International Journal of Informatics and Computation (IJICOM)
Vol.7, No.1, 2025
ISSN: 2685-8711, E-ISSN: 2714-5263 DOI: 10.35842/ijicom

Detection of Oil Palm Seedling Disease Based on Leaf Images Using the MobileNetV2-CNN Architecture

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Abstract
This study aims to develop and implement a plant disease detection system for oil palm seedlings based on leaf images using the MobileNetV2 architecture, which is based on Convolutional Neural Networks (CNN). The model was trained using a dataset of oil palm leaf images to detect several types of plant diseases. In the experiments, the applied model showed excellent results, with training accuracy increasing from 79% in the first epoch to 96% in the 15 epoch, and validation accuracy also increasing from 89% to 97%. These results demonstrate that the model can effectively detect plant diseases with good generalization ability on unseen data. With stable loss reduction and continuously improving accuracy, this study proves that the MobileNetV2 architecture can be efficiently used for plant disease detection. The research also highlights the potential integration of the model into an application to provide a practical solution in oil palm plantation management and to support decision-making and improve agricultural outcomes.

Keywords: Plant Disease Detection, MobileNetV2, Convolutional Neural Network, Deep Learning

1. Introduction

Oil palm (Elaeis guineensis) is one of Indonesia's primary plantation commodities, significantly contributing to the national economy. The productivity of oil palm is greatly influenced by plant health, especially during the seedling stage. Diseases affecting oil palm seedlings can lead to a decline in plant quality, ultimately impacting long-term production yields. The detection of oil palm seedling diseases, particularly leaf spot disease and Basal Stem Rot (BSR) poses significant challenges in the agricultural sector. Recent advancements in technology, particularly in image processing and machine learning, have shown promise in addressing these issues. Therefore, early detection of diseases in oil palm seedlings is a crucial step in maintaining plantation productivity and efficiency [13].

Traditional methods of disease detection in oil palm seedlings often rely on manual inspection by experts, which is time-consuming, labor-intensive, and prone to human error. To address the traditional approaches' drawbacks, many communities proposed artificial intelligence methods, particularly in digital image analysis for plant disease detection. One widely used approach is the Convolutional Neural Network (CNN), which has proven to be effective in object classification and detection in images. For instance, an article applied CNN methods to detect diseases in potato leaves, achieving an accuracy rate of up to 80% [2]. A study implemented CNN methods for disease classification in corn plants, reporting

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a training accuracy of 91.5% and a validation accuracy of 91% [3]. Additionally, another research compared several transfer learning architectures and found that MobileNetV2 performed well in classifying rice plant diseases, achieving an accuracy of 96% [4]. A systematic review also confirmed that CNN is a superior method for plant disease identification and classification, showing highly promising results for industrial-scale applications [5]. In line with previous studies, a study developed a CNN model based on ResNet50 to classify the quality of oil palm seedlings, achieving a high image recognition accuracy. This indicates that CNN is effective in identifying patterns in seedling images, which can assist farmers in the early detection and management of diseases and pests [8].

MobileNetV2, as an efficient CNN architecture, offers an optimal solution for plant disease detection with lower computational requirements, making it suitable for implementation on resource-limited devices. Several previous studies have demonstrated the effectiveness of CNN in detecting plant diseases. A paper found that the MobileNetV2 architecture was highly effective in detecting anthracnose and fruit rot in cayenne peppers, achieving high accuracy in training and validation datasets. By integrating the MobileNetV2-CNN architecture, this approach automates the detection process, enabling rapid and accurate identification of diseases from leaf images. The use of MobileNetV2, a lightweight and efficient deep learning model, is particularly innovative as it allows for real-time disease detection on resource-constrained devices, such as mobile phones or drones. This makes the technology accessible to farmers in remote areas with limited access to advanced computing infrastructure. Additionally, the CNN with MobileNetV2 enhances the model's ability to generalize across diverse datasets, even with limited training data, which is a common issue in agricultural applications [1].

Based on these findings, this study aims to develop and implement a disease detection system for oil palm seedlings based on leaf images using the MobileNetV2-CNN architecture. The trained model will be integrated into an application to facilitate more practical and accurate disease prediction or classification. With this system, it is expected that disease detection can be conducted more quickly and efficiently, assisting farmers in making informed decisions regarding oil palm plantation management. The implementation of MobileNetV2-CNN Architecture introduces several novel aspects that address critical challenges in agricultural technology.

Another significant novelty of this implementation lies in its potential to improve early disease detection, which is crucial for preventing the spread of infections and minimizing crop losses. The MobileNetV2-CNN architecture is optimized to detect subtle visual patterns in leaf images that are indicative of diseases, such as discoloration, spots, or lesions. This capability is further enhanced by the model's ability to handle high-resolution images and adapt to varying lighting conditions in field environments. By providing farmers with a tool for early and accurate disease detection, this technology supports sustainable agricultural practices and helps increase productivity. Furthermore, the system's scalability and ease of integration with existing agricultural monitoring systems make it a practical solution for large-scale oil palm plantations. Overall, this implementation represents a significant advancement in precision agriculture, combining cutting-edge AI technology with real-world applicability to address a pressing global challenge.

2. Research Methodology

2.1 Literature Review

Detecting diseases in oil palm seedlings is crucial for maintaining the health and productivity of palm oil plantations. Various technological approaches have been developed to address this challenge, each leveraging different aspects of image processing and machine learning. These methods aim to provide early detection, which is essential for effective disease management and prevention of yield loss. Traditional methods proposed optimized thermal imaging technology for early detection of health issues in oil palm seedlings. By measuring plant surface temperatures using the UNI-T UTi120 Mobile thermal camera, significant temperature variations were identified between healthy and unhealthy seedlings, with a significance value of 0.025. This method allows for non-destructive monitoring, enabling farmers to detect unusual temperature changes that may indicate diseases or environmental stress [16].

Another conventional approach explored Ganoderma disease detection in oil palm plantations using C and L band SAR backscatter time series. The study utilized a time series of C-band and L-band backscatter information to identify Ganoderma-infected oil palm plants and compare the results within a designated region. The analysis incorporates $\gamma 0$ backscatter coefficients, backscatter cross-ratio, the coefficient of variation (CV) from 2019 to 2022, and second-order texture matrices using the Gray Level Covariance Matrix (GLCM) as input features. Three classification algorithms were tested: random forest, XGBoost, and quadratic discriminant analysis (QDA) for both L-band and C-band backscatter coefficients separately. Results indicate that L-band backscatter information from ALOS-2 PALSAR-2 outperforms C-band backscatter information from Sentinel-1, with QDA achieving the best performance, resulting in an F1-score of 0.86 for infected trees and 0.88 for healthy trees [14].

A recent study conducted automatic disease detection of Basal Stem Rot Using Deep Learning and Hyperspectral Imaging, a study proposed a Mask Region-based Convolutional Neural Network (RCNN). There are three models used to detect BSR: a convolutional neural network that is 16 layers deep (VGG16) model trained on a segmented image; and VGG16 and Mask RCNN models both trained on the original images. The results indicate that the VGG16 model trained with the original images at 938 nm wavelength performed the best in terms of accuracy (91.93%), precision (94.32%), recall (89.26%), and F1 score (91.72%). This method revealed that users may detect BSR automatically without having to manually extract image attributes before detection [13].

Another work developed a method for detecting leaf spot disease in oil palm seedlings using a CNN. Leaf spot disease in oil palm seedlings can hinder growth and production. CNN has proven effective in image processing and classification, particularly in plant disease detection. In this study, they utilized a dataset of images containing oil palm seedling leaves infected with leaf spot disease and healthy leaves. The study performed data processing, built a CNN model, and conducted hyperparameter tuning. The test results demonstrate that the developed CNN model achieves high accuracy in recognizing and distinguishing between oil palm seedling leaves infected with leaf spot disease and healthy ones. This research contributes to the development of plant disease detection technology that can support economic growth in the oil palm plantation sector [12].

A combination of AlexNet–CNN and the combination of AlexNet and support vector machine (AlexNet-SVM) can be a new solution to overcome the limitation of handcrafting of feature representation implemented for oil palm leaf disease identification. The images of healthy and infected leaf samples were collected, resized, and renamed before the model training. The optimal architecture of AlexNet CNN and AlexNet-SVM models was then determined and subsequently applied for the oil palm leaf disease identification. Comparative studies showed that the overall performance of the AlexNet CNN model outperformed the AlexNet-SVM-based classifier [15].

2.2 Data Collection

Data collection is a crucial stage in research, aimed at systematically obtaining data through specific scientific methods and techniques for further analysis. In this study, the dataset collection process was conducted directly at PT. Gatipura Mulya consists of 1,803 images of oil palm seedlings, which are classified into four main categories Leaf Spot (Curvularia sp), Grasshopper Pest (Valanga nigricornis), Night Beetle (Apogonia sp), Healthy Seedlings. The dataset was divided into two subsets with the following distribution: 69.94% for training data, 27.07% for validation data, and 2.99% for testing data. The dataset distribution in this study is presented in Table 1 as a reference for the subsequent data processing stages.

Table 1: Dataset of study

No	Nama	Gambar
1	Bagus (Normal)	
2	Bercak Daun (Curvularia sp.)	
3	Kumbang Malam (Apogonia sp.)	
4	Belalang (Valanga nigricornis.)	

The test data used in this study consists of four main categories, including one category for healthy oil palm seedlings and three categories affected by either disease or pest attacks. These categories are described as follows:

1. **Healthy Oil Palm Seedlings (Normal)**
   Seedlings classified as healthy exhibit clear visual characteristics, with uniformly green leaves and an orderly growth pattern. Plants in this category show no signs of disease infection or pest damage and are considered the optimal standard for seedlings.
2. **Leaf Spot Disease (*Curvularia sp.*)**
   Leaf spot disease is caused by the *Curvularia sp.* fungus, characterized by the appearance of yellow spots on the leaf surface. This infection tends to progress over time, causing the spots to turn grayish-brown. In severe cases, the leaves may wrinkle, dry out, and eventually die.
3. **Night Beetle Infestation (*Apogonia sp.*)**
   The night beetle (*Apogonia sp.*) is an insect that actively damages plants at night by feeding on leaf parts. During the day, these pests tend to hide in the soil or under polybags. An *Apogonia sp.* infestation causes visible damage in the form of small holes in the leaves, which are the result of insect bites.

4. **Grasshopper Infestation (*Valanga nigricornis*)**

   The grasshopper (*Valanga nigricornis*) primarily attacks the edges of young oil palm seedling leaves, particularly during the nursery stage. Although the impact of this attack is generally mild, a high grasshopper population can slow plant growth. In extreme cases, these attacks can even lead to seedling death due to the loss of leaf sections essential for photosynthesis

2.3 Preprocessing

Before conducting image data analysis, preprocessing is essential to enhance data quality and consistency. This process includes steps such as normalization, noise removal, and contrast enhancement, which aim to minimize unwanted distortions and highlight important features within the images. These steps ensure that the image data is ready for further analysis and help improve the accuracy of the model being developed [6]. Additionally, dividing the dataset into three subsets training data, validation data, and testing data is a common practice in machine learning. The training data is used to train the model, the validation data helps fine-tune hyperparameters and prevent overfitting, and the testing data is used to evaluate the final model performance. This partitioning ensures that the developed model can be accurately assessed and generalizes well to previously unseen data [6]. Preprocessing is a crucial step in ensuring that the analysis and model developed have a strong and reliable foundation [6].

2.4 Model Design and Testing

The proposed CNN model architecture in this study is MobileNetV2. MobileNetV2 utilizes depthwise separable convolutions, which break down convolution operations into two stages: depthwise convolution and pointwise convolution. This approach significantly reduces the number of parameters and computational load compared to standard convolutions, without significantly compromising accuracy [11]. Furthermore, MobileNetV2 implements inverted residual blocks, where residual connections are placed between bottleneck layers. The intermediate expansion layers use depthwise convolutions to filter features as a source of non-linearity. Overall, the MobileNetV2 architecture consists of an initial full convolution layer with 32 filters, followed by 19 residual bottleneck layers [9]. The key advantage of MobileNetV2 is its computational efficiency, making it ideal for applications on devices with limited power and processing capabilities. Despite having fewer parameters, MobileNetV2 delivers solid performance in image classification tasks [10].

In the context of this study, implementing MobileNetV2 is expected to enhance model performance in classifying oil palm seedling images while maintaining high computational efficiency. During the training phase, the CNN model is evaluated using the provided test data. This stage aims to assess how well the model learns from the given data. Subsequently, during the testing phase, the model is tested using images different from the training data. This evaluation is conducted to measure the model's ability to classify diseases and pests in oil palm plants and assess its overall performance.

3. Result & Discussion

An analysis and model design were conducted based on the data used. This analysis includes evaluating the model’s performance and comparing the classification results obtained.

3.1 Dataset

The initial stage of the model analysis process is the dataset configuration, where the dataset is divided into several classes, which will be presented in Table 2.

Table 2

Nama	Data Train	Data Test	Data Validation
Curvularia sp.)	508	22	196
Apogonia sp)	424	18	164
Valanga nigricornis)	111	5	43
Normal	218	9	85

3.2 Data Preprocessing

Data preprocessing is performed to ensure that the oil palm seedling images have the appropriate format before being used for model training. All images are resized to 224 × 224 pixels to maintain input consistency for the MobileNetV2 model. A random horizontal flip is applied to enhance the model's robustness to image variations and it is converted using *ToTensor(),* transforming pixel arrays into numerical tensors. This study also calculates Mean and standard deviation values from *ImageNet* are used to accelerate model convergence afterward the dataset is divided into a training set (for model training) and a validation set (for model evaluation).

3.3 MobileNetV2 CNN Architecture Modeling

At this stage, modeling is performed using MobileNetV2. MobileNetV2 is a deep learning model based on CNN (Convolutional Neural Network), designed for computational efficiency while maintaining high accuracy. The MobileNetV2 architecture utilizes depthwise separable convolutions and inverted residuals with a linear bottleneck to reduce the number of parameters while increasing inference speed. MobileNetV2 accepts input images with a size of 128 × 128 × 3 (RGB Image). After passing through the first convolutional layer, the feature map size remains 128 × 128, without any change in resolution. In the next stage, after the first pooling process, the feature map size is reduced to 64 × 64, with the number of filters n = 32.

The model continues with several convolution and pooling processes, progressively reducing the feature map size to 32 × 32, with n = 96 filters. Before reaching the flattening stage, MobileNetV2 produces a feature map of size 4 × 4 × 1280, where n = 1280 represents the final number of filters. The flattening process converts the feature tensor into 1,280 units in the form of a 1D vector. To adapt the model for this study, modifications were made to the fully connected layer, which originally had 1,000 classes in the original MobileNetV2 model. Instead, it was adjusted to 512 neurons, which were then connected to 4 output neurons.

The final output utilizes the Softmax activation function to generate predictions for 4 classes (C1, C2, C3, C4). The pre-trained weights of MobileNetV2 are retained to assist in the prediction process, while the fully connected layer is modified to better fit the requirements of this study. The MobileNetV2 framework used in this research is illustrated in Fig 1.

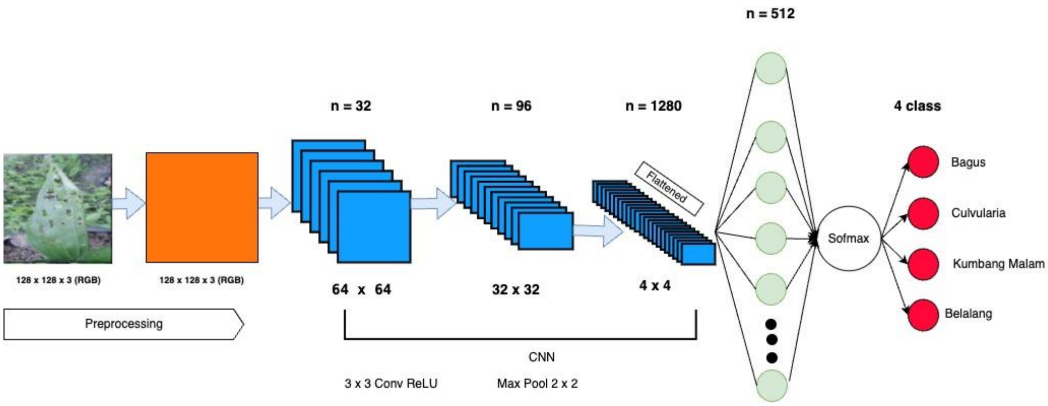

Fig. 1 MobileNetV2 Architecture to conduct experiment

Table 3 describes the MobileNetV2 layers.

Table 3

Tahap	Ukuran Feature Map	Operasi
Input Image	128 × 128 × 3	RGB Input
1st Conv Layer	128 × 128 × 32	3×3 Standard Conv, 32 filters
1st Pooling	64 × 64 × 32	3×3 Depthwise Conv, Stride 2
Bottleneck Blocks (6 Blocks)	32 × 32 × 96	1×1 Expansion, 3×3 Depthwise Conv, 1×1 Projection
Feature Extraction	4 × 4 × 1280	1×1 Conv, Linear Bottleneck
Flattening	1280 (1D)	Flattening Feature Map
Fully Connected	512 → 4	Fully Connected Layer
Softmax Output	4 Classes (C1, C2, C3, C4)	Softmax Activation

3.4 Model Training

In this study, the Batch Size is used to determine the number of data samples processed in a single iteration before updating the model parameters, thereby improving computational efficiency. Epoch refers to the number of complete cycles in which the entire dataset is used to train the model, ensuring that parameters are updated optimally without causing overfitting. For optimization, the Adam Optimizer is used, which combines the AdaGrad and RMSProp methods, allowing for more adaptive learning with improved convergence speed. The combination of these three elements aims to enhance the accuracy of the MobileNetV2 model applied in this study

Table 4

Hyper-Parameters	value
Batch Size	32
Epoch	15
Optimizer	Adam
Learning rate	0.01

The training results of the model can be analyzed based on the performance of each epoch, as presented in Table 5.

Table 5

Epoch	Loss Train	Accuracy Train	Loss Validation	Accuracy Validation	Time
1	0.58	0.79	0.3	0.89	3:2
2	0.33	0.88	0.24	0.91	2:34
3	0.29	0.91	0.21	0.92	2:33
4	0.23	0.92	0.23	0.92	2:37
5	0.23	0.92	0.17	0.95	2:33
6	0.22	0.91	0.27	0.91	2:35
7	0.16	0.93	0.15	0.95	2:34
8	0.14	0.95	0.17	0.94	2:34
9	0.1	0.97	0.15	0.93	2:35
10	0.11	0.97	0.11	0.96	2:34
11	0.11	0.97	0.2	0.93	2:45
12	0.13	0.95	0.23	0.92	2:32
13	0.16	0.95	0.12	0.96	2:31
14	0.09	0.97	0.18	0.94	2:35
15	0.12	0.96	0.1	0.97	2:35

Based on the results shown in the table, training Accuracy gradually increases from 0.79 in the first epoch to 0.96 by the 15th epoch. This indicates that the model is progressively improving in recognizing patterns within the training data. Meanwhile, Validation Accuracy is used to measure the model's performance on unseen data, ensuring that the model is not merely memorizing the training data but can also generalize effectively. Training and validation loss is shown in Fig. 2.

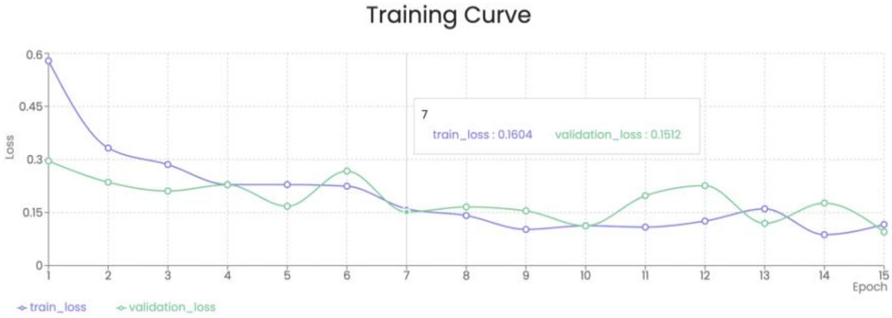

Fig. 2 Training and Validation Loss

On the other hand, Training Loss measures the extent of errors made by the model on training data, while Validation Loss evaluates the model's error on validation data. The graph shows that Training Loss significantly decreases from 0.58 in the first epoch to 0.09 by the 15th epoch, indicating that the model is becoming more accurate in predicting training data. Similarly, Validation Loss shows a relatively stable decline, despite minor fluctuations, suggesting the model's ability to generalize well to unseen data. As accuracy improves and loss decreases, the model adapts better to the training data. However, there is a possibility of overfitting, which can be observed if Validation Accuracy stagnates or declines while Training Accuracy continues to increase. In this case, Validation Accuracy continues to improve, indicating that the model maintains a good balance in generalizing to new data.

4. Implementation

The trained model is integrated into a system capable of making predictions on new data. This system allows users to select a dataset, configure parameters such as the number of classes, epochs, and batch size, and initiate the training process while monitoring metrics like Training Loss, Training Accuracy, Validation Loss, and Validation Accuracy, which are updated at each epoch. Once the model has been fully trained, the system enables users to test it on unseen data, providing real-time prediction results. Thus, the system not only offers visualization of model performance during training but also facilitates model usage for prediction and further evaluation, ensuring the practical application of the trained model.

After completing the training phase, the developed model will be used to classify images that it has never seen before. This process aims to test the model's ability to recognize patterns and features from new data that were not included in the training dataset. Fig. 3 illustrates how the model classifies new inputs based on the knowledge acquired during the training process.

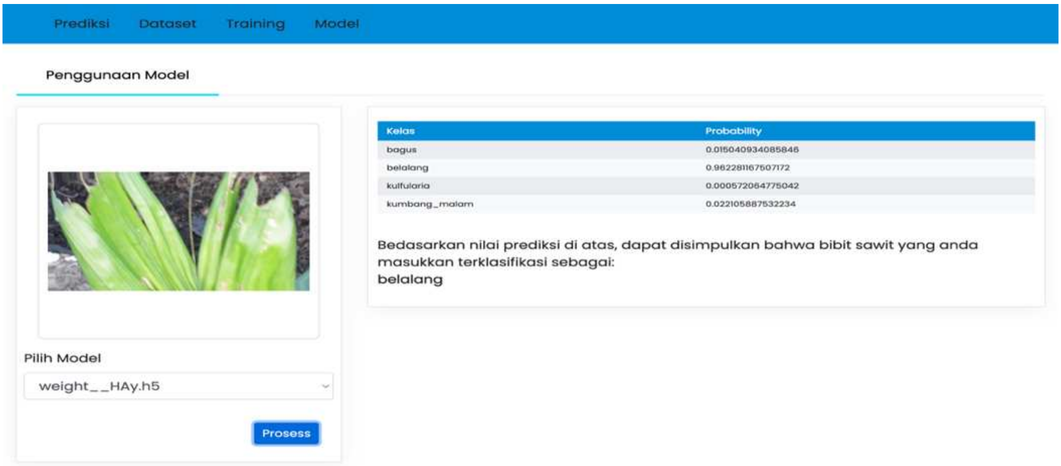

Fig. 3: Model Implementation in web-based application

In Fig. 3, the probability for grasshopper is shown as the highest, with a value of 0.96. Based on this result, it can be concluded that the model's prediction is grasshopper, and in fact, this prediction is correct.

5. Conclusion

This study developed a CNN-based plant disease detection model using the MobileNetV2 to effectively detect diseases in oil palm seedlings. The proposed model demonstrated a significant improvement in training accuracy, increasing from 0.79 in the first epoch to 0.96 by the 15th epoch, along with a stable improvement in validation accuracy, rising from 0.89 in the first epoch to 0.97 by the 15th epoch. The consistent decrease in training and validation loss indicates that the model is becoming increasingly accurate in predicting plant diseases. These results suggest that a leaf image-based system can be used for more efficient disease detection, providing substantial benefits to farmers in early disease identification and management. Implementation of this model into an application enables faster and more accurate disease detection, which can enhance oil palm plantation management and support the sustainability of the agricultural sector.

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