FROM HARVEST TO PACKAGE: AN AUTONOMOUS ROBOT FOR INTEGRATED TOMATO PICKING AND BAGGING

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用于番茄一体化采摘与包装的自主机器人

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ABSTRACT

In addressing the high labor costs and low operational efficiency of greenhouse tomato harvesting and separate packaging workflows, this study develops an integrated tomato harvesting robotic system embedded with RGB-D machine vision, 5-degree-of-freedom manipulator and vertical heat-sealing net bag packaging mechanism. The YOLOv8s lightweight detection model trained on self-built multi-light greenhouse tomato dataset (1260 annotated images covering unobstructed, semi-occluded and heavily occluded fruits) is adopted to identify ripe tomatoes with a recognition accuracy of 95.2%, and ImageJ software is introduced to conduct secondary maturity screening via RGB chromatographic analysis. A global path planning combined with TEB local trajectory optimization realizes autonomous obstacle avoidance navigation of the wheeled mobile platform, while RRT-Connect bidirectional random tree algorithm is applied for obstacle-free grasping trajectory planning inside dense tomato canopies. A total of 120 valid cyclic tests are carried out in simulated greenhouse environment to verify the full-chain automation including fruit detection, in-situ picking and instant bagging. Experimental results show that the average single-fruit processing cycle is 12.1 s, with a picking success rate of 90.8% and bagging success rate of 98.3%. Compared with skilled manual picking and packaging, the overall working efficiency is improved by approximately 30%. This system firstly realizes continuous integrated harvesting and commercial packaging operation for greenhouse tomatoes, providing a feasible technical solution for full-process intelligent protected agriculture.*

摘要

*针对温室番茄采摘、包装分离作业带来的高人力成本与低效问题，本文研发一套集成 RGB-D 机器视觉、五自由度机械臂与立式热封网袋包装机构的一体化番茄采收机器人。系统采用 YOLOv8s 轻量化检测模型，基于自建多光照温室番茄数据集（1260 张标注图像，覆盖无遮挡、半遮挡、重度遮挡样本）实现成熟番茄识别，识别精度 95.2%；配套 ImageJ 软件通过 RGB 色谱分析完成果实成熟度二次校验。采用 A * 全局路径规划结合 TEB 局部轨迹优化实现轮式移动底盘自主避障导航，RRT-Connect 双向随机树算法完成密植冠层内无碰撞抓取轨迹规划。在模拟温室环境完成 120 组完整循环试验，验证识别、就地采摘、即时套袋全流程自动化。试验结果表明，机器人单果平均处理周期 12.1 秒，采摘成功率 90.8%，套袋成功率 98.3%；相较熟练人工采摘包装综合效率提升约 30%。本系统首次实现温室番茄采收与商品化包装连续一体化作业，为设施农业全程智能化提供可行技术方案。*

INTRODUCTION

Facility agriculture, through controlled-environment production, is crucial for ensuring stable and efficient food supply. As a primary protected-field crop, tomatoes face significant harvesting challenges: concentrated fruit ripening leads to a surge in labor demand, resulting in tight operation cycles, high-intensity work, and rising costs. The aging workforce and global labor shortage trends further exacerbate this issue, making large-scale manual harvesting increasingly economically unsustainable. Consequently, developing autonomous harvesting robot systems has become an imperative for agricultural sustainability.

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To this end, extensive research has been conducted in the field of agricultural harvesting robots. International projects, such as the EU's CROPS *(Goulart, 2023)* have developed modular multi-crop operation platforms integrating perception and manipulation. Research on crops like cucumbers and grapes has also advanced solutions combining machine vision, flexible end effectors, and motion planning. While these systems have made significant strides in fruit recognition and separation, their functionality largely remains confined to the “identify-harvest” stage. Harvested fruits typically require separate manual processes for sorting and packaging, adding handling steps and increasing damage risks, thereby hindering the realization of continuous automation from plant to packaged product. Particularly, the technology for immediate online automated commercial packaging (such as protective netting bags) post-harvest remains a critical bottleneck for achieving end-to-end automation *(Marin et al., 2025).*

To advance full automation of the “harvesting-packaging” process for greenhouse tomatoes, this study designed and validated a multi-sensor fusion robotic system. This system integrates a highly compact mechanical platform (incorporating an end-effector, vertical heat-sealing bagging mechanism, and buffer collection bin) with collaborative intelligent algorithms (YOLO-based visual detection, A*/TEB and RRT-Connect/visual servo hierarchical planning, and behavior tree scheduling). It combines ripe fruit identification, precise picking, on-site bagging, and collection into a single continuous operational cycle. Simulated greenhouse experiments demonstrated a 90.8% picking success rate, 98.3% bagging success rate, and an average processing cycle of approximately 12 seconds per fruit. Overall efficiency significantly surpassed manual labor, providing a highly efficient and feasible solution for automated greenhouse tomato production *(Liu et al., 2025)*.

Matache et al. (2026) developed an AI greenhouse tomato harvesting robot that only supports fruit picking without on-site packaging, requiring repeated manual fruit transfer and causing peel damage, which fails to realize end-to-end production. Current tomato harvesting robots have three core research gaps:

Most platforms lack integrated heat-sealing bagging actuators, separating harvesting and packaging procedures. Visual systems rarely combine YOLO detection with image-based maturity grading, and few reports fully disclose YOLO version, dataset and occlusion detection performance;

No unified collaborative scheduling system exists for mobile chassis, manipulator and bagging module.

To address the above bottlenecks, this study proposes a multi-sensor fusion robot integrated with 5-axis manipulator and vertical bagging mechanism. YOLOv8s combined with ImageJ chromatographic analysis realizes precise fruit screening, while A*/TEB navigation and RRT-Connect arm planning support lossless canopy picking. The system achieves continuous identification-picking-bagging-collection operation to fill the gap of integrated post-harvest packaging.

MATERIALS AND METHODS

OVERALL DESIGN AND INTEGRATION OF THE HARVESTING ROBOT SYSTEM

System Architecture and Workflow

To achieve full automation of tomato picking, bagging, and collection, this system employs a layered, collaborative hardware-software architecture Fig. 1 *(Adochiei et al., 2025)*, thereby enabling a closed-loop operational workflow Fig. 2.

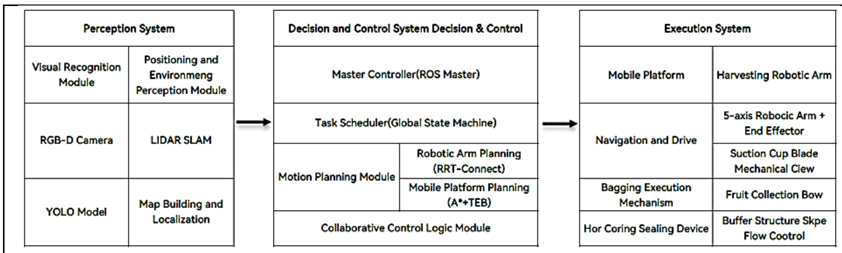

Fig. 1 - Overall System Architecture

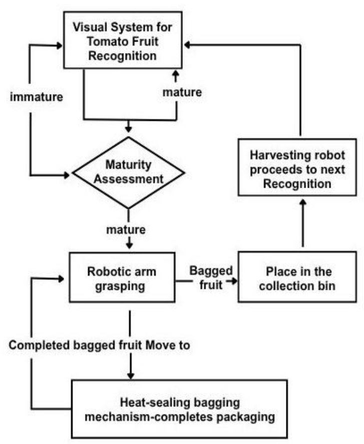

Fig. 2 - Workflow

Key Technical Parameters of the Harvesting Robot

Key design parameters are shown in Table 1.

Table 1

Summary of Key Performance Indicators for Tomato Harvesting Robots

Parameter	Technical Index
Overall Dimensions	Length 1200 mm × Width 880 mm × Height 960 mm
Whole Machine Weight	6 kg
Maximum Working Radius (Range)	2–5 m
Battery Endurance Time	2-5 h
Harvest Success Rate	85%-93 %
Bagging success rate	88%-95 %
Ripe Tomato Recognition Accuracy	95.2 %
Single Fruit Processing Cycle	10-15 s
Hourly Processing Capacity	249-400 fruits/h

In mechanical and structural design, overall dimensions must strictly comply with relevant specification constraints *(He et al., 2025)*. Concurrently, the vision system must operate stably under complex lighting conditions and identify partially obscured or overlapping fruits, achieving millimeter-level positioning accuracy to ensure precise grasping *(Wang & Liu, 2025)*.

DESIGN AND IMPLEMENTATION OF ROBOTIC MECHANICAL SYSTEMS

1. Overview of mobile platforms

A front-wheel-drive wheeled chassis with long wheelbase is adopted to enhance driving stability. The picking manipulator, heat-sealing bagging unit and fruit bin are arranged sequentially along the travel direction to match the picking-bagging-collection workflow *(Luo et al., 2017).*

After grasping, the fruit is transferred to the bagging mechanism and slides down a 20° inclined chute into the rear buffer bin. This integrated layout shortens fruit conveying paths and forms the mechanical foundation for continuous automatic operation (Fig. 3).

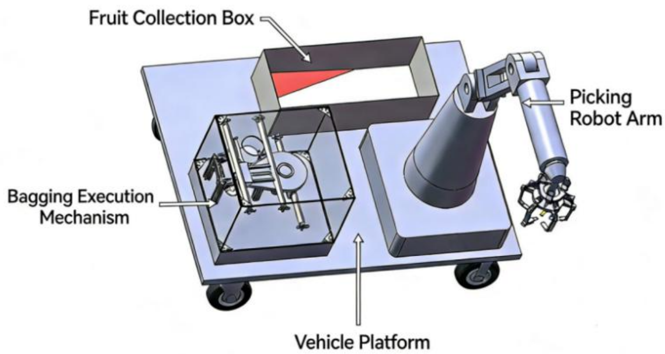

Fig. 3 - Mobile Platform

2. Design of harvesting robotic arm and end-effector

A 5-axis manipulator is equipped with 360° rotating base and wrist joints, plus a 270° elbow joint. The gripper integrates flexible protective sleeves, retractable vacuum cups and cable-driven cutting blades *(Bu et al., 2025)*. Three parallel cylinders' control gripper opening and closing for 50-100 mm diameter tomatoes. Vacuum assistance realizes gentle fruit transfer before bagging (Figs. 4-6).

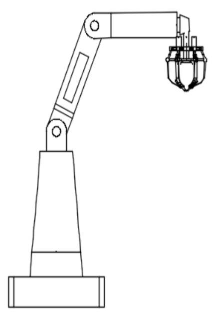

Fig. 4 - Manipulator

Fig. 5 - Gripper

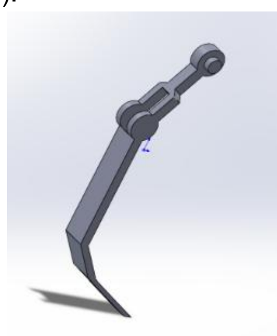

Fig. 6 - Gripper Finger

3. Bagging actuator design

A vertical hot-cut net bagging device is proposed to replace inefficient manual packaging. Its three core modules work sequentially: net bag feeding, conical expansion, and thermal sealing & cutting.

Dual friction rollers deliver mesh bags; the tapered guide expands bag openings to fit variable fruit sizes. A cam-driven hot blade completes simultaneous cutting and sealing, with adjustable speed and temperature controlled by PLC (Figs. 7-8).

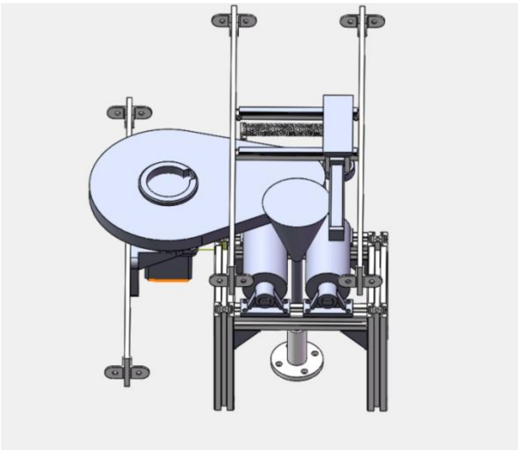

Fig. 7 - Structural Diagram of the Bagging Mechanism

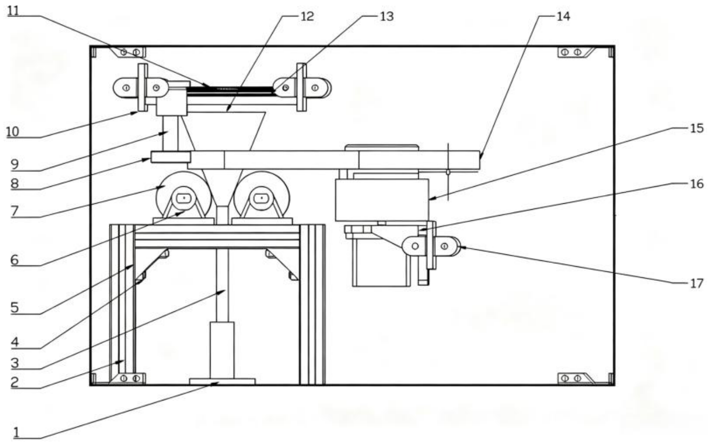

Fig. 8 - Schematic of the Bagging Mechanism

1-External Threaded Flange; 2-Support Profile; 3-Support Steel Pipe; 4-Nuts and Bolts; 5-Angle Bracket; 6-Support Frame; 7-Dual Active Friction Wheel Mechanism; 8-Rollers; 9-Connectors; 10-Support Plate; 11-Tension spring; 12-Guide cone; 13-Linear slide rail; 14-Cam mechanism; 15-Coupling; 16-Drive motor; 17-Triangular iron

4. Fruit collection bin design

The storage bin is fitted with foam anti-collision cushions and a 20°- 30° slope connecting the bagging device. Adjustable flexible partitions separate fruits by size to reduce extrusion damage while maintaining storage density (Fig. 9).

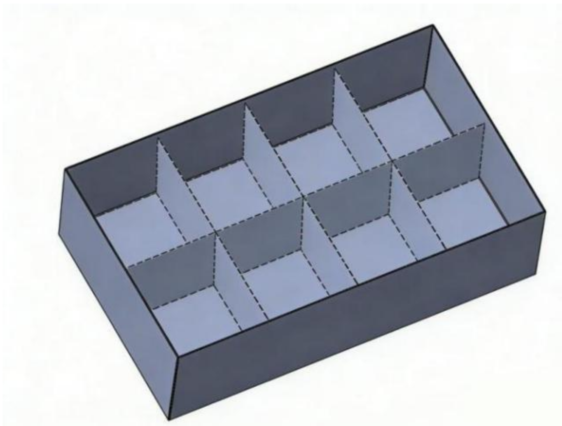

Fig. 9 - Fruit Collection Bin

MACHINE VISION-BASED TOMATO IDENTIFICATION AND HARVESTING LOCALISATION

1. Visual system hardware configuration

As shown in Fig. 10, the visual system hardware primarily consists of an industrial control computer, power supply, depth camera, robotic arm with its controller, and an electric gripper. The system employs an MK-GEB013GC-M1 camera paired with an MK-FC23M35F28-10M-A lens to capture tomato fruit images *(Yuan et al., 2023)*, meeting requirements for color recognition and spatial perception. The Model K280L Industrial Control Computer runs the visual recognition model, performs deep learning inference, controls the electric gripper, and communicates with the robotic arm controller. The robotic arm control system employs a dedicated controller equipped with a teach pendant, enabling automatic planning of the shortest motion path based on the target coordinates of the end-effector.

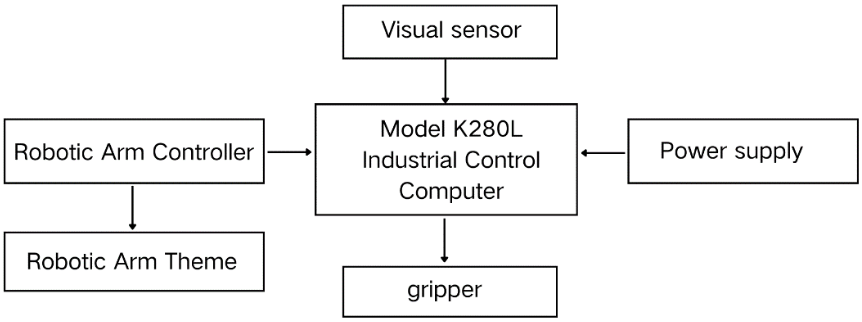

Fig. 10 - Block Diagram of the Vision System

2. Tomato recognition and localization algorithm

First, calibrate the robot to establish three Cartesian coordinate systems: the flange coordinate system, the gripper coordinate system, and the camera coordinate system *(El-sheikha et al., 2024)*. As this robot employs an ‘eye-on-hand’ mounting configuration, measurements reveal the X, Y, and Z deviation values between the camera coordinate system origin and the gripper coordinate system origin: X=20, Y=0, Z=30 (mm).

The coordinate transformation relationship between a point P in space within the flange coordinate system and the gripper coordinate system is as follows:

If a point P in space is represented as P_b in the flange coordinate system and P_g in the gripper coordinate system, then:

$$P_b = {}^bR_g P_g + {}^bt_g \tag{1}$$

$${}^bR_g = R_z R_y R_x \tag{2}$$

represents the rotation matrix, and ${}^bt_g$ denotes the translation vector calculated from the X, Y, Z offsets. When expressed in homogeneous coordinates, the transformation matrix takes the form:

$$\begin{bmatrix} X_b \\ Y_b \\ Z_b \\ 1 \end{bmatrix} = \begin{bmatrix} {}^bR_g & {}^bt_g \\ O^T & 1 \end{bmatrix} \begin{bmatrix} X_g \\ Y_g \\ Z_g \\ 1 \end{bmatrix} = {}^bT_g \begin{bmatrix} X_g \\ Y_g \\ Z_g \\ 1 \end{bmatrix} \tag{3}$$

Here, ${}^bT_g$ represents a 4×4 homogeneous transformation matrix. After image acquisition, the computer performs feature extraction (including edge detection and corner operations), classifying features into three categories: fruit stalks, leaves, and fruits. Subsequently, path planning is conducted using the RRT algorithm to navigate around stem and leaf obstacles during harvesting *(Meng et al., 2025).*

3. Determining fruit maturity and harvest readiness

Tomatoes with diameters of 30-50 mm were selected, and fruit size was determined from the images captured by the camera. As illustrated in Fig. 11, ImageJ software was used to extract the RGB intensity values of the tomato fruit images. These values were then compared with reference color characteristics to evaluate fruit ripeness, as shown in Fig. 12 *(Sepúlveda et al., 2020).*

Fig. 11 - Representative image of a tomato fruit

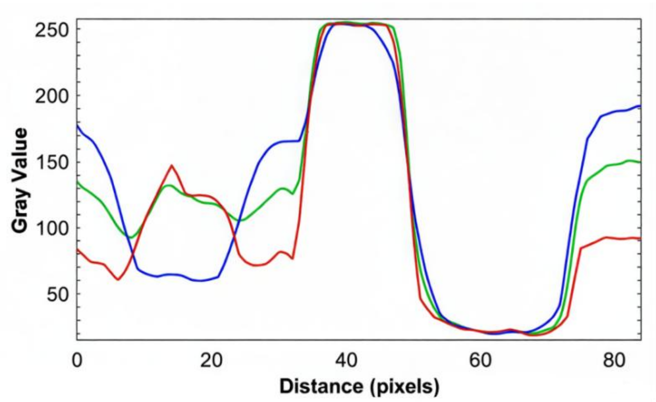

Fig. 12 - Chromatographic Range

YOLO VISUAL DETECTION MODEL AND TRAINING DATASET

This work adopts lightweight YOLOv8s for tomato recognition, leveraging C2f multi-scale backbone and decoupled detection heads to enhance detection of occluded fruits and reduce ripeness misclassification.

1. Self-Built Tomato Dataset

RGB-D images were captured under morning weak light, midday strong light and evening diffuse light, totaling 1260 samples categorized by occlusion: 520 unobstructed, 460 semi-occluded (10%-50% leaf coverage), 280 heavily occluded (>50% leaf coverage). Four labels (ripe_tomato, unripe_tomato, leaf, branch) were annotated via LabelImg. The dataset was split 7:2:1 for training, validation and testing, with random cropping, brightness jitter, flip and blur augmentation applied during training.

2. Model Training Parameters and Evaluation Metrics

Training ran on Model K280L PC with RTX 3060 GPU; BatchSize=16, initial lr=0.001, cosine annealing decay, total 150 epochs. Loss combines CIoU and cross-entropy. Evaluation metrics include mAP@0.5, Precision, Recall and single-frame inference latency, analyzed in Results.

3. Data Flow Between YOLO and ImageJ Software

The ROS vision node feeds frames into YOLOv8s to extract bounding boxes of ripe tomatoes;

Target regions are auto-cropped and batch-exported for ImageJ analysis.

ImageJ extracts RGB gray curves to match standard ripeness thresholds.

Only qualified fruit coordinates are transmitted to the manipulator planning module; underripe targets are discarded.

This two-stage screening reduces mis-harvest caused by contour-only YOLO judgment.

ROBOT MOTION PLANNING AND COLLABORATIVE CONTROL

Mobile Platform Path Planning

Equation (4) is the heuristic cost function of A* algorithm, used to search the shortest collision-free global path in greenhouse crop rows.

The A* algorithm employs a heuristic function *(Shao, 2025)*:

$$f(n) = g(n) + h(n) \tag{4}$$

to guide the search, ensuring the shortest path while enhancing efficiency.

The TEB (Timed Elastic Band) algorithm models the robot's future trajectory as a timestamped sequence of poses:

$$B = \{Q_i\}_{i=0}^{n}, \ Q_i = [x_i, y_i, \theta_i, \Delta t_i]^T \tag{5}$$

and achieves smooth, safe local motion by minimizing the total cost function:

$$F(B) = \sum_k \omega k \cdot f_k(B) \tag{6}$$

to achieve smooth and safe local motion *(Li, 2025)*.

Equations (5) and (6) model robot pose sequence and overall trajectory cost, realizing real-time local obstacle avoidance based on LiDAR point cloud data.

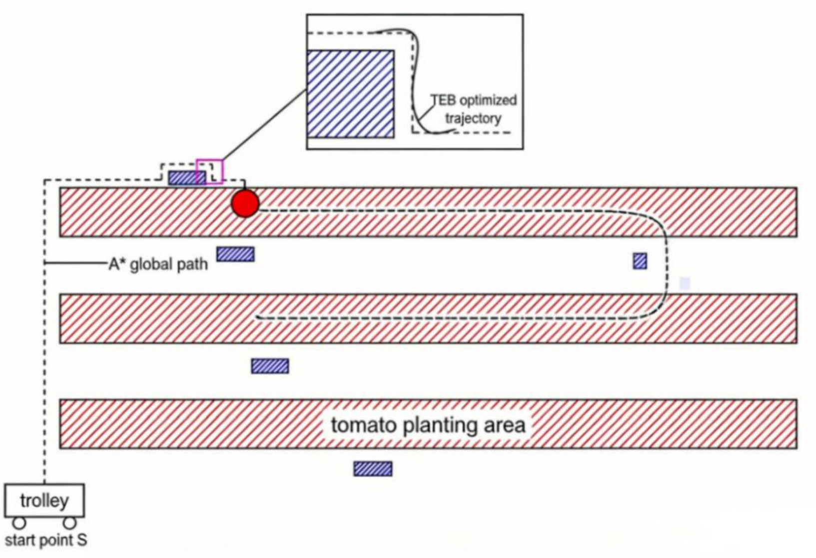

Fig. 13 - Tomato Planting Area and Mobile Platform Path

The system adopts a two-layer planning architecture of “global guidance—local optimization”. The flowchart of the A* algorithm Fig. 14 and the complete operational flowchart of A* working in tandem with TEB are shown in Fig. 15. *(Ji et al., 2023).*

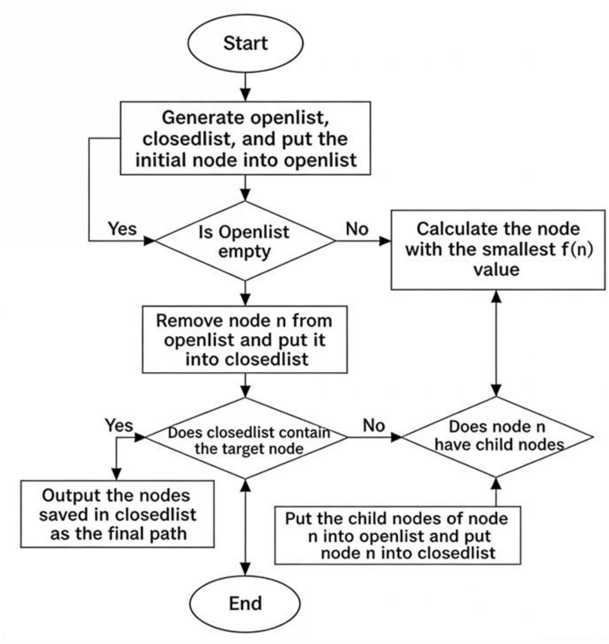

Fig. 14 - A* Algorithm Flowchart

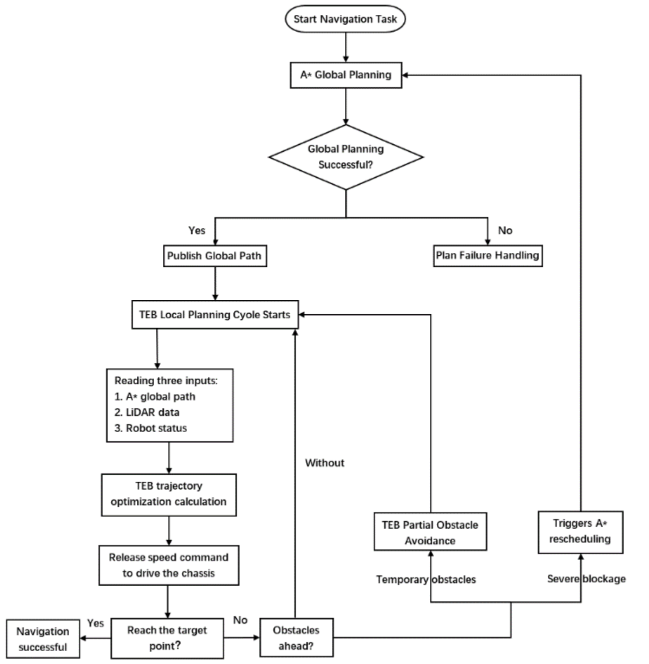

Fig. 15 - Collaborative Workflow Diagram

Robotic Arm Picking Motion Path Planning

The picking robotic arm must operate within dense, unstructured canopy structures, presenting challenges of high-dimensional configuration space search and dynamic obstacle avoidance *(Yuan & Shen, 2017)*. To address this, the system employs a comprehensive strategy combining ‘Global Sampling Planning (RRT-Connect) *(Yu et al., 2017)* + Local Visual Servoing Fine-Tuning + Semantic Layered Obstacle Avoidance’.

Global Path Planning: Employing the RRT-Connect bidirectional random tree algorithm, random trees are simultaneously grown from the start point q_{start} and the goal point q_{goal}. Through random sampling, node expansion, and collision detection, it rapidly searches for feasible paths in high-dimensional spaces with probabilistic completeness.

The node-expansion rule is defined as follows:

$$q_{new} = q_{near} + \varepsilon \cdot \frac{q_{rand} - q_{near}}{\| q_{rand} - q_{near} \|} \tag{7}$$

Equation (7) defines the node-expansion rule used in the bidirectional RRT-Connect algorithm, enabling rapid collision-free path planning within a dense tomato canopy.

Semantics-Based Hierarchical Obstacle Avoidance Strategy: See Table 2 below for details:

Table 2

Parameter Table for Stratified Obstacle Avoidance Strategy

Grade	Obstacle type	Safe distance	Constraint nature		Handling principles
Level 1	Such as greenhouse skeleton, support columns, etc.	70 mm	Hard constraint		Touching is strictly prohibited, and intrusion is regarded as a collision
Level 2	Tomato branches, leaves, vines	1 mm	Soft constraints (continuous costs)		Allow slight contact to guide the detour with a continuous penalty function
Level 3	Other fruits to be protected	3 mm	Strong repulsion constraint		Active protection gives a very high cost of repulsion to avoid collisions

System Collaborative Control and Communication Framework

To ensure the coordinated and orderly operation of the mobile platform, robotic arm, and bagging device, the system manages the temporal dependencies, spatial conflicts, and exception-handling requirements associated with the different tasks, as illustrated in Fig. 16.

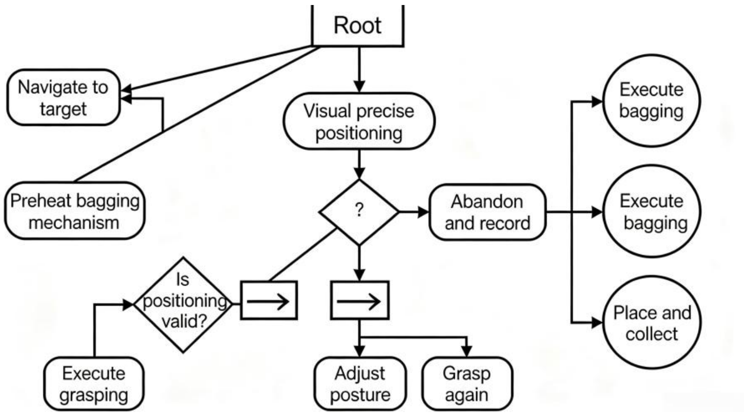

Fig. 16 - Multi-Task Coordinated Control System

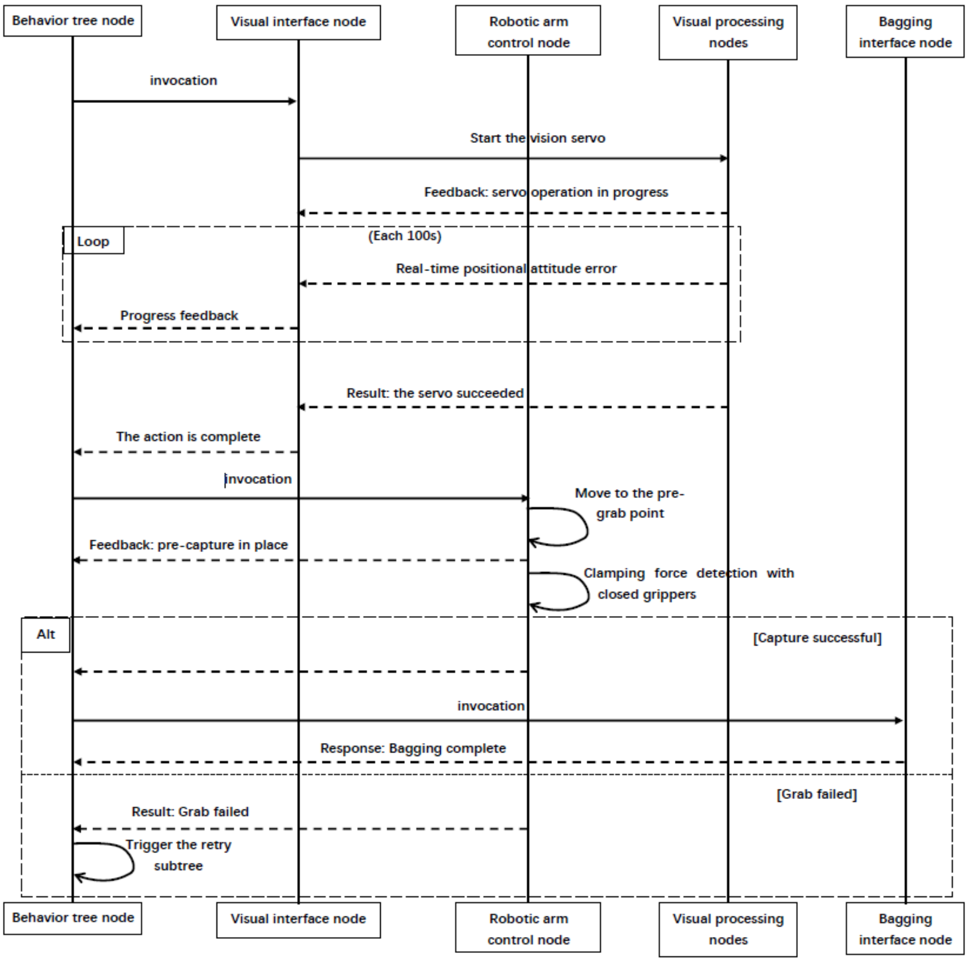

Fig. 17 - Internal Execution Logic and Multi-System Coordination Mechanism

To clearly illustrate the internal execution logic of critical action nodes within the behavior tree and the multi-system coordination mechanism, the 'Execute Harvesting Action' node serves as an example. Internally, it invokes sub-services such as visual servo, grasping, and bagging to achieve a seamless sequence from visual fine positioning to fruit grasping and bagging. Fig. 17 details this node's execution flow and the invocation relationships between its modules.

The system employs a ROS-based modular communication network, where functional nodes exchange data and execute tasks via Topics, Services, and Actions. A TF tree manages coordinate transformations, enabling real-time coordination and synchronization among the mobile platform, robotic arm, and packaging device under behavior tree scheduling.

RESULTS

System Integration and Experimental Analysis

Quantitative Performance Analysis of YOLOv8s Visual Detection Model

Detection performance under three occlusion grades is tested on the test set, as listed in Table 3.

Table 3

YOLOv8s detection performance under different fruit occlusion conditions

Occlusion Level	mAP@0.5	Precision /%	Recall /%	Single-frame Inference Time /ms
Unobstructed ripe tomato	98.6	97.3	96.8	28.6
Semi-occluded ripe tomato	94.1	94.5	93.2	29.1
Heavily occluded ripe tomato	87.3	88.1	86.5	30.2

The mAP declines with increased leaf coverage but still meets picking requirements. Combined with ImageJ secondary screening, the overall maturity discrimination accuracy reaches 93.5%. The average 29 ms inference time ensures real-time grasping response on the K280L industrial computer.

Navigation Experiment of Mobile Platform Based on A and TEB Algorithm*

A* global + TEB local dual planning is verified in simulated greenhouse ridges with static and dynamic obstacles, 20 repeated trials for each group. Comparative results are shown in Table 4.

Table 4

Comparative navigation results of A* single planning and A*+TEB dual planning

Evaluation Index	A* + TEB Dual Planning	Single A* Global Planning	Performance Improvement Rate
Global path length of standard ridge / m	18.62	18.62	-
Average single navigation time / s	22.4	28.7	22.0%
Maximum lateral deviation during obstacle avoidance / mm	36.2	94.7	-
Total collision times within 20 groups of tests	0	12	-
Average terminal positioning error / mm	±8.3	±15.6	46.8%

TEB optimizes local trajectories based on LiDAR data, eliminating collision risks and improving docking precision for manipulator picking.

Classification Statistical Test of Independent Net Bagging Operation

The robot completes single-fruit independent heat-sealed packaging. Special bagging tests are carried out for tomatoes with diameters ranging from 50 mm to 100 mm. 120 valid experimental samples are grouped by fruit size to count bagging success rate and fault distribution, as shown in Table 5.

Table 5

Bagging performance statistics of tomatoes with different diameters

Tomato Diameter Range / mm	Number of Test Samples	Successful Bagging Cases	Bagging Success Rate / %	Main Fault Types
50–70 (small fruit)	42	41	97.6	Slight net bag offset (1 case)
70–85 (medium fruit)	50	49	98.0	Thermal sealing adhesion (1 case)
85–100 (large fruit)	28	27	96.4	Fruit jamming on guide cone (1 case)
Total Summary	120	118	98.3	Total faults: 2 cases

Overall bagging reliability meets commercial standards; large-fruit jamming can be mitigated by optimizing the conical guide stroke in future work.

Efficiency Quantitative Comparison Between Robotic System and Manual Operation

120 continuous robotic cycles yield an average single-fruit runtime of 12.1 ± 1.5 s. Three skilled workers achieved 17.3 ± 2.8 s per fruit under identical operations.

Hourly throughput: Robot ≈ 298 fruits/h; Manual ≈ 208 fruits/h, corresponding to ~30% efficiency improvement, consistent with Abstract claims.

Manual efficiency drops 23% after 4 h due to fatigue, while the robot maintains stable output without labor attenuation and extra transfer steps.

Experiments and Results

To validate system performance, testing was conducted in a simulated greenhouse environment. The experiment utilized tomato plants at varying stages of maturity, requiring the system to perform continuous integrated operations on ripe fruit *(Wu and Miao, 2025).* Through over 120 effective cycles, the system's performance metrics were evaluated and compared with manual operations, with results shown in Table 6.

Table 6

System Key Performance Indicator Test Results

Experimental Parameters	Experimental Parameters Average Value/Success Rate	Note
Total number of experiments (fruit)	120 times	Includes tests under different lighting conditions (morning/afternoon)
Average total time required per fruit	12.1 ± 1.5 s	The entire process time from identification to completion of bagged recycling
Accuracy rate for identifying ripe fruit	95.2%	The proportion of mature fruit correctly identified as “ready for harvest”
Comprehensive Accuracy Rate for Maturity Assessment	93.5%	Overall classification accuracy for green-ripe, color-changing, and fully ripe fruit stages
Harvest Success Rate	90.8%	The percentage of fruit stems successfully gripped and severed without causing damage to the fruit
Accuracy of Harvest Location Positioning	96.7%	Precision of the robotic arm's end effector reaching the predetermined fruit stalk cutting point
Bagging success rate	98.3%	Percentage of successful bagging operations
Average time required for manual operations (for comparison)	17.3 ± 2.8 seconds per fruit	The average time required for skilled workers to complete picking and bagging

Table 6 summarizes all key comprehensive indicators of the integrated robot prototype under simulated greenhouse tests.

System Comparison Analysis and Summary of Advantages

To objectively evaluate the comprehensive performance and innovative value of this design, this section compares it with three representative studies from recent years: a greenhouse tomato harvesting robot focused on sequence optimization *(Li, 2024)*, a strawberry harvesting robot investigating dual-arm coordination *(Liu et al., 2026),* and the latest row-planted strawberry harvesting robot designed for narrow ridge-edge environments *(Wang et al., 2025)*. Key systematic comparisons are presented in the table below.

Table 7

Systematic Comparative Analysis Chart

Comparison Dimensions	This Design: Tomato Harvesting Robot	Greenhouse Tomato Harvesting Robot	Dual-Arm Strawberry Picking Robot	Row-planted strawberry picking robot
Perception System Solution	Multi-source Fusion Perception: Integration of RGB-D cameras (target recognition/localization) and LiDAR (SLAM navigation).	Visual Perception: Utilizes an enhanced Ghost-CAE YOLOv5 model with a depth camera (D435).	Visual and 3D Reconstruction: Employs YOLOv8-segment for instance segmentation, combined with COLMAP for scene modeling.	Visual and End-Point Sensing: YOLOv5-based picking point localization combined with end-point fiber optic sensors for trigger detection.
Planning and Control Strategy	Hierarchical Collaborative Planning: A* (global path planning), TEB (local obstacle avoidance), RRT-Connect (robot arm path planning) integrated with vision servo closed-loop control.	Harvest Sequence Optimization: We propose the “K-G method,” which integrates K-means clustering with a Gaussian kernel function to optimize sequences.	Dual-Arm Task Planning: Proposes a coordinated algorithm integrating genetic and cheetah optimization (GCO), with path planning employing RRT*.	Task Decision Model: Priority-Based Harvesting Strategy Based on Fruit Spatial Relationships; Four-Degree-of-Freedom “PRPR” Configuration Manipulator.
Key Performance Indicators	Recognition success rate: 95.2%; Picking success rate: 90.8%; Bagging success rate: 98.3%; Single fruit full cycle: ~12.1 s.	mAP Recognition Rate: 95.12%; Picking Success Rate: 95.56%; Average Picking Cycle: ~6.7 s per fruit.	(Algorithm Performance) Reduces total job time by up to 34.5% and reduces dual-arm idle time by 81.9%.	Single-arm picking cycle: 5.0 s; Average dual-arm cycle: 4.57 s; Damage-free picking success rate: 59.56%.

Mechanical and Actuator Systems	Dedicated bagging mechanism (integrated heat sealing), flexible cushioning collection bin, vacuum-assisted end-effector for transfer.	Universal Six-Axis Robotic Arm (AUBO-i5) with Adaptive Flexible Four-Finger Gripper.	A composite end effector integrating active obstacle clearance (low-voltage blower) with passive obstacle avoidance (soft gripper).	Non-destructive mechanical gripper employing a spatial cam and spring steel plate for rapid gripping and shearing.
System Autonomy and Collaboration	Based on ROS and behavior trees, achieve adaptive coordination and task scheduling among the mobile platform, robotic arm, and bagging unit.	Achieved a closed-loop autonomous picking system for a single arm, without involving complex multi-motor unit coordination.	Establish a “dual cargo bay-dual workstation” model to optimize temporal and spatial conflicts between dual arms within overlapping work zones.	Features a distributed four-wheel independent drive/steering chassis with multiple steering modes to accommodate narrow aisle navigation.

CONCLUSIONS

This study designs and validates a fully integrated tomato harvest-and-packaging robot. The 12.1 s single-fruit cycle delivers ~30% higher efficiency than manual labor, with 95.2% fruit recognition, 90.8% picking and 98.3% bagging success rates.

The system’s performance relies on four coordinated technologies: YOLOv8s+ImageJ dual ripeness detection, A*/TEB inter-row navigation, RRT-Connect canopy obstacle avoidance and behavior tree multi-unit scheduling.

Different from single-function harvesting robots, the built-in vertical heat-sealing bagger realizes on-site commercial packaging to reduce fruit damage. This prototype provides a complete hardware and algorithm reference for full-process intelligent greenhouse agriculture.

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