A Digital Twin-Enabled Cyber-Physical System for Intelligent Green Onion Postharvest Processing

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Abstract. Postharvest green onion processing in small workshops still relies mainly on manual operations or standalone machines, resulting in inconsistent product quality and limited production continuity. Compact systems that coordinate multiple postharvest processes remain insufficiently explored. This study develops a compact digital twin-enabled cyber-physical prototype integrating a four-station indexed rotary platform, lightweight HSV-based yellow-leaf detection, and offline scheduling optimization. Under workshop test conditions, the prototype achieved a nominal throughput of 240 bundles per hour, a vision detection accuracy of 93.5% with a processing time of 42 ms per frame, and an average air-jet cleaning efficiency of 94.0% with a standard deviation of 2.1%. Offline evaluation of 48 timing configurations reduced the calculated station idle time from 10.8 to 8.9 seconds per cycle, corresponding to a reduction of 17.6%. Mixed-size feeding tests achieved an average throughput of 228 bundles per hour, with occasional interruptions associated with oversized bundles blocking the packaging chute. The results indicate the feasibility of a compact automated approach for green onion postharvest processing under the tested conditions, while long-term reliability and economic performance require further validation.

Keywords: Digital twin; Cyber-physical system; Green onion postharvest processing; Machine vision; Scheduling optimization; Agricultural automation.

1 Introduction

Green onion postharvest processing involves trimming, quality inspection, cleaning, weighing, and packaging. In small-scale workshops, these operations are still mainly performed manually or by independent single-function machines, which may result in inconsistent product quality, limited production continuity, and increased labor demand.

Cyber-physical systems and digital twin technologies have been widely studied in manufacturing for production monitoring, simulation, and process coordination [1,2,3]. Existing agricultural digital twin applications have largely focused on visualization and status monitoring, while their application in active process optimization remains less explored [4,5]. Previous agricultural automation studies have largely focused on field operations and harvesting tasks [6,7], whereas computer vision-based quality

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inspection has been widely applied in fruit and vegetable production [8,9,10]. In China, increasing labor costs and limited workshop space have promoted the demand for low-cost and compact integrated equipment [11]. However, experimental studies on multi-process coordinated postharvest systems specifically designed for green onion processing in small-scale scenarios remain limited [12]. Existing studies rarely address the integration of multi-station coordination, adaptive scheduling, and lightweight perception within compact green onion postharvest systems.

The main contributions of this work are summarized as follows.

(1) Development of a compact multi-station cyber-physical processing platform that coordinates trimming, detection, cleaning, and weighing through integrated physical execution and digital twin-assisted scheduling.

(2) Development of a lightweight HSV-based yellow-leaf detection method for embedded implementation.

(3) Establishment of a digital twin-assisted offline scheduling optimization framework evaluated through prototype experiments under multiple scenarios.

2 Proposed Digital Twin-enabled CPS Framework

The proposed system consists of four functional layers. The physical execution layer adopts a four-station indexed rotary structure that integrates multiple processing steps within a compact footprint. The four stations are responsible for feeding and clamping, visual inspection and cutting, air-jet cleaning, and weighing and packaging, respectively. The communication layer applies the MQTT protocol with a 100 ms update interval for equipment state monitoring and uses event-triggered messages for operation commands and alarms. The digital twin layer establishes a geometric, state, and process mapping to support offline simulation before deployment and status monitoring during operation. The optimization layer uses a discrete-event simulation model to evaluate station scheduling under a fixed cycle time of 15 seconds and selects the optimal timing configuration from 48 candidates. The rotary layout enables overlapping operations within a limited space, and its scheduling performance is evaluated through simulation and prototype experiments. The overall system architecture and processing workflow are illustrated in Fig. 1.

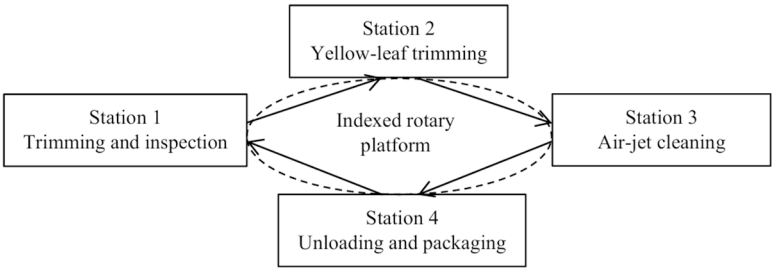


Fig. 1. System architecture and processing workflow of the proposed cyber-physical system.

3 Key Methodologies

3.1 Lightweight Yellow Leaf Detection Method

Considering the limited computational capability of embedded controllers and the requirement for stable performance under variable workshop lighting conditions, a lightweight color-based vision method is adopted to balance detection accuracy, processing speed, and deployment cost.

An industrial RGB camera is used to capture bundle images, which are transformed into the HSV color space to achieve more stable yellow-green segmentation compared with RGB representation. HSV thresholds are calibrated using an independent 50-sample dataset, which is separated from the 600-sample test dataset to prevent data leakage. Morphological operations, including 3 × 3 opening for noise removal and 5 × 5 closing for gap filling, are applied to improve segmentation quality. A connected component is regarded as a defect candidate when its area exceeds 15 mm² and its aspect ratio is within 0.3 to 3.0, reducing interference from petioles and illumination variations. A bundle is classified as defective when the total yellow area exceeds 5% of the visible leaf area, which is used as the reference criterion for performance evaluation.

Tests on the independent 600-sample dataset, including 400 normal and 200 defective samples, achieved accuracies of 96.0% under controlled illumination and 93.5% under workshop lighting. The average processing time was 42 ms per frame, which satisfies the timing requirement of the 15-second operation cycle. The algorithm pipeline and representative detection results are presented in Fig. 2.

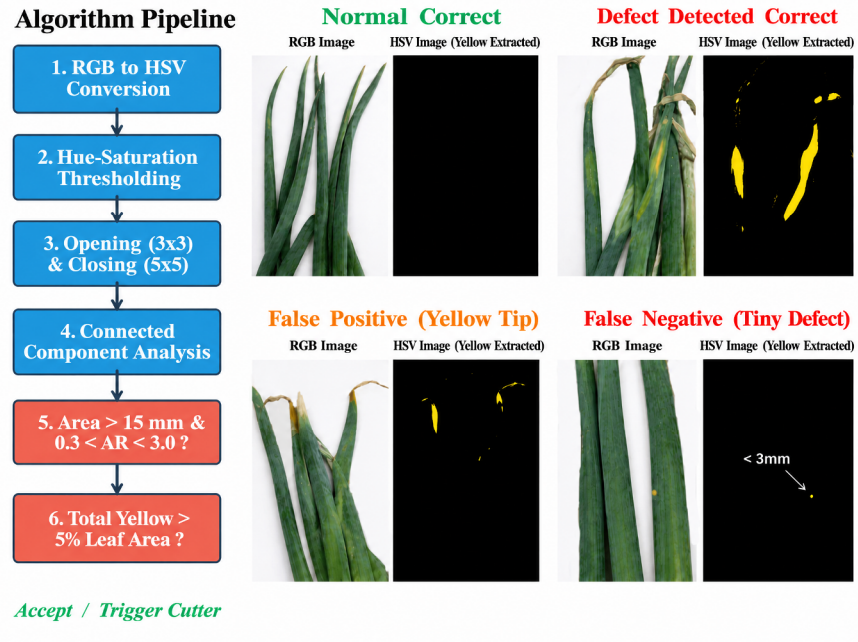


Fig. 2. Vision detection pipeline and representative detection results.

3.2 Digital Twin-assisted Scheduling Optimization

The optimization objective is to minimize total idle time within each cycle. Four station start offsets relative to the indexing signal are selected as optimization variables and discretized into 3 to 4 values with a step interval of 0.2 seconds, resulting in 48 feasible configurations for exhaustive evaluation. The optimization constraints include a maximum cycle time of 15 seconds, a fixed indexing time of 1.2 seconds, a fixed processing sequence, minimum station processing durations, and a minimum gripper safety clearance of 50 mm. A Python-based discrete-event simulation model is developed to evaluate each configuration by tracking station states, including idle, processing, and indexing conditions. The digital twin workflow was developed based on the concepts of state perception, virtual mapping, simulation, parameter update, and physical execution [13].

The selected configuration reduces the calculated idle time per cycle from 10.8 seconds to 8.9 seconds, corresponding to a reduction of 17.6%. This result indicates the potential benefit of scheduling optimization under the tested conditions. A comparison of station timing before and after scheduling optimization is shown in Fig. 3.

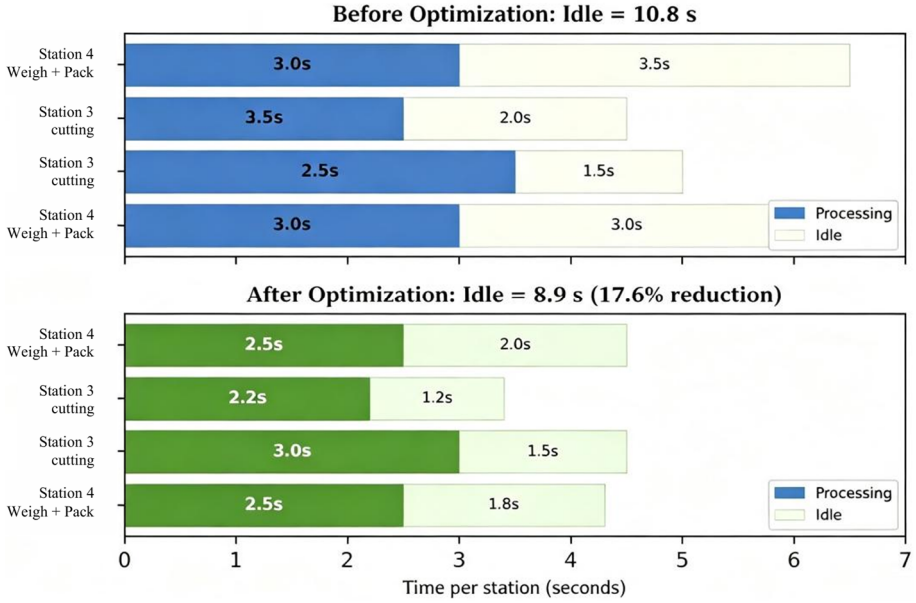


Fig. 3. Station timing comparison before and after scheduling optimization.

The developed digital twin system provides a visual interface for synchronizing equipment status, cycle parameters, and alarm information through MQTT communication, as shown in Fig. 4.

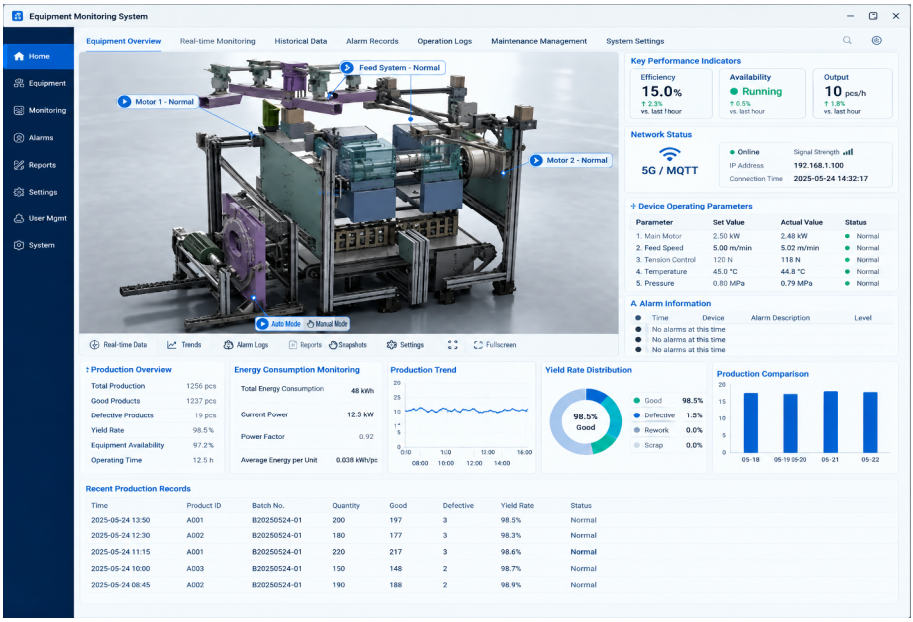


Fig. 4. Digital twin monitoring interface for equipment state synchronization and scheduling evaluation.

3.3 Physical System Implementation

The overall structure of the developed prototype is shown in Fig. 5, including the indexed rotary platform and four functional stations.

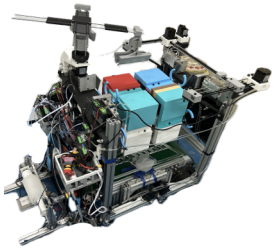


Fig. 5. Overall structure and main components of the developed prototype.

A non-contact air-jet cleaning method is adopted to reduce surface moisture accumulation and eliminate the need for additional drying procedures associated with conventional washing processes [12]. The cleaning unit consists of 12 conical nozzles with a 1.2 mm orifice, arranged in two circumferential rows with a 30° angular interval. The nozzle arrangement was determined based on digital twin-assisted flow-field analysis. The nozzle standoff distance is 80 mm, and the jet angle is set to 45° relative to the axial direction. Prototype tests identified 0.50 to 0.52 MPa as the suitable pressure range

under the tested conditions, with a jet duration of 0.8 seconds per cycle. The main modules, including the vision camera, nozzle manifold, and weighing unit, are designed for independent replacement to facilitate maintenance.

4 Experimental Verification and Analysis

4.1 Experimental Setup

Experiments were conducted using the prototype under workshop conditions. Green onion bundles were categorized according to stalk number and bundle diameter. Small bundles contained 2 to 3 stalks with diameters of 30 to 50 mm, medium bundles contained 3 to 4 stalks with diameters of 50 to 70 mm, and large bundles contained 4 to 5 stalks with diameters of 70 to 90 mm. All bundles were trimmed to an approximately uniform length of 60 cm before testing. These conditions represent typical small-workshop processing scenarios, although they do not fully reproduce seasonal variations in raw material quality and operator feeding behavior.

4.2 Vision Performance and Failure Cases

The detection accuracy was 96.0% under controlled illumination and 93.5% under workshop lighting, with a processing time of 42 ms per frame. These results are comparable with previous color-based agricultural product defect detection studies [8,9]. Compared with deep learning-based approaches, the lightweight implementation reduces computational requirements, although a direct performance comparison was not conducted in this study.

Table 1 presents the confusion matrix obtained from the 600 independent test samples. The precision, recall, and F1 score were 87.8%, 93.5%, and 90.6%, respectively. The higher recall compared with precision indicates that the method tends to reduce missed detections, which may be beneficial for defect removal but can also increase unnecessary cutting operations.

Table 1. Confusion matrix of the yellow-leaf detection method.

	Predicted defect	Predicted normal	Total
Actual Defect	187	13	200
Actual Normal	26	374	400
Total	213	387	600

False negatives mainly occurred in cases involving tiny defects smaller than 3 mm and leaf occlusion, with an increased occurrence rate under low illumination conditions. False positives were mainly associated with naturally chlorotic leaf tips, as fixed HSV thresholds have limited adaptability to natural variations in leaf color. Compared with controlled illumination, non-uniform workshop lighting reduced accuracy by 2.5 percentage points. These results suggest that illumination variation remains a challenge for lightweight vision methods [14,15].

4.3 Throughput, Cleaning and Scheduling

As mentioned in the methodology section, offline scheduling optimization achieves a 17.6% reduction in calculated idle time per cycle.

The nominal throughput is 240 bundles/h based on the 15 s design cycle. Measured throughputs were 254 ± 11 bundles/h for small bundles, 240 ± 12 bundles/h for medium bundles, and 224 ± 15 bundles/h for large bundles. The lower throughput of large bundles was associated with longer clamping movement, repositioning delay, and increased chute friction, which extended the average cycle by approximately 1 s. The above-nominal throughput of small bundles was only observed under the tested conditions and does not represent sustained production capacity. This indicates that future scheduling models should incorporate material-dependent cycle variations rather than assuming fixed processing durations.

A 100-bundle mixed-size feeding test recorded an average throughput of 228 ± 14 bundles/h, with two short pauses caused by oversized bundles blocking the packaging chute. Compared with the medium-bundle group, mixed-size feeding reduced throughput by approximately 5%, suggesting that scheduling optimization provides some tolerance to size. Cleaning efficiency was defined as the ratio of removed surface debris after one air-jet cycle and evaluated by visual inspection on a standardized area. Under the selected pressure range, the average cleaning efficiency was 94.0% ± 2.1% based on ten repeated tests. The efficiency curves under different pressures and soiling levels are shown in Fig. 6. A comprehensive summary of prototype performance metrics is provided in Table 2, and detailed throughput results for different bundle size groups are listed in Table 3.

Table 2. Summary of prototype performance metrics.

Category	Metric	Value
Processing	Nominal cycle	15 s
Processing	Nominal throughput	240 bundles/h
Processing	Measured throughput small	254 ± 11 bundles/h
Processing	Measured throughput medium	240 ± 12 bundles/h
Processing	Measured throughput large	224 ± 15 bundles/h
Processing	Mixed-size throughput	228 ± 14 bundles/h
Processing	Cleaning efficiency	94.0% ± 2.1%
Vision	Accuracy controlled	96.0%
Vision	Accuracy workshop	93.5%
Vision	Precision	87.8%
Vision	Recall	93.5%
Vision	Processing delay	42 ms/frame
Scheduling	Idle time before	10.8 s/cycle
Scheduling	Idle time after	8.9 s/cycle
Scheduling	Calculated reduction	17.6%
Engineering	Full-load power	1505 W
Engineering	Nominal cycle energy	6.27 Wh
Engineering	Idle noise	62 dB
Engineering	Peak noise	78 dB
Engineering	Observed interruption interval	~667 cycles
Engineering	Interruptions in 2000 cycles	3
Engineering	Floor area	1.2 m^2

Table 3. Throughput performance under different bundle size groups.

Bundle Size	Stalk Count	Diameter (mm)	Samples	Throughput (bundles/h)	CV (%)
Small	2-3	30-50	20	254 ± 11	4.2
Medium	3-4	50-70	20	240 ± 12	5.1
Large	4-5	70-90	20	224 ± 15	6.8
Mixed-size feeding	2-5	30-90	100	228 ± 14	8.3

The overlapping scheduling design reduces idle time under standard conditions and provides additional tolerance to size variation. The system requires one operator during operation. Compared with equivalent standalone machines arranged in series, the rotary design reduces the footprint from approximately 2.5 m² to 1.2 m². The mixed-size feeding test further suggests that the optimized scheduling strategy can maintain acceptable throughput under moderate material variation. The cycle time variation over 30 consecutive mixed-size feeding cycles is depicted in Fig. 7.

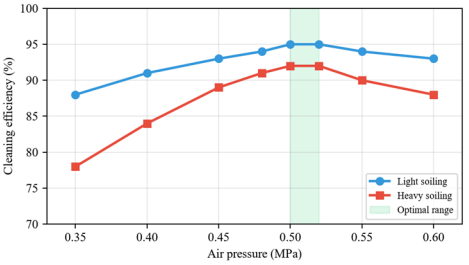


Fig. 6. Cleaning efficiency under different air pressure levels and soiling conditions.

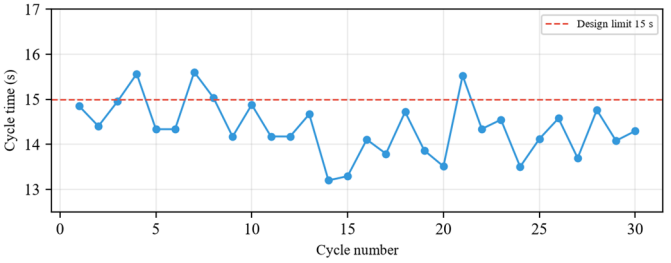


Fig. 7. Cycle time variation over 30 consecutive cycles under mixed-size feeding.

4.4 Engineering Performance and Short-term Endurance

The measured full-load power was 1505 W, corresponding to approximately 6.27 Wh energy consumption per nominal cycle. This value is a preliminary estimate rather than a long-term average. The idle noise and peak air-jet noise levels were 62 dB and 78 dB, respectively, both below the 85 dB occupational exposure limit in this test. However, formal compliance assessment requires standardized long-term measurements. Compared with water washing and drying processes, the air-jet scheme avoids heating and drying energy consumption, although its actual energy-saving ratio requires further quantitative verification.

A 2000-cycle continuous operation test recorded three minor interruptions. The first interruption was a temporary air pressure drop caused by compressor thermal protection, which occurred at approximately the 800th cycle and resulted in a 3-minute pause with approximately 12 bundles affected. The cause was insufficient compressor duty-cycle capability for continuous operation. A higher-duty-cycle compressor and pressure-based early-warning strategy may reduce pressure-related interruptions, although the expected reduction in downtime requires further validation. The second interruption involved bundle slippage during indexing and occurred at approximately the 1120th cycle, when a small bundle failed to engage with the gripper. This caused a 2-minute pause, with 8 bundles requiring reprocessing. The issue was addressed by adjusting the gripper jaw preload spring tension. The third interruption was caused by weighing drift that triggered an automatic pause at approximately the 1890th cycle and was resolved by recalibrating the load cell zero point. After widening the packaging chute inlet by 8 mm, no further jamming occurred during a follow-up test of 100 consecutive large-bundle cycles.

The three interruptions correspond to an average interval of approximately 667 cycles, which should be regarded as a preliminary operational indicator rather than a statistically verified mean time between failures. A simple extrapolation based on the observed interruptions suggests a potential downtime of approximately 2–3. Although long-term reliability has not been fully validated, the proposed framework provides a potential approach for integrating lightweight perception, process coordination, and digital twin-assisted scheduling in compact agricultural automation systems. The observed faults were related to peripheral component matching and material adaptation rather than the overall system architecture, providing preliminary support for the rationality of the compact CPS design.

5 Conclusion

This paper presents and experimentally evaluates a compact digital twin-enabled cyber-physical prototype for green onion postharvest processing, integrating a four-station indexed rotary platform, lightweight vision detection, non-contact air-jet cleaning, and offline scheduling optimization. Under workshop test conditions, the system achieved a nominal throughput of 240 bundles/h, a vision detection accuracy of 93.5%, a cleaning efficiency of 94.0% ± 2.1%, and a 17.6% reduction in calculated idle time.

Prototype tests indicate that the rotary layout enables coordinated postharvest operations within a compact space, while material size variation and feeding stability remain important factors affecting throughput performance. The developed prototype demonstrates the feasibility of integrating digital twin-assisted scheduling with compact agricultural automation equipment under small-scale processing conditions.

All results are prototype-level measurements obtained under the tested conditions, and long-term durability, economic benefits, and cross-scenario applicability require further validation. Therefore, the reported performance should be interpreted as a prototype-level demonstration rather than a full-scale production assessment.

Future work will focus on illumination-robust vision algorithms, adaptive

scheduling with fault-aware strategies, and long-term production validation to further extend the digital twin framework toward predictive maintenance applications.

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