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Application of Transfer Learning Using Inception-Resnet-V2 for Image-Based Classification of Apple Leaf Diseases

Earlando Moza, Novan Wijaya*

Faculty of Computer Science and Engineering, Universitas Multi Data Palembang, South Sumatra, Indonesia

*Correspondence: novan.wijaya@mdp.ac.id

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ABSTRACT: Apple leaf diseases posed a major challenge to agricultural productivity due to their similar visual appearance and the limitations of manual classification methods. This study aimed to develop an accurate and efficient image-based classification system for apple leaf diseases using the Inception-ResNet-V2 architecture and a transfer learning approach. The dataset consisted of 3,171 images from the PlantVillage dataset, categorized into four classes: Apple Scab, Cedar Apple Rust, Black Rot, and Healthy. The data were divided into training, validation, and test sets in a 70:15:15 ratio using stratified sampling. Image preprocessing included resizing, normalization, and data augmentation, while class balancing was applied to address class imbalance. The model was trained using the Adam optimizer through a two-stage process consisting of feature extraction and refinement. Experimental results showed that the proposed model achieved a test accuracy of 98.74%, with high precision, recall, and F1-scores across all classes, demonstrating strong classification performance and generalization ability. This study demonstrated that Inception-ResNet-V2 was effective in capturing complex visual features of apple leaf diseases. In conclusion, the proposed approach offered an effective solution for classifying apple leaf diseases and had the potential to support more efficient and accurate agricultural decision-making.

KEYWORDS: Adam optimizer; apple leaf disease; CNN; image classification; Inception-ResNet-V2; transfer learning

1. Introduction

The apple tree (*Malus domestica*) is a fruit crop with high economic and agronomic value that was widely cultivated commercially in various regions around the world, particularly in temperate climates. Apples served not only as a source of fresh food but also as a key raw material in the food and beverage processing industry, such as for juice, fruit concentrate, and jam, thereby making a significant contribution to farmers' income and the local agricultural economy. *Malus domestica* was one of the most widely consumed fruits and held significant economic and cultural importance worldwide [1].

However, apple tree productivity was often reduced due to attacks by various leaf diseases such as Apple Scab, Cedar Apple Rust, and Black Rot. Plant diseases could result in significant losses, both in terms of the quantity and quality of the harvest [2]. One of the main challenges in controlling apple leaf diseases was the difficulty in accurately classifying disease types, as the visual symptoms of different diseases often shared similarities in color, shape, and spot patterns. This made it difficult for farmers and field experts to distinguish between disease types manually using conventional methods.

The manual process of classifying plant diseases required time, labor, and specialized expertise. Furthermore, this method was inefficient when applied on a large-scale agricultural level and was highly dependent on the observer's subjectivity, making it prone to errors. Therefore, a classification system was needed that could identify plant diseases quickly, accurately, and consistently. Advances in computer vision and machine learning technologies provided innovative solutions to this problem through the analysis of plant leaf images. One of the most widely used approaches was the Convolutional Neural Network (CNN), due to its ability to extract complex features such as texture, color, and shape from images without requiring a manual feature extraction process [3].

Various CNN architectures had been developed to improve the performance of leaf disease classification, including VGGNet, ResNet, Inception, and DenseNet. One notable architecture was Inception-ResNet-V2, which combined the strengths of the Inception structure in capturing multi-scale features with the residual connection mechanism of ResNet, which accelerated convergence and reduced the vanishing gradient problem. Research conducted by [4] showed that the Inception-ResNet-V2 architecture was capable of achieving higher accuracy than conventional CNN architectures in plant leaf disease classification, with reported accuracy levels exceeding 97%, depending on the dataset and training scheme used.

Although a number of studies had explored the use of CNN architectures for apple leaf disease classification, most still focused on basic architectures such as ResNet50 or InceptionV3 without evaluating the potential of hybrid architectures like Inception-ResNet-V2. For example, research by [5] reported an accuracy of 91% using ResNet50 for apple leaf disease classification, while [6] achieved an accuracy of 95.1% on a similar dataset. This indicated an opportunity to improve the performance of classification systems through the selection of more advanced and adaptive architectures tailored to the complexity of apple leaf image features. Although various studies had successfully applied CNNs for apple leaf disease classification with high accuracy, most of these studies still used relatively conventional CNN architectures (e.g., specific versions of VGG, ResNet, or Inception) or had not specifically explored hybrid architectures designed to capture multi-scale features more stably in very deep networks. On the other hand, the complexity of symptom patterns on apple leaves, such as variations in spot texture, color changes, and visual similarities between disease classes, as well as limited data variability under certain conditions, could increase the risk of model overfitting, even though training accuracy appeared high. Therefore, further study was needed on the application of deeper and more stable CNN architectures, such as Inception-ResNet-V2, to assess their potential for improving generalization and classification performance for apple leaf diseases on the test data.

Based on this background, this study focused on the application of the Inception-ResNet-V2 architecture for the classification of apple leaf diseases using digital images. This model was expected to achieve higher classification performance compared to previous architectures, taking into account the complexity of visual patterns on infected apple leaves. The results of this study were expected to contribute to the development of a more effective, efficient, and practical plant disease classification system to support increased apple agricultural productivity in Indonesia.

2. Materials and Methods

2.1. Apple.

The apple, with the scientific name *Malus domestica*, was a fruit crop favored by people from all walks of life due to its taste and high nutritional content [7]. Apples contained various essential nutrients such as vitamin C, fiber, and antioxidant compounds that were beneficial to health, giving them high nutritional and economic value. In Indonesia, with its tropical climate, apple cultivation was established in 1934. The growth of the apple industry accelerated from the 1960s onward after the crop successfully adapted to the local climate [8].

2.2. Apple leaf disease.

Apple leaf diseases raised concerns among apple growers because they reduced crop quality and productivity. Approximately 4–6 weeks after pruning non-productive branches and leaves, early symptoms of the disease generally began to appear on the leaf surface, such as the emergence of spots, discoloration, and abnormalities in leaf tissue structure [9].

2.3. CNN.

Convolutional Neural Network (CNN) is an artificial intelligence model used to recognize and analyze images and other visual data. CNNs were designed to mimic the functioning of the human visual cortex, enabling them to process and analyze digital images. The CNN architecture was specifically developed for image recognition and classification tasks through a series of layers that extracted visual features from the input image and then produced an output in the form of a score representing the image class [10]. The layers of a CNN model are shown in Figure 1 [11].

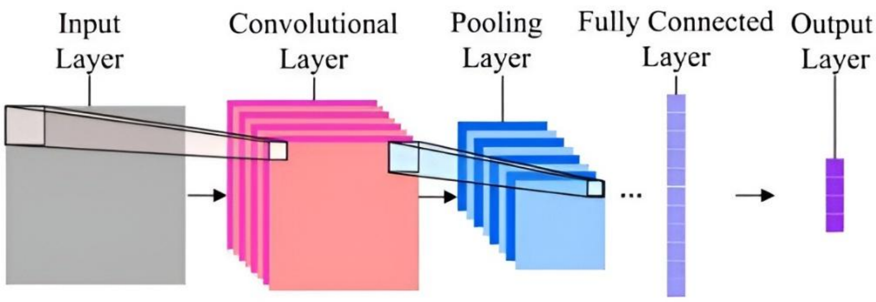

Figure 1. CNN architecture.

2.4. Inception-ResNet-V2.

Inception-ResNet-V2 is a Convolutional Neural Network (CNN) architecture built upon the Inception architecture by incorporating residual connections (ResNet) to enhance learning performance. This architecture consisted of three main modules, namely modules A, B, and C, and included a reduction block to reduce the dimension of the feature map [12]. This architecture combined the strengths of Inception in extracting features at various scales with the concept of residual learning introduced in ResNet to improve the stability of training deep neural networks. The Inception-ResNet-V2 architecture is presented in Figure 2 [13].

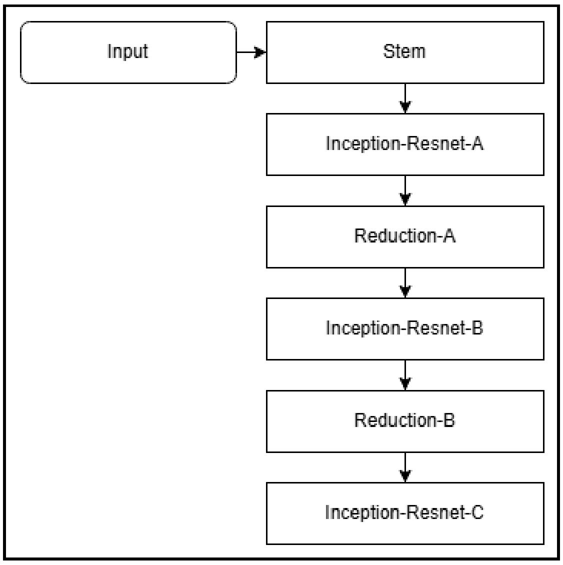

Figure 2. Inception-ResNet-V2 architecture.

2.5. Transfer learning.

Transfer learning is a method in machine learning that utilized a model that had undergone prior training to solve a specific task and was then adapted to handle another related task. This approach was typically applied when the amount of training data was limited. The transfer learning process was carried out by preserving the weights in the initial convolutional layers and training only the final layers that functioned as classifiers [14].

2.6. Adam optimizer.

Adam (Adaptive Moment Estimation) is an optimization algorithm that works by utilizing two statistical estimates of the gradient: the first moment, which represents the mean of the gradient, and the second moment, which represents the uncorrelated variance of the gradient. These two estimates are used to adaptively adjust the learning rate for each model parameter. The following is the formula for the Adam optimizer:

$$mt = \beta 1mt{-}1 + (1 - \beta 1) \,.\, gt \quad (1)$$

$$vt = \beta 2vt{-}1 + (1 - \beta 2) \,.\, gt\ 2 \quad (2)$$

$$\hat{mt} = mt\ 1{-}\ \beta 1\ t \quad (3)$$

$$\hat{vt} = vt\ 1{-}\ \beta 2\ t \quad (4)$$

$$\theta t{+}1 = \theta t - \alpha \,.\, \hat{m}\, t \sqrt{\hat{vt}} + \epsilon \quad (5)$$

In this equation, $m_t$was the estimate of the first-order gradient, $v_t$was the estimate of the second-order gradient, $g_t$represented the gradient at the t-th iteration, $\beta_1$and $\beta_2$were the exponential decay parameters, $\theta$was the updated model parameter, $\alpha$was the learning rate, and $\epsilon$was a small constant used to ensure computational stability [15].

2.7. Dataset collection.

In this study, the dataset used was a publicly available apple leaf disease dataset obtained from the GitHub website, containing 3,171 apple leaf images classified into the following categories: Apple Scab, Cedar Apple Rust, Black Rot, and Healthy [16]. The dataset was initially divided into training and validation folders. However, to ensure a more objective evaluation process and provide independent test data, all images from both folders were first combined into a single dataset. Subsequently, the dataset was divided into three subsets: 70% training data, 15% validation data, and 15% test data. The splitting process was performed using the stratified split method, which maintained the proportion of each class in every subset.

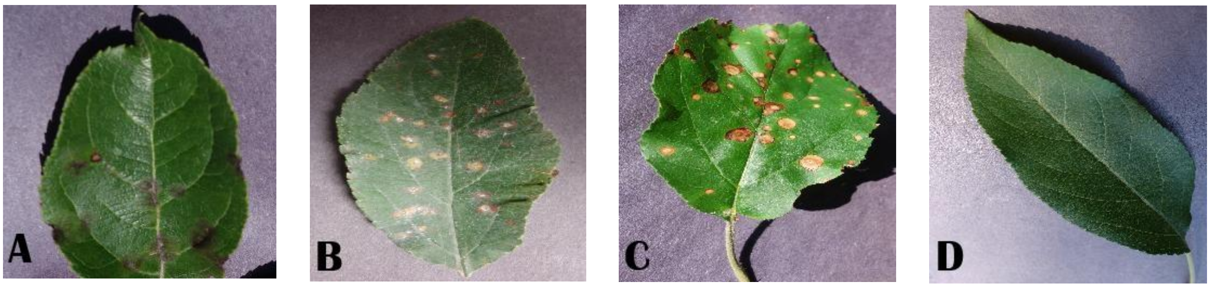

Figure 3. Apple leaf disease dataset samples: (A) Apple Scab - This disease is characterized by the appearance of dark to black spots on the surface of the leaves; (B) Cedar Apple Rust - This disease is characterized by the appearance of yellow to bright orange spots on the surface of the leaves; (C) Black Rot - Symptoms on the leaves appear as small, dark brown spots that can spread; (D) Healthy - The leaves appear fresh and green, and the leaf surfaces are intact.

2.8. Research design.

This study designed a system for classifying apple leaf diseases using the Inception-ResNet-V2 architecture with a transfer learning approach. The system design aimed to build an image classification model capable of distinguishing the condition of apple leaves based on their health status and the type of disease affecting them, namely Apple Scab, Cedar Apple Rust, Black Rot, and Healthy. The design process began with the collection and preparation of an apple leaf image dataset covering various leaf conditions, including both healthy leaves and diseased leaves. All apple leaf images then underwent a preprocessing stage, which involved resizing the images to 299×299pixels to meet the input requirements of the Inception-ResNet-V2 architecture.

In addition, pixel values were normalized using the preprocess_input function to map pixel values to an appropriate scale, thereby accelerating the convergence process during model training. To increase data diversity and reduce the risk of overfitting, data augmentation techniques were applied. The augmentation techniques included horizontal flipping, rotation, zooming, and contrast adjustment. This approach aimed to enable the model to recognize variations in the shape, orientation, and lighting conditions of apple leaves that may differ in real-world field data.

Furthermore, based on an analysis of the dataset distribution, an imbalance in the number of images across classes was identified, where the Healthy class was significantly more dominant than the other disease classes, particularly Cedar Apple Rust. To address potential model bias toward the majority class, this study applied class weighting to the loss function during the training process. Class weights were assigned proportionally based on the number of data points in each class so that classification errors in the minority classes were penalized more heavily. This approach aimed to improve the model's sensitivity to classes with fewer data points while maintaining balanced classification performance across classes.

The dataset was divided into three parts: training data, validation data, and test data, with proportions of 70%, 15%, and 15%, respectively. This division ensured that the model had sufficient data to learn patterns (training), data to monitor and adjust the training process (validation), and independent data to evaluate its final generalization ability (testing). The division was performed using stratified sampling, with the proportion of each class maintained to prevent class distribution imbalance in any subset. Additionally, data augmentation was applied only to the training data to prevent information leakage into the validation or test data.

During the model design phase, the pre-trained Inception-ResNet-V2 architecture, trained on the ImageNet dataset, was used as the feature extractor. The training process was conducted in two stages. The first stage was feature extraction, where all layers in the base model were frozen so that the pre-trained weights remained unchanged. In this stage, only the additional classification layers were trained to adapt the model to the task of classifying apple leaf diseases.

Next, a fine-tuning technique was applied by unfreezing some of the final layers of the Inception-ResNet-V2 model. At this stage, the weights in the final layers were updated using a smaller learning rate so that the model could adapt high-level features to the specific characteristics of apple leaf images without compromising the initial weights learned from ImageNet. Model training was performed using the Adam optimizer combined with categorical cross-entropy as the loss function. To address class distribution imbalance, class weight parameters were applied during training so that the error contribution from each class was accounted for proportionally to the amount of data.

The training parameters included a batch size of 32 and 30 epochs, as well as the application of early stopping to halt training if validation accuracy did not improve after several consecutive epochs. This approach aimed to prevent overfitting and improve the efficiency of the training process. The training parameters were determined to achieve a balance between model performance and computational efficiency. The number of epochs was set to 30 because this value was generally sufficient to achieve convergence in transfer learning-based training, while adding too many epochs increased the risk of overfitting, especially in leaf disease images that exhibited visual pattern similarities across classes. Additionally, the selection of 30 epochs also considered training time efficiency and computational resource constraints.

The batch size was set to 32 because it provided a good compromise between gradient update stability and memory requirements (GPU/CPU). A batch size that was too small could cause gradients to become more volatile, resulting in unstable training, while a batch size that was too large could increase memory requirements and potentially reduce generalization ability. With a batch size of 32, the training process remained stable while being efficient in terms of computational resources.

The final stage of the system design involved evaluating the model's performance using the metrics accuracy, precision, recall, and F1-score, which were calculated based on the confusion matrix. Given that the dataset had a class distribution that was not entirely balanced, the evaluation also considered macro-average values to provide a fairer representation of the model's performance across each class, particularly the minority classes. This approach ensured that classification success was not solely dominated by the majority class but reflected the model's overall ability to identify types of apple leaf diseases. The overall research workflow is presented in Figure 4.

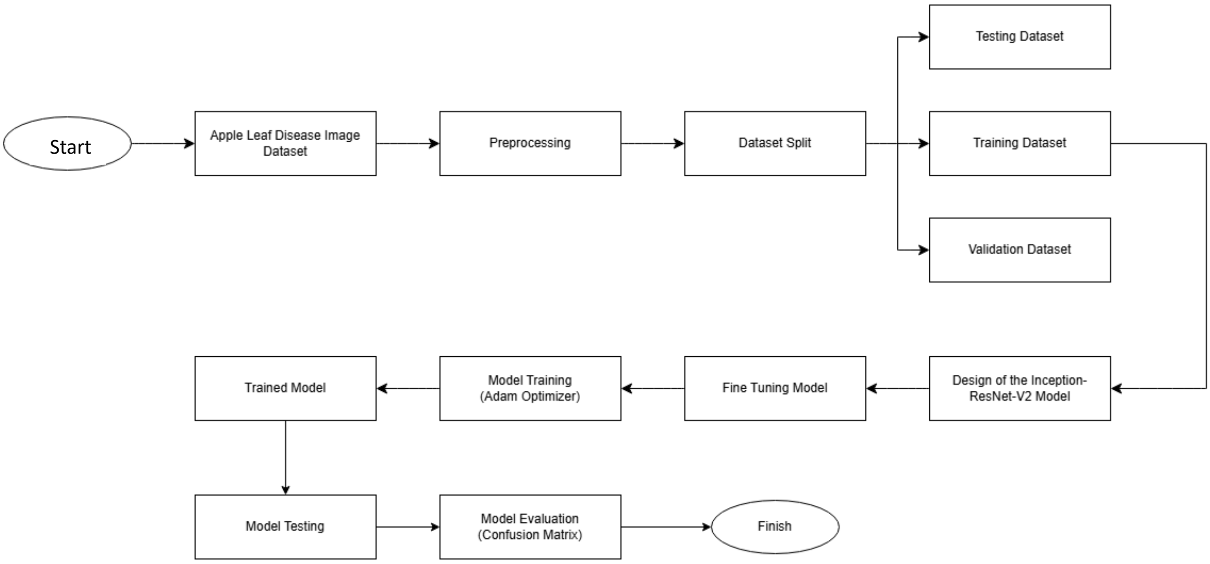

Figure 4. Diagram workflow.

2.9. Parameter configuration.

At this stage, a CNN model was implemented using the Inception-ResNet-V2 transfer learning approach for apple leaf disease classification. The model was trained using training data that had undergone preprocessing, which included image resizing, pixel value normalization, and data augmentation to increase image diversity and reduce the risk of overfitting. The parameters used in the implementation of the Inception-ResNet-V2 model are presented in Table 1.

Table 1. Inception-ResNet-V2 parameters.

Parameter	Configuration
Input Image Size	299 x 299
Dense	128
Batch Size	32
Epoch	30
Optimizer	Adam
Learning Rate	0.001
Activation Function	ReLU + Softmax

The proposed model configuration presented in Table 1 was determined based on previous studies that applied similar parameter settings in CNN-based image classification tasks. The Adam optimizer with a learning rate of 0.001 was adopted because previous research conducted by [17] demonstrated that this configuration provided stable convergence and effective optimization performance in transfer learning models, where the model achieved the highest accuracy of 100% using the same learning rate and optimizer configuration.

In addition, a batch size of 32 was selected because it offered a balance between computational efficiency and training stability during the learning process. Similar parameter settings were also employed in previous studies by [18], which reported a classification accuracy of 99.01% using the same batch size configuration. Therefore, the parameter configuration used in this study was considered appropriate to support stable model training, accelerate convergence, and improve classification performance on the apple leaf disease dataset.

2. 10. Experimental workflow.

This study was conducted in several main stages to develop an image-based apple leaf disease classification system using the Inception-ResNet-V2 architecture. The process began with the collection of an apple leaf disease image dataset from the PlantVillage dataset, which consisted of the classes Apple Scab, Cedar Apple Rust, Black Rot, and Healthy. The next stage was data preprocessing, which included resizing the images to 299×299pixels, normalizing pixel values using the preprocess_input function, and applying data augmentation to increase the variety of training data and reduce the risk of overfitting. After preprocessing, the dataset was divided into training, validation, and test sets using a stratified split with a ratio of 70:15:15.

Next, the Inception-ResNet-V2 model was designed using a transfer learning approach by leveraging initial weights from the ImageNet dataset. The training process was conducted through a fine-tuning stage using the Adam optimizer to adapt the model to the characteristics of apple leaf diseases. The trained model was then tested using the test data to evaluate its performance. The final stage of the research involved evaluating the model using a confusion matrix as well as accuracy, precision, recall, and F1-score metrics to measure the model’s classification ability for each class of apple leaf disease.

3. Results and Discussion

3.1. Training Performance Analysis.

The test results showed that the Inception-ResNet-V2 model, trained using the Adam optimizer, achieved a test accuracy of 98.74% with a minimum loss of 0.0397, indicating strong performance in classifying apple leaf diseases on unseen data. The training and validation curves presented in Figure 4 demonstrated stable learning and good generalization throughout the training process.

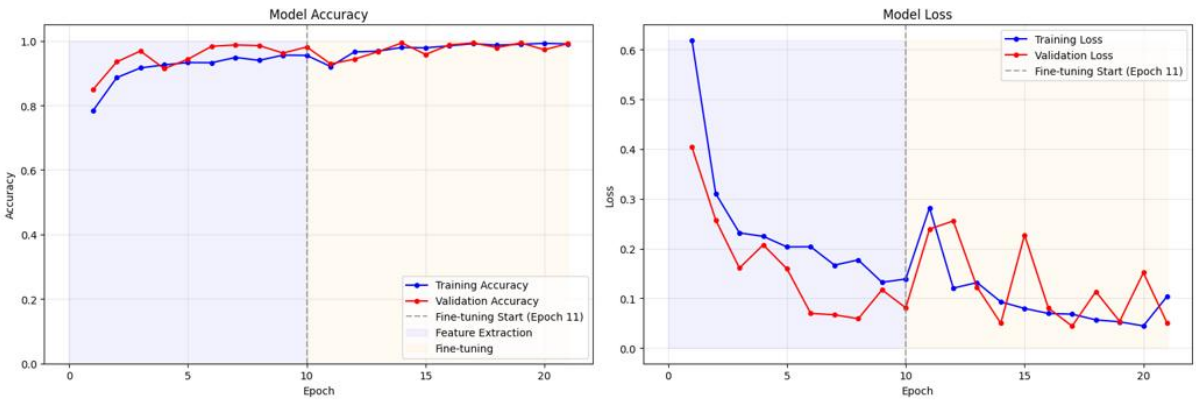

Figure 5. Accuracy and loss per epoch graph for Inception-Resnet-V2.

3.2. Performance analysis by class.

The model's performance demonstrated high classification accuracy across all apple leaf disease classes. The Cedar Apple Rust class achieved precision, recall, and F1-score values of 1.0000, indicating that the model was able to recognize the visual patterns of this disease very well without any classification errors in the test data. Meanwhile, the Healthy class also demonstrated very high performance, with an F1-score of 0.9900. This result indicated that the model could effectively distinguish healthy leaves from infected ones based on leaf color and texture characteristics.

The Apple Scab class achieved the lowest recall among all classes, at 0.9579. This indicated that some Apple Scab samples were still misclassified into other classes. The similarity of the dark spot patterns to those of Black Rot was suspected to be one of the main causes of these misclassifications. Overall, the macro-average precision of 0.9923, recall of 0.9841, and F1-score of 0.9881 indicated that the model performed consistently across all dataset classes, as presented in Table 2.

Table 2. Precision, recall, F1-Score, macro average, and accuracy.

Class	Precision	Recall	F1-Score
Apple Scab	1.0000	0.9579	0.9785
Black Rot	0.9891	0.9785	0.9838
Cedar Apple Rust	1.0000	1.0000	1.0000
Healthy	0.9802	1.0000	0.9900
Macro Average	0.9923	0.9841	0.9881
Accuracy			0.9874

3.3. Interpretation of the confusion matrix.

The model successfully classified the majority of the data. However, several misclassifications still occurred in certain classes, particularly between Apple Scab and Black Rot. These classification errors were likely caused by the similarity in visual characteristics between the two diseases, such as the appearance of dark spots on the leaf surface. Additionally, variations in lighting and texture in some images may also have affected the model's feature extraction process. On the other hand, the Cedar Apple Rust class showed a perfect classification rate with no prediction errors. This was likely because the disease had a distinctive orange color pattern, making it easier for the CNN model to recognize. The confusion matrix results presented in Figure 6 showed that the Inception-ResNet-V2 architecture was capable of capturing complex visual features effectively, despite similarities between disease classes.

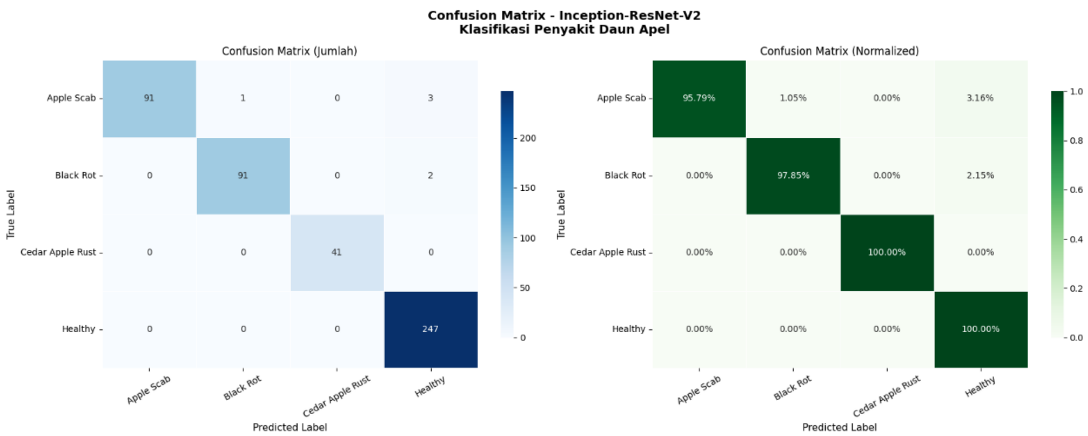

Figure 6. Confusion matrix of the model.

3.4. Impact of transfer learning.

The application of transfer learning using the Inception-ResNet-V2 architecture significantly contributed to the model’s high performance. The use of pre-trained weights from the ImageNet dataset allowed the model to leverage previously learned general visual features, such as texture patterns, shapes, and colors. Additionally, the fine-tuning process applied to several final layers helped the model adapt high-level features to the specific characteristics of apple leaf diseases. This approach enabled the model to achieve faster convergence and reduced the risk of overfitting despite the relatively limited dataset size. The combination of the Inception structure and residual connections in Inception-ResNet-V2 also helped improve training stability and multi-scale feature extraction capabilities, enabling the model to distinguish visual patterns between diseases more accurately.

3.5. Impact of data augmentation and class weighting.

Data augmentation techniques played a crucial role in improving the model’s generalization ability. Augmentation processes such as rotation, horizontal flipping, zooming, and contrast adjustment helped generate a more diverse set of training data, making the model more robust to variations in image orientation and lighting conditions. Additionally, the application of class weighting helped address the imbalance in data distribution across classes. Without class weighting, the model could potentially become more biased toward the majority class, such as the Healthy class. By assigning greater weights to minority classes, the model was able to learn a more balanced feature representation across all disease classes.

3.6. Comparison with previous studies.

Compared to previous studies, the proposed model demonstrated competitive classification performance. A study by Kulsum and Cherid using ResNet50 achieved an accuracy of 91%, while a study by Jayashree and Sumalatha achieved an accuracy of 95.1%. In this study, the Inception-ResNet-V2 architecture successfully achieved an accuracy of 98.74%. This performance improvement was believed to be influenced by the ability of Inception-ResNet-V2 to capture multi-scale features, as well as the use of more optimal transfer learning and fine-tuning strategies.

3.7. Model generalization and robustness.

The test results showed that the model had good generalization capability on unseen data. This was demonstrated by the high test accuracy and the consistent precision, recall, and F1-score values across all classes. However, the PlantVillage dataset was collected under relatively controlled environmental conditions with clean backgrounds and consistent lighting. In real-world conditions, images of apple leaves may be affected by variations in lighting, background noise, shooting angles, and different camera qualities.

4. Conclusions

This study demonstrated that the application of the Inception-ResNet-V2 architecture with a transfer learning approach was highly effective for the classification of apple leaf diseases based on image data. The proposed model achieved a high test accuracy of 98.74%, along with strong precision, recall, and F1-score values across all classes, indicating its ability to accurately distinguish between Apple Scab, Cedar Apple Rust, Black Rot, and Healthy leaf conditions. The integration of transfer learning, data augmentation, and class weighting contributed significantly to improving model generalization and handling class imbalance. Furthermore, the use of fine-tuning allowed the model to adapt high-level features specifically to the characteristics of apple leaf diseases, resulting in stable training performance and minimal overfitting. Overall, the results confirmed that the Inception-ResNet-V2 architecture was capable of capturing complex visual patterns, such as variations in color, texture, and lesion structure, making it a reliable approach for plant disease classification.

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Competing Interest

The authors declare no competing interest.

Data Availability

The dataset used in this study is available in the PlantVillage Dataset repository at: https://doi.org/10.3389/fpls.2016.01419.

Author Contribution

Earlando Moza conceived the study and designed the methodology. Earlando Moza conducted the experiments and collected the data. Earlando Moza performed the formal analysis and created the visualizations. Earlando Moza and Novan Wijaya wrote the initial draft. Earlando Moza and Novan Wijaya reviewed and edited the manuscript. All authors read and approved the final manuscript.

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