Evaluating the use of an artificial neural network to figure out leaf area

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Abstract: An essential factor in plant monitoring is leaf area. For an accurate measurement of leaf area, an automated approach is required. This paper outlines a process for The measuring of leaf area automatically from images is suggested. The Without referencing the thing, a leaf was photographed. From the picture, four features were retrieved and utilised as input for estimating leaf area, an artificial neural network. The Results from tests indicate that the suggested approach can with a mean absolute relative error of less than when measuring leaf area calculation time of 1% or less.

Keywords— image processing, autonomous leaf-area measuring, artificial neural network

INTRODUCTION

In addition to monitoring plant development, competition, and productivity, leaf area is crucial for plant monitoring [1]. Additionally, leaf area may be used to gauge how well a plant's internal mechanisms are working [2].Traditionally, grid counting method [3-5] or paper weighing method [1] can be used to manually estimate leaf area. Although these techniques are straightforward in execution, they take time. Furthermore, the operator's skill determines how accurate the measurements are for various procedures.A number of different methods for measuring leaf area have been offered to address the issues with the standard method. Semi-automatic techniques for calculating leaf area have been presented by Córcoles, et al. [6] and Amiri and Shabani [7]. They used a general linear regression model (GLM) [6] and an adaptive neural-based fuzzy inference system (ANFIS) [7] to estimate leaf area after physically measuring the length and breadth of each leaf. The techniques have achieved excellent coefficients of determination and have been confirmed using a variety of leaves. However, the accuracy of the approaches greatly depends on how well the operator can physically measure length and width.

Automatic approaches to quantify leaf area by using image processing methodology have been proposed by Gong, et al. [2], Lü, et al. [3], Patil and Bodhe [4], and Radzali, et al. [5].

The suggested approaches used a camera to take a picture of the measured leaf and a reference item whose area was known in order to calculate the leaf's area. The picture was then converted into a binary image by processing. In order to determine the leaf area, the binary image's number of leaf pixels and object reference pixels were compared, and the result was multiplied by the real object reference area. The suggested procedures have been tested and yielded results with little error. However, employing object references might cause issues during the segmentation process, which would ultimately result in a reduction in measurement.

Additionally, the technique Gong, et al.'s [2] segmentation method was not entirely automated; human input was still required. Consequently, an automated technique for measuring leaf area It does not require human input or object reference should be created. A combination of image processing artificial neural network (ANN) and method considered in an effort to solve the issues. An ANN is a nonlinear a basic, human-nervous-system-imitating model calculating [8]. ANN has been used to address categorization and prediction issues in several fields, including utilising computer vision to identify natural produce [9], egg Using computer vision to quantify volume [10], biodiesel Production improvement [11], as well as gas concentration For an electronic nose, an estimate [12]. In this paper, an ANN-based approach for measuring leaf area based on images is proposed. The length, breadth, area, and perimeter of the leaf are retrieved from the picture of the measured leaf in the proposed technique, and these attributes are then utilised as input to an ANN to forecast the area of the leaf. Therefore, without object reference or human input, the suggested approach may be utilised to estimate leaf area. The order of the remaining text is as follows. The information and specifics of each step utilised in the suggested strategy are explained in Section 2 in full. The experimental setup for evaluating the suggested strategy is described in Section 3. Experimental findings are presented and discussed in Section 4. Finally, Section 5 draws a conclusion.

MATERIALS AND METHOD

Hardware for the suggested solution included a camera, two flat acrylic boards, a computer, a USB cable, and more, as illustrated in Fig. 1. The image of the measured leaf was taken with a Logitech® HD Webcam c270h. A USB connection was used to link the camera to the computer, which was placed 50 cm away from the leaf that was being measured above and was oriented such that the picture plane was parallel to the leaf surface. The measured leaf was put between two flat acrylic boards to flatten it. The lower board was painted white and served as the background for the image capture process. To operate the camera, process the captured image, and calculate leaf area, the suggested system used a 2.20GHz Intel Core 2 portable computer with 4GB of RAM and Windows 7 as its operating system.
30 leaf samples were randomly selected from the region near Universitas Surabaya in order to validate the suggested methodology.

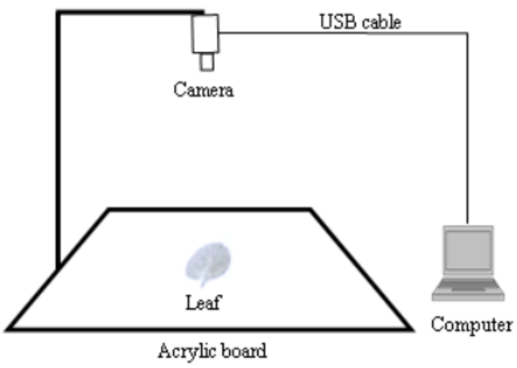

Fig. 1 Hardware for the specified leaf area measuring technique.
The samples were made up of 10 leaves each of kailan (Brassica oleracea Alboglabra Group), ipecac (Cephaelis ipecacuanha), and wild betel (Piper sarmentosum Roxb. Ex Hunter). Using the paper weighing method, the precise area of each sample was determined by hand [1].

The suggested approach for measuring leaf area involved a number of processes, beginning with picture capture and continuing with segmentation, features extraction, and leaf area calculation. The following subsections provide explanations of each step's specifics.

III) Picture Capture
During image capture, the measured leaf was situated halfway between two flat acrylic boards. The camera with a white background was used to take a picture of the measured leaf. The white backdrop was used since, in typically, leaves have colours other than white. As a result, during the segmentation process, leaf pixels and background pixels could be readily distinguished. The image was taken in RGB colour space, and a PNG file was afterwards created and processed. Each leaf sample was recorded twice, once in each of the two orientations. In Fig. 2, samples of captured images are displayed.

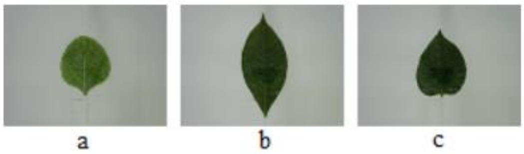

Fig. 2. Examples of objects in the illustration include (a) kailan, (b) ipecac, and (c) wild betel.
2) Preparation
By computing the weighted average of the R, G, and B values for each pixel in the acquired image, the RGB colour space image was transformed to a grey scale image during the preprocessing stage. A 55 Gaussian filter [13] was applied to the grey scale picture to decrease camera noise. The example of a preprocessing result is shown in Fig. 3.

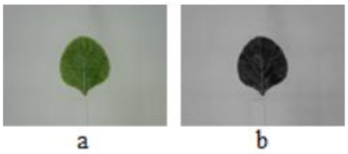

Fig. 3The recorded picture in (a) and the grayscale image in (b) are examples of preprocessing results.
No. 3: Segmentation
In the grey scale picture, the background pixels and leaf pixels were divided using a segmentation step. In this phase, the suggested methodology used the thresholding approach [13]. Utilising the Otsu approach, the threshold value T was picked out automatically [14]. As seen in Fig. 3(b), the intensity of the background pixel was greater than that of the leaf pixel in the grey scale image. As a result, any grey scale image pixel with intensity less than T was classified as a background pixel with binary value 0 (black pixel) or as a leaf pixel with binary value 1 (white pixel). Fig. 4 depicts the binary picture that emerged from the segmentation process.

a b

Fig. 4. The observed envision in (a) and the binary image in (b) are examples of segmentation results.

Extraction of Features:

In this stage, the binary image's leaf pixels were used to extract four features. The following stage was estimating the measured leaf's area using the retrieved characteristics. The characteristics were perimeter, area, area, and length.

• The length of the observed leaf's principal axis, measured in pixels, was designated as length (L). The binary image's greatest distance between two pixels on the leaf boundary was used to establish the main axis, as seen in Fig. 5(a).

• The length (in pixels) of the minor axis of the measured leaf was used to define width (W). According to the binary definition, the minor axis is the line that connects two pixels on the leaf boundary and is perpendicular to the major axis in fig 5(b).Pixels of leaves were used to determine Area (A).The binary picture in Fig. 5(c) has (white pixels).• The quantity of pixels on a perimeter (P) is as shown in the binary image's depiction of the leaf border,Fig. 5 (d).

a b c d

Fig. 5. The extracted features: a) length, b) breadth, c) area, d) circumference

5) Estimation of Leaf Area

The suggested technique utilised an artificial neural network based on the characteristics acquired in the previous stage to estimate the observed leaf's area. An input layer, a hidden layer, and an output layer made up the three layers that made up the ANN architecture. One neuron that represents the leaf area was present in the output layer. The amount of characteristics utilised to estimate the measured leaf's area determined how many neurons were present in the input layer. By feeding every conceivable combination of characteristics into the ANN, a feature selection was carried out to achieve high leaf area estimation accuracy.As a result, there were 15 ANNs with various input.

In an experiment, the number of neurons in the buried layer was heuristically found to be between 2 and 5. High estimation accuracy for leaf area is produced by the ANN. The transfer functions employed by the ANN from the input layer to the hidden layer and from the hidden layer to the output layer, respectively, were hyperbolic tangent sigmoid as in (1) and linear functions as in (2). The mean square error (MSE) was employed as the performance function when the ANN was trained using the back propagation approach [15]. To prevent one characteristic from dominating the others and to expedite the training process, all features were scaled before the training procedure[9].

$$f(x) = \frac{1-e^{-2x}}{1+e^{-2x}} \quad (1)$$

$$f(x) = x \quad (2)$$

III. EXPERIMENTAL SETUP

A laboratory experiment has been done to verify the suggested method. In the experiment, each leaf sample was taken twice, once in each of the two directions.

As a result, there were 20 photographs of each variety of leaf, for a total of 60 images.

Sixty leaf photos were utilised to provide training and testing data, which was then cross-validated five times [16]. All image data were separated into five equal-sized, mutually exclusive subdata at random. Four of the remaining subdata were used as training data, while one subdata was utilised as testing data. Five iterations of this method were completed in order to use each subset of data as testing data once. Every time an ANN was trained, 15 different input combinations and a different number of hidden layer nodes were used. For testing data, MSE was calculated between the actual area and its estimation to assess the effectiveness of ANN throughout each training phase. The suggested method then employed the ANN with the lowest MSE. The training time was also taken into account when choosing the ideal ANN.

Additionally, all samples' leaf areas were measured using the suggested approach. To assess the precision of the suggested method, the absolute relative error (ARE) between the actual area and the area measured using it was determined for each sample. ARE was computed utilising (3)

$$ARE = \frac{|A_E - A_P|}{A_E} \times 100\% \quad (3)$$

where, respectively, AE and AP represent the precise area and the area as determined by the proposed method.

IV. RESULT AND DISCUSSION

The proposed technique was put into practise in a piece of software using Visual C++ and the free, open-source OpenCV 231 library [17]. The experiment employed the programme to calculate the leaf area of each sample. The following subsections provide an explanation of the experiment's findings.

A. The Architecture of ANN

TABLE I provides a summary of the findings from the studies on hidden layers' feature selection and calculating the number of hidden nodes. , as seen in TABLE I. If W, A, and P were employed as input features along with three nodes in the hidden layer, as shown in TABLE I, the greater accuracy was attained with an average MSE of 0.249. For this ANN architecture, the training period took 2.983 s. From TABLE I, it is also clear that using L and A as input features and four nodes in the hidden layer allowed for the second highest estimation accuracy, with an average MSE of 0.251. However, there was a 1.504 s increase in training time while employing this architecture.

TABLE 1. THE RESULTS OF THE HIDDEN LAYER EXPERIMENTS FOR FEATURE SELECTION AND ESTABLISHING THE NUMBER OF HIDDEN NODES

The Number of Nodes in Hidden Layer	**Average MSE**			
	2	*3*	*4*	*5*
Input Features				
L	34.562	35.786	30.901	**25.443**
W	148.050	**117.069**	121.946	122.131
A	0.536	0.398	**0.355**	1.160
P	**11.224**	15.888	13.500	12.737
L, W	1.386	1.293	1.063	**0.956**
L, A	0.345	0.340	**0.251**	0.279
L, P	11.186	19.587	**10.649**	10.768
W, A	0.347	0.669	0.352	**0.271**
W, P	2.632	**2.170**	3.295	2.667
A, P	0.554	**0.255**	0.349	0.299
L, W, A	0.357	0.380	0.510	**0.344**
L, W,P	1.251	1.384	1.311	**1.173**
L, A, P	0.476	0.337	**0.274**	0.449
W, A, P	0.401	**0.249**	0.341	0.384
L, W, A, P	0.471	0.341	0.308	**0.277**

The suggested method used two ANN designs to estimate leaf area in light of these findings. The initial architecture had two input nodes each for the L and A features in the input layer, four nodes in the hidden layer, and one node each for the leaf area in the output layer, as shown in Fig. 6. The second architecture had three input nodes each for the W, A, and P features in the input layer, three nodes for the hidden layer, and one node for the leaf area in the output layer, as illustrated in Fig. 7.

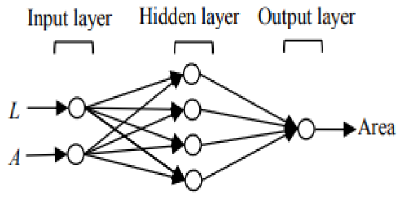

Fig.6 The original ANN architecture employed in the suggested technique.

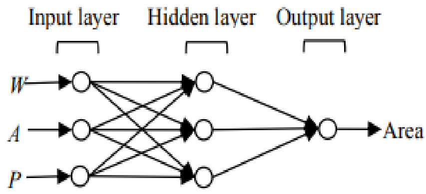

Fig.7 The proposed method's second ANN architecture

A.Leaf Area Measurement

TABLE II and TABLE III, respectively, provide summaries of the outcomes of the leaf area measurement experiment for all samples utilising the suggested method with the first and second ANN architectures. The average leaf area calculated using the suggested method with the first and second ANN architectures closed to precise leaf with mean ARE smaller than 1% can be shown in TABLE II and TABLE III. These findings demonstrate that the suggested method can accurately measure the leaf area of all samples with high precision.

TABLE 2. USING THE PROPOSED METHOD WITH THE FIRST ANN ARCHITECTURE, THE MEASUREMENT RESULT

Leaf Sample	**Average Area(cm^2)**		**Mean ARE (%)**
	Exact	***Proposed method***	
Kailan	29.996	30.060	0.783
Ipecac	52.809	52.939	0.586
Wild betel	36.896	36.869	0.939
All samples	39.900	39.956	0.769

TABLE 3. USING THE PROPOSED METHOD WITH THE SECOND ANN ARCHITECTURE, THE MEASUREMENT RESULTS

Leaf sample	Average Area(cm^2)		Mean ARE (%)
	Exact	*Proposed method*	
Kailan	29.996	29.912	0.635
Ipecac	52.809	52.802	0.301
Wild betel	36.896	37.000	0.871
All samples	39.900	39.905	0.602

The proposed approach, when used to measure ipecac and wild betel leaves, produced the lowest and highest mean ARE for both ANN designs. The first ANN architecture used in the suggested strategy resulted in a mean ARE of 0.7796%. On the other hand, the proposed technique yielded a lower mean ARE, which is 0.602%, with the second ANN architecture. This implies that the suggested method will generate more accurate results for measuring leaf area by using the second ANN design. The linear relationship between the actual leaf area and the leaf area measured with the suggested method was also examined for additional investigation. This linear relationship is depicted for the first and second ANN architectures, respectively, in Figures 8 and 9. As demonstrated in Figures 8 and 9, there was a strong linear correlation between the precise leaf area and the leaf area measured using the proposed method, with coefficients of determination (R2) over 0.99 for both ANN architectures. This indicates that a linear relationship with leaf area determined using the suggested method may account for more than 99% of the variation in the precise leaf area. The proposed method required
less than 0.1 seconds of computing time to measure the area of a leaf.

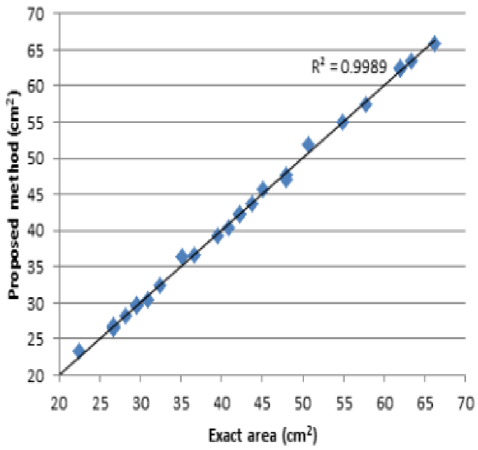

Fig. 8. The linear relationship between exact area and area measured using the proposed method with the first ANN architecture

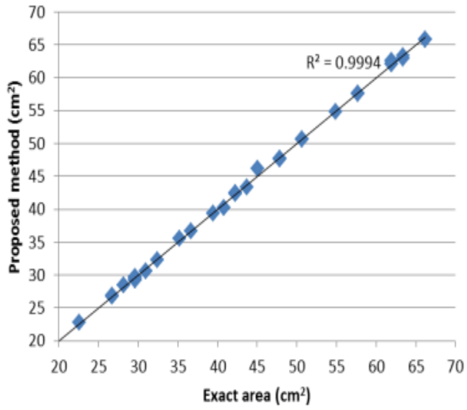

Fig. 9. The linear relationship between exact area and area measured using the proposed method with the second ANN architecture

CONCLUSION

In this paper, an artificial neural network (ANN) based approach for calculating leaf area is provided. Using a camera, the technique took a picture of the measured leaf from a 50 cm distance. The picture was altered to create a binary picture. There are four features in the binary image. were gathered, used as input to an ANN, and estimated leaf size. area. Three types of data have been used to test the suggested technique. in an extract of leaf, kailan, ipecac, and wild betel experiment. The outcomes of the experiment demonstrate that the Compared to exact, the approach has higher measurement precision. 1% or less mean absolute relative inaccuracy in the area. In Additionally, leaf area determined by the suggested technique has a strong linear correlation with the precise leaf area. In order to quantify leaf area, the suggested method might be seen as an alternative to hand measurement. Future research should look into how the suggested method might be used to monitor plant growth.

REFERENCE

[1] S. K. Pandey and H. Singh, "A Simple, Cost-Effective Method for Leaf Area Estimation," Journal of Botany, vol. 2011, p. 6, 2011.
[2] A. Gong, X. Wu, Z. Qiu, and Y. He, "A handheld device for leaf area measurement," Computers and Electronics in Agriculture, vol. 98, pp. 74-80, 2013/10/01/ 2013.
[3] C. Lü, H. Ren, Y. Zhang, and Y. Shen, "Leaf Area Measurement Based on Image Processing," in 2010 International Conference on Measuring Technology and Mechatronics Automation, 2010, pp. 580-582.

[4] S. B. Patil and S. K. Bodhe, "Betel leaf area measurement usingimage processing," International Journal on Computer Science and Engineering, vol. 3, pp. 2656-2660, 2011.
[5] M. H. Radzali, N. A. M. Kamal, and N. M. Diah, "Measuring Leaf Area using Otsu Segmentation Method (LAMOS)," Indian Journal of Science and Technology, vol. 9, pp. 1-6, 2016.
[6] J. I. Córcoles, A. Domínguez, M. A. Moreno, J. F. Ortega, and J. A. de Juan, "A non-destructive method for estimating onion leaf area," in Irish Journal of Agricultural and Food Research vol. 54, ed, 2015, p. 17.
[7] M. J. Amiri and A. Shabani, "Application of an Adaptive NeuralBased Fuzzy Inference System Model for Predicting Leaf Area," Communications in Soil Science and Plant Analysis, vol. 48, pp. 1669-1683, 2017.
[8] J. Siswantoro, A. S. Prabuwono, A. Abdullah, and B. Idrus, "A linear model based on Kalman filter for improving neural network classification performance," Expert Systems with Applications, vol. 49, pp. 112-122, 2016.
[9] J. Siswantoro, A. S. Prabuwono, A. Abdullah, and B. Indrus, "HybridNeural Network and Linear Model for Natural Produce Recognition Using Computer Vision," Journal of ICT Research and Applications, vol. 11, pp. 185-199, 2017.
[10] J. Siswantoro, M. Hilman, and M. Widiasri, "Computer vision system for egg volume prediction using backpropagation neural network," in IOP Conference Series: Materials Science and Engineering, 2017, p. 012002.
[11] F. Kusumo, A. Silitonga, H. Masjuki, H. C. Ong, J. Siswantoro, and T. Mahlia, "Optimization of transesterification process for Ceiba pentandra oil: A comparative study between kernel-based extreme learning machine and artificial neural networks," Energy, vol. 134, pp. 24-34, 2017.
[12] S. I. Sabilla, R. Sarno, and J. Siswantoro, "Estimating gas concentration using artificial neural network for electronic nose," Procedia Computer Science, vol. 124, pp. 181-188, 2017.
[13] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2nd ed.: Prentice Hall, 2002.
[14] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms," Systems, Man and Cybernetics, IEEE Transactions on, vol. 9, pp. 62-66, 1979.
[15] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," in Parallel Data Processing. vol. 1, D. Rumelhart and J. McClelland, Eds., ed Cambridge: MIT Press, 1986, pp. 318–362.
[16] E. Alpaydin, Introduction to machine learning, ke-2 ed. Cambridge, Massachusetts: MIT Press, 2010.
[17] G. Bradski, "The OpenCV Library," Dr. Dobb's Journal: Software Tools for the Professional Programmer, vol. 25, pp. 120-123, 2000