SWP-Leaf NET: a novel multistage approach for plant leaf identification based on deep learning

ali beikmohammadi\(^1\), karim faez\(^a\), ali motallebi\(^a\)

\(^a\)Department of Electrical Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran

**Abstract**

Modern scientific and technological advances are allowing botanists to use computer vision-based approaches for plant identification tasks. These approaches have their own challenges. Leaf classification is a computer-vision task performed for the automated identification of plant species, a serious challenge due to variations in leaf morphology, including its size, texture, shape, and venation. Researchers have recently become more inclined toward deep learning-based methods rather than conventional feature-based methods due to the popularity and successful implementation of deep learning methods in image analysis, object recognition, and speech recognition.

In this paper, a botanist’s behavior was modeled in leaf identification by proposing a highly-efficient method of maximum behavioral resemblance developed through three deep learning-based models. Different layers of the three models were visualized to ensure that the botanist’s behavior was modeled accurately. The first and second models were designed from scratch. Regarding the third model, the pre-trained architecture MobileNetV2 was employed along with the transfer-learning technique. The proposed method was evaluated on two well-known datasets: Flavia and MalayaKew. According to a comparative analysis, the suggested approach was more accurate than hand-crafted feature extraction methods and other deep learning techniques in terms of 99.67% and 99.81% accuracy. Unlike conventional techniques that have their own specific complexities and depend on datasets, the proposed method required no hand-crafted feature extraction, and also increased accuracy and distributability as compared with other deep learning techniques. It was further considerably faster than other methods because it used shallower networks with fewer parameters and did not use all three

---

\(^1\) Corresponding author.

*Email addresses: * dr.abm@aut.ac.ir (ali beikmohammadi), kfaez@aut.ac.ir (karim faez), ali3motallebi@aut.ac.ir (ali motallebi)
models recurrently.

Keywords: SWP-Leaf NET, deep learning, Plant leaf recognition, Convolutional neural network

1. Introduction

In agronomy, an important task is to identify and classify plants (with approximately 50,000 species) for botanical research and agricultural products (Hall et al., 2015; Kalyoncu and Toygar, 2015; Kumar et al., 2012) because plants serve as the backbone of all forms of life on Earth and provide humans with food and oxygen. As a result, it is necessary to have a proper perception of plants to help identify new or rare species of plants in order to improve the pharmaceutical industry, ecosystem balance, and agricultural productivity and sustainability (Cope et al., 2012).

In botany, plants are typically identified based on the shapes of their leaves and flowers. Botanists use the changes of leaf characters as a comparative tool to study the plants (Clarke et al., 2006; Cope et al., 2012) because the leaf characters of deciduous trees, annual plants, or year-round in evergreen perennials are available for observation and analysis. In fact, leaves are always employed to provide important detective characters for the identification of plants.

For this purpose, many researchers of computer vision have used images of leaves as a tool to identify species of plants (Hall et al., 2015; Kalyoncu and Toygar, 2015; Kumar et al., 2012). Given scientific and genetic advances, many of the hybrid plants cannot be identified by ordinary individuals and even experts (Ferentinos, 2018). Therefore, machine vision and machine learning techniques are used more often to solve this problem (Kamilaris and Prenafeta-Boldú, 2018; Lee et al., 2015). Shape (Mouine et al., 2012; Neto et al., 2006; Xiao et al., 2010), texture (Cope et al., 2010; Naresh and Nagendraswamy, 2016; Tang et al., 2015), and venation (Charters et al., 2014; Larese et al., 2014) are the characters used mainly to identify the leaves of different species.

In computer vision, despite many attempts (e.g., the use of complicated computer vision algorithms), plant identification is still known as a challenging and unsolved problem because plants are characterized by shapes and colors, resembling others in nature. Moreover, the history of plant identification methods indicates that existing solutions depend significantly on
the ability of experts to encrypt the domain knowledge. Regarding many of the morphological features predefined by botanists, researchers employ hand-engineering methods to define their dedicated characters. They seek specific methods and algorithms, which can extract a great deal of information for predictive modeling. Based on the efficiency of those methods and algorithms, a subset of very important features is selected to describe leaf data. Recently, deep learning methods have been employed for the automated extraction of features, something which has alleviated researchers’ tasks in the explicit selection of features.

Deep learning includes a category of machine learning techniques, consisting of numerous processing layers, making it possible to learn the representation of data concepts at multiple levels. Deep learning is an opportunity to create and extract new features of raw representation of input data without clearly defining what features are used and how they are extracted.

In recent years, deep learning has brought about significant development in machine learning and artificial intelligence. Since 2012, all the top ranks of ImageNet Large Scale Visual Recognition Challenge (ILSVRC), known as the machine vision world cup, have used deep neural networks. Moreover, all the top methods of MNIST handwritten digit image classification (21 errors in 10,000) and CIFAR natural images (less than 5% error) are belonged to deep neural networks.

As deep learning has been successful in various fields, it has recently entered agronomy and food production. The agricultural applications of deep learning include plant disease recognition, Earth coverage classification, product-type classification, plant identification, plant phenology recognition, root-soil separation, production estimation, fruit enumeration, obstacle recognition, weed recognition, product recognition and classification, soil moisture forecast, animal studies, and weather forecast (Kamilaris and Prenafeta-Boldú, 2018).

Regarding plant identification, various studies have focused on the methods and algorithms maximizing the use of leaf databases, a fact which leads to a norm indicating that leaf features may change with different leaf data and feature extraction techniques. There has always been a vague subset of features representing leaf data. Instead of addressing a display of features in the same way as previous approaches, this study first analyzed the steps taken by a botanist on a leaf for plant recognition. Then it was decided to model the same process. For this purpose,
deep learning was employed to extract specific features by limiting the input. Then the successful simulation of a botanist’s behavior was visualized.

The remaining sections were organized as follows: Section 2 presents a review of the literature on plant leaf classification. Then, Section 3 introduces the proposed method inspired by a botanist’s behavior in plant recognition from leaves.

Section 4 includes performance analysis and reports the simulation results of the suggested approach. For this purpose, the well-known datasets such as Flavia (Wu et al., 2007) and MalayaKew (MK) (Lee et al., 2017; Lee et al., 2015) were employed. In addition, this section also compares the proposed method with several methods proposed by other researchers, reviewed in Section 2. Section 5 presents the research conclusion and makes suggestions for future studies.

2. Related Studies

The representation of leaf features is a critical component of leaf identification and classification algorithm. All the existing methods follow two general approaches to the representation of features extracted from images of leaves to classify species: hand-crafted feature extraction (Charters et al., 2014; Naresh and Nagendraswamy, 2016; Neto et al., 2006) and deep learning feature extraction (Grinblat et al., 2016; Lee et al., 2017; Lee et al., 2015; Liu et al., 2015).

In practice, designing hand-crafted features depends significantly on the ability of computer vision experts to encrypt the morphological features predefined by botanists (Lee et al., 2017). Nevertheless, deep learning features are capable of automated learning, benefiting from the advantages of deep learning algorithms. Hence, deep learning methods for leaf identification, have become more popular recently. Thus, this work reviews related deep learning-based studies.

There have been considerable developments in deep learning methods. The deep learning method introduced by (Su et al., 2014) is employed to reduce data dimensions in convolutional neural networks (Chollet, 2017) and deep belief networks (Simonyan and Zisserman, 2014). These methods have extensively been used for image classification, speech recognition, and object recognition (Angelov and Sperduti, 2016). Learning-based representation and
particularly deep learning have introduced the concept of end-to-end learning by employing trainable feature extractors and trainable classifiers (Szegedy et al., 2017; Szegedy et al., 2016).

Recently, a few feature extraction methods for leaf classification have been proposed through deep learning (Barré et al., 2017; Bodhwani et al., 2019; Grinblat et al., 2016; Hedjazi et al., 2017; Hu et al., 2018; Lee et al., 2017; Lee et al., 2015; Liu et al., 2015; Sun et al., 2017). (Liu et al., 2015) used a conventional convolutional neural network (CNN) for feature extraction, then they employed a support vector machine (SVM) to classify images of leaves.

(Grinblat et al., 2016) first, segmented the venation pattern of a leaf through a hit-or-miss transform (UHMT) to obtain the segmented binary venation images. Then they trained a CNN with these segmented binary images instead of the main input images. In fact, deep learning and hand-crafted feature extraction were integrated in this method. (Barré et al., 2017) developed the CNN-based LeafNet network and evaluated it on Flavia, LeafSnap, and Foliage resulting in 97.9%, 86.3%, and 95.8% accuracy rates, respectively.

(Lee et al., 2015) proposed the DeepPlant network for the recognition of images of plant leaves. They also used a deconvolutional network (DN) (Shelhamer et al., 2016) to obtain an insight into the designated features resulting from the CNN model. According to them, deep learning should be used in either a bottom-up or top-down method for plant identification. First, they proposed a CNN model for the automated learning of feature representation for plant species, a method that meets the need to design hand-crafted feature extraction in previous methods. Then they identified and recognized the representation of features obtained by the CNN model through a DN-based visualization strategy. This means avoiding the CNN model as a black box solution. It also gives researchers an insight into how an algorithm “observes” or “perceives” a leaf. Finally, they collected a new dataset named MalayaKew (MK) through complete labeling and made it available to other researchers.

Empirically, the method proposed by (Lee et al., 2015) outperformed the state-of-the-art solutions based on hand-crafted feature extraction in the classification of 44 different plant species. Therefore, it indicates that feature learning through CNN can provide a better representation of images of leaves than hand-crafted feature extraction. In addition, tests were
conducted on the images of entire leaves and images of leaf segments, the results of which show that venation is an important feature in the identification of different plant species and outperforms conventional solutions.

In the paper reviewed by (Lee et al., 2017), perfected their previous study significantly and proposed a two-stream convolutional neural network (TwoCNN), including two feature learning streams trained on the entire and segments of images, respectively. Like the paper reviewed by (Lee et al., 2015), first defined a method for quantifying the necessary features to show leaf data and trained a CNN based on raw leaf data to learn a resistant representation of images of leaves. Then they employed a DN method to observe how to describe leaf information through CNN. They determined the characters of features of each CNN layer quantitatively and found out that the layer transfer network would reach from a general mode to specific types of leaf features. They employed feature visualization techniques to explore, analyze, and perceive the most important subset of features. Interestingly, this study follows the definitions of characters, given by botanists, to classify plant species.

According to (Lee et al., 2017), CNNs trained on both the entire leaves and leaf patches indicated different contextual information from leaf features. As a result, they classified the information as global features, describing the entire leaf structure and local features focusing on venation. Finally, they proposed a new hybrid model titled TwoCNN to extract global-local features for leaf data. This model merges the information through two trained CNNs by using different data formats extracted from the same species. Although the proposed global-local feature extraction hybrid models can enhance the distinctive information of plant classification systems at different scales (i.e., both the entire images and patches of images), the training process requires a more complicated sample set because both the entire images and patches of images must be prepared.

Most of the existing leaf identification methods normalize the entire images of a plant leaf at the same rate and identify them on the same scale, a fact which leads to inappropriate results. For this reason, (Hu et al., 2018) tried to integrate multi-scale features with convolutional neural networks and develop a model titled MSF-CNN to classify plant leaves on multiple scales. The idea of integrating multi-scale features with CNNs was proposed by
(Du and Gao, 2017) and also (Rasti et al., 2018) introducing multi-scale convolutional neural networks (MSCNNs). These MSCNNs consist of multiple branches of learning features on different scales.

In the paper reviewed by (Du and Gao, 2017), each branch learns information from patches of images in various sizes. However, in the paper reviewed by (Rasti et al., 2018), each branch learns information from the input images in different sizes. The main difference between MSCNNs and MSF-CNN proposed by (Hu et al., 2018) is that the multi-scale features learned by MSCNNs are integrated into one layer. Nonetheless, they are integrated with each other in a step-by-step manner in an MSF-CNN. Hence, MSF-CNN is cost-effective and economical because it needs no multiple branches of learning features.

In the processing steps of the method proposed by (Hu et al., 2018), an input image is first transformed into several low-resolution images by reducing the sampling rate through a list of two-way interpolation operations. Then these input images are given to the MSF-CNN architecture on different scales through various strides to learn distinctive features at diverse depths. In this step, the integration of features is performed through concatenation operation between two different scales. In fact, these operations interconnect the mappings of features learned from multi-scale images in a channel view. Along the depth of the MSF-CNN, multi-scale images ae gradually moved, and corresponding features are merged. Eventually, the last MSF-CNN layer collects distinctive information to obtain the final features to predict the plant species of an input image. (Hu et al., 2018) conducted a few experiments on both famous datasets of this area, i.e. MalayaKew (MK) and Leafsnap, and claimed that the MSF-CNN outperformed the most advanced methods of leaf identification. They also performed a mutual dataset evaluation to represent the generalizability of their method by training MK and testing Leafsnap.

(Hedjazi et al., 2017) modified a trained model for plant recognition. They showed how to use a mode, previously trained on a large dataset, for a small dataset. They did not train their model from the beginning. Instead, they selected a CNN model previously trained on ImageNet. They worked on ImageClef2013, a dataset including images with clean backgrounds. Given the deficiency of training data, a fitness problem was possible. Thus, they
used transfer learning to avoid this problem. They fine-tuned an AlexNet model with the help of the Caffe framework and obtained 71.17% of accuracy on validation datasets and 70.0% of accuracy on testing datasets.

(Sun et al., 2017) analyzed BJFU100 consisting of 100 species of ornamental plants, each of which had 100 different pictures of 4208x3120 pixels. They compared ResNet26 (with 26 layers) with the ResNet models of 18, 34, and 50 layers and introduced ResNet26 as the best solution for the optimization and capacity problems. According to them, ResNet26 had enough trainable parameters to learn distinctive features. Their model obtained 91.78% of accuracy.

(Bodhwani et al., 2019) analyzed Leafsnap with 185 different plant species and employed the residual deep learning framework with 50 layers (in five classes) to classify the dataset. Their proposed model obtained 93.09% of accuracy.

Table 1 depicts an overview of the literature review of papers using feature extraction with deep learning.

Table 1. An Overview of Related Works on Feature Extraction through Deep Learning in Leaf Classification for Plant Identification

| Publications               | Method                               |
|----------------------------|--------------------------------------|
| (Liu et al., 2015)         | CNN + SVM                            |
| (Lee et al., 2015)         | DeepPlant (CNN, DN)                  |
| (Grinblat et al., 2016)    | UHMT + CNN                           |
| (Hedjazi et al., 2017)     | Pre-trained AlexNet                  |
| (Sun et al., 2017)         | ResNet26                             |
| (Barré et al., 2017)       | LeafNet                              |
| (Lee et al., 2017)         | TwoCNN (CNN, DN)                     |
| (Hu et al., 2018)          | MSF-CNN                              |
| (Bodhwani et al., 2019)    | ResNet50                             |

Although researchers have become interested in using deep learning approaches, plant leaf classification is still challenging due to the high resemblance of leaves of diverse plants regarding shape, color, and morphological variations such as changes in size, texture, shape, and venation. In addition, there are many dimensions of numerous species of plants or even the same species of one plant in various growth conditions or photography periods. As a result, plant leaf identification is still a challenging problem, which should be taken into consideration.
in different aspects to improve leaf identification performance.

3. The Proposed Method

This section first addresses the process of recognizing a plant species by botanists. Then a method is proposed to show the maximum resemblance to a botanist’s behavior. For this purpose, the proposed method is introduced in general and in detail by describing the structures of all three architectures thoroughly in addition to the termination conditions at each step.

3.1. Species Recognition Process Proposed by Botanists

According to the flowchart shown by Figure 1, botanists should take the following steps to recognize plant species:

First, some leaves should be cut and used as specimens, which should immediately be taken physically to a botanical laboratory. Then a botanist analyzes leaf appearance and general features, including its margins and overall form. If the initial analysis can help distinguish the leaf from other species of the geographical region, the botanist provides an inquirer with the plant species and information. If the initial analysis is prone to uncertainty, the botanist remembers the specimens and starts to analyze them thoroughly by scrutinizing their colors, shapes, and venations. If the botanist can turn uncertainty of the first step into certainty by integrating the knowledge from the first step with the information of the second step, the plant species recognition process is completed. However, if the botanist is still skeptical about several plant species, he/she starts running microscopic and laboratory tests on the plant by concentrating on venations in order to provide the inquirer with the accurate name and information of the plant species by combining the knowledge previously obtained from the first and second steps.
The botanists may not determine the name and characters of the plant species even after the third step for various reasons, such as the low quality of the laboratory specimen and genetic changes applied to the plant. In this case, he/she provides the inquirer with a list of most plausible plant species resembling the one delivered to the laboratory. This simple process is based on striking a balance between simplicity in recognition of specific species and accuracy in recognizing complicated species. This process can prevent wastage of time and resources for analyzing species, which can easily be distinguished from other species. It facilitates the accurate recognition of suspicious species, which are hard to distinguish from others. For this purpose, it was decided to implement the proposed method based on the above-mentioned approach and introduce a fast-paced, accurate, and distributable system for the identification of plant species.

3.2. The Proposed Method for Species Recognition: SWP-LeafNet

After presenting a complete introduction to the species recognition process used by a botanist, it was decided to propose a method bearing the closest resemblance. Figure 2 illustrates a flowchart for a simple perception of the proposed method. This flowchart also eases the comparison of the suggested approach with the botanist’s plant recognition process.
The following steps are recommended for the recognition of species through the proposed method. First, an image of the plant under study should be taken as a specimen, which should be given as an input to the system. As shown in Figure 3, the system then performs a preprocessing procedure only to analyze the general appearance of leaves, including margins and forms. In this preprocessing procedure, the leaf background is colored in black, whereas the entire leaf is colored in white. If the plant species can be distinguished from the other species of the same geographical region after applying the image to the first model known as S-LeafNet when the termination conditions of the first step are met, then the system provides the inquirer with the plant species and plant information. However, if the termination conditions of the first step are not met because the botanist is skeptical about different species, the most plausible species are remembered because the final answer lies definitely among them. Then the botanist starts to analyze colors, shapes, and venations of leaves more thoroughly than before.

For a more in-depth analysis of the plant, a colorful image of the leaf is given as an input to the
second model known as W-LeafNet. The plant species recognition process ends if the uncertainty of the first step changes to certainty when the initial knowledge from the first step is integrated with the information of the second step to meet the termination conditions of the second step. However, if the system is still skeptical about several plant species, it starts to run a microscopic analysis of the plant by focusing on venations in order to provide the inquirer with the accurate name and information of the plant species by combining the previous knowledge resulting from the first and second step and the outputs of the final step.

As shown in Figure 4, for the microscopic analysis of the plant in the third step, a specific and adjustable number of patches are first extracted automatically from the original image. The resultant image should entirely be enclosed within the leaf. Then each of these patches is given as the input to the third model known as P-LeafNet. The plant species recognition process successfully ends if the combination of initial knowledge, obtained from the first and second steps, and the information of the third step can meet the termination conditions of the third step.

![Figure 4. Preprocessing Performed in the Third Step of the Proposed Method](image)

Finally, if the system cannot determine the name and characters of a plant species even after the third step for different reasons such as the low-quality image of leaves or genetic changes applied to the plant species, a list of most plausible species resembling the delivered species is given as output. Like what was discussed regarding the plant recognition process by a botanist, the system and the proposed method can strike a balance between speed and accuracy in addition to presenting disreputability.

3.3. The First Model, Termination Conditions, and Initial Knowledge Transferred to the Next Steps

According to Figure 5, the S-LeafNet model consists of five CBR layers (convolutional, Batch normalization (Ioffe and Szegedy, 2015), and ReLU activation function layers) as well as five pooling layers. Except for the last pooling layer, which is an average pooling layer, all of them are of max pooling. In addition, the dropout layer includes the second pooling layer with different
dropout rates to help prevent the overfitting problem by using L2 regularization and batch normalization.

![Diagram of the S-Leaf Net model](image)

**Figure 5.** The First Model Architecture: S-Leaf Net

In the model input, a picture is first converted into a binary image through preprocessing. In this binary image, the leaf is colored in white to be distinguished from the black background. The input picture size is 128x128 pixels, and its binary version has a depth of 1. The first CBR layer uses 64 convolutional filters, sized 3x3, in a stride of 1 and input dimensions retaining padding in the output. As a result of applying this layer to the input, the output will be sized 128x128 in a depth of 64. After passing through the convolutional layer, batch normalization and ReLU activation function are applied to the output dimensions without any changes.

In the second layer, max pooling is applied to the first layer with 2x2 dimensions and a stride of 1, as a result of which dimensions will decrease to 64x64 with a depth of 64. The third layer uses the same parameters as the first CBR layer but with a different number of filters, i.e. 128. As a result, the output dimensions will be 64x64, with a depth of 128. In the fourth layer, max pooling is applied to the third layer with 2x2 dimensions and a stride of 1, as a result of which dimensions will decrease to 32x32 with a depth of 128. Then the dropout layer (Srivastava et al., 2014) is used with a dropout rate of 0.1. The fifth layer uses the same parameters as the first CBR layer but with a different number of filters, i.e. 160. As a result, the output dimensions will be 32x32, with a depth of 160.

The sixth layer employs max pooling with the same parameters as the fourth layer, and the dimensions will decrease to 16x16 with a depth of 160. Then the dropout layer is used with a rate of 0.2. The seventh layer uses the same parameters as the first CBR layer with a different numbers...
of filters, i.e. 224. As a result, the output dimensions will be 16x16, with a depth of 224. The eighth layer uses max pooling with the same parameters as the fourth layer and decreases the dimensions to 8x8 with a depth of 224. Then the dropout layer is used at a dropout rate of 0.3. The ninth layer utilizes the same parameters as the first CBR layer but with a different numbers of filters, i.e. 256. As a result, the output dimensions will be 8x8, with a dimension of 256.

Finally, the average pooling of 2x2 dimensions is applied to the ninth layer with a strider of 1 in the tenth layer. As a result, dimensions will decrease to 4x4 with a depth of 256. Then a dropout layer is used at a rate of 0.4. After that, a multi-class sigmoid (also known as Softmax), including the same number of classes used in datasets, is employed to finish designing the first model. It should be mentioned that the entire number of parameters in this model is approximately 1.3 million. Except for 1664 parameters, the rest of the parameters will be trained. Moreover, the model weights require 4.9 megabytes of storage space.

One of the termination conditions of the first step should at least be met so that the system can decide to stop the process of analysis, validate the result of the first model, and introduce it as the final result. These conditions are as follows:

- min_prob_seg: obtaining the least probability by the predicted class
- min_delta_seg: reaching the shortest probabilistic distance between the predicted class and the second possible class (the probabilistic distance between top-1 and top-2)

If one of these two conditions is met, the result of the first model will be presented as the final result. Otherwise, the system retains the initial knowledge obtained from the first model for the next models and starts using the second model. The initial knowledge obtained from the first step is described as follows:

- top_seg: transferring N first guesses from the first model on the correct class (storing predicted classes with the probability of each up to top-N)

3.4. The Second Model, Termination Conditions, and the Initial Knowledge Transferred to the Next Steps

According to Figure 6, the W-LeafNet model consists of seven CBR layers with seven pooling layers, all of which of max pooling. In addition, different dropout rates have been used after the
pooling layer from the second layer to one before the pooling layer so that it can help prevent overfitting by using L2 regularization and batch normalization.

Figure 6. The Second Model Architecture: W-Leaf Net

The model input includes the colored image provided without preprocessing in the dimensions of 196x196 pixels. This image has a depth of 3 because of its RGB format. The first CBR layer consists of 64 convolutional filters sized 3x3 with a strider of 1. The padding maintains the input dimensions in the output. As a result of applying this layer to the input, there will be an output sized 196x196 with the depth of 64. After passing through the convolutional layer, batch normalization and ReLU activation functions are applied to the output dimensions of this layer without any changes. The second layer consists of max pooling sized 2x2 with a strider of 1 applied to the first layer. As a result, the dimensions will decrease to 98x98 with a depth of 64.

The third, fifth, seventh, ninth, and eleventh layers use the same parameters as the first CBR layer with different number of filters, including 128, 160, 192, 224, and 320 filters, respectively. At the same time, the fourth, sixth, eighth, tenth, and twelfth layers use max pooling sized 2x2 with a strider of 1 with the dimensions of 49x49, 24x24, 12x12, 6x6, and 3x3, respectively. After applying max pooling to these layers, the dropout layer is used with different dropout rates of 0.1, 0.2, 0.3, 0.4, and 0.5, respectively. After passing through these layers, there will be 320 feature maps with the dimensions of 3x3. The thirteenth layer benefits from the same parameters as the first CBR layer with a different numbers of filters, i.e. 256. As a result, the output dimensions will be 3x3, with a depth of 256.

Finally, the fourteenth layer uses the same max pooling parameters as the second layer. As a result, the dimensions will decrease to 1x1 with the depth of 256. After this layer, a multi-class sigmoid (also known as the Softmax) is used in the number of classes existing in datasets to finish
designing the second model. It should be mentioned that there are approximately 2.3 million parameters in this model. Except for 2688 parameters, the others are trainable. The model weights require 8.9 megabytes of storage space.

The termination conditions of the second step must be met so that the system can decide to stop running analyses and introduce the second model as the final result in addition to confirming the initial knowledge of the first model. These conditions are as follows:

- Availability of a class predicted by the second model of the first top-N model, and:
  - min_mean_L1L2pred: the sameness of the class predicted by the first model as the second model and obtaining the minimum mean by both the first and second models, or
  - min_prob_whole: obtaining the minimum probability by the predicted class, or
  - min_delta_whole: having the minimum probabilistic distance between the predicted class and the second possible class (probabilistic distance between top-1 and top-2)

If one of these conditions is met in addition to the first condition, the result of the second model will be regarded as the final result. Otherwise, the system starts using the third model by retaining the knowledge obtained from the first and second steps for the final step. The initial knowledge obtained from the second step includes the following:

- top_whole: transferring the first M presumption from the second model on the accurate class (storing predicted classes along with the probability of each up to top-M)

According to the first and second termination conditions, using the initial knowledge, resulting from the first step has an obvious impact on the decisions made about the announcement of results obtained from the second model. The first condition, which should necessarily be true, indicates that although the first model failed to introduce the right class as the first choice, its first N presumptions are important because they affect the final result. The second condition is true when the first model fails to meet the least certainty conditions, despite presuming the right class. In this case, this presumption is confirmed by the second model to access the result less sensitively.

3.5. The Third Model, Termination Conditions, and Introduction to the Most Plausible Species

According to Figure 7, the P-LeafNet model is based on the developed transfer learning. This
concept is known through two general models (Beikmohammadi and Faez, 2018):

- Retaining the major pre-trained network and updating weights based on the new training dataset
- Employing a pre-trained neural network for feature extraction and performing representation through a global classifier such as support vector machines

Among the models winning the ILSVRC, MobileNetV2 (Sandler et al., 2018) was selected as the pre-trained network to develop the third model on the ImageNet dataset. The first approach was employed to update the model weights with the help of the research dataset. The last MobileNetV2 layer was dropped out, and a Softmax layer was replaced in proportion to the number of classes in the dataset. Then the entire new network was fine-tuned on the leaf dataset.

![Figure 7. The Third Model Architecture: P-Leaf Net](image)

MobileNetV2: Each line describes a sequence of 1 or more identical layers, repeated n times. All layers in the same sequence have the same number of output channels. The first layer of each sequence has a stride and all others use stride 1. All spatial convolutions use 3x3 kernels.

Total params: 2,764,908
Trainable params: 2,730,796
Non-trainable params: 34,112

In the model input, a specific number of patches of a colored image is provided first. The patches are included merely inside the leaf. Then these patches are separately fed to the third model in the dimensions of 96x96. The input depth is 3 because image patches are of the RGB format. After passing through 88 different layers of MobileNetV2, a multi-class sigmoid (also known as Softmax) is used in the number of classes existing in datasets to finalize the third model. This model includes nearly 2.8 million parameters totally. Except for 34112 parameters, the others are trainable. The model weights require 10.9 megabytes of storage space.
The termination conditions of the third step should be met so that the system can decide to introduce the results of the third model as the final results in addition to validating the initial knowledge resulting from the first and second models. After extracting P patches of the main image in this step, the mean of probabilities of classes on P image patches will be determined. Therefore, the third model output is a probability vector, including the probability of each class, for P image patches. The termination conditions are as follows:

- The presence of a class predicted by the third model except for the first top-N model and the second top-N model, and
  - min_mean_L1L3pred: the sameness of the class predicted by the first model as the one predicted by the third model and obtaining the minimum mean through both the first and third models, or
  - min_meanL2L3pred: the sameness of the class predicted by the second model as the one predicted by the third model and obtaining the minimum mean through both the second and third models, or
  - min_prob_patch: obtaining the minimum probability through the predicted class, or
  - min_delta_patch: reaching the minimum probability distance between the predicted class and the second plausible class (probability distance of top-1 from top-2)

If the first condition is met along with at least another condition, the result of the third model is regarded as the final result. Otherwise, the system fails to introduce the definite result and resorts to reporting the most plausible species through the two following approaches:

- vote_rate: initial voting between the classes predicted by the third model on P image patches, or
- vote_merge_rate: general voting on the outputs of three models in case the initial voting result is deficient, and the sufficient minimum probability is obtained from the first and second models.

The termination conditions of the first, second, and third models clearly indicate the effects of using the initial knowledge obtained from the first and second steps on making decisions about announcing the results obtained from the third model. According to the first condition which must
be met, although the first and second models have not correctly introduced the right class as the first choice, their first N and M guesses are still important and effective in the final result. The second and third conditions are for a time when the first and second models fail to meet the minimum certainty conditions, despite guessing the right class. In this case, the result will be accepted less sensitively by confirming this guess through the third model.

4. Evaluation of Proposed Method

This section addresses the performance of the proposed method by conducting tests on the two famous datasets, i.e. MalayaKew (MK) and Flavia, after introducing the training configuration of networks. Then it is compared with other methods. In addition, visualization techniques are employed to analyze different layers of each model and show how much the features of our interest have succeeded in making the proposed method a botanist’s method.

4.1. Training Configurations and Settings

This paper used nearly the same training settings for the models employed in the proposed method. These settings are dealt with in detail here. As a result, the model name is referred to as only when models differ in training configuration.

- **Cost Function:** The categorical cross-entropy function was used.

- **Optimizer Algorithm:** The Adam (Kingma and Ba, 2014) optimization algorithm was used in this paper.

- **Learning Rate:** The cyclical learning rate (CLR) has been employed to regularize the learning rate (Smith, 2017). In fact, this learning regularization policy increases the basic value of the learning rate in a cyclical mode. In the paper reviewed by (Smith, 2017), authors showed that CLR could accelerate convergence in the neural network architectures. This policy, with a value of 0.001 was used as the basic learning rate. It was used with the value of 0.006 as the maximum learning rate when the triangular2 mode was employed with the strider of 40.

- **Weight Initialization:** The homogenous Xavier was used in the first and second models for weight initialization (Glorot and Bengio, 2010).

- **Regulator:** In this paper, an L2 regulator was used with a parameter value of 0.001.

- **Batch Size and Epoch:** For each of the three models, the number of epochs was considered
10000 to store the weights having the highest accuracy on the validation set. The batch sizes of the first, second, and third models were 256, 128, and 512, respectively.

The accuracy of the testing dataset was regarded as the performance evaluation criterion of the proposed method in comparison with other techniques. This criterion is obtained by dividing the number of correct predictions on the testing dataset by the total number of testing datasets. Python was employed to perform the software tasks along with its dedicated deep learning libraries, such as Tensorflow and Keras. Moreover, Nvidia GeForce GTX 1080 8 GB was used in the evaluation system.

4.2. Performance Analysis of Proposed System on MalayaKew

This section first introduces the leaf dataset MalayaKew (MK) (Lee et al., 2017; Lee et al., 2015) and then analyzes the results on it. After that, the results are compared with those of other methods on the same dataset.

4.2.1. MalayaKew (MK) Introduction and Preparation

The leaf dataset MalayaKew (MK) was collected from Royal Botanic Gardens, Kew, England. This dataset includes the scanned images of leaves in 44 classes. This dataset is very challenging because the leaves of classes of its different species resemble each other greatly. Figure 8 shows a sample of this leaf dataset.

This dataset includes two subsets, i.e. MK-D1 and MK-D2:

- MK-D1: This dataset includes segmented leaf images sized 256x256. It consists of 2288 and 528 training and testing images, respectively.
- MK-D2: This dataset includes leaf images sized 256x256 pixels. It consists of 34672 and 8800 training and testing images, respectively.

In this dataset, each image has been rotated for 45, 90, 135, 180, 225, 270, and 315 degrees in seven different directions to enhance leaf images.
For training the first model, it is necessary to use binary images, on which the background and entire leaves are black and white, respectively. Therefore, OpenCV and Pillow were used as image processing tools to generate these images from 2288 colored images dedicated for training. For all three networks, all the inputs were divided by 255 because the maximum number of inputs was 255. To ensure learning improvement and generalizability of the designed networks, different data augmentation techniques such as 45-degree rotation, transverse displacement for 0.1 of the entire image, longitudinal displacement for 0.1 of the entire image, horizontal mirror, vertical mirror, and shuffle techniques were employed.

Hence, 2288 images were employed for training the first and second models, whereas 34672 images were utilized for training the third model. For each epoch of 10000 epochs, a combination of data augmentation techniques was randomly applied to images to prevent the overfitting problem in addition to enhancing the generalizability of models. It is impossible to say how many unique images each model experienced during the training process. However, it is clear that all the training datasets were employed along with images generated from data augmentation based on the main images. Furthermore, the entire system input included 528 images of the testing dataset in the
testing step. In addition, 528 images of the testing dataset were used separately to evaluate the first and second models, and 8800 image patches were considered in the dataset to test the third model.

4.2.2. Evaluation of Proposed Method on MalayaKew (MK)

After finishing training each of the three models used in the proposed method implemented on MalayaKew (MK), it was necessary to integrate the three models to develop the proposed system. The second column of Table 2 shows the parameters introduced in the previous section for the termination of each step, and the previous knowledge transferred to the next step for MalayaKew (MK).

| Parameter             | MK Value | Flavia Value | Comments                                                                                      |
|-----------------------|----------|--------------|---------------------------------------------------------------------------------------------|
| min_prob_seg          | 0.98     | 0.95         | Minimum probability for the class predicted by the first model                               |
| min_delta_seg         | 0.95     | 0.91         | Minimum probabilistic distance of the predicted class from the second plausible class predicted by the first model |
| top_seg               | 10       | 6            | The first N presumption of the first model on the right class                                |
| min_mean_L1L2pred     | 0.80     | 0.70         | Minimum mean of both the first and second models in case of the sameness of the classes predicted by them |
| min_prob_whole        | 0.89     | 0.78         | Minimum probability for the class predicted by the second model                             |
| min_delta_whole       | 0.85     | 0.60         | Minimum probabilistic distance of the predicted class from the second plausible class predicted by the second model |
| top_whole             | 6        | 10           | The first M presumption of the second model on the right class                               |
| vote_rate             | 0.71     | 0.71         | Minimum rate after initial voting between the classes predicted by the third model on P image patches |
| vote_merge_rate       | 0.56     | 0.56         | Minimum rate after general voting on the outputs of three models in case of insufficient certainty of initial voting and having the minimum sufficient probability through the first and second models |

Separate tests were conducted on each of the models introduced by the proposed method to obtain 96.59%, 97.35%, and 95.35% of accuracy for the first, second, and third models, respectively. According to Table 3, these models showed no defendable performance in comparison with the most-recent algorithms in terms of accuracy. Hence, since these models are characterized by shorter depth and fewer parameters than the other deep learning-based models, they can result in higher speeds and reduce the memory space required for storage and processing. After integrating these three models and developing the proposed system, accuracy reached a perfect rate of 99.81%.
According to Table 3, the proposed method outperformed all the other methods evaluated on MalayaKew (MK).

| S. No. | Publications                  | Method                        | Accuracy  |
|-------|------------------------------|-------------------------------|-----------|
| 1     | Proposed method (Combine)    | SWP-Leaf Net                  | 99.81%    |
| 2     | Proposed method (First model)| S-Leaf Net                    | 96.59%    |
| 3     | Proposed method (Second model)| W-Leaf Net                   | 97.35%    |
| 4     | Proposed method (Third model)| P-Leaf Net                    | 95.35%    |
| 5     | (Hu et al., 2018)            | MSF-CNN                       | 99.05%    |
| 6     | (Lee et al., 2017)           | DeepPlant+ SVM (linear)       | 98.10%    |
| 7     | (Lee et al., 2017)           | DeepPlant+MLP                 | 97.70%    |
| 8     | (Hall et al., 2015)          | Combine (SVM (linear))        | 95.10%    |
| 9     | (Hall et al., 2015)          | HCF (SVM (RBF))               | 71.60%    |
| 10    | (Hall et al., 2015)          | HCF-ScaleRobust (SVM (RBF))   | 66.50%    |
| 11    | (Kumar et al., 2012)         | LeafSnap (NN)                 | 58.90%    |
| 12    | (Kumar et al., 2012)         | LeafSnap (SVM (RBF))          | 42.00%    |
| 13    | (Yang et al., 2009)          | SIFT (SVM (linear))           | 58.80%    |

In comparison with conventional methods (9-13), the proposed method achieved much higher accuracy rates. In addition, it requires no hand-crafted feature extraction, having specific challenges, and depending greatly on datasets. Compared with deep learning-based methods (5-7), one might wonder if the superiority of the proposed algorithm lies only in terms of accuracy improvement.

To answer this question, the proposed method is much faster than other methods, benefiting from the pre-trained AlexNet (6 & 7) or the simultaneous integration of a multi-input network (5), due to the use of shallower networks with fewer parameters and also separate use of each model. It further enhances accuracy. The most important superiority of the proposed method is that its guesses can be used as a botanist’s opinions when unknown species or genetic changes are observed because the research purpose was to model a botanist’s behavior.

Another advantage of the suggested approach is distributability. In other words, the first model was installed on a user’s mobile phone, whereas the second model was installed on a user’s computer, and the third model was installed on a server. Now, most of the images can successfully be processed on the user’s mobile phone, and there is no need to communicate with the next
models. At the same time, the second and third models are used in case of more complicated images. This very simple distributability of the suggested algorithm was absent in all the compared deep learning-based algorithms. The only flaw of the proposed method is the system complexity in training and regularizing parameters of termination and transferring previous knowledge to the next step. However, all of these problems should be dealt with by developers, and users are unaware of them while using and testing the system, which can be used easily.

When the proposed system encounters 528 MalayaKew (MK) datasets, the first model makes the final decision on 441 images. If the termination conditions of the first step are met, the process of analyzing these images, ends. Out of 441 images, only one image was predicted wrongly. This false predicted image pertains to class 2, and the system attributed it wrongly to class 27. Figure 9 shows this sample with an image of the true class and an image of the false class. Obviously, similarity to class 27 is much stronger than similarity to the right class 2; therefore, the system’s decision matches the decision made by observing both classes.

Figure 9. A Sample of MalayaKew (MK) on Which Wrong Predictions Were Made: (Left) A Sample of Class 2 Images; (Middle) A Sample of Class 2, Wrongly Predicted as a Part of Class 27; (Right) A Sample of Images from Class 27

In fact, the 87 images on which the first model was unable to make firm decisions were given to the second model, which decided on 78 of them. Fortunately, the decisions of the second model on these 78 images are totally right with no errors. Finally, the 9 remaining images are given to the third model. After the automated extraction of image patches from each of these 9 images, they are predicted. In this step, the prediction was performed with no errors. Eventually, it is fair to say that the proposed model allocated 527 of 528 test images of MalayaKew (MK) correctly to the right class.

It should also be mentioned that the parameters of Table 2 were obtained empirically, and that it was decided to strike a balance between the minimum and maximum speeds. In other words, it was decided to evaluate most of the images definitively in the first step by resorting to the second and
third models less often so that the algorithm could run at the maximum power. At the same time, it was meant to reach the maximum accuracy possible. Obviously, if more images are entered into the second and third models for evaluation, the model reliability will increase; however, the algorithm execution speed will decrease. Instead, if the first model is used as much as possible, the proposed system will have a lower reliability rate while the algorithm execution speed reaches the maximum rate.

The higher reliability rate of the three models is defendable because each of these three models experienced a different view of data. Thus, the integration of these distinctively trained features can greatly help distinguish the right class more reliably. For this purpose, all layers of the three models were visualized to show what leaf features each model focused on, and if it was possible to model a botanist’s behavior. Figure 10, Figure 11, and Figure 12 show the images of different layers from the first, second, and third models, respectively. Accordingly, the first model focused only on the general shape of the leaf. However, the second model took a general look at the leaf. It also analyzed the color and venation, although the general shape of the leaf was more important. Finally, the third model focused only on venation. Thus, botanist’s behavior was successfully modeled.

Figure 10. A Number of Feature Maps of the First Four Convolutional Layers of the First Model Trained on the
Black-and-White Images Obtained from MalayaKew (MK). The First Model Focused Only on the General Shape of the Leaf.

**Figure 11.** A Number of Feature Maps of the First Four Convolutional Layers of the Second Model Trained on the Colored Images Obtained from MalayaKew (MK). The Second Model Took an Extensive Look at the Leaf. However, It Focused on the Colors and Venations of Leaves, Although the General Shape was Much More Important to It.
4.3. Performance Evaluation of Proposed Method on Flavia

After introducing Flavia (Wu et al., 2007), this section analyzes the results of the proposed method and compares them with those of other methods on this dataset.

4.3.1. Introducing and Preparing Flavia

Flavia is another well-known leaf identification dataset, introduced by (Wu et al., 2007). It consists of 1907 leaf images of 32 different species. The images are sized 1600x1200 pixels. Figure 13 shows one of them.
For the evaluation of the proposed method on this dataset, binary images are required for training the first model. The background of these images should be black, whereas the entire leaf should be white. Image processing tools such as OpenCV and Pillow were employed to generate these images from 1907 dedicated colorful training images. For training the third model, image patches were obtained from the main images. As a result, 801 image patches were automatically generated for each class. The leaves accounted for at least 98% of each image. Therefore, there were 25632 image patches generated for training the third model. For each of the three networks, all the inputs were divided by 255 because the maximum numerical value of inputs was 255. Rotation up to 45 degrees, traverse displacement up to 0.1 of the entire image, longitudinal displacement up to 0.1 of the entire image, horizontal mirror, vertical mirror, and shuffle techniques were performed to ensure learning improvement and generalizability of the designed networks.
Since Flavia lacks separate sections for training and testing, 16.7% of this dataset (nearly 10 samples of each class) was randomly separated to develop a testing dataset in order to compare the results fairly with those of other methods. Hence, 1603 images were employed for training the first and second models when 21376 image patches were utilized for training the third model. For each epoch of 10000 epochs, a random combination of data augmentation techniques was applied to the images to enhance the generalizability of models and prevent the overfitting problem. As a result, it is impossible to say how many unique images each model experienced in the training process. However, it is obvious that all the training datasets were used along with the images generated through data augmentation based on the main images. In addition, the entire system input included 304 testing dataset images generated randomly. Furthermore, 304 testing dataset images were developed separately to test the first and second models. However, 4256 image patches were generated randomly from a total number of 25632 images to test the third model. Despite the random separation of the training dataset from the testing dataset, the process was repeated five times. The reported results were obtained from the mean of these tests.

4.3.2. Evaluation of Proposed Method on Flavia

After finishing training each of the three models on Flavia, it is time to integrate them to achieve the proposed method. The third column of Table 2 shows the parameters introduced in the previous section for the termination of each step, and the previous knowledge transferred to the next step for Flavia.

Separate tests were conducted on each of the three models in the proposed method to show that the first, second, and third models achieved 88.81%, 95.07%, and 97.72% accuracy rates, respectively. According to Table 4, these models showed no defendable performance in comparison with the latest algorithms in terms of accuracy. In fact, the performance was evaluated in the mean accuracy obtained from each model after conducting five tests. As discussed previously, it is necessary to mention that these models had shorter depths and fewer parameters than the other deep learning-based models. As a result, they managed to increase the processing speed and decrease the required storage space for processing. After integrating these three models and developing the proposed system, accuracy reached an excellent rate of 99.67%. According to Table 4, the suggested approach outperformed all the other methods evaluated on Flavia.

**Table 4.** Accuracy Rates of Different Methods on Flavia
In comparison with conventional methods (7, 9, 10, and 11), the proposed method required no hand-crafted feature extraction, having specific complexities and depending greatly on data. It also improved accuracy. In comparison with deep learning-based methods (5, 6, and 8), the proposed method performed much faster than other pre-trained models such as ResNet26 (5), AlexNet (6), and ResNet50 (8) because of using shallower networks with fewer parameters and also using all three models distinctively. It also enhanced accuracy. As discussed in the analysis of the previous dataset, another advantage of the proposed method lies in the successful modeling of a botanist’s behavior and its distributeability. Table 5 shows each of the five tests for the more detailed analysis of results.

| S. No. | Publications                          | Method                                      | Accuracy  |
|--------|--------------------------------------|---------------------------------------------|-----------|
| 1      | Proposed method (Combine)            | SWP-Leaf Net                                | 99.67%    |
| 2      | Proposed method (First model)        | S-Leaf Net                                  | 88.81%    |
| 3      | Proposed method (Second model)       | W-Leaf Net                                  | 95.07%    |
| 4      | Proposed method (Third model)        | P-Leaf Net                                  | 97.72%    |
| 5      | (Sun et al., 2017)                   | ResNet26                                    | 99.65%    |
| 6      | (Lee et al., 2017)                   | DeepPlant+MLP                               | 99.40%    |
| 7      | (Saleem et al., 2019)                | Shape & Statistical & Vein Features, PCA + KNN | 98.75%    |
| 8      | (Barré et al., 2017)                 | LeafNet CNN                                 | 97.90%    |
| 9      | (Naresh and Nagendraswamy, 2016)     | Modified LBP (NN)                           | 97.60%    |
| 10     | (Wang et al., 2016)                  | PCNN + SVM                                  | 96.97%    |
| 11     | (Goyal and Kumar, 2018)              | 12 features (7 shape, 5 vein). PCA + SVM   | 88.79%    |

Table 5. Results of Five Tests Conducted on 304 Testing Data Selected Randomly from Flavia
When the proposed method encounters 304 testing data obtained randomly from Flavia, it has a relative equilibrium on every five tests. It meets the termination conditions with nearly 83% of data and decides on them. Regarding 15% of data, the second model is sufficient, and there is no need to continue the algorithm. Therefore, only 2% of data will continue the algorithm to the end. On average, the first model managed to make accurate decisions on data, meeting the termination conditions of the first step with the success rate of 99.76%. The success rates of the second and third models were 99.14% and 100%, respectively. Finally, it is fair to say that the proposed model managed to correctly allocate 99.67% of testing data from Flavia on average.

In the end, all layers of the three models were visualized on this dataset to show what leaf features each model focused on. According to Figures 14, 15, and 16, the first model focused only on the general shape of the leaf. However, the second model took a more extensive look at the leaf. It also paid attention to color and venation, despite the fact that the general shape of the leaf was much more important to it. Finally, the third model focused only on venation.

| General Accuracy of Proposed Method | 100% | 99.34% | 99.67% | 100% | 99.34% | 99.67% |
|------------------------------------|------|--------|--------|------|--------|--------|

*Figure 14. A Number of Feature Maps of the First Four Convolutional Layers of the First Model Trained on the Black-and-White Images Obtained from Flavia. The First Model Focused only on the General Shape of the Leaf.*
Figure 15. A Number of Feature Maps of the First Four Convolutional Layers of the Second Model Trained on the Colored Images Obtained from Flavia. The Second Model Took an Extensive Look at the Leaf. It Paid More Attention to Color and Venation, Although the General Shape of the Leaf Was Much More Important to It.

Figure 16. A Number of Feature Maps of the First Four Layers of the Third Model Regularized on the Image Patches Obtained from Flavia. The Third Model Focused only on Venation.
5. Conclusion

This paper proposed a method with a maximum behavioral resemblance with a botanist’s behavior. Three deep learning-based models (S-Leaf Net, W-Leaf Net, and P-Leaf Net) were employed to develop the proposed method. The first and second models were designed from scratch, and the third model employed the pre-trained MobileNetV2 model. The tests were conducted on the two well-known datasets of leaf identification, i.e. MalayaKew (MK) and Flavia. According to the results, the proposed method obtained 99.81% and 99.67% of accuracy and outperformed all the other methods. Compare to conventional methods, the suggested approach required no hand-crafted feature extraction, having specific complexities and depending greatly on datasets. In comparison with other deep learning-based techniques, the proposed method enhanced accuracy. It also acted much faster than other methods because of using shallower networks, fewer parameters, and further using the three models repeatedly.

The most important superiority of the proposed system is that its guesses can be used as a botanist’s theories when unknown species or genetic changes are observed because the method was developed to model a botanist’s behavior. To prove this, visualization techniques were employed to analyze different layers of each model and show that the expected features were successful in modeling a botanist’s behavior. Another advantage is the distributablity of the proposed method. In comparison with other methods, the only flaw is the system complexity in training and regulating termination parameters and transferring previous knowledge to the next step. Nonetheless, it is fair to say that all of these problems will be experienced by developers, and users will be unaware of any difficulties in using and testing the system. Thus, users can easily use the system.

In the future, it is recommended to obtain the optimal and semi-optimal values of termination parameters through heuristic and meta-heuristic algorithms by defining an appropriate cost function to increase accuracy and pass fewer steps in a bid to perfect the proposed method. In addition, it is possible to identify other components of plants such as roots, flowers, and stems simultaneously to develop a hybrid system to enhance accuracy and efficiency in plant identification. It is also necessary to use complicated datasets obtained from real environmental conditions and develops a system for the successful identification of images.

References
Angelov, P., Sperduti, A., 2016. Challenges in deep learning, Proc. ESANN, pp. 489-495.
Barré, P., Stöver, B.C., Müller, K.F., Steinhage, V., 2017. LeafNet: A computer vision system for automatic plant species identification. Ecological Informatics 40, 50-56.

Beikmohammadi, A., Faez, K., 2018. Leaf Classification for Plant Recognition with Deep Transfer Learning, 2018 4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS). IEEE, pp. 21-26.

Bodhwani, V., Acharjya, D., Bodhwani, U., 2019. Deep Residual Networks for Plant Identification. Procedia Computer Science 152, 186-194.

Charters, J., Wang, Z., Chi, Z., Tsoi, A.C., Feng, D.D., 2014. Eagle: a novel descriptor for identifying plant species using leaf lamina vascular features, Multimedia and Expo Workshops (ICMEW), 2014 IEEE International Conference on. IEEE, pp. 1-6.

Chollet, F., 2017. Xception: Deep learning with depthwise separable convolutions. arXiv preprint, 1610.02357.

Clarke, J., Barman, S., Remagnino, P., Bailey, K., Kirkup, D., Mayo, S., Wilkin, P., 2006. Venation pattern analysis of leaf images. International Symposium on Visual Computing. Springer, pp. 427-436.

Cope, J.S., Corney, D., Clark, J.Y., Remagnino, P., Wilkin, P., 2012. Plant species identification using digital morphometrics: A review. Expert Systems with Applications 39, 7562-7573.

Cope, J.S., Remagnino, P., Barman, S., Wilkin, P., 2010. Plant texture classification using gabor co-occurrences, International Symposium on Visual Computing. Springer, pp. 669-677.

Du, C., Gao, S., 2017. Image segmentation-based multi-focus image fusion through multi-scale convolutional neural network. IEEE access 5, 15750-15761.

Ferentinos, K.P., 2018. Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture 145, 311-318.

Glorot, X., Bengio, Y., 2010. Understanding the difficulty of training deep feedforward neural networks, Proceedings of the thirteenth international conference on artificial intelligence and statistics, pp. 249-256.

Goyal, N., Kumar, N., 2018. Plant Species Identification using Leaf Image Retrieval: A Study,
Grinblat, G.L., Uzal, L.C., Larese, M.G., Granitto, P.M., 2016. Deep learning for plant identification using vein morphological patterns. Computers and Electronics in Agriculture 127, 418-424.

Hall, D., McCool, C., Dayoub, F., Sunderhauf, N., Upcroft, B., 2015. Evaluation of features for leaf classification in challenging conditions, Applications of Computer Vision (WACV), 2015 IEEE Winter Conference on. IEEE, pp. 797-804.

Hedjazi, M.A., Kourbane, I., Genc, Y., 2017. On identifying leaves: A comparison of CNN with classical ML methods, 2017 25th Signal Processing and Communications Applications Conference (SIU). IEEE, pp. 1-4.

Hu, J., Chen, Z., Yang, M., Zhang, R., Cui, Y., 2018. A Multiscale Fusion Convolutional Neural Network for Plant Leaf Recognition. IEEE Signal Processing Letters 25, 853-857.

Ioffe, S., Szegedy, C., 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. arXiv preprint arXiv:1502.03167.

Kalyoncu, C., Toygar, Ö., 2015. Geometric leaf classification. Computer Vision and Image Understanding 133, 102-109.

Kamilaris, A., Prenafeta-Boldú, F.X., 2018. Deep learning in agriculture: A survey. Computers and Electronics in Agriculture 147, 70-90.

Kingma, D.P., Ba, J., 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Kumar, N., Belhumeur, P.N., Biswas, A., Jacobs, D.W., Kress, W.J., Lopez, I.C., Soares, J.V., 2012. Leafsnap: A computer vision system for automatic plant species identification, Computer vision–ECCV 2012. Springer, pp. 502-516.

Larese, M.G., Namfás, R., Craviotto, R.M., Arango, M.R., Gallo, C., Granitto, P.M., 2014. Automatic classification of legumes using leaf vein image features. Pattern Recognition 47, 158-168.
Lee, S.H., Chan, C.S., Mayo, S.J., Remagnino, P., 2017. How deep learning extracts and learns leaf features for plant classification. Pattern Recognition 71, 1-13.

Lee, S.H., Chan, C.S., Wilkin, P., Remagnino, P., 2015. Deep-plant: Plant identification with convolutional neural networks, Image Processing (ICIP), 2015 IEEE International Conference on. IEEE, pp. 452-456.

Liu, Z., Zhu, L., Zhang, X.-P., Zhou, X., Shang, L., Huang, Z.-K., Gan, Y., 2015. Hybrid Deep Learning for Plant Leaves Classification, International Conference on Intelligent Computing. Springer, pp. 115-123.

Mouine, S., Yahiaoui, I., Verroust-Blondet, A., 2012. Advanced shape context for plant species identification using leaf image retrieval, Proceedings of the 2nd ACM international conference on multimedia retrieval. ACM, p. 49.

Naresh, Y., Nagendraswamy, H., 2016. Classification of medicinal plants: an approach using modified LBP with symbolic representation. Neurocomputing 173, 1789-1797.

Neto, J.C., Meyer, G.E., Jones, D.D., Samal, A.K., 2006. Plant species identification using Elliptic Fourier leaf shape analysis. Computers and electronics in agriculture 50, 121-134.

Rasti, R., Rabbani, H., Mehridehnavi, A., Hajizadeh, F., 2018. Macular OCT classification using a multi-scale convolutional neural network ensemble. IEEE transactions on medical imaging 37, 1024-1034.

Saleem, G., Akhtar, M., Ahmed, N., Qureshi, W., 2019. Automated analysis of visual leaf shape features for plant classification. Computers and Electronics in Agriculture 157, 270-280.

Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., Chen, L.-C., 2018. Mobilenetv2: Inverted residuals and linear bottlenecks, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 4510-4520.

Shelhamer, E., Long, J., Darrell, T., 2016. Fully convolutional networks for semantic segmentation. arXiv preprint arXiv:1605.06211.

Simonyan, K., Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.
Smith, L.N., 2017. Cyclical learning rates for training neural networks, 2017 IEEE Winter Conference on Applications of Computer Vision (WACV). IEEE, pp. 464-472.

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R., 2014. Dropout: a simple way to prevent neural networks from overfitting. The journal of machine learning research 15, 1929-1958.

Su, Y.-C., Chiu, T.-H., Yeh, C.-Y., Huang, H.-F., Hsu, W.H., 2014. Transfer Learning for Video Recognition with Scarce Training Data for Deep Convolutional Neural Network. arXiv preprint arXiv:1409.4127.

Sun, Y., Liu, Y., Wang, G., Zhang, H., 2017. Deep learning for plant identification in natural environment. Computational intelligence and neuroscience 2017.

Szegedy, C., Ioffe, S., Vanhoucke, V., Alemi, A.A., 2017. Inception-v4, inception-resnet and the impact of residual connections on learning, AAAI, p. 12.

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z., 2016. Rethinking the inception architecture for computer vision, Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2818-2826.

Tang, Z., Su, Y., Er, M.J., Qi, F., Zhang, L., Zhou, J., 2015. A local binary pattern based texture descriptors for classification of tea leaves. Neurocomputing 168, 1011-1023.

Wang, Z., Sun, X., Zhang, Y., Ying, Z., Ma, Y., 2016. Leaf recognition based on PCNN. Neural Computing and Applications 27, 899-908.

Wu, S.G., Bao, F.S., Xu, E.Y., Wang, Y.-X., Chang, Y.-F., Xiang, Q.-L., 2007. A leaf recognition algorithm for plant classification using probabilistic neural network, Signal Processing and Information Technology, 2007 IEEE International Symposium on. IEEE, pp. 11-16.

Xiao, X.-Y., Hu, R., Zhang, S.-W., Wang, X.-F., 2010. HOG-based approach for leaf classification, Advanced intelligent computing theories and applications. with aspects of artificial intelligence. Springer, pp. 149-155.

Yang, J., Yu, K., Gong, Y., Huang, T., 2009. Linear spatial pyramid matching using sparse coding for image classification, 2009 IEEE Conference on computer vision and pattern recognition.
IEEE. pp. 1794-1801.