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MACHINE VISION-GUIDED FOUR-AXIS ROBOTIC ARM FOR LETTUCE SORTING IN CONTROLLED ENVIRONMENT AGRICULTURE (CEA)

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ABSTRACT

This work introduces a low-cost, machine-vision-guided four-axis robotic arm for automated pick-and-place sorting of leafy vegetables in Controlled Environment Agriculture (CEA). The system consists of an articulated robotic arm, SG90 servo actuation, a PCA9685 PWM driver, a pneumatic parallel gripper, an Arduino-based controller, an ESP32 Wi-Fi data logging, and an OpenCV-based pipeline for HSV color classification. Three lettuce cultivars (Red Oak, Green Oak, and Red Coral) were tested in 27 trials (3 sessions, 3 trials per cultivar). The system achieved an overall classification accuracy of 96.3%, with one Red Coral sample misclassified due to low color saturation near the HSV threshold boundary. The mean cycle times were 26.73, 32.64, and 37.03 s for Red Oak, Green Oak, and Red Coral lettuce, respectively. The prototype demonstrated stable repeatability, no specimen drops, and no visible leaf damage at a gripping force of 0.8 N. The results demonstrate the practical viability of reducing repetitive manual sorting tasks in small and medium greenhouse operations. However, threshold-based HSV classification is sensitive to lighting and cultivar color variability. Future work should integrate CNN-based classification, improved end-effector compliance, and validation in long-duration greenhouse trials.

Keywords: Agricultural robotics, Controlled environment agriculture, Lettuce sorting machine vision HSV, Segmentation robotic gripper, Greenhouse automation.

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1. INTRODUCTION

High-quality vegetables are increasingly being grown in Controlled Environment Agriculture (CEA), including hydroponic greenhouses, vertical farms, and plant factories – in areas with limited land, water, and labor resources (Charoenrak et al., 2024; Bhattarai et al., 2025; Burritt et al., 2025; Watcharinrat et al., 2026). CEA systems provide improved climate control, reduced pesticide use, and more consistent crop quality, but much of the post-harvest work remains labor-intensive. The sorting of leafy vegetables, in particular, involves repeated visual inspection, manual handling and the placement of cultivars. Long harvest periods are characterized by repetitive operations which are susceptible to fatigue, lighting variation and variation in worker skill, making it difficult to maintain throughput and classification consistency (Shamshiri et al., 2018; Ojo & Zahid, 2022; Petropoulou et al., 2023). The availability of labor is a major challenge in greenhouse production. This has resulted in considerable interest in agricultural robotics as a means of reducing reliance on manual labor, and improving process repeatability in harvesting, handling and sorting operations (Droukas et al., 2023; Fulcher et al., 2023; Marinoudi et al., 2024). Previous reviews have shown that agricultural robots can assist field and greenhouse operations and have also identified persistent barriers, including high cost, difficult system integration, sensitivity to unstructured environments, and limited adaptability to crop morphology (Bac et al., 2014; Bechar & Vigneault, 2016; Grieve et al., 2019; Kootstra et al., 2021; Mail et al., 2023; Fontani et al., 2025; Spagnuolo et al., 2025). These barriers are particularly relevant for small and medium greenhouse enterprises, where commercial industrial robots may be out of reach in terms of capital budgets and may require specialized programming skills. Recent advances in low-cost microcontrollers, open-source software, compact cameras and lightweight actuators have made entry-level agricultural robotic platforms more accessible. For proof-of-concept agricultural automation, modular robotic

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systems can be constructed by linking servo drivers, Wi-Fi telemetry and local databases with Arduino and ESP32 platforms (Jaime et al., 2014; Sathitbunanan & Ritthong, 2017; Simo et al., 2022; Luo et al., 2023; He et al., 2025). At the same time, machine vision has emerged as a key enabling technology for crop recognition, defect detection, maturity estimation and robotic guidance. Camera-based systems are particularly suitable for sorting leafy vegetables, as cultivar identity is often associated with visible colour, leaf texture, and morphology (Zhang et al., 2020; Ojo & Zahid, 2022). Agricultural image classification can be done using rule-based image processing or machine learning. Rule-based methods include RGB, HSV, and Lab colour-space segmentation, which are computationally lightweight, transparent, and suitable for real-time operation on low-cost hardware. HSV-based classification is especially useful when hue and saturation are well discriminative of target classes. However, such methods are sensitive to illumination intensity, background color, camera white balance and cultivar color variability (Kamilaris & Prenafeta-Boldú, 2018). Deep learning methods, particularly convolutional neural networks (CNNs), can learn more robust color-texture features and generally outperform simple thresholds when large labelled datasets are available (Hassim et al., 2020; Benos et al., 2021; Sánchez-Molina et al., 2024). However, implementing CNNs requires more training images, greater computational resources, and careful model validation, which may not be immediately feasible for small-scale greenhouse prototypes. Lettuce varieties were chosen for this study because they are commonly grown in CEA systems, typically sorted by cultivar type and appearance, and exhibit clear differences in color and leaf morphology. Red Oak Lettuce, Green Oak Lettuce and Red Coral Lettuce were selected as representatives of three visually distinguishable groups: red-burgundy compact leaves, green rosette leaves and red-violet lobate leaves. These cultivars provide a convenient test set for a low-cost vision-guided sorting platform as they include both relatively simple color separation and more difficult boundary cases due to pigmentation variability. This choice also reflects real greenhouse operations in Southeast Asia, where several leafy vegetable cultivars are often grown in the same greenhouse and need to be quickly sorted after harvest (Xiong & Hong, 2025; Tabassum et al., 2026). A further problem in robotic handling of vegetables is the design of the end-effector. Leafy vegetables are delicate biologicals and can be bruised, torn or permanently deformed if too much gripping force is applied. Pneumatic and soft robotic grippers have been extensively investigated for delicate crop handling as they can provide compliant contact and fast actuation with reduced mechanical damage (Navas et al., 2024; Zhang & Wang, 2025; Zhang et al., 2025a; 2025b). The soft grippers allow greater adaptability to object shape, but the pneumatic parallel grippers remain attractive for low-cost sorting systems, as they are mechanically simple, easy to control, and appropriate for fixed-position pick-and-place handling when the crop mass and geometry are bounded. There is some progress in agricultural robotics and crop classification based on vision. However, many published works address only one subsystem, i.e. robotic arm mechanics, vision classification or gripper design. Fewer studies have presented a fully integrated and experimentally validated low-cost system that combines machine vision, robotic motion control, pneumatic gripping, real-time data logging and multi-cultivar lettuce sorting in a single CEA-oriented platform. This leads to a knowledge gap for small and medium greenhouse enterprises, which need practical evidence on system performance, repeatability, classification accuracy, specimen integrity and implementation limitations. The novelty of this work lies in the development and experimental evaluation of a complete machine-vision-guided four-axis robotic arm for automated lettuce sorting in CEA. The contribution is fourfold: (i) a low-cost integrated architecture combining a 2D camera, OpenCV-based HSV classification, Arduino-PCA9685 servo control, pneumatic gripping, and ESP32-MySQL data logging; (ii) experimental performance evaluation across 27 trials involving three lettuce cultivars; (iii) quantitative reporting of cycle time, repeatability, classification accuracy, confusion matrix metrics, gripper performance, and throughput; and (iv) practical discussion of limitations and future improvements, including CNN-based classification, soft gripping, and commercial greenhouse scalability.

2. MATERIALS AND METHODS

2.1. System Architecture Overview

The experimental system consisted of four integrated subsystems: (1) a four-axis articulated robotic arm with a pneumatic end-effector, (2) a 2D area-scan camera and image-processing pipeline running on a host computer, (3) an Arduino Mega 2560 microcontroller connected to a PCA9685 16-channel PWM servo driver through I2C communication and (4) an ESP32 Wi-Fi module connected to a MySQL database for operational logging. The control pathway followed the sequence: camera acquisition, host-computer image processing, serial command transmission, Arduino interpretation, PWM servo actuation, pneumatic valve control, and cycle data logging. The system architecture is shown in Fig. 1.

2.2. Experimental Design and Lettuce Cultivar Selection

Three lettuce cultivars were selected to represent common leafy vegetable types in greenhouse production: Red Oak Lettuce, Green Oak Lettuce, and Red Coral Lettuce. These cultivars were used because they differ in hue, saturation, and leaf morphology, allowing the machine-vision classifier to be evaluated under both clear and boundary color conditions. Each cultivar was tested in three independent sessions with three technical trials per session, giving nine trials per cultivar and 27 trials in total. Fresh specimens with an approximate mass of 100 g were used for the trials to avoid repeated handling effects such as leaf deformation, moisture loss, or color change. Each trial consisted of specimen placement, image capture, classification, robotic pick-up, transport to the target angular position, release, return to home position and cycle-time recording. The experimental workflow is summarized in Fig. 2.

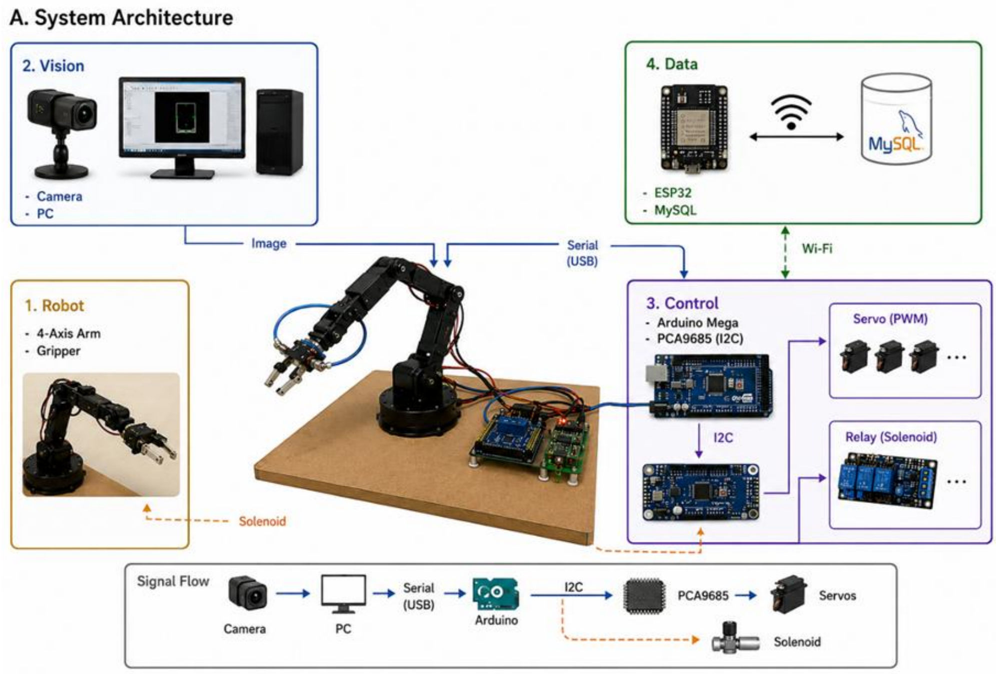

Fig. 1: Integrated robotic system architecture showing machine-vision processing, Arduino-based motion control, pneumatic gripping mechanism, Wi-Fi communication, and MySQL database logging for automated manipulation and operational monitoring tasks.

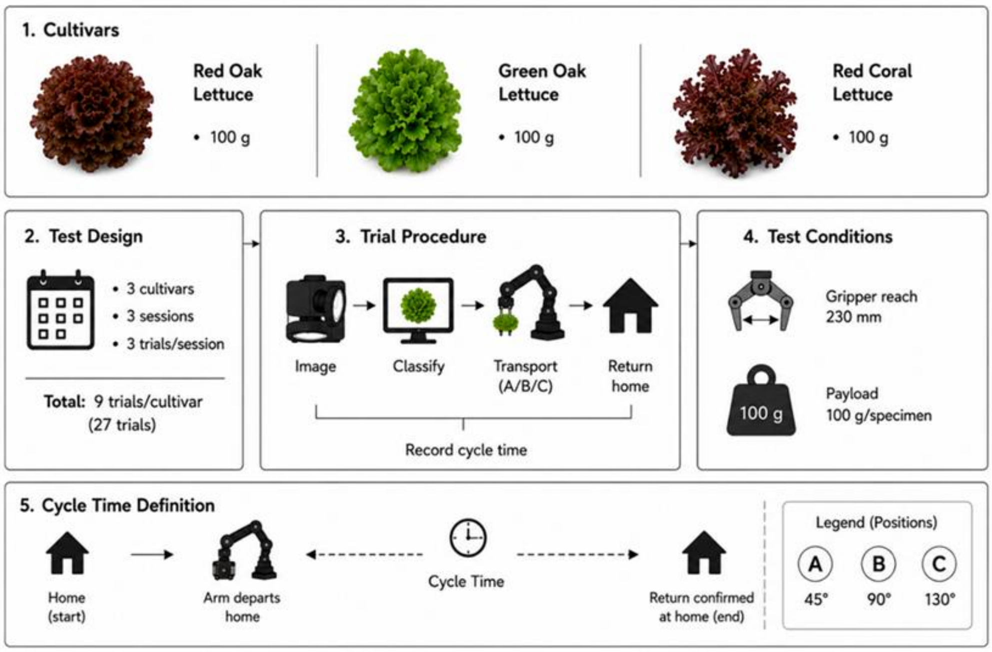

Fig. 2: Experimental workflow for automated lettuce classification and robotic handling, including cultivar selection, repeated trial design, imaging, transport, payload-controlled, and cycle-time.

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2.3. Robotic Arm Mechanical Design and Kinematic Model

The robotic arm was defined as a four-degree-of-freedom articulated chain including a waist joint, shoulder joint, elbow joint, and pneumatic gripper axis (Wang, et al., 2023; Garje et al., 2026). The total arm reach was 300 mm, and sorting was performed at a stable effective reach of 230 mm. Red Oak, Green Oak and Red Coral lettuce were targeted at 45°, 90° and 130° relative to the home position, respectively. The mechanical setup is shown in Fig. 3.

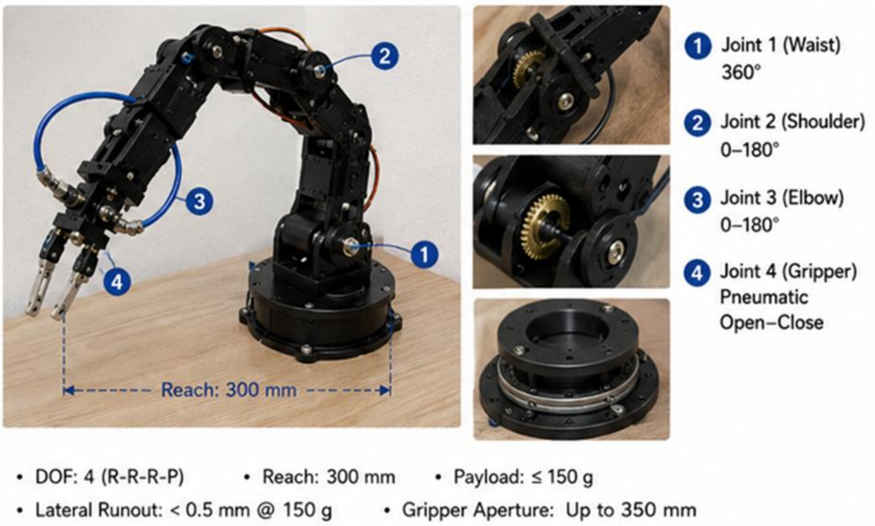

Fig. 3: Four-axis robotic arm showing joint allocation, reach, payload range, pneumatic gripper, and lightweight structure for vegetable handling.

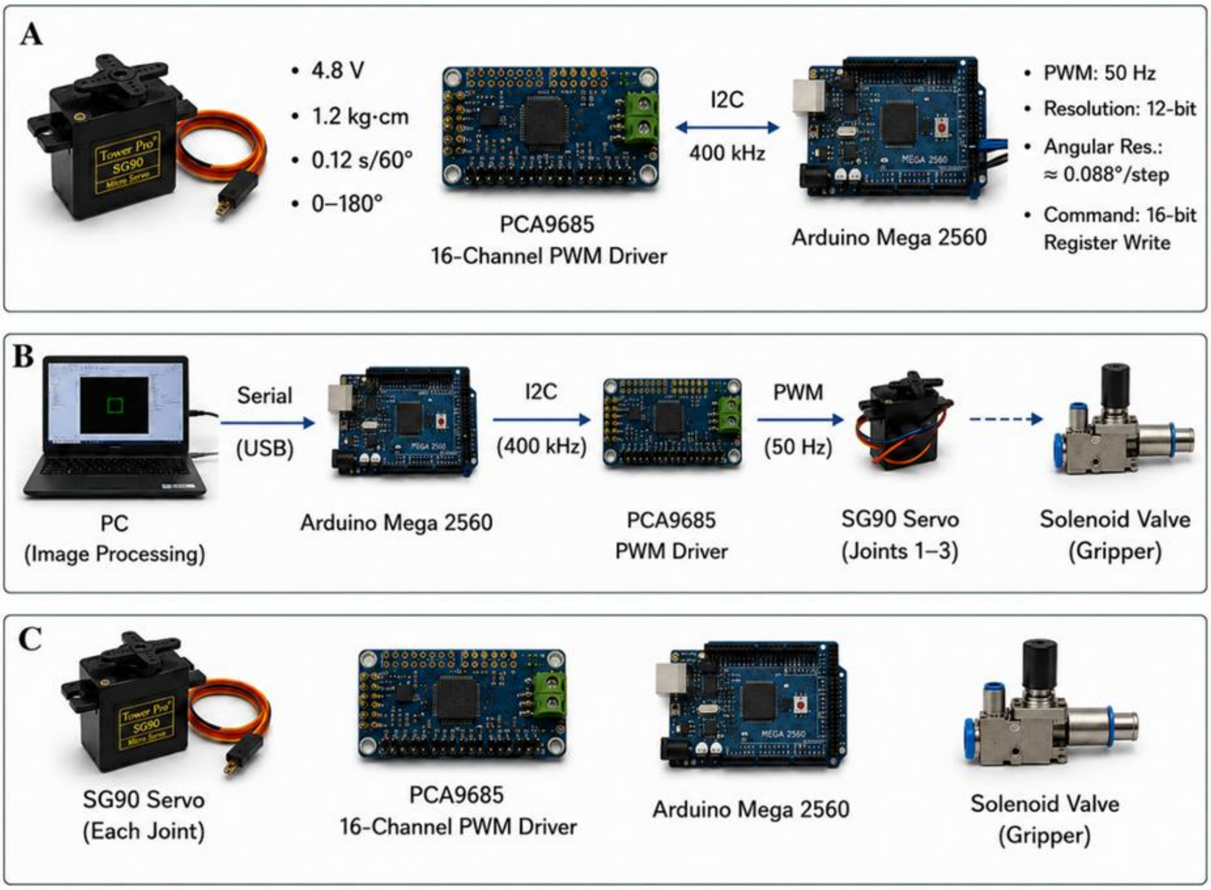

Fig. 4: Integrated actuator and control-electronics configuration, including SG90 servo motors, PCA9685 PWM driver, Arduino Mega 2560, and pneumatic solenoid actuation.

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For a simplified planar analysis, the arm was modelled as a two-link revolute chain representing shoulder and elbow movements, and the sorting direction was determined by the waist angle. The position of the end-effector in the horizontal working plane was approximated by:

$$x = L_1\cos(\theta_1) + L_2\cos(\theta_1 + \theta_2) \tag{1}$$

$$y = L_1\sin(\theta_1) + L_2\sin(\theta_1 + \theta_2) \tag{2}$$

Where L_1 and L_2 are the effective link lengths, θ_1 is the shoulder angle, and θ_2 is the elbow angle. The waist rotation angle, θ_0 was used to orient the arm towards the target sorting bay. The joint command sequence was implemented as a five-stage trajectory: home, approach, grip, transfer, release and return. Servo actuation and electronic control are shown in Fig. 4.

2.4. Pneumatic Gripper and Specimen Handling

The end-effector was a pneumatic parallel gripper supplied at 0.4 MPa with 4 mm polyurethane tubing. The open-close state was controlled by a 5/2 solenoid valve, and the gripper position was monitored via reed-switch binary signals (Korotych et al., 2026). A gripping force of approximately 0.8 N per finger was adjusted to hold 100 g lettuce specimens without visible mechanical damage. Gripper performance was evaluated in terms of engagement confirmation time, dropped-specimen events, and visual inspection of the specimens after each full pick-place-return cycle. Fig. 5 shows the pneumatic system.

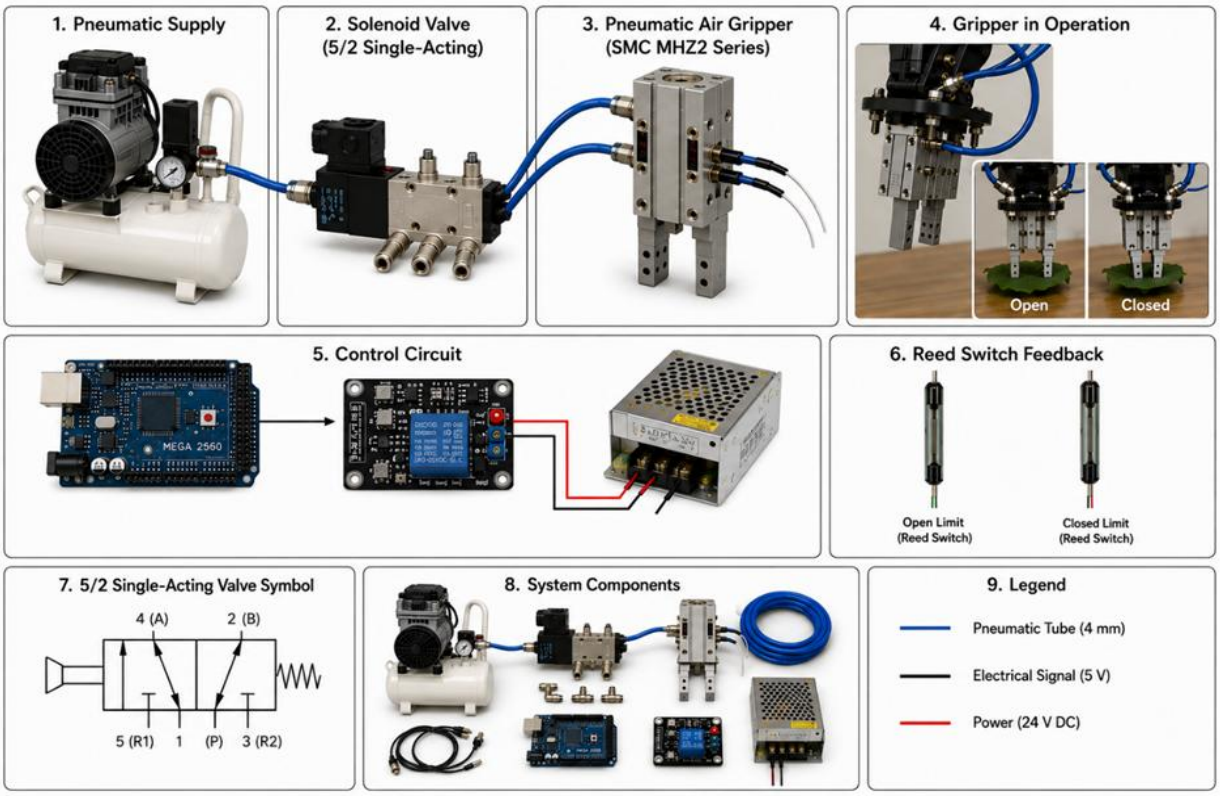

Fig. 5: Pneumatic gripping and valve-control system showing compressor supply, 5/2 solenoid valve operation, parallel gripper, relay control, and reed-switch feedback.

2.5. Camera, Image Processing, HSV Thresholding and Lighting Calibration

A 2D USB area-scan camera (1920x1080 pixels) was mounted vertically above the imaging zone at a working distance of 350 mm. A ring LED light (5600 K) was installed around the camera to minimize shadows and enhance color uniformity. Before the experiments, lighting calibration was performed by fixing the camera exposure, white balance and LED intensity, and then taking a picture of a white reference background and representative samples of each cultivar. The HSV thresholds were empirically determined from pilot images by sampling the region of interest (ROI) from each cultivar and choosing hue and saturation intervals that maximized the separation among classes and minimized the inclusion of background.

Each image was converted from BGR to HSV color space using OpenCV. A Gaussian blur filter (5x5 pixels, sigma = 1.2) was applied to reduce leaf-texture noise. The classification rules were:
Red Oak Lettuce, H = 0°-15° or 340°-360° and S>0.40
Green Oak Lettuce, H = 85°-145° and S>0.35
Red Coral Lettuce, H = 280°-340° and S>0.45.

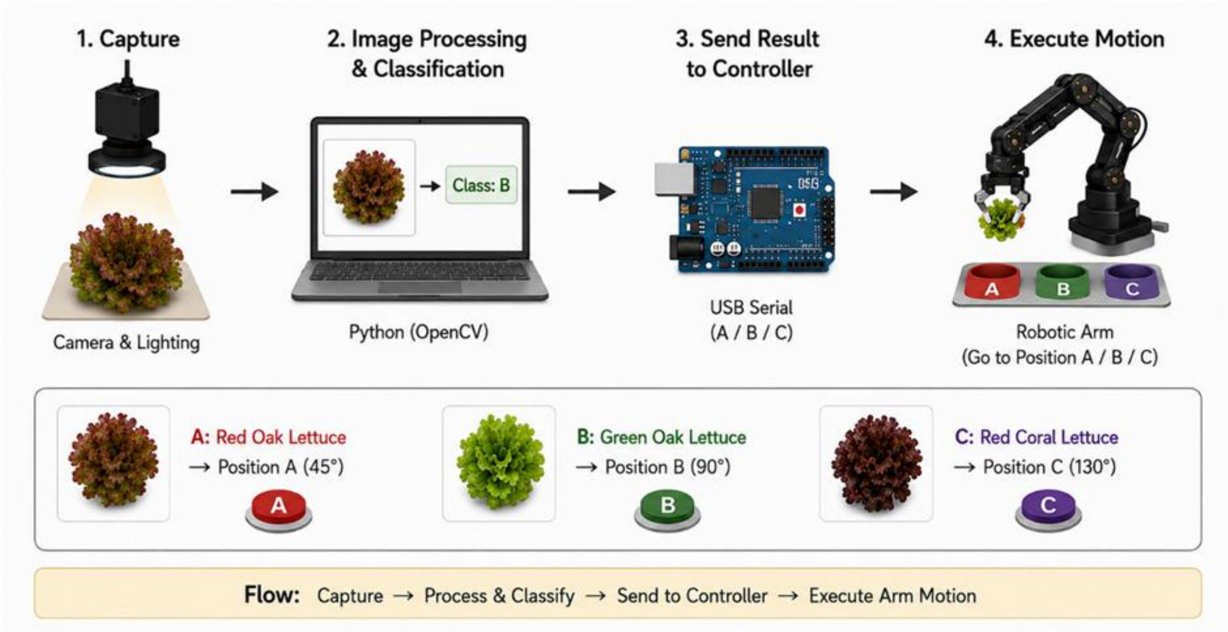

Fig. 6: Vision-guided robotic sorting workflow showing image capture, Open CV classification, serial communication, and robotic arm positioning.

These thresholds were selected because the three cultivars differ primarily by hue and saturation under controlled illumination. The complete vision-guided workflow is shown in Fig. 6, and a representative segmentation example is shown in Fig. 7.

Fig. 7: Representative image-processing stages for HSV-based lettuce segmentation raw RGB image, binary HSV mask, and segmented region of interest.

2.6. Control Software and Data Logging

The Arduino firmware was implemented using a finite-state machine with five states: IDLE, CLASSIFY_WAIT, APPROACH, TRANSFER, and RETURN. State transitions were triggered by the classification command and gripper reed-switch feedback. Joint angle interpolation between waypoints was performed using a linear ramp with a configurable delay to constrain angular velocity below 45°/s. The ESP32 module transmitted each cycle record to a MySQL database through the local Wi-Fi network. Each record included a timestamp, a classified cultivar, a target position, and a cycle duration. The software and logging architecture are shown in Fig. 8.

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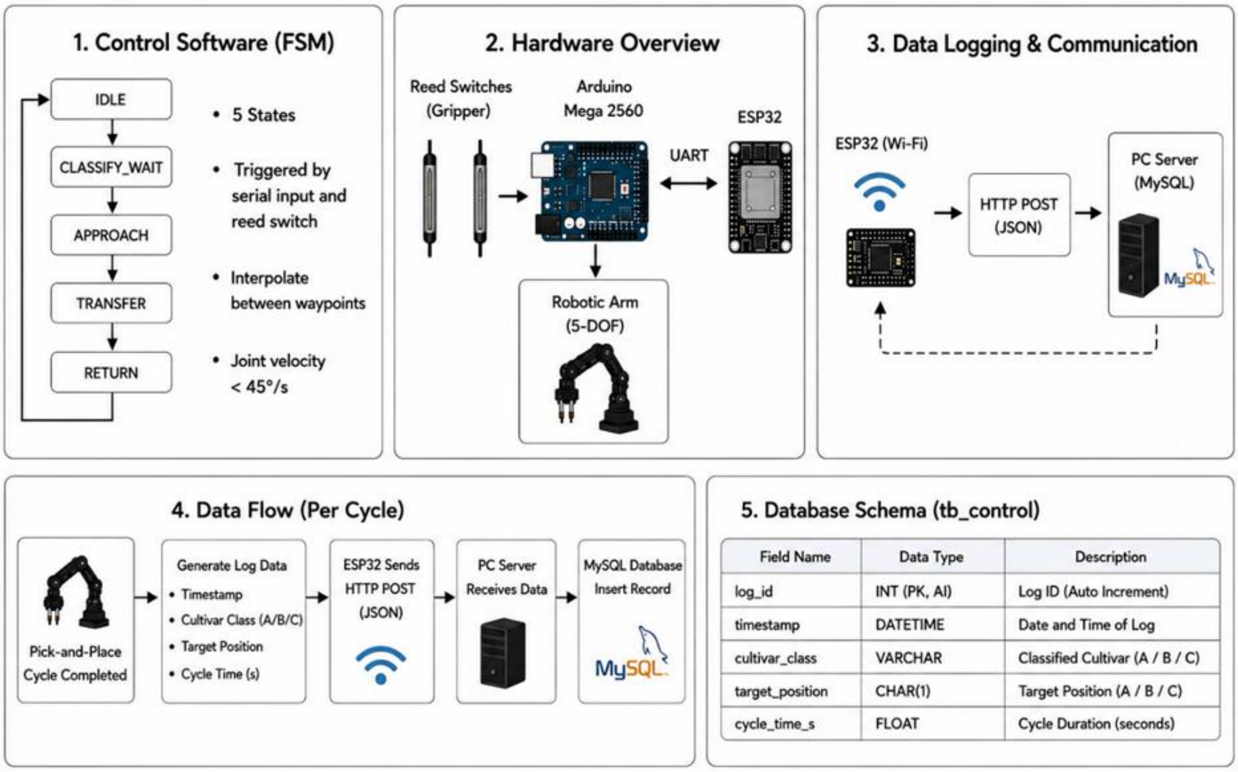

Fig. 8: Control-software and data-logging architecture showing finite-state machine operation, Arduino-ESP32 communication, Wi-Fi transmission, and MySQL storage.

2.7. Experimental Protocol

The cultivars tested were Red Oak Lettuce (average specimen mass 100 g; compact rosette morphology; deep red-burgundy pigmentation), Green Oak Lettuce (average specimen mass 100 g; erect panicle morphology; light-to-mid green pigmentation) and Red Coral Lettuce (average specimen mass 100 g; highly lobate frond morphology; red-violet pigmentation). Each cultivar was tested in three independent sessions, with three trials per session (nine trials per cultivar, 27 trials in total). For each trial, a single specimen was placed at the camera imaging position, classified, transported to the designated angular position, and returned to the home position with cycle time recorded from arm departure from home to return confirmation. All tests were performed with a constant gripper reach of 230 mm and a constant payload of 100 g per specimen. Overall, in Fig. 2.

2.8. Statistical Analysis

Statistical analysis was performed using Python 3.10 with numpy, scipy, and statsmodels. Cycle time, gripper engagement time, throughput and classification metrics were summarized using mean, standard deviation (SD), standard error (SE), coefficient of variation (CV) and 95% confidence intervals where appropriate. Cycle times among lettuce cultivars were compared using one-way analysis of variance (ANOVA) followed by Tukey's honestly significant difference (HSD) post-hoc test when differences were significant. The significance level was set at alpha = .05. Image classification was evaluated using a confusion matrix, accuracy, precision, recall, and F1-score. Discussion of practical adoption constraints based on system cost, maintenance, payload limitation and greenhouse scalability was provided qualitatively.

3. RESULTS

3.1. Cycle Time Performance

Mean cycle-time results are shown in Table 1. Red Oak Lettuce required the shortest mean cycle time because it was assigned to Position A at 45°, which required the smallest waist rotation. Green Oak Lettuce required a longer cycle time because it was assigned to Position B at 90°, while Red Coral Lettuce required the longest cycle time at Position C because of both greater angular travel and more irregular frond morphology. Statistical grouping indicates that the three cultivar-position combinations produced distinct cycle-time responses under the tested operating conditions.

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Table 1: Cycle-time performance by cultivar and target position. Different letters indicate statistically different groups at alpha = 0.05

Cultivar	Position	Angle (°)	Reach (mm)	Mean cycle time (s)	SD (s)	SE (s)	CV (%)	Significance
Red Oak Lettuce	A	45	230	26.73	1.08	0.36	4.04	a
Green Oak Lettuce	B	90	230	32.64	1.31	0.44	4.01	b
Red Coral Lettuce	C	130	230	37.03	1.48	0.49	4.00	c
Combined cycle	A-B-C	-	-	96.40	-	-	-	-

3.2. Motion Repeatability and Positioning Accuracy

Table 2 shows the evaluation of motion repeatability based on cycle-time variation and final target-zone consistency. The deterministic servo command structure showed low temporal variability for repeated point-to-point movements. The mechanical inspection also confirmed that the gripper's contact face was within the target placement zone during the 100 g payload experiments. Because joint encoders and high-resolution optical metrology were not part of the prototype, the positional repeatability presented here should be considered as lab target-zone repeatability, not industrial metrology-grade accuracy.

Table 2: Motion repeatability and observed target-zone consistency under 100 g payload conditions.

Cultivar	Target angle (°)	Cycle-time SD (s)	CV (%)	Observed target-zone repeatability
Red Oak Lettuce	45	1.08	4.04	Within the target zone, lateral runout<0.5 mm at the gripper contact face
Green Oak Lettuce	90	1.31	4.01	Within the target zone, lateral runout<0.5 mm at the gripper contact face
Red Coral Lettuce	130	1.48	4.00	Within the target zone, lateral runout<0.5 mm at the gripper contact face

3.3. Image Classification Performance

The HSV classifier correctly classified 26 out of 27 samples, with an overall accuracy of 96.3%. The only misclassification was a Red Coral sample with low saturation near the HSV decision boundary that was classified as Green Oak Lettuce. Tables 3 and 4 show the confusion matrix and classification metrics. In that order. These results suggest that HSV-based classification is suitable under controlled laboratory illumination, but boundary cases may arise due to variation in cultivar pigmentation within the same class.

Table 3: Confusion matrix for HSV-based lettuce cultivar classification

Actual / Predicted	Red Oak	Green Oak	Red Coral	Total
Red Oak	9	0	0	9
Green Oak	0	9	0	9
Red Coral	0	1	8	9
Total	9	10	8	27

Table 4: Precision, recall, and F1-score for HSV-based image classification

Class	Precision	Recall	F1-score	Support
Red Oak Lettuce	1.000	1.000	1.000	9
Green Oak Lettuce	0.900	1.000	0.947	9
Red Coral Lettuce	1.000	0.889	0.941	9
Macro average	0.967	0.963	0.963	27
Overall accuracy	-	-	0.963	27

3.4. Gripper Performance and Specimen Integrity

The pneumatic gripper successfully engaged and released all 27 lettuce specimens with zero drop-specimen events. The average confirmation time in the closed state ranged from 82 ms to 90 ms across cultivars. The full pick-place-return cycle showed no visible bruising, tearing, or deformation residue. As for Red Coral Lettuce, the engagement and confirmation period was longer due to the irregularities in frond morphology, suggesting that gripper contact geometry affects handling time for leafy vegetables (Liu et al., 2026a). As shown in Fig. 9 and Table 5, respectively.

Table 5: Gripper confirmation time and specimen integrity results

Cultivar	Closed confirmation time (ms)	Dropped specimens	Visible damage	Interpretation
Red Oak Lettuce	82 ± 11	0/9	None	Stable compact morphology
Green Oak Lettuce	83 ± 10	0/9	None	Stable contact surface
Red Coral Lettuce	90 ± 13	0/9	None	Longer confirmation due to lobate fronds

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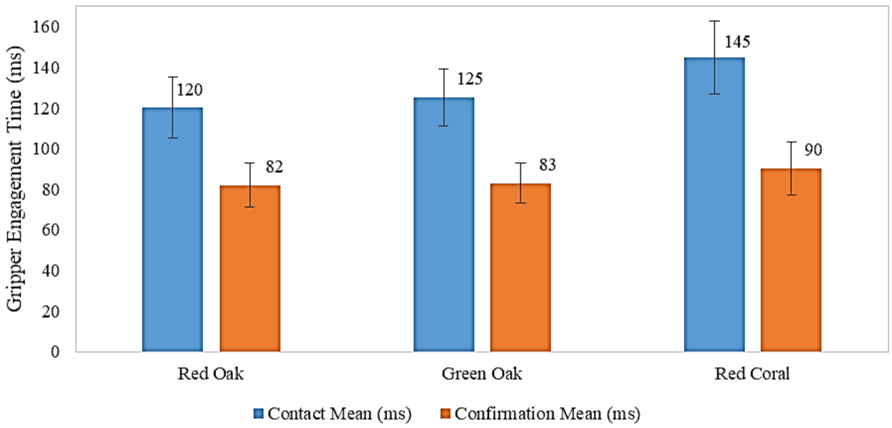

Fig. 9: Gripper performance evaluation showing engagement confirmation time, specimen integrity after handling, and cultivar-dependent gripper response.

3.5. Throughput and Labor Analysis

Throughput analysis is summarized in Fig. 10. Under single-cultivar batch arrival, the prototype produced estimated throughputs of 134.7, 110.3, and 97.2 specimens/h for Red Oak, Green Oak, and Red Coral lettuce, respectively. These results are comparable to the lower range of manual sorting rates reported for greenhouse workers under sustained operation. However, economic interpretation should be approached with caution because the prototype was tested in a controlled laboratory environment and did not include long-duration maintenance, sanitation, shift-level downtime, or full commercial integration costs.

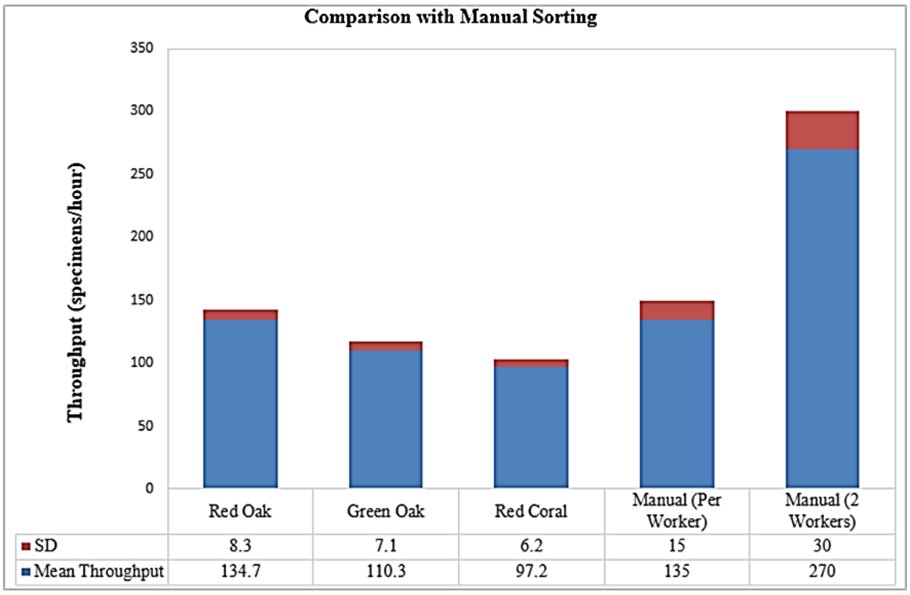

Fig. 10: Throughput and labor-comparison results under continuous and batch-arrival sorting assumptions.

4. DISCUSSION

The results show that a low-cost machine-vision-guided robotic arm can be used for repeatable lettuce sorting under controlled laboratory conditions. The system achieved 96.3% classification accuracy and completed all 27 pick-and-place trials without dropping any specimens or causing visible leaf damage. This is in line with the general direction of agricultural robotics, where low-cost robotic platforms are increasingly investigated to tackle labor constraints and repetitive post-harvest tasks (Bac et al., 2014; Bechar & Vigneault, 2016; Grieve et al., 2019; Kootstra et al., 2021; Mail et al., 2023; Fontani et al., 2025; Spagnuolo et al., 2025). The prototype is less sophisticated than commercial robotic sorting systems in terms of sensing, payload and motion control, but it provides a practical entry-level platform for small and medium greenhouse enterprises. The main advantage of the HSV-based vision pipeline is the simplicity of the computations. Standard host computers can perform HSV thresholding quickly and do not require large training datasets. This makes it attractive for greenhouse enterprises with limited technical resources. Similar color-space methods have been used in agricultural inspection and classification tasks where color is a dominant discriminating feature (Patel et al., 2012; Liu et al., 2026b). The three lettuce cultivars used in the present study were selected because they differ considerably in color and morphology. Thus, the HSV thresholds were effective at classifying most samples under the calibrated lighting conditions. But there are definite limitations to the HSV approach. The single misclassified Red Coral sample indicates that threshold-based rules are sensitive to variations in saturation and boundary cases. Environmental lighting, leaf moisture, camera white balance and cultivar-specific pigmentation can change hue and saturation values. Natural light fluctuation and shadows under commercial greenhouse conditions may be more pronounced than in the laboratory. Thus, the HSV classifier should be considered a baseline method, not a complete industrial solution. CNN-based classifiers may be more robust since they are able to learn color, texture, shape, and spatial features at the same time (Kamilaris & Prenafeta-Boldú, 2018; Zhang et al., 2020; Hassim et al., 2020; Benos et al., 2021; Ojo & Zahid, 2022). In future work, lightweight CNN architectures such as MobileNet or EfficientNet-Lite can be integrated to improve classification under variable illumination while maintaining real-time inference. The mechanical results show that the four-axis articulated configuration is enough for the fixed-position pick-and-place sorting. Predefined target positions simplified control and enabled open-loop servo actuation without expensive encoders. But it also reduces flexibility. In commercial greenhouse settings, tray positions are often inconsistent, specimen sizes vary, and packaging formats change. If the target locations are not fixed, a closed-loop visual serving system would be required. Moreover, SG90 micro servos limit payload capacity and durability over long durations. For larger vegetable heads, it would be better to replace the shoulder and elbow joints with a higher-torque servo or stepper motor with position feedback to increase load capacity and reliability.

The pneumatic parallel gripper showed a sufficient handling performance for the 100 g lettuce specimens without visible damage. This result supports the use of low-force pneumatic gripping for the manipulation of leafy vegetables. However, due to the irregular frond morphology, Red Coral Lettuce required longer confirmation time, indicating that rigid parallel gripper fingers are not equally suitable for all leaf shapes. Recently, soft robotic grippers have been studied, and compliant fingers are reported to conform to different product geometries and minimize contact stress (Navas et al., 2024; Zhang & Wang, 2025; Zhang et al., 2025a; 2025b; Hua et al., 2025). Future prototypes should benchmark the current pneumatic parallel gripper against soft or adaptive grippers based on objective damage metrics such as color change, bruising area, mass loss and mechanical compression response. From an operational perspective, the system offers a potential labor-saving approach for sorting greenhouses. The prototype achieved cultivar-dependent throughputs of about 97-135 specimens per hour. This means that a robotic sorter could help with repetitive sorting tasks, particularly during harvest periods when workers are subject to fatigue and repetitive postures. But the reduction in the labour force should not be considered a direct replacement rate without taking into account the actual commercial constraints. Time required to set up the system, sanitation requirements, actuator maintenance, air supply stability, camera cleaning, database connectivity, and operator supervision limit practical adoption. Thus, the 35-50% reduction in labor estimate should be viewed as a potential gain in good operating conditions and not necessarily a commercial result. The data-logging subsystem is a significant contribution beyond simple pick-and-place automation. Each sorting event is logged with time, cultivar class, target position and cycle time for traceability and retrospective performance analysis. This function aligns with the trends in precision agriculture and smart farming, where sensor data, connectivity, and decision-support tools are integrated to improve productivity and management transparency (Wolfert et al., 2017; Benos et al., 2021; Simo et al., 2022; Miller et al., 2025). The ESP32-MySQL architecture can be extended in future versions to cloud dashboards, anomaly detection and predictive maintenance. Several limitations need to be acknowledged. First, only three lettuce cultivars and a limited number of trials (n=27) were considered. Secondly, the imaging conditions were controlled, and the HSV thresholds may not be generalizable to changing greenhouse illumination. Third, the robotic arm was tested with 100 g specimens and a fixed reach. Larger produce or variable tray height may require a more powerful arm and additional degrees of freedom. Fourth, positional repeatability was determined by target-zone consistency, not by high-resolution metrology. Fifth, economic and labor implications were estimated from throughput assumptions and should be validated in long-duration greenhouse trials.

In summary, the study demonstrates the feasibility of combining machine vision, low-cost robotic control, pneumatic gripping, and data logging for sorting CEA lettuce. The prototype does not replace industrial robotic sorting systems but provides an accessible experimental platform that can guide further development for small and medium greenhouse enterprises. Future research should include larger data sets, CNN-based classification, adaptive gripping, closed-loop positioning, sanitation-compatible mechanical design, long-duration reliability testing, and techno-economic analysis in real greenhouse operations.

5. CONCLUSION

In this research, a machine vision-guided four-axis robotic arm for sorting lettuce in Controlled Environment Agriculture was designed and evaluated. The integrated prototype consisted of a 2D camera, HSV-based image classification, Arduino-PCA9685 servo control, pneumatic gripping, ESP32 communication and MySQL data

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logging. In 27 trials with Red Oak, Green Oak, and Red Coral lettuce, the system achieved an overall classification accuracy of 96.3% and completed all pick-and-place operations without dropped specimens or visible leaf damage. The results show that a low-cost robotic platform can provide repeatable point-to-point sorting performance and practical throughput for laboratory-scale greenhouse automation. The main scientific contribution is the integrated evaluation of vision classification, robotic motion, pneumatic handling, data logging, and cultivar-specific sorting performance within a single CEA-oriented system. The study had significant limitations, too. HSV thresholding is sensitive to lighting and color variation. The prototype was tested on a small data set, and neither a fixed operating geometry nor high-resolution positional metrology was included. CNN-based classification, larger-scale cultivar datasets, adaptive soft grippers, higher-torque actuators, closed-loop visual serving, and long-duration commercial greenhouse validation should therefore be included in future work.

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