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Web-based CNN Application for Arabica Coffee Leaf Disease Prediction in Smart Agriculture

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Abstract

In the agriculture industry, plant diseases provide difficulty, particularly for Arabica coffee production. Identifying illnesses on the leaves of Arabica coffee is the first step in eradicating and treating diseases to prevent crop failure. With the fast advancement of convolutional neural networks (CNN), Arabica coffee leaf disease may be accurately identified without the assistance of a specialist. In this study, the performance of CNN architecture will be evaluated to examine the classification of Arabica coffee leaf disease pictures by categorizing 5000 image data into five classes: Phoma, Rust, Cescospora, healthy, and Miner. 80:10:10 is the ratio between training data, validation, and testing. In the testing findings, the InceptionResnetV2 and DensNet169 designs had the highest accuracy, at 100%, followed by the MobileNetV2 architecture at 99% and the ResNet50 architecture at 59%. Even though MobileNetV2 is not more accurate than InceptionResnetV2 and DensNet169, MobileNetV2 is the smallest of the three models. The MobileNetV2 paradigm was chosen for web application development. The system accurately identified and advised treatment for Arabica coffee leaf diseases, as shown by the system's implementation outcomes.

Keywords: *Arabica Coffee, Convolutional Neural Networks, Image Processing, Leaf Disease, Machine learning.*

1. Introduction

Coffee is one of the commodities with the greatest demand as an agricultural commodity on the worldwide market, as shown by the large number of exports generated by Indonesian coffee growers in 2020, with a total export volume of 379,35 thousand tons [1]. In the first seven months of 2021/22, Indonesia was the second country to export coffee. Brazil came in first, and India came in third during the same time [2]. Sumatra has the best productivity, according to statistics [1]. However, the output is believed to still be below ideal levels since, as Zen & Budiasih [3] stated, Sumatra has the biggest coffee crop area. In contrast, production in other regions is often negligible and even declines. Due to farmers' lack of understanding, one of the challenges to boosting output, particularly in South Sumatra and Lampung, is controlling organisms that disrupt plants. The fungus Hemileia vastatrix B et Br, which causes leaf rust, is one example of a common plant-disturbing organism that may be difficult to control [4]–[6]. The efficacy of coffee leaf disease management depends on the disease's early discovery and accurate identification [7].

Disease identification and providing the required nutrients have become an important part of farming [8]. When the diagnosis is made using the naked eye, there are high chances of making a wrong diagnosis. Verbal information is usually not scientific and inaccurate, treating harmful diseases with bad chemicals and eventually harming the environment. Depending on naked-eye perception by specialists to recognize plant ailments can be prohibitively costly, particularly in developing nations. Plant infection recognition utilizes image processing strategies. The key to preventing the loss is the accurate detection and classification of leaf diseases [9]. There is great potential and a significant role for image processing and computer vision in agricultural technology. Image processing methods may provide a solution to distinguish between leaves that pests have attacked and those that problems have not harmed [10].

Identifying the disease at an early stage and suggesting the remedy to avoid the maximum harm caused to the crop yield is important. The CNN algorithm is used to classify the disease and suggest remedies [11]. A Convolutional Neural Network (CNN) is a Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects or objects in the image, and differentiate one from the other [12]. Image processing, the internet of things, and computer vision are just some of the technological advancements that have been made in recent years to assist farmers in detecting leaf disease earlier [13]. CNN-based Deep Learning algorithms and transfer learning techniques may be used to identify diseases that affect leaf disease. Using an averaging approach to several Transfer Learning models, including MobileNet, Inception, VGG16, Resnet, and Xception, improves the performance of leaf disease diagnosis [14], [15].

A previous investigation into plant diseases was carried out by Akshay Pandey and Kamal Jain (2022), and their paper was titled "A robust deep attention dense convolutional neural network for plant leaf disease identification and classification from smart phone captured real world images." In this paper, the authors proposed applying a new CNN architecture called DADCNN-5 to obtain classification robustness and higher testing accuracy. Five ADL blocks are stacked to form DADCNN-5, which is then used in a classification procedure that is both efficient and quick. The results of the experiments show that the proposed DADCNN-5 outperforms both the current machine learning designs and the traditional CNN architectures, and it attained an accuracy of 97.33%. The results showed that the sensitivity, specificity, and false positive rates corresponded to 96.57%, 99.94%, and 0.063%. The training procedure for the module lasts roughly 3235 minutes and has an accuracy rate of 99.86% [16].

Leaf image-based plant disease identification utilizing transfer learning and feature fusion was the subject of previous research into plant diseases by Xijian Fan and his associates (2022). This research proposes a feature-fusion-based approach for recognizing damaged leaves on apple trees. By using transfer learning, the traditional InceptionV3 network was enhanced, and its related features were extracted. This makes it possible to combine these features with those obtained using conventional feature extraction techniques, such as HOG, speeding up convergence and lowering training parameters. To recognize apple leaf illnesses, the model was trained with 1821 pictures of apple leaves. The experiment's findings indicate that, after integrating the conventional feature extraction approach, the model's accuracy increased to 93.19%, which is 1.91% greater than the accuracy of the model without the fusion. Following data augmentation during training, the data set's recognition accuracy reaches 99.83% [17].

B. Nageswararao Naik and his colleagues conducted previous research on plant diseases under the title "Detection and classification of chilli leaf disease using a squeeze-and-excitation-based CNN model" in 2022. Five principal leaf diseases, down curl of a leaf, Geminivirus, Cercospora leaf spot, yellow leaf disease, and up curl condition, were discovered in this research. Images of each illness were taken using a digital camera and labeled. Using chili leaf data with and without augmentation using deep learning transfer, these illnesses were diagnosed using 12 distinct pre-trained deep learning networks. Each network's performance was measured using criteria including accuracy, recall, precision, F1-score, specificity, and misclassification. Among all pre-trained deep learning networks on the chili leaf dataset, VGG19 achieved the most excellent accuracy (83.54%) without augmentation, while DarkNet53 got the best performance (98.82%) with augmentation [18].

For this reason, a system is built in this paper that can automatically classify Arabica coffee leaf diseases. The images used are five classes, namely Phoma, Rust, and Cescospora, healthy, and Miner on Arabica coffee plants. The continuous development of digital image processing technology can help solve various daily problems, one of which is image classification. By utilizing the Convolutional Neural Network (CNN) method as a Deep Learning technology, the issue of classifying coffee leaf diseases will be more accessible. CNN was chosen because this method is the most optimal in the case of image classification, where one of the advantages is that image feature extraction is carried out automatically, so it can save time and effort.

2. Research Methods

Outline the actions that will be followed in the process of carrying out this study. The progression of this research is depicted in Figure 1, which can be seen below.

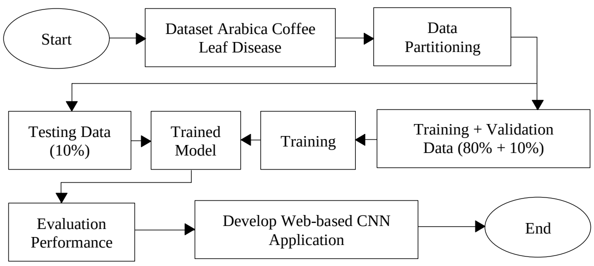

Figure 1. Research Stage Flowchart

2.1. Dataset

At the outset, the picture dataset of Arabica coffee leaf disease from the Mendeley data source is used [19]. The dataset includes 18985 images of healthy coffee leaves, 8337 images of coffee leaves with coffee Rust disease, 16979 images of coffee leaves with coffee leaf Miner, 6572 images of coffee leaves with Phoma leaf spot disease, and 7682 images of coffee leaves with Cescospora leaf spot disease. In total, five image classes were collected which are Phoma, Rust and Cescospora,

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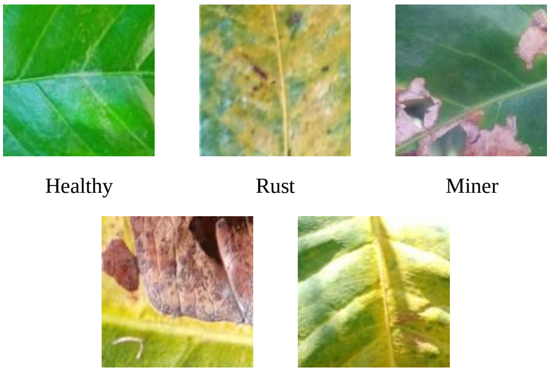
healthy and Miner. There are 58555 picture data in total. The dataset used has been subjected to data pre-processing, including noise filtering, cropping, and data augmentation. Each of the five classes in the dataset, healthy leaves, coffee rust, coffee leaf miner, phoma leaf spot disease, and cercospora leaf spot disease, has its leaf state depicted in Figure 2.



Healthy Rust Miner

Phoma Cercospora

Figure 2. Sample images on each class

2.2. Data Partitioning

In the second phase, the dataset undergoes preliminary processing, such as data splitting, to create distinct data sets for training, testing, and validation. Model training requires training and validation data, while test data is used for making predictions about data that has not yet been observed using learned models. The data for coffee leaf disease will be divided into 80% for training, 10% for validation, and 10% for testing. Furthermore, there are 5000 datasets, with 4000 serving as training data, 500 serving as validation data, and 500 serving as test data. In addition, training data is used to educate the CNN model.

2.3. Model Architecture

The Keras library provides several common classification methods. In this paper, we investigate the efficacy of four different neural network architectures, ResNet50, InceptionResNetV2, MobileNetV2, and DensNet169, using a dataset including information on Arabica coffee leaf disease. These models were trained via transfer learning. Following is a description of the four neural network topologies currently in use:

1. ResNet50
   ResNet50, or Residual Networks, is a 50-layered model that incorporates the notion of skipping layers, which enables the model to skip layers at times, so reducing overfitting, resolving the issue of vanishing gradient, and allowing upper layers to perform as well as lower ones [20].

2. InceptionResNetV2
   InceptionResNetV2 integrated the concept of very deep inception architecture with residual connections. This design dramatically expedited the training of such deep neural networks [21].

3. MobileNetV2
   MobileNetV2 incorporates a unique layer module, the inverted residual with linear bottleneck, greatly decreasing the amount of memory required for processing [22].

4. DensNet169
   The encoding route comprises 169-layer DenseNet as the network architecture's backbone. Each layer of the DenseNet takes input from the layer below it and delivers its output to the layer above it [23].

2.4. Evaluation Performance

This research assessed the network performance using the precision, recall, accuracy, and F1-score assessment indices. Precision and recall are both inside the interval [0,1], as shown by Equations (1)-(4). Precision reflects the fraction of actual instances among the detected photos within the prediction results. The recall is the fraction of real cases within all test set samples. Accuracy is the average of all behavioral accuracy rates, and the greater the figure, the greater the algorithm's recognition accuracy. The F1-score represents the harmonic mean of precision and recall-the greater the value, the greater the algorithm's efficiency [24].

$$recall = \frac{TP}{TP+FN} \tag{1}$$

$$precision = \frac{TP}{TP+TN} \tag{2}$$

$$accuary = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$F1 - score = \frac{2 * precision * recall}{precision + recall} \tag{4}$$

2.5. Develop Web-based CNN Application

The model saved in the .hdf5 file is then loaded and passed as a parameter to the prediction function. The WebApp is then improvised on the application front by adding custom HTML and CSS using the markdown API provided by the Streamlit library. The WebApp is tested for its true functionality by running it on localhost:8501. And the website is propagated as a publicly accessible URL using a Streamlit share.

3. Results and Discussions

The findings of each experiment are discussed in the section that follows. On both training and validation sets of data, experiments were conducted using architectural models such as CNN ResNet50,

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InceptionResNetV2, MobileNetV2, and DenseNet169. This experiment aims to determine the accuracy, loss, and computation time requirements for each architectural model during the data training phase. Ten training epochs will be used for this experiment—table 1 displays each CNN architecture's accuracy, loss, and training calculation time.

Table 1. Four models' performance after ten training iterations

CNN Arsitektur	Train Acc (%)	Val Acc (%)	Train Loss	Val Loss	Time (Minute)
ResNet50	100.00	60.80	0.335	1.539	450.58
Inception ResNetV2	100.00	100.0	1.071	1.168	501.54
MobileNet V2	99.95	98.40	0.190	0.209	126.29
DensNet 169	100.00	100.0	0.184	0.158	663.47

The CNN architectural models InceptionResnetV2 and DensNet169 with the highest validation accuracy are InceptionResnetV2 and DensNet169 with a validation accuracy rating of 100.0%. Then, MobileNetV2 architecture, with 98.40% accuracy, was followed by ResNet50 architecture, with 60.80% accuracy. DensNet169 and InceptionResnetV2 have the highest accuracy of all trained architectures but need the most computing time to complete ten training epochs (663.47 and 501.54 minutes, respectively). MobileNetV2 reaches ten epochs in the shortest time, 126.29 minutes, followed by ResNet50 with 450.58 minutes of processing time.

The training loss of each trained CNN architectural model is also shown in Table 3. DensNet169, with a value of 0.184, is the architecture with the lowest training loss, followed by MobileNetV2, with a value of 0.190, ResNet50, with a value of 0.335; and InceptionResnetV2, with a value of 1.071. Figures 3-6 show the accuracy and loss charts used throughout the training process.

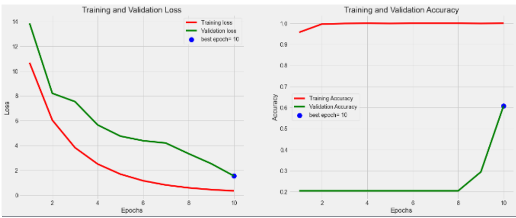

Figure 3. Accuracy dan loss training ResNet50

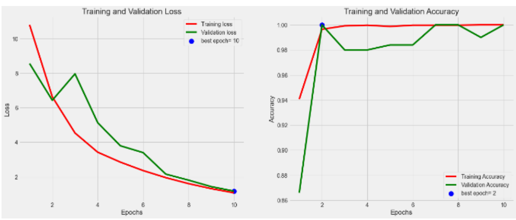

Figure 4. Accuracy dan loss training InceptionResnetV2

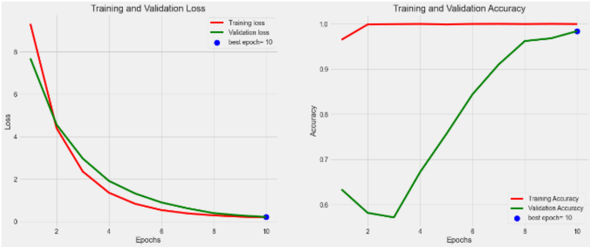

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Figure 5. Accuracy dan loss training MobileNetV2

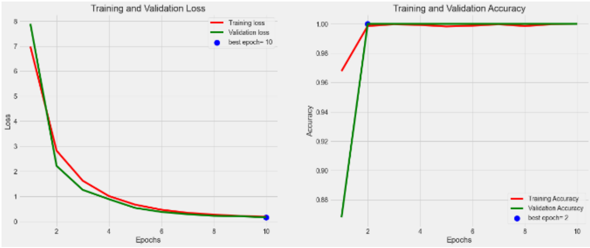

Figure 6. Accuracy dan loss training DensNet169

Table 2. Evaluation of model training with data testing

CNN Arsitektur	Test Acc (%)	Precision (%)	Recall (%)	F1 score (%)	Size (MB)
ResNet50	59	84	61	60	282
Inception ResNetV2	100	100	100	100	633
MobileNet V2	99	99	99	99	34
DensNet 169	100	100	100	100	156

The confusion matrix with data testing for the ResNet50 architecture is shown in Figure 7. There are 204 samples with misclassified data out of the 500 samples analyzed. Figure 7 displays the 69 samples of incorrectly classified Phoma class data, 57 samples of incorrectly classified Phoma class data, 6 incorrectly classified Healthy data samples, and 72 incorrectly classified Cerscospora class data samples. Table 2 displays the accuracy, precision, recall, and F1 Score results.

The findings of the InceptionResnetV2 architecture model confusion matrix with data testing are shown in Figure 8. No data were misclassified among the 500 samples that were analyzed. Figure 8 illustrates that all data were accurately categorized—table 2 displays the accuracy, precision, recall, and F1 score values.

The confusion matrix with data testing for the MobileNetV2 architectural model is shown in Figure 9. There are five examples of misclassified data out of the 500 samples analyzed. Figure 9 shows two examples of misclassified Phoma class data and three misclassified Miner class data samples. Table 2 displays the accuracy, precision, recall, and F1 Score results.

The confusion matrix with data testing for the DensNet169 architecture is shown in Figure 10. No data from the 500 samples analyzed were misclassified. According to Figure 10, all data were appropriately

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categorized. Table 2 shows the accuracy, precision, recall, and F1 score data.

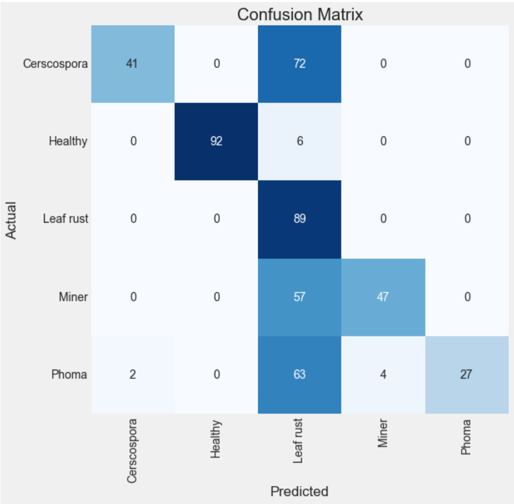

Figure 7. Confusion matrix of ResNet50

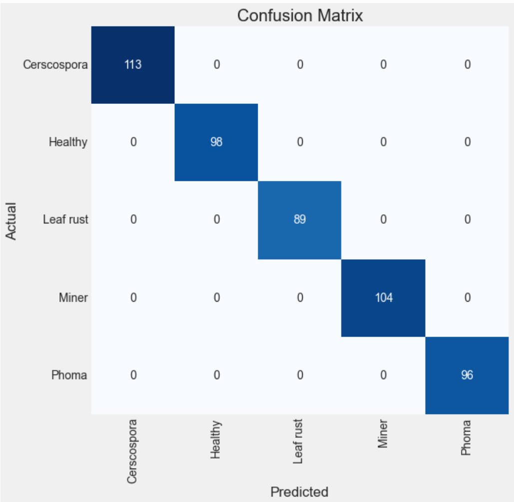

Figure 8. Confusion matrix of InceptionResnetV2

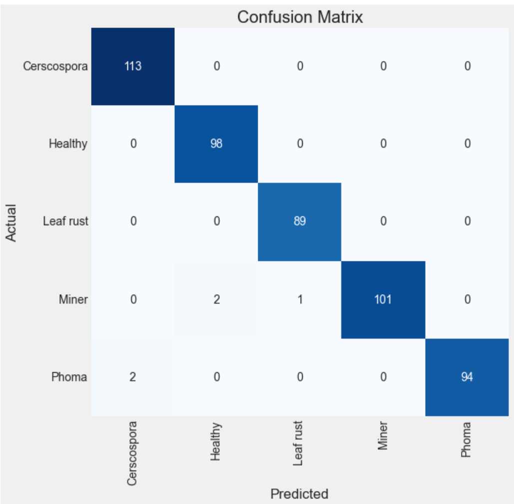

Figure 9. Confusion matrix of MobileNetV2

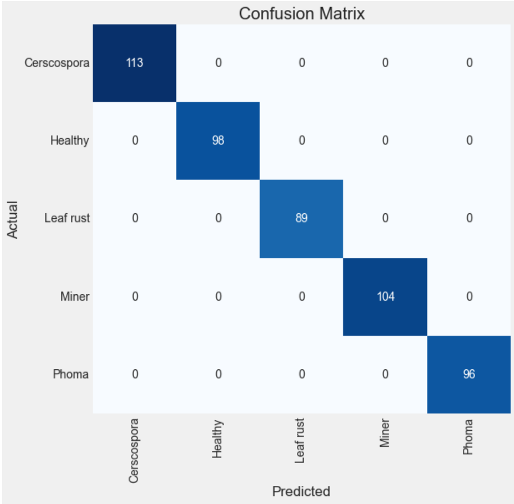

Figure 10. Confusion matrix of DensNet169

Even though MobileNetV2 is only 99% accurate, whereas InceptionResnetV2 and DensNet169 are 100% correct, MobileNetV2 is the smallest network topology, measuring just 34 MB in size. To develop a web application, the MobileNetV2 paradigm was chosen. A simple model is required to provide quicker picture prediction in a web application. It has been effectively determined if an Arabica coffee leaf is healthy or sick, and treatment options are given for sick leaves. When we launch our online application, the initial screen includes options to choose a picture and make predictions. When we choose a picture, we have a variety of possibilities. The alternatives are directly capturing from the camera or importing pictures from the gallery. We can capture the images we want by selecting any one of the options. The image must be sharp and focused. The create prediction button must then be clicked to determine if the Arabica coffee leaf is healthy or unhealthy. Since we have already trained the system with our datasets, using the create prediction button will only take a short while since there is no ongoing training process. If the photograph is of a sick Arabica coffee leaf, it will identify the afflicted plant, describe its ailment, and provide remedies. Figures 11, 12, and 13 depict what is occurring with the application's front end. The prototype system has a user-friendly interface that enables speedy retrieval of diagnostic findings and simply uploading test photos, demonstrating its viability in distant field conditions. You may access the prototype system at https://mlforarabicacoffee.herokuapp.com.

4. Conclusion

InceptionResnetV2 and DensNet169 are the most accurate architectures for classifying Arabica coffee leaf disease based on an evaluation of each CNN model's experimental results. The accuracy of MobileNetV2 architecture is 99%, whereas ResNet50 architecture is 59%. Even though MobileNetV2 is not more accurate than InceptionResnetV2 and DensNet169, MobileNetV2 is the smallest of the three models. The MobileNetV2 paradigm was chosen for web application development. The algorithm has been taught to correctly diagnose the illness of new plants supplied by the user through the phone's camera or gallery. Using a content-based filtering recommender system method, the system could suggest treatment for the identified ailment. The created web application is quick, lightweight, and produces excellent results. Some optimization approaches will be used for the application in future development. Using IoT, sensor statistics will connect the application to provide the farmer with individualized data.

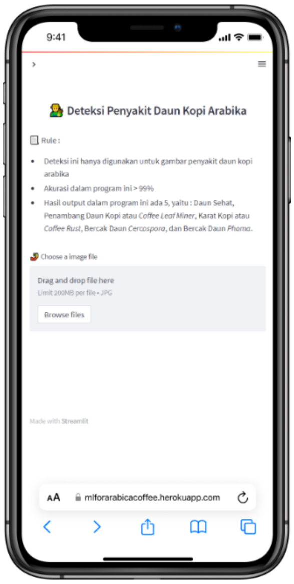

Figure 11. Home screen

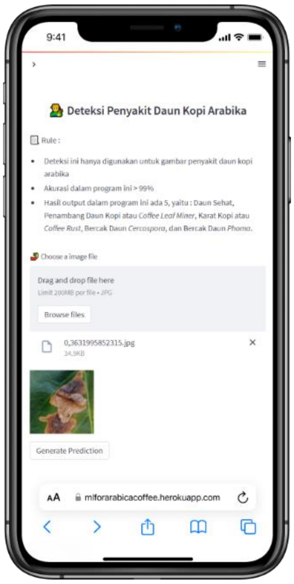

Figure 12. The view image selected

Figure 13. Result of the processed image

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