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Analysis of Constant Values of Leaves of the Durian Cultivars Monthong and Bawor Using Digital Image Processing

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Abstract. *Durian (Durio zibethinus), particularly the cultivars Monthong and Bawor, is a leading horticultural commodity with high economic value. Accurate leaf area estimation is essential for supporting physiological studies and plant growth modeling. However, conventional measurement methods are often characterized by their slow and destructive nature. This study aimed to analyze and identify the constant (k) values of the leaves of durian cultivars Monthong and Bawor using a digital image processing approach. A total of 40 leaf samples from each cultivar were analyzed. Image acquisition was performed using a smartphone camera, while image processing and leaf area measurement were conducted with the ImageJ software. The leaf constant was calculated as the ratio of the digitally measured leaf area to the product of manually measured leaf length and width. The results showed that the mean leaf constant for Monthong durian was 0.702, while for Bawor durian, it was 0.691. These results exhibited narrow value distributions, devoid of any outliers. The correlation between the measured and predicted leaf area yielded very high coefficients of determination (R^2 of 0.997 for cultivar Monthong and R^2 of 0.999 for cultivar Bawor). Further statistical evaluation confirmed that the predictive model had very high accuracy, evidenced by its low RMSE values ($\leq$ 1.059), an NRMSE of 0.01, an NSE of at least 0.997, and a Willmott's index of agreement (d) of at least 0.999. These results indicate that leaf constant values derived from digital image processing can generate precise leaf area estimates and offer a fast, efficient, and non-destructive alternative to conventional measurement methods. In practical terms, this approach enhances precision agriculture by enabling more accurate monitoring of leaf growth dynamics, which is essential for crop management and yield optimization. This finding presents opportunities for further application across other durian cultivars and the broader adoption of similar methods in other plant commodities within the context of precision agriculture and plant growth modeling.*

Keywords: *Durio zibethinus; leaf constant; leaf area; non-destructive estimation; precision agriculture.*

Type of the Paper: Regular Article.

1. Introduction

Durian (*Durio zibethinus*) is a prominent horticultural commodity in Southeast Asia [1], including Indonesia, renowned for its distinctive taste and aroma [2]. The demand for durian is increasing in both domestic and international markets [3], rendering the improvement of durian cultivation increasingly important. Among the numerous durian cultivars, Monthong and Bawor are the most widely cultivated due to their superior fruit quality, large size, and high economic value [4,5]. In their cultivation, effective management requires an understanding of morphological

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characteristics [6,7], one of which is leaf morphology.

Leaves are vital plant organs that function as the primary sites of photosynthesis and transpiration [8–10]. The correlation between leaf area and light absorption efficiency [11,12], plant growth rate [13,14], and the leaf area index (LAI) [15,16] is well documented. The leaf area index is a widely used metric in plant growth models. In order to support agronomic studies, a fast, practical, and accurate method for measuring leaf area is needed. One commonly used method is the Montgomery-based dimensional approach [17–19], which involves multiplying leaf length by leaf width and a correction factor known as the leaf constant (k). This constant represents a correction for shape differences between species and cultivars [20,21]. The method has gained a widespread popularity due to its simplicity, cost-effectiveness, and efficiency [22–24]. However, to ensure accurate results, it requires the use of an optimized correction factor [20,25].

Advancements in technology have led to the development of digital image processing as a method for measuring leaf morphometric characteristics. This method has been widely adopted due to its higher precision and non-destructive nature [18,26,27]. Previous studies have applied this method in the context of various crop species, reporting precision levels ranging from 99.95% to 100% in the measurement of leaf area for three apple cultivars [25]. Research has shown that digital image analysis is a viable method for determining constant values of the rambutan leaf and the water apple leaf [20]. However, to date, there is a lack of studies that have specifically addressed the determination of the constant of leaf of durian, especially the durian cultivars Monthong and Bawor. Considering the variation in leaf shape and size among durian cultivars, a specific measurement approach is essential for generating valid and accurate area estimates using the dimensional method.

The research gap highlights the absence of cultivar-specific leaf constants for the durian cultivars Monthong and Bawor obtained through digital image-based methods. The availability of these constants is crucial to facilitate leaf area estimation at various observational scales, whether in field studies or advanced research in plant physiology [28,29] and growth modeling [30,31]. Moreover, there is a paucity of studies that have integrated image acquisition using accessible tools such as smartphones with high-accuracy data processing.

Therefore, this study aims to analyze and identify the constant values of leaves from the durian cultivars Monthong and Bawor using digital image processing. The novelty of this study lies in the use of smartphone-based image acquisition, which is both low-cost and widely accessible, combined with open-source analytical software to produce accurate estimations of leaf area and leaf constants. The results of this study are expected to make significant contributions to the development of more efficient and applicable leaf morphometric methods for durian cultivation and research.

2. Materials and Methods

2.1. Research Type and Location

This study is a quantitative and comparative study conducted to identify and analyze the constant (k) values of leaves from *Durio zibethinus* cultivars Monthong and Bawor. The study was conducted at the Agrotechnology Laboratory, Faculty of Agriculture, University of Pekalongan.

2.2. Sample and Tools

A sample of durian leaves was collected from healthy, mature Monthong and Bawor durian plants cultivated in Pekalongan Regency, with 40 leaves obtained from each cultivar. The instruments used included a smartphone equipped with a 12-MP camera for image acquisition, a ruler, white background paper, a black reference object (5 × 5 cm), a laptop, and ImageJ software for image processing.

2.3. Image Acquisition

Each leaf was photographed using a smartphone camera positioned vertically at a fixed distance under controlled lighting using a softbox to ensure uniform illumination and reduce shadows and reflections. A black reference object was included in each image to serve as a scale for converting pixel units to area units (cm^2) [18]. To enhance contrast during the image segmentation process, leaves were arranged in a flat configuration on a white background.

2.4. Image Processing

Image processing was conducted using ImageJ software [32], following the procedures developed by Al Ramadhani et al. [18]. The first step was image calibration, whereby a reference object was employed as a fixed scale to convert pixel units to square centimeters. The RGB images were then converted to grayscale and segmented using Otsu's thresholding method. This method automatically determines the optimal threshold value to separate the leaf from the background, ensuring precise extraction of the leaf shape. Following the segmentation process, the actual leaf area was measured by calculating the number of pixels and subsequently converting the result into square centimeters (cm^2) based on the calibration scale. To ensure the reliability of ImageJ in representing the "actual" area, calibration was cross-validated using a black square reference object with a known area of 25 cm^2 (5 × 5 cm). The measured area obtained from ImageJ corresponded to the reference, confirming the accuracy of the digital measurement. Furthermore, leaf length and width were manually measured using a ruler with 0.5 mm accuracy to support the calculation of the leaf constant (k). The leaf constant was then calculated using the following formula (1) [18,20,25].

$$k = \frac{LA}{L \times W} \tag{1}$$

Description:

k : leaf constant

LA : actual leaf area (as determined by image analysis)

L : leaf length

W : leaf width

2.5. Statistical Analysis

The measured k values were analyzed in Microsoft Excel to obtain statistical metrics, including the mean, standard deviation, Q1, Q2 (median), Q3, minimum, and maximum values. These statistical outputs were presented in the form of a boxplot [20], as shown in Fig. 1.

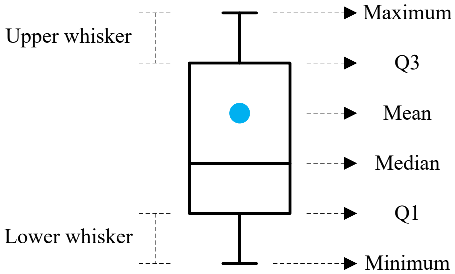

Fig. 1. Boxplot

To evaluate the performance of the leaf area prediction model based on the dimensional method (length × width × *k*), the predicted leaf area was compared with the actual area obtained from digital image analysis using ImageJ. This comparison aimed to assess the accuracy of leaf constant-based estimations. Statistical analyses were performed using the following indicators: coefficient of determination (R^2), root mean square error (RMSE), normalized root mean square error (NRMSE), Nash–Sutcliffe efficiency (NSE), and Willmott's index of agreement (*d*). The corresponding formulas are as follows (2–6).

$$R^2 = \left[\frac{\sum(O_i - \bar{O}) - (P_i - \bar{P})}{(O_i - \bar{O}) \times \sum(P_i - \bar{P})}\right] \quad (2)$$

$$RMSE = \sqrt{\frac{\sum(P_i - O_i)}{n}} \quad (3)$$

$$NRMSE = \frac{1}{\bar{O}}\sqrt{\frac{\sum(P_i - O_i)^2}{n}} \times 100 \quad (4)$$

$$NSE = 1 - \frac{\sum(P_i - O_i)^2}{\sum(O_i - \bar{O})^2} \quad (5)$$

$$d = 1 - \frac{\sum(P_i - O_i)^2}{\sum(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad (6)$$

Description:
O_i : observed data
$\bar{O}$: mean of the observed data
P_i : predicted data
$\bar{P}$: mean of the predicted data
n : number of data points
d : *index of agreement*

The coefficient of determination (R^2) was used to assess the strength and linearity of the relationship between predicted and actual leaf area; a value approaching 1 indicates a very strong linear correlation [33,34]. The root mean square error (RMSE) quantifies the mean magnitude of prediction error. A smaller RMSE value indicates a more accurate model [35,36]. The normalized root mean square error (NRMSE) is the RMSE normalized to the mean of actual values, providing a relative error measure in percentage terms [37,38]. The Nash–Sutcliffe efficiency (NSE) indicates the efficiency of a predictive model in comparison to the mean of observed values. Models with NSE values close to 1 are considered highly efficient [30,39]. Willmott's index of agreement (d) is used to assess how closely predicted values match actual observations, with values approaching 1 denoting a high degree of agreement [18,30]. In general, a predictive model is considered to be accurate and reliable when R^2, NSE, and d are close to 1, while RMSE and NRMSE are close to zero.

2.6. Novelty in Method

Contrary to the methodologies employed in previous studies that used scanners [25] or professional cameras [18,20], this study emphasizes the practicality of using a smartphone for image acquisition. This approach demonstrates that accurate leaf morphometric analysis can be conducted at low cost and is highly suitable for field conditions and rural applications.

3. Results and Discussion

The acquisition of leaf images was executed through the utilization of a smartphone camera, employing a contrasting background and a reference object as a scale. Fig. 2 illustrates the image acquisition and processing stages of Monthong and Bawor durian leaves, consisting of original RGB images and their segmentation results using thresholding methods. As illustrated in Fig. 2, the RGB images of Monthong and Bawor durian leaves were captured on a white background, with a fixed-size black reference object (5 × 5 cm, equal to 25 cm^2) included in every image. This object served as a calibration scale, facilitating the conversion of pixel measurements into standard area units (cm^2). The object's known dimensions also enabled the verification of ImageJ measurement accuracy.

The segmentation process was implemented to isolate the leaf object from the background using Otsu's automatic thresholding method, as shown in Fig. 2. This method automatically calculates the optimal threshold value based on image histogram distribution, making it robust against minor variations in brightness. Furthermore, the use of a softbox during the image acquisition process mitigated lighting inconsistencies, thereby ensuring uniform conditions for segmentation. This segmentation transformed the leaf into a solid black object against a white background (or vice versa, depending on inversion). The utilization of segmented images enabled digital leaf area measurement using ImageJ software by enumerating pixels within the designated leaf area, which is then converted into square centimeters (cm^2) using the reference scale [18,20,32]. This approach ensures that the measured leaf area accurately reflects the actual size, eliminating the influence of background noise or shadow interference. The accuracy of the thresholding process was validated through a visual comparison of the segmented outputs with the original leaf contours, which showed a high degree of consistency. Despite the absence of quantitative metric such as Intersection over Union (IoU), the high contrast between the leaf and background, in conjunction with controlled lighting and scale calibration, ensured reliable segmentation results. The accuracy of this step directly affects the precision of the calculated leaf constant (k) [18], since k is determined by the ratio between the actual leaf area from digital processing and the estimated area using the formula of *length* × *width* × *k.*

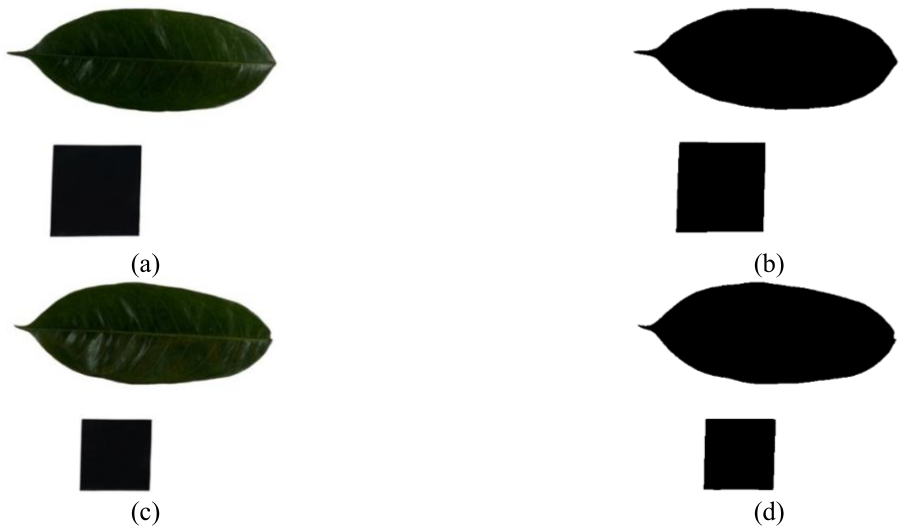

Fig. 2. Digital image acquisition and processing of durian leaf images: (a) RGB image of Monthong durian leaf, (b) threshold result of Monthong durian leaf, (c) RGB image of Bawor durian leaf, (d) threshold result of Bawor durian leaf

Table 1 presents the measurement results of the area, dimensions, and calculated constants (k) of the leaves of durian cultivars Monthong and Bawor through digital image analysis. To ensure consistency in measurement, leaf length was determined by measuring from the petiole base to the tip of the leaf apex, while leaf width was ascertained at the widest part of the lamina. This approach accommodates the pointed and narrow leaf tip characteristic of durian leaves. The k values were computed using **Error! Reference source not found.**). These data reflect the morphological v ariability within each cultivar and confirm the consistency of leaf constant values required for rapid estimation methods. For the durian cultivar Monthong, k ranged from 0.687 to 0.714, with a mean of 0.702, while for the durian cultivar Bawor, k ranged from 0.676 to 0.704, with a mean of 0.691. The elliptical shape of both Monthong and Bawor durian leaves contributes to the stability of the calculated leaf constant. However, Monthong durian leaves exhibit more uniformity in size and curvature, whereas Bawor durian leaves show slightly greater variation in their elliptical shape. These variations in morphology directly impact the correction factor (k) used in the estimation of leaf area. This reinforces the notion that the application of a generic constant without the requisite consideration of varietal differences may culminate in significant estimation errors [24,25,31,40].

Table 1. The results of the leaf area measurement and leaf constant identification processes through digital image analysis

Sample	Durian cultivar Monthong				Durian cultivar Bawor			
	Leaf area (cm^2)	Length (cm)	Width (cm)	*k*	Leaf area (cm^2)	Length (cm)	Width (cm)	*k*
1	133.089	23	8.2	0.706	99.45	18	8	0.691
2	117.109	21.9	7.6	0.704	146.27	23.4	9	0.695
3	102.763	19	7.6	0.712	87.73	18.2	7	0.689
4	124.219	22.4	7.8	0.711	102.90	21.3	7	0.690
5	136.164	23.9	8.1	0.703	82.25	18.3	6.5	0.691
6	102.586	20	7.3	0.703	69.42	16	6.3	0.689
7	99.497	19.1	7.3	0.714	77.61	16.4	7	0.676
8	78.532	16	6.9	0.711	95.81	18.4	7.4	0.704
9	89.804	18	7	0.713	102.28	19.5	7.5	0.699
10	79.715	17.5	6.6	0.690	131.34	22.6	8.5	0.684
11	103.624	20.4	7.3	0.696	123.35	22	8.1	0.692
12	143.993	23.9	8.5	0.709	107.88	20.5	7.6	0.692
13	103.512	20	7.5	0.690	64.82	17.5	5.4	0.686
14	106.738	20.2	7.4	0.714	71.54	15.6	6.6	0.695
15	134.537	23.5	8.1	0.707	82.93	19.1	6.3	0.689
16	98.887	20	7.1	0.696	91.44	18.2	7.3	0.688
17	127.810	22.5	8.1	0.701	71.52	17	6.1	0.690
18	122.156	20.5	8.5	0.701	63.19	16	5.8	0.681
19	99.179	19.7	7.3	0.690	81.73	18.5	6.5	0.680
20	112.334	20	8.1	0.693	86.30	18.2	6.8	0.697
21	97.496	18.6	7.5	0.699	71.61	17	6.1	0.691
22	107.617	20.5	7.4	0.709	49.76	14.4	5	0.691
23	98.138	20.4	7	0.687	32.65	10.6	4.4	0.700
24	89.106	19.3	6.6	0.700	101.58	19.3	7.6	0.693
25	104.122	19.5	7.6	0.703	58.03	14.5	5.8	0.690
26	74.120	16.8	6.2	0.712	39.44	12.1	4.8	0.679
27	85.143	17.7	6.9	0.697	59.97	14.2	6	0.704
28	111.248	21.1	7.6	0.694	67.68	14.6	6.6	0.702
29	78.227	18.7	6	0.697	80.02	18.5	6.3	0.687
30	83.817	19	6.3	0.700	60.13	14.8	6	0.677
31	98.849	20	7	0.706	99.25	20.5	6.9	0.702
32	95.557	19.8	7	0.689	38.45	14	4	0.687
33	98.600	19.4	7.2	0.706	44.53	13.3	4.8	0.698
34	91.261	18.9	7	0.690	84.91	17.6	7	0.689
35	97.527	19.5	7.1	0.704	25.94	9.2	4.1	0.688
36	101.732	19.7	7.4	0.698	73.35	16.9	6.3	0.689
37	71.580	17.5	5.8	0.705	93.82	18.5	7.2	0.704
38	88.436	18.2	6.9	0.704	76.76	18	6.1	0.699
39	59.492	15.4	5.5	0.702	87.23	18.5	6.8	0.693
40	87.968	18	7	0.698	93.93	18.3	7.4	0.694

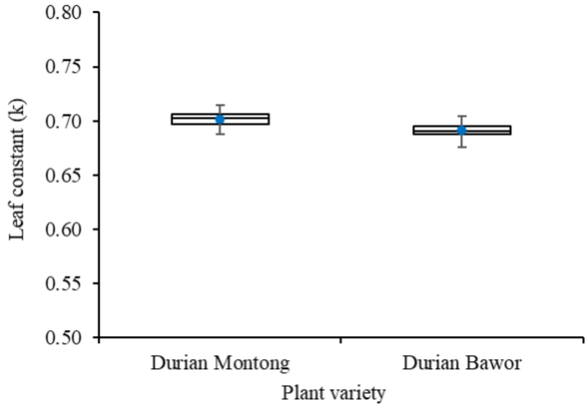

Fig. 3. Boxplot of leaf constant values

Fig. 3 displays the distribution of leaf constant values (k) for the durian cultivars Monthong and Bawor in the form of boxplots. The chart illustrates data spread, median values, and variability among samples, facilitating analysis of morphological homogeneity in each cultivar.

As illustrated in Fig. 3, the median k value for Monthong is marginally higher than that of Bawor. The blue dots representing the mean are proximate to the median, indicating a relatively symmetrical distribution without skewness. This result suggests that Monthong leaf samples exhibit a consistent length-to-width ratio, which is evident in the stability of the leaf constant values. The leaf constant (k), by definition, does not directly represent the absolute leaf area; rather, it serves as a correction factor linking leaf length and width to the estimated leaf area [24,25,31,40]. Thus, the stability of k indicates the reliability of length–width measurements in predicting leaf area across different samples. Meanwhile, the durian cultivar Bawor shows a slightly lower distribution, with a median that fell below that of cultivar Monthong. However, the k value range remained narrow, signifying that this method maintains its stability when applied to the leaves of the durian cultivar Bawor, notwithstanding the greater diversity in leaf morphology exhbited by the latter. The difference in median values reinforces prior findings, which indicate that leaf morphology is strongly influenced by varietal genetics [41–43].

The absence of noticeable outliers in both boxplots further supports the consistency of the data and the reliability of the image acquisition and processing methods used in this study. The narrow interquartile range (between Q1 and Q3) indicates that the majority of data points are clustered around the median, implying low morphological variability within each cultivar. Overall, the visualization supports the conclusion that leaf area can be estimated using cultivar-specific constants with a high degree of accuracy and efficiency. The stability of k values is essential for the success of length-width-based predictive models [40,44,45].

Fig. 4 presents the correlation charts between the leaf area measured via digital image processing (actual values) and the leaf area predicted using the dimensional method (length × width × k), with k being the average constant obtained from this study. Fig. 4 provides a visual representation for the durian cultivar Monthong, while Fig. 4 offers a similar representation but for cultivar Bawor.

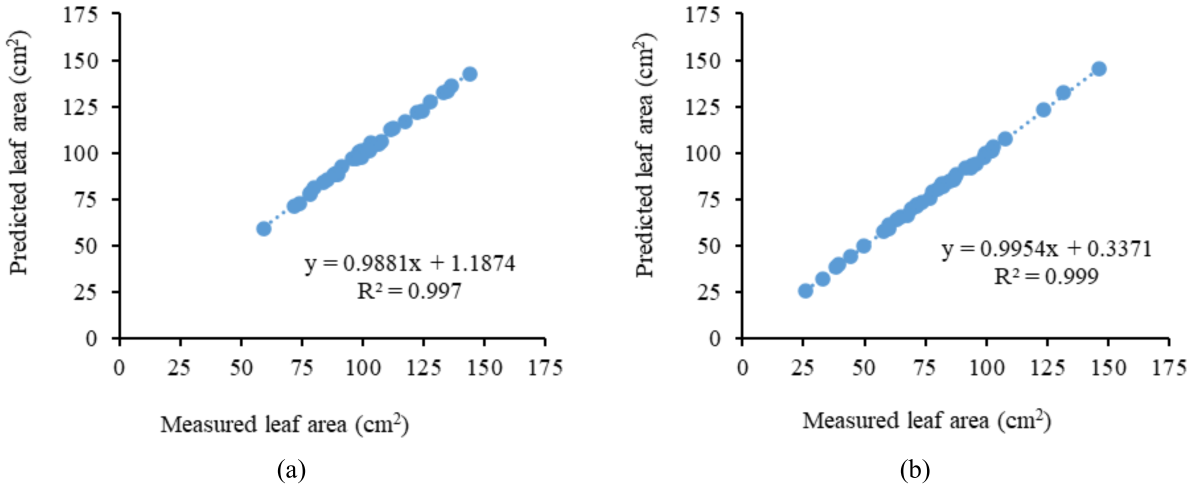

Fig. 4. Correlation charts of measured leaf area (as determined by digital image analysis) and predicted leaf area (as calculated using the dimensional method with derived constants) for two durian cultivars: (a) Monthong and (b) Bawor

As demonstrated in Fig. 4, the coefficient of determination (R^2) was found to be highly significant (approaching 1) for both cultivars, indicating a strong linear correlation between the actual and predicted leaf areas. In other words, the dimensional method, using the derived leaf constants, exhibited a high degree of predictive accuracy. The regression line slope for both cultivars was found to be close to 1, suggesting that the model does not suffer from systematic bias (overestimation or underestimation). The small intercept values indicate minimal baseline prediction errors.

These findings affirm the validity and reliability of the leaf constants derived from digital image processing are for use in predictive models [18,20,24,25,31,40]. The model has demonstrated a high degree of accuracy, rendering it suitable for various agronomic applications, including the monitoring of plant growth [46–48], the determination of leaf area index (LAI) [15,16], and the physiological modeling of durian [49–51] based on fast and non-destructive morphometric input [30,52]. Evidence from correlation charts indicates that the length-width measurement approach, calibrated with cultivar-specific constants, can effectively replace manual or destructive methods without sacrificing accuracy.

As illustrated in Table 2, a statistical analysis was conducted to compare the actual leaf area obtained from digital image processing with the predicted values using the dimensional method (length × width × *k*). A total of 80 leaves, comprising 40 leaves of Monthong durian and 40 leaves of Bawor durian, were sampled for this comparison. This ensured that the statistical evaluation was based on sufficient data representation from both cultivars. The evaluation was conducted using four statistical parameters, namely, RMSE, NRMSE, NSE, and Willmott's index of agreement (*d*), which are widely used indicators for evaluating regression and numerical prediction models [18,30,53,54].

Table 2. The statistical analysis results of measured leaf area as compared to predicted leaf area

Durian Cultivar	RMSE (cm^2)	NRMSE (%)	NSE	*d*
Monthong	1.059	0.01	0.997	0.999
Bawor	0.8	0.01	0.999	1

The RMSE values were 1.059 for cultivar Monthong and 0.800 for cultivar Bawor, indicating low average prediction errors in the same units as actual leaf area [36,55], with cultivar Bawor showing slightly better performance. Both cultivars had an NRMSE of 0.01, suggesting an exceptionally low normalized error and thus indicating excellent model performance [56,57]. The NSE values were 0.997 for cultivar Monthong and 0.999 for cultivar Bawor, indicating near-perfect predictive efficiency and the model's ability to explain almost all variability in the observed data [58,59].

In addition, the Willmott index (*d*) values were found to be remarkably high, with values of 0.999 for cultivar Monthong and 1.000 for cultivar Bawor, indicating an excellent agreement between the predicted and actual values [60–62]. These results affirm that the dimensional method, using the derived constants (*k*), demonstrates a high degree of reliability in estimating the area of durian leaf. This high degree of agreement serves as indication of the robustness of the model, demonstrating its capacity to function reliably across a range of leaf morphologies, both uniform and variable. It further suggests that the method can be reliably applied to other physiological and agronomic models that rely on accurate leaf area measurements.

The statistical findings have confirmed that the leaf area estimation method using the formula of *length* × *width* × *k*, calibrated with the average constants obtained in this study, is highly accurate and valid for both durian cultivars. The low prediction errors and the extremely high model efficiency and agreement indices support the utility of this approach as a rapid, practical, and non-destructive alternative method in durian cultivation and research. This approach confers significant benefits, particularly in field-based studies where time and resource efficiency are critical. Additionally, it offers a scalable solution for large-scale monitoring in precision agriculture applications, particularly in regions where access to advanced equipment is limited.

4. Conclusions

This study successfully identified the constant values of leaves from the durian cultivars Monthong and Bawor using smartphone-based digital image processing. The resulting leaf constants were 0.702 for the durian cultivar Monthong and 0.691 for the durian cultivar Bawor, with a very strong correlation ($R^2 \geq 0.997$) observed between the measured and predicted leaf area. The statistical validation confirmed the model's high accuracy, as indicated by the low RMSE, the NSE of ≥ 0.997, and Willmott's index of agreement (d) of ≥ 0.999. This method has proven to be efficient, accurate, and non-destructive. In practice, this approach offers a readily accessible and cost-effective instrument for farmers, extension workers, and researchers, particularly in regions with limited access to sophisticated equipment. This enables more precise and timely horticultural management of durian plantations.

Future studies are recommended to expand the application of this approach to other durian cultivars and to validate its robustness across different leaf developmental stages and environmental conditions. Furthermore, the extension of the application to other perennial and annual crops could further enhance its applicability. Nevertheless, caution should be exercised when extrapolating the leaf constant values obtained in this study to other species or broader geographic regions, as morphological variations, growth environments, and genetic diversity may influence the accuracy of predictions. The findings contribute to the development of leaf area estimation techniques based on leaf constants and digital imaging, and are recommended for further application across other cultivars or crop commodities.

Abbreviations

k	Leaf Constant
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
NRMSE	Normalized Root Mean Square Error
NSE	Nash–Sutcliffe Efficiency
d	Willmott's Index of Agreement

Data availability statement

All data are available in the authors' articles, as contained in the references. Should there be a necessity for data to be shared, this will be done upon request by the readers.

CRediT authorship contribution statement

Bayu Dwi Arfiyanto: Investigation, Data Curation, Resources, Writing – Original Draft Preparation. **Farchan Mushaf Al Ramadhani**: Conceptualization, Investigation, Data Curation, Formal Analysis, Methodology, Resources, Supervision, Validation, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing. **Sajuri**: Project Administration, Resources, Supervision.

Declaration of Competing Interest

The authors of this manuscript have no conflicts of interest to declare.

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