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# Implementation of EfficientNet-B0 CNN Model for Web-Based Strawberry Plant Disease Detection

**Sultan Choirullah Rafi Anggraris[1], Wiyli Yustanti[2]**
[1,2] *Universitas Negeri Surabaya, Surabaya, Indonesia*
sultanchoirullah.21010@mhs.unesa.ac.id, wiyliyustanti@unesa.ac.id

## ABSTRACT

Strawberry production in Indonesia has high economic value but is often hindered by plant diseases that reduce yield quality and quantity. Manual disease identification requires time, cost, and expertise, making it inefficient for farmers. This study proposes a web-based strawberry disease detection system by applying a Convolutional Neural Network (CNN) model using the EfficientNet-B0 architecture. The dataset consists of leaf, fruit, and flower images of strawberries in both healthy and infected conditions. The research followed the CRISP-DM framework, including business understanding, data preparation, modeling, evaluation, and deployment. The model was trained using transfer learning and fine-tuning techniques, with evaluation conducted through a confusion matrix and K-Fold Cross Validation. Experimental results indicate that the EfficientNet-B0 model achieved an overall accuracy of approximately 95.2% and demonstrated stable performance in classifying various strawberry plant diseases. The model achieved perfect accuracy (100%) in several classes such as Healthy Leaf, Leaf Spot, and Healthy Flower, while maintaining high accuracy in other classes like Fruit (95.2%) and Anthracnose Fruit Rot (94.7%), confirming its effectiveness in capturing essential visual features for accurate disease classification. The deployment of the model into a website using the Streamlit framework enables users to upload strawberry images and obtain automatic, fast, and accurate disease detection results. This system is expected to provide a practical solution to help farmers improve productivity and minimize losses caused by plant diseases.

**Keyword:** Convolutional Neural Network, Deep Learning, Disease Detection, EfficientNet-B0, Strawberry.

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**Corresponding Author**
Sultan Choirullah Rafi Anggraris
Universitas Negeri Surabaya, Surabaya, Indonesia
Sultanchoirullah.21010@mhs.unesa.ac.id

## 1. INTRODUCTION

Strawberries (*Fragaria × ananassa*) are among the most economically valuable horticultural commodities, cultivated in both tropical and subtropical regions. In Indonesia, the demand for strawberries continues to grow due to their nutritional value and applications in the food, beverage, and cosmetic industries [1]. However, production is often hindered by diseases such as leaf spot, anthracnose fruit rot, powdery mildew, and gray mold, which reduce both quality and yield [2]. According to the Indonesian Central Bureau of Statistics (BPS), strawberry production increased significantly from 9,860 tons in 2021 to 28,895 tons in 2022 but declined to 27,721 tons in 2023, partly due to plant diseases [3].

Manual disease identification, commonly carried out by farmers or experts, requires time, cost, and specialized knowledge, making it inefficient. This highlights the need for faster, more accurate, and more accessible solutions. Advances in *artificial intelligence* (AI), particularly *deep learning*, have created new opportunities in agriculture. Convolutional Neural Networks (CNNs) are widely recognized for their effectiveness in image classification tasks, as they can extract complex features from visual data [4].

Previous studies have demonstrated the success of CNNs in detecting plant diseases. For instance, ResNet and VGG16 architectures have been applied to corn and rice disease classification, achieving accuracies above 90% [5], [6]. More recently, EfficientNet, introduced in 2019, has gained attention for its balance between accuracy and computational efficiency. EfficientNet-B0, the baseline model, is lightweight yet delivers strong performance, making it highly suitable for web-based applications with limited computational resources [7]. This study proposes the application of the EfficientNet-B0 model for web-based strawberry disease detection. The dataset used consists of 5,000 strawberry images of leaves, fruits, and flowers in both healthy and diseased conditions. The research process followed the CRISP-DM framework, from business understanding to deployment [8]. The model was trained using transfer learning and fine-tuning, then evaluated using a confusion matrix and K-Fold Cross Validation. The results showed that EfficientNet-B0 achieved an average accuracy of 93.2% in detecting strawberry diseases [9].

The novelty of this research lies in the integration of EfficientNet-B0 into a web-based detection system using the Streamlit framework, enabling users to upload strawberry images and obtain real-time disease predictions. While most previous studies were limited to desktop applications or different crops, this study specifically addresses strawberry diseases in Indonesia. The system is expected to provide farmers with a practical tool for early disease diagnosis, thereby improving productivity and reducing losses caused by plant diseases.

## 2. METHODS

This study is classified as applied research with a quantitative approach, aiming to develop a web-based system for detecting strawberry plant diseases using Convolutional Neural Networks (CNN) [10]. The research methodology follows the *Cross-Industry Standard Process for Data Mining* (CRISP-DM), which consists of business understanding, data understanding, data preparation, modeling, evaluation, and deployment phases [11]. The dataset used comprises 5,000 strawberry images of leaves, fruits, and flowers in both healthy and diseased conditions, obtained from public repositories and field documentation. Data collection was carried out through web scraping and direct image acquisition using digital cameras, followed by preprocessing steps such as resizing, normalization, and data augmentation to improve model generalization [12]. The EfficientNet-B0 architecture was selected as the main CNN model due to its balance between accuracy and computational efficiency [13]. The training process applied transfer learning and fine-tuning techniques, while model performance was evaluated using confusion matrix metrics (accuracy, precision, recall, and F1-score) along with K-Fold Cross Validation to ensure robustness [14]. The trained model was then deployed into a web application using the Streamlit framework, enabling users to upload strawberry images and obtain automatic, real-time disease classification results. This methodological framework ensures scientific validity, reproducibility, and practical applicability for supporting strawberry farmers [15].

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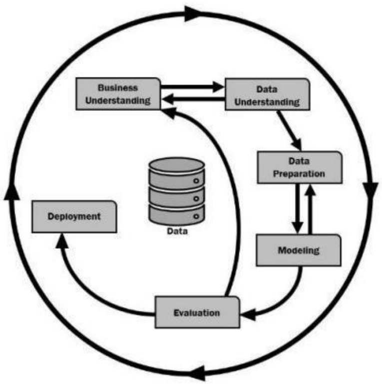


Figure 1. CRISP-DM Arsitecture

## 3. RESULTS AND DISCUSSION

### 3.1 Data Understanding

This stage aims to analyze the dataset used. The dataset from Kaggle was standardized by resizing all images to 224×224 pixels, normalizing them to the range [0,1], and converting them to RGB to match the EfficientNet-B0 architecture. This process reduces noise and improves input consistency.

The distribution of the Strawberry Disease Classification dataset is presented in Table 3.1, which divides the data into training, validation, and testing for three object types: leaf, fruit, and flower.

Table 1 Dataset Distribution per Class

| No | Object Type | Train | Validation | Test | Total |
|---|---|---|---|---|---|
| 1 | Leaf | 1100 | 300 | 600 | 2000 |
| 2 | Fruit | 950 | 200 | 450 | 1600 |
| 3 | Flower | 850 | 114 | 436 | 1400 |
| Total | | 2900 | 614 | 1486 | 5000 |

The dataset consists of strawberry images labeled with diseases on leaves, fruits, and flowers, enabling the model to be trained not only to detect diseases but also to recognize the specific location of infection.

### 3.2 Data Preparation

The Data Preparation phase was carried out to ensure data quality prior to model training, consisting of several key steps. First, *data cleansing* was performed by removing blurry or low- quality images to retain only representative samples. Next, *data augmentation* was applied through transformations such as rotation, shifting, shearing, zooming, and flipping to increase data diversity and prevent overfitting. Class imbalance was addressed using *class weighting* and additional augmentation on minority classes, while the dataset was split using stratified sampling into 70% training, 15% validation, and 15% testing. Furthermore, texture features were extracted using the *Gray Level Co-occurrence Matrix* (GLCM), producing indicators such as contrast, homogeneity, entropy, and energy. These features were normalized using Z- score and combined with CNN features, forming a *hybrid representation* that integrates low-

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level textural and high-level semantic information. This comprehensive preparation ensured high-quality, balanced, and information-rich data, ultimately enhancing the model's accuracy in detecting strawberry plant diseases.

## 3.3 Modeling

In the modeling stage, the system was developed using the EfficientNetB0 CNN architecture due to its efficiency and accuracy in image classification. The process was divided into two steps: (1) classifying strawberry plant organs (leaf, fruit, flower), and (2) detecting diseases specific to each organ. Transfer learning was applied using pre-trained ImageNet weights, where 50% of the early layers were frozen and the remaining layers were fine-tuned to adapt to the strawberry dataset. The model configuration included the Adam optimizer (learning rate 1e-4), categorical crossentropy loss, dropout of 0.4–0.5, and callbacks such as early stopping and reduce learning rate on plateau. The trained models were then saved in *.h5 format for integration into the automated detection system.

Table 2 Hyperparameter Optimization Results of EfficientNet-B0 Model

| Experiment | Optimizer | Learning Rate | Batch Size | Epoch | Dropout | Accuracy (Test) | Loss (Test) |
|---|---|---|---|---|---|---|---|
| 1 | Adam | 0.001 | 32 | 50 | 0.3 | 94.5% | 0.21 |
| 2 | Adam | 0.0005 | 64 | 50 | 0.3 | 95.8% | 0.16 |
| 3 | Adam | 0.0001 | 32 | 50 | 0.4–0.5 | 97.9% | 0.08 |
| 4 | Adam | 0.0001 | 64 | 50 | 0.4 | 96.8% | 0.12 |

Based on the optimization experiments, the best configuration was obtained in experiment 3, with a learning rate of 0.0001, batch size of 32, dropout 0.4–0.5, and early stopping at epoch 38. This configuration achieved the highest test accuracy of 97.9% and the lowest test loss of 0.08. Therefore, this setup was selected as the final model for strawberry disease detection.

## 3.4 Evaluation

The evaluation stage was conducted to assess the performance of the strawberry disease classification model, and the testing results demonstrated good accuracy in recognizing patterns from unseen data.

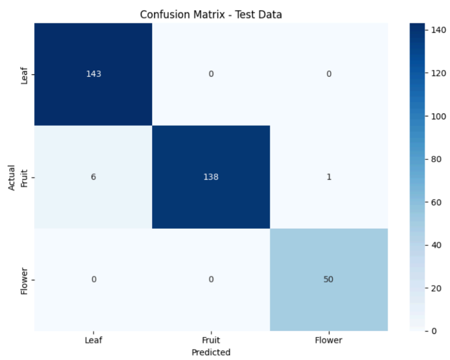


Figure 2. Confusion Matrix Organ Detection.

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The prediction results showed 100% accuracy for the Leaf (143 samples) and Flower (50 samples) classes, while the Fruit class achieved 95.2% accuracy with 138 out of 145 samples correctly classified and 6 misclassified as Leaf.


Figure 3. Confusion Matrix for Fruit Disease Detection

The confusion matrix for fruit disease detection indicates that the model performed reasonably well, although misclassifications occurred among diseases with similar visual symptoms. Out of 38 Anthracnose Fruit Rot samples, 36 were correctly classified and 2 misclassified as Gray Mold. For 41 Gray Mold samples, 33 were correct, 1 was misclassified as Healthy Fruit, and 5 as Powdery Mildew Fruit. Meanwhile, from 36 Powdery Mildew Fruit samples, 25 were correctly classified, 1 was misclassified as Anthracnose Fruit Rot, and 10 as Gray Mold. These results highlight that while the model is reliable, challenges remain in distinguishing certain strawberry fruit diseases with similar visual characteristics.

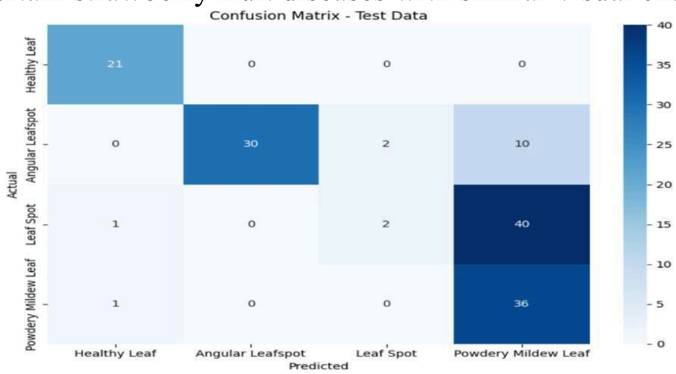


Figure 4. Confusion Matrix for Detecting Leaf Diseases

The confusion matrix for leaf disease detection shows that the model achieved good performance, although some misclassifications occurred among visually similar diseases. All 21 Healthy Leaf samples were correctly classified. Out of 42 Angular Leafspot samples, 30 were correctly classified, 2 misclassified as Leaf Spot, and 10 as Powdery Mildew Leaf. For 43 Leaf Spot samples, 40 were correctly classified, 1 misclassified as Healthy Leaf, and 2 as Angular Leafspot. Overall, the model demonstrated high accuracy but still faced challenges in distinguishing strawberry leaf diseases with similar visual symptoms.

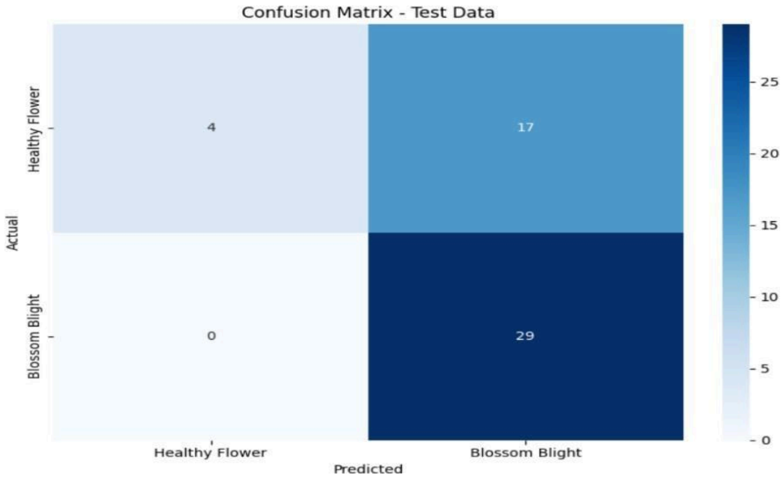

Figure 5. Confusion Matrix for Detecting Flower Diseases

The confusion matrix for flower disease detection shows mixed results. For the Healthy Flower class, only 4 out of 21 samples were correctly classified, while 17 were misclassified as Blossom Blight. In contrast, the Blossom Blight class achieved perfect performance, with all 29 samples correctly classified. This indicates that the model tends to classify flowers as Blossom Blight, even when they are actually healthy, resulting in suboptimal performance for the Healthy Flower class.

### 3.5 Implementation

This web application is designed to help users identify strawberry plant organs (leaves, fruits, or flowers) and detect potential diseases that may affect them. The user interface is kept simple and intuitive using the Streamlit framework, making it accessible even for beginners. The process begins by uploading an image through the provided upload feature, which includes. a designated area labeled "Choose an image" with options for *drag and drop* or "Browse files," along with information on file size limits (200MB) and supported formats (JPG, JPEG, PNG). As shown in the screenshot, a file named *63ba9d9050a26.jpg* was successfully uploaded to the system.

Figure 6. Upload Image

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Once the image is successfully uploaded, the system automatically initiates the analysis process consisting of two stages. The first stage is organ identification, where the machine learning model analyzes the image to determine whether the organ is a leaf, fruit, or flower. For instance, when a strawberry fruit image is uploaded, the application displays the label "🧠 Detected Organ: Fruit (Confidence: 100.0%)," indicating that the organ has been recognized as a fruit. The second stage is disease identification, in which the system applies a model specifically trained for the detected organ. If the detected organ is a fruit, a fruit-specific disease detection model is applied. In the example screenshot, the application shows the result "Health Condition: Anthracnose Fruit Rot (Confidence: 77.2%)," indicating that the strawberry fruit is affected by Anthracnose Fruit Rot with a confidence level of 77.2%.

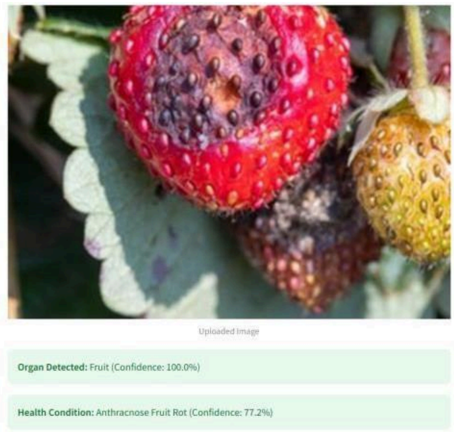


Figure 7. Detection Results

## CONCLUSION

This research has successfully addressed the formulated problem statement by demonstrating that the Convolutional Neural Network (CNN) with the EfficientNet-B0 architecture is effective in detecting and classifying various types of strawberry plant diseases. Using a dataset consisting of strawberry leaves, fruits, and flowers in both healthy and infected Conditions, the model was able to recognize visual patterns that distinguish each class. The evaluation results showed excellent performance, with an overall accuracy of approximately 97.9% based on test data. Moreover, the model achieved perfect accuracy (100%) in several classes such as *Healthy Leaf*, *Leaf Spot*, and *Healthy Flower*, while maintaining high accuracy in others such as *Fruit* (95.2%). These findings confirm that EfficientNet-B0 is highly capable of capturing the essential visual features required for accurate strawberry disease classification.

The theoretical contribution of this research lies in the evidence that EfficientNet-B0 can achieve high accuracy with computational efficiency, particularly in the field of deep learning-based agriculture. In addition, the integration of the trained model into a Streamlit-based web application provides practical value with an interactive and lightweight user interface. The system enables real-time predictions, making advanced technology accessible to non-technical users such as farmers and agricultural practitioners

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