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Research Article

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A Deep Learning-Enhanced Vision System for Precision Target Spraying in Chinese Cabbage Cultivation

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Abstract

Aiming at the issue that increasing the forward speed during target spraying of calcium and other agents onto the heart and inner leaf margins of Chinese cabbage plants leads to changes in the effective sprayed area covered per unit time and the pesticide spray volume, a target spray control system based on deep learning was designed. This system aims to investigate the relationship between the forward speed of target spraying and the spray volume and coverage in the scenario of applying calcium agents to the heart of Chinese cabbage plants. Firstly, the structure and working principle of the target spray control system were elaborated. Secondly, the general YOLOv8 model was improved, proposing a lightweight BWT-YOLO model that integrates long-range recognition, sprayer forward speed, and spray response frequency. Utilizing a Jetson Xavier NX controller equipped with the lightweight BWT-YOLO model, a pressure-stabilized execution unit and a target control unit were designed, and the system performance was tested through intermittent spray experiments. During the experiments, the forward speed of the spray platform was gradually increased, and the spray volume of the corresponding nozzle was obtained based on the response frequency of the solenoid valve. The response times of the three main parts of the target spray system were recorded: the average image processing time was 29.50 ms, the decision signal transmission time was 6.40 ms, and the spray process duration was 88.83 ms. Comprehensive analysis indicated that the total response time of the target spray lagged behind the electrical signal by approximately 124.73 ms. By compensating for the solenoid valve response lag time and conducting acquisition experiments, the difference between the actual spray volume after compensation and the required volume was derived. It was determined that under the condition of 7.2 km/h speed, the corresponding difference between actual and required volume was 0.01 L/min, which was the smallest difference and met the operational requirements for target spraying. This study provides a reference for the application of target application robots in spray systems and the selection of operational parameters.

Keywords: Target application; Deep learning; System frequency; Response time; Nozzle spray volume; BWT-YOLO

1. Introduction

Tipburn is a common disorder in various vegetables. Specifically, Chinese cabbage tipburn has been widely reported globally, with its incidence severity and affected area gradually increasing,

making it one of the major diseases of Chinese cabbage (Vu et al., 2023). In the later stages of tipburn, diseased plants show no apparent external abnormalities, but the inner leaf margins become dry and yellowed (Wei et al., 2022).

Target spray technology started relatively early in foreign research, covering various aspects including identification (Deng et al., 2021; Shi et al., 2025), navigation (Yang et al., 2021; Ma et al., 2020), and crop detection (Liu et al., 2024; Zhao et al., 2022). Relatively mature vision recognition systems were applied to plant protection robots as early as the last century (Weihua et al., 2024; An et al., 2022; Yu et al., 2026). Due to the random plant spacing in vegetable cultivation and the challenge of weed identification, Jin et al. (2021) used the CenterNet model for vegetable detection; this model focuses solely on identifying vegetables, thereby avoiding the processing of various weeds. Perugachi-Diaz et al. (2021) found that AlexNet could achieve an average recognition accuracy of 94% for cabbage seedlings. To address the impact of walking speed and spray pressure on nozzle spray volume in precision target sprayers, Sun et al. (2016) developed a precision spraying robot control system for wheat plant protection, with a C310 industrial controller as its core, achieving an error of less than 5% between actual target spray volume and theoretical dosage. Jalal et al. (2021) developed a small agricultural robot for precision spraying, showing that increasing the robot's travel speed could reduce chemical usage by up to 76%. In contrast, target spray technologies based on machine vision in China started later but have developed rapidly (Zhao et al., 2023; Zheng et al., 2024). Scholars have conducted research in areas such as target spraying for field vegetables (Zhao et al., 2022; Wu et al., 2025), target spraying for field weeds (Quan et al., 2017; Yu et al., 2026), indoor target spraying (Xiaofei et al., 2023), and target spray robots for orchards (A. M. M. et al., 2022; Villacrés and Vougioukas, 2024). The main factors affecting target spray volume error and coverage are the response time, spray pressure, and speed of the target spray system. However, current related research primarily considers the influence of spray pressure (Fabula et al., 2021; Sun et al., 2024), height (Zhou et al., 2021), and delay time on target spraying. Further exploration is needed regarding the nozzle spray volume error (Mangus et al., 2017) and the corresponding effective target coverage (Hasan et al., 2021; Yu et al., 2026) in target spraying.

To improve the application quality in the target spraying process, a target spray system for the heart of Chinese cabbage plants was designed and implemented, based on a lightweight BWT-YOLO object detection model. Building upon the determination of the delay time, the corresponding spray volume of the nozzle at different spray frequencies was investigated, and the system's spray coverage was derived through experimental analysis. This study aims to provide a reference for the application of target spray technology in agricultural plant protection and the selection of operational parameters, with the goal of reducing pesticide waste and improving pesticide utilization efficiency.

2 Design of the Target Spray Control System

2.1 Overall Structure

The target spray control system proposed in this study is primarily designed for target spraying operations on the heart of Chinese cabbage plants with a spacing of 30-50 cm. The target spray system is shown in Figure 1 and mainly consists of four key modules: the traveling mechanism, the pressure-stabilized liquid supply module, the target recognition module, and the target spray module. The core of the system lies in its control mechanism and operational workflow. The camera, as the core component of the target recognition module, is responsible for real-time acquisition of field

ground information to the Jetson Xavier NX controller board. The Jetson Xavier NX board performs target extraction on the images and makes decisions regarding the opening and closing of solenoid valves based on the extraction results. Subsequently, the control board sends the extraction results in the form of data frames in real-time via a serial port to the STC89C52 microcontroller. After parsing the data frames, the microcontroller sets the pin connected to the relay to a high level. The relay then amplifies the signal and drives the solenoid valve bank to open or close, thereby achieving target spray operation. In this process, the pressure-stabilized liquid supply module plays a crucial role. Its built-in pressure stabilizing tank and safety valve can effectively suppress pressure fluctuations in the pipeline caused by the intermittent switching of the relay, ensuring stable liquid supply pressure for the entire system and consequently guaranteeing the atomization quality of the spray.

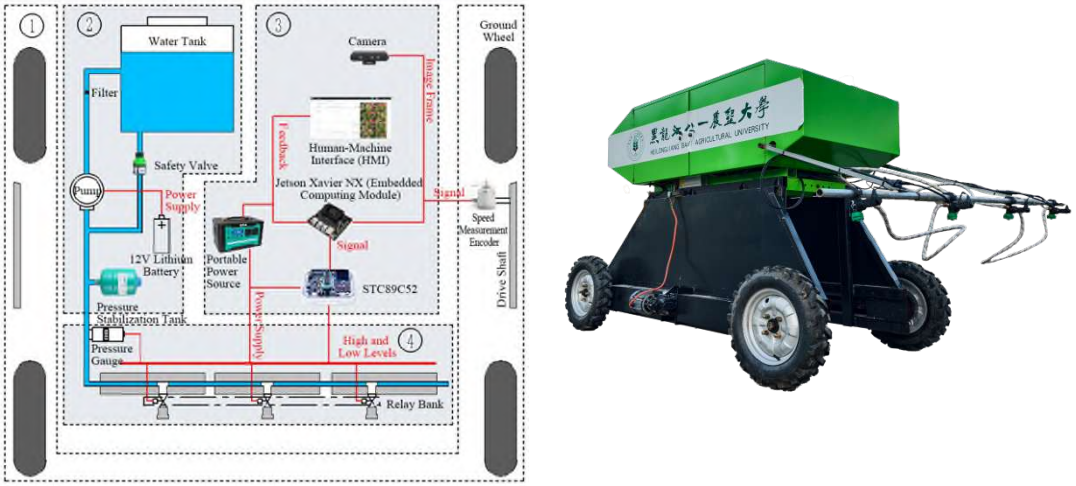


Figure 1 Target spray control system

2.2 Pressure-Stabilized Liquid Supply Pipeline System

The design of the pressure-stabilized liquid supply pipeline is critical, as it ensures the stable flow of liquid throughout the system, thereby guaranteeing the efficiency and accuracy of the spraying operation. The pipeline mainly connects key components such as the liquid tank, filter, diaphragm pump, pressure stabilizing tank, and safety valve to form a system that provides a stable supply of liquid from the tank to the nozzles.

The plunger pump serves as the power source, providing continuous and stable power output for the entire supply pipeline. Under the command of the control system, the plunger pump draws liquid from the tank and sends it to the next stage of the system. As the liquid flows through the filter, impurities and particulate matter are effectively removed. The filtered liquid then enters the pressure stabilizing device. The pressure stabilizing tank inside this device contains a compressed capsule. When a solenoid valve closes instantaneously, the pressure in the pipeline surges momentarily. The compressed capsule inside the pressure stabilizing tank rapidly releases gas to buffer and stabilize the pipeline pressure, ensuring stable system operation. If the pressure in the pipeline exceeds the preset safety value, the safety valve is forced open, discharging part of the liquid back into the tank, thereby effectively reducing the system pressure and preventing damage due to excessive pressure. The power output of the plunger pump is provided by a 24V lithium battery. To ensure the normal operation of other electronic devices in the system, such as the controller and relay bank, a 12V mobile power supply is used for their power supply.

2.3 Target Spray Control System

The core components of the target spray system include a Gemini-3D depth camera, a human-machine interface (HMI), a Jetson Xavier NX controller board, an STC89C52 microcontroller, a speed-measuring encoder, among others. The structure of the control system is shown in Figure 2. This design aims to ensure the efficient and accurate execution of target spray operations. First, the Gemini-3D depth camera, serving as the visual core of the system, possesses excellent performance parameters. It features an ultra-small blind zone as low as 0.15 m and a depth measurement range of up to 10 m, with a maximum resolution of 1,920 × 1,080 pixels. Its built-in depth engine, the MX6600, is responsible for processing depth data quickly and accurately, providing strong support for subsequent image processing and recognition. The Jetson Xavier NX controller board is responsible for receiving image data transmitted from the depth camera and performing efficient image processing and recognition. Utilizing the BWT-YOLO algorithm, the Jetson Xavier NX board can rapidly identify the heart of Chinese cabbage plants, convert the recognition results into electrical signals, and transmit them in real-time to the microcontroller to control the opening and closing of the nozzles. This control method for target spraying ensures that the spray liquid is accurately applied to the target area, improving application efficiency. The relay bank is a crucial component connecting the control board and the nozzles. The system employs DC 3.3-5 V compatible relays for control, ensuring system stability and reliability. Simultaneously, the system is configured with three nozzles installed at equal distances, enabling coverage of a wider operational area. The solenoid valves are directly connected to the spray bodies, reducing the time loss during liquid transmission and improving the system's response speed. The speed-measuring encoder is used to monitor the travel speed in real-time and transmit the speed information to the HMI for display. The entire control system is powered by a mobile power supply. In summary, the control system achieves efficient and accurate execution of target spray operations through integrated components and precise control methods.

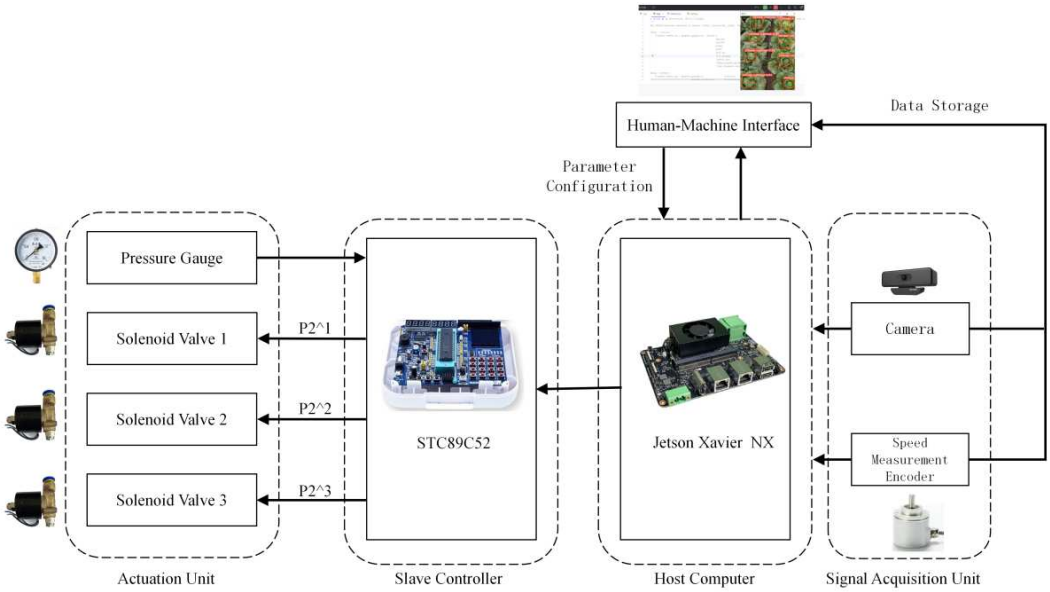


Figure 2 Integration diagram of target spray control system

3 Design of the Target Spray Control Algorithm

As one of the widely cultivated vegetables, Chinese cabbage requires appropriate control of plant spacing during cultivation to ensure sufficient growing space and nutrient supply. According

to general agronomic standards, the plant spacing for Chinese cabbage is recommended to be between 33-50 cm. This range aims to ensure that competition between plants is not overly intense while making full use of land resources. Similarly, the application rate is also one of the important factors affecting crop growth. For Chinese cabbage, the application rate is typically recommended to be between 300-450 L/ha. Due to differences in natural conditions such as climate and soil in different regions, adjustments are also made to the planting spacing and application rate for Chinese cabbage (Kong, 2024).

In this study, taking the experimental conditions of a planting spacing of 50 cm and an application rate of 450 L/ha as an example, the optimization strategy for speed and spraying frequency in target spraying operations was thoroughly investigated. The interaction between the canopy width of the target crop (target width), the distance from the spray boom to the target (target distance), and the forward speed of the machine was analyzed, which determines the opening and closing time of the solenoid valve during the target spraying process. Therefore, an operating speed suitable for the current planting conditions helps achieve precise control of target spraying technology, improves application effectiveness and resource utilization efficiency, and provides strong support for the healthy growth and yield increase of vegetables such as Chinese cabbage.

3.1 BWT-YOLO Target Detection Algorithm

YOLOv8 is renowned for its efficiency, innovativeness, versatility, scalability, ease of use, and performance improvement. Furthermore, it supports a wide range of hardware and native custom datasets, making it one of the commonly used target detection algorithms in the current field of vegetable recognition.

To address the challenges of leaf occlusion, motion blur, and limited computing power of edge devices in detecting the heart of Chinese cabbage plants under dynamic field operations, this study introduces targeted improvements based on the YOLOv8 foundation model, proposing a lightweight BWT-YOLO detection model. This model aims to enhance detection accuracy and anti-interference capability without significantly increasing the number of parameters.

3.1.1 Baseline Model Selection and Problem Analysis

The YOLO (You Only Look Once) series algorithms transform object detection into a regression problem, directly predicting target categories and locations through a single neural network, balancing detection speed and accuracy. It is one of the most widely used algorithms in the current field of agricultural vision detection (Sun et al., 2023; Yuan, 2023). This study selects YOLOv8 as the baseline model. It employs an improved PANet structure for multi-scale feature fusion, which can effectively capture feature information at different levels. However, in the scenario of Chinese cabbage heart detection, it still has the following limitations:

The mature Chinese cabbage heart is wrapped by outer leaves, resulting in low feature distinguishability. Furthermore, the field background is complex with many weed interferences, making it difficult for ordinary convolutions to effectively extract the core features of the heart.

Images captured during the dynamic operation of the sprayer are prone to motion blur, leading to the loss of high-frequency features. The model's detection accuracy decreases significantly as the operating speed increases.

Edge computing devices (such as onboard Jetson series controllers) have limited computing power, requiring the model to have lightweight characteristics to guarantee real-time performance.

The native network structure of YOLOv8 is shown in Figure 3. The C2f convolutional layers in its neck network and the feature extraction structure of the backbone network still have room for

optimization. The detection requirements for agricultural scenarios can be better adapted by improving convolution methods and introducing attention mechanisms (Yang, 2024).

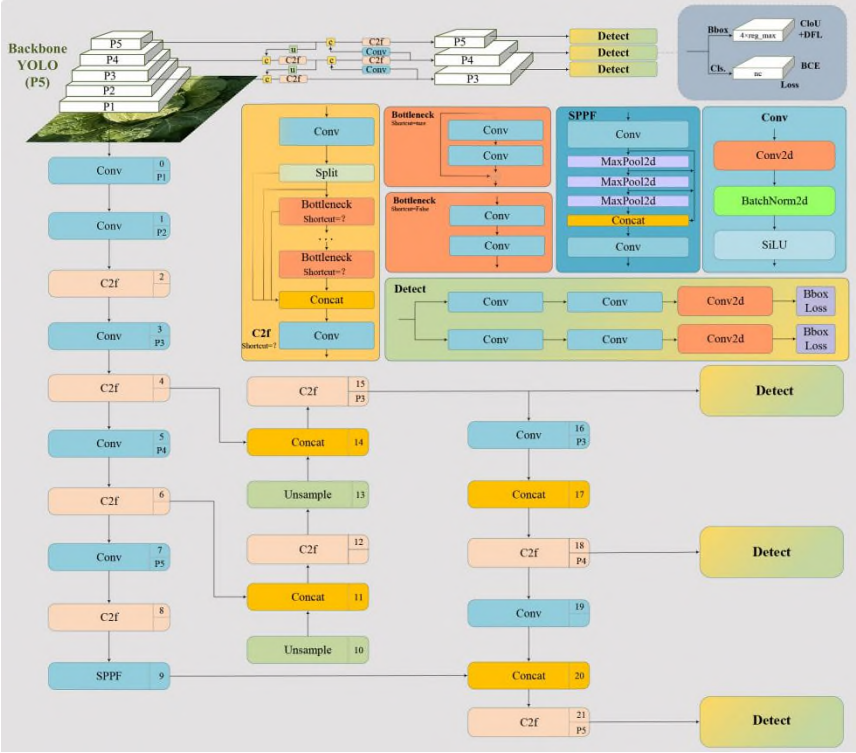


Figure 3 Original YOLOv8 network structure diagram

3.1.2 Core Model Improvement Scheme

To address the issue of quadratic parameter growth when expanding the receptive field and to enhance the model's robustness against image degradation such as motion blur, this study introduces a convolution module based on wavelet transform, namely the Wavelet Transform Convolution (WTConv) module. The core idea of this module is to perform convolution operations within the wavelet domain, thereby capturing broader contextual information of the input image with fewer parameters. WTConv utilizes the Haar wavelet transform to decompose the input image X into subbands of different frequencies. For a two-dimensional image, a one-level 2D discrete wavelet transform is implemented through a set of fixed convolution kernels. The key innovation of WTConv lies in performing lightweight depthwise convolutions on the different frequency subbands obtained from the wavelet decomposition separately, followed by reconstruction back to the original image space via the Inverse Wavelet Transform (IWT).

The WTConv module achieves effective expansion of the receptive field by performing separated frequency-space convolution in the wavelet domain. Compared to standard convolution, WTConv enhances the modeling capability for global contextual information of the image with lower computational complexity, which is particularly important for mitigating feature loss caused by motion blur in images of Chinese cabbage seedlings captured under dynamic conditions. In this study, WTConv was used to replace part of the C2f convolutional layers in the original YOLOv8 neck network, aiming to improve the model's adaptability to complex field scenes and its detection accuracy.

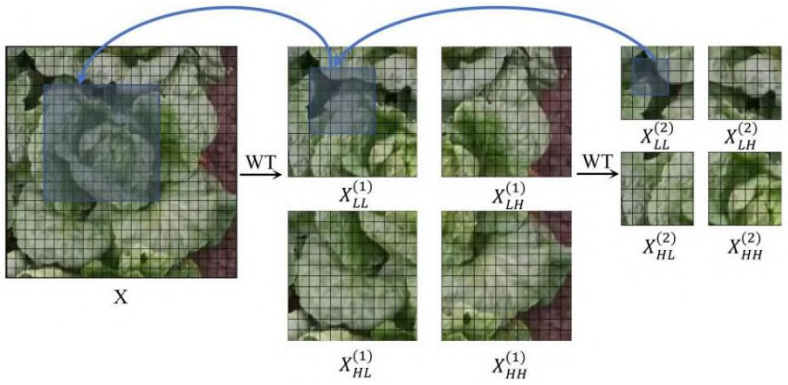


Figure 4 Flowchart of capturing global receptive field by 2-level wavelet transform

The Bi-level Routing Attention (BRA) mechanism is a technique different from traditional attention mechanisms, characterized primarily by selective focus, sparsity, and adjustability (Li et al., 2024; Jin, 2021). Selective focus means it is not necessary to compute relationships between all elements, but only between a subset of elements. It focuses on and computes relationships between elements that have a greater impact on model performance, ignoring those with lesser impact. Sparsity is another important feature of sparse attention mechanisms; ignoring elements with smaller impacts on performance can reduce computational complexity and storage requirements. Adjustability is another advantage of sparse attention mechanisms, allowing control over the number of elements being computed by adjusting parameter values, thereby finding a balance between computational efficiency and model performance.

In the task of detecting Chinese cabbage seedlings, the objective is focused on accurately detecting the seedlings without considering other non-target objects such as weeds. This task requirement allows for a certain degree of limitation on the model's attention computation scope, improving computational efficiency without sacrificing detection accuracy. To accommodate the constraint of limited computational space resources on the sprayer, a specific attention mechanism, namely the Bi-level Routing Attention (BRA) mechanism, was chosen for introduction into the YOLO model. The working principle of the BRA attention mechanism (Ye et al., 2024; He et al., 2024) is illustrated in Figure 5.

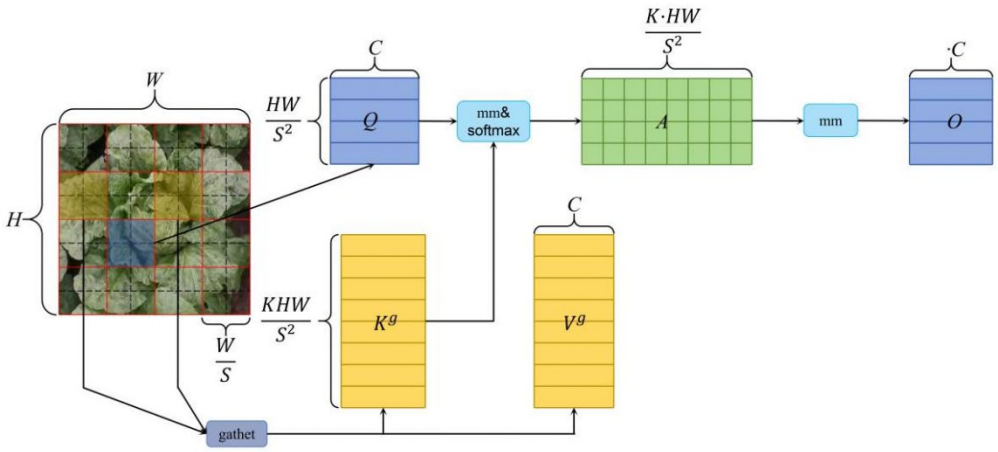


Figure 5 BRA attention workflow

3.1.3 BWT-YOLO Model Network Structure and Training Results

The target spray system employs a real-time inference and decision-making approach for

spraying, which is efficient, precise, and environmentally friendly, making it suitable for precision spraying on vegetables. However, the target system is constrained by the computational power of the sprayer, with relatively small memory, making it difficult to deploy large detection models.

The C2f modules in the deep layers (closer to the output) of the Backbone were replaced with BRA multi-scale attention mechanism modules to increase the receptive field of the deep layers. The feature maps in the deep layers of the Backbone have lower resolution but stronger semantic information. Increasing the receptive field at this stage can capture broader contextual information, enhancing detection capability for large targets or complex scenes. Multi-scale features enhance semantic information, making it suitable to extract features of different granularities through multi-scale modules, thereby increasing the diversity of high-level semantics.

In the feature fusion path of the Neck, standard convolutions were replaced with WTConv. The Neck is the core of multi-scale feature fusion; FPN/PAN is responsible for fusing feature maps of different resolutions. Before feature map fusion, using the WTConv convolution method to increase the receptive field of the features can better integrate low-level details and high-level semantics.

The convolutions before the Head detection head were replaced with WTConv. The feature maps of the Head have higher resolution, making them suitable for capturing detailed information through a large receptive field, which can improve the detection performance for medium and small targets, as well as adaptability to changes in target scale and pose.

Therefore, the BRA attention mechanism was integrated into the YOLOv8 model, constructing a lightweight network model named BWT-YOLO, composed of WTConv modules. The BWT-YOLO network structure is shown in Figure 6.

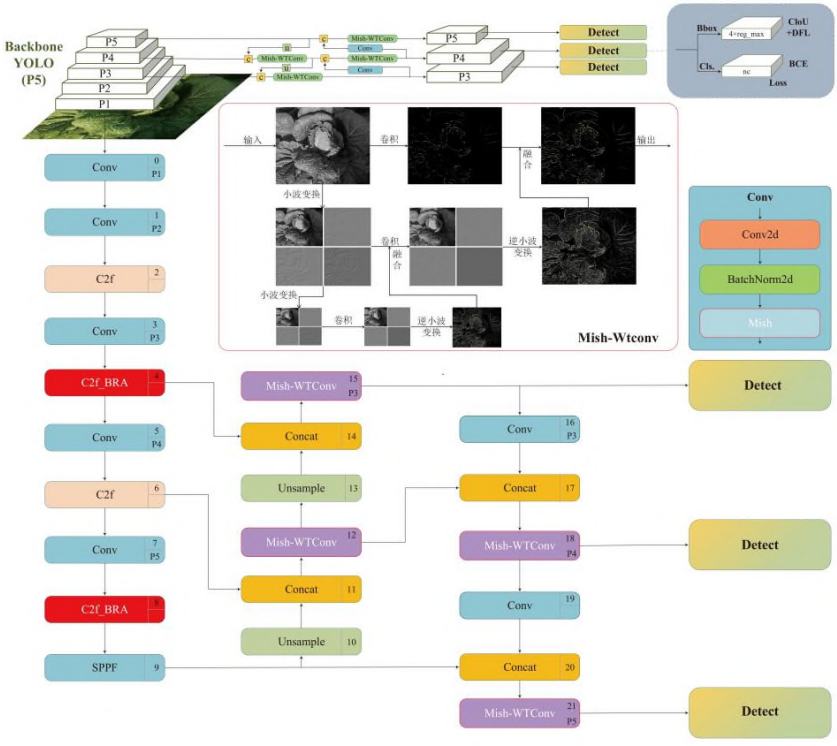


Figure 6 Improved BWT-YOLO network structure diagram

After model training, the BWT-YOLO model demonstrated outstanding performance in recognizing the heart of Chinese cabbage. Compared to the YOLOv8 model, both the number of parameters (Params) and computational complexity were significantly reduced. It enhanced the

detection accuracy for the Chinese cabbage heart and also showed better robustness when handling complex field environments. Its precision was 93.6%, recall was 92.4%, and mAP50 was 94.7. The training results of the BWT-YOLO network with the replaced backbone are shown in Figure 7.

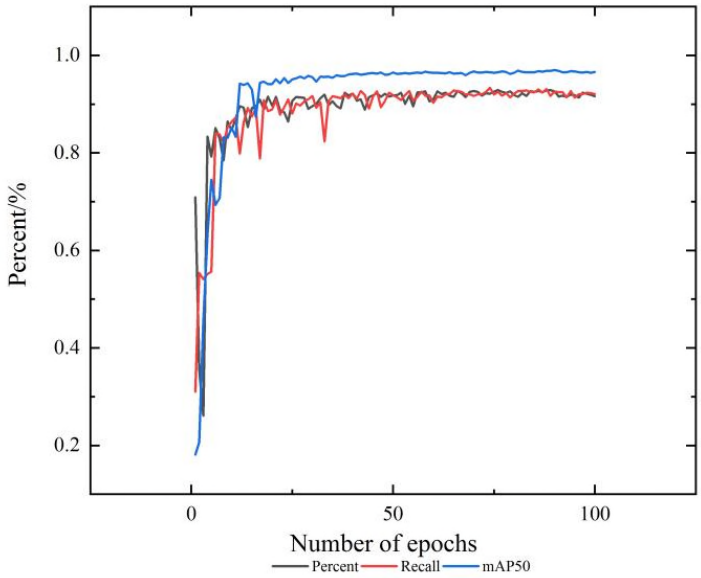


Figure 7 BWT-YOLO Training Result Graph

To verify the improvement effect of the BWT-YOLO model used in this study for the Chinese cabbage heart recognition task, the performance of YOLOv8 was compared with that of BWT-YOLO. The results are shown in Table 1. The improved BWT-YOLO model increased the mean Average Precision (mAP) value by 1.2%, increased Frames Per Second (FPS) by 8 frames, reduced Params by 0.7 M to only 6.5 M, making the model more lightweight.

Table 1. Research on Improvement Results of Chinese Cabbage Recognition Model Based on YOLOv8

Detection Model	mAP50	GFLOPs	FPS	Params
YOLOv8	93.2	10.8	75	7.2
BWT-YOLO	94.7	9.2	83	6.5

The recognition range of the target spray system is divided into recognition zones. An execution box is drawn for each zone, corresponding to the nozzle that needs to be opened. When the intersection area between the prediction box and the execution box reaches a set threshold, the host computer transmits the spray signal to the lower computer via serial communication. After delay processing by the lower computer, it controls the opening and closing of the solenoid valve. In practical applications, BWT-YOLO can accurately detect the heart of Chinese cabbage and control the spray system in real-time, ensuring the spray liquid is accurately applied to the target area, as shown in Figure 8.



a. Target recognition test result 1 b. Target recognition test result 2

Figure 8 Test results of testing Chinese cabbage with BWT-YOLO

3.2 Response Frequency Calculation Method

The Gemini-3D depth camera captures images forward at a 20° elevation angle. In the calculation, the following parameters were set: target width 50 cm, target distance 50 cm, the electromagnetic nozzle is 50 cm relative to the camera, and the nozzle height from the ground is also set to 50 cm. These relative positional relationships are shown in Figure 9. Based on the forward speed, target position, and the spatial position of the camera, data preprocessing was performed using Formula (1) to Formula (3) to calculate the response frequency of the spray. According to the camera installation position, the nozzle is fixed on the suspension frame, considered as a rigid connection, which helps ensure the accuracy and stability of the spray.

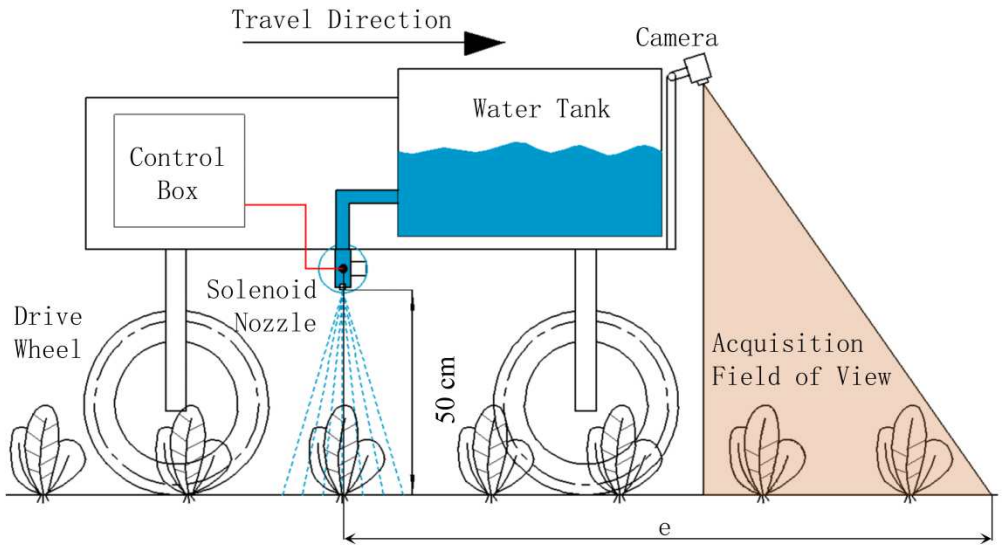


Figure 9. Space installation position of electromagnetic nozzle of target spray control system

$$T_1 = \frac{W_{target}}{v} \quad (1)$$

$$T_2 = \frac{d}{v} \quad (2)$$

$$f = \frac{1}{T_1 + T_2} \quad (3)$$

Where: W_{target} is the target width (cm); d is the corresponding target distance (cm); v is the forward speed (m/s); f is the switching frequency of the solenoid valve (Hz); T_1 is the opening time of the solenoid valve (s); T_2 is the closing time of the solenoid valve (s).

3.3 Real-time Control Method

3.3.1 Delay Analysis

In the target spraying process, ensuring consistency between target detection and spraying is one of the key points. Let the vertical distance between the camera's capture range and the nozzle be S. The system time t_{system} is the time taken for the sprayer to travel a distance L at a constant speed v, as shown in Formula (4):

$$t_{system} = \frac{S}{v} \quad (4)$$

Let $t_{inherent_delay}$ be the system response time. When $t_{system} > t_{inherent_delay}$, the sprayer can achieve consistency between target detection and spraying through system delay compensation. When $t_{system} < t_{inherent_delay}$, the time taken for the machine to advance is less than the system's time for image processing and response. Target spraying is achieved by changing the camera angle and the relative position S between the camera and the nozzle.

To determine the system's delay time, it is first necessary to measure the overall response time of the system.

3.3.2 Response Time Measurement Points

The main sources of response time for the target spray system were divided into three parts for measurement:

(1) The image processing time, measured as t_1. In the experiment, the trained BWT-YOLO target detection model was deployed and run on the Jetson Xavier NX controller for detection. By processing 250 frames of field Chinese cabbage images, the total time consumed was 7,643.9 ms, the average time per frame was 29.50 ms, and the single-frame maximum time was 32.5 ms. The detection data is shown in Figure 10.

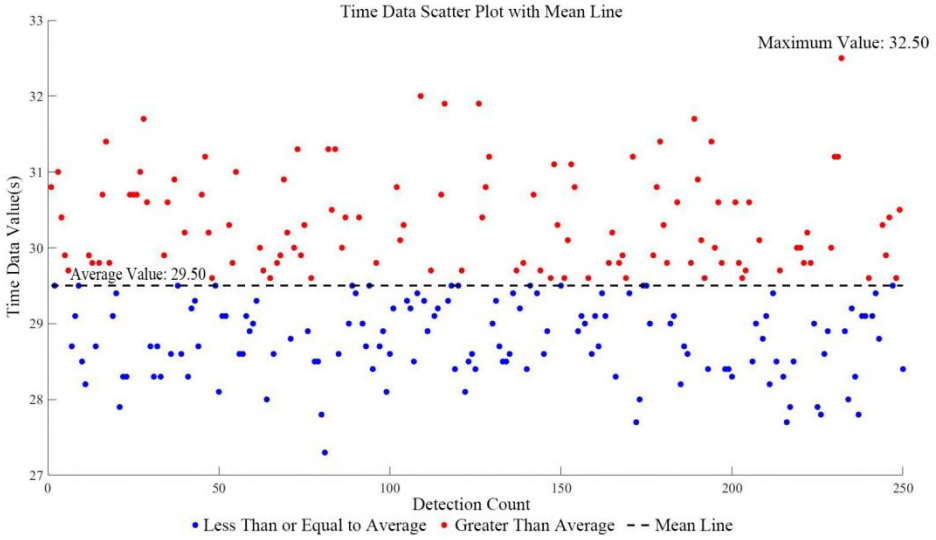
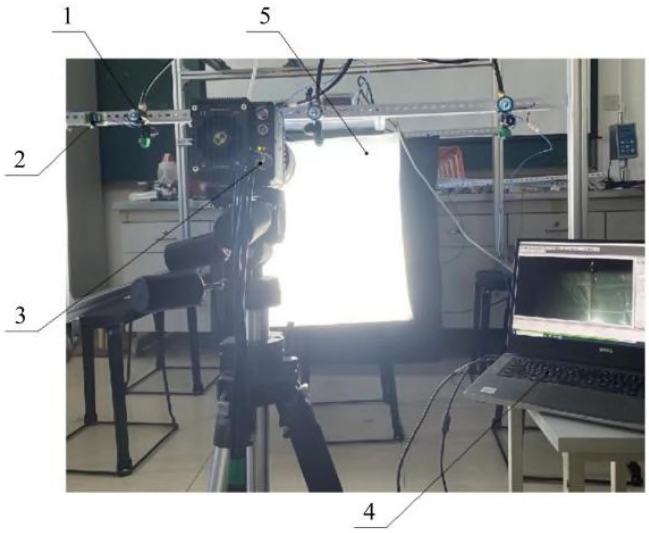


Figure 10. 250-frame Chinese cabbage image processing takes time

(2) The transmission time of the spray decision signal, measured as t_2. After the onboard

computer completes processing the target image, the signal is amplified by the relay bank output and finally drives the solenoid valve bank. This process was measured with an oscilloscope, taking 6.4 ms.

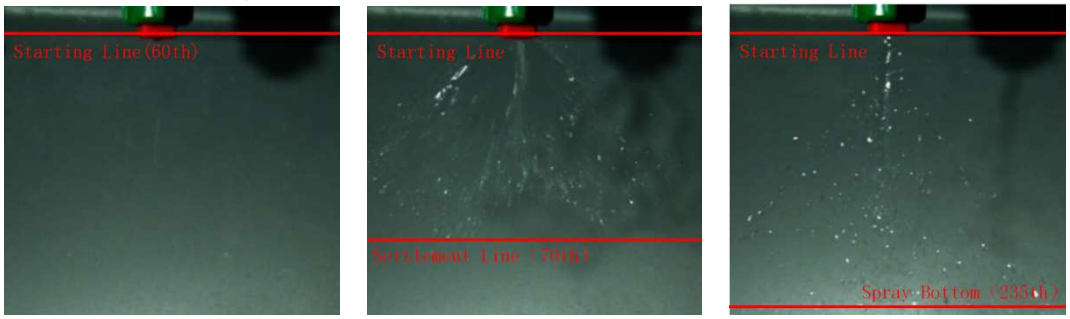
(3) The target spray duration, measured as t_3. After receiving the target spray decision, the solenoid valve opens for spraying, and pressurized pesticide is atomized through the nozzle and deposited onto the target. A high-speed camera was used to film the spray process. The filming system included a PCO.dimax CS3 camera host and a NIKON 24-85mm F2.8-4D wide-angle zoom lens. The filming site is shown in Figure 11.



Note: 1. Electromagnetic nozzle 2. Relay 3. High-speed camera 4. Computer 5. Fill light

Figure 11. High-speed shooting target spraying time-consuming scene

Under specific conditions (pipeline pressure 0.3 MPa, nozzle height relative to target 50 cm), the shooting frequency was 5,000 fps, and the exposure time was 3.26 μs. By analyzing 350 frames of images, key nodes of the spray process were determined: the solenoid valve received the spray signal from the relay at frame 26, spray began to emerge from the nozzle at frame 60, liquid atomization was complete and continuous spraying started at frame 70, followed by the relay indicator light turning off at frame 75, until the spray completely stopped at frame 235. After calculation, the entire spray process took t_3 = 88.83 ms. The recorded process of the target spray duration is shown in Figure 12.



a. Start of spray b. Spray deposition c. End of spray

Figure 12. High-speed camera photographs single signal spray process

According to the time consumption Formula (5):

$$t = t_1 + t_2 + t_3 \quad (5)$$

Where: t is the lag time of the target spray response (s). Finally, it can be concluded that the target spraying response lags behind the electrical signal by approximately 124.73 ms. This provides data support for the selection of forward speed, pressure, and delay processing for spray decisions of the target sprayer, and its measurement method has certain applicability.

Based on the hysteresis of the target spray control system, the sprayer's advance time must be greater than the system response time, i.e.,$t_{system} > t_{inherent_delay}$, which requires the sprayer's forward speed $v \leqslant 14.4$km/h.

4 Target Spray Volume and Coverage Acquisition Experiment

4.1 Experiment Purpose and Content

To ensure a constant pesticide dosage applied to the target crop during target spraying and to investigate the changes induced by the rapid on/off switching of electromagnetic nozzles in order to optimize spraying operation efficiency. Based on actual agronomic application requirements and the response lag time of target spraying, the impact of electromagnetic nozzles on the system at different switching frequencies was explored. Through flow rate acquisition experiments, the difference between the actual spray volume and the required spray volume was clarified, and based on this, the optimal forward speed suitable for target spraying was determined. The specific experimental contents are as follows:

(1) According to the preset agronomic conditions, including plant spacing and target width, the sprayer speed was set to 3.6, 7.2, 10.8, and 14.4 km/h, respectively. Corresponding electromagnetic nozzle output switching frequencies were set based on these speed conditions. During the experiment, the spray volume corresponding to a single on/off cycle of the electromagnetic nozzle at different frequencies was measured, and the cumulative value over 1 minute of switching was calculated.

(2) To obtain more accurate experimental data, multiple test results were recorded, and the average value was calculated. Origin software was used for curve fitting of the data to more intuitively show the relationship between spray volume change and switching frequency. The fitted curves were compared, relative error values were calculated, and the accuracy of the experimental results was evaluated.

(3) The experimental results were analyzed in depth. The actual performance of the spray under different switching frequencies of the solenoid valve was evaluated to determine a suitable operating speed.

(4) Under different speeds, continuous target spraying operations were performed on 100 Chinese cabbage plants in the field, recording the recognition time for a single plant and the overall operation time. The spray coverage on the heart of each single Chinese cabbage plant and the spray volume were recorded to verify whether they met practical needs.

4.2 Experimental Materials and Methods

Field experiments were conducted in a Chinese cabbage experimental field located in Anda City, Suihua City, Heilongjiang Province, in August 2025.During the experiment, based on an application rate of 450 L/ha and a speed selection range of 3.6 km/h to 14.4 km/h, the nozzle model and spray pressure for target spraying were determined according to the testing standard for agricultural and forestry machinery - sprayers in use (GB/T 32250.2-2022, 2022). The planting spacing and row spacing of the Chinese cabbage were both 50 cm, therefore the number of Chinese

cabbage plants per hectare could be estimated to be approximately 40,000. The required dosage per plant, i.e., the required spray volume per single on/off cycle, was obtained by dividing the required spray volume per hectare by the number of Chinese cabbage plants per hectare. The test protocol for obtaining the spray volume is shown in Table 2.

Table 2. Test protocol for obtaining the spray volume of the target spray system

Application Rate (L/ha)	Speed (km/h)	Nozzle Model	Spray Pressure (MPa)	Frequency (times/s)
450	3.6	ST110-04	0.2	1
450	7.2	ST110-06	0.4	2
450	10.8	ST110-10	0.3	3
450	14.4	ST110-15	0.25	4

Carmine red dye was added to the liquid tank. A meter ruler and a 10 m long white filter paper were arranged on the left side of each row of Chinese cabbage (when water mixed with carmine red is sprayed onto the filter paper, it turns red). The proportion of the colored area was used to obtain the target spray coverage. A measuring cylinder was installed below the nozzle to read the actual spray volume during the target spraying process. The coverage for each Chinese cabbage plant was calculated, and finally the average spray coverage was obtained. The target spray test site is shown in Figure 13.



Figure 13. Test site of Chinese cabbage on target spray

4.3 Experimental Results and Analysis

Since the switching frequency of the electromagnetic nozzle was too fast at a speed of 14.4 km/h, making it impossible to quickly measure the spray volume per single on/off cycle, the nozzle opening time was controlled to 0.125 s and the closing time to 1 s for measuring the single-cycle spray volume, leaving sufficient time for measurement at 14.4 km/h. To reduce experimental error, five repeated trials were conducted under the same conditions, and the average of the repeated trial results was taken as the final result. The measured single-cycle spray volume and the cumulative 1-minute spray volume corresponding to the four speeds of the target spray system are shown in Table 3.

Table 3. Study on Spray Amount Acquisition of Target Spray Control System

Nozzle Model	Spray Pressure (MPa)	Speed (km/h)	Frequency (times/s)	Actual Target Spray Volume (L)		Required Target Spray Volume (L)		Relative Error (%)	
				Single-Cycle	1-min Cumulative	Single-Cycle	1-min Cumulative	Single-Cycle	1-min Cumulative

ST110-04	0.2	3.6	1	0.014	0.86	0.0108	0.65	30	32
ST110-06	0.4	7.2	2	0.012	1.36	0.0112	1.35	7.1	0.7
ST110-10	0.3	10.8	3	0.010	1.58	0.0104	1.95	3.8	19.0
ST110-15	0.25	14.4	4	0.010	2.76	0.0061	2.95	63.9	6.4

The experimental results were processed, and a bar chart for the four different speed groups was plotted, as shown in Figure 14.

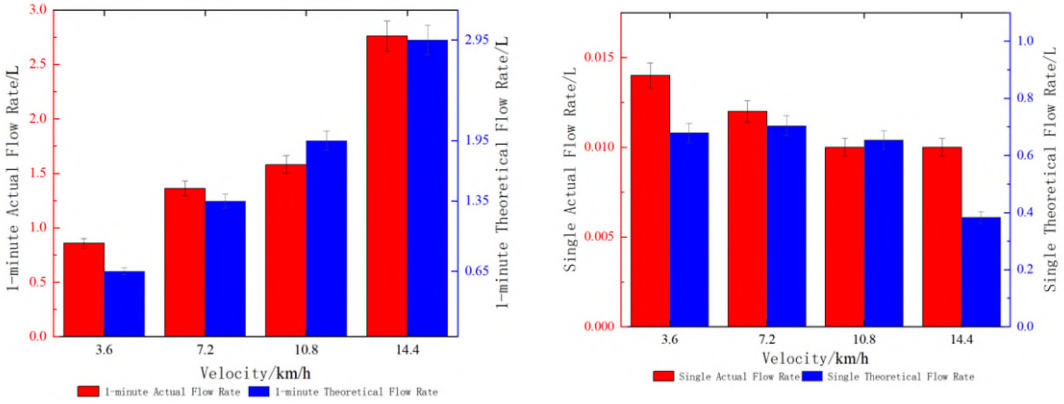


Figure 14. Obtain test results for target spray flow rate

As can be seen from Figure 11, the variation in spray volume difference caused by a single on/off cycle is relatively small. However, as time accumulates, speed increases, and the spray switching frequency rises, the difference in spray volume under different operating conditions becomes significant. In particular, at a speed of 10.8 km/h, both the single-cycle and 1-minute actual spray volumes were less than the required values, failing to meet the operational requirements. At 3.6 km/h, both the single-cycle and 1-minute actual spray volumes exceeded the required values. At 14.4 km/h, although the 1-minute actual spray volume did not differ greatly from the required volume, the spray volume per single cycle showed a large discrepancy. Only at a speed of 7.2 km/h did the operational spray volume meet the requirements, and the actual spray volume basically matched the required spray volume.

The carrying platform advanced at the set speeds. After each trial, the system detection time was exported, and each sprayed target was photographed individually. The actual spray volume from the measuring cylinder and the start and end scales of the carmine red water stain on the filter paper strip were read and recorded in EXCEL. Figure 15 shows the target spray coverage at a speed of 7.2 km/h.



Figure 15. Target spray coverage rate of Chinese cabbage plant center at 7.2 km/h speed

At a speed of 3.6 km/h, the average coverage rate for target spraying on 100 Chinese cabbage plants was 88%, with an actual spray volume of 156 mL. As the speed increased, the average coverage rate of target spraying gradually decreased, and the spray volume gradually reduced. When the speed reached 14.4 km/h, the average coverage rate for 100 cabbage plants was 77%, with an actual spray volume of 57 mL. The specific experimental results are shown in Table 4.

Table 4. Target Spray Test Results of Plant Core Coverage of Chinese Cabbage

Nozzle Model	Spray Pressure (MPa)	Speed (km/h)	Single Plant Recognition Time (ms)	Overall Time (ms)	Average Coverage (%)	Actual Spray Volume (mL)	Required Liquid Volume (mL)
ST110-04	0.20	3.6	38.6	4020	88	156	108
ST110-06	0.40	7.2	37.9	3982	86	135	112
ST110-10	0.30	10.8	38.5	4001	82	102	104
ST110-15	0.25	14.4	37.6	3958	77	57	61

5 Conclusion

This study designed a machine vision-based target spray control system for the recognition of the heart and inner leaf margins of Chinese cabbage plants. The system covered the construction and configuration of the hardware platform, introduced targeted improvements to the deep learning algorithm to achieve efficient identification of the Chinese cabbage heart, and conducted algorithm verification experiments. The following conclusions were drawn:

(1) An improved BWT-YOLO model for Chinese cabbage heart recognition was constructed. Its precision, recall, and mAP50 reached 93.6%, 92.4%, and 94.7%, respectively. Compared to the general YOLOv8 network model, mAP50 increased by 1.2%, FPS increased by 8 frames, and Params decreased by 0.7 M to only 6.5 M, ensuring the accuracy of target spraying.

(2) The response time of the target spray system was systematically measured and analyzed. The image processing averaged 29.50 ms, decision signal transmission took 6.40 ms, and the spray duration was 88.83 ms. Combining these three key stages, the total response lag time of the target application system relative to the electrical signal was approximately 124.73 ms. This temporal data provides a basis for optimizing the spray control system.

(3) Based on the target spray volume and coverage acquisition experiments, this study found that under the condition of 7.2 km/h speed, the difference between the actual and required values for a single switching cycle was small, and the variation in the difference over 1 minute was also minimal. This ensures that the spray volume meets the requirements without causing excessive

waste of liquid.

(4) In practical operation, at a speed of 7.2 km/h, every Chinese cabbage plant was successfully identified with no missed detections. The average spray coverage for a single Chinese cabbage plant was 86%, and the spray volume met the actual operational requirements.

CRediT authorship contribution statement

Changxi Liu: Writing – review & editing, Writing – original draft, Software, Methodology, Data curation, Conceptualization. Hao Sun: Validation, Supervision, Investigation. Hang Shi: Writing – review & editing, Validation, Investigation. Hui Zhang: Investigation, Validation, Writing – review & editing. Qingda Li: Resources, Project administration, Funding acquisition. Jun Hu: Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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