Imagery based plant disease detection using conventional neural networks and transfer learning

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ABSTRACT

Ensuring the sustainability of global food production requires efficient plant disease detection, challenge conventional methods struggle to address promptly. This study explores advanced techniques, including convolutional neural networks (CNNs) and transfer learning models (ResNet and VGG), to improve plant disease identification accuracy. Using a plant disease dataset with 65 classes of healthy and diseased leaves, the research evaluates these models' effectiveness in automating disease recognition. Preprocessing techniques, such as size normalization and data augmentation, are employed to enhance model reliability, and the dataset is divided into training, testing, and validation sets. The CNN model achieved accuracies of 95.45 and 94.52% for 128×128 and 256×256 image sizes, respectively. ResNet50 proved the best performer, reaching 98.38 and 98.63% accuracy, while VGG16 achieved 97.99 and 98.34%. These results highlight ResNet50's superior ability to capture intricate features, making it a robust tool for precision agriculture. This research provides practical solutions for early and accurate disease identification, helping to improve crop management and food security.

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1. INTRODUCTION

Plant pests and diseases pose significant threats to global food security, with up to 40% of crop production lost annually due to these factors [1]. The Food and Agriculture Organization (FAO) reports that up to 40% of global crop production is lost annually due to weeds, pests, and diseases, and these losses could worsen without proper pest and disease management [2]. Within the agricultural sector, one major factor contributing to economic losses is plant disease, recognized as a risk due to its challenging early detection and identification. As it affects crop yield, the sustainability of the agro-economic sector is jeopardized, ultimately posing a threat to the food security of a given region. Early disease detection is crucial for farmers to control the spread and impact on crop yield. Prevention and treatment methods vary based on crop types and susceptibility to specific diseases [3]. Analyzing disease characteristics, symptoms, and severity is essential for addressing fundamental questions in plant stress biology. Timely disease analysis information enables rapid management decisions, enhancing the overall operation and health of plantations. Traditionally, plant diseases are identified through visual symptom interpretation and subsequent laboratory assessments [4]. However, these methods require expertise in plant pathology and considerable time for diagnosis.

Recognizing these limitations, modern technologies such as machine vision and remote sensing have been developed to detect and identify plant diseases, offering improved reliability, precision, and accuracy. Advancements in image analysis, particularly through data learning techniques like convolutional neural networks (CNNs), have revolutionized disease identification. Numerous studies have been conducted on the automatic identification of plant diseases, paving the way for the development of automatic imaging techniques for plant disease diagnosis, classification, plant recognition, fruit counting, and weed detection. These technologies have the potential to assist farmers in adopting better farming techniques, implementing good agricultural practices, and ultimately enhancing food security [5].

CNNs are widely used in various fields due to their ability to automatically extract essential features from data [6]. This feature extraction capability is crucial in tasks like image recognition, where CNNs can learn hierarchical local and global features without the need for manual feature extraction [7]. Additionally, CNNs are known for their adaptability in extracting raw signal features, leading to high classification accuracy [8]. ResNet50 and VGG16 are specific architectures within the realm of CNNs that offer distinct advantages. ResNet50 can achieve impressive depths of up to 152 layers while maintaining lower complexity compared to VGGnets [9]. On the other hand, VGG16, known for its fine-grained convolution operation, excels in classification problems [10]. Moreover, CNNs, including ResNet50 and VGG16, have been successfully utilized in various applications such as image recognition, anomaly detection, and even in fields like finance for exchange rate forecasting [11]. These networks have shown superior performance in tasks like image classification and segmentation, with models like VGG16 being used as feature extractors in conjunction with other architectures for tasks like fatigue crack initiation site detection [12].

Various studies have delved into advanced approaches for plant disease detection through CNNs, Kumar *et al*. [13] proposed a deep learning-based image recognition system, exploring faster R-CNN, R-CNN, and SSD architectures. The resulting system efficiently detected diverse diseases, boasting a validation accuracy of 94.6%. Similarly, Islam [14] utilized a CNN model, achieving a 94.29% accuracy in detecting plant diseases, particularly benefiting cultivators in enhancing crop production. Sharma *et al*. [15] investigated image segmentation for CNN models, outperforming full-image models, and achieving 98.6% accuracy on unseen data. Ferentinos [16] developed CNN models, attaining an impressive 99.53% success rate in plant disease detection and diagnosis. Agarwal *et al*. [17] proposed an efficient CNN model for tomato crop disease identification, surpassing traditional methods with a notable 98.4% accuracy. Baranwal *et al*. [18] showcased CNN effectiveness, achieving 98.54% accuracy in apple leaves disease detection. Sagar and Jacob [19] explored transfer learning, achieving 98.2% accuracy in classifying and detecting diseases across 38 different classes. Chen *et al*. [20] demonstrated deep transfer learning's robustness, reaching a minimum validation accuracy of 91.83%. Studies also evaluated different deep architectures for plant leaves disease detection. Optimal results were obtained using the GoogleNet architecture, with ResNet50 and ResNet101 performing exceptionally well. Barbedo [21] investigated the impact of dataset size and variety on deep learning and transfer learning for plant disease classification, emphasizing their crucial role in model effectiveness. Lastly, Fan *et al*. [22] proposed a feature-fusion method for identifying apple tree diseased leaves, achieving a recognition accuracy of 99.83% after data augmentation. These studies collectively highlight the diverse applications and successes of CNNs in advancing plant disease detection.

Previous research has explored the development of a low-cost smart irrigation system integrating internet of things (IoT) technology and fuzzy logic, demonstrating its effectiveness in optimizing water usage for agricultural applications [23]. The integration of IoT and fuzzy logic in irrigation represents an advanced approach that enhances efficiency and sustainability in water management. Furthermore, historical weather data has been leveraged to forecast reference crop evapotranspiration, enabling precise estimation of water requirements at different growth stages through neural networks, particularly long short-term memory (LSTM) techniques within recurrent neural networks (RNN) [24]. Additionally, investigations into the impact of compost application in salt-affected soils within automated greenhouse irrigation systems have provided valuable insights into soil salinity management and its implications for plant growth. By comparing various irrigation methods and monitoring physico-chemical parameters, these studies have underscored the potential of compost in mitigating the adverse effects of salinity on agricultural productivity [25].

Building upon these advancements in precision agriculture, recent research has extended the scope of intelligent agricultural systems towards plant disease detection using deep learning techniques. Inspired by these developments, this study focuses on exploring, analyzing, and comparing CNN models for plant disease detection, with an emphasis on transfer learning techniques utilizing ResNet and VGG architectures. The proposed approach seeks to enhance disease identification accuracy by systematically evaluating the performance of these models.

This paper is structured as follows: section 2 describes the materials and methods employed in this research, detailing the proposed disease detection framework and providing a comparative analysis of the selected models. Section 3 presents the results obtained from systematic experimentation. Finally, section 4 concludes the study with a summary of key findings and future research directions.

2. MATERIALS AND METHOD

In the proposed approach illustrated in Figure 1, a plant leaf disease database (details in Table 1) is utilized. The process begins by renaming the images in the database so that each image corresponds to its respective class name. Next, the images undergo size normalization and augmentation techniques to enhance the dataset. The augmented dataset is then split into training, validation, and test sets. The training and validation sets are used to train and validate three models: CNN, ResNet50, and VGG16. After training, the models are evaluated using the test set. The results are compared to assess the performance of each model in classifying plant leaf diseases. This method provides a structured and thorough analysis of the models' effectiveness.

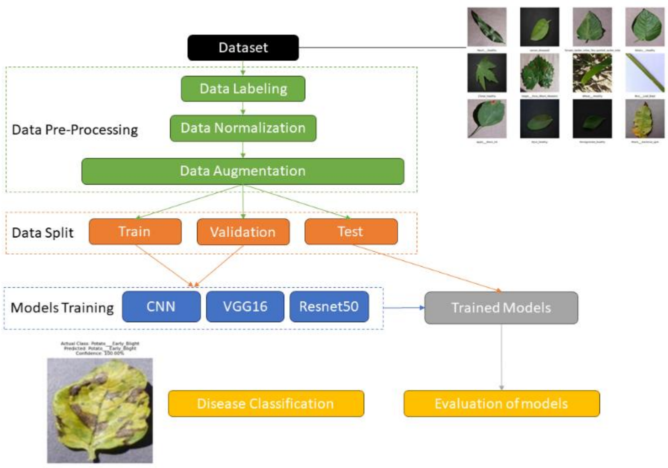

Figure 1. Proposed approach for imagery-based plant disease detection: comparison between CNNs, VGG16, and ResNet50

Table 1 summarizes the dataset used in this approach, showing the distribution of plant species, disease classes, and the number of images in each category. The total number of images in the dataset is 62,577 images. It includes a variety of plant species, such as wheat, corn, rice and potato, with both healthy and diseased samples. The dataset covers various disease conditions, like wheat rust, corn leaf blight, rice blast, and potato blight, providing a diverse and comprehensive basis for training and evaluating the classification models.

2.1. Data pre-processing

The aim of image pre-processing is to prevent the extraction of characteristic parameters against the influence of background, leaf size and shape, light conditions, and camera variations in disease diagnosis [26]. In the data pre-processing step, each image in the dataset undergoes a series of essential transformations. The first step involves class labeling, where each image is assigned to a specific class corresponding to the plant species and health condition it represents. The image labeling is structured such that each image is named as "class_name+(i)," providing a clear identifier for both the class and the image index. Subsequently, image height and width normalization are applied to ensure uniformity across the dataset. Images are resized to two distinct dimensions, 128×128 and 256×256 pixels. This choice allows for the exploration of model performance with inputs of varying sizes, providing insights into the network's ability to adapt to different resolutions. Such an approach helps assess the model's robustness and generalization across a range of input dimensions, contributing to a more comprehensive understanding of its capabilities. To further enhance model generalization and robustness, data augmentation techniques are implemented. These include rotation (rotation_range=30), width shift (width_shift_range=0.2), height shift (height_shift_range=0.2), zoom, horizontal flip (horizontal_flip=True), and vertical flip. These augmentations introduce variability into the training set, effectively expanding its diversity and improving the model's ability to handle different orientations, shifts, and scales during training. Additionally, a rescaling factor of 1/255 is applied to normalize pixel values. This step ensures that the input data falls within a suitable range for optimal model performance, preventing potential numerical instability. After the comprehensive pre-processing steps, the dataset is divided into training, validation, and test subsets, with an 80-10-10 split, respectively. This partitioning strategy allows for proper evaluation of the model's performance on unseen data, aiding in the assessment of its ability to generalize beyond the training set. The resulting data processing pipeline contributes to the creation of a well-prepared dataset, optimizing the performance of CNNs for accurate plant disease identification.

Table 1. Dataset distribution: species, classes and number of images

Species	Classes	Nbr. of images	Species	Classes	Nbr. of images
Alstonia Scholaris	Diseased	254	Peach	Bacterial spot	2297
	Healthy	179		Healthy	360
Apple	Apple scab	630	Pepper bell	Bacterial spot	997
	Black rot	621		Healthy	1,478
	Cedar apple rust	275	Pomegranate	Diseased	272
	Healthy	1,645		Healthy	287
Arjun	Diseased	232	Pongamia	Diseased	276
	Healthy	220	Pinnata	Healthy	322
Blueberry	Healthy	1,502	Potato	Early blight	1,000
Cherry	Cherry (including sour) healthy	1,052		Healthy	152
	Cherry (including sour) powdery mildew	854		Late blight	1,000
Chinar	Diseased	120		Healthy	371
	Healthy	103	Rice	Brown spot	613
Corn	Cercospora leaf spot gray leaf spot	513		Healthy	1,488
	Common rust	1,192		Leaf blast	977
	Gray leaf spot	513		Neck blast	1,000
	Healthy	1,162	Soybean	Healthy	5,090
	Northern leaf blight	985	Squash	Powdery mildew	1,853
Guava	Diseased	142	Strawberry	Healthy	456
	Healthy	277		Leaf scorch	1,109
Grape	Esca (black measles)	1,383	Tomato	Bacterial spot	2,127
	Healthy	423		Early blight	1,000
	Leaf blight (isariopsis leaf spot)	889		Healthy	1,591
Jamun	Diseased	345		Late blight	1,909
	Healthy	279		Leaf mold	952
Jatropha	Diseased	124		Septoria leaf spot	1771
	Healthy	133		Spider mites Two spotted spider mite	1676
Lemon	Diseased	77		Target spot	1404
	Healthy	159		Mosaic virus	373
Mango	Diseased	265		Yellow leaf curl virus	3209
	Healthy	170	Wheat	Brown rust	902
Orange	Huanglongbing (citrus greening)	5507		Healthy	1116
				Yellow rust	924

2.2. Convolutional neural networks

The CNN stands as a pioneering architecture in the realm of computer vision and image processing. Renowned for its ability to automatically learn hierarchical representations, CNNs have become instrumental in diverse applications, including plant disease detection. The convolutional layers of a CNN are adept at capturing intricate patterns within plant leaf images, allowing the model to discern subtle visual cues indicative of various diseases as shown in Figure 2. By learning and extracting features hierarchically, CNNs provide a powerful tool for automated identification of plant health issues, contributing significantly to precision agriculture and sustainable crop management. Within our plant disease detection framework, the CNN model serves as a foundational pillar. Employing a sequential structure, this model harnesses the power of convolutional layers with (3, 3) filters and rectified linear unit (ReLU) activation, facilitating the extraction of nuanced features from plant leaf images. We applied a stride of (1, 1) in all convolutional layers. Striding refers to the step size taken by the filter as it moves across the input image. A stride of 1 ensures that the filter moves one pixel at a time, maximizing the spatial coverage of the image. The padding technique used is 'same' padding. This ensures that the output dimensions of the convolutional layers match the input dimensions by adding zeros to the borders of the input. It prevents the image from shrinking after each convolution operation, maintaining resolution. Augmented by batch normalization and max-pooling layers, the CNN model excels in hierarchical pattern recognition. Further refinement includes a global average pooling layer for spatial reduction and dense layers with 1,024 units and ReLU activation for robust feature representation. Employing dropout with a 0.3 rate mitigates overfitting, culminating in a final dense layer with SoftMax activation for precise multi-class classification. Optimized through the Adam optimizer with a learning rate of 0.0001, the CNN model stands as a crucial component in our pursuit of automated plant disease identification.

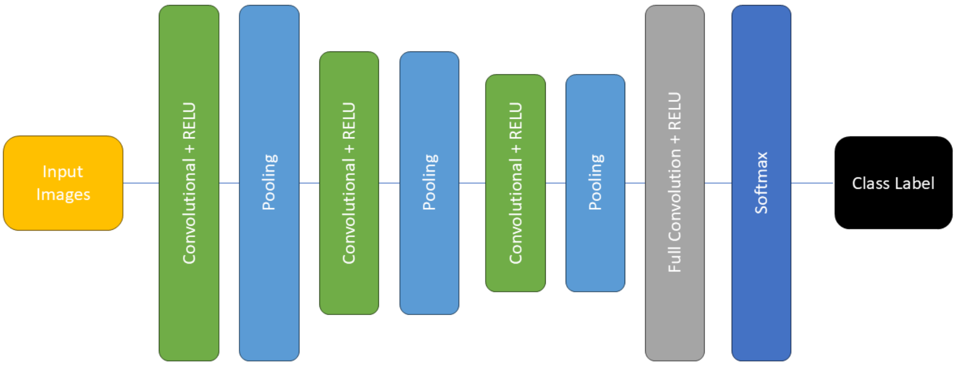

Figure 2. CNN basic architecture

2.3. Residual network

ResNet [9] represents a groundbreaking advancement in deep learning, specifically designed to address challenges associated with training very deep neural networks. ResNet's unique feature, the introduction of residual connections Figure 3, enables the model to skip certain layers during training, facilitating the learning of more nuanced representations. In the context of plant disease detection, ResNet's ability to handle deep architectures proves pivotal. The model excels in capturing subtle and complex patterns within plant images, allowing for accurate disease identification. The resilience of ResNet is particularly beneficial when dealing with the diverse and intricate visual manifestations of plant diseases. In our exploration of automating plant disease detection, ResNet model emerges as a pivotal player. Built upon a pre-trained ResNet50 base, this architecture embraces residual learning principles, facilitating the training of deep neural networks. Global average pooling, coupled with dense layers featuring 1,024 units and ReLU activation, ensures effective feature extraction. With a dropout rate of 0.5 strategically implemented, the ResNet model guards against overfitting. The final dense layer, endowed with SoftMax activation, enables the classification of plant leaves into diverse disease categories. Fine-tuning of upper layers, coupled with the Adam optimizer set at a learning rate of 0.0001, empowers the ResNet model to dynamically adapt to the intricacies of our plant dataset, rendering it indispensable in our pursuit of accurate disease identification.

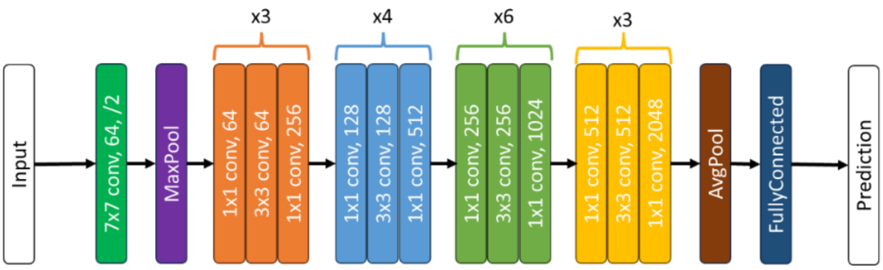

Figure 3. ResNet50 basic architecture

2.4. Visual geometry group16

Developed by the VGG at Oxford University, VGG16 [27] is a deep CNN. Its architecture incorporates a small 3×3 convolution filter to enhance accuracy. With 16 convolution layers Figure 4, VGG16 undergoes extensive training on the ImageNet dataset [28], demonstrating superior accuracy when utilized for training models with a limited number of images. The model features a total of 5 2×2

Max pooling layers and concludes with 3 fully connected layers. In the realm of agriculture, VGG's ability to systematically learn hierarchical features from images of plant leaves proves invaluable. By comprehensively understanding the visual characteristics associated with various diseases, the VGG model contributes significantly to the automated identification and classification of plant health issues. Its versatility and robustness make it a valuable asset in the pursuit of sustainable and technology-driven agriculture practices. VGG model, rooted in the VGG16 architecture, stands as a cornerstone in our comprehensive study of plant disease detection. Distinguished by convolutional layers with (3, 3) filters and global average pooling, this model excels in capturing intricate patterns within plant leaf images. Dense layers, incorporating 1,024 units and ReLU activation, amplify the model's capability for effective feature representation. A dropout rate of 0.5 is strategically applied for regularization, ensuring generalization. The final dense layer, characterized by SoftMax activation, facilitates multi-class classification with precision. Fine-tuning involves all layers of the pre-trained VGG16 base, and optimization is achieved through the Adam optimizer with a learning rate of 0.0001. The VGG model encapsulates a profound understanding of plant diseases, contributing significantly to our research in automating plant disease identification.

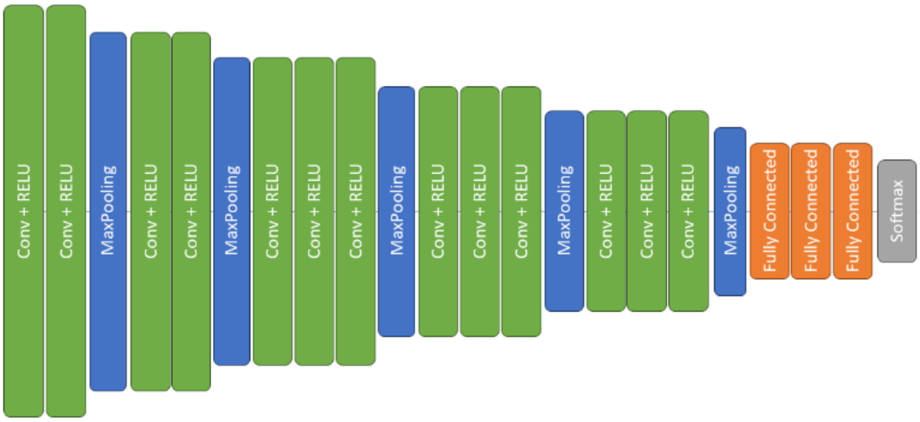

Figure 4. VGG16 basic architecture

Our methodology involves the meticulous design and implementation of three distinct deep learning models-CNNs, ResNet, and VGG tailored for the precise task of plant disease detection. The models' architectures were carefully configured with consideration given to specific parameters, ensuring optimal performance and robustness Table 2. These models, armed with carefully selected parameters, underwent systematic training and validation on the PlantVillage dataset, allowing for a comprehensive assessment of their efficacy in automating plant disease detection.

Table 2. CNN, ResNet, and VGG architectures

Model	CNN	ResNet	VGG
Base architecture	Sequential	ResNet50 base (pre-trained)	VGG16 base (pre-trained)
Conv layers	Conv (32, (3, 3), ReLU), BN, MaxPool Conv (64, (3, 3), ReLU), BN, MaxPool Conv (128, (3, 3), ReLU), BN, MaxPool		-
Pooling	MaxPool	GlobalAvg	GlobalAvg
Dense layers	(1024, ReLU)	(1024, ReLU)	(1024, ReLU)
Dropout	0.3	0.5	0.5
Output activation	Dense (65, SoftMax)	Dense (65, SoftMax)	Dense (65, SoftMax)
Fine-tuning	No	Yes (Upper layers)	Yes (All layers)
Optimizer	Adam	Adam	Adam
Learning rate	0.0001	0.0001	0.0001
Loss function	categorical_crossentropy	categorical_crossentropy	categorical_crossentropy

3. RESULTS AND DISCUSSION

This section presents the outcomes of training and evaluating three models-CNN, ResNet50, and VGG16-on plant disease classification tasks using image sizes of 128×128 and 256×256 pixels. The models were trained over 50 epochs, with performance metrics including training and validation losses, as well as accuracies, carefully monitored. Comparative analyses between the models and their ability to handle different image resolutions provide insights into their strengths and limitations for precision agriculture applications. The following subsections detail the performance trends and key findings for each model.

The training process for the CNN with an input size of 128×128 demonstrated promising outcomes across 50 epochs, as depicted in Figure 5. In the initial epoch, the model registered a loss of 1.8445 and an accuracy of 51.01%, gradually improving over subsequent epochs. As training advanced, the loss consistently decreased, culminating in 0.1154 by the final epoch, accompanied by a steady rise in accuracy to 95.45%. The validation set mirrored this pattern, with the loss decreasing from 1.1245 to 0.2897, and the accuracy improving from 68.38 to 89.33%. Noteworthy mean values for this training include mean training loss ≈ 0.1746 and mean training accuracy ≈ 90.04%, while the validation set exhibited mean validation loss ≈ 0.2695 and mean validation accuracy ≈ 89.03%. These values underscore the effectiveness of the CNN architecture in detecting and classifying plant diseases, showcasing its practical applicability in precision agriculture. Likewise, the CNN model with an input size of 256×256 displayed robust performance over 50 epochs, as illustrated in Figure 6. The initial epoch recorded a loss of 1.8425 and an accuracy of 50.49%, steadily improving throughout the training process. By the final epoch, the loss remarkably decreased to 0.1408, accompanied by an accuracy increase to 94.52%. The validation set exhibited a parallel trend, with the loss decreasing from 1.1509 to 0.1433 and the accuracy improving from 67.08 to 94.04%. Notable mean values for this configuration include mean training loss ≈ 0.0503 and mean training accuracy ≈ 97.56%, while the validation set demonstrated mean validation loss ≈ 0.1227 and mean validation accuracy ≈ 95.31%. The validation accuracy reaching 94.04% emphasizes the positive impact of a larger image size on the CNN model's performance in plant disease detection and classification.

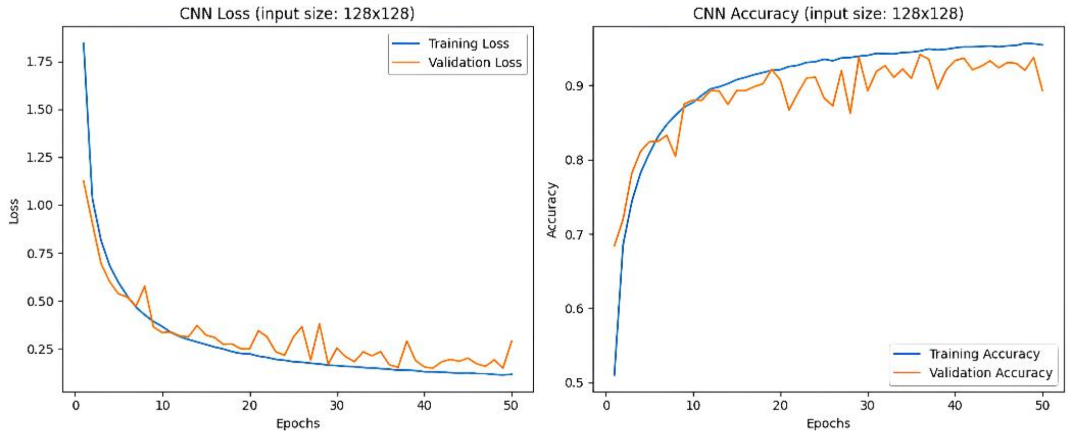

Figure 5. CNN model loss and accuracy for 128×128 images

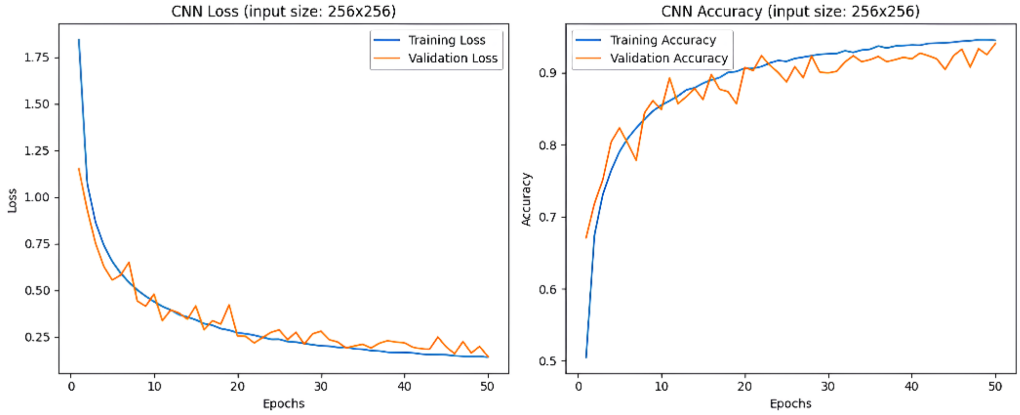

Figure 6. CNN model loss and accuracy for 256×256 images

The ResNet50 model, configured with an image size of 128×128 pixels, exhibited robust performance across multiple training epochs, as illustrated in Figure 7. Commencing with an initial loss of 0.628 and an accuracy of 82.08%, the validation metrics were recorded at a loss of 0.7212 and an accuracy of 81.05%. Demonstrating continuous improvement, the model reached a loss of 0.0366 and an accuracy of 98.38%, with validation metrics showing similar positive trends. Noteworthy mean values for this configuration include mean training loss ≈ 0.0654 and mean training accuracy ≈ 97.06%, while the validation set displayed mean validation loss ≈ 0.1172 and mean validation accuracy ≈ 95.69%. These results underscore the ResNet50 model's efficacy in capturing intricate features for plant disease detection and classification, positioning it as a promising tool for precision agriculture. Upon testing the ResNet50 model with an increased image size of 256×256 pixels, Figure 8 depicted notable performance improvements. Starting with a loss of 0.5537 and an accuracy of 84.09%, the model consistently progressed to achieve an accuracy of 98.63%. The validation metrics supported this positive trend, culminating in a final accuracy of 96.53%. Noteworthy mean values for the larger image size configuration include mean training loss ≈ 0.0482 and mean training accuracy ≈ 98.28%, while the validation set exhibited mean validation loss ≈ 0.1291 and mean validation accuracy ≈ 95.84%. The consistent improvement observed suggests that the ResNet model, with its larger image size, enhances its capability to discern complex patterns in plant images, making it a potential solution for real-world applications in precision agriculture.

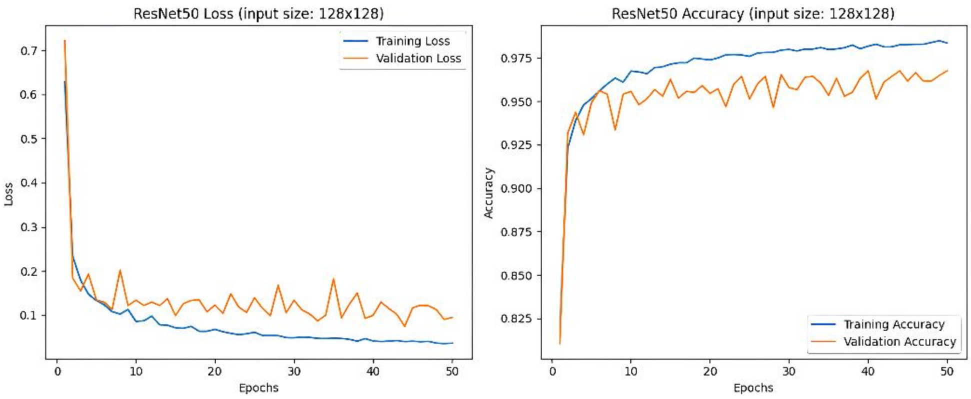

Figure 7. ResNet50 model loss and accuracy for 128×128 images

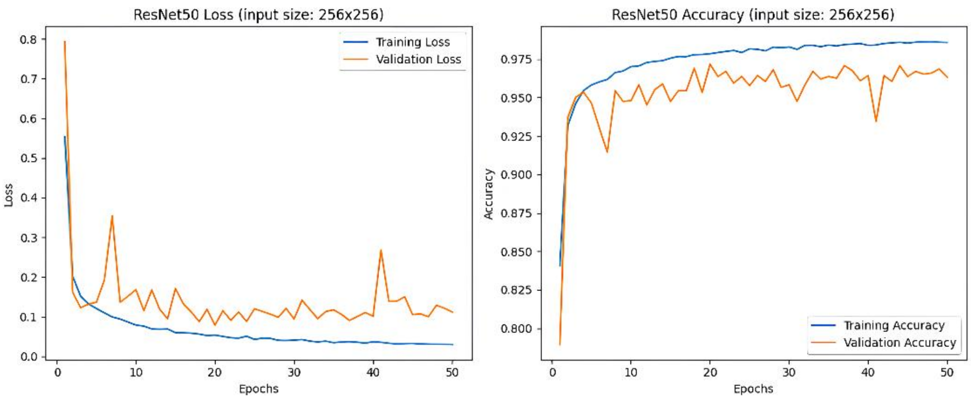

Figure 8. ResNet50 model loss and accuracy for 256×256 images

The VGG16 model, trained on a 128×128 pixels image size, exhibited consistent improvement throughout the training epochs, as depicted in Figure 9. Commencing with an initial loss of 1.4928 and an accuracy of 57.98%, the model steadily progressed to an accuracy of 97.99%, with the training loss decreasing to 0.0492. The validation metrics mirrored this positive trend, concluding with a final accuracy of 96.53%. Notable mean values for this configuration include mean training loss ≈ 0.0804 and mean training accuracy ≈ 97.11%, while the validation set displayed mean validation loss ≈ 0.1507 and mean validation accuracy ≈ 94.49%. These results highlight the effectiveness of the deep architecture of the VGG16 model in capturing complex patterns in plant images, making it a valuable asset for plant disease detection and classification tasks. Upon testing the VGG16 model with an increased image size of 256×256 pixels, consistent improvement was observed, indicating effective learning and convergence, as illustrated in Figure 10. The initial loss was 1.5284, with an accuracy of 58.12%, steadily improving to 98.34%. The training loss decreased to 0.0403, and the validation metrics followed a similar positive trend, culminating in a final accuracy of 95.99%. Noteworthy mean values for the larger image size configuration include mean training loss ≈ 0.0788 and mean training accuracy ≈ 95.44%, while the validation set exhibited mean validation loss ≈ 0.1292 and mean validation accuracy ≈ 95.55%. These findings reinforce the capability of the VGG model, with its deep architecture, to capture intricate features in plant images, positioning it as a valuable tool for plant disease detection and classification tasks. The gradual decrease in both training and validation losses suggests robust learning and generalization capabilities, indicating good performance on both seen and unseen data.

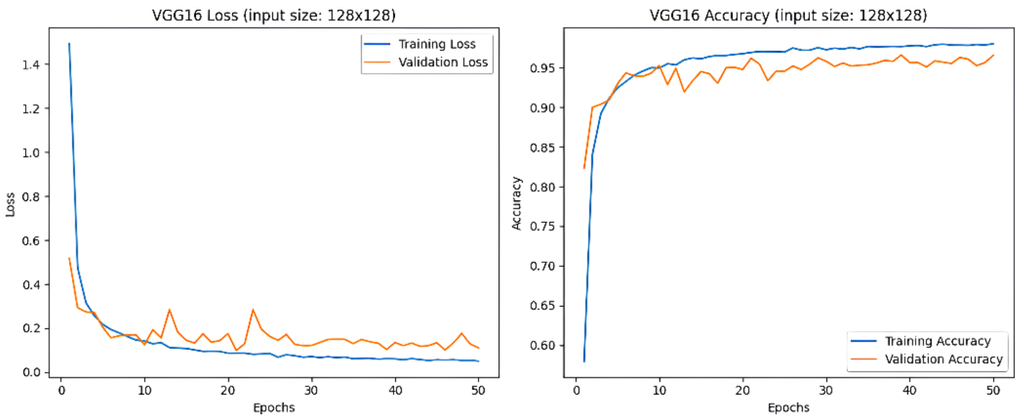

Figure 9. VGG16 model loss and accuracy for 128×128 images

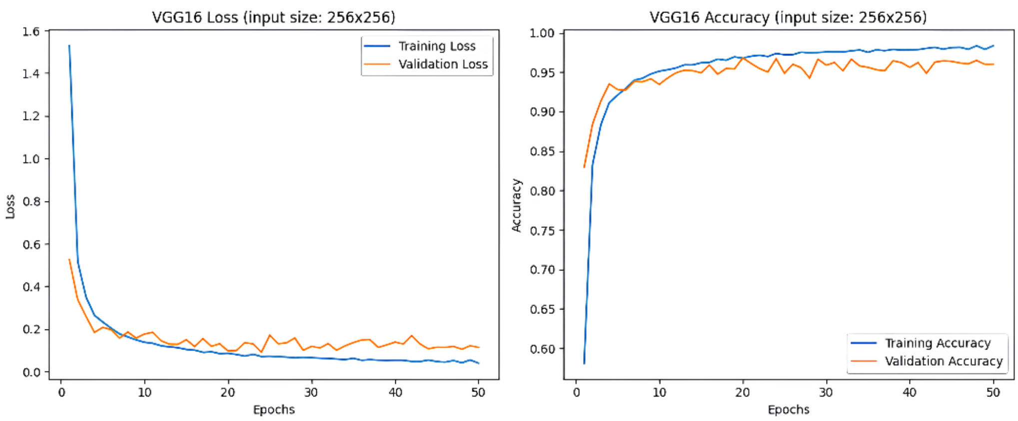

Figure 10. VGG16 model loss and accuracy for 256×256 images

In the landscape of plant disease detection and classification, CNN, VGG16, and ResNet50 models each bring distinctive strengths to the Table 3. The CNN model demonstrates proficiency, achieving commendable accuracies of 95.45 and 94.52% for image sizes of 128×128 and 256×256 pixels, respectively. VGG16, known for its deep architecture, consistently delivers high accuracy, reaching 97.99 and 98.34% at the same image sizes. However, ResNet50 emerges as a frontrunner, showcasing unparalleled performance with accuracy rates of 98.38 and 98.63% for 128×128 and 256×256 image sizes, respectively. Notably, ResNet50 achieves the lowest final losses, underscoring its capability to capture intricate features effectively. While all three models demonstrate efficacy, ResNet50's exceptional accuracy, low loss, and adaptability to varying image sizes make it a compelling choice for plant disease detection and classification tasks, positioning it as a potential cornerstone for precision agriculture applications. The choice between these models ultimately hinges on specific requirements, computational resources, and the nuanced demands of the target application.

Table 3. Performance comparison of CNN, ResNet50, and VGG16 models on plant disease detection across 128×128 and 256×256 image sizes

Model	Image size	Final training loss	Final training accuracy (%)	Final validation loss	Final validation accuracy (%)	Mean training loss	Mean training accuracy (%)	Mean validation loss	Mean validation accuracy (%)
CNN	128×128	0.1154	95.45	0.2897	89.33	0.1746	90.04	0.2695	89.03
CNN	256×256	0.1408	94.52	0.1433	94.04	0.0503	97.56	0.1227	95.31
ResNet50	128×128	0.0366	98.38	0.1172	95.69	0.0654	97.06	0.1172	95.69
ResNet50	256×256	0.0482	98.63	0.1291	96.53	0.0482	98.28	0.1291	95.84
VGG16	128×128	0.0492	97.99	0.1507	94.49	0.0804	97.11	0.1507	94.49
VGG16	256×256	0.0403	98.34	0.1292	95.55	0.0788	95.44	0.1292	95.55

In Northern Morocco, Belattar *et al*. [29] explored models for detecting mint plant diseases and found that DenseNet201 was the most effective, achieving 94.12% accuracy. While this performance is slightly lower than the hybrid approach, it still highlights DenseNet201’s strength in tackling diseases affecting specific plants, such as mint, within a localized agricultural context. In Indonesia, Aufar and Kaloka [30] implemented MobileNetV2 for classifying coffee leaf diseases and achieved an accuracy of 99.93%. MobileNetV2’s lightweight design is particularly suited for deployment on mobile devices, making it a viable option for field applications. The study also reported high accuracy with other architectures such as DenseNet169 (99.74%) and ResNet50 (99.41%). The choice of model depends on specific requirements. ResNet50 and hybrid models offer top-tier accuracy, making them strong candidates for environments that prioritize precision over computational cost. In contrast, EfficientNetB0 and MobileNetV2, while slightly less accurate, present advantages in terms of computational efficiency and portability, making them suitable for real-world deployment. DenseNet201, while not the highest performer, is a viable option for specialized crops such as mint in Northern Morocco, providing an essential solution for local agricultural challenges.

4. CONCLUSION

In conclusion, the comprehensive evaluation of the CNN, ResNet50, and VGG16 models in the realm of plant leaf disease detection and classification provides meaningful insights into their respective performances. The VGG16 model, particularly when trained on an increased image size of 256×256 pixels, not only demonstrated consistent improvement but also achieved an impressive final accuracy of 98.34%. This underscores the model's efficacy in capturing intricate features within plant images, positioning it as a highly valuable tool for precise plant disease detection. The ResNet50 model exhibited robust performance across multiple training epochs, reaching a remarkable accuracy of 98.63% when tested with an image size of 256×256 pixels. These results underscore the model's ability to discern complex patterns, making it a promising solution for real-world applications in precision agriculture. The CNN architecture, especially with an input size of 256×256 pixels, showcased notable efficacy, with a final accuracy of 94.52%. This reinforces the positive impact of a larger image size on the CNN model's performance in plant disease detection and classification. These values, such as the final accuracies of VGG16 98.34%, ResNet50 98.63%, and CNN 94.52%, provide tangible evidence of the models' capabilities. These findings contribute significantly to advancing the field of automated plant disease diagnosis, emphasizing the potential for deploying these models in real-world precision agriculture scenarios While the results of this study are promising, it is important to consider the potential impact of uncertain conditions that may arise in real-world agricultural environments. Factors such as varying weather conditions, soil types, and unexpected pest infestations can introduce uncertainties that may affect the performance of the models. Future research could explore the robustness of these models under such uncertain conditions, possibly by incorporating data augmentation techniques, domain adaptation methods, or ensemble learning approaches. By addressing these challenges, future studies can enhance the reliability and applicability of deep learning models in diverse and dynamic agricultural settings.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
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O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] Y. Tang, C. Chen, A. C. Leite, and Y. Xiong, “Editorial: precision control technology and application in agricultural pest and disease control,” *Frontiers in Plant Science*, vol. 14, 2023, doi: 10.3389/fpls.2023.1163839.

[2] T. M. M. M. Amaro, J. Cope, and B. Franco-Orozco, “Current status of plant pathogens of agricultural importance for Colombia. A review,” *Revista Colombiana de Ciencias Horticolas*, vol. 15, no. 2, 2021, doi: 10.17584/rcch.2021v15i2.12425.

[3] F. Martinelli *et al.*, “Advanced methods of plant disease detection. A review,” *Agronomy for Sustainable Development*, vol. 35, no. 1, pp. 1–25, 2015, doi: 10.1007/s13593-014-0246-1.

[4] K. Alemu, “Detection of diseases, identification and diversity of viruses: a review,” *Journal of Biology, Agriculture and Healthcare*, vol. 5, no. 1, pp. 204–214, 2015.

[5] B. Tugrul, E. Elfatimi, and R. Eryigit, “Convolutional neural networks in detection of plant leaf diseases: a review,” *Agriculture*, vol. 12, no. 8, pp. 1–21, 2022, doi: 10.3390/agriculture12081192.

[6] T. L. Mahyari, “Image separation using multi-layer image segmentation for translucent partially overlapped objects,” *Ph.D. thesis*, Department of Engineering, Electrical and Computer, Carleton University, Ottawa, Canada, 2021, doi: 10.22215/etd/2021-14596.

[7] S. A. Nezhad, T. Khatibi, and M. Sohrabi, “Proposing novel data analytics method for anatomical landmark identification from endoscopic video frames,” *Journal of Healthcare Engineering*, vol. 2022, 2022, doi: 10.1155/2022/8151177.

[8] T. Zan, H. Wang, M. Wang, Z. Liu, and X. Gao, “Application of multi-dimension input convolutional neural network in fault diagnosis of rolling bearings,” *Applied Sciences*, vol. 9, no. 13, 2019, doi: 10.3390/app9132690.

[9] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[10] N. Chen, “Visual recognition and prediction analysis of China’s real estate index and stock trend based on CNN-LSTM algorithm optimized by neural networks,” *PLoS ONE*, vol. 18, 2023, doi: 10.1371/journal.pone.0282159.

[11] S. Wanjiru, A. Waititu, and A. Wanjoya, “Deep convolution neural network with dropout in modeling exchange rate volatility,” *International Journal of Data Science and Analysis*, vol. 8, no. 2, pp. 38–46, 2022, doi: 10.11648/j.ijdsa.20220802.14.

[12] S. Y. Wang and T. Guo, “Transfer learning-based algorithms for the detection of fatigue crack initiation sites: a comparative study,” *Frontiers in Materials*, vol. 8, 2021, doi: 10.3389/fmats.2021.756798.

[13] S. Kumar, V. Chaudhary and S. K. Chandra, “Plant disease detection using CNN,” *Turkish Journal of Computer and Mathematics Education*, vol. 12, no. 12, pp. 2106–2112, 2021.

[14] M. T. Islam, “Plant disease detection using CNN model and image processing,” *International Journal of Engineering Research & Technology (IJERT)*, vol. 9, no. 10, pp. 291–297, 2020.

[15] P. Sharma, Y. P. S. Berwal, and W. Ghai, “Performance analysis of deep learning CNN models for disease detection in plants using image segmentation,” *Information Processing in Agriculture*, vol. 7, no. 4, pp. 566–574, 2020, doi: 10.1016/j.inpa.2019.11.001.

[16] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/j.compag.2018.01.009.

[17] M. Agarwal, S. K. Gupta, and K. K. Biswas, “Development of efficient CNN model for tomato crop disease identification,” *Sustainable Computing: Informatics and Systems*, vol. 28, 2020, doi: 10.1016/j.suscom.2020.100407.

[18] S. Baranwal, S. Khandelwal, and A. Arora, “Deep learning convolutional neural network for apple leaves disease detection,” *SSRN Electronic Journal*, 2019, doi: 10.2139/ssrn.3351641.

[19] A. Sagar and D. Jacob, “On using transfer learning for plant disease detection,” *Sustainability*, vol. 11, no. 1. pp. 1–14, May 2020, doi: 10.1101/2020.05.22.110957.

[20] J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, “Using deep transfer learning for image-based plant disease identification,” *Computers and Electronics in Agriculture*, vol. 173, 2020, doi: 10.1016/j.compag.2020.105393.

[21] J. G. A. Barbedo, “Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification,” *Computers and Electronics in Agriculture*, vol. 153, pp. 46–53, Oct. 2018, doi: 10.1016/j.compag.2018.08.013.

[22] X. Fan, P. Luo, Y. Mu, R. Zhou, T. Tjahjadi, and Y. Ren, “Leaf image based plant disease identification using transfer learning and feature fusion,” *Computers and Electronics in Agriculture*, vol. 196, 2022, doi: 10.1016/j.compag.2022.106892.

[23] A. Mhaned, S. Mouatassim, M. El Haji, and J. Benhra, “Low-cost smart irrigation system based on internet of things and fuzzy logic,” *Communications in Computer and Information Science*, pp. 78–89, 2022, doi: 10.1007/978-3-031-20490-6_7.

[24] A. Mhaned, M. Salma, E. H. Mounia, and B. Jamal, “Contribution to smart irrigation based on internet of things and artificial intelligence,” *Lecture Notes in Networks and Systems*, pp. 537–549, 2023, doi: 10.1007/978-3-031-28387-1_45.

[25] S. Fouguira, A. Mhaned, M. B. Abbou, E. Ammar, M. E. Haji, and J. Benhra, “Effectiveness of compost use in salt-affected soil in an automated greenhouse irrigation system,” *E3S Web of Conferences*, vol. 364, pp. 1-6, 2023, doi: 10.1051/e3sconf/202336403002.

[26] J. K. Patil and R. Kumar, “Advances in image processing for detection of plant disease,” *Journal of Advanced Bioinformatics Applications and Research*, vol. 2, no. 2, pp. 135–141, 2011.

[27] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in *arXiv-Computer Science*, 2015, pp. 1–14.

[28] J. Deng, W. Dong, R. Socher, L. J. Li, K. Li, and L. Fei-Fei, “ImageNet: a large-scale hierarchical image database,” in *2009 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2009*, 2009, pp. 248–255, doi: 10.1109/CVPR.2009.5206848.

[29] S. Belattar, O. Abdoun, and H. El Khatir, “Comparing machine learning and deep learning classifiers for enhancing agricultural productivity: case study in Larache Province, Northern Morocco,” *International Journal of Electrical and Computer Engineering*, vol. 13, no. 2, pp. 1689–1697, 2023, doi: 10.11591/ijece.v13i2.pp1689-1697.

[30] Y. Aufar and T. P. Kaloka, “Robusta coffee leaf diseases detection based on MobileNetV2 model,” *International Journal of Electrical and Computer Engineering*, vol. 12, no. 6, pp. 6675–6683, 2022, doi: 10.11591/ijece.v12i6.pp6675-6683.

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