Smartphone-Based RGB Phenotyping of Hydroponic Lettuce Growth Dynamics

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Abstract.

Hydroponic lettuce production requires frequent, accurate growth assessment to optimize yield and crop uniformity within short growth cycles. Smartphone-based imaging offers a practical alternative for scalable proximal phenotyping, yet its quantitative reliability under operational hydroponic conditions remains insufficiently documented. This study evaluated a smartphone-based RGB phenotyping protocol for monitoring growth dynamics of commercially grown nutrient film technique (NFT) hydroponic Lactuca sativa 'Lalique' lettuce. To our knowledge, this is one of the first cross-device, multi-cycle evaluations of smartphone-based phenotyping workflows under commercial NFT hydroponic conditions. The objectives were: (1) to compare image-derived plant area (IDPA) (cm²) estimations from different smartphones; and (2) to evaluate the relationship between manually measured plant area and IDPA across growth cycles.

Experiments were conducted in 2025 at the Avnei Eitan Research Station, Israel, in a 500 m² net house with four nitrogen treatments (e.g. 50, 100, 150, 200 mg L^{-1} N) arranged in a randomized complete block design (12 channels and 168 plants per treatment). Two production cycles of Lalique were monitored in winter and spring. Image campaigns (3–5 per cycle) were carried out using multiple smartphones (iPhone 15, iPhone EX, Samsung A50), with an in-frame calibration target for pixel-to-metric scaling. Manual caliper measurements of plant diameter (length and width) followed each campaign for benchmarking. A Python-based workflow combined pixel-to-metric calibration with Segment Anything Model (SAM)-based segmentation to estimate IDPA.

IDPA measurements from different smartphones showed strong cross-device correlations (winter: R^2=0.99; spring: R^2=0.995), demonstrating protocol robustness. The relationship between manual and IDPA estimates was moderately strong overall (R^2≈0.87 for both cycles) but improved *substantially to R^2=0.97 when harvest-day data were excluded, confirming that canopy occlusion is the primary limitation. At harvest, 25-33 days after planting (DAP), IDPA exceeded manual measurements, with higher standard deviation, pointing to overestimation when canopy complexity increases.*

Smartphone-based RGB phenotyping provides robust, cross-device reproducible growth estimates during early-to-mid vegetative stages (approximately DAP 0–20), enabling frequent, low-cost monitoring without dedicated infrastructure. The protocol reliably tracks growth trajectories and crop uniformity, offering a practical pathway to integrate everyday smartphones into hydroponic phenotyping workflows. While canopy overlap at harvest limits accuracy for definitive harvest thresholds, the approach effectively complements manual assessment in precision horticulture.

Keywords.
Smartphone phenotyping; RGB imaging; hydroponics; lettuce; plant area; precision horticulture; digital agriculture.

Introduction

Smartphone-based imaging offers a practical route to scalable proximal phenotyping, but its quantitative reliability under operational hydroponic conditions remains insufficiently documented (Li et al., 2020). In commercial hydroponic lettuce production, growers typically monitor growth through manual methods: visual inspection of plant size, measuring head diameter or weight at harvest, and occasional destructive sampling for fresh weight (Ojo et al., 2024). These manual assessments are labor-intensive, time-consuming, and provide only discrete snapshots rather than continuous monitoring, creating a practical need for automated, low-cost phenotyping tools.

Image-based plant data can be acquired from RGB, multispectral, hyperspectral, and thermal proximal sensors, yet platform choice determines measurement precision, system cost, deployment complexity, and farm suitability. In controlled-environment agriculture, phenotyping studies have relied on fixed camera systems to monitor growth dynamics (Rahman et al., 2025) and estimate nitrogen content (Adhikari et al., 2020), and dedicated platforms to estimate lettuce size and biomass proxies (Li et al., 2020; Gang et al., 2022). However, these approaches are typically infrastructure-heavy, spatially constrained, and less transferable to commercial production where flexible, low-cost tools are needed.

Image analysis methods vary from threshold segmentation and edge-based approaches (Katz et al., 2023) to deep learning models (Han et al., 2021). RGB with depth sensor and deep learning approaches improve lettuce phenotyping accuracy by incorporating structural information not captured in 2D images (Gang et al., 2022; Zhao et al., 2025), but require specialized hardware and greater computational resources. By contrast, smartphones are widely available and capture images at multiple locations without dedicated infrastructure, suggesting strong potential for operational phenotyping if outputs are robust and reproducible (Li et al., 2020). Still, limited evidence exists that smartphone-derived canopy metrics remain accurate across devices, growth stages, and dense canopies typical of hydroponic lettuce production.

Hydroponic lettuce exhibits a characteristic sigmoidal growth curve: slow initial growth during establishment, rapid exponential expansion during vegetative development, and plateauing as canopy closure occurs near harvest (Ojo et al., 2024). This trajectory creates phenotyping challenges—early-stage plants are easily segmented, but mid-to-late stage plants develop overlapping leaves and rosette self-occlusion that inflate projected area estimates (Gang et al., 2022). Hydroponic lettuce is particularly relevant due to its short cycle (25–35 days), high value, and sensitivity to spacing and nutrient management, making frequent growth monitoring useful for production decisions (Adhikari et al., 2020; Ojo et al., 2024). Existing studies demonstrate that image-derived traits track lettuce growth effectively in controlled systems, but fewer have tested smartphone-based workflows under commercial hydroponic conditions, across seasons, and across devices (Li et al., 2020).

Therefore, this study evaluated a smartphone-based RGB phenotyping protocol for monitoring growth dynamics of *Lactuca sativa* ‘Lalique’ lettuce grown in a commercial nutrient film technique (NFT) hydroponic system, to determine whether a low-cost imaging workflow can complement or partially replace manual assessment in practical precision agriculture settings. The specific objectives were:

(1) to compare image-derived plant area (IDPA) (cm²) calculations from different smartphones; and

(2) to evaluate the relationship between manually measured plant area and IDPA across growth cycles.

Methods

Research area

The study was conducted during 2025 at the Avnei Eitan Research Station, Israel, in a 500 m² net house with a NFT system with four nitrogen treatments arranged in a randomized complete block design (12 channels and 168 plants per treatment) (**Fig. 1**). Two production cycles Lalique lettuce were monitored in winter, between 9 Jan 11 Feb 2025 (33 days) with treatments 50, 100, 150, 200 mg L⁻¹ [N] and spring, between 4 April and 29 April 2025 (25 days) with treatments 100, 150, 200, 250 mg L⁻¹ [N]. During each growth cycle, nutrient solutions were monitored for nitrate concentration, electrical conductivity, pH, and water level. These parameters determined when to replenish the nutrient solutions.

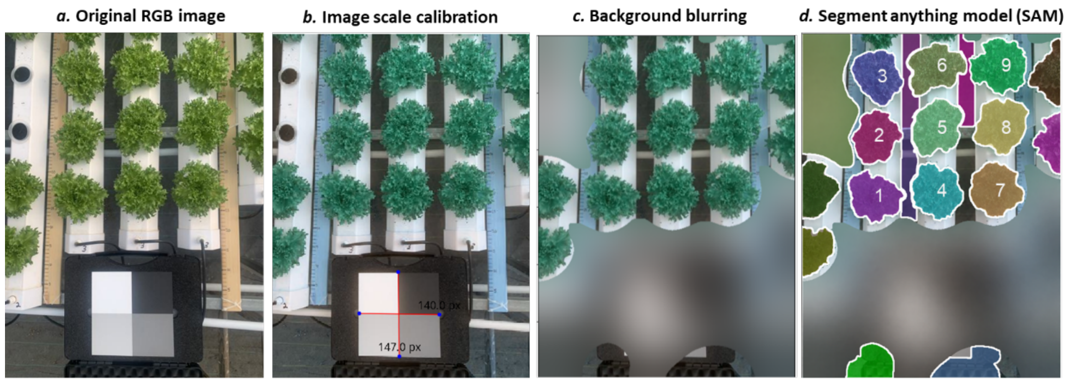
Fig. 1 Nutrient film technique (NFT) hydroponic system located in the Avnei Eitan Research Station, Israel.

In each growth cycle, the first nine plants (first three plants in three channels) (n=9) of one block were designated as measurement plants. Four nutrient concentrations were monitored, therefore, 36 plants were monitored per growth cycle.

Image-derived plant area (IDPA)

Image campaigns: Three image campaigns were executed during the winter growth cycle and five throughout the spring cycle. Each image campaign included three images per treatment using each camera: iPhone EX, iPhone 15, and Samsung Galaxy A50 (during winter growth cycle). A Zenith Lite™ (SphereOptics, Herrsching, Germany) diffuse reflectance target was place in each image for pixel size calibration. Image campaigns took place between 11:30 and 12:00.

Image analysis pipeline: A smartphone-based RGB phenotyping workflow was developed to calculate the image-derived plant area (IDPA) (cm²) per lettuce plant (Katz et al., 2026) (**Fig. 2**). IDPA is defined as the projected 2D plant area estimated from top-down camera imagery, and represents the visible plant footprint of the plant. The primary pipeline steps included: 1) smartphone imagery campaign, 2) pixel-to-metric calibration using reflectance target, 3) Gaussian bur of background for improved plant separation, 4) plant segmentation using Segment Anything Model (SAM) (Meta AI), and 5) calculation of IDPA per lettuce plant. Python programming language used for steps two through five.



e. IDPA (cm^2)

Plant	IDPA (cm^2)
1	118.2
2	109.2
3	111.6
4	124.3
5	126.3
6	123.5
7	121.9
8	128.6
9	132.7

Fig. 2 Image-derived plant area (IDPA) pipeline for smartphone-based RGB phenotyping of hydroponic lettuce. Primary steps included: (a) smartphone imagery campaign (e.g. iPhone EX); (b) image scale calibration using 20 cm X 20 cm reference board shown in false color display; (c) background blurring with Gaussian blur; (d) segmentation of individual lettuce plants using the Segment Anything Model (SAM); and (e) calculation of IDPA (cm^2) per lettuce plant.

Data collection and analysis

Manual measurements: Following each image campaign, the length (L) (cm) and width (W) (cm) of all plants were measured using an S_Cal EVO Smart electronic caliper (Sylvac, Yverdon, Switzerland).

The oval length radius (r_L) (cm) and oval width radius (r_W) (cm) were calculated using **Eq. 1** and **Eq. 2**, respectively. **Eq. 3** was used to calculate the average radius per plant (r_{avg}) (cm).

$$r_L = \frac{L}{2} \tag{1}$$

$$r_W = \frac{W}{2} \tag{2}$$

$$r_{avg} = \frac{r_L + r_W}{2} \tag{3}$$

The plant area (A), hereinafter *manual plant area (*cm^2*)*, was then calculated (**Eq. 4**):

$$A = \pi r^2{}_{avg} \tag{4}$$

Data analysis

A comparison of estimated plant area, using the manual measurements and the developed IDPA method, was executed per treatment, measurement day, growth cycle, and season. Descriptive statistics, including mean, standard deviation (SD), and coefficient of variance (CV) were calculated with Excel (Microsoft, Redmond, USA). Data distribution was calculated and presented in box-plot format with Python. The relationships between: 1) IDPA estimated with different smartphones, and 2) manual plant area and IDPA were evaluated with Excel using fitting of linear model, coefficient of determination (R^2), and root mean square error (RMSE) calculation. Statistical inference, for the determination of significant differences between measurement platforms, measurement days, and nitrogen treatments was performed using JMP statistical software (JMP Inc., Cary, USA). An analysis of variance (ANOVA) was used to evaluate differences among nitrogen treatments. A repeated-measures ANOVA was used to compare plant area estimates obtained from the three measurement methods, followed by paired tests with Bonferroni correction for pairwise comparisons. In addition, a repeated-measures linear mixed model was applied to examine temporal differences among measurement.

Results

A representative growth trajectory of Lalique lettuce enabled both visual and quantitative monitoring over time, including comparison between manual and IDPA estimates (**Fig. 3**). During the spring cycle under the 200 ppm treatment, the SD increased over time in IDPA data for both smartphones. The IDPA (iPhone EX) SD increased from 4.0 cm^2 (4 April) to 38.3 cm^2 (29 April). Similarly, the manual plant area SD increased from 4.9 cm^2 (4 April) to 38.4 cm^2 (29 April). This is likely attributable to increased canopy complexity, including leaf overlap and occlusion, as well as spatial constraints associated with advanced plant growth. The significant difference between the IDPA and manual was seen in the mean plant area values on 29 April: 243.4 cm^2 and 199.3 cm^2, respectively ($p<0.05$). This exemplifies that IDPA overestimated the manual plant area at harvest.

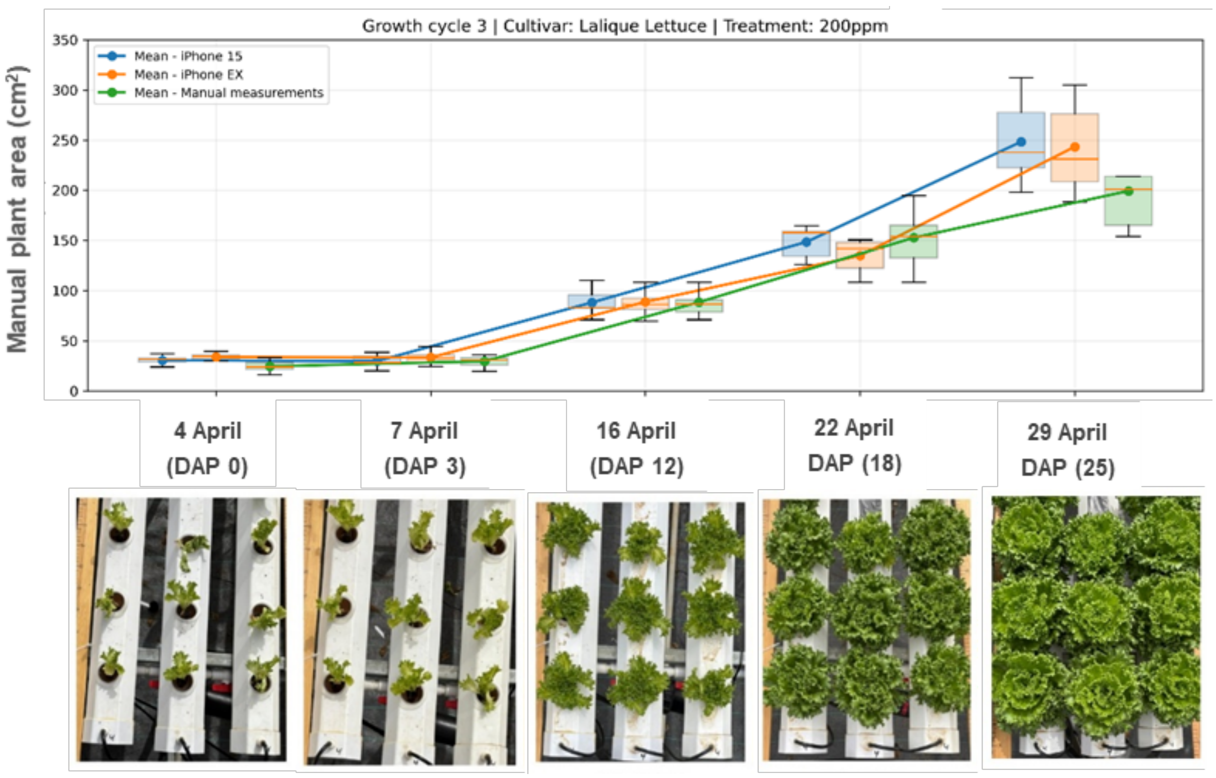


Fig. 3 ***Lactuca sativa*** **'Lalique' lettuce representative growth trajectory in spring growth cycle (between 4 April and 29 April 2025, days after planting (DAP) 0 to 25) in 200 ppm nitrogen [N] treatment. Box plots (n=9) and mean values per method: side-view canopy area (SVCA) with iPhone 15 images (*blue*), iPhone EX images (*orange*), and manual plant area (*green*). Presented images acquired using iPhone 15.**

Comparable IDPA values were obtained with both smartphones across the growing cycles (**Fig. 4**). IDPA measurements from the two devices were strongly and positively correlated in the winter cycle *(*R^2=0.99, *slope*=1.03) and the spring cycle (R^2=0.995, *slope*=0.99), indicating that the IDPA protocol and image-analysis pipeline were robust and reproducible.

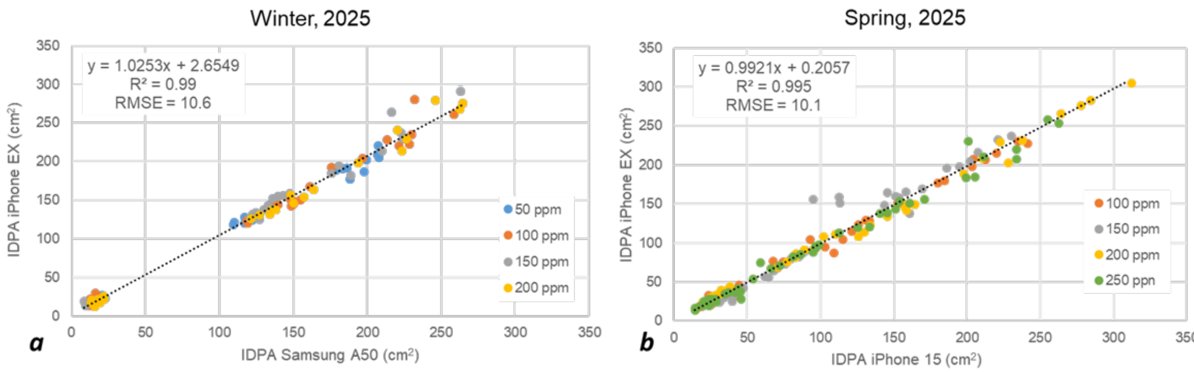


Fig. 4 Correlation between image-derived plant area (IDPA) (cm^2) of *Lactuca sativa* 'Lalique' lettuce during: (a) winter cycle, between 9 Jan 11 Feb 2025, using iPhone EX and Samsung Galaxy A50 smartphones (n=106); and (b) spring cycle, 4 April and 29 April 2025, using iPhone EX and iPhone 15 (n= 174). Nitrogen [N] treatments included 50 ppm (*blue*) (only in the winter cycle), 100 ppm (*orange*), 150 ppm (*grey*), and 200 ppm *(yellow*) and 250 (*green*) (only in the spring cycle) treatments.

The relationship between manual plant area and IDPA (iPhone EX) was positive and moderately strong overall, with differences between growth cycles (**Fig. 5**). During the winter cycle, the relationship was positive and moderately strong (R^2=0.87, *slope*<1) (**Fig. 5a**). However, this relationship was influenced by data collected on the harvest day, 11 Feb, 33 days after planting (DAP), when the SD of IDPA increased from 11.6 cm^2 (29 Jan) to 34.0 cm^2 (11 Feb) in treatment 100 ppm. When only data from 9 Jan (DAP 0) and 29 Jan (DAP 20) were included in the linear model, the relationship substantially improved (R^2=0.97, m≈1). On these dates, lettuce plants were smaller and did not touch or overlap. The IDPA values as harvest point to overestimation of plant area.

During the spring cycle, the overall relationship between manual plant area and IDPA (iPhone EX) was also positive and moderately strong (R^2=0.88, *slope*<1) (**Fig. 5b**). Generally, the SD of the manual plant area and IDPA estimation increased with plant development and peaked at harvest on 29 April (DAP 33), most likely due to the high degree of overlap between plants. Similarly, to the winter cycle, the high values of IDPA at harvest point to slight overestimation of plant area and highlight the limitations of the current IDPA method.

The SD was greater than expected on 16 April (DAP 12) and 22 April (DAP 18), in the 100 ppm and 250 ppm treatments, differing from the trend in the winter cycle. Additionally, for both treatments, the SD manual plant area was higher (20.6 cm^2) in comparison to the SD of the IDPA (13.9 cm^2) on 16 April in the 250 ppm treatment. This trend continued on 22 April, where the SD manual plant area was also higher (24.1 cm^2) in comparison to the SD of the IDPA (19.6cm^2) on 16 April. This increased variability, earlier in the growth cycle, may be attributed to technical difficulties with filters combined with frequent power outages during this growth cycle.

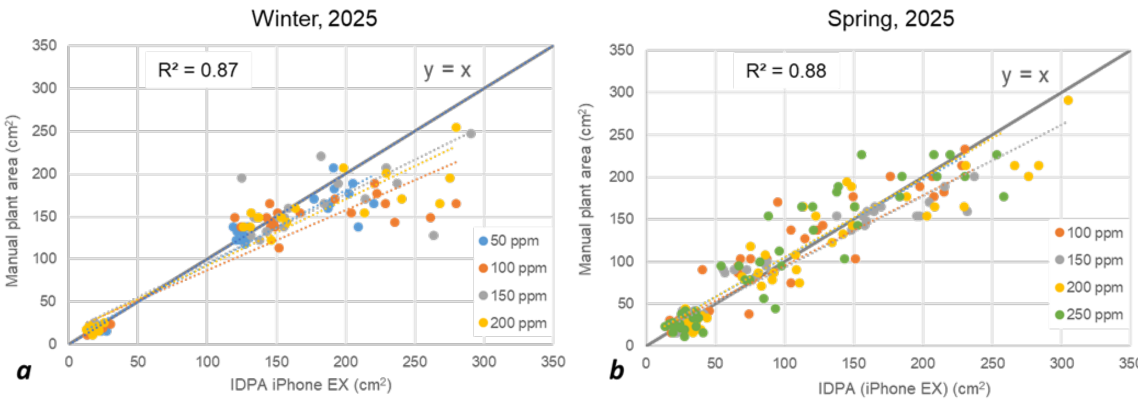


Fig. 5 Relationship between manual and image-derived plant area (IDPA) (cm²) using iPhone EX smartphone of *Lactuca sativa* 'Lalique' lettuce growth cycles during: (a) winter, between 9 Jan 11 Feb 2025; and (b) spring, between 4 April and 29 April 2025. Nitrogen [N] treatments included 50 ppm (*blue*) (only in the winter cycle), 100 ppm (*orange*), 150 ppm (*grey*), and 200 ppm *(yellow*) and 250 (*green*) (only in the spring cycle) treatments.

Discussion

The strong cross-device correlations (R^2>0.98) demonstrate that smartphone-based RGB phenotyping can reliably monitor hydroponic lettuce growth across different devices, validating the protocol's robustness for future farm-scale implementation. The critical finding is that IDPA accurately predicts manual estimates only when plants are non-overlapping (R^2=0.97 excluding harvest data), revealing that canopy occlusion is the fundamental limitation of top-down RGB imaging. This aligns with the scientific literature showing that image-derived plant area diverges from manual measurements at harvest due to rosette self-occlusion in dense canopies (Li et al., 2020; Ojo et al., 2024). The systematic overestimation at harvest suggests that IDPA should be interpreted as projected plant area rather than true plant area, particularly in mature plants where overlap is inevitable. The current IDPA protocol was unable to detect nitrogen treatment effects reveals important methodological and experimental constraints. While this contrasts with expectations that validated phenotyping should distinguish nutrient strategy effects, the likely contributors—space constraints limiting horizontal growth, and technical difficulties with solution filters, suggest the limitation is contextual rather than fundamental to the protocol.

The IDPA protocol's primary value for farm integration lies in its simplicity and cross-device robustness, enabling frequent, low-cost monitoring during vegetative growth without dedicated hardware. However, the systematic overestimation at overlap and harvest means IDPA is most reliable for early-to-mid growth stages (approximately DAP 0–20 in this study). For practical deployment, growers should use IDPA as a quantitative measurement layer for tracking growth trajectories and crop uniformity. A hybrid workflow—IDPA for frequent vegetative monitoring combined with traditional manual assessment near harvest—maximizes advantages while mitigating limitations.

Future work should address the fundamental limitations identified by prioritizing: (1) experiments with non-limiting space to eliminate spatial constraints that masked treatment effects; (2) additional imaging dates to define the precise transition point where IDPA accuracy degrades; (3) protocol improvements including SAM model optimization to reduce computational demand for real-time field application on standard farm hardware without specialized infrastructure, and overlap correction algorithms to address systematic overestimation when plants overlap; (4) multi-dimensional validation adding height and weight measurements throughout the growing cycle; (5) evaluation across additional varieties and hydroponic systems to assess generalizability; and (6) evaluation of RGB- and multispectral-based vegetation indices across nitrogen treatments to address limitations while maintaining practical advantages.

Conclusion

Smartphone-based RGB phenotyping using IDPA provides a robust, cross-device workflow for monitoring hydroponic lettuce growth dynamics under operational NFT conditions, especially during early-to-mid vegetative stages with non-overlapping canopies. By quantifying growth trajectories and variability across cycles, devices, and nitrogen treatments, this work shows that everyday smartphones can deliver reproducible plant area estimates that closely align with manual measurements for most of the growth period, while systematically overestimating area once canopy overlap intensifies near harvest. These findings position smartphone imaging as a practical, low-cost complement to traditional measurements for tracking crop uniformity and system variability, while highlighting the need for overlap-aware algorithms and additional structural traits to improve harvest-stage accuracy.

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