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Visualizing Crop Disease Detection Exploring Deep Learning with Custom CNN Model and XAI for Enhanced Interpretability

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Abstract—**Accurately detecting plant diseases is essential for safeguarding food security and promoting agricultural sustainability. This study presents an advanced deep learning approach using Convolutional Neural Networks (CNNs) to classify plant leaf diseases. Utilizing the Plant Village dataset, a custom CNN model was developed, which achieved superior accuracy of 96.11%, surpassing popular transfer learning models such as ResNet152-v2 (94%), VGG16 (91%), and Inceptionv3 (88%). Key aspects of this work include the implementation of robust data preprocessing techniques like image augmentation and the design of an optimized CNN architecture to enhance performance while maintaining computational efficiency. Furthermore, explainability was explored using Layer CAM, which provided more detailed visual explanations than Grad-CAM, thereby increasing the model's transparency and trustworthiness. These results confirm the effectiveness of the proposed method for accurate plant disease identification, positioning it as a promising tool for agricultural disease diagnosis. Future efforts will focus on expanding the dataset, improving model generalization, and deploying the model for real-time field applications.**

Keywords— Plant disease detection, CNN, deep learning, transfer learning, layer CAM

I. INTRODUCTION

Agriculture has long been the backbone of human civilization, serving as a crucial link between people and the land [1]. From small-scale subsistence farming to large commercial operations, crop production is vital to sustaining life on Earth [2]. However, the agricultural sector faces persistent challenges, particularly the impact of diseases caused by bacterial, fungal, viral, and other pathogens. These diseases can significantly reduce crop yields, with losses ranging from 10% to as high as 95%, negatively affecting agricultural products' quantity and quality [3]. Early detection and intervention are essential to mitigate these losses, yet many farmers, especially in rural and remote areas, still rely on manual inspection methods. These traditional methods are often inefficient, inaccurate, and time-consuming [4]. In contrast, integrating modern technology offers a more reliable disease detection solution, potentially enhancing agriculture productivity and sustainability [5].

More efficient methods have been made possible in recent years by developments in deep learning and machine learning. Deep learning models, especially CNNs, provide a more sophisticated method for classifying diseases than traditional machine learning techniques, which frequently rely on visual characteristics like color, texture, and shape [6]. By detecting subtle disease symptoms in high-resolution images, these models can achieve significantly higher accuracy than traditional methods [7]. CNNs have revolutionized image recognition and other fields, such as speech recognition and autonomous driving, highlighting their versatility and potential for broader agricultural applications [8]. Besides, the increased availability of GPUs and advanced embedded processors has further accelerated the application of CNNs in farming technology, enabling real-time and large-scale disease detection [9]. For instance, a study by Chen et al. [10] demonstrated that a CNN-based approach, combining the Inception module with VGGNet, achieved an impressive average accuracy of 92% in classifying rice plant images, even in complex environments. This model also maintained a validation accuracy of 91.83% on widely accessible datasets, highlighting the effectiveness of CNNs in agricultural applications. Similarly, another study by Sunil et al. [11] investigated the analysis of plant leaf pictures for disease identification using deep learning models like AlexNet, ResNet50, and VGG16. The study proposed an inexpensive approach to early disease diagnosis that produced remarkable results, with 100% accuracy for binary datasets and 99.53% accuracy for multi-class datasets. According to these results, deep learning has the ability to revolutionize plant disease management, offering precise and efficient solutions that can be scaled across different agricultural contexts. Another significant development [12], introduced an innovative deep-learning model for the realtime identification of apple leaf diseases. Their approach, which combined Rainbow concatenation with the Google Inception framework, achieved rapid detection rates and high accuracy, outperforming previous benchmarks. The study by Jiang et al. [13] also highlighted the effectiveness of CNNs in diagnosing plant diseases, with precision levels ranging from 91% to 98% across 13 diseases. This high level of accuracy, achieved using the Caffe Deep Learning framework, demonstrates the potential of CNNs to enhance disease identification and intervention in agriculture.

Despite the substantial progress in using deep learning for plant disease detection, current models often focus on specific diseases or crops, limiting their generalizability and practicality. Developing more adaptive models, such as those leveraging transfer learning, could enhance the universality and effectiveness of disease detection systems [14]. Transfer learning allows models to apply knowledge obtained from one area to another, making it a possible route for expanding the scope of plant disease diagnosis technologies. [15]. Integrating advanced technology with traditional agricultural practices is pivotal, driving the sector toward more sustainable and productive outcomes [16].

Overall, integrating deep learning, particularly CNNs, into agriculture has the potential to address longstanding challenges related to plant disease detection and crop management. As models become more adaptable and efficient, they offer a promising future for enhancing agricultural productivity and sustainability.

The paper is organized as follows: Section II outlines the Materials and Methods, where the dataset, experimental setup, and machine learning models used for plant disease detection are described. Section III presents the Experimental Results and Discussion, providing a detailed analysis of the model's performance, comparison with existing methods, and evaluation based on accuracy and efficiency. Finally, Section IV concludes the paper with a summary of key findings, implications of the study, and potential future research directions.

II. MATERIALS AND METHODS

This section outlines the research framework, covering the dataset, preprocessing techniques, and the custom CNN developed for plant disease detection. The proposed CNN is compared with ResNet152-v2, VGG16, and Inception-v3, demonstrating its superior performance.

A. Proposed deep learning model

This section presents a customized CNN architecture for better leaf image-based plant disease diagnosis. The methodology includes data collection, preprocessing, model training, and evaluation, as Figure 1 illustrates the detection workflow.

Using scaling, normalization, and augmentation approaches, we gathered and preprocessed plant leaf picture data in order to maximize input for our proprietary CNN model. The convolutional, pooling, and dense layers model was trained to capture complex patterns, with explainable AI techniques like GradCAM and Layer-CAM enhancing interpretability. Its performance was evaluated against benchmark transfer learning models.

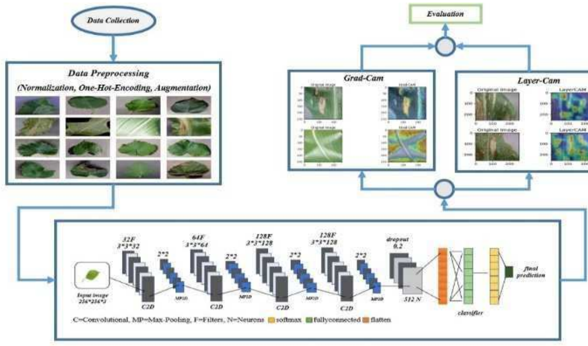

Fig. 1: Proposed methodology for enhancing plant disease detection

Data pre-processing was essential for preparing the dataset and improving model performance in this research. The initial step involved resizing all images to 256x256 pixels to ensure uniform input dimensions, facilitating efficient processing and model training. Pixel normalization was applied to standardize the data, using the equation (1)

$$Normalized\_Pixel\_Value = \frac{Orginal\_Pixel\_Value}{255} \quad (1)$$

By scaling pixel values to a range of [0, 1], this modification reduces sensitivity to changing illumination conditions and helps the model converge. We applied various augmentation techniques to address the class imbalance and increase dataset variability. These included shearing, zooming, flipping the image horizontally and vertically, shifting the width and height by up to 20%, random rotations up to 40 degrees, and brightness modifications between 0.5 and 1.5. The augmentation process was managed using the keras image data generator module, which performed these transformations dynamically during training to enhance the diversity of the dataset and improve model robustness.

Three subsets of the dataset were created to guarantee reliable model evaluation and training. To be more precise, 10% of the photos were used for testing, 20% for validation, and 70% for training. This distribution provided a comprehensive framework for assessing model performance while mitigating overfitting risks. Data augmentation further enhanced model robustness by introducing variability into the training data, thereby improving the model's generalization capabilities.

Fig. 2: Image of leaves

Three subsets of the dataset were ultimately created: 3,214 for testing, 6,425 for validation, and 22,488 for training. This strategic split ensured comprehensive model evaluation and reduced the risk of overfitting. The model's generalizability was enhanced by the data augmentation strategies, which also made it more resilient and less prone to overfit the training set.

Table I: partition of data sets

Partition	Number of images
train	22,488
validation	6,425
test	3,214

The architecture of the proposed deep learning model:

We introduce a custom CNN model designed for plant disease classification, optimized for input images 256×256×3. The architecture features a series of convolutional layers, starting with 32 filters (3×3) and max-pooling (2×2), followed by layers with 64, 128, and 128 filters, each paired with maxpooling. This process makes it possible to extract ever more intricate elements from the pictures. The feature maps are flattened by the model after the convolutional stages and then run through a dense layer of 512 units with ReLU activation. To avoid overfitting, a 20% dropout layer is used. 16 units with softmax activation for multi-class classification are present in the output layer.

For multi-class classification problems, the model is constructed with categorical cross-entropy loss and the ADAM optimizer. Training involves 20 epochs, with validation after each epoch, ensuring performance evaluation and adjustment. This design, combining convolutional layers, dropout, and activation functions, is optimized to effectively handle plant disease detection challenges.

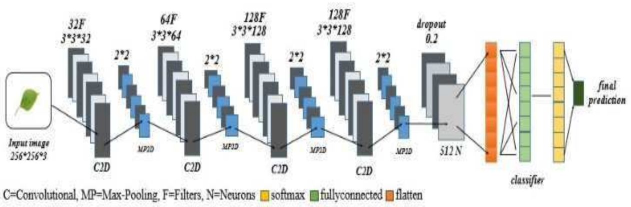

Fig 3: the architecture of the proposed CNN model

Implementation details:

Our deep learning model was implemented in a local computer environment that had a 250 GB SSD, 12 GB of RAM, and an Intel Core i5 10th generation processor. Tensorflow and Keras were used to build and train the CNN during the Python 3.8 programming process. The CNN architecture was meticulously designed and optimized using specific hyperparameters. A 32-batch size was used for the training procedure. The ADAM optimizer was used to train the model over 20 epochs, and overfitting was minimized by using a dropout rate of 0.2. The combination of these parameters and the robust local hardware setup facilitated an efficient and effective training process, enabling the development of a high performing model for plant disease classification.

B. Transfer learning model

Transfer learning enhances task performance using pretrained models from large-scale image recognition challenges. Notable architectures like ResNet152-v2, VGG16, and Inception-v3 are widely recognized for their unique designs and proven effectiveness.

ResNet152-v2:

ResNet152-v2 is a deep convolutional neural network that utilizes residual connections or skip connections to address the vanishing gradient problem commonly encountered in very deep networks. By incorporating identity skip connections, ResNet152-v2 allows gradients to flow through the network more effectively during training, thus facilitating the construction of deeper models without performance degradation. This model has shown remarkable proficiency in handling complex image classification tasks and has become a cornerstone in transfer learning applications [17].

VGG16:

VGG16 is renowned for its simplicity and uniform architecture. Convolutional, pooling, and fully connected layers are among its 16 layers. The model's strength lies in its deep stack of convolutional layers with small (3x3) filters, This makes it possible to extract complex information from input photos. The architecture of VGG16 is distinguished by its depth and consistent use of small convolutional filters, has made it a popular choice for various image classification tasks and serves as a reliable baseline for transfer learning [18].

Inception-v3:

The inception modules included in Inception-v3 allow the model to execute several convolutions with varying filter sizes at the same time. This architecture allows Inceptionv3 to capture various features at different scales and improve computational efficiency by optimizing the network's depth and width. The model's innovative design, including dimensionality reduction and auxiliary classifiers, contributes to its exceptional performance in large-scale image recognition tasks and has solidified its role as a robust transfer learning tool [19].

Table II: Summary of the DL models

Model	Architecture	Key focus	variants
ResNet152-v2	Deep, layered CNN	For vanishing gradients, identity skip connections are used.	ResNet-152, ResNet-101, ResNet-50
VGG16	Several layers of CNN with tiny filters.	Deep Stack of convolutional layers with 3x3 filters	VGG19
Inception-v3	CNN with inception modules and several layers	Different filter widths for different convolutional operations	Inceptionv1, Inceptionv2, Inceptionv3

C. Explainable AI (XAI)

In deep learning and artificial intelligence, Explainable AI (XAI) plays a pivotal role in enhancing the interpretability and transparency of complex models. A deeper comprehension of decision-making is made possible by XAI approaches, which promote accountability and trust by revealing how models make their predictions. In this research, two prominent XAI methods, Grad-CAM and Layer-CAM, are employed to visualize and interpret the inner workings of convolutional neural networks (CNNs).

Grad-CAM:

Grad-CAM (Gradient-weighted Class Activation Mapping) is a powerful technique used to generate class-specific heatmaps that show the areas of a picture that have the biggest impact on a model's prediction [20]. This technique creates these visuals by utilizing the target class's gradients with respect to the final convolutional layer's feature maps. Grad-CAM determines which aspects of the image have the greatest influence on the model's judgment by calculating the gradient of the output score in relation to the feature maps. This enables users to visualize the areas most significant for the classification task, thereby providing a clear understanding of the model's focus during prediction.

Layer-CAM:

Layer-CAM (Layer-wise Class Activation Mapping) extends the concept of Grad-CAM by generating heatmaps at various convolutional layers within the network. Unlike Grad-CAM, which focuses on the final convolutional layer, Layer-CAM allows for a more granular analysis by examining the contribution of different layers to the final prediction. This method involves computing class activation maps for multiple layers and combining them to produce a comprehensive visualization. Layer-CAM provides insights into how different network layers contribute to the model's decision-making process, revealing how lower-level features combine to form higher-level representations [21].

III. Experimental Results and Discussion

This section provides a comparison of the proposed CNN model against leading transfer learning architectures, focusing on accuracy and other key metrics to highlight the proposed method's superior performance in plant disease classification.

A. Performance evaluation and comparison

Statistical metrics such as specificity, sensitivity, precision, accuracy, and F1-score were used to assess the models' performance as detailed in equations (2)-(6).

$$Specificity = \frac{TN}{TN+FP} \tag{2}$$

$$Sensitivity\ (Recall) = \frac{TP}{TP+FN} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

$$F1-Score = 2 \times \frac{Precision \times Sensitivity}{Precision+Sensitivity} \tag{6}$$

True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are indicated below. These measures provided a comprehensive understanding of the model's ability to correctly classify plant diseases, minimizing both false positives and false negatives.

In order to evaluate multiclass deep learning models for plant disease classification, this study used confusion matrices to gauge how well the proposed CNN model performed (Figure 4), alongside ResNet152-v2 (Figure 5), VGG16 (Figure 6), and Inception-v3 (Figure 7). As shown in Table 3, the proposed CNN model outperformed all transfer learning models across multiple performance metrics. Its superior results are attributed to a well-optimized architecture, five convolutional layers, max-pooling, fully connected layers, and ReLU activation algorithms are all included. Preprocessing methods like data augmentation and normalization also improved image quality and pattern identification. The proposed CNN achieved the highest accuracy of 96.11%, with precision, recall, and F1-scores of 97%, demonstrating its robustness in detecting plant diseases.

In comparison, while ResNet152-v2 and VGG16 performed well with accuracies of 93.71% and 88.64%, respectively, they exhibited slightly lower precision and recall values. Inception-v3, with an accuracy of 87.92%, further highlights the superior performance of the proposed CNN in this domain.

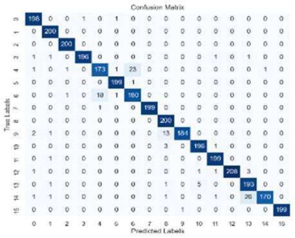

Fig. 4: Confusion Matrix of Proposed CNN

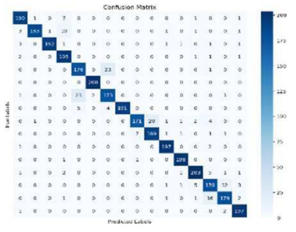

Fig. 5: Confusion Matrix of ResNet152-v2

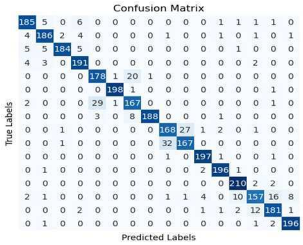

Fig. 6: Confusion Matrix of VGG16

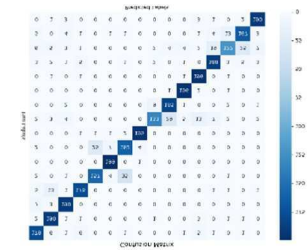

Fig. 7: Confusion Matrix of Inception-v3

Table III: Comparative Performance Analysis

Model	Precision	Accuracy	Specificity	Sensitivity	F1score
Proposed CNN	97%	96.11%	97%	97%	97%
ResNet152-v2	93.71%	94%	94%	94%	94%
VGG16	88.64%	91%	91%	91%	91%
Inception-V3	87.92%	88%	88%	88%	88%

Improving the performance of the proposed CNN model required adjusting important hyperparameters such as learning rates, dropout ratios, and batch sizes in order to maximize. In Table 4 a comparative performance evaluation between the proposed CNN and other deep learning models used in the study. The proposed CNN achieved the highest training and validation accuracy of 96.11%, demonstrating superior sensitivity and specificity in plant disease detection while effectively minimizing false positives. Figures 8 to 11 provide a visual representation of the accuracy and loss metrics for all models, with the proposed CNN consistently outperforming the others, further affirming its overall effectiveness.

Table IV: Performance evaluation of proposed CNN and other DL model

Model	Train-MSE	Test-MSE	Bias	Variance
Proposed CNN	0.000138	0.000019	0.000137	0.249725
ResNet151-v2	0.041599	0.044467	0.041899	0.191598
VGG16	0.251162	0.250074	0.251162	0.000528
Inception-v3	0.128295	0.134735	0.128295	0.125323

B. Comparison between the proposed model and the current existing models

The proposed model's comparison study with the state-of-the-art is shown in Figure 12. By surpassing state-of-the-art models in every important metric, the comparison analysis demonstrates the superiority of the suggested CNN model in plant disease detection. With a precision, accuracy, specificity, sensitivity, and F1-score of 97%, the proposed CNN significantly surpasses ResNet151-v2 (94%), VGG16 (91%), and Inception-v3 (88%) in performance. By reducing error and improving precision, its sophisticated design and preprocessing methods establish a new benchmark for plant disease identification and establish the CNN model as a dependable option for real-world uses.

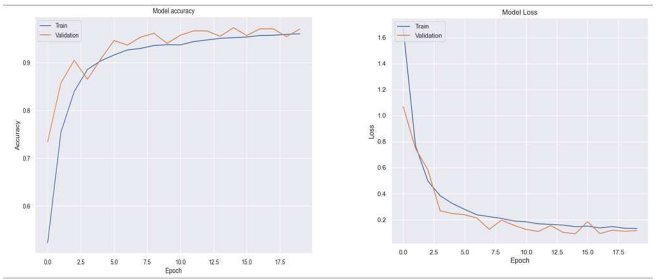

Fig. 8: Accuracy and Loss Curve of Proposed CNN

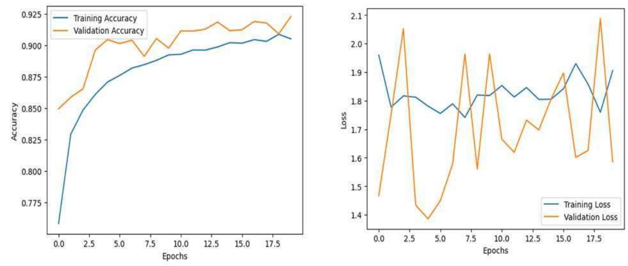

Fig. 9: Accuracy and Loss Curve of ResNet152-v2

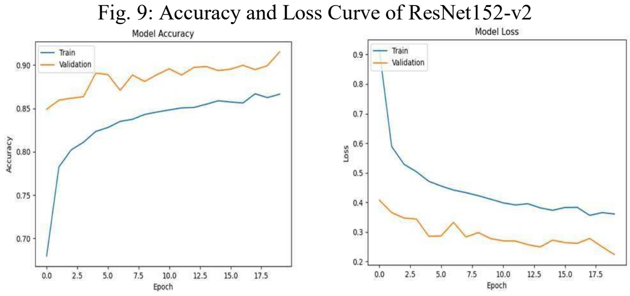

Fig. 10: Accuracy and Loss Curve of VGG16

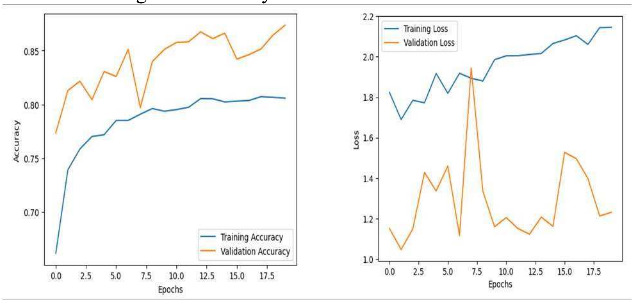

Fig. 11: Accuracy and Loss Curve of Inception-v3

The Area Under the Curve (AUC) and Receiver Operating Characteristic (ROC) curves for the four assessed models are shown in Figure 12: (a) the proposed CNN, (b) ResNet152-v2, (c) VGG16, and (d) Inception-v3. The ROC-AUC curve is a graphical representation of the model's performance in distinguishing between classes, with the AUC score indicating the degree of separability. The proposed CNN demonstrates the highest AUC, reflecting its superior ability to correctly classify plant diseases with minimal false positives and negatives. In contrast, ResNet152-v2, VGG16, and Inceptionv3 show slightly lower AUC values, highlighting the CNN's edge in overall classification accuracy and robustness in this domain.

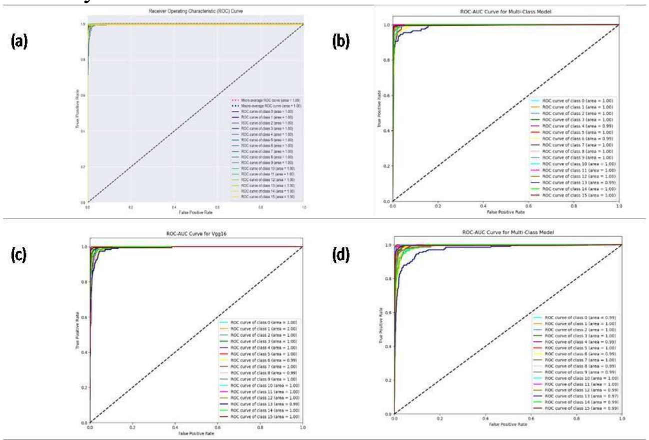

Fig. 12: ROC-AUC curve (a) Proposed CNN, (b) ResNet151-v2, (c) VGG16, and (d) Inception-v3

C. Comparison Between Grad-CAM and Layer-CAM

Our research compared Grad-CAM and Layer-CAM to visualize the focus of CNN in plant disease detection, as shown in Figure 13. Grad-CAM (Figure 13a), which computes class activation maps using gradients from the final convolutional layer, provides valuable insights but often results in coarse localization and is limited by its reliance on a single layer. In contrast, Layer-CAM (Figure 13b) improves upon Grad-CAM by incorporating activations from multiple convolutional layers, offering more detailed and precise visualizations. This method captures a broader range of features and provides finer localization, crucial for accurately identifying important regions in plant images.

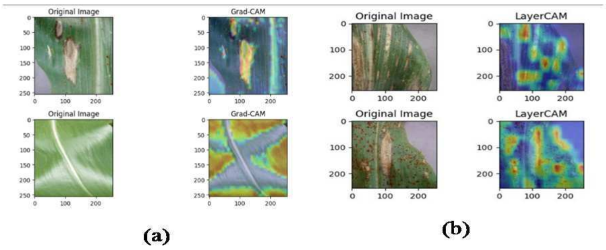

Fig. 13: (a) Grad-CAM, (b) Layer-CAM

IV. CONCLUSION

This work presents a novel method for improving the categorization of plant leaf diseases using deep learning techniques. By leveraging a custom-designed Convolutional Neural Network (CNN), we have created a methodology that greatly raises the precision and dependability of plant disease identification. Our approach effectively addresses common challenges such as image noise and variability through advanced preprocessing techniques, including data augmentation and image data normalization. The proposed CNN model outperforms existing methods in the field, as evidenced by its superior performance metrics across various evaluation parameters, such as F1-score, recall, accuracy, and precision. The detailed performance analysis, including ROC curves and confusion matrices, confirms the model's exceptional ability to accurately classify plant leaf diseases and distinguish between healthy and infected samples. Our results demonstrate the model's stability and effectiveness in comparison to both old and modern models, highlighting its potential to establish new benchmarks in plant disease identification. The high accuracy achieved by our CNN demonstrates its capability to provide reliable diagnostic insights, which is crucial for effective disease management in agriculture. In order to improve classification accuracy across a wider spectrum of plant diseases, future research should concentrate on improving the CNN architecture and investigating hybrid models that incorporate multiple deep-learning approaches. Furthermore, using explainable AI techniques will increase user transparency and confidence by offering insightful information about the model's decision-making process. Developing user-friendly applications and tools for real-time plant disease detection could significantly benefit agricultural practices, especially in resource-limited settings. By making advanced diagnostic technologies more accessible, we can support farmers and researchers in identifying and managing plant diseases more effectively, ultimately contributing to improved crop health and agricultural productivity. In summary, our study demonstrates how sophisticated deep learning methods can revolutionize the classification of plant diseases and points to future lines of inquiry and implementation in this crucial field.

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