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Plant Leaf Identification based on Machine Learning Algorithms

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***Abstract*—**Classical plant identification process is time-consuming and complicated. On the other hand, knowledge of plants and the ability to identify the plant species are depleting through generations. This lack of knowledge and drawbacks of manual identification were the underlying causes to develop this study. Hence, the main objective is to compare the performance of different machine learning algorithms and select the best algorithm to be used for further development of a mobile application to identify herbal, fruits, and vegetable plants available in Sri Lanka using their leaves. In this regard, this article focuses on pre-processing and effective classification of manually collected leaves datasets. In the pre-processing stage, noise handling, image enhancement, and transformation were done. Then, features were extracted with respect to shape, texture, and color. Subsequently, five machine learning algorithms were employed on the dataset for classification after normalizing the data. Finally, classification accuracies of the algorithms were obtained with accuracy and loss curves of the Multilayer Perceptron algorithm. The classification accuracies of Support Vector Machine, Multilayer Perceptron, Random Forest, K-Nearest Neighbors, and Decision Tree algorithms are 85.82%, 82.88%, 80.85%, 75.45%, and 64.39% respectively. According to the results, Support Vector Machine and Multilayer Perceptron algorithms exhibited satisfactory performance.

***Keywords*—**Plant identification, Leaves, Pre-processing, Machine learning algorithms, Classification

I. INTRODUCTION

The world consists of billions of plants in which few of the plants are disclosed to the human by environmental scientists. Approximately 400,000 species are known to science (Wang *et al.,* 2008). However, the identification of plants is much important in applications like biodiversity, ecology, agriculture, food and nutrition, medicine, and pharmacology. A plant consists of different kinds of components like leaves, flowers, stems, roots, etc. Researches conducted for plant identification using flowers as an identifying component were able to obtain satisfying results (Nilsback Zisserman, 2010). However, most researchers in this arena utilized leaf as the component of the plant for classification due to several reasons such as the ease of accessibility, availability at all times, and availability of image collection (Hong *et al.,* 2004). On the other hand, it is more difficult to deal with the structure of the flower which has a more complex 3D structure (Lee Chen, 2006) and the survival periods of leaves are longer than flowers (Cope *et al.,* 2012).

Traditional plant identification undergoes a systematic manual process which is more time-consuming and complicated. Apart from that, lack of knowledge relates to plants is less in new generations due to the gap between the environment and human. As a result of that, the identification of plants is very weak which is increasing from generation to generation. A complex and competitive lifestyle is the main reason while urbanization is also contributing partially. Technology is a huge part of today's lifestyles. Therefore, technological tools like mobile applications can be used to solve this problem. There are several mobile applications for plant identification like ApLeaf (Zhao *et al.,* 2015), LeafSnap (Kumar *et al.,* 2012), etc. Some researchers introduced different approaches for plant identification, which are also vital to develop applications and solve this problem as well. These studies have been using various types of pre-processing technologies in the image processing domain. For example, they have been using filters (Gaussian, Median, Gabor, etc.), morphology operation, watershed algorithm, and so on for different purposes in image pre-processing. Shape, texture, and color are the most widely used feature types in leaf identification. Researches have been utilizing basic machine learning algorithms to deep learning algorithms for the classification process.

Machine learning applications can be mainly divided into two types, which are supervised and unsupervised applications. Supervised machine learning applications can be of two types which are regression in which outputs are continuous values and classification in which outputs are discrete values. According to this classification, our application is a supervised classification problem. These problems define a set of target classes. Then, models are trained to recognize images using labeled images. The training can be achieved using several kinds of supervised algorithms. For example, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naïve Bayes (NB), Neural Networks (NN), and Decision Tree (DT).

Ahmed Hussein (2020) proposed a machine learning based leaf identification scheme. This research used shape features of leaves. In their proposed approach, the centroid of the leaf shape was calculated by obtaining a continuous contour using Radial Basis Function Neural Networks (RBFNN). Then, the distances between predetermined points and the centroid were calculated. Subsequently, those distances were normalized. Then, they compared the classification results with respect to RBFNN and SVM algorithms. They used, SVM with optimization techniques using Salp Swarm Algorithm (SSA) which provided more improvement over RBFNN and SVM. They didn't apply pre-processing techniques like enhancing images by reducing noises in their approach. Our approach provides some pre-processing methods to improve the image quality. Kaur Kaur (2019) proposed another approach for plant identification by leaves. They removed noises of images using the Gaussian filter. In the feature extraction stage, they used texture and color features. They also performed color-based segmentation using k-means clustering which was used for feature extraction. Finally, they used SVM for the classification. The Gaussian filter is an acceptable tool, which can be used for noise reduction. Our study used the similar tool as this research. However, binary images may contain some imperfections. Therefore, our study used morphology operation after applying the Gaussian filter to remove these imperfections.

Removing shadows of images during pre-processing is a vital task, and it was achieved by the study which was done by (Begue *et al.,* 2017). To remove it, they converted the image into HSV format and then split it into different color channels. After that, they reduced the noises by using the median blur filter and converted them into binary images using the Otsu threshold method. They extracted length, width, area of the bounding box, area of the leaf, perimeter of leaf, hull area, hull perimeter, number of vertices, horizontal and vertical distance map, 45-degree radial map, and original RGB values of each pixel. Finally, Random Forests (RF) algorithm was used for the classification. As the above study, this research also utilized a median filter for noise reduction. In addition to a filter, our research applied morphology operation too. In this study, they used two types of features, which are, a large number of shape features and color features. However, our study used a balanced set of three feature types such as shape, color, and texture. Liu Kan (2016) conducted a study for plant identification. In the pre-processing, first, they converted images into grayscale images. They used the Gaussian filter and Median filter for noise reduction. Then, they obtained the binary image using the Otsu threshold method and the edge was extracted using the morphology operation. As a result of that, they could calculate boundary rectangle as our approach which can be used to obtain shape features. They used Gabor filters, Gray-Level Co-occurrence Matrices (GLCM), and Local Binary Patterns (LBP) methods for texture feature extraction while Fourier descriptors and Hu invariant moments were used for shape features. Finally, they used Deep Belief Network (DBN) with the dropout method for the classification. Instead of developing their own dataset, they used the ICL dataset. Nevertheless, our study used a dataset that was developed by ourselves. On the other hand, this study only depends on two feature types of leaves which are shape and texture. But our study utilized another important feature type which is color. Le *et al.* (2014) introduced another approach for plant identification. In the pre-processing step, they separated the leaf region from the background using the watershed algorithm. Then images were converted into grayscale and resized. The patch-level features were utilized in the feature extraction and three types of kernels were taken into account which are gradient, local binary pattern, and color. Image level features were extracted using the spatial pyramid. After the feature extraction, they applied SVM for the classification. As the above study, this research also used two existing datasets, which are Flavia and ImageClef 2013 datasets. They obtained satisfactory accuracy for 97.5% for the Flavia dataset and very less accuracy for ImageClef 2013 dataset, which is 63.4% for the same approach. Therefore, the proposed approach may contain some amount of unfitting.

In our proposed solution, first, leaf images were captured and the dataset was developed. Then images were converted into grayscale images. Subsequently, the Gaussian filter was applied to reduce noises. Then, images were converted into binary images and morphology operation was applied to reduce noises furthermore as mentioned above. In the feature extraction stage, our approach used three types of features which are shape, texture, and color. Finally, the study compared the accuracies of five supervised machine learning algorithms in the classification stage.

The rest of this paper is organized as follows. In section II, the methodology utilized in this study is described comprehensively. Results that were obtained from the proposed model are shown in section III and discussion on those results was included in section IV. Finally, a conclusion of this study is presented in section V.

II. METHODOLOGY

The proposed methodology consists of several stages from data collection to classification that are elaborated in the flow chart in Figure 01.

A. Data Collection

In the data collection stage, images were captured and the dataset was developed, which contains 3,150 leaf images belonging to 25 types of herbal, fruit, and vegetable plants in Sri Lanka as shown in Figure 02. An average range

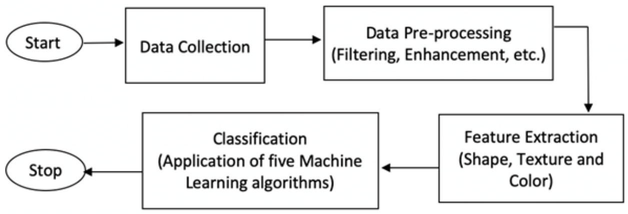

Figure 1: Flow chart of the overall methodology.

of 120-136 images for each plant species was obtained using randomly selected several leaves of the plant. A 20-megapixel camera in a mobile phone was used to capture images. Some researchers carried out their studies in which images were photographed on a uniform background (Jamil *et al.,* 2015; Wang, Chi Feng, 2003; Yahiaou, Mzoughi Boujemaa, 2012). Our study also used a uniform white background. Approximately the same distance between the leaf and camera point (20-25 centimeters) was maintained when images were captured. On the other hand, images were captured during the daytime without any significant time gap. Though images were captured during the daytime, lighting conditions fluctuated in a small range. As a result of that, the background color was changed in a small range. A merit of the image capturing process is, all images were captured in eight different angles, separated by 45 degrees.

Figure 2: The 25 plant species used to develop the dataset of the study.

B. Pre-processing

First, color images were converted into grayscale images. Noise handling is an important task in image processing. Therefore, the Gaussian filter was used to reduce noises of the grayscale image as shown in Figure 03, which is also called as Gaussian smoothing.

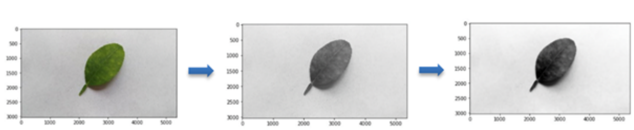

Figure 3: Transformation of the color image to grayscale and application of the Gaussian filter.

Then, the enhanced images were transformed into binary images using the Otsu threshold method that is usually used to separate pixels into two classes. These binary images may contain imperfections. Therefore, morphology operation was used to reduce them, which was employed on binary images as shown in Figure 04.

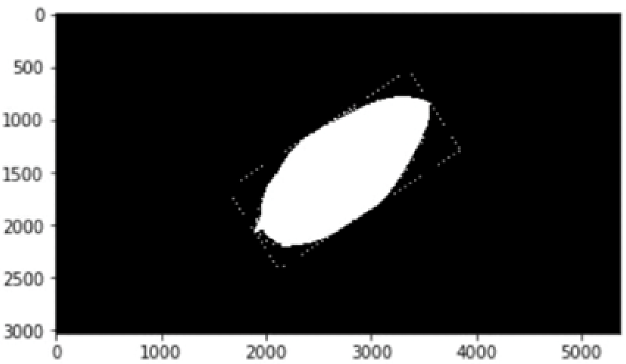

Figure 4: Application of morphology operation.

C. Feature Extraction

This study used three types of features of a leaf which are shape, texture, and color features. First, the study extracted area and perimeter features by calculating moments using contours. Our approach was developed on fully-grown and not tempered leaf images as the study conducted by Kaur Kaur (2019). Then our approach focused on generating the best-fit rectangle and ellipse as shown in Figure 05 in order to extract another three shape features for the feature space which are aspect ratio, rectangularity, and circularity. Apart from these features, length and width were also extracted as shape features.

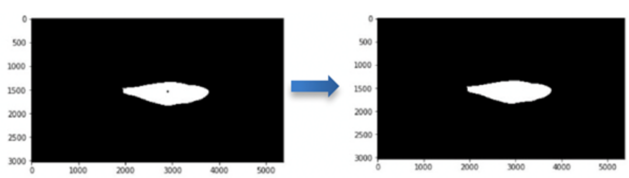

Figure 5: Generating best fitting rectangular and ellipse.

Texture-based features are also an important feature category of a leaf. The term texture defines various properties of an image like coarseness, smoothness, and regularity in image processing. Four texture features such as contrast, correlation, inverse difference moments, and entropy were extracted in this study using Haralick moments.

Color-based features can be used in image classification (Huang et al., 2010). Each digital color image pixel is a combination of RGB (Red, Green, Blue) values. Thus, the RGB color model of a digital image consists of three components as shown in Figure 06. In our study, mean and standard deviation values of RGB channels of each image were calculated using equation (1) and equation (2) (Zhao *et al.,* 2015) where and are mean and standard deviation respectively. The Pij denotes jth pixel value of ith color channel while N denotes the number of images.

$$E_i = \sum_{i=1}^{N} \frac{1}{N} P_{ij} \tag{1}$$

$$\sigma_i = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (P_{ij} - E_i)^2} \tag{2}$$

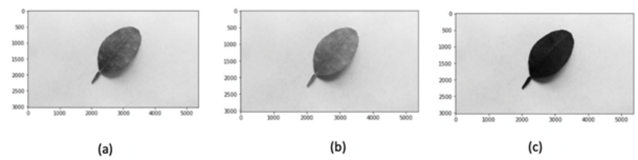

Figure 6: RGB components of images (a) Red channel, (b) Green channel, (c) Blue channel.

D. Classification

In the feature extraction stage, our study extracted 17 features under three main categories as mentioned in section III. C. Feature extraction. According to the observations, the extracted data were in a highly distributed range. Therefore, the min-max normalization technique was used to guarantee that all features have the exact same scale. Equation (3) (Pandey Jain, 2017) was used for the min-max normalization process where X_i represents the ith data point. X_{min} denotes the minimum value of data while X_{max} denotes the maximum value. After the normalization process, the dataset was divided into training, validation, and testing sets. In order to achieve this task, the splitting operation in the NumPy library was used. The dataset was divided into 70% for training (2205 images), 15% for validation (472 images), and 15% for testing (473 images).

$$X_{scaled} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{3}$$

According to the study by Haddadi *et al.* (2010) which compares machine learning algorithms for leaf identification, RF, Multilayer Perceptron (MLP), and SVM have high accuracies. According to the studies referred in the literature review section, algorithms like SVM, RF, NN, etc. are also used for the classification. Therefore, our study selected five machine learning algorithms, which are MLP, SVM, RF, KNN, and DT since this problem is a supervised application. Our first focus was MLP with a backpropagation algorithm, which changes weights recursively by passing error from the output layer to hidden layers (Haddadi *et al.* 2010). The MLP of our model consists of two hidden layers in which the first layer consists of 32 neurons and the second layer contains 28 neurons. There are a number of activation functions for neural network implementation (Sibi, Jones, Siddarth, 2013). ReLU is one of the powerful activation functions, which was used for the hidden layer of our model. He_uniform is one of the kernel initializers, which is highly applicable to the ReLU activation function. Therefore, it was used as the kernel initializer for hidden layers of our model. Softmax activation function was used in the output layer with glorot_uniform initializer since the classification deals with multiple classes. After the MLP analysis, we applied four other supervised machine learning algorithms in order to compare the effectiveness of the algorithms as shown in the result section.

III. RESULTS

This section evaluates the performance of the proposed methodology to recognize the plant species. Selected machine learning algorithms were tested to evaluate the performance of the overall proposed approach.

A. ANN Classification

As the first stage of evaluation, the proposed ANN model was evaluated during the training process, which is represented by Figure 07 and Figure 08. The model provided an accuracy of 86.02% against the validation dataset and 82.88% against the testing data set.

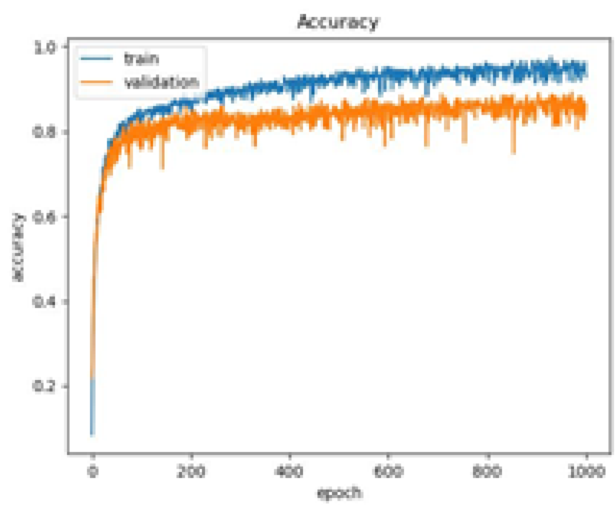

Figure 7: Training and testing accuracy curves of the proposed ANN model.

B. Classification using other algorithms

In the second evaluation stage, the other four algorithms were also tested independently for proper comparison. The results, which were produced by the algorithms, are shown in Table 01.

Table I: Accuracies of algorithms

Algorithm	Accuracy (%)
Support Vector Machine	85.82
Random Forest	80.85
K-Nearest Neighbors	75.45
Decision Tree	64.39

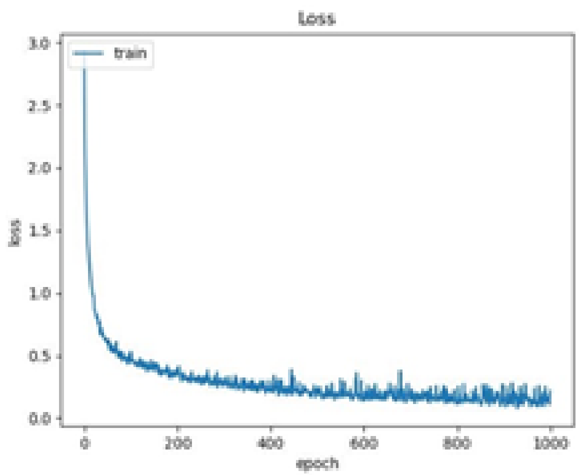

Figure 8: Training loss curve of the proposed ANN model.

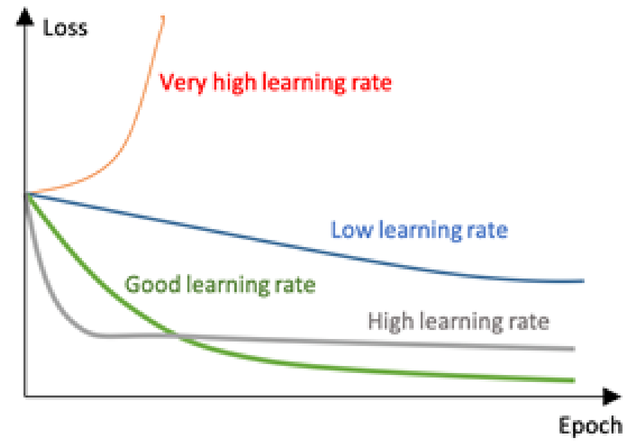

Figure 9: Description of learning rates of different loss curves in ANN models.

The next stage of the evaluation is the comparison of the above results with the state-of-the-art methods proposed by Haddadi et al. (2010) and Kaur Kaur (2019). Table 02 and Table 03 represent the results of our proposed methodology in comparison with state-of-the-art methods, which are discussed in the discussion section.

Table II: Accuracy of SVM obtained in the study by Kaur and Kaur (2019) and our proposed method

Method	**Accuracy (%)**
The method based on the study by Kaur and Kaur (2019)	93.26
Our proposed method based on SVM	85.82

Table III: Accuracies of multiple machine learning algorithms in the study by Haddadi et al. (2010) and our proposed method

Accuracy (%)					
SVM	**MLP**	**RF**	**NB**	**KNN**	**DT**
Method proposed by Haddadi et al. (2010)					
87.40	88.20	90.10	84.30	82.50	NA*
Our proposed method					
85.82	82.88	80.85	NA*	75.45	64.39

NA* – Not Applied

IV. Discussion

Figure 07 and Figure 08 represent the accuracy curve and the loss curve of the ANN model. The loss curve is one of the important curves to analyze neural networks as shown in Figure 09.

The model showed a good learning rate, see Figure 08 and Figure 09. On the other hand, accuracy curves can be used to understand the amount of overfitting and the loss curve can be used to understand the underfitting of the model. The gap between training and validation accuracy curves represents the overfitting of the model while the shape of the loss curve shows the amount of underfitting. If there is a small gap as in Figure 07, the model has less amount of overfitting. If the loss curve does not remain flat and continues to decrease until the end of training as in Figure 08, the underfitting of a particular model will be less.

Table 02 compares the results of one of the state-of-the-art methods proposed by Kaur Kaur (2019) and our proposed method. In both studies, the SVM algorithm was utilized for the classification. According to Table 02, the accuracies provided by the classifier are equal to some extent. Table 03 shows the comparison between the accuracies of the study by Haddadi *et al.* (2010) and our method. Both studies used multiple supervised machine learning algorithms to compare the proposed approaches on different algorithms. The DT algorithm was used in our approach in addition to the study by Haddadi *et al.* (2010) while they utilized the NB algorithm which was not used in our approach. According to Table 03, it is observed that the KNN algorithm exhibits the lowest performance with respect to both approaches. Similar to the previous comparison, the SVM has relatively equal accuracies in both approaches. On the other hand, the SVM classifier provided the highest accuracy in our proposed method while the RF algorithm provided the highest accuracy in the study (Haddadi *et al.,* 2010).

V. Conclusions

This article proposes an approach for leaf identification that consists of three main stages which are pre-processing, feature extraction, and classification. Under the pre-processing step, noise handling, image enhancement, and transformation of color images to grayscale and binary images were done. The study extracted 17 features under three feature categories which are shape, texture, and color using a manually built dataset. The feature space was normalized before the classification. In the classification stage, an MLP model was trained first. Subsequently, four major algorithms were also trained so as to compare the performance of different algorithms on the proposed approach. According to the results, the proposed approach showed a satisfactory performance with SVM and MLP algorithms, and those algorithms could be recommended under this approach. Apart from that, MLP also showed a high learning rate, low overfitting, and underfitting. Future work of our research will focus on the ratio of length and width as a feature, further improvement of the dataset, experiment with other algorithms to increase the accuracy, and develop a mobile application.

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