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I-NusaPlant Apps: Indonesian Medical Plants Leaf Identification Using Convolutional Neural Network with Pre-trained Model MobileNetV2

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Abstract

Indonesia has about 30,000 different kinds of medicinal plants, a huge number compared to the total of 40,000 that exist worldwide. Along with other Asian countries like China and India, Indonesia has one of the highest concentrations of medicinal plants globally. Identifying functional medicinal plants requires expertise, but the number of such experts is quite limited. Convolutional Neural Networks (CNNs) and transfer learning have proven to be effective tools for identifying Indonesian medicinal plants, as these methods are highly accurate in object classification tasks. Transfer learning, in particular, accelerates the process and enhances accuracy by reusing knowledge from prior training. This study used 5000 images divided into 20 categories. The MobileNetV2 model was conducted, achieving 100% accuracy across all categories during the experiments. The method for identifying Indonesian medicinal plants developed in this study has been implemented in the I-NusaPlant mobile-based application. The app was tested for performance, demonstrating a maximum usage of 17% CPU and 197 MB of memory. It is compatible with all Android versions from 8.0 to 13.

Keywords: *Convolutional neural network, image classification, Indonesian medical plants, transfer learning.*

INTRODUCTION

Indonesia boasts an extraordinary level of biodiversity, hosting 22,500 of the world's 422,000 plant species (Schippmann *et al.* 2002). For centuries, plants have been used for medicinal purposes, and Indonesia, alongside other Asian countries like China and India, remains one of the primary regions utilizing medicinal plants (Schippmann *et al.* 2002). Researchers, students, and practitioners have identified numerous medicinal plants through surveys and ethnobotanical studies conducted in various locations across Indonesia. However, despite this rich biodiversity, only 1,000 out of Indonesia's 22,500 native plant species—just 4.4%—are currently utilized in traditional medicine (Schippmann *et al.* 2002). This limited use reflects a broader issue: much of Indonesia's biodiversity remains inaccessible to the general public due to a lack of readily available information.

The knowledge base of Asian medicinal plants is essential for effective conservation and sustainable use (Astutik *et al.* 2019). This requires knowledge of species names, local names, medicinal use, and parts used (Rahayu *et al.* 2020). Identifying medicinal plants has traditionally relied on examining their physical features, which requires significant expertise and experience. Problems that arise in identifying medicinal plants in Indonesia include the limited number of local people who know and understand the diversity of medicinal plants and their benefits (Rahayu *et al.* 2020), the limited number of guidebooks for identifying medicinal plants and often these guidebooks have many pages, making them difficult to carry to the field, and also the limited number of taxonomist that can scientifically identify the vast number of plant species (Herdiyeni *et al.* 2013; Jadid *et al.* 2020).

The identification process becomes even more challenging as experienced researchers retire, and technological advancements in this area lag. Addressing these challenges requires

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innovative solutions, such as developing systems that leverage digital tools to identify medicinal plant species. One promising approach is using digital image-based leaf morphology for classification (Zhang *et al.* 2020). Plants can be classified based on their leaves' shape, colour, texture, and structure. Classifying leaves plays a fundamental role in studying how plants have evolved and become different (Roopashree and Anitha 2021).

Advancements in technology have enabled image classification to be applied in various fields, including medicine, business, agriculture, defense, and maritime affairs. Image classification aims to classify input images into predefined classes. Computer vision is a science that adapts human abilities to understand information from digital images so that computers can recognize objects in images as humans do (Nixon and Aguado 2019). Medicinal plant identification, often performed through visual observation, can leverage computer vision to analyze leaves' shapes, textures, and colours (Camargo and Smith 2009). This method is cost-effective, easy to use, non-invasive, and does not harm plants (Vibhute and K. Bodhe 2012; Brosnan and Sun 2004). The resulting systems can be deployed on computers, providing the public with an accessible tool to identify medicinal plants.

An approach often used in the computer vision domain is using Artificial Neural Network (ANN) (de Oliveira *et al.* 2016). ANN is an artificial intelligence algorithm that can learn from data and does not require a long time to create a model (Abiodun *et al.* 2018). However, ANN has a weakness: it requires image segmentation and extraction processes to produce optimal performance. One development of ANN that can handle this problem is the Convolutional Neural Network (CNN). CNN is a type of deep learning that can be used to identify objects in digital images (Razavian *et al.* 2014). Deep learning, a subset of artificial intelligence, utilizes multi-layered neural networks to solve problems ranging from simple to highly complex (Ian Goodfellow and Yoshua Bengio 2016). Unlike machine learning techniques, which require manual feature selection, deep learning automatically extracts features directly from the input data (Lecun *et al.* 2015). Many deep-learning applications have demonstrated success in recognizing leaf images (Arsenovic *et al.* 2019).

Building a detection model using the CNN algorithm can be done using two techniques: 1) building and training a CNN model from scratch and 2) using the transfer learning method using an existing (ready-to-use) model without retraining (Dalklran *et al.* 2023). Deep learning's multi-layered architecture, coupled with high-performance computing techniques, enables it to process vast amounts of data. However, the need for millions of data points to train a deep neural network from scratch can be prohibitively expensive for researchers. Given the small size of the custom dataset, training a Convolutional Neural Network (CNN) from scratch would be suboptimal, as CNNs typically require larger datasets for effective evaluation. Transfer learning provides a more suitable approach, enabling the training of CNN models on smaller datasets while reducing training time and mitigating overfitting (Iman *et al.* 2023). The method is to reuse knowledge from existing pre-trained models for other tasks. This transfer-learning method can be used for classification, regression, and clustering (Tammina 2019).

There are several well-known CNN architectures, including AlexNet (Krizhevsky *et al.*_2017), VGG16 (Simonyan and Zisserman 2015), InceptionV3(Szegedy *et al.* 2016), ResNet (He *et al.* 2016), and MobileNetV2 (Sandler *et al.* 2018), which are widely used in image processing and classification tasks. Convolution operations play a crucial role in these tasks. However, large and deep network structures, such as those found in AlexNet, VGG16, InceptionV3, and ResNet, can lead to increased processing time and computational cost. In contrast, MobileNetV2 uses an inverse residual structure and linear bottleneck design, which reduces computational complexity and enhances memory efficiency. This makes MobileNetV2 particularly well-suited for mobile applications. Gulzar's study on fruit image classification highlighted MobileNetV2's superior performance over other models. While VGG16 showed lower accuracy, and InceptionV3 performed marginally better than AlexNet and ResNet, MobileNetV2 consistently outperformed all (Gulzar 2023).

This research addresses the challenge of medicinal plant identification using AI technology and the CNN transfer learning approach. The study aims to develop a model based on pre-trained architectures and implement a digital image-based system for classifying medicinal plant leaves. Recognizing that vegetation surveys often occur in remote areas with limited access to cloud computing, the research focuses on creating a mobile application. This application will identify plant species and provide detailed recommendations for medicinal plants, offering a practical solution for researchers and the general public alike.

METHOD

The complete sequence of the proposed research methodology is illustrated in Figure 1. In this study, we collected publicly available medical plant leaf images from well-known sources, Kaggle and Mendeley, and combined them to create a dataset. To prepare the images for the CNN model, they were resized to a uniform size, a critical step to ensure consistent processing by the model. Additionally, the dataset was divided into training and validation subsets. This division allowed the model to learn patterns from the training data and be evaluated on the validation data, ensuring its ability to generalize to unseen images effectively.

To enhance the model's performance, pre-trained CNN models were fine-tuned using the medicinal plant leaf dataset. This fine-tuning process utilizes knowledge gained from large-scale image datasets, thereby improving accuracy and reducing the need for extensive training on smaller datasets. The model's performance was then assessed to evaluate its strengths, weaknesses, and overall effectiveness in classifying medical plants. For the augmentation task, data preparation and the Tensorflow and Keras libraries have been utilized. Figure 1 illustrates a step-by-step process of our proposed methodology, which employs transfer learning on pre-trained convolutional neural networks (CNNs).

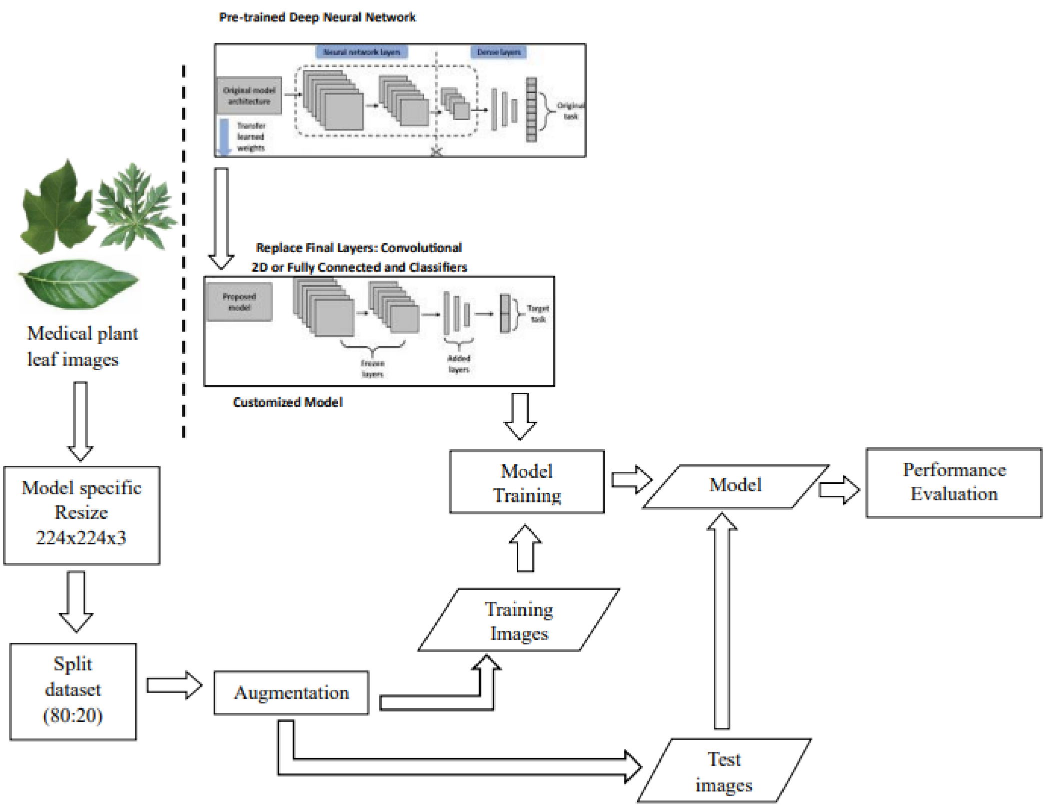

Figure 1 The overall flow of model development

Dataset

Medicinal plant leaf images were collected from reputable sources, including Mendeley and Kaggle. This dataset comprises 640 images from 20 distinct types of medicinal plant leaves.

Data Preprocessing

The acquired data is appropriately labeled based on their respective classes throughout the labeling procedure. Next, the preprocessing step is performed to standardize the pixel dimensions between two images. The objective is to decrease the picture value and enhance its accessibility throughout the training process due to the high computational expenses and time-consuming nature of deep learning (Shorten and Khoshgoftaar 2019). Using the TensorFlow library, images were resized to a uniform dimension of 224x224 pixels, facilitating an efficient and less resource-intensive training process.

Data Augmentation

Data augmentation was used to artificially expand the dataset by generating additional training samples. This method is particularly beneficial for overcoming limitations posed by small datasets, as deep learning models generally perform better with larger datasets (Mikołajczyk and Grochowski 2018). Augmentation helps improve model accuracy and reduces the risk of overfitting (Hirahara *et al.* 2020). The parameters used in this research are zoom_range with a value of 0.2, fill_mode with the nearest value, rotation_range with a value of 20, width_shift_range with a value of 0.2, height_shift_range with value 0.2, shear_range with value 0.2, and horizontal_flip with value true. Figure 2 shows the sample data from the augmentation results.

Convolutional Neural Network

Deep learning techniques are a type of machine learning that is based on neural networks, which are a type of supervised learning algorithm. A neural network is an often-utilized machine learning technique. This algorithm constructed a Neural Network, including several neurons that transmit data signals to one another. A typical neural network structure has three layers: the input layer, the hidden layer, and the output layer. Deep learning refers to the advancement of neural networks.

CNN is one type of deep learning algorithm (Convolutional Neural Network). Because it can recognize significant features without human assistance, it is frequently used to process, identify, detect, and categorize data in photos. A Convolutional Neural Network (CNN) is an improved version of neural networks. The CNN layer comprises a convolutional layer and a fully connected layer. Furthermore, the convolutional layer has multiple pooling layers that effectively decrease the spatial dimensions of the input. Transfer learning, a key aspect of this research, leverages pre-trained CNN models trained on extensive datasets. This approach allows for adapting existing architectures to new datasets without building models from scratch. Certain layers retain their pre-trained weights, while others are retrained to accommodate the new dataset. For this study, the base model, combined with the optimal weighting scheme, is fine-tuned to classify the dataset effectively.

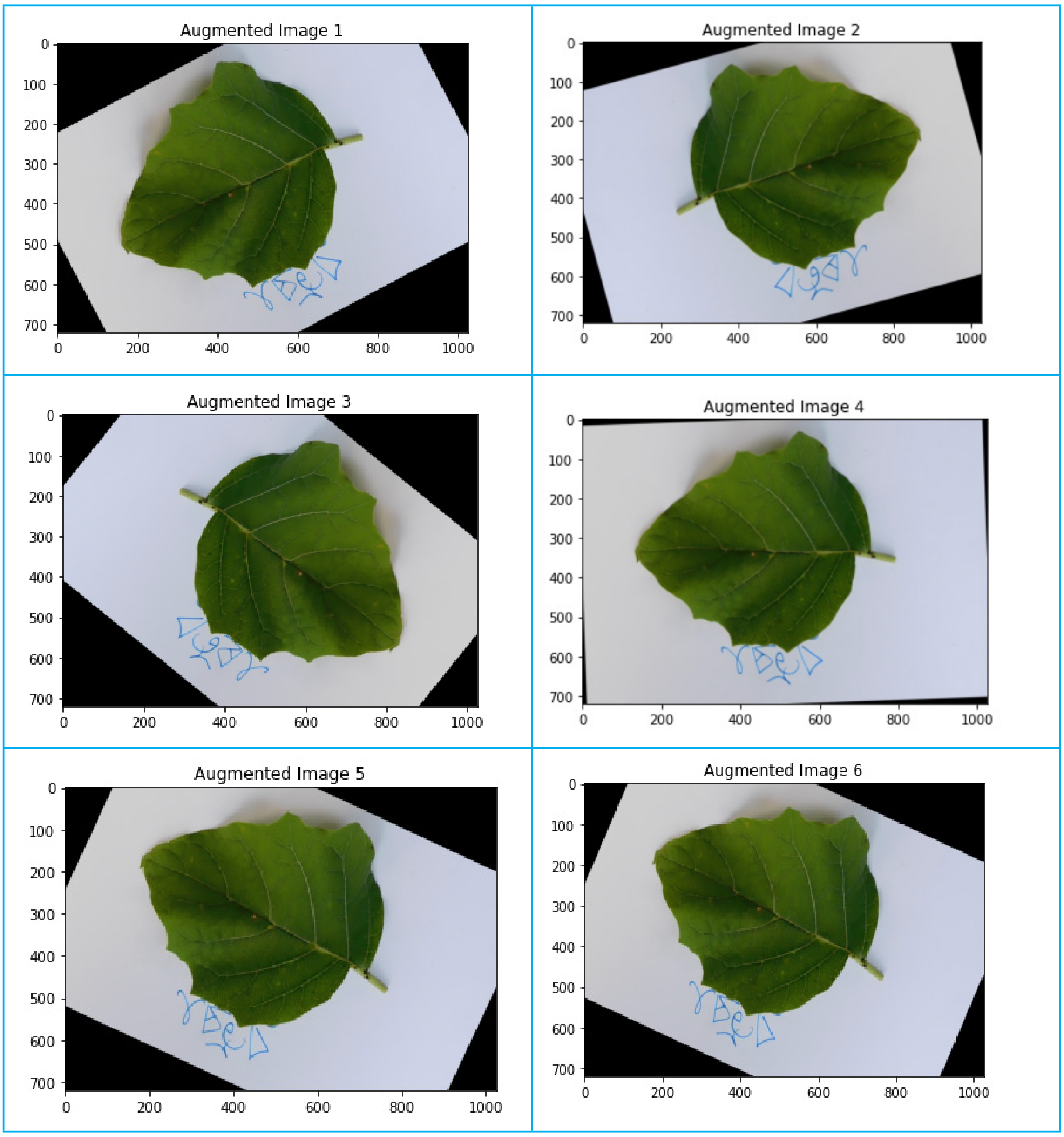

Figure 2 Augmentation results from the image

Transfer Learning with Mobilenetv2

Transfer learning eliminates the need to train a CNN model from scratch by utilizing pre-trained models, such as those trained on ImageNet, a dataset with over 1000 image classes. This approach involves adapting a pre-trained Convolutional Neural Network (CNN) to a new task by fine-tuning specific layers while keeping others frozen. Deep neural networks are layered structures with many adjustable hyperparameters. The initial layers are responsible for capturing general features, while later layers concentrate on the specific task at hand. It is logical to fine-tune the higher-level feature representations in the base model to make them more suitable for the specific task. We can re-train some layers of the model while keeping some frozen in training. Freezing the initial layers of the pre-trained model is crucial to avoid the unnecessary effort of training the model to learn fundamental features. Freezing the early layers prevents the loss of learned foundational features and avoids redundant computational effort while fine-tuning higher layers adapts the model to the new task.

For transfer learning in this study, the MobilenetV2 base model is utilized. The study reports on the performance of bottleneck shortcuts compared to expanded layer shortcuts, demonstrating the superiority of the inverted residual connection implemented by MobilenetV2. MobilenetV2 not only incorporates the residual layer but also a linear bottleneck that anticipates the non-linearity activation function, which frequently taints data in low-dimensional space. This bottleneck can enhance the model's performance, particularly on spurious correlations that have been examined. One further factor that contributes to the efficiency of MobilenetV2 as a base model is its relatively reduced parameter count in comparison to other base models like VGG.

We utilized pre-trained models from the ImageNet dataset. To adapt these models to our specific task of rice leaf disease classification, we modified the initial and final layers, such as fully connected, convolutional, softmax, and output layers. Lower layers of pre-trained models typically capture generic features, while higher layers learn task-specific features. By adjusting the higher layers, we can fine-tune the pre-trained model for our specific task, leveraging the knowledge gained from the original dataset. All models were trained for 10 epochs using identical hyperparameters, including a learning rate of 0.001 and the Adam optimizer for network training.

Performance Evaluation Metrics

To evaluate the model's effectiveness, we employed the following classification metrics: accuracy, precision, recall, and F1-score. These metrics provide insights into the model's performance and help us understand its strengths and weaknesses. Accuracy measures the overall correct classifications of disease samples. Precision assesses the proportion of correct positive predictions among all positive predictions. Recall evaluates the proportion of correctly identified positive samples among all actual positive samples. The F1 score provides a balanced measure of precision and recall, considering both false positives and false negatives.

RESULT AND DISCUSSION

Data augmentation is a key technique used to enhance model performance when working with limited datasets. It increases both the quantity and variability of training data, enabling the model to better generalize. In this study, augmentation was performed using random horizontal and vertical flips, along with random rotations of up to 20 degrees. These techniques expanded the dataset sixfold, creating a diverse set of training images. Figure 2 illustrates sample augmented images. After augmentation, the dataset was split into training and testing sets with an 80:20 ratio. Furthermore, 10% of the training data was designated as a validation set.

The next step is the training process, where the processed data will be fed into models built with MobileNetV2. Models developed with MobilNet V2 utilize image weights and do not include the final layer in the applied architecture. We included Global Average Pooling2D and a dropout layer with a rate of 0.2. Finally, we concluded with a dense layer that has 20 output classes and uses softmax activation. The model that has been created was compiled using Adam optimization, learning rate 0.001, and loss categorical cross-entropy.

The results of the model using the MobileNetv2 architecture show a training accuracy of 100% and a validation accuracy of 100%. Apart from that, the model gets a training loss of 0.0075 and a validation loss of 0.0106. Figure 3 presents a graph of accuracy and loss. From the test results using testing data, an accuracy score of 100%, precision of 100%, recall of 100%, and f1-score of 100% were obtained. Figure 4 presents the confusion matrix results of the MobileNet architecture model using the test data. Out of the 1000 tested sample data, none were misclassified.

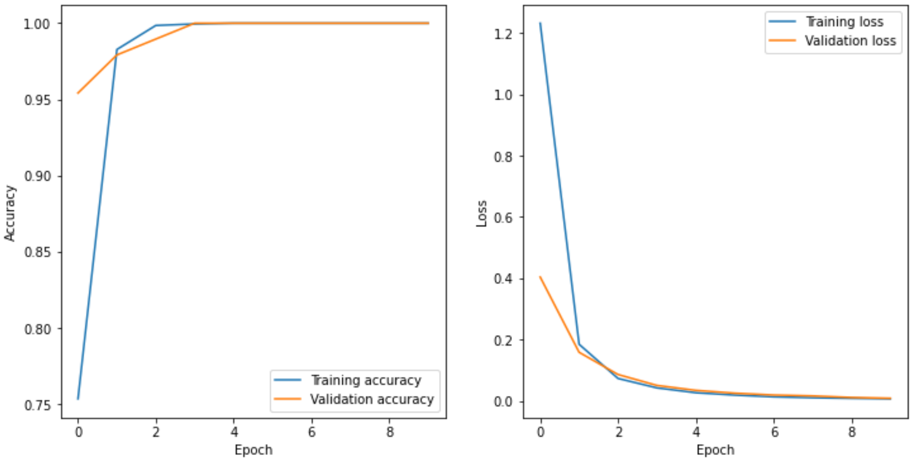

Figure 3 Accuracy dan loss training MobileNetV2

Next, the model is saved in the form of a .h5 extension and converted into the .tfflite file extension, which will be embedded into the Android application being developed. In building the model, the Python programming language was used with an IDE, namely Jupyter Notebook, by importing the Keras framework and TensorFlow. Applications or models in Jupyter Notebook are saved in the .ipynb format. Models are also saved in a .h5 and .tflite hard files via the transfer learning method. Once the model is available, the Android application development process is then carried out. In the process, the Dart programming language with the Flutter framework is used to build this application. In the assets folder, the model with the .tflite file extension will be saved in this folder. A file in .txt format will be created, which contains 20 variables in the model.

The application consists of three main pages: the About page, the Home page, and the Detection page. The About page describes the application, including its purpose and features. The Home page guides users on how to operate the application, outlining the steps to use its features effectively. The Detection page enables users to test the pre-trained model by uploading new medicinal plant images. Once the model predicts the plant type, users can click the “Details” button to view a detailed guide on preparing the medicinal plant concoction, as shown in Figure 5.

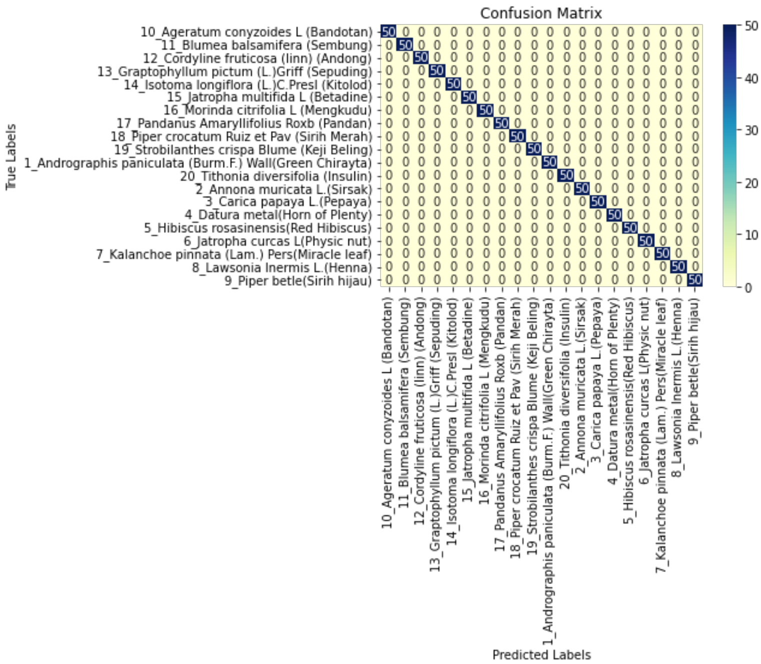

Figure 4 Confusion matrix of MobileNet

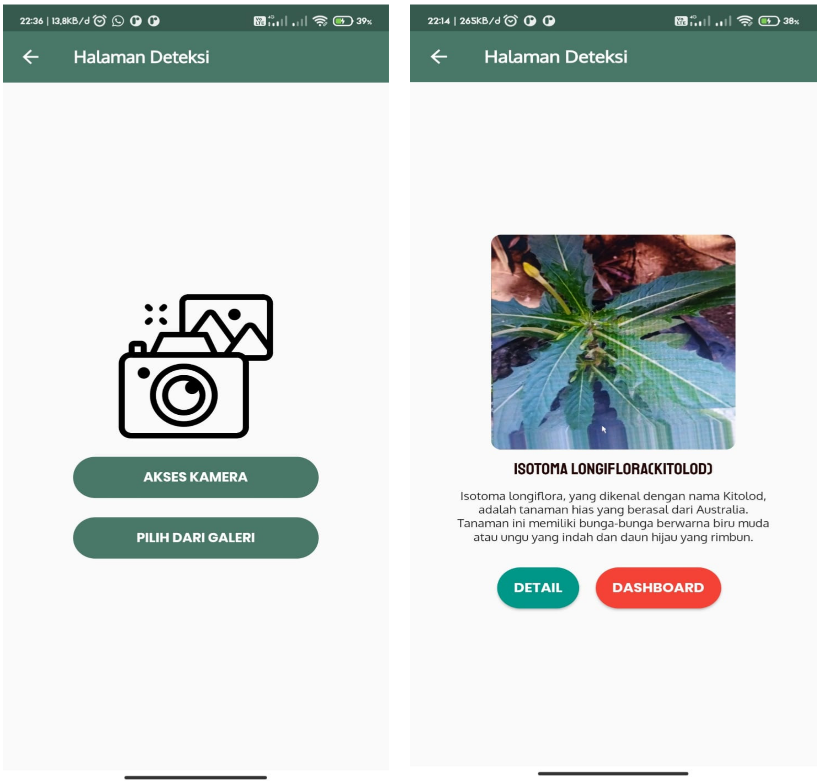

Figure 5 How machine learning works on I-NusaPlant apps

Comprehensive testing was conducted using the Firebase Test Lab to ensure the quality and performance of the I-NusaPlant application. Performance testing shows a maximum CPU usage of 17% (Figure 6). The CPU usage range is between 8.45%-28.2%, which is still relatively low and far from the maximum tolerable limit. Maximum memory usage is 167,532 MB (Figure 7). The application was tested on various Android versions, from Android 8.0 (Oreo) to Android 13 (Tiramisu). It was confirmed to be compatible with all tested versions, ensuring broad accessibility across different smartphone devices.

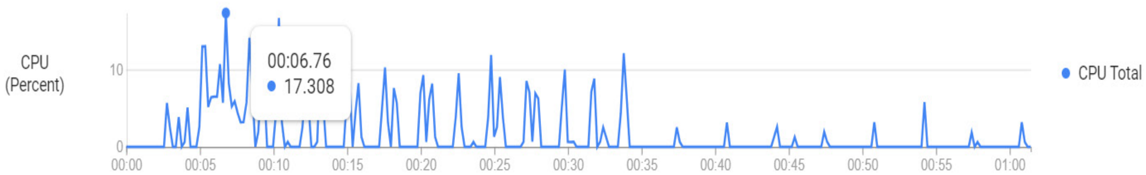

Figure 6 I-NusaPlant application CPU usage

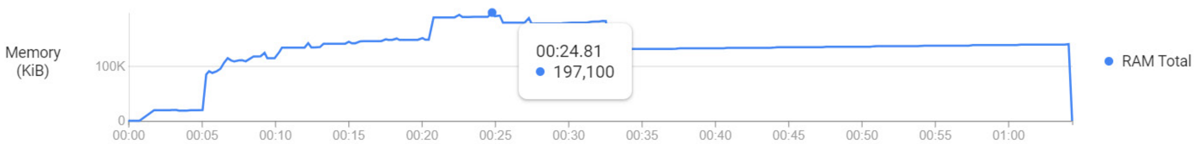

Figure 7 I-NusaPlant application memory usage

CONCLUSION

This study uses 5000 image data with 20 classes. The model employed is MobileNetV2. According to the experimental results, MobileNetV2 achieved an accuracy of 100% across all classes. The identification of the Indonesian medical plants method in this study has been implemented in the I-NusaPlant mobile-based application. Performance efficiency testing indicated that the maximum CPU and memory usage reached 17% and 197 MB, respectively. This app works on all Android versions 8.0 (Oreo) to 13 (Tiramisu).

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