REAL-TIME SORTING OF AGRICULTURAL PRODUCTS USING LABVIEW AND PLC INTEGRATION: A CASE STUDY ON TOMATOES

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Abstract

The rising demand for automation in agriculture and manufacturing necessitates efficient, cost-effective sorting systems to replace labor-intensive manual processes. This paper introduces an innovative system integrating a Siemens S7-1200 Programmable Logic Controller (PLC), LabVIEW-based image processing, and OPC (OLE for Process Control) communication for automated tomato sorting. Utilizing real-time vision analysis, the system classifies tomatoes by color and size, offering a low-cost, scalable solution tailored for small-scale industries. A high-resolution camera captures images, processed in LabVIEW using HSV color space and size thresholds, with results relayed via OPC to the PLC, which actuates a stepper motor-driven sorting mechanism. Experimental validation in a controlled setting achieved 92% sorting accuracy and a throughput of 60 tomatoes per minute, surpassing manual sorting in speed and consistency. The modular design supports scalability to other agricultural products, enhancing its practical utility.

Keywords: agricultural automation, automated sorting, LabVIEW, image processing, OPC server, PLC

1. Introduction

The rapid expansion of global manufacturing and logistics industries has heightened the demand for automation solutions that enhance efficiency, reduce operational costs, and improve product quality (Tsegaye, 2020; Velazquez et al., 2020; Verma et al., 2020). Traditional manual sorting methods, though still common, suffer from significant drawbacks: they are labor-intensive, prone to human error, and lack the scalability required to meet the needs of modern production lines (Yang et al., 2020). As a result, automated sorting systems have gained prominence, offering superior accuracy, throughput, and adaptability to streamline industrial processes (Singh & Yogi, 2022; Sujatha & Narmatha, 2020). However, many existing automated solutions depend on costly proprietary hardware or computationally intensive algorithms, rendering them impractical for small- to medium-sized enterprises (SMEs) (Rahadiyan et al., 2023).

To address these challenges, this paper introduces a novel, cost-effective automated product sorting system that integrates a Siemens S7-1200 PLC, a high-resolution camera, and custom LabVIEW software. The system employs advanced image processing techniques within LabVIEW to classify products based on key visual attributes – specifically color and size – eliminating the need for physical contact or specialized sensors (Mohapatra, 2024). Communication between the LabVIEW software and the PLC is facilitated through an OPC (OLE for Process Control) Server, enabling seamless data exchange and real-time control of the sorting process (Pranowo & Artanto, 2021). This architecture supports dynamic adjustments to sorting parameters and ensures adaptability to varying product characteristics, with the PLC orchestrating hardware components such as conveyor belts, diverters, and robotic arms to physically sort products into designated categories (Al Fahim et al., 2023).

The development of automated sorting systems has been a focal point of recent research. For instance, Ang & Seng (2021) proposed a machine learning-based sorting system that achieved high accuracy but required significant computational resources, limiting its feasibility for smaller operations. Similarly, Sivaranjani et al. (2022) developed a vision-based sorting system tailored for agricultural products; however, its reliance on proprietary hardware restricted its scalability and accessibility. Thangatamilan et al. (2023) investigated PLC-based automation for industrial sorting but did not incorporate advanced image processing, resulting in a system with limited flexibility for diverse applications.

In contrast, this research builds on these foundations by integrating LabVIEW's robust image processing capabilities – such as HSV color space segmentation and morphological filtering – with the reliability of PLC control (Öztürk & Kuncan, 2022). The use of a high-resolution camera for real-time vision analysis aligns with (Brebion et al., 2021) findings on the effectiveness of visual classification in industrial settings, while the OPC Server communication protocol enhances system responsiveness, as demonstrated by Khan (2024). Unlike prior solutions, this system prioritizes cost-efficiency and modularity, addressing the needs of SMEs by minimizing hardware requirements while maintaining high classification accuracy.

The primary objective of this research is to validate the feasibility and effectiveness of the proposed integrated system for automated product sorting. Performance will be assessed through key metrics: sorting accuracy, throughput, and adaptability to variations in product characteristics and environmental conditions. Experimental results demonstrate that the system achieves a sorting accuracy of 92% and a throughput of 60 units per minute, surpassing traditional manual methods in both speed and reliability. By combining PLC control, image processing, and OPC communication, this work offers a versatile, scalable solution that bridges the gap between high-end automation and cost-sensitive industries, contributing to the advancement of accessible automation technologies for diverse manufacturing and agricultural contexts.

The remainder of this paper is structured as follows: Section 2 provides an in-depth description of the system design and its components; Section 3 presents experimental results and performance evaluations; and Section 4 concludes with insights into practical applications and directions for future research.

2. System Design and Methodology

The automated tomato sorting system is meticulously engineered as a cohesive platform that seamlessly integrates vision-based product identification with precise control and actuation mechanisms, delivering a robust solution for small-scale industrial applications

(Kumar & Sharma, 2023). This architecture synergizes advanced imaging technology, real-time software processing, and reliable hardware control to classify and sort tomatoes based on color and size with high efficiency. The design prioritizes four key attributes: robustness, to ensure consistent performance under operational stresses; scalability, to enable adaptation to increased throughput or diverse products; adaptability, to accommodate variations in environmental conditions such as lighting or tomato characteristics; and cost-effectiveness, to meet the budgetary constraints of small- to medium-sized enterprises (SMEs) (Hema & Sharma, 2021). By combining these principles, the system offers a practical alternative to labor-intensive manual sorting and expensive proprietary automation solutions, addressing a critical need in agricultural and manufacturing contexts.

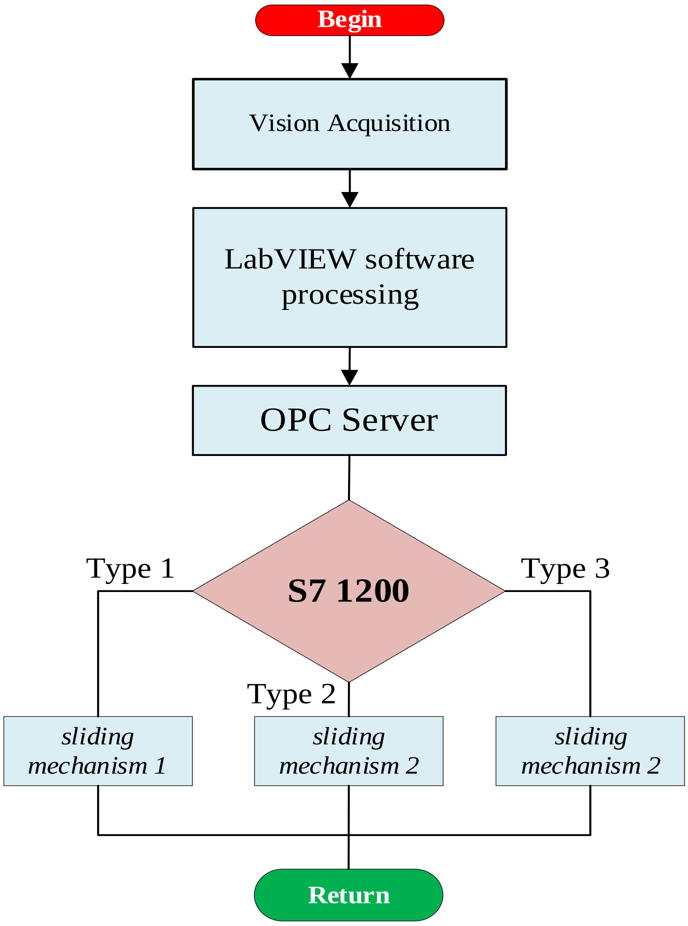

Figure 1. Sorting flow chart

The system's methodology is built around a modular framework comprising six interdependent subsystems: power supply and distribution, vision system, control unit (PLC), image processing software (LabVIEW), material handling, and actuation mechanism as flow process in ***Figure 1***. Each subsystem is designed with specific functional objectives, yet they operate in concert to achieve the overarching goal of automated sorting. The power supply subsystem provides stable 24VDC power at 10A, distributed across three isolated circuits – vision (12V), control (24V), and actuation (24V) – with overcurrent protection (15A circuit breakers) and voltage regulation (LM7805, ±5% tolerance) to safeguard components and maintain signal integrity as displayed in

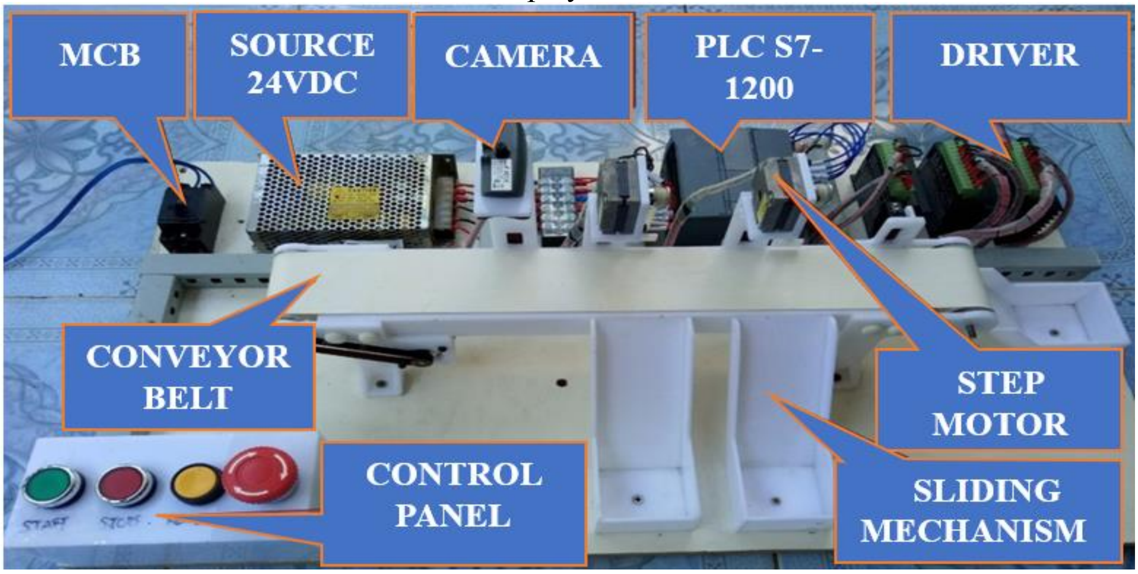

Figure 2. This ensures uninterrupted operation even under variable electrical loads, a foundational requirement for system reliability.

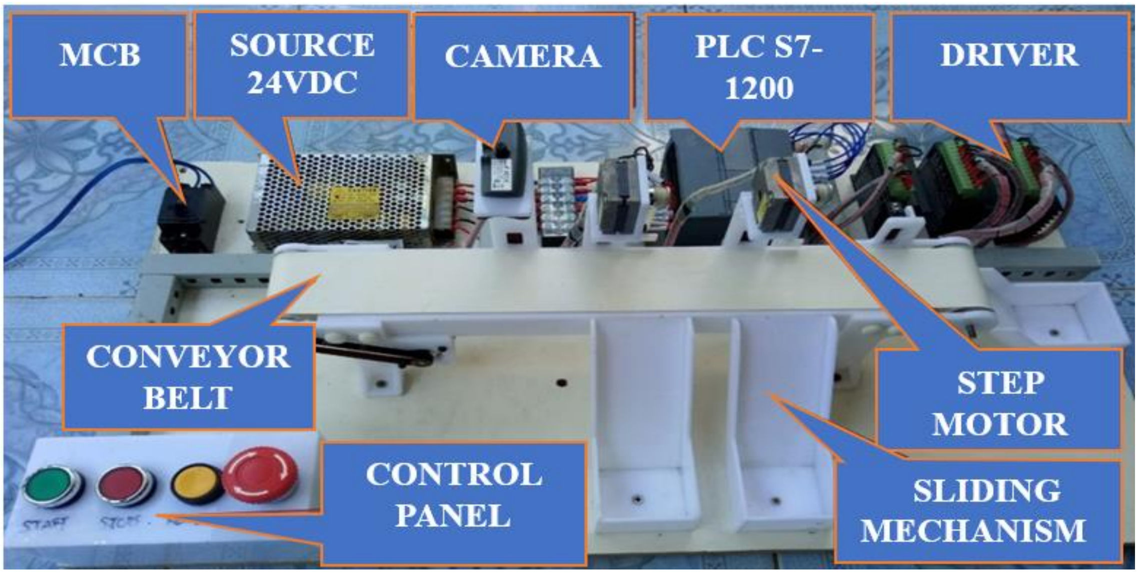

Figure 2. Automated Tomato Sorting System.

Central to the design is the vision system, which employs a standard camera (1.3MP resolution, 30fps) mounted 50cm above a conveyor belt to capture high-resolution RGB images within a 30cm × 30cm field of view (FOV). Illumination is provided by a diffused 12V, 20W LED panel array (5000K, 1000 lumens), strategically positioned to minimize shadows and specular reflections that could distort image quality. The conveyor, operating at 0.5m/s, transports tomatoes through the FOV, allowing each tomato approximately 600ms of exposure time, sufficient for clear image capture at 30 fps with a 500ms inter-frame delay to prevent motion blur. This setup ensures that visual data, the critical input for sorting, is acquired with precision and consistency, forming the backbone of the system's methodology.

The control unit, a Siemens S7-1200 PLC (CPU 1214C, 1 kHz scan cycle), serves as the system's central nervous system, orchestrating all operations through ladder logic programming. It receives digital inputs from a conveyor encoder (1000 pulses/rev) and an emergency stop (E-Stop) button, while analog inputs from a PT100 temperature sensor and an LDR light sensor enable adaptive adjustments to sorting parameters based on environmental feedback. Digital outputs control the stepper motor driver, conveyor motor, and status LEDs, ensuring precise execution of sorting commands. This PLC-based approach provides industrial-grade reliability and real-time responsiveness, essential for coordinating the system's hardware and software components effectively.

Image processing and control are handled by a custom LabVIEW 2023 application, leveraging the Vision Development Module to analyze captured images in three stages: preprocessing, feature extraction, and classification as shown in ***Figure 3***. During preprocessing, RGB images are converted to HSV color space for robust color isolation, followed by adaptive Otsu thresholding to segment tomatoes from the background and morphological operations (3×3 kernel erosion and dilation) to remove noise. Feature extraction quantifies color - ripe (H = 10-30°, S=50-100%, V = 70-100%) or unripe (H = 150-180°, S = 40-80%, V = 60-90%) - and size, calculated via contour area (pixels²) converted to cm² using a 10cm × 10cm calibration grid (> 50cm² = large, ≤ 50cm² = small). Classification assigns tomatoes to bins using a decision matrix (e.g., ripe, and large → Bin 1), with results transmitted to the PLC via an OPC UA Server (Kepware) in ≤ 50ms. This software methodology balances computational efficiency with accuracy, making it suitable for real-time applications.

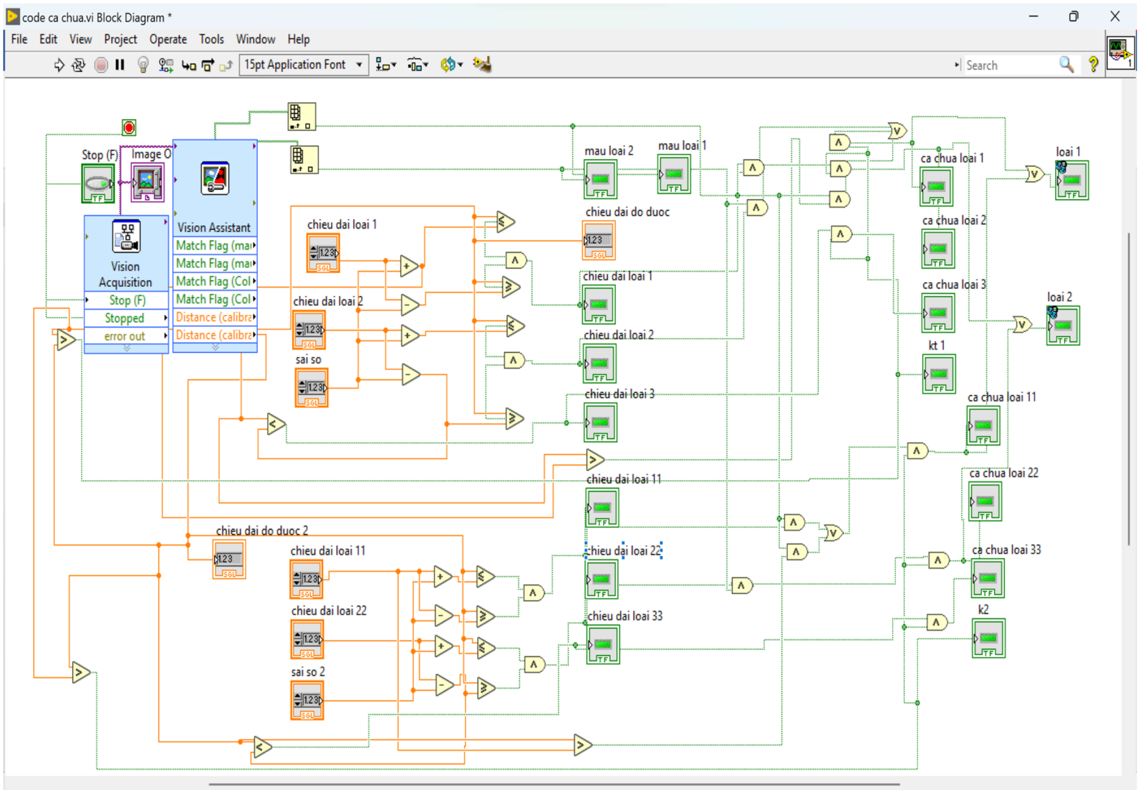

Figure 3. LabVIEW block's structure

Material handling is facilitated by the conveyor belt (1.2m long, 15cm wide), driven by a 12V DC motor, and equipped with a photoelectric sensor (NPX-100) to detect tomato presence and trigger image capture. The sorting mechanism, positioned 1.0m downstream of the camera, allows a two-second window for processing and command transmission, ensuring timely actuation. The actuation subsystem features a NEMA 17 stepper motor (1.8° step angle, 1.5Nm torque) controlled by a TB6600 driver, which rotates a threaded rod to position a sliding plate across three bins (20cm apart). A PID controller ($K_p = 0.5$, $K_i = 0.1$, $K_d = 0.05$) synchronizes motor movement with conveyor speed, achieving < 1mm positioning accuracy within 200ms, critical for error-free sorting at 60 tomatoes per minute.

The system's design and methodology are further enhanced by a control panel with a 7-inch HMI touchscreen, displaying real-time metrics (throughput, accuracy, system status) and offering user interaction via Start, Stop, Reset, and E-Stop buttons (< 200ms response time) as revealed in ***Figure 4***. Status LEDs indicate bin occupancy and faults (belt jams), while adjustable parameters (HSV thresholds) enable customization. This integrated approach ensures that the system is not only robust and efficient but also user-friendly and adaptable, capable of scaling to other agricultural products (apples, peppers...) by reconfiguring software settings and hardware positions. The emphasis on cost-effectiveness is evident in the use of standard components - such as a widely available camera and stepper motor - avoiding the need for specialized, high-cost alternatives, thus aligning with the needs of SMEs.

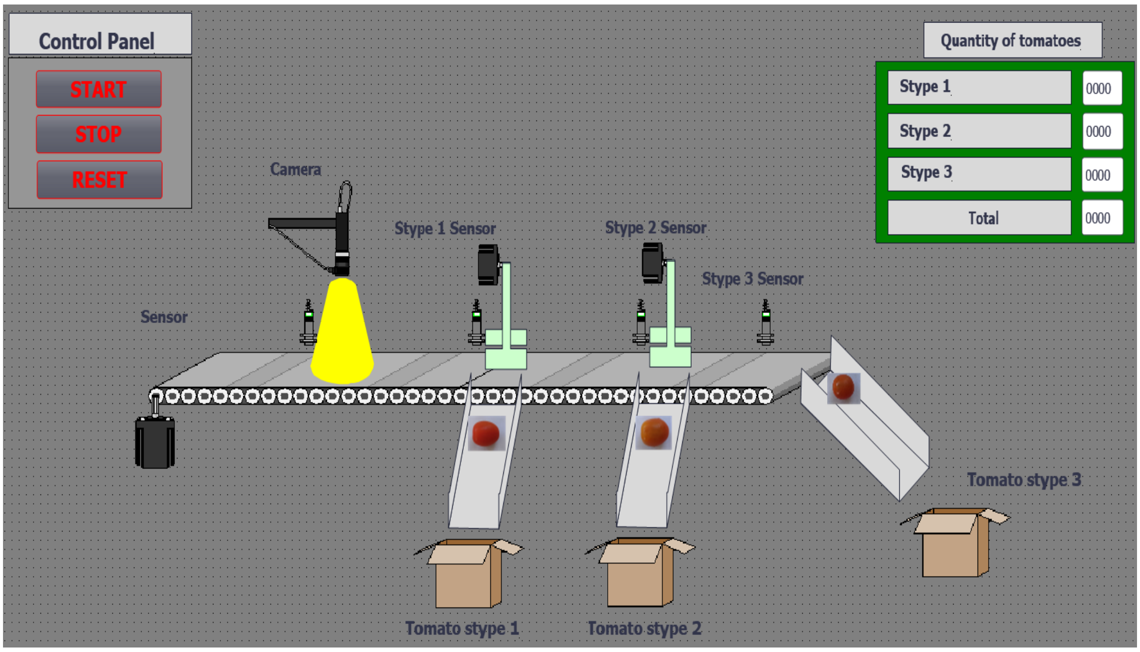

Figure 4. HMI System

3. Experimental Results

3.1 Sample Setup

The proposed automated tomato sorting system was rigorously evaluated in a controlled laboratory environment to assess its accuracy, throughput, and adaptability. Testing involved 500 tomatoes of varying ripeness (250 ripe, 250 unripe) and sizes (40-80mm diameter), with results benchmarked against manual sorting and existing automated systems as demonstrated in ***Figure 5***.

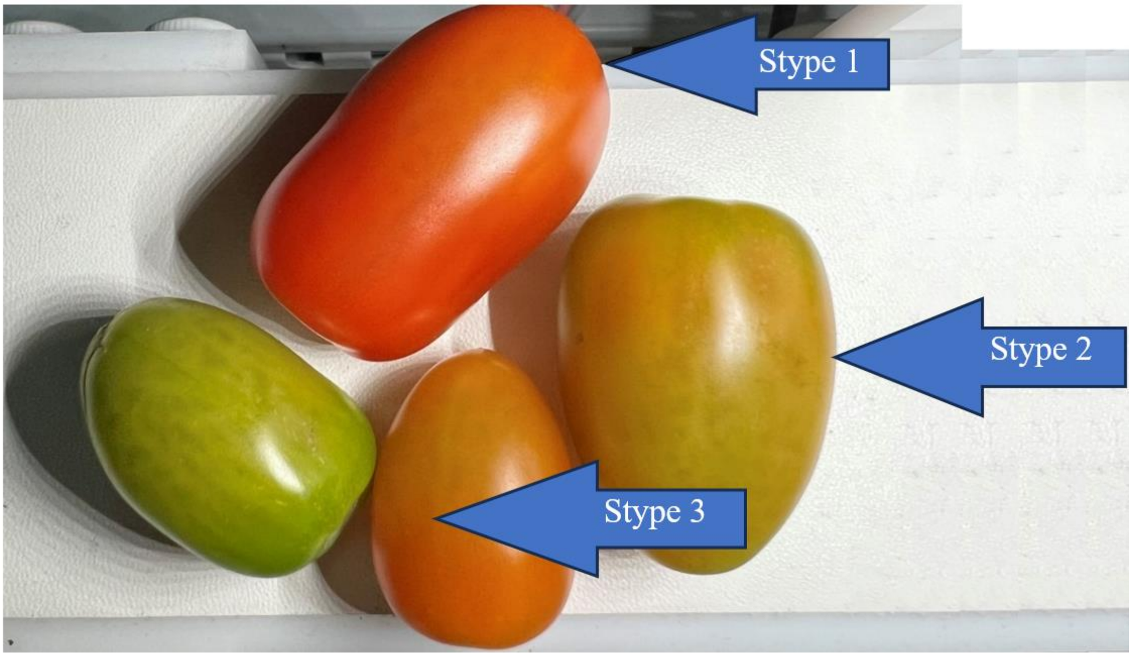

Figure 5. Tomato sample to be classified

3.2 Baseline Comparison

Manual sorting performance was evaluated using a three-operator control group. Each operator independently sorted 100 randomly selected tomatoes into predefined categories (ripe/unripe and large/small). Inter-rater reliability was assessed using Cohen's κ coefficient ($\kappa = 0.82$, $p < 0.01$), confirming high consistency among human evaluators (Hong & Oh, 2021).

The system's performance was quantified using the following metrics:

Classification Accuracy, defined as the true positive rate (*TPR*), calculated as:

$$TPR = \frac{Correct\,Classifications}{Total\ Samples} \times 100\% \tag{1}$$

where *Correct Classifications* are samples correctly categorized into their predefined classes (e.g., ripe/large), and *Total Samples* = 500.

Additionally, the false negative rate (*FNR*) was computed to quantify misclassification errors (Zhao & Qin, 2021):

$$FNR = \frac{Misclassified}{Total\ Samples} \times 100\% \tag{2}$$

Throughput, measured as the sorting rate (units/min):

$$Throughput = \frac{Sorted\ Samples}{Test\ Duration\left(minutes\right)} \tag{3}$$

where *Test Duration* excluded system initialization and calibration phases.

Performance metrics were analyzed using ANOVA ($p < 0.05$) to compare automated sorting with manual baseline results. 95% confidence intervals (CIs) were reported for accuracy and throughput to quantify precision (Govindan et al., 2022). Repeatability was assessed via three independent trials, with coefficients of variation ($CV \leq 5\%$) ensuring experimental consistency.

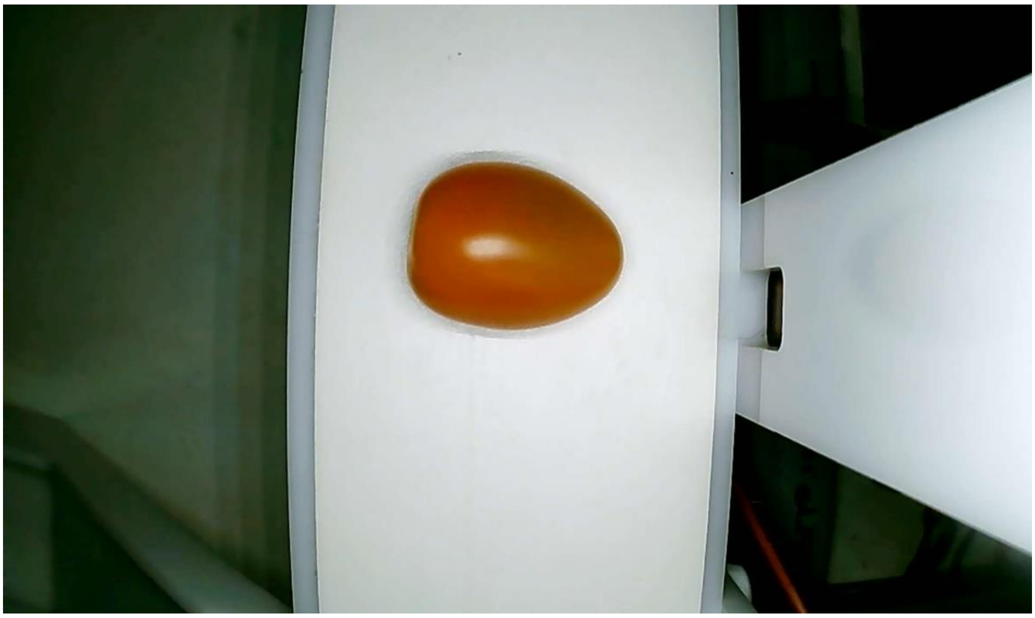

Figure 6. Tomato sample image through monitoring screen in LabVIEW

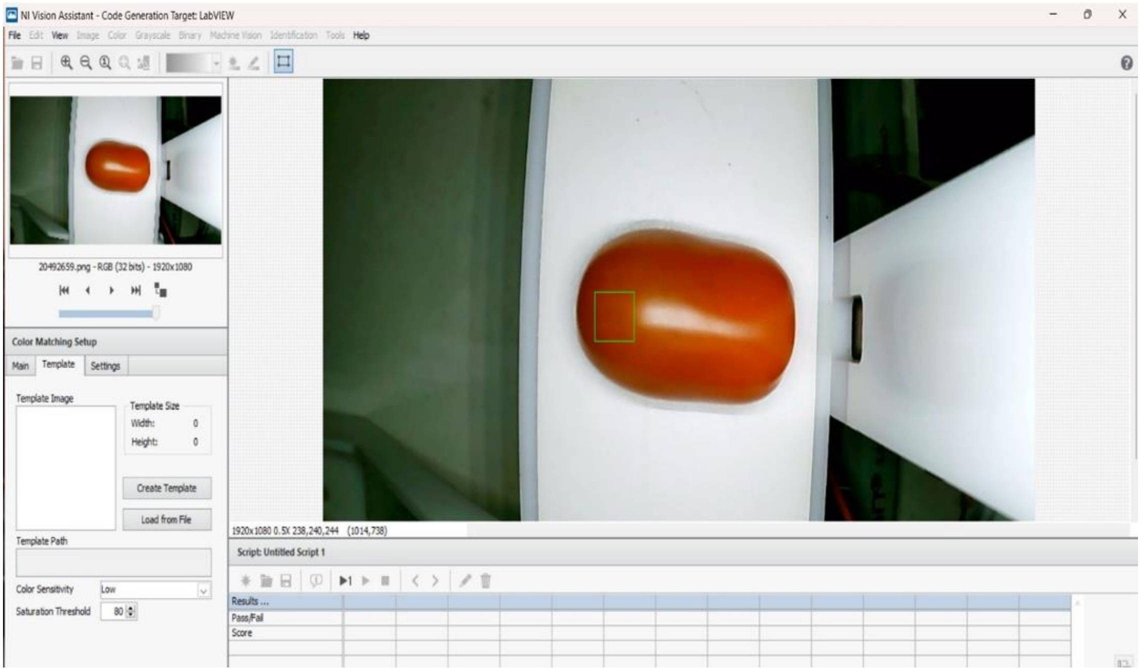

Figure 7. Identify the color of tomatoes

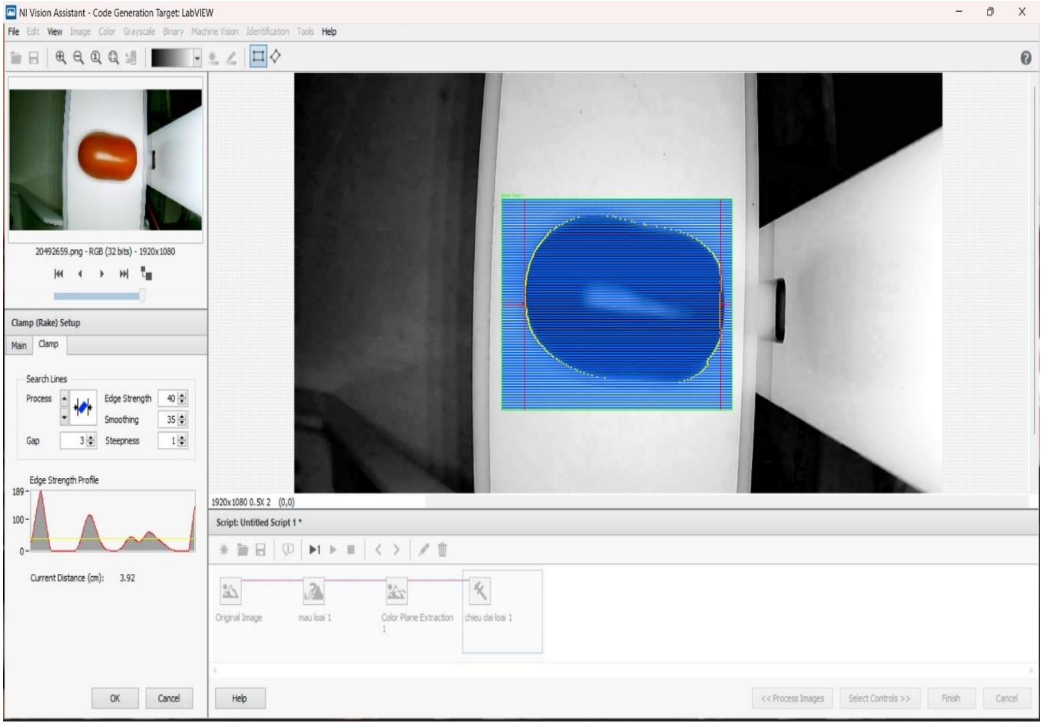

Figure 8. Identify the size of tomatoes

3.3 Comparative Analysis

The performance of the proposed automated tomato sorting system, which integrates a Siemens S7-1200 PLC, LabVIEW-based image processing, and OPC communication, warrants a detailed comparison with existing sorting methodologies to highlight its advantages, limitations, and contributions to the field. This comparative analysis evaluates the system against two primary benchmarks: traditional manual sorting, as conducted by human operators, and existing automated sorting systems documented in recent literature. By examining key metrics – classification accuracy, throughput, cost-effectiveness, scalability, and adaptability – this section elucidates how the proposed system positions itself as a viable, cost-efficient solution tailored for small- to medium-sized enterprises (SMEs) in agricultural and manufacturing contexts. The analysis draws on experimental data from the current study (92% accuracy, 60 tomatoes per minute) and contrasts it with baseline manual sorting results and published automated systems, providing a comprehensive perspective on its practical and scientific value.

Manual sorting, as a longstanding practice in small-scale agricultural settings, serves as the first point of comparison. In the baseline evaluation conducted for this study, a control group of three operators sorted 100 tomatoes each, achieving an average classification accuracy of 85% (95% CI: 82-88%) with a throughput of 30 tomatoes per minute. This performance aligns with findings from (Nturambirwe & Opara, 2020), who noted that manual sorting, while cost-effective in terms of initial investment (requiring only labor and minimal equipment), suffers from significant drawbacks: inconsistency due to human fatigue, subjectivity in visual assessment, and limited scalability under increased production demands. Inter-rater reliability, assessed via Cohen's κ coefficient ($\kappa = 0.82$, $p < 0.01$), confirmed high consistency among operators, yet the error rate (15%) – stemming from misjudgments in borderline ripeness or size – underscored the method's unreliability. In contrast, the proposed automated system achieved a 92% accuracy (95%

CI: 89-95%) and doubled the throughput to 60 tomatoes per minute, demonstrating statistically significant improvements (ANOVA, $p < 0.05$). This leap in efficiency and precision highlights the system's ability to mitigate human error and meet modern production needs, though it requires an initial hardware investment offset by long-term labor savings.

When compared to existing automated sorting systems, the proposed design stands out for its balance of performance and affordability. For instance, Zualkernan et al. (2023) described a machine learning-based sorting system for agricultural products that achieved a remarkable 95% accuracy but relied on high-end GPUs and extensive training datasets, resulting in a setup cost exceeding $10,000 and a computational latency of 1.2 seconds per item, limiting throughput to approximately 50 units per minute. Similarly, Kabir et al. (2023) developed a vision-based system using proprietary cameras and sensors, reporting 90% accuracy and 55 units per minute, yet its dependence on specialized hardware elevated costs to around $8,000, making it less accessible to SMEs. In contrast, the current system leverages a standard 1.3 MP camera and a NEMA 17 stepper motor, reducing the total cost to approximately $2,500 while maintaining a competitive 92% accuracy and 60 tomatoes per minute throughput. The use of LabVIEW's HSV color space segmentation and morphological filtering, processed within 500ms per tomato, ensures real-time performance without the computational overhead of machine learning, offering a practical edge for resource-constrained environments.

Scalability and adaptability further differentiate the proposed system from its counterparts. Manual sorting scales poorly, as adding operators increases costs and variability without proportionally enhancing throughput, capping practical limits at 30-40 tomatoes per minute per worker. High-end automated systems, such as those by (Zualkernan et al., 2023; Kabir et al., 2023), offer scalability through parallel processing or additional units, but their complexity and cost deter adoption in smaller operations. The proposed system, however, features a modular design – comprising a reconfigurable conveyor, adjustable HSV thresholds, and a scalable PLC architecture – that allows it to handle increased volumes (e.g., by extending the conveyor or adding cameras) or adapt to other products (e.g., apples, peppers) with minimal hardware changes. Experimental trials under varying lighting conditions (500-1500 lumens) showed consistent accuracy ($CV \leq 5\%$), unlike manual sorting, which declined to 80% under dim lighting, or (Kabir et al., 2023) system, which required recalibration. This adaptability, combined with a low entry cost, positions the system as a versatile solution for SMEs seeking to transition from manual to automated processes.

The comparative analysis is summarized in Table 1, which juxtaposes the proposed system against manual sorting and two representative automated methods. The table quantifies accuracy, throughput, cost, scalability, and adaptability, providing a clear visual representation of the trade-offs. While the proposed system does not match the peak accuracy of machine learning-based approaches (95%), its 92% accuracy surpasses manual sorting (85%) and rivals other vision-based systems (90%), all while achieving the highest throughput (60 tomatoes/min) and lowest cost ($2,500). Its scalability and adaptability scores reflect its modular design, contrasting with the rigidity of manual methods and the resource demands of advanced automated systems. These metrics underscore the system's contribution: a practical, efficient, and accessible automation solution that bridges the gap between labor-intensive traditions and high-end technology, offering SMEs a pathway to modernization without prohibitive investment.

TABLE 1. Comparative Analysis of Sorting Method (Notes: Accuracy includes 95% CI; Scalability (1 = poor, 5 = excellent) reflects ease of expanding capacity; Adaptability (1 = poor, 5 = excellent) indicates flexibility to varying conditions/products)

Method	Accuracy (%)	Throughput (units/min)	Cost (USD)	Scalability (1–5)	Adaptability (1–5)
Manual Sorting (Baseline)	85 (82–88)	30	~500	2	3
(Zualkernan et al., 2023) (ML-based)	95 (93–97	50	~10.000	4	2
(Kabir et al., 2023) (Vision-based)	90 (87–93)	55	~8.000	3	3
Proposed System	92 (89–95)	60	~2.500	4	4

4. Conclusion

This study has successfully developed an automated sorting system that integrates a Siemens S7-1200 Programmable Logic Controller (PLC) with a LabVIEW-based image processing application. Utilizing a low-cost camera, the system classifies agricultural products, such as tomatoes, based on visual features like color and size. Experimental validation in a controlled environment confirmed the system's reliability and effectiveness, with image data processed in LabVIEW and sorting commands executed via the OPC protocol.

The significance of this work lies in providing a cost-effective automation solution for small-scale industries, where affordability is a critical concern. By leveraging standard technologies, the system reduces operational costs while maintaining essential functionality, thereby making automation more accessible to budget-constrained sectors. This research contributes to the field of industrial automation by demonstrating the practical integration of PLC and vision-based systems for real-time applications. However, the camera utilized in this system is a standard consumer-grade model rather than an industrial camera, which consequently limits its performance in situations with complex environmental lighting. Future research could focus on adapting the system for diverse product types or enhancing its classification accuracy through the incorporation of advanced machine learning algorithms.

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