DESIGN AND EXPERIMENT OF AN INTEGRATED PLUG SEEDLING SORTING AND REPLANTING MACHINE BASED ON A LOW-DAMAGE GRASPING STRATEGY

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基于低损夹取策略的穴盘苗分选补栽一体机设计与试验

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ABSTRACT

To overcome the inefficiency and lack of system coordination caused by the separation of plug seedling sorting and replanting processes, this study designed and developed an intelligent integrated operation system that combines both sorting and replanting functions. The system aims to enhance the overall operational synergy and automation level of plug seedling management. It integrates modules for seedling grading, grasping parameter generation, and transplanting execution, thereby achieving autonomous identification, intelligent grasping, precise replanting, and efficient collection and reuse of weak seedlings. In the grading module, a comparative analysis of YOLO series models was performed, and YOLOv11 was selected for accurate identification of robust and weak seedlings. For the grasping strategy, a lightweight grasping pose parameter prediction network (LRGN) was introduced to generate optimal grasping angles and widths, effectively minimizing physical damage to the seedlings. Experimental results indicated that, for trays with a 4×8 cavity configuration, the recognition accuracy reached 96.0%, sorting success rate 96.67%, replanting success rate 96.0%, and leaf damage rate 2.15%. For trays with a 5×10 configuration, the recognition accuracy was 96.33%, sorting success rate 95.83%, replanting success rate 94.67%, and leaf damage rate 2.88%. The proposed system provides reliable technical support and a practical reference for advancing the intelligent and precise operation of plug seedling cultivation equipment.

摘要

针对穴盘苗分选与补栽功能分离导致的效率低、系统协同性差问题，本研究设计并开发了一种集分选与补栽功能于一体的智能作业系统，以提升整体作业的协同效率与自动化水平。该系统集成等级识别、夹取参数生成及栽植执行模块，实现了穴盘苗的自主识别、智能夹取、精准补栽以及弱苗的收集与再利用。在等级识别模块中，通过对 YOLO 系列模型的对比分析，选用 YOLOv11 实现壮苗与弱苗的准确识别；在夹取策略方面，引入轻量化夹取姿态参数预测网络 LRGN，生成最优夹取角度与宽度，以降低对穴盘苗的物理损伤。实验结果显示，在 4×8 穴盘规格下，识别准确率为 96.0%，分选成功率为 96.67%，补栽成功率为 96.0%，叶片损伤率为 2.15%；在 5×10 穴盘规格下，识别准确率为 96.33%，分选成功率为 95.83%，补栽成功率为 94.67%，叶片损伤率为 2.88%。本研究为育苗装备的智能化与精细化作业提供了可靠的技术支持与实践依据。

INTRODUCTION

Plug seedling cultivation, as a crucial component of modern protected agriculture, can effectively shorten the seedling growth cycle and improve the uniformity of seedlings. However, during the seedling cultivation process, factors such as disease occurrence, uneven nutrient distribution, and irrigation inconsistencies often result in the poor growth of some seedlings, thereby affecting the overall quality of the seedling trays. At present, many small- and medium-sized seedling enterprises still rely on manual inspection and replanting to handle low-quality seedlings. This approach is labor-intensive, inefficient, and unable to ensure consistent replanting quality. Therefore, it is urgently necessary to develop efficient operational equipment that integrates intelligent seedling condition recognition, weak seedling sorting, and automatic replanting, in order to enhance the automation and intelligence level of the seedling cultivation process.

In terms of seedling grading, most studies rely on image processing and machine vision techniques to distinguish between healthy and weak seedlings through the extraction of morphological features. *Mingyong Li et al.,* (*2021*), established a grading model for pepper plug seedlings based on stem width, achieving selective transplanting of robust seedlings. *Xin Jin et al.,* (*2021*), employed a machine vision algorithm to identify healthy seedlings, damaged seedlings, and empty cells, integrating the recognition system with an end-effector to achieve a seedling grasping success rate of 96.38%. *Junhua Tong et al.*, (*2021; 2013*), utilized an improved watershed segmentation method combined with a leaf area threshold for pepper seedling identification, attaining an accuracy of 95.2%, and later enhanced the recognition algorithm using a leaf pixel threshold, increasing the accuracy to 99.5%. *Yatao Li et al., (2024)*, combined neural networks with regional segmentation and applied an area threshold to assess seedling health status, achieving an accuracy of 96.9%. *Wei Fu et al.,* (*2022*), estimated leaf area by integrating grayscale conversion, threshold segmentation, and morphological processing, reaching an overall accuracy of 85.71%. These approaches have continuously improved recognition accuracy; however, most of them depend on single feature parameters, resulting in insufficient robustness under complex environmental conditions.

In the field of grasping control, research has primarily focused on the structural design of end-effectors and the optimization of seedling picking strategies to improve grasping success rates and reduce seedling damage. *Chaoyang Ren et al.,* (*2025*), proposed a stem-clamping seedling-picking mechanism, achieving a success rate of 96.3%. *Lühua Han et al.,* (*2025*), designed a multi-needle clamping mechanism that combines inclined insertion and parallel clamping, resulting in a seedling plug integrity rate exceeding 97%. *Wei Liu et al.,* (*2024*), optimized a diagonal insertion-type end-effector through orthogonal experiments to obtain the best holding performance. *Zhiwei Tian et al.,* (*2022*), employed the response surface methodology to analyze the effects of needle diameter, insertion depth, and speed on substrate integrity, thereby revealing the influence mechanism of grasping parameters on the seedling formation rate. *Shuangyan Hu et al.,* (*2022*), developed a flexible clamping device based on a cam–gear–rack mechanism to achieve stable gripping of seedlings. *Xiong Zhao et al.,* (*2022*), optimized the grasping path planning to minimize leaf damage. Overall, these methods have achieved significant progress in grasping stability and substrate retention; however, most grasping strategies still operate with fixed parameters, making it difficult to adapt to the morphological variability of seedlings, which limits their effectiveness under complex working conditions.

In terms of transplanting device design, research has progressively evolved from single-function mechanisms toward multifunctional integration. *Shengyi Zhao et al.,* (*2022*), proposed a multifunctional transplanting system that achieved dynamic detection and synchronized operation, attaining a transplanting qualification rate of 99.33%. *Jiangtao Ji et al.,* (*2019*), implemented full-process monitoring through pressure sensors and limit switches, reaching a seedling picking success rate of 95%. *Xinwu Du et al.,* (*2023*), developed a vision-guided integrated replanting system with an average success rate of 95%. *Mengjiao Yao et al.,* (*2024*), employed a finite state machine combined with multi-sensor fusion to achieve coordinated seedling picking and simplify the operational workflow. *Zeyu Yan et al., (2023)*, utilized YOLOv5x for hole detection and automatic replanting, achieving a success rate of 91.7%. *Xin Jin et al.,* (*2022*), integrated depth information with path planning to realize low-damage transplanting, achieving a success rate of 94.9%. *Xianglei Xue et al.,* (*2020*), applied a multi-objective genetic algorithm to optimize mechanical parameters, thereby improving the seedling picking efficiency. Although these studies have enhanced the precision and stability of transplanting devices, most have focused on the independent optimization of functional modules. A close integration between grading and replanting processes is still lacking, and overall operational efficiency and resource utilization require further improvement.

Although significant progress has been achieved in plug seedling recognition, gripping control, and transplanting device design, most existing systems treat sorting and replanting as separate processes without coordinated control. This limitation reduces operational efficiency. In addition, commonly adopted strategies such as retaining robust seedlings while discarding weak ones lead to resource waste, whereas fixed-parameter gripping methods fail to accommodate morphological variability, often resulting in mechanical damage.

To overcome the aforementioned limitations, this study proposes an integrated framework for plug seedling sorting and replanting, in which perception, decision-making, and actuation are unified within a closed-loop operational process. Unlike previous studies that primarily focus on isolated perception tasks or standalone mechanical execution, the proposed framework establishes a continuous workflow from seedling recognition to autonomous sorting and replanting, achieving system integration. The main contributions of this study are summarized as follows:

(1) A closed-loop integrated sorting–replanting system is developed, overcoming the limitations of conventional decoupled architectures in which grading and replanting are treated as independent processes, and enabling coordinated operation of grading, decision-making, and actuation within a unified framework.

(2) The conventional practice of directly discarding weak seedlings is replaced by transplanting them into a centralized collection tray, thereby effectively improving resource utilization efficiency.

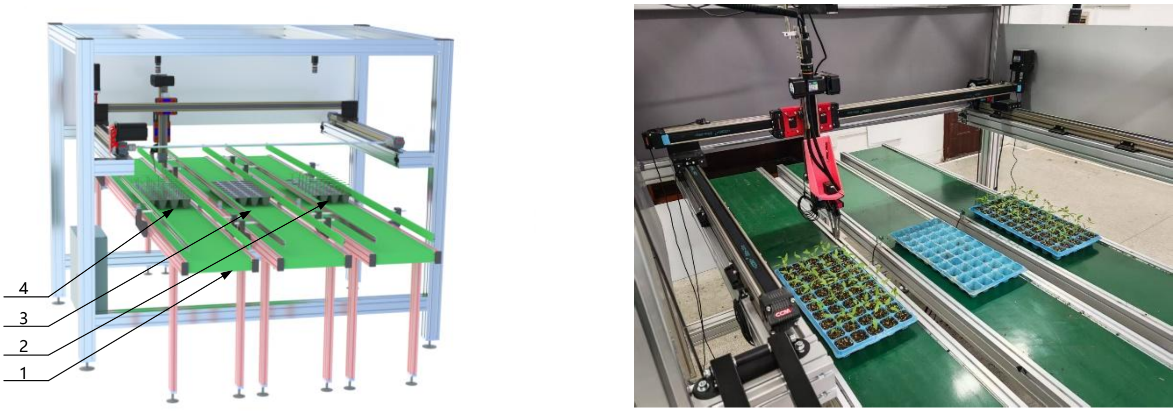
(3) By embedding a pretrained lightweight grasping pose estimation model (LRGN) into the control loop, adaptive manipulation in response to morphological variations of seedlings is achieved, effectively reducing the risk of mechanical damage.

MATERIALS AND METHODS

Overall structural design

The integrated plug seedling sorting and replanting machine consists of a conveying mechanism, an image acquisition module, a sorting and replanting module, and a control system. The overall dimensions of the device are 2000 mm in length, 3000 mm in width, and 1700 mm in height. The system adopts a modular architecture design. The conveying mechanism is composed of a geared motor, a position sensor and three conveyor belts, forming a closed-loop conveying system that ensures millimeter-level positioning accuracy of the plug trays. To synchronize image acquisition with mechanical execution, the conveyor operates in a segmented, constant-speed mode at 50 mm/s during experiments. When the photoelectric sensor detects that a plug tray has reached the designated position, the conveyor immediately stops and triggers the camera to capture an image. Subsequently, the execution mechanism performs the grasping and replanting operations within a fixed plug tray coordinate frame. After the operation is completed, the conveyor restarts to transport the tray to the next workstation.

The image acquisition module consists of two industrial cameras and a bar-shaped LED light source. The sorting and replanting module is built upon an XYZ three-axis linear motion platform and an end-effector, enabling the classification and replanting of seedlings. The control module integrates an industrial computer, a programmable control unit based on the STM32F407IGT6 microcontroller, and communication interfaces to achieve coordinated control between image processing and multiple functional modules. The overall structure of the system is illustrated in Fig. 1.



Three-dimensional model *Actual prototype*

Fig. 1 - Plug seedling sorting and replanting integrated machine

1: Conveying mechanism; 2: Seedling tray to be graded; 3: Weak seedling collection tray; 4: Seedling tray to be graded

Design of the gripping mechanism

To enhance the adaptability and gripping precision during the seedling grasping process, an adaptive gripping mechanism capable of automatically adjusting the gripping angle and width was designed. As shown in Fig. 2, the mechanism consists of a stepper motor, a servo motor, a linkage system, and gripper components.

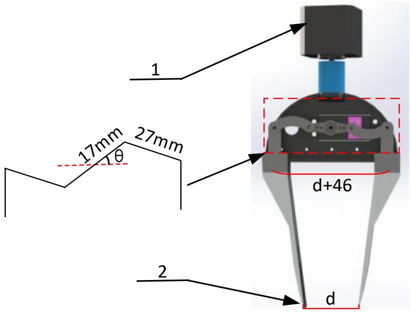


Fig. 2 - Physical view of the grasping mechanism

(1: Stepper motor; 2: Grasping distance; θ: Rotation angle of the servo motor relative to the horizontal)

The two gripper jaws are connected to the servo motor output shaft through a linkage structure, allowing synchronized opening and closing movements driven by the servo's rotation. This configuration enables the mechanism to effectively adapt to plug seedlings of varying shapes and sizes.

The system determines the optimal gripping angle and clamping width for each seedling based on the feature information provided by the image recognition module. The clamping width, defined as the distance between the two gripper jaws, is adjusted through servo angle control. According to the geometric configuration of the gripper, the functional relationship between the servo rotation angle θ and the clamping width d is established as follows:

$$d + 46 = 2\left(17cos\theta + \sqrt{27^2 - (17sin\theta)^2}\right) \tag{1}$$

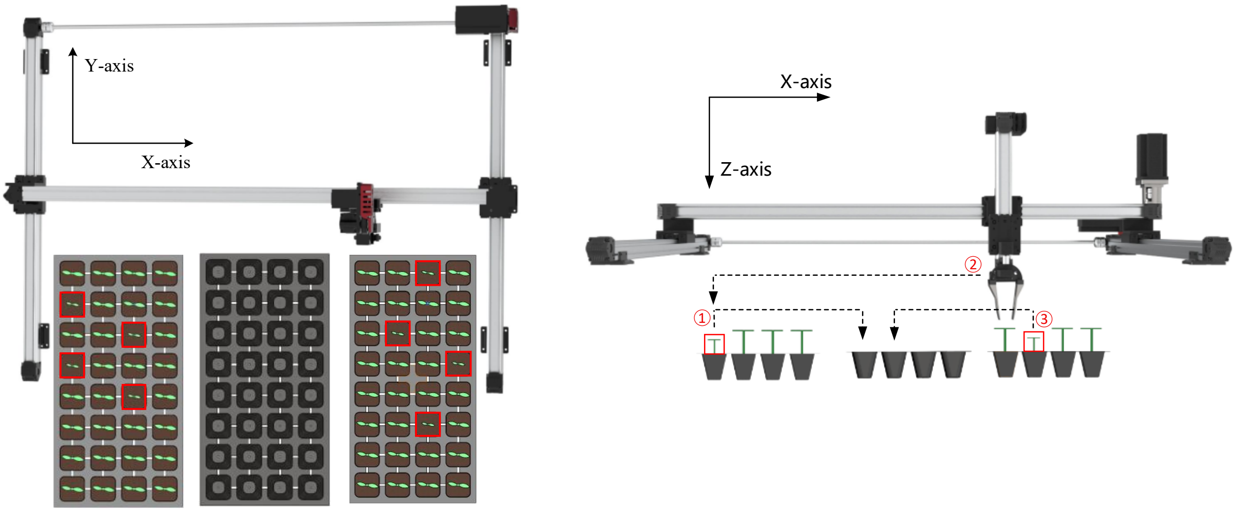
To derive the expression for θ, an intermediate variable is introduced as A=17cosθ. By applying the trigonometric identity $(sin\theta)^2 = 1 - (cos\theta)^2$, the square root term can be simplified to $\sqrt{440 + A^2}$, Consequently, the following relationship can be further derived:

$$\theta = \arccos\left(\frac{(d + 46)^2 - 1760}{68(d + 46)}\right) \tag{2}$$

Based on this model, the system can inversely calculate the required servo angle according to the morphological characteristics of each seedling. Meanwhile, a gripping angle adjustment strategy is introduced prior to the grasping operation. By rotating the end-effector gripper through the stepper motor, the gripper aligns with the target plug seedling at the optimal angle before descending, thereby minimizing unintended contact with non-target areas. The mechanism features adaptive adjustment of gripping angle (0°-180°) and gripping width (0-40 mm), enabling precise gripping and low-damage handling of plug seedlings with diverse morphological characteristics.

Plug seedling sorting and replanting execution mechanism

The plug seedling sorting and replanting mechanism constitutes a core component of the system's operational workflow, as its performance directly affects the efficiency and precision of weak seedling removal and empty-cell replanting. This mechanism must accomplish functions such as spatial positioning, grasping and transporting seedlings, and precise release at target locations. Therefore, its structural design emphasizes simplicity, compactness, and high responsiveness.



Top view *Front view*

Fig. 3 - Sorting and replanting execution mechanism

As illustrated in Fig. 3, the system adopts a Cartesian coordinate structure, consisting of X, Y, and Z-axis synchronous belt slide modules and an end-effector gripper. In this configuration, the Z- and X-axes are mounted on the Y-axis and driven via synchronous belts. The effective travel of the X, Y, and Z axes is 1500 mm, 1150 mm, and 400 mm, respectively, each driven by a motor.

Plug Seedling Grading

The acquisition of plug seedling images is a prerequisite for achieving accurate sorting. To ensure high-quality image acquisition, the information acquisition module uses a color industrial camera equipped with dual-side CCD strip light sources mounted above the imaging area to provide uniform and sufficient illumination. By adjusting the camera height and focal length, high-resolution images are captured with a size of 3072 × 2048 pixels. The camera is fixed directly above the conveyor belt in a top-down view, allowing a single exposure to cover the entire plug tray field of view.

Image capture is triggered when the plug tray reaches the designated position and is detected by the photoelectric switch. Illumination is provided continuously by the two strip lights, minimizing the effects of ambient light interference and geometric distortions caused by changes in viewing angle.

To achieve rapid grading and recognition of plug seedlings prior to transplanting operations, this study constructed a pepper plug seedling image dataset comprising 400 RGB color images, captured from plug trays of 4×8 and 5×10 configurations. Each image in the dataset was manually annotated with the corresponding seedling category and bounding box. Classification criteria were primarily based on the Agricultural Industry Standard of the People’s Republic of China-General Technical Requirements for Full-Chain Management of Solar Greenhouses (Pepper), as well as the practical experience of seedling cultivators accumulated over long-term cultivation. On this basis, seedlings were categorized into robust seedlings and weak seedlings for subsequent model training and validation.

Regarding model selection, several YOLO-series*(glenn-Jocherglenn-Jocher., 2022; Khanam and Hussain., 2024; Li et al., 2022; Tian et al.; Ultralytics. 2023; Wang et al., 2024; Wang et al., 2023; Wang et al., 2024)* object detection algorithms were systematically evaluated and compared. To satisfy the dual requirements of detection speed and accuracy during the grading stage, YOLOv11, which achieved the best performance on this dataset, was selected as the recognition model. The model integrates multi-scale feature extraction with a lightweight attention mechanism, providing excellent fine-grained object detection capability suitable for identifying small and densely distributed targets in plug seedling trays.

Although recognizing only weak seedlings is sufficient to perform basic sorting and replanting tasks, this study classifies plug seedlings into both weak and robust categories to enhance recognition accuracy and system robustness. The detection and annotation of both categories are performed uniformly within the recognition module.

Prediction of Gripping Posture Parameters for Plug Seedlings

To enable low-damage grasping of pepper plug seedlings with varying postures, this study adopts the lightweight gripping pose estimation network (LRGN), previously proposed and validated in our earlier work (*Yuan et al., 2025*). The network is incorporated as a visual perception module within the proposed plug seedling sorting and replanting system, providing real-time estimation of grasping-related parameters for end-effector control.

The LRGN processes real-time images acquired during system operation and outputs the grasping position, clamping width, and grasping angle relative to the horizontal direction, as illustrated in Fig. 4. These outputs are directly utilized by the control system to regulate the end-effector, enabling precise and stable grasping of plug seedlings under varying morphological conditions.

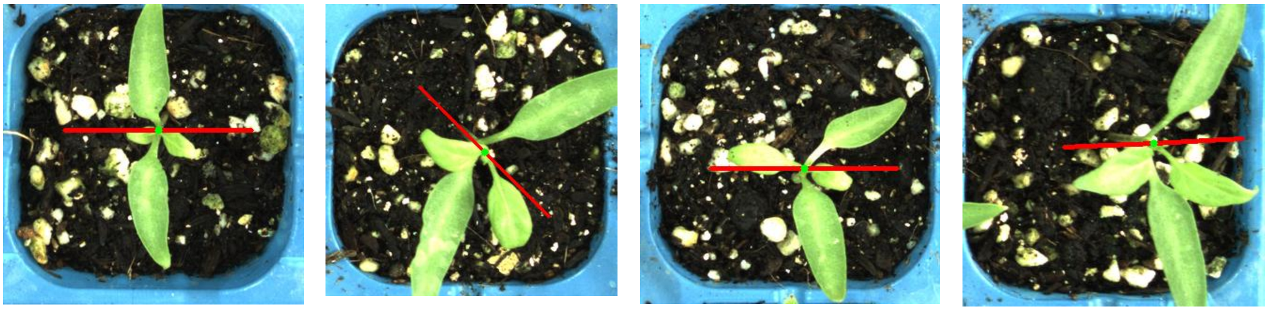


Fig. 4 - Schematic diagram of plug seedling grasping pose

System Workflow

The operational workflow of the integrated machine begins with system initialization, where the X, Y, and Z-axis motors achieve precise homing via photoelectric limit switches. The operator places the tray to be sorted (left), the weak seedling collection tray (middle), and the robust seedling supply tray (right) onto the conveyors. Once activated, the conveyors position the trays, and the system proceeds to image acquisition and recognition. The acquired images are processed by the upper-level computer using a deep learning model to obtain seedling grades and gripping parameters, which are then converted into action sequences for the lower-level controller.

During operation, the end-effector extracts identified weak seedlings from the left tray and transfers them to the middle collection tray, immediately replenishing the empty cells with robust seedlings from the right tray. This iterative process continues until the left tray is fully populated with robust seedlings. The system then processes the right tray in a similar alternating manner. This coordinated strategy ensures centralized weak seedling collection and continuous robust seedling replenishment under cyclic operation. The workflow schematic is shown in Fig. 5.

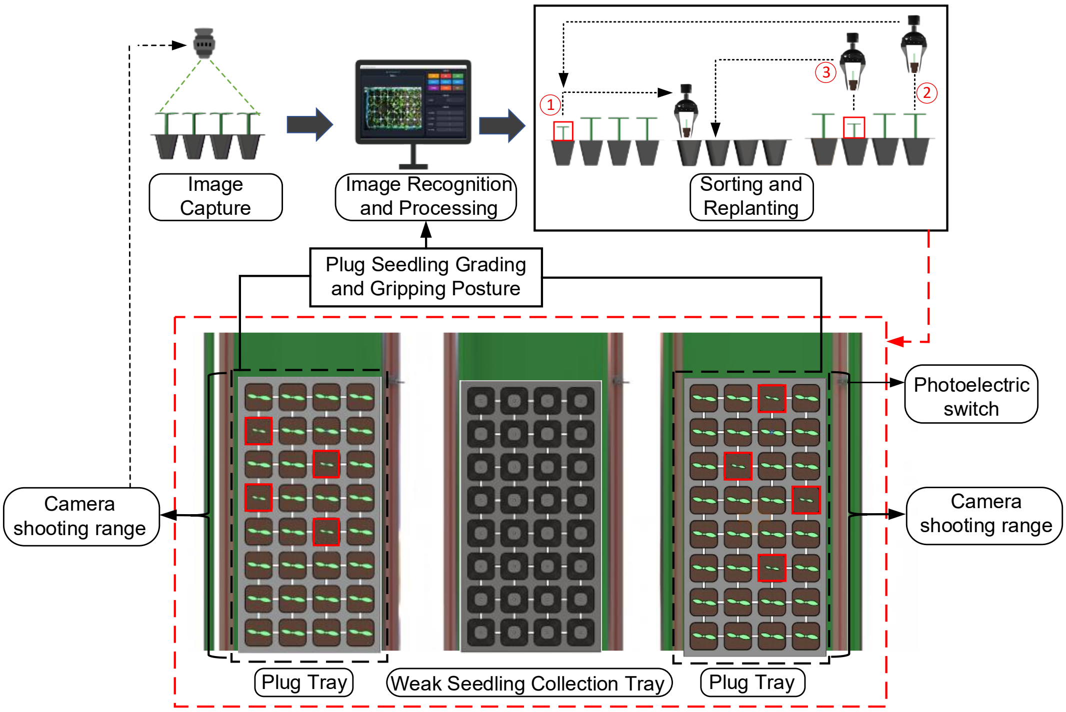


Fig. 5 - Workflow diagram

Sorting and Replanting Path

This study adopts a coordinated strategy of weak seedling transfer and robust seedling replenishment to establish the system's sorting and replanting path. Weak seedlings are randomly distributed in the left plug tray, and the system processes them sequentially from row 1 to row 5, moving from left to right within each row, based on recognition results. The end-effector grasps each seedling according to the corresponding clamping angle and width, and transplants it to the middle weak seedling collection tray. Subsequently, the end-effector moves to the right robust seedling tray, adjusts the gripping angle and width, and grasps robust seedlings in the same sequential order to replenish the original positions of the weak seedlings. This path establishes a closed-loop "sorting–replanting" workflow, which is repeated until all weak seedlings in the left tray have been processed.

Control System Design

The control system ensures efficient closed-loop coordination among the vision module, sorting mechanism, and conveyors, with emphasis on real-time response and system stability. An STM32F407 microcontroller serves as the lower-level execution core, working in tandem with an upper-level computer that performs image processing and task-level command generation.

The system architecture is based on coordinated sensing, perception, and actuation. The system performs image acquisition based on tray position signals, and the upper-level computer processes the data to extract key parameters, including seedling grade and gripping pose (angle and width). These parameters are subsequently translated into motion commands and transmitted to the STM32F407 for real-time execution.

The three-axis positioning is driven by stepper motors, with photoelectric limit switches providing boundary protection and position feedback. The end-effector rotation is controlled by a dedicated stepper motor, while the grasping action is actuated by a high-torque servo motor. Based on the predicted gripping parameters, the gripper adaptively adjusts its clamping state, ensuring stable and precise handling of seedlings with varying morphological characteristics.

This closed-loop control framework integrates perception, decision-making, and execution, forming a coordinated and continuous operation mechanism that supports efficient and automated sorting and replanting. The control system architecture is shown in Fig. 6.

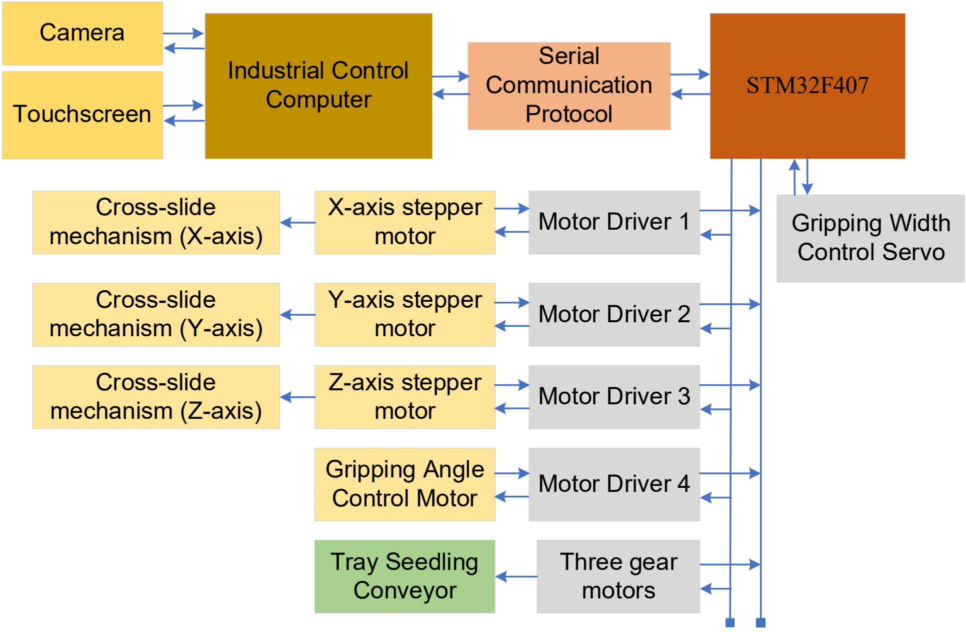


Fig. 6 - Block diagram of the plug seedling grading and replanting control system

RESULTS

To meet the practical requirements of pepper seedling sorting and replanting operations, this study developed an automated sorting and replanting prototype platform based on the design specifications of the system's functional modules. The prototype underwent manufacturing, assembly, debugging, and functional testing. On this experimental platform, the performance of critical processes—including seedling grading, weak seedling sorting, and robust seedling replanting—was comprehensively evaluated, along with the overall coordination capability of the system.

Four-leaf pepper seedlings were selected for the experiments. The growing substrate was prepared by mixing peat, vermiculite, and perlite in a 3:1:1 ratio. Standard plug trays with 32 and 50 cells were used to verify the system's adaptability to different tray specifications. Seedlings were arranged with a 9:1 ratio of robust to weak seedlings to reflect the distribution typically observed in actual production environments. Temperature and humidity were controlled according to industrial seedling cultivation standards, and the pepper seedlings were grown for 21 days to ensure uniform age and stable growth conditions.

The main performance metrics for evaluating the device included plug tray seedling grading accuracy (α), sorting success rate (η_1), replanting success rate (η_2), and damage rate during the sorting and replanting process (β). Grading accuracy (α) represents the proportion of actual weak seedlings correctly identified as weak, serving as a measure of the system's overall recognition capability. The sorting success rate (η_1) denotes the proportion of detected weak seedlings successfully sorted, while the replanting success rate (η_2) indicates the proportion of sorted weak seedlings or replenished robust seedlings accurately placed at the target position. The damage rate (β) reflects the proportion of leaves damaged during the sorting and replanting process relative to the total number of leaves.

$$\alpha = \frac{S_1}{S} \tag{3}$$

$$\eta_1 = \frac{S_1 - S_2}{S_1} \times 100\% \tag{4}$$

$$\eta_2 = \frac{S_1 - S_3}{S_1} \times 100\% \tag{5}$$

$$\beta = \frac{n}{N} \times 100\% \tag{6}$$

Here, S represents the actual number of weak seedlings in the tray to be processed; S_1 denotes the number of weak seedlings detected in the tray; S_2 indicates the number of weak seedlings for which sorting failed; S_3 represents the number of seedlings for which replanting failed; n is the number of pepper seedling leaves damaged during the sorting and replanting process; and N is the total number of pepper seedling leaves in the tray during the process.

In the experimental statistics, misidentified weak seedlings, as well as seedlings for which sorting failed but subsequent replanting was successful, were included in the calculation of the corresponding performance metrics. This approach ensures that indicators such as sorting success rate and replanting success rate accurately and comprehensively reflect the system's performance under actual operational conditions.

Table 1

Statistical Results of Sorting and Transplanting Experiments for 4×8-Specification Pepper Plug Seedlings

Tray Specifications	Number of weak seedlings	Number of identified weak seedlings	Number of Sorting Failures	Number of replanting failures	α (%)	η_1 (%)	η_2 (%)	B (%)
4×8	5	5	0	1	100%	100%	80%	4.76%
	3	3	0	0	100%	100%	100%	0
	4	4	0	0	100%	100%	100%	5.56%
	5	4	0	0	80%	100%	100%	0
	4	4	0	0	100%	100%	100%	5.26%
	4	4	0	0	100%	100%	100%	0
	5	4	0	1	80%	100%	80%	0
	3	3	1	0	100%	66.7%	100%	0
	4	4	0	0	100%	100%	100%	5.89%
	3	3	0	0	100%	100%	100%	0
	Average				96%	96.67%	96%	2.15%
	SD				8.43%	10.53%	8.43%	2.79%
	CV				8.78%	10.89%	8.78%	—

Table 2

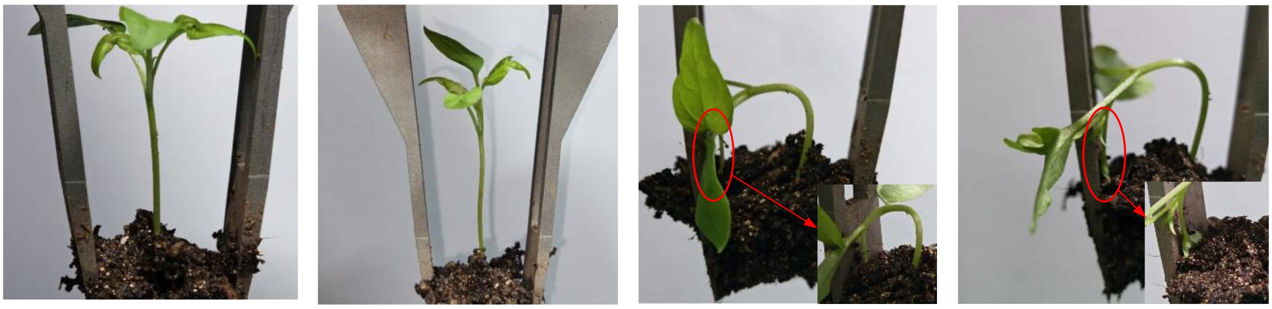
Statistical Results of Sorting and Transplanting Experiments for 5×10-Specification Pepper Plug Seedlings

Tray Specifications	Number of weak seedlings	Number of identified weak seedlings	Number of Sorting Failures	Number of replanting failures	α (%)	η_1 (%)	η_2 (%)	β (%)
5×10	6	6	0	1	100%	100%	83.33%	4.5%
	4	4	0	0	100%	100%	100%	5.88%
	5	5	1	0	100%	75%	100%	0
	6	5	0	0	83.33%	100%	100%	3.84%
	4	4	0	0	100%	100%	100%	0
	6	6	1	0	100%	83.33%	100%	3.7%
	4	4	0	0	100%	100%	100%	4.16%
	6	6	0	1	100%	100%	83.33%	0
	4	4	0	0	100%	100%	100%	6.67%
	5	4	0	1	80%	100%	80%	0
	Average				96.33%	95.83%	94.67%	2.88%
	SD				7.77%	9%	8.64%	2.63%
	CV				8.06%	9.39%	9.12%	—

The results indicate that for the 4×8 pepper seedling trays, the tray seedling grade recognition accuracy (α) reached 96.0%, the sorting success rate (η_1) was 96.67%, the replanting success rate (η_2) was 96.0%, and the average damage rate (β) was 2.15%. For the 5×10 trays, the recognition accuracy (α) was 96.33%, the sorting success rate (η_1) was 95.83%, and the replanting success rate (η_2) was 94.67%. Although the overall performance was slightly lower than that of the 4×8 trays, it remained at a high level, with a slightly increased leaf damage rate (β) of 2.88%.

Regarding system stability, both the standard deviation (SD) and coefficient of variation (CV) were used to quantitatively evaluate the variability of the proposed system across repeated experiments. For α, η_1, and η_2, the SD values remain at relatively low levels (7.77%-10.53%), suggesting limited absolute fluctuations in system outputs. Correspondingly, their CV values (8.06%-10.89%) further confirm satisfactory stability under different tray configurations.

In contrast, for the damage rate (β), the standard deviation (SD) remained low, with values of 2.79% for the 4×8 trays and 2.63% for the 5×10 trays, respectively, indicating limited absolute fluctuation across repeated trials. Damage events were infrequent: most trials exhibited no damage, while only a small number showed minor failures. Under these conditions, the mean value of β is close to zero, which can lead to an artificially inflated coefficient of variation (CV) and consequently reduce its interpretability. Therefore, CV is not considered an appropriate metric for assessing the variability of β in this study. Instead, the stability of the damage rate is more reliably characterized by its SD, which corroborates the consistently low-damage performance of the proposed system.



(a)Example diagram of intact grasping

(b)Example diagram of pinch injuries

Fig. 7 - Schematic diagram of grasping-induced damage

Fig. 7 presents representative image examples of seedling conditions during the gripping process, including both successful non-damaging grips and cases with visible damage. Fig. 7(a) shows a successfully grasped seedling with no damage, where the leaf structure remains intact and the gripping posture is well aligned. In contrast, Fig. 7(b) depicts seedlings exhibiting varying degrees of leaf-edge tearing and petiole bending, primarily caused by plant inclination or insufficient adjustment of the gripper angle. The proportion of such damage cases was relatively low across all experiments. These findings indicate that by fine-tuning the gripping angle and gripper opening width, the system can effectively adapt to different seedling postures, significantly reducing structural damage caused by unintended contact, thereby further validating the practicality of the proposed low-damage gripping strategy.

CONCLUSIONS

To address the demand for intelligent seedling grading and automatic replanting in plug seedling cultivation, this study proposes and implements an integrated intelligent operation system that combines grading and replanting functions, achieving a complete workflow from seedling status detection to automatic transplanting. The main conclusions of this study are as follows:

1) A vision-guided integrated grading and replanting platform was developed, establishing a closed-loop process for weak seedling identification and automatic replanting. The system demonstrated stable and efficient collaborative performance throughout the entire workflow.

2) A weak-seedling collection and reutilization mechanism was introduced, replacing the traditional approach of discarding weak seedlings. Identified weak seedlings were instead transplanted into a centralized collection tray, improving resource utilization efficiency while ensuring the overall quality of commercial seedlings.

3) A lightweight gripping posture parameter prediction network (LRGN) was employed in the gripping stage to generate optimal gripping angles and widths. This enhanced the adaptability of the end-effector to different seedling morphologies and effectively reduced the risk of mechanical damage during gripping.

4) System performance validation was conducted using two plug tray specifications of chili seedlings. Results showed that for 4×8 plug trays, the grading accuracy reached 96.0%, the sorting success rate was 96.67%, the replanting success rate was 96.0%, and the average damage rate was 2.15%. For 5×10 plug trays, the grading accuracy was 96.33%, the sorting and replanting success rates were 95.83% and 94.67%, respectively, with a damage rate of 2.88%. Although the overall performance for the 5×10 trays was slightly lower than that for the 4×8 trays, the system still maintained high operational stability and adaptability under different seedling density conditions. Furthermore, statistical analysis based on standard deviation (SD) and coefficient of variation (CV) indicates that the key performance metrics exhibit low variability across repeated trials, confirming the good repeatability and stability of the proposed system.

The proposed low-damage integrated grading and replanting machine effectively achieves automated seedling grading and replanting while minimizing seedling damage, validating the feasibility of the system in both seedling recognition and transplanting operations. Future research will focus on integrating flexible gripping and force-control strategies to further reduce mechanical stress on seedlings. Additionally, optimizing path planning and motion control can help minimize non-operational time during transplanting, thereby improving overall operational efficiency.

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