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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 Inception-v3 (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].

In recent years, machine learning and deep learning advances have paved the way for more effective solutions. Traditional machine learning techniques often rely on visual features like color, texture, and shape to classify diseases, but deep learning models, particularly CNNs, offer a more refined approach [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] explored deep learning models such as AlexNet, ResNet50, and VGG16 to analyze plant leaf images for disease identification. The study proposed a low-cost method for early disease detection that achieved exceptional accuracy, reaching 100% for binary datasets and 99.53% for multi-class datasets. These findings underscore the potential of deep learning to

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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 real-time 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 enables models to apply knowledge gained from one domain to another, making it a promising avenue for improving 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 structure of 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 introduces a custom CNN architecture for improved plant disease detection using leaf images. The methodology includes data collection, preprocessing, model training, and evaluation, as Figure 1 illustrates the detection workflow.

We collected and preprocessed plant leaf image data using resizing, normalization, and augmentation techniques to optimize input for our custom CNN model. The convolutional, pooling, and dense layers model was trained to capture complex patterns, with explainable AI techniques like Grad-CAM and Layer-CAM enhancing interpretability. Its performance was evaluated against benchmark transfer learning models.

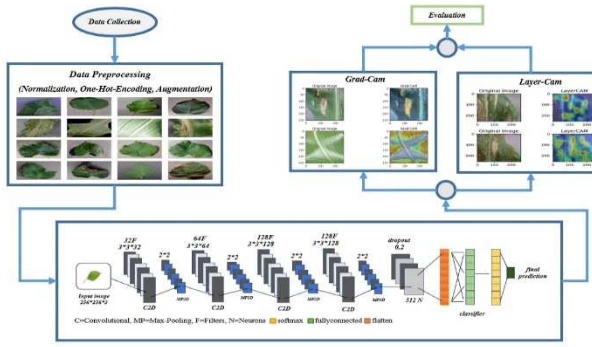

Fig. 1: Proposed methodology for enhancing plant disease detection

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)

$$Normalized\_(Pixel\_Value) = \frac{\text{Original\_(Pixel\_Value)}}{255} \quad (1)$$

This transformation scales pixel values to a range of [0, 1], which aids in model convergence and mitigates sensitivity to varying lighting conditions. We applied various augmentation techniques to address the class imbalance and increase dataset variability. These included random rotations up to 40 degrees, width and height shifts up to 20% of the image dimensions, shearing, zooming, horizontal and vertical flips, and brightness adjustments within a range of 0.5 to 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.

The dataset was divided into three subsets to ensure robust model training and evaluation. Specifically, 70% of the images were allocated for training, 20% for validation, and 10% for testing. 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

Finally, the dataset was divided into three subsets: 22,488 images for training, 6,425 for validation, and 3,214 for testing. This strategic split ensured comprehensive model evaluation and reduced the risk of overfitting. The data augmentation techniques improved the model's generalizability, making it more robust and less likely to overfit the training data.

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 max-pooling. This progression enables the extraction of increasingly complex features from the images. After the convolutional stages, the model flattens the feature maps and passes them through a dense layer of 512 units with ReLU activation. A 20% dropout layer is applied to prevent overfitting. The output layer contains 16 units with softmax activation for multi-class classification.

The model is compiled with the ADAM optimizer and categorical cross-entropy loss, ideal for multi-class classification tasks. 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.

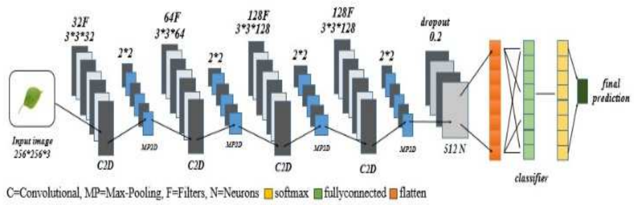

Fig 3: the architecture of the proposed CNN model

Details implementation:

The implementation of our deep learning model was executed using a local computing environment equipped with an intel core i5 10th generation processor, 12 GB of RAM, and a 250 GB SSD. The programming was conducted in Python 3.8, utilizing tensorflow and keras to construct and train the CNN. The CNN architecture was meticulously designed and optimized using specific hyperparameters. For the training process, a batch size of 32 was employed. The model was trained over a total of 20 epochs using the ADAM optimizer, and a dropout rate of 0.2 was applied to mitigate overfitting. 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 pre-trained 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. It comprises 16 layers, including convolutional, pooling, and fully connected layers. The model's strength lies in its deep stack of convolutional layers with small (3x3) filters, which enables the extraction of intricate features from input images. VGG16's architecture, characterized 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:

Inception-v3 incorporates inception modules that enable the model to simultaneously perform multiple convolutions with different filter sizes. This architecture allows Inception-v3 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	Utilizes identity skip connections to address vanishing gradients	ResNet-152, ResNet-101, ResNet-50
VGG16	Multi-layer CNN with small filters	Deep stack of convolutional layers with 3x3 filters	VGG19
Inception-v3	Multi-layer CNN with inception modules	Various convolutional operations with different filter sizes	Inception-v1, Inception-v2, Inception-v3

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. By providing insights into how models arrive at their predictions, XAI techniques facilitate a deeper understanding of decision-making, fostering trust and accountability. 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 highlight the regions of an image most influential in a model's prediction [20]. This method leverages the gradients of the target class concerning the feature maps of the last convolutional layer to produce these visualizations. By computing the gradient of the output score with respect to the feature maps, Grad-CAM identifies which parts of the image contribute most to the model's decision. 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 presents a comparative analysis 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

The models' performance was evaluated using statistical measures, including specificity, sensitivity, precision, accuracy, and F1-score, as detailed in equations (2)-(6).

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

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

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

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

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

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

This study evaluated multiclass deep learning models for plant disease classification, utilizing confusion matrices to assess the performance of the proposed CNN model (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, consisting of five convolutional layers, max-pooling, fully connected layers, and ReLU activation functions. Additionally, preprocessing techniques, such as normalization and data augmentation, further enhanced image quality and pattern recognition. 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.

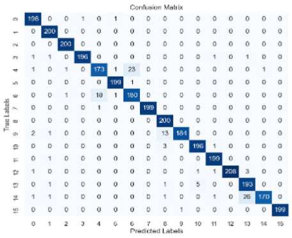

Fig. 4: Confusion Matrix of Proposed CNN

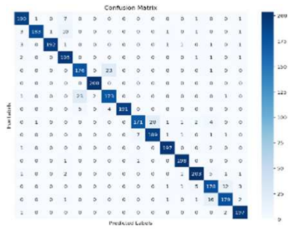

Fig. 5: Confusion Matrix of ResNet152-v2

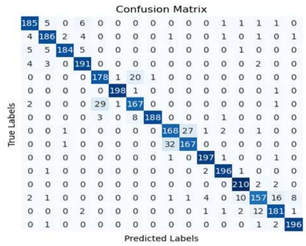

Fig. 6: Confusion Matrix of VGG16

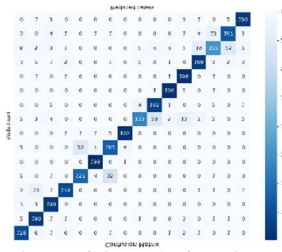
Fig. 7: Confusion Matrix of Inception-v3

Table III: Comparative performance analysis

Model	Precision	Accuracy	Specificity	Sensitivity	F1-score
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%

To optimize computational efficiency, fine-tuning key hyperparameters such as learning rates, dropout ratios, and batch sizes was essential for enhancing the performance of the proposed CNN model. Table 4 presents 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

Figure 12 depicts the comparative analysis of the proposed model with state-of-the-art. The comparative analysis highlights the superiority of the proposed CNN model in plant disease detection, outperforming state-of-the-art models across all key metrics. 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. Its advanced architecture and preprocessing techniques contribute to minimal error and enhanced precision, setting a new standard for plant disease detection and positioning the CNN model as a reliable solution for practical applications.

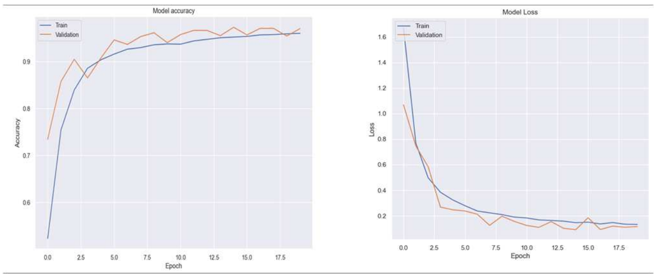

Fig. 8: Accuracy and Loss Curve of Proposed CNN

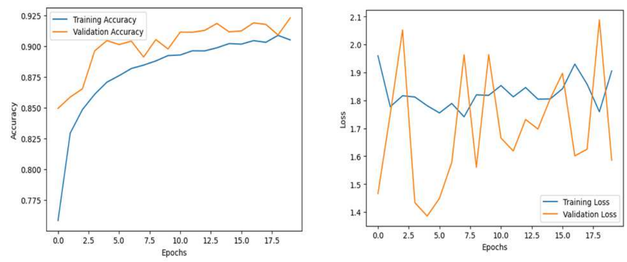

Fig. 9: Accuracy and Loss Curve of ResNet152-v2

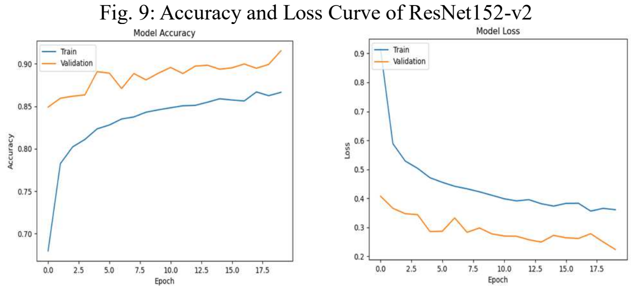

Fig. 10: Accuracy and Loss Curve of VGG16

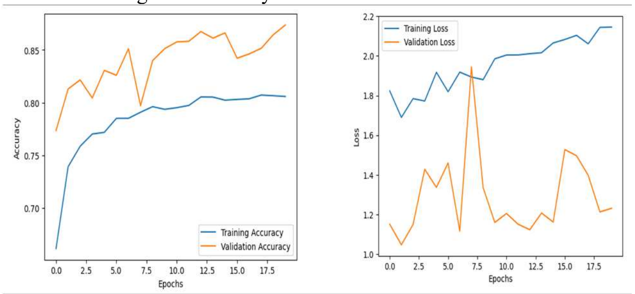

Fig. 11: Accuracy and Loss Curve of Inception-v3

Figure 12 presents the Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) curves for the four evaluated models: (a) the proposed CNN, (b) ResNet152-v2, (c) VGG16, and (d) Inception-v3. The ROC-AUC curve is a graphical representation of the models' 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 Inception-v3 show slightly lower AUC values, highlighting the CNN's edge in overall classification accuracy and robustness in this domain.

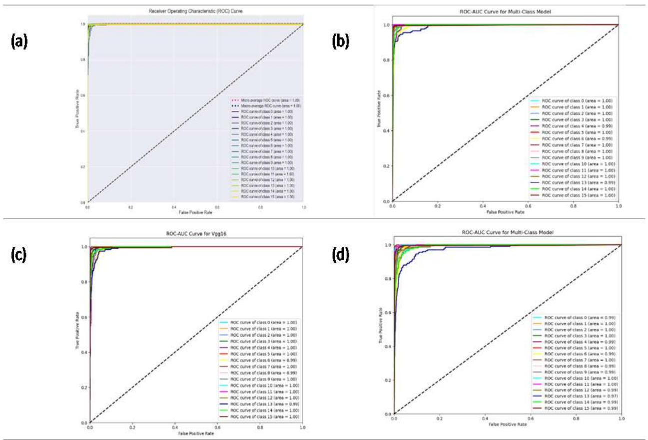

Fig. 12: ROC-AUC curve (a) Proposed CNN, (b) ResNet151-v2, (c) VGG16, and (d) Inception-v3

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.

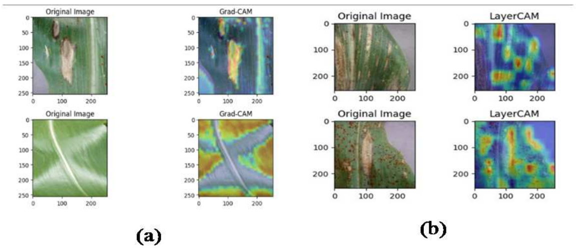

Fig. 13: (a) Grad-CAM, (b) Layer-CAM

IV. Conclusion

This study introduces an innovative approach to enhancing plant leaf disease classification through deep learning techniques. By leveraging a custom-designed Convolutional Neural Network (CNN), we have developed a model that significantly improves the accuracy and reliability of plant disease detection. 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 criteria, including accuracy, precision, recall, and F1-score. 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 findings highlight the model's potential to set new standards in plant disease detection, showcasing its robustness and effectiveness compared to traditional and contemporary models. The high accuracy achieved by our CNN demonstrates its capability to provide reliable diagnostic insights, which is crucial for effective disease management in agriculture. Future research should focus on refining the CNN architecture and exploring hybrid models that integrate various deep-learning techniques to enhance classification accuracy across a broader range of plant diseases. Additionally, incorporating explainable AI methods will provide valuable insights into the model's decision-making process, fostering greater user transparency and trust. 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 underscores the potential of advanced deep learning techniques in transforming plant disease classification and highlights future directions for research and application in this critical area.

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