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Implementation of MobileNetV2 Transfer Learning for Image-Based Classification of Cocoa Fruit Diseases

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Abstract
Cocoa is one of the high-value agricultural commodities in Indonesia; however, its productivity continues to decline due to the increasing prevalence of plant diseases, particularly Black Pod Disease and attacks by Helopeltis spp. Traditional disease detection, which is generally performed manually by farmers, is often inefficient and prone to errors, thereby highlighting the need for an intelligent and technology-assisted early diagnosis system. This study aims to develop a disease classification model for cocoa plants using a Convolutional Neural Network (CNN) based on the MobileNet-V2 architecture, which is recognized for its computational efficiency and strong performance in image analysis. The dataset consisted of 300 images divided into three categories: healthy cocoa pods, Black Pod Disease, and damage caused by Helopeltis. Following the Pareto principle, 80% of the data were allocated for training and 20% for testing. The model was trained for 10 epochs with a batch size of 32 and was supported by data augmentation to improve data variability. Experimental results demonstrated a significant improvement in performance, with the highest validation accuracy of 93.75% achieved at the seventh epoch. The confusion matrix further confirmed that the model classified each category with a high level of precision. These findings indicate that MobileNet-V2 is an effective approach for automatic cocoa disease detection and has strong potential to assist farmers in improving disease management practices in the field.
***Key words:** Convolutional Neural Network; MobileNet-V2; Cocoa Disease Classification; Helopeltis spp.; Deep Learning*

1. Introduction

Cocoa (Theobroma cacao) is a perennial woody plant that typically reaches a height of 3–4 meters. Its leaves are oval to elliptical in shape, tapering at the tip with a rounded base, dark green in color, and approximately 15–30 cm in length and 5–10 cm in width. The cocoa fruit is elongated to oval with a length of about 10–25 cm. The seeds inside the fruit are also oval-shaped, measuring around 1–2.5 cm, and are covered by a mucilaginous and sweet layer known as pulp. Cocoa is one of the leading plantation commodities with high economic value and makes a significant contribution to the growth and development of the agricultural sector in Indonesia. Based on the latest FAO statistics cited in the study, Indonesia is recorded as the third-largest cocoa producer in the world after Côte d'Ivoire and Ghana, with annual production exceeding 667 thousand tons of cocoa beans, contributing to global market supply [1]. Despite its important global position, national cocoa productivity still lags behind major cocoa-producing countries. One of the main constraints is the emergence of various plant diseases, including Black Pod Disease and attacks by mirid bugs. The main focus of this study is image classification using cocoa fruit images to identify Black Pod Disease, cocoa mirid bug attacks (Helopeltis sp.), and an additional class representing healthy or normal cocoa fruit.

West Seram Regency, located in Maluku Province, is one of Indonesia's promising cocoa-producing areas due to its supportive agroecological conditions. However, recent data from the Maluku Provincial Department of Agriculture shows a significant decline in cocoa productivity, from 1,463.93 kg/ha to 546.38 kg/ha. This decline is caused by an increased incidence of Black Pod Disease due to Phytophthora palmivora infection and attacks by Helopeltis spp. Black Pod Disease is considered one of the most damaging diseases in cocoa plantations because it directly affects fruit development and significantly reduces both the quality and quantity of cocoa yields. A study conducted in West Seram Regency, Maluku, reported that P. palmivora, the causal agent of Black Pod Disease, caused an average fruit damage intensity of 24%, with some locations reaching up to 29%, indicating a moderate level of disease severity [2]. Previous studies show that P. palmivora infection can cause yield losses of around 20–30%, and under severe conditions, production losses may exceed 90%, especially when sanitation and crop management are poorly implemented [3], [4]. These findings confirm that plant disease pressure plays a significant role in reducing cocoa productivity in Maluku Province.

Black Pod Disease in cocoa fruits is caused by infection from the fungus Phytophthora palmivora, which leads to dark brown to black discoloration of the fruit and progressive rotting across the fruit surface. This disease can significantly reduce cocoa quality and yield. Previous research has shown that Bacillus spp., particularly Bacillus velezensis, can inhibit the growth of this pathogen and has potential as a biological control agent to suppress pod rot development in cocoa [5]. The pathogen infects cocoa fruits, causing the surface to darken and decay, ultimately reducing both the quality and quantity of harvests. Meanwhile, Helopeltis spp., an insect belonging to the order Hemiptera and the family Miridae, is a major pest that attacks various plantation crops in the Euphorbiaceae family, including cocoa plants. This insect attacks young shoots, flower buds, and fruits by inserting its mouthparts into plant tissue, causing brown necrotic spots that gradually dry out [6]. The high intensity of disease and pest attacks indicates that farmers still face major challenges in monitoring and accurately identifying plant conditions in a timely manner. The main problem is that the identification of cocoa diseases and pests is still carried out manually by farmers, resulting in slow and inaccurate detection. This leads to delayed treatment, faster disease spread, and an increased risk of crop failure.

Previous research by Blikon [7], which is relevant to this study, examined image classification of healthy and diseased cocoa fruits using KNN (k-Nearest Neighbors) and SVM (Support Vector Machine) methods. The study used image embeddings from Inception V3 as a feature extraction stage before classification. A total of 4,390 images of healthy and diseased cocoa fruits were used as the dataset. The results showed that the SVM method achieved an accuracy of 82.5%, while KNN achieved 82.3%. Although this study demonstrated that machine learning methods can effectively detect cocoa fruit conditions, several limitations remain. SVM and KNN heavily depend on specific feature extraction processes, which limit their ability to capture complex image patterns, especially under varying environmental conditions such as lighting differences and image quality. In addition, traditional classification methods have more limited automatic feature extraction capabilities compared to deep learning approaches.

Furthermore, Gado *et.al* [8] developed an Android-based system to classify cocoa fruit diseases using a CNN (Convolutional Neural Network) model with the NASNet-Mobile architecture. The results showed a testing accuracy of 94.88% and an implementation accuracy of 93.33% on Android devices. Although the model achieved high overall accuracy, the precision value was only 57.1%. This indicates a relatively high number of false positives, where the system incorrectly identifies healthy cocoa fruits as diseased. In addition, model performance is highly dependent on image quality. Blurry images or images taken from too far away often lead to misclassification, indicating the need for a more robust model capable of improving classification reliability and reducing prediction errors under various field conditions.

Research by Sari *et.al* [9] applied Transfer Learning using the MobileNetV2 architecture for cocoa fruit disease classification. The model achieved strong performance, with an accuracy of 92.86%, an F1-score of 92.79%, a precision score of 92.78%, and a recall of 92.86%. Despite these strong results, the study has limitations in terms of dataset size, which restricts the diversity of disease characteristics learned by the model. Similar visual symptoms lead to misclassification, particularly between Cocoa Pod Borer and Helopeltis classes. Another limitation is the exclusive use of MobileNetV2, leaving the possibility unexplored that other deep learning architectures may yield better performance. These findings indicate the need for further model development to improve recognition of various cocoa diseases and enhance classification accuracy in real-world conditions.

Furthermore, Khaerani Hamzidah [10] applied the YOLOv8 algorithm to diagnose cocoa plant diseases, achieving a mean Average Precision (mAP) of 90%. This study also shares similar limitations, as the relatively small dataset restricts the variability of disease features learned by the model. In addition, misdetections still occur in diseases with similar visual characteristics, and the model has not been able to optimally detect several cocoa disease categories. These limitations highlight the need for further model improvement, particularly through dataset expansion to enrich visual diversity, improve recognition of similar disease patterns, and enhance model generalization in real-world applications.

Therefore, this study proposes the MobileNetV2 architecture as a Convolutional Neural Network (CNN) model to improve cocoa disease classification performance. The use of MobileNetV2 is expected to produce a more efficient and lightweight detection system with improved classification capabilities. This architecture enables higher accuracy in automatic feature extraction from image data. The main objective of this study is to develop a cocoa plant disease classification model based on CNN using MobileNetV2 architecture, which is expected to help farmers automatically identify disease symptoms through cocoa fruit images. The proposed system is expected to support faster and more accurate disease classification, thereby improving disease management practices in the field.

2. Methodology

This study will apply a deep learning method using an experimental approach based on a Convolutional Neural Network (CNN) with the MobileNetV2 architecture to classify diseases in cocoa plants. The research methodology consists of several main stages.

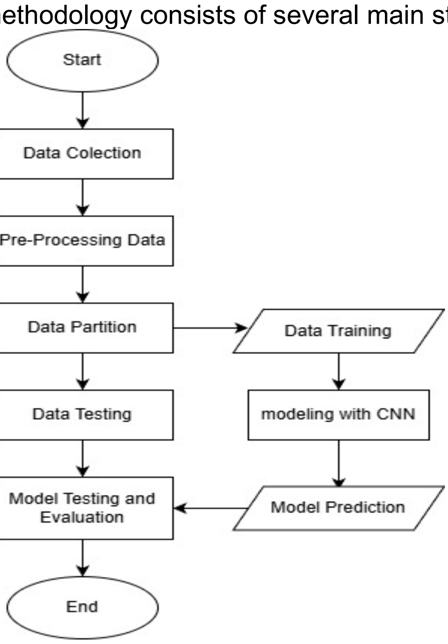

Figure 1. Research Flow Diagram

The research procedure is illustrated in a research flow diagram that is carried out systematically following the predetermined stages. The process begins with data collection, which includes the acquisition of cocoa fruit images directly from plantations in Kairatu Village, West Seram Regency, as well as the collection of supporting information from the local Department of Agriculture. A total of 300 cocoa fruit images were obtained and categorized into three classes: healthy cocoa fruits, cocoa fruits affected by Black Pod Disease, and fruits infected by Helopeltis. All images were captured using a smartphone camera under natural lighting conditions at a distance of approximately 20–40 cm to represent actual field conditions of cocoa fruits. After the data collection process, the images undergo a preprocessing stage. This stage includes resizing all cocoa fruit images to 224×224 pixels to meet the input requirements of the CNN model, pixel value normalization using a scaling factor of 1/1000, and the application of data augmentation techniques such as horizontal flipping, vertical flipping, and height shifting. This augmentation process is expected to increase data diversity and reduce the risk of overfitting.

Next, the dataset is divided using the Pareto principle-based data partitioning stage. The training process is allocated 80% of the dataset, or 240 images, while the testing phase uses 20%, or 60 images. The MobileNetV2 architecture with pretrained ImageNet weights is used to develop the CNN model during the training phase. Transfer learning is applied by setting the parameter include_top = False so that the original classification layer is excluded, and all base layers are frozen. Subsequently, several additional layers are added, consisting of a Global Average Pooling layer, a fully connected Dense layer with 1,024 neurons using the ReLU activation function, and an output layer in the form of a Dense layer with three neurons using the Softmax activation function to generate probability distributions for each target class. The model is then trained using the Adam optimizer with a learning rate of 0.0001, the categorical cross-entropy loss function, and evaluation metrics including accuracy, precision, and recall. The model is trained with a batch size of 32 for 10 epochs using the ImageDataGenerator utility in Google Colab to automatically manage training and validation data.

After the training process is completed, the model enters the prediction and testing phase, where it is evaluated using the test dataset to measure its performance on previously unseen data. A confusion matrix and performance metrics are used to evaluate the model, including precision, accuracy, recall, and loss. The purpose of this evaluation is to assess the effectiveness of the proposed model in accurately classifying cocoa fruit conditions and to indicate the completion of the research process.

3. Results and Discussion

3.1. Data Collection

The data collection stage was carried out directly in cocoa plantations owned by farmers in Kairatu Village, West Seram Regency. It began with the identification of cocoa fruits in healthy conditions, fruits affected by Black Pod Disease, and fruits infested by Helopeltis. Image acquisition was performed using a smartphone camera under natural lighting conditions at a distance of 20–40 cm from the object. The resulting dataset consisted of 300 JPG images categorized into three classes: Black Pod–infected cocoa fruits, healthy cocoa fruits, and fruits infested by Helopeltis spp. Each image was saved in a uniform resolution to maintain data quality.

Figure 2. Sample Images of Black Pod Disease, Helopeltis Infestation, and Healthy Cocoa Pods

3.2. Data Pre-Processing

After the image data has been collected, the preprocessing stage begins with the aim of preparing the images according to the input specifications of the CNN model and improving data quality prior to the training process. All image dimensions are resized to 224×224 pixels to meet the input requirements of the MobileNetV2 architecture. Next, pixel values are normalized using a scaling factor of 1/1000 to standardize the pixel intensity range and enable the model to achieve faster convergence during training. In deep learning, normalization is a crucial step as it contributes to improved numerical stability and enhances the efficiency of the optimization process [11]. In addition, several data augmentation techniques are applied, including horizontal flipping, vertical flipping, and height shifting. Data augmentation is used to generate new variations from the available training data, thereby increasing dataset diversity without the need for additional data collection. By introducing variations in object orientation and spatial position, the model is expected to become more robust, enabling better recognition of patterns in new data and minimizing the tendency of overfitting.

Figure 3. Image Resizing Results

3.3. Data Partition

In the data partitioning stage, the previously processed dataset is divided into two groups: training data and testing data. The data split follows the Pareto principle with an 80:20 ratio, where 80% of the data (240 images) is allocated for model training, while 20% (60 images) is used for model performance evaluation. The strategy of dividing the dataset into three subsets—training, validation, and testing—is a common practice in deep learning and machine learning, as it enables effective model training while ensuring evaluation on independent data. This approach is applied to assess model performance and ensure its ability to produce reliable predictions on data that was not used during the training process [12].

Table 1. Dataset Distribution

Class	Training	Testing
Healthy	80	20
Black Pod	80	20
Helopeltis	80	20

3.4. Modeling with CNN

The cocoa disease classification system in this study is implemented using the MobileNetV2 architecture with a Convolutional Neural Network (CNN) approach. The convolution operation in CNN is highly effective for image classification as it automatically extracts visual features, particularly in identifying patterns and characteristics of diseases in cocoa fruits. The CNN model is built by initializing MobileNetV2 with pretrained ImageNet weights and then adapting it using a transfer learning approach. To accelerate the training process and improve model performance, pretrained weights are utilized, especially when working with a limited dataset. The MobileNetV2 model is initialized without including the built-in classification layers by setting the parameter include_top = False, so that only the feature extraction component is used as the base model. All pretrained classification layers are set as non-trainable (frozen) to ensure that the pretrained weights are preserved and not updated during the training process.

To enable the model to classify diseases in cocoa fruits, several additional classification layers are added. The first layer is a Global Average Pooling layer, which aggregates values across each feature map channel to produce a more compact feature vector, thereby reducing the computational requirements of subsequent classification layers. Next, to enhance the model's ability to learn non-linear feature relationships, a fully connected Dense layer with 1,024 neurons and ReLU activation is added. Class prediction is then performed using a Dense output layer with three neurons and Softmax activation, allowing the model to generate a probability distribution across three classes: healthy, Black Pod Disease, and Helopeltis spp.

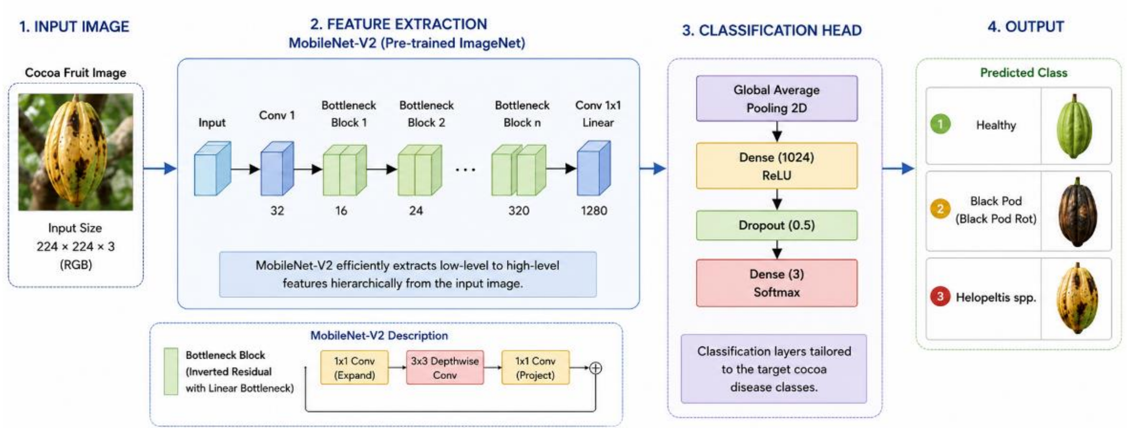

Figure 4. MobileNet-V2 CNN Architecture

The Adam optimizer is configured with a learning rate of 0.0001 during the CNN model compilation stage. In addition, the categorical cross-entropy loss function is selected to optimize the learning process for the multiclass classification task. The model is trained using 240 training images with a batch size of 32 over 8 epochs. During training, the model gradually learns the visual patterns of each cocoa disease class through a weight optimization process aimed at minimizing the loss value and improving classification accuracy. Evaluation of the training process is conducted by observing changes in accuracy and loss values presented in graphical visualizations. The accuracy graph illustrates changes in classification performance achieved by the model on both training and validation data across each epoch. The training results show that accuracy values on both training and validation data consistently increase in each epoch. This condition indicates that the model is able to effectively recognize the visual characteristics of diseases in cocoa fruits.

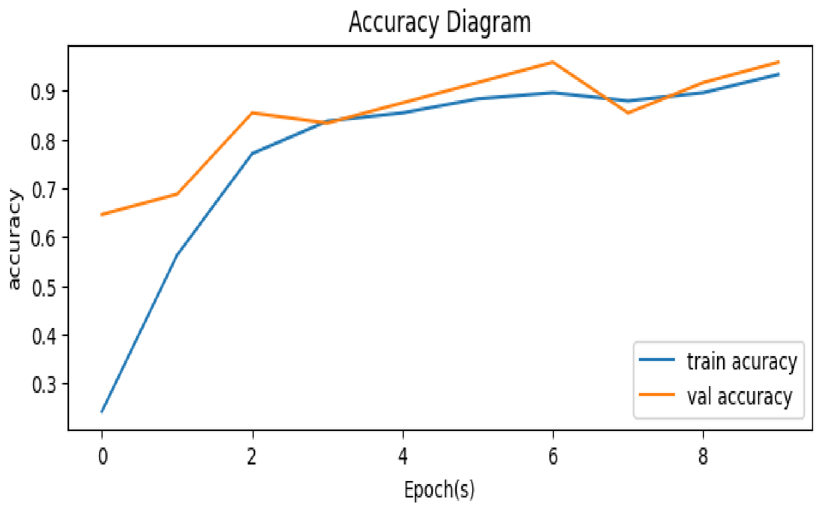

Figure 5. Accuracy Graph of CNN Model Training and Validation

The loss graph illustrates the changes in error values produced by the model during both the training and validation stages. A consistent decrease in loss throughout the training process indicates that the optimization process is progressing effectively, leading to continuous improvement in model performance. The difference in loss between the training and validation data remains relatively small, indicating stable optimization, no overfitting, and good generalization capability of the model.

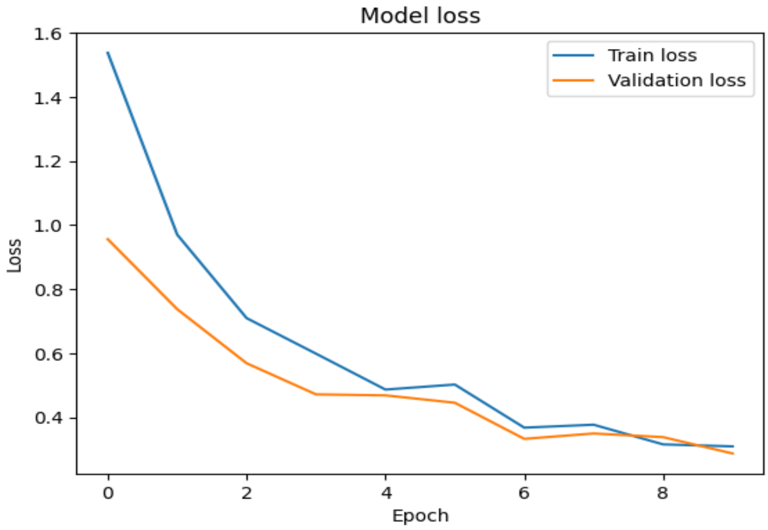

Figure 6. Loss Graph of CNN Model Training and Validation

The MobileNetV2 model demonstrates stable learning performance and achieves high classification accuracy in identifying the condition of cocoa fruits. This is evident from the results presented in the accuracy and loss graphs. These findings indicate that the combination of transfer learning and data augmentation techniques effectively enhances the model's ability to recognize disease patterns in cocoa plants, including on previously unseen data. The model's performance is evaluated using three metrics: precision, accuracy, and recall, which are defined by the following equations:

$$\boldsymbol{Accuracy = \frac{TP+TN}{TP+TN+FP+FN}} \quad (1)$$

$$\boldsymbol{Precision = \frac{TP}{TP+FP}} \quad (2)$$

$$\boldsymbol{Recall = \frac{TP}{TP+FN}} \quad (3)$$

In the equations above, the number of positive samples that are correctly predicted is referred to as True Positive (TP), while the number of negative samples that are correctly predicted is referred to as True Negative (TN). Conversely, False Positive (FP) represents the number of negative samples incorrectly predicted as positive, whereas False Negative (FN) refers to the number of positive samples incorrectly predicted as negative. These evaluation metrics are used to measure the overall accuracy, reliability, and effectiveness of the proposed model in identifying and classifying diseases in cocoa fruits.

3.5. Model Prediction

The prediction stage is performed after the model training process to evaluate the capability of the MobileNetV2-based CNN model in recognizing cocoa fruit conditions on data outside the training dataset. At this stage, each cocoa fruit image is mapped by the model into one of three target classes: healthy cocoa fruit, cocoa fruits infected with Black Pod Disease, and cocoa fruits infested by Helopeltis spp. The classification accuracy is determined by comparing the predicted results with the actual labels of each test sample. Based on the testing results, the model demonstrates strong performance in recognizing the visual characteristics of healthy cocoa fruits and fruits infested by Helopeltis spp. Most images are correctly classified due to clear visual features, such as distinct color differences, well-defined surface texture, and good lighting conditions during image acquisition. In addition, the data augmentation process applied during preprocessing also contributes to the model’s ability to recognize variations in object shape and orientation.

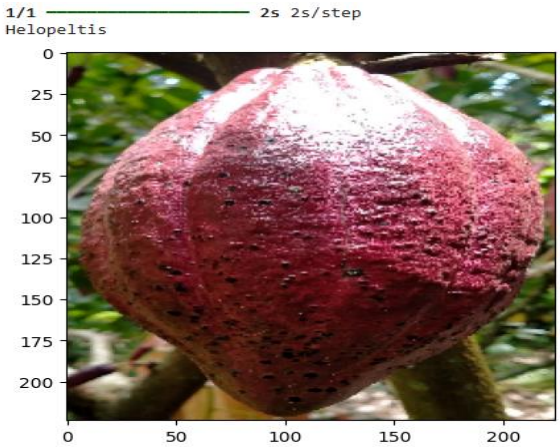

Figure 7. Successful CNN Model Predictions

Figure 7 shows several examples of correctly predicted results identified by the model. Healthy cocoa fruits and fruits infested by Helopeltis spp. are successfully classified because they exhibit distinctive visual symptoms, such as small necrotic spots caused by pest stings. Clear disease symptoms, stable natural lighting, and good image quality are the main factors contributing to the model's successful predictions. Based on the evaluation results, MobileNetV2 demonstrates very good performance in identifying diseases in cocoa fruits with high accuracy. However, improvements are still needed, including increasing the dataset size, adding variations in lighting conditions, and incorporating images that represent different levels of disease severity. These enhancements are expected to improve the model's ability to handle new data and produce more accurate predictions in future research.

3.6. Model Evaluation

Model evaluation aims to measure the learning performance and capability of the MobileNetV2-based model in recognizing various disease conditions in cocoa fruit images. This evaluation stage is an essential step in deep learning model development, as it enables the assessment of the model's ability to maintain performance on independent data. Thus, the effectiveness of the learning process is not only measured using training data but also through data that has never been used during the testing phase [13]. The model is evaluated using two evaluation schemes, namely on the training dataset and the test dataset. The test dataset is an independent subset separated during the data splitting stage, consisting of 20% of the total data or 60 cocoa fruit images. This dataset includes three target classes: cocoa fruits affected by Black Pod Disease, healthy cocoa fruits, and cocoa fruits infested by Helopeltis spp. The use of an independent test dataset aims to objectively assess the model's classification capability on unseen data. This approach enables a more accurate evaluation of model performance while minimizing potential bias and overfitting that may occur if evaluation is conducted using data that has already been used during the training stage [14].

The model performance is then evaluated using a confusion matrix, which illustrates the distribution of correct and incorrect predictions for each class. The confusion matrix provides a detailed overview of the model's classification effectiveness, including its ability to distinguish between classes and identify patterns of misclassification, such as errors in differentiating healthy cocoa fruits from fruits showing disease symptoms [15].

The normalized confusion matrix in Figure 8 shows that the MobileNetV2 model performs very well across all three classes: Healthy Pods, Black Pod Disease, and Helopeltis. For the Healthy Pods class, the model achieves 98% correct predictions, with only 2% misclassified as Helopeltis, which is likely caused by shadows or small spots in the images. For the Black Pod Disease class, the accuracy reaches 80%, while 9% of samples are misclassified as Healthy Pods and 11% as Helopeltis. This condition is likely influenced by high visual similarity, such as darkened fruit tissue or early-stage decay symptoms. The Helopeltis class achieves an accuracy of 94%, with 6% misclassification caused by mild symptoms or suboptimal lighting conditions.

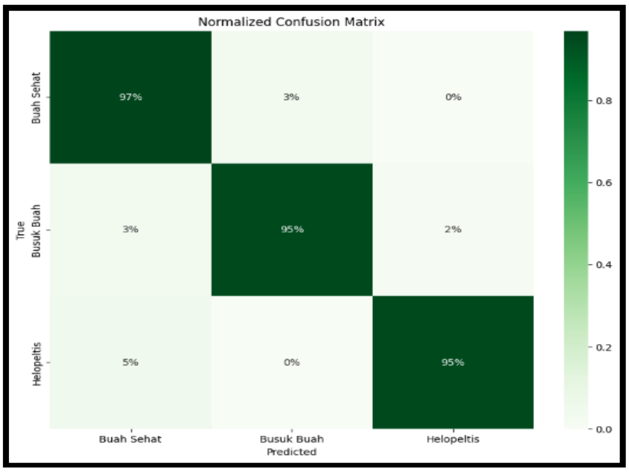

Figure 8. Training Confusion Matrix

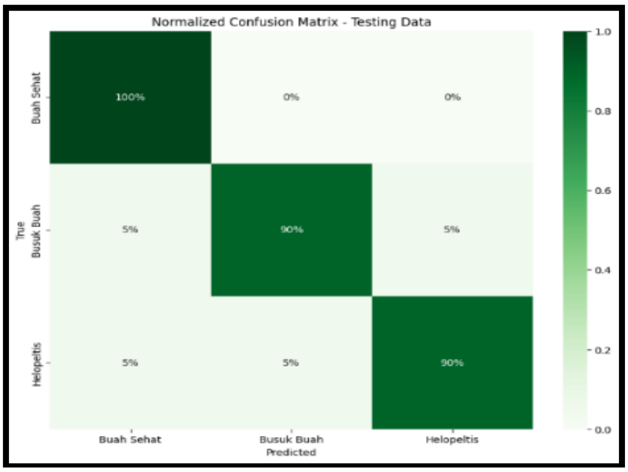

Figure 9. Testing Confusion Matrix

The confusion matrix in Figure 9 further confirms the model's performance. The Healthy Pods class is classified with perfect accuracy (100%), while Black Pod Disease is the most difficult class to recognize, with only 65% correctly identified and the remaining samples misclassified as Healthy Pods (15%) or Helopeltis (20%). The Helopeltis class again shows high accuracy (95%), although 5% of cases are predicted as Healthy Pods. The evaluation indicates that the model is able to recognize the Healthy Pods class with a very high level of accuracy, as all healthy samples are correctly classified, demonstrating consistent recognition of healthy fruit characteristics. The Helopeltis class also shows strong performance with only minor misclassification. However, Black Pod Disease remains a challenge for the model due to overlapping visual features with the other classes.

In addition to the confusion matrix, model performance evaluation also uses the Receiver Operating Characteristic (ROC) curve to provide further validation through analysis on both training and testing datasets. ROC curve analysis is conducted by examining the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) across various threshold values, allowing the quality of class separation produced by the model to be assessed [16], [17], [18]. ROC analysis on the training dataset reflects the model's effectiveness in learning and separating class representations during the training phase, while the ROC results on the testing dataset indicate the model's ability to generalize the learned features to unseen samples outside the training data.

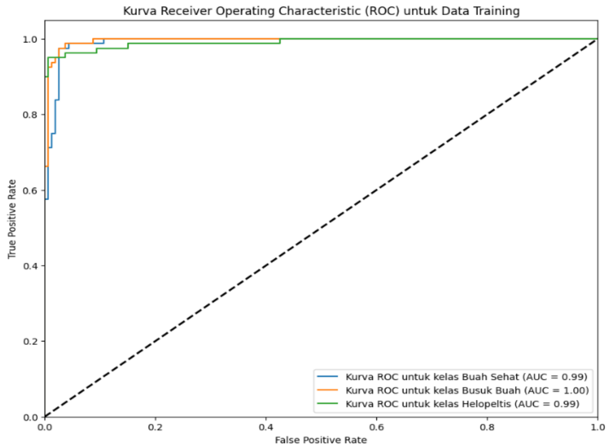

Figure 10. ROC Curve for Training Data

Based on the ROC curve obtained from the training data, the model demonstrates a high level of discriminative ability in classifying each target class. The ROC curve illustrates the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR), where curves that are farther from the diagonal reference line and closer to the upper-left corner indicate better classification performance. An Area Under the Curve (AUC) score of 0.99 for the Healthy Pods class indicates a very high level of classification accuracy. The ROC curve position, which is far from the random classification baseline, suggests that the model is able to effectively recognize the target class while maintaining a low false positive rate. The Black Pod Disease class shows the best performance with an AUC of 1.00, indicating nearly perfect classification on the training data. The Helopeltis class also achieves an AUC score of 0.99, reflecting very strong model performance and consistent reliability in recognizing pest infestation. The high AUC scores across all classes indicate that the model maintains strong discriminative power throughout the training process.

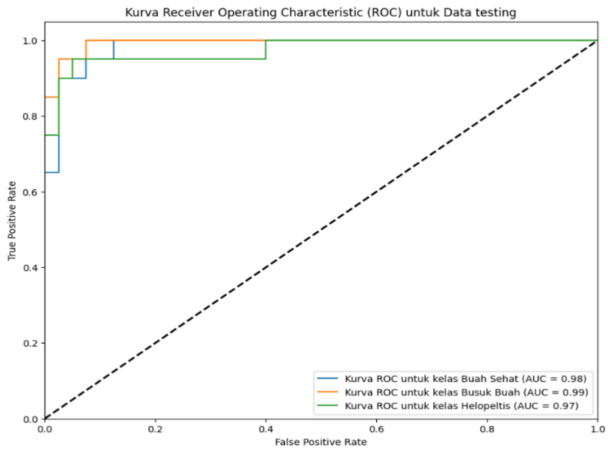

Figure 11. ROC Curve for Testing Data

The ROC curve analysis on the test data indicates that the model is able to effectively distinguish between all classes. The position of all ROC curves, which are far from the diagonal reference line, shows that the model has a high level of discriminative power across all target classes. The obtained AUC values are 0.98 for the Healthy Pods class, 0.99 for the Black Pod Disease class, and 0.97 for the Helopeltis class. These AUC scores, which are close to 1, indicate that the model has strong discriminative ability, allowing each category to be consistently distinguished on unseen data outside the training set.

The performance of the developed CNN model demonstrates a high level of accuracy in distinguishing cocoa fruit conditions. The obtained precision and recall values across all classes indicate the effectiveness of the model in recognizing the visual characteristics of cocoa fruit diseases. A high precision value indicates a low proportion of false positives, while a high recall value shows that most positive samples are successfully identified by the model. The loss value during the testing phase indicates that the optimization process has reached convergence, while the level of overfitting remains low. These findings suggest that the application of transfer learning and data augmentation techniques contributes positively to improving both the performance and stability of the model. Based on all evaluation results, the CNN architecture based on MobileNetV2 demonstrates strong potential to be implemented as a decision-support tool for the detection and classification of diseases in cocoa plants using digital image-based analysis.

3.6 Discussion

This study applies the MobileNetV2 architecture as the base model of a Convolutional Neural Network (CNN) to identify cocoa fruit conditions into three classes: Healthy Pod, Black Pod Disease, and fruits infested by Helopeltis. The training results show that the model achieved an accuracy of 91.59% on the training data and 89.58% on the validation data. These results indicate that the visual patterns of each class are well learned by the model. On the test data, the AUC scores for each class are 0.98 for Healthy Pod, 0.99 for Black Pod Disease, and 0.97 for Helopeltis. These values indicate that the model is able to effectively separate the three classes. Based on the confusion matrix, all samples in the Healthy Pod class are correctly classified (100%), while the Helopeltis class achieves an accuracy of 95%. In contrast, Black Pod Disease remains the most challenging class to identify due to its visual similarity with other categories.

The findings of this study strengthen previous research on cocoa disease classification using image-based approaches. The MobileNetV2 model in this study achieves higher performance compared to the method used in previous research by Blikon et al. [7], which applied Support Vector Machine (SVM) and k-Nearest Neighbors (KNN) algorithms with accuracies of 82.5% and 82.3%, respectively. These results indicate that representation learning in deep learning architectures provides advantages over conventional machine learning approaches that rely on handcrafted features. Therefore, this finding provides additional evidence supporting the effectiveness of CNN-based methods for cocoa disease classification.

The results of this study show a similar trend to several previous studies on the use of deep learning architectures for image-based cocoa disease classification. Gado [8] reported a testing accuracy of 94.88% using the NASNet-Mobile architecture, while Sari et al. [9] achieved an accuracy of 92.86% using a MobileNetV2-based transfer learning approach. Consistent with these studies, the findings of this research indicate that the use of lightweight CNN architectures is capable of maintaining high classification accuracy without sacrificing computational efficiency. In addition, misclassification in the Black Pod Disease class is also consistent with the findings of Sari et al. [9], which show that diseases with overlapping visual characteristics remain a major challenge in automated cocoa disease diagnosis systems.

These findings are further supported by recent studies in plant disease classification. Shafik et al. [19] demonstrated that transfer learning significantly improves plant disease recognition by enhancing feature learning, improving model generalization, and reducing overfitting. Similarly, Alkanan and Gulzar [20] reported that MobileNetV2 combined with transfer learning delivers strong classification performance along with computational efficiency for plant disease identification tasks. These results are consistent with the present study, where the integration of MobileNetV2, transfer learning, and data augmentation produces high AUC values and stable classification performance. This consistency indicates that MobileNetV2 is a reliable architecture for image classification applications in the agricultural domain.

The research findings show promising results; however, several aspects still require improvement. The relatively small dataset size may limit the diversity of disease characteristics learned by the model, while variations in color patterns, texture, fruit maturity levels, and lighting conditions during image acquisition may affect classification accuracy. These factors are likely to contribute to misclassification in the Black Pod Disease class. To further improve the model's generalization capability, future research is recommended to expand the dataset by adding samples collected from various environments and different geographical regions. Overall, the findings indicate that MobileNetV2 is a suitable architecture for cocoa disease classification, as it is able to maintain good performance while remaining computationally efficient. Its potential application also extends to supporting image-based early disease detection systems in cocoa plantations.

4. Conclusion

The digital image-based classification of cocoa fruit conditions in this study was successfully implemented using a CNN model built on the MobileNetV2 architecture. The main results show that the developed model is able to accurately identify three cocoa fruit conditions: Healthy Pod, Black Pod Disease, and Helopeltis infestation. The model achieved an accuracy of 91.59% on the training data and 89.58% on the validation data. These results reflect the success of the learning process in forming discriminative feature representations while maintaining generalization capability on unseen data. Based on the confusion matrix, all samples in the Healthy Pod and Helopeltis classes were correctly classified (100%). However, the Black Pod Disease class remains the most difficult to classify due to overlapping visual characteristics with other classes. In addition, ROC curve analysis shows that the AUC scores for all classes are in the high category. These findings reflect the model's ability to construct decision boundaries that effectively separate each class. The results indicate that the transfer learning strategy using MobileNetV2 contributes to improving the model's ability to learn visual representations of cocoa diseases without significantly increasing computational cost. The achieved performance demonstrates strong potential for implementing the model in digital image-based analysis systems for automated identification and classification of cocoa diseases. Such a system can facilitate faster, more efficient, and consistent disease identification, thereby supporting more effective disease control strategies and ultimately improving cocoa plantation productivity.

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