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An improved efficientnet-B5 for cucurbit leaf identification

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ABSTRACT

Plant diseases significantly impact the quality and productivity of crops, leading to substantial economic losses. This paper introduces two enhanced EfficientNet-B5 architectures, EfficientNetB5-sigca and EfficientNetB5-sigbi, specifically designed to detect and classify diseases in cucurbit leaves. We employ EfficientNet-B5 for feature extraction, using a 456×456×3 input and omitting the top layer to generate feature maps with Swish activation. A global average pooling 2D layer replaces the conventional fully connected layer, producing a flattened vector. This is followed by a dense layer with four output units, L2 regularization, and sigmoid activation, using either categorical or binary cross-entropy as the loss function. We also developed a novel image dataset targeting cucumber and cantaloupe leaves, including 11,425 augmented images categorized into four disease classes: anthracnose, powdery mildew, downy mildew, and fresh leaf. Our experiments dataset demonstrates that the EfficientNetB5-sigbi achieves an accuracy of 97.07%, marking a significant improvement in classifying similar diseases in cucurbit leaves.

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1. INTRODUCTION

The Cucurbitaceae family, also known as the gourd or cucurbits family, encompasses a diverse range of agriculturally significant crops, including cucumbers and cantaloupes, which are pivotal to local and global food economies. These crops are rich sources of nutrients such as carotenoids, terpenoids, saponins, and phytochemicals [1]. As we delve deeper into the challenges confronting the Cucurbitaceae family, it becomes crucial to spotlight the diseases that pose significant threats to these agriculturally valuable crops. Among these, anthracnose, downy mildew, and powdery mildew are particularly detrimental, epitomizing the array of pathogens - viruses, fungi, and bacteria - that endanger the health and productivity of cucumbers, cantaloupes, and their kin [2]. These diseases compromise these crop’s quality and yield, which pose a substantial risk to the broader agricultural ecosystem. Dealing with these threats effectively is essential for maintaining the viability and sustainability of cucumbers, cantaloupes, and the entire Cucurbitaceae family, ensuring they continue to play their critical role in global food economies and nutritional security.

The widespread nature of anthracnose [3], downy mildew [4], and powdery mildew [5] within the Cucurbitaceae family underlines the necessity for early detection and accurate diagnosis. Based on manual inspection and expert analysis, traditional disease detection methods are fraught with challenges, including time consumption, labor intensity, and the potential for subjective errors which underscore the urgent need for innovative solutions in the agricultural sector, highlighting the potential of machine learning and other advanced technologies to revolutionize disease detection and management in these vital crops. The field of machine learning, advancements in computer vision [6], and artificial intelligence have significantly propelled the development of capabilities in diagnosing plant diseases and creating automated solutions. They have become a popular method for plant disease recognition, accommodating the challenge of identifying multiple diseases on a single leaf by considering a range of features, including color, texture, and shape [6]. Convolutional neural networks (CNNs) stand out as a foundational network structure in deep learning algorithms, enabling the automatic learning of key features directly from data and eliminating the need for manual feature extraction [7]. CNNs have been effectively used in complex tasks such as image classification, semantic segmentation, and pattern recognition. The evolution of deep learning classification methods has seen the development of CNN-based architectures like AlexNet [8], VGGNet [9], and MobileNet [10]. These architectures have achieved heightened accuracy through network depth and width innovations and optimizing model parameters. Howard *et al.* [10] introduced MobileNet, a new series of efficient models distinguished by their use of depth-wise separable convolutions. This technique effectively divides standard convolutions into depth-wise and pointwise convos, enhancing model efficiency. EfficientNet, introduced by Tan and Le [11], enhances model’s precision and operational efficiency by minimizing their size and the number of floating-point operations without compromising model quality. This architecture was developed through a method known as neural architecture search [12], enabling the scaling of the base model to produce various EfficientNet variants.

Deep learning has thus become a vital tool in plant disease image recognition, with studies using the widely used PlantVillage dataset [13], [14]. With data collected from various sources, the faster R-CNN model is recorded with an average precision score of 87.01% for recognizing disease on tomato leaves [15], or disease detection [16]. Ma *et al.* [17] developed a dataset consisting of 1,184 images for four cucumber diseases and applied a deep CNN, demonstrating a significant performance improvement compared to traditional classifiers like random forest and support vector machines (SVM), achieving a recognition accuracy of 93.4%, similarly, Zhang *et al.* [18] introduced a method utilizing a global pooling dilated CNN for identifying six common cucumber diseases, reaching an accuracy rate of over 94%. Further advancing the field, Zhang *et al.* [19] explored the use of transfer learning with EfficientNet for classifying four types of cucumber diseases, achieving an impressive accuracy of 97%, with EfficientNet-B4 being identified as the most effective model for their study. The above studies show that deep learning models increase diagnostic accuracy with various processing techniques. However, despite the numerous studies and diverse methodologies developed to detect plant diseases, most of these investigations focus on specific diseases or individual crop types, often needing more accuracy and are unavailable for various plants. In summary, the main contributions of this study are as follows:

- A new cucurbit leaves dataset, specifically cucumber and cantaloupe, has been developed for disease classification. This dataset visually represents the appearance of cucurbit diseases through visible light images. It is categorized into four classes: anthracnose, powdery mildew, downy mildew, and fresh leaf. The dataset initially consisted of 2,275 original photos collected from real fields under natural weather conditions with inconsistent lighting. After preprocessing and augmentation, the dataset now comprises 11,425 images. This dataset is publicly available to the research community.
- The EfficientNet-B5 model has been enhanced by replacing traditional fully connected layers with a global average pooling 2D layer, which averages across spatial dimensions to produce a flattened vector. A dense layer with four output units incorporates L2 regularization and a sigmoid activation function to prevent overfitting. It employs either categorical or binary cross-entropy as loss functions, enhancing robustness and generalization across diverse datasets. The base model, with a 456×456×3 input size, uses a Swish activation function. Our model outperforms previous proposals on public datasets and our actual-world dataset. According to experiments, the proposed model has 98.2% classification accuracy on the training set and 97.5% on the validation set.

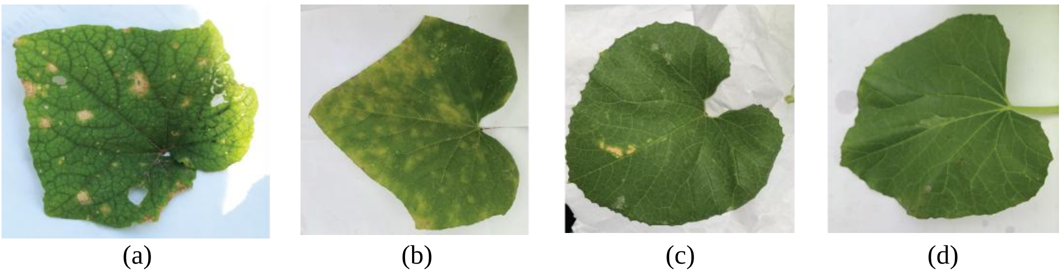
The structure of this paper is organized as follows: section 2 presents the method with an experimental design to collect the dataset and modified models. In section 3 discusses the experimental metrics and the results obtained. Lastly, the conclusions are shown in section 4.

2. METHOD

2.1. Image dataset

The image dataset of cucurbit leaf diseases, particularly for cantaloupe, is rarely available, highlighting a significant gap in the resources needed for effective disease detection. To address this, we proposed a novel cucurbit dataset aimed at precise object detection and localization of diseases on the leaves. The dataset comprises several infected leaves collected from four distinct locations: cucumbers from a greenhouse at the Vietnam National University of Agriculture, Gia Lam District, Hanoi City, Vietnam (cucumbers); fields in Hai Phong City, Vietnam; GenXanh Farm in Dan Phuong District, Hanoi City, Vietnam; and cantaloupes from a greenhouse in Long Bien District, Hanoi City, Vietnam. The cucumbers were cultivated in nutrient-rich loamy soil, renowned for their excellent water retention and aeration properties. In contrast, the cantaloupes were grown in a sandy loam mixed with coconut coir, which combines the drainage and aeration advantages of sandy loam with the moisture retention and organic enrichment benefits of coconut coir. Figure 1 presents visual representations of the experimental environments from which data were gathered. On the left, the fields in Hai Phong are illustrated, while the right side features the greenhouse in Long Bien. This dataset contains 2,275 original photos as shown in Figure 2, categorized into four types of diseases: anthracnose (Figure 2(a)), downy mildew (Figure 2(b)), powdery mildew (Figure 2(c)), and fresh leaf (Figure 2(d)). We also divided it into training and test sets at an 80:20 ratio. The images were captured using an iPhone XS Max with a resolution of 3,024×4,032 pixels, a focal length of 26 mm, an aperture of f/1.8, and a shutter speed of 1/50s. To enhance the dataset, we applied data augmentation techniques such as rotation at 60 degrees, zooming to 0.5 times, and adjusting brightness to 1.2 times. From 2,275 original images, we received 11,425 augmented images. The proportions of anthracnose, downy mildew, powdery mildew, and fresh leaf are 26.8%, 20.3%, 31.8%, and 21.1%, respectively as shown in Table 1.

Figure 1. Real cucumbers in Hai Phong (left) and cantaloupes in the field in Hanoi, Vietnam (right)



(a) (b) (c) (d)

Figure 2. Sample images for each class in the dataset: (a) anthracnose, (b) downy mildew, (c) powdery mildew, and (d) fresh leaf

Table 1. Statistics of the cucurbit dataset

Dataset	Classes	Original images	Augmented images
Training	Anthracnose	490	2,940
	Downy mildew	371	2,226
	Powdery mildew	583	3,498
	Fresh leaf	386	2,316
Testing	Anthracnose	123	123
	Downy mildew	93	93
	Powdery mildew	133	133
	Fresh leaf	96	96
Overall		2,275	11,425

2.2. Methods

After comparing classification performances using our dataset among various EfficientNet and MobileNet models using the study dataset, EfficientNet-B5 had the best performance and was selected for further optimization as shown in Table 2. Initially, we discarded the pre-trained weights to allow a more tailored adaptation to our dataset, focusing on cucurbit diseases [20]. We replaced the traditional fully connected layer with a global average pooling 2D layer, simplifying the model's architecture by averaging the spatial dimensions of width and height into a flattened vector while preserving the depth. This step enhances the model's capability to manage spatial hierarchies effectively. Following the pooling layer, we incorporated a dense layer configured with four output units corresponding to our classification categories, ensuring alignment with our specific classification objectives. This dense layer employs L2 regularization with a factor of 0.01 to mitigate overfitting, maintaining minimal model weights to foster better generalization. A sigmoid activation function is also used to produce probability outputs for each class, which is crucial for effective multi-label classification. The sigmoid function [21] is:

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{1}$$

The base model, EfficientNet-B5, operates without its top layer and serves as a feature extractor, producing a set of feature maps. These feature maps are activated by a Swish activation function, enhancing the non-linearity of the processing and potentially improving the model's learning capability. The Swish activation formula [21] is:

$$Swish(x) = x * sigmoid(\alpha * x) \tag{2}$$

where α is a trainable parameter.

Table 2. Performance comparison of 10 ten kinds of classification networks

Network	Accuracy (%) No pre-trained weights	ImageNet weights	PlantVillage weights
EfficientNet-B4	72.13%	20.22%	77.53%
EfficientNet-B5	**82.25%**	61.12%	**82.25%**
EfficientNetV2-B0	24.94%	21.57%	21.57%
EfficientNetV2-B1	23.60%	19.33%	27.64%
EfficientNetV2-B2	21.57%	21.57%	21.57%
EfficientNetV2-B3	16.85%	28.76%	26.29%
EfficientNetV2-S	15.28%	32.81%	17.53%
MobileNetV2	78.65%	79.78%	76.18%
MobileNetV3-Large	21.57%	29.89%	27.64%
MobileNetV3-Small	19.78%	18.88%	21.57%

Related to the loss functions, we have created two separate model variations to cater to distinct classification requirements:

- EfficientNetB5-sigca: utilizes categorical cross-entropy as the loss function, suitable for multi-class classification tasks. The standard categorical cross-entropy function [22] is:

$$J_{cce} = -\frac{1}{N} \sum_{k=1}^{K} \sum_{i=1}^{l} y_i^k \log\left(h_\theta(x_i, k)\right) \tag{3}$$

- EfficientNetB5-sigbi: employs binary cross-entropy as the loss function, optimized for binary classification tasks. The standard binary cross-entropy function [22] is given as:

$$J_{bce} = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log\left(h_\theta(x_i)\right) + (1 - y_i) \log(1 - h_\theta(x_i))] \tag{4}$$

These adaptations provide targeted solutions to different classification challenges, enhancing the 'model's accuracy and efficiency across diverse scenarios. In (3), N signifies the total count of training examples, with K indicating the distinct number of classes involved. The expression y_i^k is defined as the target label for the i_{th} training example specific to the class k, while x is the input corresponding to the i_{th} example. Here, h_θ represents the model structured by the neural network weights θ. For (4), N denotes the number of training samples, where y_i is the target label for each training example indexed by i, and x_i is the respective input for that example. The model, symbolized by h_θ, is defined by the neural network weights θ.

The function $y_i * \log(h_\theta(x_i))$ is incorporated to minimize the occurrence of probabilistic false negatives during the model training phase. The modified EfficientNet-B5 architecture is in Figure 3.

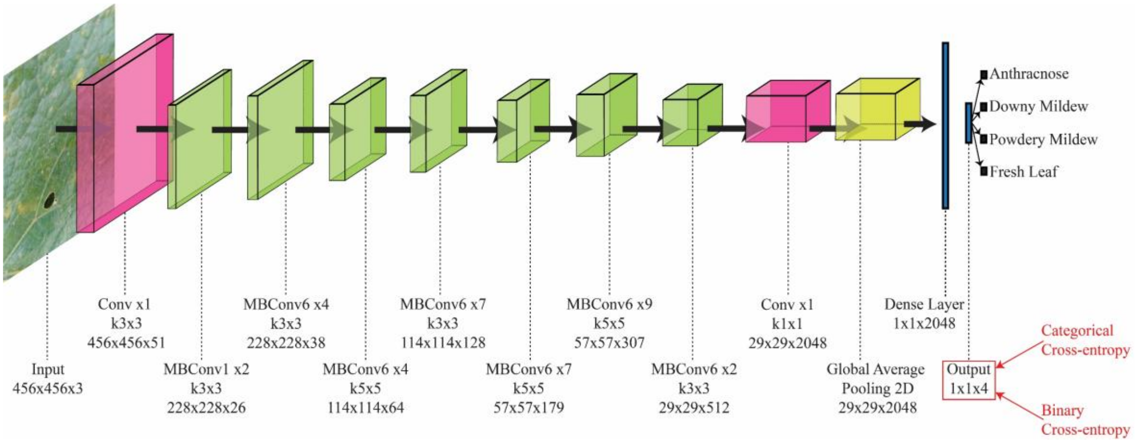


Figure 3. The architecture of modified Efficient-B5

3. RESULTS AND DISCUSSION

3.1. Performance evaluation metrics

In this study, the data were partitioned into training and test sets at an 80:20 ratio, as detailed in Table 1. Subsequent experimental analyses were conducted using the Matplotlib software environment [23] on a laboratory computer equipped with a 2080Ti Nvidia GeForce graphics card, 32Gb RAM, and Intel® Xeon® Processor E5-2680. The hyperparameters, illustrated in Figure 3, were consistent across both proposed models and included a batch size of 8, a learning rate of 0.001, and a duration of 50 epochs. The evaluation metrics employed in this research included accuracy, recall, precision, and F1-score [24] were analyzed in conjunction with a confusion matrix with receiver-operating characteristic (ROC) curves to assess model performance [3] comprehensively. These metrics allowed us to measure the effectiveness of the models in identifying true positives, true negatives, false positives, and false negatives, ultimately enabling a robust analysis of the classifier’s performance across various thresholds.

3.2. Results and discussion

This study investigated the effects of two modifications to the EfficientNetB5 model for cucurbit leaf disease detection. While earlier studies have explored various deep learning techniques for plant disease recognition, they have not explicitly addressed the influence of incorporating a sigmoid activation function combined with a binary cross-entropy loss on model stability and overall performance across diverse evaluation metrics. Our experiments revealed that both proposed modifications demonstrated a continuous upward trend in accuracy during training and validation. Notably, EfficientNetB5-sigbi showed a more stable performance, as evidenced by Figure 4, which illustrates the consistent increase in accuracy, recall, and precision. EfficientNetB5-sigbi achieved a stable recall of 98.02% and maintained a validation precision of 97.5%, while EfficientNetB5-sigca exhibited fluctuations (for example, a recall dip to 70.68% at epoch 7 before recovering to 92.7%). Further analysis using the confusion matrices Figure 5 and Figure 6 shows ROC curves for EfficientNetB5-sigca in Figure 6(a) and EfficientNetB5-sigbi in Figure 6(b) confirmed these observations, and an F1-score comparison summarized in Table 3 indicated that EfficientNetB5-sigbi (96.42%) outperformed EfficientNetB5-sigca (80.73%).

Our findings suggest that the integration of the sigmoid activation function and binary cross-entropy loss in EfficientNetB5-sigbi significantly enhances model precision and stability. When compared with previous studies in Table 4 - such as those by Zhang *et al.* [19] and others using EfficientNetB4-Ranger or MobileNetV2 [25] - the superior performance metrics of EfficientNetB5-sigbi highlight its robustness and improved generalization across unseen data, marking a clear advancement in the detection of cucurbit leaf diseases. Despite these promising results, the study has certain limitations. The curated dataset, consisting of 11,425 images across four disease categories, was limited to cucurbit leaves. As a result, questions remain regarding the model’s adaptability to other plant species and varying environmental conditions. These factors could potentially impact the generalizability of the model’s performance and warrant further investigation.

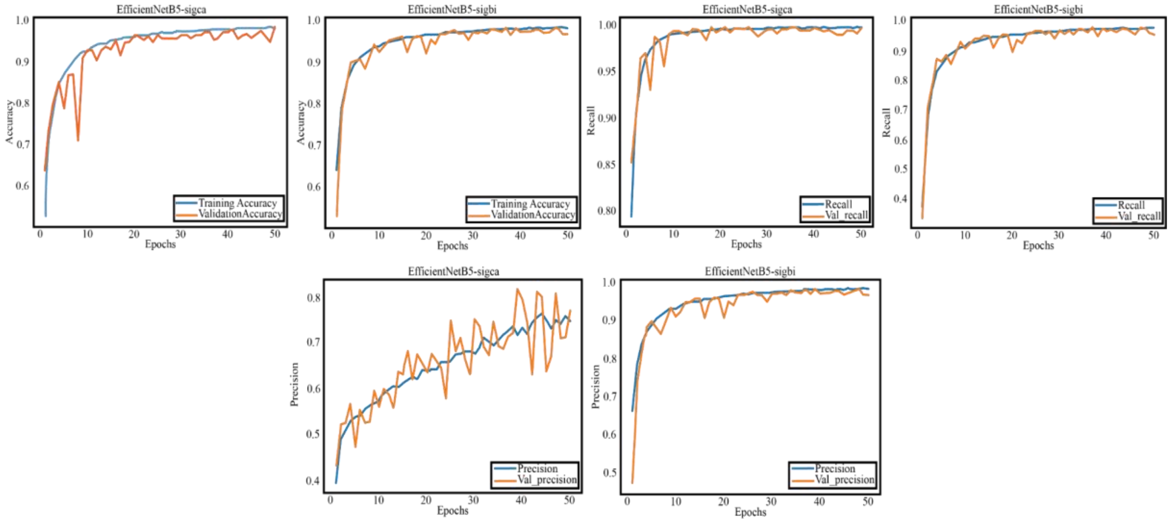


Figure 4. Accuracy, recall, and precision results on the training set

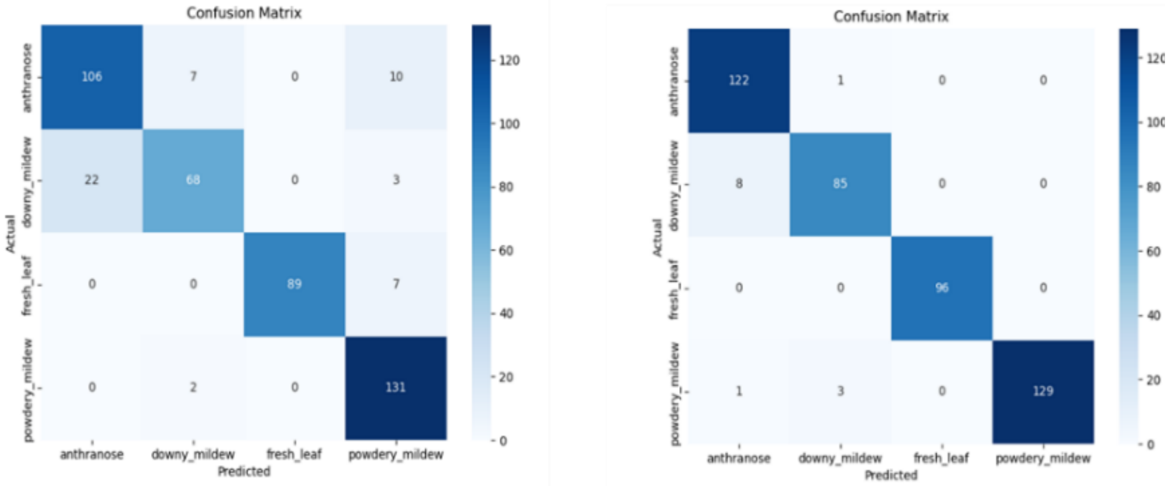
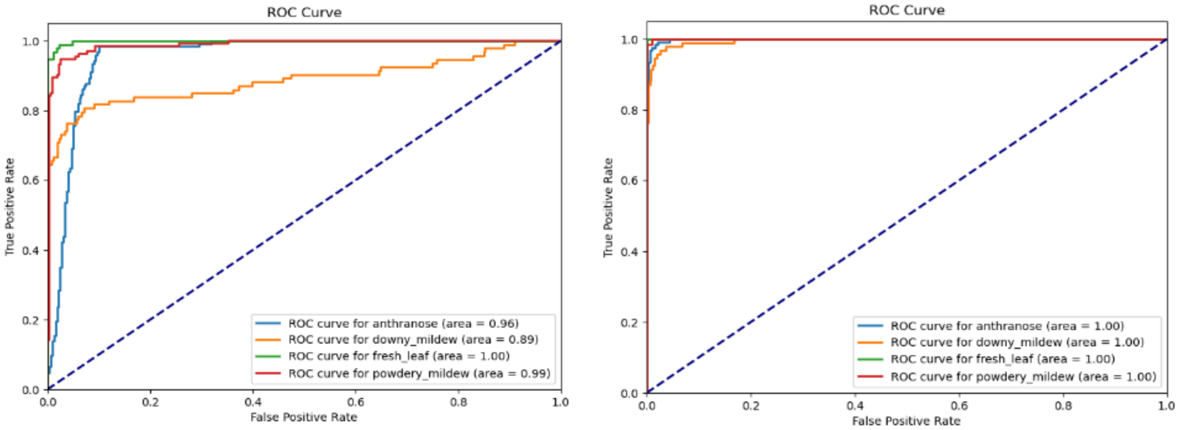


Figure 5. Confusion matrix of EfficientNetB5-sigca (left) and EfficientNetB5-sigbi (right)



(a) (b)

Figure 6. ROC curve of (a) EfficientNetB5-sigca and (b) and EfficientNetB5-sigbi

Our study lays the groundwork for future research avenues. Expanding the dataset to encompass a wider range of disease types and environmental scenarios could enhance model robustness. Additionally, future studies might explore the real-time deployment of EfficientNetB5-sigbi on edge devices for agricultural monitoring. Integrating hyperspectral or multispectral imaging also presents a promising opportunity to improve early-stage disease detection further, bridging the gap between laboratory performance and practical, field-level applications. In conclusion, the results from Figures 4 to 6, along with the performance metrics detailed in Table 3 provide conclusive evidence that EfficientNetB5-sigbi offers state-of-the-art performance in cucurbit leaf disease detection. The study demonstrates that advanced image segmentation techniques, when combined with appropriate activation and loss functions, significantly enhance model performance. These findings not only outperform previous methodologies but also pave the way for future innovations in agricultural disease management.

Table 3. Comparison of performance between EfficientNet-B5 versions

Network	Accuracy (%)	Recall (%)	Precision (%)	F1-score
EfficientNet-B5 [11]	82.25%	91.80%	82.54%	82.17%
EfficientNetB5-sigca	88.54%	94.61%	70.4%	80.73%
EfficientNetB5-sigbi	97.07%	98.02%	95.78%	96.42%

Table 4. Comparing EfficientNetB5-sigbi with other relevant studies

Study	Number of layers	Original data	Network	Test accuracy	
				Their data	Our data
Mia *et al.* [25]	7	525	MobileNetV2	93.23%	89.66%
Zhang *et al.* [19]	4	2816	EfficientNetB4-Ranger	96.39%	96.56%
This study	4	2275	EfficientNetB5-sigbi	-	**97.07%**

4. CONCLUSION

Our study establishes a robust foundation for detecting and differentiating plant diseases in controlled environments, significantly contributing to the field. We have developed a novel dataset featuring 11,425 augmented images of cucumber and cantaloupe plants, categorized into four disease classifications: anthracnose, powdery mildew, downy mildew, and fresh leaf. We provide a publicly available resource that has the potential to drive future research and innovation in plant disease management. Additionally, we introduced an enhanced classification model, the EfficientNetB5-sigbi, which utilizes the EfficientNet-B5 architecture fine-tuned with a sigmoid activation function and binary cross-entropy loss, achieving an impressive accuracy of 97.07%, demonstrating its capability for precise disease identification and classification. However, the scope of this research extends beyond its immediate results. The dataset needs to be expanded to include more data from a wider range of species within the Cucurbitaceae family. While the current dataset focuses on cucumber and cantaloupe plants, other significant crops in the family, such as watermelon, squash, pumpkin, and zucchini, should be incorporated to increase diversity and make the model applicable to a broader spectrum of cucurbit diseases. Furthermore, collecting data under varying environmental conditions, such as different humidity levels, temperatures, and light exposures, will enhance the model's robustness and adaptability to real-world scenarios. Including images of plants at different growth stages and varying severities of disease symptoms will also allow the model to identify early-stage infections and provide a more granular classification. Expanding the dataset to include hyperspectral and multispectral imaging could enhance recognition accuracy and enable early-stage disease detection, addressing a pressing need in real-world agricultural scenarios.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Quang Hung Ha	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓			
Trong-Minh Hoang		✓		✓					✓					
Minh Trien Pham	✓	✓		✓	✓		✓	✓	✓	✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
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

Derived data supporting the findings of this study are available from the corresponding author M.T.P on request.

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