Scientific Journal of Engineering Research
futuristech PT. Teknologi Futuristik Indonesia
Date of publication January 17, 2026, date of current version January 17, 2026.
e-ISSN: 3109-1725
Digital Object Identifier 10.64539/sjer.v2i1.2026.337

Article

Integrated Vision-PLC Control Architecture for High-Performance Delta Robot Sorting in Industrial Automation

Kim-Thanh Vo[1], Bui-Duc Nghia[1], Huy-Vu Tran[1,*], Thanh-Tuan Huynh[1], Huy-Bao Nguyen[1], Phong-Luu Nguyen[1], Van-Tuan Nguyen[2], Anh-Quoc Phan[1], Son-Thanh Phung[1], Van-Dong-Hai Nguyen[1], Binh-Hau Nguyen[3], Van-Hiep Nguyen[1], Thanh-Binh Nguyen[1]

[1] Faculty of Electrical and Electronics Engineering (FEEE), Ho Chi Minh City University of Technology and Engineering (HCM-UTE), Ho Chi Minh City (HCMC), Vietnam; 20151433@student.hcmute.edu.vn
[2] Faculty of Vehicle and Energy Engineering, Ho Chi Minh City University of Technology and Engineering (HCM-UTE), Ho Chi Minh City (HCMC), Vietnam
[3] Department II of Electrical Engineering, Posts and Telecommunications Institute of Technology, Ho Chi Minh City (HCMC), Vietnam
* Correspondence

This work was supported by HCM-UTE under Grant No. SV 2026-303.

Abstract: The rapid development of automation and robotics has increased the demand for high-performance industrial systems, in which Delta robots play a crucial role due to their lightweight structure, high speed, and precise positioning capability. This study aims to design, implement, and evaluate a Delta robot-based product classification system integrating PLC S7-1200 control and Machine vision. The proposed system employs a camera to detect object shape, color, and position on a conveyor, while a PC processes the image data and computes the robot's inverse kinematics before transmitting control commands to the PLC. A hardware model of the Delta robot was designed and fabricated, and a dual-mode control application was developed to monitor and operate the robot in real time. Experimental results demonstrate that the system achieves stable operation, with a classification speed of up to 20 products per minute and an accuracy of approximately 95.7% for picking and placing tasks. The findings confirm the feasibility and effectiveness of integrating vision-based detection with high-speed parallel robot control for industrial sorting applications. The study also provides a foundation for further optimization in processing speed, mechanical design, and advanced image-processing techniques to enhance system performance in practical manufacturing environments.

Keywords: Delta Robot; PLC S7-1200; Machine vision; Automation; Product sorting.

Copyright: © 2026 by the authors. This is an open-access article under the CC-BY-SA license.

1. Introduction

The rapid development of science and technology in recent years has significantly promoted the automation process in modern manufacturing systems. The increasing demand for higher productivity, precision and operational stability, especially after the disruptions caused by the COVID-19 pandemic, has emphasized the essential role of industrial robots in reducing dependence on manual labor and ensuring continuous production [1]. Among the various robot architectures, the Delta robot, first introduced by Clavel in the late 1980s, stands out for its lightweight parallel kinematic structure, high rigidity, low motion inertia and outstanding kinematic performance, making it well suited for high-speed pick and place, sorting and packaging tasks [2], [3].

The Delta robot uses three identical kinematic chains forming parallelogram links, maintaining a fixed orientation while enabling rapid translational motion in 3D space. Due to these advantages, Delta robots have been widely deployed in industries such as electronics manufacturing, food processing, pharmaceutical packaging, and logistics automation [2], [4]. However, the application of Delta robots to flexible sorting tasks requires a tight integration of mechanical design, forward and inverse kinematics, real-time control, machine vision, and conveyor synchronization mechanisms. Many studies have attempted to address these aspects individually, but there are still many shortcomings when these components are combined into a unified system [5], [6].

Initial efforts to design a cost-effective Delta robot platform focused on educational or experimental models using stepper motors and microcontrollers. Cong and Phuong (2023) presented a compact Delta robot using an Arduino and a monocular camera for object localization [7]. A similar low-cost prototype has been developed, mainly based on 3D printed structures, although its real-time accuracy and mechanical strength are still not up to industrial standards [8]. Meanwhile, extensive research has been devoted to improving control algorithms, including PID, sliding mode, adaptive, fuzzy, and neural network-based controllers [9], [10]. Reinforcement learning has even been applied to Delta robots to improve dynamic manipulation performance [11]. Although novel, these methods often rely on PC-based controllers, limiting their industrial applicability.

In parallel with advances in mechanics and control, machine vision-assisted sorting systems have also developed. Conventional systems that use color and shape detection, such as Bhole's Raspberry Pi-based design [12], often lack the processing speed required for high-speed robotic applications. More advanced works, such as Nguyen (2025) and Petersen (2025), have used deep learning or RGB-filtered illumination to improve detection accuracy, but they rely on serial controllers or PLC-only conveyors instead of Delta robots [13], [14]. Similarly, PLC-based automation systems have demonstrated high reliability in industrial environments. For example, Almtireen (2025) developed a PLC-integrated YOLOv8 sorting system for waste sorting [15], but the lack of integration with high-speed parallel robots limits scalability.

Efforts to integrate Delta robots with PLCs are still limited. Akshay (2023) used a PLC-controlled Delta mechanism for pick and place applications, although without vision integration [16]. Öztürk et al. (2022) combined PLC control with a linear Delta robot and image processing, but the system lacked real-time performance and multi-criteria sorting capabilities [17]. Additionally, several studies have considered high-precision calibration, vibration damping, and adaptive trajectory control for Delta robots [2], [10], [18]. While these strategies improve robot performance, they rarely address the issue of complete system-level integration with vision, PLC control, and conveyor tracking.

A thorough review of existing research reveals a fragmented landscape. Microcontroller-based Delta robots are affordable but lack industrial robustness. PLC-based sorting systems offer stability but often rely on simple actuators or serial controllers. Vision guidance systems achieve high recognition accuracy but often neglect integration with high-speed parallel mechanisms. Meanwhile, studies focusing on Delta robot dynamics often overlook the challenges of vision and conveyor synchronization. To the best of our knowledge, no published work fully integrates Delta robots, PLC controllers, and real-time machine vision modules into a unified product sorting system capable of sorting objects by color, shape, and location on a moving conveyor.

To address these shortcomings, this study proposes a fully integrated Delta robot-based sorting system, controlled by a Siemens S7-1200 PLC and enhanced with a real-time machine vision module for object detection and classification. The system extracts position, shape, and color information from a camera, calculates inverse kinematics, and performs precise pick and place operations in real time. Experimental results demonstrate a sorting accuracy of 95.7% and a productivity of 20 products per minute, confirming the feasibility of combining a Delta robot with PLC control and machine vision to create a flexible and cost-effective automation system. In addition to providing detailed system architecture, hardware configuration, and control algorithms, this study establishes a practical foundation for future developments of smart manufacturing systems, including AI-based perception, trajectory optimization, and multi-robot coordination.

The remainder of this paper is organized as follows: Section 2 presents the methodology, including the Delta robot kinematic model, the image processing technique, the dataset, and the evaluation metrics. Section 3 details the practical implementation of the classification system, presents the quantitative results from field experiments, and provides the detailed performance discussion and comparative analysis. Section 4 presents the conclusions of the study, and Section 5 outlines the scope for future work.

2. Methodology

2.1. System Overview and Control Architecture

The control architecture is divided into three logical layers: the overall system workflow, the PLC motion control loop, and the Machine vision processing process.

The operating logic of the entire system is illustrated in Figure 1. After initialization, the system establishes a connection with the PLC. The workflow is then divided into branches based on the user's mode selection:

- Manual mode: Used for calibration and inspection. The system receives direct positioning or joint angle commands, calculates the required velocity, and transmits these parameters to the PLC for execution.

  Automatic mode: This is the main production loop. The system connects to the camera and starts a continuous cycle of image acquisition and processing. When an object is identified, its coordinate data is sent to the PLC to trigger the pick and place sequence. This loop continues until a "Close" signal is received.

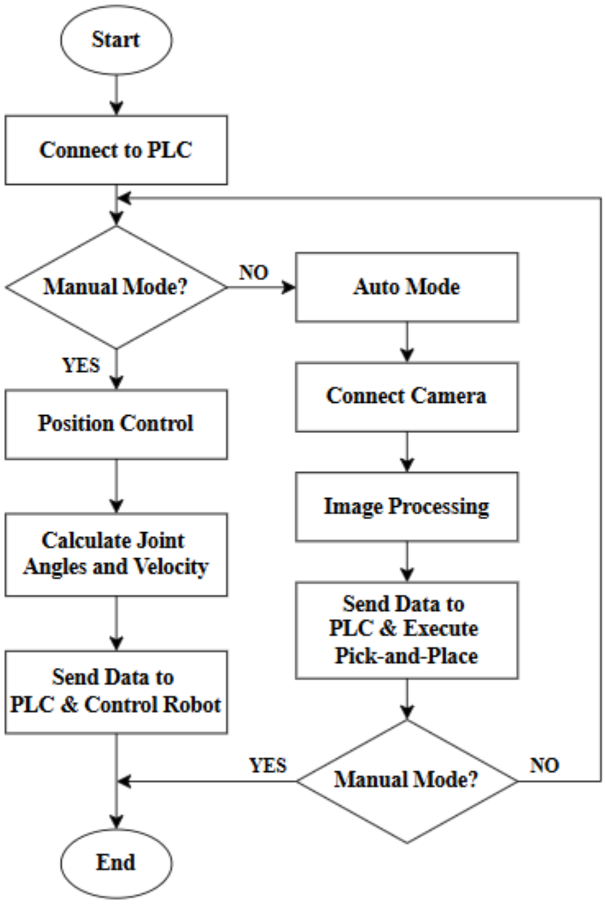


Figure 1. General system control flowchart.

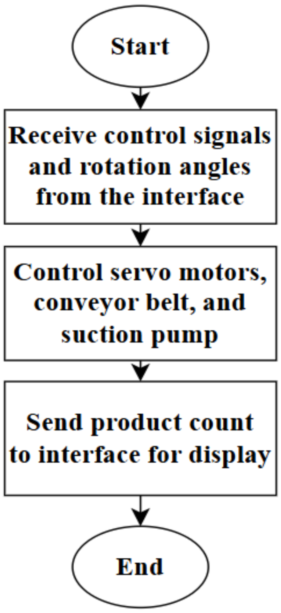


Figure 2. PLC control algorithm flowchart.

PLC Control Logic: Low-level control is performed by Siemens S7-1200 PLC as shown in Figure 2. Acting as a sub-controller, the PLC waits for the control signal and the calculated joint angle (θ_1, θ_2, θ_3) from the computer. Once received, it generates a high-speed Pulse Train Output signal to drive the three servo motors to the desired position. At the same time, it manages the auxiliary devices, controls the conveyor speed, and turns on/off the vacuum pump for clamping. Finally, the PLC feedbacks the sorting count to the user interface for real-time monitoring before the end of the cycle.

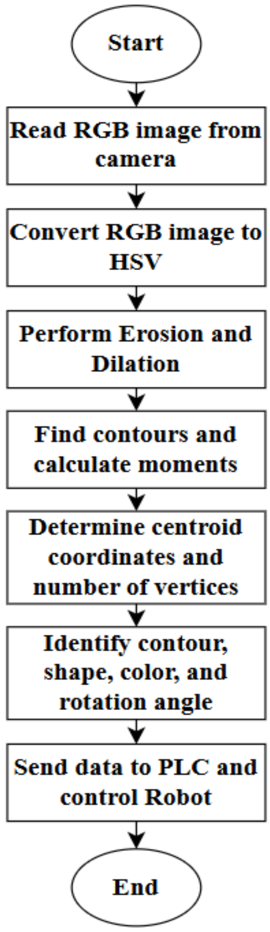


Figure 3. Image processing algorithm flowchart.

The Machine vision Algorithm, implemented in Python/OpenCV, is detailed in Figure 3. The process begins with the acquisition of an RGB image from the camera. To enhance robustness against ambient light fluctuations, the image is converted to the HSV color space. Morphological operations, namely Erosion and Dilation, are then performed to remove high-frequency noise and refine the geometric structure of the object. Next, contour analysis algorithms are applied to delineate the object boundaries, which are then processed with image moments to determine the centroid coordinates and vertex number. These extracted features facilitate the classification of the object's morphology (Circle, Square, Triangle), color, and orientation. Finally, the obtained parameters are formatted and transmitted to the PLC to coordinate the trajectory of the robot's end-effector.

2.2. Delta Robot Kinematic Model

The Delta Robot is a parallel robot mechanism consisting of three identical mechanical chains connecting the fixed arm to the mobile end actuator. Each chain consists of a motor-driven upper arm of length r_f and a passive lower parallelogram arm of length r_e, ensure that the final actuator moves purely linearly in 3-dimensional space.

2.2.1. Inverse Kinematics

Inverse kinematics is a central problem in robot control, which is to determine the rotation angles (θ_1, θ_2, θ_3) of three servo motors based on the target coordinates of the gripper head $E_0 = (x_0, y_0, z_0)$. The problem is solved geometrically based on the intersection of the lower arm sphere and the upper arm plane. This intersection determines the passive joint position j_i, from which the corresponding joint angle is calculated:

$$q_i = \tan^{-1}\frac{z_{ji}}{yF_i + y_{ji}} \quad (1)$$

Due to the symmetry of the mechanism, after determining θ_1, the angles θ_2 and θ_3 are calculated by rotating the coordinate system around the z axis ±120° and applying the same algorithm.

2.2.2. Forward Kinematics

The forward kinematics determines the coordinates $E_0 = (x_0, y_0, z_0)$ of the gripper head given the joint angles (θ_1, θ_2, θ_3). Each passive joint j'_i creates a sphere of radius r_e, and the gripper head is located at the intersection of these three spheres:

$$r_e^2 = (x_0 + x_{jc})^2 + (y_0 + y_{jc})^2 + (z_0 + z_{jc})^2 \quad (2)$$

Solving this system of equations allows to uniquely determine the gripper head position in the workspace.

2.2.3. Workspace Simulation

The workspace describes the entire volume accessible to the gripper, depending on mechanical parameters such as r_f, r_e, f, e and the angular limits of the joints. The research team used MATLAB to simulate the workspace, thereby determining the effective operating area for the pick-and-place operations on the conveyor, ensuring accuracy and continuity, and supporting the optimization of the system design.

2.3. Machine Vision Technology

In this study, images are acquired from a visual sensor (webcam) and pre-processed to serve the purpose of detecting and locating objects. The original image is converted to HSV color space to separate the color information of the object from the background, then quantized into a binary image using the InRange function. Morphological operations, including Erosion and Dilation, are applied to remove noise and smooth the object contour. Next, the Contours and Moments methods are used to determine the contour and center of the object. The Approximation Contour algorithm helps to identify the basic shapes of the object, thereby providing accurate information about the position and shape for the Delta robot control system.

2.4. Dataset

The system was validated using a comprehensive set of experimental trials conducted on the custom-built sorting platform (Figure 4). The image dataset was acquired directly from the system's visual sensor (webcam) and pre-processed to serve the purpose of object detection and localization.

The experimental protocol comprised 420 discrete trials, which were stratified equally across seven categories.

- Product Classes: Six valid product classes were tested, drawn from combinations of three basic geometric shapes (square, circle, triangle) and two distinct colors (Orange and Blue).
- Control Group: A control group was included for defective products to test the system's rejection capability.
- Protocol: The process involved real-time image acquisition, inverse kinematic computation, and PLC-controlled pick-and-place execution for each trial, ensuring the evaluation covered both the vision recognition phase and the mechanical execution phase.

2.5. Evaluation Metrics

The core performance metric defined a 'success' as the conjunction of accurate Machine vision recognition and the successful execution of the pick-and-place maneuver. The overall performance is quantified primarily using Accuracy, calculated as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (3)$$

Where TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively.

3. Results and Discussion

This section details the practical implementation of the classification system, the software interface, and quantitative results from the field experiments.

3.1. Experimental Setup

3.1.1. Real mode

The experiments were performed on the custom-built sorting platform, shown in Figure 4. This platform is composed of two primary assemblies: the Delta Robot System (left) and the Control Cabinet (right). The Delta Robot System includes the aluminum fixed frame, the 3-DOF parallel arms (actuating and passive arms), the conveyor belt, and the vacuum pump end-effector.

The Control Cabinet, shown in detail in Figure 5, houses the core electronic components, including the Siemens S7-1200 PLC, the three Yako servo drivers, and the 24VDC switching power supply.

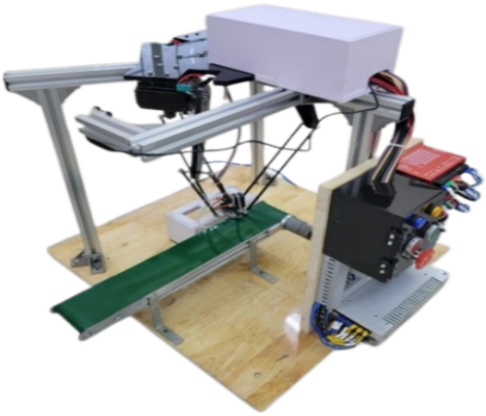


Figure 4. The completed physical system.

Figure 5. A detailed view of the Control Cabinet.

3.1.2. Operational Results

The system is controlled via a custom Graphical User Interface developed in Python. As shown in Figure 6, the application launches with a title screen displaying the project name and links.

As illustrated in Figure 7a, the Manual Control area is dedicated to kinematic maintenance and testing. This area has two separate panels: “FORWARD KINEMATICS” for adjusting individual joint angles (θ_1, θ_2, θ_3) and “INVERSE KINEMATICS” for entering precise Cartesian coordinates (X, Y, Z). This layout allows the operator to directly validate the robot’s motion algorithms before full operation.

Conversely, Figure 7b depicts the Auto control area, which is the primary interface for the sorting task. In this mode, the manual inputs are cleared to reduce clutter, focusing the operator's attention on the configuration block. Here, dropdown menus allow for the assignment of specific product types (e.g., Blue Circle, Orange Square) to specific output destinations (Product 1, Product 2).

This area also contains the main function buttons for operation:

- SET HOME (Returns the robot to its home position),
- AUTO/MANU (Switches the operating mode between Manual and Automatic),
- PUMP OFF (Turns the pump on or off manually)
- CLOSE (Ends the program and closes the user interface).

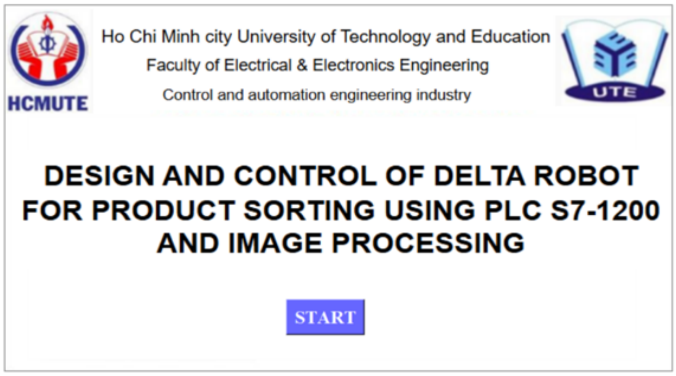
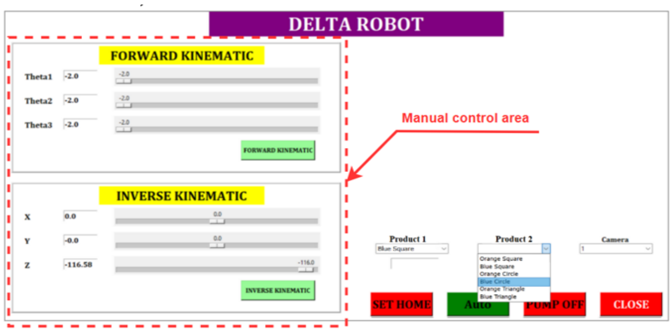
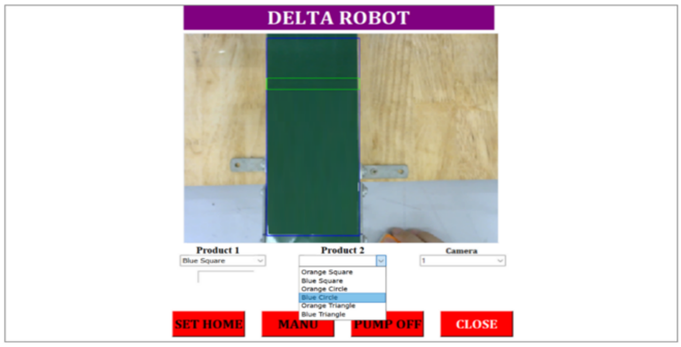


Figure 6. User interface.



(a)



(b)

Figure 7. Control interface, with (a). manual, (b). auto.

3.2. Operational Results

The validation of the Machine vision algorithm was a critical part of the experiment. The system was tested against objects of different colors (Orange, Blue) and geometric shapes (Square, Circle, Triangle).

The actual results of the image recognition process, illustrating successful object segmentation and feature extraction, are presented in Figure 8.

The accuracy of the image recognition process is demonstrated by the successful segmentation of object boundaries and the subsequent identification of their corresponding centroid coordinates. Figure 8a illustrates the detection of a square object. The system precisely calculates and displays the centroid coordinates (X, Y) in pixels, which are then converted to millimeters for processing, for each object. Specifically, the orange square was located and labeled "Orange," while the blue square was identified as "Blue." These coordinates provide the precise positioning points necessary for subsequent robot control actions.

(a) (b) (c)

Figure 8. Image processing results, for (a). square objects, (b). triangle objects, and (c). circle objects.

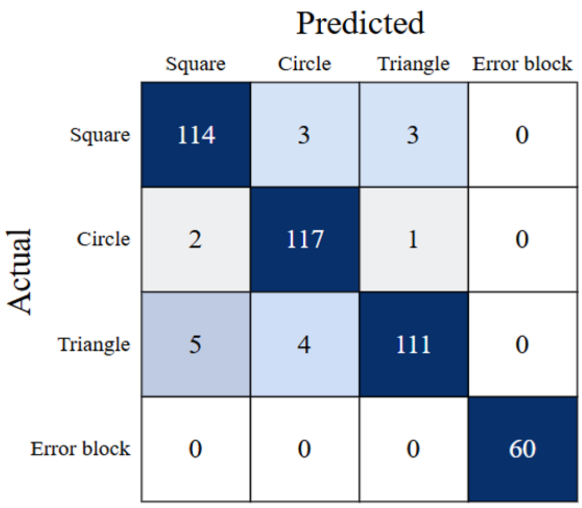


Figure 9. Confusion matrix for geometric shape classification performance.

The system maintained high fidelity across a diverse range of geometries, demonstrating its ability to accurately classify complex shapes such as circles in Figure 8c and triangles in Figure 8b, while simultaneously identifying their specific chromatic attributes (Orange vs. Blue). Similar to the rectangular objects, the vision algorithm achieved a high degree of precision for these shapes by not only detecting the geometric center within the image frame but also accurately mapping the pixel values to the required real-world millimeter coordinates.

The observed consistency in object localization, alongside the object's morphological characteristics and color attributes, serves as a strong validation of the image processing algorithm's robustness against environmental noise. Consequently, these calculated coordinates provide the essential, high-frequency, real-time positional data stream required for the PLC to compute the inverse kinematics and execute precise actuation for the color and shape-based product sorting tasks.

To provide a robust statistical assessment of the system's efficacy, a comprehensive experimental protocol was executed. The validation phase comprised 420 discrete trials, stratified equally across seven categories: six valid product classes (drawn from combinations of three geometric shapes and two colors) and a control group for defective products. The performance metric defined a 'success' as the conjunction of accurate Machine vision recognition and the successful execution of the pick-and-place maneuver.

The empirical data resulting from these classification trials is summarized visually in Figure 9, which details the system's performance across four classes: Square, Circle, Triangle, and the Error Block (defective product group).

- The matrix illustrates the high reliability of the vision system, achieving a total of 342 True Positives (sum of diagonal values: 114 + 117 + 111) out of the 360 combined trials for valid product shapes.
- The highest classification accuracy was achieved for Circle objects (117 correct out of 120 trials).
- The largest sources of error occurred when the system confused Triangle objects with Square objects (5 instances) and Square objects with Triangle objects (3 instances), confirming that the geometric complexities of non-symmetric shapes introduced minor classification difficulties.

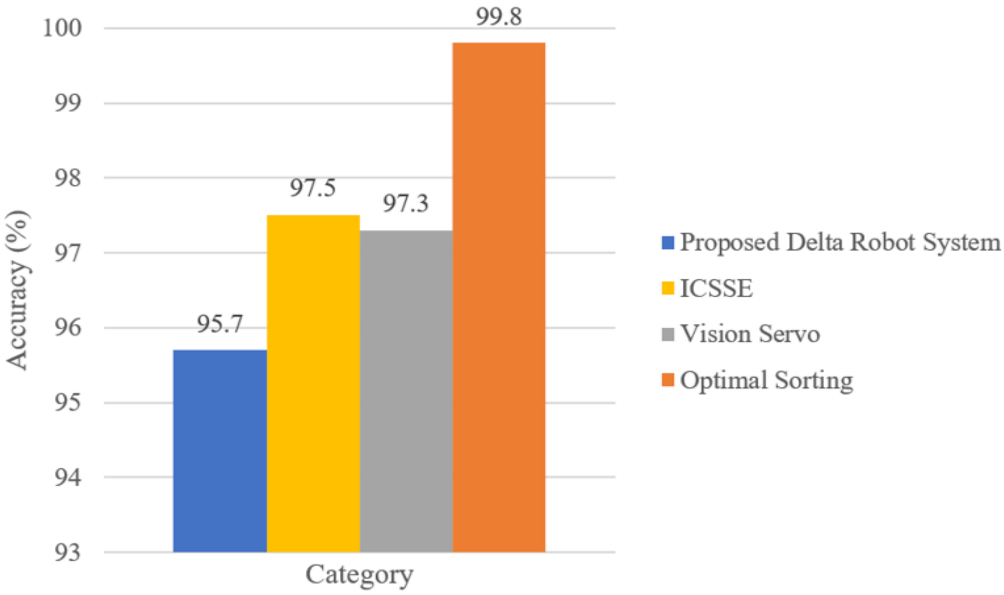


Figure 10. Comparative analysis of overall system accuracy.

- The control group for defective products was correctly identified in all 60 trials (represented by the 60 in the 'Error block' row/column), demonstrating the system's ability to reject unqualified parts with 100% accuracy for this class.
- The overall system performance, combining all successful recognition and execution steps, resulted in an Aggregate Accuracy of 95.7%.

3.3. Discussion

The system achieved an aggregate accuracy of 95.7%. Cycle times were observed to stabilize at around 2.0-2.5 seconds, easily meeting the throughput target of 20 products per minute.

An important step in validating the proposed system is to benchmark its performance against established robotic classification research, as illustrated in Figure 10. This comparative analysis primarily focuses on the Overall Classification Accuracy (the combined success rate of image recognition and pick and place performance). The proposed system, using a cost-effective PLC/Vision architecture, achieves an overall accuracy of 95.7%. When compared to similar projects based on image processing, the system performance is highly competitive with the ICSSE conference [19], which reported an accuracy of 97.5%, and the Vision Servo method [20], which achieved 97.3%. The highest accuracy benchmark, demonstrated by the optimized classification algorithms [21], achieved 99.8%. This gap is understandable, as highly optimized systems typically employ complex dynamic compensation algorithms to reduce the margin of error to less than 1%. The results confirm that while the proposed system uses a simple, low-cost morphological processing technique, its powerful PLC-Vision integration delivers a fully consistent accuracy of 95.7% and is very cost-effective for industrial sorting applications, effectively combining sensor-based approaches and high-precision segmentation.

The root cause of the 4.3% error rate could be attributed to four main factors:

- Sensitivity of the vision system: The performance of the algorithm is affected by ambient lighting conditions. Specular reflection sometimes causes glare, while darkness distorts the shape of objects, leading to misidentification.
- System latency: There is a cumulative latency, including visual processing time and communication delay between the computer and PLC. Since the motion compensation offset is a fixed value, fluctuations in processing time leads to small position errors during high-speed tracking.
- Mechanical vibration: At maximum operating speed, the robot frame vibrates slightly, contributing to small accuracy during pick and place.
- Conveyor speed drift: The control algorithm assumes a constant conveyor speed. The lack of a real-time encoder feedback loop means that the system cannot automatically compensate for small changes in conveyor speed, resulting in position drift.

4. Conclusions

This study completed an integrated solution for automatic product sorting by combining a customized 3-DOF Delta robot mechanism, S7-1200 PLC motion control, and Machine vision. As a result, the developed method maximizes the sorting accuracy up to 95.7%, meeting the high-accuracy requirements for industrial pick and place tasks. In addition, the system achieves a stable throughput of 20 products per minute (approximately 2 seconds/cycle), demonstrating the effectiveness of applying inverse kinematic modeling and morphological image processing in real-time control situations. The successful synchronization between the vision system and the PLC confirms the robustness of this platform in recognizing and processing objects based on complex shape and color criteria.

5. Future work

The current system needs to be improved to enhance robustness under various ambient lighting conditions, and Deep Learning techniques need to be studied to improve its classification accuracy and noise resistance. Optimization for dynamic object tracking should be integrated to enable the system to handle products on moving conveyor belts, expanding its industrial applications. Further research should explore the potential of advanced adaptive trajectory planning algorithms to minimize system latency and reduce the marginal error rate to less than 1%, aiming for performance comparable to highly optimized solutions. Extending the model application to process chains with real-time data integration would make it suitable for complex logistics and flexible manufacturing applications.

6. Abbreviations

Abbreviation	Definitions
3-DOF	Three-Degrees-of-Freedom
FEEE	Faculty of Electrical and Electronics Engineering
HCMUTE	Ho Chi Minh City University of Technology and Education
HSV	Hue, Saturation, Value (Color Space)
ICSSE	International Conference on System Science and Engineering
PLC	Programmable Logic Controller

7. Declarations

7.1. Author Contributions

Huy-Vu Tran: Conceptualization, Methodology, Software, Validation, Project administration, Writing - Original Draft, Supervision. **Kim-Thanh Vo, Duc-Nghia Bui:** Formal analysis, Investigation, Data Curation, Writing - Original Draft. **Binh-Hau Nguyen, Van-Hiep Nguyen, Phong-Luu Nguyen:** Methodology, Software, Investigation, Resources. **Van-Dong-Hai Nguyen, Thanh-Binh Nguyen, Van-Tuan Nguyen, Anh-Quoc Phan, Thanh-Tuan Huynh, Huy-Bao Nguyen:** Investigation, Resources, Writing - Review & Editing.

7.2. Institutional Review Board Statement

Not applicable.

7.3. Informed Consent Statement

Not applicable.

7.4. Data Availability Statement

The data presented in this study, including raw experimental logs, kinematic parameters, and system operation videos, are available on request from the corresponding author.

7.5. Acknowledgment

This research was funded by Ho Chi Minh City University of Technology and Engineering (HCM-UTE), under grant No. SV2026-303. We, authors, are grateful for this support. Video of operation of system is shown in: https://www.youtube.com/watch?v=-lC7Yz4N3-M.

7.6. Conflicts of Interest

The authors declare no conflicts of interest.

8. References

[1] Z. Hu, Y. Zhang, Q. Li, and C. Lv, "Human–machine telecollaboration accelerates the safe deployment of large-scale autonomous robots during the COVID-19 pandemic," *Frontiers in Robotics and AI*, vol. 9, Apr. 2022, https://doi.org/10.3389/FROBT.2022.853828.

[2] N. Edoimioya, C. E. Okwudire, "A generalized and efficient control-oriented modeling approach for vibration-prone delta 3D printers using receptance coupling," *IEEE Transactions on Automation Science and Engineering*, vol. 20, no. 3, pp. 1539 – 1550, 2023, https://doi.org/10.1109/TASE.2022.3197057.

[3] L. Rey and R. Clavel, "The delta parallel robot," *Parallel Kinematic Machines*, pp. 401–417, 1999, https://doi.org/10.1007/978-1-4471-0885-6_29.

[4] W. Sun, Y. Ma, C. Li, B. Li, Y. Zhao, and Q. Liu, "Kinematic analysis and trajectory planning of two-limb 4-DOF high-speed parallel robot," *2024 IEEE International Conference on Mechatronics and Automation, ICMA 2024*, pp. 1237–1242, 2024, https://doi.org/10.1109/ICMA61710.2024.10633179.

[5] S. Zhang, Q. Han, H. Zhu, H. Wang, H. Li, and K. Wang, "Real time task planning for order picking in intelligent logistics warehousing," *Scientific Reports*, vol. 15, no. 1, p. 7331, Mar. 2025, https://doi.org/10.1038/s41598-025-88305-9.

[6] T. Su, H. Zhang, Y. Wang, S. Wu, J. Zheng, J. Chang, "Sorting system algorithms based on dynamic picking for delta robot," *7th International Conference on Information Science and Technology, ICIST 2017 - Proceedings*, pp. 450–457, May 2017, https://doi.org/10.1109/ICIST.2017.7926802.

[7] H. P. Le, C. V. Duy, H. T. Thanh, "Design a Low-cost Delta Robot Arm for Pick and Place Applications Based on Computer Vision.," *FME Transactions*, vol. 51, pp. 99-108, 2023. https://doi.org/10.5937/fme2301099P.

[8] A. Elassal, M. Abdelaal, M. Osama, H. Elhnidy, "Low-cost parallel delta robot for a pick-and-place application with the support of the vision system," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 8, 2024, https://doi.org/10.1016/j.prime.2024.100518.

[9] D. W. Seleem, M. A. Shamseldin, and H. Eleashy, "Design and Control of Delta Robot (Mini Review)," *Future Engineering Journal*, vol. 5, no. 1, 2025, https://digitalcommons.aaru.edu.jo/fej/vol5/iss1/2.

[10] M. Wu, A. Rupenyan, and B. Corves, "Iterative learning control with mismatch compensation for residual vibration suppression in delta robots," *Nonlinear Dynamics*, vol. 113, no. 16, pp. 21631–21651, Aug. 2025, https://doi.org/10.1007/S11071-025-11299-6.

[11] A. Louette, G. Lambrechts, D. Ernst, E. Pirard, G. Dislaire, "Reinforcement Learning to improve delta robot throws for sorting scrap metal," *arXiv preprint arXiv:2406.13453*, 2024, https://arxiv.org/abs/2406.13453.

[12] M. Bhole, R. Bamane, R. Jadhav, P. More, and R. Ture, "PLC Based Object Sorting System Using Image Processing," *International Journal of Scientific Research in Engineering and Management (IJSREM)*, vol. 5, no. 5, 2021.

[13] V. T. Nguyen, P. T. Nguyen, S. F. Su, P. X. Tan, and T. L. Bui, "Vision-Based Pick and Place Control System for Industrial Robots Using an Eye-in-Hand Camera," *IEEE Access*, vol. 13, pp. 25127–25140, 2025, https://doi.org/10.1109/ACCESS.2025.3536496.

[14] M. Petersen, B. Lakenen, K. Chavan, P. Waghmare, A. Sergeyev, and N. Rawashdeh, "Conveyor Line Color Object Sorting using A Monochrome Camera, Colored Light and RGB Filters," *arXiv preprint arXiv:2502.08419*, 2025, https://doi.org/10.48550/arXiv.2502.08419.

[15] N. Almtireen, V. Reddy, M. Sutton, A. Nedvidek, C. Karn, M. Ryalat, H. Elmoaqet, and N. Rawashdeh, "PLC-controlled intelligent conveyor system with ai-enhanced vision for efficient waste sorting," *Applied Sciences*, vol. 15, no. 3, p. 1550, 2025, https://doi.org/10.3390/app15031550.

[16] N. Akshay, B. V. Reddy, C. G. Saranya, D. K. Karthik, "PLC Operated Pick and Place Robotic Arm with a Low-Cost Interface in a SCADA System," in *2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS)*, 2023. https://doi.org/10.1109/ICACRS58579.2023.10405235.

[17] S. Öztürk and F. Kuncan, "Linear Delta Robot Controlled with PLC Based On Image Processing," *Kocaeli Journal of Science and Engineering*, vol. 5, no. 2, pp. 150–158, Nov. 2022, https://doi.org/10.34088/KOJOSE.1058559.

[18] Y. Tang, F. Wu, X. Gong, C. Chen, H. Liu, J. Ma, Y. Qin, H. Pu, and J. Luo, "An iterative learning-based integrated motion planning and control method for autonomous patrolling of unmanned surface vehicles," *Measurement Science and Technology*, vol. 35, no. 12, 2024, https://doi.org/10.1088/1361-6501/ad7b66.

[19] T. V Do, N. Q. Nam, D. D. Vinh, N. Q. Viet, P. N. Dat, and T. Van Hung, "Design of Delta Robot Using Image Processing for Product Sorting Process," in *2021 International Conference on System Science and Engineering (ICSSE)*, pp. 210–214, 2021, https://doi.org/10.1109/ICSSE52999.2021.9538412.

[20] C.-J. Lin, J. Shaw, P.-C. Tsou, and C.-C. Liu, "Vision servo based Delta robot to pick-and-place moving parts," in *2016 IEEE International Conference on Industrial Technology (ICIT)*, 2016. https://doi.org/10.1109/ICIT.2016.7475005.

[21] H. Ni, Y. Liu, C. Zhang, Y. Wang, F. Xia, and Z. Qiu, "Sorting system algorithms based on machine vision for delta robot," *Robot*, vol. 38, pp. 49–55, Jan. 2016, https://doi.org/10.13973/j.cnki.robot.2016.0049.