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MikrobatX: The Use of SIFT Feature Extraction in a Deep Learning Approach for Identification and Classification of Microscopic Fragments of Medicinal Leaves

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***Abstract*—Due to a lack of references that contain standard references, it is still difficult to evaluate the accuracy of the raw material for the medicinal plant *Simplicia* powder based on microscopic testing in the pharmaceutical industry. Furthermore, it takes much time to manually match the findings of microscopic tests with standard reference materials. For these reasons, artificial intelligence must be used so that researchers can rapidly and reliably forecast the kinds of medicinal plants based on microscopic fragments. Deep learning performance in computer vision has demonstrated encouraging outcomes in recent years. Convolutional neural networks (CNN) enhanced by SIFT feature extraction, dubbed "*MikrobatX*," are used in the proposed work to identify and classify microscopic fragment images of the medicinal plant *Simplicia*. This technique plays a key role in the microscopic identification and classification of medicinal plant *simplicia*. Using microscopic photographs of the leaves of medicinal plants, *MikrobatX* was able to extract essential *Simplicia* characteristics. Our proposed model may produce the greatest accuracy value of 89.42% for microscopic medicinal leaf *Simplicia* image problems, according to experimental results utilizing the *Mikrobat* dataset. Due to the lack of comparable research using the Microbat dataset, these findings cannot be compared to earlier investigations.**

***Keywords*— Artificial intelligence; feature extraction; medicinal plant *simplicia*; microscopic fragments.**

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I. INTRODUCTION

Botanical research has proven that the earth is vibrant. A variety of millions of plant species can be found easily on the surface of this earth. However, this creates a new problem, namely with the large number of species that require a lot of time and effort to identify them. This study discusses medicinal plants used as raw materials for traditional and modern medicine [1]. Traditional medicinal products derived from plants, animals, and minerals are known as herbs [2]. *Simplicia* is a natural ingredient that has been dried for treatment and not processed.

In the study of scientists, the identification of medicinal plants is made traditionally by macroscopic and microscopic organoleptic tests using *Simplicia* powder. Macroscopic tests use the five senses, while microscopic tests use a microscope to obtain images of fragments. After that, it is necessary to match the microscopic test results with reference books to find the truth, while reference books are still limited and incomplete. This manual matching takes a long time, and the level of accuracy is low because the possibility of human error or the image of the microscopic test results is unclear.

Medicinal plant research articles still lack information about microscopic tests. Some of them only mention microscopic fragments without discussing the truth of the *simplicia* material, which should be the goal of the test [3]–[8]. In addition, some studies are limited to looking for the characteristics of the content of *Simplicia* with microscopic tests [9], [10]. Various literature and research on information technology have also been carried out, including various techniques to identify plant species and parts, such as leaf recognition and visual classification of plants with image processing and computer vision [11], [12]. Image recognition is a challenge in itself and requires various efforts to overcome it. Usually, plants are recognized by recognizing their organs, such as stems, skin, leaves, flowers, or a combination thereof, but it differs from *simplicia,* which has become powder. Then the identification will be carried out on the resulting microscopic test results in the form of *Simplicia* microscopic images.

Experts have found many types of leaves using machine learning (ML) classification [13]–[16]. Fast classification recognition and plant species can be completed in seconds [17]. With advances in artificial intelligence and neural networks, automatic plant recognition using image processing can produce 80% to 97% accuracy [18], [19]. Deep Learning (DL) is one of the ML implementation techniques used to simulate how the human brain functions using an Artificial Neural Network (ANN) or artificial reasoning network. Deep Learning will use numerous algorithms as "neurons" to jointly identify and process particular traits in a data set. Programs in Deep Learning usually use more complex capabilities to study, digest, and classify data. DL algorithms have taken the top place in object recognition because they can improve performance [20], [21]. The class of convolutional neural networks (CNN) was first proposed by LeCun [22]. CNN has the highest accuracy value when compared to others, such as Time Delay Neural Network (TDNN) [23] and Multi-Layer Perceptron (MLP) [24], [25]. CNNs in various ways in computer vision, natural language processing, and speech recognition [26]–[29].

Meanwhile, there are currently several methods for feature extraction in object recognition, face recognition, and image matching. The first method of finding feature points is the Harris angle detector [30], which uses a point with many changes by comparing the number of changes in the value in various directions. However, this method has a weakness that is not strong against changes in image scale. Therefore, the Harris method was developed [31], a complementary method for finding the Harris corner point on several scales and then detecting the maximum point for scale changes. Meanwhile, Shi and Tomasi [32] proposed the Shi & Tomasi angle by considering the affine change. However, the well-known feature extraction method is Lowe's Scale Invariant Feature Transform (SIFT) [33]. How SIFT calculates the Gaussian difference (DoG) not only on the original image but also on the image to which the scale is applied to find the maximum amount of change.

From several related kinds of literature, there has yet to be a discussion of the microscopic identification of medicinal plant *simplicia*, as we proposed. Therefore, this research was carried out as an innovative step by applying deep learning with CNN and feature extraction using SIFT to identify and classify medicinal plant species on *Simplicia* microscopic fragment images. The purpose of this paper is twofold. First, a powerful feature extractor, "*MikrobatX*" (an abbreviation for "Microscopic Medicinal Plants" in the Indonesian Language, and X for feature-eXtraction), was constructed, which is capable of extracting characteristic features from simple microscopic images of medicinal plants. Second, using features from the *MikrobatX* model, this study offers an identification and classification approach for carrying out independent classification experiments on the *Mikrobat* dataset.

The remainder of this paper is organized into four sections. Section 1 deals with the introduction. Section 2 reviews some related research on algorithms and microscopic approaches. Furthermore, the proposed methodology is described in section 3. Section 4 describes the dataset used, and section 5 describes the experimental results of the proposed work. Finally, section 6 discusses the limitations of the presented work and concludes the article by providing opportunities for future work in the medicinal plant *Simplicia* microscopy.

II. Material and Method

A. Recent Works

Artificial intelligence (AI) has been trending in the research community for the past few years. Researchers and companies widely use artificial intelligence, machine learning, and deep learning in digital image processing by researchers and companies, for example, for plant identification and classification [34]–[38]. Previous research has carried out several recognition techniques using shape, size, texture, and descriptors. For example, using probabilistic neural networks to classify leaf features from 32 plants resulted in accuracy values above 90% [39]. They were then refined by Yahiaoui et al. [40] using a boundary-based approach with the Otsu algorithm resulting in a better classification level. In addition, past studies have used the shape base as one of the classification characteristics [14], [41].

In machine learning, several studies use Particle Swarm Optimization (PSO) [42] and Principal Component Analysis (PCA) [43] for the feature selection process. On the other hand, the classification process is the most popular using Support Vector Machines (SVM) [44], in addition to Random Forest [45], Adaboost machine learning algorithm [46], and so on. In contrast, deep learning is a popular method widely used in Convolutional Neural Networks (CNN) [47], [48]. CNN has several well-known architectures among researchers because of their uniqueness and ability to obtain high accuracy. Among them are LeNet-5, made by LeCun et al. [22], AlexNet created by Krizhevsky et al. [49], Network in Network (NN), created by Lin et al. [50], VGG-16 prepared by Simonyan et al. [51], Inception by Szegedy et al. [52], ResNet created by He et al. [53], EfficientNet [54], and others. The most popular feature selection in deep learning is Scale Invariant Feature Transform (SIFT) [33], in addition to using traditional machine learning approaches, namely Gray Level Co-occurrence Matrix (GLCM) [55], [56], Gradient-oriented Histogram (HOG) [57], and so on.

CNN for plant recognition has also been proposed by a study by Varghese et al. [58], which obtained an accuracy value of up to 99.6%, and they concluded that the leaf shape attribute should be avoided as a plant classification option. However, the venation structure is an important feature in distinct plant species. Another study on identifying medicinal plants was also carried out [59] using deep learning, and they classified leaves based on a combination of shapes and dimensions. In contrast to that study, Fataniya et al. [44] have identified Licorice and Rhubarb by processing microscopic images using SVM, resulting in the area under the ROC curve for licorice being 0.7051 and for rhubarb being 0.9487. Another study by Aono et al. [60] used a stomatal classification and detection system in microscopy images of maize cultivars. The results of this study obtained an estimated accuracy value of 97.1% in identifying the stomata area using a classifier based on deep learning features.

According to several related research results, deep convolutional neural networks are the recommended approach for automatic feature extraction, replacing the need to define image descriptors. Furthermore, the introduction of deep learning in various fields of science has resulted in more efficient models and has broken previous assumptions that were considered unpredictable.

Meanwhile, research on the identification and classification of microscopic images still needs to be studied more deeply, mainly for discussing the introduction of the medicinal plant *Simplicia*, which has not been found. So different from previous research, this study proposes the application of deep learning using CNN and feature extraction using Scale Invariant Feature Transform (SIFT), with the selection of the EfficientNet model, which has high top accuracy but uses low graphics processing unit (GPU) [54]. This is very suitable because the proposed model will be used in mobile-based applications in future research.

B. Proposed Methodology

The proposed approach consists of two main stages, as shown in Figure 1. The first stage is image construction, namely preparing a dataset of microscopic images of medicinal plant *simplicia* for processing. The second stage is making the *MikrobatX* model, which is a model for extracting microscopic features of the medicinal plant *Simplicia* based on CNN and SIFT with the enhanced EfficientNetB0 model.

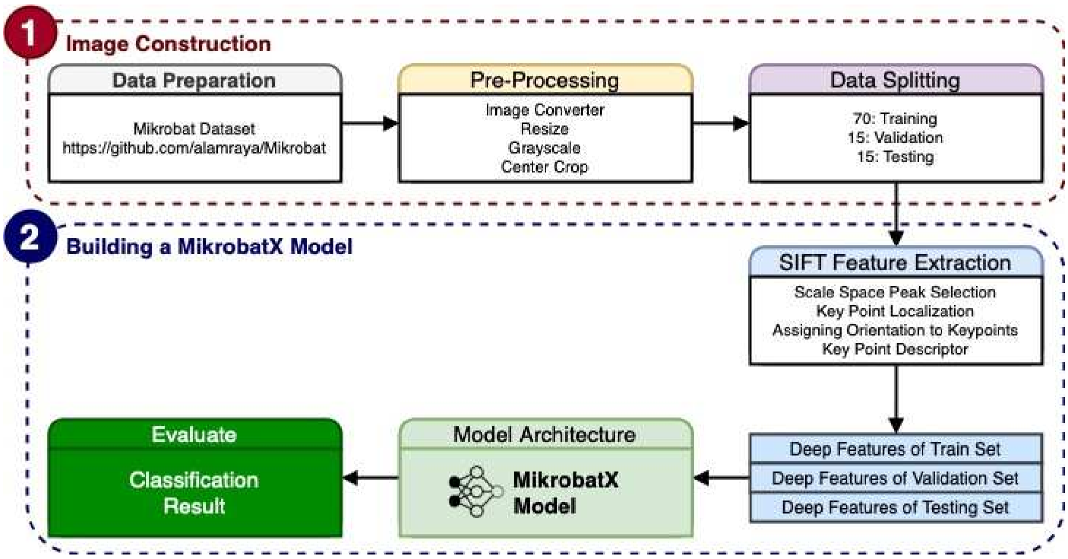

Fig. 1 The overall methodology for microscopic recognition of medicinal plant *simplicia*

1) Image Construction

- Data Preparation

Images of the medicinal plant *Simplicia* microscopic data set were divided into training, validation, and testing sets using the `train_test_split` selection model. Section 3 provides a detailed description of the dataset. The initial dataset we collected from the Farmakope Herbal Indonesia (FHI) and Material Medika Indonesia (MMI) sourcebooks had limited data. Microscopic data of medicinal plant *simplicia* is still challenging, so to support this research, we, together with the pharmaceutical team, conducted direct microscopic tests in the laboratory. The data collection results are packaged into an open dataset called the *Mikrobat* dataset.

- Pre-processing

This stage starts by changing the image data format from RAW image *.jpg to *.png image format. Then proceed with dimensional uniformity by resizing the image to 500x300 pixels. After that, the image is changed to grayscale. The last stage is to do a center crop with the desired dimensions of 300x300 pixels.

- Data Splitting

Because the Microbat dataset is still limited and challenging to obtain, then the image from the dataset is divided into training, validation, and testing sets, by looking at the number of existing datasets so that the image division is divided into 70% training, 15% validation, and 15% testing using `sklearn.model_selection.train_test_split`.

2) MikrobatX--Medicinal Plant Simplicia Microscopic Model

- Scale Invariant Fourier Transform (SIFT)

The SIFT detector detects the desired points in the input image. This allows the identification of local features in the image that are important in applications such as:

- Object recognition in images
- Path detection and obstacle avoidance algorithm
- Gesture recognition, mosaic creation, etc

Contrary to the Harris Detector, which depends on image characteristics like the angle of view, depth, and size, SIFT may detect features without these characteristics. By converting the image data into scale-invariant coordinates, this is accomplished. According to reports, the SIFT detector is comparable to the method utilized in the visual system of primates.

- Scale Space Peak Selection. The space scale concept is about applying a continuous range of Gaussian filters on the target image so that the chosen Gaussian has different sigma parameter values. Scale Space is the name of the obtained plot.

- Key Point Localization. The process of keypoint localization includes improving the key points chosen in the earlier phase. Critical points with low contrast, unstable contrast, and key points towards the edges are all removed. This is accomplished by computing the Laplacian of the key points discovered in the previous stage. The extreme values are calculated in equation (1).

$$z = -\frac{\partial^2 D^{-1}}{\partial x^2}\frac{\partial D}{\partial x} \quad (1)$$

In the expression in equation (1), D represents the Gaussian Difference. To eliminate unstable key points, the z value is calculated, and if the function value at z is below the threshold value, the point is removed.
- Assigning Orientation to Keypoints. Orientation needs to be estimated for the critical locations to achieve detection independent of image rotation. This is accomplished by taking into account the keypoint's environment and computing the strength and direction of its gradient. A histogram with 36 bins is built using the results to represent 360 degrees of orientation (10 degrees per bin). As a result, if a given point has a gradient of, let us say, 67.8 degrees, a value is added to the bin for 60-70 degrees that are proportionate to the size of the gradient at that site. Histogram peaks above 80% are transformed into new key points that are utilized to establish the orientation of the original key points.
- Key Point Descriptor. Each key point's environment is used to construct a descriptor for that key point. Key details in the image are matched using this descriptor. The description of the key point is defined using the keypoint's 16x16 environment. First, blocks within this 16x16 habitat are separated. Each of those sub-blocks is a separate 4x4 contiguous and non-overlapping space. Next, eight bins are generated with the same orientation for each sub-block, as was explained in the Orientation Task. Finally, the 128 bin values (16 sub-blocks * 8 bins per block) are expressed as vectors to create the keypoint descriptor.

- Model Architecture

The proposed MikrobatX deep learning model uses transfer learning from the EfficientNetB0 model. The EfficientNetB0 model was then modified by adding several layers consisting of the layers in Figure 2. This model comprises Conv2D, MaxPooling2D, Flatten, Dense, and Dropout layers. To prevent overfitting, a Dropout layer is used by removing neurons in the form of hidden and visible layers in the network and batch normalization. Batch normalization is a technique for training deep neural networks that standardize the input to the layer for each mini-batch.

Figure 3 is a visualization of the deep learning model in this work. The loss function used is categorical entropy. This is because the label has been encoded at the pre-processing stage. The optimization used is Adaptive Momentum (ADAM). The classic stochastic gradient descent (SGD) method is replaced by the optimization algorithm Adam, which iteratively updates the network weights based on the training data.

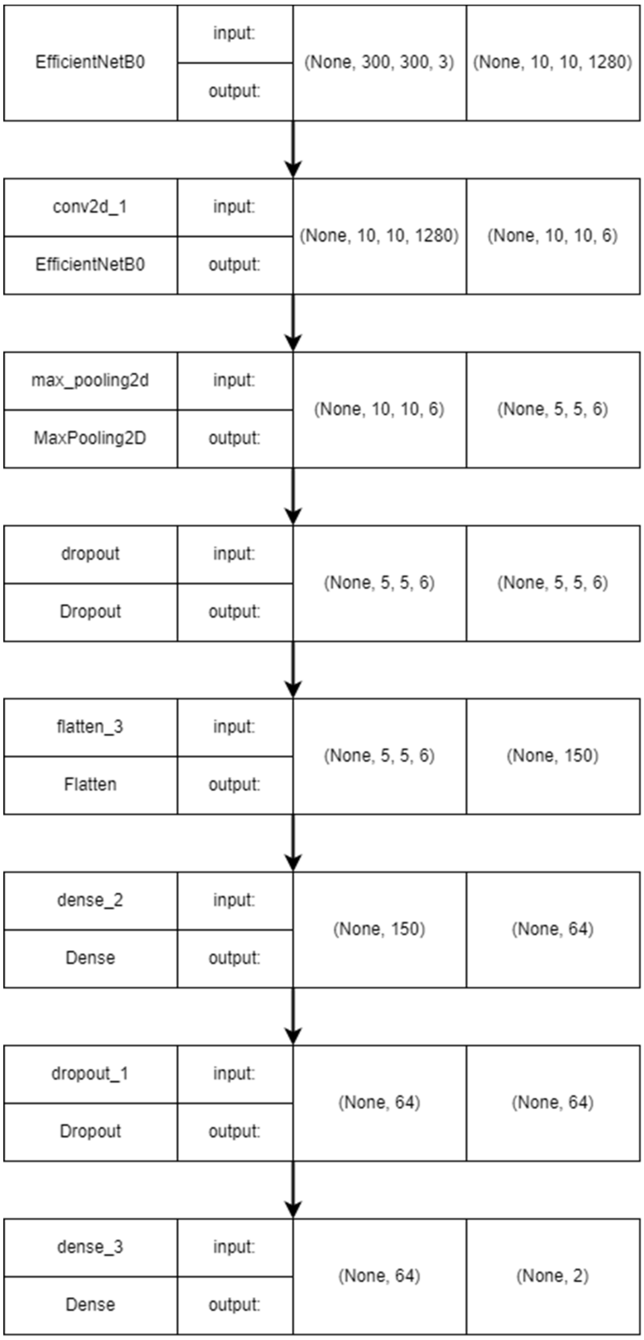

Fig. 2 Deep Learning Layer Model


Fig. 3 Deep Learning *MikrobatX* Model Visualization

- Training Process Strategy

One of the advantages of transfer learning is that the data set is small to train full-scale models from scratch. The stage that is carried out begins with creating an instance of the EfficientNetB0 architecture by importing it from Keras.applications, disabling the top layer, and replacing it with an input layer of size (300,300,3). After that, the model was modified by adding the proposed model as a way to improve the model, thereby improving its overall performance. Models are trained using that data set but with minimal learning speed by melting all layers. This fine-tuned model is referred to as *MikrobatX* and is then used for efficient and powerful feature extraction in species recognition or classification tasks based on microscopic images of medicinal plant *Simplicia* powder, in this case, two types of *piper betle* leaves and *piper crocati* leaves.

- Implementation Process Details

In deploying the MikrobatX model, all network layers are initialized with pre-trained EfficientNetB0 model weights trained on ImageNet to address the key data shortage challenges prevalent in the scientist domain. The tissue has been adapted to study the specific patterns of parts of plant tissue by training the tissue in succession using processed images. The network was trained for 50 epochs with a learning rate of 0.001 during the training phase. The cost function utilized for network training is categorical cross-entropy. The hyperparameters used during the training are shown in Table 1. Figures 7 and 8 display the loss and accuracy graphs of the training and validation datasets during the first stage of model training. The TensorFlow library's open-source Keras DL API interface implements the network. The Google Collaboratory graphics processing unit (GPU) is used to train the network.

TABLE I
HYPERPARAMETERS ARE USED DURING TRAINING

Parameters	Values
Cost Function	Categorical cross-entropy
Optimizer	Adaptive Momentum (ADAM)
Learning rate	0.001 (Default)
Epochs	50
No. of parameters trained	4,209,348

III. RESULT AND DISCUSSION

A. Mikrobat Dataset

The medicinal plant *Simplicia* microscopic dataset is *Mikrobat* (in the Indonesian language: Mikroskopik Simplisia Tanaman Obat) `https://github.com/alamraya/Mikrobat`, has microscopic image data of medicinal *piper betle* and *piper crocati* which is the most extensive collection at the time of this paper. Microbats are a dataset of dry leaf *Simplicia* microscopic fragments obtained from various sourcebooks and laboratory test results with a total data of 716 images. Trained experts classify all images of *Simplicia* microscopic sections using a standard classification scheme based on laboratory microscopic tests. Figure 4 shows an image of a *simplicia* microscopic sample of the medicinal plant *piper betle* leaves and *piper crocati* leaves.

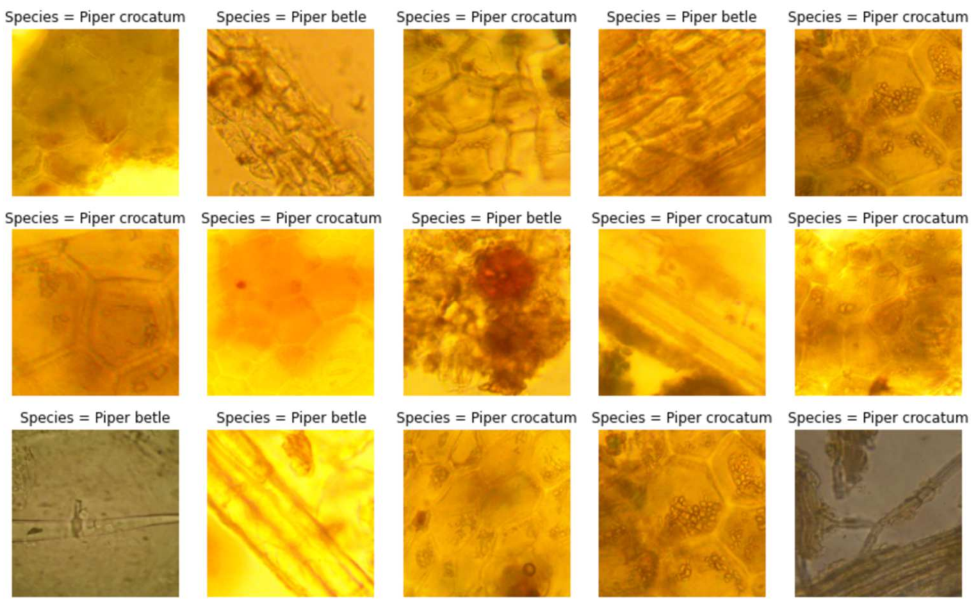

Fig. 4 Sample images of *simplicia* microscopic images of *piper betle* leaves and *piper crocati* leaves in the Microbat data set.

B. Evaluation Metrics

The deep learning model that has been built is evaluated using a classification report. A classification report is a performance evaluation in machine learning that shows important metrics, namely precision, recall, F1 Score, and support of a classification model. Each class's precision, recall, and F1 score were calculated using equations (2)–(4).

There are several categories of possible cases [61]:

- True Positive (TP): the case where the predicted microscopic matches the (Positive) class and actually matches the (True) class.
- True Negative (TN): the case where the predicted microscopic does not match the (Negative) class and actually does not match the (True) class.
- False Positive (FP): the case where the predicted microscopic matches the (Positive) class and turns out not to match the (False) class.

- False Negative (FN): the case where the predicted microscopic does not match the (Negative) class and turns out to be a valid (True) class.

Precision (P) is the ratio of the correct prediction to the overall positive predicted result. Precision explained, "What percentage of plant species are following the class of all predicted species according to their class." Precision uses the function in equation (2).

$$Precision\ (P) = \frac{True\ Positive\ (TP)}{(True\ Positive\ (TP) + False\ Positive\ (FP)} \quad (2)$$

The recall is the correct prediction ratio to the total number of correct data. Recall explained, "What percentage of plant species are following the class of all predicted species according to their class." Recall using the function in equation (3).

$$Recall\ (R) = \frac{True\ Positive\ (TP)}{(True\ Positive\ (TP) + False\ Negative\ (FN)} \quad (3)$$

F1 Score is a weighted ratio of the average precision and recall. F1 Score using the function in equation (4).

$$F1\ Score = \frac{2X\ (Recall\ (R) x\ Precision(P))}{(Recall\ (R) + Precision\ (P)} \quad (4)$$

Accuracy is the ratio of the correct predictions of the actual data. Accuracy explains, "What percentage of plant species are following the class of all predicted species according to their class." Accuracy uses the function in equation (5).

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + FP + FN + TN} \quad (5)$$

C. *Experimental Result and Discussion*

The experimental environment was carried out using a laptop with a 64-bit Windows 11 operating system, 16 GB RAM, with an AMD Ryzen 9 processor running in Google Collaboratory using a GPU from Google Collaboratory. The results of applying SIFT Feature extraction can be seen in Figures 5 and 6. In Figure 5 (a), the left is the original image from the training and testing results, while in Figure 5 (b), the right is the keypoint detection with size and without size. The results of the keypoint detection are matched to the original image as input and compared with images that have gone through the training process. Figure 6 shows the best matching points in the sample *piper betle* leaves microscopy image.

We had 403 microscopic images of the medicinal plant piper betle leaves and 313 crocati leaves for the experiment. In addition, several images from the dataset were used as training images, with a 70% split mechanism, for validation 15%, and for testing 15% of the microscopic images of *piper betle* leaves and *piper crocati* leaves, respectively.

This effort has culminated in the suggested *MikrobatX* model. By visualizing the investigated filters and feature maps, an examination of the features recognized by the suggested model is thus accomplished. Figures 7 and 8 are the results of the training and validation accuracy of the *MikrobatX* model on the *Mikrobat* dataset. Figure 9 illustrates the workflow of the *MikrobatX* model classification, starting from the input data (original image microscopy), pre-processing, feature extraction, and deep learning with the *MikrobatX* model to issue the prediction results.

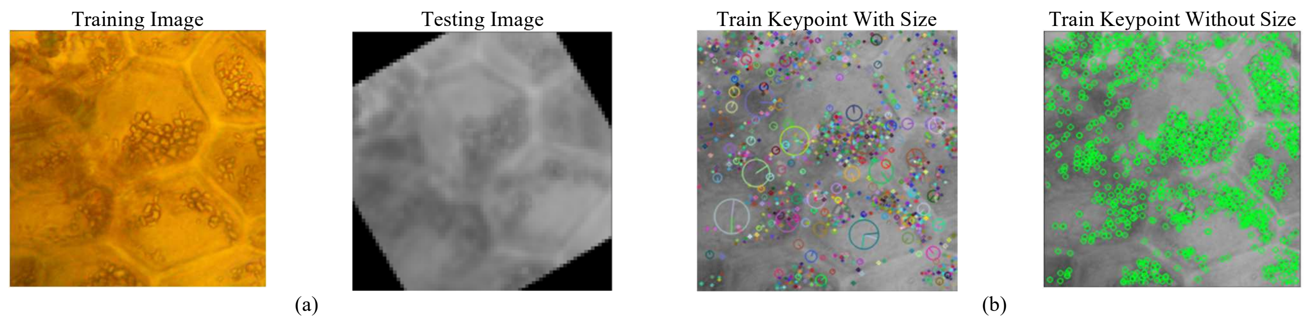

Fig. 5 Original image (a), Detect keypoints and create descriptor (b) of the upper epidermis and prismatic calcium oxalate crystals on microscopic piper betle leaves.

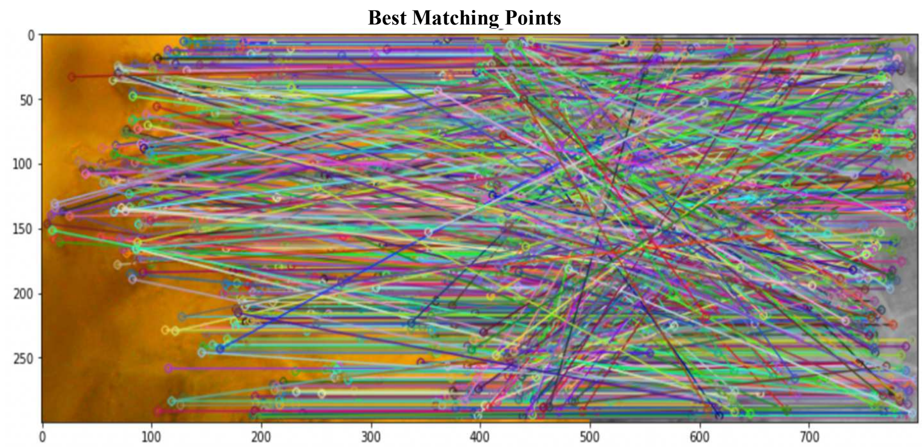

Fig. 6 Matching key points in the upper epidermis and prismatic calcium oxalate crystals on piper betle leaves microscopy.

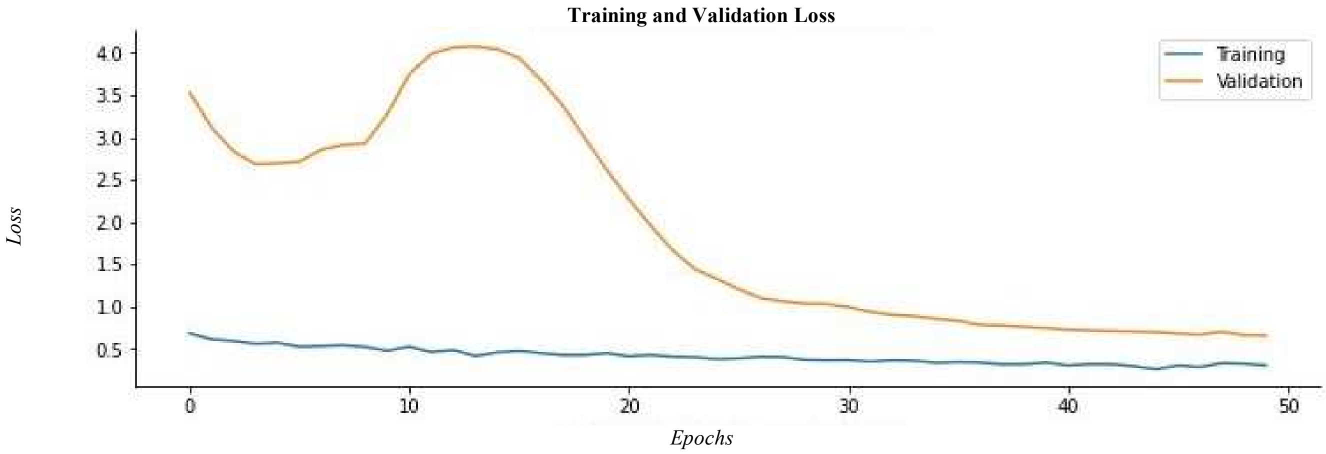

Fig. 7 Loss graphs of training and validation data during model training

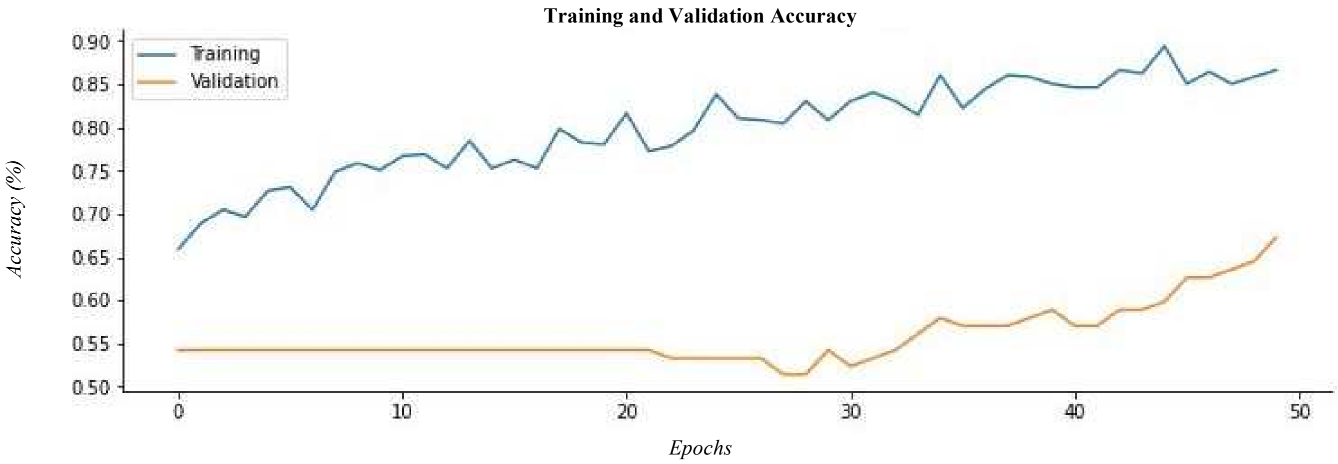

Fig. 8 Accuracy graphs of training and validation data during model training

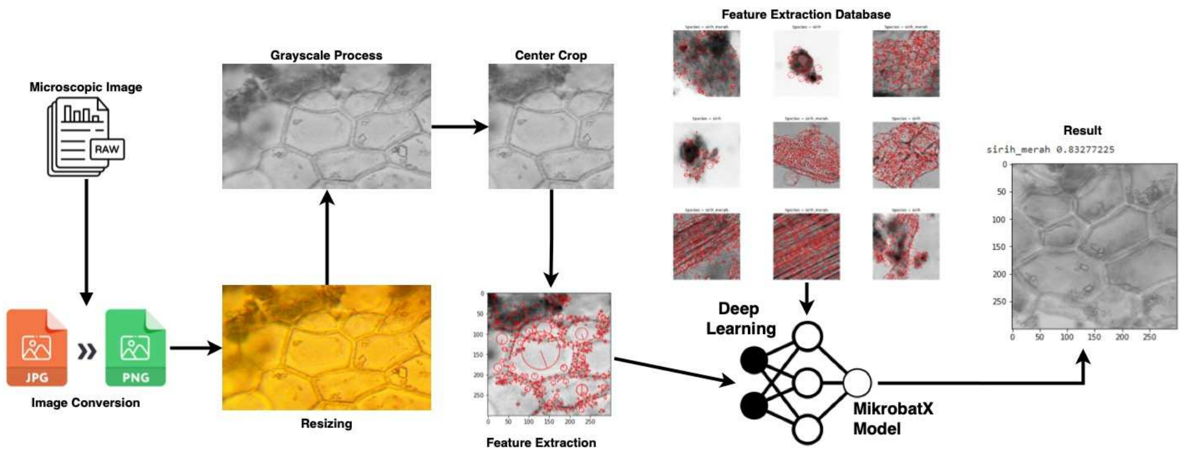

Fig. 9 Drawing of a workflow diagram for the microscopic classification of medicinal plant *simplicia*

This effort has culminated in the suggested *MikrobatX* model. By visualizing the investigated filters and feature maps, an examination of the features recognized by the suggested model is thus accomplished. Figures 7 and 8 are the results of the training and validation accuracy of the *MikrobatX* model on the *Mikrobat* dataset. Figure 9 illustrates the workflow of the *MikrobatX* model classification, starting from the input data (original image microscopy), pre-processing, feature extraction, and deep learning with the *MikrobatX* model to issue the prediction results.

Using the Microbat dataset with Deep Learning and Transfer Learning from EfficientNetB0 with further adjustments to the Convolutional Neural Network (CNN) layer, we suggest enhancing the introduction to the microscopic classification of medicinal plants. In order to further enhance the model based on the findings of various earlier studies, we have also integrated the ADAM optimization method. Training data comprise 70% of the dataset, validation 15%, and testing 15%, with a weighting of 70:15:15.

The developed model can successfully resolve the classification issue. A classification report using test data is then used to assess the outcomes of this deep learning modeling. This classification report is shown in Table 2. The most recent epoch's training accuracy and validation accuracy results were 86.63% and 67.29%, respectively, with the best training accuracy of 89.42%.

TABLE II
EXPERIMENTAL RESULTS ON MIKROBAT DATASETS

Index	Label (Species)	Precision	Recall	F1-Score
0	*Piper Betle*	0.75	0.38	0.50
1	*Piper Crocati*	0.64	0.90	0.75
Accuracy				0.67
Macro Avg		0.70	0.64	0.62
Lighted Avg		0.69	0.67	0.65

When compared with a similar study [62] with different datasets and techniques, this research can achieve 95.42% accuracy. So that the results of this research accuracy still need to be improved, especially datasets that are very influential on the results of the data science studied. This is an opportunity for further research development in increasing accuracy with an enhanced model.

IV. CONCLUSION

For the *simplicia* picture problem of microscopic medicinal plants, the suggested *MikrobatX* model can efficiently extract important and pertinent characteristics with the most excellent accuracy value of 89.42%. This proposed model can yet be enhanced, however. There are still issues in correctly identifying microscopic pictures of medicinal plants.

The new *MikrobatX* model can be upgraded and used as a feature extractor to improve further the efficiency of microscopic classification of medicinal plant *simplicia* with improved model settings. Any intelligent system for the microscopic classification of medicinal plants must have a recognition model that can recognize image key points under all conditions. Models must outperform the data set they are trained to develop robust systems. The given technique can train classifiers to predict and recognize other varieties of medicinal plants by using features from other dataset photos. This method speeds up decision-making and saves time examining slides under a microscope.

An interesting future work direction is dataset optimization and dataset combination experiment. Meanwhile, the model that has been produced can be developed into a mobile-based application to facilitate the work of identifying the types and microscopic classification of medicinal plant *simplicia*.

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