Journal of Environmental Biology
p-ISSN: 0254-8704 • e-ISSN: 2394-0379 • CODEN: JEBIDP

JEB®

Original Research Paper
Volume 47 Issue 6 November 2026 pp. 1312-1320
DOI: http://doi.org/10.22438/jeb/47/6/MRN-5981

J. Environ. Biol., 2026
© Triveni Enterprises, Lucknow (India)
Journal website : www.jeb.co.in ★ E-mail : editor@jeb.co.in

QuickLeaf-LWA high-throughput software: automated digital image analysis for accurate measurement of leaf shape and size

H.C. Verma[1], A.K. Trivedi[2]* and A. Yadav[1]

[1]*Division of Crop Improvement and Biotechnology, ICAR – Central Institute for Subtropical Horticulture, Lucknow-226 101 India*
[2]*Division of Post Harvest Management, ICAR – Central Institute for Subtropical Horticulture, Lucknow-226 101 India*

Received: 09 February 2026 **Revised:** 15 April 2026 **Accepted:** 19 May 2026

***Corresponding Author Email:** ajayakumartrivedi@gmail.com ***ORCiD:** https://orcid.org/0000-0002-0733-1027

Online copy

Abstract

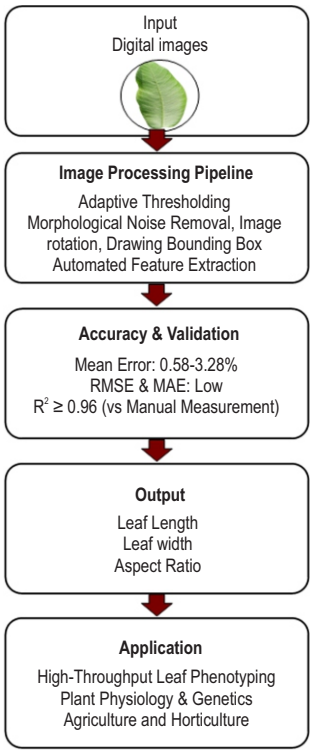
Aim: Leaf size and shape are key character for assessing photosynthesis, growth, genetic diversity, and plant health. Manual measurement is labor-intensive, time-consuming, and error-prone, particularly in large-scale phenotyping studies. This study aimed to develop QuickLeaf-LWA, a software tool for rapid, precise, and automated estimation of leaf size (length and width) and shape (aspect ratio) from digital images.

Methodology: QuickLeaf-LWA integrates high-throughput automation (HTA) with comprehensive trait management and morphological analysis workflows. The software employs a robust image-processing pipeline using adaptive threshold for accurate leaf segmentation from complex backgrounds, followed by morphological operations to reduce noise. Leaf dimensions and aspect ratio are calculated using a rectangular-bounded, radially rotated image approach.

Results: Accuracy assessment showed low mean error rates (0.584–3.283%) and high accuracy (96.717–99.416%). Root mean square error (RMSE) and mean absolute error (MAE) values were low (0.150–0.564 and 0.082–0.476, respectively), with strong correlations to manual measurements ($R^2 \geq 0.96$).

Interpretation: QuickLeaf-LWA enables rapid analysis of hundreds of leaves within minutes offers an intuitive interface with batch-processing capability, making it a practical tool for plant physiology, genetics, agriculture, horticulture, and leaf phenotyping research.

Key words: Aspect ratio, Digital image analysis, Leaf phenotyping, QuickLeaf-(LWA)



Quick Leaf – LWA: Automated Leaf Size and Shape Analysis

How to cite: Verma, H.C., A.K. Trivedi and A. Yadav: QuickLeaf-LWA high-throughput software: automated digital image analysis for accurate measurement of leaf shape and size. *J. Environ. Biol.*, **47,** 1312-1320 (2026).

Introduction

The morphological character of plant leaves, viz. length, width, and aspect ratio, are important physiological features that reflect plant growth, health and genetic diversity (Zhang *et al.,* 2023). Leaf surface area is key functional characteristic which influence radiation interception, energy exchange, transpiration, and crop development and yield (Mack *et al.,* 2017). Leaf morphology is most apparent external characteristic of leaves and plays an important role in studies of plant evolution and adaptation (Li *et al.,* 2020a). Traditional research methods for studying leaf morphological characteristics, such as manual measurement, photograph collection, and descriptive analysis of large number of leaves, are widely used but are time-consuming and labor-intensive (Qi *et al.,* 2024). Research on leaf morphological traits has numerous applications in ecology, conservation and agriculture. Leaf characters are used to track plant health, identify diseases, and evaluate the effects of climate change on plant populations. Accurate measurement of leaf dimensions is therefore essential for understanding the plant health, growth and productivity (Li *et al.,* 2020b). Several studies have explored the use of image processing in plant phenotyping. Kolhar and Jagtap (2023) evaluate the potential application of convolutional neural networks (CNNs) for leaf segmentation.

Despite these developments, accurate quantification of leaf dimensions remains challenging due to variations in leaf morphology, overlapping leaves and noisy images. These factors complicate reliable segmentation and measurement. The present work builds upon existing frameworks by providing comprehensive and flexible approach for leaf dimension estimation that addresses common limitations in image-based measurements. Edge detection is a fundamental image-processing step for accurate boundary identification. Among the available techniques, canny edge detection algorithm is regarded as one of the most rigorously defined and reliable methods for precise edge detection and matching (Gonzalez and Woods, 2018). The primary drawbacks of traditional manual measurement methods are their inefficiency and susceptibility to human error. Given the importance of leaf metrics in ecological studies and phenotyping characterization, recent advances in image processing offer accurate and automated alternatives.

This paper presents an image-processing-based method for highly precise measurement of leaf length, width, and aspect ratio. Computational techniques employed are described in detail and the performance of the proposed approach is evaluated and compared with conventional manual measurement procedures. Currently, leaf length and width are important shape descriptors widely used in automatic leaf recognition and leaf area estimation. High-performance techniques have been developed to measure the linear distance between the petiole and leaf tip (Hui *et al.,* 2018; Wu *et al.,* 2018; Li *et al.,* 2020c), the minimum distance between the petiole and tip (Elnashef *et al.,* 2019), and skeleton-based extraction between the tip and petiole (Wu *et al.,* 2019; Xiang *et al.,* 2019). Accurate estimation of leaf dimensions, including length, width and aspect ratio, is essential for plant phenotyping, crop management practices and physiological research. The scale and resolution of plant phenotyping studies are often constraint by the labor-intensive, time-consuming, and error-prone nature of manual measurements (Atefi *et al.,* 2021). Plant leaves are vital organs responsible for photosynthesis, transpiration, and gas exchange (Simkin *et. al.*, 2019). Key phenotypic traits, such as leaf length, width, and derived aspect ratio, provide understanding into a plant genetic makeup, developmental stage and responses to environmental stimuli (Hao *et al.,* 2025; Su *et al.,* 2021; Pérez *et al.,* 2021).

Accurate and efficient measurement of these characters is, therefore, critical across diverse areas of plant science, including breeding programs, genetic mapping, ecological studies, and climate change research. Historically, leaf morphometric data have been collected manually using rulers, callipers, or graph paper (Klein and Svoboda, 2017). Although simple, these methods are laborious, time-consuming and prone to errors, thereby limiting sample size and statistical strength. Advances in digital imaging technologies have created new opportunities for automated, high-throughput plant phenotyping.

Despite recent progress, there remains a need for user-friendly automated software for estimation of leaf dimensions with minimal human intervention. To address these challenges, this study introduces QuickLeaf-LWA, a novel software solution designed to automate the entire workflow from image preprocessing to data output, thereby accelerating leaf phenotyping pipelines. Over the past decade, researchers have actively investigated automated analysis of leaf characteristics from digital images (Hussein *et al.,* 2021).

Many existing approaches rely on controlled imaging conditions, such as scanning leaves against uniform backgrounds, to simplify segmentation (Wei *et al.,* 2026; Sermwuthisarn and Phumeechanya, 2025). However, accurate segmentation under complex backgrounds, variable lighting, shadows, and leaf overlap remains challenging and often leads to measurement errors. To address these issues, various image-processing techniques have been explored. Thresholding methods, including Otsu's algorithm, are commonly used to generate binary leaf masks (Otsu, 1979), although they may be sensitive to variations in illumination and leaf color.

Following segmentation, accurate determination of leaf length and width requires reliable geometric analysis. A common approach involves rotating the major axis of the segmented leaf image to align with the horizontal axis and fitting a bounding box around the leaf. QuickLeaf-LWA builds upon these established concepts by integrating adaptive threshold with an automated and simplified pipeline for strong segmentation and precise estimation of leaf length and width. By providing an accessible platform, QuickLeaf-LWA bridges the gap between advanced image-analysis techniques and the practical requirements of plant science community.

Online Copy

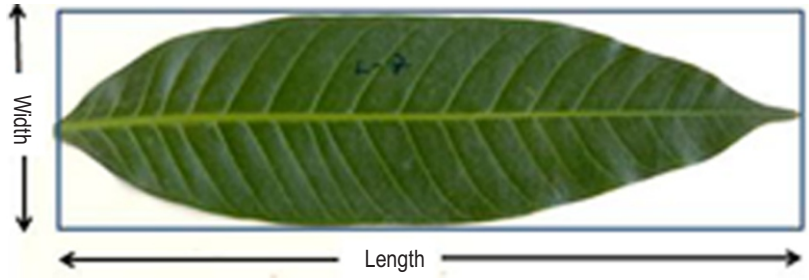


Fig. 1: Leaf image depicting its length and width.

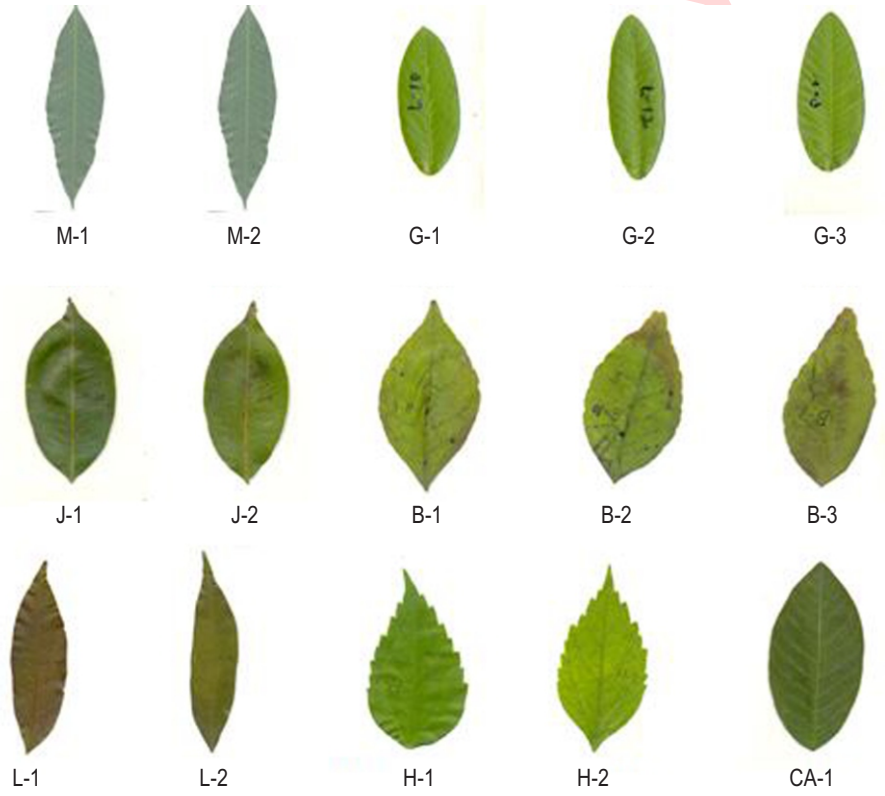


Fig. 2: Sample leaf images (size is reduced); (M- Mango, J- Jamun, B- Bael, L=Litchi, H- Hibiscus, CA- Custard Apple).

Materials and Methods

Plant Material Collection: The study was conducted at ICAR–Central Institute for Subtropical Horticulture, Rehmankhera, Lucknow, India. Fully expanded, healthy leaves of different plant species—mango (*Mangifera indica*), guava (*Psidium guajava*), jamun (*Syzygium cumini*), custard apple (*Annona squamosa*), bael (*Aegle marmelos*), litchi (*Litchi chinensis*) and hibiscus (*Hibiscus rosa-sinensis*) were randomly collected. Leaves were thoroughly examined to ensure they were free from diseases, pest infestations, and nutritional disorders. Longest dimension of a leaf, typically measured from the tip of the leaf blade to the base where it joins the petiole was considered as leaf length (Fig. 1) whereas, distance between opposite leaf margins, usually measured across the centroid of the leaf lamina is considered as leaf width. Four leaf shapes (oval, elliptical, lanceolate, ovate) were collected, with 17 leaves per shape (Fig. 2). Leaves were transported in paper bags and scanned using a flatbed scanner at 300 dpi (TIFF format). Manual measurements of leaf length and width were recorded using callipers for validation. Image based measurements were performed in MATLAB R2015a (MathWorks Inc., Natick, USA).

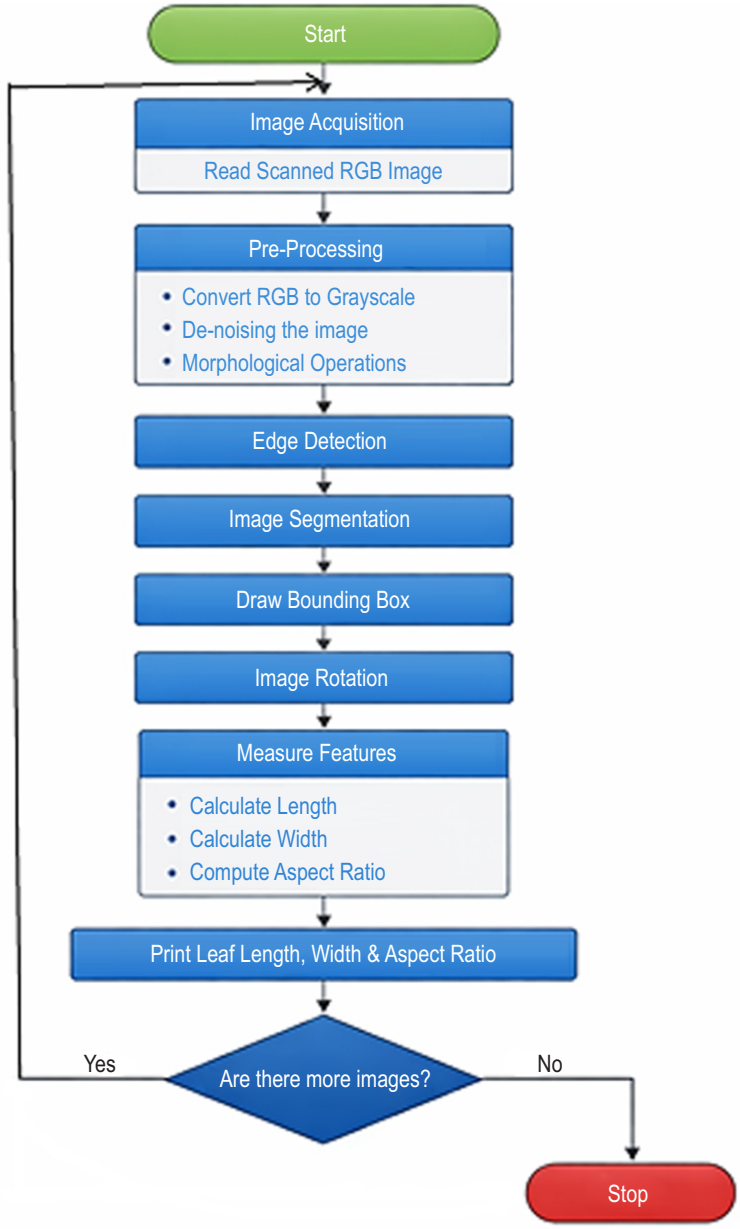


Fig. 3: Flowchart showing the procedures for measuring the leaf' length, breadth and aspect ratio.

QuickLeaf-LWA Software Development: QuickLeaf-LWA software was developed that automates image preprocessing, segmentation, rotation, feature extraction, and computation of leaf length, width, and ratio of length to width (Fig. 3).

Image Acquisition and Pre-processing: Leaf images were captured on a uniform contrasting background. Software accepts JPEG, PNG and TIFF formats, and processes images sequentially from a folder. Pre-processing stage involved background removal, contrast enhancement, artifact reduction and conversion to grayscale (Fig. 4a–c).

Segmentation and Morphological Operations: Leaves were segmented using adaptive threshold. Morphological operations refined the binary mask: closing (dilation + erosion) filled internal holes, and opening (erosion + dilation) removed small noise pixels (Fig. 5).

Rotation and Bounding Box: Scanned leaves were often tilted; a MATLAB function rotated each image to align the leaf's major axis vertically. A rectangular bounding box was then drawn tightly around the leaf for accurate length and width extraction (Fig. 6 and 7).

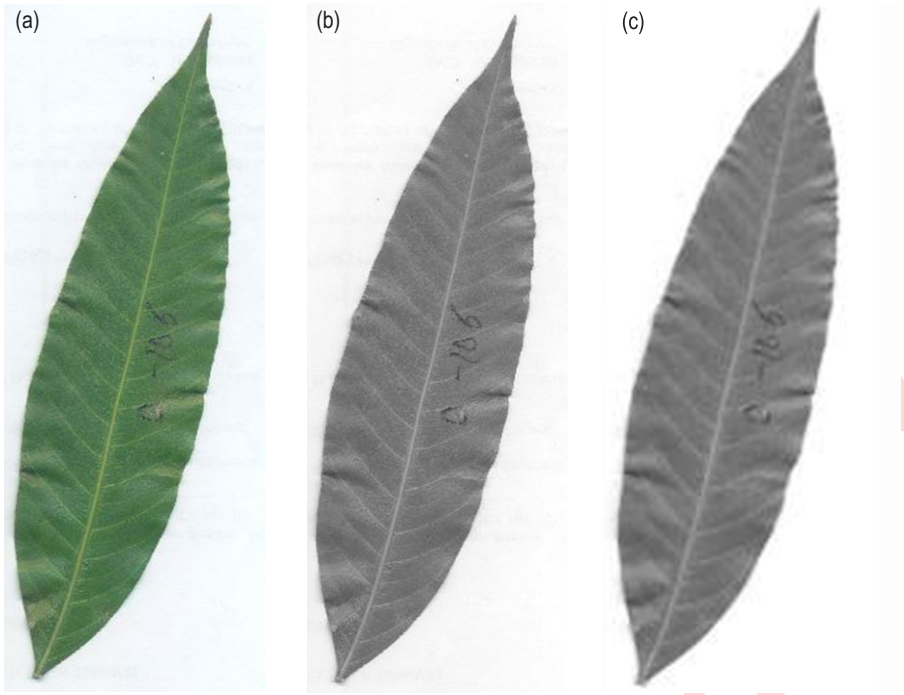


Fig. 4: Pre-processed leaf image (a) Original color image (b) Color image converted to grayscale (c) Sharpened image after filtering.

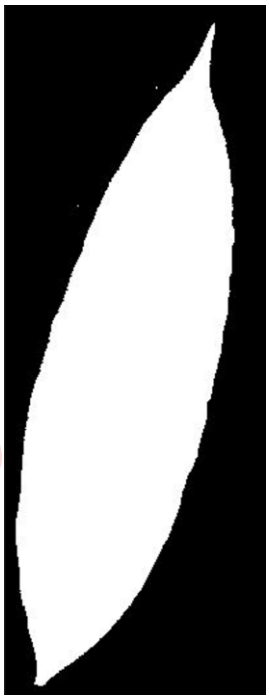


Fig. 5: Image segmentation through thresholding and morphological operations.

Feature Extraction and Aspect Ratio: Leaf length and width were measured as the major and minor axes of the bounding box, respectively. Leaf aspect ratio was calculated as the ratio of a leaf's length to its maximum width, indicating how elongated or broad the leaf is. Aspect ratio measurements were exported to MS Excel 2016 (XLS) for analysis. Batch processing allows analysis of entire folders with a single command.

Testing and Validation: Software was validated using leaves of various shapes and species. Accuracy was assessed by comparing software-derived measurements (calculated leaf Length/ Width/ AR) with manual measurements (measured leaf Length/ Width/ AR). Four indices were used to evaluate performance.

Coefficient of determination R^2): Evaluates correlation between manual and computed measurements. The details of its computation can be found in Jierula *et al.* (2021).

Accuracy rate (%): Ratio of correct measurement to actual.The mathematical formula for calculating it accuracy rate (%) can be found in Valverde-Albacete and Peláez-Moreno (2014).

Root mean square error (RMSE): RMSE is a quadratic scoring rule that measures the average magnitude of the error in regression tasks. The formula for calculating RMSE can be found in literature by Hodson (2022).

Mean absolute error (MAE): MAE is used to measure the average magnitude of errors in a set of predictions, without considering their direction (Hodson, 2022). It represents the average of the absolute differences between prediction and actual observation where all individual differences have equal weight.

Error rate (%): Percentage difference between estimated and true values (Ali *et al.,* 2012). All analysis was performed on MATLAB R2015a, confirming high precision and reliability of QuickLeaf-LWA across multiple leaf shapes and species.

Results and Discussion

Linear regression analysis revealed high correlation between automated and manual measurements, with R^2=0.98 for leaf length and R^2=0.96 for leaf width (Table 1; Fig. 7). These results align with the findings from recent phenotyping studies demonstrating high correspondence between image based trait estimates and manual measurements (Huang *et al.,* 2023; Rice *et al.,* 2024). Accurate automated measurement is critical for reliable morphological trait extraction, as established in high throughput phenotyping pipelines (Yao *et al.,* 2025).

QuickLeaf LWA delivered low mean error rates (0.584 %–3.283 %) and high accuracy rates (96.717%–99.416%), with low RMSE (0.150–0.564) and MAE (0.082–0.476) values. These error metrics are consistent with performance benchmarks seen

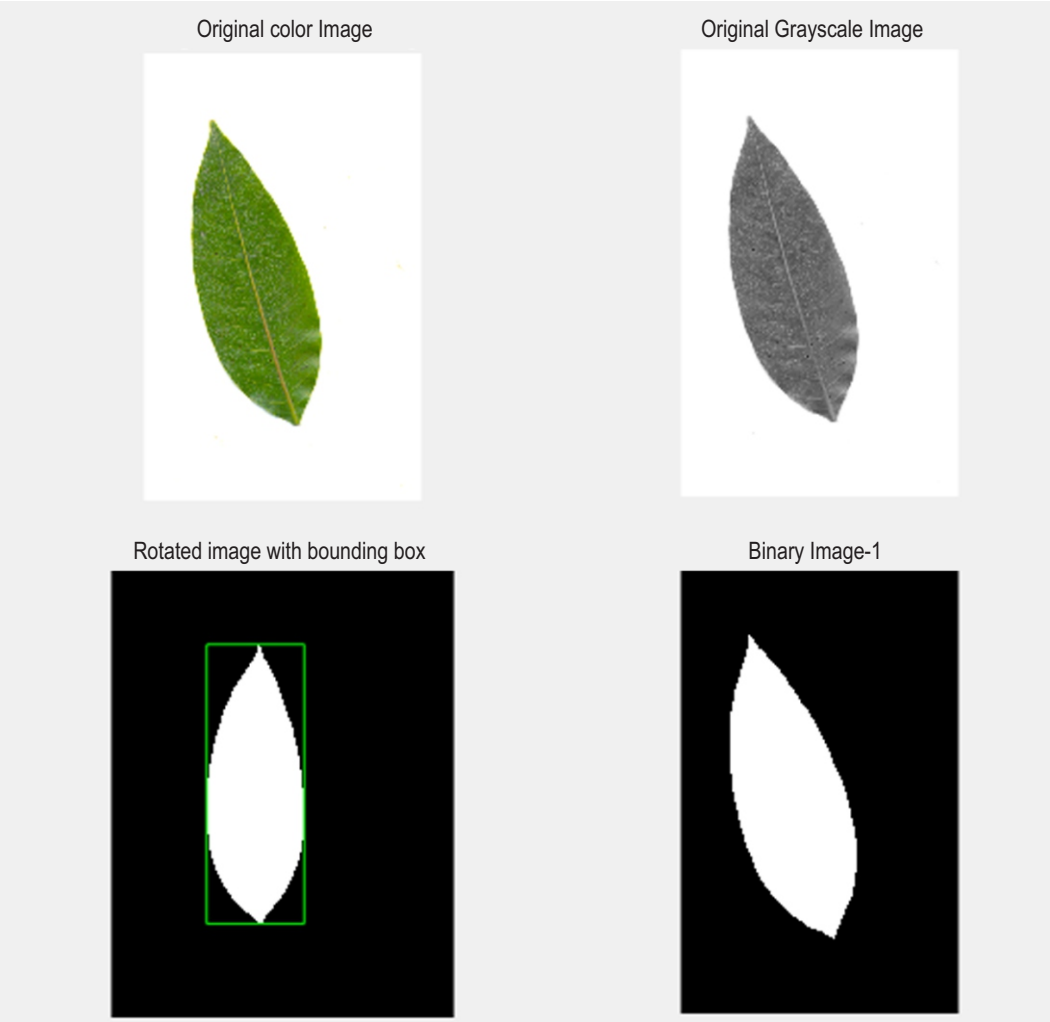


Fig. 6: Screenshot depicting the image correction and segmentation.

in other imaging systems, such as automated leaf imaging for citrus (Suarez *et al.,* 2025) and machine vision phenotyping in cereals (Aharon, 2020). High accuracy and low measurement error are essential for quantitative studies, as small deviations can amplify in downstream analysis such as GWAS and QTL mapping (Lagergren *et al.,* 2023; Cobb *et al.,* 2013). High coefficients of determination and favorable error statistics indicate that QuickLeaf LWA provides precise and reliable measurements over a range of leaf morphologies, capture variations among shapes such as ovate, lanceolate, and elliptical forms. These observations are supported by methodological advances in leaf image segmentation reported in the literature (Xia *et al.,* 2021), which emphasize the importance of segmentation quality for accurate attribute extraction.

Moreover, QuickLeaf LWA demonstrated significant processing efficiency. Analysis of 68 images completed in approximately 3 min on a standard desktop computer, corresponding to an average of less than 3 sec per image. Manual measurements for the same dataset required several hours, emphasizing the time saving benefits of automation. Rapid throughput is necessary for large scale phenotyping studies, where thousands of images may be processed (Li *et al.,* 2024).

Success of QuickLeaf LWA can be attributed in part to its adaptive threshold segmentation, which adjusts to local image characteristics and enhances segmentation reliability under flatbed scanner conditions. Adaptive threshold has been shown to outperform fixed global threshold in leaf segmentation, especially when background intensity varies (Otsu, 1979). Morphological operations further clean segmented masks by filling holes and removing noise, a strategy validated in prior leaf imaging research (Maloof *et al.,* 2013; Tao *et al.,* 2023). Batch processing capability is strength of QuickLeaf LWA, enabling the

Table 1: Comparative evaluation of leaf length and width measurement softwares

Software	Strengths	Weaknesses
ImageJ	• Widely used, open-source, with strong community support. • High customization using plugins or macros. • Accurate for length and width if properly calibrated.	• Basic measurements often require manual steps, such as setting scales and selecting regions of interest. • Manual or semi-automated; time-consuming for batch processing. • Aspect ratio calculations require manual scripting or plugin. • Calibration is needed.
LAMINA	• Designed for automated batch processing of leaf traits. • Leaf area, length, breadth, and shape measurements, are automatically extracted. • Suitable for large datasets.	• Limited to specific image quality and background contrast. • May not handle overlapping or damaged leaves accurately. • Less flexible than ImageJ for customization.
LeafJ (an ImageJ plugin)	• Streamlined measurement of length, width, area, and shape features directly in ImageJ. • Good automation for leaf series with mid vein tracking. • Efficient and accurate aspect ratio estimation.	• Requires correct mid vein orientation for best performance. • Performance drops if leaves are curled, overlapping, or have unclear mid veins. • Less intuitive UI compared to LAMINA.

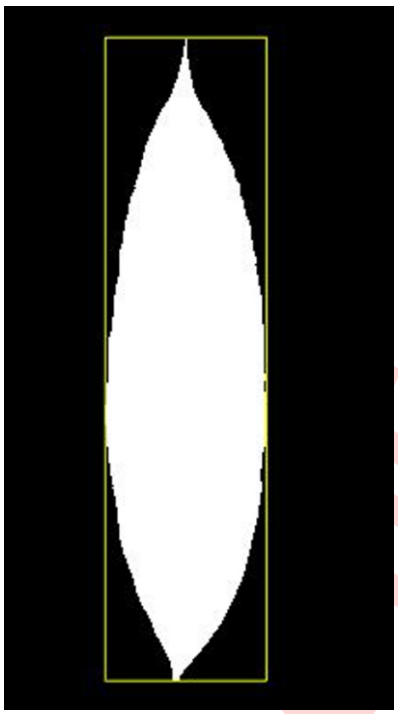


Fig. 7: Construction of a rectangular bounding box and turning the tilted leaf image to a perpendicular position.

processing of entire folders of leaf images with minimal human intervention. This feature is important for high throughput phenotyping frameworks that prioritize scalability and reproducibility (Tisné *et al.,* 2013). By minimizing manual preprocessing and parameter tuning, the software reduces user bias and operational variability, issues commonly noted in semi automated image analysis workflows (Tejani *et al.,* 2024). Recent developments in machine learning–based segmentation offer potential paths for future enhancement. Deep learning models — such as convolutional neural networks (CNNs) and transformer based architectures — have achieved high accuracy in complex segmentation tasks, including overlapping leaves and variable illumination (Tamvakis *et al.,* 2022). Incorporating such approaches could improve QuickLeaf LWA for field acquired images, where backgrounds and lighting conditions are less controlled than scanner environments. In addition to segmentation improvements, expanding the feature extraction sets to include additional leaf traits - such as leaf area, perimeter, color indices and texture metrics - would widen QuickLeaf LWA's application.

Multifaceted trait extraction is increasingly important in plant science with studies integrating structural and physiological phenotypes to enhance genotype–phenotype association (Wang *et al.,* 2024). Phenotyping platforms that combine linear measurements with area and color analysis support complete biological interpretation and enable linkage with functional quality (Parihar *et al.,* 2020). Automated leaf phenotyping tools also facilitate longitudinal studies that monitor growth dynamics over time. Although QuickLeaf LWA focuses on static morphological traits from single images, its high throughput and automation suggest feasibility for integration into temporal phenotyping workflows, where repeated measurements among development stages yield prediction into growth rates and stress responses (Gage *et al.,* 2017; Miraj *et al.,* 2023).

Resilience of QuickLeaf LWA among different species and shapes underscores its utility for comparative analysis in ecological and evolutionary studies (Przybylska *et al.*, 2023; Cornelissen *et al.,* 2003). Although traditional image processing performs well under controlled scanner conditions, additional challenges arise in *In situ* field phenotyping, such as occlusion, shadows, and heterogeneous backgrounds. Future advanced

Online Copy

segmentation and model based corrections could enhance performance in these contexts, aligning with research trends in field phenomics (Li *et al.,* 2024). QuickLeaf LWA is a high-throughput, user-friendly tool that automates the measurement of leaf morphological traits like length, width and aspect ratio with high accuracy. By integrating adaptive image processing and batch analysis, it significantly reduces the processing time and human error compared to manual methods. Proven effective across diverse species and shapes, it is a valuable asset for plant breeding, ecology and genetic research, with future updates planned to incorporate machine learning for expanded trait analysis in field conditions.

Acknowledgement

Authors are thankful to the Director, ICAR-Central Institute for Subtropical Horticulture, Lucknow for providing necessary facilities for the research.

Authors' contribution: H.C. Verma: Conceptualization, methodology, visualization, formal analysis, investigation, resources, data curation and writing, original draft preparation; **A. Yadav:** Revision and editing; **A.K. Trivedi:** Investigation, resources, data curation, writing, original draft preparation and editing.

Funding: Work was done under institute project. Hence, no funding was provided.

Research content: The research content of manuscript is original and has not been published elsewhere.

Ethical approval: Not applicable.

Conflict of interest: The authors declare that there is no conflict of interest.

Data availability: Not applicable.

Consent to publish: All authors agree to publish the paper in *Journal of Environmental Biology.*

References

Aharon, S.: Image based high throughput phenotyping of cereals: evaluation of 2 D and 3 D modeling approaches for early vigor traits in triticale. *Rem. Sens.,* **12**, 3877 (2020).

Ali M.M., A. Al-Ani, D. Eamus and D.K.Y. Tan: A new image processing based technique for measuring leaf dimensions. *American-Eurasian J. Agric. Environ. Sci.,* **12**, 1588-1594 (2012).

Atefi, A., Y. Ge, S. Pitla and J. Schnable: Robotic technologies for high throughput plant phenotyping: Contemporary reviews and future perspectives. *Fronti. Plant Sci.,* **12**, 611940 (2021).

Cobb, J. N., G. Declerck, A. Greenberg, R. Clark and S. McCouch: Next-generation phenotyping: requirements and strategies for enhancing our understanding of genotype–phenotype relationships and its relevance to crop improvement. *Theore. Appl. Gene.,* **126**, 867–887 (2013).

Cornelissen, J.H.C., S. Lavorel, E. Garnier, S. Díaz, N. Buchmann, D.E. Gurvich, P.B. Reich, H. Ter Steege, H.D. Morgan, M.G.A. van der Heijden, J.G. Pausas and H. Poorter: A handbook of protocols for standardised and easy measurement of plant functional traits worldwide. *Austral. J. Bot.,* **51**, 335–380 (2003).

Elnashef, B., S. Filin and R.N. Lati: Tensor-based classification and segmentation of three-dimensional point clouds for organ-level plant phenotyping and growth analysis. *Comput. Electron. Agric.,* **156**, 51–61 (2019).

Gage, J.L., N.D. Miller, E.P. Spalding, S.M. Kaeppler and N. de Leon: TIPS: a system for automated image-based phenotyping of maize tassels. *Plant Meth.,* **13**, 21 (2017).

Gonzalez, R.C. and R.E. Woods: Digital Image Processing. 4th Edn., Pearson Education, New York, 1022 pages (2018).

Hao, S., D. Zhang and Y. Wen: Leaf phenotypic variation of Chuanqian Crape Myrtle in natural populations. *HortScience,* **60**, 399–403 (2025).

Hodson, T.O.: Root-mean-square error (RMSE) or mean absolute error (MAE): When to use them or not. *Geoscien. Model Develop.,* **15**, 5481–5487 (2022).

Huang, Y., L. Zhang and X. Liu: Evaluation of automated image-based phenotyping accuracy relative to manual trait measurements in crop plants. *J. Plant Phenotyp.,* **6**, 101–115 (2023).

Hui, F., J. Zhu, P. Hu, L. Meng, B. Zhu, Y. Guo, B. Li and Y. Ma: Image-based dynamic quantification and high-accuracy 3D evaluation of canopy structure of plant populations. *Ann. Bot.,* **121**, 1079–1088 (2018).

Hussein, B.R., O.A. Malik, W.H. Ong and J.W.F. Slik: Automated extraction of phenotypic leaf traits of individual intact herbarium leaves from herbarium specimen images using deep learning based semantic segmentation. *Sensors*, **21**, 4549 (2021).

Jierula, A., S. Wang, T.M. OH and P. Wang: Study on accuracy metrics for evaluating the predictions of damage locations in deep piles using artificial neural networks with acoustic emission data. *Appl. Sci.,* **11**, 2314 (2021).

Klein, L.L. and H.T. Svoboda: Comprehensive methods for leaf geometric morphometric analyses. Bio-protocol, **7**, e2269 (2017).

Kolhar S.K. and J. Jagtap: Plant trait estimation and classification studies in plant phenotyping using machine vision – A review. *Informa. Process. Agricul.,* **10**, 114-135 (2023).

Lagergren, J., M. Pavicic, H.B. Chhetri, L.M. York, D. Hyatt, D. Kainer, E. M. Rutter, K. Flores, J. Bailey-Bale and J. Streich: Few-shot learning enables population-scale analysis of leaf traits in *Populus trichocarpa*. *Plant Phenomics,* **5**, 0072 (2023).

Li, X., M. Chen, S. He, X. Xu, L. He, L. Wang, Y. Gao, F. Tang, T. Gong, W. Wang and W. Liu: Estimation of soybean yield based on high-throughput phenotyping and machine learning. *Fronti. Plant Sci.,* **15**, 1395760 (2024).

Li, Y., D. Zou, N. Shrestha, X. Xu, Q. Wang, W. Jia and Z. Wang: Spatiotemporal variation in leaf size and shape in response to climate. *J. Plant Ecol.,* **13**, 87-96 (2020b).

Li, Y., H. Zhang and Y. Yang: A method for obtainging plan morphological phenotypic parameters using image processing technology. *J. For. Eng.,* **5**, 128–136 (2020c).

Li, Z., R. Guo, M. Li and Y. Chen: A review of computer vision technologies for plant phenotyping. *Compu. Electro. Agricul.,* **176**, 105672 (2020a).

Mack, E.M., J.D. Smith and R.L. Thompson: Leaf surface area dynamics and their effects on radiation interception, water and energy fluxes, and crop productivity. *J. Plant Ecol. Biophys. Proces.,* **12**, 245–258 (2017).

Maloof, J.N., K. Nozue, M.R. Mumbach and C.M. Palmer: LeafJ: An

Online Copy

ImageJ plugin for semi-automated leaf shape measurement. *J. Visuali. Experim.,* **71**, e50028 (2013).

Meraj, T., M.I. Sharif, M. Raza, A. Alabrah, S. Kadry and A.H. Gandomi: Computer vision-based plant phenotyping: a comprehensive survey. *iScience,* **27**, 108709 (2023).

Otsu, N.: A threshold selection method from gray-level histograms. IEEE Transactions on Systems, Man and Cybernetics, **9**, 62-66 (1979).

Parihar, A., R. Singh and S. Singh: Development of a high-throughput image-based plant phenotyping platform for quantifying morphological and color traits. *J. Phenotyp. Imag.,* **5**, 45–59 (2020).

Pérez, R., M. Gámez and I. Blanquer: High-throughput plant phenotyping: a review of the state of the art and the new challenges. *Plant J.,* **108**, 896-913 (2021).

Przybylska, M. S., C. Violle, D., Vile, J. F. Scheepens, B. Lacombe, X.L. Roux, Sales-Mabily L. Perrier, M. Laumond, M. Vinyeta, P. Moulin, G. Beurier, L. Rouan, D. Cornet and F. Vasseur: AraDiv: a dataset of functional traits and leaf hyperspectral reflectance of *Arabidopsis thaliana*. *Scientific Data*, **10**, 314 (2023).

Qi, M., F.K. Du, F. Guo., K. Yin and J. Tang: Species identification through deep learning and geometrical morphology in oaks (*Quercus* spp.): Pros and cons. *Ecol. Evolu.,* **14**, e11032 (2024).

Rice, J.P., M.E. Thompson and R.L. Garcia: High-throughput image-based phenotyping shows strong correlation with manual trait assessment in rice breeding trials. *Plant Methods,* **20**, 65 (2024).

Sermwuthisarn, P. and N. Phumeechanya: Integration of U-Net and FastSAM for accurate leaf image segmentation in complex backgrounds. *Enginee. Technol. Appl. Sci. Res.,* **15**, 30119-30129 (2025).

Simkin, A. J., P. A. López-Calcagno and C. A. Rains: Feeding the world: improving photosynthetic efficiency for sustainable crop production. *J. Exp. Bot.*, **70**, 1119–1140. (2019).

Su, Y., M. Renz, B. Cui, X. Sun, Z. Ouyang and X. Wang: Leaf morphological and nutrient traits of common woody plants change along the urban–rural gradient in Beijing, China. *Fronti. Plant Sci.,* **12**, 682274 (2021).

Suarez, E., M. Blaser and M. Sutton: Automating leaf area measurement in citrus: The development and validation of a Python based tool. *Appl. Sci.,* **15**, 9750 (2025).

Tamvakis, P. N., C. Kiourt, A.D. Solomou, G. Ioannakis and N.C. Tsirliganis: Semantic image segmentation with deep learning for vine leaf phenotyping. *IFAC-PapersOnLine*, **55**, 83–88 (2022).

Tao, F., J. Guan and R. Li: Image processing based plant segmentation for high throughput phenotyping systems: a comparison of thresholding and morphological post processing methods. *Plant Methods,* **19**, 10 (2023).

Tejani, A.S., Y.S. Ng, Y. Xi and J.C. Rayan: Understanding and mitigating bias in imaging artificial intelligence. *RadioGraphics,* **44**, 1-13 (2024)

Tisné, S., Y. Serrand, L. Bach, E. Gilbault, R. Ben Ameur, H. Balasse, R. Voisin, D. Bouchez, M. Durand Tardif, P. Guerche, G. Chareyron, J. Da Rugna, C. Camilleri and O. Loudet: Phenoscope: an automated large scale phenotyping platform offering high spatial homogeneity. *Plant J.,* **74**, 534–544 (2013).

Valverde-Albacete, F.J. and C. Peláez-Moreno: 100% classification accuracy considered harmful: The normalized information transfer factor explains the accuracy paradox. *PLoS ONE,* **9**, Article e84217 (2014).

Wang, Z., J. Hao, X. Shi, Y. Liang, B. Li, Q. Liu and Y. Ge: Integrating dynamic high throughput phenotyping and genetic analysis to monitor growth variation in foxtail millet. *Plant Methods,* **20**, 168 (2024).

Wei, T., Z. Chen, X. Yu, S. Chapman, P. Melloy and Z. Huang: A large-scale in-the-wild dataset for plant disease segmentation. *Scientific Data*, **13**, 205 (2026). DOI: 10.1038/s41597-025-06513-4

Wu, L.; Long, Y., H. Sun, N. Liu, W. Wang and Q. Dong: Length measurement of potato leaf using depth camera. *IFAC Pap,* **51**, 314–320 (2018).

Wu, S., W. Wen, B. Xiao, X. Guo, J. Du, C. Wang and Y. Wang: An accurate skeleton extraction approach from 3D point clouds of maize plants. *Front. Plant Sci.*, **10**, 248 (2019).

Xiang, L., Y. Bao, T. Lie, D. Ortiz and M.G. Salas-Fernandez: Automated morphological traits extraction for sorghum plants via 3D point cloud data analysis. *Comput. Electron. Agric.*, **162**, 951–961 (2019).

Xiao, S., H. Chai, K. Shao, M. Shen, Q. Wang, R. Wang, Y. Sui and Y. Ma: Image-based dynamic quantification of aboveground structure of sugar beet in field. *Remote Sens.,* **12**, 269 (2020).

Yao, J., W. Wang, H. Fu, Z. Deng, G. Cui, S. Wang, D. Wang, W. She and X. Cao: Automated measurement of field crop phenotypic traits using UAV 3D point clouds and an improved PointNet++. *Front. Plant Sci.,* **16**, 1654232 (2025).

Zhang, Y., H. Liu, L. Wang and J. Chen: Variation and genetic parameters of leaf morphological traits of eight *Populus simonii* × *P. nigra* hybrid families. *Forests,* **11**, 1319 (2023).

Online Copy