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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. A first step in eliminating and treating infections to avoid crop damage is recognizing ailments on Arabica coffee leaves. Convolutional neural networks (CNN) are rapidly advancing, making it possible to diagnose Arabica coffee leaf damage without a specialist's help. CNN is aimed to find features adaptively through backpropagation by adding layers including convolutional layers and pooling layers. This study aims to optimize and increase the accuracy of Arabica coffee leaf disease classification utilizing the neural network architectures: ResNet50, InceptionResNetV4, MobileNetV2, and DensNet169. Additionally, this research presents an interactive web platform integrated with the Arabica coffee leaf disease prediction system. Inside this research, 5000 image data points will be divided into five classes—Phoma, Rust, Cescospora, healthy, and Miner—to assess the efficacy of CNN architecture in classifying images of Arabica coffee leaf disease. 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. One such plant-disturbing organism that may be challenging to manage is the fungus *Hemileia vastatrix* B et Br, which produces leaf rust [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]. There is a substantial risk of making a false diagnosis when making a diagnosis with an unaided eye. Verbal knowledge is often non-scientific, imprecise, and ultimately destructive to the environment by treating dangerous illnesses with poor chemicals. Experts might be prohibitively expensive to diagnose plant problems with their naked eyes, especially in impoverished countries. 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]. Early disease detection and treatment recommendations are crucial to preventing the greatest possible loss in crop production. The illness is classified using the CNN algorithm, which also offers treatments [11]. CNN is a

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Deep Learning system that can analyze an input picture, give relevance (learning biases and weights) to various characteristics or objects in the image, and discriminate between them [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].

Akshay Pandey and Kamal Jain's inquiry into plant illnesses was conducted in the past, and their publication from 2022 presents a powerful deep attention dense convolutional neural network for identifying and classifying plant leaf diseases from real-world photos taken by a smart phone. The authors of this article suggested using the DADCNN-5 CNN architecture to improve testing accuracy and classification resilience. The DADCNN-5, made up of five ADL blocks, is utilized in a rapid and effective categorization process. The trials' findings demonstrate that the suggested DADCNN-5 works better than the existing machine learning schemes and the conventional CNN architectures, achieving an accuracy of 97.33%. According to the findings, the sensitivity, specificity, and false positives rates were 96.57%, 99.94%, and 0.063%, respectively. The module's training process lasts around 3235 minutes and has a 99.86% accuracy rate [16].

Previous plant disease research by Xijian Fan and colleagues focused on detecting plant diseases based on leaf images using transfer learning and feature fusion (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].

Prior work on identifying and categorizing chili leaf illness using a squeeze and excitation-based CNN model was carried out in 2022 by B. Nageswararao Naik and colleagues. Five principal leaf diseases, up curl condition, down curl of a leaf, yellow leaf disease, Geminivirus, and Cercospora leaf spot, were discovered in this research. Images of each illness were taken using a digital camera and labelled. These diseases were identified using 12 different pre-trained deep learning networks utilizing the chili leaf dataset with and without reinforcement on deep learning transfer. Each network's performance was measured using criteria including recall, accuracy, misclassification, precision, specificity, and F1-score. On the chili leaf dataset, VGG19 had the highest accuracy (83.54%) among all pre-trained deep learning networks, whereas DarkNet53 had the highest performance (98.82%) after 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 healthy leaves, coffee rust, coffee leaf miner, phoma leaf spot disease, and cercospora leaf spot disease 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 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. The main contribution of this paper is as follows: Arabica coffee leaf disease prediction: This paper provides an algorithm to predict the Arabica coffee leaf disease based on the given symptoms using state-of-the-art machine learning classification algorithms; Analysis of the results of model accuracy and size: Based on previous studies [19], [20], researchers tried to compare other models. The models used in this research are neural network architectures: ResNet50, InceptionResNetV2, MobileNetV2, and DensNet169; Web-based interactive platform: The study also presents an interactive platform integrated with the disease prediction system along with other essential features for a more Arabica coffee leaf disease management system.

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. Next, alter the dataset's images' resolutions. Data grouping findings will then be processed after the data partitioning step. The model will be trained using the training and validation data, and the test data will be utilized to verify the test findings using the model and parameters that have been defined. Using a dataset that contains data on Arabica coffee leaf disease, we examine the effectiveness of four distinct neural network architectures: ResNet50, InceptionResNetV2, MobileNetV2, and DensNet169.

The best neural network architecture will be selected and used to develop a web-based CNN application.

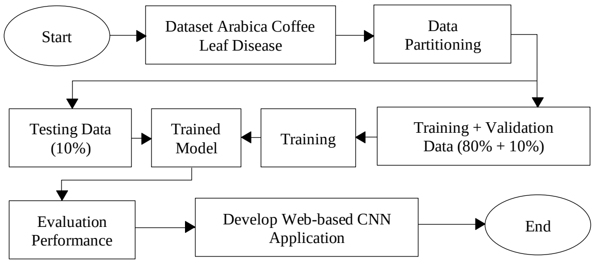

Figure 1. Research Stage Flowchart

2.1 Dataset

At the outset, the picture dataset of Arabica coffee leaf disease from the Mendeley data source is used [21]. 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 healthy leaves, coffee rust, coffee leaf miner, phoma leaf spot disease, and cercospora leaf spot disease. 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.

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 and use the default architecture of each model. Following is a description of the four neural network topologies currently in use:

ResNet50, short for residual networks, is a 50-layer model that uses the concept of skipping levels to reduce overfitting, solve the problem of vanishing gradient, and ensure that higher layers function as well as lower ones [22]. Figure 3 shows the detailed architecture of the ResNet50 [23].

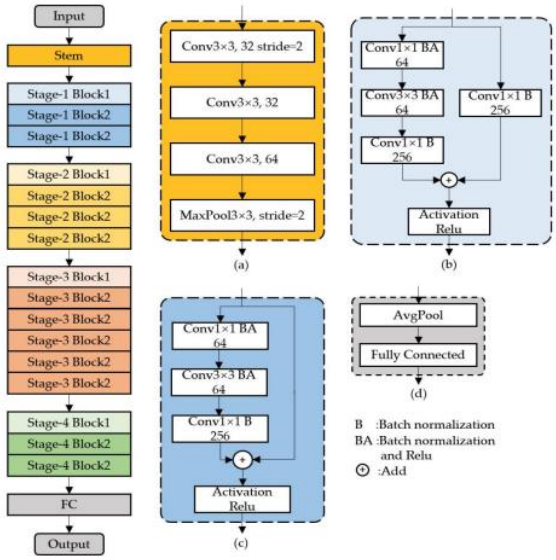

Figure 3. Resnet50 Architecture

InceptionResNetV2 integrated the concept of very deep inception architecture with residual connections. This design dramatically expedited the training of such deep neural networks [24]. Figure 4 shows the basic architecture of the InceptionResNetV2 [25].

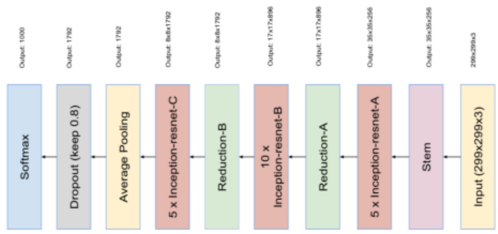

Figure 4. InceptionResNetV2 Architecture

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MobileNetV2 incorporates a unique layer module, the inverted residual with linear bottleneck, greatly decreasing the amount of memory required for processing [26]. Figure 5 shows the detailed architecture of the MobileNetV2 [27].

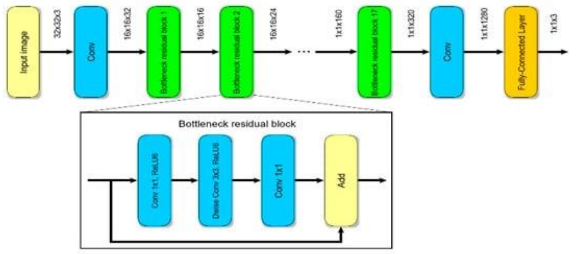

Figure 5. MobileNetV2 Architecture

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 [28]. The layered architecture of the DenseNet169 presented in Figure 6 [29].

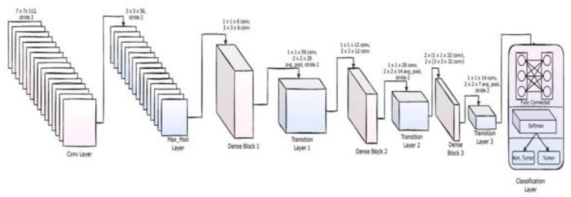

Figure 6. DensNet169 Architecture

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 [30].

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

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

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

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

2.5 Develop Web-based CNN Application

The model recorded in the.hdf5 file is then loaded and supplied to the prediction function as a parameter. The Streamlit library provides a markdown API that can be used to modify the appearance of the WebApp via the addition of custom HTML and CSS. The Web application's genuine functionality is checked by executing it on localhost:8501. Using Streamlit sharing, the website is propagated as a publicly available URL.

3. Results and Discussions

The architecture of the Convolutional Neural Network (CNN) model proposed in this study consists of the input layer, convolution layer, pooling layer, dropout layer, batch normalization, and fully connected layer. In the convolution layer, the filter used has a value of (32, 64, 128, 256), the kernel size to be used is a value of (3, 3), the stride has a value of 1, padding has the same value, and the activation used is Swish. The pooling layer will use max-pooling with a pool size of (3, 3) and the same padding value. The dropout layer will be divided into two parts based on its location, on the fully connected layer and after the pooling layer. This research used the hyperparameter tuning method to determine the optimizer parameters, dropouts on the fully connected layer, dropouts after the pooling layer, and the right dense layer for the proposed model. Model training when hyperparameters are carried out using 10 epochs. Detailed parameters to be compared during hyperparameter tuning can be seen in Table 1. This study uses Adam optimization to optimize hyperparameters. Adam optimizer is a well-known algorithm that adaptive gradient-based momentum updates learning rates using the past gradients.

Table 1. Compared during hyperparameter

	Parameter
Optimizer	Adam, Adamax
Dropout after pooling layer	0.05, 0,1
Dropout fully connected layer	0.25, 0,1
Dense layer	64, 128

The findings of each experiment are discussed in the section that follows. Experiments were carried out employing architectural models such CNN ResNet50, InceptionResNetV2, MobileNetV2, and DenseNet169 on both training and validation sets of data. During the data training phase, this experiment assesses each architectural model's accuracy, loss, and computation time requirements. Ten training epochs will be used for this experiment—table 2 displays each CNN architecture's accuracy, loss, and training calculation time.

Table 2. Four models' performance after ten training iterations

CNN Architecture	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

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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 completes ten epochs in the least amount of time, 126.29 minutes, followed by ResNet50 at 450.58 minutes.

Also included in Table 2 is the training loss for each CNN architecture model. The architecture with the lowest training loss is DensNet169 (0.184), followed by MobileNetV2 (0.190), ResNet50 (0.335), and InceptionResnetV2 (1.071). These accuracy and loss charts (Figures 3-6) were utilized extensively throughout training.

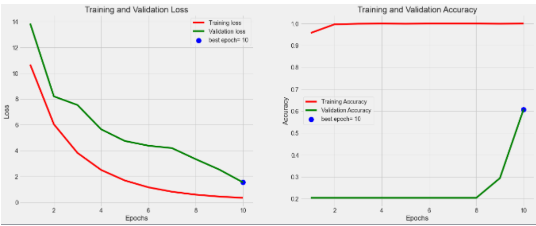

Figure 3. ResNet50 accuracy and loss training

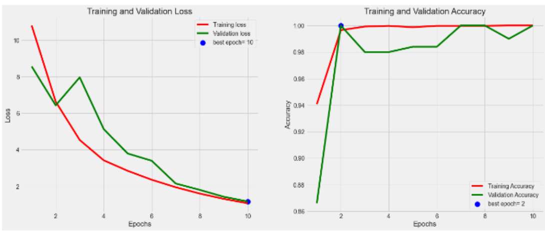

Figure 4. InceptionResnetV2 accuracy and loss training

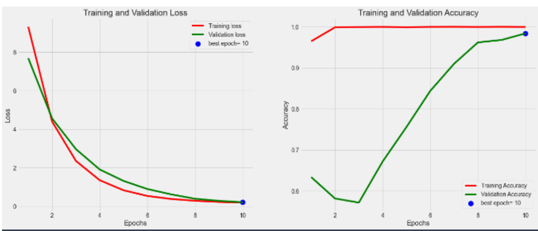

Figure 5. MobileNetV2 accuracy and loss training

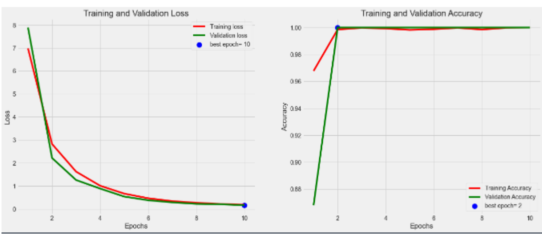

Figure 6. DensNet169 accuracy and loss training

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.

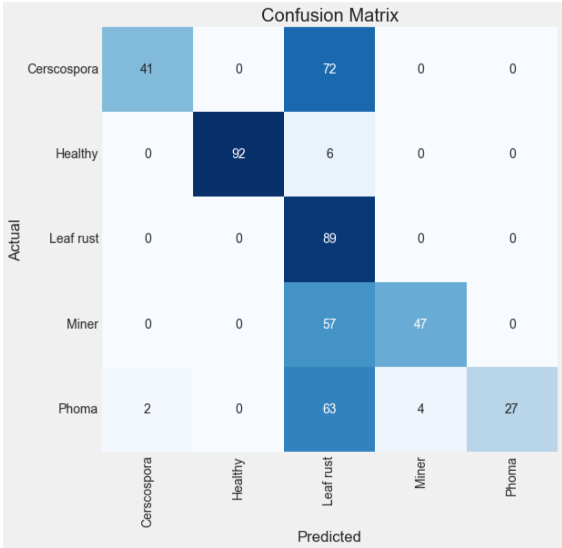

Figure 7. Matrix of ResNet50 Confusion

Table 3 displays the accuracy, precision, recall, and F1 Score results.

Table 3. Testing of data and evaluation of model training

CNN Architecture	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

Figure 8 displays the data testing results on the confusion matrix generated by the InceptionResnetV2 architecture model. No data were misclassified among the 500 samples that were analyzed. Figure 8 illustrates that all data were accurately categorized—table 3 displays the accuracy, precision, recall, and F1 score values.

Figure 9 presents the confusion matrix for the MobileNetV2 architectural model, along with the data testing results. 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 3 displays the accuracy, precision, recall, and F1 Score results.

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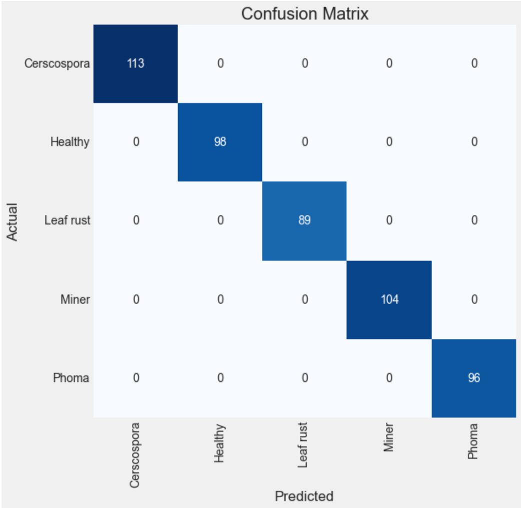

Figure 8. Matrix of InceptionResnetV2 Confusion

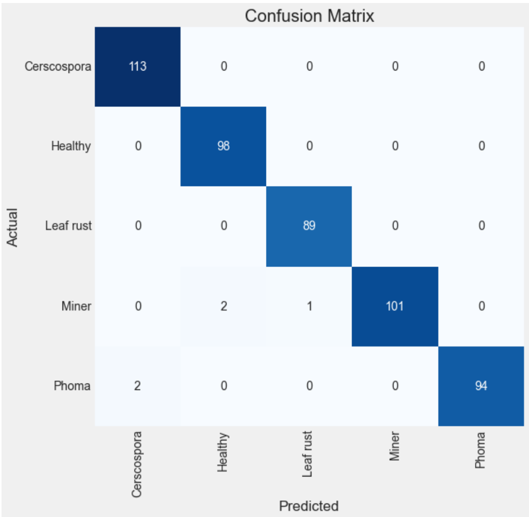

Figure 9. Matrix of MobileNetV2 Confusion

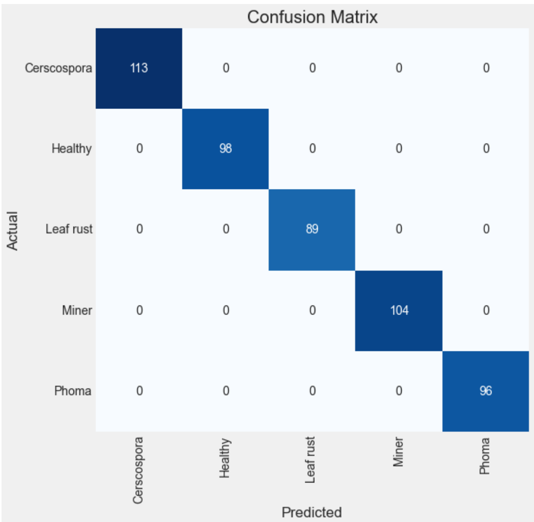

Figure 10. Matrix of DensNet169 Confusion

Figure 10 depicts the confusion matrix with data testing for the DensNet169 architecture. The 500 samples that were tested yielded no misclassified data. Figure 10 shows that all data were correctly classified. The statistics for accuracy, precision, recall, and F1 score are shown in Table 3.

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.

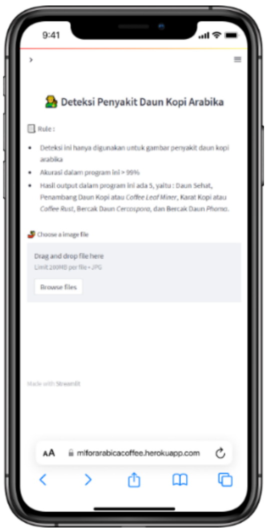

Figure 11. Home screen

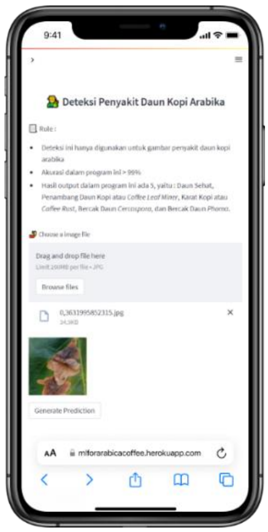

Figure 12. The view image selected

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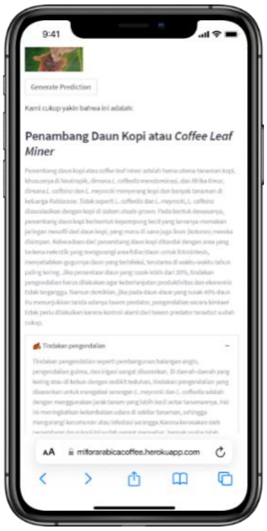

Figure 13. Result of the processed image

4. Conclusion

The difference between this study and that conducted by Putra [19] lies in the method used. Putra uses Arabica and Robusta coffee plants as a dataset and gets results the highest accuracy of 97.67% compared to LeNet, AlexNet, ResNet-50, and GoogleNet with an accuracy rate of 97.20%, 95.10 %, 72.35%, and 82.16%, respectively. In this study, it succeeded in surpassing Putra's results with the MobileNetV2 architecture, which reached 99% accuracy. 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.

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