



Research Article

Indabot: A Simulation-Based Study of Low-Cost, ArUco Marker-Based Autonomous Navigation for Indoor Plant Phenotyping

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ABSTRACT

Autonomous robotic platforms are of critical importance for high-throughput plant phenotyping in controlled agricultural environments. The vast majority of existing systems are designed for open-field deployment and rely on satellite-based navigation, which is not suitable for enclosed greenhouse settings. This study presents the design, simulation-based performance analysis of Indabot, an autonomous mobile robot developed for wheat phenotyping in indoor environments. Each wheat sample is uniquely tagged with an ArUco marker, enabling drift-free, plant-level localization without the need for any GPS infrastructure. A rotation-based random search navigation scenario was designed in the Webots R2023b environment, in which the OpenCV ArUco module was combined with discrete-time PID controllers and lidar distance feedback. The system achieved a 100% target detection rate across 13 independent simulation runs, with a mean mission completion time of 282.4 ± 6.2 s ($n=13$, $CV=2.2\%$), a marker centering error of 3.06 ± 0.51 pixels, and an average approach time per target of 19.4 ± 0.4 s. The findings demonstrate that the Indabot platform, operating under ArUco-based guidance, offers a consistent, scalable, and low-cost autonomous phenotyping alternative for indoor agricultural environments. All performance metrics reported in this study were obtained exclusively within the Webots simulation environment; no physical validation of the platform has yet been conducted, and this constitutes a key limitation of the present work.

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1. INTRODUCTION

Global food security is under serious threat due to population growth, climate change, and the diminishing availability of arable land. Breeding efforts aimed at improving the productivity of wheat, which provides approximately 20% of the global caloric demand, rely heavily on accurate phenotypic measurements [1]. The high labor requirements and subjective nature of traditional manual methods have given rise to the concept of High-Throughput Phenotyping (HTP), which encompasses advanced sensing and robotic technologies [2]–[4]. Controlled Environment Agriculture (CEA) facilities are ideally suited for reproducible research thanks to the precise environmental control they provide [5]. The use of artificial intelligence-based models in such

environments enables detailed growth analyses [6]. However, the confined geometry of indoor spaces and the absence of GNSS signals restrict the deployment of existing field robots—such as BoniRob [7] and Thorvald II [8]—in these settings. More recent platforms such as PhenoRob-F [9] support both open-field and potted-plant phenotyping but rely on pre-defined navigation paths and lack mechanisms for individual plant-level identification via fiducial markers. While fixed indoor systems offer high precision, they lack flexibility and scalability. To overcome these limitations, ArUco fiducial markers offer a low-cost localization alternative [10]. The ArUco system enables 6-degree-of-freedom pose estimation through the Perspective-n-Point algorithm [11] and has been further enhanced through sensor fusion [12], 3D marker boards [13], and optimal placement strategies [14]. Although such

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markers have been employed in agricultural applications such as robotic arm calibration [15], their use for sequential autonomous phenotyping navigation through individual plant identification has not yet been sufficiently investigated in the literature.

Since physical testing of autonomous robots is costly, simulation environments are indispensable [16]. The Webots platform [17] provides high accuracy in the kinematic simulation of agricultural robots operating at low speeds. Although Webots is widely used for testing agricultural algorithms, a notable gap remains in the literature regarding the simulation of marker-based indoor phenotyping strategies. This study presents a GPS-independent, low-cost autonomous phenotyping platform that, unlike existing phenotyping robots designed primarily for GPS-dependent open-field deployment, eliminates the cumulative drift problem inherent to SLAM by assigning a unique ID to each plant via ArUco markers in enclosed greenhouse environments. The algorithmic novelty of this study lies in the rotation-based random search navigation strategy formulated under the assumption that marker locations are not known a priori, together with the dual PID architecture that simultaneously performs forward distance regulation and pixel-based heading deviation correction. The modular and reproducible hardware design—achieved through a sigma-profile chassis, hoverboard hub motors, and consumer-grade components—provides a reference architecture for research groups that lack access to high-cost systems.

Finally, the statistical validation conducted across 13 independent Webots runs and supported by target-based dispersion analyses establishes a level of methodological rigor that is rarely reported in comparable systems.

2. MATERIAL AND METHODS

2.1. Indabot Hardware Architecture

The Indabot platform is constructed from 30×30 mm aluminum sigma profiles, which enable straightforward assembly without the need for welding. The robot has approximate dimensions of $300 \times 350 \times 250$ mm (L $\times$ W $\times$ H) and a total weight of approximately 15 kg. The structural layout and the assembled platform are illustrated in Figure 1. Locomotion is provided by two hoverboard-type BLDC hub motors with a 165 mm wheel diameter, configured in a differential drive arrangement. This design eliminates the need for external gears, belts, or chain transmissions. The motors are driven by an ODrive 3.6 BLDC controller implementing the Field-Oriented Control (FOC) algorithm and communicate bidirectionally with the main computing unit over UART at 115200 baud. The computing unit is an NVIDIA Jetson Orin NX single-board computer. The LiDAR is used to measure distances to surrounding objects, while the camera serves both for the recognition of ArUco markers and for image acquisition. The technical specifications of the hardware are summarized in Table 1.

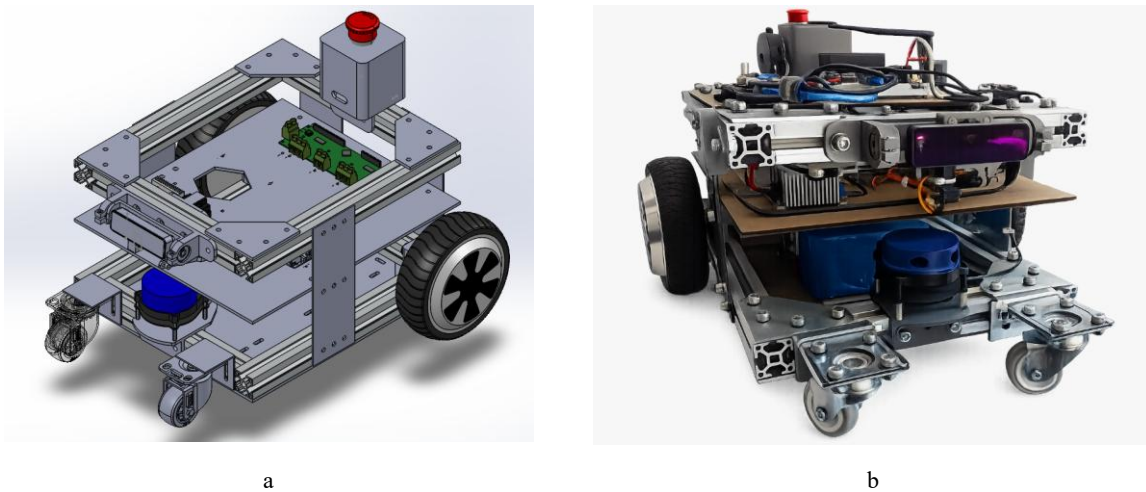
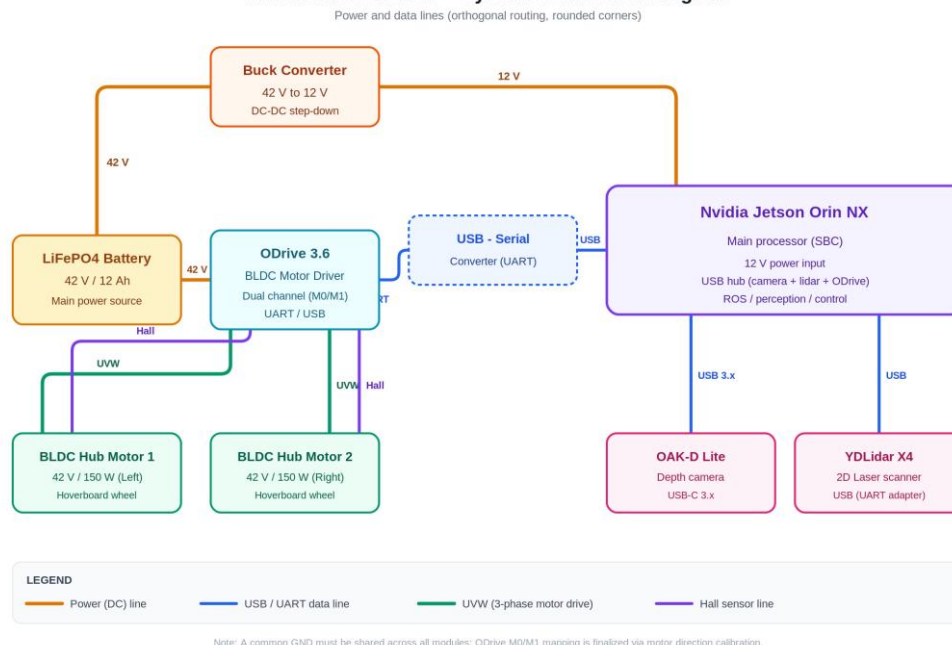


Figure 1. The Indabot autonomous phenotyping platform. **(a)** SolidWorks CAD model illustrating the structural layout and component placement. **(b)** Assembled physical platform showing the sigma-profile chassis, BLDC hub motors, OAK-D Lite stereo camera, and LiDAR sensor.

Component	Technical Specification	Role in the System
Motor Driver	ODrive 3.6 (FOC)	BLDC speed/position control, battery voltage monitoring
Drive Motors	Hoverboard BLDC Hub (Ø165 mm)	Differential drive locomotion
Battery	42 V, 12 Ah LiFePO4 (~500 Wh)	Main power source
Computing Unit	NVIDIA Jetson Orin NX (8 GB)	Image processing, navigation logic
Depth Camera	Luxonis OAK-D Lite (IMX214)	ArUco detection, RGB phenotyping
LiDAR Sensor	YDLidar X4 (360°, 0.12–10 m)	Distance measurement, safety monitoring
Chassis Frame	30 × 30 mm sigma profile	Structural support, modular assembly
Power Regulation	DC-DC buck converter (12 V)	Peripheral hardware power supply

The electrical subsystem is organized around a 42 V, 12 Ah LiFePO₄ battery (Figure 2). The battery directly powers the ODrive 3.6 and the two BLDC hub motors, while a DC-DC buck converter generates regulated 12 V output for the Jetson Orin NX and peripheral hardware. Optical isolation is implemented in the USB-to-serial converter. The separation of the motor and computing power lines minimizes electromagnetic interference arising from motor switching transients. The approximately 500 Wh capacity provides around 5 hours of continuous operation under typical phenotyping workloads.



2.3. Sensing and Computing Architecture

adaptive thresholding is applied to the grayscale image, and quadrilateral candidates are identified through contour detection and polygonal approximation; (iii) Marker Identification — each candidate quadrilateral is rectified via perspective transformation and binarized, then compared against the dictionary using Hamming distance matching; (iv) Center Computation — for each detected marker, the image-plane center is computed as the mean of opposite corners (Equation 2):

$$c_x = (x_{TL} + x_{BR}) / 2, \quad c_y = (y_{TL} + y_{BR}) / 2 \quad (2)$$

Here, c_x and c_y denote the horizontal and vertical pixel coordinates, respectively, of the ArUco marker's center point in the image plane. The values x_{TL} and y_{TL} represent the pixel coordinates of the marker's top-left corner, while x_{BR} and y_{BR} correspond to those of the bottom-right corner. These corner points are obtained from the four-corner vector returned in clockwise order by the `cv2.aruco.detectMarkers` function of the OpenCV library. Since the top-left and bottom-right corners constitute the diagonal corners of the marker, the arithmetic mean of these two points yields the geometric center of the marker.

The horizontal alignment error between the marker center and the camera's optical axis is defined as follows (Equation 3):

$$e_{\text{alignment}} = |c_x - W/2| \quad (3)$$

Here, $W = 640$ pixels denotes the image width. The marker is considered to be aligned when $e_{\text{alignment}} < 20$ pixels, which corresponds to an angular deviation of less than 2.25° given the camera's 73° horizontal field of view. Captured images are archived using a naming convention that incorporates the current timestamp and the ArUco marker ID associated with the corresponding plant.

2.5. PID-Based Motion Control

The robot's motion control system employs four independent discrete-time PID controllers. The standard discrete-time PID control law is formulated as follows (Equation 4):

$$u(k) = K_p \cdot e(k) + K_i \cdot \sum_{\tau=0}^k e(\tau) \Delta t + K_d \cdot [e(k) - e(k-1)] / \Delta t \quad (4)$$

Here, $u(k)$ is the controller output at time step k , $e(k)$ is the error signal, K_p , K_i , and K_d are the proportional, integral, and derivative gains, respectively, and $\Delta t = 0.05$ s is the sampling period derived from the Webots simulation time step. All controller outputs are clipped to the range $[-5, +5]$ rad/s to prevent actuator saturation. The controller parameters are listed in Table 2. The gain values listed in Table 2 were determined empirically through an iterative manual tuning procedure conducted within the Webots simulation environment, rather than through a formal auto-tuning method such as Ziegler–Nichols. For each controller, multiple candidate gain

combinations were tested, and their effect on the approach speed and the marker centering (alignment) error was systematically observed; the combination yielding the most stable and accurate performance for each controller was retained. This empirical approach was adopted because the simulated actuator dynamics differ from the idealized analytical plant models typically assumed by classical tuning methods, making manual adjustment a more practical choice for the present application.

Table 2. PID controller gains and functional assignments ($\Delta t = 0.05$ s; output range $[-5, +5]$ rad/s).

Controller	Kp	Ki	Kd	Setpoint	Function
pidx	3.0	0.025	0.08	1.0 m	Forward approach distance regulation
pidBackward	3.0	0.08	0.05	Variable	Reverse motion: return to pre-approach pose
pidYaw	3.0	0.2	0.07	0.0	Heading correction during in-place rotation
pidYawApproach	3.0	0.02	0.07	0.0	Steering during forward approach

The velocity controller (pidx) uses the forward distance measured by the LiDAR as its process variable and ensures that the target approach distance of 1.0 m is reached within a tolerance of ± 0.05 m. The heading controller (pidYawApproach) provides real-time steering correction during the drive-and-turn approach phase. In this mode, the pixel error is normalized to the range $[-1, +1]$ (Equation 5):

$$e_{\text{deviation}} = (W/2 - c_x) / (W/2) \quad (5)$$

Here, $e_{\text{deviation}}$ denotes the PID input signal, while $u_{\text{deviation}}$ denotes the PID output. The normalized error is fed into pidYawApproach, and its output $u_{\text{deviation}}$ modifies the left and right wheel velocities differentially: $v_{\text{left}} = v_{\text{forward}} + u_{\text{deviation}}$, $v_{\text{right}} = v_{\text{forward}} - u_{\text{deviation}}$. This dual PID architecture enables the robot to maintain visual centering while simultaneously reducing the distance to the target.

2.6. Webots Simulation Environment and Digital Twin

The navigation algorithm was developed and validated in the Webots R2023b environment prior to physical deployment. A three-dimensional robot model replicating the geometry, mass distribution, and joint configurations of the physical platform was created at 1:1 scale in SolidWorks, exported to URDF format using the SolidWorks-to-URDF plugin, and subsequently converted into the PROTO format used by Webots. The simulated robot incorporates virtual counterparts of all physical

sensors (Figure 3).

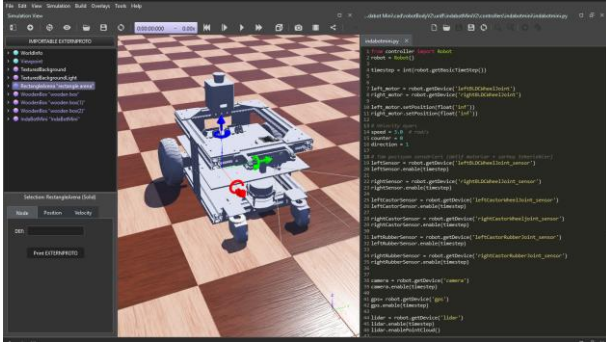


Figure 3. Webots simulation environment and robot control interface.

2.7. Navigation Scenario: Rotation-Based Random Search

A number of ArUco marker IDs equal to the number of plants is generated, starting from 0. The ArUco markers are placed on the plants without regard to ordering. The marker with ID 999 is reserved for terminating the operation; upon detecting marker 999, the robot completes the search task and initiates the parking procedure. The number and locations of the ArUco markers are not known in advance. Since the robot performs the search by rotating in place, the ArUco markers must be oriented to face the center of the simulation environment. The scenario consists of the following steps: (i) navigation to the center of the environment (gotoMidPoint), (ii) a 180° turn followed by a slow rotational scan, (iii) marker detection, alignment, and approach, (iv) image capture and timestamped archiving, and (v) return to the initial pose and continuation of the cycle. The robot measures its distance to the opposing wall using the angle and range data provided by the LiDAR within the 135°–225° sector (Equation 6):

$$d_{\text{wall}} = \max\{|\cos(\theta_i)| \cdot r_i\}, \quad i \in [135, 225] \quad (6)$$

Once the center point is reached, the robot performs a 180° turn and initiates a slow rotational scan (left motor at 1.0 rad/s, right motor stationary). The robot maintains a list of the IDs of previously visited plants. When an unvisited marker is detected, the alignToMarker procedure rotates the robot until centering is achieved. Once the marker is precisely centered in the camera image, the approachToMarker procedure is executed to initiate the approach maneuver. During the approach phase, a dual PID strategy is employed: pid_x regulates the forward velocity while pid_{YawApproach} simultaneously provides heading correction. When the robot's distance to the plant reaches 1 m, the robot halts. An image is captured and archived together with the marker ID and timestamp. The ArUco marker ID corresponding to the plant is then added to the list of visited markers. The robot subsequently returns to its initial pose. The cycle is repeated until the termination marker with ID 999 is detected. Upon

detecting ID 999, the robot approaches the marker, performs a 180° turn, and reverses into the parking position. A snapshot of the scenario running in Webots is shown in Figure 4. The video recording of the simulation in the Webots environment is provided in [18].

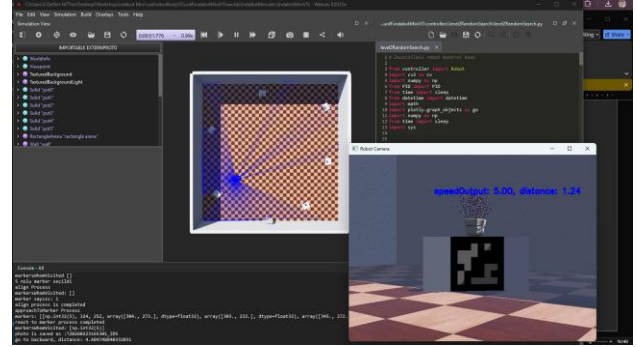


Figure 4. Webots simulation of the rotation-based random search scenario

3. RESULTS AND DISCUSSION

3.1. Marker Detection Performance

Under the uniform illumination of the simulation environment, the ArUco detection module achieved a 100% detection rate for markers within the camera's field of view at distances of up to approximately 4 m (Table 3). No false-positive detections or marker identity classification errors were recorded in any of the trials.

Table 3. Mission and detection performance metrics from 13 independent Webots runs (6 phenotyping + 1 parking target).

Performance Metric	Result
Marker detection rate	100%
Alignment accuracy (pixels)	≤ 20
Approach distance error (m)	± 0.05
Image capture success rate	100%
False-positive detections	0
Number of active PID controllers	4
Mission completion rate	100%

3.2. PID Performance and Statistical Results

The PID controllers exhibited stable convergence within the specified tolerance bands across all navigation phases, with no observable overshoot. The forward approach controller (pid_x) reached the target distance of 1.0 m within a tolerance of ±0.05 m in all 13 trials. Although $K_i = 0.025$ is modest in magnitude, it proved decisive in eliminating steady-state error under variable initial distances, while $K_d = 0.08$ provided sufficient damping to suppress oscillation during the final approach phase. The dual PID strategy ensured that the normalized pixel error remained below the 20-pixel threshold along more than 95% of the approach trajectory. The overall statistics obtained from 13 independent runs are presented in Table 4. The mean times across the 13 runs for the ordered ArUco marker IDs and the search-terminating marker (ID 999) are provided in Table 5.

Table 4. Overall statistics computed across 13 independent Webots runs.

Metric	Mean	SD	Min	Max
Total mission duration (s)	282.39	6.23	278.0	302.0
Mean detection time (s)	3.35	0.11	3.17	3.50
Mean alignment time (s)	3.44	0.15	3.17	3.67
Mean approach time (s)	19.44	0.43	18.50	20.00
Mean per-target visit time (s)	37.27	0.70	35.67	38.83
Mean alignment error (px)	3.06	0.51	2.50	3.83
Total duration of 6 regular visits (s)	223.62	4.17	214.0	233.0
Parking (999) sequence duration (s)	35.54	1.71	31.0	38.0

Table 5. Target-level mean timing and accuracy statistics (n = 13 runs per target).

ID	n	Detection (s)	Alignment (s)	Approach (s)	Visit (s)	Error (px)	Distance (m)
0	13	2.69	3.38	21.85	40.54	3.00	5.24
1	13	3.77	3.23	15.85	30.00	3.23	2.90
2	13	2.38	3.62	23.08	43.62	2.23	5.63
3	13	2.23	3.38	17.92	33.92	3.46	3.69
4	13	3.38	3.62	20.08	39.62	3.23	4.76
5	13	5.62	3.38	17.85	35.92	3.23	3.62
999	13	3.62	3.31	15.77	35.54	2.69	2.90

Target-based analysis reveals that the per-target visit time exhibits a positive correlation with the initial distance to the target: the most distant markers (ID 0, mean 5.24 m; ID 2, mean 5.63 m) yielded the longest visit times (40.54 s and 43.62 s, respectively). In contrast, the closest marker (ID 1, 2.90 m) was the fastest to be fully visited (30.00 s). However, this correlation is not strictly monotonic, as variations in the robot's initial heading orientation at the start of each search cycle introduce minor deviations in detection and alignment times. The system maintained the alignment error within a narrow band (mean 3.06 ± 0.51 pixels) regardless of the target distance.

3.3. Comparative Analysis with State-of-the-Art Systems

A comparison of Indabot with prominent autonomous phenotyping platforms reported in the recent literature is presented in Table 6. While PhenoRob-F [9] offers deep learning-based feature extraction and BoniRob [7] employs multi-sensor fusion with high-resolution imaging, both platforms primarily target field deployments or structured potted-plant phenotyping with predefined navigation paths and entail substantially higher hardware costs. Indabot, in contrast, addresses a hitherto underserved niche by providing a low-cost, GPS-independent, indoor-specific phenotyping robot that leverages fiducial markers for plant-level identification. To enable a common basis for comparison, throughput is expressed as the number of targets processed per hour. Based on the mean mission completion time (282.4 ± 6.2 s for 6 phenotyping targets), Indabot achieves an operational throughput of approximately 76.5 targets per hour. For comparison, PhenoRob-F has been reported to process up to 1875 potted plants per hour under its potted-plant phenotyping mode [9]. This order-of-magnitude difference reflects the differing operational scopes of the two systems: PhenoRob-F performs rapid imaging of

plants at fixed, pre-mapped positions, whereas Indabot autonomously searches for, approaches, and visually centers on each target within an unstructured arena, a task that inherently requires additional navigation and alignment time.

Table 6. Comparative overview of the Indabot platform against state-of-the-art autonomous phenotyping robots.

Feature	Indabot (This Study)	PhenoRob-F	BoniRob	Thorvald II
Target environment	Indoor/greenhouse use	Field + potted plants	Open field	Mixed
Localization	ArUco + LiDAR	Predefined path + rail	GPS + IMU	GPS + Laser
Plant identification	Fiducial marker (unique ID)	Deep learning	Spectral	Row counting
Computing unit	Jetson Orin NX	Industrial PC	Embedded PC	Embedded PC
GPS dependency	None	Partial (field only)	Required	Required
Simulation	Webots R2023b	Not reported	Not reported	Gazebo
Estimated cost	Low–Medium	High	High	Medium–High
Modular design	Yes (Sigma profile)	Partial	Yes	Yes
Throughput	~76.5 targets/h (47.1 s/target, mission-based)	~1875 plants/h (potted-plant scenario) [9]	Not reported	Not reported

3.4. Limitations and Discussion

The experimentally tuned gain parameters yield response characteristics that are well suited to the low-speed, structured greenhouse environment in which dynamic obstacles are absent and marker locations are predictable. Compared with SLAM, which entails high computational cost and is susceptible to cumulative drift during long-term operation, the ArUco marker-based plant identification approach provides absolute and drift-free identification at a negligible computational expense. The limitations of this study are as follows: (i) the simulation environment provides idealized conditions characterized by uniform illumination, the absence of dynamic obstacles, and noise-free sensor models; factors such as natural illumination variability, reflections from greenhouse glazing, dust accumulation, and partial occlusion by foliage will require explicit mitigation strategies in physical deployment; (ii) the encoder-based dead reckoning used during turning maneuvers is susceptible to wheel slip and may lead to cumulative angular drift over long operational sequences; (iii) the system performs image capture but does not yet incorporate automated phenotypic trait extraction; and (iv) comprehensive validation on the physical platform will be reported in a subsequent publication.

To help benchmark the expected sim-to-real performance gap, comparable Gazebo-based greenhouse

robot studies have reported successful transfer of simulation-validated navigation algorithms to physical hardware with only minimal additional tuning [19], while a recent review of the sim-to-real "reality gap" in robotics indicates that performance degradation upon physical deployment is common but can be substantially mitigated through techniques such as domain randomization and closely matched physical parameters [20]; these findings provide a qualitative reference point for the physical validation of Indabot planned for future work.

4. CONCLUSIONS

This study has presented the Indabot platform for autonomous wheat phenotyping under ArUco marker guidance in controlled indoor environments. The system integrates an ODrive 3.6 BLDC driver, hoverboard hub motors, a 42 V LiFePO4 battery, an NVIDIA Jetson Orin NX, a Luxonis OAK-D Lite camera, and a YDLidar X4 LiDAR on a modular sigma-profile chassis, combining OpenCV-based ArUco detection, discrete-time PID control, and LiDAR distance feedback within a Python-based software framework.

Across 13 independent Webots runs, the system successfully visited all targets (6 phenotyping missions + 1 parking maneuver) with a 100% success rate, achieving a mission completion time of 282.4 ± 6.2 s (CV = 2.2%), a mean per-target approach time of 19.4 ± 0.4 s, and a marker centering error of 3.06 ± 0.51 pixels.

The target-based analysis reveals that the approach time exhibits a positive correlation with the initial distance to the target, while the system maintains a consistent pixel-level accuracy that is independent of range. The comparative analysis demonstrates that Indabot fills a distinct niche in low-cost, GPS-independent, fiducial marker-based indoor phenotyping. Future work on Indabot will proceed along the following directions: (i) deployment of the developed algorithms on the physical Indabot platform within an operational greenhouse facility and validation under real-world conditions; (ii) automated extraction of quantitative morphological traits—such as plant height, leaf area, and growth rate—from temporal image sequences; (iii) correction of the cumulative angular and positional drift incurred during long-term operation through visual odometry or ArUco-aided SLAM methods; (iv) development of multi-robot coordination strategies to enable the simultaneous phenotyping of large plant populations; and (v) quantitative evaluation, through controlled greenhouse experiments, of the labor savings, data throughput, and measurement consistency gains afforded by the autonomous system relative to manual methods.

Declaration of Ethical Standards

This study is based entirely on simulation-generated data and did not involve human participants, human tissue,

animals, or patient-specific records. Therefore, ethical approval and informed consent were not required for this work.

Credit Authorship Contribution Statement

The conceptualization, software development, simulation, and data curation were carried out by Fikret Uysal. The formal analysis and validation of results were performed by Kadir Sabanci. The original draft was written by Fikret Uysal; review, editing, and supervision were undertaken by Kadir Sabanci.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The simulation scenario is publicly available at <https://doi.org/10.5281/zenodo.21372809>; additional resources and datasets are available from the corresponding author upon reasonable request.

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