Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

SimpliScopeX: Enhanced Deep Learning Model for Identification of Microscopic Image of Simplicia Fragments of Medicinal Plant Leaves

Ricky Indra Gunawan[1], Alam Rahmatulloh[1], Rianto[1,*], Irfan Darmawan[2], Randi Rizal[3], Vinda Maharani Patricia[4], Nur Widiyasono[1]

[1] Department of Informatics, Faculty of Engineering, Siliwangi University, Siliwangi Street, Tasikmalaya, Indonesia
[2] Department of Information Systems, Faculty of Industrial Engineering, Telkom University, Bandung, Indonesia
[3] Department of Computer Science, Faculty of Information and Communication Technology, Technical University of Malaysia Melaka, Malaysia
[4] Department of Pharmacy, Faculty of Mathematics and Natural Sciences, Bandung Islamic University, Bandung, Indonesia

ARTICLE INFO

Article history:
Received 3 November 2023
Received in revised form 12 July 2024
Accepted 15 August 2024
Available online 5 September 2024

Keywords:
Simplicia leaves; medicinal plants; image classification; deep learning

ABSTRACT

As the "Back to Nature" trend progresses, people are switching from chemical medicine to herbal medicine or traditional medicine derived from nature. One form of traditional medicine is the simplicia of medicinal plant leaves. The authenticity of dried simplicia powder of medicinal plants can be determined through a microscopic test by looking at the identifier fragments. However, this remains difficult for humans to identify due to the need for more information on standard references. The dataset from microscopic images of simplicia fragments of medicinal plant leaves still needs to be improved. In addition, manual matching of microscopic test results with standard reference books requires quite a long time. It allows for human error, so it is necessary to apply artificial intelligence that can assist researchers in quickly and accurately predicting the species of medicinal plants and their fragments based on microscopic images. Deep learning performance has shown promising results in computer vision in recent years. Inspired by sophisticated deep learning techniques, the proposed work presents a deep learning method to identify and classify images of microscopic fragments of simple medicinal plants and their enhanced fragments using data augmentation techniques, modified EfficientNetB0 architecture, and the use of the ReduceLROnPlateau function in the training process, which is referred to as "SimpliScopeX". The SimpliScopeX model can also automatically extract microscopic image features of simplicia fragments of medicinal plant leaves. Experimental results using the new dataset show that our proposed model can produce the highest accuracy value of 80.25% for the test data for microscopic image problems of medicinal leaf simplicia. The implications of this research are petrified in the pharmaceutical world in fast and accurate microscopic identification.

* *Corresponding author.*
E-mail address: rianto@unsil.ac.id

https://doi.org/10.37934/araset.51.2.117

1. Introduction

Millions of plant species exist on Earth. Humans can utilize plants as a source of food, clothing, and medicine. Medicinal plants can be used as raw materials for traditional and modern medicine. Along with the development of the "Back to Nature" trend, people are starting to turn to herbal medicine or traditional medicine derived from nature. The community likes herbal medicine because it is relatively cheap and easily accessible. The community also believes that using herbal medicines derived from plants has fewer side effects than chemical drugs. Therefore, traditional drug producers are increasingly active, and people are starting to cultivate medicinal plants with the term TOGA (Family Medicinal Plants) [1].

Various parts of medicinal plants can be utilized as raw materials for medicine, such as leaves, rhizomes, fruits, roots, barks, flowers, seeds, tubers, sap, and hanging roots [2]. Since ancient times, these herbal plants have been used effortlessly, such as boiling and taking water from the skin or leaves by mashing them until they are smooth and mixed to cure various diseases. The community has been doing this for generations, but not all have been identified [3]. Plants usually used as simplicia are plant materials that do not change shape and are only dried [4]. The drying process may be accomplished by using the wind, the sun, or an oven with a temperature of not more than 60oC [5].

The correctness of medicinal plant simplicia can be identified in two ways, namely plant determination using wet simplicia and organoleptic testing macroscopically by observing the distinctive color, taste, and smell of simplicia powder or microscopically using a microscope to obtain clear images [6]. This test is intended to identify fragments in simplicia powders [7-9].

Information regarding microscopic tests in medicinal plant research must be made available. Some of them only mentioned microscopic fragments without any discussion regarding the correctness of the simplicia, which should have been the aim of the test [9-13].

In determining the correctness of the simplicia material, of course, it must go through matching the microscopic test results with the reference. References for standard microscopic parameters of simplicia powder still need to be completed for all medicinal plants. Some currently available references are the Indonesian Herbal Pharmacopoeia [14] and the Indonesian Materia Medika [15]. Manual matching takes quite a long time and is only partially accurate due to the possibility of human error and unclear images of the microscopic test results.

In the era of the digital industry 4.0, technological advances are driving very fast, so the role of technology in identifying dry simplicia powder as a standard reference for microscopic test results is expected to be faster and more accurate. Image processing is one way to identify the fragments of dry simplicia powder. Image processing can be done by enhancing the image [16]. One of the image enhancement approaches used in microscopic images is converting them to grayscale, followed by applying the BCV threshold to enhance the images in the spatial domain [17]. To prevent interference from the color sample during the feature extraction process, another image enhancement technique has also been used in the case of image classification on microscopic images of the leaf epidermis. This technique involves converting the image to grayscale and using a contrast enhancement procedure [18].

In addition to image processing, images need to be extracted into features so that images can be processed into machine learning models. This process can be carried out using various methods, including the Gray Level Co-Occurrence Matrix (GLCM). Energy, contrast, correlation, and homogeneity are the extracted features, and these features could be used to build a high-accuracy model [19] or classified using the Euclidean distance [20]. Furthermore, a study has been conducted

on image identification of rice leaf diseases using the Gabor Wavelet and K-Means Clustering methods with an accuracy rate of up to 70% [21].

Besides traditional machine learning, machine learning modeling can also be done using deep learning methods. The deep learning method has automatic feature extraction in images [22-24]. One type of deep learning capable of performing image classification is the Convolutional Neural Network (CNN). Several previous studies are related to the use of Convolutional Neural Networks in the case of image classification, as has been done by [23,25]. Apart from using the Convolutional Neural Network, several studies use pre-trained deep learning models by implementing the transfer learning method on the Convolutional Neural Network. Based on research conducted by [26] in the case of the classification of microscopic images of unstained skin samples, it was found that EfficientNetB0 produced the highest accuracy value of 98.52%, AUC of 0.99, and F1 score of 0.98 with a sensitivity of 97.6% and a specificity 99.4% compared to other popular pre-trained deep learning model architectures, such as VGG16, ResNet50, and MobileNet. The research was also conducted by [24] using the ensemble method on the Inception, ResNet, and VGG-16 architectures. Research related to the microscopic topic of medicinal plant leaf simplicia was conducted by [27], who compared the architectures of VGG16, InceptionV3, MobileNet, and Xception and obtained results that the VGG16 architecture leading with an accuracy of 95.42%. In addition, based on research conducted by [28,29], it produces a validation accuracy of 67.29% using the MikrobatX model, a modified version of EfficientNetB0.

One of Google's popular open-source code libraries is used to develop deep learning models, namely TensorFlow. TensorFlow computations can be executed with little or no modification on a wide range of heterogeneous systems, from mobile devices like phones and tablets to large-scale distributed systems with hundreds of machines and thousands of computational devices like GPU cards [30]. Meanwhile, Keras is a lightweight framework with a high-level application programming interface (API) built on top of TensorFlow [31]. TensorFlow is best suited for tasks requiring high accuracy, as it provides greater flexibility in the integration process and how a network can be defined and trained, with greater control over the training flow due to complexity, resulting in higher overall accuracy [32].

Thus, this research was carried out as an innovative step through the application of technology to identify parts of microscopic fragments of dried leaf simplicia and names of medicinal plant species using the proposed deep-learning model architecture. The proposed model is projected to produce and outperform other deep learning models in previous studies, starting from the completeness of the dataset used, determining optimal hyperparameters, using layers in the proposed model architecture, and the performance of the proposed model. The resulting knowledge, algorithms, and models are stored in a file with an HDF5 format, which can later be applied to an application, both web-based and mobile. This study contributes by providing a new dataset, investigating the most recent research in the field of microscopic image analysis and identification of simplicia fragments from medicinal plant leaves, suggesting a new deep learning model that can produce better accuracy than previous research, and comparing the proposed model architecture with the basic model to find out how much influence the proposed model has with the various strategies that have been given and experimented compared to the baseline model.

1.1 Related Work

Based on the study results and analysis of the latest survey papers and technical papers, several requirements must be met in developing a deep learning model that can be used to classify microscopic images of simplicia leaf fragments. Some of these needs include applying techniques

used in image processing, feature extraction techniques, and the required deep learning model architecture.

Based on the description of the various needs studied from the various previous studies, the following is a review of the state-of-the-art and related research that will be discussed.

1.1.1 Image processing

Image processing is one of the tasks that is quite important in the case of image classification. In recent years, researchers have used many image-processing techniques and methods as the subject of discussion in image-processing tasks. Color Conversion, Segmentation, Edge Detection, and Noise Reduction or Image Restoration are some of them. The choice of image processing technique depends on the condition of the image to be used.

Previous studies involving microscopic images, such as studies conducted by [17,24,28,33] used Grayscale Conversion on average. However, some do not do any preprocessing like research conducted by [27]. According to these research, the grayscale color conversion technique is generally used for image processing. Therefore, in this study, the color conversion method will be carried out with the addition of center cropping to adjust the image shape and size to match the image size required in the EfficientNetB0 architecture model.

1.1.2 Feature extraction

Feature extraction aims to transform the original data into a more usable, smaller, or denser size to increase classifier efficiency. Feature extraction techniques for the classification process are very diverse. Based on research conducted by [20], the GLCM technique could extract texture features in images, but the weakness of the GLCM technique was that it could not extract shape features. On the other hand, studies use the Regionprops Operator [17] and Hu's Moment [33] techniques, which can extract shape features but cannot extract texture features. In addition, studies are using the SIFT algorithm with CNN, as was done by [28]. However, research shows that CNN achieves performance comparable to SIFT in accuracy and outperforms Bag of Visual Words (BoVW). SIFT match is limited to small databases, while CNN and BoVW can be used for moderate databases and quickly expand for large-scale retrieval. CNN and BoVW are faster for feature extraction and fetching than SIFT, but SIFT outperforms accuracy. Because this research uses data, the use of SIFT is omitted because it is not suitable for use on large datasets, so it does not take up a sizeable computational process and takes a long time.

This is also supported by a series of other previous studies that have used CNN as automatic feature extraction in the case of macroscopic and microscopic image classification, as was done by [23,24,26,28,34,35]. Therefore, in this study, the CNN concept will automatically extract features available in the EfficientNetB0 architecture.

1.1.3 The architecture of deep learning models

Based on a study conducted by [26], it can be concluded that a model composed of the EfficientNetB0 architecture produces higher final accuracy results than other pre-trained models, such as VGG16, MobileNet and ResNet50 in the case of classification of microscopic images of skin samples. In addition, research on the microscopic classification of medicinal plant leaves has also been carried out by [27] using the VGG16, MobileNet, Xception, and InceptionV3 architectures. Research in the case of microscopic classification of medicinal plant leaf simplicia using EfficientNetB0

was the first time conducted by [28]. However, this study still needs to improve, namely the relatively low accuracy, around 67.29% in validation accuracy. Therefore, to fill the research gap, it is necessary to add or modify layers and hyperparameter tuning to a model based on the EfficientNetB0 architecture for cases of classification of microscopic images of medicinal plant leaf simplicia, which are expected to produce better accuracy.

Based on the explanation that has been described, this research has an update in terms of problems that add to the types of plants identified and the literature available in this case, as well as updates in terms of the methods used in the process of image processing, feature extraction, and machine learning models using deep learning in the case of identification of species and parts of simplicia fragments of medicinal plant leaves based on microscopic images. This study will use two models, namely the SimpliScopeX model and the baseline model, as a comparison.

2. Methodology

This work's deep learning development methodology begins with building the dataset, then data preparation and modeling. The final step is to evaluate the results of the model training process. The schematic of the proposed model for identifying species and fragments of medicinal plant leaf fragments based on microscopic images is shown in Figure 1. The dataset was then processed using the EfficientNetB0 architecture. The novelty of this work comes from the use of image processing techniques and the ReduceLROnPlateau in callback functions. Subsequently, various data augmentation techniques were employed in this study.

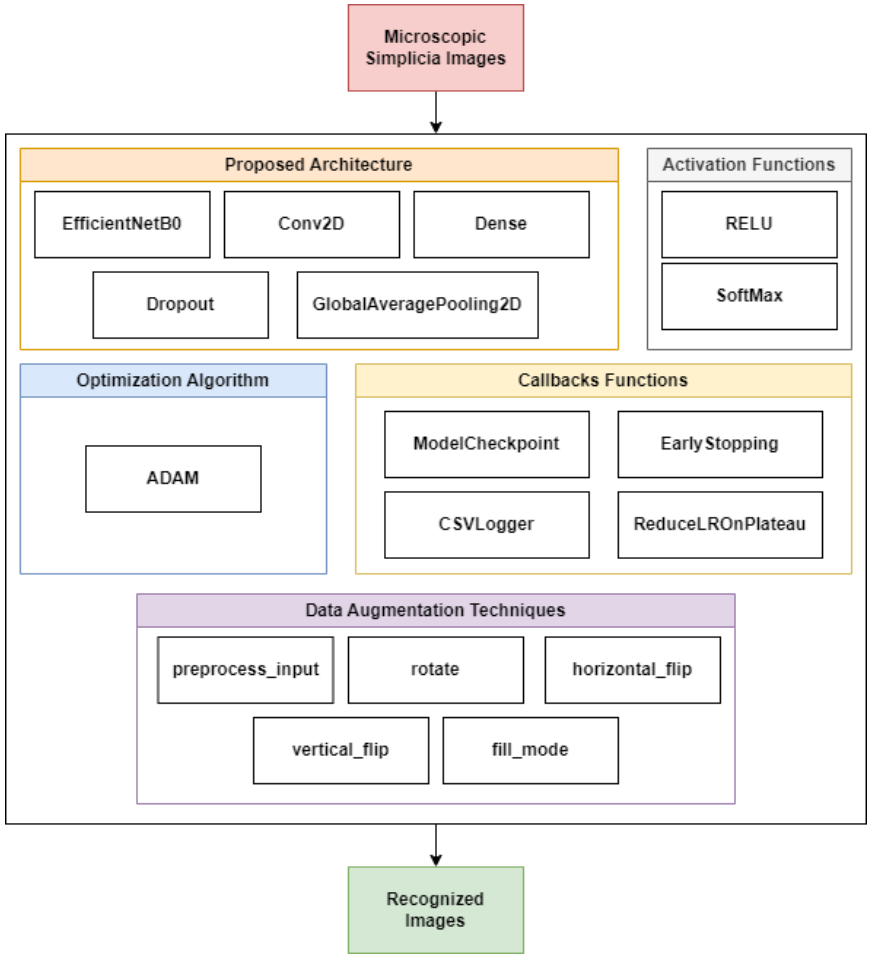


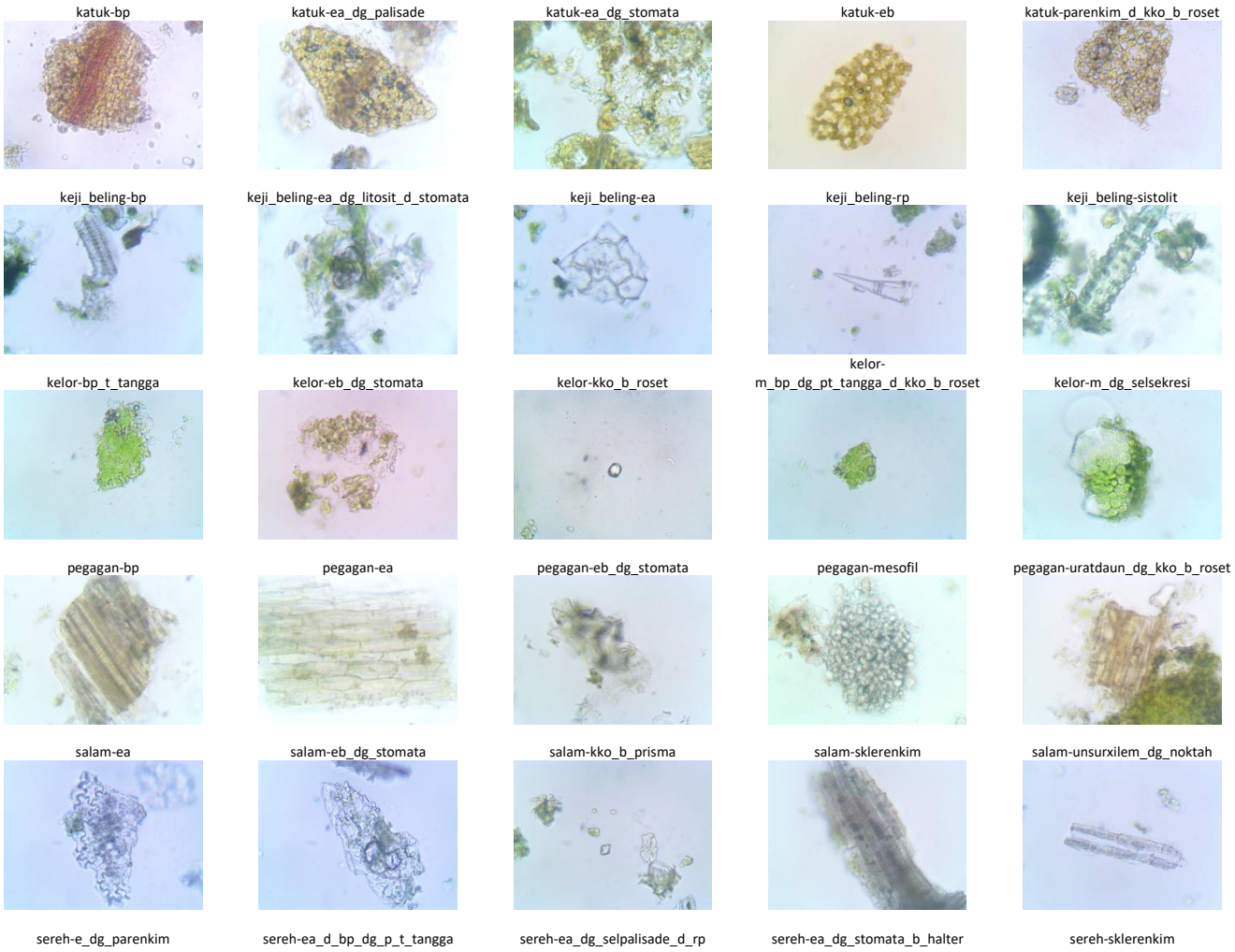
Fig. 1. The proposed microscopic simplicia identification scheme

2.1 Dataset

In this research, image data sets have been collected from 6 different types of medicinal plants. Each medicinal plant consists of 5 fragments. Each fragment contains 200 image data, so one plant species has 1000 images. Because six types of medicinal plants were studied, the total number of images collected was 6000. Images were taken manually using a binocular microscope with a magnification of 40x. The images taken have the provisions of the planned image data. These provisions are contained in Table 1. Figure 2 is an example of data obtained from microscopic images using a microscope with a magnification of 40x.

Table 1
Image Term

Parameter	Information
Image Formats	The uniform image format is .png.
Image Size	The homogeneous image size is 640*480 pixels, which will be cut to 480*480 pixels when performing image preprocessing.
Image Interpretation	Emphasizes the object by placing the object's position in the center of the image.
Number of Samples Tested	To avoid accumulation in the fragmented leaf images, the samples to be tested are placed in small quantities to prevent accumulation.



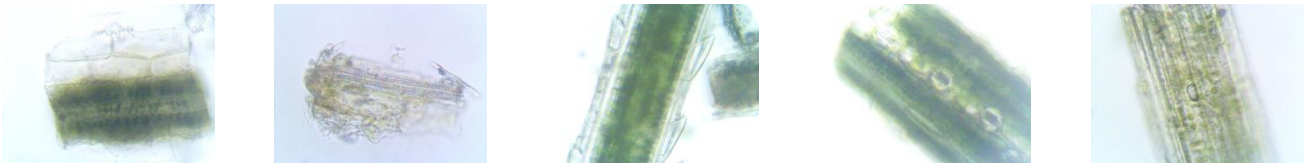


Fig. 2. Example of microscopic image data of simplicia of medicinal plant leaves

2.2 Data Preparation

Data preparation stages as a whole are illustrated in Figure 3. In order to lessen the bias toward color features, the image data is first subjected to a grayscale conversion, which turns RGB images into grayscale images. Following that, the center-cropping method changes the image's shape and size to meet the image dimensions required by the EfficientNetB0 architectural model.

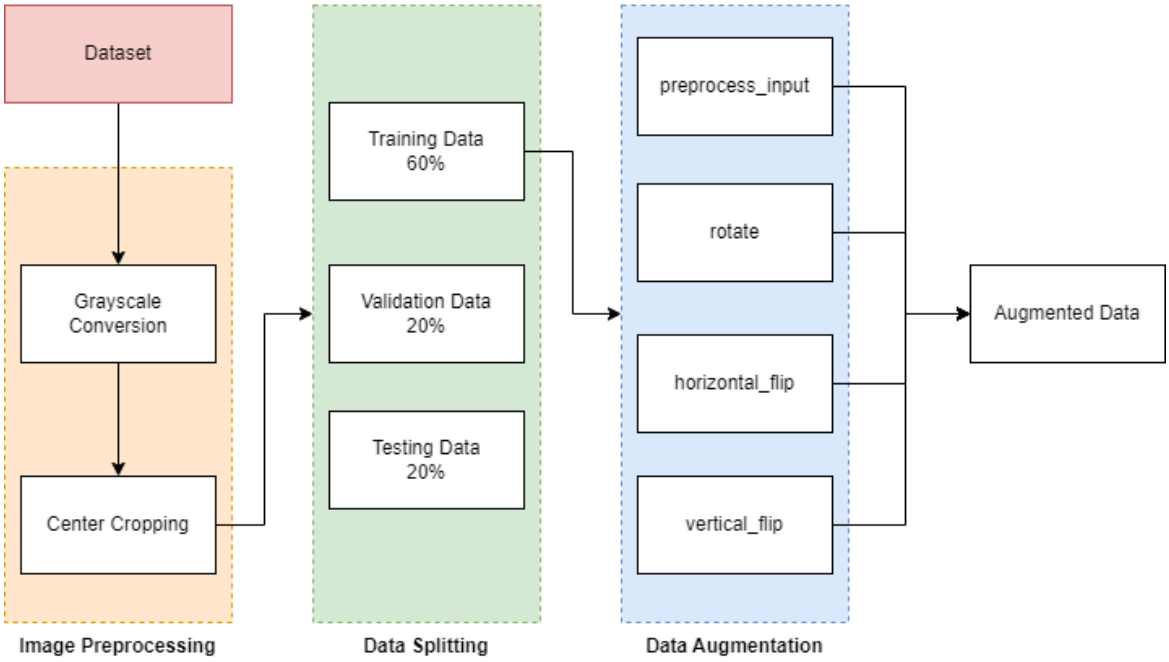


Fig. 3. Data preparation stages

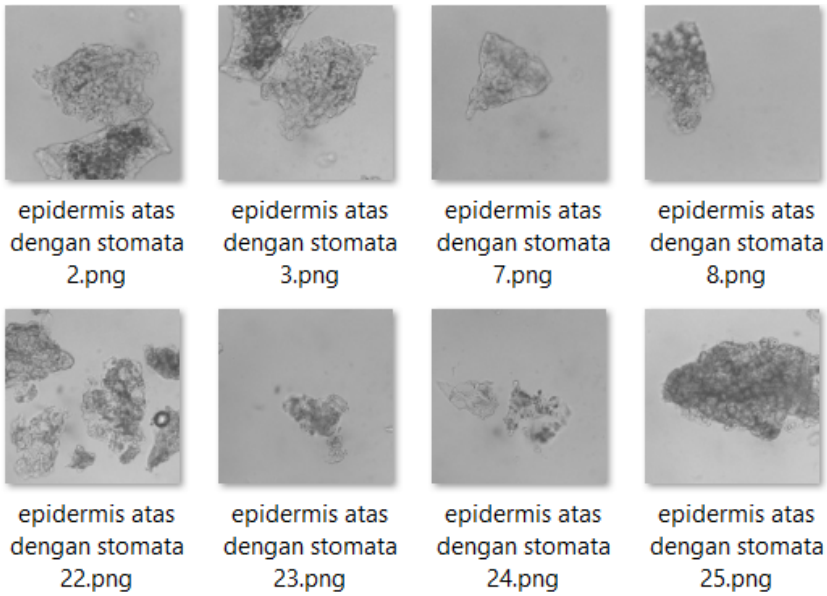


Fig. 4. Example of image data that has been processed

Figure 4 shows the image processing of katuk leaves, the upper epidermis fragments with stomata. After that, the entire dataset is divided into training data, validation data, and testing data with a ratio of 60:20:20, so that obtained training data for 60% of the total number of images, validation data for 20% of the total number of images and testing data of 20 % of the total number of images.

Table 2
Dataset Details

Species	Fragments	Class Code	Number of Images
Daun katuk (*Sauropus androgynous*)	Vascular Bundle	katuk-bp	200
	Upper Epidermis with Palisade	katuk-ea_dg_palisade	200
	Upper Epidermis with Stomata	katuk-ea_dg_stomata	200
	Lower Epidermis	katuk-eb	200
	Parenchyma and Rosette-shaped Calcium Oxalate Crystals	katuk-parenkim_d_kko_b_roset	200
Daun keji beling (*Strobilanthes cripus*)	Vascular Bundle	keji_beling-bp	200
	Upper Epidermis	keji_beling-ea	200
	Upper Epidermis with Lithocyst and Stomata	keji_beling-ea_dg_litosit_d_stomata	200
	Leaf Hair	keji_beling-rp	200
	Cystolith	keji_beling-sistolit	200
Daun kelor (*Moringa oleifera*)	Vascular Bundle	kelor-bp_t_tangga	200
	Lower Epidermis with Stomata	kelor-eb_dg_stomata	200
	Rosette-shaped Calcium Oxalate Crystals	kelor-kko_b_roset	200
	Mesophyll, Vascular Bundle, and Rosette-shaped Calcium Oxalate Crystals	kelor-m_bp_dg_pt_tangga_d_kko_b_roset	200
	Mesophyll with Secretion Cells	kelor-m_dg_selsekresi	200
Daun pegagan (*Cantella asiatica*)	Vascular Bundle	pegagan-bp	200
	Upper Epidermis	pegagan-ea	200
	Lower Epidermis with Stomata	pegagan-eb_dg_stomata	200
	Mesophyll	pegagan-mesofil	200

	Leaf Vein with Rosette-shaped Calcium Oxalate Crystals	pegagan-uratdaun_dg_kko_b_roset	200
Daun salam (*Syzygium polyanthum*)	Upper Epidermis	salam-ea	200
	Lower Epidermis with Stomata	salam-eb_dg_stomata	200
	Prism-shaped Calcium Oxalate Crystals	salam-kko_b_prisma	200
	Sclerenchyma	salam-sklerenkim	200
	Xylem with points	salam-unsurxilem_dg_noktah	200
Daun sereh (*Cymbopogon nardus (L.) Rendl.*)	Epidermis with Parenchyma	sereh-e_dg_parenkim	200
	Upper Epidermis and Vascular Bundle	sereh-ea_d_bp_dg_p_t_tangga	200
	Upper Epidermis with Palisade Cells and Leaf Hair	sereh-ea_dg_selpalisade_d_rp	200
	Upper Epidermis with Halter-shaped Stomata	sereh-ea_dg_stomata_b_halter	200
	Sclerenchyma	sereh-sklerenkim	200
	Total	30	6000

Figure 5 is an example of a sample of data that has gone through the augmentation process. While at the data augmentation stage, several techniques were carried out, including rotation, horizontal flip, vertical flip, and fill. Details regarding the parameters in the data augmentation process can be seen in Table 2.

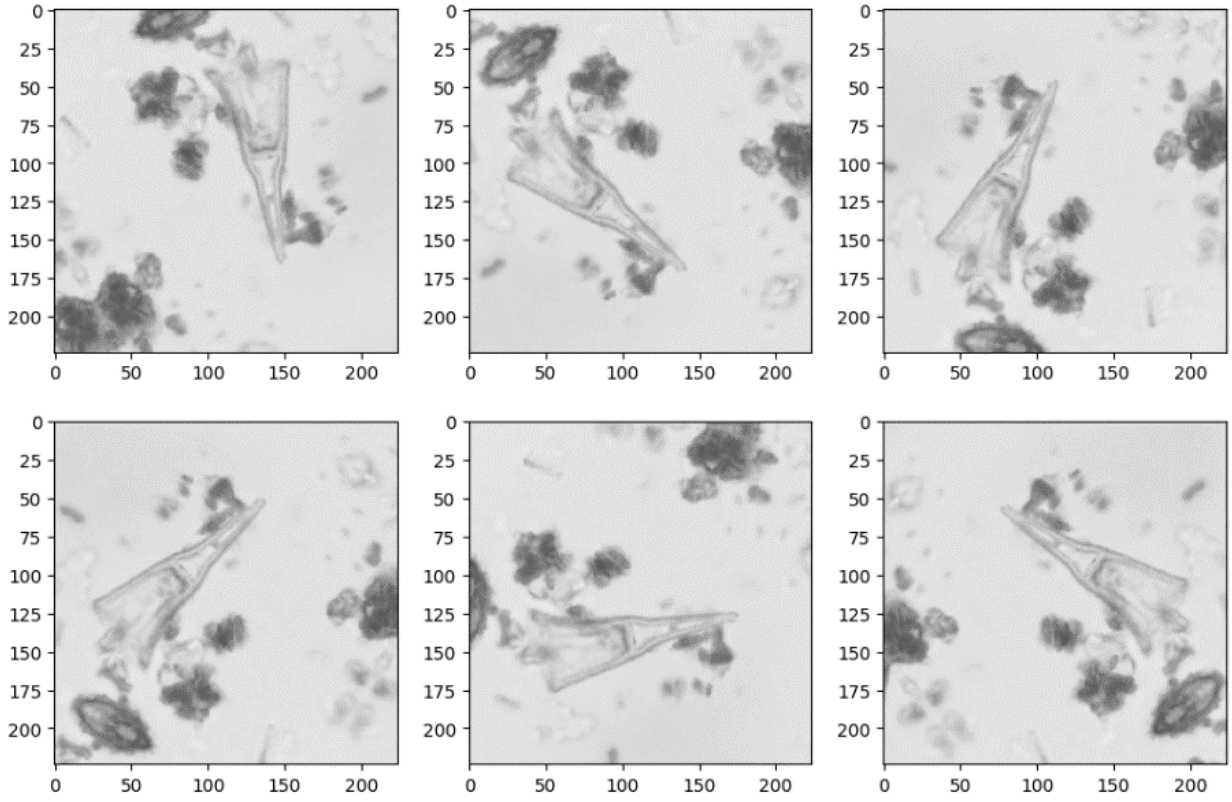


Fig. 5. Example of augmented image data

2.3 Modeling and Optimization

The pre-trained model architecture will be used as the basic model architecture (baseline model), namely EfficientNetB0, which will conduct experiments to modify or add layers to the architecture. Figure 6 is the architectural baseline model used as a reference point to analyze comparisons.

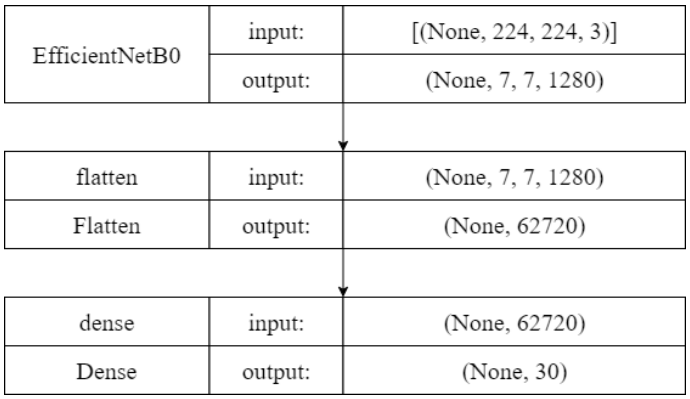


Fig. 6. Baseline model architecture

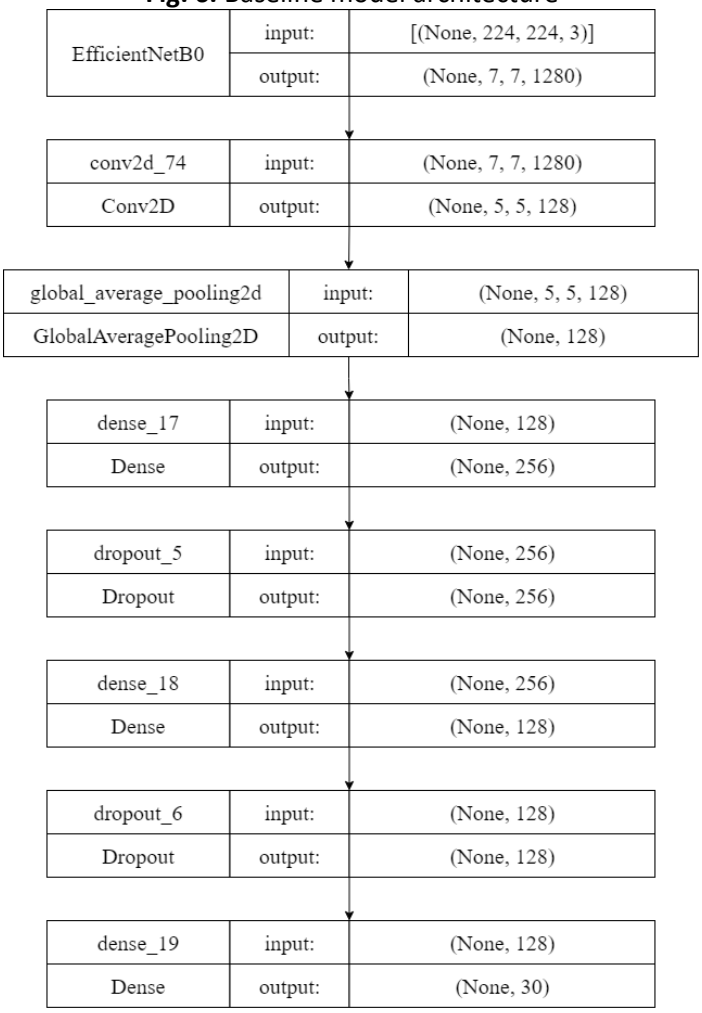


Fig. 7. The architecture of the SimpliScopeX model

At this stage, hyperparameter tuning is also carried out, and the optimizer function is determined. The hyperparameters used during model training are detailed in Table 3. Since this study is a multi-class classification task and the class labels were encoded during preprocessing, categorical cross-entropy was used as the loss function. Adaptive Moment Estimation (Adam) is the optimization approach used in this study. The weighted network is iteratively updated using Adam's optimization algorithm instead of the conventional stochastic gradient descent (SGD) method based on training data.

Table 3
Data Augmentation

Parameter	Value
rotation_range	90
horizontal_flip	true
vertical_flip	true
fill_mode	'reflect' / 'nearest' (to be experimented)
preprocessing_function	preprocess_input
batch_size	32

In addition, it is also necessary to pay attention to the callback function when carrying out the training process. Table 4 shows the details of the parameters in the callbacks used.

Table 4
Hyperparameter Model

Parameter	Value
Cost Function	Categorical Cross-entropy
Optimizer	Adaptive Moment Estimation (Adam)
Learning Rate	0,001 (default)
Epochs	50
validation_steps	valid.samples//batch_size = 112
steps_per_epoch	train.samples//batch_size = 75

Figure 1 depicts the improved deep learning model's deep learning layers. This model is built on a modified EfficientNetB0 architecture with additional layers such as Conv2D, GlobalAveragePooling2D, Dense, and Dropout. The Dropout layer prevents overfitting by eliminating some neurons' contributions to the following layer while leaving all others alone. The hyperparameter model configuration in Table 4 is used for the training process on the Baseline and the SimpliscopeX model. Figure 7 depicts a detailed architectural SimpliScopeX model.

Table 5 is the callback function used in this study, both the Baseline and the SimpliscopeX Model. Several callback functions have been installed: CSV Logger, Model Checkpoint, EarlyStopping, and ReduceLROnPlateau.

The CSV Logger function records the training results for each epoch in .csv format to make evaluating the model's performance easier during training. Model Checkpoint saves the model or weight (in the checkpoint file) at specific intervals so that the model or weight can be loaded later to continue training from the saved state. Early Stopping functions stop the training process when the monitored metrics do not improve. ReduceLROnPlateau works to reduce the learning rate when the metrics do not improve. The ReduceLROnPlateau callback is one of the issues that need to be tested to determine how much impact the use of the callback has. Table 6 shows a scenario comparison between the baseline model and the SimpliScopeX model.

Table 5
Callbacks Function

Callback Type	Parameter
EarlyStopping	monitor='val_accuracy', min_delta=0.001, patience=10, verbose=2, mode='max', baseline=None, restore_best_weights=True
ReduceLROnPlateau	monitor='val_accuracy', factor=0.2, patience=5, verbose=2, mode='max', min_delta=1e-4, min_lr=1e-5
ModelCheckpoint	filepath="/content/drive/MyDrive/Experiments/HasilTraining_*/HasilModelCheckpoint_*/Model1_Best.h5", monitor="val_accuracy", verbose=1, save_best_only= True
CSVLogger	filepath='/content/drive/MyDrive/Experiments/HasilTraining_*/HasilCSV_*/log_training.csv'

Table 6
Scenario differences between the Baseline Model and the Simpliscope Model

Baseline Model	SimpliScopeX Model
EfficientNetB0 architecture without modification (only one flattened layer and one output layer at the end of the model architecture).	EfficientNetB0 architecture with modifications as in Scenario 4, but there is a reduction of 1 Conv2D layer.
Train data augmentation with fill_mode = 'nearest'.	Train data augmentation with fill_mode = 'reflect'.
Without using the ReduceLROnPlateau callback function.	Using the ReduceLROnPlateau callback function.

2.4 Evaluation Procedure

The most commonly used measures among the several performance indicators for multi-label classification issues are precision, recall, accuracy, and F-measure. It can be done using the classification report function from *the scikit-learn* library. Precision is the ratio of true positives to the total of false positives and true negatives, also known as positive predictive value. The mathematical equation of precision is shown in Eq. (1).

$$Precision\ (P) = \frac{True\ Positive\ (TP)}{(True\ Positive\ (TP) + False\ Positive\ (FP))} \tag{1}$$

The recall is the proportion of positives our model can detect by labeling them as positives, also known as true positive rate. The mathematical equation of precision is shown in Eq. (2).

$$Recall\ (R) = \frac{True\ Positive\ (TP)}{(True\ Positive\ (TP) + False\ Negative\ (FN))} \tag{2}$$

The harmonic mean of accuracy and recall is used to determine the F1 score, also known as F-measure. The F1 score reaches its best score at one and worst value at 0. The formula for F1 score is shown in Eq. (3).

$$F1\ Score = 2 * \frac{(Recall * Precision)}{(Recall + Precision)} \quad (3)$$

Accuracy is defined as the ratio of correct predictions out of all predictions obtained by the algorithm. The equation of accuracy is shown in Eq. (4).

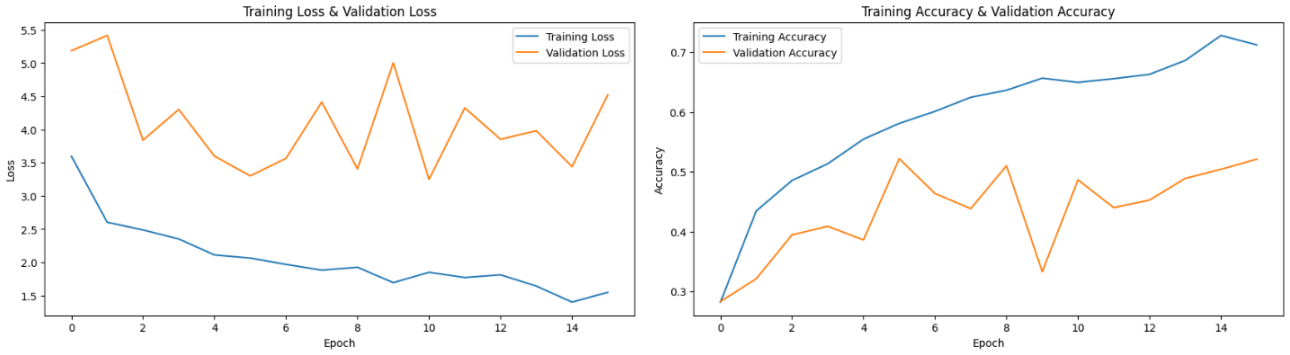
$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + FP + FN + TN} \quad (4)$$

3. Results

The device specifications used in this study are the Windows 11 64-bit operating system, 16 GB RAM, with an AMD Ryzen 9 processor running on Nvidia T4 GPU at Google Colaboratory. This study used Google Colaboratory, which an Nvidia T4 GPU runs. This research also uses the TensorFlow library version 2.9.0. Several of the outcomes obtained include:

3.1 Baseline Model

Figure 8 shows (a) the training results and (b) validation accuracy, as well as the values derived from the dataset loss function, by using the base model with the EfficientNetB0 model architecture. The Baseline model configuration has been set for 50 epochs, but when the training process takes place, it stops at the 16th epoch because the EarlyStopping function works. EarlyStopping functions to stop the training process when the monitored metrics do not improve. EarlyStopping will be called in this study if the validation accuracy does not increase by ten epochs with a minimum change in the monitored quantity to qualify as an increase of 0.001.



(a) (b)

Fig. 8. Training (a) Loss Metrics from Baseline Model, (b) Accuracy Metrics from Baseline Model

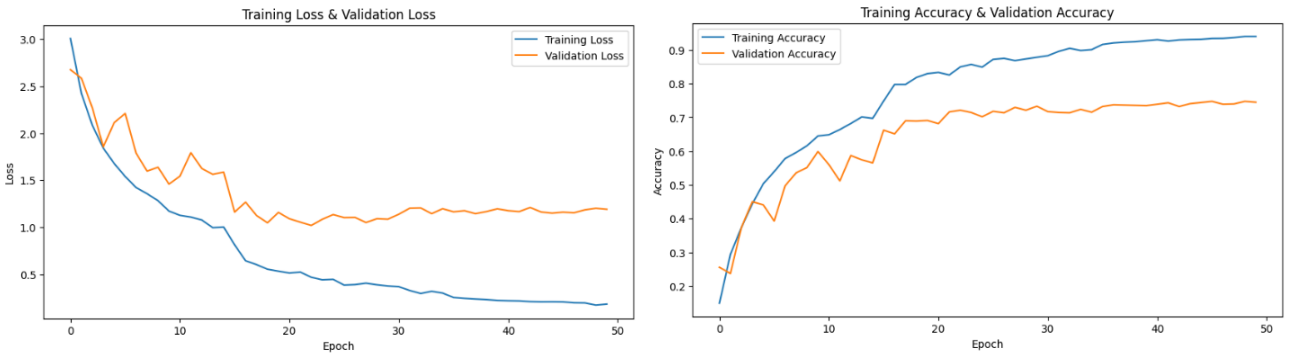
Figure 9 displays the outcomes of this deep learning modeling, which were then assessed using test data by the classification_report() function from the scikit-learn package.

	precision	recall	f1-score	support
katuk-bp	0.26	0.60	0.36	40
katuk-ea_dg_palisade	0.57	0.30	0.39	40
katuk-ea_dg_stomata	0.48	0.38	0.42	40
katuk-eb	0.32	0.30	0.31	40
katuk-parenkim_d_kko_b_roset	0.42	0.35	0.38	40
keji_beling-bp	0.61	0.35	0.44	40
keji_beling-ea	0.49	0.82	0.61	40
keji_beling-ea_dg_litosit_d_stomata	0.42	0.70	0.53	40
keji_beling-rp	0.53	0.80	0.64	40
keji_beling-sistolit	0.53	0.75	0.62	40
kelor-bp_t_tangga	0.86	0.15	0.26	40
kelor-eb_dg_stomata	0.43	0.75	0.55	40
kelor-kko_b_roset	0.54	0.33	0.41	40
kelor-m_bp_dg_pt_tangga_d_kko_b_roset	0.50	0.47	0.49	40
kelor-m_dg_selsekresi	0.47	0.47	0.48	40
pegagan-bp	0.54	0.65	0.59	40
pegagan-ea	0.57	0.57	0.57	40
pegagan-eb_dg_stomata	0.55	0.40	0.46	40
pegagan-mesofil	0.49	0.50	0.49	40
pegagan-uratdaun_dg_kko_b_roset	0.55	0.28	0.37	40
salam-ea	1.00	0.45	0.62	40
salam-eb_dg_stomata	0.80	0.88	0.83	40
salam-kko_b_prisma	0.64	0.80	0.71	40
salam-sklerenkim	0.38	0.42	0.40	40
salam-unsurxilem_dg_noktah	0.75	0.07	0.14	40
sereh-e_dg_parenkim	0.95	0.53	0.68	40
sereh-ea_d_bp_dg_p_t_tangga	0.62	0.45	0.52	40
sereh-ea_dg_selpalisade_d_rp	0.73	0.90	0.81	40
sereh-ea_dg_stomata_b_halter	0.82	0.78	0.79	40
sereh-sklerenkim	0.57	0.80	0.67	40
accuracy			0.53	1200
macro avg	0.58	0.53	0.52	1200
weighted avg	0.58	0.53	0.52	1200

Fig. 9. Classification report from baseline model

The last epoch's training accuracy and validation accuracy results were 71.24% and 52.11%, respectively, with the most excellent validation accuracy at 52.20%. For the test data, the model's accuracy was 53.33%.

3.2. SimpliScopeX Model



(a) (b)

Fig. 10. Training (a) Loss Metrics from SimpliScopeX Model, (b) Accuracy Metrics from SimpliScopeX Model

Figure 10 shows (a) the training and (b) validation accuracy outcomes and the values obtained from the dataset's loss function after applying the modified and improved model. Figure 11 displays the outcomes of this deep learning modeling, which were then assessed using test data by the `classification_report()` function of the scikit-learn package. The training process was successfully carried out for 50 epochs because the EarlyStopping function was not called. This was because the accuracy validation continued to increase and met the minimum increase requirements.

	precision	recall	f1-score	support
katuk-bp	0.69	0.62	0.66	40
katuk-ea_dg_palisade	0.69	0.62	0.66	40
katuk-ea_dg_stomata	0.70	0.78	0.74	40
katuk-eb	0.66	0.68	0.67	40
katuk-parenkim_d_kko_b_roset	0.47	0.45	0.46	40
keji_beling-bp	0.82	0.57	0.68	40
keji_beling-ea	0.86	0.93	0.89	40
keji_beling-ea_dg_litosit_d_stomata	0.80	0.80	0.80	40
keji_beling-rp	0.95	0.93	0.94	40
keji_beling-sistolit	0.84	0.93	0.88	40
kelor-bp_t_tangga	0.71	0.75	0.73	40
kelor-eb_dg_stomata	0.88	0.88	0.88	40
kelor-kko_b_roset	0.76	0.62	0.68	40
kelor-m_bp_dg_pt_tangga_d_kko_b_roset	0.66	0.62	0.64	40
kelor-m_dg_selsekresi	0.61	0.78	0.68	40
pegagan-bp	0.79	0.95	0.86	40
pegagan-ea	0.88	0.90	0.89	40
pegagan-eb_dg_stomata	0.95	0.90	0.92	40
pegagan-mesofil	0.78	0.80	0.79	40
pegagan-uratdaun_dg_kko_b_roset	0.80	0.80	0.80	40
salam-ea	0.92	0.85	0.88	40
salam-eb_dg_stomata	0.91	0.97	0.94	40
salam-kko_b_prisma	0.89	0.80	0.84	40
salam-sklerenkim	0.87	0.68	0.76	40
salam-unsurxilem_dg_noktah	0.67	0.80	0.73	40
sereh-e_dg_parenkim	0.95	0.95	0.95	40
sereh-ea_d_bp_dg_p_t_tangga	0.86	0.95	0.90	40
sereh-ea_dg_selpalisade_d_rp	0.95	0.95	0.95	40
sereh-ea_dg_stomata_b_halter	0.97	0.90	0.94	40
sereh-sklerenkim	0.86	0.93	0.89	40
accuracy			0.80	1200
macro avg	0.81	0.80	0.80	1200
weighted avg	0.81	0.80	0.80	1200

Fig. 11. Classification report from SimpliScopeX model

The last epoch's training accuracy and validation accuracy results were 93.97% and 74.49%, respectively, with the best validation accuracy at 74.75%. For the test data, the model's accuracy was 80.25%.

4. Conclusions

In this proposed paper, we discuss developing and optimizing a deep learning model to solve microscopic image identification cases of simplicia fragments of medicinal plant leaves using the EfficientNetB0 architecture as the basic model. Our model is based on the fine-tuning and modification of EfficientNetB0 architectures using different model training strategies, which, fused in a final result, gains higher performance than the baseline model.

Various efforts have been made to develop and improve model performance in order to improve the model, such as using different data augmentation techniques, modifying and adding layers to the EfficientNetB0 architecture, using the Adam optimization algorithm, and using various callback functions, such as ReduceLROnPlateau. The deep learning model architecture that has been developed also automates the feature extraction process.

The dataset has been separated into three portions with weights of 60:20:20, with training data accounting for 60%, validation data accounting for 20%, and testing data accounting for 20% of the overall data set. The baseline model could only provide an accuracy of 53.33% of the test data and training and validation accuracy gained in the training phase in the latest epoch, which was 71.24% and 52.11%, respectively. With an accuracy of 80.25% of the test data, the created SimpliScopeX model can solve the classification problem successfully. The training and validation accuracy obtained in the latest epoch was 93.97% and 74.49%, respectively. As a result, the SimpliScopeX model outperforms the baseline model in terms of accuracy.

The research development direction can be carried out further by increasing the variety of datasets, using other pre-trained model architectures, and experimenting with different image processing and image data augmentation techniques. The results of the model that has been built can be applied in the form of an application so that it can facilitate work in identifying the type and classification of microscopic fragments of simplicia of medicinal plants.

Acknowledgment
The Ministry of Education and Culture funded this research through the Fundamental Research grant program, Directorate of Research and Community Service (DRPM). The author would like to thank the team who helped this research so that it could run smoothly.

References

[1] Harefa, Darmawan. "Pemanfaatan Hasil Tanaman Sebagai Tanaman Obat Keluarga (TOGA)." *Madani: Indonesian Journal of Civil Society* 2, no. 2 (2020): 28-36. https://doi.org/10.35970/madani.v2i2.233

[2] Irawati, Irawati, Eniek Kriswiyanti, and AA Ketut Darmadi. "Pemanfaatan Tumbuhan Pekarangan Sebagai Bahan Obat Alternatif Di Desa Jimbaran, Kecamatan Kuta Selatan, Kabupaten Badung." *Bali. Journal of Biological Sciences* 70, no. 1 (2018): 64-70.

[3] Bahalwan, Farida, and Nina Yuliana Mulyawati. "Jenis tumbuhan herbal dan cara pengolahannya (studi kasus di negeri luhut*):* uban kecamatan kepulauan manipa kabupaten seram bagian barat)." *BIOSEL (Biology Science and EducationJurnal Penelitian Science dan Pendidikan* 7, no. 2 (2018): 162-177. https://doi.org/10.33477/bs.v7i2.653

[4] Handoyo, Diana Lady Yunita, and M. Eko Pranoto. "Pengaruh variasi suhu pengeringan terhadap pembuatan simplisia daun mimba (Azadirachta indica)." *Jurnal Farmasi Tinctura* 1, no. 2 (2020): 45-54. https://doi.org/10.35316/tinctura.v1i2.988

[5] Wardiah, Wardiah, Hasanuddin Hasanuddin, and Muthmainnah Muthmainnah. "Etnobotani Medis Masyarakat Kemukiman Pulo Breuehselatan Kecamatan Pulo Aceh Kabupaten Aceh Besar." *Jurnal EduBio Tropika* 3, no. 1 (2015).

[6] Widiyastuti, Yuli. "Pengembangan Parameter Standar Simplisia Untuk Menjamin Mutu Dan Keamanan Obat Tradisional: Orasi Pengukuhan Profesor Riset Bidang Tanaman Obat dan Obat Tradisional." (2020).

[7] Departemen Kesehatan RI, *Parameter Standar Umum Ekstrak Tumbuhan Obat. Direktorat Jendral Pengawasan Obat dan Makanan*. 2000.

[8] Sentat, Triswanto, and Susiyanto Pangestu. "Uji Efek Analgesik Ekstrak Etanol Daun Kersen (Muntingia calabura L.) Pada Mencit Putih Jantan (Mus musculus) Dengan Induksi Nyeri Asam Asetat." *Jurnal Ilmiah Manuntung* 2, no. 2 (2016): 147-153. https://doi.org/10.51352/jim.v2i2.59

[9] Supomo, R. Supriningrum, and R. Junaid, "Karakterisasi Dan Skrining Fitokimia Daun Kerehau (Callicarpa longifolia Lamk.)," *Jurnal Kimia Mulawarman*, vol. 13, no. 2, 2016 [Online]. Available: http://jurnal.kimia.fmipa.unmul.ac.id/index.php/JKM/article/view/205

[10] Fikayuniar, Lia, Julia Ratnawati, and Yenny Febriani Yun. "Uji Pendahuluan dan Karakterisasi Simplisia Herba Picisan (Drymoglossum piloselloides (L.) presl)." *Pharma Xplore: Jurnal Sains dan Ilmu Farmasi* 1, no. 1 (2016). https://doi.org/10.36805/farmasi.v1i1.52

[11] Y. Utami, A. Umar, R. Syahruni, and I. Kadullah, " Standardisasi Simplisia dan Ekstrak Etanol Daun Leilem (Clerodendrum minahassae Teisjm. & Binn.)," *Journal of Pharmaceutical and Medicinal Sciences*, vol. 2, no. 1, 2017 [Online]. Available: https://www.jpms-stifa.com/index.php/jpms/article/view/40

[12] Mentari, Ika Ayu, Wirnawati Wirnawati, and Maulina Rahmawati Putri. "Karakterisasi simplisia dan ekstrak daun bandotan (Ageratum conyzoides L) sebagai kandidat obat karies gigi." *Jurnal Ilmiah Ibnu Sina* 5, no. 1 (2020): 1-9. https://doi.org/10.36387/jiis.v5i1.346

[13] Fitriyanti, Fitriyanti, Syamratul Qalbiyah, and Putri Indah Sayakti. "Identifikasi Kulit Batang Kalangkala (Litsea Angulata Bi) Secara Makroskopik, Mikroskopik, Dan Skrining Fitokimia." *Parapemikir: Jurnal Ilmiah Farmasi* 9, no. 2 (2020): 1-9. https://doi.org/10.30591/pjif.v9i2.1832

[14] Kementrian Kesehatan RI, *Farmakope Herbal Indonesia Edisi II*. Jakarta: Direktorat Jendral kefarmasian dan Alat Kesehatan, 2017.

[15] Departemen Kesehatan RI, *Materia Medika Indonesia Jilid IV. Jakarta: Direktorat Jendral Pengawasan Obat dan Makanan*. 1995.

[16] Ackar, Haris, Ali Abd Almisreb, and Mohamed A. Saleh. "A review on image enhancement techniques." *Southeast Europe Journal of Soft Computing* 8, no. 1 (2019). https://doi.org/10.21533/scjournal.v8i1.175

[17] Fataniya, Bhupendra, Prachi Manishkumar Patel, Tanish Zaveri, and Sanjeev Acharya. "Microscopic image analysis method for identification of Indian herbal plants." In *2014 International Conference on Devices, Circuits and Communications (ICDCCom)*, pp. 1-5. IEEE, 2014. https://doi.org/10.1109/ICDCCom.2014.7024730

[18] Da Silva, Núbia Rosa, Marcos William da Silva Oliveira, Humberto Antunes de Almeida Filho, Luiz Felipe Souza Pinheiro, Davi Rodrigo Rossatto, Rosana Marta Kolb, and Odemir Martinez Bruno. "Leaf epidermis images for robust identification of plants." *Scientific reports* 6, no. 1 (2016): 25994. https://doi.org/10.1038/srep25994

[19] Setiawan, K. Novar, and IM Suwija Putra. "Klasifikasi citra mammogram menggunakan metode K-Means, GLCM, dan Support Vector Machine (SVM)." *J. Ilm. Merpati (Menara Penelit. Akad. Teknol. Informasi)* 6, no. 1 (2018): 13-24. https://doi.org/10.24843/JIM.2018.v06.i01.p02

[20] Widyaningsih, Maura. "Identifikasi Kematangan Buah Apel Dengan Gray Level Co-Occurrence Matrix (GLCM)." *Jurnal Saintekom: Sains, Teknologi, Komputer dan Manajemen* 6, no. 1 (2016): 71-88. https://doi.org/10.33020/saintekom.v6i1.7

[21] Dhiah Rusdiana Priindaryanti, "Pengenalan pola citra penyakit tanaman padi pada daun menggunakan Gabor Wavelet dan algoritma K-Means," Universitas Sanata Dharma Yogyakarta, 2017.

[22] Raja, D., and M. Karthikeyan. "Content based image retrieval using reptile search algorithm with deep learning for agricultural crops." In *2022 7th International Conference on Communication and Electronics Systems (ICCES)*, pp. 1038-1043. IEEE, 2022. https://doi.org/10.1109/ICCES54183.2022.9835839

[23] Azadnia, Rahim, Mohammed Maitham Al-Amidi, Hamed Mohammadi, Mehmet Akif Cifci, Avat Daryab, and Eugenio Cavallo. "An AI based approach for medicinal plant identification using deep CNN based on global average pooling." *Agronomy* 12, no. 11 (2022): 2723. https://doi.org/10.3390/agronomy12112723

[24] Vivek, Tammineedi Venkata Satya, Ayesha Naureen, Mohd Shaikhul Ashraf, Sanhita Manna, Ahmed Mateen Buttar, P. Muneeshwari, and Mohd Wazih Ahmad. "Biomedical microscopic imaging in computational intelligence using deep learning ensemble convolution learning-based feature extraction and classification." *Computational Intelligence and Neuroscience* 2022 (2022). https://doi.org/10.1155/2022/3531308

[25] Anton, Anton, Novia Farhan Nissa, Angelia Janiati, Nilam Cahya, and Puji Astuti. "Application of deep learning using convolutional neural network (CNN) method for Womenâ€™ s skin classification." *Scientific Journal of Informatics* 8, no. 1 (2021): 144-153. https://doi.org/10.15294/sji.v8i1.26888

[26] Rajitha, K. V., Sowmya Bhat, P. Y. Prakash, Raghavendra Rao, and Keerthana Prasad. "Classification of microscopic images of unstained skin samples using deep learning approach." In *2022 IEEE 19th International Symposium on Biomedical Imaging (ISBI)*, pp. 1-4. IEEE, 2022. https://doi.org/10.1109/ISBI52829.2022.9761484

[27] Marwaha, Rohan, and Bhupendra Fataniya. "Classification of Indian Herbal Plants based on powder microscopic images using Transfer Learning." In *2018 Fifth International Conference on Parallel, Distributed and Grid Computing (PDGC)*, pp. 500-505. IEEE, 2018. https://doi.org/10.1109/PDGC.2018.8745922

[28] Rahmatulloh, Alam, and Hendy Suhendy. "MikrobatX: Deep Learning Approach for Microscopic Identification and Classification of Medicinal Leaf Simplicia Fragments Using Sift Feature Extraction." *Available at SSRN 4226649* (2022). https://doi.org/10.2139/ssrn.4226649

[29] Rahmatulloh, Alam, Hendy Suhendy, and Ricky Indra Gunawan. "MikrobatX: The Use of SIFT Feature Extraction in a Deep Learning Approach for Identification and Classification of Microscopic Fragments of Medicinal Leaves." *International Journal on Advanced Science, Engineering & Information Technology* 13, no. 4 (2023). https://doi.org/10.18517/ijaseit.13.4.18436

[30] Abadi, Martín, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado et al. "Tensorflow: Large-scale machine learning on heterogeneous distributed systems." *arXiv preprint arXiv:1603.04467* (2016). [Online]. Available: http://download.tensorflow.org/paper/whitepaper2015.pdf

[31] "GitHub - keras-team/keras: Deep Learning for humans." .

[32] Novac, Ovidiu-Constantin, Mihai Cristian Chirodea, Cornelia Mihaela Novac, Nicu Bizon, Mihai Oproescu, Ovidiu Petru Stan, and Cornelia Emilia Gordan. "Analysis of the application efficiency of TensorFlow and PyTorch in convolutional neural network." *Sensors* 22, no. 22 (2022): 8872. https://doi.org/10.3390/s22228872

[33] Fataniya, Bhupendra, Meet Joshi, Urmil Modi, and Tanish Zaveri. "Automatic identification of licorice and rhubarb by microscopic image processing." *Procedia Computer Science* 58 (2015): 723-730. https://doi.org/10.1016/j.procs.2015.08.093

[34] Ahmad, Muhammad Umair, Sidra Ashiq, Gran Badshah, Ali Haider Khan, and Muzammil Hussain. "Feature extraction of plant leaf using deep learning." *Complexity* 2022 (2022). https://doi.org/10.1155/2022/6976112

[35] Malik, Owais A., Nazrul Ismail, Burhan R. Hussein, and Umar Yahya. "Automated real-time identification of medicinal plants species in natural environment using deep learning models—a case study from Borneo Region." *Plants* 11, no. 15 (2022): 1952. https://doi.org/10.3390/plants11151952