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TRANSFER LEARNING-BASED CLASSIFICATION OF BELL PEPPER LEAF DISEASES USING VGG16 AND EFFICIENTNETB3 ARCHITECTURES

Siti Nurhasanah Nugraha[1*]; Evita Fitri[1]; Muji Ernawati[2]

Information System[1]
Informatics[2]
Universitas Nusa Mandiri, Jakarta, Indonesia[1,2]
https://nusamandiri.ac.id[1,2]
siti.nhg@nusamandiri.ac.id*, evita.etv@nusamandiri.ac.id, muji.mei@nusamandiri.ac.id

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

Abstract— *Diseases affecting pepper leaves can significantly reduce crop productivity and quality, while manual disease identification remains subjective, time-consuming, and prone to error. Therefore, an accurate automated classification system is required to support early disease detection. This study aims to evaluate and compare the performance of a conventional Convolutional Neural Network (CNN) with two transfer learning–based architectures, VGG16 and EfficientNetB3, for classifying pepper leaf images into healthy and bacterial spot classes, as well as to analyze the impact of applying a soft voting ensemble method on classification performance. The dataset was obtained from Kaggle and divided into training, validation, and test sets. Image preprocessing included resizing all images to 224×224 pixels and applying data augmentation to improve model generalization. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. The experimental results indicate that EfficientNetB3 outperforms the conventional CNN and VGG16 models. Furthermore, the application of the soft voting ensemble enhances prediction stability, achieving an accuracy of 99.68% on the test dataset with balanced precision and recall across both classes. These findings demonstrate that the integration of transfer learning and soft voting ensemble methods is an effective approach for image-based pepper leaf disease classification under the experimental conditions, and provides a basis for further validation using more diverse datasets.*

Keywords: *CNN, EfficientNetB3, Ensemble Soft Voting, Pepper leaf classification, Transfer learning.*

Intisari— *Penyakit pada daun paprika dapat menurunkan produktivitas dan kualitas hasil panen secara signifikan, sementara proses identifikasi penyakit secara manual masih bersifat subjektif, memerlukan waktu, dan rentan terhadap kesalahan. Oleh karena itu, diperlukan sistem klasifikasi otomatis yang akurat untuk mendukung deteksi dini penyakit tanaman. Penelitian ini bertujuan untuk mengevaluasi dan membandingkan kinerja model Convolutional Neural Network (CNN) konvensional dengan dua arsitektur berbasis transfer learning, yaitu VGG16 dan EfficientNetB3, dalam mengklasifikasikan citra daun paprika ke dalam kelas sehat dan Bacterial spot, serta menganalisis pengaruh penerapan metode ensemble soft voting terhadap performa klasifikasi. Dataset yang digunakan diperoleh dari Kaggle dan dibagi ke dalam data pelatihan, validasi, dan pengujian. Proses prapemrosesan meliputi pengubahan ukuran citra menjadi 224×224 piksel serta penerapan augmentasi data untuk meningkatkan kemampuan generalisasi model. Evaluasi kinerja dilakukan menggunakan metrik akurasi, presisi, recall, dan F1-score. Hasil eksperimen menunjukkan bahwa EfficientNetB3 memberikan performa terbaik dibandingkan CNN konvensional dan VGG16. Selain itu, penerapan ensemble soft voting mampu meningkatkan stabilitas prediksi dan mencapai akurasi sebesar 99,68% pada data uji dengan nilai presisi dan recall yang seimbang pada kedua kelas Temuan ini menunjukkan bahwa kombinasi transfer learning dan ensemble soft voting merupakan pendekatan yang efektif dan andal untuk klasifikasi penyakit daun paprika berbasis citra dalam kondisi eksperimental yang* *digunakan, serta berpotensi dikembangkan lebih lanjut melalui pengujian pada dataset yang lebih beragam dan kompleks.*

***Kata Kunci**: CNN, EfficientNetB3, Ensemble soft voting, Klasifikasi daun lada, Transfer learning.*

INTRODUCTION

The bell pepper plant (Capsicum annuum var. grossum) is a high-value horticultural commodity widely cultivated in Indonesia due to strong market demand, both domestically and internationally [1], [2]. Bell pepper cultivation has expanded to several regions in Indonesia, including West Bandung, Cianjur, Bogor, Garut, Wonosobo, Batu City, Bali, West Nusa Tenggara, and Bantaeng in South Sulawesi [3]. Despite increasing demand, bell pepper productivity often declines due to pest attacks and leaf diseases [4]. This condition makes it difficult for farmers to distinguish between healthy and diseased leaves in a timely manner, leading to delayed treatment and a reduction in both the quality and quantity of the harvest [5].

The development of deep learning technology has created new opportunities for automatic plant classification. Deep learning is a branch of machine learning that utilizes multilayer neural network architectures to identify and learn patterns from complex datasets [6]. Among various deep learning approaches, the Convolutional Neural Network (CNN) is one of the most widely used methods for image processing due to its ability to extract visual features—such as color patterns, textures, and shapes—through convolutional and pooling layers [7].

The transfer learning approach enables models to leverage knowledge from neural networks pre-trained on large-scale datasets, thereby making training more efficient even with limited data [8]. This technique not only accelerates the training process but also improves accuracy, as the model already possesses robust low-level and high-level feature representations [9]. In addition, data augmentation increases the diversity of the training data and reduces the risk of overfitting, allowing the model to produce more stable and accurate predictions when classifying healthy pepper leaves and those affected by diseases or pests [10].

In this study, three modeling approaches were employed: a conventional CNN and two transfer learning architectures, VGG16 and EfficientNetB3, to evaluate improvements in classification performance. After training the three models, a soft voting ensemble method was applied to combine their predictions and enhance the stability of the final results. VGG16 features a simple and consistent architecture with 3×3 convolutional kernels across its 16 layers, making it effective for learning fundamental image features [11]. In contrast, EfficientNetB3 achieves superior efficiency through compound scaling, which proportionally balances network depth, width, and input resolution to deliver high accuracy with reduced computational complexity [12], [13].

Research on plant disease classification based on leaf images has advanced rapidly in parallel with developments in deep learning technology. Numerous studies have demonstrated the effectiveness of CNN in classifying diseases in rice, tomatoes, grapes, and other horticultural crops. For instance, in rice leaf disease classification, the application of CNNs combined with transfer learning using the VGG16 architecture achieved an accuracy of 93%, outperforming standard CNN models [14]. Studies on corn plants also reported the effectiveness of EfficientNetB1–B3 architectures, achieving an accuracy of 97.77%, which indicates that modern architectures can efficiently handle large-scale datasets [15]. Furthermore, research on chili plants comparing VGG16 and MobileNetV2 found that MobileNetV2 performed better, achieving an accuracy of 92%, making it more suitable for leaf disease classification under diverse data conditions [16]. Another study on bell pepper leaves using the DenseNet-201 architecture achieved an accuracy of 99.5%, highlighting the strong potential of transfer learning for precise leaf disease detection [6].

Another study showed that an optimized CNN model was able to achieve a very high accuracy of 99.89% in distinguishing between healthy pepper leaves and leaves infected with bacteria [17]. Another study evaluated the effectiveness of transfer learning with MobileNetV2 and InceptionV2 architectures for detecting bacterial spot disease on pepper leaves, showing that MobileNetV2 provided the best performance with an accuracy of 99.96%, making it more effective for classifying pepper leaf diseases than InceptionV2 [18]. In addition, there is also a literature review that confirms that CNN architectures such as VGG, EfficientNet, GoogleNet, and Resnet are the best performing models for plant disease image classification [19].

However, research related to pepper leaf disease classification is still limited and generally only uses one CNN architecture, without conducting

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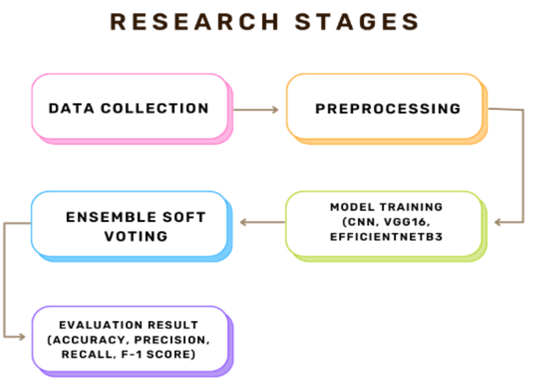
multi-model comparisons between conventional CNNs and transfer learning approaches such as VGG16 and EfficientNetB3. In addition, most previous studies have not evaluated ensemble learning strategies, particularly the soft voting ensemble method, as an approach to improve model prediction robustness and stability. As a result, the potential benefits of combining multiple models in an early diagnosis system based on pepper leaf images have not been comprehensively explored, especially in limited dataset conditions.

Based on these issues, this study aims to analyze and compare the performance of conventional CNN, VGG16, and EfficientNetB3 in classifying healthy pepper leaves and disease-infected pepper leaves, as well as to evaluate performance improvements through the application of the soft voting ensemble method. The results of this study are expected to provide recommendations for more effective and efficient models to support the development of an automatic plant disease diagnosis system based on images.

MATERIALS AND METHODS

This study conducted a deep learning-based classification experiment by comparing the performance of three models, namely conventional CNN and two transfer learning architectures, VGG16 and EfficientNetB3. All models were developed to classify bell pepper leaves. After model training and testing were completed, the output probabilities of the three models were combined through ensemble soft voting to produce a more stable and accurate final prediction. The stages of this research can be seen in Figure 1.



Source: (Research Results, 2025)
Figure 1. Research Stages

Data Collection

At this stage, data collection was carried out to be used as a dataset for the classification process in this study. The dataset used was obtained from the Bell Pepper Dataset on Kaggle (https://www.kaggle.com/datasets/manjuphoenix/bellpepper/). The original dataset consisted of two classes of bell pepper leaf images, namely 3,989 images of leaves with bacterial spots and 5,905 images of healthy leaves.

However, to maintain data balance while ensuring image quality, this study used 3,111 images, consisting of 1,598 Healthy class images and 1,513 Bacterial spot class images. All images were resized to a resolution of 224 × 224 pixels and divided into three data subsets, namely 80% for training data, 10% for validation data, and 10% for testing data. A sample of bell pepper leaf images can be seen in Figure 2.

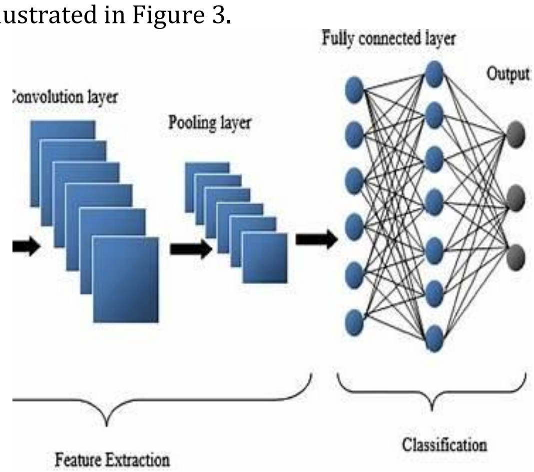
Source: (Research Results, 2025)
Figure 2. Research Dataset

Preprocessing

The preprocessing stage was carried out through image augmentation using ImageDataGenerator. Data augmentation parameters are selected to simulate real-world variations that are often encountered during image capture in field conditions. Rotation in the range of ±20° represents camera angle variations, while a zoom factor of 0.2 simulates differences in camera distance. Horizontal and vertical shifts of 0.2 take into account object shifts and perspective changes. This augmentation aims to improve model robustness and reduce overfitting.

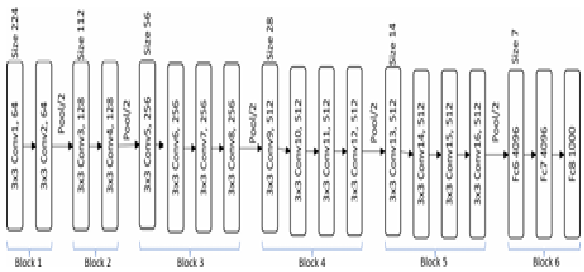
Model Training

This study employs three modeling approaches: a conventional CNN and two transfer learning architectures, VGG16 and EfficientNetB3, for pepper leaf classification. The conventional CNN model in this study was developed and trained from the ground up, comprising several convolutional and pooling layers to extract features from leaf images, followed by a fully connected layer to perform binary classificationThe CNN architecture used is adapted from the model proposed in [20], as illustrated in Figure 3.



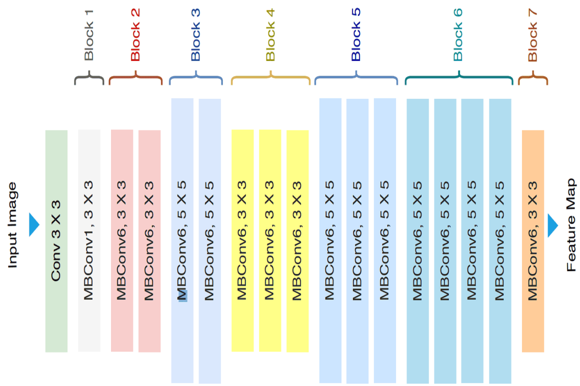
Source: (Kumar [20], 2023)
Figure 3. Conventional CNN Architecture Used in Bell Pepper Leaf Classification

The VGG16 architecture is used as the backbone model with a transfer learning approach, which utilizes pretrained weights from the ImageNet dataset. The original classification layer is removed and replaced with a new classification layer that is adjusted to the number of classes in the paprika leaf dataset. This architecture refers to the model introduced by [21], as shown in Figure 4.



Source: (Nguyen [21], 2022)
Figure 4. VGG16 Architecture Used in Bell Pepper Leaf Classification

Meanwhile, the EfficientNetB3 architecture was applied with the compound scaling principle, which balances the depth, width, and resolution of the network. Similar to VGG16, this model uses pretrained ImageNet weights before adding a classification layer tailored to the paprika leaf dataset. This architecture refers to the model introduced by [22], as shown in Figure 5.



Source: (Atila [22], 2021)
Figure 5. EfficientNetB3 Architecture Used in Bell Pepper Leaf Classification

All three models were trained using identical training parameters to ensure an objective performance comparison: 20 epochs, a batch size of 32, a learning rate of 0.0001, the Adamax optimizer, and the categorical cross-entropy loss function. In addition, the ModelCheckpoint callback was utilized to store the optimal model weights according to validation accuracy.

Ensemble Soft Voting

After the three models generate class probability outputs, a soft voting ensemble strategy is applied to combine the predicted probabilities from each model. In the soft voting approach, the probability outputs from each individual model are averaged, and the class with the highest aggregated probability is chosen as the final prediction. This ensemble strategy aims to enhance model stability and classification accuracy compared to individual models [23].

Evaluation Result

Model performance was assessed using four key metrics: accuracy, precision, recall, and F1-score to ensure a comprehensive evaluation. Accuracy reflects the overall correctness of the classification, whereas precision and recall measure the model's effectiveness in accurately distinguishing between healthy and diseased leaves. The F1-score was selected as an important metric because it balances precision and recall, making it particularly suitable for datasets that may exhibit class imbalance. The evaluation was conducted on a test dataset that had not been used during the training or validation phases, ensuring that the results accurately reflect the model's ability to classify bell pepper leaf images.

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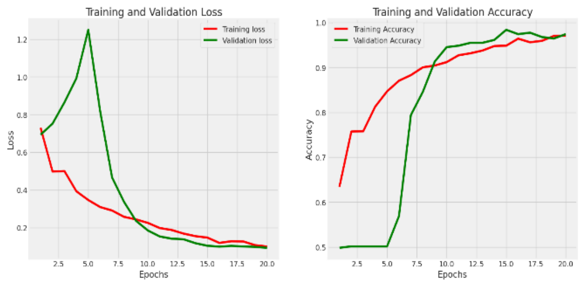
RESULTS AND DISCUSSION

Performance of Individual Models

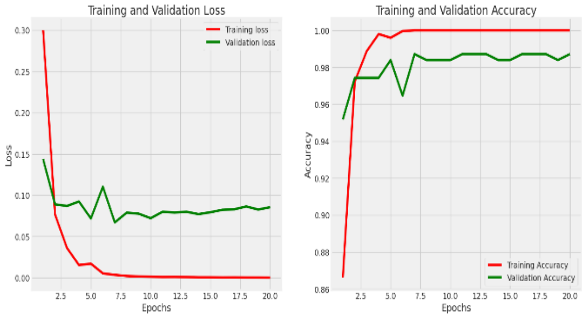
The training and validation loss curves of the CNN model show a steady decrease as the number of epochs increase, indicating that the model is effectively learning feature representations from bell pepper leaf images. Although a slight increase in validation loss is observed during the early training stages, the loss subsequently decreases and stabilizes toward the final epochs. This behavior suggests that the CNN model does not suffer from significant overfitting. Furthermore, the training and validation accuracy curves show an increasing trend with closely aligned values, reflecting stable classification performance and good generalization on the validation dataset. The curves depicting training and validation accuracy and loss for the CNN model are shown in Figure 6.



Source: (Research Results, 2025)
Figure 6. Training and Validation Accuracy and Loss Curves for The CNN Model

In Figure 6, at the final training epoch, the model achieved a training accuracy of approximately 97% with a training loss of 0.10, while the validation accuracy reached approximately 97% with a validation loss of 0.09. The close alignment between training and validation performance indicates a stable learning process and suggests that the model does not suffer from significant overfitting.

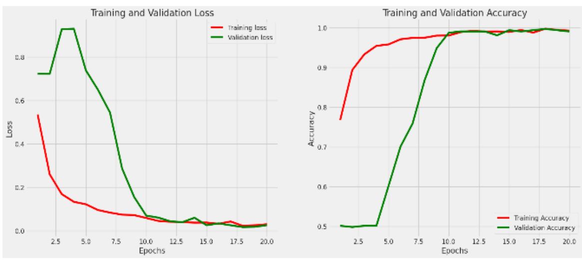
Furthermore, the training and validation loss curves of the VGG16 model show a substantial reduction in training loss to near-zero values, indicating that the model effectively learns feature representations from bell pepper leaf images. The validation loss remains relatively stable with minor fluctuations, suggesting the absence of significant overfitting and good generalization capability. Consistent with this trend, the training and validation accuracy curves exhibit a rapid and steady increase, with high and closely aligned accuracy values. These results indicate that the VGG16 model achieves stable and strong classification performance. The training and validation loss and accuracy curves for the VGG16 model are presented in Figure 7.



Source: (Research Results, 2025)
Figure 7. Training and Validation Accuracy and Loss Curves for The VGG16 Model

In Figure 7, at the final training epoch, the VGG16 model achieved a training accuracy of approximately 100% with a training loss close to 0.00, while the validation accuracy reached approximately 99% with a validation loss of around 0.08. The relatively close alignment between training and validation performance indicates stable convergence and suggests that the model does not experience significant overfitting under the given experimental setup.

The training and validation loss curves of the EfficientNetB3 model exhibit a significant and consistent decline as the number of epochs increases for both training and validation data. The parallel reduction in these loss curves indicates that the model effectively learns feature representations from bell pepper leaf images without exhibiting significant overfitting. In addition, the training and validation accuracy curves show a rapid increase toward near-maximum values, with the validation accuracy closely following the training trend. The close alignment between training and validation accuracy suggests that EfficientNetB3 achieves strong classification performance and good generalization on the validation dataset. The training and validation loss and accuracy curves for the EfficientNetB3 model are presented in Figure 8.



Source: (Research Results, 2025)
Figure 8. Training and Validation Accuracy and Loss Curves for The EfficientNetB3 Model

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In Figure 8, at the final training epoch, the EfficientNetB3 model achieved a training accuracy of approximately 100% with a training loss close to 0.01, while the validation accuracy also reached approximately 100% with a validation loss of around 0.02. The close alignment between training and validation accuracy, along with consistently low loss values, indicates stable convergence and suggests that the model learns discriminative features effectively without exhibiting significant overfitting under the experimental conditions.

Overall, the combination of decreasing loss values and increasing accuracy across the training and validation datasets indicates that the adopted model architectures effectively learn feature representations from bell pepper leaf images. The absence of substantial discrepancies between training and validation performance suggests that the models do not suffer from overfitting, indicating their readiness for further evaluation on the test dataset.

Comparison of Model Performance

A performance comparison among the conventional CNN, VGG16, and EfficientNetB3 models based on the test dataset is presented in Table 1. This comparison aims to evaluate the effectiveness of each architecture in classifying bell pepper leaf images and to assess the impact of transfer learning on classification performance.

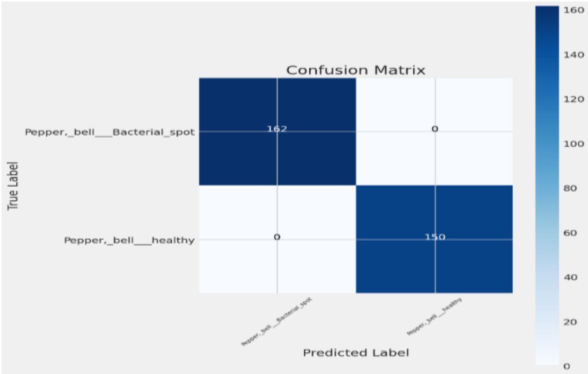
Table 1. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Conventional CNN	0.9776	0.98	0.98	0.98
VGG16	0.9872	0.99	0.99	0.99
EfficientNetB3	1.0000	1.00	1.00	1.00

Source: (Research Results, 2025)

Based on the performance comparison presented in Table 1, EfficientNetB3 achieved the highest performance, attaining perfect scores of 1.00 for accuracy, precision, recall, and F1-score. The VGG16 model ranked second with an accuracy of 98.72%, followed by the conventional CNN with an accuracy of 97.76%. The superior performance of EfficientNetB3 can be attributed to its efficient feature extraction capability through the compound scaling approach, which enables the model to learn richer and more representative leaf image features [24]. In contrast, the conventional CNN employs a simpler architecture, resulting in more limited feature learning capacity compared to transfer learning–based models.

In addition, the evaluation was performed using standard performance metrics and a confusion matrix. The confusion matrix presented in Figure 9 corresponds to the best-performing model, EfficientNetB3, and illustrates its optimal classification performance.



Source: (Research Results, 2025)
Figure 9. Best Confusion Matrix Model (EfficientNetB3) on Test Dataset

The confusion matrix presented in Figure 10 indicates that the EfficientNetB3 model achieves high classification performance with minimal misclassification for both bacterial spot and healthy leaf classes. These results are consistent with the high accuracy, precision, and recall values obtained, and they highlight the model's strong potential for application in automatic leaf disease classification systems.

Ensemble Soft Voting Evaluation

To enhance prediction stability and reliability, this study applies a soft voting ensemble method by combining the output probabilities of all individual models. The ensemble is performed after each model has been trained and evaluated independently. The results of the soft voting ensemble evaluation are presented in Table 2.

Table 2. Ensemble Soft Voting Evaluation Results

Model	Accuracy	Precision	Recall	F1-Score
Ensemble Soft Voting	0.9968	1.00	1.00	1.00

Source: (Research Results, 2025)

Based on the evaluation results presented in Table 2, the soft voting ensemble model achieved an overall accuracy of 99.68%, with macro-averaged and weighted-averaged precision, recall, and F1-score values close to or equal to 1.00. Although the ensemble accuracy is slightly lower than that of the standalone EfficientNetB3 model, the ensemble approach helps mitigate potential bias and prediction errors associated with individual models. These results indicate that the ensemble

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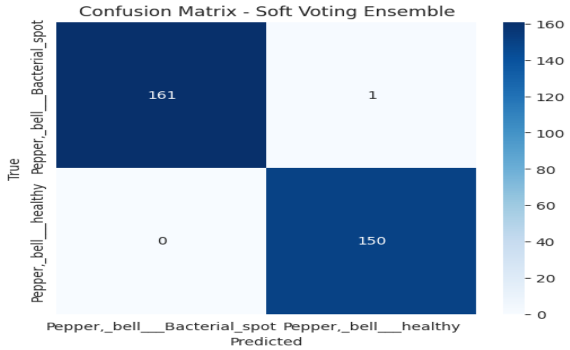
method not only maintains high overall accuracy but also provides more balanced performance across both classes. Consequently, the soft voting ensemble effectively integrates the strengths of each base model to deliver more stable and reliable predictions than a single model. Moreover, the confusion matrix corresponding to the soft voting ensemble evaluation is presented in Figure 10.



Source: (Research Results, 2025)

Figure 10. Confusion Matrix of Soft Voting Ensemble Results

Based on the confusion matrix presented in Figure 10, the soft voting ensemble method demonstrates high classification performance in distinguishing healthy pepper leaves from those affected by bacterial spot. Out of 162 test images in the bacterial spot class, 161 were correctly classified, while only one image was misclassified as a healthy leaf. In contrast, all 150 images in the healthy class were correctly classified without any misclassification.

The dominance of values along the main diagonal indicates that the soft voting ensemble effectively reduces classification errors and achieves clearer class separation. By combining the prediction probabilities from multiple base models, this approach yields more stable and robust classification decisions across variations in the test data, thereby enhancing the reliability of the bell pepper leaf disease classification system.

Discussion

The results of this study indicate that applying transfer learning with the VGG16 and EfficientNetB3 architectures provides better classification performance than conventional CNNs. This finding is consistent with previous work [25], which reports that CNN models initialized with ImageNet-pretrained weights exhibit stronger and more stable feature extraction capabilities for plant disease classification tasks compared to models trained from scratch.

In addition, the implementation of the soft voting ensemble in this study improves prediction stability and reliability compared to using a single model. This observation aligns with ensemble learning theory, which suggests that combining multiple models with diverse learning characteristics can reduce bias and variance, leading to more stable and robust predictions. Ensemble methods have consistently demonstrated superior performance over individual models across various classification problems. [26].

However, the very high performance achieved in this study—including accuracy, precision, recall, and F1-score values that approach or reach perfect scores for the EfficientNetB3 and soft voting ensemble models—should be interpreted with caution. Such ideal performance may indicate potential overfitting or reflect the relatively controlled and limited nature of the dataset, as this study only utilized two classes (Healthy and Bacterial Spot) from a publicly available Kaggle dataset. Moreover, model evaluation was conducted using a single dataset without cross-validation or external dataset testing; therefore, the generalization capability of the proposed models under more diverse real-world conditions has not yet been fully validated.

Furthermore, this study did not incorporate model interpretability techniques, such as Grad-CAM, to visualize the image regions contributing to the model's decision-making process. The scope of the research was also limited to three deep learning architectures, without comparison to other widely used architectures such as ResNet or DenseNet, nor to conventional machine learning methods as baseline models. In addition, computational cost, inference time, and the feasibility of deploying the proposed system on resource-constrained devices commonly used by farmers were not discussed in detail. Therefore, future research is recommended to employ larger and more diverse datasets, perform cross-dataset or external validation, integrate interpretability techniques, and consider computational efficiency and real-world deployment aspects to ensure the robustness and generalizability of the proposed approach.

CONCLUSION

This study demonstrates that the application of deep learning methods for pepper leaf classification achieves strong performance, particularly when transfer learning–based models are employed. The experimental results show that EfficientNetB3 outperforms the conventional CNN and VGG16 models, achieving very high accuracy, precision, recall, and F1-score values on the test dataset. In addition, the comparative analysis indicates that the use of pretrained weights enables more effective and stable feature learning, especially when dealing with datasets containing a limited number of classes.

Furthermore, the application of the soft voting ensemble method enhances the reliability of the classification system by integrating the complementary strengths of each base model. This approach yields more stable predictions across variations in the test data and reduces classification errors commonly observed in single-model approaches. Based on the overall experimental results, it can be concluded that the combination of transfer learning–based CNN architectures and a soft voting ensemble provides an effective solution for image-based bell pepper leaf classification.

For future research, the proposed approach can be extended by incorporating larger and more diverse datasets with multiple disease classes to improve generalization performance. Further evaluation using external or cross-dataset validation is recommended to assess robustness under real-world conditions. In addition, future studies may integrate model interpretability techniques and explore efficient deployment strategies to support practical implementation in agricultural environments.

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