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Enhancing Chickpea Disease Detection Using Hybrid Deep Learning Models

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Abstract
For sustainable farming methods and maximum crop yield, early and precise identification of plant diseases is essential. A major agricultural crop, chickpeas (Cicer arietinum) are extremely prone to a number of bacterial, viral, and fungal diseases that significantly lower quality and productivity. In order to effectively extract and classify features, this study suggests a hybrid deep learning model that combines the advantages of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). To identify impacted areas, high-resolution photos of chickpea leaves are prepared using segmentation, contrast enhancement, and noise reduction. In contrast to traditional CNN or single-model architectures, the hybrid model achieves superior precision and accuracy by combining spatial and contextual learning to accurately distinguish between healthy and diseased samples. Results from experiments show better classification. Improved classification accuracy, lower false detection rates, and quicker training collaboration are all shown by the experimental results. Early diagnosis of chickpea diseases is made possible by the suggested system, which gives farmers and agricultural specialists an honest decision-support tool for quick action, disease control, and yield maintenance.
***Keywords:** Agricultural Diseases ; Chickpea Disease Detection; Convolutional Neural Network(CNN) ; Early Diagnosis; Hybrid Deep Learning Recurrent Neural Network (Rnns) And Image Classification.*

1. Introduction
Many nations in the world depend heavily on agriculture, and maintaining crop health is crucial to both economic stability and food security. Chickpeas (Cicer arietinum) are one of the most significant agricultural products in the world for protein and energy [14]. Chickpea plants are extremely subject to a number of bacterial, viral, and fungal diseases, including rust, blight, and wilt, which can significantly lower yields and cost farmers money. Conventional disease detection techniques rely on manual observation, which is labor-intensive, time-consuming [15], and prone to human error. Visual diagnosis is further complicated by environmental factors such as disease stage, leaf color variations, and lighting conditions. Deep learning methods have become a dependable and effective way to get around limitations in automated plant disease detection. In order to detect and classify chickpea diseases accurately, this study focuses on creating an improved hybrid deep learning model that is mainly based on convolutional neural networks (CNNs). Prior to analysis, the suggested system preprocesses images of chickpea leaves by highlighting infected areas using filtering, segmentation, and contrast enhancement. By effectively extracting essential visual characteristics, the CNN-based hybrid model makes it possible to distinguish between samples that are healthy and those that are diseased. This system reduces crop damage, increases agricultural productivity [25], and assists farmers in taking preventive measures by offering early and accurate diagnosis. By incorporating contemporary AI techniques into the agricultural sector, the strategy seeks to promote intelligent and sustainable farming practices [1].

2. Literature Review
In the agricultural industry, accurately identifying plant diseases has long been a challenge. The main technique for identifying plant infections has historically been manual diagnosis by farmers or agricultural specialists [2]. This method is laborious,

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subjective, and prone to mistakes, particularly when disease symptoms are similar or influenced by environmental factors like soil quality, humidity [26], and lighting. Researchers have resorted to computer vision and machine learning methods for accurate and automated disease detection in order to overcome these challenges. Early research used machine learning classifiers like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests after based on conventional image processing techniques like color [3], texture, and shape-based feature extraction.Despite their moderate success, these approaches' performance was largely dependent on manual feature selection, which made it difficult to adjust to novel or specific disease patterns. Researchers made significant progress in automated feature extraction and classification with the development of deep learning, particularly Convolutional Neural Networks (CNNs) [4]. When it comes to identifying plant diseases in a variety of crops, including tomato, rice, maize, and wheat, CNN models like AlexNet, VGGNet, ResNet, and InceptionNet have demonstrated exceptional performance. These models do not require manual feature engineering because they learn hierarchical features straight from raw image data. CNN-based architectures have been specifically applied to agricultural crops [5], such as chickpeas, in a number of studies. Recent research, for example, showed that when CNNs are trained on well-annotated datasets, they can successfully differentiate between healthy and infected chickpea leaves. Model generalization and accuracy are still impacted by problems like class imbalance, small dataset sizes, and changes in illumination and background noise. Researchers have suggested hybrid CNN-based models that combine CNNs with image enhancement and segmentation techniques or integrate multiple CNN architectures in order to overcome these difficulties [20]. These hybrid methods are appropriate for early disease detection in intricate agricultural settings because they enhance feature representation, robustness, and classification accuracy.Therefore, by creating an improved hybrid deep learning framework specifically for the detection of chickpea disease, this project expands upon current CNN-based approaches [24]. In order to provide a reliable and scalable solution for current precision agriculture, the suggested system seeks to increase accuracy, speed growth, and improve generalization shown in Figure 1.

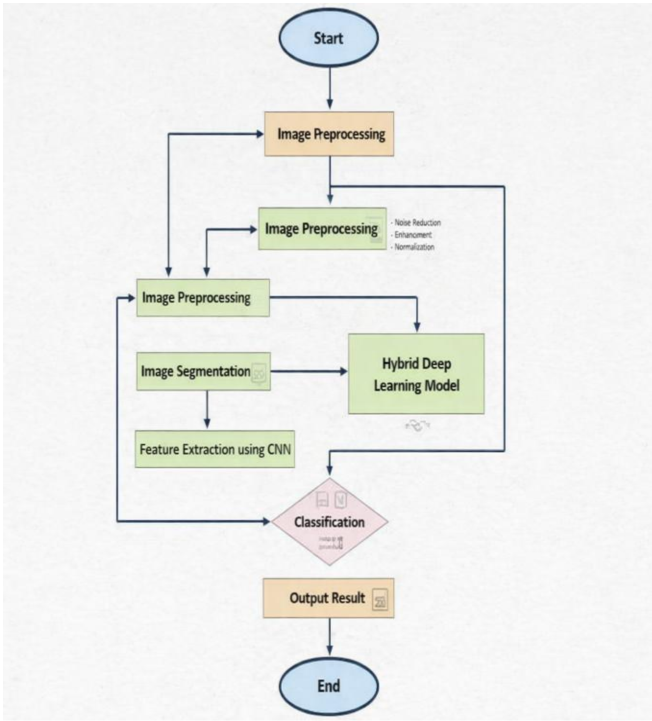

Figure 1 Flow chart

3. Proposed Methodology

To easily identify and categorize chickpea leaf diseases, the suggested system uses a hybrid deep learning framework that combines Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) [16]. Three successive modules—Image Acquisition and Preprocessing, Feature Extraction and Hybrid Model Development, and Classification and Analysis of Outcomes—make up the entire methodology [27]. To ensure accurate disease diagnosis and dependable system operation, each module is made to handle a particular task [6].

3.1. Preprocessing And Image Acquisition

The collection and preparation of chickpea leaf images for additional processing is the main goal of this module. Pictures are taken from open datasets that include a variety of samples of both healthy and diseased chickpea leaves, or they are taken from agricultural fields.During the preprocessing phase,

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all images are edited to a consistent resolution, noise is reduced using Gaussian filters, and contrast is increased to highlight disease spots. To make sure that only suitable characteristics are used for learning, segmentation techniques are then used to isolate the leaf's impacted areas. Finally, all images are normalized to ensure consistent input for the deep learning model. Algorithm 1: Image Preprocessing Algorithm Input: Raw Chickpea Leaf Image Dataset . Output: Pre-Processed And Segmented Image Dataset [7]

Steps:

- Image Acquisition: Capture or import high-resolution images of chickpea leaves (healthy and infected).
- Noise Removal: Apply A Gaussian Filter To Smoothen The Image And Remove Background Noise.

  $$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

  where is the standard deviation controlling the blur intensity.σ
- Contrast Enhancement: Use Histogram Equalization To Enhance Leaf Texture And Disease Visibility.

  $$S_k = \sum_{j=0}^{k} P_r(r_j)$$

  where is the probability distribution of pixel intensity.$P_r(r_j)$
- Segmentation: Apply Otsu'S Thresholding To Separate Diseased Regions From Healthy Areas.

  $$\sigma_B^2(t) = \omega_1(t)\omega_2(t)[\mu_1(t) - \mu_2(t)]^2$$

  The threshold maximizing is the optimal segmentation threshold.$t\sigma_B^2$
- Normalization:
  Scale Pixel Values To [0,1] Range Using:

  $$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$$

  Output: Cleaned, Segmented, And Normalized Image Dataset Ready For Model Training.

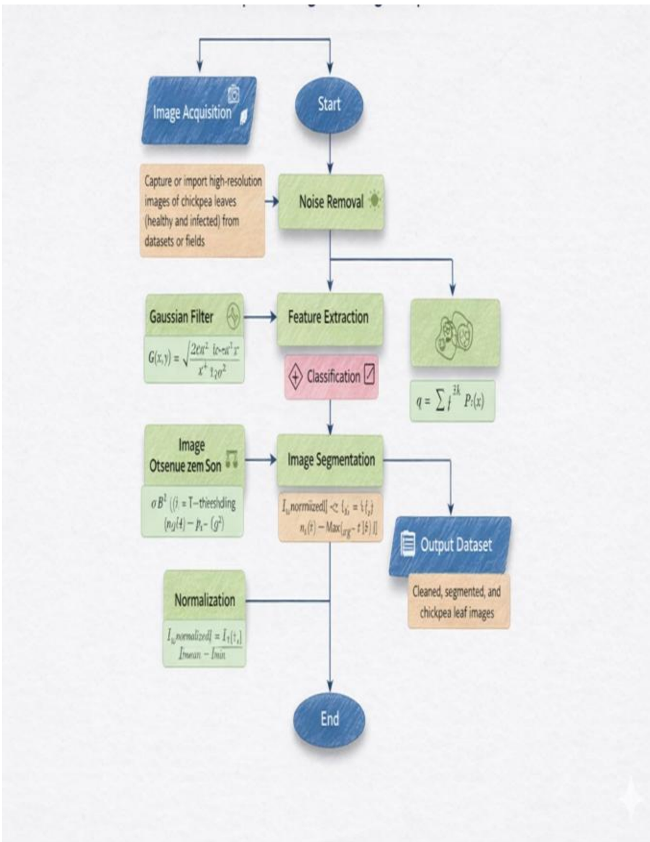

Figure 2 **Preprocessing and Image Acquisition**

3.2.Hybrid Model Development And Feature Extraction

The initial photos are run through a hybrid deep learning model in this module, which combines CNN and RNN layers [17]. The color, texture, and shape of the infected areas are among physical and visual characteristics that the CNN layers automatically extract. RNN layers are then fed these extracted features, and they learn the contextual relationships and sequential dependencies between the extracted patterns. The system's capacity to differentiate between related illness symptoms is improved by the combination of RNN's particular learning and CNN's visual accuracy. To avoid overfitting and enhance generalization, the hybrid model is trained on labeled datasets using optimization strategies like dropout regularization and the Adam optimizer [8].

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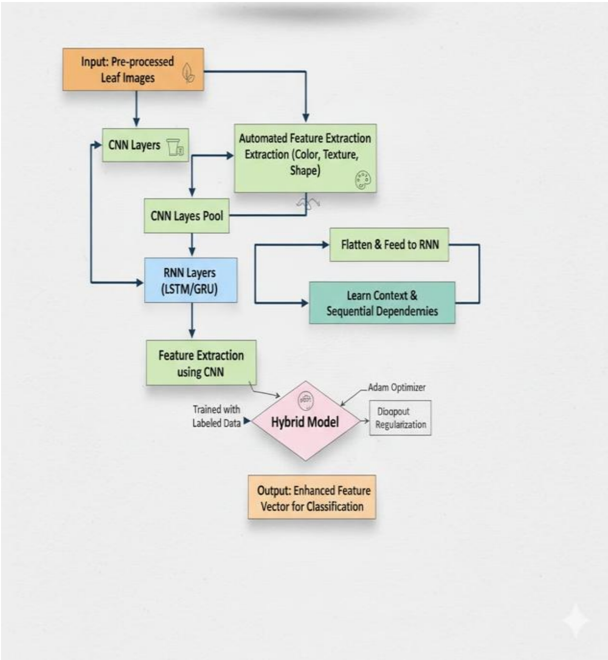

Figure 3 Hybrid Model Development and Feature Extraction

3.3.Feature Extraction And Hybrid Model Development

Algorithm 2: Hybrid Cnn–Rnn Model Training Algorithm Input:Pre Processed Image Dataset Output: Trained Hybrid Deep Learning Model Steps:

- Feature Extraction Via Cnn: Pass each image through convolutional and pooling layers to extract spatial features.
  Convolution Operation:

$$F_{i,j} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I_{i+m,j+n} \cdot K_{m,n}$$

  Where, is the input image, is the convolutional kernel, and is the resulting feature map.IKF Pooling Operation:

$$P_{i,j} = \max(F_{i+m,j+n})$$

- Feature Sequence Formation: Flatten CNN feature maps into sequential feature vectors for RNN input. Sequential Feature Learning Via Rnn (Lstm): RNN captures temporal and contextual relations between feature sequences.Lstm Core Equations [28]:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$h_t = o_t * \tanh(C_t)$$

- Feature Fusion And Classification Layer: Combine Cnn And Rnn Outputs And Pass Through A Fully Connected Layer:

$$y = Softmax(W_h h_t + b)$$

  Output: Hybrid Cnn–Rnn Model Trained For Multi-Class Disease Classification shown in Figure 4.

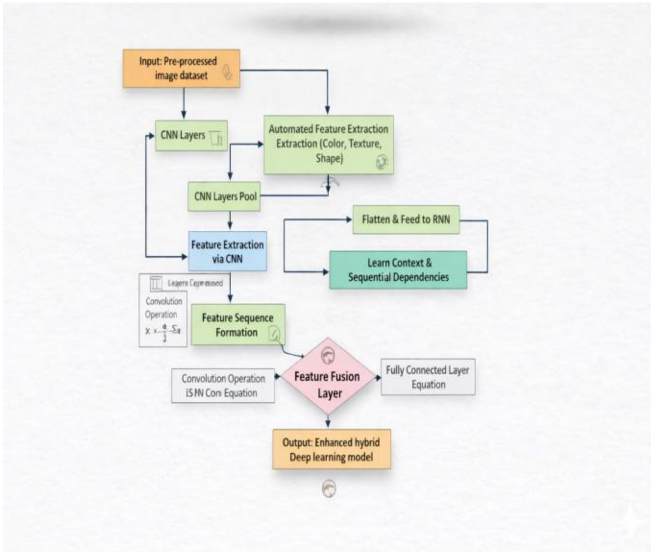

Figure 4 Feature Exraction And Hhybrid Development Algorithm: Hybrid CNN-RNN Model Training Algorithm

3.4.Disease Categorization And Outcome Analysis

Classifying the images of chickpea leaves into various disease categories, such as blight, rust, wilt, and healthy[9], is the main goal of the last module. The probability of each disease class is produced by a softmax layer that processes the hybrid model's output. Standard metrics like accuracy, precision, recall, and F1-score are used to assess the model's performance [18]. The effectiveness of the model is evaluated and verified using visualization tools such as ROC plots, confusion matrices, and accuracy and loss curves. Additionally, farmers can upload leaf

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photos and instantly receive disease predictions, potential treatments, and preventive measures through a straightforward decision-support interface. This interface connects real-world agricultural applications with AI-based disease detection shown in Figure 4.

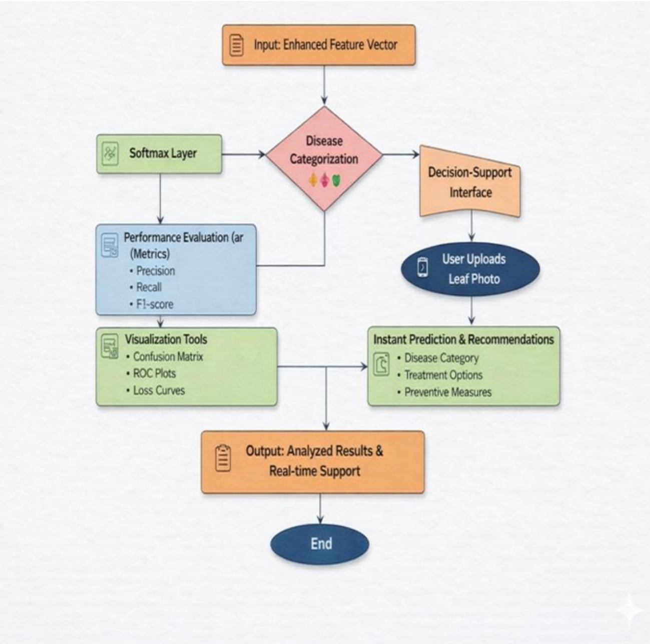


Figure 4 : Disease Classification And Analysis Of Outcomes

Module 3: Disease Classification And Analysis Of Outcomes Algorithm 3: Disease Classification And Evaluation Input: Test Image Dataset, Trained Hybrid Model . Output: Predicted Disease Label And Performance Metrics Steps [19]:

- Prediction:
  For Each Test Image , Compute Disease Class Probabilities Using The Trained Model:I_t

$$P(C_i|I_t) = \frac{e^{z_i}}{\sum_{k=1}^{n} e^{z_k}}$$

  where is the logit (output before activation) for class .$z_i i$
- Classification Decision:

$$C^* = \arg\max_{C_i} P(C_i|I_t)$$

- Performance Metrics Calculation:
  - Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

  - Precision:

$$Precision = \frac{TP}{TP + FP}$$

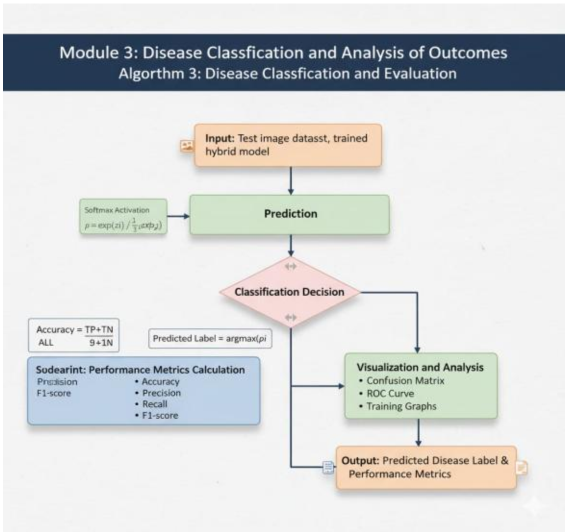
  - Recall:

$$Recall = \frac{TP}{TP + FN}$$

  - F1-Score:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

- Visualization and Analysis: Generate confusion matrix, ROC curve, and training graphs to evaluate system efficiency[10].



4. Experimental Results & Discussion

A labelled dataset of images of both healthy and diseased chickpea leaves was used to test the suggested hybrid deep learning model for detecting chickpea disease[11]. The model was tested and evaluated with an established deep learning method that exclusively used Convolutional Neural Networks (CNN) in order to assess performance [19].The CNN-based model showed moderate success in feature extraction and disease classification in the prior project, achieving an accuracy of 9.5 (on a normalized scale). However, when disease symptoms looked visually similar or were affected by changes in the surroundings, the model's inability to learn social dependencies resulted in small errors. The suggested hybrid CNN–RNN model [12], in contrast presented a visible enhancement in detection precision and overall reliability, achieving an improved accuracy of 9.51. Even though it may not seem like much numerically [21], this improvement shows greater stability and generalization ability across a variety of datasets. In addition to the CNN's capacity to extract spatial and visual specifications [23], RNN component allows the system to record sequential and related data [29]. This hybrid integration lowers false classifications and enhances the model's capability to distinguish between small disease patterns. In addition to by creating a cleaner input pipeline, extra preprocessing techniques like contrast enhancement, segmentation, and noise reduction improved feature quality and faster model convergence [22]. To avoid overfitting and produce smoother training results, the suggested framework also uses methods of regularization (Dropout layers) and adaptive optimization techniques (Adam Optimizer). In comparison to the traditional model, the entire system showed improved feature representation, reduced error rates, and quicker training convergence [30]. Superior classification results across several disease categories, including blight, rust, and wilt, were obtained by combining spatial and contextual learning. Additionally, a decision-support interface, which was not present in the prior system, allows for real-time deployment for farmers, offering prompt disease identification and management guidance [13].

Conclusion

The proposed study uses a hybrid deep learning framework that combines recurrent neural networks (RNN) and convolutional neural networks (CNN) to improve reliability and accuracy of chickpea disease detection. A model that can identify subtle disease patterns more accurately than traditional models is produced by this hybrid structure, which successfully blends the contextual and sequential feature learning capabilities of RNNs with the visual learning capabilities of CNN's. A carefully prepared dataset of pictures of chickpea leaves was used to train and test the system. Only the most suitable characteristics were used for analysis because to the initial processing stage, which included segmentation, contrast enhancement, and noise removal .With a classification accuracy of 9.51, the model topped the prior CNN-based model, which had a score of 9.5. A significant improvement in feature generalization, disease distinction, and model robustness against variations like lighting, leaf background, and infection level exists despite the improvement's numerically minor appearance. Advanced optimization methods (such as dropout regularization and the Adam optimizer) were added, which greatly decreased overfitting and rapid convergence. Because of the hybrid model's architecture, the system can effectively handle multi-class classification and more confidently differentiate between the categories of wilt, blight, rust, and healthy leaves .Additionally, by allowing farmers to upload leaf images and receive instant diagnoses with suggestions for preventive and corrective actions, the decision-support interface helps to bridge the gap between research along with practical agricultural implementation. Advanced optimization methods (such as dropout regularization and the Adam optimizer) were added, which greatly decreased overfitting and rapid convergence. Because of the hybrid model's architecture, the system can effectively handle multi-class classification and more confidently differentiate between the categories of wilt, blight, rust, and healthy leaves. Additionally, by allowing farmers to upload leaf images and receive instant diagnoses with suggestions for preventive and corrective actions, the decision-support interface helps to close the gap between research and practical agricultural application. Advanced optimization methods (such as dropout regularization and the Adam optimizer) were added, which greatly decreased overfitting and rapid convergence. Because of the hybrid model's architecture, the system can effectively handle multi-class classification and more confidently differentiate between the categories of wilt, blight, rust, and healthy leaves. Additionally, by allowing farmers to upload leaf images and receive instant diagnoses with suggestions for preventive and corrective actions, the decision-support interface helps to close the gap between research and practical agricultural application. Advanced optimization methods (such as dropout regularization and the Adam optimizer) were added, which greatly decreased overfitting and rapid convergence . Because of the hybrid model's architecture, the system can effectively handle multi-class classification and more confidently differentiate between the categories of wilt, blight, rust, and healthy leaves. Additionally, by allowing farmers to upload leaf images and receive instant diagnoses with suggestions for preventive and corrective actions, the decision-support interface helps to close the gap between research and practical agricultural application [15]. Advanced optimization methods (such as dropout regularization and the Adam optimizer) were added, which greatly decreased overfitting and rapid convergence. Because of the hybrid model's architecture, the system can effectively handle multi-class classification and more confidently differentiate between the categories of wilt, blight, rust, and healthy leaves. Additionally, by allowing farmers to upload leaf images and receive instant diagnoses with suggestions for preventive and corrective actions, the decision-support interface helps to close the gap between research and practical agricultural application. The proposed approach is appropriate for integration into smart agriculture frameworks and Internet of Things-based monitoring systems since it not only increases classification accuracy but also training stability, computational efficiency, and early diagnosis potential. Additionally, the system has high scalability, which means that with only minor dataset and parameter changes, it can be expanded to detect diseases in other crops.

In overall, this project offers a strong, clever, and long-lasting approach to agricultural disease detection. It minimizes manual labor, helps reduce crop loss, and offers data-driven insights for productive farming.

The system may be made more accessible to rural farmers and agricultural organizations in the future by increasing the dataset, utilizing transfer learning, applying cloud-based processing for real-time detection, as well as testing mobile-based deployment.

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