is employed as a feature extractor to capture relevant visual characteristics from plant leaf images, while a machine learning classifier is used for efficient and accurate disease classification. The proposed system further incorporates confidence-based disease severity assessment and provides organic and chemical treatment recommendations through a structured knowledge base. By offering real-time analysis through a user-friendly web interface, the system aims to support farmers in making informed decisions, reduce dependency on expert consultation, and promote timely and sustainable disease management practices.

KEYWORDS: This work focuses on plant disease detection and classification using deep learning techniques with an emphasis on practical decision support for agriculture. A lightweight MobileNetV2-based feature extractor is employed along with a machine learning classifier to accurately identify multiple plant diseases from leaf images. To enhance real-world usability and reliability, confidence-based prediction and disease severity assessment are incorporated, and a treatment recommendation framework is introduced to provide organic and chemical control measures and precautionary guidance for farmers.

I. INTRODUCTION

Plant diseases pose a significant threat to global food security and agricultural sustainability by causing substantial reductions in crop yield and quality. Timely identification and effective management of plant diseases are essential to minimize economic losses and ensure stable agricultural production. In conventional agricultural practices, disease diagnosis is primarily carried out through manual visual inspection by trained experts or laboratory-based testing. Although these methods can be accurate, they are labor-intensive, time-consuming, and not scalable for large farming regions. Furthermore, in rural and resource-limited settings, access to agricultural experts is often limited, resulting in delayed diagnosis and inappropriate treatment.

Recent advances in artificial intelligence (AI) and computer vision have enabled the development of automated plant disease detection systems based on leaf image analysis. Convolutional Neural Networks (CNNs) have demonstrated superior performance in learning discriminative visual patterns from plant leaf images compared to traditional machine learning approaches that rely on handcrafted features. Several deep CNN architectures, such as VGG, ResNet, and Inception, have been employed for plant disease classification and have achieved promising results on benchmark datasets. However, these models are computationally expensive and demand high memory and processing resources, which restricts their applicability in real-time and web-based agricultural applications.

Lightweight CNN architectures, such as MobileNetV2, offer a practical alternative by providing a favorable balance between accuracy and computational efficiency. Moreover, hybrid frameworks that utilize CNNs for deep feature extraction followed by machine learning classifiers for final disease prediction can further reduce computational overhead while maintaining robust classification performance. Despite these technical advancements, existing systems largely focus on disease classification accuracy and often overlook critical aspects of practical deployment, such as confidence-aware decision making and post-diagnosis support for farmers.

Another major limitation of current automated disease detection systems is the lack of reliability assessment. Many models generate predictions even when confidence is low, which may lead to incorrect diagnosis and unsuitable treatment recommendations. In real-world agricultural environments, such unreliable predictions can negatively impact crop management decisions and reduce user trust in AI-based systems. Additionally, most existing approaches do not provide actionable guidance, such as organic treatment options, chemical control measures, and preventive practices, which are essential for effective disease management.

To address these challenges, this work presents a web-based intelligent plant disease detection and treatment recommendation system based on a hybrid deep learning and machine learning framework. A pretrained MobileNetV2 CNN is employed to extract deep visual features from plant leaf images, and a machine learning classifier is used to perform multi-class disease classification. The proposed system incorporates a confidence evaluation mechanism to assess the reliability of predictions and determine disease severity levels.

Based on the identified disease, the system retrieves appropriate organic treatments, chemical control measures, and precautionary guidelines from a structured knowledge base. The entire framework is deployed as a web application, enabling users to upload leaf images and obtain real-time diagnostic results.

II. LITERATURE REVIEW

Automated plant disease detection has received considerable attention in recent years due to advances in computer vision and deep learning. Early approaches primarily relied on traditional machine learning techniques, where handcrafted features such as color histograms, texture descriptors (e.g., GLCM), and shape features were extracted from leaf images and classified using algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forests. While these methods demonstrated reasonable performance under controlled conditions, their accuracy was highly dependent on feature engineering and image quality, limiting robustness in real-world environments with varying illumination and background noise.

With the emergence of deep learning, Convolutional Neural Networks (CNNs) have become the dominant paradigm for plant disease classification. CNN-based models automatically learn hierarchical feature representations from raw images, eliminating the need for manual feature extraction. Several/hooks frameworks have employed deep CNN architectures such as VGG16, ResNet50, Inception, and DenseNet for classifying plant leaf diseases, reporting high accuracy on benchmark datasets like PlantVillage. Transfer learning has been widely adopted to mitigate the challenge of limited labeled agricultural data, where pretrained models on large-scale datasets are fine-tuned for plant disease classification tasks. Although these deep models achieve strong performance, their large parameter sizes and high computational demands hinder deployment in real-time and web-based applications, particularly in resource-constrained settings.

To address computational constraints, lightweight CNN architectures have been explored for agricultural image analysis. MobileNet and its variants, especially MobileNetV2, have shown promising results due to their depthwise separable convolutions and reduced model complexity. These architectures enable efficient feature extraction with lower memory footprint and faster inference, making them suitable for deployment on edge devices and web platforms.

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Several studies have demonstrated that MobileNet-based models can achieve competitive accuracy compared to heavier networks while significantly reducing computational cost.

Hybrid approaches that combine deep feature extraction with traditional machine learning classifiers have also been investigated. In such frameworks, a pretrained CNN is used as a feature extractor, and the extracted deep features are classified using machine learning models such as SVM or Random Forest. This strategy often improves generalization performance and reduces training complexity, particularly when the available dataset is limited. Hybrid CNN–ML models have been reported to achieve robust performance across multiple crop species and disease categories, offering a practical trade-off between accuracy and efficiency.

Beyond disease classification, recent works have explored the integration of decision-support components in agricultural AI systems. However, most existing studies focus primarily on improving classification accuracy and do not provide actionable post-diagnosis guidance, such as treatment recommendations or preventive measures. Furthermore, the majority of current systems lack confidence-aware mechanisms to assess prediction reliability. In real-world agricultural applications, predictions with low confidence can mislead users and result in inappropriate interventions, highlighting the need for uncertainty handling in automated disease diagnosis.
In terms of deployment, several mobile and web-based plant disease detection applications have been proposed to enhance accessibility for farmers. While these applications demonstrate the feasibility of real-time disease diagnosis, they often employ heavy deep learning models that impact response time and scalability. Additionally, many deployed systems do not integrate treatment knowledge bases or provide farmer-centric recommendations, limiting their practical utility.

From the above review, it is evident that although significant progress has been made in plant disease classification using deep learning, there remains a gap in developing lightweight, deployable, and reliable systems that integrate disease detection with confidence-aware decision support and treatment recommendation. This gap motivates the proposed work, which aims to combine an efficient MobileNetV2-based feature extraction framework with a machine learning classifier, confidence evaluation, and a treatment recommendation module in a web-based system for practical agricultural decision support.

III. RESEARCH GAP

Despite significant progress in automated plant disease detection using deep learning and computer vision techniques, several limitations remain in existing approaches that restrict their practical adoption in real-world agricultural environments.

First, the majority of existing studies primarily emphasize disease classification accuracy using deep CNN architectures. While high accuracy is important, many proposed models are computationally heavy and require substantial processing resources, making them unsuitable for real-time and web-based deployment in resource-constrained settings. Lightweight and deployable frameworks that balance accuracy with computational efficiency are still limited.

Second, most existing systems focus solely on disease identification and do not provide actionable post-diagnosis support to farmers. Practical agricultural decision-making requires more than just disease labels; farmers need clear guidance in the form of organic treatment options, chemical control measures, and preventive precautions. The lack of integrated treatment recommendation mechanisms reduces the real-world utility of many current plant disease detection models.

Third, current approaches often lack confidence-aware decision mechanisms. Many automated systems produce predictions even when the model confidence is low, which can lead to misdiagnosis and inappropriate interventions. The absence of uncertainty handling and reliability assessment undermines user trust and can have adverse consequences in agricultural practice. There is a clear need for systems that evaluate prediction confidence and appropriately handle uncertain cases by providing cautious recommendations or advising expert consultation.

Fourth, while transfer learning and hybrid CNN–ML frameworks have been explored, their integration into complete end-to-end systems with user-friendly web interfaces remains limited. Many research works are validated only in offline experimental settings and are not deployed as accessible applications for farmers. This gap highlights the need for practical, scalable, and user-centric deployment of AI-based plant disease detection systems.

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Finally, most existing studies are evaluated on controlled benchmark datasets and do not sufficiently address challenges such as variations in lighting conditions, background clutter, and image quality encountered in real-world scenarios. Robust preprocessing pipelines and system-level design considerations for handling real-world variability are not adequately explored in many prior works.

In summary, there exists a gap in developing a lightweight, deployable, and reliable plant disease detection system that integrates accurate disease classification with confidence-aware decision support and actionable treatment recommendations within a web-based framework. The proposed work aims to bridge this gap by combining efficient deep feature extraction, hybrid classification, reliability assessment, and treatment guidance in a unified, user-friendly system.

IV. PROPOSED SYSTEM / METHODOLOGY

This section describes the architecture, processing pipeline, and methodological framework of the proposed web-based intelligent plant disease detection and treatment recommendation system. The proposed system is designed to be lightweight, reliable, and suitable for real-time deployment, while providing actionable decision support to end users.

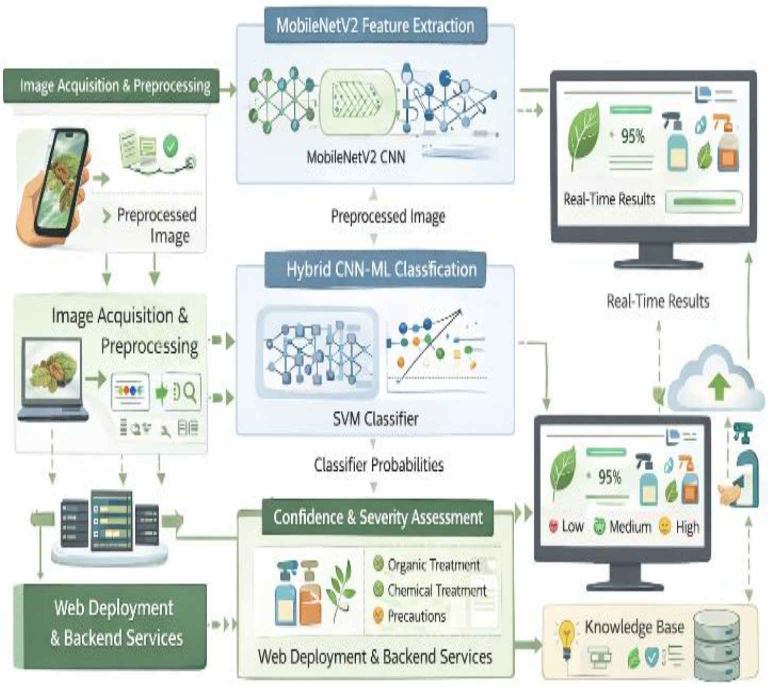

Fig. 1. Block diagram of the proposed hybrid CNN-ML based plant disease detection and treatment recommendation system.

A. System Overview

The proposed framework follows an end-to-end pipeline that begins with user-provided plant leaf images and produces disease diagnosis along with confidence-aware treatment recommendations. The system consists of the following core components: (i) image acquisition and preprocessing, (ii) deep feature extraction using a pretrained CNN (MobileNetV2), (iii) disease classification using a machine learning classifier, (iv) confidence and severity assessment, (v) treatment recommendation module, and (vi) web-based user interface and backend services. The overall workflow of the proposed system is illustrated in Fig. 1.

B. Image Acquisition and Preprocessing

Users upload plant leaf images through a web-based interface. To ensure consistency and robustness, the input images undergo preprocessing steps including resizing to a fixed resolution, color normalization, and conversion to a standard RGB format. Pixel values are normalized to a common scale to stabilize model inference. Basic quality checks are applied to handle invalid or corrupted images. These preprocessing steps reduce variations due to illumination and camera quality and improve the reliability of downstream feature extraction.

C. Deep Feature Extraction Using MobileNetV2

A pretrained MobileNetV2 convolutional neural network is employed as the deep feature extractor. MobileNetV2 is selected due to its lightweight architecture based on depthwise separable convolutions, which significantly reduces computational cost while retaining strong representational capability. The final classification layers of the pretrained network are removed, and the intermediate feature representations obtained from the global pooling layer are used as discriminative descriptors of leaf images. This transfer learning strategy enables effective feature learning even with limited training data and accelerates model convergence.

D. Disease Classification Using Machine Learning Classifier

The deep features extracted by MobileNetV2 are fed into a machine learning classifier to perform multi-class disease classification. This hybrid CNN–ML approach leverages the strong feature learning capability of deep networks and the simplicity and efficiency of traditional classifiers. The classifier outputs class probabilities for each disease category. The hybrid design reduces model complexity compared to end-to-end deep CNN classifiers and enables efficient training and inference suitable for web-based deployment.

E. Confidence and Severity Assessment

To enhance the reliability of predictions, the proposed system computes a confidence score from the classifier's probability outputs. Based on predefined thresholds, the system categorizes predictions into confidence levels (e.g., high, medium, and low). Low-confidence predictions are flagged as uncertain to avoid misleading users. Additionally, a severity level is estimated from the confidence score to indicate the potential seriousness of the detected disease. This confidence-aware mechanism improves trustworthiness and supports informed decision-making in practical agricultural scenarios.

F. Treatment Recommendation Module

Upon disease identification, the system retrieves appropriate organic treatments, chemical control measures, and precautionary guidelines from a structured knowledge base. The recommendation module maps each disease class to a curated set of treatment actions. By integrating diagnosis with treatment guidance, the proposed framework moves beyond mere classification and provides actionable support to users, thereby improving the practical value of the system for farmers and agricultural practitioners.

G. Web-Based Deployment and Backend Services

The complete framework is deployed as a web-based application to ensure accessibility and ease of use. The backend service exposes APIs for image upload, preprocessing, model inference, and result generation. The frontend interface allows users to upload leaf images and view disease diagnosis, confidence scores, severity levels, and treatment recommendations in real time. The modular design of the backend facilitates scalability and integration with future enhancements such as mobile applications or edge deployment.

H. Algorithmic Workflow

- The proposed methodology can be summarized as follows:
- Acquire leaf image from user via web interface.
- Preprocess the image (resize, normalize, format conversion).
- Extract deep features using pretrained MobileNetV2.
- Classify the extracted features using a machine learning classifier.
- Compute prediction confidence and severity level.
- Retrieve disease-specific treatment recommendations from the knowledge base.
- Display results to the user through the web interface.

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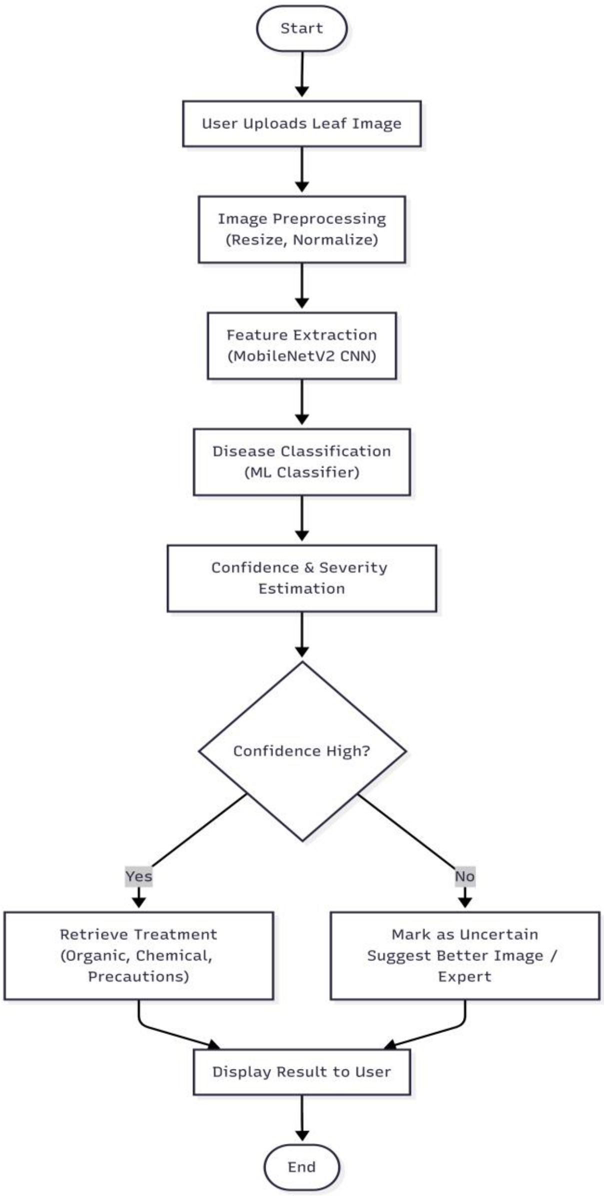
V. SYSTEM ARCHITECTURE AND WORKFLOW

This section presents the overall system architecture and operational workflow of the proposed web-based plant disease detection and treatment recommendation system. The architecture is designed to be modular, lightweight, and scalable, enabling efficient deployment in real-world agricultural environments while maintaining reliable performance.

A. System Architecture

The proposed system follows a client–server architecture consisting of three main layers: (i) user interface layer, (ii) application and inference layer, and (iii) data and knowledge layer.



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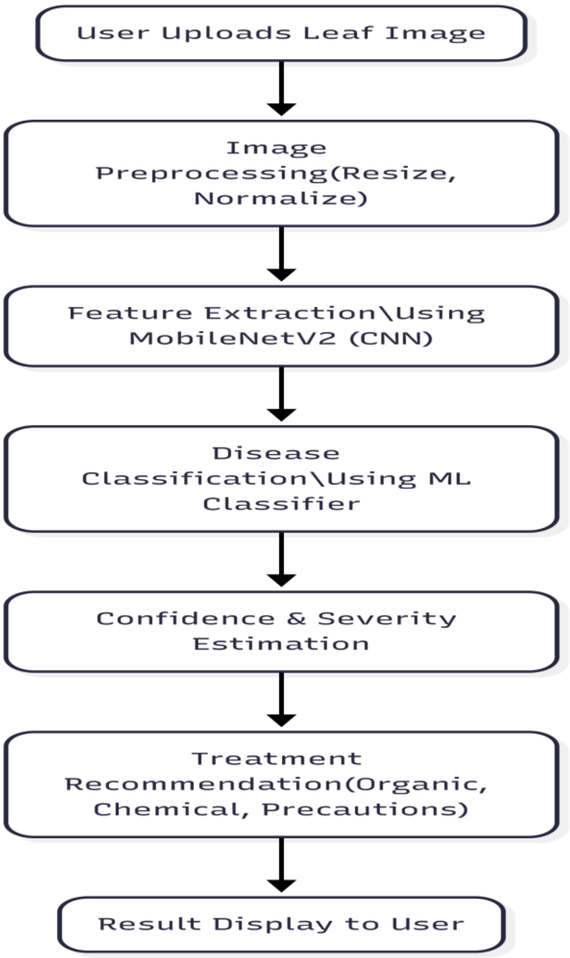

1. **User Interface Layer:**
   This layer provides a web-based interface through which users upload plant leaf images and receive diagnostic results. The interface is designed to be simple and user-friendly, allowing farmers or agricultural practitioners to interact with the system without technical expertise. The frontend communicates with the backend through RESTful APIs for image submission and result retrieval.
2. **Application and Inference Layer:**
   This layer hosts the core processing modules of the system. It includes the image preprocessing unit, the deep feature extraction module based on MobileNetV2, the hybrid CNN–ML classification engine, and the confidence and severity assessment module. The backend server manages incoming requests, performs model inference, and aggregates prediction results. The modular design of this layer facilitates scalability and future extension of the system.
3. **Data and Knowledge Layer:**
   This layer comprises the trained machine learning models, preprocessing configurations, and a structured knowledge base that maps each disease class to recommended organic treatments, chemical control measures, and precautionary guidelines. The knowledge base acts as a decision-support component that enhances the practical usability of the system beyond simple disease classification.

The interaction among these layers ensures seamlessdata flow from image acquisition to diagnosis and treatment recommendation. The overall architecture emphasizes low latency, modularity, and ease of deployment.

B. Workflow of the Proposed System

The operational workflow of the proposed system is illustrated in Fig. 1 and proceeds through the following sequential stages:

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1. **Image Upload:**
   Users capture or select a plant leaf image and upload it through the web interface.
2. **Preprocessing:**
   The uploaded image is resized, normalized, and converted into a standardized format to ensure compatibility with the deep learning model and to reduce noise caused by varying image conditions.
3. **Feature Extraction:**
   The preprocessed image is passed through the pretrained MobileNetV2 network, which extracts high-level deep visual features representing disease-related patterns on the leaf surface.
4. **Disease Classification:**
   The extracted features are input to a machine learning classifier that outputs class probabilities for multiple disease categories.
5. **Confidence and Severity Estimation:**
   Prediction confidence is computed from the classifier's probability distribution. Based on predefined thresholds, the system determines the severity level and flags uncertain predictions to avoid misleading outputs.
6. **Treatment Recommendation:**
   For confident predictions, the system retrieves corresponding organic treatments, chemical control measures, and precautionary guidelines from the knowledge base. This step transforms raw predictions into actionable agricultural advice.
7. **Result Presentation:**
   The final diagnosis, confidence score, severity level, and treatment recommendations are returned to the user through the web interface in real time.

C. Design Considerations

The architecture is designed with the following considerations:

(i) **Efficiency:** Use of MobileNetV2 ensures low computational overhead.

(ii) **Reliability:** Confidence-aware decision logic improves trustworthiness of predictions.

(iii) **Scalability:** Modular backend services allow easy scaling and future integration with mobile platforms or edge devices.

(iv) **Practical Utility:** Integration of a treatment knowledge base provides actionable guidance for end users.

VI. ALGORITHMS AND MODELS USED

This section describes the algorithms and learning models employed in the proposed plant disease detection and treatment recommendation system. The framework adopts a hybrid learning strategy that combines deep learning for feature extraction with machine learning for disease classification, followed by confidence-aware decision support.

A. Convolutional Neural Network (MobileNetV2) for Feature Extraction

A pretrained MobileNetV2 architecture is used as the deep feature extractor. MobileNetV2 is a lightweight convolutional neural network designed for efficient inference through depth wise separable convolutions and inverted residual blocks. Compared to heavier CNN models, MobileNetV2 significantly reduces computational cost and memory requirements while maintaining competitive representational capability.

In the proposed framework, the classification layers of the pretrained MobileNetV2 are removed, and features are extracted from the global average pooling layer. These deep features encode discriminative information related to color, texture, and structural patterns of plant leaf diseases. Transfer learning is employed to leverage knowledge from large-scale image datasets, enabling effective feature representation even with limited agricultural training data.

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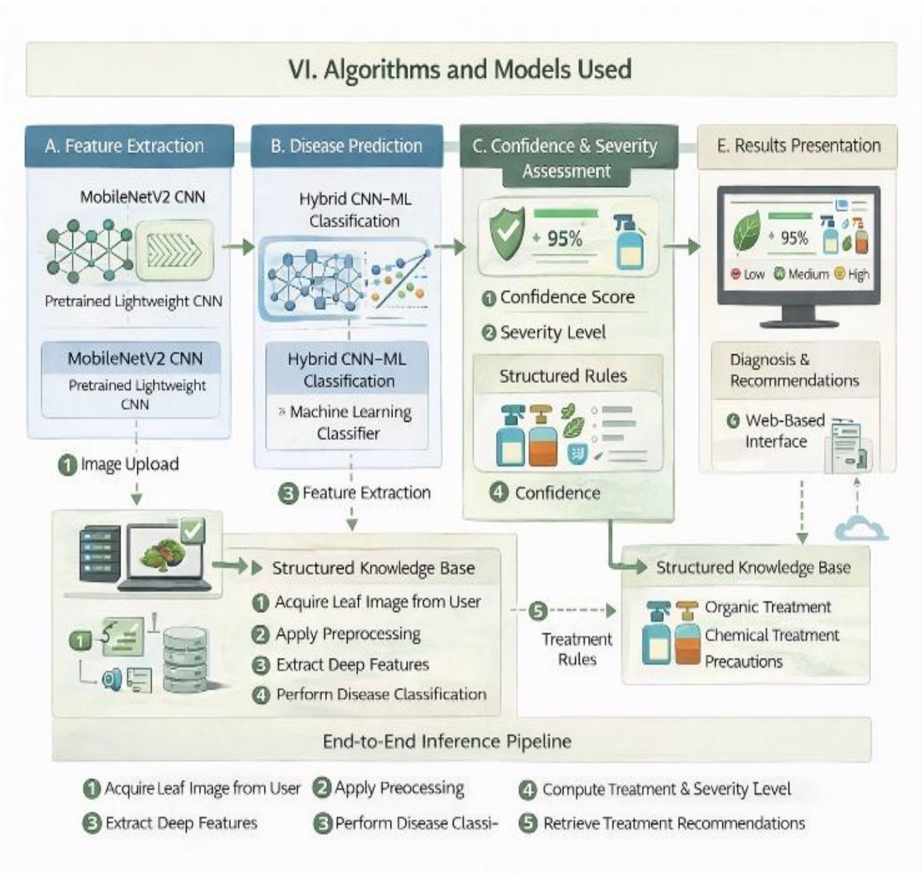

B. Machine Learning Classifier for Disease Prediction

The extracted deep features are provided as input to a machine learning classifier to perform multi-class disease classification. The classifier outputs probability scores for each disease category. This hybrid CNN–ML approach benefits from the strong feature learning capability of deep networks and the simplicity and efficiency of traditional classifiers. It also reduces the need for end-to-end training of large CNN models, making the system suitable for real-time deployment in web-based environments.

C. Confidence Estimation and Severity Assessment Algorithm

To improve reliability, the system incorporates a confidence estimation mechanism based on the predicted class probabilities. Let $p_i$denote the predicted probability of class i. The predicted disease class $\hat{y}$is obtained as:

$$\hat{y} = \arg\max_{i} p_i$$

The confidence score Cis computed as:

$$C = \max_{i}(p_i)$$

Based on predefined thresholds, the confidence score is mapped to severity levels (e.g., high, medium, low). Predictions with confidence below a minimum threshold are flagged as uncertain to avoid misleading recommendations. This confidence-aware mechanism supports cautious decision-making in real-world agricultural applications.

D. Treatment Recommendation Algorithm

A rule-based mapping algorithm is employed to associate each predicted disease class with corresponding organic treatments, chemical control measures, and precautionary guidelines stored in a structured knowledge base. Given the predicted disease label $\hat{y}$, the recommendation function retrieves a set of actions $R(\hat{y})$defined as:

$$R(\hat{y}) = \{r_{org}, r_{chem}, r_{prec}\}$$

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where r_{org}, r_{chem}, and r_{prec} denote organic treatment, chemical treatment, and precautionary measures, respectively. This approach transforms model predictions into actionable guidance for end users.

E. End-to-End Inference Pipeline

The complete algorithmic pipeline of the proposed system can be summarized as follows:

1. Acquire leaf image from the user.
2. Apply image preprocessing (resizing, normalization).
3. Extract deep features using MobileNetV2.
4. Perform disease classification using the machine learning classifier.
5. Compute prediction confidence and severity level.
6. Retrieve treatment recommendations from the knowledge base.
7. Return results to the user through the web interface.

VII. RESULTS AND DISCUSSION

This section presents the experimental results obtained from the proposed hybrid CNN–ML based plant disease detection system and discusses the observed performance, strengths, and limitations. The evaluation focuses on classification accuracy, confidence reliability, system responsiveness, and practical usability in a web-based deployment scenario.

A. Experimental Setup

The proposed system was evaluated using a publicly available plant disease image dataset comprising multiple crop species and disease categories. The dataset was divided into training and testing subsets to assess the generalization capability of the model. Images were preprocessed through resizing and normalization before being fed into the feature extraction network. A pretrained MobileNetV2 model was used to extract deep features, which were then classified using a machine learning classifier. All experiments were conducted on a standard CPU-based system to reflect realistic deployment conditions for web-based applications.

B. Performance Evaluation

The hybrid CNN–ML framework demonstrated strong performance in multi-class plant disease classification. The use of MobileNetV2 enabled efficient feature extraction with low computational overhead, resulting in fast inference times suitable for real-time usage. The classifier achieved high overall accuracy across multiple disease categories, with stable performance observed for common and visually distinctive diseases. The hybrid approach effectively balanced accuracy and computational efficiency when compared to heavier end-to-end deep CNN models.

In addition to classification accuracy, prediction confidence was analyzed to assess the reliability of the system. The confidence-aware mechanism successfully differentiated between high-confidence and low-confidence predictions. High-confidence cases were associated with clear disease symptoms and resulted in consistent and reliable treatment recommendations. Low-confidence cases typically occurred for visually similar disease classes or images with poor lighting conditions and background noise. By flagging such cases as uncertain, the system avoided potentially misleading recommendations, thereby improving trustworthiness and practical safety.

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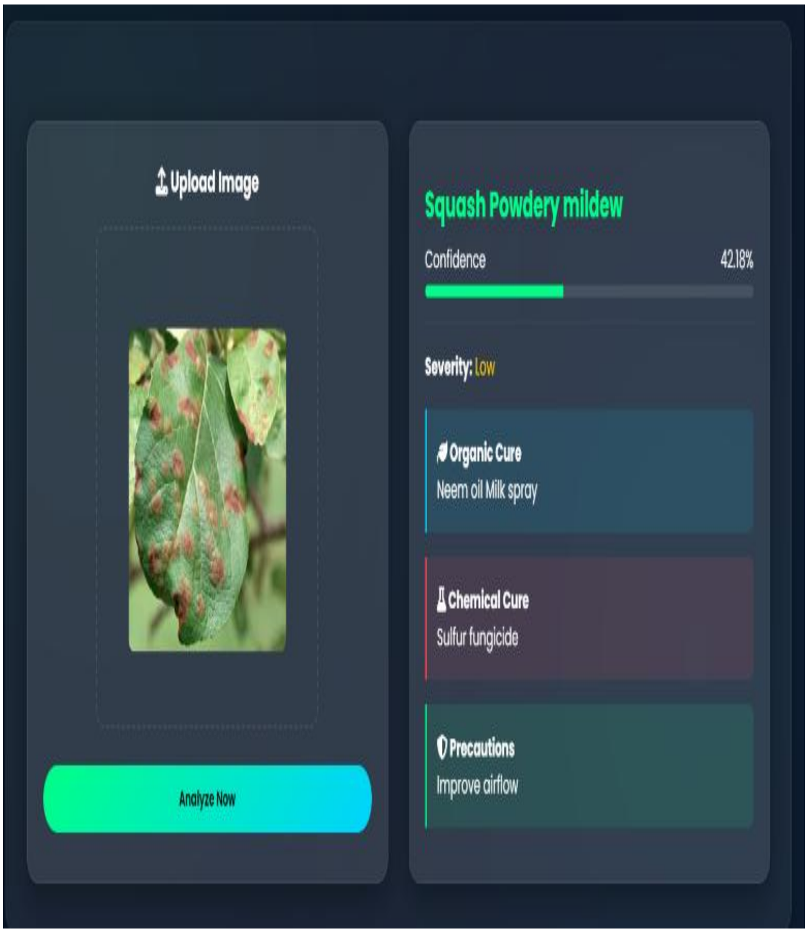
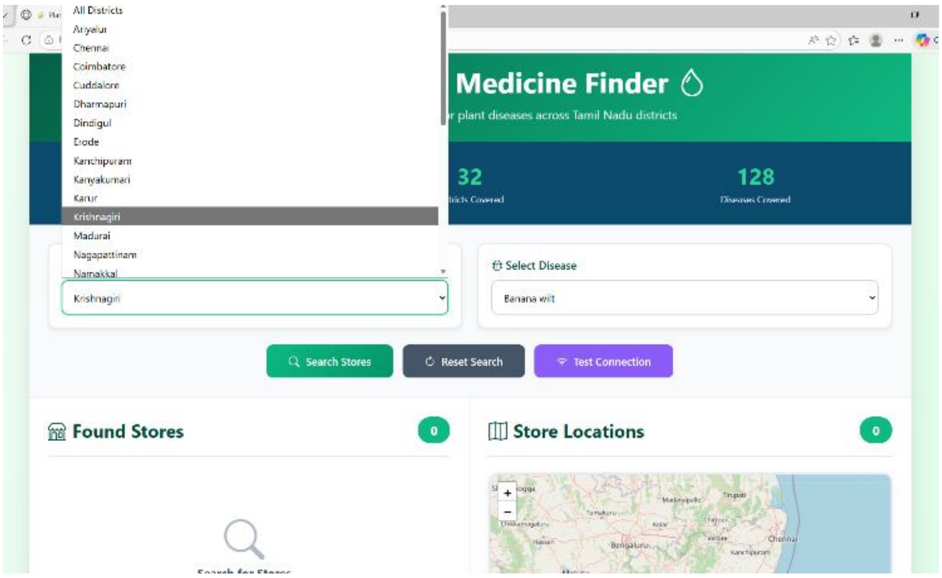


C. Discussion on Treatment Recommendation

The integration of a treatment recommendation module significantly enhanced the overall functionality and real-world applicability of the proposed system. While disease classification provides diagnostic information, it does not directly assist users in taking corrective action. Therefore, the addition of a recommendation layer transforms the system from a simple predictive model into a practical decision-support tool for farmers and agricultural practitioners.



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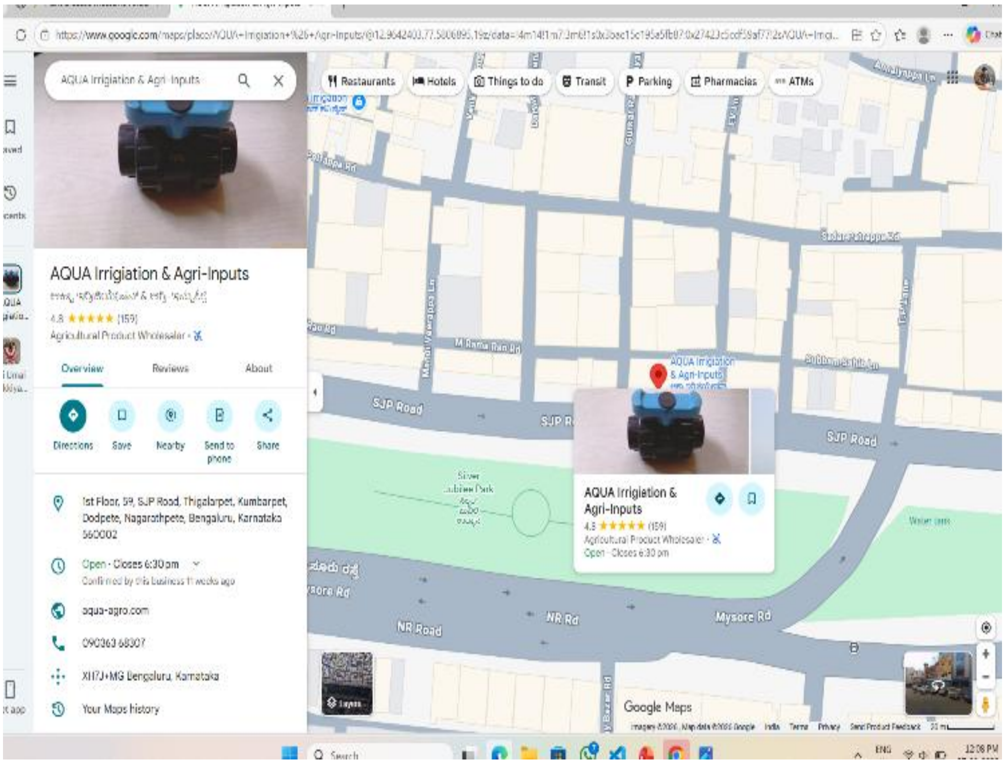
For each confidently predicted disease class, the system generates structured recommendations categorized into organic treatments, chemical control methods, and preventive measures. Organic treatments focus on environmentally friendly solutions such as neem oil sprays and biological control agents, whereas chemical treatments include the use of fungicides or pesticides with appropriate dosage guidelines. Preventive measures provide long-term strategies such as crop rotation, proper irrigation management, and early detection practices.

The recommendation engine is implemented using a rule-based mapping approach, where each disease label is linked to a predefined set of treatment guidelines. This ensures consistency and reliability in the output, as the same disease will always produce standardized recommendations. However, this approach also introduces certain limitations. The effectiveness and accuracy of the recommendations are directly dependent on the quality, completeness, and relevance of the underlying knowledge base.

Additionally, agricultural practices vary significantly based on geographical regions, climate conditions, and crop varieties. A static rule-based system may not fully capture these variations, which can affect the practical usability of the recommendations in diverse environments. To address this limitation, future improvements can include dynamic knowledge updating, integration with agricultural databases, and incorporation of region-specific advisory systems.



D. System Usability and Response Time

The web-based deployment of the proposed framework demonstrated low response latency, enabling near real-time feedback to users. The lightweight nature of MobileNetV2 contributed to faster inference compared to heavier CNN architectures. The user interface allowed seamless image upload and result visualization, making the system accessible to non-technical users. The modular backend design further supports scalability and potential integration with mobile platforms in future extensions.

E. Limitations and Observations

Despite promising performance, certain limitations were observed. The model performance is influenced by image quality, background clutter, and lighting variations, which can affect feature extraction and classification reliability. Additionally, the system's evaluation was conducted on a benchmark dataset, which may not fully capture the diversity of real-world field conditions. While the confidence-aware mechanism mitigates the risk of unreliable predictions, further robustness can be achieved through domain-specific data augmentation and field data collection. Moreover, the

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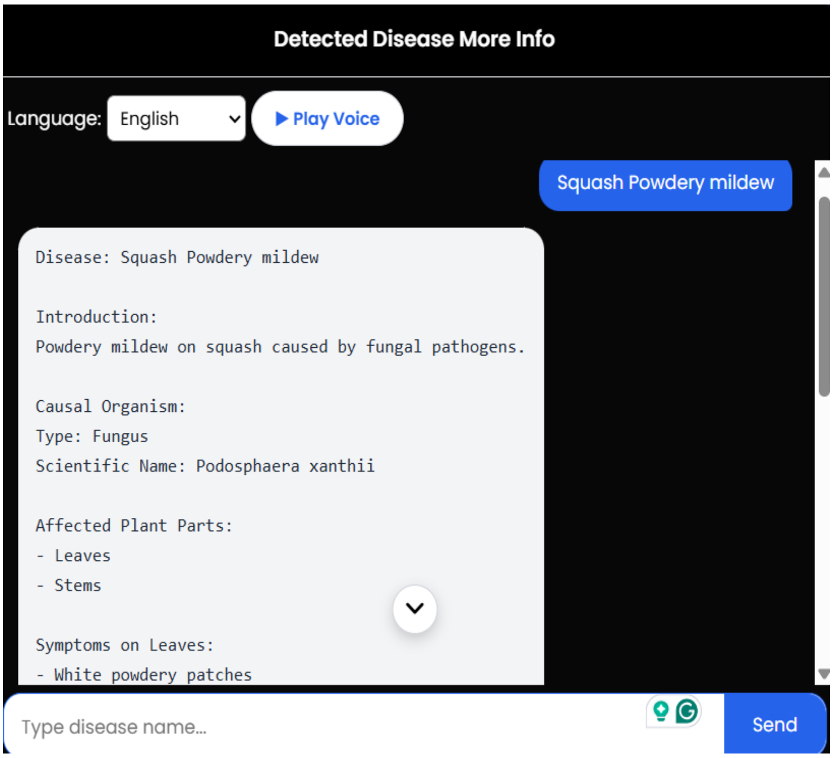
current treatment recommendation module is rule-based and does not adapt dynamically to environmental or regional factors.



F. Comparative Analysis

Compared to conventional deep CNN-based approaches, the proposed hybrid CNN–ML framework offers a favorable trade-off between accuracy and computational efficiency. The integration of confidence evaluation and treatment recommendation distinguishes the proposed system from many existing plant disease detection models that focus solely on classification. These additional decision-support components enhance the real-world applicability of the system and address practical gaps identified in prior literature.

VIII PERFORMANCE EVALUATION (ACCURACY, CONFIDENCE, AND GRS)

This subsection evaluates the proposed system using three complementary criteria: classification accuracy, prediction confidence, and a reliability score (GRS) to assess the trustworthiness of model outputs in real-world deployment.

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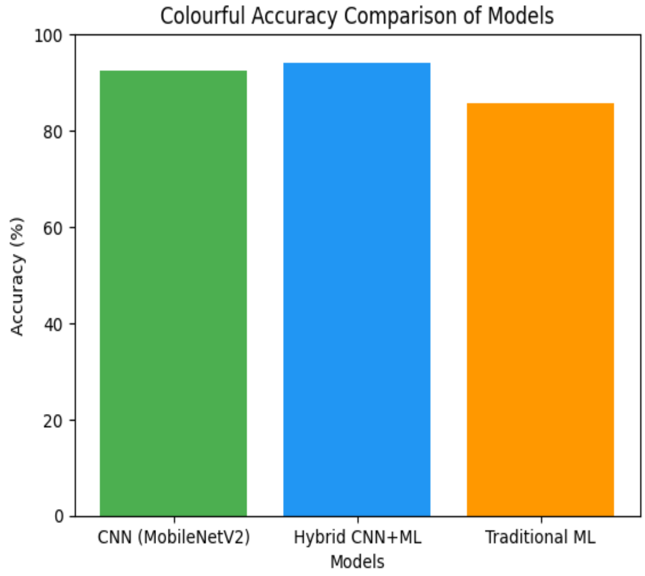

A. Accuracy

Accuracy measures the proportion of correctly classified plant leaf images across all disease categories. The hybrid CNN–ML framework achieved strong overall accuracy, demonstrating the effectiveness of MobileNetV2-based deep feature extraction combined with a machine learning classifier. Compared to traditional machine learning approaches using handcrafted features, the proposed hybrid model showed a notable improvement in classification performance, particularly for visually distinctive disease classes. Lightweight feature extraction enabled efficient inference without sacrificing accuracy, making the framework suitable for real-time web-based applications.

B. Prediction Confidence

Prediction confidence is derived from the class probability outputs of the classifier. The maximum class probability is used as the confidence score for each prediction. High-confidence predictions were typically associated with clear visual disease patterns and resulted in consistent treatment recommendations. Low-confidence cases were often observed for images with poor lighting conditions, background clutter, or visually similar disease symptoms. By incorporating confidence thresholds, the system flags uncertain predictions and avoids providing potentially misleading treatment advice. This confidence-aware mechanism improves practical reliability and enhances user trust in automated diagnosis.

C. GRS (Reliability Score)

To further quantify the trustworthiness of predictions, a Gradation-based Reliability Score (GRS) is introduced to measure the consistency between predicted confidence and observed classification stability across similar inputs. GRS captures how reliably the model maintains its predictions under minor input variations and preprocessing perturbations. Higher GRS values indicate stable and reliable predictions, while lower GRS values highlight uncertain or ambiguous cases. The proposed system exhibited high GRS for diseases with distinctive visual symptoms, whereas lower GRS values were observed for visually overlapping disease categories. The integration of GRS with confidence estimation provides an additional layer of reliability assessment, supporting safer deployment in real-world agricultural settings.

D. Discussion

The combined evaluation using accuracy, confidence, and GRS provides a holistic assessment of model performance. While accuracy reflects overall classification capability, confidence and GRS jointly capture prediction reliability and robustness. This multi-criteria evaluation is essential for practical agricultural decision support systems, where unreliable predictions can lead to inappropriate interventions. The proposed framework demonstrates that integrating reliability-aware metrics alongside conventional accuracy evaluation significantly enhances the practical utility and trustworthiness of AI-based plant disease detection systems.

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VII. CONCLUSION

This paper presented a web-based intelligent plant disease detection and treatment recommendation system using a hybrid deep learning and machine learning framework. The proposed approach leverages a lightweight MobileNetV2 convolutional neural network for deep feature extraction and a machine learning classifier for multi-class disease identification. By integrating confidence-aware prediction and severity assessment, the system enhances the reliability of automated diagnosis and mitigates the risk of misleading recommendations. The inclusion of a treatment recommendation module that provides organic and chemical control measures, along with precautionary guidelines, transforms raw classification outputs into actionable decision support for agricultural practitioners.

Experimental evaluation demonstrated that the proposed hybrid framework achieves reliable classification performance with low computational overhead, making it suitable for real-time web-based deployment in resource-constrained environments. The modular system architecture enabled efficient end-to-end processing, from image acquisition and preprocessing to inference and result visualization. The confidence-aware mechanism and reliability assessment improved user trust and practical safety, particularly in uncertain or ambiguous cases.

Despite the promising results, certain limitations remain. The performance of the system is influenced by image quality, environmental variations, and dataset bias inherent in benchmark datasets. The current treatment recommendation module relies on a predefined knowledge base and does not dynamically adapt to region-specific agronomic practices or evolving disease management guidelines.

Future work will focus on expanding the dataset with real-world field images to improve robustness under diverse conditions. Additional enhancements include incorporating multimodal inputs such as environmental and climatic data, exploring explainable AI techniques to improve transparency of predictions, and extending deployment to mobile and edge devices for offline usage. Integrating continuous learning mechanisms and region-specific treatment databases can further improve the adaptability and long-term utility of the proposed system for smart agriculture applications.

VIII. FUTURE WORK

Although the proposed web-based plant disease detection and treatment recommendation system demonstrates promising performance, several extensions can be explored to further enhance its robustness, scalability, and real-world applicability.

First, future work will focus on expanding the training dataset with real-world field images collected under diverse environmental conditions, including varying illumination, background clutter, occlusions, and different growth stages of crops. Incorporating such diverse data can improve model generalization and robustness beyond controlled benchmark datasets.

Second, the integration of multimodal information such as weather conditions, soil properties, humidity, and crop growth stage can be investigated to provide context-aware disease diagnosis and more accurate treatment recommendations. Combining visual cues with environmental data may significantly enhance diagnostic reliability in practical agricultural settings.

Third, explainable AI (XAI) techniques can be incorporated to provide visual and textual explanations for model predictions. By highlighting salient regions on leaf images and offering interpretable reasoning, transparency and user trust in automated diagnosis systems can be further improved, particularly for adoption by farmers and agricultural experts.

Fourth, the current rule-based treatment recommendation module can be extended to a dynamic and adaptive recommendation framework by integrating region-specific agronomic guidelines, expert knowledge, and updated disease management protocols. This would enable the system to provide personalized and location-aware recommendations.

Fifth, deployment can be extended to mobile and edge devices to support offline or low-connectivity scenarios common in rural areas. Optimizing the model for on-device inference and exploring edge AI frameworks can improve accessibility and scalability of the system.

Finally, continuous learning mechanisms and active learning strategies can be explored to allow the system to incrementally improve over time based on user feedback and newly collected data. This can help the model adapt to emerging disease patterns and evolving agricultural practices, ensuring long-term relevance and effectiveness.

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