Convolutional Neural Network Approach for Different Leaf Classification

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ABSTRACT

There are millions of plant species with different shapes of a leaf. Those unfamiliar or outside the field may have difficulty recognizing the plant based on leaf appearances. A system that can provide an automatic response when a kind of leaf is exhibited may need to be developed. The system should provide the name of the leaf and other related information according to the input image. Therefore, in this paper, a research work on developing a system that can classify the leaf types is performed. The Convolutional Neural Network (CNN) architecture is applied with the help of TensorFlow for modeling the training data and testing. The classification accuracies are evaluated and tested on the leaf datasets where the unknown leaf image is used as input, and the name of the plant species belonging to the input image is classified as the system's output. The assessment shows that the trained model can achieve a performance accuracy of more than 95%, which provides a promising system for the public to classify leaves and understand nature much more deeply.

1   INTRODUCTION

Plants were treated as one of the essential elements for humans and all living things, which is not only for protecting the environment, such as air quality, but also for food. Though some plants are parasitic on humans or animals, it still provides a substantial amount of the world's oxygen and medicinal purposes. However, due to human intervention, especially for development, many plant species are going to exterminate [1]. It would be helpful to have an automated process to classify plants, and there is active research in the field [2,3]. The components that are usually considered to classify plants are leaves, flowers, or other parts; where the leaf is most considered due to its rich source of information with more features such as color, shape, texture, veins, and other appropriate morphological features [4]. Although the classification or identification of plant leaves is reliable via visually, the large number of plant species makes it challenging if performed through manual inspection. Therefore, to ease the classification process, an approach for automating the classification of plants using the image processing technique has produced excellent work [5,6].

The leaf classification can be achieved by different appearances such as leaf texture, shape, or color, where these unique leaf features have created interest in developing a machine vision-based plant classification. Many techniques, including convolution neural networks, are implemented for leaf

classification, where the main principle is finding the leaf shape features and the selection of extraction techniques. For convolution neural network-based system, it requires a large amount of data, and it can lead to constraints on the usage in the application when the amount of data is limited. Through this paper, we intend to present a basic implementation of leaf classification by applying the recent techniques with the help of leaf images. By feeding it into a specific algorithm such convolutional neural network, the characteristics of leaves can be extracted by modeling the mathematical characteristic for classification. In this paper, the rationale of the research work is to assess the classification performance through the learning process of a convolutional neural network algorithm with good generalization accuracy. Combination of the dataset from Mendeley, Leafsnap and Google Images are considered with the hope that it will increase the variety of the leaf images for a better training model.

The remainder of this paper is organized as follows. In Section 2, we present the related work regarding the plant identification and classification system based on the leaf frame. In Section 3, we present the methodology that have been performed for assessing the algorithm based on CNN technique. In Section 4, we discuss the results of the system. Finally, we conclude the paper in Section 5.

2   RELATED WORKS

With the advancement of image processing and pattern recognition techniques, this field of study has become one of the fundamental tasks in producing precise automated systems in mainstream agricultural technology [7]. Many studies have suggested leaf shapes for finding shape information for leaf identification or classification to reduce the computational complexity [8]. To obtain accurate shape and texture features, most studies have usually used individual leaf images in the selected background [9,10] or images from the natural background [11]. For example, as proposed by Wang and Wang [12], the Siamese network framework for a few shots learning method has been used to overcome the problem of classifying leaf, which functions to learn from a few examples of the dataset. The network framework will learn from the input and differentiate it to learn the similarity rather than trying to classify the input. To improve the accuracy, they used spatial structure optimizer (SS0) and kNN for classifying the leaves but required appropriate metric space to overcome the problem of similar and dissimilar samples.

Another effort for plant classification through leaf is proposed by Chaki and colleagues [13] where the numerous components of the leaf are joined to produce an effective and solid classification using a hierarchical architectural design. The combination of several visual features, data modeling techniques, and classifiers is utilized for performing the design. They also proposed another feature selection called feature-based shape selection template (FSST) for choosing the shape features from different types of leaves. The choice of the shape feature depends on the aspect ratio of the leaf images. The algorithm which can select a portion of valuable and resourceful discriminative features in the leaf images based on manifold learning for dimensionality reduction has also proposed in assessing a leaf classification system [14].

Probabilistic neural network (PNN) has been proposed for classifying a set of datasets known 'Flavia' using the reduced leaf features with five variables as an input feature vector to the PNN classifier [15]. In another study [16], PNN has also applied where the input features to the classifier are the combination of five geometric features, ten morphological features, and leaf vein features as input

features vector to the classifier with the reduction on the features vector over the principal component analysis (PCA). Besides PNN, k-nearest neighbor (KNN), decision tree, naïve Bayes, and support vector machine (SVM) are also applied as a classifier in another study [2,17], and they evaluated all these different classifiers by using various handcrafted visual leaf features. Extraction based on Fourier descriptors with slimness ratio, roundness ratio, and dispersion of the leaf shape from color images has also been proposed for a PNN classifier [18].

From many classifiers, a convolutional neural network (CNN) is a well-known plant identification approach that has been reviewed in many literatures. For example, Liu and Wang [19] have reviewed and outlined the advantages and disadvantages of the CNN deep learning technique from the perspective of three standard networks: classification, detection, and segmentation. M. Vilasini and P. Ramamoorthy have discussed CNN-based approaches for Indian leaf species identification from white backgrounds using smartphones [20]. The proposed work has utilized a cluster of edge detection algorithms to segment and edge detection before furthering the classification process properly. To identify the diseases from tea leaves where the multiscale feature extraction in improved deep CNN of CIFAR10-quick model has also been suggested [21], specifically proposed to improve the extraction process of image features. To reduce the calculation of the CNN model and the number of model parameters, they have performed the depth-wise separable convolution method, where they claimed that the accuracy is higher than that of traditional machine learning methods and classical deep learning. An extended version of CNN known as global pooling dilated convolutional neural network (GPDCNN) has also been introduced for plant research topics [14]. The method has been performed by combining dilated convolution and global pooling for cucumber plant disease identification. Generally, CNN systems provide high performance for most problems, but it requires a massive volume of data and is time-consuming in training session. However, using the pre-trained models for similar tasks provides promising help when employing the CNN framework.

3   METHODOLOGY

In this article, we collaborate the CNN-based deep learning-based plant classification with the image padding method to yield desired standardized datasets to the network. Figure 1 shows the overall flow of the system with the TensorFlow Deep Learning framework as the tool that is used for training the model. A leaf classification system is developed through the application of the image processing field assisted by machine learning. In this work, the machine learning will learn from the features of the leaves images, which are previously preprocessed and consists of rescaling and padding for a standardized size of images. The standardized image size of 128 × 128 is considered for passing through several layers of a network in a convolution neural network consisting of convolution, maximum pooling, flattening, and dense layers.

In Figure 1, the training parameters, such as the number of epochs and batch size, are adjusted to obtain desired training and validation result. Through the training process, the features in the images are learned to create the appropriate model. While in classification, the task could be carried out by loading the model and predicting the class of the external leaf image. This work intends to use CNN based model to perform the leaf species classification problems. The complete processes of training and validating the model for leaf species classification using the CNN are described further by separating into several stages in the following subsection.
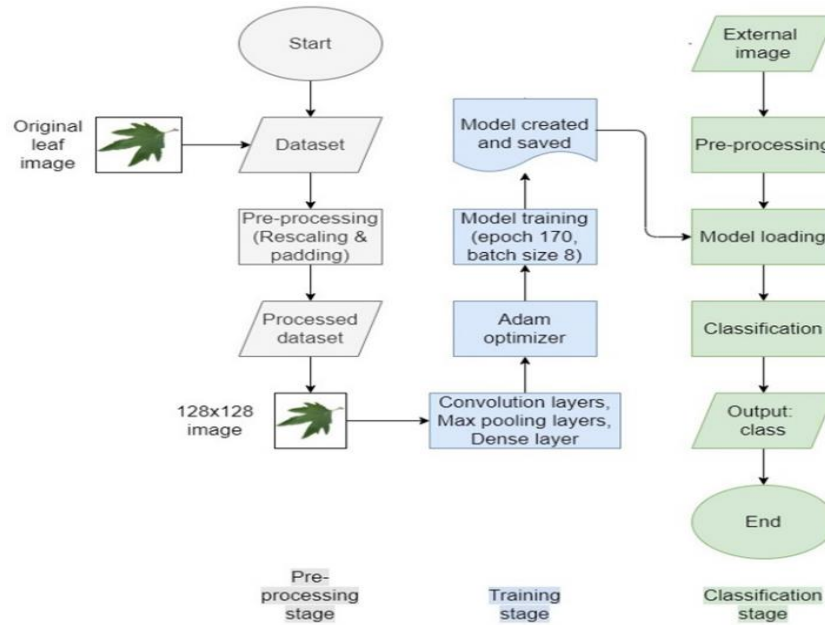
Figure 1: Overall flow of the system

3.1 Dataset

The leaf images are downloaded from Mendeley [22], Leafsnap [23] and Google Images to increase the variety of leaf images to train a better model for different classes for training and testing the CNN model. Ten classes of species are chosen randomly which are: Aesculus Flavia(43 samples), Ailanthus Altissima(80 samples), Albizia Julibrissin(52 samples), Amelanchier Arborea(135 samples), Basil(116 samples), Chinar(164 samples), Guava(92 samples), Jatropha(116 samples), Mango(72 samples) and Pongamia Pinnata(84 samples). All datasets are colored leaf images with white backgrounds. Colored leaf images are chosen for the dataset instead of digital binary leaf images to let the model learn the leaf's texture more accurately. The size of 128 × 128 are considered where image padding techniques are implemented to obtain an appropriate image quality in terms of dimensions, as shown in Figure 2. For image padding, the shape of the image, including width and height, is calculated using Equations 1 and 2 to find the indices of the center of the original image array. The indices are then placed at the upper left point of *index_width* and *index_height* to align the entire image at the center.

$$index\_width = \frac{maximum\ size - width}{2} \tag{1}$$

$$index\_height = \frac{maximum\ size - height}{2} \tag{2}$$

The total number of datasets used is 954, of which 80% (764) are used as training sets, whereas 20% (190) are used as validating sets. The validating dataset is repeatedly used for each generated model during particular parameter settings to validate or test the capability of the model to produce promising performance. We then used almost 20 images for the external image testing for each leaf category to test the generated model.
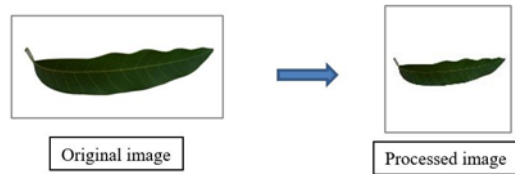

Figure 2: Example of processing with padding technique.

3.2   Convolutional Neural Network

CNN comprises a stack of layers that feeds in an input image, performs a mathematical operation, and predicts the label probabilities at the output. The raw pixel intensity of the input is taken as a flattened vector. CNN automatically learns the complex features present in the image through different layers. These layers contain kernels, and the combination of the result obtained from these kernels can predict the class of the image. In general, CNN architecture consists of five parts: the input layer, convolution layer, pooling layer, full connection layer, and output layer. The proposed CNN model for extracting and processing leaf features is shown in Figure 3. Three pooling layers follow three convolution layers in the proposed structure are involved. In the process, the characteristic parameters will be transferred through fully connected layers. The proposed model is one-way transmission in which the input is responsible for extracting the training images with a standard size of 128 × 128. Each layer extracts more image features from the previous layer and passes them to the next layer for processing.
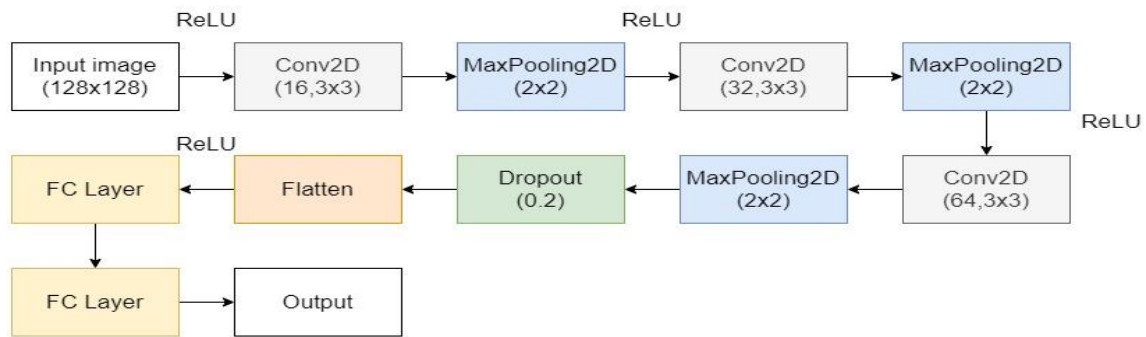

Figure 3: Proposed Convolutional Neural Network.

4   RESULTS AND DISCUSSION

The system is started by training the model with a smaller number of classes, such as 3 classes. After achieving the desired accuracy, the number of classes is increased stage by stage. Otherwise, the model is trained again with a set of adjusted parameters. Several runs or models are created where the training process is repeated to examine and obtain the best parameter values for batch size, epoch number, and learning rate. The dropout layer is investigated during the testing for these 3-class models to see the accuracy and the losses.

Figure 4 shows an example of how the accuracy and loss graphs of a typical model and a model with a dropout layer are dispersed after performing the evaluation. Compared to the model with the dropout layer, as shown in Figure 4(b), it is found that the validation loss for the model without the dropout layer, as shown in Figure 4(a), is a bit higher than the training loss. The dropout layer can decrease the validation loss and thus reduce the separation between the validation and training lines. If the separation is significant, the system may have an overfitting issue. Therefore, the result shows that overfitting could be prevented with the help of the dropout layer. Several models created also have relatively high accuracy without adding a dropout layer. Thus, the layer can be optional if the model trained has good performance and does not have an overfitting issue.

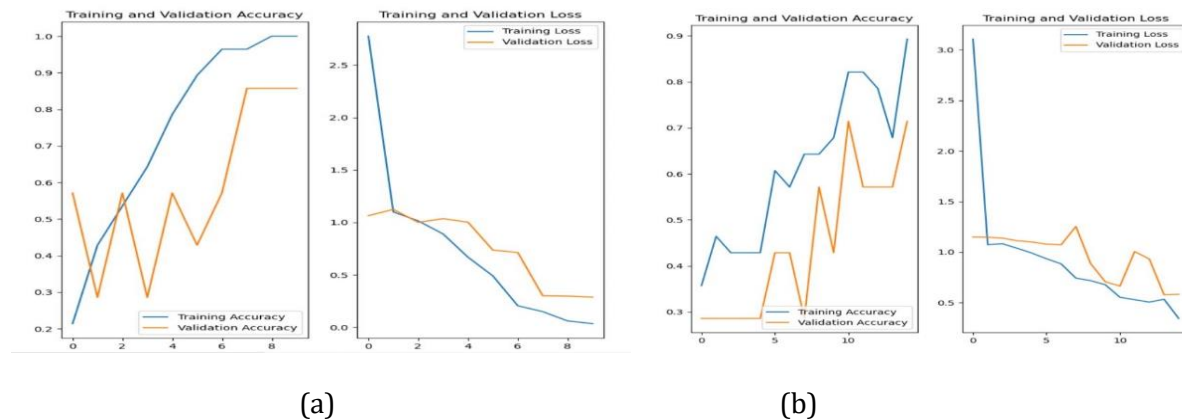(a)   (b)

Figure 4: (a) Model without dropout layer. (b) Model with dropout layer.

It was also found that the number of samples present in a particular class may affect the system's accuracy, especially when there are more than two classes of the leaf which are nearly identical in shape, for example, Basil and Amelanchier Arborea species. Therefore, more datasets should be added to these classes respectively so that the system can train the model from more samples and thus learns more features.

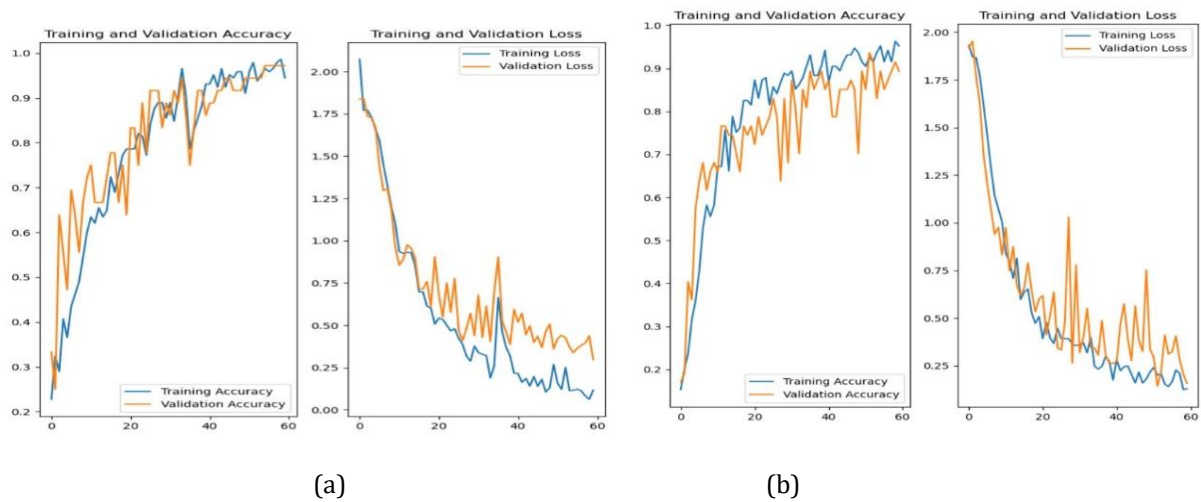(a)   (b)

Figure 5: Accuracy and loss graphs for models trained with epoch number of 60, batch size of 8 and class size of 7. (a) before adding dataset. (b) after adding the dataset.

As shown in Figure 5, two models are created with the same class size, epoch number and other parameters. However, the validation loss of the first model gets higher than the training loss when the epoch number increases, as shown in Figure 5(a), and the difference in these two lines is noticeable, leading to the overfitting issue. To avoid overfitting issue, it has been done by adding more samples where the difference between the validation loss and training loss was decreased, and the validation loss was reduced, as shown in Figure 5(b).

From the results we have in Figure 5, the training parameter, batch size, and epoch number are assessed and evaluated. Figure 6 shows the models created using a different set of parameters. From the experiments, it is found that the accuracy of the system increases when the epoch number increases. However, over-increasing the epoch number may cause an over-fitting issue. Therefore, to avoid overfitting issues, the epoch number is stopped when the validation data error rate has reached a minimum level. The considered batch size during the training stage is in the power of two, such as 8, 32, and 64. After adjusting a few times, it was found that the system can achieve the best performance when the parameter values are set at epoch number 170 and batch size of 8.
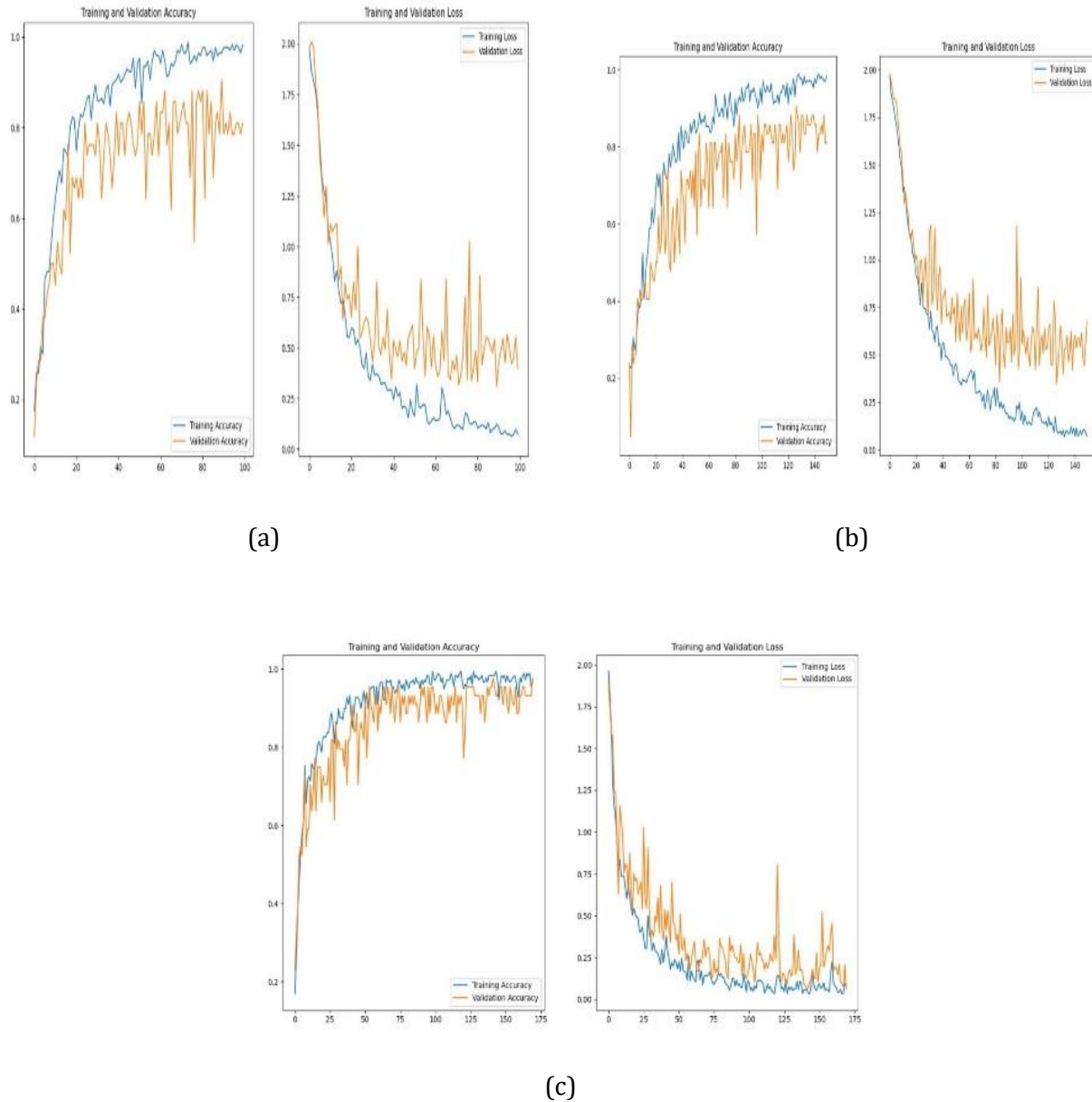
(a)

(b)

(c)

Figure 6: (a) Model with epoch number 100, batch size 32. (b) Model with epoch number 150, batch size 64. (c) Model with epoch number 170, batch size 8.

After several testing and training, a final model with 10 classes is achieved with the parameter batch size of 8, epoch number of 170, and learning rate of 0.0005. The graph for accuracy and loss of the system with different epoch numbers and batch sizes is shown in Figure 7. It is found that the training accuracy and loss can reach 99.4% and 3.2%, respectively, whereas the validation accuracy and loss reached 99.5% and 2.9%, respectively. The result shown in Figure 7 shows that the accuracy is relatively high and low in validation loss. The loss graph, with a small loss value, indicates that the training dataset is perfectly learned and able to fit the model to the new data. This also indicates that

the model with the mentioned training parameters is well generalized and provides promising for a leaf classification system.
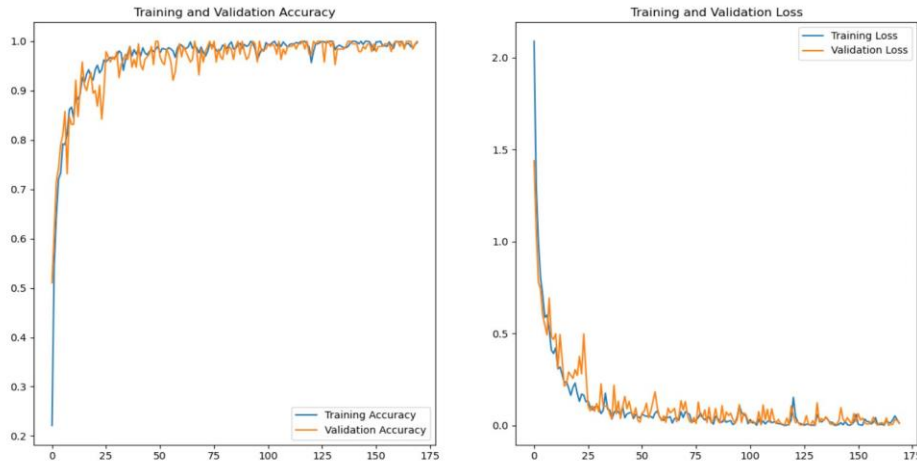

Figure 7: Accuracy and loss graph

Overall, after experimenting with the proposed approach, it can be concluded that an average of more than 98% accuracy are achieved. Figure 8 shows the performance achievement for the individual leaf.
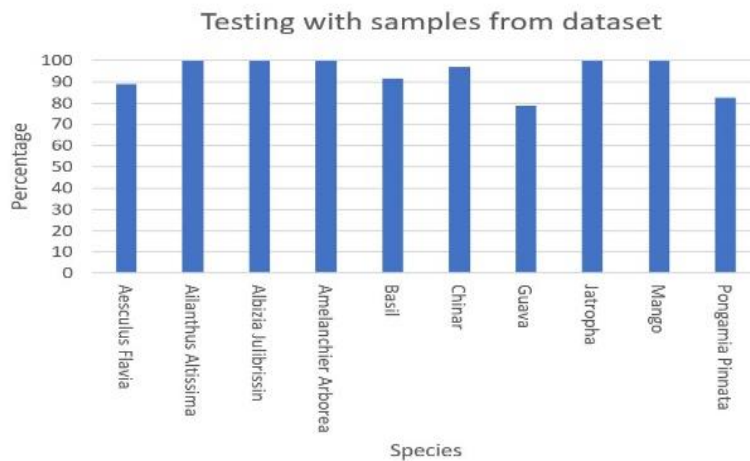

Figure 8: Accuracy performance for each leaf

To access the system's practicability, the images selected from different resources via Google Images are used in this testing stage. The term external images are referred to the images taken from various resources than Mendeley and Leafsnap dataset. Therefore, in this case, we have differences in background, quality of images, and so on. The experiment found that the system has reached between 70% to 100% classification accuracy, and it depends on the leaf species, where the results are shown in Figure 9. With the result, it is believed that the system is able to provide promising performance with an acceptable generalization of the model toward external images. The experiment also found that the system can accurately classify the input leaf image from the background, which is not totally

with the white background. Besides the assigned ten classes, the system can also provide "Unknown" results when a non-leaf image is detected or the external input leaf image is unrecognized. It allows the system to provide 10 + 1 classes for the final output, which means the system can detect other than the image class in the dataset.
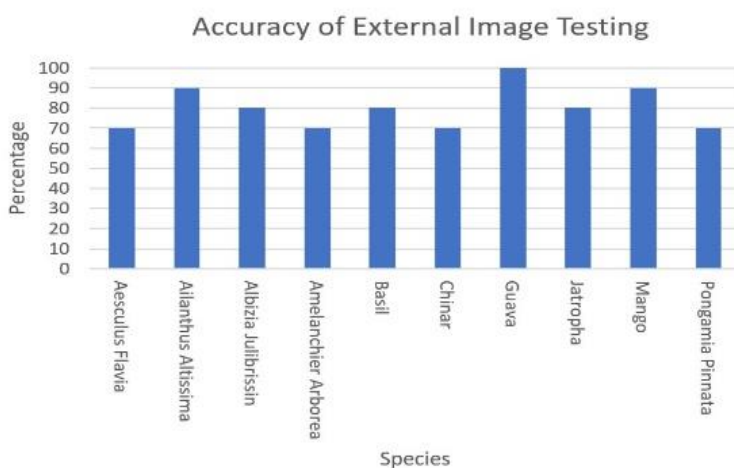

Figure 9: External leaf image testing result

Comparing our results with the previous works on different classifiers, as shown in Table 1 has revealed that though the proposed approach is implemented with a different CNN model and dataset, the outcome of the proposed CNN model is promising. Please note that though other classification metrics can be considered for performance evaluation, in this paper, only the accuracy parameter is chosen for uniformity performance benchmarking with others. We believe that our proposed CNN framework offers decent potential for the leaf classification system.

Table 1: Comparison with other classifiers

Classifier	Accuracy, %
PNN [15]	90.3
ANN [24]	93.3
ANN [25]	96.0
CNN [2]	99.48
Proposed	**98.50**

5   CONCLUSION

In summary, a leaf classification with training and validation accuracy of more than 95% is successfully developed with the aid of the CNN framework. The system is able to detect ten classes of leaf species and one "Unknown" class to indicate unrecognized species. The system is also tested with the external image to assess the trained model generalization, which can achieve more than 70% classification accuracy from different image resources. In the future, more data can be included and developed with more advanced interactive web application systems for more impressive specifications in education or research.

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