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Disease Identification on Fig Leaf Images Using Deep Learning Method

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***Abstract*—The fig plant, known as Ficus carica, has been cultivated worldwide, including in Indonesia. It has nutritional benefits and medicinal properties. However, there are still difficulties in growing it, making the plant scarce. The scarcity of fig plants in Indonesia is mainly due to the threat of diseases and viruses that affect them. Various diseases affect fig plants, including leaf rust (*Cerotelium* fici), mosaic disease, and *Bemisia tabaci* (whitefly) disease. Infected fig plants become unhealthy, experiencing stunted growth and deformed fruits; thus, it is necessary to identify the diseases accurately using technological assistance. This research aimed to identify diseases in fig leaves automatically. The method began by digitizing fig leaf images and consulting botanical experts specializing in fig plants to determine the types of diseases present. The research produced a dataset of fig leaf images consisting of four classes of fig leaves: *Cerotelium fici*, mosaic disease, whitefly, and healthy fig leaves. The dataset resulted in the confirmation of 300 fig leaf images. The augmentation techniques were applied to increase the number of images to 3,300 fig leaf images. This dataset was then divided into subsets for training, validation, and testing. For the classification and identification, a Deep Learning approach was used with three models: VGG16, VGG19, and MobileNet. Among these models, MobileNet achieved the highest accuracy of 98.79%. Subsequently, the identification system was implemented by converting the generated model into TensorFlow Lite and integrating it into the Android Studio software, enabling it to function as a mobile application on Android devices.**

***Keywords*— Image processing; fig leaf; deep learning.**

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I. INTRODUCTION

The fig plant or tin plant (*Ficus carica*) is a diploid species in the *moraceae* family and has more than 1400 species belonging to 37 genera, the name tin itself is taken from Arabic because tin fruit is one of the five plants mentioned in the holy book of Qur'an [1], [2], [3]. Fig plants mostly grow in the Mediterranean region due to its warm climate [4]. Fig plants are cultivated worldwide to produce over one million tons or about 80% of the overall production which occurs in the United States (27.1 K Metric Tons), Spain (59.9 Metric Tons) to Turkey (320 K Metric Tons) due to its nutritional and medical properties [5], [6], [7].

In Indonesia, the fig plant gained popularity and developed due to its numerous beneficial properties [8]. The plant is composed of various parts such as stems, leaves, fruits, roots, and twigs [9]. This plant offers multiple health benefits, including antifungal, antibacterial, antioxidant, antimicrobial, anti-inflammatory, anti-cancer, and hypoglycemic properties, and can help overcome hypolipidemia [14]. In fig leaves, there are active compounds such as *psoralen*, *bergapten*, *insulin*, *selenium*, and *selenoprotein*, which function as antioxidants and regulate thyroid hormone metabolism [10], [11], [12], [13], [14], [15], [16], [17]. Experts from the George Washington University Medical Center state that consuming a fig plant provides a long-term guarantee of health [18]. Figs are becoming scarce in Indonesia due to the increasing demand for figs by consumers, which is often not met. The threat of diseases and viruses that attack the fig plant is the leading cause of its scarcity. Fig leaves infected with this virus exhibit slow growth and defects in the fruit. Moreover, diseases that attack fig plants cannot be treated immediately because they must first be examined and analyzed for the type of disease. As for the handling, errors can occur, such as misdiagnosing the kind of disease and carrying out the wrong treatment [19]. The analysis of diseases in fig leaves has been explored in recent years such as who applied DCNN and Transfer-Learning to differentiate the types of fig leaves and this study applied image processing techniques such as segmentation, feature extraction, and classification of healthy leaves and diseased leaves whose results were used to assist farmers in monitoring the condition of the crop [20], [21]. Although many techniques and algorithms have been developed in this regard, there is still room for further development.

In previous research, the C4.5 algorithm was reported to detect and classify healthy and diseased fig leaf images with 87.5% accuracy. In comparison, the Naïve Bayes algorithm achieved 90% accuracy on 120 fig leaf images, both of which require segmentation through Gray Level Co-occurrence Metrics (GLCM) features. Research on fig leaf classification still needs to be further developed, especially related to the classification of fig leaf diseases such as leaf rust disease (*Cerotelium fici*) which attacks fig leaves with symptoms that appear on the leaves in the form of small angular spots of yellowish green, then enlarged and yellowish green brown [8], [22]. Mosaic disease, first reported in California in the early 1930s, affects fig plants with highly variable disease symptoms. These symptoms include discoloration, yellowing, various spot patterns, chlorosis spots, vein bands, vein clearing, chlorotic or necrotic ring spots, and stripe patterns on the leaves of affected trees. Figs can show yellow spots, longitudinal stripes, ring spots, and can fall prematurely [23].

This research aimed to identify the types of diseases in fig leaf images using image processing techniques. Before entering the classification process, the image must be digitized to convert analog data into digital and confirmed by the fig botanist to recognize the types of diseases in the leaf image, which will be used as a dataset. The image pre-processing stage involves augmentation techniques, resizing, and conversion. In the classification process, the author uses a deep learning algorithm with several architectural models, namely VGG16, VGG19, and MobileNet. In the final process, the highest classification results are integrated into an Android-based mobile application system, enabling the quick and effective detection of disease types in fig leaves.

II. MATERIALS AND METHOD

The stages of the research methodology carried out in the study can be seen in Figure 1.

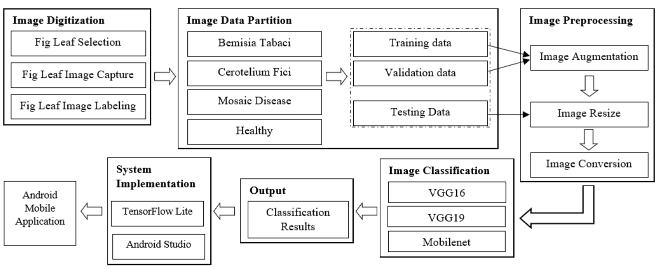

Fig. 1 Research method flow

A. Image Digitization

A method used to change an image, namely from an analog image to a digital image in the form of pixels, is called image digitization, so that the computer can perform image processing to get a good and more aesthetic image display [24]. The equipment used in the process of digitizing the fig leaf image is smartphones, scanners, and digital cameras. Things that must be considered in the image digitization process include distance, resolution, lighting, magnification, object movement, and camera movement, as well as the angle of image taking [8], [25]. This study utilizes a Canon EOS 1200D camera, which is connected to a laptop and scanner for scanning. This allows for digital processing of the image, consultation with a botanist, and subsequent steps. The following process of digitizing the fig leaf image can be seen in Figure 2.

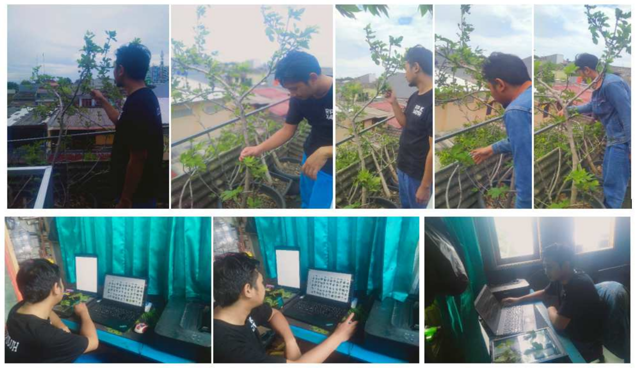

Fig. 2 Image digitization

B. Image Augmentation

The process of changing or modifying an image in a way that the computer detects as a different image, yet humans recognize as the same, is known as image augmentation [26]. Augmentation can increase the accuracy of the trained algorithm model because it provides additional data that can be useful for creating models that generalize better. Augmentation techniques performed randomly on fig leaf images in this study are horizontal flip, vertical flip, width shift, height shift, brightness, shear, rotation, and zoom.

C. Image Resize

Image resizing is a process that changes the image resolution and pixel information. Resize is also performed to achieve a uniform image resolution across all images [27]. Image resizing is a pre-processing stage in this study to facilitate the training process and help the training process achieve the maximum level of model accuracy [28]. In this study, the original image of fig leaves was resized to a size of 224 x 224 pixels.

D. Image Conversion

By default, the image reading process uses the BGR color model; therefore, you must convert the color model as needed every time you read it [29]. Consequently, it is necessary to convert the fig leaf image from BGR to RGB (Red, Green, and Blue) so that the color display on the fig leaf image can be used by Matplotlib correctly.

E. Data Partition

Partitions on a dataset usually consist of a training set, a validation set, and a testing set. Training sets are used to create learning models, and validation sets are typically used to adjust hyperparameters during training. The testing set is a sample of data unseen by the previously trained model, which is used to evaluate the performance of the algorithm model [30]. The dataset used in this study is private. After performing the image digitization stage, 300 fig leaf images were found. In the pre-processing stage, the image results were found to be 3300 fig leaf images, which were divided into four classes as shown in Table 1.

TABLE I
RESULT OF DIGITIZATION AND PRE-PROCESSING TIN LEAF IMAGE

Class Name	Original Fig Leaf Image	Augmented Fig Leaf Image
Bemisia Tabaci	84	924
Cerotelium Fici	51	561
Mosaic Disease	105	1.155
Healthy	60	660
Total	300	3300

Including *Bemisia Tabaci* (BT), *Ceratolium Fici (CF), Mosaic Disease (MD),* and Healthy (HL). Then, at the next stage, it can be seen in Table 2 that the dataset is divided into three sets, namely training data, testing data, and validation data.

TABLE II
DATASET PARTITION

Data Type	Fig Leaf Image
Training Data	1980 Images
Testing Data	660 Images
Validation Data	660 Images
Total	3300 Images

F. Image Classification

Image classification is a method of grouping based on the characteristics of each image object or data set. Classification is a function that categorizes data into classes, indicating the data's contents [31]. The stages of image classification in this study, the image is classified using the proposed method of 3 deep learning architectural models to get the best accuracy values, including VGG16 Model Architecture, VGG19 Model Architecture, and Mobilenet Model Architecture [32], [33], [34], [35], [36], [37].

G. Confusion Matrix

The confusion matrix is the most widely used and easiest way to measure performance with two or more class types in any classification problem. This study uses a confusion matrix to measure the performance level of the algorithm on the dataset used. The result of this matrix is to see the value of the level of accuracy, precision, recall, and f1-score with units of percent (%). This level of accuracy will later be used as a reference for researchers regarding the performance of the classification algorithm [38].

H. TensorFlow Lite

The first TensorFlow Lite inference installed occurred on 8 November 2020 [39]. TensorFlow Lite is a set of tools that enables machine learning on smartphones or other mobile devices using the FlatBuffer serialization format. The binary footprint of a code viewer is usually less than two kilobytes, enabling developers to run models on mobile, embedded, and edge devices [40], [41].

I. Android Studio

Android Studio is an environment for development, namely the Integrated Development Environment (IDE), which is officially integrated and specially designed for application developers who use Google system [42]. In Android Studio requires several development kits, including Java Development Kit (JDK) as a tool for translating code, Software Development Kit (SDK) is a text editor for converting Java and XML files and debugging applications, and Extensible Markup Language (XML) which is a modern system for annotating documents in a way that is syntactically distinguished from text [43].

III. RESULTS AND DISCUSSION

A. Image Digitization Results

In this paper, the digitization results obtained by researchers from a total of 300 fig leaf images have been confirmed by fig botanists. Among them are 84 pictures of fig leaves affected by whitefly pests (*Bemisia tabaci*), 51 pictures of fig leaves affected by leaf rust disease (Cerotelium fici), 105 pictures of fig leaves affected by the mosaic virus (mosaic disease), and 60 pictures of healthy fig leaves. Examples of the results of digitizing fig leaf images can be seen in Figure 3.

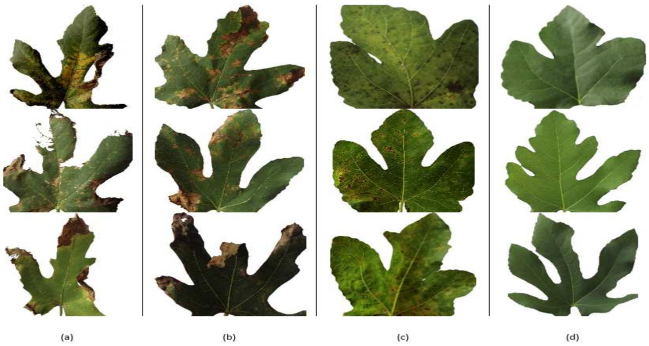

Fig. 3 Image digitization sample results, (a) *Bemisia Tabaci*, (b) *Cerotelium Fici*, (c) Mosaic Disease, (d) Healthy

B. Image Augmentation Results

In this paper, the pre-processing results are divided into three parts, namely the image augmentation process with several modification techniques such as flip, rotate, zoom, shear, brightness, width, and height. Next, the image resizing process is performed at a size of 224x224 pixels, followed by the image conversion process. This ensures that the color display on the fig leaf image functions properly with Matplotlib, and an example of the augmented fig leaf image is provided. The process is carried out using several techniques, as shown in Figure 4.

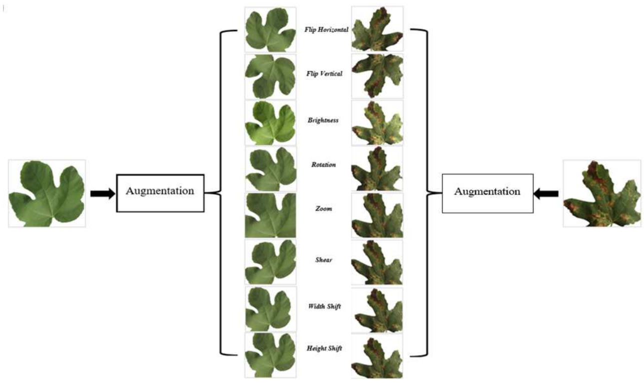

Fig. 4 Example of image augmentation results

C. Classification Results

In this paper, deep learning methods are used, namely the VGG16 architectural model, the VGG19 architectural model, and the Mobilenet architectural model. From the proposed architectural model, the training and validation process is carried out using 20 epochs, with each epoch having 21 steps. The results of the training and validation processes of each model can be seen in Figure 5.

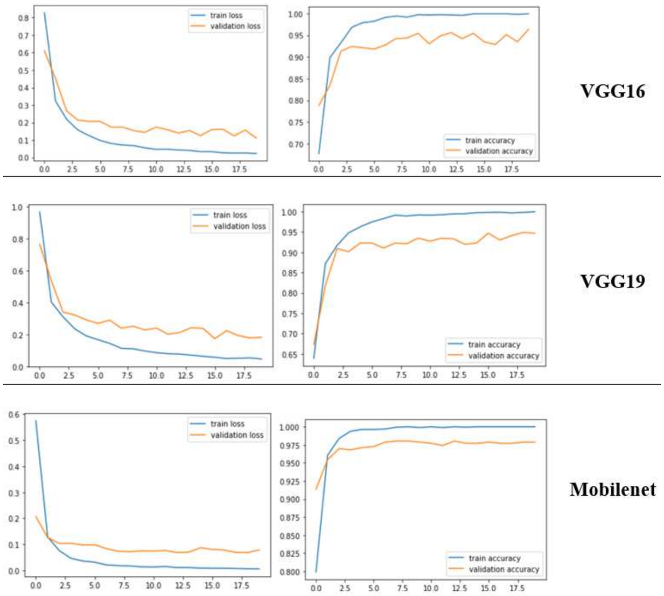

Fig. 5 Graph of training and validation results

After completing the training and validation process, a testing process is conducted to produce an accuracy value. The accuracy value of the testing process is presented in the form of a percentage graph, which can be seen in Figure 6. The experiment results demonstrate the performance of three different architecture models: VGG16, VGG19, and Mobilenet. Accuracy is the measure used to evaluate how well the models can predict or classify data correctly. The VGG16 architecture model has an accuracy of 95.61%. VGG16 consists of 16 deep and complex convolutional layers, enabling it to extract more complex features from images. The strong performance of VGG16 indicates its ability to classify data with a high level of accuracy. The VGG19 architecture model has an accuracy of 96.36%. VGG19 is another variant of the VGG architecture model, featuring 19 convolutional layers. With the additional layers, VGG19 can extract more complex and abundant features compared to VGG16. The higher accuracy demonstrates that VGG19 has better capabilities in classifying data compared to VGG16. The Mobilenet architecture model has an accuracy of 98.79%. Mobilenet is specifically designed for mobile devices or devices with limited resources. It utilizes a lighter and more efficient computational approach while still retaining the ability to extract essential features from images. The high accuracy of Mobilenet highlights its superiority in classifying data compared to the previous two models.

Furthermore, all three architecture models outperform previous research that employed the Naive Bayes algorithm and the C45 algorithm. The Naive Bayes algorithm achieved an accuracy of 90%, while the C45 algorithm achieved an accuracy of 87.52% [2]. Both of these algorithms are classification methods with simpler approaches compared to complex architecture models like VGG and Mobilenet. Therefore, the experiment results indicate that architecture models have better performance in classifying data compared to traditional classification methods such as Naive Bayes and C45. This finding contributes to the research.

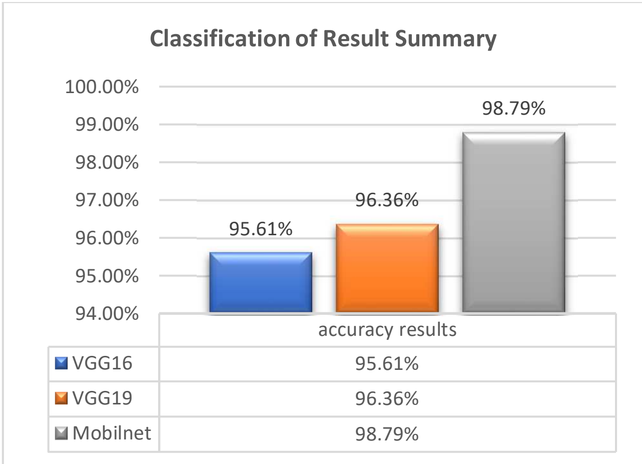

Fig. 6 The accuracy of results from 3 architectural models

The results of the confusion matrix testing for 4 classes of fig leaf imagery are presented in Table 3-5. The confusion matrix is a table used to evaluate the performance of a classification model [37]. In the given tables, 3, 4, and 5, there are four predicted labels by the respective models: HL (Highland), BT (Bukit Tinggi), CF (Cameron Highlands), and MD (Melaka). Each cell in the table represents the number of data points classified into the corresponding labels. For example, in Table 5, there are 229 data points correctly classified as HL and truly belonging to the HL class. This means that the VGG16 model correctly predicted 229 data points for the HL label.

TABLE III
CONFUSION MATRIX MODEL VGG16

	BT	CF	MD	HL
Bemisia Tabaci	209	2	0	0
Cerotelium Fici	6	80	9	4
Mosaic Disease	0	5	123	3
Healthy	0	0	0	229

However, there are also 4 data points incorrectly classified as CF by the model. Similarly, in tables 6 and 7, we can see the number of data points correctly classified by the VGG19 model.

TABLE IV
CONFUSION MATRIX MODEL VGG19

	BT	CF	MD	HL
Bemisia Tabaci	205	4	0	2
Cerotelium Fici	3	86	6	4
Mosaic Disease	0	3	127	1
Healthy	0	0	1	218

And both Mobilenet models and the data points were misclassified. From these three tables, it can be concluded that the Mobilenet model performs better compared to the other two models. This is evident from the highest number of correctly classified data points in the Mobilenet model.

TABLE V
CONFUSION MATRIX MODEL MOBILENET

	BT	CF	MD	HL
Bemisia Tabaci	211	0	0	0
Cerotelium Fici	0	93	4	2
Mosaic Disease	0	2	129	0
Healthy	0	0	0	219

D. Implementation of The System

The implementation of the system into an Android-based mobile application is carried out so that the system can be understood and used efficiently by users who are the contributors to this research. The application was developed with Android Studio Bumblebee Software. The Android mobile-based application that was built consists of a menu for selecting testing images, identifying images, and displaying processing results. This application utilizes GUI components already available in Bumblebee's Android Studio software, including linear layout, ImageView, button, and TextView. To select an image to be identified, click the select image button, which will then switch to phone storage to select an image file, as shown in Figure 7.

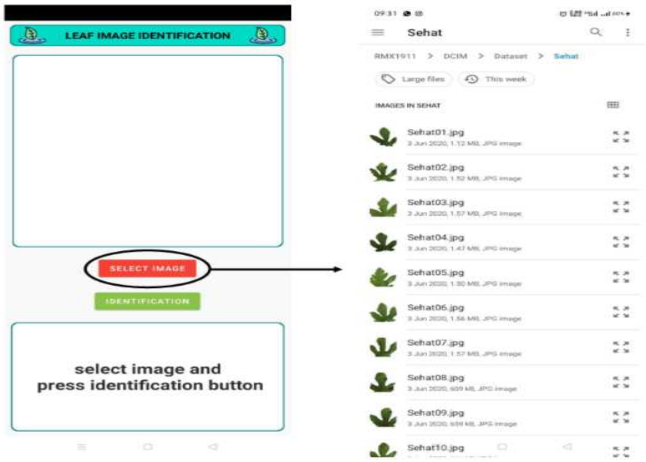

Fig. 7 Tin Leaf Image Selection Display

After pressing the identification button, the image identification process begins. The leaf image is then automatically subjected to classification processing using the Mobilenet architecture model. The outcomes of this identification process stage are displayed in a text view or box, as depicted in Figure 8.

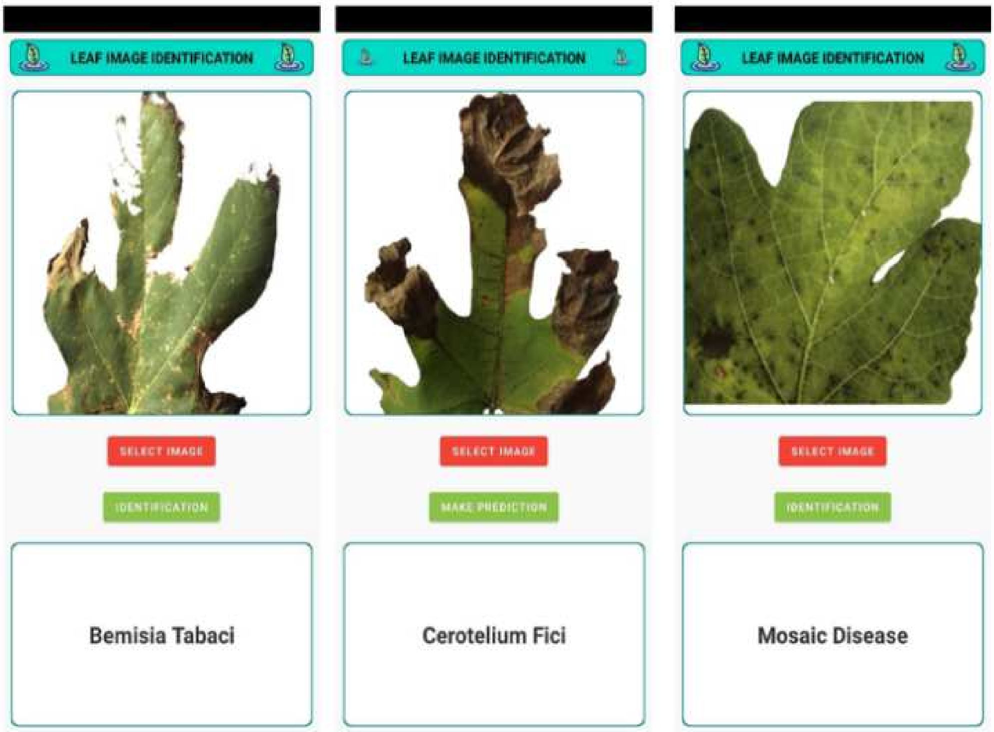

Fig. 8 Tin leaf image display identification results

IV. CONCLUSION

The research conducted in this study presents several novel aspects. Firstly, the dataset used in the research was obtained through a confirmed image digitization process from fig botanists. This process resulted in a dataset of 300 fig leaf images, which were then subjected to various preprocessing techniques such as augmentation, resizing, and conversion. As a result, the dataset was expanded to 3300 fig leaf images, representing three classes of disease types (*bemisia tabaci, cerotelium fici*, and mosaic disease) as well as a healthy class.

The novelty of this research lies in the proposed deep learning algorithm method, which outperforms previous studies in classifying fig leaf images. The VGG16 architecture model achieved an accuracy of 95.61%, the VGG19 architecture model achieved 96.36% accuracy, and the Mobilenet architecture model demonstrated the highest accuracy of 98.79%. This indicates that the models developed in this research have improved upon the performance of previous methods.

Furthermore, an additional novelty of this study is the conversion of the Mobilenet model into TensorFlow Lite

(.tflite) format. This conversion enabled the integration of the model into the Android Studio software, allowing for its implementation as a mobile application system. The developed mobile application provides a practical and accessible solution for disease identification in fig leaves based on the Android platform.

In conclusion, this research contributes novel advancements in the field of classifying fig leaf images. The proposed deep learning models, specifically VGG16, VGG19, and Mobilenet, exhibit superior accuracy compared to previous studies. Moreover, the integration of the Mobilenet model into the Android platform enhances the practicality and usability of the research findings for disease identification in fig leaves.

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